Mapper, Web link), is one of the popular drone data processing software which offers a range of desktop processing packages for aerial mapping applications for various sectors, including structure and site surveying, agriculture, and 3D rendering.

In this paper we discuss one such indigenously integrated with the body frame parts and other sensors from COTS hardware and built using open source technologies and software tools for better configurability and security during the flight and also enable us to use the swappable payload camera operated through the programming SDK or auto scripts loaded in the camera. Milind-1 also uses the on board computing for receiving the signal from GAGAN and stamping of the information to the Images being captured during the flight time.

3. MILIND-1—CUSTOM DRONE PLATFORM FOR REMOTE SENSING APPLICATIONS

In this section we first illustrate the back ground and motivation for development of Milind-1, followed by hardware components and software tools used in the development of Milind-1 UAS are described.

3.1 Back ground and motivation

Though, the COTS drones have many advantages like stability, more proven, handy to use, however, they have major drawbacks in usage especially in terms of configurability and security, because the hardware, software modules supplied/bundled along with the drone are closed box which are based on vendor lock in technology. In majority of the cases, the APIs and internal hardware/software details are not provided for the developers/integrators. Also, the payload cameras to use are mostly from the same vendor, and majority of the cases the cameras come with integrated to the system, which does not allow any other camera operations for imaging. Hence, the above said aspects have led to the development of an indigenous UAS system Milind-1, which provides configurability in terms of swappable payload camera, change of indigenous navigation and finally data processing both on board as well as on ground.

Below, we describe the salient features of Milind-1 followed by several major components used for building the drone and open standard software and hardware protocols.

3.2 The salient features of Milind-1

The salient features of Milind-1 are i) the custom built drone for aerial applications are ii) Do It Yourself (DIY) drone built with COTS hardware iii) Maximum All Up Weight (AUW) is 16 kg, with 1.5 mtr diameter Octocopter iv) 30 Ah Battery, however can be swappable/configurable battery depending on the flight time required v) able to fly from several meters to 1 km altitude vi) swappable payload camera and with a provision for programmable camera to operate during the flight time vii) endurance of 25 minutes for a payload of 6 kg with 30Ah battery for an altitude of 500 m viii) GPS/GAGAN/IRNSS sensor for precise positioning ix) mission planning open source based software module x) secured flight path and flight logs xi) provision for on board processing for compression, image enhancement etc xii) Image processing software tools for Point Cloud, DSM and Ortho mosaic generation.

3.3 Custom drone tailored for Aerial surveillance - Milind-1: Components, System Architecture and interfacing

Drones rely on a number of sophisticated technologies, but many of these are still under development both in technical and functional aspects. Building the drone for custom/tailored applications still pose many challenges as they demand both technical and functional challenges to bring them in force/action. Here, we discuss one such drone namely Milind-1 built for aerial surveying applications with swappable payload camera and geo stamping on the image with GAGAN sensor. We first describe the components of the Milind-1 Octocopter followed by system architecture and interfacing of the components. The Components of Milind-land their arrangement on the octocopter frame are shown in Figure 4.

3.1 Essential Elements for building customization drone – Technical challenges

The essential elements/parts used for building the Milind-1 are described in Table 1, which presents the brief description of the sensors and the specifications of the sensors used.
Figure 5. System Architecture (Component interface diagram) – Milind-1

Table 1. Technical specifications of the parts/sensors in Milind-1

<table>
<thead>
<tr>
<th>S.no.</th>
<th>Component Name</th>
<th>Description</th>
<th>Milind1 – specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Frame</td>
<td>All the drone components are mounted to the frame. The frame should have sufficient place to mount all the components and should be very stable. Frames usually come in various shapes and sizes made with different material like plastic, foam, carbon fibre etc.</td>
<td>Carbon fibre having 400 mm diameter circular frame, having 8 mounts to placing arms and provision to fasten the arms to the frame. Provision to place the battery flight controller, GPS and other on board computing systems, GAGAN receiver. Provision to mount the camera on the bottom of the frame with a vibration dampening straight/nadir looking.</td>
</tr>
<tr>
<td>2</td>
<td>Arms</td>
<td>Used to for mounting the motors. The arms are chosen such that there is very less vibration on the body to have very minimal blur during the imaging.</td>
<td>The arms are made with carbon fibre, which are light weight and strong. The arms are picked such that they introduce no or less vibration during the imaging. The approximate length of the arm is 600 mm.</td>
</tr>
<tr>
<td>3</td>
<td>Power Distribution Board (PDB)</td>
<td>Printed circuit board that is used to distribute the power from battery to all different components of the multi rotor.</td>
<td>PDB chosen has enough copper points to connect 8 nos of ESC and is connected to the battery via the power module.</td>
</tr>
<tr>
<td>4</td>
<td>Power Module</td>
<td>Power module (PM) provides enough power for the flight controller and to power distribution board.</td>
<td>The power module selected here takes a maximum of 25.2 volt and minimum of 4.5 V, with 6-pos DF13 cable is used to connect to Pixhawk flight controller.</td>
</tr>
<tr>
<td>5</td>
<td>Motors</td>
<td>The motors are fitted to the arms. Usually Brushless DC motors (BLDC) which creates a minimal friction. A cylindrical shell of magnets rotates on precision bearings around a core of tightly and nearly coiled wire.</td>
<td>Brushless DC motor with Kv 288 configuration, which can take a load of 2 kg to 3.5 kg maximum with each motor weight of 213 grams is used. Motors are mounted to the arms and are used for mounting the propellers.</td>
</tr>
<tr>
<td>6</td>
<td>Electronic Speed Controller (ESC)</td>
<td>ESCs translate signal to electrical supply, with every motor connected to ESC to adjust its speed. The major factor for any ESC is the current rating the maximum it can draw, which should be more than the current drawing rate motor connected. Generally, 30A for medium/large quads and 10 to 12 A for small quad is sufficient. A medium sized hexa copter can easily draw 40A.</td>
<td>The ESC chosen here is 6S supported which can give a maximum thrust of 60Amp. There are 8 such ESCs are used for building/customization of the drone.</td>
</tr>
<tr>
<td></td>
<td>Propeller</td>
<td>Carbon fibre propellers are used here, with twin blade 18 inch in length, with pitch of 5.5 inch. Here, 4 propellers rotate in clock wise and other 4 in anti clock wise direction.</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>-----------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Propeller</td>
<td>Propellers play a vital role in vertical lifting of the drone. The propellers are usually measured in inches. The smaller propellers are usually selected for higher Kv motor to have more speed, and larger propeller with correspondingly low Kv rating of the motor is used for nominal flight speed, which is generally suitable for imaging applications.</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Battery</td>
<td>LiPO battery with 6 Cell, 30 Ah capacity with maximum continuous discharge of 25C and maximum burst of 50C is used with a voltage of 22.2 V to 25.2 V.</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Remote/Radio Controller</td>
<td>RC operating in 2.4 GZ frequency is used for operating the drone. The ground module is 8 channel configured to operate for throttle, pitch, roll, yaw and other control parameters like Return to Home (RTH), hovering, GPS lock mode, auto mode set. The module on the drone placed is 2.4 GHZ transceiver.</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Remote/Radio Controller</td>
<td>The device used for monitoring the information about the aircraft. During the flight the logs are transmitted to the ground module for monitoring the important flight logs like location at which the flight is operating, altitude, speed, distance etc. Usually they operate in ISM band.</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Telemetry</td>
<td>Telemetry used here is 915 MHz ISM band with both on board and ground module. The telemetry used here provides a range of approximately 2 km. The telemetry is also used for loading the mission planner/flight path way points to the flight controller.</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Flight Controller</td>
<td>Flight Controller is a an important which is an important component in the drone. Usually flight controller are microcontroller running Real Time operating System (RTOS) to operate the drone as they receive command from the operator. They contains IMU sensors and provides other interfaces to connect ESC, GPS, telemetry and RC flight modules etc. Here, we used PIXHAWK 2.4.8 ardupilot supported flight controller.</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>GPS, GAGAN, and other sensors like compass, and gyro etc.</td>
<td>GPS sensor provides the position information to the drone, which is very essential for the drone to operate in auto flight mode. Compass offers the direction to the flight and other IMU sensors like gyro and barometer provides the movement and air pressures to the flight. IMU sensors are part of the Flight controller and GPS and compass is interfaced to the flight controller as an external interface. Ublox Neo6M GPS with compass is used with ceramic path antenna with 6-pin D13 connector to connect flight controller. The device is with water resistant casing and protective case. GAGAN information is logged to the on board SOC and subsequently the images would be time stamped on the ground after the flight.</td>
<td></td>
</tr>
</tbody>
</table>
Flight mission planning software

Flight mission planner is used to plan the flight and dump/transfer the generated transects to the flight controller. The flight travels in the predefined path as defined in the transect files. For aerial imaging the missions are planned with the overlap across the image frames both in horizontal (along track) and side overlap across track.

Ardupilot mission planner is used for planning the mission. The generated mission planner files/transects are in turn transferred to the flight controller via USB interface or telemetry module.

Programmable camera

Cameras play a major role for capturing the good quality and stable images during the flight. There are many COTS cameras in the market which are suitable for aerial imaging.

The cameras we use are programmable cameras operated through Software Development Kit (SDK) supported by the respective vendor.

In the below section we describe the image planning methods, data acquisition and processing techniques for Milind-1.

4. MISSION PLANNING, IMAGE ACQUISITION AND PROCESSING

In this section we describe the methods for mission planning the mission using the open source ardupilot software, and image acquisition using COTS point and shoot DSLR programmable cameras and data processing methodology. Here, we also present the methods for geo stamping the images using GAGAN signal to the Image frame using Exif Tool. There are three major steps to be carried out viz a) mission planning b) image acquisition ii) geo stamping and iii) processing as described below.

4.1 Mission Planning

Mission planning is carried out using Ardupilot mission planning software. The sample diagram of the Ardupilot mission planner is shown in Figure 6. The right side of the picture depicts the google maps which are used as the back drop map for the mission planning. The left side top indicates the gyro movement, and left bottom box indicates the telemetry signals (Ardupilot, weblink). Figure 7 depicts the sample planned mission planning file for one of the test flights, during the planning, the payload camera configuration parameters are to be set with the mission planner, as explained in the Ardupilot mission planner guide (Ardupilot, weblink).

4.2 Image Acquisition

Image acquisition is carried out during the flight, however, before the mission flight it is essential to set the payload camera settings in the mission planner before the generation of way point grid file. After the waypoint selection is made, the survey grid generation, the overlap (side and adjacent) is to be setup as a parameter, in general the overlap parameter is set such that is not less than 60%, which is essential required to generate the point cloud data. Here, we use programmable DSLR cameras which can be operated via script or through Camera SDK (CSDK) APIs. Milind-1 is tested with Sony camera offer Camera Software Development Kit (CSDK) for operating the camera through the WiFi mode with REST (Representational State Transfer) APIs calls. The on board computing system can talk to the Camera and operate the camera with the built in programs working through the CSDK. Here, NvidiaTegra TK1 (Jetson TK1 Development Kit, web link) board as well as Raspberry Pi as on board computing device are tested via Wi-Fi module interface to the camera. The modules running on board will send a command to the camera at the regular intervals (which is configurable) and subsequently reads the on board data from the GAGAN receiver. The camera setting/programs are used to operate the camera at regular intervals of time say 5 seconds, and is flown at an altitude to achieve with the at an altitude required based on the best Ground Sampling Distance (GSD) required, and the height of built up facilities to avoid collisions if any.
4.3 Drone Aerial Data Processing (Map making with drones)

Aerial mapping software plays a vital role in processing the image/frames imaged by the on board camera on board. There are many types of software tools both COTS and Open Sources are available for aerial data processing. Like Pix4D, PhotoScan, ARCGIS drone2map and Open source software packages like OpenDroneMap. The data flow diagram for generating DSM and ortho mosaic for Milind-1 data processing software is depicted in Figure 8. Here, the raw data frames from the camera memory card are transferred to the ground based data processing system after the flight, to carry out the data processing operations. At first, the raw data frames are updated with the exif Meta data information with the geo location and the corresponding time stamp. This updation is carried out by in house built software module for the mission flown with GAGAN on board with Ardupilot mission planner for the missions with GPS only. Such time stamped raw data is transferred to image alignment module for computing the correspondence across the image frames. Image alignment process computes the correspondence relationship among images with varying degrees of overlap; the technique is based on the feature matching as explained (Richard, 2006). The matched features are given as input for Bundle Adjustment process for stitching the images. The stitched images are transferred to point cloud generation process, which uses triangulation method to generate the dense point clouds. The generate points clouds are used for generating the Digital Surface Model (DSM), and Textured 3D model and Ortho mosaic as described in Photoscan manual (Agisoft 2013).

The sample flight flown in auto pilot mode having Canon 16 Mega Pixel DSLR programmable point and shoot camera on board for the generation of Ortho image, Digital Surface Model (DSM) and 3D models is presented here. Two missions are flown; one is in the morning and another in the evening for the applications of change detection. Here, the scope is to process the data and generation of ortho and other related images, but not to study the change detection process. Each mission has resulted around 140 images, for total flight duration of 12 minutes. The flight is flown at an altitude of 100 mtr with a speed of 5 m/second with an overlap of side and adjacent approximately 60% for each frame of the image during the flight. The altitude flown is around 100 m from the ground level this resulted in 3 cm of ground sampling distance approximately. On board GAGAN is used for getting the position and location information, and will be time stamped after the mission as EXIF information using the custom built Exif tool. The images are processed using Photoscan software package for point Clouds, 3D models, and ortho photos generation of still images from each flight in Figure 9, Figure 10 and Figure 11 depicting ortho maps and Digital Surface Model (DSM) respectively.
5. CONCLUSIONS AND FUTURE WORK

The drone Milind-1 discussed is a custom built, configurable and secured UAS with the swappable payload camera and on board computing platform for limited processing and logging essential parameters. The solution provides high configurability in terms of selection of COTS components, selection of payload for different applications and finally use of ground processing software for generating desired result. Milind-1 platform is built using COTS based frame, motors, arms, ESC etc., and open source Pixhawk flight controller. A case study for mapping a corridor is performed where the flight path is planned using the ardupilot software and data is acquired using Canon A2500 camera. For ground processing we have used COTS package Photoscan and open source opendronemap software. The results are verified with ground truth and results are found to be satisfactory. At present, GPS ground truth is not used for processing, however, in future; it is proposed to use PPK and RTK GPS for achieving higher accuracies. At present, the system is operating with a LiPO battery, in future it is planned to extend or build for operating with both Battery and generator to have the improved endurance flight. It is planned to test the mission with different types of payloads ranging from multispectral to thermal for applications like agriculture, security/surveillance etc. Also, it is planned to use the communication payload such as UHF device to establish ADHOC communication to provide the communication facility in the non-reachable zone areas.

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VALUE ADDITION TO SATELLITE IMAGERY FOR MAPPING – AN IMAGE PROCESSING PERSPECTIVE

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ABSTRACT

A single satellite sensor meeting all the requirements of a good mapping is highly time consuming and economically not viable. In the present scenario of availability of multiple satellite imagery with varying resolutions, sensors and imaging techniques, efficient mapping can be achieved with value addition to the existing products. The objective of this paper is to present a methodology for high resolution mapping from multi sensor, multi resolution and multi temporal images from value added products. The value addition in terms of registration, pan-sharpening and mosaicking with focus on automation is proposed in the paper. In satellite imagery, panchromatic images have higher spatial resolution as compared with multispectral images. In order to obtain high resolution multi spectral images for mapping pan-sharpening approach is an efficient technique. The prerequisite for pan-sharpening is image registration. An automatic image registration based on multiresolution pyramids and Thin Plate Splines is adopted. The registered images are pan-sharpened with proposed modified Brovey for the specific sensor spectral characteristics to achieve better spatial resolution. Since the focus in mapping is to give more preference to spatial than spectral preservation, a cloud detection algorithm for selection of cloud free images is explained. Finally, an efficient automatic mosaicking methodology is used to combine pan-sharpened images to generate large canvas. Analysis and results are presented in the paper.

KEYWORDS : Value added products, automatic registration, mosaic , pan-sharpening, modified Brovey

1. INTRODUCTION

Remote sensing data provides much essential and critical information leading to an information revolution for mapping and management of Earth Resources. Earlier, it was through aerial photography but with the advent of high resolution satellite remote sensing, and due to its advantages as explained in the paper (Shibendu Shankar Ray) which are wide area coverage for a synoptic view, accuracy, repetitivity, inaccessible area coverage, multi sensor, multi spectral and temporal data, it has proved to be very practical and economical means (relatively inexpensive data per square kilometer) for a precise mapping. HRSI offers an alternative to line maps for various cartographic applications. Because image products come for a fraction of the cost of conventional maps, they contribute immensely towards the exploration and economic development of the less developed areas of the nation. The Indian Remote Sensing High Resolution Satellite constellation provides global, accurate, high resolution imagery for mapping, monitoring, and development. A high-resolution satellite imaging system is conceived with a series of design trades as explained in the paper (Firouz Abdullah Al-Wassai, 2013). The primary tradeoff is between spatial resolution and swath width. Similarly, between revisit time and off-nadir viewing angle, revisit time gets poorer if we want nadir images. Another tradeoff is between data transmission rates and number of spectral bands with better resolution. In order to overcome these limitations value addition internals of image registration, PAN sharpening and mosaicking is required for achieving high resolution spectral data, wider swath and use of multi sensor data for better mapping.

The proposed value addition processes lead to generation of products of region of interest which require a higher level of image processing to handle products based on multi sensor, multi resolution and multi temporal imagery data. Figure 1 shows the schematic data flow diagram for mapping depicting the important components of Value Added Product Generation processes. Data received in ground Station undergoes Data Processing Chain to generate ortho products. Data Qualifier will ensure selection of usable data only for mapping.

The volume of the remote sensing data is potentially large for high resolution images as the increase in spatial resolution leads to an exponential increase in data quantity. In order to handle large volumes of data for mapping there is a need for automation in the generation of value added products. The paper specifically focuses on automation of image registration, PAN sharpening and mosaicking processes for generation of value added products towards mapping. The Value Added Products are based on Ortho Image Products. Since value addition entails higher level of processing, there are certain criteria to be met that are explained in the paper (Moon-gyu Kim, 2001) and are listed as follows:

- Maximum automation for higher efficiency, low processing time, less human intervention, higher throughput
- Handling of higher Data Rates
- Single Point of Failure should be avoided to achieve highly reliable system
- All the components of system should be integrated efficiently for smooth operations.
- A generic solution with future expandability for multi mission multi sensor handling.
- System should be secure enough to only allow authorized access

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Registration is the process of overlaying two or more images of same area taken at different times by the same sensor or different sensors by taking corresponding control points and fitting a transform such that two images are geometrically aligned. With the large volumes of data available for processing and analysis, automatic approaches are required to achieve faster generation time and higher accuracies consistently. The robustness and time efficiency of the automatic registration process is critically dependent on the search scheme for identification of control points. Several papers discussed automatic image registration from the point of selection of control points assuming that the images of corresponding regions are extracted and made available (Alexander Wong 2007, Jordi Inglada 2004, Youcef Bantoutou 2005, Siavash Zokai 2005). A generalized search scheme for automatic registration (Suresh Kumar P, 2012) of multi resolution and multi sensor remote sensing data is adopted and shown in figure-2. It comprises of three levels of search ranging from coarser to finer. This process is capable of registering images to sub-pixel level accuracies and robustness to rotation and scale variations and also translations between images. The methodology consists of three broad levels of processing. The image registration is achieved step by step as the image passes through different levels. A reference image is defined as an image which is geocoded or precision products to which other images will be registered. A target image is an image which is to be registered with respect to reference image. In this scheme Mutual Information (MI) is used as a similarity measure and a non-rigid transformation Thin Plate Spline (TPS) is used for achieving sub-pixel registration accuracies (Lyubomir 2006, Stefan Klein 2007, Claude Cariou 2008). Mutual Information method is one of the area-based methods for image matching. MI is found to be better for identification of match points even for images that are radiometrically non-linear. In order to reduce the low pass effect of multiple transformations involved in the multi-level registration process, a direct correspondence between the reference image and target image was established so that a single resampling need to be applied. This correspondence also helps to generate products at any desired pixel size or to keep the original resolution intact.

The performance of an image registration depends on the accuracy of match points and the ability of transformation function to utilize the match points effectively. TPS is widely used as transformation function for non-rigid bodies and adapted for registration of remote sensing images (Goshtasby 2006). Unlike global transformation methods, use of non-rigid transformation like TPS achieves sub-pixel accuracy in the moderate hilly regions as well as high hilly regions where relief displacements are high, provided sufficient number of control points are generated. This will take care of internal distortions, which cannot be corrected by global transformations like affine and polynomial transformations. This transformation gives global coefficients and corrects internal distortions locally.
2.1. Accuracy and Robustness of Registration Process

Figure-3 shows the match points of registration process as explained above applied between PAN and Multispectral images of different resolutions. A quantitative analysis has been carried out to estimate the registration accuracy. To check the consistency and accuracy of the registration process, three multi-date images named as ImgA, ImgB, and ImgC. ImgB and ImgC are registered independently with ImgA as reference. The registration accuracies are found to be 0.06 pixels. The accuracy between ImgB and ImgC found to be 0.08 pixels which is a measure of consistency of the registration process.

Figure 3. Match Points/Tie Points between Reference and Target Image

3. PAN SHARPENING

Pan-sharpening is the process of merging different sensors (from same or different satellite) on a pixel to pixel basis in a composite image without introducing artifacts. In this process a merged/pan-sharpened/fused product with both high spatial (from Panchromatic image) and high spectral (from Multispectral image) resolution is generated. It has several advantages and applications for better image analysis capability for cartographic applications and better image classification capability for remote sensing applications. Many techniques for PAN sharpening were developed (W.J. Carper Apr 1990, Z. Wang Jun 2005) with primary objective to preserve spatial and spectral information contained in High Resolution PAN Image and Low Resolution Multispectral Image respectively.

Figure-4 shows the proposed methodology for PAN sharpening (R. Chandrakanth, Apr 2014). High Spatial Resolution Panchromatic image and High Spectral Resolution Multispectral image are taken. They are automatically registered. Further, Modified Brovey Transformation is applied on registered PAN and MX pair to get Merged Product. The result of applying PAN sharpening process on PAN and Multispectral images is shown in Figure-5.

Table 1 shows the analysis of different methods for Pan sharpening. It illustrates a balanced performance in preservation of spectral and spatial information through ERGAS, RMSE, SAM and correlation measures of spatial and spectral qualities (Yun Zhang 2008, Shuang Li Mar 2010).
Table 1 Evaluation of PAN Sharpening

<table>
<thead>
<tr>
<th>Evaluation Parameter</th>
<th>Pyramid Method</th>
<th>Modified Brovey Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERGAS (best close to 0)</td>
<td>1.283425</td>
<td>3.021916</td>
</tr>
<tr>
<td>RMSE (best close to 0)</td>
<td>6.936729</td>
<td>16.372886</td>
</tr>
<tr>
<td>SAM (best close to 0)</td>
<td>0.347552</td>
<td>0.101019</td>
</tr>
<tr>
<td>Correlation Coefficient (best close to 0)</td>
<td>0.147977</td>
<td>0.193681</td>
</tr>
<tr>
<td>Spatial Correlation (best close to 0)</td>
<td>0.891064</td>
<td>0.963212</td>
</tr>
</tbody>
</table>

MOSAICKING

Image mosaicking is the process to join two or more overlapping images to increase the coverage area and create a full product according to the requirement. Mosaicking helps to seamlessly stitch more than one image to form a big canvas which serve the purpose of mapping and generating city/district/country level products. There are many challenges viz. a) High volumes of data b) handling of many images c) seamless stitching d) feature continuity across scenes e) radiometric normalizations among multi-date and multi-sensor images. Overview of mosaic system based on feature matching and blending is explained (M. Brown, 2007).

Due to the high agility of the satellites image acquired on different dates may have different view angles, which can cause discontinuity / break in high raised features. The changes in the illumination conditions, seasonal variations, atmospheric effects create radiometric mismatch in the overlap and adjacent scenes. Constellation of satellites is being used to create reference layers for the purpose of cartographic mapping applications. So the relative radiometric differences due to non-uniformity across sensors are common problem to be addressed for mosaicking. Different image based stitching are explained in the paper (Shikha Arya, 2015). Due to availability of more number of satellites, the number of images to be stitched and image sizes is also large due to use of high resolution images for the above said applications. So, mosaicking involves handling of huge volume of data to create big canvas image. For large-scale applications of remote sensing image mosaicking usually requires significant computational capabilities. Several studies have been attempted (Lajiao Chen, 2015) to apply parallel computing to improve image mosaicking algorithms and to increase the throughput.

The success of automatic mosaic process to get seamless product depends on the selection of images, establishing of feature continuity in the overlap regions, global radiometry between the adjacent scenes, seam line construction and correction. Based on these requirements and limitations at every stage, we proposed suitable and efficient techniques in every process of correction. Optimal sequencing of individual products is established to get better overlaps and better radiometric normalization and stitching. Robust automatic registration tool is used for establishing feature continuity. Automatic irregular seam line construction is proposed to avoid the limitations that arise with high rise building features in high resolution images. Multiresolution based approach is proposed for seam correction to overcome the limitations with $\alpha$-blending and averaging techniques. Figure 6 shows the proposed flow diagram for automatic image mosaic.
5. RESULTS

The methodologies proposed in registration, pansharpening and mosaic is applied on different PAN and multispectral images with different resolutions. In this paper results on PAN and multispectral data involving value additions for mapping are presented. Figure 8 shows the result of 60 PAN data products and 20 Multispectral data products.
6. CONCLUSIONS

A generalized and automatic approach for value addition to high resolution remote sensing images for mapping applications is presented. The effective approach for automatic registration of multi sensor, multi date image is presented. Further using this registered output various value added product as pan-sharpening and mosaicking methodologies are explained. These methodologies are found to be very effective in application in terms of sensor and satellite. The approach was applied on wide spectrum of images.

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UTILITY SPATIAL MAPPING AND MANAGEMENT USING QGIS WITH CARTOSAT-1 IMAGERY AND MOBILE TRACKNDIGITIZE TOOL BASED ON GPS/GAGAN

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ABSTRACT

Utility spatial mapping and management of mapped utilities in geospatial format is an important task for any organization to have their utilities mapped and managed in geospatial database. Such mapped utilities in geospatial format are used further for spatial study and analysis to understand its relationship with other assets or features, interpret the features, patterns, trends and subsequently visualize such mapped utilities to gain insights of the developments being taken place over a time period.

In this paper we address one such utility mapping and spatial management using Open Source QGIS Software package. The various utilities mapped here are Office complex, Service areas, Residential Buildings, Green Cover, Road Network, Water & Drainage System, Bore wells, Electrical Network, etc. Here, for mapping the utilities Cartosat-1 satellite imagery with 2.5 m spatial resolution is used as reference layer for the utilities which are covered and have the greater visibility for mapping. In the case of non-coverage and non-visibility of the areas to be mapped, an indigenously developed Mobile Application called TrackNDigitize is used, which collects the geo positions using GPS/GAGAN receiver on the backdrop of Google maps. Finally, all such digitized features are collated in QGIS package for generation of the spatial vector layer. The paper presents the mapping of the above said utilities and also describes various utility attributes like Building Type, Year of Construction, and Areas under green cover, Bore well Yields, Preventive Maintenance of Utilities, UG Cables Layout, etc. The proposed utility mapping and management system allows the organizations to have a constant watch around their vicinity and monitor the developments being happening using Geo spatial techniques.

Apart, the proposed Utility Management System will help all the Maintenance Engineers / Users for immediate decision making process, prioritising the maintenance activities and also effective monitoring of the facilities in and around the campus.

KEYWORDS: GIS, Utility Mapping, QGIS, Remote Sensing, TrackNDigitize, GPS, GAGAN

1. INTRODUCTION

The world is changing with the manmade features being built around us with the new developments taking place so frequently. In this process, there is a requirement of updating the existing as well as new such facilities being built becomes more critical and crucial for present and future analysis of the geographical data. Hence it becomes necessary to map such built in features around us as utilities along with their key features being captured in the organized way. The significant feature required for managing the information and retrieval of such information as per requirement requires an efficient mechanisms and software tools for easy updating and quick retrieval of geographical data. In today’s era Geographic Information System has found its use in almost every field of Science & Technology for systematic way of organizing the data and retrieval of the same as required.

According to ESRI, GIS is defined as an organised collection of Computer hardware, Application software, Geographic data and personnel designed to efficiently capture, store, update, manipulate, analyse and display all forms of Geographic referenced information [ESRI].This technology can be used by anyone for making decisions based on spatial data all the time. GIS with its high potential of creating spatial digital database by digitization of existing maps and other data sources thus serves our purpose.

The attribute data is the metadata information which is related to each utility and can also be linked using GIS Platform. Thus GIS is both a database system with specific capabilities for spatially referenced data as well as a set of operations for working with the data. In a more generic sense, GIS applications are tools that allow users to create interactive queries (user created searches), analyse spatial information, edit data, maps, and present the results of all these operations. [Angarakh 2009].

An Open Source QGIS Software - QGIS version 2.14.2 is used for creating Geo-Spatial Database of our campus. QGIS provides a window that is used to explore, access, analyse, and create various types of Geographic data. The kind of data include here is Raster files, Vector files Geo-databases and Web services. QGIS canvas allows us one to interact with both spatial and non-spatial data.

The details of the Housing Colony campus boundary were not available in any of the forms recognised by QGIS. Hence an indigenously developed mobile based digitisation application namely TrackNDigitise is used to generate/mark the boundaries from the other areas in Housing colony campus. These Geo-Positions were recorded using GAGAN receiver which are subsequently mapped as Point Layer and then imported into QGIS platform. A separate georeferenced vector layer was thus created using Google earth Imagery for this location.

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Here, Section 2 describes the Literature Review, Section 3 illustrates methodology used for Utility mapping using open source technologies and in house built mapping devices, Section 4 presents the Information retrieval and presentation on the GIS platform, Section 5 describes Conclusions and future work.

2. LITERATURE REVIEW

Since the late 1960s computers have been used to store and process geographically referenced data. Early examples of GIS-related work from the late 1960s and 1970s include Computer mapping at the University of Edinburgh, the Harvard Laboratory for Computer Graphics, and the experimental Cartography Unit, Canada Land Inventory and the subsequent development of the Canada Geographic Information System. Publication of Ian McHarg’s Design with Nature and its inclusion of map overlay method for suitability analysis, Introduction of an urban street network with topology in the U.S. Census Bureau’s DIME (Data Independent Map Encoding) system.

In the past three decades, a host of professions have been in the process of developing automated tools for efficient storage, analysis and presentation of geographic data. These efforts have apparently been the result of increasing demands by users for the data and information of a spatial nature. This rapidly evolving technology has come to be known as “Geographic Information Systems (GIS)”. The uses of this technology are vast and cut across virtually all professions. According to Kang Tsung Chang - GIS is a computer system for capturing, storing, querying, analysing and displaying geographically referenced data [Chang 2006].Pine studied the use of GIS in Utility management and how to achieve effective results in that situation by using GIS. In his study, Pine reviewed GIS elements, GIS as a system and the benefits of GIS. Moreover, he found that developing a GIS system involves an investment in five areas viz. Computer Hardware, Software, Geographic data, Procedures and Trained Staff [Pine 1998].

As [Diererees and Howard] said, the most important benefit of digital tracking of Projects is that integration of GIS and GPS technology will reduce the amount of administrative time spent by Engineers and Management on the Project. [Bansal and Pal (2011)] studied the GIS applications for Maintenance cost and visualisation. [Jha and Iyer (2007)] studied the impacts of different factors/attributes on Utility Management performance. They concluded that Five M’s of Applied GIS viz Mapping, Measuring, Modelling, Monitoring and Managing helps to arrange review of techniques used for Utility Management. The first GIS users in India in the early 90s were mostly national mapping agencies, educational and research institutes. Several government pilot projects like NRDMS, IMS, NNRMS started using GIS concepts. While the early focus was on government managed projects, it was the universities that played a major role in creating interest among students about the use of spatial technologies. National projects like NRIS, environment capacity building project, state level data base building and pilot projects by state RSACs consolidated GIS in India. Indian geospatial industry simultaneously has become a global source of quality and an optimally priced data conversion service provider.

This technology can be used by anyone for making decisions based on spatial data all the time. For example, the location of workplace, site and the various materials and equipment kept in the site are included in spatial database. These data or information are normally stored in a spatial information system, i.e., in a geographical information system. Thus, a GIS is both a database system with specific capabilities for spatially referenced data, as well as a set of operations for working with the data.

The above mentioned works signifies the use of Geo spatial technology for several mapping applications. In this paper, we present one such approach using Open source geo spatial methodologies specifically for mapping the utilities, followed by organizing such mapped utilities into the database for further use. Here, the required plugins have been installed to meet our requirement and the available master plans (in Autocad .dwg format) of campus were used as base layer for creating various vector layers pertaining to all utilities viz. Campus Boundary, Buildings, Roads, Water Supply Networks, UG Cable Layout, Green Cover and host of other features. DWG is the proprietary format of AutoCAD, which cannot be opened by most freeware/open source software like QGIS. Hence conversion to *.DXF is required, and here we have used “Any DWG DXF Converter “for converting the available Autocad files in ‘.dwg’ format to ‘.dxf’ format for enabling them to be imported as Shape Files in QGIS canvas. These layers were georeferenced using Cartosat-1 Satellite Imagery with resolution of 2.5 metres. The attributes against each utility were created as CSV files and the same were linked to the corresponding Vector Layers. Various Interactive queries viz Simple and Advanced queries, are also generated using the available toolsets in QGIS platform.

In the next section, we describe the methodology used in utility mapping followed by feature digitization using TrackNDigitize tool.

3. METHODOLOGY

The methodology followed for creation of the Geo-Spatial Database for mapping various Utilities and their Management is shown in Figure 1. Figure 1 depicts the workflow, where the satellite data of the required area can be collected and will geo referenced using QGIS tool. For geo referencing one can use Ground Control Points (GCPs) and other reference data taking from GCPs or any other data like Google or Bhuvan. Often it would be difficult to get the accurate GCPs, hence, in order to do here we use TrackNDigitize tool a mobile based Application to collect the GCPs and also to digitize the feature.

The next step after the geo referencing is to digitize the features (utilities) and organize them in the proper data base which is shown in the diagram. Also a provision is made to import the files or any other legacy data being generated from other software tools ( like shp, dwg, dxf, csv etc.) to import to the database. The several utilities being mapped are depicted in the Figure 1. Later, the queries can be used to retrieve the information as required for further analysis.
Below we describe the generation of shape files and georeferencing procedure.

3.2 GENERATION OF SHAPE FILES AND GEOREFERENCEING

The available master plan of the campus (in Autocad .dwg format) which was a legacy data used to create base vector layer comprising of all Polygons pertaining to each and every building structure in the campus like Main Building, Service Buildings, Campus Boundary, Roads etc. GIS projects require geo-referencing of raster data like satellite data or scanned toposheet or aerial photograph etc. Geo-referencing is the process of assigning real-world coordinates to each pixel of the raster data. This can be done by doing field surveys - collecting coordinates with a GPS device for some easily identifiable features in the image or map. Alternately to digitize scanned maps, we can obtain the coordinates from the markings on the map image itself. Using these sample coordinates or GCPs (Ground Control Points), the image is warped and made to fit within the chosen coordinate system. In this project geo referenced Cartosat-1 Imagery was used as base layer for creating various shape files as tabulated below.

Table 1 describes the several layers which are generated along with the geometry type used with the relevant attribute information used for organizing all such layers.

<table>
<thead>
<tr>
<th>LAYER NAME</th>
<th>GEOMETRY TYPE</th>
<th>ATTRIBUTES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td>Polygon</td>
<td>Name, ID, Type, Year of Construction, No.ofFloors, Height, Plinth Area, Carpet Area</td>
</tr>
<tr>
<td>Campus Boundary</td>
<td>Polygon</td>
<td>Name, ID, Area, Perimeter</td>
</tr>
<tr>
<td>Lawns</td>
<td>Line</td>
<td>Name, ID, Area, Perimeter</td>
</tr>
<tr>
<td>Roads</td>
<td>Line</td>
<td>Name, ID, Length, Width, Year of Construction, Lanes, Slope, Median, SW Drain</td>
</tr>
<tr>
<td>Water/Sewage Lines</td>
<td>Line</td>
<td>Name, ID, Length, Nominal Bore, Year of Laying, Material of Pipe</td>
</tr>
<tr>
<td>HT Cables</td>
<td>Line</td>
<td>Name, ID, Make, Model, Length, Date of Installation, Size, No of Runs</td>
</tr>
<tr>
<td>Borewells</td>
<td>Point</td>
<td>ID, Name, Diameter, Depth, Average Yield</td>
</tr>
<tr>
<td>OHT</td>
<td>Point</td>
<td>ID, Name, Capacity, Material of Tank</td>
</tr>
</tbody>
</table>

Table 1. Spatial Layers and Geometry Types with Attributes
The sample diagram after the creation of above said vector layers in the QGIS platform is shown in Figure 2.

![Figure 2. Creation of Vector Layers using QGIS](image)

### 3.3 GIS DATABASE CREATION AND LINKING OF SPATIAL & NON-SPATIAL DATA

The most crucial part in any of the GIS projects is creation of database in the required format for easy analysis and updation. GIS has very high potential of working with both spatial and non-spatial data and acts as a bridge between spatial and non-spatial attributes of a particular feature reflected on GIS platform. Digitizing is one of the most common crucial and time consuming tasks. A large amount of time is spent in digitizing raster data to create vector layers. QGIS has powerful on-screen digitizing and editing capabilities. Various Snapping toolset to minimise the digitising errors like Undershoot or Overshoot are available in QGIS. All the features are added to the vector layers created earlier using this tool. In many real-life situations, we get additional non-spatial data in the form of spreadsheets or text files.

When we need information which is not in the current table but in another, we can link these tables together based on a common attribute. This is possible when a common attribute exists in the tables (often primary and foreign keys). In QGIS, users can establish this kind of link by joining. We can load CSV files by using Add Layer. In this project standard attributes are defined for each layer and the data was tabulated against each attribute in MS Excel and stored as CSV files. These files were then linked with the attribute table of corresponding layer thereby creating a complete dataset for every vector layer. For Example- The vector layer named Buildings was created with details like Name, Type, Area and Perimeter of Building. These fields were linked to the other parameters of building like Year of Construction, Number of Floors, Type of Construction, Fire Extinguishers etc., which were stored in CSV files. The creation of attribute data and linking the same with the CSV file is depicted in Figure 3.

![Figure 3 Creation of Attribute Data and Linking with CSV Files](image)
3.4 RECORDING GEO-LOCATIONS USING GPS/GAGAN RECEIVER

The Indian Space Research Organization (ISRO) and Airports Authority of India (AAI) have implemented the GPS Aided Geo Augmented Navigation- GAGAN project as a Satellite Based Augmentation System (SBAS) for the Indian Airspace. The objective of the GAGAN to establish, deploy and certify satellite based augmentation system for safety-of-life civil aviation applications in India has been successfully completed. GAGAN provides the additional accuracy, availability, and integrity necessary for all phases of flight, from enroute through approach for all qualified airports within the GAGAN service volume. The GAGAN a blue tooth based IoT device along with the in house built TrackNDigitize tools is used for collecting Geo-Locations for marking the Compound wall boundary of Housing Colony campus, the IoT GAGAN receiver is shown in Figure 4 and the sample screens of TrackNDigitize tool is shown in Figure 5.

![GAGAN Receiver](image)

3.5 FEATURE DIGITIZATION APPLICATION – TRACK AND DIGITIZE (TRACKNDIGITIZE)

The Feature digitization applications offer the digitization of the features on the ground. The several features that can be digitized are i) line ii) poly line iii) polygon. The application offers two modes of digitization such as i) Navigation mode ii) On Screen Digitization (OSD) mode. In the case of navigation mode, one of the features from line, poly line or polygon can be digitized while moving around in the field with the device in the hand. The device gets the geo graphical positioning and it digitizes the feature. This mode is very useful to digitize the features while on the move in the ground. Such digitized features can be saved as the feature vector, and this feature can be used as way point file while someone would like to take the similar path on the field. The OSD mode allows digitizing on the screen and storing the features as a vector file.

![Feature Digitization Application](image)

In this Project, TrackNDigitise feature was used to digitise the Housing Colony Campus Boundary and the results were imported as Point Layer in QGIS canvas. These Points were over laid over base satellite Imagery and the precise location of Compound wall was marked and saved as separated Polygon Vector Layer as shown in Figure 6 below.

![Feature Digitization Application](image)
In the following section we describe the information retrieval and some of the spatial queries for retrieval of the data as required.

4. INFORMATION RETRIEVAL

One of the key features of any GIS platform is its ability to interact with the available datasets and display the outputs meeting the specified criterions. To select features according to properties that we cannot see on the map we can write a query. The Query selects feature that meet the specified condition using the values present in the feature attribute table and displays the features meeting the conditions. These are referred as Non Spatial Queries. Spatial queries are the ones which involves conditions related to the topological relationships. Based on these the features are selected and highlighted on the Screen.

4.1. Spatial Query for showing the Buildings in the campus having its Plinth area more than 400 Sqm

We have created a Polygon Vector Layer namely Buildings having all the details in the form of attribute table. One of the fields which are automatically updated based on the geometry created in QGIS enables it to calculate its Area and Perimeter by default. Using the 'Select Feature with expression tool' a query is generated for displaying the buildings having Area more than 200 Sq.m. It can be seen from Fig.7 that only those buildings are highlighted whose areas are more than 200 Sq.m. This certainly helps in planning the other Utilities in the campus with reference to its geographic locations and topology. Figure 7 depicts the sample spatial queries in QGIS platform.
4.2. Non-Spatial Query for showing the Borewells which are having its Yield more than 1500 LPH

We have created a Point Vector Layer namely Bore well having the details related to its Name/ID/Number etc. in the form of attribute table. The sample diagram is shown in Figure 8, with the locations details of these bore wells are recorded precisely in the Point Vector Layer with default attributes as Bore well Name/ Number or ID. The other non-spatial information like Size, Type, Year of Construction, Depth of Bore well, Average Yield of Bore well was collected and recorded in MS Excel and stored as CSV Files. A common field to default attribute table and CSV File namely Bore well ID was kept and both were linked using the ‘Join ’ tool in Layer Properties in QGIS. This will enable us to integrate the data and perform queries on the combined data thus generated. Using the ‘Select Feature with expression tool ’ a query is generated for displaying the most yielding bore well in the campus. This feature has also helped in planning the rain water harvesting zones adjacent to the most yielding bore wells which has inturn helped in enhancing the yield of the Potential bore wells.

![Figure 8. Non Spatial Queries using QGIS for showing the most yielding Bore well in the campus](image)

4.3 Composition of Utility Web Maps

This is one of the unique features of any GIS platform which enables us to develop any sort of Utility maps showing Campus boundary, utilities, facilities and infrastructure present in the campus as per the requirements for better analysis. QGIS to Web Plugin in GIS enables us to create Web Maps of any of the Layers generated from the QGIS canvas. According to the specific requirements only selected layers can be selected and different web maps can be generated with proper legends. A web map depicting all Utilities in campus viz. Buildings (Facility, Office, Residential, Service), Campus Boundary, Lawns, Roads, Parking, Pathways, Trees, Bore wells, Sewer Line, HT Cable Line, Inspection Chambers, Water Line, Solar Panels Location etc. could also be generated.

![Figure 9. Buffer tool using QGIS (Vicinity of facilities from each other)](image)
5. CONCLUSIONS AND FUTURE WORK

GIS is one of the fast emerging fields being utilized in various civil engineering projects and is widely used for Utility Management applications. GIS is a continuously evolving technology and there are many tools which are directly relevant for management of natural resources, land and water management, vegetation, transport network, telecommunications, ground water etc. Here, we presented Geospatial Database for Utility Management created for campus viz. the Geographic area, spread of facilities, buildings, roads, water harvesting Structures etc. This database will act as an effective tool for Planning/ Design and also for varieties of Geospatial queries, analysis and decision making. These Utility maps are very helpful for proper Maintenance and effective monitoring of each and every facility and services. Attribute Data corresponding to each vector layer allows us to manage, retrieve, update and integrate the data available in different formats. GIS with its large storage and retrieval capacity is extremely useful for detailed studies regarding various parameters like Solar & Rain Water Potential. Various maps can be generated using Vector analysis module running simple and advance queries. This GIS based Utility Management System will help all the Engineers and Users in crucial decision making process, prioritising the maintenance activities and also effective monitoring & easy updation of various attributes of facilities in and around the campus.

The scheme of managing the utilities as GIS management platform can be further improved for future activities, for which various Maps can be generated and several spatial and non-spatial queries can be employed as required. The proposed system with the utility database can be useful for further Research and Development in construction activities and taking the decision based on the utilities and information being made available. This will help in easy decision making for procurement of funds or materials, knowing the exact status of the project and also having a 3-D view of the geographical information. The capability of GIS based Utility Management System can be further enhanced to develop modules for generating alerts regarding preventive maintenance, Status of Complaints etc.

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ESRI Website: www.esri.com

GIS Primer Website: www.gisprimer.com

GPS Website: www.gps.com

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HIGH PERFORMANCE DATA PROCESSING SCHEMA - FOR VERY HIGH RESOLUTION REMOTE SENSING SATELLITES

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ABSTRACT

Ever increasing demand for finer resolution and better swath images is making the remote sensing satellite payload arrangement more-and-more complex. This complex arrangement of sensors in satellite is demanding time consuming image processing algorithms for image formation in the ground segment. Mapping applications demand processing of huge volumes of data and thereby faster processing for its use effectively. To reduce the turnaround time in data processing, efficient usage of compute resources is inevitable. Availability of parallel compilers, libraries, multicore systems, high performance storage systems and high bandwidth networks provide the opportunity to implement parallel processing techniques to increase the throughput. Understanding the underlying architecture of the system is essential for mapping the image processing algorithms to best utilize the available compute resources. As the data rates in every generation of Indian Remote Sensing (IRS) satellites are increasing many folds, there is need for designing efficient data processing schema. In this paper, we present the data processing schema designed for very high resolution satellite data processing to reduce turnaround time to the end user for further exploitation. Thread parallelism and task parallelism is implemented for efficiently utilizing the processor cores. To hide the latency in reading the file from storage, block processing is implemented with I/O interleaved with compute, while a block of data is getting processed in CPU, next block of data is fetched into memory. File writing latency is hidden by further dividing the data block into smaller chunks and interleaving the processing and writing of the blocks. The design and performance gains are explained in the paper.

KEYWORDS: Image Processing, High Resolution Satellites, Parallel Processing, Remote Sensing

1. INTRODUCTION

As Remote sensing user community demand for finer spatial, spectral and temporal resolution images, data volume of daily acquired data is exponentially increasing. These high volumes of data need to be processed with minimal delay to enable quick decision making. To meet the growing demand, complex payload arrangement is being followed in the satellite. For example, previous generation IRS satellites were using conventional push broom Charge-Coupled Devices (CCD), but current generation satellites are employing more complex Time Delay and Integration (TDI) technology in a butting arrangement. These increasing complexities in the payloads also increase the computation requirements in the ground segment. With availability of multicore processors and parallel compilers it is imperative to utilize the compute resources efficiently (Yan, 2015).

IRS satellites such as Cartosat-2S capture images of earth in sub-meter resolution and transmit to the ground during the visibility period of the ground station. These acquired data undergo various operations on-board, such as compression for reducing size, encryption for making the data secure during transmission and encoding for correction of the transmission errors, inverse of these operations is run on the data on ground to recover the original data. Figure 1 shows the ground segment for IRS satellites.

![Figure 1. Ground Segment for Satellite Data Processing](image)

High performance computing is the recent development, which is evolved to meet the demands from processing large volumes of data in various fields. It is amalgamation of several technologies such as hardware, compilers, algorithms and programs. It is essential to gather and process large amount of satellite data which is the need of an hour. But due to the demand for finer resolution images from user community, data volumes are increasing manifolds day-by-day. This makes the data processing suitable for using HPC techniques to reduce the turnaround time (Plaza, 2011). In recent years, Graphics Processing Units (GPU) has been used in remote sensing data processing because of their highly parallel architecture (Pramod, 2014). However, porting the existing algorithms with similar results proves to be a highly demanding job.

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2. METHODOLOGY

The scope of the data processing (DP) system for high resolution Cartosat-2S series satellites is to handle image data acquired from satellite system to generate system level and ortho products for image exploitation. The Data Processing software performs pre-processing on Level-0 data that are video file format handling, grid file generation using aux data, radiometric corrections and geometric corrections. It also generates ortho products along with Rational Polynomial coefficients (RPC).

2.1 Radiometric corrections

Radiometric correction algorithms employed in Data Processing are highly dependent on sensor characteristics, atmospheric characteristics and payload arrangement in the satellite (Teillet, 1986). Figure 2 shows the Radiometric corrections for optical imaging systems, these are Non uniformity correction (NUC), Residual stripe reduction, Optical butting estimation and correction, Restoration and Noise removal etc.

2.1.1 Non uniformity correction: Non-uniform responses of CCD elements manifests in the form of striping and banding in imagery. Light Transfer Characterization (LTC) of the camera system which will be carried out before launch is used for evaluation and calibration of the camera. It is further used for generation of Lookup Table (LUT). Applying the LUT on the Level-0 data normalizes the radiometric imbalances.

2.1.2 Residual stripe reduction: If Residual stripes appear and are inconsistent even after NUC correction using the LUT due to change in integration time of different data sets, a local statistics based algorithm is used to remove the residual stripes.

2.1.3 Optical Butting correction: To realize large swath in Carto-2S, TDI devices are arranged in orthogonal planes. This arrangement is called as optical butting and may result in image degradation in the butting region that needs to be corrected. Some of the effects are vignetting, MTF drop in overlap region, Degradation of SNR and Alignment effects.

2.1.4 Restoration: During image acquisition process, many factors will cause image degradation due to aberration of the optical system, performance of CCD sensors, motion of the satellite platform and atmospheric turbulence. Due to these imperfections in the imaging and capturing process, the images invariably represent a degraded version of the original scene. In majority of these cases the degradation can result in image blur. A methodology based on improved Wiener filter was incorporated for restoration of degraded image.

2.1.5 Noise filter: Removes the noise present in the image by automatically extracting the noise characteristics present in the image (Suresh Kumar, 2003).

2.2 Geometric corrections

Figure 3 presents methodologies that are designed to cater to the needs of geometric correction requirements for Data Processing system.

A Sensor Model reconstructs the viewing geometry. Sensor Model is the transformation that connects image space to object space. Reconstruction of the viewing geometry includes the exterior and interior orientations of the sensor. The exterior orientation describes the location of the projection centre and altitude of the bundle of rays, while the geometry of the bundle of rays will be reconstructed by the measured image position and interior orientation. CCD-array satellite images will have one set of exterior orientation parameters for each image line and the interior orientation is restricted to this line. Therefore, for satellite image sensors, the reconstruction of the imaging geometry involves a mixing of the interior and exterior orientations (Radhadevi, 2013).
A sensor model is formed by collinearity equation with state vector, ephemeris, and payload geometry. This module consists of two important functions which maps each pixel on the CCD to the corresponding ground coverage (IGFOV). They are

(a) Image to ground transformation (I2G)
(b) Ground to Image transformation (G2I)

![Figure 3. Geometric corrections](image)

3. ANALYSIS & DESIGN

This section describes the analysis of the data processing system for designing a multithreaded architecture to utilize the available resources.

Primary design goal of the system are:

i. To process any image size (3GB data to ~100GB data)
ii. To utilize all the processor cores to reduce the turnaround time
iii. Logical partition of the strips to smaller sub scenes for easier image handling

The data from Single image in Cartosat-2S can go up to several 10s of GBs depending on length of the area to be imaged. During the processing, input data file is read into main memory, after all the corrections final output is written to disk. During this period data resides in memory. If full image needs to be processed at the same time in the system, Random access memory (RAM) may not be sufficient to hold the input, intermediate and output images. To overcome the RAM size limitation for the larger strips, the data is divided into blocks. If the total data length is more than the predefined block size, image is divided into blocks. Block size can be configured depending on the available RAM.

Data Processing system has to load and write large volumes of data from storage system to memory, which would introduce intensive I/O operations and overhead. The system has to be idle for several CPU cycles while accessing the data, if not taken care properly the overheads would impose time delays in the data processing system. The technique adopted is block processing with Interleaved I/O.

So the block based processing with Interleaved I/O solves the two problems:

i. Any strip length can be processed with the available RAM
ii. I/O overheads can be hidden by asynchronous I/O

3.1 Design

Figure 4 shows the design of the Data Processing pipeline. All the modules in the pipeline are multithreaded. Analysis of the system brings out the independent modules which can be executed concurrently.

For larger strips, image sizes are of the order of several Giga Bytes. To make the data handling easier these larger strips are divided into smaller sub scenes. For each sub-scene, Rational Polynomial Coefficients (RPC) and grid files are generated, generation of these files is independent of radiometric operations and it can be executed concurrently. After generating grid, corner file for full strip, sub-scene grid file, RPC generation and radiometric processing are executed concurrently. This hides the latency of sub-scenes geometric processing.

In the Radiometric processing, data is divided into equal sized blocks based on the RAM and strip size. Since there are several blocks of data to be processed, File read latency can be hidden by reading the next block of image to be processed into memory while processing the current block as shown in Figure 4.

Parallel tasks are represented with circled 1 and 2 in Figure 4.
3.2 Optimal Thread Size Estimation

Multithreaded modules are designed in such a way that number of threads to execute is controlled from calling function in-order to provide the flexibility to pass the number of threads based on available cores. So it is essential to find the optimal number of threads for each module so that optimum numbers of threads are assigned to that module. All the modules are profiled with thread count ranging from 1 (single thread) to number of threads where the performance starts degrading with increase in thread count.

Table 1 shows the execution time for NUC module for different number of threads for a block size of 400000 lines and 16000 pixels. Execution time is achieved minimum of 4 secs for 64 parallel threads and is constant up-to 256 threads. For 512 threads the execution starts increasing. So optimal number of threads for NUC module is 64. This is profiled on a system with 64 physical cores (128 logical cores with Hyper-Threading).
Table 1. Number of Threads Vs Time for NUC module

<table>
<thead>
<tr>
<th>Number of Threads</th>
<th>Time in Secs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>55</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
</tr>
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</tr>
<tr>
<td>32</td>
<td>5</td>
</tr>
<tr>
<td>64</td>
<td>4</td>
</tr>
<tr>
<td>128</td>
<td>4</td>
</tr>
<tr>
<td>256</td>
<td>4</td>
</tr>
<tr>
<td>512</td>
<td>5</td>
</tr>
</tbody>
</table>

Figure 5 shows the graph for NUC module with number of threads vs running time in seconds until four parallel threads runtime follows a linear profile, after that doubling the number of threads doesn’t halve the running time.

Figure 5. Graph of Number of Threads Vs Time for NUC module

Table 2 shows the optimal number of threads for the radiometric modules viz., NUC, Residual Stripe Removal, Optical Butting, Restoration and Noise filter for the image size of 4 lakh lines by 16000 pixels. Restoration module is the most time consuming of all the modules, as expected, since it involves calculating two dimensional Fourier transform of the input image and point spread function (PSF), convolution in Fourier domain and inverse two dimensional Fourier transform. Optimal thread numbers for each module are stored in a configuration file and passed to the module during the runtime. The time given shows only compute time and I/O time is not included.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Module</th>
<th>Optimal Number of Threads</th>
<th>Time in Secs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NUC</td>
<td>64</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>Residual Stripe Removal</td>
<td>16</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>Optical Butting</td>
<td>64</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>Restoration</td>
<td>64</td>
<td>500</td>
</tr>
<tr>
<td>5</td>
<td>Noise Filter</td>
<td>32</td>
<td>160</td>
</tr>
</tbody>
</table>

Table 2. Optimal number of Threads for Radiometric Modules
3.3 Software Implementation Specifications

The entire software is built on Linux server. Programming language chosen is C++. For task and data parallelism OpenMP threading API is used. Intel compiler is used for generating the multithreaded libraries and application since it provides platform specific optimizations for Intel Processors.

4. TEST RESULTS

The system configuration for Data Processing system is shown in Table 3. It is a four socket machine, populated with 64GB RAM per processor in Non-uniform memory access (NUMA) configuration, 128 logical cores when Hyper-threading enabled.

<table>
<thead>
<tr>
<th>CPU</th>
<th>4x16-core</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Memory</td>
<td>256GB DDR3</td>
</tr>
<tr>
<td>Operating System</td>
<td>RHEL 7.2</td>
</tr>
<tr>
<td>Hard Disk</td>
<td>5TB</td>
</tr>
<tr>
<td>Compiler</td>
<td>Intel Compiler 2016</td>
</tr>
</tbody>
</table>

Table 3. System Configuration

Table 4 shows the data processing time for various strip lengths for optimized and non-optimized versions. There is increase of ~3X in performance between single threaded and multi-threaded implementation. Block size chosen is 4 lakh lines. In order to remove the dependency on network throughput during the testing, input and output files are accessed from local storage. For the NUC module speedup achieved is ~7X, but due to the restoration module overall speed-up is limited to 3X.

<table>
<thead>
<tr>
<th>Strip Length - Kms</th>
<th>Single Threaded - Time (hh:mm:ss)</th>
<th>Multi-Threaded - Time (hh:mm:ss)</th>
</tr>
</thead>
<tbody>
<tr>
<td>63</td>
<td>00:10:20</td>
<td>00:03:03</td>
</tr>
<tr>
<td>103</td>
<td>00:18:00</td>
<td>00:06:10</td>
</tr>
<tr>
<td>390</td>
<td>00:53:00</td>
<td>00:15:40</td>
</tr>
<tr>
<td>770</td>
<td>02:03:00</td>
<td>00:40:00</td>
</tr>
</tbody>
</table>

Table 4. Strip Length and Timings for Single& Multi-threaded implementations

5. CONCLUSIONS

Satellite data processing of new generation very high resolution satellites is highly computational intensive due to large volumes of acquired data. It is critical to process the high volumes of data in a reasonable time for enabling quick decision making. The proposed system achieves 3X performance improvement over the non-optimized version. Future work is proposed to include other optimization techniques such as process pipelining, which we expect to achieve better performance gains than the existing results. And also to explore Xeon Phi accelerator, on which existing CPU code can be directly compiled and run.

ACKNOWLEDGEMENTS

Authors would like to thank Data Processing team for their support, Sri S.S. Solanki for supporting geometric processing system and specifically Sri P. Suresh Kumar, Deputy Project Director for his continuous support during the development of entire Data Processing System.

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OpenMP 4.0, http://www.openmp.org


DECISION SUPPORT SYSTEM FOR GEOSPATIAL APPLICATION USING OPEN SOURCE TOOLS

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ABSTRACT

Traditionally Decision making in operations planning including site suitability and route planning are done manually using topographic maps. In this paper, authors are presenting decision support solution for site suitability and route planning using open source GIS and digital maps updated from high resolution satellite images. Decision support system for spatial data adopts Modelling. Multi-criteria decision making techniques like Analytical Hierarchy Process (AHP), Ideal Point Analysis are used to solve problems like site suitability analysis involving conflicting and compromising criteria.

In this solution multiple criteria/parameters in terms of spatial data layers are analysed to support in decision making. Relative importance of the criteria can be derived from AHP or by assigning manual weights. A Unique framework has been developed to dynamically select subset parameters from given superset of parameters before performing the analysis.

Total solution is built around open source packages. QGIS is used for vector, raster data management and visualization. GRASS GIS, having rich set of vector and raster analysis functions, is used for implementing site suitability and route models. With the combination of these open source software, spatial models were successfully developed. Open source OSG Earth is integrated to visualize data layers and outputs in 3D geospatial environment.

While implementing spatial models a unique framework was realized using which spatial model can be created and modified with minimal programming knowledge. Intermediate scripting language is used for define the spatial models. Using the generic framework, models can be mapped to either commercial implementation or open source implementation. Each single spatial model is optimised by experimenting with vector processing and raster processing. Models are further optimised by separating independent steps in to separate processes based on number of CPU cores available. A site suitability model with 18 parameters for 15x15 sq. km area can be executed with in 1 minute to help quickly in decision making.

KEYWORDS: SDSS, MCDA, Spatial Models, GIS, Site Suitability

1. INTRODUCTION

Recent advances in remote sensing enabled rich data for the users. Data derived from satellite images can be used for effective resource planning like site suitability. Suitability is the characteristic of possessing the preferred attributes or requirements for a specific purpose. Suitability analysis is a GIS-based process used to determine the appropriateness of a given area (land resource) for a specific use, i.e. agriculture, forestry, business, urban development, livelihood projects, etc.

Traditionally GIS are considered to perform basic functions on spatial data: input, storage, analysis and output. A variety of map description and manipulation functions are defined by commercial vendors as being ‘Spatial analysis’. If these basic GIS functionalities are used along with modeling techniques efficient Spatial Decision Support systems can be developed. Modeling has three broad aspects: (a) To explain a phenomenon, (b) To predict a trend or future, (c) to act as a tool of discovery. In the present context Spatial Modeling is done to identify suitable sites for planning.

Spatial data modelling adopts multi-criteria decision making techniques like Analytical Hierarchy Process (AHP), Ideal Point Analysis for solving multi-criteria decision making problems like site suitability analysis involving conflicting and compromising criteria. Spatial data modeling involves selecting appropriate spatial data as parameters and their weights. GIS analysis functions are applied on these parameters before combining them for multi criteria decision. These GIS functionalities include from basic buffer function to advanced visibility, line density etc...

In traditional processing the processing logic is implemented in the code and parameters are fixed at logic building time. so there will not be a provision to choose parameters at runtime. Also as the logic is implemented inside the code to make small changes in the logic, programming knowledge is required. This kind of solutions is tightly bound to underlying GIS packages. If the solution has to be migrated to another GIS package, then entire solution has to be rebuilt.

In this paper, the authors are presenting a framework for representing spatial model and to process them in optimized way. If the model logic is built using a high level scripting, which is very simple and easy to edit for analyst, small changes in the logic can be handled by analyst himself. As the script will be interpreted at runtime some parameters can be bed ropped if user wants. If the solution has to be migrated to another GIS package no need to change the script only mapping from script function to GIS module needs to be changed. The new scripting framework adopted by the authors avoids the problem of being tightly bound to underlying GIS packages.

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2. METHODOLOGY

Spatial decision problems typically involve a large set of feasible alternatives & multiple evaluation criteria. At the most rudimentary level, a multicriteria decision problem involves a set of alternatives that are evaluated on the basis of conflicting and incommensurate criteria according to the decision maker’s preferences. Important steps to be followed in spatial decision support system are shown in figure 1.

![Flowchart showing steps for spatial decision support](image)

### Multi-Criteria Evaluation (MCE)

Steps:
1. Set the goal/define the problem
2. Determine the criteria (factors/constraints)
3. Standardize the factors/criterion scores
4. Determine the weight of each factor
5. Aggregate the criteria
6. Validate/verify the result

Here the problem is site suitability. Criteria are Terrain parameters. Terrain related parameters are used for site suitability prediction. These parameters include spatial data like land use, roads, villages, junctions, curves, slope, forest entry exit points, culverts etc. These parameters used for multi criteria optimization. Each parameter is given certain weight/importance in the scale 1 to 100. Buffer is applied for some parameters which are not continuous. After buffer, value100 is assigned to the polygon if it is preferable and 1 is assigned to the polygon if it is not preferable. Categorical parameters are assigned values 1 to 100 based on category.

All the parameters are combined based on below ideal point analysis formula (1).

$$S^p_i = \left\{ \sum_{k=1}^{n} \left( W_k \left( \frac{a_{ik}^* - a_{ik}^*}{a_{ik}^* - a_{ik}} \right)^p \right) \right\}^{\frac{1}{p}}$$  \hspace{1cm} (1)

Where:
- $S^p_i$ is the distance (or separation) between the value associated with $i$-th alternative and the ideal point based on parameter $p$;
- $a_{ik}^*$ denotes the best value of the $k$-th criteria;
- $a_{ik}$ is the worst value of the $k$-th criteria;
- $a_{ik}$ is the actual value of $i$-th alternative for the $k$-th criteria;
- $W_k$ is the weight of the $k$-th criteria.

The range of parameter $p$ is $[1, \infty)$. Different $p$ values indicate different contributions of individual separations from ideal point. The greater the parameter $p$ is; the greater emphasis is placed on the larger separations. If the $p = 1$, indicates that the
overall score of alternative i is the sum of weighted deviations associated with all criteria. In this case, total compensation between criteria is assumed, which means that a decrease of one unit of one criterion can be totally compensated by equivalent gain on any other criterion (Pereira and Duckstein, 1993). As the p value increases, with higher scores has greater influence on the overall score, while the impacts from other terms may become negligible. The best solution should be the one has the smallest overall score. Therefore, the decision criteria in selecting the compromise solution become the ‘avoidance of low performance in any criteria’ as the increased value of p (Karni and Werczberger, 1995).

3. DESIGN

In the Framework Each Spatial model will be represented by set of text files. One text file contains parameter names. Another text file contains script to list the operations needs to be performed on parameters. One more text files to list parameter mapping to data (vector files and raster files).

For example, take a spatial model with 8 parameters. In this model all parameters are listed in text file as shown in figure 2. As shown in figure 3 each parameter will take data from particular shape file or raster file. Finally, a script file as shown in figure 4 will list out all the operations to be performed on each parameter including weighted summation. For route model script includes steps to calculate cost by combining necessary layers then cost path function to find the best and alternate routes. Framework has also provision for defining thresholds, weights(importance) and other parameters required.

![Figure 2. Parameters for example suitability model](image1)

![Figure 3. Parameters data binding](image2)

![Figure 4. Script file which lists steps to be performed](image3)

Script file includes steps to combine parameters using formula (1) shown in methodology, for example Unionweight step combines all the parameter in to single raster or vector according to given weightages. All the data including roads, villages, waterbodies etc. are digitized from high resolution satellite images.
3.1. Framework Execution Sequence

When a user wants to execute a spatial model, as shown in figure 5 framework first reads parameter file and show the parameters and their importance to user. User can drop some parameters and can add new parameter. User can change the importance of the parameter. When user clicks execute button framework will read the script file and execute the commands one by one. While executing the command framework will check whether the parameter involved in the command is dropped or not if parameter is dropped that command will not be executed.

![Typical Workflow of the Framework](image)

3.2. Implementation using ARCGIS

Total framework is built using VB.net. First implementation was done using commercial GIS package ARCGIS. Basic GIS functionalities are mapped from script to arcobjects. Whenever framework needs to be executed underlying arcobjects function will be called.

```vba
mf1 = New modelfunctions()
mf1.index = 0
mf1.name = "Buffer"
mf1.operation = AddressOfMe.Buffer
mf1.continuewithoutparam = False
mf1.notavailableval = 0
mf.Add(mf1)
```

![Analysis Function Lookup Creation](image)

As shown in figure 6 each function is mapped to a script command or operation via model functions. For example, buffer command/operation of script is given the address of function Buffer. Inside the buffer function call to arc objects buffer is made. Same way all the GIS functions list is maintained and mapped to corresponding script command/operation. Initially data is stored in File Geodatabase.

Parameter weights can be given manually from 1 to 100. User can give importance to the parameters through ranking. Ranks given by user will be converted to weights by framework. Users also have option to use AHP to give weights to parameters.
Using AHP user can compare two parameters and give importance to parameters and finally weights will be derived using pair wise comparisons

3.3. Optimization

First Implementation is based on raster processing i.e. input vectors are converted to raster and then combined using raster arithmetic. With ARCGIS and file geodatabase as input, for 225 SqKm area, model with 18 parameters was taking 20 minutes’ time to execute. Analysis showed that layers accessing from geodatabase itself is taking more time. To reduce the data access time experimented with shape files as input. At the same time instead of converting each input from vector to raster then combining, total model is implemented with vector processing. In raster processing, combining is done through raster arithmetic where as in vector way of processing combining operation implemented with union. Weighting and arithmetic is implemented using ODBC queries on polygon attributes.

For optimizing the execution time, framework allows to split the script in to multiple independent scripts. Whenever framework finds multiple script files under same model name it launches multiple processes to execute the scripts. In the scripting language wait command/operation is provided to wait for particular process.

<table>
<thead>
<tr>
<th>Model1_Script_Process_0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buffer;Village;Vill_buff</td>
</tr>
<tr>
<td>wait;1</td>
</tr>
<tr>
<td>Combine;Road_buff;Vill_buff</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model1_Script_Process_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buffer;Road;Road_buff</td>
</tr>
</tbody>
</table>

Table 1. Dividing steps in to two processes

As shown in the above table 1, each model can be divided into multiple scripts with same model name but with different process ids. With vector processing, shape file as input and two processes for one model, execution time of model with 18 parameters is reduced to 2 minutes on a system with specifications shown in table 2.

<table>
<thead>
<tr>
<th>Dell Precision T7600</th>
</tr>
</thead>
<tbody>
<tr>
<td>Windows 7 64 bit</td>
</tr>
<tr>
<td>Intel Xeon 2 Ghz E5-2650</td>
</tr>
<tr>
<td>16GB RAM</td>
</tr>
<tr>
<td>500 GB Harddisk</td>
</tr>
</tbody>
</table>

Table 2. Specification of the system used for testing execution time

<table>
<thead>
<tr>
<th>Spatial Model with 18 Parameters</th>
<th>Area 225 Sq. Km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Time in minutes</td>
</tr>
<tr>
<td>Raster based</td>
<td>20</td>
</tr>
<tr>
<td>Vector based, Arithmetic operations as SQL ODBC queries</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3. Execution Time using ARCGIS

3.4. Opensource Implementation

The same framework is implemented using open source GIS software. For data editing and visualization QGIS is used. QGIS is customized using python to support Spatial modeling. GIS analysis functions are implemented using GRASS. Through .net necessary GRASS GIS executables are called to implement GIS analysis functions.

First change in the framework is to implement GIS functions for script commands/operations. This is done by just replacing earlier arcobjects call to GRASS calls. As the framework reads script for each command in script file GRASS executables will be called.

3.5. Optimization for Opensource Implementation

Vector based implementation with ARCGIS reduced the processing time, interestingly vector based processing with open source GIS increased the processing time from 2 minutes to 6 minutes
After analysis for open source, raster based processing was adopted. Raster based processing and MIMD kind of parallel processing (3 process for each model) reduced execution time to 50 seconds. Timelines are shown in table 4.

<table>
<thead>
<tr>
<th>Spatial Model with 18 Parameters</th>
<th>Area 225 Sq. Km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>Open source GIS</td>
</tr>
<tr>
<td>Raster based</td>
<td>50</td>
</tr>
<tr>
<td>Vector based</td>
<td>360</td>
</tr>
</tbody>
</table>

Table 4. Execution Time using open source GIS

4. RESULTS

Following Figure shows site suitability model GUI form developed. Using this form user can drop some parameters. User can add a new parameter. User can change weight, buffer distance and category weights.

![Parameter and weightage selection from for Site Suitability Model.](image)

Figure 7. Parameter and weightage selection from for Site Suitability Model.

Based on the given parameters and weights following site suitability output shown by the system (input data layers are waterbodies, settlements, landuse, slope, roads)

![Site Suitability Model Output](image)

Figure 8. Site Suitability Model Output

After executing the model total area is categorized in to 10 classes from rank 1 to 10. Rank 1 is best suitable site according to given parameters and weights. Rank 10 is least suitable site. Open source OSGEarth is integrated in to the framework and model outputs can be visualized in 3D environment. Following figure9 shows cross country route model output.
5. CONCLUSION

For spatial problems like site suitability and route finding, to support in decision making a framework is realized using multi criteria decision analysis method and open source GIS tools. This framework allowed the authors to experiment with commercial and open source packages. It allowed migrating from commercial package to open source with minimal effort. It separated modeling logic from coding so that analyst without or with minimal coding knowledge can change the logic. The framework enables to maintain modeling logic and code separately so that change in model logic will not affect software in terms of bugs. The framework enabled authors to introduce parallel processing, by which processing time reduced considerably. This Spatial Decision Support System incorporated provisions to allow users to dynamically select parameter and add new parameter before executing the model. In the future Framework will be extended to provide a GUI based model creation feature with which analyst will be able to create spatial models with ease.

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GRASS GIS, https://grass.osgeo.org/

QGIS, https://qgis.org/
MAP UPDATION USING SATELLITE IMAGES
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ABSTRACT
Today due to advances in remote sensing technologies there exists many sources for high resolution images. At the same time there is a need to have updated maps for vulnerable areas. Complete mapping of these areas is possible only through authorities/local users concerned, with the help of high resolution images. Authorities/local users only can map features which are not available in the high resolution images using local knowledge. In this paper authors are presenting the work which is carried out to enable the concerned people to update/create digital maps using high resolution images. Schema is adopted to update regular layers like roads, waterbodies, land use as well as field information. Standardization is followed in terms of codes, scale and quality. The basic need for digital map updation is GIS software to handle Raster images and to create Vector layers. Open source GIS software QGIS is customized to ease the process of digitization using satellite images, which enabled to install free of cost mapping software in huge number of user systems. Plugins are developed for auto population of required fields using entered codes. Plugins are implemented to check geometry errors that enabled the users with tools to correct errors. Database checker is implemented to report the overall errors in terms of schema and features. Tools are provided to auto derive some of the features like road junctions, slope, drainage order and contours etc. instead of digitization. With efforts presented in this paper, extensive training, using high resolution images with 0.6 m resolution from various sources and local knowledge, authors enabled users to update digital maps of large area. These maps are used for site suitability and other applications including visualization.

KEYWORDS: Remote sensing, Digital maps, Satellite images, GIS, Schema

1. INTRODUCTION
The recent availability of high resolution satellite imagery has led to increased interest in the use of satellite data for large scale mapping applications and detailed land use assessments (Amuyunzu and Bijl, 1999). This growing interest not only emanates from the fact that satellites provide a synoptic coverage, have a high repetitive cycle, and carry multispectral band sensors that provide information beyond the ordinary ability of the human eye, but also because they offer a cost-effective source of data that enables timely detection of changes, the monitoring and mapping of urban development, assessment of deforestation extents, evaluation of post fire vegetation recovery, the revision of topographic maps among numerous other environmental assessments. Conventional mapping techniques are still pegged on the use of black and white aerial photographs and extensive field work exercises. This method is both slow and cumbersome and is also very costly. No wonder, most Survey of India Maps are very old and out dated and thus unsuitable for planning and navigation purposes. It is almost axiomatic that accurate, reliable, and up-to date information is essential for wise and efficient decision-making. This is particularly true in the management of natural resources which fall within spatially and temporally complex dynamic systems. Data of high precision as well as state of the art analytical techniques are needed to derive maximum information about earth resource features and phenomena. Given the diversity and heterogeneity of the natural and human altered landscape, it is obvious that the time-honored and laborious method of ground inventory is inappropriate for mapping land use and land cover over large areas. A moresynoptic vantage point, such as provided by remote sensing is required for effective detection, identification, classification, delineation, and analysis of landscape features. Satellites equipped with high resolution sensors thus provide a platform for wide area land use and land cover mapping. There is therefore an urgent need for rapid and cost-effective mapping techniques in order to constantly update their maps for sound and sustainable planning. This paper articulates through a case study, the methodology of using high resolution satellite data to undertake mapping exercises at relatively lower costs and within shorter time-frames.

There is a need to have updated maps for vulnerable areas. Complete mapping of these areas is possible only through authorities/local users concerned, with the help of high resolution images. Authorities/local users only can map features which are not available in the high resolution images using local knowledge. Concerned people are enabled to update/create digital maps using high resolution images. Schema is adopted to update regular layers like roads, waterbodies, land use as well as field information. Standardization is followed in terms of codes, scale and quality. The basic need for digital map updation is GIS software to handle raster images and to create vector layers. Open source GIS software QGIS is customized to ease the process of digitization using satellite images

2. METHODOLOGY
Map updating procedure is done using high resolution satellite remote sensing data and Geographic Information Systems (GIS). This was implemented in five stages as shown in figure 1. These stages were: (i) data collection and pre-processing, (ii) image interpretation & digitization (iii) field verification (iv) error correction, (v) quality control.

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Figure 1. Steps for Updating using Satellite Images

2.1. Data collection and pre-processing
This step includes collection required satellite images, ancillary data and preprocessing. An example of collected high resolution satellite image is shown in figure 2. If the satellite image location accuracy is not within acceptable limits then the satellite images are registered with respect to known references. References include Digital SOI Maps, Carto-1 Imagery, Landsat Imagery. Then enhancement techniques to improve contrast and brightness are used for better interpretation. In interpreting and classifying various features from remote sensed data, the quality of the interpretation is improved by the integration of ancillary data. These ancillary data including SOI Maps, public domain data, field photographs, reports and personal experience are collected in this phase.

Figure 2. Multispectral Satellite Image with spatial resolution 0.6m

2.2. Image interpretation & Digitization
Manual interpretation conducted based on the implicit and explicit use of collateral information which included maps, photographs, reports and personal experience of the interpreters and was done using a predefined classification system. Color, tone, pattern, texture, association, shape, size, shadows, and site clearly enabled protomorphic delineation of line and polygon features to produce the preliminary maps. Interpreters were extensively trained with respect to satellite image interpretation and GIS based digitization in this phase.

Schema for data layers to be interpreted/digitized was established and made available to the users. Schema includes data layer names, geometry type, attribute names, code for different categories of features etc. In order to reduce the errors in following the schema an EmptyGDB with all the layers and attributes is prepared and supplied to the users. Users can copy EmptyGDB and rename to their study area name and start digitization of layers without worrying about the naming of layers and attributes and codes. Table 1 show the database schema followed during digitization.
As shown in Table 1 all the features are not interpretable from satellite images some of the features have to be digitized after getting information local knowledge and field. As the map updation training is given to the local authorities who regularly do field visits and gather information they will be in a position to update all the layers. Interpretation was done on a scene by scene and theme by theme basis using customized QGIS GIS software. Land use / land cover polygons, hydrological features, road network and all the layers shown in Table 1 were thus digitized as independent thematic layers. All the layers are digitized using WGS-84 datum and Geographic projection.

<table>
<thead>
<tr>
<th>Shape File</th>
<th>Code Name</th>
<th>Attributes assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CAN Code</td>
<td>Description</td>
</tr>
<tr>
<td>Canal Line</td>
<td>CAN Code</td>
<td>Description</td>
</tr>
<tr>
<td>01</td>
<td>MAIN CANAL</td>
<td></td>
</tr>
<tr>
<td>02</td>
<td>BRANCH CANAL</td>
<td></td>
</tr>
<tr>
<td>03</td>
<td>CANAL UNDER CONSTRUCTION</td>
<td></td>
</tr>
<tr>
<td>04</td>
<td>DISTRIBUTARY CANAL</td>
<td></td>
</tr>
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<td>070101</td>
</tr>
<tr>
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<td>Dry</td>
<td>070102</td>
</tr>
<tr>
<td>04</td>
<td>Undefined / Unreliable</td>
<td>070102</td>
</tr>
<tr>
<td>Drainage Poly</td>
<td>DRNP Code</td>
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<td>070101</td>
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<tr>
<td>03</td>
<td>Lakes / Ponds</td>
<td>070302</td>
</tr>
<tr>
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<td>Bridge Over Rail</td>
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<td>Pack Track in hills</td>
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<td>Tracks</td>
<td>Cart Track</td>
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<td>090001</td>
<td>Bushes/elephant grass</td>
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Table 1. Database Schema
### Table 2. Codes used as part of data base schema

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<th>SCHEMA</th>
<th>HOW TO UPDATE FEATURE(S)</th>
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<td>ObservationPosts.shp</td>
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<td>WellPoint.shp</td>
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</tr>
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</tr>
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<tr>
<td>Market.shp</td>
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<td>PoliceStation.shp</td>
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<td>WaterDepth</td>
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<td>Derived from DEM</td>
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<td>MAPS (SOI MAP) RASTER</td>
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</tr>
<tr>
<td>CARTO (SATELLITE IMAGES) RASTER</td>
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</tr>
</tbody>
</table>

**2.3. Field Verification**

Sample points across the entire study area were selected during the preliminary interpretation. Whereas emphasis for designating sample sites was based on feature ambiguity, representative sampling of all classes within the classification system was also done to enable authentication of feature identity as specified in the interpretation and to some extent assist verify the appropriateness of the classification system. To ensure actual access to each sample site, proximity to the road network was given high weighting in the sampling criteria. Fieldwork forms were prepared and coordinate of the sample points acquired directly from the digital satellite images for entry into the GPS. The actual fieldwork exercise entailed compass and GPS aided navigation based on the coordinates of the sample points as entered into the GPS. Once on site, the area was sampled based on the fieldwork form. Information collected included actual site GPS position readings, area name,
land use / land cover, topographic data, and socio-economic data. Also sampled were other land use / land cover types omitted in the classification system. Site photographs were also taken as additional records of the field observation.

2.4. **Error Correction**

Field verification findings were incorporated to refine preliminary image interpretation. In some cases, this stage involved re-labeling and redrawing of certain feature boundaries to give the actual representation as revealed by the field observation exercise. Accuracy assessment between the laboratory and field classification and interpretation were also undertaken. In this phase geometry errors like duplicate nodes, duplicate polygons, invalid geometry are corrected. Each thematic layer was then edited to eliminate digitization errors.

![Figure 3. Tool to detect Geometry Errors in digitization](image1)

![Figure 4. Examples for Topological Errors](image2)

2.5. **Quality Control**

Quality control involved cross-checking the feature boundaries to ensure accurate and consistent interpretation. Also important was the confirmation of feature codes/labels, polygon closures, and where applicable, line feature continuity among many other topological issues. Errors like dangling node, overlap polygons, gaps, undershoot, overshoot are corrected. Figure 4 shows some of the Topological Errors. Topological Checker Plugin for QGIS is used to detect topological errors and editing tools are used to correct those errors.

Prints of the preliminary digitization were then made at the same scale as the original images so as to allow direct 1:1 overlay evaluation of the quality and accuracy of the digitization and coding. Whenever errors were identified, the necessary Correction was made. Additional feature information was then input and appended to the GIS database. Following approval of the quality of the digitized themes, adjacent digital themes were edge-matched and joined together to produce single thematic map.

A tool named DBcheker was developed to check all the layers and report which layers empty and which layers are not following database schema. DBchecker checks all compulsory attributes and reports if any unaccepted values are filled by the user.

![Figure 5. Database Cheker Tool](image3)
3. CONCLUSION

Cost-effective and rapidly updated maps of the study areas were produced using satellite images collected from various sources including public domain images, commercial satellite images. The map carried land use / land cover classes, hydrological features, the transportation infrastructure, and the administrative boundaries and field collected information. A rich GIS database containing both spatial and non-spatial information was developed. From the flexibility of scale and thematic overlays, scalable thematic maps of study areas can be generated at fairly short notice from the massive database. Despite various limitations, the appropriateness of this mapping methodology was tested, refined and is thus suitable for mapping of vulnerable area especially. The satellite image interpretation accuracy was about 80% indicating that the methodology is robust and reliable if well executed.

The results of this project indicate that high resolution data can be reliably and rapidly used to update maps at both national and regional levels. However, it should be noted that use of remote sensing data has certain limitations. These include: Geometric inaccuracies and errors: satellite mapping carries high possibilities of inheriting and cumulatively propagating inaccuracies and errors through both the source data and methodology. It is therefore important that potential users are aware of these limitations and thus use the maps as a general information source and not for site specific studies. As with any earth resource issue, regulatory and policy decisions demanding the most accurate and precise information will require more detailed data, especially those from ground observations. It should also be recognized that the spatial properties of the final data are a combination of the geometries of the individual source data layers i.e. (a) the use of geocoded and in-house geometrically-corrected data; and (c) the integration of ancillary data whose geometry has been altered somewhat in the raster-to-vector conversion. However, the geometric fidelity of each dataset, combination of datasets, and products derived through image processing operations in this case were carefully scrutinized at each stage of the mapping project to maintain the highest level of co-registration possible.
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QGIS, https://qgis.org/
Automatic water-body extraction is an emerging requirement as the large volumes of high resolution remote sensing imagery is available and digitizing water-bodies manually is a tedious job. The water-bodies are dynamic in nature, that depends upon the season and environmental conditions. Conventional, water-body extraction methods are applied on multispectral images due to the presence of spectral signatures in the form Normalized Difference Water Index (NDWI). Though, multispectral images are available at high spatial resolution but as compared with panchromatic images they are usually three to four times poorer in spatial resolution for any sensor. In order to extract smaller water-bodies to the maximum extent, a methodology is proposed based on high resolution panchromatic images. Unlike multispectral images, panchromatic images don’t have unique signatures for water-body. Because of the poor signature they are easily confused with shadows and wet agricultural lands, where many of the water-body extraction algorithms fail. Also the naturally formed water-bodies having irregular boundaries will take more time for manual digitization. Some applications like DEM generation, flood monitoring and other environmental studies require very accurate boundaries. Earlier approaches are based on the training sets with predefined window size. The use of training sets is not suitable for all types of water bodies like clear, sediments that are acquired in different seasons with different sensors. Considering all these issues we are proposing an automatic methodology using statistical approaches for water-body extraction. It is based on reflectance, texture and Human Activity Index. Initial segmentation of water-body is based on the automatic estimation of a threshold value using entropy maximization principle. The false alarms are further reduced by using the object level statistics like human activity index by separating homogenous and non-homogenous objects. In this paper an algorithm for contour refinement is also incorporated for accurate boundaries and delineation of small land portions within the water bodies. The proposed methodology was applied on Cartosat-1 images. The evaluation results have showed that detection efficiencies better than 90% can be achievable. 

KEYWORDS: Panchromatic, Entropy, NDWI, High Resolution, Water body.

1. INTRODUCTION

Detection of water bodies using satellite data finds its important use in DEM generation, flood monitoring, assessing the damage caused by floods, assessment of the risk due to lakes that are damaged either naturally or artificially etc. Various methodologies are in use for automatic detection of water bodies using the multi-spectral data. Most of them are based on the utilization of the near infrared band as the water reflectance in this band is very low. With the advent of high resolution images, it is now possible to generate good DEMs using the high resolution stereo images. However, there are some limitations in generating the accurate elevation points by using the panchromatic stereo data over the regions of water bodies, snow, forest, settlements, etc. The automated DEM generation procedures using the stereo data require that these features be identified so that separate strategies can be employed to generate accurate DEM over these regions. The elevation of any pixel on the surface of the water body should be the same. But due to the fact that presence of conjugate match points by stereo matching procedures leads to inaccurate DEMs over these surfaces. Hence one has to utilize water body layers, in conjunction with the DEM generation techniques, to resolve this issue. These methods can be applied either during the DEM generation process or at the post-processing level after the DEM is generated. Though some open source data also readily available, e.g., SRTM Water Body Data (SWBD) for the entire globe for free download in the form of shape files, but only big water body shape files were available with SRTM as the resolution of SRTM is low and also it will not exactly overlay on the water bodies of high resolution data due to differences in accuracies. The naturally formed water-bodies having irregular boundaries will take more time for manual digitization. Some applications require very accurate boundaries. Though multispectral images are available at high spatial resolution but as compared with panchromatic images they are usually three to four times poorer in spatial resolution. Conventionally water-body extraction methods are applied on multispectral images by use of spectral indices in the form of NDWI. A new model based EOS/MOSDIS model which can segment the water body and extracted by the criteria of NDWI is explained in (zhang quiwen,2007). A supervised classification algorithm explained in (Habibullah U Abbasi), (Ana Carolina Nicolsi da Rocha Gracioso 2005), (Young-Joon Jeon, 2004). SVM based classification is discussed in (GIdudu Anthony, 2007). The water-bodies are dynamic in nature, that depends upon the season and environmental conditions. Supervised classification methodologies depend on the number and size of the training sets and they may not be accurate to get proper boundaries as some of the applications require exact boundaries. The data fusion technique is used to characterize and delineate flood damage in (G.M. Petrie, 1994). Analysis of multi-temporal images has been discussed in several papers in a special issue (IEEE Trans, 2003). The use of multi-temporal data for monitoring water bodies needs registration for establishing of correspondence. There are several automatic registration procedures discussed in (Suresh Kumar pillala, 2012), (Alexander Wong , 2007), (Youcef Bentoutou, 2005).

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NDWI based methodology on multispectral images has been discussed in (MC Feetres, S.K., 1996). In view of the above factors and in order to extract smaller water-bodies to the maximum extent, a methodology is proposed based on high resolution panchromatic images. Unlike multispectral images, panchromatic images don’t have unique signatures for water-body. Because of the poor signature they are easily confused with shadows and wet agricultural lands, where many of the water-body extraction algorithms as explained above may fail. Considering all these issues a new methodology is proposed for extraction of water bodies automatically on panchromatic images based on reflectance, textural and Human Activity Index measures and achieved better than 80% detection efficiency. Further, a semi-automatic approach introduced to detect the remaining water bodies based on seed point and region growing algorithm using local statistics.

2. METHODOLOGY

Though, water exhibits lowest reflectance in the spectral bandwidth of the panchromatic band, it is not easy to delineate water bodies automatically. This is because, apart from the wet lands shadows of the mountains, clouds, and buildings also exhibit lower reflectance values and thereby overlap with those of water pixels, making their separation very difficult. Further, if the water is turbid then these pixels exhibit higher reflectance and may create confusion with other land features, and the difficulty increases if there is a varying degree of turbidity levels. The system architecture for extraction of water body layers is shown in figure 1.

Figure 1. System Architecture for extraction of water body layers

2.1 Automatic Extraction

In this methodology multi-level segmentation approach is introduced to detect probable water-bodies based on lower reflectance and further refined using textural measures to separate the cloud shadows and wet agricultural lands. Entropy based threshold technique is used to get the lower reflectance automatically. The false alarms are further reduced by using the object level statistics like human activity index by separating homogenous and non homogenous objects. Figure 2 shows the complete scheme for automatic water body extraction.

Figure 2. Scheme for automatic water body extraction
2.1.1 Initial Segmentation

As the water bodies in panchromatic data exhibits lower reflectance value as compared with other features of the image, entropy maximization auto threshold principle is used to separate lower reflectance features automatically. Pun (Jain, A.K., 1989) proposed an approach to compute the threshold value automatically for separating the object from the background using the concept of entropy maximization.

Let $H_b$ be the posterior entropy of the background and $H_w$ be the posterior entropy of the foreground which can be estimated as

$$H_b = \sum_{i=1}^{I} p_i \ln(p_i)$$  \hspace{1cm} (1)

$$H_w = -\sum_{i=t+1}^{N} p_i \ln(p_i)$$  \hspace{1cm} (2)

Where $p_i$ is the probability at intensity ‘i’ and ‘t’ is the threshold value, the threshold ‘t’ for separating background and foreground is computed when $H = H_b + H_w$ is maximum. The segmented image gives the probable water-bodies in the image with other features like cloud shadows, building shadows and wet agricultural lands. This can be further refined using textural measures.

2.1.2 Refined Segmentation

The segmented output in previous step is further refined by using texture measures explained by (Haralick Robert M. Haralick, 1973). In the proposed methodology two textural measures are used viz., Sum of difference squares and Entropy to differentiate the shadows, wet agricultural lands from water bodies.

2.1.3 Morphological Operations

After initial segmentation the water bodies will be in the form of disjoint entities. In order to combine disjointed entities in to a single water body and also to remove noisy entities, a set of morphological operations (Jain, A.K., 1989) are applied.

2.1.4 Refined water bodies

After Morphological operation, each entity is extracted as single water body using connected component labelling for further processing to reduce false alarms by computing human activity index of each object which is defined based on sum of variance in the texture measures.

2.2 Semi-Automatic Extraction

The above explained automatic extraction methodology applied on different panchromatic images have achieved 80% detection efficiency. To get the remaining water bodies which are missed in automatic process a semi automatic procedure is proposed based on seed point and region growing using local statistics. In this approach user has to draw one bounding rectangle around the water body. Using the bounding rectangle, seed point is selected based on the automatic threshold as discussed in the initial segmentation process of automatic process. Using the seed point and region growing process and homogeneity criteria exact shape of the water body is extracted. Figure. 3 shows the processing scheme for semi automatic water body extraction.

Figure 3. Scheme for semi-automatic water body extraction

3. WATER BODY MONITORING

Once the water bodies are extracted for an input image, there is a need to detect the changes on the same area acquired on multiple dates which is helpful in getting accurate information on the extent of water bodies that may be useful for flood inundation, monitoring and relief purposes. The prerequisite to monitor water body changes between the images acquired on different dates is pixel to pixel image registration. A scheme is proposed to compare the multiple date images even there is mis-registration between pre and post event images.
3.1 Scheme for Matching of Water Bodies

A feature table for each image (pre and post) is maintained which consists of latitude, longitude, centroid (Center Scan, Center Pixel), area, perimeter and irregularity for each extracted water body in the image. Both the tables are sorted according to area in descending order, as the idea is to give emphasis on the larger water bodies. Then the first three water bodies (W1, W2, W3) from feature table (Pre) is matched with three water bodies (W1’, W2’, W3’) from feature table (Post) using Latitude and Longitude information. The remaining water bodies are matched based on the distances between the extracted water bodies.

![Scheme for monitoring water bodies](image)

Figure 4. Scheme for monitoring water bodies

4. RESULTS AND EVALUATION

4.1 Results

The proposed methodology has been applied on several panchromatic images. The detected water-body layers are generated in the form of ESRI shape files which can be read from any IP software. Here, results of automatic and semi-automatic process are shown at different stages. Figure 5 shows the segmented image using automatic threshold and texture measures. Figure 6 shows the extracted water bodies automatically and overlay of the shape file with the original image. Figure 7 illustrates the extracted water body using semi automatic process. This software also handles the non-water body regions within the bigger water bodies while creation of shape files. Once water bodies extracted by automatic and semi-automatic process is completed, a report can be generated with the attributes like centre latitude, longitude, area and perimeter. After report generation one can view, add, delete and edit the respective water bodies. The evaluation studies using this methodology were explained in the next section.

![Extracted water bodies](image)

Figure 5. Extracted water bodies from Cartosat-1 Panchromatic data

![Cartosat-1 Image](image)

![Extracted Water Bodies](image)
Table 1 depicts the sample report on list of matched and unmatched water bodies with the indication of percentage of change in area of water bodies in the monitoring process.

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Scan1 (Pre)</th>
<th>Pixel1 (Pre)</th>
<th>Area (Pre)</th>
<th>Scan2 (Post)</th>
<th>Pixel2 (Post)</th>
<th>Area (Post)</th>
<th>% of Change In Area</th>
<th>Conclusions</th>
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<td>4741</td>
<td>532</td>
<td>92389</td>
<td>4789</td>
<td>314</td>
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<td>7966</td>
<td>3673</td>
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<td></td>
<td>765</td>
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<td>61017</td>
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<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
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</tr>
</tbody>
</table>

Table 1. A Sample report showing list of Matched and Unmatched Water Bodies
4.2 Evaluation

The evaluation is carried out based on detection efficiency, false alarms and figure of Merit on different input images of Cartosat-1 data with different terrains and contents like dam, lake, river, water body, cloud shadow etc. The following measures given in equations (3), (4) and (5) are used to assess the performance of automatic detection. The evaluation results are shown in table 2.

\[
\text{Detection Efficiency} = \frac{E_w}{A_w} \times 100 \quad (3)
\]

\[
\text{False Alarm Rate} = \frac{F_w}{A_w} \times 100 \quad (4)
\]

\[
\text{Figure of Merit} = \frac{E_w}{(A_w + F_w)} \times 100 \quad (5)
\]

Where,
\[A_w \quad \text{---- actual number of water bodies present in the image}\]
\[E_w \quad \text{---- total number of extracted water bodies}\]
\[F_w \quad \text{---- number of false alarms}\]

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Actual Water Bodies</th>
<th>True Positive</th>
<th>True Negative (Omission)</th>
<th>Figure of Merit</th>
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Table 2. Evaluation results of Water Bodies applied on seven sample data sets

5. CONCLUSIONS

The results shown above has demonstrated that the methodology is robust and accurate for extracting water-body layers from panchromatic images and detection efficiency of better than 90% is achievable. This approach drastically reduces the man power involved in digitizing the water-bodies. This methodology was applied on high resolution remote sensing images like Cartosat-1, Cartosat-2 and found to be consistent for map updation. This can be further improved to reduce the false alarms by introducing temporal data analysis.

ACKNOWLEDGMENTS

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GENEARTION OF CITY MODELS FROM WORLDVIEW-03 AND CARTOSAT-01 STEREO IMAGES USING SITE AND CITY MODEL GENEARTION APPLICATION

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ABSTRACT
India has witnessed rapid urbanization in last few decades. By 2030, it is estimated that about 40.76 percent of country's population will be residing in urban areas. Although, urbanization has helped in growth of economy, employment creation, global exposure, it has also lead to unorganized and unplanned growth of the cities. Efforts are being made to ensure the sustainable development of cities. One such effort is by Ministry of Urban Development, Government of India, to develop 100 smart cities across India. However, use of geospatial data and techniques greatly are valuable in such efforts. The 3D city models are very important resources for urban planning, infrastructure development, navigation and routing, assessing energy requirements, solar illumination, crisis management and many more other applications.

The Site and City Model Generation Application is an application software indigenously developed at ADRIN for generation of Site and City model from high and very high resolution stereo images acquired by satellites. The application was originally developed to work for a small area. The application is augmented for generation of city models. The application is supporting multiview data from Cartosat-2, stereo data from Cartosat-1, stereo data from Quickbird -02 and Worldview-03 stereo data.

KEYWORDS: Site and City Model, Stereo data, Multiview, Epipolar geometry, Geometrically constrained image matching, Digital Surface Model

1. INTRODUCTION

Rapid urbanization and growth of urban population in India in last few decades lead to economic growth, better employment and medical facilities, global exposure and infrastructure development. However, often the growth of cities were unplanned, which lead to lowering the quality of living for many urban dwellers. Ministry of urban development, government of India has been working towards sustainable development of the cities.

In urban planning, use of geo-spatial data is very important. Two dimensional layout of cities are being prepared under various government scheme. However, inclusion of third dimension provide planners a much more realistic scenarios of cities. Application like energy consumption requirement, solar illumination, crisis management, population density assessment, impact of flooding etc need detail 3D city model of the area.

Extraction of 3D information needs stereo acquisition of area of interest. India's Cartosat-1 is one of the mission to acquire the data in stereo mode. The new era satellites, have better specification related to manoeuvring and agility. It is common to use single camera system to acquire stereo data of area of interest by appropriate payload programming. India 's Cartosat-2 and Cartosat-2S series of satellite can work in a specific mode, called multiview mode to acquire the image data of are from different view angles. Digital Globe's Quickbird and Worldview series of satellites also acquire image data in stereo mode.

We have indigenously developed algorithms and software application for generation of site model from Catosat-2 multiview images (ISPRS, 2012). The application was limited to generate 3D model of an area of limited extent. The application was further modified for including Cartosat-1, Quickbird -02,Worldview-1 and Worldview-03 stereo data.

The process starts with rigorous sensor modelling for each supported satellite, updating the orientation parameters, generation of Rational Polynomial Coefficients, Epipolar image generation, geometrically constrained image matching, digital surface model generation, followed by building height computation and model generation in open Flight or Skyline's .Fly format.

Building height computation and verification with ground calibrated data was also done. From Cartosat-2 series of satellites the achieved building height accuracy is of the order 2 meters (Root Mean Square).

The application was modified to generate 3D city models. Compared to working for small area of extent, city model generation poses many challenges. The buildings are often closely packed and it is very difficult to locate the ground. As the number of buildings are very high, getting the building boundary by digitization also pose practical challenge. To overcome this difficulty, we made use of open source data on outline of building boundaries.

As the resolution of the image increases, the amount of data to be handled for various image handling operations also increases. The procedures for epipolar image generation, orthoimage generation, digital surface model generation were modified to divide in grids and perform parallel processing.

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The paper describes in brief the methodology followed, details of the application, results and conclusion. The application is a generic application and can operationally generate city models of any area acquired in stereo mode for supported satellites.

2. DETAILS OF THE SATELLITES

2.1 Cartosat-1

The Cartosat-1 satellite was launched in 2005. The satellite has panchromatic sensor with nominal ground sampling distance of 2.5 meters. Cartosat-1 has a two camera system capable of acquiring images at -5 deg and +26 deg view angles. The sensor acquires the data in panchromatic band. Over past thirteen years the satellite has acquired data over India and other parts of the world.

The B/H ratio of the stereo acquisition from Cartosat-1 is 0.6. thus theoretically the achievable height accuracy is about 4 meters for parallax equivalent to one pixel. Although, the data is medium resolution and the height accuracy is coarse for city model application, the global availability of stereo data is certainly a big advantage, specifically in areas where high rise buildings are more.

2.2 Worldview-03

Worldview-3 satellite was launched in August 2014. The nominal ground sampling distance for panchromatic band is 31 cm. The satellite also has SWIR, CAVIS and multispectral bands. The nominal ground sampling distance of multispectral data is 1.2 meters. The specification for geometric accuracy is 3.5 m CE90 without using any ground control points. The spacecraft acquires the stereo images of the area of interest by manoeuvring the satellite. The position and orientation information is available at every 0.2 seconds.

2.3 Details of data sets

Worldview-3 data of western part western Hyderabad was obtained on 16 Feb 2016. The product level is Stereo 1B with radiometric correction. Nominal pixel resolution of PAN data is 31 cm. The pair is an along track stereo pair with in-track look angle of -6 deg and +26 deg. PAN image is acquired with 48 TDI level and number of pixels per line are 42500. Associated geometric calibration files and auxiliary information is also provided with the data. The images are radiometrically corrected but geometrically unprocessed.

The Cartosat-1 stereo pair of Delhi is covered by two stereo pairs, covering 1800 sq kms of area. The date of pass for one data set is 21 April 2011 and for the other one it is 2 May 2011.

3. METHODOLOGY

The block diagram of city and site model generation process is depicted in figure 3.1. The basic inputs are at least two multiview/stereo images. The attitude and position information is available in ancillary files. The process allows the user to use either ancillary information (i.e. position and orientation information) or the available rational polynomial coefficients.

If user chooses to process using ancillary information, the rigorous sensor modelling is done for the data set using the physical sensor model, the absolute and relative orientation parameters are estimated and the rational polynomial coefficients are computed in terrain independent mode.

Afterwards the epipolar images are generated for these views. As the size of images are very big the total scene is divided into grids and each grid is processed in parallel to generate the epipolar image. Once epipolar is generated a dense DSM is used for generating Digital Surface Model. Iterative orthoimage rectification technique is used to generate the Digital Surface Model. The starting Digital Surface Model for orthoimage generation is Shuttle Radar Topographic Mission. It is updated incrementally by image matching at regular interval.

The final Digital Surface Model is filtered to generate the Digital Terrain Model which is further used for generating the Ortho image. The edges of buildings are delineated by 2-D digitization and refinement procedures. If open source building outlines are available they are also used to get the building boundary after refinement.

Geometrically constrained image matching procedure match the edges of building boundary in epipolar images. The ground height of the building is either picked from DTM or obtained through matching of nearby ground points.

At present the building top is assumed to be flat, rooftop is not modelled. The orthoimage, Digital Terrain Model, building boundaries with computed height are input to object modelling and visualization process. The object modelling process output can be open flight or .fly format.
4. DETAILS OF THE DEVELOPED APPLICATION

The application is developed as end to end process starting with basic inputs. The supported satellites are Cartosat-2 series of satellites, Quickbird -02, Worldview-03 and Cartosat-1. The user can select the options to work either with ancillary information file or the rational polynomial coefficient file. The data preparation module allows user to automatically identify the reference point from Landsat Data Continuity Mission-8 orthoimages. The height for the reference points are obtained from Shuttle Radar Topographic Mission 30 m posting Digital Surface Model. The user also has option to import the Ground Control Points for data preparation process. If the system level accuracy of the satellite is good without using any ground control point, user can obviate the process of Ground Control points identification.

User can select either full scene for processing or select a portion of the scene for processing. All the processes are automated except the boundary of the buildings needs to be digitized if they are not available through open source data.

The application is developed in C# on .NET platform using object oriented design and implementation. The Graphic User Interface (GUI) is developed using Windows Presentation Framework (WPF) for easy access to all the functionalities of the application. The application is tested extensively to enhance reliability of the software. Fig 4.1 shows the front end of the application.
5. RESULTS

The city model of part of western Hyderabad was generated using the developed application. Good number of buildings are available as open source data for the area of interest. The terrain is moderately undulating in the area of interest, Fig 5.1 shows the part of city model of Hyderabad. The data sets are from Worldview-03 stereo data. The city model of part of Delhi was generated using two scenes acquired on two different dates from Cartosat-1 stereo pair. Large number of building outlines are available from open source data. Fig 5.2 shows the part of city model of Delhi.
6. CONCLUSION

The paper described in brief the methodology of city model generation and details of the application for operational use. Results are presented for city model of part of Hyderabad and part of Delhi using Worldview-03 and Cartosat-1 stereo data respectively. Use of open source data has reduced the manual effort considerably. The generated city models can be used for applications such as urban planning, energy consumption estimation, population density estimation etc.

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AN ALGORITHM FOR GENERATION OF COUNTRYWIDE/STATEWIDE MOSAIC OF ORTHOIMAGES USING CARTOSAT-1 IMAGES

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ABSTRACT

In past thirteen years Cartosat-1 has acquired data over globe in stereo mode. Availability of contiguous data has helped to develop many new applications such as creating maps, visualizing terrain over very large areas, preparing base layers using Cartosat-1 orthoimages etc. However, the data is acquired over different orbits and dates. Obtaining a seamless feature continuity has been a challenge. Many different techniques have been developed to ensure the feature continuity between orthoimages. The paper presents a new technique which assumes that the residual orientation error can be modelled as bias. The error correction model computes line and pixel offsets for Rational Polynomial Coefficients. To estimate the bias, reference points are generated using automated matching procedures using Landsat-8 orthoimages and SRTM-30 m Digital Surface Model. An application is developed to implement the algorithm. The developed application termed as System for Terrain Modelling and Visualization (STEM-V) provides facility to submit automatic seamless orthoimage generation and geometric quality evaluation in batch mode. There is no limitation on the number of the images which can be submitted for seamless orthoimage generation. The paper presents results obtained for ten Indian states. The continuity of orthoimages is within two pixels for country and statewide areas.

KEYWORDS: Stereo Viewing, Feature Continuity, Image Matching, Orthoimages, Digital Elevation Model, Rational Polynomial Coefficient

1. INTRODUCTION

Indian Space Research Organization has indigenously designed, developed and launched Cartosat-1 in the year 2005. The satellite was designed to provide much awaited stereo coverage of entire country for generation of digital elevation model. Since 2005, Cartosat-1 has covered entire India and many parts of the world in stereo mode. The data has been used globally to generate high quality Digital Surface Models and orthoimages. Many study groups have evaluated accuracy of the generated Digital Elevation Models and Commercial Off the Shelf software provided solution to process Cartosat-1 stereo data.

Due to availability of contiguous data, state-wise and country wide orthoimages and Digital Surface Models were generated. One popular method to achieve geometric continuity is Bundle Block Adjustment. The procedure is an established procedure in photogrammetry. However, the mathematical complexity and the quality of inputs is stringent to achieve desired accuracy.

In many case user does not have required number of precise ground control points, or manual identification of control points slows down the process. The developed method use only two parameters, residual bias in roll and residual bias in pitch direction as unknown parameters. The parameters reflect as updation of line and pixel coefficient in RPC file. The process works with orthokit product provided by National Remote Sensing Centre. The orthokit product provides radiometrically corrected, geometrically raw image and associated rational polynomial coefficients. The accuracy of rational polynomial coefficients depends upon the level of processing.

The developed method utilizes Landsat-8 and SRTM-30 m Digital Surface Model as reference points. Hierarchical image matching technique is used to automatically extract reference point common between LDCM-8 orthoimage and Carto-1 aft image.

The developed application runs in batch mode to process all the images submitted for processing. Inbuilt geometric quality assessment tool automatically evaluates the accuracy of generated orthoimages. The continuity of the orthoimages is checked by displaying all the orthoimages of a region of interest in a visualization application.

The merit of the process lies in complete automation of the process, capability to process the inaccessible areas where ground control points are not available and able to work with set of images even if there are gaps between images. The paper describes in brief about Cartosat-1 mission, methodology, and results generated over ten Indian States. As precise Ground Control Point library all over country is not available, the outputs are compared with LDCM-8 orthoimages. Results are presented for two places where GPS surveyed precise Ground Control Points are available.

2. CARTOSAT-1 MISSION

2.1 Cartosat-1 Imaging Process

The spacecraft was designed to have three axis stabilized platform. Onboard system for orbit and attitude determination include differential GPS, SPS and two star trackers and gyroscopes. The spacecraft is mounted with an optical system having two cameras viewing the earth at +26 deg and -5 deg look angles.

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The stereo images are acquired in along-track mode with approximately 52 second separation. Due to very short time gap between two stereo acquisitions, the orbital and orientation parameters are correlated. The radiometry of the scene does is almost same due to the acquisition geometry. As Cartosat-1 has a fixed camera system, spacecraft need not to be manoeuvred to acquire stereo images, which is an added advantage towards maintaining the stability of the spacecraft.

2.2 Impact of onboard measurement specification on modelling process

The initial specification for system level accuracy using onboard measurement was within 150m (3 sigma) considering contributions from orbit, attitude, alignment angles and gyro calibration factors. However, in-flight calibration and recalibration of gyro has helped to improve the system level accuracy. The spacecraft has specification for drift rate of 3 \( \times 10^{-4} \) deg per second with a measurement accuracy of the order of \( 10^{-5} \) deg per second. The line integration time, that is the time record one line is of the order of 0.3 ms, which means that to cover a scene consisting of twelve thousand lines, it takes about four seconds. The processing of star tracker data and gyro data is done at Level-0 processing. As the least count of the drift rate measurement is of the order of \( 10^{-5} \) deg per second, the attitude determination process is able to account for the change in attitude due to drift over imaging of a scene. Once these values are appropriately used in rigorous sensor model, the remaining uncertainty could be due to in bias in attitude. It is easier to estimate the model the bias in roll and pitch direction compared to yaw. If yaw bias is present, very precise distributed control points are needed to compute.

2.3 Generation of Rational Polynomial Coefficients

After receiving the Cartosat-1 data is corrected for radiometric errors. The stereo strip triangulation process at NRSC data centre processes the data geometrically. The terrain independent approach is utilized to generate the Rational Polynomial Coefficient. The rational polynomial coefficients are generated for fore (acquired with +26 deg angle or higher look angle image) and aft (-5 deg or near nadir look angle image). Two radiometrically corrected but geometrically raw images along-with rational polynomial coefficients forms a set for stereo processing of the Cartosat-1 stereo data.

3. METHODOLOGY

The objective of the development of this algorithm was to process the Cartosat-1 data in completely automated mode with feature continuity. Another requirement was to process the data acquired inaccessible areas such as mountainous terrain where collecting precise ground control is very difficult task.

Availability of open source data such as LDCM-8 orthoimages and SRTM-30 over globe has been very useful. The specification for LDCM-8 orthoimages is 12 m CE90 globally. SRTM-30 m Digital Surface Model provides relative height accuracy of about 6 m at 30 meters posting. It was decided to use LDCM-8 orthoimages as planimetric co-ordinate for creating a reference point. The height for the reference point is associated using bilinear interpolation technique by interpolating SRTM-30 m data at desired location. Near nadir image and SRTM-30 m Digital surface model is used for orthoimage generation.

To automatically collect the image position of reference point from Cartosat-1 images, hierarchical image matching technique is used. A good number of well distributed reference points are collected over each Cartosat-1 image. The residual error is computed using the reference points, it is modelled as residual orientation error in roll and pitch direction. As only RPC coefficients are available, the equivalent value is computed and updated as line and pixel offsets. All the orthoimages re-evaluated using automated data quality evaluation module.

3.1 Orthoimage Generation

The orthoimage generation procedure needs input image, corresponding rational polynomial coefficients and Digital terrain model at suitable spacing. The projection and datum needs to be defined. The developed process use UTM as standard map projection and WGS-84 as horizontal datum and Geoid as vertical datum. LDCM-8 orthoimage database is available. The image extent of Cartosat-1 data may fall in multiple orthoimages of LDCM-8. The corresponding area from image extents is mosaiced and is available as reference. Digital Surface Model of the area corresponding to image extent is extracted from available SRTM-30 m digital elevation model. The image object relation is established using the updated rational polynomial coefficients. The orthoimages are generated at 2.5 meter resolution.

3.2 Hierarchical Image matching Process

Digital image matching algorithms can be classified into two basic approaches: area matching and feature matching. In area matching, the gray levels within a window are matched against the gray levels within the window in other image. In feature matching, extracted feature such as interest points, line segments and closed contours are matched between the images. To obtain the homologous points between Cartosat-1 and LDCM-8 orthoimages, we have used Forstner operator to find interest points. Image pyramid is constructed to reduce the pull-in range. Normalized cross correlation is used as similarity measure. A good number of well distributed points are generated through the matching procedures. Multiple filtering techniques are used to weed out wrong matched points. The image position in the Cartosat-1 image is part of the reference point.

3.3 Estimation of Residual Bias

Hierarchical image matching procedure explained above provides the correspondence between Cartosat-1 image and Landsat-8 orthoimage. Image position in Cartosat-1 image (line, pixel) and ground co-ordinates (latitude, longitude and height using Landsat-8 orthoimage and SRTM-30 Digital Surface Model) forms reference point. The reference points co-ordinates are limited by the
accuracy of the Landsat-8 orthoimages and SRTM-30 Digital Surface Model. The relative height accuracy of SRTM-30 Digital Surface Model data is better than 10 m in non-mountainous regions. The correction procedure is limited by the accuracy of input reference points. However, as system level specification of Cartosat-1 is coarser than 12 meters and precise ground control points are not available everywhere, it is relevant to improve the accuracy of all Cartosat-1 orthoimages within a pixel of reference input images. The residual orientation parameters are computed by taking into account all valid reference points. The rational polynomial coefficients are updated using the estimated parameters as line and pixel offsets. No yaw bias is computed.

3.4 Geometric Quality evaluation

Generated orthoimages are submitted for evaluation of geometric accuracy. This process is also completely automated and each and every orthoimage is checked for geometric quality assessment. The procedure includes hierarchical image matching between generated Cartosat-1 orthoimages and Landsat-8 orthoimages. Both orthoimages are in UTM projection system and geoid is taken as vertical datum. The homologous points obtained through image matching procedure are attached the UTM co-ordinates. The difference between map projected co-ordinate of reference orthoimage and Cartosat-1 orthoimage is obtained. It is ensured that good number of well distributed points are used for Geometric Quality Evaluation. Root mean Square value of difference between corresponding northing and easting value is computed for each Cartosat-1 orthoimage.

At two places precise Ground Control points from GPS surveying are available. Cartosat-1 orthoimages were evaluated using these points, however the GPS points were not used for generation of the orthoimages.

3.5 Visual inspection of Orthoimages for assessment of continuity

In a visualization system, all orthoimages for area of interest(area/countrywide) were displayed simultaneously and checked for continuity of the features. Specific attention was given to mountainous terrain. SRTM-30 Digital Surface Model was also visualized in background to validate effect of shadows for orthoimages generated using different season data.

4. RESULT AND ANALYSIS

Cartosat-1 data sets are available over India. State wise datasets were separated and processed. Figure 1 to Figure 10 shows the results of geometric quality evaluation for ten Indian states. Each figures shows the graphical representation of the root mean square error in northing and easting direction. The x-axis shows the data set number. Figure 4.1 shows the results for state of Andhra Pradesh. Total 435 data sets were generated and evaluated. There could be matching errors or not finding enough number of points. In such cases, the computed errors are high, such products are routed for manual identification of reference points.

Figure 4.1 RMS Error in Easting and Northing direction for Andhra Pradesh (Total 449 data sets)

Figure 4.2 RMSE in Easting and Northing for Kerala (Total 78 data sets)
Figure 4.3 RMSE for Jharkhand State (Total 489 data sets)

Figure 4.4 RMSE for Goa (Total 23 data sets)

Figure 4.5 RMSE for Maharashtra (Total 622 data sets)
Figure 4.6 RMSE for West Bengal state (Total 175 data sets)

Figure 4.7 RMSE for Tamilnadu (Total 273 data sets)

Figure 4.8 RMSE for Odissa State (Total 470 data sets)
Figure 4.9 RMSE for Jammu and Kashmir (Total 491 data sets)

Figure 4.10 RMSE for Karnataka (Total 285 data sets)

Figure 4.11 (a) and (b) Easting and Northing Error at GPS surveyed points
Figure 4.12 Orthoimages for a mountainous terrain and feature continuity at original resolution

Figure 4.13 Visualization of orthoimages and DSM (Himalayan region)

Figure 4.1 to fig 4.10 shows the graphical representation of the error for different states of India. The RMS error with respect to the reference image is contained within a pixel of reference image. Fig .4.11 (a) and (b) shows the geometric quality evaluation using GPS surveyed points. In this case, the reference point for rational polynomial updation and orthoimage updation are taken from
LDCM-8 and SRTM-30 meter Digital Surface Model. The evaluation is done using GPS surveyed point to ascertain absolute accuracy of the orthoimages. If precise control points are available over all reaps, it will be a good exercise to ascertain the absolute accuracy of orthoimages.

The feature continuity is checked manually by displaying all orthoimages simultaneously for a state. The continuity is well within a pixel except few cases. Even in the highly mountainous regions such as Jammu and Kashmir feature continuity is maintained. Fig 4.13 shows the visualization of Cartosat-1 orthoimages over Digital Surface Model. The co-registration of ridges and peaks in orthoimages and corresponding Digital Surface model is observed.

5. CONCLUSION

The developed algorithm was used to generate and evaluate a total of three thousand three hundred fifty five orthoimage. All the orthoimages are within a pixel of reference images. Evaluation at two areas where ground control points are available, the absolute RMS error is within 7 meters despite of using reference points from LDCM-8 orthoimages. The generated orthoimages covers different terrain types. The regions covered are flat, moderately undulating and mountainous regions. Feature continuity is maintained without affecting the positional accuracy. The orthoimages covers about 2.44 million sq km of the area. Orthoimages are suitable for applications requiring seamless products.

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DEEP LEARNING BASED MULTI-CLASS OBJECT DETECTION IN REMOTE SENSING IMAGES

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ABSTRACT

Object detection is a fundamental task that facilitates automatic interpretation and analysis of remote sensing images. The abundant spatial and contextual information with advance of remote sensing technology makes object detection more difficult. Recently, convolutional neural network (CNN) based methods have been outperformed over handcrafted or shallow learning based feature representations on object detection in natural scene images. These methods are not effective to deal with rotation variation and appearance ambiguity that ever present in the remote sensing images. Discrimination among the multi-class objects further becomes very challenging with variations of type, pose, and size. This paper proposes an effective methodology to learn a model that describes rotation by customizing the existing CNN based framework for multi-class object detection. An experiment is carried out on Ten-class object detection data set from very high resolution Google Earth remote sensing images using TensorFlow Deep learning framework. Proposed methodology demonstrates an improvement in the mean Average Precision (mAP) of Ten-class object detection over the existing approaches.


1. INTRODUCTION

The rapid development of remote sensing technologies has rendered many satellite and aerial sensors to provide optical imagery with high spatial resolution, facilitating a wide range of applications such as disaster control, land planning, urban monitoring and traffic planning (W. Liu et al., 2011; G. Cheng et al., 2013; J. Han et al., 2014; X. Li et al., 2010). In these applications, automatic detection of natural or man-made objects is a fundamental task and has received increasing research interests. The abundant spatial information and detailed structural information of objects contained in optical RSIs has offered new opportunity to address this challenging task.

The rich information contained in the optical RSIs with high spatial resolution has more details of objects whereas feature descriptors used by existing object detectors are still insufficiently powerful to characterize the structural information of the objects. The limited understanding of the spatial and structural patterns of objects in optical RSIs leads to a tremendous semantic gap for the object detection task. It can be observed that man-made facilities, such as airplanes, vehicles and airports, always have intrinsic structural property with specific semantic concepts, which has obvious difference from the background areas in optical RSIs. Consequently, building of the high-level structural and semantic features is a promising way for the interpretation of the optical RSIs and object detection task.

Recently, convolutional neural network (CNN) based methods have been outperformed over handcrafted or shallow learning based feature representations on object detection in natural scene images. However, these methods are not directly applicable to deal with very high resolution remote sensing images (VHRRSI) that comprise rotation variation and appearance ambiguity. Hence, discrimination among the multi-class objects further becomes very challenging with variations of type, pose, and size. This paper proposes an effective methodology to learn a model that describes rotation by customizing the existing CNN based framework for multi-class object detection. Here, Object detection task has been performed on open source 10 classes datasets using deep learning framework. The rest of the paper is organized as follows: Section 2 lists out the issues in object detection task. Literature survey of classical approaches in brief and deep learning approaches for object detection in the last couple of years is described in Section 3. In Section 4, some publicly available benchmark datasets for object detection are discussed.

2. ISSUES WITH OBJECT DETECTION

Object detection in optical RSIs often suffers from several increasing challenges including the large variations in the visual appearance of objects caused by viewpoint variation, occlusion, background clutter, illumination, shadow, etc., the explosive growth of RSIs in quantity and quality, and the various requirements of new application areas. Following are the main issues in object detection:

2.1 Variable number of objects

In general, the data is represented as fixed-sized vectors, when training machine learning models. Since the number of objects in the image is not known beforehand, the correct number of outputs may vary. Thus, some post-processing is required, which adds complexity to the model. However, the variable number of outputs has been tackled using a sliding window based approach, generating the fixed-sized features of that window for all the different positions of it. After getting all predictions, some are discarded and some are merged to get the final result.

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2.2 Size of objects

Another big challenge is the different conceivable sizes of objects. When doing simple classification, object that cover most of the image is classified. On the other hand, some of the objects could be as small as a dozen pixels (or a small percentage of the original image). Traditionally this has been solved with using sliding windows of different sizes, which is simple but very inefficient.

2.3 Formulation

A third challenge is solving two problems at the same time. Ideally a single model that combines the two different types of requirements i.e., location and classification is often a need.

3. LITERATURE SURVEY

This section explains both classical and deep learning approaches for object detection.

3.1 Classical Approaches

In the last decades, a large number of classical methods have been developed for object detection from aerial and satellite images. This section outlines the two most popular classical approaches for object detection.

The first one the Viola-Jones framework (Viola and Jones, 2001) which is fast and relatively simple, so much that it’s the algorithm implemented in point-and-shoot cameras. This enabled real-time face detection with little processing power. Another traditional and similar method is using Histogram of Oriented Gradients (HOG) features (N. Dalal et al., 2005) and Support Vector Machine (SVM) for classification. It still requires a multi-scale sliding window, and even though it’s superior to Viola-Jones, it’s much slower.

3.2 Deep learning approaches

This subsection provides complete overview on the evolution of deep learning approaches for object detection in the recent years. OverFeat (Pierre Sermanet et al., 2014) is one of the first advances in using deep learning for object detection. They proposed a multi-scale sliding window algorithm using Convolutional Neural Networks (CNNs).

R-CNN (Regions with CNN features) (Girshick et al., 2014) was proposed with a three-stage approach as follows:

- Extract possible objects using a region proposal method (the most popular one being Selective Search).
- Extract features from each region using a CNN.
- Classify each region with SVMs.

While it achieved great results, the training had lots of problems. To train it you first had to generate proposals for the training dataset, apply the CNN feature extraction to every single one (which usually takes over 200GB for the Pascal 2012 train dataset) and then finally train the SVM classifiers.

Fast R-CNN (Girshick, 2015) is similar to R-CNN that uses Selective Search to generate object proposals, but instead of extracting all of them independently and using SVM classifiers, it applied the CNN on the complete image and then used both Region of Interest (RoI) Pooling on the feature map with a final feed forward network for classification and regression. Not only was this approach faster, but having the RoI Pooling layer and the fully connected layers allowed the model to be end-to-end differentiable and easier to train. The biggest downside was that the model still relied on Selective Search (or any other region proposal algorithm), which became the bottleneck when using it for inference.

Faster R-CNN (Ren Shaoqing et al., 2015) added a Region Proposal Network (RPN) as shown in Figure 1, in an attempt to get rid of the Selective Search algorithm and make the model completely trainable end-to-end. RPNs output objects based on an “objectness” score. These objects are used by the RoI Pooling and fully connected layers for classification.

R-FCN network (Jifeng Dai et al., 2016) consists of shared, fully convolutional architectures as is the case of FCN (J. Long et al., 2015). We extract candidate regions by the Region Proposal Network (RPN), which is a fully convolutional architecture in itself. Given the proposal regions (RoIs), the R-FCN architecture is designed to classify the RoIs into object categories and background. In R-FCN, all learnable weight layers are convolutional and are computed on the entire image. The last convolutional layer produces a bank of k2 position-sensitive score maps for each category, and thus has k2(C+1)-channel output layer with C object categories (+1 for background). The bank of k2 score maps correspond to a k x k spatial grid describing relative positions. For example, with k x k = 3 x 3, the 9 score maps encode the cases of \{top-left, top-center, top-right, ..., bottom-right\} of an object category.
YOLO (Redmon et al., 2016) proposed a simple convolutional neural network approach which has both great results and high speed, allowing for the first time real time object detection. Prior work on object detection proposes classifiers to perform detection. Instead, we frame object detection as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimized end-to-end directly on detection performance.

SSD (Single Shot multi-box Detector) (Liu et al., 2016) discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location. At prediction time, the network generates scores for the presence of each object category in each default box and produces adjustments to the box to better match the object shape. Additionally, the network combines predictions from multiple feature maps with different resolutions to naturally handle objects of various sizes. SSD completely eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network.

4. PROPOSED METHOD

The success of Faster R-CNN is largely attributed to the ability of the RPN to generate multiscale and translation invariant region proposals in the natural scene images. However, Faster R-CNN is not effectively deal with the rotation and appearance ambiguity characteristics of geospatial objects.

The proposed methodology has two phases. First phase contains formulation and incorporation of a layer that mainly learns the rotation involved in the test data with respect to the original input. Second phase is a traditional Faster R-CNN method used for object detection. The two kinds of features are later combined in the final layers of processing in order to form a powerful joint representation.

5. EXPERIMENT AND RESULTS

In this section, the dataset considered for experiment is explained in brief followed by results. Experiments are conducted on a computer with a single Intel core i7 CPU, an NVIDIA Tesla K40 GPU, and 12 GB of memory.

5.1 Data Sets and Experimental Setup

A 10-class geospatial object detection dataset is considered and used for multi-class objects detection task. This dataset contains totally 800 VHR optical RSIs out of which 715 color images were acquired from Google Earth with the spatial resolution ranging from 0.5-m to 2-m, and 85 pan-sharpened color infrared (CIR) images with a spatial resolution of 0.08-m.

In the experiment, we use 600 remote sensing images as training data, and the rest of the 200 images as test data. We consider a detection to be correct if its bounding box overlaps more than 50% with the ground truth bounding box; otherwise, the detection is considered as a false-positive (FP).
5.2 Evaluation Metrics

Precision–Recall curve (PRC) and mean average precision (mAP) are considered to quantitatively evaluate the performance of an object detection system. Figure 2 shows a number of object detection results with the proposed approach. The ten numbers from 1 to 10 on the rectangles denote the object categories of airplane, ship, storage tank, baseball diamond, tennis court, basketball court, ground track field, harbour, bridge, and vehicle, respectively. We consider all region proposals with $\geq 0.5$ IoU overlap with a ground truth box as TPs, and the rest as FPs.

Figure 3 and Table 1 show the quantitative comparison results of four different methods, measured by PRCs and mAP values, respectively.

Figure 3. PRCs for baseball diamond, tennis court, bridge, and vehicle classes, respectively.
<table>
<thead>
<tr>
<th></th>
<th>Transferred CNN</th>
<th>COPD</th>
<th>RICNN</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airplane</td>
<td>0.6614</td>
<td>0.6225</td>
<td>0.8835</td>
<td>0.8912</td>
</tr>
<tr>
<td>Ship</td>
<td>0.5693</td>
<td>0.6887</td>
<td>0.7734</td>
<td>0.8254</td>
</tr>
<tr>
<td>Storage tank</td>
<td>0.8432</td>
<td>0.6371</td>
<td>0.8527</td>
<td>0.8985</td>
</tr>
<tr>
<td>Baseball diamond</td>
<td>0.8163</td>
<td>0.8327</td>
<td>0.8812</td>
<td>0.9512</td>
</tr>
<tr>
<td>Tennis Court</td>
<td>0.3499</td>
<td>0.3208</td>
<td>0.4083</td>
<td>0.8724</td>
</tr>
<tr>
<td>Basket Ball</td>
<td>0.4592</td>
<td>0.3625</td>
<td>0.5845</td>
<td>0.6954</td>
</tr>
<tr>
<td>Ground Track Field</td>
<td>0.7998</td>
<td>0.8531</td>
<td>0.8673</td>
<td>0.9012</td>
</tr>
<tr>
<td>Harbor</td>
<td>0.6201</td>
<td>0.5527</td>
<td>0.6860</td>
<td>0.7937</td>
</tr>
<tr>
<td>Bridge</td>
<td>0.4229</td>
<td>0.1479</td>
<td>0.6151</td>
<td>0.6079</td>
</tr>
<tr>
<td>Vehicle</td>
<td>0.4287</td>
<td>0.4403</td>
<td>0.7110</td>
<td>0.7423</td>
</tr>
<tr>
<td>mAP</td>
<td>0.5971</td>
<td>0.5458</td>
<td>0.7263</td>
<td>0.81792</td>
</tr>
</tbody>
</table>

Table 1. Performance comparisons of four different methods in terms of mAP values.

6. CONCLUSION

We have formulated and incorporated a model that describes rotation by customizing the existing CNN based framework for multi-class object detection. The proposed object detection method has been demonstrated on the ten-class VHR object detection data set. The results of the proposed method have been quantitatively analysed over existing methods. It is also shown that the proposed method outperforms the existing methods of the object detection task with a progressive margin of mAP.

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POLARIMETRIC SIGNATURE ANALYSIS OF NATURAL AND MANMADE FEATURES USING C-BAND POLARIMETRIC SAR DATA

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ABSTRACT

Urban and semi urban areas represent a unique composite, with a combination of manmade objects along with natural terrain set-up. Polarimetric SAR system measures the complex scattering matrix \([S]\) of a surface or object with quad polarisations. Analysis of polarimetric signatures using quadpole SAR data contribute profusely in characterizing the scattering mechanism of objects and surface features, in turn understanding feature clutter in a better way through polarimetric feature decomposition. Present paper analyses polarimetric signatures to characterize urban/ semi-urban features using C band quad polarized SLC data covering different landscapes. Coherent as well as incoherent polarimetric decomposition methods (namely Krogager, Freeman & Durden, Yamaguchi) were applied to characterize the scattering behaviour and to evaluate the potential of these decomposition technique for differentiation of features. It is found that in complex urban areas with feature clutter, the purity of polarimetric signature is reduced in medium resolution SAR data. Analysing in conjunction with polarimetric response plots revealing supporting information to confidently identify various features and their scattering mechanisms. Incoherent decomposition methods provide better results as double bounce component is enhanced

KEYWORDS: Synthetic Aperture Radar (SAR), Polarimetry, features, decomposition, incoherent, urban

1. INTRODUCTION

Polarimetric Synthetic Aperture Radar (SAR) has wide applications for earth & ocean observations, forest mapping, biomass estimation, paleo-channel detection and land cover mapping. Compared to single-polarization SAR data, quad-polarisation data provide unique information of the natural and manmade land features from the observations of various polarizations. Analysis of urban and semi urban areas based on SAR imagery have received less attention compared to studies of vegetation, soils, geology and other parameters of physical landscape. Information extraction using medium resolution SAR data poses significant challenge for mapping urban land-use/land-cover. The reason is high variability of the urban landscape and complexities of the interactions between the radar signal and the human built-up environment, wide range of variability of materials combined with the occurrence of feature cluttering. Present paper explores the scope of analysing polarimetric SAR imagery for providing manmade and natural feature details in discriminating different land covers at urban and semi urban area.

2. STUDY AREA AND DATASETS

A fully polarimetric (quad polarized) SAR sensor has all 4 channels HH, HV, VH and VV. Polarimetric C band (5.3 GHz/5.7 cm wavelength) SLC (Single Look Complex)dataset acquired in Fine-beam quad polarization mode of SAR satellite RADARSAT-2 is taken as test data for this study. The data acquired on 15th April,2008 in descending orbit (right look) with a resolution of 4.73m in range and 14.61 m in azimuth direction. The incidence angles are 19.83° in near range and 21.86° degree far range. The test area belongs to a temperate area of Canada near Vancouver. Subset of the full scene are taken to clearly visualize the land cover classes in output. An FCC (Fig-1) of HH (red), VH (green) and VV (blue) indicates the inherent strength of quad-pole radar data in comparison with single polarised data. The area represents diverse land cover types such as water bodies (Ocean and river), forests/vegetation, urban areas, agricultural land with crops, fallow land, open areas, golf courses and wetlands etc. The urban area is arranged in rectangular blocks characterised by regular structured urban residential buildings, High-rise and multi-storied commercial buildings, sheds and warehouses, roads, parks, bridges, airport and other man-made features. It depicts the ocean and river appear as Magenta colour (prominent VV component), vegetation and

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agricultural land with crops appeared in green (prominent HV-HV component) and urban area appeared in a mix of pink, yellow and green (prominent HH and mixture of HV, VV components). The appearance of the image is affected by speckle and mixture of colours which restricts its use for land-use using digital classifications.

3. METHODOLOGIES

In this paper SAR data analysis for feature analysis is carried out involving polarimetric data calibration, analysis of covariance and coherency matrices, polarimetric parameters computation, polarization decomposition and polarimetric signature analysis. Scattering matrix is transformed to covariance matrix (C3) and coherency matrix (T3) in single look and multi-look processing (3 in range and 1 in azimuth direction). Lee-sigma filter with sigma value of .9 (window size 7X7) is applied to reduce the speckle, but simultaneously it reduces the effect of point scatterers and double bounce effects. Different polarimetric parameters are computed from scattering matrix to understand the behaviour with respect to different types of natural and manmade distributed features in each band. Finally, coherent and incoherent polarimetric feature decomposition techniques are implemented and the results are analysed for scattering behaviour in each decomposition for different land-use features. European Space Agency’s SNAP (version 5.0) and PolSAR pro version 5.1 are used for processing and analysis of SAR data. In-house developed ShARP+ software is used for polarimetric signature analysis.

3.1 Backscattering components

Sigma nought values (intensity) of all 4 channels namely, HH, HV, VH and VV (in dB) are derived to estimate backscattering from different features in each polarimetric channel (Fig-2). Land-water boundary is much easily delineable at HV band (cross polarised). HH and VV band is more sensitive to urban structures and soil moisture (high dielectric constant). VH and HV is equally sensitive to urban structures and vegetation as well as soil moisture in general. The histograms and scatter plots (Fig -3) indicate the data distribution in each polarisation band and their relationships. The mean is around -14 for HH and VV polarisation but around -27 for HV and VH polarisation in the data. The reciprocity theorem applied while considering natural features (HV = VH). The histogram and scatter plots indicate that large amount of pixels in HH and VV channel are around -25 dB to 0 dB (yellow and red colour) and small amount of pixels are with lower values (black colour) at < -30 dB. Sigma nought ($\sigma^0$) values in HH and VV channels are more co-related than HH-HV channels or VV-VH channels (scatterplots at Fig-3).
The Span indicate the amount of total power of the system distributed in different channels (Fig- 4a). It has no information about how the total power is distributed among polarisation channels. Span of urban high-rise structures are high among all features and smoother surfaces (runway, taxiway, fallow land and area with grass etc) has lower span. In medium resolution complex urban area produces feature clutter which produces scattering from averaging out of different kind of scattering. Therefore, span doesn’t provide a clear indication for mixed urban areas and produce slight ‘salt and pepper’ effects in Span. Pedestal height is the minimum value of polarisation intensity, which represents the amount of non-polarised power in the received signal. If a single feature is scattering and the backscattered wave is fully polarised, the pedestal height is ‘0’ (Fig-4b). It indicates the number of different types of scattering mechanisms found in averaged samples of multiple dissimilar scatterers present in a distributed feature. Rough surfaces have more multiple scattering and higher pedestal heights as compared to smoother surfaces (low backscattered power value). Highest pedestal values occur for the thick forest/vegetation areas with higher branch density (multiple and volume scattering) suggesting existence of variation on the scattering properties of the adjacent pixel. An increased variability in species and forest structure resulting an increased pedestal size. Lower pedestal values occur for ocean and river water, wetland area, fallow lands. Urban areas have low pedestal height similar values like fallow agricultural land, cropland area. Urban blocks rotated away from radar look direction generates more multiple scattering and higher pedestal heights which is visible in medium resolution image also.

### 3.2 Polarimetric matrices

A full-polarimetric SAR measures the 2x2 scattering matrix [S], for each resolution cell. The scattering matrix (Equation-1) relates the transverse components of the field scattered by the observed scene Es to the incident one Ei

\[
\begin{bmatrix}
E_s^x' \\
E_s^y'
\end{bmatrix}
= \begin{bmatrix}
S_{xx} & S_{xy} \\
S_{yx} & S_{yy}
\end{bmatrix}\begin{bmatrix}
E_i^x \\
E_i^y
\end{bmatrix}
\] (1)

The covariance [C] and coherency matrices [T], shown below (Equation 2 and 3) are polarimetric descriptors, able to characterize the scattering behaviour of distributed scatterers(Van Zyl et al., 1987).

\[
C = |S_{xx}|^2 \begin{bmatrix}
|S_{xx}|^2 & 2|S_{xy}|^2 \\
2|S_{xy}|^2 & |S_{yy}|^2
\end{bmatrix}
\] (2)

\[
T = \begin{bmatrix}
|S_{xx}|^2 + 2|S_{xy}|^2 & 2|S_{xy}|^2 \\
2|S_{xy}|^2 & |S_{yy}|^2
\end{bmatrix}
\] (3)

The diagonal terms of the covariance matrix are real and represent power in each of the polarizations. The off-diagonal terms are complex and provide phase information to understand the scattering mechanisms better.

The coherency matrix [T] is closely related to the physical and geometric properties of the scattering process, and thus provides better and direct physical interpretation. Coherency Matrix components is depicted with RGB component where [T22], [T33] and [T11] are assigned in red, green and blue color respectively (Fig-4b). Backscatter values \((\sigma^{\text{HH}})\) and \((\sigma^{\text{HV}})\) of the study area is covering a wide range of surface roughness which is influenced by terrain features, vegetation type & cover, crop-type and moisture conditions. The backscattering intensity changes with these parameters and produces image brightness variations in the pixel color levels of images. The natural color composite of optical imagery belonging to the

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**Fig-4a Span**

- Low
- High

**Fig-4b Pedestal Height**

- RGB (T22, T33, T11)

**Fig-4c Phases – C23, C13, C12**
same area (Fig-4a from open source) is used as reference for different land-use categories. Different phase components (C12, C13 and C23), extracted form covariance matrix are represented as RGB (Fig-4c). For ocean and river water a very prominent high C12 (HH-HV) and low C23 (HV-VV) components are present because of rough ocean surface. Forest, vegetative areas are with low C12 and prominent moderate C13 (HH–VV) phase in a bit random way which indicate lack of any consistent phase relationship. This is because in volume scattering the responses from the leaves and branches of trees introduce completely random phase. For urban area a prominent higher C12 (HH-HV) is present and higher C13 is present for high-rise buildings, bridges etc. Phase distributions for regular urban blocks indicate a strong amount of trihedral response (multiple bounce) or surface scattering from structures like regular residential areas, warehouses. Phase distribution from grass and agricultural land with low crops or fallow land indicate a moderate C23 (HV-VV) and a very high C12 (HH-HV) component.

### 3.3 Polarimetric Signatures

The polarisation states of Electric fields $E_v$ and $E_h$ are associated with radar backscatter sigma-nought ($\sigma^0$) and the dependence of amplitude & orientation angles of the transmitted wave, defining a three dimensional surface plot called polarisation signatures. To synthesize the polarisation signature for any desired combination of transmit and receive antenna polarizations, the scattering matrix is generally converted to a 4x4 real matrix ($K$) called Kennaugh matrix. The scattering power can be determined as a function of the wave polarization variables ($\sigma^0$, the incident and backscattered orientation ($\psi$) angles and ellipticity ($\chi$). Orientation angle is angle of semi major axis with X axis in Poincare sphere and ranging from 0-180°. Ellipticity is the oval shape of the ellipse (linear polarisation with ‘0’ ellipticity angle and circular polarisation have 45°). To simplify the visualization, the backscattered polarizations are restricted to be either the same polarization (Co-pol) or the orthogonal polarization (Cross-pol) as the incident wave. Kennaugh matrix is the key element for polarization synthesis which can be performed, for any combination of transmit and receive antenna polarization, according to the following formula.

$$\sigma = K S^T x Kennaugh Matrix x S^T$$  \hspace{1cm} (4)

Co pol and cross pol polarimetric signatures (Fig-5) are plotted for different types of feature (indicated in Fig4-a) identification. Cross polarised responses behave in exactly opposite manner to the co-polarisation responses. Ocean area (A in Fig-4b) with surface scattering is depicting a polarimetric signature at 5a and 5b, which are more prominent at T11 component (blue) of coherency matrix. This scattering mechanism corresponds to the single scattering from a plane surface or sphere. Urban area shows strong coherence between co- and cross-pol polarizations, but with opposite polarity due to the difference in the rotation direction. Double bounce scattering (B in Fig-4b) corresponds to dihedral scattering (polarimetric signature at Fig- 5c and 5d) is more prominent at T22 component (red) of coherency matrix. Co-polarisation and cross polarisation shows peaks corresponding to high amount of oriented backscatter for building structures indicated by pedestal heights (Orange line at Fig.-5c). Vegetation with tall stands and grown crops (C in Fig-4b) are more prominent at T33 component (green) and corresponding to volume scattering (polarimetric signature at Fig- 5e and 5f). These polarimetric signature plots are delineated with pure pixels. Polarimetric signatures are very sensitive to the orientation of features relative to the radar line of sight. Several types of scattering are usually present within distributed features like mixed urban areas where urban blocks are with irregular shape, oriented buildings, closely spaced multiple manmade features with concrete and metallic features etc are not oriented towards radar look direction (D in Fig-4b). Polarimetric signature plots of those areas resemble more to volume scattering (5c and 5f). Polarimetric response plots of a partial polarised pixel will be different in shape and angle from polarimetric signatures of pure pixels. Polarised signature of a feature is not unique due to different combinations of scattering mechanisms. This may be caused by structural composition of forest features (density and type of trees, regular or irregular spatial distribution of trees, trunk diameter, density of twigs and branches, moisture content in the leaves and in soil, differently oriented buildings dielectric constant of

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**Fig - 5a & 5b. Ocean signature indicated by A**

**Fig – 5c and 5d Building Signature indicated by B**

**Fig – 5e and 5f Vegetation Signature indicated by C**
the feature etc). Polarimetric signatures of a feature may also vary with variations in radar frequency and local incidence angle. Many features may produce similar plots but the shape of the co-polarisation, cross polarisation signature plots and pedestal height indicate information about the type of scattering dominant from the feature. In complex urban areas with feature clutter, the purity of polarimetric signature is reduced in SAR data with medium resolution.

4. POLARIMETRIC DECOMPOSITIONS

SAR observables (parameters) obtained by Polarimetric decompositions focus on the generation of efficient descriptors from the scattering coefficients. These parameters provide physical interpretations like scattering mechanisms or polarimetric properties and utilised as input parameters for classification of polarimetric SAR data. Different types of coherent and incoherent polarimetric feature decompositions namely Pauli, Krogager, Freeman & Durden, Yamaguchi decompositions are generated. They are assessed to measure the scattering behaviour of natural distributed features and manmade features for deriving polarimetric SAR parameters. Commonly used Pauli decomposition (Fig-6) is with 3 decomposition components corresponding to 3 diagonal elements of the coherency matrix. The components are:

- \( (0.5|S_{hh} + S_{vv}|^2) \) represents surface scattering (Ps)
- \( (0.5|S_{hh} - S_{vv}|^2) \) indicates double-bounce scattering (Pd)
- \( (0.5|S_{hv} + S_{vh}|^2) \) associated with volume scattering (Pv)

Ocean and river water (surface scattering) appeared in violet (more blue and less red). Fallow agricultural land appeared in different shades of cyan to dark blue depending on smoothness of the surface and moisture content. Runway, taxi-track, apron, major roads railway line and some part of the river/coastal ocean appeared in bluish black colour because of specular reflection or very less scattering. Urban area with buildings and intermittent vegetation appeared in pink colour (double bounce from building structures) with intermittent green (volume scattering from vegetation and parks). Agricultural land with small crops as well as open area within airport appeared in darker green shades because of combined surface and volume scattering. Crops with foliage in agricultural land and vegetation/forest area appeared in green because of profound multiple bounce. Pauli components are strong indicators of crop growth development and phenology with measurement of volume scattering and the double-bounce. Secondary roads (dark colours) and agricultural field boundaries perpendicular to look direction are delineable in single look image but losts their identity in multilook image. Pauli decomposition is more effective and useful for assessing the natural features but not ideal for highlighting manmade features as physical interpretation of the resulting RGB image is difficult for urban areas. Model based decomposition (incoherent) methods like Freeman & Durden and Yamaguchi are assessed for the same.

4.1 Freeman and Durden decompositions

Freeman-Durden decomposition (Fig-7) is fitting a physically based, 3-component scattering mechanism model (double bounce, canopy layer and rough surface) to SAR observations under the reflection symmetry assumption without utilizing any ground truth measurements. It has been widely used because of its simplicity and stability. Freeman decomposition models scattering as the contribution of three scattering mechanisms. They are canopy scatter from a cloud of randomly oriented dipoles (forest), even or double-bounce scatter from two orthogonal surfaces (buildings) and bragg scatter from a moderately rough surface (subsets at top in Fig-7). It shows that the rough surface contribution describes texture characteristic more clearly than other contributions. Ocean and river water appeared in blue (violet in Pauli) because of bragg scattering. Double bounce scattering component is depicted more clearly with much lesser spill-over effect in comparison with Pauli decomposition. Urban area at the upper right corner of the image appeared in green (strong volume scattering) instead of double bounce in both Pauli and Freeman decomposition because of orientation of buildings. In both of these decompositions volume scattering components assume the scattering reflection symmetry, which is not applicable for this sector of urban area.
4.2 Yamaguchi decompositions

Rotated buildings at urban sector (mentioned in section 1.1) produce strong cross-pol backscatter which can be determined by model-based classifications. Scattering mechanism these regions are being dominated by volume scattering which is characteristic of natural vegetation environments. Yamaguchi introduced a four-component scattering model (Fig-8) with an additional helix component corresponding to non-reflection symmetry (cross-pol components) and de-orientation (rotation) compensation. Other 3 components are volume scatter from a cloud of randomly oriented dipoles (forest), even or double-bounce scatter from two orthogonal surfaces (buildings) and bragg scatter from a moderately rough surface (subsets at top in Fig-8). This helix scattering power is prominent in heterogeneous areas (complicated shape feature or man-made structures) and negligible in areas with natural distributed scattering. The scattering power shifts from volume to double bounce with a minimisation of T33 element and reduction of \( \frac{\text{HH-VV}}{\text{HH-HH}} \) (applicable when reflection symmetry exists). A very prominent salt and pepper effect is present in the helix components, which reduces its direct use as input in classification.

However, none of these decomposition techniques are sufficient for urban areas particularly in segments of cities with urban blocks that are orthogonal to the SAR look direction. Further the problem becomes more complicated using medium resolution SAR imagery with mixed backscattering signature and scattering. A better resolution image in linear quad polarisation may provide better decomposition results. Analysing decomposition components in conjunction with polarimetric response plots revealing supporting information helps in identifying various features and their scattering mechanisms.

5. OBSERVATIONS

Polarimetric parameters and feature decompositions contribute to a great extent in segregating the manmade and natural distributed features. Krogager in a coherent decomposition method, Freeman and Yamaguchi are in-coherent decomposition method. Different features are compared in RGBs which are generated with decomposed scattering component for Pauli, Krogager, Freeman and Durden and Yamaguchi (Fig 10a, b and c). In C band flowing water (ocean and river water), fallow agricultural lands with different moisture levels and sparse vegetation produce less radar returns and appear as different shades of blue and cyan colors (surface scattering). Medium level of vegetation, agricultural crops, some part of urban areas (oriented) and moderately rough surfaces present moderate backscatter (green and yellow colors). Dense vegetation, rough surface, irrigated croplands are with high backscattering. Man-made objects (urban buildings and infrastructures) can be identified by bright reflections in red, magenta yellow and orange colors). Terrain slopes towards radar having very high to high backscatter in all channels. Runway and other concrete / tar surfaces (taxiway, apron), part of inland lakes or river, sandy beaches (dry) show smooth dark surfaces because of very low backscatter. Among the implemented methods of decomposition, Freeman and Durden decomposition produces better feature depiction (Fig 10c). Prominent observations from natural and manmade feature are as follows-

Urban features – Urban environments (Fig-9b and 10) present numerous dihedrals and trihedrals, each of which can add incrementally to the backscatter from that pixel. Urban high-rise buildings oriented towards radar look direction shows strong backscattering in all 3 components (yellow and white colour) in Pauli (Fig-10a) and Freeman decomposition (Fig-10c) and double bounce in Krogager decomposition (Fig-10c). Double bounce (mix of pink and yellow) is prominent in all 3 decompositions for urban high-rise buildings oriented towards radar (P in Fig 10a and c). Urban structures perpendicular to look direction shows double bounce (Q in Fig 9b). For buildings and roads which are rotated relative to the radar look direction the double bounce component is different from conventional double bounce because of violation in reflection symmetry. For lesser oriented buildings, the double bounce component happens with a smaller amplitude and
mixed with other direct scattering mechanisms. When the rotation of buildings is more than a certain angle (R in Fig -9) multiple bounce is most prominent (R in Fig-10a, b, c). Runways, taxi-tracks (S in Fig 9b and Fig-10a, b, c), major roads are depicted in dark colour (very less surface scatter or specular reflection) in all 3 decompositions but Freeman and Durden generates the best results with more sharpness. Secondary roads are also depicted in Freeman decomposition in single look (Fig- 10c) but lost in multi-look processing. Double bounce (pink and yellow) and multiple bounce (green) effects are seen in bridges over the river (T in Fig-9b and Fig-10a, b, c) depending on their orientation towards look direction, pier height and number of levels. Multiple bounce effects created by the pillars, stands and ropes of the bridges are depicted very prominently next to the bridge on river water. Freeman decomposition (T in Fig-10c) preserves better details in comparison to Pauli and Krogager decomposition. Double bounce effect is very prominent for aerobridges and light masts (red dots) in Freeman and Durden decomposition (M in Fig- 9b and 0c).

Vegetation- In Pauli and other model-based decompositions, the HV is used to depict the multiple bounce or volume scattering. For area with vegetation/ forest with medium canopy (V in Fig 10a, b and c), polarimetric responses of volume scattering (appeared in green colour) are contributed by back scattering components from geometry of scatterer elements. Biophysical parameters and arrangements include structure and density of canopy, number of individual bush/ trees and their height indicated distinct polarimetric signature with different pedestal height. For the area with grass (open area around airport) and small vegetation multiple bounce is dominant in Pauli and Krogager decomposition but Surface bounce is dominant in Freeman decomposition (V in Fig- 10c) as the main contribution is from flat ground rather than grass. For golf area (GF in Fig 10a, c and Fig-11) multiple bounce is prominent in all the three decompositions. The broad leaves crops show mainly volume scattering, whereas the small stem crops present both the double-bounce and volume scattering. Rough surface scattering by non-vegetated surface or low vegetation can cause significant depolarization and shows significant randomness. Consequently, a rough surface may be characterised by volume scattering and then could be misinterpreted as vegetation.

Soil Moisture - C-band SAR signal depicts a higher sensitivity to soil moisture and this sensitivity is higher for HH and VV than in HV polarizations. As per literature in C band, with HV or VV the soil moisture is getting over-estimated in comparatively dry soil and under-estimated with moist soils. For Fallow agricultural field the backscattering coefficient is more sensitive to volumetric soil moisture in HH and VV than in the HV polarization. Regions with homogenous SAR properties found within agricultural and natural forest areas are mostly large in size.

Polarimetric parameters for can contribute significantly for discriminating features natural features with substantial size and contribute to classification. In urban environment with multiple features with different orientation, material and geometry, the contribution is restricted by medium resolution images.

6. CONCLUSION

Quad polarized SAR data is extremely useful in segregating and interpreting features in comparison with Single polarisation SAR data in area with natural features as well as with urban area. Polarimetric signatures and decompositions are extremely useful using quad polarized data for understanding the scattering behavior of natural and manmade features. Feature decomposition provides significant scattering information about the natural features like water vegetation, forest, open area. This establishes a physical interpretation for the polarimetric response of area with natural features and can be a direct input for digital classification. In urban area polarimetric response plots and signatures of urban structures and features sensitive to the orientation towards radar look angle. It is further complicated by the fact that polarimetric response plots and signatures for some of the urban features are different from the polarimetric signature of pure target in medium resolution SAR data. Feature decompositions model the urban environments as clusters of dihedrals and trihedral strongly associated with orientation of urban structures. The rotation of urban structures and building to SAR look direction significantly alters the characteristic double-bounce signature of urban regions in all the decomposition methods. Freeman and Durden produces better feature decomposition components and comparatively better depiction than other decomposition methods. It is also able to preserve better details with much less noise for both naturally distributed features and manmade features.
Polarimetric SAR data may be exploited with increased resolution for information extraction in urban areas along with contextual as well as knowledge based approach.

ACKNOWLEDGEMENTS

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SMART PHONE AND GAGAN BASED PERSONNEL TRACKING AND ROUTE MAPPING IN NON GSM AREAS

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ABSTRACT
Location services, generally utilize map/direction applications available on mobile devices and help users to find nearby businesses and other areas of interest. Location based services initially designed for military use. Most of the applications require internet connectivity or mobile connectivity to use location based services. Applications such as disaster monitoring, search and rescue, controlling law and order and security operations usually occur in remote areas/places where Internet/GSM signals are low or not available. We propose a location based tracking application called Track&Digitize, for tracking the field personnel even in the absence of internet or GSM connectivity. The proposed solution is based on mobile application augmented with GPS Aided Geo Augmented Navigation (GAGAN) receiver and UHF modem. Mobile application sends location information to Command and Control center and similarly receives location information of all personnel involved in operation via Command and Control center. Application also has provisions to create, digitize, export the digitized files to KML format, data logging and messaging. All the messages exchange between devices and Command center are secured using low footprint custom cipher algorithm.

KEYWORDS: Mobile application, GSM, UHF, GAGAN, Security, Digitization.

1. INTRODUCTION
There has been a tremendous increase in mobile devices usage from past decade. Almost everybody in the world now have access to a huge amount of data through mobile devices. In addition to the data, mobile devices can access the location information. Location based tracking applications have given a significant impact on the peoples’ daily life. Location services, generally utilize map/direction applications available on mobile devices and help users to find nearby businesses and other areas of interest. Location based services initially designed for military use, USA based GPS provides position information and is also equipped on most mobile devices. GAGAN with GPS provides accurate location than GPS.

Usage of the location based services by security agencies have also increased in their operations. But these applications require internet connectivity or mobile connectivity to get the locations or send the locations to base station. Moreover, the exchange of location information is not secure. In the existing systems, a device is equipped with GPS and GSM. It transmits messages with location to the intended base station so that base station tracks the target. Although sending location information through wireless networks is effective when both target and tracker are in the network’s radio range. When a target unable to connect the network it is impossible to perform the network tracking.

Earlier work such as the Active Location Badge system (Want et al., 1992) uses infra-red technology to provide products in the realms of outdoor location-tracking, using GSM and GPS technologies. Such location-based services are limited to mobile phones. There are some other commercially products, such as Webraska, IntelliWhere, Openwave, and Esri (Dey et al., 1999), which are regarded as geo-referenced mobile phone applications. Most applications (Hassan I.Mathkour, 2011) in the market are not user friendly, do not provide precise data, nor allow multiple ways to access the data, such as SMS, web access and real time feedback to the requester. The proposed system is meant to resolve such deficiencies. It uses the cell phone service provider to locate the requester for a registered service. It is not necessary to have an Internet connection as the requester can use SMS to request a service location.

As per our knowledge no location based service application track mobile devices in the absence of GSM/GPRS. We propose a location based tracking application for tracking the field personnel even if there is no internet or GSM connectivity. Application sends the location information to command and control center and also gets others’ locations from command and control center. It has Provision to create, digitize, export the digitized files to Shape and KML format. Each mobile device has UHF modem to connect to neighbouring nodes if there is no internet or GSM connectivity. The connectivity between GMS/GPRS and UHF is done by using gateway.

Moreover, this application uses GAGAN receiver to get the location accurately. Location information is shared to Command and Control center through availability of the network such as GPRS, GSM, UHF. Section 2 describes the Architecture and working of the application. Section 3 presents the conclusions and future work

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2. ARCHITECTURE

The overall holistic view of the system with command and control center (server), ranges covered by GSM and UHF devices is depicted in Figure 1. The proposed system is planned to use in the fields where no complete coverage of one network is available and needs the combination of networks to overcome the network connectivity limitations. The server is connected to GSM/GPRS modem. Mobiles which are in GSM network range directly send location information to server through GSM/GPRS. Mobiles which are not in the GSM range use UHF modems to communicate with the GSM/UHF gateway for sending the location information to the server. So, the range is extended by cellular networks with a 3-5 km range using VF/UHF transceivers; this range covers is covered by the non-cellular network zones. The extended coverage has a gateway that communicates the message to the command and control center or server through cellular network is available. Each mobile device has Track & Digitize application.

![Figure 1 UHF communication Augmented with GSM/GPRS network](image)

Track&Digitize mobile application is being developed to track the field personnel/assets/vehicles in the field. This application records the locations using GPS/GAGAN and sends them to centralized server through GSM/GPRS network. If network is not available it uses UHF network. The locations exchanged between application and server are end-end encrypted using custom algorithm. The application has features to display his own as well as the locations of other personnel. This application also has features to enter locations and paths visited by troops which can be viewed in desktop/enterprise GIS. The application also has distress button to send alert to nearest neighbourhood for rescue.

2.1 Server with GSM/GPRS Network

Server is hosted in the internet with the public IP connectivity. The server is connected with GSM modem, to receive the messages over GSM network. The messages and geo locations are transferred from mobile application to the server either with GPRS or GSM networks, or UHF communication link. The server is running with mysql data base and the customized open source tracking platform called Traccar. Figure 2 shows the screen shot of the server side application.

The device tracker applications called as Resource Traccar software, used to track and monitor the devices from the web based system. The Resource Traccar application has the following benefits. Usually, this application is used by the managers at the command and control center to monitor/track all the devices in the field. The device locations are updated to the server periodically with the preconfigured time interval. The view of the Tracking application is described below (Figure 2).

i. **Monitoring/tracking of the devices** – The devices with the geo location coordinates along with the corresponding time stamping can be viewed in the left side panel.

ii. **Device Information Panel** – Just below the tracking list of the devices, is the Device Information Panel. This panel depicts the information about the device like make, latitude, longitude, time stamp, battery life etc.

iii. **Tracking History Panel** – Tracking history panel, shows the log or history of the devices of interest over a time period.

iv. **Map Panel** - The map panel shows the Open Street Map (OSM) as a back drop map, on which the device positions can be monitored (Red and Green points).
2.2 Feature Digitization Application – Track and Digitize

The Feature digitization application offers the digitization of the features on the ground. The several features that can be digitized are i) line ii) poly line iii) polygon. The application offers two modes of digitization such as i) Navigation mode ii) On Screen Digitization (OSD) mode. In the case of navigation mode, one of the features from line, poly line or polygon can be digitized while moving around in the field with the device in the hand. The device gets the geographical positioning and it digitizes the feature. This mode is very useful to digitize the features while on the move in the ground. Such digitized features can be saved as the feature vector, and this feature can be used as way point file while someone would like to take the similar path on the field. The OSD mode allows to digitize on the screen and store the features as a vector file. Way points can be added on the OSD and also shows the path between two way points.

Figure 3 shows the TrackNDigitize application screen. When application opens it shows the location of this mobile device on map. Main screen also contains Locate other devices, Digitize in track, Digitize on screen and Distress button.

Figure 3 shows the TrackNDigitize application screen. When application opens it shows the location of this mobile device on map. Main screen also contains Locate other devices, Digitize in track, Digitize on screen and Distress button.

Locate other device button is used to get other devices locations from the server. These location points are displayed on the map. Server IP address can be configured in Menu. Digitize buttons are used to select the points from the map while travelling online or through selected points on the map. The points can be converted to shape or kml format and store in a file. Distress button is used to send emergency message to nearby users. This is a broadcast message.
The process of TrackNDigitize is described below.

- **Creating the project** - The project creation involves giving the appropriate name to the project. This creates the work space for storing the intermittent files those are created during the process of digitization of the features.
- **Feature Digitization** - The selection of digitization mode, such as On screen or Navigation mode, followed by the type of the feature to be digitized. The types are line, polyline, polygon described above.
- **Taking the picture through the camera** - Once the feature is digitized, the corresponding picture of the area can be taken, using the camera module available as part of the application. Thus taken pictures are organized in the project, and can be loaded in the future if it is required.
- **Tracking the other devices** - This feature enables the view of the other devices in the field. This talk to the service (REST Service) at the Traccar manager server, and fetches all the devices and their corresponding geo locations. Thus retrieved device information is depicted on the map as pins. The section of the pin will show the device name.
- **Storing the digitization as Vector/shape files** - The digitized features can be stored as vector or shape files in the project.
- **Saving the project** - The created projects can be stored for later usage.
- **Loading the projects for the later use** - The projected created can be used later for loading and viewing the same.

2.3 Non Cellular or Dead Zone connectivity

The problem of non-cellular connectivity zones is addressed using the Adhoc network. The Adhoc nodes work as intermittent nodes to transmit the messages to the Gateway mobile. The gateway mobile is connected with both GSM and UHF network, which in turn sends the message to the Server.

![Figure 4. Feature Digitization Application](image)

3. CONCLUSION

This paper presents the TrackNDigitize application for geo location transfer, tracking and feature digitization. The usage of mobile devices in Cellular and non-cellular zones is also shown. Here, the application runs on the mobile devices. The application is tested successfully in the field with GSM/GPRS and UHF network. The main challenges are communicating the locations to centralized server and getting the others’ locations from server reliably in presence of UHF network. Developing custom GIS based application with less resources to run on mobile devices, build and maintain compatibility with different android OS versions. This application is useful to know the troop/asset movements for efficient execution of field operations.

REFERENCES


AIRBORNE HYPERSPECTRAL DATA ANALYSIS FOR SPECTRAL DISCRIMINATION OF CLAY MINERALS IN JAHAZPUR BELT OF RAJASTHAN, INDIA

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ABSTRACT
Multi-spectral space borne data with SWIR bands have been widely used in the field of mineral exploration in different parts of the world. However, AVIRIS-NG data has several advantages over ASTER and Hyperion data due to its better spectral and spatial resolution. The present study highlights the efficacy of airborne hyperspectral data (AVIRIS-NG) for discriminating different clay minerals (Kaolinite, Talc and Illite) in Jahazpur belt of Bhilwara district of Rajasthan. Spectral pattern of different clay minerals from AVIRIS-NG image were compared using spectral feature fitting with field/laboratory and USGS/IGCP library spectra. Different hyperspectral image processing algorithms (MNF, PPI, n-D visualisation) have been applied for extracting end members (pure to impure pixels). Linear Spectral Unmixing technique is used for classification of the image with spatial distribution of Kaolinite, Talc and Illite minerals. Geospatial analysis also helped in preparation of clay mineral abundant zones by integrating hyperspectral image processing output, coupled with ground information like geology, field spectra and geochemical analysis of rocks and soil samples.


1. INTRODUCTION
Airborne and Space borne images are capable for discriminating various rock types in identification of mineral resources in a region (Mars and Rowan, 2010; Rajendran et al., 2013, 2011a; Rowan and Mars, 2003). Multispectral and hyperspectral remote sensing sensors were used for geological applications, ranging from a few spectral bands to more than 100 contiguous bands, covering the visible to shortwave infrared regions of the electromagnetic spectrum (Clark et al., 1991; Crowley et al., 1989; Gad and Kuskly, 2007; Goetz, 2009; Kruse et al., 2003; Mars and Rowan, 2011; Rowan et al., 2003, 2005, 2006; Sabins, 1999; Van der Meer et al., 2011). Spectral identification of minerals in potential areas of hydrothermal alteration is a common application of remote sensing to mineral exploration using image processing techniques (Sabine, 1999; Iwasaki et al., 2002). Satellite images with hyperspectral data processing techniques have the capability for detecting calcium and magnesium bearing rocks, mapping of carbonate rocks and associated mineralization (Corrie et al., 2010; Jain and Sharma, 2018; Mars and Rowan, 2010; Rajendran et al., 2013, 2011; Rowan and Mars, 2011).

Most of the earlier researchers have used space borne data with SWIR bands to characterise silicate bearing (hydroxyl and non-hydroxy) minerals. However, spectral discrimination of different clay minerals (kaolinite, tacle, illite, montmorillonite/smectite etc) using AVIRIS data is very rare. It is very important to understand the spectral absorption characteristics of such minerals with similar mineralogical compositions and to distinguish those using absorption spectra for better mapping and exploration (Boardman, 1993; Boardman et. al., 1995; Clark et al., 1993; Vane et al., 1993; Verdal et al., 2001). In the present study, hyperspectral remote sensing data (AVIRIS-NG) has been analysed along with the field spectro radiometer data analysis to discriminate varieties of clay mineral deposits. Hyperspectral data processing with characteristic absorption features in SWIR bands is used for detecting altered hydroxyl bearing clay minerals (kaolinite, tacle and illite) in Jahazpur area. Further, extracted end members have been selected as input for generating different clay abundance maps (pure to impure pixels) using linear spectral unmixing technique.

2. STUDY AREA

2.1 Geology of Jahazpur Area
Jahazpur area in Bhilwara district of Rajasthan is represented by low-grade meta-sedimentary sequence in the southeast of Aravalli Hill Ranges (Figure 1). Geologically, the area is occupied by the rocks of the Bhilwara Supergroup (Proterozoic age) comprised of Mangalwar Complex, Hindoli and Jahazpur Groups (GSI, 2004). Berach Granite is emplaced during late orogenic phases of the Bhilwara Supergroup. The basement rock is represented mainly by garnet bearing mica schist, gneiss and dolomite of the Potla Formation of the Mangalwar Complex. The Hindoli Group of rocks is comprised of metagreywacke, phyllite and dolomite of the Sujanpura Formation. These rocks are intruded by amphibolite and quartz veins. The Jahazpur Group of rocks is represented by conglomerate/gritty quartzite, phyllite, metatuff, Banded Iron Formation (BIF) and dolomite of the Jawal Formation; conglomerate/gritty quartzite, grey phyllites of the Ummedpura formation. A NE-SW trending thrust in the NW has brought the rocks of the Mangalwar Complex in juxtaposition with the rocks of the Jahazpur Group. Fine-grained crystalline, hard compact, grey, white pink dolomite is the major rock types of Jahazpur Group of Bhilwara Supergroup. In most of the areas the dolomite is talcose in nature and is suitable for block mining. The hard, compact, fine grained, grey dolomite has been used as flux in steel industry.

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2.2 Clay Mineral Deposits

Clay is the earthy hydrous aluminium silicate formed by the decomposition of preferably feldspathic materials which possess the property of plasticity by absorption of water. The commercial value of clays depends mainly on their physical properties like plasticity, strength, shrinkage, vitrification range and refractoriness, fired colour, porosity and absorption. A large number of mines are present in Jahazpur area with clay minerals like talc and kaoline with industrial name as china clay, ball clay or fire clay. It is an altered product derived by weathering or hydrothermal action from rocks rich in feldspar as well as dolomite. The china clays may be of primary, secondary or residual in origin. Extensive good quality clay deposits are reported from Jahazpur area where three varieties of clay minerals are found viz. kaolinite \( [\text{Al}_2\text{Si}_2\text{O}_5(\text{OH})_4] \), talc \( [\text{Mg}_3\text{Si}_4\text{O}_{10}(\text{OH})_2] \) and illite \( [\text{K}_0.8\text{Al}_2(\text{Al}_0.8\text{Si}_3.2)\text{O}_{10}(\text{OH})_2] \).

2.3 Spectral Properties of Clay Minerals

Clay minerals have distinguishing spectral absorption features in SWIR region (1950-2300nm) which is used for mapping smectite, kaolinite, montmorillonite and illite (Chabril lat et al. 2002, Iwasaki et al., 2002; Raggatt et al. 2004; Suresh et al, 2014). Previous studies have demonstrated the identification of specific minerals such as alunite, kaolinite, calcite, dolomite, chlorite, talc and muscovite by analysis of ASTER SWIR bands (Crosta et al., 2003; Di Tommaso and Rubinstein, 2007; Ducart et al., 2006; Petit et al., 2004; Rowan and Mars, 2003; Rowan et al., 2003, 2005, 2006). Due to having better spectral resolution of AVIRIS-NG data, it is possible to discriminate different clay minerals with characteristic absorption features at particular spectral bands which may miss in ASTER bands. Shape, position and strength of the absorption bands of any spectra are the main characteristic features and parameters to identify a mineral which is different from the other mineral spectra. To identify any mineral, spectra generated from images are matched/fitted with the reference spectrum (Van der, 2004; Van der and Jong, 2003).
3. MATERIAL AND METHODS

3.1 Data Requirement

3.1.1 Airborne Data

AVIRIS-NG data in Jahazpur area was acquired on 4th February, 2016 to measure reflected radiation in 425 spectral bands in VNIR-SWIR region (380 to 2510nm) at 5nm band interval. Swath of AVIRIS-NG is approximately 5-6km and spatial resolution of 4 to 8m, depending upon flight altitude. Thus, AVIRIS-NG data has good spectral and spatial resolution in comparison to space borne hyperspectral sensors. It provides both Level-1 (calibrated radiances) and Level-2 (atmospherically-corrected surface reflectance) data for analysis. Detailed specifications of AVIRIS-NG data is given in Table 1. AVIRIS-NG image (RGB with 80, 50, 30 bands) of Jahazpur area with rock exposures and clay mines are shown in Figure 2.

Table 1. Specifications of AVIRIS-NG Product, used in the Study

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Data Level (Product Definition)</th>
<th>Data content</th>
<th>Spectral Range</th>
<th>Spatial Resolution</th>
<th>Band Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVIRIS-NG</td>
<td>Level-1 (Calibrated Radiance)</td>
<td>Radiance Image + GLT, IGM &amp; LOC Files</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Level-2 (Atmospherically corrected surface reflectance)</td>
<td>Surface Reflectance Image, water absorption file</td>
<td>0.38–2.51 μm</td>
<td>8.1 m</td>
<td>5 nm ± 0.5 nm</td>
</tr>
</tbody>
</table>

Figure 2. AVIRIS-NG VNIR FCC showing dolomite and quartzite rock exposures and the existing clay mines (white patches) in Jahazpur belt.

3.1.2 Reconnaissance Field Survey and Laboratory Analysis

Spectral reflectance measurements were made twice in the field viz. concurrent observation with aerial imaging during 2-4 February, 2016 and post field visit during 28-30 March, 2017. For this purpose, portable spectroradiometer SVC HR 1024 was used extensively, which records spectra in 1024 channels with contiguous wavelength range between 0.35 to 2.50μm. For different rocks/mineral samples, reflectance spectra were measured in the field as well as in the laboratory (under controlled illumination). Then the spectral data of both AVIRIS-NG and hand held spectroradiometer is resampled to 1nm using linear interpolation technique for correlating field and airborne spectral data. Minerals and rock samples were also
collected from field through a systematic sampling and then pallets were prepared from its grinded powder for lab analysis. Major oxides along with trace elements were analysed for each rock/mineral sample using X-ray fluorescence technique (XRF).

3.1.3 Spectral Library of Minerals

For spectral matching of image pixels from different clay minerals, three standard spectral libraries with different band intervals have been used viz. USGS Library (2nm in VIS, 5nm in NIR, 10nm in SWIR bands), JPL Library (1 nm in VIS, 4nm in NIR-SWIR) and JPL Library (2nm in NIR-SWIR).

3.2 Hyperspectral Data Processing

Digital image processing techniques help in generating maps of mineral occurrence, abundance and distribution from the imagery. Hyperspectral data processing with AVIRIS-NG involves Pre-processing, Post-processing and Image classification steps before archiving the target. Brief methodology of mineral abundance mapping is shown in Fig. 3. Due to having voluminous data with large number of bands, these datasets have been processed in ENVI software version 5.2.

(a) Pre-processing - It includes geometric correction, conversion of radiance to reflectance image, spatial/spectral subsetting and mosaicking.
(b) Post-processing - This process includes Minimum Noise Fraction (MNF), Pixel Purity Index (PPI), n-D Visualisation.
(c) Image Classification – Spectral Feature Fitting (SFF) for endmember extraction which is used for mineral abundance mapping using Linear Spectral Unmixing (LSU).

Figure 3. Flow chart showing methodology of hyperspectral data processing techniques and the targeted mineral abundance mapping.

4. RESULTS AND DISCUSSION

4.1 Geological and Geochemical Analysis

Modified geological map of the study area in the southwest of Jahazpur (Figure 1) shows a thrust contact between the rocks of Jahazpur Group and Mangalwar complex. All these rocks are trending along NE-SW direction with moderate dip towards west. A large number of open-cast mines (20 small to medium size) of different clay minerals is scattered in Jahazpur area (298.04sq.km). The present study area is comprised of exposed rocks of dolomite, quartzite, phyllite and schist and agricultural lands. It has been observed that most of the existing clay mines are located in and around dolomites which is possibly the host rock for the altered products. Although these clay mines appear in bright white tone on optical images (AVIRIS-NG) but they cannot be separated out in VNIR FCC. Therefore, spectral discrimination in SWIR bands is very much essential in targeting clay minerals such as kaolinite, talc and illite. Further, hyperspectral data analysis (linear spectral unmixing) helped in preparation of spectral abundance mapping of different clay minerals from known (pure pixels) to unknown areas (impure pixels) in Jahazpur area. To ascertain the composition of clay minerals and its parent rocks, geochemical analysis of nine samples of kaolinite, talc, illite and dolomite were analysed. The XRF analysis was
implemented on pallets using X-ray fluorescence BRUKER S4 PIONEER in the IIC laboratory at IIT-Roorkee. The results of major oxide percentage of each sample are shown in Table 2. It has been observed that Kaolinite is rich in Al₂O₃, Talc is rich in MgO and Illite is rich in SiO₂ and K₂O. Higher MgO component in talc is possibly derived from the host rock of dolomite which is rich in both MgO and CaO. Kaolinite and Illite was probably formed by hydrothermal alternation of dolomites and associated rocks.

Table 2. XRF Analysis of Clay Minerals in Jaha
zpur area, Bhilwara District, Rajasthan
(Samples analysed at Institute Instrumentation Centre (IIC), IIT-Roorkee in April, 2018)

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Clay Mineral / Rock</th>
<th>Sample No</th>
<th>SiO₂</th>
<th>Al₂O₃</th>
<th>Fe₂O₃</th>
<th>K₂O</th>
<th>MgO</th>
<th>CaO</th>
<th>Total Major Oxides (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kaolinite</td>
<td>S12</td>
<td>43.27</td>
<td>30.25</td>
<td>1.64</td>
<td>1.17</td>
<td>1.06</td>
<td>0.75</td>
<td>78.13</td>
</tr>
<tr>
<td>2</td>
<td>Talc</td>
<td>S11</td>
<td>55.86</td>
<td>0.63</td>
<td>0.93</td>
<td>0.14</td>
<td>32.72</td>
<td>0.71</td>
<td>90.99</td>
</tr>
<tr>
<td>3</td>
<td>Illite</td>
<td>S17</td>
<td>69.77</td>
<td>14.13</td>
<td>2.23</td>
<td>3.44</td>
<td>1.46</td>
<td>0.72</td>
<td>91.74</td>
</tr>
<tr>
<td>4</td>
<td>Dolomite</td>
<td>S2</td>
<td>20.81</td>
<td>0.26</td>
<td>0.82</td>
<td>0.06</td>
<td>24.68</td>
<td>25.72</td>
<td>72.35</td>
</tr>
</tbody>
</table>

4.2 Spectral Characteristics of Clay Minerals

To characterise different clay minerals (kaolinite, talc and illite), reflectance spectra for 8-9 different pixels (locations) in AVIRIS-NG image are plotted within a range of 2100 to 2400nm in SWIR bands. Though, different pixels of clay minerals show varying reflectance (30-60%), but spectral pattern of all the pixels of a particular clay mineral show similar absorption pattern with characteristic dips. Average spectra of all these clay minerals have been generated using spectral math algorithm which shows absorption dip for kaolinite (2159.53 and 2209.61nm), talc (2289.75 and 2314.80nm) and illite (2214.62 and 2349.86nm). These spectral bands in AVIRIS-NG are compared with the available USGS/IGCP library as well as field and lab spectra of samples (Figure 4). Kaolinite and talc shows characteristic doublet shaped spectral pattern which is easily identified due to having narrow spectral band width (5nm) in AVIRIS-NG data.

![Figure 4. Continuum removed plots of average reflectance spectra of clay minerals (a) Kaolinite (b) Talc and (c) Illite. Spectral variation of clay minerals with AVIRIS-NG data and USGS/IGCP spectral library can be compared.](image)
4.3 Segregation of Pure to Impure Pixels

Spectral analysis of a large number of image pixels in the study area showed characteristic absorption bands to identify pure variety of clay minerals (kaolinite, talc and illite). However, thorough analysis of AVIRIS-NG data shows some pixels with mixed spectra of two minerals, indicating impure variety of clay minerals e.g. Talc and Kaolinite, Kaolinite and Illite, Illite and Talc etc. It has been observed that some of the pixels in darker areas show complex spectra with two absorption pattern in SWIR range (2100 to 2400nm) viz. doublet shape at lower wavelengths (2159.53 and 2209.61nm) indicating kaolinite and doublet shape at higher wavelengths (2289.75 and 2314.80nm) indicating talc (Figure 5). A False Color Composite (FCC) is prepared using AVIRIS-NG bands (RGB – 368, 388, 368) in order to identify the mineral endmembers and their spatial distributions within the study area. FCC highlights the locations of talc in light magenta color, kaolinite in parrot green colour and illite in sea green color. Thus, the study area represent mixed clay deposits with the distribution of pure to impure talc at different locations. The mystery has been resolved by linear spectral unmixing technique (sub-pixel classification) during clay abundance mapping.

![Figure 5. Spectral plot of impure pixel resembles pure kaolinite at lower \( \lambda \) and pure talc at higher \( \lambda \).](image)

4.4 Mineral Abundance Mapping

After MNF transform, PPI and n-Dimensional visualization, Spectral Unmixing algorithm (statistical procedures to end member extraction) is applied to estimate mineral abundances. Prior to that, SFF (least square regression) based technique is implemented between the unknown spectra and standard reference spectra using Spectral Analyst and Mapping Methods tools of ENVI. Best spectral match between image spectra of AVIRIS-NG and USGS/IGCP spectra is decided based on the highest score of SFF. In the study area, average spectra of kaolinite pixels in AVIRIS-NG image is found to be the best match with Kaolinite-6 (SFF=0.865) out of eight USGS spectra (Kaolinite-1 to 8). Similarly, highest SFF score was also estimated for talc in AVIRIS-NG (SFF=0.828) with talc in IGCP library (TL-2702) and illite in AVIRIS-NG (SFF=0.965) with USGS illite (IL-105) respectively. For each mineral analysis, a score of 0 to 1 was generated for SFF, where a value of 1 indicates a perfect match and 0 indicating no match. End member spectra were matched with those of the minerals as available in the spectral library. As discussed in the previous section, Jahazpur area is comprised of different varieties of clay minerals. Therefore, spatial distribution of a targeted clay mineral deposit has been mapped based on estimation of spectrally pure pixels to impure pixels. For this purpose, linear spectral unmixing technique is applied for mineral abundance mapping. Initially, talc mineral is targeted to extract pure to impure endmembers, having spectral characteristics of talc as well as talc and kaolinite mixture, The weightage assigned for each pixels in the image (0 to 1.36) is sliced into four categories viz. very low (30-50%), low (50-70%), medium (70-90%) and high (>90%). Due to poor pixel correlation with weightage (<0.3), around 97.96% area remain unclassified which is assumed to be insignificant talc abundance of the study area. Similarly, linear spectral unmixing technique is also applied for kaolinite and illite. Mineral abundance map of these three clay minerals is shown in Figure 6. The results show varying percentage of pure to impure quality clay minerals in Jahazpur area viz. kaolinite in 1.26 sq.km, talc in 6.075 sq.km and illite in 1.091 sq.km.
5. CONCLUSION

Airborne hyperspectral data (AVIRIS-NG), having better spectral and spatial resolution, is found to be extremely useful in discriminating clay minerals in SWIR region. Kaolinite and Talc are characterised by doublet shaped spectral pattern with strong absorption dips at 2209.61nm and 2314.80nm respectively. Illite mineral can be identified by the spectral absorption dip at 2214.62nm. Linear spectral unmixing technique is found to be useful in classifying pixels (spectrally pure to impure) into different proportion of kaolinite, talc and illite minerals. Integrated analysis of hyperspectral data along with ground information like geology, field spectra and geochemical analysis of samples helped in generating mineral abundance map of clay minerals from known to unknown areas.

ACKNOWLEDGEMENTS

Authors are grateful to the Director, National Remote Sensing Centre (NRSC), Hyderabad and the Chief General Manager, Regional Centres/NRSC, Hyderabad for their inspiration to carry out the present work. Fruitful discussion with Shri Satadru Bhattacharaya, SAC, Ahmedabad and lab support by Prof. A.K. Sen, IIT-Roorkee are duly acknowledged.

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IDENTIFICATION OF OPTIMAL LOCATION FOR COMMUNITY SOLAR POWER UNITS IN A VILLAGE USING DRONE MAPPING AND GIS BASED CLUSTER ANALYSIS

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ABSTRACT

Some of the villages in Rural Districts of TamilNadu lack reliable supply of electricity particularly when the demand is more than the generation of electricity. Shortage of Power is often observed due to lack of coal supplies to thermal power plants leading to shutting down of generation units. The Government is promoting alternate sources of energy like solar energy rather than relying on thermal energy alone. The household electricity consumption in the Keerapakam village, Thiruvallur District, TamilNadu was carried out by mapping each house from Drone image associated with collection of socio-economic characteristics of people using ground verification survey. Clustering techniques were used to group the buildings with similar socio-economic characteristics for defining a community, in turn to calculate cumulative electricity requirement of that community. A GIS based suitability analysis was conducted for finding the optimal location for the implementation of solar power units to generate the power required for each cluster. A cost benefit analysis was carried out to understand economic feasibility of the solar power units. This helps in uninterrupted gain of electrical power which benefits the cottage industry, farming and education to rely upon solar energy fulfilling the dream of solar electricity scheme for villages in India.

KEYWORDS: Solar Energy, Drone Mapping, Clustering Analysis, GIS

1. INTRODUCTION

Is there a certainty of the mineral (coal) over the next decade will prolong its existence as a source of electricity. As of now, it is a primitive measure of alternating the source of electricity. Although there are some measures by which the quantified electricity gained through the photovoltaic cell as the efficiency improved over a certain period. Government of India initiated the renewable energy as the alternate source for the generation of electric power. However the consumption of electricity for individual household for the entire village has been calculated. The amount of solar radiation over the given view shed has been analyzed as Global solar insolation. Predicting the required electricity for the next decade and the sun map estimation of insolation as well as finding the optimal location for the calculated array of solar panel through the high resolution Drone imagery through which the supply divided based on socio-economic data of the entire area. Uninterrupted supply of electricity benefits through the driven solar installation helps various sectors such as public, cottage industries dependable.

Study Area

The site area chosen to initiate the implementation of distributing the renewable energy as the supply of electricity through solar insolation is Keerapakam village, Thiruvallur District, TamilNadu. The site area has the spatial extent of 2.23 sq.km fig 1.1 also specifies point location of 13.43 latitude and 80.18 longitude. The consumption of electricity for the entire village should be calculated in order to know the actual usage of electricity distributed over the Grid from Devampattu.

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2. RESULT AND DISCUSSION

Collection of Data

For the initiation of the solar power project, the foremost thing to have known is the total quantity required for the area. To attend this, the individual consumption of electricity from each house has to be found out by direct field survey. A lot of information has been gathered via field surveying of individual household.

Drone Imagery

High Resolution Imagery is used for this work which was taken from Drone, flying at an average height of 250m from MSL that gives the imagery in RBG band gives the Spatial Resolution of 4cm. Having this imagery, digitizing and mapping every house that includes finding the optimal location for the solar panels in ArcGIS software and entitling the consumption of electricity of that house labeled on top it.

Solar Radiation

The solar radiation emitted from the sun as it comes through gets distorted further and further by the atmospheric features (aerosols, fog, rain, cloud, haze, dust) and finally intercept the surface of the earth in three possible ways such as direct, diffuse and reflected radiation, the one which meets the surface directly without any scattering through the atmospheric windows are direct solar radiation. All these radiations come together called as total solar radiation.

The calculation for the amount of solar radiation is performed in ArcGIS from the solar radiation tool which calculates the solar insolation potential when the view shed comes under direct sunlight during day time. View shed is the sun’s position as well as sky direction to take the radiation for the respective location.

The solar radiation for each day in a month, say from (Jan to December 2017) for the entire study area is observed by overlaying the Digital Elevation model Aster DEM having the 13.478 latitude of the study area. Calculations of solar radiation is done by importing the DEM in solar radiation tool thus gives the perfect insolation map fig 2.3. The highest solar potential from the above said calculation is 14781Wm\(^2\)fig 2.1 and the mean solar potential for the given keerapakam village is 5101.8Wm\(^2\) fig 2.2. However the average hours of direct solar insolation per day for the 13.478 latitude is 5.5 ½hours and the final value taken for the solar potential is 5100Wm\(^2\).
3. ESTIMATION

Initiating a design for the solar PV system involves: 1. Load estimation, 2. Estimation of number of PV panels and battery bank, 3. Cost estimation of the system. The analysis has been performed to differentiate the consumption of units shown in fig 4.2. Such details are collected and the usage (consumption) of electricity for the particular houses are picked up through the TANGEDCO website and summed up.

Three colors indicating three categories namely orange (up to 100), pink (100-200), Green (200-500) units of thermal power used by each household fig 3.2 and are analyzed cluster wise from the collected socioeconomic data. Thus by doing so, the total amount of the consumption of electricity for the given two years is found to be 37Mw.

- The Total consumption of electricity for two months over the entire village is 37,000 KWh
  → No. of units / one month = 18500/30 = 616.66 KWh / day

This is the Electricity consumption per day of the entire village. Solar Panels comes in various watts say below 40 to 350 watts. Although various wattages has been used for numerous purpose. But the 315 watts solar panel defined in this system is currently best and used.

- Solar Insolation generated by one panel over a period of 30 days
  → 0.315 * 5.5 * 30 = 52KWh
- Total number of solar panels required
  → 18500/52KWh=356 solar panels
- System loss and Storage loss of solar panels taken into consideration also called as operating factor. Those losses are included system loss=0.9%, Storage loss=0.75% Calculating power by adding losses for one panel,
  → 1.7325 * 0.9*0.75=1.169* 30=35KWh
- Number of solar panels required to satisfy the given estimation
  → 18500/35=528
- Calculation of the Inverter size
  → 617 KWh / 3 kWh=206 no. of inverters

Since the required amount is 617 KWh / day, the array of solar panels thus produces the power is to be stored by the big inverters, the choice of the inverter should be 3000 watts. It is to be noted that 206 numbers of 3000 watt inverter is essential and are wired parallel by the technique called solar stacking to store the DC power from the solar to convert into AC.

- Area required for solar panel
  One solar panel covers 78.46 inch 39.4 inch = 2 sqm of the area thus weighting about 47.6 pounds, amps 8.71 and voltage 36.5and the required total area for the erection and installation of the solar panels 1056 sq m area.
  → Area528*2=1056sq m
The foremost part in the installation of solar power plant is the cost estimation that actually depends on the materials required. However quality, high efficient and cost effective materials focusing the next decade should be chosen. The efficiency of the solar panels increased over the years and so 315 watt panel suits best for the project which costs around Rs 13,000 /-. 

\[ 13000 \times 528 = 68,64,000 /- \]

Adding the cost of battery bank that stores the power produced by the solar in broad daylight and can be consumed throughout the day, the other requirement such as wires, workmanship for the installation of solar power project sums the cost of the solar panels by 20%. Hence the overall amount for all the necessary requirement is Rs 82,36,800/-

### 4. OPTIMAL LOCATION FOR THE SOLAR PANELS

Normally the location of the solar panel nowadays will be on roof top, the length, breadth and area of the roof top for the entire village has been calculated in fig 4.1 by digitizing each house’s roof top using ArcGIS software with the high resolution imagery from Drone. There are about 335 houses in the village and the area of each has been calculated and displayed in fig 4.2. As per the houses’ consumption mentioned in fig 4.2 the panel which suits best will be placed on roof top, thus producing the electricity based on their consumption.

![Figure 4.1](image1.png)

![Figure 4.2](image2.png)

Since 43% of the land is agriculture land, 22% are settlement and 35% are tanks (water body). However there is no such called waste land or barren to find the optimal location. Although roof topping gives best results for the location of panels, an alternate optimal location such as placing on tank is to be found out since half of the area covered with water body and does suits the location for the erection of 528 solar panels as an array covering 1056 sq.m in fig 4.3. Also, it acts as back water cooling system for the panels neglecting the operating factor of losses. The water body covering the top of the village which is Pulicat Lake suits the optimal location to hold 426 solar panels about 852sq m is perfectly suitable for the solar panels to float fig 4.2.

![Figure 4.3](image3.png)

![Figure 4.4](image4.png)
Cluster wise Houses are divided based on their socio economic and power consumption. Initial price for the installation of the solar panels are categorized into three; users up to 100 unit has to share five thousand Indian rupees, 100 to 200 unit users share fifteen thousand rupee; users up to 500 ought to share twenty five thousand each, thus rely on renewable solar energy nearly for a decade.

5. CONCLUSION

The source of energy thus produced by the renewable resources will eliminate the demand of electricity for the next decade. In spite of having renewable energy by other ways, still the solar insolation over the years drastically increased in efficiency. The project specified here is a future determined and at times needs some maintenance. Land acquisition is the challenging role without depleting the available agricultural land; it is possible to find out the optimal location for the erection and installation of the enormous grid of solar panels on the tank as a floating solar panel in village level. The panels are made to float by thick polystyrene sheets and are bound together in the form of array. When times of rainfall the tank collects water and make the solar panel to float on it, also acts as a barrier for the evaporation of water during summer.

Apart from the benefits in generating power by the solar panels, it also benefits the reduction of the emission of 579kg of CO₂ per day and ashes too from the thermal power plant affects the health of living beings resulting in asthma, even affects plants as it covers the leaves imparts photosynthesis. Government of India supports subsidizing the initiation of renewable energy like solar power projects by Jawaharlal Nehru National solar mission scheme up to 50% bearable helps people depend more likely on renewable energy. The other half expense shared among the houses on the basis of consumption. Although the work for the project seems little yet it stands mightily as an 18.5Mw power producing for a year.

Floating solar plant in a village level might be the first self-dependent project in India. As it welcome Government, NGO, researches and students to have an interest rather than depending on thermal energy but also to depend on the renewable energy.

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POINT SPREAD FUNCTION (PSF) ESTIMATION BY CONVEX MIRROR FOR SPATIAL CHARACTERISATION AND RESTORATION OF HIGH RESOLUTION CARTOSAT IMAGERY

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ABSTRACT

Advanced Cartosat-2 series of satellites launched recently by ISRO, carry panchromatic (PAN) and multi-spectral (MX) sensor, primarily for cartographic applications. One of the most important spatial characterization parameter defining image quality for high resolution sensor is the point spread function (PSF). In this paper, in-flight estimation of PSF for high spatial resolution sensors using artificial target (convex mirror)& its use for image restoration is described. Convex mirror used in this experiment was specially designed & deployed at Space Applications Centre (SAC), Ahmedabad sports (SRC) ground synchronous to satellite pass. Processing of mirror image was carried out to estimate sensor specific spatial characterization parameters - effective spatial resolution & encircled energy. Image restoration scheme comprising of photon noise correction, Wiener deconvolution &Wavelet de-noising is proposed using estimated Mirror PSF & laboratory measured noise characteristics as input. Tuning of restoration parameters is carried out to achieve improved spatial resolution with minimal ringing. Image restoration by proposed approach gives improvement in effective spatial resolution while preserving SNR.

KEYWORDS: PSF, Spatial characterization, Effective spatial resolution, image restoration, de-convolution, noise, ringing

1. INTRODUCTION

Advanced Cartosat-2 series of remote sensing satellites was successfully launched by ISRO during 2016-2018 primarily for cartographic applications. It carries onboard panchromatic (PAN)and multi-spectral (MX) sensors with multi-staged time-delay and integration (TDI) capability on agile platform to provide high resolution, multi-spectral imagery for user requested locations. One of the most important spatial characterization parameter of a high resolution sensor is the point spread function (PSF), which gives the response of a sensor to an impulse (point source). PSF gives a representation of blurring or spatial energy spread of an input impulse caused due to systematic degradations in imaging process. Degrading factors contributing to blurring in image are sensor aberrations, platform dynamics and also atmospheric effects in the acquired scene. Other type of degradation present in the image is noise, originating due to photon uncertainty and sensor electronics. It is important to characterize the sensor PSF and noise in-order to correct the above degradations through Image restoration, to improve image quality.

Noise characterization is carried out as part of pre-launch laboratory calibration. PSF of optical assembly is well characterized in laboratory, however to derive the net PSF including TDI averaging, platform motion/stability effects, in-flight PSF estimation or spatial characterization is undertaken post-launch as part of initial phase calibration exercise. PSF can be estimated by imaging distant stars [1] (point sources) by sensor, however due to absence of atmosphere and difference in star scanning profile as compared to image scan profile, it does not bring out the realistic blurring that is typically seen in images acquired under normal viewing conditions.

To estimate typical sensor PSF, Convex mirror target was deployed at sports (SRC) ground, Space Applications Centre, Ahmedabad, synchronous to satellite pass. The convex mirror produces sun’s image with sub-pixel occupancy, which is primary requirement of a point target. In this paper, the methodology of in-flight PSF estimation for the sensor through convex mirror target is described. Spatial characterization parameters - effective spatial resolution & encircled energy are derived for PAN & MX sensor. Further, image restoration scheme for de-blurring and de-noising the image is proposed. Laboratory characterized photon noise profile is provided as input to edge-preserving de-noising filter. De-noised output is de-convolved using specially designed Wiener restoration filter. Frequency dependent blue noise in de-convolved image is corrected through wavelet based de-noising filters. In restored PAN and MX images, visual improvement in terms of sharpness is seen. Improvement in quality of restored image in terms of effective spatial resolution and signal-to-noise ratio (SNR) is also quantified.

The contents of this paper are organized as follows. In section-2, the convex mirror target and its layout is described. Section-3 describes the methodology of Point Spread Function (PSF) estimation from convex mirror. For PAN camera, the estimated PSF parameters are presented in detail. In section 4, Restoration model based on Wiener filtering is proposed for de-blurring PAN image. De-noising procedures pre & post deconvolution are described. Results of restored images for PAN & MX sensor are presented. Tuning of restoration model parameters using quality criteria of effective spatial resolution, SNR & ringing is discussed. Quantitative improvement in terms of effective spatial resolution, SNR is shown. Lastly, conclusions are summarized in section 5.

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2. SAC-SRC EXPERIMENT WITH CONVEX MIRROR

Satellite pass was planned over SAC, Ahmedabad on 15-Feb-2018 by coordination with Mission/NDC teams. Acquisition details are shown in Table-1. The pass time was IST – 10:25 am.

Table-1 Acquisition details of SAC-SRC scene by Cartosat sensor

<table>
<thead>
<tr>
<th>Date of Pass</th>
<th>Orbit</th>
<th>Mode</th>
<th>Session/Strip/Scene</th>
<th>Roll (deg)</th>
<th>Pitch (deg)</th>
<th>Yaw (deg)</th>
</tr>
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<td>15-2-2018</td>
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<td>2/1/5</td>
<td>-13.35</td>
<td>0.63</td>
<td>2.25</td>
</tr>
</tbody>
</table>

For spatial characterization of sensor using convex mirror requires imaging the reflection of sun by the sensor through the mirror target. To achieve this objective, alignment of mirror needs to be in such a way that the Sun and sensor are encompassed in the field of view of Convex mirror target. Convex mirror used in this experiment is made of stainless steel specially designed & fabricated indigenously, having an aperture of 1400 mm and sag of 150 mm. The focal length is 1.708m and half angle of 55deg [2]. The alignment angle of mirror is previously calculated based on sun geometry & sensor information as obtained one day earlier through pass-schedule file. Sun angles (Azimuth & Elevation) were calculated using the NOAA solar angle calculator. The sensor elevation was computed based on roll angle. Figure 2 shows the sun & sensor angles on the day of experiment for SAC-SRC ground location. The mirror was tilted by 32.5° toward Sun/Sensor in-order to capture the reflection of sun accurately in sensor image.

![Figure 2. Sun-Sensor & Mirror Geometry with insets showing Convex Mirror & Tilted Mirror](image)

Figure 3 shows the mirror image acquired by the PAN & MX sensors.

![Figure 3. Deployed Mirror viewed by PAN, MX sensors](image)
In this image, the mirror is seen on the backdrop of dark cloth. The methodology followed to extract the PSF is explained in the following section.

3. PSF ESTIMATION FROM CONVEX MIRROR

Mirror as seen by the PAN sensor is shown in Figure 4 (a). 11×11 image chip was extracted around the peak as shown in Figure 4(b). Average dark count value corresponding to black cloth was estimated from the corners of image & subtracted from the chip. Further, the gray values were normalized with respect to maximum peak gray value at center, giving PSF as shown in Figure 4(c).

![Figure 4 (a) Mirror Image, (b) 11x11 chip around peak, (c) PSF (PAN)](image)

To estimate PSF for individual MX bands, same procedure as described for PAN was followed, additionally suitable shifts to image were applied to compensate for band-to-band mis-registration to get aligned mirror peaks in all bands. It was observed from MX mirror images, that high background reflectance of black cloth (63 %) in B4, resulted in low contrast image in B4. Therefore, to avoid uncertainty in PSF estimation, B1 to B3 are selected for further processing. Also in future experiments, suitable low reflectance background will be selected for B4.

![Figure 5. Along(AL)/Across(AX) track PSF profiles (a) PAN (b) MX(B1)](image)

To estimate PSF parameters with sub-pixel accuracy, PSF image was zoomed by FFT interpolation method adopted for impulse functions. Interpolated high resolution point spread profiles extracted through center are shown in Figure 5 for PAN and MX (B1). Effective spatial resolution at full width half maximum-(FWHM) in terms of pixels, as estimated from Mirror is shown in Table-6.

![Table 6. PSF Parameters for PAN and MX](image)

For PAN, the total encircled energy of point source is 90% within 7x7 pixels around peak. Effective spatial resolution in along (AL) & across (AX) directions is 1.8 & 3.7 pixels respectively. A higher spread in across track direction as compared to along track direction is observed.

For MX, symmetric spread is observed for all MX bands in along & across track directions. FWHM computed for three bands is shown in Table-3. The encircled energy of is found to be 90% within 3x3 pixels around peak for B1 to B3. In the next section, image restoration of PAN & MX (B1 to B3) using the derived PSF is discussed.
4. IMAGE RESTORATION

Based on knowledge of systematic degradation (blur and noise), Image restoration is an important data processing technique applied to improve image quality. Image Restoration proposed here is similar to approach adopted for restoration of Cartosat-1 sensor [3], which comprises of sequential application of Adaptive photon noise removal, Wiener de-convolution & Wavelet-based noise filtering on radiometrically corrected data product (Figure 7).

Photon noise is a signal dependent noise observed in optical sensors with high spatial & radiometric resolution. The photon-noise variance is found to increase linearly with the input gray value. Photon noise estimated during laboratory experiment is shown in Figure8.

Photon noise correction is the first step performed in spatial domain to remove signal-dependent noise at initial stage. An edge-preserving, adaptive noise filtering algorithm based on [4] is used for de-noising PAN/MX data. In this type of filtering, under assumption of known noise characteristics, variation around a pixel is apportioned into noise and signal. Accordingly, the smoothened and actual values are weighted and averaged to produce the noise removed value. The proposed filter adapts to the local changes in image statistics based on a non-stationary mean, non-stationary variance model. The general form of the filter is given in (1):

\[ f(i, j) = \alpha \cdot GL_{(i,j)} + (1 - \alpha) \cdot g(i, j) \]  

(1)

Where

\[ GL_{(i,j)} \] is the local adaptive mean

\[ \alpha = \frac{\sigma^2_{n}(i,j)}{\sigma^2_f(i,j)} \]  

(2)

\[ \sigma^2_{n}(i,j) \] is the noise variance level at given pixel \( g(i,j) \) which is known for Photon-noise, \( \sigma^2_f(i,j) \) is the local adaptive variance estimated with \( g(i,j) \) as center. For low signal-to-noise ratio (SNR) the filter puts more weight on the GL (adaptive mean), conversely, for high SNR, the filter puts more weight on the noise observation and tends to preserve the edge sharpness.

In the next step, non-iterative technique for image de-convolution is adopted for de-blurring in which a minimum mean square error (MMSE) filter also known as Wiener filter [5] is designed in frequency domain based on knowledge of systematic degradations of blur and noise. Wiener Filter is given by (3):

\[ H^*(\omega_X, \omega_Y) = \frac{H^*(\omega_X, \omega_Y)}{|H(\omega_X, \omega_Y)|^2 + nsr(\omega)} \]  

(3)

\[ nsr(\omega) \] is the noise-to-signal ratio.
where $H$ is degradation function derived from Mirror PSF, $\omega_x$ and $\omega_y$ are spatial frequencies & ‘nsr’ is ratio of Power Spectrums of Noise and Signal, modeled as function of ‘$\omega$’ which is radial distance from origin.

Since the power spectrum of un-degraded signal & noise are not known, their behavior is realistically modeled as exponential function of spatial frequency ‘$\omega$’ (2) with values ranging from $\text{nsr}_{\text{min}}$ at $\omega = 0$ & $\text{nsr}_{\text{max}}$ at $\omega = \omega_{\text{max}}$.

$$\text{nsr}(\omega) = k e^{t \omega} \quad (4)$$

‘$\text{nsr}_{\text{min}}$’ is determined theoretically as ratio of noise power to signal power at zero (DC) frequency. For white noise, noise power is constant & equal to its variance (Parseval theorem). DC value of signal is the average of input values. Hence the ratio ‘$\text{nsr}_{\text{min}}$’ is a fractional value (<<1) due to signal power being considerably more than noise at zero frequency. For a 11-bit quantization system, this value corresponds to $10^{-7}$. ‘$\text{nsr}_{\text{max}}$’ is chosen as 1 because at highest frequency, the signal & noise power are equal. The parameters of exponential function $k$, $t$ are accordingly computed. Plots of degradation function ‘$H$’ and restoration filter (3) in spatial frequency domain are shown in Figure 7.

As seen from Figure 9, the restoration filter amplifies mid and high frequencies resulting in de-blurring of edges. However, during the process, noise also gets amplified. Frequency dependent “blue” noise is known to dominate the de-convolved image. “Ringing” is another artifact observed in the restored image, visually seen as intensity overshoots/undershoots at high intensity transition regions. It is also known as “Pseudo-Gibbs Phenomenon”. Ringing can be partially controlled by tuning the regularization factor or nsr in the Wiener filtering process, however cannot be totally eliminated [6]. A trade-off is therefore observed in the amount of ringing and the sharpness-level of the restored image. Very low value of $\text{nsr}_{\text{min}}$ gives effect of inverse filtering and results in noisy restored image. Therefore, for refining output image quality $\text{nsr}_{\text{min}}$ was increased to 0.0001, 0.001, 0.01, 0.1 and given as input to de-convolution filter. The original & de-convolved mirror images (PAN) for different $\text{nsr}_{\text{min}}$ values are shown in Figure 10. The point spread is greatly reduced in Figure 10 (b-d) as compared to original spread shown in Figure 10 (a), but ringing effect is seen as presence of undershoots around the central peak.

To objectively evaluate image quality & decide value of nsr, Signal-to-Noise ratio (SNR), Effective spatial resolution (ERE) and Percentage Overshoot (ringing) were estimated from de-convolved (PAN) image. For each restored image, average SNR at homogenous regions of image was computed. From zoomed profiles of mirror images (Figure 10 b-e), Effective spatial resolution in along/across track directions was computed. From zoomed profiles, magnitude of secondary peak with respect to central peak was computed as percentage overshoot. The objective quality measures computed for different values of $\text{nsr}_{\text{min}}$ are shown in Table 11.

As seen from Table 11, $\text{nsr}_{\text{min}}$ value of $10^{-3}$ gives considerable improvement in spatial resolution (across direction) of ~0.9 pixel with values 2.8 pixel as compared to 3.7 pixels in original, and also with ringing < 6% in both directions, therefore
selected as optimum value for further processing. The comparison of along/across original & restored profile for PAN is shown in Figure 12.

**Table 11. Quality Parameters of Restored PAN Images**

<table>
<thead>
<tr>
<th>nsr min</th>
<th>Effective Spatial Resolution</th>
<th>SNR</th>
<th>%Overshoot (Ringing)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AL</td>
<td>AX</td>
<td></td>
</tr>
<tr>
<td>$10^{-1}$</td>
<td>2.6</td>
<td>3.9</td>
<td>89.9</td>
</tr>
<tr>
<td>$10^{-2}$</td>
<td>2.1</td>
<td>3.3</td>
<td>72.6</td>
</tr>
<tr>
<td>$10^{-3}$</td>
<td>1.8</td>
<td>2.8</td>
<td>52.4</td>
</tr>
<tr>
<td>$10^{-4}$</td>
<td>1.7</td>
<td>2.4</td>
<td>32.2</td>
</tr>
</tbody>
</table>

Figure 12. Comparison of Original & Restored PSF (PAN) profile

Original and restored PSF profiles for MX(B1) are shown in Figure 13. After restoration, effective spatial resolution (in pixels) is computed as - B1-1.4(AL)/1.4(AX), B2-1.3(AL)/1.5(AX) and B3-1.3(AL)/1.5(AX) as compared to original values given in Table 6, maximum improvement (~0.2 pixels) is seen in B1 & B3. In the restored MX images, ringing was found to be < 5%.

Figure 13. Comparison of Original & Restored PSF (MX-B1) profile

As discussed earlier, post-restoration, frequency dependent “blue” noise dominates the de-convolved image. Wavelet based noise removal methods [7] are known to effectively separate signal from noise and preserve texture & edge details during de-noising regardless of its frequency content. Therefore, they are more suitable for post-restoration noise correction. Here, Open CV implementation of Wavelet based de-noising with soft thresholding is applied on de-convolved image for blue noise correction. Results generated for PAN & MX are shown in Figures 14, 15.
Figure 14. (a) Original PAN image, (b) Photon noise corrected, (c) De-convolved, (d) De-convolved + Wavelet de-noise

Figure 15. (a) Original MX, zoomed rooftop (inset), (b) Restored MX
It can be seen visually that edge sharpness is significantly improved in processed PAN and MX images. Improvement in effective spatial resolution is quantified in Table 11, while ringing is in acceptable limits.

Table 16. SNR Comparison, Original & Post-Restoration

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Original</th>
<th>Photon noise corrected</th>
<th>De-convolved</th>
<th>De-convolved + Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAN</td>
<td>64.6</td>
<td>88.4</td>
<td>52.4</td>
<td>61.9</td>
</tr>
<tr>
<td>MX-B1</td>
<td>61.4</td>
<td>76.6</td>
<td>66.3</td>
<td>66.6</td>
</tr>
<tr>
<td>MX-B2</td>
<td>54.9</td>
<td>70.9</td>
<td>53.3</td>
<td>56.4</td>
</tr>
<tr>
<td>MX-B3</td>
<td>46.6</td>
<td>53.1</td>
<td>47.3</td>
<td>47.8</td>
</tr>
</tbody>
</table>

SNR was computed at different stages of restoration for PAN and MX images. Typical SNR at sample homogeneous regions shown in Table 16 indicates that SNR is nearly preserved during image restoration.

5. CONCLUSION

Spatial characterization of high resolution sensors of advanced Cartosat-2 series was carried out using specially designed convex mirror target. Mirror alignment angles based on known sun-sensor geometry were computed & target was successfully imaged by both sensors. Detailed exercise of PSF estimation was carried out to estimate PSF parameters – effective spatial resolution & encircled energy. Image restoration scheme comprising of photon noise correction, Wiener deconvolution & Wavelet based de-noising is proposed using estimated Mirror PSF & lab measured noise characteristics as input. Tuning of restoration parameters is carried out to achieve improved spatial resolution with minimal ringing. Quantitative evaluation of restored images show that proposed restoration approach gives improvement in effective spatial resolution while preserving SNR.

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LAND COVER CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

The process of classifying satellite images has made rapid progress in recent years. Satellite image classification involves a multi-disciplinary approach involving remote sensing, machine learning and computer vision. With the help of new technologies like deep learning, it has become even easier to classify Red, Green and Blue (RGB) images. However, the need for the near infra-red band is felt as RGB images will provide insufficient features to train a deep learning classifier. This paper proposes to analyse different deep learning based image classification models to classify the satellite images such as Convolutional Neural Network (ConvNet), AlexNet and Visual Geometric Group (VGG). All these models are trained for the images with 4 bands RGB and NIR. These models are trained using an Open Dataset - DeepSat Image Repository containing two different datasets having different number of classes. One dataset contains four classes barren land, trees, grassland and others. Second dataset contains six classes barren land, trees, grassland, roads, water bodies and others. Python programming language and its modules are used to implement an Open Source deep learning solution. The Deep learning image classification model is trained with the help of Keras. The performance of all the architecture mentioned above is also analysed on both datasets.

On dataset with four classes ConvNet gives 96.6% accuracy on the training set and 97.78% on the test set, whereas AlexNet gives 98.95% accuracy on training set and 98.9% on test set, when trained on training set of 2,00,000 samples with uneven sample distribution in each class. On training both models on training set of 50,000 samples uniformly distributed in each class, ConvNet gives 95.7% accuracy on training set and 97.56% on test set, whereas AlexNet gives 98.52% accuracy on training set and 98.91% accuracy on test set. On dataset with six classes ConvNet gives 98.2% accuracy training set and 99.15% on test set, whereas AlexNet gives 98.8% accuracy training set and 99.38% on test set, when trained on training set of 2,00,000 samples with uneven samples in each class. On training both models on training set of 48,000 samples with 8,000 samples in each class, ConvNet gives 98.39% accuracy training set and 99.4% on test set, whereas AlexNet gives 99.32% accuracy training set and 99.47% on test set. Test accuracy was tested on test set of 10,000 samples for both datasets. At the time of submitting this abstract the VGG model was still in the training phase.

KEYWORDS: Land cover classification, Deep learning architectures, Open source modelling, ConvNet, AlexNet, VGG

INTRODUCTION

Aerial imagery has emerged as the tool to gather more information about the structures and semantic patterns which resides on the earth’s surface and act as a data source of great significance for earth observation. With its wide availability, aerial images have made a viable impact in studying the natural complex geometrical structures and in other real-world applications. In past, the pixel level information (both spectral and temporal), has been widely used to classify the images. But with the evolution of technology, pixel level information has become ineffective as single pixels tend to “lose their thematic meanings and discriminative efficiency to separate different types of land covers” (Xia et al., 2017). The ability to learn and represent the data in an unsupervised manner and hypothesize the relation among the unseen data samples has made deep learning popular among the scientist and researchers.

Much literature is available on different general land cover classification methods which were based on level low-level, mid-level, and high-level features of aerial images. Low-level visual features deal with pixel level based classification, whereas mid-level visual representation methods attempt to develop a “holistic scene representation through representing high order statistical patterns” formed by the extracted local visual attributes (Xia et al., 2017). The high-level feature represents the deep learning computer vision approaches which are attaining noteworthy outcomes on many numerous computer vision problems. Image classification, object and scene recognition, and image retrieval are a few examples of its application. On comparing these aerial scene classification approaches, (Xia et al., 2017) concluded that the high-level methods give better results over other methods. The worst performance was observed while using low-level features.

In the field remote sensing, aerial scene classification refers to classifying aerial images with common spatial patterns. This has become a major research topic in remote sensing and countless techniques have been introduced in recent years, including many data-driven and machine learning approaches. As highlighted above, deep learning classification methods provide good results with high resolution aerial images and should similarly outperform on satellite imagery datasets (Kussul et al., 2017). The purpose of this study is to use different deep learning based classification models for classification of land patches and to analyze their performance.

Convolutional Neural Network (ConvNet), AlexNet and Visual Geometric Group (VGG) architectures are analyzed in this study. Several collections of classified aerial images (Xia et al., 2017, Basu et al., 2015, Helber et al., 2017) are available for

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deep learning, which often requires large datasets for training. These models are trained using an Open Dataset “DeepSat Image Repository” (Basu et al., 2015) – containing two different datasets having the different number of classes. One dataset has four classes which are trees, grassland, barren land, and others. The second dataset has six classes which are water bodies, buildings, barren land, trees, grassland, and roads. Once the models are trained they are evaluated on the basis of the factors like their training time, the complexity of the model, performance over unseen data, etc.

Anthropological and physical environment is not only affected by the land cover, but it is one of the crucial factors which acts as a link between both of them. Changes across the globe can be summarized by the land cover change. Land cover denotes the physical and biotic character of the land surface and studied largely by natural scientists (Di Gregorio et al., 1998). Land use refers to the usage of the land resources by humans. Thus in the field of remote sensing, land cover classification is considered as a significant tool in the process of creating maps. These maps are significant to answer the queries related to land use and land cover change of physical environment.

The models trained in this study are suitable to predicting the land cover as it performs well over the unseen data and the assessment of the different models provides a clear picture of their usage.

1.1 DATASET ACQUISITION

Land cover classification models were trained on the “DeepSat Image Repository” (Basu et al., 2015). Images for dataset were extracted from the National Agriculture Imagery Program (NAIP) dataset. The NAIP dataset consists of a total of 330,000 scenes spanning the whole of the Continental United States (Basu et al., 2015). The dataset is in .mat file format i.e. MATLAB file which can be accessed in Python using SciPy library. The sample images provided in the dataset are of size 28x28 pixels having BGR (Blue, Green and Red) and NIR (Near Infrared Region) bands. This dataset was in form of two groups in original source with name SAT-4 and SAT-6 having test and training labels for 4 and 6 classes respectively.

Image samples provided in each class of dataset were not equal. So both datasets were further improvised for analysis purpose in the project. Two separate datasets were created from the existing datasets SAT-4 and SAT-6 which contain the equal number of training samples, namely Dataset A and Dataset B, and are encoded in MATLAB .mat file format.

SAT-4 dataset has 500,000 sample images covering four land cover classes which include trees, grasslands, barren land and others. Table 1 represents a table which gives the statistics about the dataset. SAT-4 dataset was improvised further in two datasets A and B having 500,000 and 2, 68,000 image samples respectively. Dataset A has an uneven number of image samples in each class whereas Dataset B has equal number of image samples in each class. Only 200,000 out of 400,000 training image samples of Dataset A were used for training the models and rest were used for testing purpose.

The SAT-6 dataset has 405,000 sample images covering six land cover classes which include buildings, trees, water bodies, barren land, roads and grasslands. This dataset was also improvised further same as the SAT-4 dataset and two new datasets were created which are Dataset A and Dataset B having 405,000 and 96,000 image samples respectively. These two datasets were also similar to datasets created for SAT-4. Only 200,000 out of 405,000 training image samples of Dataset A were used for training the models and rest were used for testing the models.
2. METHODOLOGY

2.1. Land Cover Classification Models

Three different deep learning based land cover classification models were created which follows the different Neural Network Architectures. These models are created in Python programming language with the help of Keras library. The architecture of the models differs in the number of trainable parameters, convolutional layers, fully connected layers, dropout layers, and other layers used in a Neural Network.

All the models are created using the Model class of Keras library. Another way of creating the model in Keras is by creating a sequential model. In the sequential model, we add the layers to neural network one after another, although it may increase the lines of code, resulting in increasing the complexity of the model.

2.2. Training the Models

Once the model is created it is trained using over the dataset with the help of Keras library (Chollet et al., 2015). As shown in Figure 1, the dataset is loaded from the MATLAB .mat file using SciPy library, after that the variables are extracted from the .mat file which will be in the form of the NumPy array. After extracting the variables, the data is normalized before feeding it for training the model. Normalized data is further processed and converted into batches with the definite batch size using ImageDataGenerator class provided by Keras. Batch means a group of training samples. A batch is a group of instances or samples of the dataset. A huge dataset cannot be fed into the training process as it may lead to the memory issues in the system.

To overcome this condition, the dataset is further divided into batches with the finite number of samples in each batch. The model is trained on these batches, which leads to the decrease in training time and loss gradually. After the batching process, the model is trained using the Keras library. Keras automatically handles the Feedforward and Backpropagation changing the weights of the models accordingly. Adam optimizer was used for training all models. Adam optimizer has the learning rate of 0.001 by default. Binary cross entropy loss function was used for training with the metrics set to accuracy. Metric, a function that is used to judge the performance of the model, is provided to the compile function. All of the models were trained for 300 epochs with 20 steps per epoch. Steps per epoch decide the number of batches of the training set.

Validation dataset was also used while training the models, on the basis of which the performance of the model was monitored. Two models were saved at the end of training - one with the highest accuracy over validation dataset and other model trained after 300 epochs irrespective of its accuracy. Models for SAT-4 and SAT-6 dataset were trained separately, where the model trained on SAT-4 dataset has the resultant probability as the 1x4 vector for 4 classes, whereas the model trained on the SAT-6 dataset has the resultant probability as the 1x6 vector for 6 classes. These trained models can be used further in any algorithm using Keras library (Chollet et al., 2015).

As shown in Figure 2, all models were able to successfully classify the images with the accuracy above 90 % over all the datasets. On SAT-4 dataset AlexNet model have the maximum accuracy of 98.90% with Dataset A and AlexNet model also have the maximum accuracy of 98.91 % with Dataset B. On SAT-6 dataset VGG model have the maximum accuracy of...
99.42% with Dataset A it also has the maximum accuracy of 99.49% with Dataset B. These accuracies are respect to validation set of 10000 sample images. From the Figure 3 and Table 2, we can outline some significant outcomes as follows:

1. Increase in the number of parameters of the model leads to an increase in training time of the model. AlexNet takes less time to train than the other two models due to having less number of parameters in the model.
2. Increase in the number of classes has less effect on ConvNet and AlexNet, whereas VGG shows more deflection in training time with the increase in the number of classes.
3. Training the models on the subset of SAT-4 and SAT-6 dataset i.e. Dataset A, Dataset B reveals that, AlexNet and ConvNet takes the nearly same amount of time on training the models on both datasets. AlexNet training time is reduced by few seconds on Dataset B while accuracy remains nearly the same. Although VGG shows different behavior by taking more training time on the Dataset B than Dataset A of both SAT-4 and SAT-6 while accuracy remains almost the same.
4. VGG has shown behavior while training that, it takes more time to train on a small dataset rather than a large dataset.
5. In terms of accuracy with less number of classes, AlexNet was able to achieve more accuracy over the other models, whereas on more number of classes VGG outperforms other although it takes more time to train on the same dataset.
6. It is observed that with the increase in parameters there are more fluctuations in validation accuracy and validation loss while training. This indicates that the model is more prone to overfitting with the increase in parameters as the same case occurs with VGG model.
7. Another fact that emerged from the figures it that on training the models over the dataset with the equal number of samples of each class increases the accuracy of the models.
8. AlexNet and VGG are at the same level in terms of accuracy, whereas the performance of ConvNet is less in comparison to the other two models.
9. Overall the AlexNet performance is better than other two models in terms of accuracy, loss and training time.

![Figure 3. This image shows the relationship between training time VS number of parameters in the models over different datasets](image)

**4. CONCLUSION**

This study addresses the land cover classification problem using deep learning. We have gone through the phase of training three different models which are based on different Neural Network architectures ConvNet, AlexNet, and VGG. To have used dataset provided by DeepSat repository and improvised it further for analysis purpose. We trained the models using Python programming language with the help of Keras Python library. After gathering data about different models in training process and measuring their performance on the different dataset, we concluded to the fact that AlexNet outperforms other two models ConvNet and VGG in terms of training time, accuracy over training dataset and accuracy over validation dataset. Although VGG shows performance similar to AlexNet in terms of accuracy, it is observed that it takes more time to train and reach the accuracy level, which was achieved by AlexNet in very less amount of time. A fact is also discovered that AlexNet performs better on the model with the small number of output class, whereas VGG performs well over the models with more output classes. On SAT-4 dataset AlexNet model have the maximum accuracy of 98.90% with Dataset A. AlexNet model have the maximum accuracy of 98.91% with Dataset B. On SAT-6 dataset VGG model have the maximum accuracy of 99.42% with Dataset A and it also have the maximum accuracy of 99.49% with Dataset B. The accuracy of the models is about the validation set of 10,000 samples of image. This study can be further improved by (1) changing model parameters, (2) adding more data, (3) increasing number of spectral bands, and by (4) reducing the ground sampling distance.
Table 2. This table represents the training and test data of all three models ConvNet, AlexNet and VGG. In the above table colored cells represents the best case scenario. First table represents the data for SAT-4 and the second table represents the data for SAT-6.

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REFERENCES


ABSTRACT

Landslide detection and delineation is always a challenging task due to non-uniqueness in the spectral properties of landslides. Current techniques by means of satellite, airborne and terrestrial remote sensing, facilitate the production of landslide maps, reducing the time and resources required for their compilation and timely update. Even then the methodology for generating landslide maps using the above means is still in its moulding stage and mostly relies on some iterative procedures. In this work, we have investigated the amalgamation of new and existing technologies for landslide mapping and proposed a new methodology for automatic landslide delineation in a deep learning framework.

Deep learning based algorithms learn representations of data with multiple levels of abstraction. The strength of deep networks in classification task has gained significant attention in computer vision and geo science fields. This study mainly uses multispectral satellite images of northeast part of India especially covering Mizoram and Assam regions. The images are taken with Resourcesat-2 LISS IV satellite sensor with a resolution of 5.8 m. The proposed Landslide Detection network (LsD-n) incorporates deep features in landslide mapping and thus improved the quality of landslide maps with a very good sensitivity (> 87% on test data) and is able to map even smaller landslides of size 33m².

KEYWORDS: Deep learning, Convolutional neural network, Multi layer perceptron, Remote sensing, Feature extraction

1. INTRODUCTION

The analysis of optical, Lidar as well as SAR remote sensing image data has become a reliable procedure in disaster management activities. The salient features derived from these multi-modal data by manual or automatic assessment may be helpful in monitoring the physical characteristics of an area. Landslides are considered as the one of the most destructive geological processes that cause enormous damage to roads, bridges, houses and also cause loss of life. These are highly unpredictable and besides slope, a number of other terrain factors are responsible for the occurrence of landslides. The detection and mapping of landslides is an important task within disaster management framework.

The detection and delineation of landslide from a continuous and accurate source like remote sensing data plays a vital role to know the extent of landslide phenomena in a certain region, to investigate the recurrence and statistics of slope failures and to determine the landslide susceptibility, hazard, vulnerability and risk. The term “landslides” are defined as the movement of a mass of rock, debris or earth down a slope due to gravitational force (Cruden and David, 1991). The movement in landslides involves sliding, falling, toppling etc. Landslide mapping is a tedious and challenging task as the chance of overrating other land cover types as landslides is very high. Generally newly triggered landslides can be identified easily from optical images, because of their high reflectance. But cloud and snow coverage regions will also have the high brightness, which can be misclassified as landslide. The barren lands/escarpments coverage is highlighted in the Fig.1(a), having equal brightness with newly triggered landslide. As shown in the Fig.1(b), landslides occurred beside the river can be difficult to discriminate from the non-landslide. Old landslides are also difficult to identify from the data.

The advancement of deep learning technique in computer vision field for big data analysis, was deemed as a major breakthrough and an extremely powerful tool in many fields. The ability of deep neural networks to learn deep representation from raw image data and the possibility to use those features in various problems like detection, classification etc. is the key point behind its success. The enormous success encountered in several areas of research motivated us to apply the same formula in remote sensing field too in an efficient way. This paper proposes an idea of deep neural network in landslide delineation problem as a pixel based approach.

The proposed LsD-n (Landslide Detection network) learns a set of hierarchical deep features from a set of annotated post landslide multispectral satellite image data by supervised learning paradigm. The performance evaluation of the proposed network indicates

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that, LsD-n brings out a decent deep architecture for automatic landslide mapping. Unlike conventional convolutional neural networks, the LsD network exploit not only the feature representations learned exclusively from data but also other superior data derived handcrafted features for generating an enhanced feature map for pixel-wise classification. The proposed procedure also includes a vegetation index based post processing technique to refine the LsD-n model prediction result at the final end.

THE DATASET

The proposed LsD-n based methodology for landslide mapping, and post processing technique to filter out false positives from landslide candidates demands a generic network for forecasting landslide pixels over different data sets across sites. To implement the proposed methodology, bi temporal image datasets have been chosen from the frequently landslide prone areas of Mizoram and Assam regions. These are highly landslide hazardous areas because of a combination of an abrupt relief and geological structures. The study area of Mizoram region is located in India with the GPS coordinates of 23° 54’ 43.4772” N and 92° 44’ 19.8708” E. The total study area spread over an area of 705.27 sq km for 83D15 and 706.66 sq km for 83D16 toposheet.

The images are taken with Resourcesat-2 satellite with a high resolution sensor Linear Imaging Self-scanning System IV (LISS IV). The high resolution multispectral image data is of 5.8 m spatial resolution and have 3 spectral bands viz. green (0.52-0.59 m), red (0.62-0.68 m) and near infra-red (0.76-0.86 m). The images are orthorectified to remove the distortions across the image caused by distortions from the sensor and the earth’s terrain. In this study, post event multispectral image data along with both pre and post event data derived features are used as in change detection based threshold analysis.

FEATURE EXTRACTION

The proposed process of detection of landslides from high resolution optical satellite data requires both automatic feature extraction from post event data as well as extraction of pre and post event data driven features. As the convolutional neural network itself take care of the automatic feature preparation from training, this section describes only about the handcrafted feature preparation from the bi temporal data. The proposed deep network model makes use of the following data derived features for processing.

1.1. Top of Atmospheric reflectance (ToA)

LISS-IV sensor capture reflected solar energy from the surface, convert them to radiance and then digitized to 10 bits onboard the satellite. Since these radiance includes radiations reflected from the surface, bounced in from neighbouring pixels and reflected from clouds, atmospheric aerosols and gases above the area of pixel (Jensen, 2009). So ToA can be computed to adjust the difference in DN values during image acquisition (Martha et al., 2012). ToA can be calculated by following steps.

1.1.1 DN to radiance

The conversion of DN to radiance can be done by two ways. First method, conversion can be done by using gain and Bias values from satellite meta data. Formula to convert gain and bias is given in the Eq.1. Second, uses the LMIN and LMAX spectral radiance scaling factors Eq. 2. The meta data for LISS IV is given in the table 1.

\[ L_\lambda = gain \times DN + bias \]  

Where  
\( L_\lambda \) - Cell value as radiance  
\( DN \) - Cell value digital number DN Digital Number  
\( gain \) - gain value for a specific band
Bias - bias value for a specific band

\[ L_{\lambda_0} = \alpha \times (QCAL - QCALMIN) + LMIN_{\lambda_0} \] (2)

\[ \alpha = \frac{LMAX_{\lambda} - LMIN_{\lambda}}{QCALMAX - QCALMIN} \] (3)

Where 
- \( L_{\lambda_0} \) - Cell value as radiance
- QCAL - digital number
- LMIN_{\lambda} - spectral radiance scales to QCALMIN
- LMAX_{\lambda} - spectral radiance scales to QCALMAX
- QCALMIN - Minimum quantized calibrated pixel value (typically = 1)
- QCALMAX - Maximum quantized calibrated pixel value (typically = 255)

### 1.1.2 Radiance to reflectance

The formula used for this conversion is as follows:

\[ \rho_{\lambda} = \frac{\pi L_{\lambda} d^2}{ESUN_{\lambda} \cos \theta_s} \] (4)

Where 
- \( \rho_{\lambda} \) = Unitless planetary reflectance
- \( L_{\lambda} \) = Spectral radiance (from earlier step)
- \( d \) = Earth-Sun distance in astronomical units
- \( ESUN_{\lambda} \) = Mean solar exoatmospheric irradiances
- \( \theta_s \) = Solar zenith angle

After a landslide event, appearance of landslide affected areas are more reflected due to exposure of rock or debris. So the difference in pre event ToA and post event ToA (DToA) will be helpful in discriminating landslides and non landslides candidates.

### 1.2. Normalized Difference Vegetation Index (NDVI) and Green Normalized Vegetation Index (GNDVI)

Satellite maps of vegetation show the density of plant growth over the entire globe. The most common measurement is called the Normalized Difference Vegetation Index. NDVI is highly useful in detecting the surface features of the visible area which are extremely beneficial for municipal planning and management. The vegetation analysis can be used for the situation of unfortunate natural disasters to provide humanitarian aid, damage assessment and furthermore to device new protection strategies. Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1). The NDVI is calculated from these individual measurements as follows:

\[ NDVI = \frac{(NIR - Red)}{(NIR + Red)} \] (5)

Changes in NDVI value indicates the loss in vegetation (\( DNDVI = NDVI_{pre} - NDVI_{post} \)). The Green Normalized Difference Vegetation Index (GNDVI) is an index of plant “greenness” or photosynthetic activity. It is a modified version of NDVI. Small changes (\( DGNDVI = GNDVI_{pre} - GNDVI_{post} \)) in the chlorophyll of plant can be identified by using the GNDVI.

### 1.3. Principal Component (PC)

Lu et al. (2011) assessed that the signature of newly triggered landslides were primarily concentrated in the PC4. Principal components are generated by stacking the pre and post landslide images. PC analysis combines all six bands of pre and post LISS-IV
images and transforms these bands into six uncorrelated components. Based upon training assessment discussed in Lu et al. (2011), PC4 and PC5 are good measure to identify the newly triggered landslides.

2. PROPOSED METHODOLOGY

This paper aims to develop a network model for landslide delineation in deep learning framework. The recent success of deep neural network in semantic segmentation tasks motivated us to apply the same formula in remote sensing field too. The state of art methods follows object based analysis for landslide classification and yields good results as it analyses both spectral and spatial/contextual properties of pixels in satellite image. In contrast to that, the proposed network model handles the landslide detection problem as a pixel wise classification task. The traditional pixel based approaches may examine only the same pixel intensity value which value may indicate different land cover class like barren land, cloud cover, etc. Unlike this traditional pixel based methods, we are dealing with an encoder- decoder type deep network, which directly learn relevant spatial/contextual features from the data that improve the classification accuracy. The study area contains both larger and smaller landslides and may not be clustered and annotated properly while doing super pixel generation of a given size. Hence the LsD-n model solves this problem in a pixel wise classification way rather than using a super pixel or object based approach.

The proposed deep neural network model called LsD-n (Landslide Detection network) is a CNN-MLP fusion based neural model which combines deep features and data derived handcrafted features together for the classification task. The block diagram of proposed LsD-n model is given in fig.2. The detector CNN network will make a deep representation of post landslide event data and the detector MLP takes care of the pre and post bi temporal data derived features for enhancing the classification capability of whole LsD-network model. The output feature maps of both of these models are fused together and given to a trainable softmax classifier which predicts a classification score on both landslide and non-landslide class for each pixel in the data. The Detector CNN is a modified version of SegNet basic with encoder- decoder type architecture and detector MLP is a multi layer perceptron with four hidden layers. The proposed methodology to automatically identify landslides from bi-temporal satellite images involves a three step process.

- Dataset preparation
- LsD-network model training and prediction
- Post-processing for false positive removal

Dataset preparation involves the tiling and selection of post landslide image patches as well as handcrafted features for training and testing. Then the LsD network model is trained using supervised learning paradigm such that the trained LsD-n is able to classify each pixel into 2 classes; i.e. either landslide or non-landslide. The segmented or predicted result at the end of softmax classification layer may consists of a number of false positives, because of the inadequate number of landslide pixels in training and due to the class imbalance between landslide and non-landslide pixels in the dataset. To eliminate these false landslides a NDVI based feature mask is used at the final end.

2.1 Implementation Details

The state of art methods make use of satellite imagery for landslide delineation through object based feature identification and change detection based analysis procedures. Here the classification decision is based on the manually generated feature thresholds as well as expert opinions and interventions. The proposed methodology using deep neural network tries to overcome the above mentioned low accuracy tedious procedure in a better way. The whole pipeline of proposed methodology for landslide delineation is given in fig. 3 is detailed below.
2.2 LsD network model

The LsD-network is characterized by the fusion of two network models, i.e. detector CNN and detector MLP. From the tiled post image data set, the detector CNN model extracts deep representations of landslides and the handcrafted (data derived) features at the input of detector MLP is used to train the model to learn the dependency between the input and ground truth. Detector CNN is an encoder-decoder like architecture derived from SegNet-Basic model (Badrinarayanan et al. 2015). The encoder part of detector CNN resembles the first 4 layers of VGG-Net architecture. The encoder accepts an input image of 16x16 size with 3 channels. The model will have a max pooling layer only at the first layer of encoder layer. This is because, as the input image size is of 16x16, applying pooling operation in all the encoder layers may make the feature map too smaller at the final end. We have added dropout and batch normalization layers to avoid over fitting of the model. Each encoder layer has a corresponding decoder layer and hence the decoder network also has 4 layers. These encoder feature maps are convolved with a trainable decoder filter bank and produce a multi-channel dense feature maps. MLP is a network of simple neurons called perceptrons. The detector MLP consists of 4 hidden layers which will learn the dependency between input and ground truth during training process. It is noticed that the addition of MLP layer will improve the network model recall to a satisfactory level. The features like DTOA, DGNDVI, DNDVI, PC5 and PC4 are given at the input of MLP.
2.3 Dataset Preparation

The study area of Mizoram and Assam regions considered here consists of 429 landslides on 83D15 tile and 317 landslides on 83D16 tile of different size and shape. Training a network in such a big image of size 5084x5549x3 with a pixel resolution of 5.8 m, won't be feasible during testing. Since the labelled landslide multispectral images are less in number and the difficulty of processing such a higher dimensional image using CNN, the primary step was to create multiple non-overlapping image patches from the 83D15 post landslide orthorectified image data. As the 83D15 tile contains both smaller and larger landslides, the smaller patch size will be more helpful for extracting contextual information using CNNs. So a window of size 16x16 was taken for tiling the post image data. For general classification problem using CNNs, a 16x16 window is too small. But here a single patch covers a total area of 92.8m x 92.8m and hence we constrained to use a contextual window having a maximum dimension of 16x16. The tiled image patch will be of size 16x16x3 including R, G and NIR bands. Due to geo-referencing, there will be a tilt in images which may create blacked out edge tiles during tiling. These tiles are removed before further processing. Otherwise these edge tiles with zero information content on the 3 bands may create false positives during network model prediction. After removing edge tiles there will be around 1 lakh, 16x16 image patches for processing from the 83D15 data.

Figure 4 a) 83D15 Post ortho-rectified multispectral landslide image data, b) A single 16x16 image patch of post landslide image

2.4 Training data selection and class balancing

For a classification task the samples must be balanced for proper training of the neural network. Otherwise the network will be locked to dominant class. This biased constant prediction although not informative and can yield high accuracy and small loss. Here non-landslide image patches dominates over landslide image patches, so a proper sampling of image tiles is required for the selection of training data. We sampled the tiled images in such a way that, the selected training data set will contain at least one landslide pixel. After sampling we got 641 image patches with at least one landslide pixel. We also added around 50 randomly selected non-landslide image patches along with the selected 641 tiles to increase the training data count with affecting class balance. The selected 691 image patches are divided as 483 image patches for training and 104 image patches for validation and 104 for testing.

Even after proper sampling of image patches, class imbalance exists between the number of non-landslide pixels and landslide pixels. There are more number of non-landslide pixels over landslide pixels. At this stage there is a need to penalize each loss differently based on the true class. Here we used median frequency balancing where the weight assigned to a class in the loss function is the ratio of the median of class frequencies computed on the entire training set divided by the class frequency. This implies that larger classes in the training set have a weight smaller than 1 and the weights of the smallest classes are the highest.

2.5 Data derived feature processing

As mentioned in the above section, based on the studies the pre and post satellite data derived features such as DToA, DGNDVI, DNDVI, PC4 , PC5 etc. are used for improving the recall factor of detector CNN network. Since both the Detector CNN and Detector MLP layers in the LsD network are fused and trained together, the above mentioned hand crafted features also must be tiled as post image data tile size for processing. So the corresponding features for 16x16 image patch should be selected as MLP inputs. We stack all the features one by one such that the input to MLP network will be of size 16x16x7. The input to MLP will be also in image matrix format (not as vectorized input) as we replace the fully connected layers of MLP with convolution layer of 1x1 kernels. This is because fully connected layers are equivalent to 1x1 convolutions for a pixel wise classification problem, where the input and output image dimensions remains the same. As we can’t completely rely on the threshold settings in change detection based threshold analysis method (Martha et al., 2012), which may fail in some situations, we fuse this MLP network to use the hand crafted features of bi-temporal satellite images.
2.6 Training, Testing and Prediction

The data set which we have prepared in the previous section with the corresponding ground truth labels are used for training LsD network. The ground truth data prepared by experts of NRSC, based on bi-temporal image analysis and field study are used for training. The LsD network is built on top of the Keras deep learning library. LsD-n learns to predict pixel-wise class labels from supervised learning. The network is trained using NVIDIA Titan Xp 12 GB GPU with cuDNN v5.1. The trained LsD-n model is tested on image patches (not used for training) of 83D15 data and also on 83D16 data. The Fig. 5a) shows LsD-n prediction on 83D15 data.

2.7 Removal of false positives using NDVI feature

The LsD-n prediction on landslides may contain some false positives like roads, buildings, barren lands etc. As land resources can be easily interpreted by computing their NDVI, we employed NDVI feature mask for maximum suppression of false landslides. The post and pre NDVI feature sets are categorized in to 3 classes using of k-means clustering algorithm, showing the different level of vegetation based on spectral reflections. The clusters will be a) A group of pixels with very high vegetation loss or sparsely vegetated areas (Naturally unvegetated) b) A group of pixels with medium vegetation loss c) A group of pixels with zero or sparse vegetation loss ie. highly vegetated area. The assumption made in this procedure is that the common very high vegetation loss clusters in pre and post NDVI feature will be something other than landslide pixels like barren lands, roads, water bodies etc. So by doing logical ‘AND’ operation between the very high vegetation loss clusters of pre and post NDVI feature or simply taking very high vegetation loss clusters of pre NDVI only, we will obtain a mask for eliminating false landslides. Fig. 6 shows feature mask, the common unvegetated areas obtained from both pre and post NDVI features. Fig. 5a) shows LsD-n prediction on landslides. Fig 5b) indicates the NDVI feature mask obtained for false positive removal. Fig. 6 shows the results obtained after doing NDVI based false positive removal.

Figure 5. a) LsD-n prediction (red colour) on 83D15 post event data including all false predictions b) NDVI mask (Intersecting unvegetated areas in both pre and post NDVI) to remove FPs

Figure 6. a) After removing FPs using NDVI mask b) Enlarged view of resultant shape file of landslides after post processing (red marking shows ground truth)
3. RESULTS AND DISCUSSION

The performance of this LsD-n based prediction followed by NDVI based filter masking technique is evaluated as follows. Given any input, a binary classifier predicts either of two outcomes: positive, or negative. For the pixel classification problem here, landslide pixels are considered positive, and non-landslide pixels, negative. Out of 404 landslides in 83D15 dataset, 379 landslides are predicted by the LsD network by hit or miss kind of classification. Let us assume TP, FP and FN are the true positive, false positive and false negatives respectively. We have measured the performance of proposed methodology in terms of recall; which is the ratio of correctly predicted positive observations to the all observations in actual class.

\[
Recall = \frac{TP}{TP+FN}
\]

The below tables summarizes the evaluation metric of proposed methodology for 83D15 and 83D16 dataset, where the network is trained using some image patches of 83D15 data.

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>83D15 dataset</th>
<th>83D16 dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>404</td>
<td>117</td>
</tr>
<tr>
<td>FN</td>
<td>25</td>
<td>17</td>
</tr>
<tr>
<td>Recall</td>
<td>0.941</td>
<td>0.873</td>
</tr>
</tbody>
</table>

Table 1. Summary of the proposed LsD network model prediction and followed NDVI based post processing technique.

4. CONCLUSION

The proposed LsD deep learning network of automatic landslide mapping is showing competitive performance compared to other statistic landslide classification methods like maximum likelihood method, MNB classifier method etc due to its adaptability for real time multi-resource data and no predefined assumption. The single trainable LsD network with two parallel streams of CNN and MLP reduces the overall complexity of the model and provides good performance in landslide detection task without any human intervention and expertise. The NDVI based feature masking method to improve the quality of detection by eliminating a large number of false positives from the LsD-n prediction results. The experiments indicate that the proposed methodology can assist landslide investigation efficiently and automatically. Moreover, areas susceptible to landslides can be identified by the retrospective investigation of landslide events which can be beneficial for future landslide risk assessment.

ACKNOWLEDGEMENTS

Authors would like to thank Indian Institute of Space Science and Technology (IIST) Trivandrum for funding this project and also National Remote Sensing Centre (NRSC) Hyderabad for providing the data sets used for training and testing of proposed LsD-n model. Special thanks to Ms. Mrinalni K., JRF, NRSC for preparing the ground truth data set for this project.

REFERENCES


HEAT – GREEN COVER FEATURE MODELING USING REMOTE SENSING SURROGATES FOR URBAN ECO-MANAGEMENT

R.Vidhya*, S. Reeta and P. Swaramanjari
Institute of Remote Sensing, Anna University, Chennai

ABSTRACT

Climate change in cities has received much focus in the past few decades. Heat stress in urban areas has an adverse effect on human health and is expected to worsen in the future due to the changing climate. Vegetation has been proved to mitigate this effect, but introducing 'green' areas into the metropolitan space is a challenging task. The urban growth and its effects understood as a function of “heat – green cover feature vector” can enable the urban planners and managers to handle urban thermal environment more sensibly.

This study attempts to understand heat – green cover function with surrogate parameters derived from remote sensing images in order to arrive at the percentage green cover needed for a specific land development in the city of Mumbai, a city where the development is imperative and environment is fragile. The change in built up area and the vegetal cover between 2010 and 2015 and the statistical relation between them were studied through LST, NDVI and NDBI of Land SA T data. When studied the pattern of LST and NDVI for distinct land use classes, the correlation varied with respect to each land use classes owing to the extent of imperviousness and the building materials used. This led to the study of relationship of LST to NDVI and NDBI to understand the effect of land covers on the LST and grading of imperviousness across the city. The study demonstrated the scope of remote sensing based surrogate parameters to address the land management and planning issues in urbanized areas.

KEYWORDS: heat- green cover feature vector, LST, NDVI, NDBI, imperviousness, surrogate parameters

1. INTRODUCTION

Heat stress in urban areas has an adverse effect on human health and is expected to worsen in the future due to the changing climate. The increased infrastructural needs have put pressure on the urban and even rural environment lately that has attention on the relationship to local climatic change and habitat comfort. It is also being understood that urbanization-associated land use and land cover (LULC) changes lead to modifications of surface microclimatic and hydrological conditions. Specially the urban areas has a rapid transformations and the relief is usually provided by the vegetal cover. Then it becomes imperative for the urban planners to understand the effects of each land cover change on the local microclimatic conditions such as temperature in order to find the balance. Today the most imperative problem in an urban area is increasing surface temperature because of dramatic alteration of the natural surface as natural vegetation is removed and replaced by non-evaporating, non-transpiring surface. With the availability of synoptic and repetitive coverage of the land surface by space or Sir borne sensors, it has become viable to study the influence of the urban land use classes at its thermal environment through the indicators derived from such data.

The surface temperature is key factor for studying of urban climatology. Satellite thermal imageries, especially high resolution imagery, has the advantage of providing dense grid of temperature and green cover data that can effectively be used for urban thermal and eco management. The urban growth and its effects understood as a function of “heat – green cover feature vector” can enable the urban planners and managers to handle urban thermal environment more sensibly.

Here an attempt is made to understand the relation between the land surface temperature and the vegetal cover proportion that will help drawing a quantitative guideline for optimizing the open and vegetated spaces in the cities. to understand heat – green cover function with surrogate parameters derived from remote sensing images in order to arrive at the percentage green cover needed for a specific land development in the city of Mumbai, a city where the development is imperative and environment is fragile.

The specific objectives of this study are

- To create the databases for Mumbai city which include impervious layer, pervious layer and partially impervious layer.
- To retrieve remote sensing parameters like LST, NDVI, NDBI, and NDWI.
- To relate LST with NDVI, NDBI and NDWI through statistical analysis at aggregated levels.
- To study the impact of urban growth on the ambient temperature and environment of the city as a function of “heat – green cover feature vector”.

*Corresponding author: vidhya.v.vanan@gmail.com
The scope of this study is to find the percentage of vegetal cover needed to be improved over the pockets of Mumbai city which are experiencing high heat stress for the reduction of one unit temperature.

2. MATERIALS AND METHOD

2.1 study area – Mumbai city

The surface temperature is key factor for studying of urban climatology. It modifies the air temperature of the lowest layers of the urban atmosphere and also helps to determine the internal weathers of buildings and affects the energy balances that affect the comfortable city life. Mumbai, a capital city of Maharashtra is the case study of this research. Mumbai is a coastal island-city with excessively large population density, having undergone constantly a series of reclamations and transformations. Mumbai has urbanized over the past 60 years and urbanized rapidly from its origins. Along with the neighboring regions of then Mumbai Metropolitan Region, it is one of the most populous urban regions in the world and the second most populous metropolis in India, with a population of 20.7 million as of 2011. Mumbai lies on the west coast of India and has a deep natural harbor. In 2009, Mumbai was named an alpha world city. The rise in the population of Mumbai, from 8 million in 1971 to 21 million now shows the drastic growth of population. Since 1971 industrialization also took drastic rise around the Mumbai city. The Climate of Mumbai is a tropical wet and dry climate. The mean maximum average temperatures are about 32 °C (90 °F) in summer and 30 °C (86 °F) in winter. Even though Mumbai is enveloped with enough green cover, rivers and lakes, forests than other metropolitan cities the development of urban is in a very drastic manner. So it is necessary to improve the green spaces over the pockets of city which are experiencing high heat.

2.2 Data used

For this work, LANDSAT 8, 15th May 2015 and LANDSAT 4-5 TM, 10th May 2010 were used. Google Earth image and LANDSAT 8 are used for preparing landuse map for the Mumbai city. For disaggregated analysis of NDVI Vs. LST, ward maps provided by Municipal Corporation of Greater Mumbai was used.

The wavebands of Landsat 8 used were

<table>
<thead>
<tr>
<th>SPECTRAL BAND</th>
<th>WAVELENGTH (nm)</th>
<th>RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 3 green</td>
<td>0.52-0.60</td>
<td>30</td>
</tr>
<tr>
<td>Band 4 red</td>
<td>0.63-0.68</td>
<td>30</td>
</tr>
<tr>
<td>Band 5 near infrared</td>
<td>0.845-0.885</td>
<td>30</td>
</tr>
<tr>
<td>Band 6 short wavelength infrared</td>
<td>1.56-1.660</td>
<td>30</td>
</tr>
<tr>
<td>Band 7 short wavelength infrared</td>
<td>2.100-2.300</td>
<td>30</td>
</tr>
<tr>
<td>Band 8 panchromatic</td>
<td>0.500-0.680</td>
<td>15m</td>
</tr>
</tbody>
</table>

The wavebands of Landsat 8 used were

<table>
<thead>
<tr>
<th>SPECTRAL BAND</th>
<th>WAVELENGTH (nm)</th>
<th>RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 2 green</td>
<td>0.52-0.60</td>
<td>30m</td>
</tr>
<tr>
<td>Band 3 red</td>
<td>0.63-0.69</td>
<td>30m</td>
</tr>
<tr>
<td>Band 4 near infrared</td>
<td>0.76-0.90</td>
<td>30m</td>
</tr>
<tr>
<td>Band 5 middle infrared</td>
<td>1.55-1.75</td>
<td>30m</td>
</tr>
<tr>
<td>Band 6 thermal infrared</td>
<td>10.40-12.50</td>
<td>120m</td>
</tr>
<tr>
<td>Band 7 middle infrared</td>
<td>2.08-2.35</td>
<td>30m</td>
</tr>
</tbody>
</table>

2.3 Software used

The retrieval of remote sensing parameters and the preparation of landuse map are carried out by ArcGIS 10.3. The regression analysis is carried out by LabFit.

2.4 Retrieval of LST

Land surface temperature (LST) is generally defined as the skin temperature of the ground. For the bare soil surface, LST is the soil surface temperature; for dense vegetated ground, LST can be viewed as the canopy surface temperature of the vegetation; and in sparse vegetated ground, it is the average temperature of the vegetation canopy, vegetation body and soil surface under the vegetation.
The spectral radiance was computed as

\[ L_\lambda = M_\lambda \cdot Q_{\text{cal}} + A_\lambda \quad (1) \]

\( L_\lambda \) = TIRS spectral Radiance
\( M_\lambda \) = Band Specific Multiplicative Rescaling Factor (0.0003342)
\( A_\lambda \) = Band Specific Additive Rescaling Factor (0.1000)
\( Q_{\text{cal}} \) = Quantized and calibrated standard product pixel value

Computing brightness temperature from Thermal infrared Spectral radiance using thermal constant

\[ T = k_2 \ln \left( k_1 / L_\lambda + 1 \right) \quad (2) \]

\( T \) = At-satellite Brightness Temperature
\( L_\lambda \) = TIRS spectral Radiance
\( k_1 \) = Band specific thermal conversion constant from Meta data
\( k_2 \) = Band specific thermal conversion constant from Meta data

In these \( k_1 \) and \( k_2 \) thermal conversion constant are obtained from metadata, for band 10 \( k_1 = 774.8853 \), \( k_2 = 1321.0789 \) and for band 11, \( k_1 = 480.8883 \) and \( k_2 = 1201.1442 \), substitute these in the formula using raster calculator. The proportion of vegetation is calculated from the maximum and minimum values of normalized difference vegetation index. Using the maximum and minimum values the proportion of vegetation was calculated, using these land surface emissivity map was generated.

\[ PV = \left( \text{NDVI} - \text{NDVI}_{\text{min}} / \text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}} \right)^2 \quad (3) \]

\( PV \) = proportion of vegetation

\[ e = 0.004 \cdot PV + 0.986 \quad (4) \]

\( e \) = land surface emissivity

derivation of land surface temperature using the at satellite temperature and land surface emissivity, the map shows the land surface temperature for mumbai at may 2015.

\[ \text{LST} = BT / 1 + W \cdot (BT / p) \ln (e) \quad (5) \]

where

\( \text{LST} \) = Land surface Temperature
\( BT \) = At satellite Temperature
\( W \) = wavelength of emitted radiance
\( P = h \cdot c / s \) (14378)
\( e \) = land surface emissivity

2.5 RETRIEVAL OF NDVI

The NDVI is calculated from these individual measurements as follows:

\[ \text{NDVI} = (\text{NIR} - \text{IR}) / (\text{NIR} + \text{IR}) \quad (6) \]

Values ranges from -1 to +1.

2.6 RETRIEVAL OF NDBI

Impervious surface is one of the most important land cover types and also a key indicator of urban expansion and urban heat island effect. NDBI can be computed using the following expression:

\[ \text{NDBI} = (\text{MIR} - \text{NIR}) / (\text{MIR} + \text{NIR}) \quad (7) \]

NDBI has a native scaling of -1 to +1.

2.7 RETRIEVAL OF NDWI

NDWI is used to identify the water bounded areas and their conditions. The formula used to calculate NDWI is,

\[ \text{NDWI} = (\text{GREEN} - \text{NIR}) / (\text{GREEN} + \text{NIR}) \quad (8) \]

This formulation of NDWI produces an image in which the positive data values are typically open water areas; while the negative values are typically non-water features (i.e. terrestrial vegetation and bare soil dominated cover types). Like NDVI, NDWI has a native scaling of -1 to +1.

2.8 PREPARATION OF ‘I’ - imperviousness MAP

‘I’ map is index map which includes the proportion of pervious and imperviousness of features of landuse map. This map has to be prepared by reclassifying the land use map of Mumbai city with 21 ward boundaries on the basis of open spaces and green cover of the features the landuse map contains. ‘I’ map contains 11 classes which emphasis pervious and
imperviousness so that the role of pervious and imperviousness can be analyzed with the help of LST retrieved from the satellite image

2.9 LST, NDVI and NDWI maps

The NDVI, NDWI and LST maps were generated for the said 2010 and 2015 data. The maximum temperature value is 37.7 degree C and the minimum temperature is 21.93 degree C for 2015, which was compared against the data provided by IMD for the date and it compared well. The maximum NDVI value is 0.52 and the minimum NDVI value is -0.19. The NDBI values were generated and the values were cross verified with the building density; the NDBI values were high for the high density regions and vice versa proving the dependability of the index. On the verification of these indices with respect to two dates namely 2010 and 2015, based on field information and satellite data the following premises could be well correlated.

- Forests have been degraded and so there is increase in temperature
- Green cover has been degraded
- Buildings have been developed
- Water bodies have been degraded

2.10 Regression analysis

The surface temperature is mainly affected by the land use types and is also controlled by the various land cover parameters like the roof materials and use of building. The indexes NDVI, NDBI, and NDWI are the three main influencing factors. The regression analysis was performed between various indices and the imperviousness map generated based on the land use / landcover to understand the effect of various biophysical and impervious surfaces on eh temperature. This was used to draw a conclusion on the fraction of the vegetal cover to be developed for reducing one degree C of temperature for various urban fabric elements.

3. RESULTS AND DISCUSSION

The regression analysis conducted between various indices for different impervious surfaces are discussed here.

3.1 The regression analysis of indices

The indexes NDVI, NDBI, and NDWI are the three main influencing factors. The correlation between LST and NDVI, LST and NDBI, LST and NDWI is found by regression analysis using LabFit. Samples were collected keeping in mind these parameters for regression analysis. The scatplot between LST and NDVI had correlation coefficient of -0.955. The correlation value is 0.75 which indicate LST tends to correlate positively with NDBI. The correlation value is -0.7 which indicates that LST tends to negatively correlate with NDWI.

![Figure 1. Scatter plot between (a) LST vs. NSVI (b) LST vs. NSBI and (c) LST vs. NDWI](image-url)
3.2 The regression analysis for urban fabric element

The regression analysis was performed separately for different urban fabric that is the distinct urban classes with unique impervious fractions for ex. Slum, open spaces and fully built up.

The following table gives the correlation between the surrogate parameters considered for different urban fabric elements.

<table>
<thead>
<tr>
<th>RS PARAMETERS</th>
<th>SLUM</th>
<th>BUILDING</th>
<th>VEGETATION</th>
<th>OPEN SPACE</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST VS NDVI</td>
<td>-0.721</td>
<td>-0.790</td>
<td>-0.731</td>
<td>-0.8069</td>
</tr>
<tr>
<td>LST VS NDBI</td>
<td>0.968</td>
<td>0.947</td>
<td>0.7277</td>
<td>0.9705</td>
</tr>
</tbody>
</table>

3.3 Imperviousness ‘I’ map

The imperviousness map was prepared based on the land use map by considering the impervious fractions present in the region and employing reclassification. The following map show the land use and imperviousness map.

![Land Use Map](image1)

![Imperviousness Map](image2)

It is observed that more imperviousness exhibit more temperature except in the case of water bodies which exhibit low temperature. Construction materials also play a major role in high temperature. The concrete based construction materials with little vegetal cover exhibits moderate temperature whereas the other roof materials like asbestos sheet exhibits very temperature around 32°C. NDVI range for the minimum LST to maximum LST has been noted down so that the improvement of percentage of green cover over an area for the reduction of 1°C temperature can be computed by assuming percentage of green cover for each range of NDVI as below.

3.4 Vegetal cover for one degree C Temperature reduction

The of NDVI values for percentage cover was derived from the land use map and tabulated as below.

<table>
<thead>
<tr>
<th>LST</th>
<th>NDVI range</th>
<th>%GC</th>
</tr>
</thead>
<tbody>
<tr>
<td>37</td>
<td>0.03</td>
<td>20</td>
</tr>
<tr>
<td>36</td>
<td>0.05</td>
<td>23</td>
</tr>
<tr>
<td>35</td>
<td>0.06</td>
<td>27</td>
</tr>
<tr>
<td>34</td>
<td>0.07</td>
<td>30</td>
</tr>
<tr>
<td>33</td>
<td>0.08</td>
<td>35</td>
</tr>
<tr>
<td>32</td>
<td>0.09</td>
<td>38</td>
</tr>
<tr>
<td>31</td>
<td>0.10</td>
<td>40</td>
</tr>
<tr>
<td>30</td>
<td>0.15</td>
<td>43</td>
</tr>
<tr>
<td>29</td>
<td>0.18</td>
<td>45</td>
</tr>
<tr>
<td>28</td>
<td>0.20</td>
<td>50</td>
</tr>
<tr>
<td>27</td>
<td>0.25</td>
<td>55</td>
</tr>
<tr>
<td>26</td>
<td>0.30</td>
<td>60</td>
</tr>
<tr>
<td>25</td>
<td>0.38</td>
<td>65</td>
</tr>
<tr>
<td>24</td>
<td>0.40</td>
<td>70</td>
</tr>
<tr>
<td>23</td>
<td>0.43</td>
<td>80</td>
</tr>
<tr>
<td>22</td>
<td>0.46</td>
<td>90</td>
</tr>
<tr>
<td>21</td>
<td>0.48</td>
<td>100</td>
</tr>
</tbody>
</table>
A linear regression analysis is made between LST and NDVI using the above table values for LST and NDVI.

![Figure 3. The regression between NDVI range and LST](image)

Based on the above analysis the increase in vegetal cover desired for reduction of one degree C at various temperature regimes was derived as follows.

<table>
<thead>
<tr>
<th>LST range</th>
<th>37 TO 36</th>
<th>36 TO 35</th>
<th>35 TO 34</th>
<th>34 TO 33</th>
<th>33 TO 32</th>
<th>32 TO 31</th>
<th>31 TO 30</th>
</tr>
</thead>
<tbody>
<tr>
<td>% VG</td>
<td>3%</td>
<td>4%</td>
<td>3%</td>
<td>5%</td>
<td>3%</td>
<td>2%</td>
<td>3%</td>
</tr>
</tbody>
</table>

From above table, to reduce 37°C to 36°C temperature, it is necessary to improve green cover by 3% more than the feature has already in an urban region. Similarly it can be done for other temperature range also according to the land cover units.

### 4. CONCLUSION

From the above analysis, the correlation between Remote sensing parameters like LST, NDVI, NDBI, NDWI are computed. It reveals that there is a strong positive correlation between LST and NDBI whereas there is a negative correlation between LST and NDVI. Features which are exhibiting high heat are analyzed through the comparison of LST-NDVI with landuse map. In such cases temperature can be reduced by improving the green cover over the high heat exhibiting places and it is analyzed through ‘I’ map. ‘I’ map reveals the major role of imperviousness in increase in temperature. For example the pervious and imperviousness ratio 20:80 exhibits more temperature than 30:40. When the impervious increases further, the temperature also increases. But in the case of water bodies, 100% imperviousness exhibits low temperature. Temperature is also increasing based on the roof materials used for the construction. So the city planners should design the city to maintain the pervious and imperviousness ratio which balance green cover and temperature.

### ACKNOWLEDGEMENTS

The authors wish to record their acknowledgements to Carolin Jenisha, Priyanka, Sowmya Kini and Vinithra, students of under graduate program for their help in processing.

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PERFORMANCE ANALYSIS OF NAVIC RECEIVER FOR POSITIONING APPLICATIONS

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ABSTRACT

Satellite Navigation system provides positioning and timing information based on a global network of satellites. It has many advantages compared to conventional navigation systems in the field of mapping and surveying. Satellite navigation systems are classified as global and regional based on the coverage of the satellites. GPS, GLONASS, Galileo and Compass are global systems whereas QZSS and NavIC are the regional navigation systems. NavIC (NAVigation with Indian Constellation) is an Indian Regional Navigation Satellite System (IRNSS) developed by ISRO which is designed to provide accurate position information service to users in India as well as in the region extending up to 1500 km from its boundary. NavIC operates in two frequency bands namely L5 (1176.45 MHz) and S1 (2492.02 MHz) and is available to civilians with full constellation. This study provides the outcome of performance analysis of NavIC user receiver carried out at NRSC. NavIC receiver provides observables from IRNSS, GPS and GAGAN-SBAS constellations. This receiver was installed on a known survey marker and the data was acquired in different modes such as L5, S1, L1 alone, L5+S1 (IR dual), IR+GPS L1, IR+GPS+GAGAN SBAS. This study provides the outcome of performance metrics in terms of positional accuracy, GDOP (Geometric Dilution of Precision), C/N0 (Carrier to Noise Ratio), TTFF (Time To First Fix) and clock bias for the above constellations. Based on this study, it is understood that IGS receiver provides better TTFF and better GDOP due to multi constellation tracking and thereby provides enhanced positional accuracy. The signal strength of IRNSS signals are high compared to the C/N0 of GPS. IGS receiver provides high quality IRNSS data with minimum cycle slips. Also, enhanced positional accuracy is achieved using GAGAN SBAS option in IGS receiver.

KEYWORDS: NavIC, GNSS, GAGAN-SBAS, GDOP

1. INTRODUCTION

Satellite Navigation system provides positioning and timing information based on a global network of satellites. It has many advantages compared to conventional navigation systems in the field of mapping and surveying. Satellite navigation systems are classified as global and regional based on the coverage of the satellites. GPS, GLONASS, Galileo and Compass are global systems whereas QZSS and NavIC are the regional navigation systems. NavIC (NAVigation with Indian Constellation) is an Indian Regional Navigation Satellite System (IRNSS) developed by Indian Space Research Organization (ISRO), Dept. of Space, India. It is developed to provide positional information to users in Indian region extending up to 1500 km from its boundary.

IRNSS system mainly consists of three segments viz. Ground segment, Space segment and User Segment (Parimal Majithiya et al. 2017). IRNSS space segment was planned with configuration of seven satellites at 36000 km altitude. Three of the satellites are located in geostationary orbit at 32.5° E, 83° E, and 131.5° E longitude. Four satellites are in geosynchronous orbit at 35,786 km with an inclination of 29° to the equatorial plane with their longitude crossing at 55° E and 111.75° E (two satellites in each plane). Such an arrangement would mean all seven satellites would have continuous radio visibility with Indian control stations. IRNSS operates in two frequency bands namely L5 (1176.45 MHz) and S1 (2492.02 MHz) and is available to civilians with full constellation (A.S Ganeshan et al, 2015). IRNSS-I1 was successfully launched on 11-4-2018 in place of 1A. With IRNSS-II up in space, space segment of first phase of IRNSS constellation was completed. At present full constellation of 7 satellites namely IRNSS-1B, 1C, 1D, 1E, 1F, 1G & 1I have been placed in orbit as shown in Figure 1. These seven IRNSS satellites are continuously broadcasting the navigation signals and autonomous 3D positioning over the intended service area.

![Figure 1. IRNSS constellation](image-url)
2. OBJECTIVE

This study provides the outcome of

- Performance metrics of the IGS receiver in terms of
  - Positional accuracy
  - GDOP (Geometric Dilution of Precision)
  - C/N0 (Carrier to Noise Ratio)
  - TTFF (Time To First Fix)
  - Satellites visibility (Elevation angle) and
  - Clock bias of IGS receiver

- Position analysis in different modes
  - IR-L5, IR-S1 and GPS-L1 alone,
  - IR dual frequency and hybrid modes such as IR+GPS, IR+GPS+GAGAN
  - GAGAN-SBAS accuracy

2.1 IGS RECEIVER

IRNSS/GPS/SBAS user receiver which is called as IGS receiver is capable of providing observables from IRNSS (IR-L5 &IR-S1 bands), GPS (GPS-L1 band) and GAGAN-SBAS (PRN 127 & 128) constellations. It was jointly developed by ISRO and Accord Software & Systems PVT Ltd. The IGS receiver consists of Antenna, Antenna Mount and Receiver unit with 4.3” LCD display for real time monitoring of the receiver parameters. The receiver is accompanied by AC/DC and DC/DC adapter to suit the wide range of power sources. Windows based GUI called IRNSS-UR was installed on to a Laptop and this GUI is used to communicate with the IGS receiver for commanding, monitoring, data logging and visualization purposes. The receiver is with total 32 channels and 12 channels are allotted for GPS L1, 11 channels for each IR-L5 and IR-S1 and 2 channels for GAGAN-SBAS. The IGS receiver collects data in raw and NMEA0183 formats. This data can be converted to RINEX v3.03 using UR Data Extractor which comes with IRNSS-UR GUI. The schematic diagram of the IGS receiver, Controller, Receiver, antenna, skyplot is shown in Figure 2.

The receiver can be operated in various modes, by selecting IR-L5, IR-S1, GPS-L1 in different combinations and GAGAN-SBAS enable or disable option. GAGAN-SBAS will provide correction signals in real time for GPS-L1 to get precise coordinates. The IGS user receiver mainly does four important functions i.e., tracking, acquisition, decoding and position solution.

![Figure 2. Schematic diagram of the IGS receiver](image-url)
3. STUDY OF PERFORMANCE METRICS (METHODOLOGY)

NRSC/ISRO is equipped with IGS receiver which provides observables from IRNSS, GPS and GAGAN-SBAS constellations.

3.1 Establishment of known marker co-ordinates

The known survey marker (Zero order station) which was established during GCPL (Ground Control Point Library) project was used as the reference point for analysis of IGS results. To derive the reference station co-ordinates, the GPS data was collected for 8 hrs for 3 days successively using geodetic grade R7 GNSS receiver on survey marker. The co-ordinates were derived precisely with 10 cm accuracy using PPP (Precise Point Positioning) technology. In this process, precise ephemeris information and clock parameters were used.

3.2 Installation of IGS Antenna and system setup

The IGS antenna was installed on the monument of known marker using tribatch and tripod. The centering and leveling procedure was carried out to install the antenna precisely on the survey marker of the brass plate. The antenna height was measured properly after installation which is used during process to derive the co-ordinate of survey marker. The antenna is connected to the receiver and laptop computer is connected to the IGS receiver which serves as user controller for the receiver. The laptop computer is installed with IRNSS-UR and extraction software.

3.3 Data collection using different modes

This receiver was installed on a known survey marker and the data was logged in different modes as given below with 1Hz data rate and mask angle 5° to analyse the performance of the receiver. The data was collected for duration of one week in each mode.

- Single frequency (L5, S1, L1)
- Different combinations of dual frequency (L5+S1, L5+L1, L1+S1)
- IR+GPS+GAGAN SBAS mode

The extract software supplied by SAC, ISRO is used to convert the raw data to excel files (*.csv) which contain the position information, GDOP, SNR, Clock parameters etc. It also provides RINEX v3.03 data files as well as NMEA data file.

3.4 Data analysis for performance metrics

The extracted data was analyzed to study the performance metrics of the IGS receiver in terms of positional accuracy, GDOP, C/N0, TTFF and clock bias for the above constellations. Analysis is also made with different observation periods. The data collected in different modes is also validated with known marker co-ordinates.
4. ANALYSIS & RESULTS

4.1 C/N0:

The performance of a receiver is assessed by its ability to precisely measure the pseudo range and carrier phase, which depend on noise linked to the signals in the receiver’s tracking loops. C/N0 is expressed as the ratio of the carrier power and the noise power per unit bandwidth. It is expressed in decibel-Hertz, dB-Hz (Sophie HETET, 2000). The larger is the ratio, the stronger is the signal. C/N0 of the GPS signals varies with satellite elevation angle and azimuth, and from satellite to satellite. It varies from 36 (very week signal) to 59 (very strong signal) (Paul Collins, 1999). The C/N0 values of L5, S1 and L1 of IGS receiver are derived from the raw data and shown in Table 1. The C/N0 values of IGS receiver are in the expected range of 36 to 59.

Table 1. C/N0 values of IGS receiver for all frequencies

<table>
<thead>
<tr>
<th>Frequency</th>
<th>C/N0 in dB-Hz</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
</tr>
<tr>
<td>L1 (IGS)</td>
<td>35</td>
</tr>
<tr>
<td>L5 (IGS)</td>
<td>25</td>
</tr>
<tr>
<td>S1 (IGS)</td>
<td>25</td>
</tr>
<tr>
<td>L1 (GNSS)</td>
<td>35</td>
</tr>
</tbody>
</table>

From Figure 4, it is observed that C/N0 values of L5 and S1 are higher compared to C/N0 value of L1 i.e. signal strength of IRNSS is high compared to GPS.

4.2 GDOP

GDOP (Geometric Dilution Of Precision) indicates the error caused by the relative position of the GNSS satellites with respect to the GNSS receiver. From the observer’s point of view, if the satellites are spread apart in the sky, then receiver will have a good GDOP. If the satellites are close together, then there will be poor GDOP. This lowers the quality of positioning by meters. In general, for a GNSS receiver an average GDOP value of 2 to 5 will be observed. During the early stages of IRNSS satellite configuration, when 4 satellites only were launched, the GDOP value used to go up to 1000 at every 12 hours due to co-planar condition. (T.E. Rani et al, 2015). After the launch of 5th satellite, the GDOP values were in normal range of 3 to 4 (Reference).

The Figure 5 shows the GDOP values of IGS receiver for different modes i.e., L5+S1+L1, L5+S1, L5 only, S1 only and L1 only. It is observed that in L5+S1 mode, the GDOP values record 3 to 4 consistently. The GDOP is better when data is collected in hybrid mode i.e. including L1 GPS.
4.3 CLOCK BIAS/OFFSET

GPS/IRNSS receivers are usually equipped with quartz crystal clocks, which are relatively inexpensive and compact. They have low power requirements and long life spans and they’re less accurate compared to atomic clocks. Signal travel time (dT) is derived using receiver and satellite clock time. Due to the less accuracy of receiver clock, the receiver time is not perfectly synchronized to satellite clock. The difference of synchronization is called the receiver clock offset. Receiver clock offset is the time difference between receiver clock time and the actual time determined by GNSS atomic clock. Receiver clock bias/offset is the one of the largest error sources for position computation. The receiver clock bias of IGS receiver is compared with the data collected in different modes.

When data is collected with IRNSS Dual mode, the clock offset is recording 5 to -20 ns and the corresponding SEP position error values are recording 1 to 3 meters as shown in Figure 6.

When data is collected in hybrid mode i.e. IR Dual + GPS L1 and in GPS-L1 only mode, the clock offset values are in the expected range of 10 to -20 ns. The corresponding 3D RMS positional error values are in the expected range of 0 to 4 meters.

4.4 ELEVATION ANGLE AND SATELLITE VISIBILITY

The elevation angle is the angle between the line of sight of the satellite, GNSS receiver and the line of direction to the horizon starting from antenna measured in the vertical plane. The GPS satellites cover 0 to +90 degrees elevation since it is a global constellation. But it is observed that at few instances only 2 - 4 GPS satellites are available in the high elevation angles (50-90 degrees elevation). Hence if GPS L1 only mode is used in urban canopy regions, it will degrade the position solution accuracy because of the availability of less number of GPS satellites and poor GDOP. The elevation angles are plotted against time to observe coverage of the GPS and IRNSS satellites. It is observed that the IRNSS satellites cover 25 to 70 degrees elevation and continuously available in high elevation angles. As IRNSS satellites are not in lower elevation
angles, the atmospheric related errors will be less compared to GPS satellites. Also the multipath noise created by IRNSS signals will be less as the IRNSS signals will be more vertical due to higher elevation angles.

When data is collected in IRNSS Dual + GPS L1 mode (Figure 7), the receiver will have better availability of GPS satellites in urban canopy regions thereby gets better coverage and improved positional accuracies. In Figure 7, the red lines represent IRNSS satellites and blue lines represent GPS satellites.

4.5 POSITION ACCURACY

In this section, we discuss the modes of data collection and the achieved positional accuracies in each mode of operation. The data was collected in the following modes and the results are compared with each other.

- L5 alone
- S1 alone
- L1 alone
- L5+S1 (dual on)
- L5 + L1 (dual off) no dual on option
- S1 + L1 (dual off) no dual on option
- L5 + S1+L1 (dual on)
- GAGAN SBAS on and off with GPS L1 mode

Positional accuracy is expressed in terms of DRMS, CEP and SEP as explained in the Table 2. The position co-ordinates are derived with the pseudo range data not with phase data.

Table 2. Description of Accuracy measures

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Dimension</th>
<th>Accuracy measure</th>
<th>Probability (%)</th>
<th>Typical usage</th>
<th>Definition</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2D</td>
<td>Distance Root Mean Square (DRMS)</td>
<td>68</td>
<td>Horizontal</td>
<td>The square root of the average of the squared errors (σ) - for straight line “error distances” in x,y direction</td>
<td>( \sqrt{\sigma_x^2 + \sigma_y^2} )</td>
</tr>
<tr>
<td>2</td>
<td>2D</td>
<td>Circular Error Probable (CEP)</td>
<td>50</td>
<td>Horizontal</td>
<td>The radius of circle centered at the true position, containing the position estimate with probability of 50%.</td>
<td>( 0.83 \times \text{DRMS} ) Or ( 0.62 \sigma_x + 0.56 \sigma_y )</td>
</tr>
<tr>
<td>3</td>
<td>3D</td>
<td>Spherical Error Probable (SEP)</td>
<td>50</td>
<td>Horizontal + Vertical</td>
<td>The radius of sphere centered at the true position, containing the position estimate in 3D with probability of 50%</td>
<td>( 0.51 \times \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2} )</td>
</tr>
</tbody>
</table>

To calculate the DRMS, the established coordinates of the survey marker is used. The error with reference to the known location for easting, northing and altitude (x,y,z) are derived. The square root of the average of the squared errors for 24 hours continuous data set was derived in each direction and they were represented as \( \sigma_x \), \( \sigma_y \), \( \sigma_z \) respectively. The DRMS, CEP and SEP of all the modes as described in the Table 2 are derived and shown in Figure 8 and Table 3. The maximum and minimum error of navigation solution for each mode is shown in Table 3. It can be seen that accuracy measures in hybrid mode i.e. IR Dual + GPS L1 with dual on is the most accurate among all the available modes. The positional measure of all single frequencies is high compared to dual frequencies. In another study, the effect of SBAS on 3DRMS is
analyzed. The data is collected in both SBAS on and off modes. It is observed that SBAS on is more accurate compared to SBAS off. This is also shown in Figure 8.

Table 3. Positional errors in different modes

<table>
<thead>
<tr>
<th>Measure (in meters)</th>
<th>L5_S1_L1 (Hybrid)</th>
<th>L5_S1 (Dual)</th>
<th>L5_L1 (Dual)</th>
<th>L1_S1 (Dual)</th>
<th>L5 only (SBAS ON)</th>
<th>L1 (SBAS ON)</th>
<th>L1 only (SBAS Off)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max error (DRMS)</td>
<td>2.32</td>
<td>4.12</td>
<td>2.1</td>
<td>3.44</td>
<td>3.7</td>
<td>4.37</td>
<td>2.61</td>
</tr>
<tr>
<td>Min error (DRMS)</td>
<td>0.001</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>CEP</td>
<td>0.24</td>
<td>0.55</td>
<td>0.66</td>
<td>0.8</td>
<td>0.85</td>
<td>0.94</td>
<td>0.44</td>
</tr>
<tr>
<td>SEP</td>
<td>0.32</td>
<td>0.8</td>
<td>0.97</td>
<td>1.13</td>
<td>1.2</td>
<td>21</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Figure 8. Positional error of IGS receiver in different modes for 24 hours data set.

4.6 TIME TO FIRST FIX (TTFF)

Time to first fix (TTFF) is the time taken by GNSS receiver to acquire the satellite signals, almanac data and navigation data to calculate a position fix. It is the difference in time between when a GNSS receiver is switched on and it is able to obtain its position or coordinates. Generally, the TTFF values are in the order of seconds. TTFF is affected by environmental conditions, sky visibility to the receiver, indoors and outside conditions. Under static environmental and outdoor conditions, TTFF can be used to assess the ability of the receiver for quicker position fixes. IRNSS receiver logs data is analyzed to know the time taken by the receiver to acquire both GPS signals and IRNSS signals. The observations were shown in Figure 9 for IGS receiver in IRNSS Dual, GPS Only and IRNSS+GPS modes. The TTFF values for multi-GNSS constellation are less compared to single GNSS constellation, both GPS and IRNSS. This reiterates the fact that using multi-constellation data is beneficial for less TTFF, thereby quicker position fix.

Figure 9. TTFF in different constellations
5. CONCLUSIONS

In this study, the performance metrics of the IGS receiver in terms of Positional accuracy, GDOP (Geometric Dilution of Precision), $C/N_0$ (Carrier to Noise Ratio), TTFF (Time To First Fix), Satellite coverage (Elevation angle) and Clock bias are analyzed. Positional accuracies are analyzed with range data.

- It was observed that $C/N_0$ values of L5 and S1 are high compared to $C/N_0$ value of L1 i.e. signal strength of IRNSS is high compared to GPS (Figure 4).
- It was observed that the GDOP of hybrid mode i.e. $(IRNSS + GPS)$ is better compared to $IRNSS$ only (Figure 5).
- The clock offset is observed in the range of 5 to -20 ns when the data is collected in all modes i.e. GPS+IR Dual, IR Dual and GPS L1 only mode (Figure 6).
- All the IRNSS satellites are nearly vertical over horizon by virtue of geo-stationary and geo-synchronous orbits. Therefore IRNSS satellite visibility in ‘urban canopy’ is much better than GPS constellation. Also the multipath noise and atmospheric errors observed by IRNSS signals will be less (Figure 7).
- Position accuracy for 24 hours continuous datasets of $IRNSS$ only mode is about 0.8 to 1.2 meter and hybrid mode $(IRNSS + GPS)$ is about 0.2 to 0.4 meter (Figure 8). GAGAN SBAS ON option on L1 frequency is improving the positional accuracy by around 1 meter. However the Maximum and Minimum values of navigation solution for a given single epoch are 2.32 meter and 0.001 meter respectively for the hybrid mode. The better positional accuracies are due to utilization of iono model and troposphere model and GAGAN SBAS real time corrections which are in-built in the IGS receiver.
- The TTFF values for multi-GNSS constellation are less compared to single GNSS constellation, both GPS and IRNSS (Figure 9). This reiterates the fact that using multi-constellation data is beneficial for less TTFF, thereby quicker position fix.

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T.E.Rani, B.Satish Kumar, P.Krishnaiah and S.Muralikrishnan, Preliminary data analysis of IRNSS for PNT services, INCA35 conference at New Delhi, 2015.
POTENTIAL OF CARTOSAT SERIES SATELLITE STEREO DATA FOR VOLUMETRIC ANALYSIS


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ABSTRACT

Terrain related activities viz. information about changes in geomorphology, landslides, information about mining requires volume calculations. Based on this information, planners can think about the impact of terrain related activities on environment and make proper planning and decision for reclamation proposals and where in photogrammetry can be used effectively. IRS satellites like Cartosat-1 is a dedicated stereo mission with twin cameras where as other single camera agile satellite missions like Cartosat-2 can also cater to the need of generating Digital Elevation Model (DEM), by using photogrammetric techniques. With DEMs generated from multi temporal cartosat-1 stereo data, volume of heaps or depressions, height/depth of material can be calculated. From these DEMs, 3D visual perceptions of volumetric data can be made for better understanding of terrain profiles. Cartosat-1 satellite acquires stereo along track with fixed (B/H) ratio of 0.62, spatial resolution of 2.5 m and swath of 30km. Cartosat-2 is high resolution satellite with single camera which acquires data at 1.0 m resolution and swath of 10km. The Cartosat-2 satellite being agile, it can acquire the stereo data with variable B/H ratio. Photogrammetric processing of high resolution satellite stereo data is done using Rational Polynomial coefficient (RPC) model, which gives the relationship between image and ground. Refinement of RPC is done with control points. In this paper potential Cartosat-1 stereo data is explored for volume computation of mining quarry in part of Bengaluru.

KEYWORDS: DEM, B/H ratio, RPC, terrain volume, Cartosat-1

1. INTRODUCTION

Photogrammetry is process of making terrain related measurements by processing images obtained by metric cameras mounted on either aerial, satellite platforms. Measurements can be like planimetric as well as elevation with respect to datum if data is of stereo type. Subsequently planimetric maps can be made and volumes of terrain can be estimated relatively and absolutely. In photogrammetry height can be obtained based on apparent displacement of terrain features on successive images taken from two different perspective view or acquired with different direction. Planimetric details can be delineated on images rectified for terrain and perspective scale, tilt distortions. Aerial photograhic stereo data can be acquired at very high resolution to medium resolution depending on flying height with the same camera. Advantage of aerial data is that area of interest can be flown according to choice of resolution and time but limitation is that is expensive. Same photogrammetric task can be done by cameras mounted on satellite. Pros of this system is that large area can be covered by single Scene. Hence to map topographic details of larger areas like entire country, satellite photogrammetry can be beneficially resorted to. More over satellites can cover same area systematically at regular interval of period which further help to monitor the changes that take place planimetric and volumetrically on terrain over the time. Cartosat-1 is Indian satellite with dedicated stereo image acquiring sensor system, and it is launched in May 2005, with twin linear array cameras of 12000 CCDs having one camera looking forward with angle of 26° and another backward with 5° angle along it path of pass from north to south. The data acquired from cartosat-1 stereo data is used to generate DEM for entire country (Srivastava et.al, 2007; Muralikrishnan et.al, 2012). Advantage of this system of sensor is that it can acquire the stereo data in along the path with same illumination condition, and hence automatic image matching for DSM can be better achieved. It has fix B/H ratio which yields same vertical accuracy of 4 meters. Satellite can acquire data in wide mono other than stereo mode (Cartosat-1 Data User’s Handbook, 2006) resulting wider swath of 56km by controlling yaw rotation. The specifications of the Cartosat-1 satellite is given below (table 1).

<table>
<thead>
<tr>
<th>1. Nominal Spatial Resolution: GIFOV (m) (Across-track x along-track) for fore and aft images</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5 x 2.78m 2.22 x 2.23</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>2. Altitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>618km</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>3. Spectral Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) No. of Bands, b) Bandwidth</td>
</tr>
<tr>
<td>1 Panchromatic</td>
</tr>
<tr>
<td>500 nm to 850 nm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>4. Radiometric Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) Saturation Radiance, b) Quantization</td>
</tr>
<tr>
<td>55mw/cm² cm/str/micron</td>
</tr>
<tr>
<td>10 bits</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>5. Swath (km) (Stereo), Fore + Aft Combined (Mono) Km.</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 , 56</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>6. CCD Parameters:</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) No. of Detectors elements, b) Detector Element Size</td>
</tr>
<tr>
<td>12000 per camera</td>
</tr>
<tr>
<td>7 x 7 microns</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>7. Optics: a) No. of Mirrors, b) Effective Focal Length (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3, 1980, +/- 1.08</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>8. Integration Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.336</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>9. Time delay of acquisition between fore and aft camera</th>
</tr>
</thead>
<tbody>
<tr>
<td>52 seconds</td>
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<table>
<thead>
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<th>10. Nominal B/H Ratio for Stereo</th>
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<td>0.62</td>
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<table>
<thead>
<tr>
<th>11. The Revisit rate/ Repetivity for Cartosat-1 is five days</th>
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<tr>
<td>5 days/126 days</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>12. Vertical accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-4 m</td>
</tr>
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</table>

Table 1. Cartosat-1 specifications

*Corresponding author: shashivardhan_r@nrsc.gov.in
Since the Cartosat_1 stereo data can be acquired over same the terrain at interval of 4 months depending on the climatic conditions, it can be utilized for monitoring of vertical changes volumetrically and elevation wise by taking multi-temporal Stereo data.

1.1 Study area and Data used

The granite quarry site located in outskirts of Bengaluru is taken as study area. Four temporal sets of cartosat-1 stereo data covering the study area are used as input data. The date of acquisition of the data sets viz 20-Mar-2006, 27-Apr-2009, 30-Jan-2012, and 26-Jan-2015.

In the present study an attempt is made to explore the potential of cartosat-1 stereo data for calculating parameters of a mining site viz. volume of excavation, maximum depth of cut and overburden volume.

2. METHODOLOGY

Photogrammetric processing of any satellite data involves recreation of geometry i.e geometry of camera, and relation between image and ground coordinate system which exists at the time of acquisition. In situations when the sensor geometry and attitude information is not available or accessible, generic sensor modelling is very useful in defining the mathematical relationship between the image and the object space. The rational function model (RFM) which is ratio of two polynomial models is popular among the generic sensor model (Di et al., 2003; Liu and Tong, 2008). The rational polynomial coefficient (RPC) modeling has been widely used method for the last one decade especially with the launch of Ikonos satellite with a GSD of 1m (Liu and Tong, 2008). This continued and further gained popularity with the launch of other high resolution satellite sensors like Quickbird, Cartosat, Worldview, Geoeye etc. Now all the above mentioned data sets are supplied with the coefficients of the RFM without disclosing the sensor model (Dowman and Dolf, 2000; Tao and Hu, 2001). In rational polynomial functions, each scan line number and pixels can be expressed as a function of ground coordinates in terms of ratio of cubic polynomials (Grodecki and Dial, 2003). Hence each scan line number and pixel number are given as:

\[
\frac{s}{p} = \frac{P_1(X,Y,Z)}{P_2(X,Y,Z)} \quad \text{and} \quad \frac{s}{p} = \frac{P_3(X,Y,Z)}{P_4(X,Y,Z)}
\]

Where \(X, Y, Z\) are the normalized object space coordinates i.e normalized latitude, longitude and height respectively. \(s\) and \(p\) are the normalized scan line number and pixel number between \((-1,+1)\).

\[
P_1(X,Y,Z) = a_0 + a_1Y + a_2X + a_3Z + a_4XY + a_5XZ + a_6ZX + a_7Y^2 + a_8X^2 + a_9Z^2 + a_{10}XY^2 + a_{11}YZ^2 + a_{12}X^2Y + a_{13}X^2Z + a_{14}YZ^2 + a_{15}Y + a_{16}Y^3 + a_{17}X^3 + a_{18}Z + a_{19}XYZ
\]

\[
P_2(X,Y,Z) = b_0 + b_1Y + b_2X + b_3Z + b_4XY + b_5XZ + b_6ZX + b_7Y^2 + b_8X^2 + b_9Z^2 + b_{10}XY^2 + b_{11}YZ^2 + b_{12}X^2Y + b_{13}X^2Z + b_{14}YZ^2 + b_{15}Y + b_{16}Y^3 + b_{17}X^3 + b_{18}Z + b_{19}XYZ
\]

\[
P_3(X,Y,Z) = c_0 + c_1Y + c_2X + c_3Z + c_4XY + c_5XZ + c_6ZX + c_7Y^2 + c_8X^2 + c_9Z^2 + c_{10}XY^2 + c_{11}YZ^2 + c_{12}X^2Y + c_{13}X^2Z + c_{14}YZ^2 + c_{15}Y + c_{16}Y^3 + c_{17}X^3 + c_{18}Z + c_{19}XYZ
\]

\[
P_4(X,Y,Z) = d_0 + d_1Y + d_2X + d_3Z + d_4XY + d_5XZ + d_6ZX + d_7Y^2 + d_8X^2 + d_9Z^2 + d_{10}XY^2 + d_{11}YZ^2 + d_{12}X^2Y + d_{13}X^2Z + d_{14}YZ^2 + d_{15}Y + d_{16}Y^3 + d_{17}X^3 + d_{18}Z + d_{19}XYZ
\]

Cartosat-1 stereo data is supplied along with RPC, and the refinement of it carried with ground control points (GCPs). The methodology adopted in the present study is given in Fig.1.

**Figure 1. Flowchart depicting sequence of steps carried out for the study**

The major steps involved are viz. (i) Block adjustment of Cartosat-1 stereo data (ii) Quality checking of block adjustment (iii) Digital Surface Model (DSM) for respective stereo model of the year (iv) Volumetric analysis.
(i) Block adjustment of Cartosat-1 stereo data

A project has been created with WGS-84 datum and UTM 43 projection. Four number of Cartosat-1 stereo data sets are imported along with RPC files. For each image, pyramid file is generated, to enable faster access of the image in image matching. Automatic tie points are generated across the 4 models (8 images) and points are added manually where sufficient points are not generated. A total of 250 tie points which spread across entire image space are used for precise relative adjustment. The refinement of RPC is done by 1st order linear adjustment using 5 number of GCPs. The GCPs are taken from existing aerial orthoimage data (20 cm GSD) and DEM (1m posting). The planimetric and vertical datum for GCPs is on WGS-84 ellipsoid and MSL datum respectively. Root mean square error (RMSE) of all the tie points in image domain is 0.25 pixels. In the present study Leica Photogrammetry suite of Imagine (2016) is used for block adjustment of Cartosat-1 stereo data sets. Distribution of tie and control points on data sets is shown in Fig.2.

(ii) Quality checking of block adjustment

Accuracy of products like DSM and orthoimage depends on accuracy of block adjustment. Quality checking of block adjustment is evaluated both in image domain and ground domain for control points. Control points quality analysis in image domain in x and y direction are done for 8 images and are given in table 2 and 3.

<table>
<thead>
<tr>
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<tr>
<td>12</td>
<td>0.251</td>
<td>0.253</td>
<td>0.602</td>
<td>0.305</td>
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<tr>
<td>52</td>
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<td>-0.685</td>
<td>-0.759</td>
<td>-0.088</td>
<td>-0.077</td>
<td>-0.078</td>
<td>-0.088</td>
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<tr>
<td>54</td>
<td>0.497</td>
<td>0.425</td>
<td>0.413</td>
<td>0.573</td>
<td>-0.271</td>
<td>-0.236</td>
<td>-0.241</td>
<td>-0.272</td>
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<tr>
<td>62</td>
<td>0.176</td>
<td>0.67</td>
<td>-0.247</td>
<td>-0.609</td>
<td>-0.032</td>
<td>-0.028</td>
<td>-0.029</td>
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<tr>
<td>65</td>
<td>-0.43</td>
<td>-0.88</td>
<td>0.555</td>
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<td>-0.077</td>
<td>-0.079</td>
<td>-0.089</td>
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<tr>
<td>Mean error in pixels</td>
<td>0.1282</td>
<td>0.0506</td>
<td>0.1276</td>
<td>0.0296</td>
<td>-0.0784</td>
<td>-0.0684</td>
<td>-0.0698</td>
<td>-0.079</td>
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<tr>
<td>RMSE in pixels</td>
<td>0.3309</td>
<td>0.5503</td>
<td>0.5237</td>
<td>0.5959</td>
<td>0.1399</td>
<td>0.1217</td>
<td>0.1244</td>
<td>0.1402</td>
</tr>
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</table>

Table 2. Control Points Errors in image Domain in x direction (a= aft image, f= fore image)

<table>
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<td>12</td>
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<td>-0.70123</td>
<td>-0.604</td>
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<td>-0.526</td>
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<td>0.26</td>
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<td>0.112</td>
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<td>-0.158</td>
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<td>-0.796</td>
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<td>0.143</td>
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<td>0.1</td>
<td>0.322</td>
<td>-0.062</td>
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<td>65</td>
<td>0.47</td>
<td>0.73</td>
<td>0.257</td>
<td>-0.509</td>
<td>0.175</td>
<td>0.566</td>
<td>-0.105</td>
<td>0.289</td>
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<tr>
<td>Mean error in pixels</td>
<td>0.108</td>
<td>0.170554</td>
<td>-0.148</td>
<td>-0.1082</td>
<td>0.1522</td>
<td>0.2104</td>
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<td>0.2568</td>
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<tr>
<td>RMSE in pixels</td>
<td>0.4023</td>
<td>0.5528</td>
<td>0.4801</td>
<td>0.4194</td>
<td>0.3741</td>
<td>0.4429</td>
<td>0.1339</td>
<td>0.5180</td>
</tr>
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</table>

Table 3. Control Points Errors in image Domain in y direction (a= aft image, f= fore image)

In ground domain, control and check point residuals are computed. A total of 4 checkpoints are used and the residual are shown in table 4, 5.
(iii) Digital Surface Model (DSM) Generation

DSM is Digital elevation information of the terrain at surface level. There are many automatic stereo matching techniques based on area based and feature based algorithms for generation of DEM. In this study semi global dense stereo matching module of LPS software is used for generating DSMs. The posting of DSM is at 2.5 m. The generated points are manually evaluated for vertical accuracy by super imposing over stereo model and most of the places DSM points were exactly sitting over the surface except at vertical cuts and at places where images are in poor contrast. To depict the quarry cuttings and deposits precisely break lines have been manually added where ever they are required. DSM generated for the respective stereo data for the four years. Validation of DEM is done by checking the accuracy of 236 match points falling with in stereo pair. For this analysis, DSM generated from Cartosat stereo pair (2015) is selected. A plot is drawn between vertical accuracy Vs frequency of points falling within the error range and is shown in fig.4. Using the DSMs, orthoimages are generated for the respective years. Fig.5 shows the orthoimages for year 2006, 2015 and perspective view.

<table>
<thead>
<tr>
<th>GCP ID</th>
<th>Residual (X)(m)</th>
<th>Residual (Y)(m)</th>
<th>Residual (Z)(m)</th>
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<td>0.94</td>
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<td>-0.70</td>
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<td>0.15</td>
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<td>65</td>
<td>0.13</td>
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<table>
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<th>Checkpoint ID</th>
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<td>-0.52</td>
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<td>8</td>
<td>0.94</td>
<td>0.43</td>
<td>-1.53</td>
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<td>11</td>
<td>-1.20</td>
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<tr>
<td>13</td>
<td>0.62</td>
<td>0.12</td>
<td>-1.13</td>
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Table 4. Ground control point error in ground domain
Table 5. Check point error in ground domain

![Figure 4. Vertical accuracy vs frequency of elevation points for DSM validation](image)

![Figure (5a). Orthoimage of year 2006. (b) Orthoimage of year 2015. (c) Perspective view of DSM draped over orthoimage.](image)
(iv) Volumetric analysis

For volumetric analysis, DSMs for the year 2006, 2009, 2012 and 2015 are used as input. By taking DSM year 2006 as reference, three difference DSMs are computed viz. (i) DSM2009- DSM2006. (ii) DSM2012-DSM2006 (iii) DSM2015-DSM2016. Subsequently Various parameters like volume of excavation, maximum depth of cut, height of overburden, surface areas and theoretical accuracies are derived. Results are shown in table 6 and scenario of mining are shown in Fig.6.a, 6b, 6c

![Difference between 2009-2006](image1)

![Differences between 2012-2006](image2)

![6 (c) DSM Difference between 2012-2006](image3)

<table>
<thead>
<tr>
<th>SNo</th>
<th>Years</th>
<th>Vol. of excavation (million m$^3$)</th>
<th>Max depth of cutting (m)</th>
<th>Surface area of cutting (m$^2$)</th>
<th>% of volume accuracy</th>
<th>Vol. of over burden (million m$^3$)</th>
<th>Surface area of overburden (m$^2$)</th>
<th>Max height of over burden (m)</th>
<th>% of Volume accuracy</th>
</tr>
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<tr>
<td>1</td>
<td>2006-2009</td>
<td>4.7</td>
<td>21.5</td>
<td>137360</td>
<td>92</td>
<td>0.25</td>
<td>11231</td>
<td>4</td>
<td>87</td>
</tr>
<tr>
<td>2</td>
<td>2006-2012</td>
<td>6.3</td>
<td>27.3</td>
<td>167356</td>
<td>93</td>
<td>0.864</td>
<td>25212</td>
<td>7</td>
<td>92</td>
</tr>
<tr>
<td>3</td>
<td>2009-2015</td>
<td>10.1</td>
<td>38.0</td>
<td>256821</td>
<td>93</td>
<td>1.456</td>
<td>43621</td>
<td>14</td>
<td>91</td>
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</table>

Table 6. Volumetric analysis of the Mining site
3. DISCUSSION AND CONCLUSIONS

In the present study multi temporal Cartosat-1 stereo data are used for the studying volumetric excavation of a mining site. Photogrammetric adjustment of 4 Cartosat-1 stereo models is done using RPC model. Table 2.3 shows control point residual in image domain in xy direction. It can be inferred from both tables, that all the control points have been post pointed in all the images to the precision of less than 0.59 pixels (RMSE) in x direction and 0.55 pixels (RMSE) in y direction in image domain. The precision with which control points are identified depends on the clarity of control points in image pair. Control point and check point residuals also computed in ground domain in table 4.5. From the two tables, it can be seen that control and check points are better than 0.85 m in X 0.65 m in Y direction and 1.145m in z direction. From the results(table 2,3,4 and 5), it can be summarised that it is possible to achieve better than a pixel accuracy at block adjustment of data using RPC model with GCPs.

After block adjustment, DSM is generated for each Cartosat-1 model pertaining to different years using semi global matching technique. The DSM is validated by 236 points from the stereo model. From the fig 4, it is inferred that more than 92 % of points are below error of +/- 3 m.

By using DSM from the year 2006 as reference, difference DSMs have been generated for years 2009, 2012 and 2015 for computation of change in excavation of mining. From table 6 it is observed that even though, the cumulative volume of excavation is gradually increasing with respect to year 2006, but relatively it is random with previous data sets. Surface areas, Depth of cutting and height deposit is gradually increasing and hence it is inferred that, mining of quarry is active. Since the vertical accuracy of Cartosat-1 stereo is +/- 3m, theoretical accuracy of volume can be computed as product of surface area and vertical accuracy with respect to total volume. From the numerical derived from the volume estimations, accuracy of volumes are deduced as 92%.

The above study shows that Cartosat-1 dedicated stereo missions can be potentially utilized for estimating and monitoring of excavations that take place at mining sites. The advantage of mission is that it has fixed B/H ratio which in turn yields same vertical accuracy for all stereo pairs and DSMs. Missions of this kind of dedicated stereo pairs with very high resolutions in future find utility in computing values more precisely. The limitation in evaluating volume is that quarry should be dry. Quarry with water may deviate from actual results.

REFERENCES


MODELLING VERTICAL GROWTH OF CITY FROM HIGH RESOLUTION IMAGERY

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ABSTRACT

Growth of city will be the single largest influence on development in the first half of twenty first century. Metropolitan cities will contain over 60% of total urban population of the world. Vertical Growth of city means the changes of city in height direction caused by scarcity of land, industrialization and high priced land, population growth and people migration to cities. The increased availability of high-resolution images in support of detailed terrain elevation models using photogrammetric techniques, assist urban planners and municipal managers to create a city model for different years. Three dimensional visualization models of city have a variety of applications in geography and urban studies such as accurate cartographic feature extraction, map updating, military operations, disaster management, mapping of buildings and their heights, simulation of new buildings. Coregistration of images acquired at different time periods using photogrammetric processing is done using Rational Polynomial Coefficients (RPC) and dense point cloud is derived using image matching techniques. The change in the height of the city was derived by comparing high resolution Digital Surface Models from the urban areas. This paper explains the methodology of modeling vertical growth of urban cities from high resolution images. Qualitative assessment of building heights derived using automatic DSMs and normalized DSM (nDSM) is done and from Cartosat-1 stereo data buildings with floor level difference can be extracted.

KEYWORDS: High Resolution Stereo Imagery, DSMs, nDSM, Vertical Growth

1. INTRODUCTION

Vertical growth represents height changes of the city i.e. construction of tall and super tall building. The city is home to the headquarters of numerous high-tech companies that house their offices in major tall and super tall buildings. Vertical growth of buildings is also a matter of agglomeration in business districts. Another reason for structural growth is price of the land in major cities. Land prices always have been a prime driver for constructing tall buildings. In large cities, properties are very expensive, and buildings logically grow upward. Newman and Ken worthy (1988) found that urban sprawl causes more travel from the suburbia to the central city and thus more fuel consumption. Tall buildings maximize building area with a minimum physical footprint. Accommodating the same number of people in a tall building of 50 stories versus 5 stories, for example, requires about one-tenth of the land. Rather than horizontal growth, Vertical growth aims at preserving following things:

- Preserving many different types of open spaces, including natural areas in and around cities
- Recreational spaces, Critical environmental areas
- Farm and ranch lands, places of natural beauty
- Savings in auto fuel
- Travel time
- Reduction in losses in power lines, water supply.

Model provides the ability to visualize the result in two dimensional or three dimensional for better understanding. Several municipalities decide nowadays to build models in order to clearly understand the cities’ real situations. The importance of vertical growth model is to identify structures for the organization of urban information which can be used in a broad range of applications, e.g., for analysis in urban planning, disaster management, and environmental simulations. Almost all previous studies are focused on how cities are expanding outward. Because other sources of remote sensing data are not able to capture the vertical and volume dimension. Normally Change detection of city or urban area using automated image processing methods is a very important topic in satellite image processing. Numerous detection methods using various image types have been developed to satisfy a wide range of applications and user requirements (Lu et al 2003).

One major problem often met that there is only 2D information extracted from satellite images, and there is the lack of monitoring height changes, the 3D component of the surface to be analyzed. Thereby only changes related to the reflectance values and/or local textural changes are detected. However, changes in the vertical direction are completely ignored. Such information could play an important role in different applications such as urban area construction and/or destruction monitoring, applications for urban planning and development etc., (Alobeid et.al(2011)). Moreover, with the increasing availability of high resolution stereo imagery acquisition and aerial images, the height change detection or vertical growth is possible (Buyuksalih G and Jacobsen, 2007). Aerial stereo images have high resolution, but its cost effectiveness is high. Along track and across track scanning Satellite system provides stereo images used for urban area analysis. Raw aerial photography and satellite imagery have large geometric distortion that is caused by various systematic and nonsystematic factors.

The photogrammetric modeling based on collinearity equations eliminates these errors most efficiently, and creates the most reliable stereo images from the raw imagery.

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In case of satellite data instead of delivering the interior and exterior orientation parameters for eliminating those distortions the properties related to physical Sensor i.e. Rational Polynomial co-efficient (RPC) are supplied for satellite photogrammetric processes (Grodecki et.al, Gopalakrishna et.al). The accuracy of the DSMs generated from stereo images largely depends on the radiometric data quality, the GSD of the data, the convergence angle of the stereo data and the amount of stereo pairs (Tian et al,2014).

1.1 Study area
Hi-tech city and its surroundings, part of Hyderabad is taken for the study and it covers 10.65 square kilometers of Hyderabad city (650 km²). It lies in 17° 21′ 57.6″ N Latitude, 78° 28′ 33.6″ E Longitude.

1.2 Data used
Satellite stereo images and aerial stereopairs of years 2013, 2016 covering hitech city and surroundings have been selected for modeling the vertical growth of city.

i. Pleides Stereo Pairs (2013) of resolution 50cm

ii. Aerial data of 20cm resolution(2016)

2. METHODOLOGY
The Multi sensor’s stereo pairs were taken from two time periods for modeling the vertical growth of city. Then co-registration has been done between the images for getting epi-polar images in photogrammetric software. Automatic Digital surface model are generated using MATCH-T DSM of Inpho and Intergraph software. The Figure 1 explains the methodology for image orientation and automatic DSM generation. Digital surface model from Aerial images of resolution 20cm and Pleides of resolution 50cm are generated using Semiglobal matching (Hirschmüller) technique and Hybrid matching (Area, Feature, Cost matching) techniques.

![Flow chart for DSM extraction](image)

Figure 2 shows the RGB point cloud generated automatically using Semiglobal matching (SGM) technique from Pleides data at 1m spacing.
2.1 Normalised Digital surface Model (nDSM)

Ground classification (Digital Elevation model) of Digital Surface Model is done by generating rulesets in Object based image analysis (OBIA) software. The ground classified DEM generated automatically for Pleaides data is shown in Figure 3.

Normalised Digital surface Model (nDSM) containing manmade objects (buildings, bridges..) and trees are generated by subtracting Digital Surface Model (DSM) from Digital Elevation model (DEM) and the flowchart is shown in Fig. 4.

Normalised Digital surface Model (nDSM) in point cloud format are generated for Aerial data of 50cm spacing and compared with nDSM from Pleaides of 1m spacing. The methodology for generation of nDSM using spatial model editor is shown in Figure 5.
Heights of buildings and above ground objects for Pleaides data is shown as shaded relief map in Fig.6.

Vertical profiles of nDSMs of Pleaides and aerial data shows the vertical growth of city with elevation values of buildings, flyover constructions etc and segregation of buildings into different types

(i) Type 1 (New buildings that are built after removing vegetation)
(ii) Type II (New buildings that are built on bare earth or low vegetation or on top of existing buildings),
(iii) Type III (demolished or damaged buildings) and
(iv) Type IV (existing buildings that have little or no changes)

3. RESULTS AND DISCUSSION

Accuracy of height change detection depends on precise co-registration of images acquired at different time periods from multi sensors and its resolution. It also depends on illumination and stereo angle properties of each sensor. In this paper high resolution images from aerial and satellite sensors of resolution 20cm and 50cm are co-registered using ground control points. DSMs are generated automatically using robust Semi global matching and cost based matching techniques. The difference between DSM and DTM gives the heights of above ground objects or Normalized DSM (nDSM). Height Accuracy of above ground objects (nDSM) depends on precise generation of DSM and DEM extraction (Bare earth). Ground classification from dense point cloud (DSM) is done using rulesets in object based image classification. Shaded relief maps of Normalised DSMs of Pleaides (2013) and elevation profiles at different locations are shown in Fig.7.

Figure 5 nDSM generation using Spatial model editor

Figure 6. nDSM point cloud of Pleaides data (2013)

Vertical profiles of nDSMs of Pleaides and aerial data shows the vertical growth of city with elevation values of buildings, flyover constructions etc and segregation of buildings into different types

(i) Type 1 (New buildings that are built after removing vegetation)
(ii) Type II (New buildings that are built on bare earth or low vegetation or on top of existing buildings),
(iii) Type III (demolished or damaged buildings) and
(iv) Type IV (existing buildings that have little or no changes)

Shaded relief maps of Normalised DSMs of Pleaides (2013) with their profile locations are shown in Fig.8 and Fig.9 and the elevation profiles of lines 1, 2 from nDSM of Pleaides data are shown in Fig 8 (a),(b) and corresponding Fig 9 (a),(b) shows nDSM of Aerial data.
Figures 8 and 9 illustrate elevation profiles in Pleaides data. Figure 8 (a) shows Profile 1 indicating Type I and II buildings in nDSM of Pleaides data (2013). Figure 8 (b) shows the same profile in aerial data. Figure 9 (a) shows Profile 2 in Pleaides data (2013). Elevation Profile 8 indicates Type I, II buildings in nDSM of Pleaides (Figure 8(a)) and Aerial (Figure 9(a)) data.
Elevation Profile 2 indicate Type I, II, IV buildings in nDSM of Pleaides (Fig. 8(b)) and Aerial (Fig. 9(b)) data. From the profiles the heights of buildings are measured automatically and segregation of buildings into different types (I, II, III, IV) is possible.

Figure 10. Profile 3 in Pleaides data (2013) - Metrorail

Figure 11. Profile 6 in Pleaides data (2013) - Flyover

Shaded relief maps of Normalised DSMs of Pleaides (2013) with their profile locations are shown in Fig. 10 and Fig. 11 which indicate metrorail and flyover constructions with building height changes. The elevation profiles of lines 3, 6 from nDSM of Pleaides data are shown in in Fig 10 (a), (b) their corresponding locations from nDSM of Aerial data in Fig 11 (a), (b).

Elevation Profiles 3 indicate Type I, II buildings and metrorail construction in nDSM of Pleaides (Fig. 10(a)) and Aerial (Fig. 11(a))

Elevation Profiles 6 indicate flyover construction in nDSM of Pleaides (Fig. 10(b)) and Aerial (Fig. 11(b)) data
The above figure indicates Construction of flyovers and metrorails that was carried out during the period 2013 and 2016 are shown in Digital Surface Models (DSMs) of Aerial data and their elevation profiles depict the heights of them.

This methodology is an automatic process with image matching techniques, object based image classification and series of processing steps in GIS. Since the proposed method is fully automatic it eliminates the need for manually measuring building heights and above ground objects from stereo pair of images, height changes during different time periods and reduces Turn Around Time (TAT) for modeling them.

4. CONCLUSIONS

Vertical growth model is gaining more and more importance in science, government, and private industry. The satellite and aerial stereo images are used for mapping and quantifying the change in urban area including height change of the building, construction of new buildings and its extent. The increased availability of high-resolution images with detailed surface and elevation models from photogrammetric techniques can be used for change detection applications.

In this paper, the vertical growth of city from 2013 to 2016 was modeled using dense point cloud from high resolution satellite and aerial images. The heights of buildings, vegetation and above ground objects is calculated through the differences between photogrammetric point cloud (DSM) and Digital Elevation Model by Spatial Model Editor. This methodology is fully automatic and can be used for multi temporal 3D change detection in urban areas. With the use of this data change detection based applications such as urban planning and land management is possible. The vertical growth model or the building height change can be estimated without manual measurement on stereo models, but by using high resolution stereo images from aerial and satellite platforms.

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UAV REMOTE SENSING FOR UPDATION OF LAND RECORDS - A CASE STUDY OF SHERMOHAMMEDPET VILLAGE IN JAGGAYYAPETA MANDAL OF KRISHNA DISTRICT

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ABSTRACT

Updating land records at sub-parcel level is a basis for mapping applications which is vital for holistic and inclusive policy making and successful implementation of day-to-day operations. The aim of the study is to use UAVs (Unmanned Aerial Vehicles) for updation of Field Measurement Books (FMBs) and to compare the areas with multi dated high resolution satellite data of Shermohammedpet Village in Jaggayyapeta Mandal of Krishna District. To meet this, Village Cadastral Maps, FMBs, Record of Rights (RoR), Adangal Records, Deimos Image (50 cm), World View-3 Image (30 cm) and Drone Image (10 cm) data have been used. This study mainly focuses to use of Drone acquired data and High Resolution Satellite Imagery (HRSI) for sub-parcel mapping coupled with Differential Global Positional System (DGPS). The results revealed that 72%, 70% and 65% of the sub divisional parcel boundary can be derived from high resolution satellite imageries of 10 cm, 30 cm and 50 cm spatial resolution respectively with acceptable accuracy and precision meeting the standards of cadastral survey. The result shows that the use of drones/very high resolution satellite imageries can reduce the cost, time and human resources as compared to the traditional survey methods.

KEYWORDS: Drone, UAVs, Cadastral Maps, Sub Parcel, Field Measurement Book, HRSI, RoR

1. INTRODUCTION

Land as an asset is unique because it is immovable, its value depends on its location and with growing population, its demand keeps increasing, while its supply is limited. Access to land (or land rights) has a wide-ranging impact on livelihoods, industrial, economic, and social growth. It has been noted that people with extensive rights to land are better off than the landless, due to better access to markets and other economic opportunities that come with land rights. Land ownership is broadly defined by the access to a land title. Land title is a document that determines the ownership of land or an immovable property. Having a clear land title protects the rights of the title holder against other claims made by anyone else to the property. In India, land ownership is determined through various records such as sale deeds that are registered, property tax documents, government survey records, etc. However, land titles in India are unclear due to various reasons such as legacy issues of the zamindari system, gaps in the legal framework, and poor records such as sale deeds that are registered, property tax documents, government survey records, etc. However, land titles in India are unclear due to various reasons such as legacy issues of the zamindari system, gaps in the legal framework, and poor records. Poor land records also affect future property transactions. It becomes difficult and cumbersome to access land records when data is spread across departments and has not been updated. One has to go back several years of documents, including manual records, to find any ownership claims on a piece of property. Such a process is inefficient and causes time delays. A NITI Aayog research outcome suggests that land disputes on average take about 20 years to be resolved in India (NITI Aayog, 2018). Land disputes add to the burden of the courts, tie up land in litigation, and further impact sectors and projects that are dependent on these disputed land titles. World Bank study from 2007 states that land-related disputes account for two-thirds of all pending court cases in the country (World Bank, 2017), since these land disputes include those related to the validity of land titles and records, and rightful ownership. Geospatial data plays an important role in an estimated 80% of our daily decisions (Heipke, et al. 2008), and in various planning activities. For example, in the context of the recently accepted Sustainable Development Goals, the UN emphasises the need for high-quality and usable data, as “data are the lifeblood of decision-making” (IEAG 2014).

In order to improve the quality of land records, and make them more accessible, the government of India implemented the National Land Records Modernization Programme (NLRMP) (now Digital India Land Records Modernization Programme - DILRMP). DILRMP aimed to modernize management of land records to minimize scope of land/property disputes, enhance transparency in the land records maintenance system, and facilitate moving eventually towards guaranteed conclusive titles to immovable properties in the country. The major components of the programme are computerization of all land records including mutations, digitization of maps and integration of textual and spatial data, survey/re-survey and updation of all survey and settlement records including creation of original cadastral records wherever necessary, computerization of registration and its integration with the land records maintenance system and development of core Geospatial Information System (GIS). It also envisages deployment of modern equipments and methodology to bring efficacy in survey and creation and updation of Land Records with shorter time span with perfection and accuracy compared to traditional method of survey and record preparation.

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This state of art survey techniques like Unmanned Aerial System (UAS) based survey coupled with High Resolution Remote Sensing data can minimize the time lag without compromising quality, transparency, grievance and redressal with involvement of minimum manpower. Aerial or Satellite Imagery acquired through Remote Sensing or Earth Observation is regularly being used as primary data source for updation of basemaps at different scales (M. Koeva et al.2016). Earlier study has confirmed the use of satellite and aerial imagery as means to extract information for creating and updating maps (Alexandrov et al. 2004a; Alexandrov et al. 2004b Ali, Tuladhar, and Zevenbergen 2012).

In last decades, extensive research has focused on automatic feature extraction from aerial images and high resolution satellite (Liu and Jezek 2004; Babawuro and Beiji 2012; Gruen et al. 2012; Awad 2013). Still, the temporal resolution of conventional sensors is limited by the restricted availability of aircraft platforms and the orbit characteristics of satellites (Turner, Lucieer and Watson 2012). Other disadvantage is cloud cover, which encumbers image acquisition through these platforms. Such limitations restrict the use of satellites or manned aircrafts images for map updating purposes, as it lead to increase in cost and production time. In order to provide the high-quality and up-to-date information required to support land governance and decision-making, Van der Molen (2015) debates for land surveyors to make use of the potential of new affordable geo-spatial technologies.

An apposite example of such emerging and affordable technology is Unmanned Aerial Vehicles (UAVs), which are proving to be a competitive data acquisition technique designed to operate with no human pilot on board. The term UAV is commonly used, but other terms, such as drones, Unmanned Aerial Systems (UAS), Remotely Piloted Aircraft (RPA) or Remotely Piloted Aerial Systems (RPAS) have also been frequently used in the geomatics community (Nex and Remondino 2014). UAV refers to the aircraft itself which is intended to be operated without a pilot on-board, whereas UAS refers to the aircraft and other components that could be required such as navigation software and communication equipment etc (M. Koeva et al.2016).

With the above background, the present study has been taken up to carry out an empirical execution of land record updation by integrating UAV based Remote Sensing Images with Very High Resolution Satellite Imageries and validation through field survey and developing a comprehensive land database for ensuring transparency in governance of the state of Andhra Pradesh.

2. MATERIALS AND METHODS

2.1 Objectives

The present study is aimed at developing comprehensive land database for ensuring transparency in governance of the state with the following objectives.

i. To reproduce the field measurement book sketches.
ii. To generate seamless mosaic of FMBs at village level.
iii. To develop comprehensive sub-division wise database.
iv. To validate the utility of UAV based Remote Sensing data and HRSI in Land Records updation.

2.2 Study Area

The Sher Mohammadpet village is situated in Jaggayyapeta Mandal of Krishna District, Andhra Pradesh, India. It lies between 16o 54’ - 16o 57’ of North latitude and 80o 05’ - 80o 07’ of East Longitude. It is located 155 KM towards west from District head quarters of Krishna District i.e. Machilipatnam. It is located in east Pavikampadu, south of Jaggayyapeta town, west of Anumanchipalle, and north of Ramachandrunipeta Villages of Jaggayyapeta mandal. As per the 2011 census, the total population of Sher Mohammadpet village is 5996, of which males are 3041 and females are 2,955 living in 1282 Houses. Jaggayyapeta is the nearest Town and NH-16 passes through the Village. The location map of the study area is presented in Figure-1.
2.3 Data Used
To process the spatial data, the Softwares like CollabLand, ERDAS Imagine, PIX4D, ArcGIS, etc. were used. The data used for carrying out the above study is as follows

a. Filed Measurement Books (FMB) of Shermohammedpet village collected from Survey Settlement and Land Record (SSLR) Department, Govt. of Andhra Pradesh
b. Deimos Image (FCC) with 50 cm spatial resolution
c. World View – 3 Image (FCC) with 30 cm spatial resolution
d. UAV Images with 10 cm spatial resolution

2.4 Methodology
To arrive at the above said objectives, seven (7) steps methodology is adopted.

2.4.1 Digitization of Filed Measurement Book (FMB) of Shermohammedpet village using CollabLand software: Digitization of FMB is the process of generation of true copy of the FMB available with Mandal Revenue Officer in a computer aided environment developed by NIC, Gol i.e. CollabLand. A total 240 numbers of FMBs were collected from SSLR Dept., GoAP for the Shermohammedpet village and were digitised by entering the ladder (survey) values as it doesn’t carry any projection system. A total 434 nos. of Sub-division were carried out on 240 numbers of FMBs. 100% quality checking was carried out for each digitised FMB.

2.4.2 Establishment of Ground Control Points (GCPs): It is understood that FMB does not carry any project system and datum specifications. Thus it is essential to geo-reference each FMB to a common coordinate system to superimpose on High Resolution Satellite Image (HRSI) and UAV Image. In order to achieve this, GCPs were collected using Differential Global Position System (DGPS) at Bi-Junction, Tri-Junction and Khandams with an accuracy of less than equal to 10 cm.

2.4.3 Rectification of High Resolution Satellite Imageries (HRSI) & Geo-Reference w.r.t. GCPs: As the area / size of FMB and sub-divided FMB are small in nature i.e. 1 acre or below. Thus it is decided to use present available HRSI i.e. Deimos Image (FCC) with 50 cm spatial resolution and World View – 3 Image (FCC) with 30 cm spatial resolution. The required images were procured from NRSC and were rectified & georeferenced w.r.t the GCPs collected at different locations of the Shermohammedpet village.

2.4.4 Acquisition of UAV Images and Geo-Reference w.r.t. GCPs: High Resolution Images were acquired for the Shermohammedpet village by APSAC using survey grade UAV by maintaining spatial resolution of 10 cm. Further the UAV images were processed and rectified w.r.t the GCP mark-ups in the fields and respective readings.

2.4.5 Georeference, Mosaic and Superimpose Mosaic FMBS on HRSI & UAV Images: As mentioned above, the FMBs does not carry any project system and datum specifications, thus each FMB was georeferenced w.r.t any of the 3 sets of HRSI data i.e. Deimos Image, World View – 3 Image and UAV Image. It was updated by SSLR Dept., Govt. of A.P. that one link i.e. 20 cm is allowable / acceptable error per FMB during the survey and preparation stage. So, the accepted georeferenced error (omitted error) for each FMB may be kept minimum 20 cm. But in some cases if it is found that it is difficult to arrive at the actual length and area of FMB, then the omitted error may be acceptable up to a single pixel of the respective HRSI. For this reason, UAV based Remote Sensing images which can provide 10 cm of Spatial Resolution are considered as base for better georeferencing of the FMBs. Further all the FMBs are mosaiced in GIS platform to generate the village level mosaic and seamless land record was created. The CollabLand software which was used for digitization of the FMBs has the capability of creating automatic mosaic of FMBs by considering the principle of adjacency topology but it is observed that due to the above mentioned acceptable error and lack projection system in each of the FMB, only 50% of the total FMBs were mosaiced using CollabLand software with lots of sliver polygons and gaps. Thus before initiating the seamless mosaic activity each FMBs were georeferenced individually in GIS environment as mentioned above.

2.4.6 Validation of extent w.r.t WebLand: The extent of each FMB were validated with respect to the ownership details along with other attribute details for each FMB available in Webland database (RoR) which is the repository of the registry record of Land Management of Govt. of Andhra Pradesh. Some sample FMBs were also cross checked by field measurements in terms of its area, length, etc. w.r.t the HRSI image.

2.4.7 Migration of verified records to Land Hub: The properly validated FMBs are placed in Land Hub which is the Land Management System of Department of SSLR, Govt. of A.P. for further use.

3. RESULTS & DISCUSSION
The present study has tried to demonstrate the capability of UAV based Remote Sensing data which has capability of providing best of the spatial resolution images in comparison to present available HRSI for better land record updation. The present available land records are of more than half a century old with SSLR Dept., Govt. of A. P. which are being considered as the base for land record database for DILRMP implementation and further to be used for all kind of Land Management System like Property Registration, Mutation, Transfer of ownership, etc. With the advancement and exponential growth in the technology front, the modern survey instruments (terrestrial or aerial) are much more concerned on accuracy without compromising with quality. This has put forth a
challenge before the geospatial domain experts in correcting the inherent accepted error incurred during the preparation of the FMBs / survey records using century old traditional survey instruments and methods.

The acceptable limit of the error during the process rectification of the HRSI and UAV Images were kept within a single pixel of the specific HRSI and UAV Images which is measured by Root Mean Square Error (RMSE). The RMSE is also known as Root Mean Square Deviation, is one of the most widely used statistics in GIS. 2nd order polynomial has been used for geo-referencing the FMBs with HRSI and UAV Images for better precision. Topology validation which creates the interrelationship among entities in GIS platform was carried out for all the rectified & geo-referenced FMBs for creating accurate spatial relation and adjacency at Sub- parcel level and essential for generation of seamless mosaic of FMBs at village level.

3.1 Digitisation and Mosaic of Survey Records (FMB) in CollabLand

As mentioned above, a total 240 nos. of survey numbers or FMBs were received from SSLR, GoAP for Shermohammedpet village. During the process of digitisation 434 nos. of Sub-divisions were observed in the 240 nos. of FMBs. The CollabLand v 2.5 is also used to generate seamless mosaic of the total 240 nos. of FMBs for getting village mosaic data but it failed to generate so as there are inherent measurements errors are persisting with each of the FMB. The G Lines or the Baseline is not drawn correctly in/along the Narrow Fields and creating shape out issues. The G Lines are not properly considered at junctions of adjacent FMBs which is leading to the problems like orientations, shape, overlapping of FMBs, area mismatch, etc.

The total extent of the Shermohammedpet village as per the RSR is found to be 1251.14 Ac. Cts. where as mosaic area generated using CollabLand platform is found to be 1249.91 Ac. Cts. The difference of 5.63 Ac. Cts. is observed in the total area of the Shermohammedpet village between RoR and CollabLand derived result. It is needless to say that each cent of deviation in measurement of land parcel leads to legal issues, thus it is essential to understand the real cause behind the deviation of the measurements. Going into the root cause of the above said deviation in the measurements, it is observed that during the survey and plotting of FMBs by Surveyors, the F Line (Boundary line) is measured first followed by G Line and based on G Line offsets are drawn and subsequently placed in ladder / survey Table. This process keeps the outer boundary as well as the Area of the FMB intact which is recorded in the RoR document. But during the digitization process using CollabLand software, the Ladder Table is considered to draw the FMB, where the Offset lines are drawn after drawing G Line and finally the F lines are drawn. As the digitization process is being done in reverse manner, thus the Boundary and adjacency issues are faced during mosaic process which is leading to the mismatch in the area. The mosaic of the FMBs of the Shermohammedpet village carried out using CollabLand software is shown in Figure No. 2. It can be observed that the mosaic of the FMBs at Khandam (the Natural Features and other well demarcated features like Canal, River, Road, etc. within village are considered as Khandam) level are matching properly but at village level mosaic the errors are increased exponentially.

As discussed above, one link i.e. 20 cm. is allowable / acceptable measurement error per FMB during the survey and preparation stage of the FMBs. Thus 20 cm deviation in each FMB is leading to lots of vector base errors which in turn affecting the seamless mosaic and deviation in the extent of the areas. To overcome this, it was decided to use HRSI having spatial resolution of about 30 cm to 50 cm. coupled with UAV images with 10 cm spatial resolution is used.

3.2 Comparison of RoR Records, HRSI and UAV Images

The comparison of the area extent from HRSI and UAV data is found to 1252.82 Ac. Cts. against 1251.14 Ac. Cts. in RoR and 1245.51 Ac. Cts. against CollabLand generated mosaic. It can be observed that the difference in area from CollabLand generated mosaic and RoR is 5.63 Ac. Cts. whereas the difference is 1.68 Ac. Cts. between RoR and UAV Image based mosaic. Thus it can be inferred that though the measurements in RoR are of very old in nature but with proper projection and datum system with accurate GCPs coupled with UAV derived better resolution images the process of digitisation of land records can match with each other.

A detailed comparison of the different HRSI and UAV data used for the updation of 434 nos. of Sub-divisions for the Shermohammedpet village with different error limit in cent is shown in figure no. 3 & Table no. 1. With error range of 0-1 cent the UAV images with 10 cm spatial resolution has delivered better result i.e. 128 no. against 122 nos. from 30 cm spatial resolution HRSI. The result has been constantly positive from UAV images till with error range of 4-5 cent against 30 & 50 cm HRSI data. But with the increase in error range of >5 cent the result derived from UAV image has shown reverse result because of the distinguishable nature of the feature for better sub-division of the land parcels.

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Figure 2. FMB Mosaic of Shermohammedpet Village in CollabLand software
It is also found that around 315 nos. (72%) of sub-division of the parcels is carryout seamlessly from UAV Images with less than equal to 5 cent of error where as it is 70% and 65% with 30 cm and 50 cm HRSI images respectively. Though the difference in area from RSR w.r.t UAV Image is more than 1 Ac. with less than equal to 5 cent of error but the because of the high spatial resolution i.e. 10 cm, the rectification of the parcels are perfect. The areal difference for UAV images w.r.t RoR at more than equal to 5 cent of error has reduced to .50 cent where it is achieved 119 nos. of perfect sub-division which is about 28% of the total sub-division. From the above comparison it can be inferred that with the use of very high resolution images having resolution more than the acceptable error limit for generation of FMBs is better for updation of land records. As it is found in the present study that the accepted error for generation of each FMB is 20 cm thus the UAV Images with 10 cm of spatial resolution are giving better result for the rectification and updation of the FMBs. Sample FMB Village Mosaic overlaid on Various High Resolution data is showed in figure no. 5 for better understanding of the rectification and updation of the FMBs.

Table 1. Comparison of sub-division wise area analysis among different High Resolution Image and UAV Data

<table>
<thead>
<tr>
<th>Image Resolution</th>
<th>50 Cms</th>
<th>30 Cms</th>
<th>10 Cms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range ((\leq))</td>
<td>(\leq 5) cents</td>
<td>&gt; 5 cents</td>
<td>(\leq 5) cents</td>
</tr>
<tr>
<td>No of Sub-Divisions</td>
<td>285 (65%)</td>
<td>149 (35%)</td>
<td>306 (70%)</td>
</tr>
<tr>
<td>RoR Area (Ac. Cts.)</td>
<td>427.52</td>
<td>823.62</td>
<td>452.34</td>
</tr>
<tr>
<td>HRSI Area (Ac. Cts.)</td>
<td>427.46</td>
<td>822.33</td>
<td>451.47</td>
</tr>
<tr>
<td>Difference</td>
<td>0.06</td>
<td>1.29</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Figure 5. FMB Village Mosaic overlaid on various High Resolution data
3.3 Validation

To validate the results coming out of this process of FMB rectification and update, some sample FMBs were picked up and were measured on filed using tape survey. In figure no. 6, the RoR recorded area is about 1.07 Acre-Cents, whereas as the manually measured result in filed, UAV Images and HRSI Image with 10 cm and 30 cm spatial resolution are giving area of 1.04 Acre-Cents. Thus the infield geometrical measurements and measurements on UAV Images are 100% matching in all aspect of the FMB and thus the areas are also matching too. But a visual accuracy assessment of the same FMB in UAV Image (10 cm) and HRSI (30 & 50 cm), clearly demarcates the sub-parcels in UAV Image (10 cm) rather than other HRSI.

![Figure 6. Comparisons with different HRSI data and Field measurement (Area in Acre-Cents)](image)

In figure no. 7, the RoR recorded area is about 3.97 Acre-Cents, whereas as the manually measured result in filed, UAV Images and HRSI Image with 10 cm and 30 cm spatial resolution are giving area of 3.93 Acre-Cents whereas as 50cm HRSI is giving an area of 3.96 Acre-Cents. The comparison presented in Table no.1, clearly states that with the increase in spatial resolution the rectification and geo-referencing of FMBs are more accurate and the geometry also retained. So it is very much clear from the figure no. 7 that the area derived from HRSI with 50cm i.e, 3.96 Acre-Cents is almost matching with RoR Area i.e. 3.97Acre-Cents.

![Figure 7. Comparisons with different HRSI data and Field measurement (Area in Acre-Cents)](image)

4. CONCLUSIONS

This work demonstrates that UAV based Images provide promising opportunities to create a high-resolution and highly accurate orthophoto, thus facilitating land record creation and updating. Through an example of Shermohammedpet village which is a part of DILRMP project implementation, the UAV Images has proved to be best for the geo-referencing and rectification of FMB. From the empirical analysis coupled with filed validation as presented above, it is technically validated that more than 75% of the FMBs can be rectified and geo-referenced with proper geometry using UAV images with minimum acceptable error which can be less than the size of a pixel. 25% of the left over FMBs can be rectified with acceptable accuracy. Moreover the sub-division can be better carried out using UAV images rather than using HRSI data. Wherever there is major deviation in area or boundary is observed, it can be due to un-demarcated boundary lines which are not clearly visible in UAV images. The important part of the study shows that due to the high resolution of the UAV orthophoto, new features can be easily extracted and various outputs can be produced for land management. It can be concluded that for better and successful implementation of the DILRMP, amalgamation of FMB with UAV Images are suitable for land management.

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GT AIDE (CARTO): A USER FRIENDLY FREEWARE FOR TOPOSHEET SEARCH, GRIDDING AND SMART PHONE APPLICATIONS

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ABSTRACT
The Gt Aide software is developed in Visual Basic without using any formal database. To make it more user friendly, it is designed on ‘click & retrieve’ basis. The output data is viewed in notepad using shell command whereas the maps in Google earth as kml files. Moreover, the KML files generated by the software can be easily viewed in Smart phones which make the field works much easier and simple. Gt Aide (Carto) comprises of Six Sub divisions viz.; Topo Search, Add Layers, UTM Zones, NHO Charts, Survey and Smartphone Applications. Since the output map is viewed over Google earth, the user gets an effective visualization on variable scales. Since the Google earth is being updated periodically user will have a clear picture on the natural as well as anthropogenic changes on the Earth.

KEYWORDS: Toposheet, Add layer, Gridding, UTM zone, NHO Chart, BID-calculator, Smart phone, survey tracks

1. INTRODUCTION
Gt Aide enables a user to extract information without undergoing any formal training. The main advantage of ‘Gt Aide’ is that one can easily ‘click and retrieve’ the data and view the output in Google earth without the support of any GIS software. Gt Aide has five separate modules: Gt Aide (GTP), Gt Aide (Marine), Gt Aide (Global), Gt Aide (Academy) and Gt Aide (Carto). Gt Aide (Global) is meant for preparing various kinds of user defined grids, survey tracks and sampling points for geo scientific studies in any part of the globe which can be used for exploration, mapping and any similar studies.

Figure 1. Opening Window of Gt Aide (Carto)

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Gt Aide (GTP) is being used for Geology search, geochemical mapping (GCM) and planning of various geology related Field works. Gt Aide (Academy) is designed such a way that it becomes a teaching and learning aid for university students especially for Geology and Geography. Gt Aide (Marine) is being developed for querying marine cruise data of Geological Survey of India.

1. **Sheet Search:** Sheet search option of software provides details of Million sheets, Degree sheets and toposheets. The metadata details of all Survey of India toposheets are kept in the software data store for searching out sheets of various kinds. The search types include the following. Sheets pertaining to international boundaries, Indian coastlines, islands, state boundaries, states, districts, surrounding sheets, paired toposheets etc. The boundary of a toposheet (For ex: 64N/10) can be opened in Google earth (Fig.2) by selecting the sheet number from the list as shown in the toposheet search window. The area, bounded coordinates, geology, states and districts pertaining to every toposheet are displayed at the bottom of the opening window. The boundaries of multiple sheets are opened as kml file in Google Earth (Fig.3). A degree sheet (for ex: 58E) with all its toposheets is opened in Google Earth as shown in Fig.4. One can easily find out the surrounding sheets of any toposheet. In Fig.5, the surrounding sheets of 72O/5 are displayed. The boundary sheets along two or more state boundaries can be listed out by selecting the states from the list. The sheet numbers along international boundaries of Punjab and Pakistan are shown in Fig.6. Toposheets of entire Indian coastline or pertaining to a state also can be queried as shown in Fig.7 in which the sheet boundaries along the coastline of Karnataka are displayed. Sheet search option of Gt Aide Carto also provides information on toposheets pertaining to user defined points, polylines and polygons (Figs.8-9).

2. **Add Layers:** Boundaries of million sheets, degree sheets, toposheets, UTM Zones, Indian Geology (on 2m scale), EEZ and TW boundary of India, NHO charts and State boundaries can be superposed on Google Earth at great ease (Fig. 11-14). These layers will be helpful for planning, data interpretation and searching sheets pertaining to geology, places, geographical locations etc. (Fig 10-13)
Figure 4. Degree sheet (58E) with toposheet boundaries

Figure 5. Surrounding toposheets of 74 I/1

Figure 6. Toposheet along International boundaries

Figure 7. Toposheet along the coastline of Karnataka

Figure 8. Toposheet numbers are found pertaining to user defined points and output in Notepad & Google Earth

Figure 9. Toposheet numbers are found pertaining to user defined polylines and output in Notepad & Google Earth
3. Zone search: UTM Zones are widely being used for map preparation. Therefore to understand the limits and other details of each zone is of paramount importance. Carto gives a complete picture of UTM zones. User can plot all UTM zones and also one can extract boundaries of each longitude and latitude zones of UTM by simply selecting the zone number from the list. To get the information about the UTM zones pertaining to points, polylines and polygons a separate menu is (search zone) kept on the UTM Zone window (Fig. 14- 15).

4. Chart Search: NHO (National Hydrographic Office) charts are being used for navigation purpose around Indian subcontinent. Details of all charts pertaining to this area are listed out in the chart window. User can extract boundary coordinates, title and scale of any chart by selecting from the list. The boundaries of selected chart can also be visualized on Google earth separately. In the ‘selected chart’ by ‘scale option’, charts can be selected on the basis of scale and can be plotted on Google earth at greater ease. The NHO Charts pertaining to points, lines and polygons can be searched out using the ‘search charts option’ (Fig 16).
Figure 14. UTM Zone window of Gt Aide (Carto)

Figure 15. A. All UTM Zones opened in Google Earth

Figure 15. B. Selected UTM Zone (Longitude and Latitude) opened in Google Earth

Figure 16. Chart Search Window of Gt Aide Carto
4. Survey: ‘Survey’ option of the software facilitates to calculate area and perimeter of polygons, gridding of polygons, preparation of Survey tracks etc., Finding of toposheet pertaining to user defined points, polylines and polygons, conversion of lat-long data etc. ‘BID calculator’ is another important feature of Carto. The area and perimeter of any polygon can be calculated in various units. The resultant table will open in notepad while the polygons as kml file in Google Earth (Fig. 17). Software also provides the user to retrieve coordinates of points, lines and polygons from KML file that are created in Google Earth.

4.1 Polygon Gridding and Survey lines: polygons can be gridded at user defined intervals (Fig. 18) and also grid centroids within the polygon as shown in the Fig.19. The coordinates of the grid centroids will be automatically displayed in notepad. GtAide also facilitates to create survey tracks within single or multiple polygons along E-W, N-S or along user defined angles (Fig. 20). User can digitize the study area in Google Earth and by using the software one can prepare defined grids and survey lines. Toposheet also can be gridded at user defined intervals (Fig. 22). All this Grids and Survey lines can be exported to Arc GIS platform by Converting KML to Shape file.

4.2 BID Calculator: ‘BID calculator’ window facilitates to calculate bearing of a line by providing the end coordinats, intersection coordinates of two given lines and calculate coordinates of destination point by providing the start point, distance and bearing. This facility has also been extended to multiple data set as shown in the menu ‘Bearing’, ‘Intersection’ & ‘Destination’ (Fig. 23).
5. **Smartphone applications**: The great attraction of the software is that the kml files generated in Gt Aide can be opened in any kml supporting Smart phones using mobile applications like Map Inr. Survey lines, study area boundary, predefined points also can be uploaded in smartphone. The toposheet boundary of 57C/10 is displayed in a smart phone (Fig. 25) and a user defined polygon with grids is opened in smartphone (Fig. 24 & 26). Since the GPS of Smartphone provides live locations over the kml file, the field study becomes easy (Fig. 27).

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**Figure 20.** Polygon with Inclined survey tracks

**Figure 21.** Extraction of Coordinates and Area of polygon digitized in Google Earth

**Figure 22.** User defined gridding (1km x 1km) of toposheet 56H/2

**Figure 23.** BID-Calculator Window of Carto

**Figure 24.** Gt Aide generated User defined grid over Smart phone with live location (Map inr-mobile application)

**Figure 25.** Carto generated toposheet boundary (57C/10) opened in Smart phone using "Map-inr" mobile application
2. CONCLUSIONS

GtAide (Carto) has multiple facilities like Toposheet search, Add layers, User defined gridding, Survey line, BID calculator, Smartphone applications etc. The software enables to search out the details of any kind of toposheet pertaining to our country at great ease. ‘Add layers’ provides many useful readymade layers such as Million sheets, Degree sheets, Indian Geology, Toposheets, UTM Zones etc., for quick view. The ‘Survey’ option in Gt Aide can be utilized for gridding, creating survey tracks for multiple polygons at user defined intervals. Gt Aide also facilitates to retrieve coordinates of polygons, polylines and points digitized on Google Earth. The software provides information on toposheets pertaining to user defined points, lines and polygons. A lat-long converter that converts the geographic coordinates from one format to another is also included.

Unlike GIS software, Gt Aide (Carto) enables a user to extract information without undergoing any formal training. The main advantage of this software is that one can easily ‘click and retrieve’ data and view the output in Google earth without the support of any GIS software.

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AUTOMATIC EXTRACTION OF SHORE LINE FOR QUANTIFICATION OF EROSION AND ACCRETION CHARACTERISTICS OF INDIAN COASTAL MAINLAND AREA USING GOOGLE EARTH ENGINE

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Institute of Remote Sensing, Anna University, Chennai-25

ABSTRACT
The Indian mainland having a coastal extent of 5,422 km constitute a population of 250 million living 50 km off the coastline had undergone tremendous changes due to varying natural and human induced coastal activities. The critically varying shoreline and its dynamic process are to be monitored over time scales, for which Satellite Imagery have been proven as a primary base. Google Earth Engine (GEE) provides a single platform for spatiotemporal analysis of satellite images over years, reducing the complexity of downloading and mapping the shoreline changes. A cloud based automated mapping of the shoreline using NDWI, NDVI along the entire mainland coast of India for the period 1990 – 2018 (28 years) was carried out in this study with GEE API using JavaScript. The suitable satellite imagery for mapping shoreline was identified using an algorithm that analyzes diurnal and seasonal tidal variations. Using multi – date satellite images of Landsat series and Sentinel, the variation of Shoreline was automatically mapped and extracted to identify and prioritize the eroding areas for proper planning of coastal stretches.

KEYWORDS: Google Earth Engine, Automated Mapping, Shoreline Changes, and Erosion Protection.

1. INTRODUCTION

India – a country having its geographic entity entirely in the northern hemisphere marking off its significance in the Asian continent with Great Himalayas on north while stretching southwards at tropic of cancer tapers off into to the Indian Ocean between the Bay of Bengal on east and Arabian Sea on west. The total country covers a stretch of 7500 km coast line while the mainland peninsular India constitutes a length of 5,422 km. The coastline is a place where atmosphere, biosphere, geosphere and Ocean interact and hence it is dynamic in nature. With more than 250 million of the country’s total population lying within 50 km off the mainland coastline, the induced coastal activities have marked significant impact on the coastline changes (Halpern B.S. et al., 2015). The satellite imagery has proved a significant means of evaluating shoreline identification globally from early 70’s (García-Rubio et al., 2015). Several significant development from manual mapping to automatic extraction techniques over mosaics of single imagery for the extraction of coastline (Pardo-Pascual et al., 2012) and change monitoring over the Landsat archival (Liu et al., 2107) are done earlier. The above methods although proven consistent yet the identification of cloud free images downloading and stacking Multi-date Multi satellite image over years requires lot of data storage along with parallel computational processing and analysis are quite laborious.

The Google Earth Engine (GEE) a cloud-based geospatial platform, containing a continuously updated global satellite image archive, now enables efficient shoreline detection. Having both a petabyte satellite image collection (Landsat, Sentinel, MODIS, Aster etc.) along with parallel computation facilities combined on the server side of the platform reduces image processing time globally to fewer minutes (Gorelick et al., 2017). With the GEE Cloud based computation and analysis along with automated shoreline extraction the present study identifies shoreline change over 25 years and depict the significant accreted and eroded areas over the Indian mainland. The work process primarily involve identifying the coastal line through different indices over multi satellite images using sub-pixel approach (Hagenaaars et al., 2017) with further quantification of accretion and erosion characteristics over years.

2. STUDY AREA

The Indian peninsula has a diverse coastal environment having a significant role in the in the country's development by providing a variety of resources, living habitat and rich varied biodiversity. India has a total coastline of about 7500 km out of which 2094 km lies completely with the island territories constituting Andaman and Nicobar Islands in the Bay of Bengal and Lakshadweep Islands in the Arabian Sea. The Indian coastal mainland covering a distance of 5422.6 km forms the primary study area which consists of 9 states and 2 union territories with Gujrat (1215 km), Diu & Daman (10 km), Maharashtra (653 km), Goa (151), Karnataka (280 km), Kerala (570 km) along the western coast and West Bengal (158 km), Odisha (476 km), Andhra Pradesh (974 km), Puducherry (31 km) on eastern coast, while Tamil Nadu is the only state with coast along east, west and south comprising 907 km forming the end of Indian mainland (all coastal length mentioned are as per NHO, 2011). These states cover almost 66 coastal districts, 13 Major ports and 187 minor ports with 3288 fishing villages (as per the CMFRI Census taken in 2010) forming a major socio-economic habitat.

The varying coastal profile is highly distributed with various problems like pollution, filtration, erosion, flooding, salt water intrusion, storm surges and other anthropogenic activities. The mouth of the river has a wide variety of coastal species which gets affected due to the above activities. Hence coastal areas need to be monitored continuously for effective analysis of the variation on a local scale from time to time. The study area is defined in the following figure 1.

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3. DATA AND METHODOLOGY

The coastal processes are dynamic and need to be monitored over years. In this study, a period of 25 years from 1990 to 2018 is adopted to identify the coastline and to quantify the coastal characteristics. The study focuses on the automatic identification and evaluation of the coastline along with its predominant variation simultaneously from multiple satellite images. This process requires downloading, storing, processing and analyzing of large number of satellite image from different satellites which will result in the consumption of larger database and computational efforts. GEE provides a complete solution to overcome these shortcomings.

The GEE has a complete repository of all LANDSAT and Sentinel Series data products which forms the primary data for this study. The Landsat series are available from 1972 to 2018, while the Sentinel Optical image series is available from 2016. The multispectral Landsat series satellite data is available once every 16 day at 30 m resolution. The GEE provides the Earth Observation satellite data in its raw form as surface reflectance and top of atmosphere - TOA corrected reflectance in Tier 1, Tier 2 and RT form as processed by USGS.

To cover the study period from 1990 to 2018, the Landsat 5 and Landsat 8 top of atmosphere – TOA reflectance corrected data from Google Earth engine dataset is used in this study. Similarly, Sentinel-2 provides high resolution multi spectral data at 10 m resolution and the level – 1C product as provided by the European space Agency through Copernicus program, is used in this study. The GEE is web based computational API which works both Python and JavaScript as its input language.

The complete data set used and the corresponding period of ingestion in this study is given in Table 1.

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Year</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-5</td>
<td>1990-2012</td>
<td>Tier I - TOA reflectance</td>
</tr>
<tr>
<td>Landsat-8</td>
<td>2013-2018</td>
<td>Tier I - TOA reflectance</td>
</tr>
<tr>
<td>Sentinel 2</td>
<td>2016-2018</td>
<td>Level 1C</td>
</tr>
</tbody>
</table>

Table 1. Datasets used and period of ingestion

The Normalized Differential Vegetation Index (NDVI) is computed for the respective satellite data given by the equation (1),
\[ \text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \]  

(1)

Where, \( \text{NIR} \) = Near Infrared band. NDVI range: -1 to +1; 0 - Bright surface with no vegetation or water content

The corresponding band combinations for the respective satellites are given in Table 2.

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Year</th>
<th>NDVI Band Combination</th>
</tr>
</thead>
</table>
| Landsat-5   | 1990-2012  | Band 4 – Band 3  
              |                      Band 4 + Band 3 |
| Landsat-8   | 2013-2018  | Band 4 – Band 3  
              |                      Band 4 + Band 3 |
| Sentinel 2  | 2016-2018  | Band 8 – Band 4  
              |                      Band 8 + Band 4 |

Table 2. NDVI band combination of Satellite data used

The general Normalized Differential Water Index (NDWI) is given by equation (2),

\[ \text{NDWI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}} \]  

(2)

Where, \( \text{NIR} \) = Near Infrared band  
\( \text{SWIR} \) = Short Wave Infrared band

But in order to compute the water content water bodies (McFeeters, 1996) has suggested a modified Normalized Differential Water Index (mNDWI) which provides the best identification of water bodies represented in equation (3),

\[ \text{mNDWI} = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \]  

(3)

Where, \( \text{NIR} \) = Near Infrared band

This method suggested by McFeeters for calculating mNDWI is henceforth used in this paper wherever mentioned. Both NDVI and mNDWI obtained from the above equation for each year is used to delineate the water bound pixels along the coast, which subsequently gives the water line for the respective year.

The corresponding band combinations for the respective satellites are also provided in Table 3.

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Year</th>
<th>mNDWI Band Combination</th>
</tr>
</thead>
</table>
| Landsat-5   | 1990-2012  | Band 2 – Band 4  
              |                      Band 2 + Band 4 |
| Landsat-8   | 2013-2018  | Band 3 – Band 5  
              |                      Band 3 + Band 5 |
| Sentinel 2  | 2016-2018  | Band 3 – Band 8  
              |                      Band 3 + Band 8 |

Table 3. mNDWI band combination of Satellite data used

To remove the effects of Clouds and shadows, a yearly top of the atmosphere reflectance composite is generated which is further used to estimate the accurate surface water using dynamic thresholding method which is similar to the method adopted by Hansen.
(2013) to generate yearly composite images. A selection criterion algorithm was induced such that the algorithm will select the image with least cloud cover pixel and composite over the region of study and perform the analysis for the corresponding satellite images.

From the NDVI values and based on the performed experimental results from the inspector module of GEE a threshold value is adopted to differentiate at the vegetation pixels from water pixels to identify the line of transition. The complete methodology is shown as flowchart in Figure 2.

4. RESULTS AND DISCUSSION

The generated yearly composite image analysis reduces the tidal difference effects on the detected position of shoreline thereby, the seasonal variability in the wave characteristics are averaged out. Considering a long time shoreline change will ultimately reduce the wave effects on the detected shorelines and are likely to be minimized to the maximum extent (Arjen et al., 2018). Both Normalized Difference Water Index (mNDWI) and Normalized Difference Vegetation Index (NDVI) are estimated for the resulting composite images. A Canny edge detection filter is used to demarcate the position of the shoreline thus the water land transition is identified. Further thresholding is adapted for both mNDWI and NDVI to identify the most exact water and land transition pixel. Finally a smoothening filter is applied to smoothen the induced staircase effect on the identified pixel based shoreline. In this case, a 1D Gaussian skin smoothing filter is adopted, this is further applied to the identified shoreline which will ultimately give a continuous shoreline throughout the study area.

The maximum of NDVI and mNDWI is taken as the shoreline for the particular year. Although the analysis produces multiple shore line vectors since lakes and other channels are also detected along this, but only the most seaward position of the Shore line is considered as the shoreline of the particular year. The shoreline delineation by both NDVI and mNDWI for 2018 is shown in Figures 3a – 3f.
Both shorelines extracted from NDVI and mNDWI overlap each other to a maximum extent, there is a minor variation between the two shoreline lines along regions of dense vegetation and tidal influenced areas. The line extracted from NDVI is most accurate and matching in areas of dense vegetation (along coastal regions of West Bengal) while mNDWI provides considerable better delineation in case of tidal influenced areas (along Gulf of Khambhat). The extracted shoreline has been verified with direct in situ observations and also with high resolution satellite imagery which is provided by Google Earth Engine API (GEE) for visual overlay of the extracted shoreline.

Although GEE extracts coastline for each year automatically but in order to identify the shoreline change characteristics, a decadal changing trend of shoreline from 1990 to 2018 (viz., 1991, 2001, 2011, 2017) is considered. The mouth of the river contributes a major role in modifying the coast which ultimately induces changes in the shoreline in the subsequent years of observation. Both erosion and accretion has been occurring at the Confluence of the river with the sea or ocean. The erosion of the Shore line is primarily due to the wind, tidal impacts and also due to the storm surges that occurred during severe weather events. The accretion is due to the deposition of the river along its mouth continuously over years. The following figure 4a – 4f gives the complete change of the shoreline along the mouth of Kollidam River.

Figure 3a, 3b, 3c gives shoreline extraction from NDVI while Figure 3d, 3e, 3f shows the shoreline extracted from mNDWI.
Figure 4. Shoreline delineation and changes from 1991 to 2018 at the mouth of River Kollidam, Tamil Nadu

The Ennore port located 17 km north of the Chennai has major morphological changes forming nearly a complex shoreline characteristic change. The artificial port constructed in 2001 has significant change in modifying the movement of the sediment resulting in accretion in the south side and erosion on the north side. The Shore line around the Ennore port was mapped from 1990 to 2018 at regular interval of 10 years (Figure 5) and it is identified that the breakwater impact on the coast is considered very significant. The breakwaters along the port had stopped the free movement of sediment. Does equation has occurred on the southern side of the put it was further identified that almost 3 km north of the port has affected by moderate erosion of around 50 M and this was verified with the report given in MOEF, 2009.
5. CONCLUSION

The shoreline for Indian mainland coastal area has been extracted using Google Earth engine automatically for the years from 1990 to 2018. A continuous monitoring of the coastline for a country like India over temporal range will be much feasible with the use of GEE since multiple composite image stacking over different satellites is possible. Derivation of accretion characteristics along the Indian coast are identified using scaled Intercept which has shown that area under Gujarat coast has shown major accretion while the mouths of West Bengal and along the states of Andhra Pradesh has shown considerable erosion during the period of study. Since automatic mapping and extraction of shoreline is much simple using GEE, it'll be much helpful in identifying the areas of shoreline change characteristics thereby to priorities areas of impact and provide suitable measures for future planning along the coast.

REFERENCES


STAGES AND DEVELOPMENT OF SHORELINE CONFIGURATIONS WITH GEOMORPHIC DIVERSITIES; A STUDY IN SOUTH ANDAMAN DISTRICT USING GEO-SPATIAL TECHNIQUES

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ABSTRACT

In Andaman and Nicobar Islands, South Andaman represents the beach morphodynamics of shore platform with horizontal sloping surface backed by a cliff and fronted by seaward edge vertical bank. The erosional origin of the sloping surface is evident in the island because it usually cuts across the platform and has exposed the bedrock structures along the shoreline sections. It deals with various processes involved in the high tidal and low tidal stages of the shore platform to explain the development and modification of the beach morphology of the shore platform. The study mainly focuses on the identification of the geomorphological diversity of South Andaman with special reference to North Bay, Corbyn’s Cove, Ross Island and Wandoor Beach. The different stages of geomorphological development i.e., wide bays with eroded headlands (mature stage), coves and promontories (middle stage) and high cliff with debris slope (younger stage), are identified with the help of the identification of shoreline configuration using geo-spatial techniques. Finally, the study indicates that North Bay and Ross Island shows younger stage of shoreline configuration due to the tectonic upliftment in 2004. The Wandoor Beach indicates middle stage while Corbyn’s Cove shows mature stage due to the slow rate of subsidence and adjustment with the processes.

KEYWORDS: Beach morphodynamics, Cliff, Seaward edge vertical bank, Geomorphological diversity and Shoreline configuration

1. INTRODUCTION

Limestone Geomorphology deals with the occurrence of landform features due to the erosional & depositional activities of karst topography. The term karst applies to a distinctive type of landscape that develops from the dissolving water and soluble bedrock. Primarily limestone marble but also Dolostone, Gypsum & Halite with global view the example of karst topography can be found at all latitude and at all elevations with karst feature (Woodroffe C.D, 2002). Coastal limestone geomorphology deals with the significance features such as undercut Notches, Caves, Arc, Stack, Taffoni and Pinnacles etc. Landforms produced by chemical weathering or chemical erosion of carbonate rocks mainly Calcium Carbonate (CaCO3, Limestones) and Magnesium-Calcium Carbonate (Dolomites) by surface and sub surface water (Ground Water) are called karst topography (Masselink, G et al, 2011). Numerous caves, Stalagmites and Stalactites have been formed below the surface. It generally develops in those areas where the thick beds of massive limestone lies below the layer of surficial materials.

Rocky Coastal regions can host caves produced by karst (dissolutional) processes and caves produced by pseudokarstic (non-dissolutional) processes on the limestone coast where both the processes can be active and inter play in complex manner (Paul. A, et al, 2016). Lava tubes, Calcareous Tufa deposition and Reef growth all produces constructional caves, voids formed as the rock itself is formed. Only reef growth is an obligatory result of the marine coastal environment. Taffoni results from sub aerial weathering of variety of lithologies exposed on the cliff steep slopes, and can mimic other types of pseudokarstic caves and karst caves. Talus and fissure caves are usually caused by the failure of steep slopes and cliffs resulting into the formation of coastal erosion which can quickly remove this pseudokarstic cave types. Sea arches and sea caves are abundant on rocky coast, as the interaction of wave dynamics and rock properties create a variety of erosional voids (Paul. A, et al, 2017). Sea cave processes can overprint other cave type to produce a hybrid cave. Sea caves are likely the most common cave type in the world, but on limestone coasts, dissolutional mixing zone caves also form in great numbers, and are commonly overprinted to make abundant hybrid caves.

Pseudokarstic processes operating in coastal environments are an amalgamation of geological processes that characteristically operate in continental interiors, and processes unique to coastal settings, because the coastal landforms are the interface between the marine and terrestrial realm (Bandyopadhyay P.C, 2012) Pseudokarstic caves can be formed a wide variety of weathering mechanisms. In coastal areas, these can be expressed as taffoni, talus caves, fissure caves, sea(littoral) caves, or caves shaped by a combination of these processes.

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The Pseudokarst is defined as karst like features that are formed by processes other than dissolutions (modified from Palmer 2007). Common karst forming rocks are the carbonate rocks, limestones, dolomite and marble. Less common especially in coastal areas, are evaporate rocks such as gypsum and halite although they can be found in very arid coast lines. Evaporite rocks are highly soluble, and readily dissolve when in contact with sea water (Sharma. V et al, 2007). This rocks are also mechanically weak, and do not endure the mechanical pounding that occurs in wave-swept coastal areas. Other rock types, such as quartzite, granites and sandstones, are known to produce true karst under certain conditions, but karst caves developed by dissolution in these rocks in coastal zones are not yet recognized. Soluble rocks of sufficient mechanical strength can also form caves in coastal setting by non-dissolution, or pseudokarstic processes.

1.1. Location of the Study Area

The Andaman and Nicobar Islands are a group of islands situated off the eastern coast of India; known for its tropical rain forest, they lie amidst the waters of the Bay of Bengal and Indian Ocean on one side and the Andaman Sea on the other. They are part of a submerged mountain range related to the ArakanYoma Range of Myanmar. These pockets of islands, through diminutive in area in comparison with the sub-continent, are biologically diverse in terms of flora, fauna and ecosystems and are politically divided into South Andaman, Middle Andaman, and North Andaman. The Andaman and Nicobar Islands are a group of about 572 islands, islets rocks and keys situated off the eastern coast of India in a junction with the Bay of Bengal and Indian Ocean on the side and Andaman Sea on the other. Covered with lush green tropical rain forests, about 1200 km away from the mainland of the Indian sub-continent, these islands are also called “the Bay Islands”. The islands are mountain peaks that have emerged from the sea. They are part of a submerged mountain range related to the ArakanYoma range of Myanmar. Andaman Islands, where inhabitation is found, are comprised of South Andaman, Middle Andaman and North Andaman. The Andaman Islands are situated between 10°30’ and 13°42’ North latitude and 92°14’ and 94°16’ East longitude in the Southeast Bay of Bengal (Figure 1).
The study area chosen in the South Andaman are four islands such as north bay island located in north east portion of the Andaman sea, Corbyn’s cove island and ross island and south west portion of bay of Bengal to Wandoor. Corbyn’s cove island beach shape is crescent bay beach and rocks inclination toward the sea. This area mainly geology are based on Flysch and Ophiolite Groups of structure. North Bay Island is based on fine sandstone and mudstone and has highly vertical joint structure in the upper portion of flysch group. This area has dip direction toward the land surface. Ross Island has conglomeratic rocky structure. Wandoor Island has exposure of beach rocks and bio encrustation with calcareous master joints. There are four islands in this whole study area and they are North Bay Island, Ross Island, Corbyn’s Cove Beach and Wandoor Beach.

Corbyn’s Cove Island

Corbyn’s cove beach, the coconut-palm-fringed beach, ideal for sun basking is 6 km away from Port Blair. Historical remains like Japanese bunkers can be seen on the way. Corbyn’s cove island is crescent shaped bay beach. Corbyn’s cove beach rock constitutes 70% Flysch & Ophiolite rock and 30% coral debris. Snake Island are built in conglomeratic debris, it is situated beside the Corbyn’s cove island. This island is famous for scuba driving.

North Bay Island

North Bay Beach is just north of Port Blair. The beach and the snorkeling opportunities in its fringing coral reefs are the closest once you will find to Port Blair and therefore gets quite crowded. A ferry (9 am & 2 pm 30 minutes) will take you across the Aberdeen Jetty and bring you back after a 3 hour stay. North Bay island jetty point is situated in the east part of the island. North Bay Island beaches are sandy with highly vertically jointed in beach rock to the South western part of the island.
This small island is less than a sq. km area that stands right across Port Blair, encompassing in a way the entire life of Andaman. It was once the home of the indigenous tribe-Great Andamanese, whose number dwindled from 5,000 to just 28 within 20 years of the initial British Occupation. The island served as the capital from 1858 till 1941, when the Japanese occupied it and converted it into a POW site. The ruins of the church and the chief commissioner’s house among overcrowding vines and aerial roots are the most evocative of the remains. Private ferries operate from Aberdeen Jetty in Rajiv Gandhi Water Sports Complex at 8:30, 10:30 am & 12:30, 2pm. Ross Island, originally known as Chong-Ekee-Bood (in Andamanese dialect), erstwhile capital of British Settlement is named after the British marine surveyor Sir Daniel Ross and is situated at the mouth of Port Blair harbor approximately 800 m away from the Aberdeen Jetty. The island occupies an area of 0.6 km and acts as a shield to Aberdeen against any natural disaster.

Wandoor Beach

Wandoor Beach is a very famous tourist spot which is twenty five kms from west of Port Blair is famous for swimming & coral viewing. One can also go to Mahatma Gandhi Marine National Park from Wandoor by boat. The main attraction and the communication spot of Wandoor is the Mahatma Gandhi Marine National Park from where generally the travelling boats to Jolly Buoy Island and Red Skin Island are allowed.

Objectives:
1. To identify the Geomorphological diversity of South Andaman with special reference to North Bay Island, Ross Island, and Corbyn’s Cove Island & Wandoor Island.
2. To study the nature of shore line configuration of the present study area.

Figure 2: Methodology of the Study Area
2. RESULT & DISCUSSION

The Methodology explains the technique of acquiring the geomorphological diversities and shoreline configuration. The Landsat 8 Data have been used for the identification and with the help of ground truth verification, the final output has been generated (Figure 2).

Physiography

The physiography describes distinguish division of the landform of the earth surface. The physiography regions of the world are means of defining the landforms into distinguish landforms, the Andaman & Nicobar Islands shows the physiography of the island. The physiography of the study area has been categorised four parts mainly ---- Hilly terrain with escarpment, rolling to undulating land dotted with sporadic hillocks& interspersed valley (Figure 3).

Figure 3: Physiography map of the South Andaman

The central & the north eastern and southern parts of South Andaman covered mainly with Rolling to undulating Land dotted with sporadic hillocks. The northern part and little portion of the southern trip are covered with Hilly Terrain with escarpment. The western portion is covered with interspersed valleys and the little portion of the Port Blair covered with river valley. It can be concluded that basically the selected study area is covered with river valley with valley interspersed by the river.

Contour of South Andaman

The contour map helps us to identify the range of elevation of a geographical area. The contour is generally marked depending on the elevation range. The highest elevation recorded in the selected study area is Mt. Harriet and the lowest part is Ross Island. The contour is generally an isoline which gives of idea of equal elevations of different ranges. A contour line is a function of variables is a curve along which the function has a constant elevation, so that the curve joins points of equal elevation. The contour interval of a contour map is the difference in elevation between successive contour lines. A contour on a map is a line joining points of equal height and indicating hills, valleys and the steepness of slopes (Figure 4).
The study area shows the contour interval at 100 m. The highest contour is observed Mount Harriet near the North Bay Island. The contour line which passes the Ross Island is at 100 m. Wandoor Beach contour line passes at an interval of 100 m.

**Geomorphology of South Andaman**

The word Geomorphology derives from three Greek words: ‘geo’ (the Earth), ‘morpho’ (form), and ‘logy’ (discourse). Geomorphology is therefore a discourse on earth forms. It is the study of Earth’s physical land surface features, its landforms rivers, hills, plains, beaches, sand dunes, Limestone Morphology and myriad others. Geomorphology was first used as a term to describe the morphology of earth’s surface in the 1870s and 1880s (e.g. Margery 1886). It was originally defined as ‘the genetic study of topographic forms’ (Mc Gee 1888) (Figure 5).
The Geomorphology map has been prepared on the basis of Landsat 8 OLI Satellite image, toposheet & Google Earth. Sea ward margin of the island are fringed with developed island platform near the Port Blair in the eastern part of South Andaman. The hill ridges covered by evergreen forest are situated over north western part of South Andaman. Mangrove swamp is an easily recognized habitat along tropical and subtropical coastlines and the mangrove swamp occur in marshy areas along the coast. The mangrove swamp is observed in the western part near the tidal creek. In general the plantation is observed along the pediment slope in the central part of the island. Mainly water body is built up by anthropogenic activity in the south part of South Andaman and the tidal creek is observed in the east and western part of south Andaman. Parallel ridges are observed in the north western region of the island and also marked in the highly effected tsunami zone in Port Blair bay portion in the east part near the Andaman Sea. Finally the Shoreline Configuration shows the different stages of geomorphological development i.e., wide bays with eroded headlands (mature stage), coves and promontories (middle stage) and high cliff with debris slope (younger stage) in (Figure 6).

![Figure 6: Stages and Development of Shoreline Configuration Map of South Andaman](image)

3. CONCLUSION

The above study shows that the geomorphological diversity of the shoreline configurations of the parts of South Andaman Islands. Most of the varieties of the shoreline configurations include Headland, Bays, Coves, Promontories and Reef Terraces with raised beach platform. All the geomorphological units are fringed with depositional materials of Andaman Flysch sediment, Ophiolites, Coraline Debris, Sand Size Sediments and multiple types of bio-clasts. They are processed by the interaction of physical, biological and chemical activities under diverse energy settings of the shoreline. The nature of grain size and shape analysis method is applied in the North Bay Island and Ross Island and the Grain Size are dependent on the nature of Shore platform in the beaches. The 2004, 26 December, tsunami incidence of Andaman sticks to significant impacts over the morphology and hydrology of Andaman Island. There are tilted cliffs, sustaining cracks, subsidence, emerged platforms, salt water inundation in the area affected by subsidence and gravel ridges and bars along the shorelines. Finally, the study indicates that North Bay and Ross Island shows younger stage of shoreline configuration due to the tectonic upliftment in 2004. The Wandoor Beach indicates middle stage while Corbyn’s Cove shows mature stage due to the slow rate of subsidence and adjustment with the processes. The Ross Island is not only tilted from the east to west but also affected by central cracks from east to west. Various erosional features are also visible on the shore cliffs along the island fringes. In 2004 tsunami are highly effected at the east seaward margin of the Andaman Sea in Port Blair bay portion and it is clearly observed in Ross Island and Wandoor beaches. There are tilted cliffs, sustaining cracks, subsidence, and emerged platforms, salt water inundation in the area affected by subsidence and gravel ridges and bars along the shorelines. The geomorphological band include as fringes corals platform ,dead coral rubbles, sandy area ,gravelly beach , reef terrace and hill front cliffs. There is also a significant diversity in Geomorphological features in different areas of study. The features particularly show a variety in bay and cove areas to headland areas of island fringes. However the straight shoreline includes limited bands of Geomorphological zone based on wave energy and openness to marine environment.
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Paul A., Ghosh S., Maji T., Bandyopadhyay J., & Paul A.K. Application of geospatial technology for the assessment of coastal vulnerability index (CVI) of Digha, Shankarpur, Mandarmoni and Junput Coast.
STUDIES ON COASTAL MORPHOMETRY WITH TOTAL STATION SURVEY IN SHORE FACE OF SAGAR ISLAND TO ASSESS THE IMPACTS OF SEA LEVEL RISE

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ABSTRACT

Sagar Island is located in the extreme south western corner of the reclaimed part of Sundarban at the sea face (Bay of Bengal) of Hugli river estuary in India. The surface of the low lying deltaic Island platform separated by the Hugli River and Muriganga River system represents ideal indicator of topographic sensitivity to the variability of sea level. Total six sample sites of the shore platforms are considered for Total Station survey to estimate the micro terrain units and volume of soil loss from DEM prepared on the basis of BM points available from SOI Toposheets along the Bay of Bengal shoreline on temporal and spatial scale for the present study. Morphometric attributes are studied from DEM to represent the characteristic diversity of the coastal terrain units in the sea facing Island for sensitivity testing in rising water levels.

The nature of tides, waves, long shore currents, tidal prisms, tidal ranges and storm catastrophe with variability of sea level will modify the entire shoreline configurations of the deltaic Island in the near future. Over wash vulnerability, salt water flood areas, land ward drift of sand size sediment and salt affected lands are predicted as direct impacts of sea level rise by the present study in alluvium coasts. Mangrove forests, sand dunes and barrier spits are acting as sensitive buffers against the hydrologic stress in high energy phases in the course of time in estuarine delta of Hugli River.

KEYWORDS: Morphometry, Digital Elevation Model (DEM), Sea Level Rise and Hydrologic Stress.

1. INTRODUCTION

The south eastern shore fringing villages of Sagar Island (Shibpur, Dhablat, Boatkhali and Bishalakshmipur) are affected by erosion and repeated salt water flooding with advancing sea since the middle part of previous century. The sedimentary landforms of the deltaic shore were dominated by wide sandy sea beaches; beach fringed sand dunes (14-16 m in altitude) and backshore delta plain along the sea face of Bay of Bengal. The erosive dune cliff and mud bank section of the shoreline are studied from the region by plotting the chronostratigraphy and also by environmental facies analysis of depositional layers to separate the sand bodies from basement muds. Vertical lowering of the exposed mud bank at the sea face is achieved up to the base level of erosion. The mud bank is eroded by sheeting, gullying, wave abrasion, salt weathering and water layer weathering process along the low tide shoreline in this part of Sagar Island (Fig. 1). The entire sand bodies are now removed from the beaches and sand dunes by scarping, cliffing, wash over modification, sand drifting and long shore-cross shore transportation except the landward shifting of beach ridges or bluffs.

At every spring tide phases of pre-monsoon and monsoon months, the villages are flooded by advancing sea waters into the remaining coastal tract of the backshore delta plain, once used by settlements, plantations, agricultural paddy lands are fish pond under protective earthen embankments. The sand dunes were acted as the physical barrier against the storm surges and salt water flooding in protection of human habitation from the sea face. Stability of dune sediments was achieved with thick vegetation cover in the sandy surface and shore fringed beaches.

Figure 1. Over wash sand fan lobe across mangrove wetlands and exposure of sea front mud banks.

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Total station survey is conducted in 2016, April and 2018, April over the remaining sand bodies along the fore shores (coastal bluff) to estimate the volume of sand drift from erosion affected areas. Sediment budget is also estimated from the local area to identify the loss and gain of sand size sediments in modification of coastal configurations as well as in promotion of the movement of facies of sediment with rising sea level. Vertical lowering of the delta plain coast is more and more liable to flooding with advancing sea at present (Fig. 2).

2. MATERIALS AND METHODS

The volume of sediment exchange is estimated in between the areas of erosion, newer deposition site and open off shores in the study with the help of field study, Total Station Survey (2016-2018), SOI Toposheet (1972) and satellite images (Google Earth image 2018, Landsat 8 2016). Regular tidal elevation change records from CPT tide data and estimation of tidal prisms of Muriganga River Mouth and Boatkhali Tidal Creek over the decade provided evidences in favour of rapid erosion in this part of the shoreline. The stratigraphy and facies changes of coastal alluviums are considered in the present study to identify the past depositional layer and consequences of erosional stage with advancing sea. Some erosive sections of the shore face, available pond cutting sections and sediment cores data from pumping wells of nearby villages helped to identify the chronostratigraphy of alluvium coast. Finally, the morphometric attributes of the coastal zone are studied with the help of contour plan generated through Total Station Survey.

The lithologs of depositional surface by Hand Piston Augors, observation of wave abrasion sites, salt weathering pockets, morphological features, desiccation cracks over the mud banks, surface gradients, vertical tree stumps over the erosive surface, bank margin buttresses with current scours, and thickness of sand apron over the onshore bluff are surveyed and recorded in the field in support of coastal morphometry.
Figure 3. The former mangrove forests exposed on the shore face after removal of sand size sediments by the landward marching dune bodies across the shore fringed mangrove forests to the back shores.

A methodological flowchart is prepared to represent the various stages of work through data input, data analysis and data output process. The mangrove forests of Chemaguri Village under the impact of landward marching barrier spit dune by over wash fan lobes indicate movement of facies of sediment towards the back shores with rising sea level in the deltaic alluvium coast at present. Thus, the section of shoreline adjacent to Muriganga bank is considered to compare with eroded shore face of Shibpur- Dhablat areas along the Bay of Bengal in term of lithostratigraphic correlation in the present study (Fig. 3).

3. METHODOLOGICAL FLOWCHART

The methodology of the work is based on the following sequences to conduct the present study represented in the flowchart (Fig. 4).

Figure 4. The methodological flowchart of the present study
4. PROCESSES INVOLVED

The Shibpur-Boatkhal Mouzas (village units) were fronted by wide and elevated sand dunes of 1962 m length, 170 m in width and average 12 m in height and contained 40,02,480 m$^3$ (forty lakh two thousand four hundred eighty cubic meter) volume of sand size sediments in 1987 (Paul, 2002). Significant dune scarping (>10 m in elevation) with landward extent of vegetated sand bodies were acting as a physical barrier against the advancing sea in the shoreline adjacent of Baratala-Muriganga estuary and open marine face of the Bay of Bengal. The existing dune bodies of 1987 were also fronted by two stepped mud banks and extended from the dune base to the low tide shoreline with a significant break of slope (Fig. 5). Upper mud bank fringed with or backed by dune scarp was indicating the residues of Paleo swamp terrace with in-situ tree stumps and extensive roots of mangroves. However, the lower mud bank was heavily eroded by tidal currents and wave abrasion up to a depth of 0.90 m to 1.0 m from the upper surface. The wave breakers and shock pressures were concentrated along the break of slopes of two stepped mud banks and along the base of dune scarp wall by advancing mid tides and high tides during the pre-monsoon summer months (April, May, June) and monsoon months (July, August, September and October in the low lying deltaic coast). The lower most eroded mud bank adjacent of the low tide shore was veneered by sand sheets with long shore current deposits at east ward direction. The parts of Bishalakshmipur and Dhablat were already eaten by the advancing sea even before 1987 in this area in front of two steps mud banks. Only the stumps of palm trees and other terrestrial trees were existing with remnants of earthen embankments and village ponds along the shore face. Gradually, the entire land mass of deltaic alluviums was highly abraded and planated by waves and tidal currents with vertical lowering of earlier surface.

Remaining volume of sands of the shore fringed dune were transferred into other areas by undermining, mass wasting, over washing, cross shore currents, long shore currents and windblown activities and which was rendering the back shore areas exposed to advancing sea at current position. At high tides during eastern winds, the planted shore face is now frequently flooded by salt water encroachment. The rapid erosion was induced with the land fall of cyclones and associated tidal waves in 1988-89, 1995, 2007 and 2009 in this part of deltaic estuarine coast. Tidal prisms of Baratala-Muriganga river mouth also have been increased at present in comparison to the year 1987. It is estimated that tidal prisms were 1,85,840 m$^3$ in 1987 but gradually increased to the amount of 2,36,049 m$^3$ in 2018. Such increased volume of tidal prisms is an important factor that influenced the rapid rate of erosion on the western bank (Shibpur-Boatkhal areas) by lateral shifting of Muriganga or Baratala estuary channel (Fig. 6).
5. TOTAL STATION SURVEY AND ASSESSMENT OF COASTAL MORPHOMETRY

Total station survey was conducted over 10,708.30 m² areas on the shore face of Boatkhali-Shibpur villages in 2016 (April), and a repeat survey was also conducted in April, 2018 over 70,686.0 m² area along the shore face to estimate the volume of sediment loss under the impact of advancing sea (Paul et al., 2016). The contour plans are prepared on the basis of Total Station Survey and compared with two consecutive years (2016 and 2018) to assess the elevation change of the shore face, profile form changes across the shores as well as the changes in gradient of shore profiles of the low lying deltaic coast.

Vertical deduction of the surface is measured as 5.4 m (2016) -2.8 m (2018) = 2.6 m in between the temporal span of two consecutive years for the study area by this method of repeated profile survey. Thus, the lowering of shore face by erosion has increased flood vulnerability during spring tides in the region. The frequency of tidal inundation for each surface is also
estimated from the Hooghly tide tables (Sagar station) by considering the successive high tide elevations and measured surface elevations of the shore face. Finally, the amount of sediment volume is plotted against each surface height for the years 2016 and 2018 to find out the loss and vertical deduction of surface morphometry.

The back shore area is lower even compared with the remaining bluff area capped by sand size sediments on the fore shore region. The entire area under human habitations is now abandoned at the back shore region due to wave aberration, marine planation and embankment damages by advancing sea. The average gradient along the shore face transects is moderately reduced by the planation process in the region.

6. SEDIMENT BUDGET ESTIMATION FOR THE SHORELINE

The earlier study (Paul, 1988) shows that a large volume of sand size sediments was stored in the fore dune ridge and dune fringed sea beaches of Boatkhali-Shibpur areas of Sagar Island. During 1987, the sand size sediment of fore dune ridge of 12 m height along the shoreline length of 1,962 m and landward extension of average 170 m width had stored about 40,02,480 cubic meter volume of sands (Fig. 7).

Over time, consecutive events of cyclone (1988, 1989, 1995, 2007, 2009), increased tidal prisms of Muriganga-Baratala estuary, presence of strong long shore currents along the shoreline and shock pressures of wave breakers along the cliff line of dune scarp at HTL drifted entire volume of sand size sediments from the shore fringed dune bodies in the coast. Currently, and elongated sand spit has extended along the bank of Muriganga in NNE direction. Total volume of sand of the linear spit is estimated as 19,71,744 m\(^3\) and the sand body in the form of sand spit are advancing landward wetlands by rollover processes at rapid rate. Thus, out of the total volume of 40,02,480 m\(^3\) of sands from Boatkhali-Shibpur sand dunes only 19,71,744 m\(^3\) of sands are deposited along the linear sand spit of nearby estuary bank. Over 50 percent of sand size sediment volume (20,30,736 m\(^3\)) from earlier dune body has been lost or transported in to other areas by over wash process, windblown transport, cross shore transport and long shore drift. A few amounts of sand are deposited in to the channel mouth and also trapped by exposed ponds and front bluffs in the low lying coast at present. Wide abraded mud banks are now fringed with the shoreline which allows the high tide waters to encroach in to the low lying back shores without protection.

7. EVOLUTION OF THE SHORE FACE GEOMORPHOLOGY

A wide extensive shoaling flat with bar was developed along the sheltered bank of Muriganga-Baratala estuary during 1987 (Google Earth Image) and it was extended up to Chemaguri creek of south eastern Sagar (Paul & Bandyopadhyay, 1987). Mangrove wetlands expanded over the tidal flat and accumulate tidal deposit dominated by silts and clays with progress of time. After a series of cyclone break during 1988, 1989 and 1995 the erosion became severe in Boatkhali-Shibpur areas and a growth of narrow sand spit emerged along the nearby Muriganga channel bank in front of the mangrove wetlands in NNE direction (Table 1, 2, 3 & 4 ).
Table 1. Total Station Survey plot of Boatkhali-Shibpur sea shore (April, 2016).

<table>
<thead>
<tr>
<th>Surface No.</th>
<th>Elevation in m</th>
<th>Area in sq.m</th>
<th>Sediment Volume in m$^3$</th>
<th>Sediment Types</th>
<th>Tidal Inundation Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.6-2.1</td>
<td>12694.7</td>
<td>26658.87</td>
<td>Clayey</td>
<td>77</td>
</tr>
<tr>
<td>2</td>
<td>2.1-2.4</td>
<td>12030.0</td>
<td>28872.00</td>
<td>Clayey</td>
<td>64</td>
</tr>
<tr>
<td>3</td>
<td>2.4-2.8</td>
<td>11505.0</td>
<td>32214.00</td>
<td>Clayey</td>
<td>58</td>
</tr>
<tr>
<td>4</td>
<td>2.8-3.1</td>
<td>11850.0</td>
<td>36735.00</td>
<td>Clay loam</td>
<td>58</td>
</tr>
<tr>
<td>5</td>
<td>3.1-3.5</td>
<td>14050.0</td>
<td>49175.00</td>
<td>Clay loam</td>
<td>57</td>
</tr>
<tr>
<td>6</td>
<td>3.5-3.9</td>
<td>12505.0</td>
<td>48769.50</td>
<td>Clay loam</td>
<td>54</td>
</tr>
<tr>
<td>7</td>
<td>3.9-4.2</td>
<td>13605.5</td>
<td>57143.10</td>
<td>Sandy clay loam</td>
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</tr>
<tr>
<td>8</td>
<td>4.2-4.6</td>
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<td>46156.40</td>
<td>Sandy clay loam</td>
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</tr>
<tr>
<td>9</td>
<td>4.6-5.0</td>
<td>4400.65</td>
<td>22003.25</td>
<td>Sandy</td>
<td>31</td>
</tr>
<tr>
<td>10</td>
<td>5.0-5.4</td>
<td>4411.45</td>
<td>23821.83</td>
<td>Sandy</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>107086.30 m$^2$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Total Station Survey plot of Boatkhali-Shibpur sea shore (April, 2018)

<table>
<thead>
<tr>
<th>Surface No.</th>
<th>Elevation in m</th>
<th>Area in sq.m</th>
<th>Sediment Volume in m$^3$</th>
<th>Sediment Types</th>
<th>Tidal Inundation Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5-1.1</td>
<td>2316.55</td>
<td>2548.20</td>
<td>Clayey</td>
<td>108</td>
</tr>
<tr>
<td>2</td>
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<td>16503.2</td>
<td>24754.80</td>
<td>Clayey</td>
<td>94</td>
</tr>
<tr>
<td>3</td>
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<td>77</td>
</tr>
<tr>
<td>4</td>
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<td>68313.19</td>
<td>Sandy clay loam</td>
<td>64</td>
</tr>
<tr>
<td>5</td>
<td>2.2-2.8</td>
<td>16347.2</td>
<td>45772.16</td>
<td>Sandy clay loam</td>
<td>58</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>70686.0 m$^2$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Estimation of sediment volumes from five different surfaces by repeat profiles and repeated Total Station Survey plots in parts of Shibpur, Dhablat and Boatkhali areas.

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Sediment Volume of 2016 in m$^3$</th>
<th>Sediment Volume of 2018 in m$^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26658.87</td>
<td>2548.2</td>
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<td>2</td>
<td>28872.00</td>
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<td>3</td>
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<td>8488.44</td>
</tr>
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<td>4</td>
<td>36735</td>
<td>68313.19</td>
</tr>
<tr>
<td>5</td>
<td>49175</td>
<td>45772.16</td>
</tr>
</tbody>
</table>

Figure 8. Extracted sediment volumes plotted for years of 2016 and 2018 for the study area.

Table 4. Change in surface morphometry with reduction of height and extension between 2016 and 2018.

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Surface height of 2016 in m</th>
<th>Surface height of 2018 in m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.1</td>
<td>1.1</td>
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<tr>
<td>2</td>
<td>2.4</td>
<td>1.5</td>
</tr>
<tr>
<td>3</td>
<td>2.8</td>
<td>1.9</td>
</tr>
<tr>
<td>4</td>
<td>3.1</td>
<td>2.2</td>
</tr>
<tr>
<td>5</td>
<td>3.5</td>
<td>2.8</td>
</tr>
</tbody>
</table>
Gradually, the sand spits with dune bodies were achieved in significant length (3.57 km), in sufficient width (115 m) and in reasonable thickness or height (4.8 m to 5.0 m) as physical barrier against tidal waves and cyclone surges in the region. The events of ‘Cyclone Sidr’ (2007) and ‘Cyclone Aila’ (2009) produced storm surges up to 5 m elevation in the mouth of Muriganga-Baratala estuary which generated significant scarring at the spit front region along the High Tide Line. With progress of time, the barrier bar sediments encroached landward part across the mangrove wetlands by wash over fan lobes extension, roll over moved marching sediments, hydraulic collision regime based transport of sediments and blowout leaks sediments movement (Fig. 8 & 9). The landward marching movement of barrier has exposed mud banks of 3,572 m length and 126.6 m of width in front of the sand spit with 45,22,153 m² area. Mud banks with tree stumps are also affected by sheeting and fingering, salt water flooding and encrustation of salts, and lowering of the surface with etching process during high tides. Erosion is extensive in the areas of energy concentration at present particularly on the basis of elevation, gradient and configuration of the shoreline with progressive change of tidal prisms in estuary mouth (Masselink & Gehrels, 2013).

Gradual retreat of mud banks with significant scarping and etching process will remove the remaining mangroves of the back shores of the region as long as the high water level erosion will continues without a major cyclone landfall in the low lying delta (Table 5). Another sand spit formation with huge long shore current induced sediment transport is needed to act as the physical barrier in front of the erosive mangrove shores. High magnitude cyclone land falls (150 to 200 km per hour wind speed) usually supply sand size sediments along the shore from distant areas with increased hydraulic regimes and currents transport energies. Such dynamic behaviors of the surface will be increased in the deltaic land forms as long as the occurrence of large river floods will be reduced and frequency of high magnitude cyclone land falls will be increased with global warming induced sea level rise (Fig. 10).

The shore fringed villages of Sagar Island nearby the estuaries are therefore affected by frequent inundations of advancing sea and rapid rate of erosion as well as the significant loss of the coastal habitats at present (sand dunes and mangrove wetlands).
8. SURFACE MORPHOMETRY OF THE EROSI VE SURFACE

There were about 10 (Ten) surfaces of sedimentary depositional units occupied by specific areas and sediment volumes in the shore face in 2016. All the surfaces are categorized on the basis of elevation after plotting the contour plan prepared by Total Station Survey. The sediment types on the basis of textures as well as the frequency of tidal inundation for each depositional surface are classified and estimated to identify the nature of surface morphometry. However, the depositional surfaces of the same area were reduced into 5 (Five) units due to wave erosion and undermining by tidal currents on the shore face morphology during 2018. Total Station Survey in 2018 represents the change in surface morphometry when compared with the contour plan of 2016. Tidal inundation frequencies of each surface are also increased in 2018 in comparison to 2016. The surface gradient of shore face reduced and tidal range is increased due to erosion and removal of sediments from the beaches and dune bodies.

The earlier dune bodies are over washed and under mined by wave action in Shibpur-Boatkhali areas when beach sands were removed and narrowed by active erosion. Over time, the clay banks were exposed in front of erosive dunes by repeated inundations and associated hydraulic stress. Muriganga estuary bank morphometry was diversified with location of tidal shoals, sand spits or barriers, mangrove wetlands, narrow sandy beaches and exposed clay banks. The stickiness character of swampy muds dominated by mangroves was severely affected by marching over wash sand fan lobes in the back shores. The shore face clay banks after landward marching of sand dunes by roll over process behaves differently by shifting, spawling, fingering, splitting and scarping under waves and tides in estuary bank of Chemaguri flat. Gradual retreat of clay banks will push back the remaining sand spits by increased wave erosion and tidal current scouring in the low lying deltaic coast. The Shibpur-Dhablat and Bisalakshimpur shoreline are sufficiently curved by deluviation and channel filling process over the time (Fig. 11 & 12).

Figure 11. Total Station Survey plots of 2016 and 2018 to represent the surface morphometry of the south eastern parts (Shibpur, Dhablat, Boatkhali and Bisalakshimpur) of Sagar Island.

Figure 12. Transects across the surface morphometry plotted on the Total Station Survey derived DEM.

9. SUMMARY AND CONCLUSIONS

Following conclusions may be drawn on the basis of above study.

The rate of erosion and frequency of flooding are increased in specific areas of shoreline configurations of Sagar Island. Increased tidal prisms of estuaries, storm surges generated by landfall of high magnitude cyclones and water layered weathering are attacking the shores of south eastern and south western Sagar Island close to Muriganga-Baratala channel and Hooghly river mouth sections. The lowering of beaches and clay banks is estimated by repeated contour plans with Total Station Survey in the south eastern part of Sagar Island, and the volume of sand size sediments is also estimated in NNE ward growth of sand spit barriers and in the existing areas of shore fringed bluff with the help of Google Earth Image and
field survey methods. Estimated budget of the sand size sediments by above study (1987-2018) indicated the total of 38-40% sands from the shore face of Shibpur, Dhablat Boathkali and Bisalakshmipur Villages since 1987. Among 70 % of sand size sediments of the former sand dunes and sandy beaches of the shore face bout 50 % sands are drifted towards NNE direction in the form of younger barrier spits deposit and remaining 10-12 % of sediments are temporarily stored in the areas of shore fringed bluff at present.

Wave abrasion and wave hammering at the lower part of exposed clay bank near seaward edge not only remove the top surface of muds but also have deformed the bank margins into buttressed edge along with increased tidal scouring in rising tides into the shores. Such lowered platforms of clay banks are liable to regular flooding by high tides in the fore shores and back shores at present. Tidal current energy is concentrated in the erosive shores as soon as the depth of tidal floods is increased in the region by abrupt lowering of the shore platforms with removal of sands and muds. The settlements are abandoned in the back shores and terrestrial vegetations with the former shore fringed mangroves are widely damaged and gradually, the sea has advanced into the landward parts without protective land barriers in the low-lying deltaic coast.

The predicted sea level rise will aggravate the situation with increased hydraulic pressures and frequent inundations by tides and storm surge waves in such alluvium coast in the upcoming decades of this century (Fig. 13 & 14).

Figure 13: Shore platform transect across Boathkali-Dhablat and Bishalakshmipur areas of Sagar Island, W. B. (2018, April)

Figure 14. (A) Abandoned house at the back shore (former village) and (B) Abandoned settlements at the back shore damaged after landward advancement of sea

ACKNOWLEDGEMENTS

The Sagar-Bakkhali Development Board, Research Scholars of Vidyasagar University (Geography and Environment Management Department) and M.Sc. Students (Final Semester) of Coastal Management Special paper of the University are acknowledged for their help and cooperation in every stage of field works during the period between 2016 and 2018 in the coastal zones.

REFERENCES


ASSESSMENT OF LOSS OF STORAGE CAPACITY IN TUNGABHADRA RESERVOIR DUE TO SEDIMENTATION

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ABSTRACT

The soil erosion and deposition is a serious problem faced by the dams, which is relatively impossible to measure at source and occurs in the catchment area of the reservoirs. Tungabhadra reservoir feed the occupants water storage and deliver for waterpower and irrigation. Reduction of reservoir capacity due to sedimentation is uneconomical and it is extremely monotonous to do hydrographic survey for assessment purpose. Determining loss of storage capacity of reservoir using GIS and Remote Sensing is one of the easy, fast and economic methods. Six dates of Landsat 8 satellite data from minimum to maximum reservoir level was used to measure spatial and temporal patterns of reservoirs. After Data acquisition, all errors were removed from these satellite images. To evaluate sedimentation, Remote sensing based digital image processing technique was used. To estimate water spread area of reservoir, band ratioing technique was used i.e. Normalized Difference Water Index (NDWI) and the project was carried out using ERDAS Imagine 2014. By using Trapezoidal, formula capacity of the reservoir between maximum and minimum level was calculated. From that calculation, it was observed that volume of sediment deposited during 1953-2017 (64 years) in between the minimum to maximum observed levels (478.65 m and 490.19 m) is 411.47 M m³. The study considered uniform rate of sedimentation up to 2016-2017. The rate of sedimentation in the live zone in between the minimum and maximum was levels calculated as 6.42 M -m³/year. The loss of storage capacity in reservoir is 30% from 1953 to 2017. Sediment rate was compared with hydrographic survey analysis.

Keywords: Capacity, Water spread area, Reservoir, Remote sensing, Sedimentation, ERDAS Imagine 2014.

1. INTRODUCTION

Reservoirs are the key infrastructure for the socio-economic development of the country. Reservoirs are designed across rivers for the aim of irrigation, water supply, power generation, discharge regulation and flood control. Most of the reservoirs have been designed for a life period of hundred years or more. However, excessive siltation because of rapid erosion in the catchment is main cause or reason to reduce the storage capacity of the reservoirs. The capacity of the reservoirs is being depleted faster than the projected rate, because of extensive soil erosion in their catchments. Soil erosion is a serious problem in India. Soil erosion and sediment transport in a river basin are largely overseen by topographical, meteorological, land cover, soil and drainage characteristics in the basin. The procedure of watershed erosion, sediment transport and its successive deposition in reservoirs is an extensive occurrence. Sediment is originated in the form of erosion due to natural as well as anthropogenic activities in the catchment and propagates along with the stream flow. The suspended sediments or eroded sediments settle down in the reservoir bed and reduce the volume or storage capability of that reservoir. Annual sediment inflow into many of the reservoirs in India varies from 0.8 to 172 tonnes/hectare for catchments, excluding few well-protected catchments. Analysis of sedimentation survey details in respect of forty three major, medium and minor reservoirs with in the country indicates that the sedimentation rate varies between 0.3 and 27.8 hectare meter/ 100 Sq km/year for major reservoirs to 1.0–2.3 hectare meter/100 Sq km/year for minor reservoirs.

2. MATERIALS AND METHODOLOGY

2.1 STUDY AREA

Tungabhadra River is one of the major tributaries of Krishna River in southern part of India. The river has its beginning in the Western Ghats in Karnataka State in the form of two tributaries, namely, Tunga and Bhadra, which joins at Kundali village, 13 km. from Shimoga town, to form Tungabhadra. The stream flows for 531 km. and joins River Krishna at Sangameshwara near Kurnool town in Andhra Pradesh State. The stream reach in Karnataka State is 382 km and thereafter, it forms boundary between Karnataka State and Andhra Pradesh State for 58 km. length and for the remaining 91 km, the stream forms the boundary between Mehboobnagar district of Telangana State on the left and Kurnool district of Andhra Pradesh on the right.

Tungabhadra dam is built across the River Tungabhadra at Mallapuram village, 5 km north-west of Hospet town in Bellary District Karnataka State. It is situated at Longitude: 76° 20' 10" East and Latitude: 15° 15' 49" North. It was a major multi-purpose dam project taken up on importance immediately after India’s independence and commissioned in the year 1953. The salient feature is shown in Table 1.

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The average annual rainfall in the catchment area is 1040 mm with the maximum of 4320 mm in the Western Ghats and the minimum of 470 mm in the plains. Although the river is perennial carrying in large monsoon flows, the summer flow decreases down to 50 to 100 cusecs. At the time of construction of the Tungabhadra dam, dependable yield of the river at dam site was assessed as 336 TMC. After allowing for upstream abstraction of 57 TMC for Lakhavalli project on Bhadra river, 11.5 TMC for Tunga anicut on Tunga river and 11.0 TMC for other river works, gross flows available at Tungabhadra dam was taken as 256.50 TMC. At Full Reservoir Level (FRL), submergence area of the reservoir is 378 sq km (146 sq. miles / 93438 acre) with a maximum width of water-spread of 15.30 km near the dam and a maximum fetch distance of 85.34 km (50 miles) from the dam axis. Tungabhadra reservoir was selected one among the 11 reservoirs for sedimentation assessment. Accordingly, hydrographical survey was carried out during 1963 by the Karnataka Engineering Research Station (KERS), which gave a shocking amount of silt deposit of 41.050 acre-feet (0.6M.cft). Reddish brown soils, black clays and grey sands occupy the entire reservoir area above minimum water level. But at places rock boulders are exposed. Dharwar Meta sedimentary schistose and amphibolite are exposed on the upstream peripheral portion of reservoir and also in the tail end portion. Granitic rocks occur at places as small detached or scattered mounds, on the right and left banks of the river. They are also exposed in the narrow section in the tail end portion of the reservoir.

In this study, multi dates of Landsat 8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) Satellite data is collected from the USGS Glovis and Topographic map (Survey of India) is collected from the KSRSAC and Hydrographic survey data collected from Tungabhadra Board.

2.2 SATELLITE DATA

The Landsat 8 OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) are instruments on board of the satellite, which was launch in February of 2013. The satellite collects images of Earth with a 16-day repeat cycle. The satellite’s collections are in an 8-day offset to Landsat7. The approximate scene size is 170km North-South by 183 East-West (106mi by 114mi).

In this study, multi-dates, multispectral satellite images of Landsat 8 OLI (Spectral bands 0.52-0.59) Blue; 0.62-0.68 (Green); 0.77-0.86 (Red); 1.55-1.70 (Near Infra-Red)) were used to estimate the water spread area of the reservoir at different elevation. Six dates of Landsat 8 satellite data (21 October 2016 to 15 may 2017) were used to assess temporal and spatial patterns of the water spread area of the reservoirs. The water level of Tungabhadra reservoir had recorded between 478.65 m and 490.19 m correspondingly to the available satellite scene. Table 3 gives the detailed information of satellite data used in this study.

<table>
<thead>
<tr>
<th>Date of pass</th>
<th>Path</th>
<th>Row</th>
<th>Satellite description</th>
</tr>
</thead>
<tbody>
<tr>
<td>21 October 2016</td>
<td>145</td>
<td>49</td>
<td>Landsat 8 OLI level 1</td>
</tr>
<tr>
<td>06 November 2016</td>
<td>145</td>
<td>49</td>
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<td>08 December 2016</td>
<td>145</td>
<td>49</td>
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</tr>
<tr>
<td>30 March 2017</td>
<td>145</td>
<td>49</td>
<td>Landsat 8 OLI level 1</td>
</tr>
<tr>
<td>15 April 2017</td>
<td>145</td>
<td>49</td>
<td>Landsat 8 OLI level 1</td>
</tr>
<tr>
<td>15 May 2017</td>
<td>145</td>
<td>49</td>
<td>Landsat 8 OLI level 1</td>
</tr>
</tbody>
</table>
The Methodology adopted for this study has preprocessing of satellite data, i.e., radiometric and geometric corrections. The identification of the water pixels in terms of water spread area by using a band ratioing technique was performed with the help of ERDAS IMAGIN 2014 software (Fig. 4).

The pixels signifying water-spread area of the reservoir were clearly discernible in the False Color Composite (FCC) image. The delineation of the reservoir has been identified by using a band rationing technique, Normalized Difference Water Index (NDWI) as given in equation (1). The NDWI value ranges from -1 to 1, considering zero value as a threshold (McFeeters, 1996). Based on the NDWI value, the satellite images are categorized as water or non-water. For values of NDWI > 0, the cover type is water and if, NDWI ≤ 0, the cover type is non-water. Digital number (DN) value of water pixel is always near-Intra Red (NIR) spectral region. If the generated DN value is lower than the DN value of Band 2 and Band 3, then it must be classified as water or else as non-water. Each scene of data consists of four bands containing 7720 rows and 7560 columns. Initially, the False Color Composite of Satellite data were generated and visualize. The hydrographic survey data were also used in this study for water elevation and surface area. However, the actual water spread area of the reservoir is calculated through temporal scenes of Landsat 8 data using the trapezoidal formula Equation. (2), volume of sediments on the specific duration has been calculated for the month of October to December 2016 and March to May 2017, at full and empty reservoir level. The sediment volume is estimated by using trapezoidal method. Fig. (2). The steps which have been followed in the analysis are described below in details.

![Figure 2. Line diagram to describe the prismoidal formula](image)

### Table 2 Original Elevation-Area-Capacity for Tungabhadra reservoir.

<table>
<thead>
<tr>
<th>Elevation (m)</th>
<th>Water spread area (M-m2)</th>
<th>Capacity (M cum)</th>
</tr>
</thead>
<tbody>
<tr>
<td>475.49</td>
<td>3.186</td>
<td>1.344</td>
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<tr>
<td>477.01</td>
<td>9.871</td>
<td>9.773</td>
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<tr>
<td>478.54</td>
<td>18.155</td>
<td>21.212</td>
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<td>480.06</td>
<td>27.577</td>
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<td>481.58</td>
<td>38.971</td>
<td>50.843</td>
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<td>483.11</td>
<td>51.990</td>
<td>69.049</td>
</tr>
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<td>484.63</td>
<td>69.509</td>
<td>91.979</td>
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<td>486.16</td>
<td>90.407</td>
<td>121.539</td>
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<td>487.68</td>
<td>114.848</td>
<td>155.680</td>
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<td>489.20</td>
<td>144.71</td>
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<td>490.73</td>
<td>177.801</td>
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<td>492.25</td>
<td>212.828</td>
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<td>493.78</td>
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<td>495.30</td>
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<td>496.82</td>
<td>330.465</td>
<td>475.957</td>
</tr>
<tr>
<td>497.74</td>
<td>367.110</td>
<td>315.418</td>
</tr>
</tbody>
</table>

### 2.3 Identification of water pixels

However, spectral signatures of water are quite different from other land uses like built-up area, soil and vegetation. Identification of water pixels at the soil interface or water is very tough and depends on the interpretative ability of the analyst. Deep-water bodies have
somewhat different and clear representation in the imagery. But a very shallow, water can be mistaken for soil although saturated soil can be mistaken for water pixels, especially along the boundary of the water spread area. In addition, it is possible that a pixel, only at the water or soil interface, will be mixed condition (some part as soil and another part as water). Just by observing at the colour and tone of a pixel, it is difficult to differentiate the suspended sediment and shallow water. It is mainly the same material with same reflection assets. The shallow water has the same brightness and color as turbid water (high concentration of suspended sediment). To differentiate these two features, it is required to observe the shape as well as the change in the spatial distribution of the feature over time.

2.4 METHODOLOGY

The detailed methodology followed in the study presented in the flow chart (Fig. 3)

![Flowchart](image)

Figure 3. Methodology adopted flow chart in this study.

2.5: Normalized Difference Water Index Method (NDWI)

McFeeters has developed the Normalized Difference Water Index (NDWI) in 1996. Normalized Difference water Index (NDWI) is the ratio of subtraction of Green band and Near-Infrared to the sum of Green band and Near-Infrared. For example, water molecules absorb the NIR region of the spectrum and the sensor records the reflectance, in a water spread area. The difference of reflectance and absorption by water allows us to estimate the area of the water existing on the surface.

The index calculated as follows by using equation (1)

\[
NDWI = \frac{\text{GREEN} - \text{NEAR INFRARED}}{\text{GREEN} + \text{NEAR INFRARED}} \tag{1}
\]

Where Green is a band that contains reflected green light and NIR reflected near infrared radiation. The range of this wavelength done to,
1) Maximize the specific reflectance of water features by using green light wavelengths.
2) Minimize the small reflectance of water features and
3) Taking advantage of higher reflectance of NIR by soil and terrestrial vegetation features.

To process the multi-spectral satellite image, which contains reflected visible green, and an NIR band, where water feature has a positive values and soil features have negative value NDWI equation was used. Due to their typically higher reflectance of NIR then green light, the terrestrial vegetation and soil features have negative value. The NDWI values ranges from -1 to 1 and zero as threshold. The cover type is water if NDWI is greater than zero and cover type is non-water if NDWI is smaller than zero. The resulted image for visual interpretation is represented by multiplying equation (1) by the scale factor. The water spread area of the reservoir is calculated using Normalized Difference Water Index.

Figure 4. Water spread area of Tungabhadra reservoir satellite images and NDWI images of various dates.

2.6 Calculation of volume of sediments

The reservoir of the capacity between two successive elevations computed using Trapezoidal formula Equation. (2).

\[ V = \frac{h}{3} \times (A1 + A2 + \sqrt{A1 \times A2}) \]  

(2)

Where,

- \( V \) = volume of between two consecutive levels
- \( h \) = Difference between two consecutive elevation
- \( A1 \) = Counter Area at elevation 1
- \( A2 \) = Counter Area at elevation 2

3. RESULTS AND DISCUSSION

In the present study, volume, cumulative volumes, area of reservoir were calculated by remote sensing techniques. The assessment of reservoir capacity for the year 2016-2017, six various elevations selected based on intervals, live storage and availability of cloud free
data. By using Landsat 8 OLI satellite data and applying NDWI approach, water spread area of the reservoir calculated as shown in (Fig.3.4 to 3.9). Separating the water pixels of the reservoir from different land use features by applying Normalized Difference Water Index (NDWI) techniques. It has seen that usage of NIR band ranges from 0.77 μm to 0.86 μm is more useful than other bands to extract water pixels. Interpretation of water pixel to estimate existing capacity of the reservoir. By using Trapezoidal formula (Eq.2), difference in volume between two successive elevations levels calculated for the Tungabhadra reservoir (Table 3 and 4). Further, the Elevation-Area curves, Elevation-Capacity curves are prepared as shown in Fig 5 to 6 and sediment volume of calculation shown in Table 3 and 4. From reservoir authority, Tungabhadra Board carried out the hydrographic surveys for Tungabhadra reservoir Elevation-Area curves, Original Elevation-Area table from Tungabhadra Board (Table 2), the original in between elevation and area (basin elevation on dates of satellite pass) were obtain by linear interpolation (Figs 4). To estimate water spread area at nearer interval, a curve between elevation and water spread area was drawn (Fig 4 and 5). From these curves, the area consisting to nearer interval calculated. By using satellite data, water spread area is calculated. To estimate known sedimentation rate and loss of storage capacity analysis by remote sensing technique carried out for the year of 2016-2017, in the region variation between maximum and minimum level. The Difference between latest year (2016-2017) and cumulative capacity of original (base years) analysis gave the loss in storage area (Table 3). In addition, the Elevation-Area curves and Elevation-capacity curves for the above mentioned, dates have suggested in Figs. 5 and 6 While the capacity of the reservoir calculating, the capacity at lowest has taken as zero. The difference between the estimated and original cumulative capacity represents the loss of storage capacity due to sedimentation in the region under study. Volume of sediment deposited during 1953-2017 (64 years) in between the minimum to maximum observed levels (478.65 m and 490.19 m) 411.47 M·m³. In this study, uniform rate of sedimentation has been considered up to 1953-2004. The rate of sedimentation in the live zone in between the minimum and maximum levels calculated as 6.42 M·m²/ year. The loss of storage capacity in reservoir is 30%, from 1953 to 2017. As per hydrographic survey made by TB, authority during 1953-2004 (51 years) the minimum and maximum observed levels (478.65 m and 490.19 m) is 447.48 M·m³. In the survey study, uniform rate of sedimentation has considered up to 1953-2004. The rate of sedimentation in the live zone in between the minimum and maximum levels calculated as 8.71 M·m³/ year. The loss of storage capacity in reservoir is 33%, from 1953 to 2017. As per hydrographic survey made by TB, authority during 1953-2004 (51 years) the minimum and maximum observed levels (478.65 m and 490.19 m) is 447.48 M·m³. In the survey study, uniform rate of sedimentation has considered up to 1953-2004. The rate of sedimentation in the live zone in between the minimum and maximum levels calculated as 8.71 M·m³/ year. The loss of storage capacity in reservoir is 33%, from 1953 to 2004. It can be seen that the rate of sedimentation by remote sensing technique and hydrographic survey is almost similar. Further, the elevation area curve and elevation capacity curve plotted in (Fig.5 to 8).

Table 3: Calculation of sediment deposition between maximum and minimum elevations in Tungabhadra reservoir using remote sensing for the year 2016-2017

<table>
<thead>
<tr>
<th>Dates of satellite pass</th>
<th>Elevation (M)</th>
<th>Capacity (M-cum)</th>
<th>Satellite derived Water spread area 2016-17 (M-m²)</th>
<th>Water spread 1953 (M-m²)</th>
<th>Water spread changed (M-m²)</th>
<th>Volume (M-m³)</th>
<th>Cumulative volume (M-m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>21-10-2016</td>
<td>490.19</td>
<td>31.99</td>
<td>168.19</td>
<td>208.92</td>
<td>40.73</td>
<td>-</td>
<td>-</td>
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<tr>
<td>6-11-2016</td>
<td>486.96</td>
<td>16.88</td>
<td>108.33</td>
<td>137.70</td>
<td>29.37</td>
<td>127.36</td>
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<tr>
<td>8-12-2016</td>
<td>484.54</td>
<td>9.61</td>
<td>72.75</td>
<td>107.81</td>
<td>35.06</td>
<td>77.85</td>
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<tr>
<td>30-3-2017</td>
<td>481.32</td>
<td>3.8</td>
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<td>33.36</td>
<td>110.14</td>
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<tr>
<td>15-4-2017</td>
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<td>2.56</td>
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<td>15-5-2017</td>
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<td>32.13</td>
<td>41.61</td>
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<td>948.36</td>
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</table>

Table 4: Calculation of sediment deposition between maximum and minimum elevations in Tungabhadra reservoir using remote sensing for the year of 2004

<table>
<thead>
<tr>
<th>Elevation (M)</th>
<th>Capacity (M-cum)</th>
<th>Satellite derived Water spread area 2016-17 (M-m²)</th>
<th>Water spread 2008 (M-m²)</th>
<th>Water spread changed (M-m²)</th>
<th>Volume (M-m³)</th>
<th>Cumulative volume (M-m³)</th>
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<tr>
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<td>86.8</td>
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</table>
Hydrographic survey Results by Tungabhadra Board

Table 5: Calculation of sediment deposition between maximum and minimum elevations in Tungabhadra reservoir for 1953-2004.

<table>
<thead>
<tr>
<th>Elevation (m)</th>
<th>Water spread area 1953 (M-m²)</th>
<th>Water spread area 2004 (M-m²)</th>
<th>Water spread Change (M-m²)</th>
<th>Volume (M-m³)</th>
<th>Cumulative volume (M-m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>490.19</td>
<td>208.92</td>
<td>165.54</td>
<td>43.38</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>486.96</td>
<td>137.70</td>
<td>102.78</td>
<td>34.92</td>
<td>126.21</td>
<td>424.62</td>
</tr>
<tr>
<td>484.54</td>
<td>107.81</td>
<td>68.87</td>
<td>38.94</td>
<td>89.33</td>
<td>298.41</td>
</tr>
<tr>
<td>481.32</td>
<td>74.18</td>
<td>38.04</td>
<td>36.14</td>
<td>120.85</td>
<td>209.08</td>
</tr>
<tr>
<td>479.95</td>
<td>61.82</td>
<td>28.95</td>
<td>32.87</td>
<td>47.25</td>
<td>88.23</td>
</tr>
<tr>
<td>478.65</td>
<td>50.98</td>
<td>20.79</td>
<td>30.19</td>
<td>40.98</td>
<td>40.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Total cumulative volume</td>
<td>1061.31</td>
</tr>
</tbody>
</table>

Table 6: Calculation of sediment deposition between maximum and minimum elevations in Tungabhadra reservoir for 1953-2016/2017.

<table>
<thead>
<tr>
<th>Elevation (m)</th>
<th>Water spread area 1953 (M-m²)</th>
<th>Water spread area 2016/2017 (M-m²)</th>
<th>Water spread Change (M-m²)</th>
<th>Volume (M-m³)</th>
<th>Cumulative volume (M-m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>490.19</td>
<td>208.92</td>
<td>170.55</td>
<td>38.37</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>486.96</td>
<td>137.70</td>
<td>108.91</td>
<td>28.79</td>
<td>108.09</td>
<td>378.17</td>
</tr>
<tr>
<td>484.54</td>
<td>107.81</td>
<td>74.06</td>
<td>33.75</td>
<td>75.59</td>
<td>270.07</td>
</tr>
<tr>
<td>481.32</td>
<td>74.18</td>
<td>41.65</td>
<td>32.53</td>
<td>106.70</td>
<td>194.48</td>
</tr>
<tr>
<td>479.95</td>
<td>61.82</td>
<td>28.21</td>
<td>33.61</td>
<td>45.30</td>
<td>87.77</td>
</tr>
</tbody>
</table>
4. CONCLUSION

Determining loss of storage capacity of reservoir using GIS and Remote Sensing is one of the easy, fast and economic methods. Here six dates Landsat 8 satellite data from minimum to maximum reservoir level were used to measure spatial and temporal patterns of reservoirs. To evaluate sedimentation, Remote sensing based digital image processing has been used. To estimate water spread area of reservoir, band ratioing technique is used i.e. Normalized Difference Water Index (NDWI) and the project was carried out using ERDAS Imagine 2014. By using Trapezoidal, formula capacity of the reservoir between maximum and minimum level is calculated and that sediment rates compared with hydrographic survey analysis. The sedimentation rate was compared with the hydrographic survey analysis.

Volume of sediment deposited during 1953-2017 (64 years) in the middle of the minimum to maximum experiential levels (478.65 m and 490.19 m) 411.47 M-m3. For the study, even sedimentation of rate has measured up to 2016-2017. The rate of sedimentation in the live zone in between the minimum and maximum levels calculated as 6.42 M-m3/ year. The loss of storage capacity in reservoir is 30%, from 1953 to 2017. During 1953-2004 (51 years) the minimum and maximum observed levels (478.65 m and 490.19 m) is 447.48 M-m3. In the survey study, uniform rate of sedimentation has considered up to 1953-2004. The rate of sedimentation in the live zone in between the minimum and maximum levels calculated as 8.71 M-m3/ year. The loss of storage capacity in reservoir is 33%, from 1953 to 2004. In 2016 survey, rate of sedimentation in live zone in between minimum and maximum levels (478.65 m and 490.19 m) is 6.16M-m3/years. The loss of storage capacity of reservoir is 29.61% from 1953 to 2016 hydrographic survey. The average sedimentation rate in Tungabhadra reservoir for the periods of 64 years (1953-2017). The ground observation through hydrographic survey by Tungabhadra board estimation a sedimentation rate is 6.16 M -m3/year i.e. 29.61% loss of storage capacity in the reservoir. While the remote sensing approach comes out to be 6.42 M-m3/ year, 30% loss of storage capacity of the reservoir between two minimum and maximum observed levels. The obtained rate of hydrographic survey is compared remote sensing technique obtained rate of sediments is almost same rate of hydrographic survey. The remote sensing approach allows fast and economical, detailed calculation of storage capacity loss due to loss of sedimentation. Remote sensing survey based sedimentation are carried out in shorter intervals,
whereas in hydrographic survey must be carried out for longer intervals. Both surveys complemented each other, Hydrographic surveys need more time and cost

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SURFACE DEFORMATION ANALYSIS OF SIROBAGARH LANDSLIDE USING KALMAN FILTER

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ABSTRACT
In India, after recent landslide activities (for example in Kedarnath (2013), Pune (2014), Himachal (2017) etc.), it is essential to focus on investigating surface deformation analysis for estimating the rate of movement and assistance in remedial planning and risk reduction. Global Positioning System (GPS) has been extensively used in surface deformation monitoring applications from the past 20 years. R. E. Kalman has introduced a recursive algorithm, called Kalman Filter (KF), for state estimation of a process using uncertain measurements. The objective of this paper is to implement the kinematic deformation analysis using KF for the prediction of position of five control stations using GPS data of previous epochs and investigating its closeness to reality. The data used in this research was collected from five GPS stations at Sirobagarh landslide in three campaigns from 2015-17. A developed algorithm processes the coordinates of the GPS stations with their respective variances as input and predicts positions of GPS stations following a kinematic deformation analysis. Further, a comparative analysis between predicted and actual displacement of GPS stations revealed that the prediction of displacement of GPS stations can be done up to centimetre level.

KEYWORDS: Surface deformation, landslide, Kalman filter, GPS

1. INTRODUCTION
Movement of bedrocks, a landmass or debris flow triggered by unstable slopes, seismic or volcanic activity result into a landslide. During last few decades, number of landslides in India has been increased. The landslide results into irretrievable loss of human lives and property. Some landslides in India and associated losses with it are listed in Table 1, it becomes clear that how much hazardous a landslide may be. Landslides are common in Himalayan region, northern part of Indian subcontinent, due to its rock type, topographic relief and tectonic zones.

<table>
<thead>
<tr>
<th>Year</th>
<th>Location</th>
<th>Losses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1948</td>
<td>Guwahati landslide, Assam</td>
<td>500+ people died, an entire village buried</td>
</tr>
<tr>
<td>1968</td>
<td>Darjeeling landslide, West Bengal</td>
<td>1000+ people died, disrupted 60 km long highway</td>
</tr>
<tr>
<td>1998</td>
<td>Malpa landslide, Uttarakhand</td>
<td>380+ people died, an entire village washed</td>
</tr>
<tr>
<td>2000</td>
<td>Mumbai Landslide, Maharashtra</td>
<td>67+ people died</td>
</tr>
<tr>
<td>2001</td>
<td>Amboori landslide, Kerala</td>
<td>40+ people died</td>
</tr>
<tr>
<td>2012</td>
<td>Okhimath Landslide, Rudraprayag, Uttarakhand</td>
<td>51 people died</td>
</tr>
<tr>
<td>2013</td>
<td>Kedarnath Landslide, Uttarakhand</td>
<td>5700+ people died, 4200 villages affected</td>
</tr>
<tr>
<td>2014</td>
<td>Malin Landslide, Maharashtra</td>
<td>151+ people died, 100 missing</td>
</tr>
<tr>
<td>2017</td>
<td>Kotropi landslide, Mandi, Himachal Pradesh</td>
<td>47 people died</td>
</tr>
</tbody>
</table>

Table 1. Landslides in India

*Corresponding author: gi1601@mnnit.ac.in
Techniques being successfully used for surface and sub-surface deformation analysis are Global Positioning System (GPS), Satellite imaging, Geotechnical Investigations, Light Detection and Ranging (LiDAR) and Total Station (TS). Researchers have also proposed integrated approaches of geodetic techniques to achieve better accuracy than using individual. (Setan and Singh, 2001; Wang and Soler, 2014; Gui et. al., 2016; Moreira et al., 2013, Donnellan et al., 2002; Wang et al., 2011).

Every technique has its pros and cons. Accuracy of deformation analysis using above mentioned techniques depends on the quality of collected data i.e. provides less accurate result for noisy observations. In this case, we have two approaches to reduce noises, Least square method (LSQ) and Kalman filter. Where LSQ focuses on minimizing residuals, Kalman filter tends to minimise mean square error. Kalman filter has advantage over LSQ, it does not require whole previous data to process observations at once and provides optimum results with some assumptions. Kalman filter is a technique which can be used for prediction of a new state using previous information. Many researchers have used integrated approach of KF and GPS for landslide monitoring (Acar et al.2008; Ince and Sahin 2000; Eyo et al.2014; Bogatin and Kogoj 2008).

In the current scenario, landslide is one of the critical problems because of the socio-economic loss associated with its occurrence so it is essentially required to focus on surface deformation analysis for estimating the rate of movement for assistance in remedial planning and risk reduction. Therefore, an active system of landslide monitoring for surface and subsurface deformation is required for both monitoring purpose as well as to develop an early warning system. The objective of the research paper is to analyse the surface deformation of a landslide using Global Positioning System (GPS) and Kalman filter (KF) by predicting the displacement of control stations present at a patch of land which is prone to landslide and by determining the apparent accuracy of the implemented algorithm to the true phenomenon.

2. CHARACTERISTICS OF STUDY AREA

The Sirobagarh region (30° 14’ 30.8106”N, 78° 53’ 57.5982”E), located on the bank of Alaknanda River on the National Highway 58 (NH 58), at a distance of 12 km from Srinagar, Uttarakhand, possesses a previous history of landmass movement. GPS data for five GPS stations was observed in three campaigns conducted on 21 October, 2015, 3 June, 2016 and 16 March, 2017.

![Figure 1. Sirobagarh Landslide region](image)

3. KALMAN FILTER

According to Maybeck, Kalman filter is an optimal recursive data processing algorithm which includes all available information to provide an optimal result. To estimate the variable of interest, KF needs three informations (see figure1) (Maybeck, 1982):

(i) Knowledge of the system and measurement device
(ii) Statistical knowledge of system and measurement noise and uncertainty of models
(iii) Initial condition of variables

So, KF can also be said as set of equations with main components: a dynamic system and a series of noisy measurements (Eyo et al., 2014). It is a predictor-corrector algorithm based on time update i.e. prediction and measurement update equations i.e. correction (Welch and Bishop, 2001).
For a discrete-time linear system, system equation can be written as

\[ x_{k+1} = \Phi_k x_k + B_k u_k + w_k \]  

(1)

And observation equation,

\[ z_k = H_k x_k + v_k \]  

(2)

where,

- \( x_k \) represent the system state vector
- \( \Phi_k \) is state transition matrix
- \( B_k \) relates optional control unit to state vector
- \( u_k \) denotes input vector
- \( w_k \) indicates process noise
- \( z_k \) represents vector of observations
- \( H_k \) is measurement matrix
- \( v_k \) is measurement noise
- \( k \) denotes time-index

Assumptions are taken as both noises are zero mean Gaussian and white, i.e.

\[ E\{v_k\} = E\{w_k\} = 0 \]  

(2)

\[ E\begin{bmatrix} w_k \\ v_k \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \]  

(3)

For this system, **time-update equations** (prediction) can be given as:

\[ \hat{x}_{k+1|k} = \Phi_k \hat{x}_{k|k} + B_k u_k \]  

(4)

\[ P_{k+1|k} = \Phi_k P_{k|k} \Phi_k^T + Q_k \]  

(5)

Where \( \hat{x}_{k+1|k} \) represents a priori estimate of state vector (predicted); \( \hat{x}_{k|k} \) denotes estimate of previous state vector or initial mean of state vector; \( P_{k+1|k} \) indicates a priori covariance matrix of state vector (predicted); \( P_{k|k} \) is covariance matrix of previous state vector \( x_k \) and \( Q_k \) represents covariance matrix of process noise. The measurement update equations (correction) can be given as follows:

\[ K_{k+1} = P_{k+1|k} H_{k+1}^T (H_{k+1} P_{k+1|k} H_{k+1}^T + R_{k+1})^{-1} \]  

(6)

\[ V_{k+1} = z_{k+1} - H_{k+1} \hat{x}_{k|k+1} \]  

(7)

\[ \hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1} V_{k+1} \]  

(8)

\[ P_{k+1|k+1} = (I - K_{k+1} H_{k+1}) P_{k+1|k} (I - K_{k+1} H_{k+1})^T + K_{k+1} R_{k+1} K_{k+1}^T \]  

(9)
Where $K_{k+1}$ represents kalman gain; $R_{k+1}$ indicates covariance of measurement noise; $V_{k+1}$ denotes innovation vector; $Z_{k+1}$ is measurement (observations) vector; $\hat{x}_{k+1|k+1}$ is a posteriori estimate of state vector (corrected); $P_{k+1|k+1}$ is a posteriori covariance matrix of state vector (corrected); and $k$ shows time. Innovation vector $V_{k+1}$ is difference between actual observation and predicted observation at time $k+1$ and if value of kalman gain is high then updated state vector $\hat{x}_{k+1|k+1}$ will rely more on innovation vector and if value of kalman gain is low, updated state vector will rely more on predicted state vector $\hat{x}_{k+1|k}$.

4. KINEMATIC DEFORMATION MODEL.

Any of static, kinematic or dynamic geodetic models can be used for landslide monitoring. Static model determines only displacement; kinematic models determine displacement, velocity and acceleration. On the other hand, dynamic models include the effect of causative forces, displacement, velocity and acceleration of network stations (Yalcinkaya and Bayrak, 2005). In this paper, a KF based kinematic deformation model is presented. The time-dependent 3D kinematic model consisting of position, velocity and acceleration of GPS stations can be expressed as (Acar et al., 2008) follows:

$$
X_{k+1} = X_k + (t_{k+1} - t_k)V_{x_{k+1}} + (t_{k+1} - t_k)^2 a_{x_{k+1}} / 2
$$

$$
Y_{k+1} = Y_k + (t_{k+1} - t_k)V_{y_{k+1}} + (t_{k+1} - t_k)^2 a_{y_{k+1}} / 2
$$

$$
Z_{k+1} = Z_k + (t_{k+1} - t_k)V_{z_{k+1}} + (t_{k+1} - t_k)^2 a_{z_{k+1}} / 2
$$

Where $X, Y, Z$ are coordinates of GPS stations and $V_x, V_y, V_z$ are respective velocity and $a_x, a_y, a_z$ are respective accelerations. This model can also be written in a matrix form as follows:

$$
\begin{bmatrix}
X \\
V_x \\
a_x \\
Y \\
V_y \\
a_y \\
Z \\
V_z \\
a_z \\
\end{bmatrix}_{k+1} =
\begin{bmatrix}
1 & t & t^2 / 2 \\
0 & 1 & t \\
0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
X \\
V_x \\
a_x \\
Y \\
V_y \\
a_y \\
Z \\
V_z \\
a_z \\
\end{bmatrix}_k + W_k
$$

Where for $t = t_{k+1} - t_k$,

$$
s_{3x3} =
\begin{bmatrix}
1 & t & t^2 / 2 \\
0 & 1 & t \\
0 & 0 & 1 \\
\end{bmatrix}
$$

Equation (14) can be written as:

$$
X_{k+1} = \Phi_k X_k + w_k
$$

Where $W_k$ is process noise.

For known initial mean $\hat{x}_{k|k}$ and its covariance matrix $P_{k|k}$ of state vector, estimate of state vector and covariance matrix for next step can be determined using equation (5) to equation (10). Where process noise covariance matrix $Q_k$ for 3D kinematic model can be written as follows:
\[ Q_k = \begin{bmatrix} q_{3,3} & 0_{3,3} & 0_{3,3} \\ 0_{3,3} & q_{3,3} & 0_{3,3} \\ 0_{3,3} & 0_{3,3} & q_{3,3} \end{bmatrix} \]  

(16)

Where, \( q \) takes the following form:

\[ q_{3,3} = \begin{bmatrix} t^3 / 20 & t^4 / 8 & t^5 / 6 \\ t^4 / 8 & t^5 / 3 & t^5 / 2 \\ t^5 / 6 & t^5 / 2 & t \end{bmatrix} \]  

(17)

Where, \( S \) is power spectral density of process noise \( w_k \) and \( I = I_{k+1} - I_k \). The process noise can affect the results in case of incorrect modelling. Therefore, proper modelling of process noise is necessary.

5. METHODOLOGY

Initially, a static deformation analysis has been performed to acquire real positional displacement of GPS stations between \( \text{epoch1} \) and \( \text{epoch3} \). To determine displacement between \( \text{epoch1} \) and \( \text{epoch3} \), observation files of all five GPS stations of every epoch have been processed by a free online PPP tool GNSS Analysis and Positioning Software (GAPS) developed at the University of New Brunswick (UNB), Canada. Further, the results consisting of coordinates of all GPS stations of \( \text{epoch1} \) and \( \text{epoch3} \) are subtracted.

In the KF algorithm, GPS station coordinates and their variance from GAPS results are used as input. As mentioned earlier, the elements of state vector are coordinates, velocity and acceleration of GPS station. For initial state vector, coordinates of GPS stations are taken from GAPS results of observation \( \text{epoch1} \) and initial velocity of GPS stations is calculated by dividing the positional displacement with the time-interval between first and second observation epochs. The acceleration of GPS stations is calculated by dividing the positional displacement with the square of the time-interval between first and second observation epochs. The measurement vector is a column vector which contains coordinates of GPS stations. A Matlab code of KF is developed to process the input data and predict the state vector for \( \text{epoch3} \) to compute predicted displacement of GPS stations followed by comparison with the GAPS results. The followed methodology is summarized in flowchart (Figure 3).

Steps followed to perform kinematic deformation analysis using developed algorithm:
(a) Initial mean and Covariance matrix of state vector as input.
(b) Prediction Step: Compute a priori estimate of state vector \( \hat{x}_{k+1/k} \) and a priori covariance matrix of state vector \( P_{k+1/k} \).
(c) Correction Step: Compute a posteriori estimate of state vector \( \hat{x}_{k+1/k+1} \) and a posteriori covariance matrix \( P_{k+1/k+1} \) of state vector.
(d) Compute positional displacement between \( \text{epoch1} \) and \( \text{epoch3} \) after repeating Step1-3 for every GPS stations.

6. RESULTS AND DISCUSSION

The positional displacement of point or network during a time-interval indicates surface deformation. Static deformation analysis gives actual displacement of the GPS stations between \( \text{epoch1} \) and \( \text{epoch3} \) as shown in Table 1 (Column 2). The result of KF algorithm based on Kinematic deformation model gives the predicted displacement of the GPS stations between \( \text{epoch1} \) and \( \text{epoch3} \) (predicted) as shown in Table 1 (Column 3). Taking GAPS result as reference, it can be inferred from Table 1 (Column 4) that the difference between predicted displacement (KF result) and actual displacement (GAPS result) ranges from a centimetre to sub-centimetre level with maximum difference of 23.29 cm for station GPS5 (Y-axis) and minimum difference of 0.59 cm for station GPS1 (Z-axis). The large variation in the KF results is due to making prediction for \( \text{epoch3} \) on the basis of \( \text{epoch1} \) and \( \text{epoch2} \) while actual displacement of GPS stations between \( \text{epoch1} \) and \( \text{epoch2} \) was more than displacement between \( \text{epoch2} \) and \( \text{epoch3} \). Figure 4 shows a measure of overall deformation at every GPS station which has been calculated by taking square-root of square-sum of all three displacement. From prediction step of KF, figure 5 shows the prediction of displacement in X, Y and Z direction of GPS1 point based on the available data. But, KF prediction is suitable for short-time only.
Start

Site selection and establishment of GPS stations

GPS Data collection

3D kinematic deformation model

Processing using Kalman filter algorithm

Processing with GAPS

Kinematic Deformation model result

Comparison

End

Figure 3: Flowchart of methodology

<table>
<thead>
<tr>
<th>GPS Stations</th>
<th>GAPS Result (cm)</th>
<th>KF Result (cm)</th>
<th>Difference (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$X_{31}$</td>
<td>$Y_{31}$</td>
<td>$Z_{31}$</td>
</tr>
<tr>
<td>GPS1</td>
<td>-4.11</td>
<td>0.23</td>
<td>7.65</td>
</tr>
<tr>
<td>GPS2</td>
<td>-6.52</td>
<td>-18.11</td>
<td>-9.39</td>
</tr>
<tr>
<td>GPS3</td>
<td>15.61</td>
<td>-0.21</td>
<td>16.26</td>
</tr>
<tr>
<td>GPS4</td>
<td>-7.11</td>
<td>-30.68</td>
<td>-4.67</td>
</tr>
<tr>
<td>GPS5</td>
<td>-21.27</td>
<td>14.75</td>
<td>9.65</td>
</tr>
</tbody>
</table>

Table 1. Static and Kinematic Deformation results and their difference
7. CONCLUSIONS

A KF based kinematic model is presented in this work for surface deformation analysis of landslide. It is observed that the surface displacement can be predicted in the centimetre to sub-centimetre range following the model. The current results provide scope for understanding the ongoing deformation for further mitigation planning and risk reduction in areas that are prone to landslides. The KF algorithm can also be used to predict missing epoch data in landslide inventory management and also in research fields to develop multi-epoch data for simulation studies. There is variability in the data which suggests analysis with multi-epoch data (at least 4-5 epochs) for validating the prediction and improvisation in the algorithm.

ACKNOWLEDGEMENTS

Authors are thankful to NRDMS, DST for the providing the financial support to conduct the campaign mode GPS survey.
REFERENCES


ABSTRACT

The Chakrata-Kalsi road corridor (42 km), covering 34 Census Villages in Dehradun district of Uttarakhand state, India, is located in a rugged mountainous terrain which experiences a significant number of landslides each year owing to its structural, lithological and geomorphological complexity. The main purpose of this study is to obtain Landslide Susceptibility Index (LSI) map by using Frequency Ratio (FR) model based on observed relationship between landslide distribution and each landslide causative factor, applying geostatistical technique. First, a landslide inventory map was created from satellite images, published reports and field investigations. Then, the landslide inventory map was randomly separated into training datasets and validation datasets, (70% and 30%, respectively). For model set-up, prominent contributing factors viz., slope, aspect, altitude, lithology, fault lines, drainage network, Stream Power Index (SPI), Topographical Wetness Index (TWI), rainfall, road network, landuse/landcover (LULC), soil, and seismicity, were mapped and classified into a number of significant classes based on their relative influence on landslide occurrence. Finally, the LSI map was validated through Receiver Operating Characteristic (ROC) curve and, the model output was found reasonably accurate (82.1% at 95% confidence level). The resultant maps would be useful for landslide monitoring and regional spatial planning besides mitigating potential landslide impacts in future.

KEYWORDS: Landslide Susceptibility Index (LSI), FR model, Satellite data, Geostatistical techniques

1. INTRODUCTION

Landslides are significant amongst those hazards that can easily be disastrous to human life and property (Chingkhei et. al., 2013). In the Himalayan terrain, landslides are amongst the most common natural hazards that pose a major threat to socio-economic development of an area as well as the livelihood of the people residing there (Mathew et. al. 2007). The steeper slopes, profound weathering of bedrocks, and intense rainfall in the middle Himalayas together develops complex geological conditions favorable for landslides (Gabet et. al. 2004). According to Geological Survey of India (GSI), 0.14 million sq. km area in North West Himalayas (Uttarakhand, Himachal Pradesh and Jammu & Kashmir) are prone to landslide hazard.

Every year, landslides along the Kalsi-Chakrata road corridor located in Dehradun district of Uttarakhand results in a considerable amount of damages to roads, buildings and other infrastructure elements and, even loss of lives. The incidents reported in the national and local newspapers show that this road corridor is blocked by landslide debris every year during the monsoon season.

The predictions associated to landslide studies are always subjected to uncertainties and hence, ‘when’, ‘where’ and ‘what magnitude’ are considered as an important aspect of prediction (Singh et al. 2015). There are various advanced methods and techniques for prediction of landslides which have been applied in different parts across the globe, though their accuracy and prediction capability varies widely (Chen et al. 2016). Hence, it is significant to adopt a contemporary approach that addresses the landslide issues locally based on the above conjecture. In the past decades, there has been quite a few good research works carried out to prepare landslide susceptibility assessment based on qualitative and quantitative approaches (Guzzetti et al. 1999; Pradhan et al. 2010; Onagh et al. 2012a and 2012b; Bui et al. 2012; Bui et al. 2015b; Palenzuela et al. 2015; Gorsevski et al. 2016; Haoyuan et al. 2016; Pham et al. 2017).

The literature survey carried out on landslides in Kalsi-Chakrata road corridor reveals that so far no in-depth and holistic scientific research has been conducted for this area on landslide hazard. To fill in the lacunae, this paper proposes a detailed landslide investigation using advanced geospatial techniques to identify the most vulnerable areas that need immediate attention. The Frequency Ratio (FR) model in association with GIS and remote sensing techniques is one of the widely used statistical methods applied by the researchers for landslide susceptibility mapping (Akgun 2012; Pradhan et al. 2010; Jaafari et al. 2014; Rohan and Ambalagan 2015). The effort in this study includes detailed investigation of landslide susceptible areas that can focus on appropriate mitigation measures thus can lead to potential future economic development prospect of Kalsi-Chakrata road corridor and the neighboring areas.

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2. STUDY AREA

Chakrata is a small hill station and a famous tourist destination located in Dehradun district of Uttarakhand state, India at a height of 2,118m above sea level. This town is primarily connected to Dehradun (Capital of Uttarakhand) and Saharanpur (a market hub in Uttar Pradesh) through Vikasnagar-Chakrata road via places like Kalsi, Sahiya. The Kalsi-Chakrata road corridor selected for this study is about 42 km long and the road starts ascending from Kalsi towards Chakrata. For this research, 34 Census villages and one municipal corporation (Chakrata) have been considered that intersects with the road corridor. According to Census of India (2011) village boundary, the study area spreads over more than 72 sq km with a population of more than 16,600 residing in 2,700 households (Figure 1).

To make this research more comprehensive and concise, while the landslide hazard risk has been estimated for the entire study area.

3. DATA AND MATERIALS

The data for the present study has been selected judiciously considering higher resolution and latest vintages (Table 1).

<table>
<thead>
<tr>
<th>Descriptions</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satellite Images and Products</td>
<td>- Generated DTM from Cartosat 10 m DSM purchased from NRSC (May 2017)</td>
</tr>
<tr>
<td></td>
<td>- LISS-IV images of March 2017 procured from NRSC on May 15, 2017</td>
</tr>
<tr>
<td>Historical Landslide Events</td>
<td>- Delineated from LISS-IV satellite images, Google Earth satellite images</td>
</tr>
<tr>
<td></td>
<td>- Published data (reports and newspaper), PWD, Uttarakhand</td>
</tr>
<tr>
<td></td>
<td>- Field visit and data collection</td>
</tr>
<tr>
<td>Slope, Aspect, Altitude, Stream/ River Network</td>
<td>- Digital Terrain Model (DTM) - 1m resolution derived from Cartosat 1m DEM</td>
</tr>
<tr>
<td>Lithology</td>
<td>- Geological Survey of India (1:25,000)</td>
</tr>
<tr>
<td>Road Network/ Road Buffer, LULC</td>
<td>- LISS-IV images of March 2017</td>
</tr>
<tr>
<td>Soil Map</td>
<td>- FAO (UNESCO) Soil map, NBSS Soil map</td>
</tr>
<tr>
<td>Road Network/ Road Buffer</td>
<td>- LISS-IV images of March 2017</td>
</tr>
<tr>
<td>Seismicity</td>
<td>- From BIS Earthquake Map, modified after GSHAP 30m data</td>
</tr>
<tr>
<td>Rainfall</td>
<td>- IMD (ten districts surrounding the study area for over past 70 years)</td>
</tr>
<tr>
<td>Topographical Wetness Index (TWI), Stream</td>
<td>- Flow accumulation and Slope map derived from 1m resolution DTM</td>
</tr>
<tr>
<td>Power Index (SPI)</td>
<td></td>
</tr>
</tbody>
</table>

3.1 Landslide Inventory

In LSI models, the first important step is to identify the past and present landslide locations (Deng, 2017). This is to perform the analysis on a homogenous population considering types and magnitude of landslides. To come up with a detailed and reliable inventory map for the study area, two sources were explored including detailed field surveys and laboratory investigations: (1) the landslide records collected from the state Public Works Department (PWD), and (2) the landslide scars of past events delineated from LISS IV satellite image (5.8m spatial resolution, 2016 vintage) and Google Earth satellite images. This event location was checked thoroughly during extensive field surveys using GPS and cameras with geocoding facility (Figure 2). Next, the total landslides locations (56 nos.) were distributed into 70% as training datasets and remaining 30% as validation datasets (Deng et al. 2017). This has been delineated as a thematic binary layer in the form of ‘0’ and ‘1’ pixels representing the presence and absence of landslides.
3.2 Conditional Factors

Generally, the selection of landslide conditioning factors and subsequent data are performed based on intensive literature review and, the method and techniques are adopted based on specific site conditions (Pradhan et al. 2010; Hong et al. 2015; Xu et al. 2016). The number of conditioning factors to be used for landslide hazard assessment often varies from few factors (Pradhan et al. 2010; Akgun 2012) to a large number of factors (Catani et al., 2013; Tien Bui et al. 2015a; Xu et al. 2016). In this study, based on widespread literature review and the objective of the research, the following conditioning factors were selected: Slope, Aspect, Altitude, Thrust-Fault Proximity, Drainage Proximity, Road Proximity, Normalized Differential Vegetation Index (NDVI), Rainfall, Seismicity, Soil, Topographic Wetness Index (TWI), Stream Power Index (SPI), Lithology, Landuse / Landcover (LULC).

Figure 2. Field Photographs showing (a) major landslide area near Sahiya, (b) landslide affecting utilities, (c) landslide affecting highway and village roads, (d) solitary landslide warning board (photos taken between Aug’16 and Mar’18)

![Field Photographs showing](image-url)
4. METHODOLOGY

4.1 Selection of Training and Validation Datasets

For probability based landslide hazard analysis, a precise past landslide event database with spatial location is essential. In the present study, such past events were prepared using higher resolution satellite data, published and available reports and intensive field survey. The total landslides scars were distributed into 70% as training datasets and remaining 30% as validation datasets (Deng et al. 2017). This was delineated as a thematic binary layer in the form of ‘0 and ‘1’ pixels representing the presence and absence of landslides.

4.2 Landslide Susceptibility Index (LSI) using Frequency Ratio (FR) Model

The Frequency Ratio (FR) model is a leading probability model in Landslide Susceptibility Index (LSI) mapping. This is based on the observed spatial relationships between each landslide conditioning factor and the distribution of past landslides. Put simply, FR is the ratio of the probabilities of a landslide occurrence to a non-occurrence for a given attribute (Lee and Talib 2005). This is a complete model where more independent variables play an important role in determining the dependent variables, particularly anticipating hillside instability (Dai and Lee 2002; Abedini et al. 2017). The advantages of this model are that it can be simply implemented and its result is completely easy to comprehend (Ozdemir and Altural 2013).

In this study, the LSI was calculated using FR model by summation of each factor's ratio value using the following equation (Lee and Pradhan 2007) (Eq. 1).

\[ LSI = \sum FR \] (1)

In an area, a higher LSI value indicates a higher susceptibility to landslide while a lower LSI value indicates a lower susceptibility to landslides.
Now, the calculation for FR values, for each of the conditioning factors, is determined by the percentage of landslide cells divided by the percentage of non-landslide occurrence cells (Deng et al. 2017), denoted as:

\[ FR_{ij} = \frac{Np(S_{ij})}{\sum_j Np(S_{ij})} / \frac{Np(N_{ij})}{\sum_j Np(N_{ij})} \]  

(2)

where, \( FR_{ij} \) is the frequency ratio of class \( j \) in factor \( i \); \( Np(S_{ij}) \) is the number of pixels of landslide occurrence within class \( j \) in factor \( i \); \( Np(N_{ij}) \) is the number of pixel of class \( j \) in factor \( i \).

Here, the FR represents that of the area where landslides occurred in the entire study area (Eq. 2). The FR value of 1.0 denotes average value, whereas, a value greater than 1.0 indicates a strong correlation between landslide occurrence and their conditioning factors. On the other hand, a value lower than 1.0 indicates a weak correlation between landslide occurrence and their conditioning factors.

The first step for landslide hazard mapping is identification of landslide conditional factors in the study area. Based on this, the researcher decides the resolution of the required data. For example, if the collection of higher resolution DTM is possible for the research, the accuracy of the analysis will certainly be improved and more accurate prediction can be made through Integrated GIS and RS techniques and field investigations. FR techniques has then been applied to estimate the landslide probabilities and, after due validation, the hazard analysis result may be considered for planning and mitigation purposes (Figure 4).

LSI mapping using FR model (cell size: 5 m x 5 m) was performed using Geospatial technique though the following steps-

i. Detection of past landslide events in the study area using satellite images, reports and field survey
ii. Identification and mapping of landslide conditioning factors and their classification
iii. Overlay of raster layers, conditioning factors and past landslide events
iv. Computation of the landslide cells and non-landslide occurrence cells
v. Calculation of FR values based on Eq. 2
vi. Preparation of LSI maps by aggregating FR values based on Eqn. 1
vii. Preparation of landslide zonation maps and analysis of the results
viii. Validation of the FR model results

5. RESULTS AND ANALYSIS

5.1 Landslide Conditional Factor Analysis

The result obtained from the FR model considering training datasets using GIS and Remote Sensing techniques has been tabulated below (Table 2).

Table 2. Results derived from the analysis of FR model

<table>
<thead>
<tr>
<th>Factor</th>
<th>Unit</th>
<th>Class</th>
<th>Class %</th>
<th>LSD %</th>
<th>FR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>Degree</td>
<td>0 – 10</td>
<td>34%</td>
<td>0.9%</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10 – 20</td>
<td>29%</td>
<td>6.7%</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 – 35</td>
<td>4%</td>
<td>2.4%</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>35 – 50</td>
<td>27%</td>
<td>46.3%</td>
<td>1.74</td>
</tr>
<tr>
<td></td>
<td></td>
<td>50 – 89</td>
<td>6%</td>
<td>43.8%</td>
<td>7.26</td>
</tr>
<tr>
<td></td>
<td>Flat</td>
<td>5%</td>
<td>0.0%</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Aspect</td>
<td>Class</td>
<td>North</td>
<td>13%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NE and NW</td>
<td>33%</td>
<td>0.7%</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>S and SW</td>
<td>5%</td>
<td>53.8%</td>
<td>10.18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>E and SE</td>
<td>23%</td>
<td>8.8%</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SE</td>
<td>20%</td>
<td>36.7%</td>
<td>1.80</td>
</tr>
<tr>
<td>Altitude</td>
<td>Meter</td>
<td>39 – 500</td>
<td>8%</td>
<td>0.1%</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>500 – 1000</td>
<td>21%</td>
<td>43.8%</td>
<td>2.06</td>
</tr>
<tr>
<td>Factor</td>
<td>Unit</td>
<td>Class</td>
<td>Class %</td>
<td>LSD %</td>
<td>FR</td>
</tr>
<tr>
<td>-----------------</td>
<td>------------</td>
<td>---------</td>
<td>---------</td>
<td>--------</td>
<td>-----</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1000 – 1500</td>
<td>51%</td>
<td>55.8%</td>
<td>1.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1500 – 2000</td>
<td>8%</td>
<td>0.3%</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2000 – 2660</td>
<td>12%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td>Road Buffer</td>
<td>Meter</td>
<td>&lt; 100</td>
<td>53%</td>
<td>59.5%</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 – 200</td>
<td>6%</td>
<td>21.1%</td>
<td>3.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>200 – 300</td>
<td>7%</td>
<td>16.2%</td>
<td>2.28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>300 – 400</td>
<td>9%</td>
<td>2.9%</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>400 – 500</td>
<td>11%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt; 500</td>
<td>14%</td>
<td>0.3%</td>
<td>0.02</td>
</tr>
<tr>
<td>Drainage Buffer</td>
<td>Meter</td>
<td>&lt; 100</td>
<td>31%</td>
<td>16.9%</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 – 200</td>
<td>14%</td>
<td>24.2%</td>
<td>1.70</td>
</tr>
<tr>
<td></td>
<td></td>
<td>200 – 300</td>
<td>16%</td>
<td>19.8%</td>
<td>1.22</td>
</tr>
<tr>
<td></td>
<td></td>
<td>300 – 400</td>
<td>18%</td>
<td>17.1%</td>
<td>0.96</td>
</tr>
<tr>
<td>Seismicity</td>
<td>m/s²</td>
<td>3.5 – 3.58</td>
<td>17%</td>
<td>16.3%</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.59 – 3.64</td>
<td>19%</td>
<td>52.6%</td>
<td>2.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.65 – 3.71</td>
<td>19%</td>
<td>11.3%</td>
<td>0.59</td>
</tr>
<tr>
<td>SPI Ratio</td>
<td></td>
<td>10 – 15</td>
<td>86%</td>
<td>92.6%</td>
<td>1.08</td>
</tr>
<tr>
<td>Fault Buffer</td>
<td>Meter</td>
<td>&lt; 100</td>
<td>7%</td>
<td>5.1%</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100 – 200</td>
<td>15%</td>
<td>2.0%</td>
<td>0.13</td>
</tr>
<tr>
<td>Rainfall</td>
<td>mm</td>
<td>1339 – 1371</td>
<td>24%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1372 – 1398</td>
<td>17%</td>
<td>6.4%</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1399 – 1426</td>
<td>20%</td>
<td>18.9%</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1427 – 1453</td>
<td>17%</td>
<td>44.7%</td>
<td>2.56</td>
</tr>
<tr>
<td>TWI Ratio</td>
<td></td>
<td>0 – 4</td>
<td>71%</td>
<td>82.7%</td>
<td>1.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 – 8</td>
<td>25%</td>
<td>16.4%</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8 – 12</td>
<td>2%</td>
<td>0.7%</td>
<td>0.29</td>
</tr>
<tr>
<td>NDVI Ratio</td>
<td></td>
<td>0.5 – 0.76</td>
<td>11%</td>
<td>0.2%</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.4 – 0.50</td>
<td>21%</td>
<td>0.4%</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.3 – 0.40</td>
<td>36%</td>
<td>9.4%</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2 – 0.3</td>
<td>28%</td>
<td>56.6%</td>
<td>2.01</td>
</tr>
<tr>
<td>Soil Class</td>
<td></td>
<td>13</td>
<td>14%</td>
<td>0.3%</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>28</td>
<td>18%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>45</td>
<td>3%</td>
<td>2.7%</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td></td>
<td>35</td>
<td>65%</td>
<td>97.0%</td>
<td>1.50</td>
</tr>
<tr>
<td>Lithology Class</td>
<td></td>
<td>Shale, Phylite, Siltstone, Quartzite, Limestone, greywacke Conglomerate</td>
<td>53%</td>
<td>21.7%</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Greywacke, Shale, Quartzite, Dolomite, tuff with Dolerite</td>
<td>35%</td>
<td>71.9%</td>
<td>2.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sandstone, Claystone, Siltstone, shale</td>
<td>2%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Multicyclic sequence of brown to grey Silt clay with kankar and micaceous sand with pebbles</td>
<td>2%</td>
<td>2.7%</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Brownish grey, clay, sand and gravel with boulders</td>
<td>1%</td>
<td>0.0%</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Carbonaceous shale, slate, greywacke</td>
<td>1%</td>
<td>3.6%</td>
<td>2.76</td>
</tr>
<tr>
<td>Factor</td>
<td>Unit</td>
<td>Class</td>
<td>Class %</td>
<td>LSD %</td>
<td>FR</td>
</tr>
<tr>
<td>------------------------</td>
<td>------</td>
<td>---------------------------------------------------------</td>
<td>---------</td>
<td>-------</td>
<td>-----</td>
</tr>
<tr>
<td>Micaceous sandstone,</td>
<td></td>
<td>purple clay, mudstone</td>
<td>2%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Carbonaceous slates,</td>
<td></td>
<td>quartzite, dolomite withstromatolite and cherry</td>
<td>4%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>River &amp; Waterbody</td>
<td></td>
<td></td>
<td>1%</td>
<td>0.5%</td>
<td>0.53</td>
</tr>
<tr>
<td>Sandy area</td>
<td></td>
<td></td>
<td>1%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Settlement</td>
<td></td>
<td></td>
<td>1%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Dense Veg</td>
<td></td>
<td></td>
<td>33%</td>
<td>0.5%</td>
<td>0.02</td>
</tr>
<tr>
<td>Plantation</td>
<td></td>
<td></td>
<td>0%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Agriculture</td>
<td></td>
<td></td>
<td>8%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Sparse Veg</td>
<td></td>
<td></td>
<td>17%</td>
<td>12.5%</td>
<td>0.74</td>
</tr>
<tr>
<td>Rocky &amp; Barren land</td>
<td></td>
<td></td>
<td>0%</td>
<td>4.5%</td>
<td>22.56</td>
</tr>
<tr>
<td>Mining</td>
<td></td>
<td></td>
<td>0%</td>
<td>0.0%</td>
<td>0.0</td>
</tr>
<tr>
<td>Scrub land</td>
<td></td>
<td></td>
<td>3%</td>
<td>0.5%</td>
<td>0.17</td>
</tr>
<tr>
<td>Open area</td>
<td></td>
<td></td>
<td>36%</td>
<td>81.5%</td>
<td>1.98</td>
</tr>
</tbody>
</table>

Once the FR model was successfully calculated for all the conditioning factors in the study area, the values were used to calculate the LSI for all the pixels in each domain. The aggregated LSI values were reclassified into five landslide susceptibility classes as very high, high, moderate, low and very low using the Jenks natural breaks method and landslide susceptibility map was produced (Figure 5).

5.2 Model Results and Analysis

The results obtained from the FR model showing landslide susceptibility assessment shows that about 8.54 sq km. (10.3% ) of the study area falls in high to very high landslide susceptibility classes. More than 47.6 sq. km. (57.5%) area has been classified to fall within moderately susceptible zone where chances of future landslides may augmented without periodic observation and future study. It was observed that the highest FR weight (22.56) was obtained in case of Rocky and Barren Land from LULC class as barren and rocky land having sparse vegetation have positive correlation with the landslide occurrence. This was followed by NDVI class of <0.20 ratio (FR weight of 10.52) and South - South-west aspect class (FR weight of 10.18). The vegetation on steep slopes, binds the soil and reduces erosion and thus, lesser the vegetation cover, more chances of landslide combined with other conditioning factors. The result shows that lower the NDVI values, higher the FR weights. Among the main terrain factors, higher slope (>50°) with FR weight of 7.26 followed by altitude between 500 - 1,000 m has high FR weight of 2.06. Among the hydrological parameters of TWI and SPI, TWI (for class 0-4 ratio) has generated the FR weight value of 1.16, whereas, SPI (for class of 10-15) was 1.08 which resembles that the terrain moisture is also an important parameter affecting the landslides in an area. The other factors having higher FR weights are Road Buffer (3.54 FR weight for 100-200m distance class), Lithology (2.76 FR weight for Infra Krol Formation, Proterozoic III Upper), Seismicity (2.76 FR weight for ground acceleration of 3.59 - 3.64 m/s2), Rainfall (2.56 FR weight for higher rainfall class of 1427 - 1453 mm) and Drainage Buffer (1.70 FR weight for 100-200m distance class).

5.3 Model Validation

The results of the landslide susceptibility analysis using FR model were validated using the known landslide locations that were not used as training data sets for susceptibility analysis. The Area under the Curve (AUC) approach was used to evaluate the prediction probability. In this study, the ROC curve was generated to represent the cumulative distribution of the binary variable against the performance of the model.
output values. The ROC curve represents the true positive rates which are known as sensitivity versus the false positive rates (also known as 1-specificity) (Muhammad et al. 2012) according to the cut-off value or the threshold. It plots the cumulative distribution of the false alarm probability on the y axis and the detected probability of the variable on the x-axis (Qianqian et al. 2017). The results of the landslide susceptibility analysis using FR model were validated using the known landslide locations that were not used as training data sets for susceptibility analysis. Next, the landslide susceptibility map was compared with known landslide events (validation datasets) and rate curves were created and area under the curve was calculated (Figure 6).

The AUC value obtained for the study area, using 30% of the total observed landslides, was 82.1% at 95% confidence level from the FR model that indicates a higher accuracy in classifying the areas of existing landslides. This indicates that the FR model has a good prediction capability and the LSI map generated in this study has a close resemblance for future landslide scenarios at specified locations. Hence, due to the satisfactory result, the model is recommended in landslide prediction mapping and it has area under curve more than 0.5 which is the cut-off value of the hypothesis testing. Therefore, null hypothesis is rejected and alternate hypothesis is accepted (Sarkar 2008) and both the models used in this study are statistically significant for landslide susceptibility assessment.

6. DISCUSSION AND CONCLUSION

The methodologies to map LSI provide an useful prediction for the decision makers and authorities in landslide prone areas in adopting appropriate approaches in minimizing the potential losses. In the present study, the resultant landslide susceptibility map generated applying FR model shows that the areas with higher landslide susceptibility are mainly distributed along the south-central and central areas along the highway. It has been observed that landslides in the study area are mainly affected by slope, aspect, road construction, NDVI, lithology, rainfall and landuse changes. Among these, the lack of vegetation cover (rocky and barren land in LULC class and NDVI class with less than 0.2 value) coupled with steep slopes (greater than 50°) and greywacke type lithology are main contributing factors responsible for landslide occurrence. The utmost vital factors triggering landslide in the present study area estimated for FR model is rocky and barren land that has a FR index as high as 22.56.

In areas of high to very high landslide hazard, immediate attention is required in terms of suitable mitigation planning, whereas, periodic observations and future study is recommended in moderately susceptible landslide hazard areas, so that appropriate measures can be planned in long term to reduce future hazard risks. In general, the study reveals that the FR methods is an effective method of landslide susceptibility assessment and shows 82.1% accuracy in landslide prediction evaluated through ROC curve (at 95% confidence level). entropy values are LULC class (1.74) which constitute of mostly barren land and sparse vegetation. Hence, the FR model can be adopted for landslide susceptibility in areas similar to Kalsi-Chakrata road corridor area of Uttarakhand.

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GEOMORPHOLOGICAL FEATURES AND CERTAIN SIGNIFICANT OBSERVATIONS OF CHILIKALAGOON INLETS- A GEOGRAPHICAL ANALYSIS

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ABSTRACT

Sustainable restoration of endangered coastal ecosystems today is of great environmental interest and scientific value. Among the coastal ecosystems, the lagoon shows a wide range of geographical and ecological variation. Asia’s largest brackish water lagoon the Chilika lake, separated from Bay of Bengal by a series of barrier spits situated between the latitude 19° 28′–19° 54′ N and longitude 85° 05′–85° 38′ E in the State of Odisha, India. Siltation of the lake is becoming a matter of concern as this leads to various geomorphologic changes, and affects the shape and size of the lagoon, receiving major portion of silt through rivers Daya and Bhargovi, the southern branches of the Mahanadi River, via the Kathajodi and the Kuakhai Rivers. One of the major geomorphological aspects of Chilika is its inlet, which has played a major role in the very existence of the lagoon and because of which Chilika has got its lagoonal character. Due to the strong dynamics of these inlets, associated with a strong long shore current and littoral drift of the Bay of Bengal towards north, as the incoming wave deflect towards North due to Coriolis force, the inlet migrates in the North-East direction. This paper presents the use of advanced technologies like Remote Sensing Technique and also GIS to know the geomorphological changes of Chilika inlets for the period 1975 to 2015. The findings of this paper will provide baseline data that can facilitate the long term monitoring of the inlet and its stability.

KEYWORDS: Geomorphological changes, Brackish, Ecological variation, Coriolis force, Inlets

1. INTRODUCTION

A coastal lagoon is a distinct dynamic environment where interplay of different energy forces from land-sea atmosphere operates in a shallow body of water which is partly enclosed by a barrier and has restricted or ephemeral communication with the sea through one or more inlets (Phleger, 1960). They serve as buffer zones for nutrients storage and fluxes coming from adjacent continental drainage to the marine environment. These shallow water bodies, formed by a mixture of brackish and sea water consists of a main basin with a parallel to the coast orientation, being separated partially from the adjacent sea by sand bars formed at their mouths (Barnes, 1980). Lake Chilika, the largest coastal lagoon on the east coast of India and lifeline of the state of Odisha, is a designated Wetland of International Importance (Ramsar Site under the Convention on Wetlands) since 1981. Chilika went through a phase of rapid degradation during 1950-2000 owing to increasing sediment loads from catchments and reduced connectivity with the sea. Its fisheries underwent a major decline, invasive weeds proliferated and the wetland shrank in area and volume. This had tremendous impact on the livelihood of communities, especiallyfishers. Introduction of shrimp culture added further pressure on lagoon ecology and ultimately led to significant disruption of community institutions, which traditionally managed fisheries sustainably. This formed the background for inclusion of Chilika into the Montreux Record of Ramsar Convention in 1993. The Lagoon is a unique assemblage of marine, brackish and fresh water eco-system with estuarine characters. One of the major geomorphological aspects of Chilika is its inlets, which has played a major role in the very existence of the lagoon and because of which Chilika has got its lagoonal character. Due to the strong dynamics of these inlets, associated to a strong long shore current and littoral drift of the Bay of Bengal towards north, as the incoming wave deflect towards North due to Coriolis force the inlet migrate in the North-East direction. The tidal impact on the lagoon decreasing at an alarming rate, due to which there was reduction in the salinity level, increase in weed infestation area and chokeing of the Magarmukha channel which connects the Lagoon to Bay of Bengal, which also reduced Tidal Prism. To address the problems Chilika Development Authority, dredged an artificial mouth on 23rd September 2000 opposite the village Sipakuda. The long shore Current moves sand along the coast and the energy from the winds is transferred to the ocean producing waves that strike the shore at an angle. These waves also give rise to long shore current moving sand from the south to the north. The character of an inlet — its shape, dynamics, navigability — may change over time as the inlet adjusts to changes in the way tides and waves interact (Hine et al.1986). The origin and evolution of Chilika lagoon can be traced by studying the historical facts and literature/findings of various scientists and researchers who believed that coastal lagoons are all recent and transient geological features. The fundamental process leading to their formation is a relative change in sea level, brought by either coastal emergence or submergence (Zenkovitch, 1967). In case of an emergent coastline, shallow waters overlying and offshore-submerged beach may lead to the formation of a bar, which isolates the inshore water and thus forms a lagoon (Mee, 1978). The Geomorphological changes directly affect the amount of saline water ingress through the inlets during flood tide, which to a great extent impact the circulation pattern of the lagoon and also salinity propagation in the lagoon. This paper presents the use of advanced technologies like Remote Sensing and also GIS, to know the geomorphological changes of Chilika inlets for the period 1975 to 2015. The findings of this paper will provide baseline data that can facilitate the long term monitoring of the inlet and its stability.

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2. STUDY AREA

Chilika Lake, the largest brackish water lagoon in Asia, is a prominent biodiversity hotspot along the Indian east coast. The geomorphology, water quality and biological productivity of the lake had undergone significant changes over the years under the influence of natural events and anthropogenic interventions. Lake Chilika fluctuates in area between monsoon maximum of 1,165 km² and dry season minimum of 906 km². The pear shaped wetland spans between 19° 28′–19° 54′ N and 85° 05′–85° 38′ E with a linear axis of 64.3 km and an average width of 20.1 km. Its eastern margin is dotted by 24 islands covering an area of 18.4 km². Chilika is connected to the sea by a 32 km long channel opening into the Bay of Bengal opposite to Sipakuda, and in the south through the Palur Canal which links Chilika Rushikulya estuary. The northern periphery of Chilika is fringed by large tract of marshy alluvial plains extending to around 400 km². The lagoon boundaries fall within eight blocks of three districts, Puri, Khurda and Ganjam. Hydrological regimes of Chilika are influenced by three subsystems. The Mahanadi distributaries and streams of the western catchment bring in freshwater flows to the lake, whereas the Bay of Bengal contributes highly saline sea-water. Ecologically, Lake Chilika is an assemblage of shallow to very shallow marine, brackish and freshwater ecosystems. The wetland is classified into four sectors. The northern sector which receives direct discharge of freshwater from Mahanadi Delta has predominantly characteristics. The central sector with intermixing of fresh and marine flows is brackish. The southern sector is the deepest part of Chilika and has higher salinity levels as compared to central sector owing to the influence of Rushikulya estuary. Outer channel is the corridor for exchange between lake and the sea. The sector is characteristically marine but is marked by continual owing to the diurnal tidal oscillations. The presence of unique salinity gradient enables the lake to host a wide range of biodiversity. High biodiversity and cultural values of the lake make it one of the important tourist destinations of the Odisha state. Three hydrological subsystems control the Hydrology of the lake. The land based system comprises distributaries of the Mahanadi River on the northern side, 52 river channels from the western side and the Bay of Bengal on the eastern side. The important rivers of this drainage system are the Kansari, the Kusumi, the Janjira and the Tarimi rivers. A tropical monsoon climate over the drainage basin area of the lake. The lake experiences South–west and North-east monsoons during June to September and November to December respectively with average annual rainfall of 1,238.8 mm (48.77 in), with 72 rainy days. The maximum temperature of 39.9 °C (103.8 °F) and minimum temperature of 14 °C (57.2 °F) have been recorded. The wind speed varies from 5.3 to 16 m. (17 to 52 ft)/hour with southerly and southwesterly direction due to the influence of the South–west monsoon and from north and north easteronths.

![Fig.1. Location Map of the Study area](image)

3. OBJECTIVES

The main aims of this paper are:
- To study geomorphological changes of Chilika inlets for the period 1975 to 2015.
- To study the significant changes of chilika lagoon inlets
- To provide baseline data that can facilitate the long term monitoring of the inlet and its stability

4. METHODOLOGY

Detailed field study were carried out to access the present status of Chilika lake, to know the ecological and anthrogenic pressure and its remedial measures. Available literature regarding Chilika lake was consulted for clear understanding of the problem. Chilika Development Authority (CDA) was also contacted to get the latest status of the lake. During the field study village people around the lake was consulted to know their problems and its remedial measures. Ground truth data collected from the field/site for Geo-referencing the Satellite images. It is vital for quality assessment and evaluation of the spatial information derived from satellite data. Generation of thematic layers database is accomplished through a series of procedural steps. The steps can be broadly discussed under the heads. (i) Data inputs and preparation. (ii) Thematic Data Preparation (iii) GIS Database Creation (IV) Analysis and GIS map preparation. The software used in the present study includes Arc GIS, ERDAS and MAP SOURCE.
5. DISCUSSION

5.1 Opening of mouth to the sea helped rejuvenate Chilika

The Government of Odisha created the Chilika Development Authority (CDA) in 1991 for undertaking ecosystem restoration. With financial support of the state government and the Ministry of Environment and Forests, Government of India, CDA initiated several programmes including treatment of degraded catchments, hydrobiological monitoring, sustainable development of fisheries, wildlife conservation, ecotourism development, community participation and development and capacity building at various levels. A major hydrological intervention was carried out in the form of opening a new mouth to the Bay of Bengal which helped improve salinity levels, enhance fish landing, and decrease in area under invasive species and overall improvement of water quality. Recovery of resources led to significantly improvement in livelihoods of dependent communities. To address the problems Chilika Development Authority, dredged an artificial mouth on 23rd September 2000 opposite the village Sipakuda. The long shore current moves sand along the coast and the energy from the winds is transferred to the ocean producing waves that strike the shore at an angle. These waves also give rise to long shore current moving sand from the south to the north. The satellite data of Landsat and also IRS has been utilized for the current study. The Geomorphological changes directly affect the amount of saline water ingress through the inlets during flood tide, which to a great extent impact the circulation pattern of the lagoon and also salinity propagation in the lagoon.

Figure 2. Opening of mouth to the sea in September 2000

5.2 Complex geologic process of Chilika

The origin of Lake Chilika is attributed to a complex geologic process involving deposition of beach ridges and spits enclosing a body of sea water within the Bay. Chilika formed a part of the Bay of Bengal about 6,000 years ago, and served to be its gulf during Pleistocene. The current form of Chilika is attributed to successive recession of coastline aided by marine and fluvial dynamics over 6000-7000 years (Phlegar, 1969). The process of sand bar formation was very gradual with the sea level rise being very slow during the Holocene (15-20 cm in a century). The growth of barrier is believed to be triggered by a minor tectonic elevation, subsequently aided by coastal progradation attributed to lowering of sea levels and deposition of sediments by long shore currents (Rao and Sadakata, 1996).

Chilika and its surroundings are marked by several erosional and depositional landforms. The main rock types within the region around Chilika are khondalites, unclassified granites, laterites, charnockites, anorthosites, granulites, laterites and alluvium. Some islands of Chilika comprise Eastern Ghat rocks are North East – South West, with local variations at several places.

The western phalanges are marked by structural and denudational hills of khondalite, charnockite, gneisses, anorthosite and granite. The hills are followed by lateritic plains. The northern periphery of Chilika is fringed by large tract of alluvial plains extending to more than 400 km². This low lying tract has extremely gentle slopes and built by recent sediments. This region is drained by the Mahanadi Delta River and its distributaries Bhargavi, Luna and Makara, which have a swaggering course owing to extremely gentle elevation and sediment deposition. Two distinct shore terraces parallel to the northern shoreline mark the shoreline terraces formed due to continuous deposition and emergence of lagoon floor. A number of sandy beach ridges are present along the eastern margin separating Chilika from open sea. Some of these ridges rise upto 5-6 are occupied by creeks and marshes. The open coast is marked by presence of a prominent spit connected to the mainland at its southern end. Because of the Coriolis force (deflective force) the waves generated in Bay of Bengal strike at the Chilika coast in northeast direction (obliquely) thus the littoral deposits present in the coast are also drifted in northeast direction along with the waves. This process of longshore littoral drift formed the barrier spit of the Chilika lagoon which gradually separated from Bay of Bengal and it was formed. Regarding the time period of formation of Chilika lagoon, it might have been formed during Holocene period some 6000 to 7000 years back as the barriers of many lagoons in the
World have been formed during this time due to sea level rise (Emery and Stevensen, 1958, Phleger, 1969 and Zenkovitch, 1969). This process of bar formation was very gradual, since the sea level rise in early Holocene was only 15-20cm/100year (Phleger, 1969).

Figure 3. Map showing the changes in coastline in the Chilika area (from Tertiary to Present)

Figure 4. Map showing the changing shoreline of Chilika lagoon

Table 1. History of Inlets

<table>
<thead>
<tr>
<th>Year</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>1780</td>
<td>The Inlet in the spit was 16 km wide and was an area of deposition</td>
</tr>
<tr>
<td>1825</td>
<td>The inlet was dredged</td>
</tr>
<tr>
<td>1837</td>
<td>The inlet was silted but width was still three times more than its width in 1908</td>
</tr>
<tr>
<td>1889</td>
<td>1960-1965: The inlet was very narrow, 15m wide and 1-2 m deep, 1907 60 m wide</td>
</tr>
<tr>
<td>1914</td>
<td>Inlet located 6 km NE of Arakkhakuda (Annadale and Kamp, 1915)</td>
</tr>
<tr>
<td>1965</td>
<td>Inlet located 8 km NE of Arakkhakuda with width 1.913 km</td>
</tr>
<tr>
<td>1968</td>
<td>Inlet width was only 0.4 km</td>
</tr>
<tr>
<td>1973</td>
<td>Three inlets (Source: Landsat Images, R.N.Samal et.al. 2003)</td>
</tr>
<tr>
<td>1975</td>
<td>Three inlets (Source: Land Sat images, P. Kumar et.al. 1989)</td>
</tr>
<tr>
<td>1985</td>
<td>Two inlets (Source: Land Sat images, P. Kumar et.al., 1989)</td>
</tr>
<tr>
<td>1986</td>
<td>One inlet 4 km away from Arrakhuda</td>
</tr>
<tr>
<td>1990</td>
<td>(March): The inlet width was 55 km wide and 3 m deep</td>
</tr>
<tr>
<td>1990 (September)</td>
<td>The inlet width was 220 m wide and 10m deep</td>
</tr>
<tr>
<td>2000 (September)</td>
<td>The new inlet mouth opened at Sipakuda having width of 280 m and depth of 12 m.</td>
</tr>
<tr>
<td>2001 (November)</td>
<td>The width was 230 m and depth was 4.5 m</td>
</tr>
<tr>
<td>2002 (March)</td>
<td>The width was 250 m and depth was 4 m</td>
</tr>
<tr>
<td>2002 (September)</td>
<td>The Arakhkuda mouth silted up and the dredged mouth is active and there was narrow connection with the sea and depth was 5.5 m</td>
</tr>
<tr>
<td>2003</td>
<td>The Inlet near the Mottu village has been closed due to littoral drift</td>
</tr>
<tr>
<td></td>
<td>Major shifting of the inlet mouth takes place during June to October, when the fresh water flow from the lake to the ocean and the northward littoral drift rate is high</td>
</tr>
<tr>
<td></td>
<td>The inlet mouth remains relatively stationary during rest of the year.</td>
</tr>
<tr>
<td></td>
<td>New Mouth at Gabakunda Opened: 1st Aug, 2008 at 7 AM.</td>
</tr>
</tbody>
</table>
During the year 1975 and 1988 the geomorphic changes of sand spit shows no drastic change (Fig- 8).
But during the year 2000 and 2011 the geomorphic change of sand spit is very much dynamic because of anthropogenic process. The sand spit change near the Sipakuda and Gabakunda mouth is very dynamic because of strong long shore current and littoral drift (Fig-9).

Table 2. Shows the width of the Inlet in different years

<table>
<thead>
<tr>
<th>YEAR</th>
<th>REMARK</th>
<th>INLET WIDTH (in Meter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975</td>
<td>1 Inlet</td>
<td>358</td>
</tr>
<tr>
<td>1988</td>
<td>2 Inlet</td>
<td>351 (Arakhakuda)</td>
</tr>
<tr>
<td>2000</td>
<td>2 Inlet</td>
<td>160 (Arakhakuda)</td>
</tr>
<tr>
<td>2005</td>
<td>1 Inlet</td>
<td>395 (Sipakuda)</td>
</tr>
<tr>
<td>2008</td>
<td>2 Inlet</td>
<td>496 (Gabakunda)</td>
</tr>
<tr>
<td>2011</td>
<td>2 Inlet</td>
<td>404 (Gabakunda)</td>
</tr>
</tbody>
</table>

*1 Inlet before 23 September 23 September 2000, *2 Inlet before 1st August 2008

To understand the inlet dynamics of the Chilika lagoon the base year 1975 is fixed. The satellite images for the year 1975, 1988, 2005 and 2011 has been taken from the archive satellite data available with Chilika Development Authority (CDA). In the year 1975 there was only one inlet near the village Arakhakuda and in the year 1988 there were two inlets, one is near Arakhakuda and also a new inlet near the Mottu village. During this 13 years period the Arakhakuda inlet shifted 3.2km towards North and because of longshore transport of the sediment. Parallel to the coast and also the deposition along the shoreline the sand spit drifted by 140 m towards Bay of Bengal at north side of the Arakhakuda mouth. At Arakhakuda and Mottu mouth the sand spit was drifted towards Chilika side by 380m. And on south side of Mottu mouth the sand spit was drifted towards Chilika side by 173 m. It was concluded from the analysis that yearly the average shifting of sand spit was about 10 – 11 m towards the Bay of Bengal (Fig-10, Fig-11).

During the year 1988 and year 2000, Arakhakuda was closed and Mottu inlet was shifted 2.5 km. towards north named as Arakhakuda and shoreline drifted towards the Bay of Bengal by 260 m. It is analysed that yearly average shifting of shoreline was about 21 – 22 m and it shows maximum shift during these 12 years. In the May 2000 there was one inlet i.e. Arakhakuda and also a
new inlet was dredged on southern side of Arakhakuda at a distance of 16.7 km. in front of the village Sipakuda on 23rd September 2000 of width 80 m only. In the year 2003 Arakhakuda inlet was totally closed due to the less tidal prism (Fig. 13).

During the period from 2000-2005 the shoreline shifted by 60 m towards Chilika. From the observation it was concluded that yearly average shifting of shoreline was about 12 - 13 m (Fig-9,Fig-14).

In 2005, there was only one inlet i.e. Sipakuda, but in 2011 there are two inlets one near the village Sipakuda and another one was naturally opened in August 2008 opposite village Gabakunda due to the combined effects of the High tide, Wave height of 5.8 m at 23m depth contour off Gopalpur station. The inlet was 1.8 km away from Sipakuda in northern side. From the year 2005 to 2011 the
net shift of Sipakuda inlet is 1228 m towards north. The shoreline near Sipakuda Inlet moves towards the Bay of Bengal and the shoreline near Gabakunda Inlet moves towards Chilika (Eastern side) (Fig-14, Fig-15).

The total net shift of the Sipakuda inlet since September 2000 to March 2011 is 1512.8M. But Gabakunda inlet from the observation shows no specific net shift of the inlets. Both current and historic inlets have formed, closed and re-opened over their life spans, due to natural processes as well as human intervention. Such events directly affect the amount of water flowing through an inlet during a tidal cycle, referred to as a tidal prism. Similarly, the tidal prism of an inlet may be affected by changing the area of the bay adjacent to it; an inlet may close due to an abundance of sediment and strong long shore drift coupled with a small tidal prism. Sand is deposited as shoals just inside and outside the inlet because of the reduction in current speed in these areas. Spits occur in areas with a high rate of sediment transport alongshore and a small tidal prism; spit growth eventually may restrict tidal flow in the main channel and cause downdraft migration or closure of the inlet. Wave-dominated inlets are very unstable and prone to migration. As wave-dominated inlets migrate along the coastline, their main channel is lengthened and becomes hydraulically inefficient for tidal exchange.

3. CONCLUSION

The long shore current moves sand along the coast. The energy from the winds is transferred to the ocean producing waves that strike the shore at an angle. These also give rise to long shore current moving sand from the south to the north. The effects of monsoon / cyclone winds and waves are generally greater than the effects of none / post monsoon winds and waves. As a result, the long shore current during monsoon is stronger than the calm season and the net annual long shore current and movement of sand is from the north to south. Waves tides and currents in the sea / ocean constantly work on these materials, transport them along the shore zone and deposit them at certain sections along the coast wherever the conditions favour depositions. The seasonal change in the direction of the long shore drift causes the changes in the Shore line. This diurnal and seasonal change, the long-term change in sea levels has become a serious issue in the recent decades. The detailed Geomorphology map and the derivative information for the present study area may serve as basis for various further detailed researches, urban planning, tourism development, and coastal zone management decisions for the coastal districts, Odisha.

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VTEC OBSERVATIONS FOR NEPAL EARTHQUAKE 2015 USING GPS DATA
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ABSTRACT
Total Electron Content (TEC) estimation using Global Positioning System (GPS) is an advanced technique. In this paper, we are trying to understand the effect of earthquake in ionosphere. For that, we have derived Vertical TEC (VTEC) from Apr-2015 to May-2015 using pseudo range and carrier phase observables from two Continuously Operating GPS stations of Indian Space Research Organization (ISRO) and four GPS stations from University NAVSTAR Consortium (UNAVCO) for two earthquakes that occurred in Nepal on 25-04-2015 and 12-05-2015 with magnitudes 7.8 and 7.3, respectively. The Upper Bound (UB) and Lower Bound (LB) of VTEC were calculated with 82% confidence level by using 15days data prior to the given date. The anomaly in VTEC is identified when it crosses the UB or LB. The results show significant variation in VTEC before, during and after the earthquake events. The VTEC variations are also studied in conjunction with Solar and geomagnetic activities to find the actual cause of the anomaly.

KEYWORDS: Ionosphere, Global Positioning System, VTEC, GNSS technology, anomaly

1. INTRODUCTION
The ionosphere is an upper region of atmosphere which extends approximately from 50 to 1000 km and it is dispersive for the L-band GPS signals. The large content of electrons is formed in the ionosphere due to electromagnetic radiation. This electron content reaches its maximum during afternoon time and minimum during night time. The earth sends out transient signals, these signals may consist of local magnetic field variations and electromagnetic emissions over wide range of atmosphere and ionospheric perturbations, so the electron content varies with respect to solar activity, Geomagnetism and seismic activity (earthquakes). Especially, the Earthquake influence on ionosphere occurs through Lithosphere-Atmosphere-Ionosphere (LAI) coupling. Different research groups around the world are studying ionospheric perturbations prior to large earthquakes (Leonard R. S. 1965, Pulinets 2002, Liu, J. Y.2001 & 2006, O P Singh 2013, Zhu F 2014, Tang J 2015, Sun, Y. 2017, Weiping Jiang 2017). The Ionospheric perturbations can be observed by using different techniques namely ionospheric sounding, Global Positioning System (GPS) total electron content (TEC) measurements (Pulinets, 2002), TEC receivers, COSMOS Satellite measurements etc. Distribution of GPS/GNSS stations worldwide is becoming a powerful technique for studying the precursors of earthquakes. For example, Singh (2013) investigated the seismic effect on TEC using dual frequency GPS receivers for the period of 30 months for 22 earthquakes more than M≥5 magnitude and observed TEC anomalies are due to large earthquakes. Weiping Jiang (2017) did similar analysis of ionospheric Vertical Total Electron Content before the 2014, M8.2 Chile earthquake and observed positive anomalies 4 days before the earthquake.

The Earthquake with Mw 7.8, 2015-04-25 06:11:25 (UTC), 28.230°N 84.731°E, 8.2 km depth, 36 km E of Khudi occurred in Nepal, 32 aftershocks with M≥5 occurred in and around this area (Lat 24 to 35, Long 74 to 90). Among these aftershocks, Mw 7.3, 2015-05-12 07:05:19 (UTC), 27.809°N 86.066°E, 15.0 km depth, 19 km SE of Kodari which occurred in Nepal is high magnitude (USGS Earthquake catalog) earthquake. In this work, we have computed and studied the VTEC variations using GPS data from six stations (Figure1) for above mentioned two earthquakes (M7.8, M7.3). Among six GPS stations, two of which (Dehradun-DEHR and Manali-MANA) are operated by National Remote Sensing Center (NRSC)-ISRO and the remaining four stations (Chilime-CHLM, Besisahar-BESI, Jomsom-JMSM and Ramite-RMTE) (Figure 1.) are from UNAVCO.

Figure 1 (a). Location map of earthquakes and distribution of GPS stations used for computing VTEC (Source: Bhuvan 2D: ISRO)

These GPS stations have been selected such that to lie near to the epicenter as well as within the earthquake preparation zone (Equation. 1)

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\[ R = 10^{0.43 \times M} \text{(Dobrovolsky, 1979)} \] (1)

Where \( R \) = radius of preparation area

\( M \) = magnitude,

The radius of preparation zone for April 25th earthquake is approximately 2300 Km and for May 12th earthquake is 1378 km. Distance from the used GPS stations to the two epicenters is given in Table 1.

<table>
<thead>
<tr>
<th>S.No.</th>
<th>GPS Station used</th>
<th>Distance (Km) from April 25th epicenter</th>
<th>Distance(Km) from May 12th epicenter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>BESI</td>
<td>34.5</td>
<td>172.2</td>
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<tr>
<td>2.</td>
<td>CHLM</td>
<td>57.3</td>
<td>86.1</td>
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<tr>
<td>3.</td>
<td>JMSM</td>
<td>115.8</td>
<td>253.2</td>
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<tr>
<td>4.</td>
<td>RMTE</td>
<td>229.7</td>
<td>104.8</td>
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<td>5.</td>
<td>DEHR</td>
<td>693.32</td>
<td>832.84</td>
</tr>
<tr>
<td>6.</td>
<td>MANA</td>
<td>772.77</td>
<td>907.00</td>
</tr>
</tbody>
</table>

Table 1. GPS stations used for the study and the distance from two epicenters

2. DATA USED

Data in RINEX (Receiver Independent Exchange) format for six GPS stations (ISRO & UNAVCO) and supporting files like precise ephemeris information, Differential Code Biases (DCBs), IONEX (Ionosphere Independent Exchange) maps from Center for Orbit Determination in Europe (CODE) were used to calculate VTEC for the time period from 1-Apr-2015 to 15-May-2015, also 17-Mar-2015 to 31-Mar-2015 (15 days data) used to construct the upper and lower bound. Solar activity in terms of f10.7 index with 01 hour sample interval is taken from Omni web NASA and the geomagnetic activity in terms of Kp index with 3 hours sample interval is taken from International Service of Geomagnetic Indices (ISGI), GFZ Potsdam.

3. METHODOLOGY

The Pseudo range and carrier phase observables on L1 and L2 from RINEX observation files, supporting files like precise ephemeris, DCBs and IONEX maps have been used for computing the VTEC using equation 2. The flowchart in figure 2 Shows the entire methodology involved in this research work. IONOLABTEC v1.29 has been used for computing the VTEC. IONOLAB TEC uses a novel algorithm (Sezen U, 2012) to correct the cycle slips using carrier phase data. TEC is defined as the total number of electrons present in 1m² cylindrical cross-section. TEC Units (TECU) is \( 10^{16} \) electrons/m². The TEC measured in slant direction is called as Slant TEC and the TEC measured in Zenith direction is called as VTEC (Figure 1b). The STEC is calculated using Equation 2(a). Usually, the computed Slant TEC is projected to TEC in Zenith direction called as VTEC by using a mapping function assuming a thin shell model of ionosphere, VTEC is calculated using equation 2 (b).

\[ S \text{TEC} = \frac{1}{403} \left[ \frac{f_2^2 f_1^2}{f_2^2 - f_1^2} \right] (P_2 - P_1) + DCB \] (2a)

Figure 1(b). Vertical Profile of Ionosphere, VTEC and STEC

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Where \( f_1 = 1575.42 \text{ MHz} \),
\( f_2 = 1227.6 \text{ MHz} \),
P1 & P2 = pseudo ranges measured on L1 and L2
DCB = Differential Code Biases of Satellite and Receivers

\[ V_{TEC} = STEC \ast M(e) \]  \hspace{1cm} (2b)

Where \( M(e) = \text{Mapping function} = \sqrt{1 - \frac{R \cos e}{R+h}} \)
\( R = \text{Radius of Earth} = 6378 \text{ Km} \)
e = elevation angle
\( h = \text{height of the ionosphere shell} = 350 \text{ Km} \)

The Upper Bound (UB) and Lower Bound (LB) were calculated (equation 3. (a & b)) by using 15 days VTEC data prior to the given date. For all the stations with 82 % confidence level (P. I. Nenovski, 2014)

\[ UB = MM + 1.34STD \] \hspace{1cm} (3a)
\[ LB = MM - 1.34STD \] \hspace{1cm} (3b)

Where MM = 15 days Median of VTEC
STD = 15 days Standard deviation of VTEC

When VTEC crosses the UB or LB then it is considered as an anomaly. To find the actual cause of anomaly we have studied the solar activity in terms of \( f_{10.7} \) index and geomagnetic activity in terms of \( Kp \) index. In addition to that we have separated the positive anomaly (When VTEC crosses the UB) and negative anomaly (When VTEC crosses the LB) to understand the anomalies due to Solar activity, geomagnetism seismic activity (earthquakes).

4. RESULTS AND DISCUSSION

4 (a): Finding the anomaly using VTEC, UB, and LB

The 15 seconds data in RINEX format have been resampled to 1 minute data as there is not much change in VTEC from 15 seconds to 1 minute data. Time series of VTEC (blue), UB (Red) and LB (Green) from 1st April 2015 to 15th May 2015 with 1 minute sample interval (Figure 3. a-f). As mentioned above, the anomalies have been identified when VTEC crosses UB or LB.

In the case of 7.8 25th April 2015 earthquake the anomalies observed on the following days prior to the earthquake.
- On 02nd April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA (Figure 3.(a-f)).
- On 03rd April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA (Figure 3.(a-f)).
- On 11th April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA ((Figure 3.(a-f)).
On 14\textsuperscript{th} April 2015, the anomaly observed in GPS station DEHR ((Figure 3.(a-f)).

On 16\textsuperscript{th} April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM and RMTE ((Figure 3. (a-f)).

On 17\textsuperscript{th} April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA ((Figure 3.(a-f)).

On 18\textsuperscript{th} April 2015, the anomaly observed in GPS station MANA ((Figure 3. (a-f)).

On 20\textsuperscript{th} April 2015, the anomaly observed in GPS station MANA ((Figure 3. (a-f)).

On 24\textsuperscript{th} April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, DEHR and MANA (Figure 3. (a-f)).

On 28\textsuperscript{th} April 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA (Figure 3.(a-f)).

On 07\textsuperscript{th} May 2015, the anomaly observed in GPS stations BESI, JMSM, RMTE, DEHR and MANA (Figure 3. (a-f)).

On 10\textsuperscript{th} May 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, RMTE, DEHR and MANA (Figure 3.(a-f)).

On 11\textsuperscript{th} May 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, and RMTE (Figure 3. (a-f)).

On 12\textsuperscript{th} May 2015, the anomaly observed in GPS stations BESI, CHLM, JMSM, and RMTE (Figure 3. (a-f)).

Also we are observing an anomaly on 15\textsuperscript{th} May 2015 in all the six stations BESI, CHLM, JMSM, RMTE, DEHR and MANA. The star indicates the time of earthquake on 25\textsuperscript{th} April 2015 and 12\textsuperscript{th} May 2015. The circles shows the anomalies in which VTEC crosses the UB or LB.

The GPS station BESI lies 34.5 Km left side from M7.8 25\textsuperscript{th} April 2015 earthquake and 172.2 Km left side from M7.3 12\textsuperscript{th} May 2015. The plots for BESI station VTEC, UB and LB are shown in Figure 3a.

The GPS station CHLM lies 57.3Km right side from M7.8 25\textsuperscript{th} April 2015 earthquake and 86.1Km left side from M7.3 12\textsuperscript{th} May 2015. The plots for CHLM station VTEC, UB and LB are shown in Figure 3b.

The GPS station JMSM lies 115.8 Km left side from M7.8 25\textsuperscript{th} April 2015 earthquake and 253.2 Km left side from M7.3 12\textsuperscript{th} May 2015. The plots for JMSM station VTEC, UB and LB are shown in Figure 3c.
The GPS station RMTE lies 229.7 Km right side from M7.8 25th April 2015 earthquake and 104.8 Km right side from M7.3 12th May 2015. The plots for RMTE station VTEC, UB and LB are shown in Figure 3d.

The GPS station DEHR lies 693.32 Km left side from M7.8 25th April 2015 earthquake and 832.84 Km left side from M7.3 12th May 2015. The plots for DEHR station VTEC, UB and LB are shown in Figure 3e.

The GPS station MANA lies 772.77 Km left side from M7.8 25th April 2015 earthquake and 907.00 Km left side from M7.3 12th May 2015. The plots for MANA station VTEC, UB and LB are shown in Figure 3f.
4 (b). Study of VTEC anomalies in conjunction with solar and geomagnetic activity:

To analyze the cause of the anomaly, we have considered the solar activity in terms of $f_{10.7}$ index, geomagnetism in terms of Kp index. $f_{10.7}$ is in solar flux units (sfu): $10^{-22}$ W.m$^{-2}$.Hz$^{-1}$ and the Kp index was designed to describe the physical strength of the geomagnetic activity and it is given in a global scale ranges from 1-10.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Value</th>
</tr>
</thead>
<tbody>
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<td>$f_{10.7}&gt;150$ sfu</td>
</tr>
<tr>
<td>Geomagnetism</td>
<td>Kp&gt;4</td>
</tr>
</tbody>
</table>

Table 2. Values for high Solar activity and Geomagnetism

It is observed that the Solar activity is high (Table 2.) on 14th Apr to 23rd Apr 2015, 07th May to 15th May 2015 and Geomagnetism is high on 02nd Apr, 09th Apr, 13th to 17th Apr 2015, 05th May 12th to 13th may 2015.

We have separated the positive (when VTEC crosses the UB) and negative (when VTEC crosses the LB) anomaly of VTEC for all the stations for better understanding (Figure 4 a-d) and compared with $f_{10.7}$ and Kp index.
From the above analysis, it is observed that, minor anomalies (≤20 TECU) are occurred on 1st, 03rd, 04th, 05th, 06th, 08th, 09th, 13th, 16th, 23rd, 24th, 25th April and strong anomalies (≥20 TECU) occurred on 03rd(positive), 11th(negative), 23rd(positive) April 2015. The minor anomalies (≤20 TECU) are occurred on 26th, 28th, 30thApril, 01stto 07th, 09th, 11th May and strong anomalies (≥20 TECU) occurred on 29th (negative) 14th, 15th (Positive) May. The solar activity and geomagnetism occurred during/01 to days before the two earthquakes, anomalies in VTEC also observed in the presence of these three activities. Hence during these two earthquakes due to the presence of high solar activity and geomagnetism, it is difficult to understand the contribution of earthquake on VTEC variations.

5. CONCLUSIONS

Based on the methodology established in previous studies (Pulinets 2002, P. I. Nenovski 2014 etc.) we have computed the Vertical TEC using GPS data for 25th April 2015 and 12th May 2015 earthquakes that occurred in Nepal. Computed the Upper and Lower Bounds for VTEC using the 15 days data prior to given date. By using VTEC, UB and LB we have identified anomalies prior to earthquakes. The positive and negative anomalies in VTEC have been studied in conjunction with solar activity in terms of f10.7 index and geomagnetic activity (Kp index). It is also noticed that increased solar activity and geomagnetism before/during Nepal earthquake. Further study is required to understand the relationship between these parameters (VTEC, Solar activity and geomagnetism) and to see whether this information can be used as a precursor for earthquakes.

ACKNOWLEDGEMENTS

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SIGNIFICANCE OF CARTOSAT DEM IN DELINEATION OF DRAINAGE NETWORK AND WATERSHED BOUNDARIES FOR MORPHOMETRIC ANALYSIS AND PRIORITIZATION

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ABSTRACT

This paper describes morphometric analysis and its importance in identification, planning, management and characterization of watersheds. SRTM, ASTER, Cartosat DEM (Digital Elevation Model) were validated by deriving drainage network and it was found that Cartosat DEM is giving better 1st and 2nd order drainage network. Hence, Cartosat DEM was used in this study for extraction of drainage network, stream ordering and sub-watershed boundaries in the Tenughat reservoir catchment, which has been taken as case study. Tenughat reservoir catchment situated in the Jharkhand state and is a part of Damodar river system, covers an area of 4501.9 km². Total 37 sub-watersheds were delineated using ArcGIS hydrology tool. Linear, aerial and relief parameters such as catchment length, bifurcation ratio, drainage density, drainage frequency, texture ratio, form factor, shape factor, compactness coefficient, elongation ratio, circularity ratio, length of overland flow, basin relief, ruggedness number and relief ratio were computed. Ranking was assigned to each parameter based on its erodibility factor and Compound values (Cp) for each sub-watershed was calculated. Further, priority fixation was carried out based on Cp value. Lowest Cp value was assigned as very high priority and highest value was assigned very low priority. Subsequently other priorities like high, medium and low were carried out.

KEYWORDS: Cartosat DEM, Morphometric analysis, Sub-watershed, Prioritization, Tenughat Reservoir catchment.

1. INTRODUCTION

A watershed may be defined as a specific topographically delineated area of land on the surface of the earth having a definite water divide or boundary with a single stream outlet usually located at a lower elevation point. For a definite surface area, the different form of precipitations such as rain, snow, drizzle etc resulting into runoff flows through a single point i.e. the exit point and joins the large streams, rivers, lakes and oceans[1]. These water bodies are extensively used for agriculture, industries, drinking and different household activities, fishery etc. Hence, available water resources need to be conserved and managed properly to meet the demand. Watershed is a unit, which is considered to be ideal for the management practices. Soil erosion, excess runoff are the major issues the play vital role in the watershed that effects the health of watershed directly or indirectly [Web-1]. Thus the conservation of water and soil are the two most important factors upon which the sustainability of agriculture and environment etc. depends [Web-2]. Watershed management is a collective form of land and water resource management. The main objective of watershed management is conservation of soil & water, improving the water bearing capacity of land, rainwater harvesting, recharging the ground water by an integration of progressive, preventive, curative and corrective approach. Watershed management can also be defined as a well-balanced and proper utilization of land and water resources for obtaining maximum production with minimum hazard to the natural resources. Maintaining soil fertility, conserving water into the basins, catchments or watersheds, proper management of flood water, flood control measures, reduction in sediments in the catchment areas and increasing the productivity of the existing land uses can be done through proper watershed analysis and management [2][3]. The watershed characteristics mainly depend upon the size, shape, average slope, drainage density, different land use, soil type, vegetation cover of the definite area. The size of watersheds may vary from a small number of hectares to large number of square kilometres [2].Accordingly to the Atlas prepared by AIS & LUS, it has been stated that the mean area of a watershed should be less than 500km²±50%. This has been further classified into sub watersheds (30-50km² area), mini watersheds (10-30km² area) and micro watersheds (5-10km² area) as per The National Remote Sensing Agency [1][4]. In this case study different DEMs such as SRTM(30m), ASTER(30m), CARTOSAT(10m) has been used for deriving better and more accurate drainage system especially for the 1st and 2nd orders. Different threshold values such as 0.0005 sq km, 0.001 sq km, 0.0015 in the model were used to derive drainage networks. It was found that threshold value 0.0005 sq km give better results. Further, it was evaluated with the high resolution satellite data and found that Cartosat -1 DEM provides more 1st and 2nd order drainage network with the same threshold value with compare to the SRTM and ASTER DEM. Hence, Cartosat – 1 DEM has been used in this study for the generation of drainage network and delineation of watershed and sub-watersheds boundaries using modified and integrated ArcGIS hydrology tools. Derived drainage network and sub-watershed boundaries were used for the morphometric analysis as major input parameters. Morphometric analysis is done to measure and analyse the earth’s surface, shape and different dimensions of the landforms[5]. It is also useful for describing the surface drainage networks as it provides the quantitative description of various surface drainage systems[6]. Morphometric analysis of watershed has an important role in understanding the hydrological behaviour of a particular watershed[7]. The various morphometric parameters can be broadly classified into two categories- i) Linear aspect, ii) Aerial aspect. The linear parameters such as- bifurcation ratio, drainage density, texture ratio, length of overland flow, stream frequency have a direct relationship with the erodibility of the surface and subsurface soil of the watershed whereas the shape parameters such as- compactness co-efficient, circularity ratio, elongation ratio, shape factor and form factor have an inverse relation with this erodibility factor. Beside of different morphometric analysis,

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prioritization of watersheds plays a very important role for both soil and water conservation as well as it helps in natural resource management.[8][9] Thus the morphometric analysis and prioritization provides us an enormous data of various hydrological parameters which eventually helps us in water and soil conservation of a particular watershed.

2. STUDY AREA

The Tenughat reservoir catchment has been taken as case study. Tenughat reservoir catchment consists of an earthfill dam with composite masonry cum concrete spillway across the Damodar River at Tenughat in Petarwar block of Bokaro district in Jharkhand State. It is located between 2303’48”00”N and 85049’55”E. The total capacity of the reservoir is 6,300 acre feet which feeds mainly one of the most industrialized zones in India in Bokaro district. The total area of this watershed is 4501.9 sq km. The entire region has high to moderate undulated terrain and the height varies from 200m to 280m. The general slope of this watershed is from west to east. Damodar is the main river of this watershed along with its various tributaries. The average annual rainfall of this area is 1200 - 1300 mm. The catchment area is mainly mono-cropped and rainfed. Paddy, millet, rice, maize, pulses are the main crops grown here along with bajra, wheat and vegetables. The entire reservoir catchment area is rich in coal minerals. Minerals like quartz, limestone, sandstone etc. are also found here abundantly. Many large scale industries along with small & micro industries embellished the area for which it has became one of the most industrialized zone in India. Coal industries, Steel industries, Thermal plants of DVC, Chemical industries, Power supply industries, Cement industries, Water treatment plants, Bottling plants, Alloy industries, Rubber industries, Jute industries, Paper industries, Garment industries, Mineral industries etc enriched the area. These industries require a continue supply of water with high demand.

3. METHODOLOGY

In this case study different DEMs such as SRTM(30m), ASTER(30m), CARTOSAT(10m) has been used to derive better and more accurate drainage network with different threshold values such as 0.0005 sq km, 0.001 sq km, 0.0015 in the customized hydrology model in ArcGIS 10.3. It was found that threshold value 0.0005 sq km give better results. Evaluation was done with high resolution satellite data Cartosat -1 DEM provided more 1st and 2nd order drainage network with the same threshold value with compare to the SRTM and ASTER DEM. Hence, the Cartosat – 1 DEM has been used in this study for the generation of drainage network and delineation of watershed. A customized hydrology model in ArcGIS 10.3 has been used and Cartosat-1 DEM having 10m resolution was taken as the primary input to delineate the drainage network. This delineated drainage was used as a major input for further analysis. Pour points were generated according to the drainage pattern and sub watersheds were delineated with greater accuracy by the same hydrology model. Total 37 sub watersheds were delineated following the thumb rule of National Remote Sensing Agency (Fig-2). The basic parameters of each sub watersheds such as- area, perimeter, stream number, stream order, elevation were computed by Remote Sensing and GIS approach. These parameters were considered as vital inputs for Morphometric analysis. Horton’s law of stream ordering has been followed in the analysis.
The linear basin parameters such as - bifurcation ratio, drainage density, texture ratio, length of overland flow, stream frequency and the aerial parameters such as - compactness co-efficient, circularity ratio, elongation ratio, shape factor and form factor have been computed by using standard formulae. The computed values of all these morphometric parameters are shown in the table below (Table-1(a),(b)) Ranking was assigned to each of the linear and aerial parameters considering the highest value as rank1 for linear parameters and lowest value as rank1 for aerial parameters. Further compound parameter ($C_p$) was computed by taking the average of all the morphometric parameters (both linear and aerial) and final ranking was given to each of the sub watersheds. All these sub watersheds were the categorized based upon their $C_p$ ranking.

4. RESULTS

Scientific approach clubbed with geo-spatial technology provides accurate and reliable information for the conservation of water and soil that helps in many respect for the development and management of watersheds and its sustainability for availability of water resources for the use of agriculture and other purposes. Different DEMs that are tested in the study such as SRTM, ASTER and Cartosat to find best production of drainage network and its orders. Cartosat DEM was used in this study as it provided better and improved drainage network with compare to SRTM and ASTER. Morphometric analysis that basically deals with the geometry of watershed and its spatial extent was used for the characterization of sub-watersheds. All the parameters such as bifurcation ratio, drainage density, texture ratio, length of overland flow, stream frequency have a direct relationship with the erodibility of the surface and subsurface soil of the watershed whereas the shape parameters such as- compactness co-efficient, circularity ratio, elongation ratio, shape factor and form factor were computed in the GIS environment.

The linear parameters have a direct relationship with the basin erodibility factor whereas the aerial parameters have inverse relationship with erodibility. Higher drainage density with high stream frequency indicates higher soil erosion with low infiltration. Low bifurcation ratio indicates more stable subsurface soil and geological structures. Elongation ratio and circularity ratio has direct relation with the shape of the basin. Higher the elongation ratio (>0.9) and the circularity ratio indicates more circular basin. Hence after the morphometric analysis it has been found that 5 sub watersheds have higher drainage density with higher stream frequency and high value of bifurcation ratio. For better and more accurate assessment of the sub watersheds, all the 37 sub watersheds were further categorized based upon their $C_p$ ranking into 5 categories from very high ($\leq 12.6$), high ($12.6 < 16.8$), medium ($16.8 < 19.7$), low ($19.7 < 22.9$), very low ($22.9 < 28.1$). Thus, 5 sub watersheds were given very high priority, 8 sub watersheds were given high. Watershed development program could be initiated based the priority been derived using morphometric analysis. Sub-watershed falling under very high priority could be considered first for any development practices.
In this study, SRTM, ASTER and Cartosat DEMs were evaluated for deriving the drainage networks as well as catchment and sub-watershed boundaries. Cartosat DEM was used as primary input for deriving drainage network and sub-watershed boundaries because of better representation of 1st and 2nd order drainage network. Watersheds on high undulating terrain suffers with soil erosion and excess runoff that are the major issues and effects the health of watershed directly or indirectly. Characterization of watersheds become very important to understand the different properties of the watershed such as landforms, soils and eroded lands and their relationship in terms of availability of water resources. Morphometric analysis that provides necessary information about the character of watersheds and its present health condition. Hence, quantitative morphometric analysis was carried out in 37 sub-watersheds of Tenughat catchment using geo-spatial techniques for determining the linear aspects such as stream order, bifurcation ratio, stream length and aerial aspects such as drainage density, stream frequency, form factor, circulatory ratio and elongation ratio etc. Geo-spatial technique allows for more reliable and accurate estimation of morphometric parameters of watersheds. The morphometric analysis of different sub-watersheds shows their relative characteristics with respect to hydrologic response as well as possibilities of soil erosion. Morphometric analysis results show that sub-watersheds falling under very high priority category are prone to relatively higher erosion and soil loss. Hence, suitable soil erosion control measures and water resource conservation plans to be implemented for the better development and management of water resources and minimizing the soil erosion within the sub-watersheds.
### Table 1 (a&b)

#### Compound Values and Priorities Depending Upon the Morphometric Ranks

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<th>SW_ID</th>
<th>B_s Shape factor</th>
<th>Cc Compactness Co-eff</th>
<th>Rc Circularity Ratio</th>
<th>Re Elongation Ratio</th>
<th>Rf Form factor</th>
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<th>Fs Drainage Frequency</th>
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<th>Rs Average Bifurcation N Ratio</th>
<th>Texture Ratio</th>
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<td>18</td>
<td>7.4</td>
<td>19</td>
<td>6.7</td>
</tr>
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</table>

**Shape Factor**

19 | 28 | 32 | 6 | 10 | 30
20 | 13 | 16 | 22 | 27 | 25
21 | 4 | 10 | 28 | 34 | 14
22 | 37 | 20 | 18 | 1 | 1
23 | 18 | 38 | 30 | 22 | 22
24 | 34 | 14 | 24 | 4 | 4
25 | 38 | 25 | 22 | 1 | 1
26 | 35 | 29 | 9 | 23 | 23
27 | 1 | 5 | 33 | 17 | 17
28 | 29 | 7 | 23 | 17 | 17
29 | 25 | 23 | 15 | 13 | 13
30 | 2 | 19 | 19 | 16 | 16
31 | 12 | 24 | 25 | 13 | 12
32 | 11 | 36 | 2 | 25 | 27
33 | 16 | 1 | 37 | 26 | 18
34 | 33 | 17 | 21 | 5 | 5
35 | 6 | 31 | 7 | 12 | 12
36 | 17 | 14 | 4 | 34 | 24
37 | 18 | 38 | 15 | 23 | 23
38 | 25 | 5 | 20 | 20 | 20
39 | 34 | 37 | 37 | 17 | 17
40 | 31 | 31 | 13 | 14 | 14
41 | 36 | 4 | 4 | 19 | 9
42 | 37 | 16 | 14 | 24 | 24

**Linear Parameters**

19 | 27 | 30 | 27 | 28 | 31
20 | 24 | 18 | 24 | 24 | 23
21 | 30 | 12 | 10 | 22 | 23
22 | 29 | 28 | 9 | 18 | 18
23 | 19 | 17 | 19 | 21 | 21
24 | 31 | 26 | 11 | 9 | 15
25 | 35 | 36 | 26 | 29 | 33
26 | 17 | 22 | 17 | 28 | 27
27 | 4 | 24 | 6 | 10 | 13
28 | 29 | 29 | 13 | 31 | 26
29 | 35 | 34 | 5 | 32 | 32
30 | 25 | 35 | 25 | 38 | 36
31 | 31 | 31 | 13 | 14 | 14
32 | 18 | 27 | 18 | 4 | 24
33 | 28 | 33 | 28 | 15 | 17
34 | 37 | 37 | 37 | 17 | 17
35 | 31 | 31 | 13 | 14 | 14
36 | 4 | 4 | 19 | 9 | 9
37 | 26 | 14 | 24 | 24 | 24

**Type**

- High
- Medium
- Low
- Very Low

**Values**

- Very High: 30.6
- High: 12.2
- Medium: 6.2
- Low: 1.2
- Very Low: 0.2

**Descriptive**

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REFERENCES


https://dep.wv.gov/WWE/watershed/Pages/watershed_management.aspx

SATELLITE DERIVED INPUT FOR SOLID WASTE MANAGEMENT AND IMPROVING SURFACE WATER AVAILABILITY UNDER SMART CITY PLANNING OF TUMKURU CITY

Salma Sultana1, Sudha Ravindranath2, K.S. Ramesh2 and K. Ganesha Raj2

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ABSTRACT

The current study aims at providing inputs for Smart city planning for Tumkur city with the help of different multidate satellite data of different resolutions there by providing suitable site for solid waste disposal and improving surface water. The multidate satellite data was used to generate current road, rail, land use land cover [LULC], waterbody, drainage layers. Using LULC layer, different types of wasteland present were identified. Using criteria-based analysis which includes physical [Geomorphology, soil and slope] and socioeconomic [distance from major roads, waterbodies, settlements] factors few sites were selected. Physical factors were ranked and analysed in GIS environment. Multiple ring buffer was developed based on different suitability score for socioeconomic factors. Finally, eight suitable sites were selected for scientific disposal of solid waste.

The road network was updated which is helpful in laying of storm water drains along road network and a tentative plan was prepared for linking of Maralur Amanikere Tank with the waterbody near to Geddalahalli. The data base created was given to for Smart City Tumkur Ltd for further processing.

KEYWORDS: Smart City, Solid waste management, criteria-based analysis, Multiple ring buffer, storm water drains.

1. INTRODUCTION

The government of India (GOI) has launched the smart city mission on 25.06.2015. The objective of the mission is to improve the quality of life of its citizens by providing core infrastructure, a clean and sustainable environment and applications of smart solutions. The mission will cover 100 cities and its duration will be 5 years (2015-16 to 2019-20). The government of Karnataka (GOK) has accorded approval of implementation of smart city scheme in the state vide government order. The high-power steering committee of smart city scheme has been also constituted under chairmanship of chief secretary with representatives of various state government departments to guide the mission in the state. The Karnataka urban infrastructure development and finance corporation has been nominated as the state level nodal agency and mission directorate vide government order. The high-power steering committee has recommended selection of 6 cities, viz., Belagavi, Shivamogga, Mangaluru, Hubballi Dharward, Tumakuru, Davanagere for development under the smart cities.

1.1 Objectives

The following objectives are considered for the study:

a) Solid waste management planning
b) Improving surface water availability under smart city planning of Tumkur city

1.2 Study Area

Tumkur is the study area selected for this project. Tumkur is a malfunctional city, also an important centre for collection and distribution of agricultural commodities in the district. The city is connected by Poona-Bengaluru railway line and also by a road network. Tumkur is situated at attitude of 813.31 m (2669 feet) above the mean sea level. Tumkur is the chief urban centre in the district as a district headquarters situated in 13° 20′ N, 77° 9′ E, 70 Km from Bengaluru with which road and rail network are connected. There is 3.74% increase in the population over the decade 2001-2011. Agriculture is the key economic activity in the region. Tumkur is selected as one of the upcoming smart city under smart city mission. With the help of master plan prepared for 2031 which includes local planning area the required study area was extracted. The location map of study area is shown in Figure 1.

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2. MATERIALS AND METHODOLOGY

As Tumkur is selected as the upcoming smart city under smart city mission the selection of objectives Solid waste management and improving surface water availability planning were chosen based on the discussion with Smart city Tumkur Ltd.

2.1 Solid Waste Management

The role of Geographic Information Systems (GIS) in solid waste management is very large as many aspects of its planning and operations are highly dependent on spatial data. The methodology utilizes GIS to evaluate the entire region based on certain evaluation criteria for the analysis of landfill site suitability (Ozeair and Mohesn, 2009). To meet the required objective of solid waste management planning KSRSAC had provided the multi criterion layers i.e., geomorphology, soil, and slope layers. With the use of present satellite data [CARTOSAT 1 merged with LISS 4] of the year 2018 the features like road network, settlements, and waterbodies were digitized. Multiple ring buffer for road network, settlements and waterbodies was created using different ranking, the union of geomorphology, soil and slope was done and rankings are given depending on different criteria listed below. Finally, the comparison study is done to get the suitability map. To study the suitability of site the criteria and sub criteria used to create GIS data base is discussed in Table 1.

Table 1: The criteria and sub criteria used in development of GIS data base

<table>
<thead>
<tr>
<th>Physical criteria</th>
<th>Geomorphology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
</tr>
<tr>
<td></td>
<td>Soil</td>
</tr>
<tr>
<td>Social Economical criteria</td>
<td>Distance from Major road</td>
</tr>
<tr>
<td></td>
<td>Distance from Waterbodies</td>
</tr>
<tr>
<td></td>
<td>Distance from Settlements</td>
</tr>
</tbody>
</table>

2.1.1 Physical Criteria

i) Geomorphological criteria

Geomorphology of the surface should be given importance during site selection particularly for solid waste disposal. The suitable score given to the geomorphology of Tumkur region is well explained in Table 2.
Table 2. Suitability score given to Geomorphology

<table>
<thead>
<tr>
<th>Type of Geomorphology</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moderately weathered</td>
<td>5</td>
</tr>
<tr>
<td>Shallow Weathered</td>
<td>4</td>
</tr>
<tr>
<td>Pediment / valley floor</td>
<td>3</td>
</tr>
<tr>
<td>Pediment inselberg complex</td>
<td>4</td>
</tr>
<tr>
<td>Residual hills</td>
<td>1</td>
</tr>
<tr>
<td>Structural hills</td>
<td>1</td>
</tr>
<tr>
<td>Valley fill</td>
<td>2</td>
</tr>
</tbody>
</table>

ii) Soil criteria

The suitability score given for different types of soil of Tumkur region is shown in Table 3.

Table 3. Suitability score given to Soil

<table>
<thead>
<tr>
<th>Types of Soil</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inceptisols</td>
<td>5</td>
</tr>
<tr>
<td>Entisols</td>
<td>4</td>
</tr>
<tr>
<td>Alfisols</td>
<td>3</td>
</tr>
<tr>
<td>Rock out crops</td>
<td>1</td>
</tr>
<tr>
<td>Dyke ridges</td>
<td>1</td>
</tr>
<tr>
<td>Habitation mask</td>
<td>2</td>
</tr>
</tbody>
</table>

iii) Slope criteria

The slope is one of the important criteria for dumping Solid waste. The suitability score given for change in slope is shown in Table 4.

Table 4. Suitability score given for slope

<table>
<thead>
<tr>
<th>Slope in degrees</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>5</td>
</tr>
<tr>
<td>1-3</td>
<td>5</td>
</tr>
<tr>
<td>3-5</td>
<td>4</td>
</tr>
<tr>
<td>5-10</td>
<td>3</td>
</tr>
<tr>
<td>10-15</td>
<td>2</td>
</tr>
<tr>
<td>15-35</td>
<td>1</td>
</tr>
<tr>
<td>35-50</td>
<td>1</td>
</tr>
</tbody>
</table>

2.1.2 Social Economical criteria

i) Distance from Major roads

Road is an important factor in the process of selecting Solid waste dumping sites. The site should not be too near to the road or too far from the road then only the conveyance of waste should be smooth and more economical. In this study the major roads are selected around which multiple buffer is created. The suitability score used for distance from Major roads is shown in Table 5.

Table 5. Suitability score for Distance from Major roads

<table>
<thead>
<tr>
<th>Road Distance in meters</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-400</td>
<td>5</td>
</tr>
<tr>
<td>400-800</td>
<td>4</td>
</tr>
<tr>
<td>800-1200</td>
<td>2</td>
</tr>
<tr>
<td>1200-1600</td>
<td>2</td>
</tr>
<tr>
<td>1600-2000</td>
<td>1</td>
</tr>
</tbody>
</table>

ii) Distance from Waterbodies

The dumping of solid waste should be done in scientific way such that waterbodies are not contaminated. In this the buffer zone is created around the waterbodies. The suitability score used for distance from waterbodies is shown in Table 6.
Table 6. Suitability Score for distance from Waterbodies

<table>
<thead>
<tr>
<th>Distance from Waterbodies in meter</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-200</td>
<td>1</td>
</tr>
<tr>
<td>200-400</td>
<td>2</td>
</tr>
<tr>
<td>400-600</td>
<td>3</td>
</tr>
<tr>
<td>600-800</td>
<td>4</td>
</tr>
<tr>
<td>800-1000</td>
<td>5</td>
</tr>
</tbody>
</table>

### Distance from Settlements

Dumping of solid waste should not be done in the places where there are settlements hence, in thus study buffer zone is created and suitability score is assigned which is shown in Table 7.

Table 7. Suitability score for distance from Settlements

<table>
<thead>
<tr>
<th>Distance from Settlements</th>
<th>Suitability Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1600</td>
<td>1</td>
</tr>
<tr>
<td>1600-3200</td>
<td>2</td>
</tr>
<tr>
<td>3200-4800</td>
<td>3</td>
</tr>
<tr>
<td>4800-6400</td>
<td>4</td>
</tr>
<tr>
<td>6400-8000</td>
<td>5</td>
</tr>
</tbody>
</table>

[Note: The Suitability Score from 1 to 5 indicates, 1- not suitable, 2- very less suitable, 3- less suitable, 4- moderately suitable, 5- highly suitable]

2.2 Improving Surface Water Availability Under Smart City Planning Using GIS and RS

To obtain the required objective mentioned above which was selected after the discussion with Smart city Tumkurul Ltd. The outcome of the discussion was that there was plan to interlink all the lakes present in Tumkurul and also storm water drains to be laid along the road network. To obtain the required objectives the latest satellite data of 2018 [CARTOSAT 1 merged with LISS IV] was used to update all the road network layer and a tentative plan was prepared for linking of MaralurAmanikere Tank with the waterbody near to Geddalalahalli. The data base created was given for Smart City Tumkurul Ltd for further processing for further action at their end.
3. RESULTS AND DISCUSSION

3.1 Solid waste management planning

In the present research work data collected through primary and secondary sources processed in ArcGIS for geospatial database generation. In this study after all process in GIS environment eight suitable sites were selected for scientific disposal of solid waste. Further more data can be used in the future for better results. Figure 5 shows the suitable solid waste dumping sites where green indicates the area which is highly suitable, blue moderately, pink is less suitable among the present sites.

The database created can be used for better planning of Solid Waste Management scientifically which has its major role in development of city as smart. The location of the best suitable dumping sites and their area is shown in Table 8.
Table 8. Suitable solid waste dumping site and its area

<table>
<thead>
<tr>
<th>Site No</th>
<th>Location of waste land</th>
<th>Area [Ha]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Near to Nijagal village</td>
<td>191</td>
</tr>
<tr>
<td>2</td>
<td>Near to Danayakanapuram</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>Near to Aregujjanahalli</td>
<td>34</td>
</tr>
<tr>
<td>4</td>
<td>Near to Hiregundagal</td>
<td>24</td>
</tr>
<tr>
<td>5</td>
<td>Near to kodagihalli</td>
<td>24</td>
</tr>
<tr>
<td>6</td>
<td>Near to Kambatamahalli</td>
<td>16</td>
</tr>
<tr>
<td>7</td>
<td>Near to Honnenahalli</td>
<td>16</td>
</tr>
<tr>
<td>8</td>
<td>Near to Hirehalli</td>
<td>15</td>
</tr>
</tbody>
</table>

3.2 Improving surface water availability

As discussed in the methodology part drainage pattern is extracted using CARTODEM of 10 m resolution which shown that there is no natural connectivity between two water bodies because of urban development hence there is need to connect two water bodies by means of major road network. The road network is updated using the satellite data of 1m resolution shown in Figure 6.

![Figure 6. Road network updated using merged satellite data of CARTOSAT 1 & LISS IV](image)

A tentative plan is prepared linking Maralur Amanikere Tank with the waterbody near to Geddalahalli. Also, a sewage treatment plant should be constructed at the inlet of Maralur Amanikere tank. The tentative plan is shown in Figure 7. Yellow line shows the linking of two lakes.
4. CONCLUSION

The municipal officer involved in the solid waste management should be clear about the function and their role in terms of managing the cities effectively with the help of GIS system. These Thematic maps will help officers to identify and monitoring the more waste generated wards and scientific way of disposal can be adopted. The data base generated in this study was provided for Smart city Tumkur ltd which is helpful in initial planning process. Here it is clear that RS and GIS data can be used in Smart city planning process.

REFERENCES

ENHANCED VEGETATION INDEX BASED SPATIO-TEMPORAL CHANGES IN THE VEGETATION PATTERN USING PIECEWISE LINEAR REGRESSION

Niraj Priyadarshi¹ *, K. Chandrasekar², V.M. Chowdary³, Rituraj Gogoi⁴, Y.K. Srivastava¹, Soumya Bandyopadhyay⁴, Uday Raj²

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ABSTRACT

Monitoring changes in the vegetation pattern is important as these changes have direct relation with biophysical land-surface properties and energy transfer to atmosphere, which may influence local/regional climate change. One of the major objectives of this study is to analyze vegetation changes occurred during the period 2001-2016. In this study, time series Enhanced Vegetation Index (EVI) data were used to analyze spatio-temporal analysis of vegetation changes for three seasons namely pre-monsoon, monsoon and post-monsoon during the period 2001-2016 for Damodar River Basin, Jharkhand. The EVI data was used to measure the green vegetation vigour over the ground surface as it is sensitive to high biomass regions while minimizing soil and atmospheric influences. The piecewise linear regression algorithm was used to detect structural break point and change in the vegetation pattern in time series EVI data. The analysis of time series EVI data identified the changes in vegetation pattern in different seasons that can be utilized in climate change studies and its effect on vegetation pattern.

KEYWORDS: Time series, MODIS EVI, Vegetation trends, Break point, Piecewise regression

1. INTRODUCTION

Remote sensing of vegetation growth and dynamics play a very important role in ecology, agriculture and various environmental studies at temporal and spatial scales. Vegetation change dynamics provide important information about land cover change, status of agriculture crop and ecological responses to climate changes. In last few decades, various researchers carried out studies for monitoring of changes in vegetation growth due its importance in regulating the terrestrial carbon cycle and climate system (Zhang et al., 2013). Vegetation productivity changes directly related to the variation in terrestrial net carbon uptake and may lead to local and regional climate changes (Jackson et al., 2008; Zhao and Running, 2010). Terrestrial carbon uptake by vegetation on the earth is 1.2 times larger than the ocean carbon sink and any changes in vegetation on the earth have direct impact on the carbon balance (Zhang et al., 2013). There is uncertainty involved how vegetation change affects the terrestrial biosphere. The changes in terrestrial vegetation are partially responsible for uncertainty in the process of climate change. The uncertainty can be reduced by adopting improved land cover change algorithms, superior sensor technology for vegetation observation, improving knowledge on the process of climate change and best utilization of time series analysis techniques (Zhang et al., 2013; Jamali et al., 2014). Therefore, a substantial attention has been given to the vegetation growth and its impact on local, regional and global scale climate changes.

Changes in vegetation growth, dynamics and distribution can significantly alter the climate change by altering the global vegetation and the distribution of species (Pearson and Dawson, 2003). Vegetation change can be sudden or gradual, cyclic or seasonal and reversible or irreversible. The general causes of alteration of vegetation can be short term natural phenomena such as fire, flood, insect infestation and human induced such as deforestation, logging, tree removal for agriculture,

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resource expansion, land use conversion (de Jong et al., 2013). Changes in vegetation can be attributed to land cover changes due to anthropogenic activities, increased food demand, construction materials which directly impacting climate change (Kirby, 2013).

Figure 1. Location Map of Damodar River Basin of Jharkhand

Vegetation change rates are increasing over the last few decades in the structure and function of ecosystem due to anthropogenic land cover changes (Jamali et al., 2014). Inter-intra annual vegetation growth and dynamics can be identified using time series Satellite Pour l’Observation de la Terre (SPOT), Moderate Resolution Imaging Spectroradiometer (MODIS) and Global Inventory Modeling and Mapping Studies (GIMMS) vegetation index data. In this study, MODIS derived Enhanced Vegetation Index (EVI) time series satellite data (16-day composite product with 250m spatial resolution) available since year 2001 were utilized. The MODIS vegetation index (EVI) is widely used for remote sensing applications and it measures the amount of vegetation present on the ground (Neteler, 2004; Priyadarshi et al., 2017).

Towards, understanding the impact of climate changes on vegetation, in this study, climate-induced vegetation growth changes over the Damodar Basin for the period 2001-2016 were studied. The main goal of this study was to investigate where and when the vegetation changes occurred in the Damodar Basin during the period 2001-2016 using MODIS based EVI data. Seasonal (monsoon, pre-monsoon and post monsoon) and annual vegetation changes were analyzed using the piecewise linear regression approach, that helped to detect the change point in time series EVI data at annual and seasonal scale.

2. STUDY AREA

The Damodar River Basin spread across Jharkhand and West Bengal states, India and nearly covers geographical area of around 24,235 Sq. km (Figure 1). The study area is very rich in minerals especially coal and mica, which led to the development of vast industrial belt. The study area is also known as ‘Ruhr of India’. ‘Ruhr Valley’ located in Germany, which is very rich in minerals. The study area consists several Dams, small & big industries such as thermal and steel plants. It is also one of the most industrial areas of the India. The study area has average annual rainfall is about 1400mm. It is also known as ‘River of Sorrows’ because it causes floods in the plains of West Bengal, (Web References 1, 2). In this study, Damodar River basin lying in the part of Jharkhand is considered for the study (Figure 1). It consists of about 12 districts of Jharkhand and about 3 districts of West Bengal state.
DATA
This study has utilized the MODIS time series EVI data of study area for the period of 2001-2016. The EVI data were extracted and pre-processed using the MODIS MOD13Q1 product which is a 16-day composite product and having spatial resolution of 250m. National Aeronautics and Space Administration (NASA) has launched Terra and Aqua Satellite in December, 1998 and May, 2002 respectively and it has assembled MODIS sensor onboard. MODIS is considered much advanced, improved performance and higher spectral and spatial resolution in compare to AVHRR sensor.

Figure 2. Inter-annual variations of annual average EVI in the Damodar River Basin. Solid red lines indicate linear fit during 2003-2007(year 3-7), 2008-2010 (year 8-10) and 2011-2016 (year 11-16) respectively.

3. METHODOLOGY
The inherent noise is present in time series MODIS EVI data due to cloud contamination and atmospheric effect (Priyadarshi et al., 2017). The Savitzky-Golay filtering technique was applied to reduce the noise and suppressed disturbances present in time series EVI data while preserving features of the dataset such as relative maxima, minima, and width (Priyadarshi et al., 2017). In this study, 16-day composite product of MODIS EVI data was utilized for analysis of spatio-temporal pattern change. March to April were defined as pre-monsoon, July to September were defined monsoon and October to December were defined as post-monsoon seasons as per IMD classification. Average annual EVI data were generated for at annual and seasonal scales (pre-monsoon, monsoon and post monsoon) for the period 2001-2016 for identification of trends.

Linear regression approach is widely used approach to analyze the vegetation trends at regional to global scales. This approach is one of the simplest and widely used statistical techniques for predictive analysis and to model a relationship between two variables where one variable is independent and other is independent variable (Montgomery, 2009; Chandola et al., 2010). Piecewise Linear regression (segmented regression) is widely utilized for analysing multiple trends in a given time series EVI data. In this approach, independent variables are segmented into intervals and line is fitted to each interval or segments (Tome, 2004; Forket et al, 2013). The objective is to evaluate a potential segment in time series EVI data by estimating residual error of linear regression. In this study, piecewise linear regression was implemented for identification of change points or structural break in time series EVI data for the period of 2001-2016.

4. RESULTS AND DISCUSSION
Change in annual EVI pattern
At the regional scale, analysis of MODIS EVI time series data for the time period 2001-2016 refer two change points i.e 2007-08 and 2010-11 (Figure 2). Although a statistically significant trend (liner fit) in study area was observed over the entire study period represented in dashed line, there exists three distinct trends line includes 2003-2007(year 3-7), 2008-2010 (year 8-10) and 2011-2016 (year 11-16) respectively (Figure 2). It can be observed from Figure 2, that temporal pattern of annual average EVI changes in three mentioned points indicated an abrupt change in the EVI data.
Spatial distribution of average annual EVI during different periods 2001-2002, 2003-2007, 2008-2010 and 2011-2016 of the study area were shown in Figure 3. It can be observed that the overall vegetation distribution is very low in the year 2001-2002 in comparison to the year 2003-2007. Vegetation distribution has increased during the period 2003-2007 (Figure 2), while drastic decrease in the vegetation was observed during the period 2008-2010 (Figure 3). However, in 2011-2016 a considerable increase of vegetation is seen and shows how vegetation pattern changes in a time series EVI data. The overall linear negative trendline (dashed black line) on the EVI dataset adds to the fact that a decrease in the overall vegetation has occurred in the study area during the period 2001-2016 (16 years).

**Spatial pattern of seasonal EVI trend**

The seasonal annual means gives the most relevant and precise understanding of the vegetation of the study area. The vegetation distribution and pattern of the study area undergone many changes over the time and it can be observed in Figure 4, 5 & 6. It is also observed that the monsoon rainfall and surface temperature over India has direct impact on distribution of vegetation (Sarkar & Kafatos, 2004).

Spatial distribution of seasonal average EVI for pre-monsoon, monsoon and post-monsoon during different periods 2001-2002, 2003-2007, 2008-2010 and 2011-2016 of the study area are shown in Figures 4, 5 & 6. In the year 2008-2010, the vegetation has again decreased (Figures 4, 5 & 6) and in 2011-2016 a considerable increase of vegetation is seen and shows how vegetation patterns changes in a time series EVI data (Figure 4, 5 & 6). In Figure 5, the monsoon season clearly indicate abundance of rainfall, which is essential for the vegetation growth.

5. **CONCLUSIONS**

This study shows that vegetation distribution increased over the study area during 2003-2007 & 2011-2016 and decreased during the periods 2001-2002 & 2008-2010. Changes in the rainfall pattern or anthropogenic activities can be attributed to
identify trends in the vegetation pattern during the period 2001-2016. This study also shows the linear trend for entire study period may not match accurately with actual vegetation pattern. It can also be observed that decrease in EVI during

Figure 4. Spatial distribution of pre-monsoon (March-April) average EVI during different periods 2001-2002, 2003-2007, 2008-2010 and 2011-2016 of the study area

Figure 5. Spatial distribution of monsoon (July-September) average EVI during different periods 2001-2002, 2003-2007, 2008-2010 and 2011-2016 of the study area
Figure 6. Spatial distribution of post-monsoon (October-December) average EVI during different periods 2001-2002, 2003-2007, 2008-2010 and 2011-2016 of the study area

2001-2002 and 2008-2010 was significant and negative. The break point for time series EVI data has been attained with the robust equations of piecewise linear regression and these break points in time series data was supported the observation in this study.

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REFERENCES


EXTRACTION AND TEMPORAL MAPPING OF MANGROVE FORESTS IN INDIAN SUBCONTINENT USING GOOGLE EARTH ENGINE TOOLS

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ABSTRACT
Mangroves have an important role in supporting coastal species and in burying large quantities of organic carbon, are disappearing at an alarming rate due to rapid developments along the Indian coast. This study involves quantification of mangrove extent using multi-date LANDSAT satellite images along the Indian Coast with the help of cloud computing platform, Google Earth Engine (GEE) which provides APIs with JavaScript. Google Earth Engine is a platform for petabyte-scale scientific analysis and visualization of geospatial datasets, both for public benefit and for business and government users. Vegetation Indices like Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) were used to further classify the Mangrove Extent into dense, medium and sparse Classes. Analysis of the spatiotemporal dynamics of Mangrove Extent and Density for the period 1993-2018 has helped to understand the stress on Mangrove in Coastal Ecosystem and Seasonal Variation and to Identify Vulnerable areas of Degradation along the Indian Coast.

KEYWORDS: Google Earth Engine, NDVI, LAI, LANDSAT, Mangroves.

1. INTRODUCTION
Mangrove forests are salt-tolerant woody plants that form coastal intertidal and fragile ecosystems at the intersection between land and water (Alongi 2002). These forests provide a wide range of ecosystem services such as nursery habitats for many marine fisheries, water purification, shoreline stabilization, biological diversity, and are important to the recreation and tourism industry (Rahman et al., 2013; Giri et al., 2015). Globally, mangroves are found along coasts in the tropics and subtropics, at latitudes from the equator to about 32 N and 38 S (Spalding et al. 1997). The mangrove forest ecosystem is one of the most vulnerable ecosystems on Earth due to anthropogenic disturbance and climate change (e.g. Sea level rise). It has been reported that 20–35% of global mangrove forest lands have been lost due to deforestation since the 1980s (FAO, 2007; Rahman et al., 2013). South Asia has 1,187,476 Hectares (ha) of mangroves, which is about 7% of the total extent (Giri et al. 2015). Satellite remote sensing is now commonly used for estimating mangroves extensions and dynamics, as well as for change detection purposes (Sulaiman et al. 2013). The study involves extraction and temporal variation in areal extent of mangrove forest in the whole coastline of the Indian Sub-Continent from 1993 to 2018 to understand mangrove dynamics using multi-date LANDSAT satellite images with the help of cloud computing platform, Google Earth Engine (GEE) which provides APIs with JavaScript.

2. MATERIALS AND METHODS
2.1 Study Area
The Indian peninsula has a diverse coastal environment having a significant role in the country’s development by providing a variety of resources, living habitat and rich varied biodiversity. The present study area includes the entire coastal region of India with a total length of 7,516.6 km. The study area lies between 68°10'31.98”E to 89° 3'11.77”E longitudes and 23°50'44.07”N to 8° 4'37.63”N latitudes. The Mainland Coastal states of India includes Gujarat, Tamil Nadu, Andhra Pradesh, West Bengal, Maharashtra, Kerala, Odisha, Karnataka and Goa. These states cover almost 66 coastal districts, 13 Major ports and 187 minor ports with 3288 fishing villages CMFRI 2010) forming a major socio-economic habitat. Figure 1 shows the location of Study Area along with the Mainland Coastal States and districts. The varying coastal profile is highly distributed with various problems like pollution, filtration, erosion, flooding, salt water intrusion, storm surges and other anthropogenic activities. The mouth of the river has a wide variety of coastal species which gets affected due to the above activities. Hence a detailed assessment of the coastal is to be monitored continuously for effective analysis of the variation on a local scale from time to time.

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2.2 Google Earth Engine

Earth Engine is a platform for scientific analysis and visualization of geospatial datasets, for academic, non-profit, business and government users. Earth Engine hosts satellite imagery and stores it in a public data archive that includes historical earth images going back more than forty years. The images, ingested on a daily basis, are then made available for global-scale data mining. Earth Engine also provides APIs and other tools to enable the analysis of large datasets. GEE is a cloud-based platform for planetary-scale environmental data analysis. It combines a multi-petabyte catalog of satellite imagery and geospatial datasets, Google’s computational infrastructure optimized for parallel processing of geospatial data, Application Programming Interfaces (APIs) for JavaScript and Python, and a web-based integrated development environment for rapid prototyping and visualization of complex spatial analyses. GEE is designed so that users rarely have to worry about map projections when doing computing at large area, projection parameters are requested in the output projection. (Gorelick Net al. 2017).

2.3 Satellite Data

For this study Landsat 5, 7 and 8 images with coverage of Landsat Worldwide Reference System 2 (WRS-2) path/row for the study area during the duration of 1993 to 2018 were available as Image Collection in the Google Earth Engine Tool. Four widely used vegetation indices such as Nominalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Land Surface Water Index (LSWI), and modified Normalized Difference Water Index (mNDWI) were calculated for each imagery using the equations,

\[
NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}
\]

\[
EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + 6 \times \rho_{Red} - 7.5 \times \rho_{Blue} + 1}
\]

\[
LSWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}
\]

\[
mNDWI = \frac{\rho_{green} - \rho_{SWIR}}{\rho_{green} + \rho_{SWIR}}
\]

Where \(\rho_{Red}, \rho_{Green}, \rho_{Blue}, \rho_{NIR}, \rho_{SWIR}\) are red, green, blue, NIR and SWIR bands of Landsat images.

The 30m SRTM (Shuttle Radar Topography Mission) DEM data which are available as an image collection in the Google earth engine were utilized in this study for DEM data. The Shuttle Radar Topography Mission (SRTM, see Farr et al. 2007) digital elevation data is an international research effort that obtained digital elevation models on a near-global scale. This SRTM V3 product (SRTM Plus) is provided by NASA JPL at a resolution of 1 arc-second (approximately 30m). This dataset has undergone a void-filling process using open-source data (ASTER GDEM2, GMTED2010, and NED), as opposed to other versions that contain voids or have been void-filled with commercial sources. The SRTM data has a resolution of 30m and year 2000 is the Data availability period for the data used in this study. The 30-mSRTM DEM data and their
derived variable (slope) were used to mask out those regions of high elevation and/or steep-slope where mangrove forests are not likely to occur.

2.4 In-Situ data

For the necessary Region of Interest (ROI) to develop the algorithm for the extraction of Mangrove extent In-Situ data of the location of Mangrove extent were collected with the help of GPS instrument and were mapped in ArcGIS. The Shape file of the ROI was then uploaded into the Google Earth Engine Platform for use of algorithm development. The In-Situ data collection was done in some locations along the coast of Maharashtra, Tamil Nadu and Andhra Pradesh.

![Figure 2. Mangrove regions collected in the Tamil Nadu state as ROI for algorithm development.](image)

2.5 Methodology for Mangrove Forest Mapping

In Google Earth Engine the Landsat images are imported for the areas of ROI over the time period from 1993 to 2018 and the images are masked for ROI to estimate the four widely used vegetation indices. Three key features including: (1) evergreen trees or shrubs (greenness); (2) canopy coverage (high leaf area index); and (3) tidal inundation were proposed to identify mangrove forests as they are unique evergreen trees or shrubs at estuaries and marine shorelines where inundation by tides occurs (Bangqian Chen et al. 2017). The criteria of LSWI > 0 and EVI > 0.2 was used to map evergreen forest in tropical America, Africa, and Asia (Xiao et al., 2009). We have employed this criterion in our study for identification of the greenness of mangrove forest. The condition of NDVI > 0.3 and LSWI > 0.3 were used as criteria to identify canopy coverage of mangrove forest. Tidal inundation was identified by using the criteria of LSWI ≥ EVI or LSWI ≥ NDVI, both of which have been used for mapping paddy rice and reed wetland (Dong et al., 2016; Zhou et al., 2016). The phenology of mangrove forests and variation in tidal action could be responsible for the features of greenness, canopy coverage, and inundation from specific imagery or one image composite to be biased. Hence we use frequency-based approach for greenness, canopy coverage, and inundation from time series Landsat images to identify mangrove forest, following the method reported in mapping paddy rice in northeastern Asia (Dong et al., 2016).

For the determination of frequency based Greenness state, we consider the following condition over the entire Landsat Images.

\[
\text{Greenness} = \begin{cases} 
1 & \text{LSWI} > 0 \text{ and } \text{EVI} > 0.2 \\
0 & \text{For Other Values}
\end{cases}
\]

Thus the Greenness frequency can be determined using the equation,

\[
F_{\text{greenness}} = \frac{\sum \text{greenness}}{\sum \text{total} - \sum \text{bad}} \times 100 \quad (5)
\]

Where \(F_{\text{greenness}}\) is the greenness frequency in the range of 0 to 100%, \(N_{\text{greenness}}\) is the number of observations with LSWI > 0 and EVI > 0.2 and \(N_{\text{total}}\) is the number of total observations, \(N_{\text{bad}}\) is the number of bad observations (cloud pixels) (Dong et
al., 2016). Similarly the frequency conditions for the remaining two features namely canopy coverage and tidal inundation were generated using the criteria of \((\text{NDVI} > 0.3 \text{ and } \text{LSWI} > 0.3)\) and \((\text{LSWI} \geq \text{EVI} \text{ or } \text{LSWI} \geq \text{NDVI})\) respectively.

The Frequency conditions of greenness, canopy coverage and tidal inundation of every pixel of ROI are mapped against mean NDVI of the corresponding pixels and a Trend line is generated for each case from which Thresholds for the greenness, canopy coverage and tidal inundation are obtained.

![Graphs showing frequency vs mean NDVI for greenness, canopy coverage, and tidal inundation.](image)

Figure 3. Plots of mean NDVI against frequency of (a) Greenness, (b) Canopy Coverage, (c) Tidal Inundation

Based on the results from charts (Figure 3) mangrove forests were identified if a pixel meets the following conditions at mean time according to its annual mean NDVI.
Where $x$ is mean NDVI.

In addition to the above conditions, elevation and slope can be used to further develop the algorithm. A vast majority of mangrove forests were distributed in areas with an elevation between -5 m and 10 m above mean sea level slope of less than 10°.

Built-up and barren lands have either an impervious surface or exposed soils, which usually have low LSWI values (Xiao et al., 2005). A frequency map to identify the Built-up and barren lands with the condition LSWI<0, was generated similar to the above method. A pixel with frequency value >50% was then classified as built-up or barren land (Zha et al., 2003) which can be masked from the mangrove layer.

Yearlong waterbodies along the coastline can be separated from the mangrove layer by means of the criteria $m$NDWI > 0 used for mapping open surface water bodies (Xu, 2006). Frequency maps with the condition $m$NDWI>0 can be generated similar to the previous method, here we can mask a pixel value as the yearlong waterbodies when frequency value of $m$NDWI>0 is greater than 10%.

3. RESULT AND DISCUSSION

The frequency maps generated for the ROI enables us to develop the algorithm for extraction and mapping of the mangrove forest, by which we have extracted the extent of mangrove forest throughout the coastline of India for the duration from 1993 to 2018 with an accuracy of 95% by comparison with data collected in-situ for the validation purpose by means of GPS instrument which was then mapped and digitized in ArcGIS. Area of the mangrove extent for each year from 1993 to 2018 was calculated to denote that the change in area of the mangrove extent has decreased in linear fashion from 1993 to 2018. The area of the mangrove for each month denoting the various seasons throughout the period of 1993 to 2018 enables us to understand that there is no significant change in the area of the mangrove extent for different seasons of the year in the Indian coast. Further classify the Mangrove Extent into dense, medium and sparse Classes enables us to understand the variation of the density of mangrove forest in the Indian coast over a year for the period from 1993 to 2018.

![Figure 4. Extraction of Mangrove forest (Maharashtra Coast).](image-url)
4. CONCLUSION

This study has generated the means for the extraction of Mangrove extent using the Google Earth Engine which had enabled to do analysis of the spatiotemporal dynamics of Mangrove Extent and Density for the period 1993-2018 to understand the stress on Mangrove in Coastal Ecosystem and Seasonal Variation and to Identify Vulnerable areas of Degradation along the Indian Coast.

REFERENCES


ASSESSING THE MAPPING ACCURACY OF THE MICROUAV WITH AMATEUR GPS CAMERA FOR PROPERTY, ASSET AND RESOURCE SURVEY

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ABSTRACT
The developments of ICT and GeoICT have increased the interest in use of geospatial technology to modernize the land records and property surveys. One such supplementary is the use of drones or unmanned aerial vehicles that have the advantages of non invasive high resolution imaging of the terrain even in the inaccessible areas and ease of coupling with GIS and GPS.

In this study, an attempt has been made to use the pictures taken with UAV for mapping of a multiblock residential area and evaluating the accuracy to understand the scope of use in cadastral, property and resource survey. Assessing the planimetric and altimetric accuracy using microUAV with low cost GPs camera was the purpose. The area was mapped with microUAV with amateur GPS camera CANON sx230hs with 12,1 mp resolution from a height of 90m and 120m. The bundle block adjustment was performed for parts of the images for length and area measurement. The areas and length measurement from the block and the field measured values were compared for the images acquired for two heights. The performance in terms of length measurement and area measurement was studied. It was found that the along track accuracy was better than across track accuracy. These results threw light on the scope of using low cost micro UAV with amateur GPS camera for mapping with respect to type of application and scale, flight control, camera and geolocation capabilities needed and the launching mechanism of the UAV along with the mapping functions to be used.

KEYWORDS: UAV/drone, planimetry, altimetry, GPS, pre-and post-pointing

1. INTRODUCTION
The recent development in the imaging technology and the needs for the resource planning at micro scale has thrown light on the use of unmanned aerial vehicles for mapping. The management of resources like water or the development of the land resources needs information at a large scale. The increase in the land cost, thanks to globalization and industrialization has made the resource managers to accumulate information of the land and other resources at a more frequent intervals with greater clarity. This can be answered by the on-demand, on-the –go and handy UAVs (DeBell et al, 2016). The use of drones or unmanned aerial vehicles that have the advantages of non invasive high resolution imaging of the terrain even in the inaccessible areas and ease of coupling with GIS and GPS (Manyoky, 2011). The field equipment like total station coupled with the non-contact survey methods like GPS, Remote sensing and laser scanning have been proved to increase the dependability of the results with time efficiency(Henri Eisenbeiss, 2004). It is also proved by various researchers and practitioners that the optimized use of field and non-field survey and measurement can provide good updated land records in digital form (Eugene H. Silayo,2005). The cost involved make it more viable of multi temporal imaging for the monitoring purposes also.

At the same time, the technical knowhow with respect to the capabilities of the system and the operative guidelines and the future scope of this approach for resource and cadastral mapping should be studied carefully. The current surveying equipments and the need for accuracy have called for a more economical solution for cadastral surveying (Belle, 2003). The positional accuracy is of importance in large scale surveys and they call for a robust adjustment primarily due to the direct measurements and compilation (David , 2009). The final accuracy of the mapping has to be well understood by the user for a specific application (Tampubolon , 2014). UAV images are images which are similar to aerial photographs taken at low altitude using drone. These images are acquired using non-metric cameras The preplanning of the survey right from the control network, control point accuracy, methodology and technology is of main concern in any large scale mapping (Krishnamoorthi, 2004). The problem related to overlap variations, large rotation angles between adjacent images, and also large parallax discontinuities between features above the ground and the data mining methods are to be studied and understood well before the attempt (There is overlap variations, large rotation angles between adjacent images, and also large parallax discontinuities between features above the ground ( Yongjun, 2008; Rongjun, 2013). The possibility of using UAV technology in Cadastral application requires the following analysis

Mapping Accuracy: The accuracy of measurements obtained should satisfy the cadastral requirements and principles.

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Economic Viability: The cost of the technology should be less and economic.

Social Acceptability: The level of acceptability exhibited by the implementers of the new technology in real time and also the end users.

An attempt to use the amateur UAV at test site of Tamil Nadu Slum Clearance Board (TNSCB) project which has nearly 120 acres of land at Perumbakkam near Sholinganallur, Chennai was made. Assessing the planimetric and altimetric accuracy using microUAV with low cost GPS camera was the purpose. The specific tasks were

- To analyze and understand the various steps and challenges in processing the UAV data.
- To assess the accuracy of UAV data for mapping with different operational parameters.
- To formulate the operational procedure for Cadastral mapping using UAV data in conjunction with limited ground based modern surveying.

The experiment was conducted with 90m and 120m flying height and the results were analysed.

2. MATERIALS AND METHODS

This section discusses study area, tools and methods used.

2.1 Study site

The test site of our project was TNSCB project site which has nearly 120 acres of land at Perumbakkam near Sholinganallur, Chennai. TNSCB has completed the construction of 3,936 flats for the homeless and urban poor living along waterways in the city. The tenements have been constructed at a cost of Rs. 175 crore under the Jawaharlal Nehru National Urban Renewal Mission project site which has nearly 120 acres of land at Perumbakkam near Sholinganallur, Chennai.

2.2 Instruments used

An amateur micro UAV with 2.1 kg weight and GPS Canon sx230hs (Point and Shoot) camera was used. The UAV had the geo fence capability and 1h 30 min operating time. The UAV was built by the UG students of Sathyabama University. The camera had 5mm focal length, 3.25 µm aperture size and 12 MP resolution. For ground control, Trimble R5 with Modular 72-channel configuration with Trimble R-Track technology was used. Trimble M3 total station with Nikon optics was used for ground survey. Trimble Geomatics office was the software used for processing GPS data and Photomod lite 5.4 was the software used for processing the UAV photos.

2.3 Method

The three main tasks of this mapping are i) UAV flying and ii) Ground survey and iii) photo processing for mapping

2.3.1 Flight Planning

The flight planning was done before the fly in order to show where the photos should be captured. The parameters to be considered for flight planning are Camera and film requirements, Scale, Flying height, End and side lap, tilt and crab tolerances.

2.3.2 First and second UAV fly

The first fly of UAV was on 24th December 2014. The wind speed was around 12m/s. But unfortunately the drone got crashed due to unexpected high wind velocity and also improper calibration of camera. Hence the images could not be acquired.

Knowledge gained from First Fly

The Experience and knowledge gained from the first fly are as follows

- Proper calibration of IMU with respect to horizontal reference surface is required for a successful fly.
- Take off can be from the building terrace instead of ground as the UAV may have enough gliding time in the air before it starts to fly properly.
- Landing of UAV can be done by using nets on the terrace as the space for proper landing is not enough on the terrace.

The second fly of UAV was on 20th January 2015. The wind speed was around 8m/s. The drone was made to take off from the building terrace. The images were acquired successfully due to optimum wind velocity and proper calibration of the camera. The landing of UAV was done using “Net Catch”.

The flight was done with two flying heights namely 90m and 120m.
Table 1. Image and its Related Information

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>flying height</td>
<td>90m, 120m</td>
</tr>
<tr>
<td>speed</td>
<td>13 m/s</td>
</tr>
<tr>
<td>interval between successive captives</td>
<td>2 sec</td>
</tr>
<tr>
<td>exposure time</td>
<td>1/1000 sec</td>
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<tr>
<td>side lap</td>
<td>70%</td>
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<tr>
<td>end lap</td>
<td>65%</td>
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<td>358</td>
</tr>
<tr>
<td>no. of strips</td>
<td>10</td>
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<td>image format</td>
<td>4000 x 3000</td>
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<tr>
<td>pixel size</td>
<td>2.4 microns</td>
</tr>
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<td>area covered in a single image</td>
<td>108.8*81.6 m</td>
</tr>
</tbody>
</table>

2.3.3 Measurement of Control Points

The primary/base control used for preliminary measurements and consists of any known point capable of establishing accurate control of distance and direction is known as control point. The figure 1 shows the location of GCP in the test site. 26 pre points and 17 post points were measured for mapping.

Figure 1 The test site with pre post GPs control points

The pre and post control points were used for adjustment. The adjustment was done with Photomod lite 5.4 software the results were compared with the ground measured distances and heights.

3. RESULTS AND DISCUSSION

The flight and the bundle block adjustments were done and the measurements are obtained from the block. These distances and areas were compared with the ones taken on the ground using total stations. The results are presented. Various features on the ground and the measured distances are as follows:

Table 2. Planimetric accuracy in selected lengths and areas

<table>
<thead>
<tr>
<th>FEATURES</th>
<th>DIMENSIONS(120 m)</th>
<th>GROUND MEASUREMENTS</th>
<th>DEVIATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>FENCE</td>
<td>117.554m</td>
<td>120.052m</td>
<td>2.498m</td>
</tr>
<tr>
<td>ROAD</td>
<td>343.680m</td>
<td>348.336m</td>
<td>4.656m</td>
</tr>
<tr>
<td>ROAD WIDTH</td>
<td>4.862m</td>
<td>5.784m</td>
<td>0.922m</td>
</tr>
<tr>
<td>BUILDING BASE1</td>
<td>11.795m</td>
<td>12.8m</td>
<td>1.005m</td>
</tr>
</tbody>
</table>
An analysis of distances along the flight direction and across the flight direction in height was also done and the results are presented.

Table 3. Vertical accuracy at selected heights

<table>
<thead>
<tr>
<th>ACTUAL VALUE (m)</th>
<th>MEASURED VALUE (m)</th>
<th>DIFFERENCE (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12.8</td>
<td>11.496</td>
<td>1.303</td>
</tr>
<tr>
<td>12.8</td>
<td>11.522</td>
<td>1.277</td>
</tr>
<tr>
<td>12.8</td>
<td>11.859</td>
<td>0.940</td>
</tr>
<tr>
<td>12.8</td>
<td>11.524</td>
<td>1.275</td>
</tr>
<tr>
<td>12.8</td>
<td>14.136</td>
<td>-1.336</td>
</tr>
<tr>
<td>12.8</td>
<td>11.652</td>
<td>1.147</td>
</tr>
<tr>
<td>12.8</td>
<td>11.859</td>
<td>0.940</td>
</tr>
<tr>
<td>12.8</td>
<td>11.407</td>
<td>1.392</td>
</tr>
<tr>
<td>12.8</td>
<td>14.195</td>
<td>-1.395</td>
</tr>
</tbody>
</table>

The RMS error was 1.255m. The deviation across the flight direction was as follows

Table 4. Vertical accuracy in selected heights

<table>
<thead>
<tr>
<th>ACTUAL VALUE (m)</th>
<th>MEASURED VALUE (m)</th>
<th>DIFFERENCE (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>78.991</td>
<td>75.998</td>
<td>2.992</td>
</tr>
<tr>
<td>78.991</td>
<td>76.190</td>
<td>2.800</td>
</tr>
<tr>
<td>78.991</td>
<td>76.453</td>
<td>2.538</td>
</tr>
<tr>
<td>78.991</td>
<td>76.490</td>
<td>2.498</td>
</tr>
<tr>
<td>78.991</td>
<td>76.028</td>
<td>2.962</td>
</tr>
<tr>
<td>78.991</td>
<td>76.412</td>
<td>2.578</td>
</tr>
<tr>
<td>78.991</td>
<td>76.574</td>
<td>2.416</td>
</tr>
<tr>
<td>78.991</td>
<td>76.572</td>
<td>2.419</td>
</tr>
<tr>
<td>78.991</td>
<td>76.256</td>
<td>2.732</td>
</tr>
</tbody>
</table>

The RMS error was 2.644m. The deviations in the length and area and the height were studied to understand the reasons for the errors.

The areas and length measurement from the block and the field measured values were compared for the images acquired for two heights namely 90m and 120m and it was found the error for the block with 120m flying height was less than the of 90m height. The error was from 1% for longer lengths (fences) to about 8% for shorter lengths (buildings). The area difference was about 1% for the 120m H images and 6% for the 90m images. The along track accuracy was better than across track accuracy. These results threw light on the scope of using low cost micro UAV with amateur GPS camera for mapping with respect to type of application and scale, flight control, camera and geolocation capabilities needed and the launching mechanism of the UAV along with the mapping functions to be used.
Salient points understood by this exercise are

The camera used for our project is a simple digital camera from which the INS information for individual images could not be derived as it was in a video format without time scale. Hence, metric cameras are more suitable and more accurate for photogrammetric applications as it has a well-defined internal geometry. But the high cost is its limitation for use. Survey grade cameras can be a better option to be used in a UAV fly from which the INS information for individual images is extractable. INS information helps in generating RPC’s with which satellite image processing techniques can be incorporated while processing. This will overcome the problems due to undefined internal geometry and interior orientation. The inbuilt software in UAV system permitted the side lap range from 70% to 90%. This is not required for photogrammetric processing and also reduces the accuracy. So during any fly the flight plan can be made in such a way that, acquisition of images is with 90% overlap. Skip of one entire flight line alternatively will help in achieving the required level of side lap for photogrammetric processing.

Low altitude fly reduces the accuracy levels. This problem is confined to our study as the flying altitude could not be increased beyond 120m flying height because the test site lies in the cone region of the airport. Also our test site has tall buildings of height 30m but relatively image acquisition was at a low flying altitude. Generally B/H ratio has to be optimally around 0.6 to achieve good accuracy. But, B/H ratio for our study is 0.25 for 120m flying height and 0.33 for 90m flying height. This problem resulted in large fall over in the data obtained and was a limiting factor to achieve good accuracy in measurements. To overcome this problem, Height of the tallest building in the study area should be considered before planning the flying height. Proper ratio has to be maintained between the flying height and the tallest feature in the study region to avoid problems due to fall over and occlusion. B/H ratio has to be maintained around 0.6. The type of drone used for the project is a Micro UAV which weighs only about 2.1 kg and so less stable. This resulted in deviation of planned flight path. So, use of stable drone is recommended during fly in order to maintain the flight path as planned and to avoid the deviation from the planned flight path. Proper geo referencing and orientation is required to achieve best accuracy. During processing we faced problems in geo referencing the images which affected the accuracy in measurements obtained from the images. So, the deviations in measurements, due to problems in defining the control points and geo-referencing should be studied in depth. This will help to plan the adequate number of control points for processing the UAV images to obtain high accuracy.

4. CONCLUSION

This exercise clearly demonstrates the need for a calibrated system of unmanned carriers of camera for the mapping and surveying applications. The instruments used for the ground segment were time tested and of high quality. Hence, the serious error can be attributed to the UAV imaging and the processing needs. The camera control information are of greater importance. The knowledge on coordinates of the camera would be more interest that the imaging capabilities of the camera. The transformation required for the conversion of the WGS84 posted by the GPs to the local coordinate system is also important. In many of the experiments that followed and preceded this experiment the side lap was always large meaning the poor geometry for the block adjustment. The GPS control points were transferred from the nearby benchmark, asserting the importance. The knowledge on coordinates of the camera would be more interest that the imaging capabilities of the camera. The inbuilt software in UAV system permitted the side lap range from 70% to 90%. This is not required for photogrammetric processing and also reduces the accuracy. So during any fly the flight plan can be made in such a way that, acquisition of images is with 90% overlap. Skip of one entire flight line alternatively will help in achieving the required level of side lap for photogrammetric processing.

ACKNOWLEDGEMENT

The authors record their gratefulness to the Director, Institute of Remote Sensing to permit to go ahead with this effort. The opportunity and permission rendered by the Tamil Nadu Slum Clearance Board is acknowledged. Special thanks are due to Mr. Pragatish who built the UAV and for accepting to use it for this study.

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APPLICATION OF OBJECT BASED CLASSIFICATION FOR MAPPING TREES ON FARMLANDS: A CASE STUDY OF SUNDARGARH DISTRICT, ODISHA

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ABSTRACT
Agroforestry plays major role in climate change and food security. There is considerable area under agroforestry in India. For its mapping, remote sensing techniques can be useful, but traditional classification cannot serve the purpose. They do not accurately differentiate trees with other objects (such as scrub, Forest, Plantation) due to lack of parameters (size, shape, tone, texture). The object based classification can play major role to identify and extract trees in the scattered form, boundary and block plantations based on above parameters with training sample sand separate background pixels (other categories). In this paper, LISS-4 satellite imagery with spatial resolution 5.8m is used for agroforestry mapping in Sundargarh district of Odisha. This research compared the method of maximum likelihood and object based image analysis (OBIA) using single feature probability (SFP). SFP consider pixel cue probability matric to identify the objects with training sample and then apply more parameters such as threshold and clump, probability filter, smoothness etc. for distinguishing Agroforestry with similar spectral signature objects. Results showed that OBIA provide precious tree extraction information as compared to maximum likelihood classification with 84% accuracy. Hence for agroforestry mapping, we need more characterized approach that is possible using OBIA technique.

KEYWORDS: Agroforestry, Object Based Image Analysis, remote sensing, supervised classification, tree mapping.

1. INTRODUCTION
Agroforestry is a land use management system where trees are grown around and among the agricultural crops. The National Agriculture Policy (2000) emphasized the role of agroforestry. The task force of planning commission on Greening India for Livelihood Security and Sustainable Development (2001) also recommended that agroforestry may be promoted for sustainable agriculture. Forest conservation efforts involving reduction of deforestation and degradation may have to increasingly rely on alternatives provided by TOF (Saxena, 1997; Namwata, et al, 2012) in catering to economic demand in forest edges. Various forms of agroforestry exist in India and they occupy considerable area in the whole country.

Remote Sensing Imagery effectively captures the characteristics of the Earth’s surface, but it takes interpreter’s knowledge about shape, texture, patterns and site context to derive information about land use activities from information about land cover (Blaschke, 2010). Remote Sensing has become an effective tool for mapping and monitoring of agriculture, forestry and other earth features. Geo-spatial technologies viz. Geographic Information System (GIS), Geographic Positioning System (GPS) and satellite Remote Sensing (RS) are now being widely used in agriculture, forestry, watershed, natural resource management (Rizvi et al. 2009a). GIS and remote sensing applications in agroforestry field include estimating areas for agroforestry (Unruh and Lefebvre 1995; Rizvi et al. 2009b), suitability assessment for agroforestry systems (Bydekerke et al. 1998; Bentrup and Leininger 2002), monitoring agroforestry parks (Bernard and Depommier, 1997). Many studies attempted for mapping agroforestry area using different remote sensing data (Rizvi et al. 2016, Pujar et al. 2016, Tauqeer et al. 2017). Remote sensing technologies can provide a means to classify tree cover and variety of other continuous environmental variables over large spatial extent and moderate temporal extent (Moskal, 2004). A major problem in estimating area under agroforestry is lack of procedures for delineating the area influenced by trees in a mixed stand of trees and crops. Advance object based classifiers have shown promising results for classification of high resolution data for mapping of natural resources (Mueller et al. 2004, Bock et al., 2005 andGamanya et al., 2007).

With object oriented analysis it is possible to get better results from remote sensing information. That information may be immediately integrated in the GIS allowing the direct realization of vectoral maps (Barrile and Bilotta, 2008). OBIA approach can generate good and repeatable LULC classifications suitable for tree cover assessment in urban areas (Moskal, 2011).

The present study was carried out to explore the potential of high resolution data for identification of trees on farmlands and delineation of agroforestry using object based image classification. Results obtained by supervised and OBIA method of classification have also been compared.

2. MATERIALS AND METHODS

2.1 STUDY AREA
Sundargarh is located in the northwestern part of the Odisha state of India. It is the second largest district in the state. The district lies between 21° 35′ to 22° 32′ north latitude and between 83° 32′ to 85° 22′ east longitude. The district has a sub-tropical monsoon climate where we find seasonal rhythm, hot summers, cool winter, unreliable rainfall and great variation in temperature.

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2.2 REMOTE SENSING DATA USED

Multispectral remote sensing images of RS-2A, LISS IV (resolution- 5.8 m) were procured from National Remote Sensing Centre, Hyderabad. LISS IV scenes of path and rows 104-56 (C, D), 104-57 A, 105-56 C and 105-57 (A, B) (Date of pass-March,2017) for Sundargarh district were analyzed for both pixel based and OBIA classification. Preprocessing of these scenes includes layer stacking, mosaicing and sub setting with district boundary. Shape file of districts boundary was obtained from Survey of India, Dehradun.

2.3 REFERENCE DATA COLLECTION AND ACCURACY

Reference data on different land uses was collected from farmer’s fields and the agroforestry plots were also tracked by GPS. This reference data was used for signature creation as well as accuracy assessment of land use land cover classification of the study area. Accuracy of LULC was assessed by error matrix and kappa coefficient.

2.4 METHODS

Remote sensing data were visually and digitally interpreted using the ERDAS 2015 and ArcGIS software 10.4 for processing, analysis and integration of spatial data. Imagine objective tools from ERDAS Imagine 2015 software were employed for different feature detection and extraction. Maximum likelihood method of supervised classification was applied for the assessment of LULC in the district. Sundargarh district was classified into nine LULC classes viz. agroforestry, cropland, plantation, forest, degraded forest, wasteland, built-ups, water bodies, and sandy area (Figure 1). Accuracy of LULC was assessed by error matrix and Kappa coefficient.

Agricultural land including crop land and fallow land, and agroforestry area was masked from false color composite (FCC) with the help of LULC obtained from MLC of the district. OBIA was applied on agricultural area because agroforestry exist on agricultural land only and our objective was to capture trees on farmlands. The methodology for both the classification methods is shown in Figure 2. In this study the target object i.e. agroforestry was delineated in the form of linear, scattered and block patterns (Figure 3). Accuracy assessment of agroforestry class was assessed on the basis of 135 ground check points.

2.5 OBIA CLASSIFICATION

**Raster pixel processor:** First step is the processing of pixels with SFP and Bayesian network. Defining the training areas including trees as well as background pixels for computing the pixel cue matrix. Pixel probability layer were created which defines the object of interest i.e. Trees. Higher probability values are assigned to those pixels whose values are similar to the ones of pixels in the non-
background training samples. Lower probability values are assigned to those pixels whose values are either similar to the ones of pixels in the background training samples or significantly different from the values of pixels in the non-background training samples.

**Raster object creator:** Threshold/Clump was applied on a pixel probability layer. It keeps only those pixels which have probability greater than or equal to threshold value and it converts the remaining pixels in (0, 1). Then performs a contiguity operation (clump) on the binary values of 1. It then converts the pixel probability layer to raster object layer. For the study area the value of threshold was chosen to be 0.50. Lowering the threshold led to inclusion of some non-tree pixels.

**Raster object operator:** This operator removes all the raster objects whose zonal probability mean is less than the specified minimum probability. In this case the probability filter was chosen at 0.75.

**Raster to vector conversion:** Raster object created in previous step were converted to the polygon using polygon trace.

**Vector object operator:** After polygon conversion the Smooth filter was applied to smoothen the boundaries of trees polygons. Smoothening factor of 0.5 was chosen which was found to be optimum.

**Vector clean-up operator:** Cleaning of vector layers are done on ArcGIS by online visual interpretation (for agroforestry) to remove scrub land, trees along roads, trees along river/canal side and erroneous vector object if any.

**Accuracy Assessment**

Mapping accuracy (Hebbar et al., 2014) was carried out with the ground truth points.

\[
MA = \frac{\text{No of correctly classified GT points}}{\text{Total no of GT points}}
\]

In case of supervised classification, area under agroforestry was estimated to be 64176.54 ha (6.57%) while using OBIA (on agricultural land) area was estimated to be 86819.43 ha (8.89%) (Table 1). The accuracy of agroforestry comes out to be 77.5% with MLC and 84.1% with OBIA classification. The results obtained by MLC and OBIA methods were compared in case of agroforestry (Figure 4). In case of supervised classification, those pixels are fully captured where trees exist, whereas OBIA captures trees according to their crown shapes. This led to accurate estimation of area under trees in scattered form, in linear form and also in patch from. Therefore, OBIA could be applied for mapping all types of agroforestry (scattered trees, boundary and block plantations) exist.
on farmlands. Thus, OBIA method may be a useful and promising technique for classifying object from high resolution satellite imagery.

Table 1. Estimated agroforestry area in Sundargarh district using supervised and OBIA classification

<table>
<thead>
<tr>
<th>LULC Classes</th>
<th>MLC Area (ha)</th>
<th>MLC Area (%)</th>
<th>OBIA Area (ha)</th>
<th>OBIA Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agroforestry</td>
<td>64176.54</td>
<td>6.57</td>
<td>86819.43</td>
<td>8.89</td>
</tr>
<tr>
<td>Crop land</td>
<td>337011.87</td>
<td>34.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plantation</td>
<td>11328.32</td>
<td>1.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>466926.74</td>
<td>47.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degraded forest</td>
<td>27968.53</td>
<td>2.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Waste land</td>
<td>34699.00</td>
<td>3.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sandy area</td>
<td>4408.35</td>
<td>0.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water body</td>
<td>12409.77</td>
<td>1.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Built ups</td>
<td>17262.98</td>
<td>1.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geographical Area (ha)</td>
<td>976192.10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3. Scattered, linear and block plantations identified through OBIA classifier

The developed feature extraction model detects the tree objects in images as polygon. The challenges in object oriented classification are, identification and classification of trees require in-depth understanding of factors affecting the spectral information of trees. For trees extraction the polygon based approach shows the best result. The model is robust and can be applied to different areas (subsets). Trees are quantitatively extracted by Bayesian network model parameters and calibrated by using probabilistic approach.
4. CONCLUSIONS

The current study demonstrates the suitability of object based classification for agroforestry mapping in Sundargarh district using LISS IV data. When compared with traditional pixel based classifier, Object Based Image Analysis (OBIA) method gave better results than maximum likelihood method as far as tree mapping is concerned. Thus, OBIA method would prove to be more accurate method for mapping agroforestry using high resolution remote sensing data. Further research needs to be done for the possibility of species wise area identification under agroforestry.

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ASSESSING THE VEGETATION HEALTH OF MANGROVES OF MAHARASHTRA COAST

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ABSTRACT

Mangroves are evergreen forest which helps in ecological balance by arresting soil erosion and acts as an indicator of climate change etc. Present study focuses on assessing the health of mangroves of Thane creek, Maharashtra for 2009, 2013, 2014, 2016 using remote sensing data. Vegetation indice such as Normalised Differential Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) etc. are derived and compared to assess the health of mangrove using analytic hierarchy process (AHP) technique. Next levels of indices such as Vegetation Health Index, fragmentation are also computed using time series satellite data to assess the health from different perspectives. Time series Vegetation and Temperature Condition Indices are derived from normalized NDVI and thermal bands respectively to derive VHI. The overall vegetation health seems to be varying over the years in the west and east region of the creek. The extent of healthy mangroves is observed to be decreasing by 18.13%, 2.10%, and 4.49% in 2013, 2014 and 2016 respectively with respect to 2009. During the study period, the rate of fragmentation is decreased by 9.38% and 14.77% between 2009-2013 and 2013-2016 respectively. Vegetation health assessment can be improved by other indicators such as species diversity, sedimentation, inundation etc. which have a wider scope to get derived from multisensor/multi temporal satellite data.

KEYWORDS: ARVI, EVI, NDVI, NDII, NDWVI, AHP, Fragmentation, VHI

1. INTRODUCTION

Mangrove forest is unique, they grow and thrive in saline coastal habitats which means between sea and land. Mangroves are always large in number, wherever they are in the world because the seedling simply falls off the tree develop roots and become another plant and this mangrove forest spreads across 30,000 hectares along the Maharashtra coast (Maharashtra Forest Department, 2017). There are different species and each has a medicinal value providing a cure for smallpox, diabetes, snake bites, fish sting and many more. Mangroves have high biological productivity and multiple ecological functions. Mangroves also have a significant role in the coastal stabilization and promoting land accretion etc. Surveying mangroves from tropical and subtropical region to estimate the health is a tedious task. In such cases, remote sensing plays a vital role to monitor and study the mangroves using the satellite images. Assessing health on a timely base is one of the effective methods to monitor the health. Satellite Remote Sensing is an effective and efficient method for monitoring and analyzing mangroves which are fragile in nature.

Normalized Difference Vegetation Index (NDVI) is used in various ways by many researchers to understand the content of vegetation. The NDVI method was used at various thresholds like 0.1, 0.2 and so on, to understand the change detection of the vegetation and it has also helped to detect the natural disaster, damage assessment etc (Gandhi, 2015). Atmospheric resistant vegetation index (ARVI) when compared with NDVI, where on an average NDVI seems to be four times more sensitive to atmospheric effect than ARVI its range also varies similarly to NDVI (Kaufman, 1992). EVI to an extent removes the unfavourable outcomes like soil background and atmospheric effect and the main effect was to analyze the topographic effect using NDVI and EVI (Matsushita, 2007). Normalized Difference Infrared Index (NDII) is most commonly used to understand the water content in the leaves and canopy, NDII indicates the canopy’s water stress (Srivongsitanon, 2016). Normalized Difference Wetland Vegetation Index (NDWVI) helps us in differentiating the wetland regions and other regions and to check the availability of water (Kumar, 2017). Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) are managed by the moisture and thermal conditions of the vegetation. Vegetation Health Index (VHI) is derived from VCI and TCI. VHI directly represents the vegetation health (Kogan, 2001; Kogan, 2002; Owrangi, 2011). Fragmentation is used to analyze the temporal change of vegetation in the forest over time. Many researchers have assessed and monitored long-term forest cover changes using remote sensing and geographic information system (GIS) (Jha, 2005).

The objective of this paper is to assess the mangrove health of Maharashtra coastal region with various indices like mentioned above. Further on these indices, Analytical Hierarchal Process (AHP) was performed to understand the priority of the indices based on weights. Few higher level parameters as well like VHI and fragmentation were analyzed to analyze time series pattern change over years using Landsat satellite data.

2. STUDY AREA

Mangroves found in Thane Creek in Maharashtra are chosen for study, which is geographically situated within 72° 54’ 27.98” E 19° 02’45.50” N and 73° 01’ 11.93” E 1° 12’ 01.73” N as shown in figure 1. Mangroves in Maharashtra coverage is about 4% in India. Major mangroves are seen on both the sides of the creek. Mangroves are also a great significance source of fuelwood, honey etc. There are various other districts in Maharashtra like Mumbai, Sindhudurg, Palghar, Raigad, and Ratnagiri where

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The objective of this paper is to assess the mangrove health of Maharashtra coastal region with various indices like mentioned above. Further on these indices, Analytical Hierarchal Process (AHP) was performed to understand the priority of the indices based on weights. Few higher level parameters as well like VHI and fragmentation were analyzed to analyze time series pattern change over years using Landsat satellite data.

2. STUDY AREA

Mangroves found in Thane Creek in Maharashtra are chosen for study, which is geographically situated within 72° 54’ 27.98” E 19° 02’45.50” N and 73° 01’ 11.93” E 1° 12’ 01.73” N as shown in figure 1. Mangroves in Maharashtra coverage is about 4% in India. Major mangroves are seen on both the sides of the creek. Mangroves are also a great significance source of fuelwood, honey etc. There are various other districts in Maharashtra like Mumbai, Sindhudurg, Palghar, Raigad, and Ratnagiri where

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mangroves are present. Thane Creek in Maharashtra is the second marine sanctuary spread over 1690 hectares and about 200 bird species (Maharashtra Forest Department, 2017). The average temperature over the region is around 24°C - 30°C. The average rainfall over a year is estimated from 500mm - 700mm. Industrialization and urbanization have occurred along the creek on the east region with mangroves with Asia’s largest industry namely Thane Belapur industrialized area along with the Navi Mumbai Urban area and urbanised Mumbai and Thane region along with a good number of industries over the west region (Sharma, 2011).

Figure 1. Map showing Thane Creek and associated mangrove region

3. DATA AND METHODS

3.1 DATA USED

This study focused on determining the health of Mangroves from time series data of Landsat 8 as shown in table 1. Further, these data were used for mapping mangroves and verified using Google Earth and Survey of India.

Table 1. Time series multispectral satellite data used in the study

<table>
<thead>
<tr>
<th>SENSORS</th>
<th>PERIOD</th>
<th>SPATIAL RESOLUTION (in metres)</th>
<th>SOURCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat 5</td>
<td>2009, 2011</td>
<td>30m</td>
<td>USGS</td>
</tr>
<tr>
<td>Landsat 8</td>
<td>2013, 2014, 2015, 2016</td>
<td>30m</td>
<td>USGS</td>
</tr>
</tbody>
</table>
3.2 METHODS

3.2.1 Vegetation Health Parameters

Before determining the health of mangroves using the Landsat images, the pre-processing of the data were carried out using ErdasImagine. Followed by were the complete methods shown in figure 2. Vegetation indices such as NDVI, ARVI, EVI, NDII, NDWVI was analyzed using the formula given in table 2. AHP was used to find the best indices based on evaluation and alternate indices using paired comparisons. Pairwise Comparison Matrix (PCM) is observed from the number of comparisons given by $N^2(N-1)/2$ where $N$ is the number of indices (Saaty, 1980; Saaty, 2008). In this case, there are 5 indices considered hence will have 10 comparisons to be made. Indices are assigned weights based on Saaty’s scale and developed a single matrix pairwise comparison matrix for the criteria. The relative weights of each of the indices are calculated through the eigenvectors of PCM. The normalized eigenvector elements are then called weights with respect to the indices. The weights are then assessed using the Consistency Ratio (CR).

Consistency Index is given by $CI = \frac{\lambda_{max} - n}{n-1}$ where, $\lambda_{max}$ is the Maximum Eigen value of PCM and $N$ is the number of indices. This depends on the weights assigned to each index such that higher the weight more important is the index. The weights were assigned depending on the result obtained and the knowledge about the indices. Saaty suggests the value of CR should be less than 0.1 which means the pairwise comparisons are relatively consistent.

Above methods helped us to find the vegetation content of mangroves, which can be considered as the first level. Further to understand the health of these mangroves, the next level Health Index called the VHI was determined using the formula given in table 2. Time series Vegetation and Temperature Condition Indices are derived from normalized NDVI and thermal bands respectively to derive VHI. It is calculated using a 6 year period data (2009, 2011, 2013, 2014, 2015, and 2016) and analyzed for four year period.

Figure 2. Flow chart showing the steps involved in assessing the mangrove health
Table 2. Multispectral satellite data derived vegetation indices used in the study

<table>
<thead>
<tr>
<th>CLASS</th>
<th>FORMULA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalised Differential Vegetation Index (NDVI) (Gandhi, 2015)</td>
<td>(NIR - RED) / (NIR + RED)</td>
</tr>
<tr>
<td>Enhanced Vegetation Index (EVI) (Matsushita, 2007)</td>
<td>G * ((NIR - RED) / (NIR + C1 * RED - C2 * BLUE + L))</td>
</tr>
<tr>
<td>Atmospherically Resistant Vegetation index (ARVI) (Kauffman, 1992)</td>
<td>(NIR - RB*) / (NIR + RB*)</td>
</tr>
<tr>
<td>Normalised Difference Infrared Index (NDII) (Sriwongsitanon, 2016)</td>
<td>(NIR - SWIR) / (NIR + SWIR)</td>
</tr>
<tr>
<td>Normalised Difference Wetland Vegetation Index (NDWVI) (Kumar, 2017)</td>
<td>(SWIR - GREEN) / (SWIR + GREEN)</td>
</tr>
<tr>
<td>Vegetation Condition Index (VCI) (Owrangi, 2011)</td>
<td>(NDVI - NDVImin) *100 / (NDVImax - NDVImin)</td>
</tr>
<tr>
<td>Temperature Condition Index (TCI) (Owrangi, 2011)</td>
<td>(LSTmax - LSTi) * 100 / (LSTmax - LSTmin)</td>
</tr>
<tr>
<td>Vegetation Health Index (VHI) (Owrangi, 2011)</td>
<td>0.5 * VCI + 0.5 * TCI</td>
</tr>
</tbody>
</table>

### 3.2.2 Fragmentation

Besides the above indices, fragmentation was another parameter which was used to analyze the mangroves along the creek. Fragmentation is the process of disintegration of vegetation cover by natural or anthropogenic activities. We determine hectare wise fragmented region using its shape index (SI) obtained for each one hectare grid in the mangrove extent.

\[
SI = \frac{K \times \text{Perimeter}}{\sqrt{\text{Area}}} \tag{2}
\]

We considered one hectare of square area and determined the factor k will be equal to 0.25. Hence we get SI is equal to 1.0 which represents a non-fragmented area and the region is intact by only vegetation using the above equation. Hence, we divide it into two classes as fragmented and non-fragmented based on the SI. The SI value ranging from 1.3 - 2.0 was considered a fragmented area and less than 1.3 was considered the non-fragmented area (intact). The increased in SI determines the increase in fragmented area (more number of patches). Landscape metrics capture the various types of fragmentation which are caused by natural and anthropogenic disturbances, ecosystem characteristics and land use activities. Various studies have successfully used this method (Wulder, 2008; Reddy, 2013).

### 4. RESULTS

#### 4.1 Vegetation Indices

Different types of vegetation indices are generally used to assess the health of vegetation cover depending upon the environmental conditions. Hence various indices derived were used to find the best and obtained the results as shown in figure 3. From the figure, ARVI and EVI show a better result than NDVI, the health index of ARVI has a higher range of healthy mangroves when compared to EVI. The values of the ARVI range from a minimum of -0.08 to a maximum of 1.0 value. The values from 0.6 - 1.0 shows the healthiest region whereas EVI ranges from a minimum of -0.15 to a maximum of 0.9 and most of the healthy region varies between the range 0.3 - 0.6 value. NDVI that has been normally used to understand the vegetation cover ranges from a minimum of -0.5 to a maximum of 0.8 value. There has been a considerably varying health in the different time period over the east and west region of the creek also from the figure we can say that ARVI is giving a better result compared to others indices.

Similarly, NDII and NDWVI were obtained where NDII shows the range between -0.02 and 1.0, determining the water content in the region which has its importance in the health of the vegetation area. The region around the place Vashi where we can distinguish the water content was ranging lower which has its impact on the vegetation health of the mangroves, which can be observed in NDVI, ARVI, EVI indices as well. NDWVI is the index used to analyze the wetland region ranging from -1.0 - 3.0. The negative range determines the wetland area from which the wetland vegetation area of mangroves can be estimated.

Based on pair wise weights entered in AHP algorithm, new weights are estimated for each of the indices. The maximum weight of 0.434 was assigned to ARVI and minimum weight 0.04 was assigned to NDWVI as shown in table 3. The consistency ratio obtained for the estimation was 3.4% which is well within the accepted limit of 10%. We observed that ARVI and EVI are found to have higher priority than NDVI, NDII, and NDWVI.
Figure 3. Various Vegetation Indices obtained from top ARVI, EVI, NDVI, NDII and NDWVI
### Table 3. Ranks of the vegetation indices arrived using AHP technique

<table>
<thead>
<tr>
<th>INDICES</th>
<th>WEIGHTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARVI</td>
<td>0.434</td>
</tr>
<tr>
<td>EVI</td>
<td>0.282</td>
</tr>
<tr>
<td>NDVI</td>
<td>0.171</td>
</tr>
<tr>
<td>NDII</td>
<td>0.074</td>
</tr>
<tr>
<td>NDWVI</td>
<td>0.040</td>
</tr>
</tbody>
</table>

### 4.2 Health Indices

From the figure 4, we observe the VCI and TCI are depicted for 2009 as shown and was similarly calculated for other years. VCI depicts the vegetation condition of the mangroves showing a low vegetation health over west of the creek near Mulund east and Tagore Nagar when compared to the west side of the creek. This depicts the condition of the health in terms of percentage, where below 40% is representing a low vegetation condition and above 40% shows good vegetation condition. TCI depicts the temperature condition of the mangroves. Higher the temperature will result in lower in TCI value which depicts a low condition of the mangroves health. From the figure 4, we can see that the TCI values are over 60.0 - 80.0 value and does not have a major effect on the health in 2009. VCI and TCI consider the moisture and temperature parameter respectively.

The map shows us the relative health of the mangroves where VHI is classified as low, moderate and high as shown in figure 4. We can see the health of mangroves has been reduced from 2009 to 2013 over the west region of the creek around Tagore Nagar and Mulund East and comparatively increased in 2014 and 2016. Health seems to also have reduced along the east region of the creek around Vashi area. In 2013 over the west side of the creek, the health is declined as compared to 2009. Over the period the health over the east side of the creek is declined. But overall 2014 has the maximum health compared to 2009, 2013 and 2016 respectively. This varying health of mangroves can be due to various reasons. One reason for the increase in mangroves can be the restoration of mangroves, sedimentation etc. and the degradation of mangroves can be due to various reasons like climatic change, tidal effects etc.

Hence, from VHI we observe overall vegetation health seems to be varying over the years in the west and east region of the creek. The extent of healthy mangroves is observed to be decreasing by 18.13%, 2.10%, and 4.49% in 2013, 2014, and 2016 respectively with respect to 2009.

### 4.3 Fragmentation

Further, another parameter fragmentation was used to assess the health over Thane Creek. To understand the fragmented region over different years, we find the change in a number of fragmented patches for different years; each hectare (hec) of a patch was compared over the Thane Creek between 2009 - 2013 and 2013 - 2016. The rate of fragmentation is decreased by 9.38% and 14.77% between 2009-2013 and 2013-2016 respectively as shown in figure 5. Table 4 also represents the hectare of the region that was intact without any degradation and the fragment represents region giving us the rate at which a hectare of the area is fragmented. The change from Intact to fragment and vice versa is also given. From the table, it evidently shows that overall the health of mangroves has been increased from 2009 to 2016.

### Table 4. Fragmentation change between (a)2009 - 2013 and (b) 2013 – 2016

(a)

<table>
<thead>
<tr>
<th>2009 - 2013 (per hec)</th>
<th>Intact</th>
<th>Fragment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact</td>
<td>3201</td>
<td>269</td>
</tr>
<tr>
<td>Fragment</td>
<td>345</td>
<td>541</td>
</tr>
</tbody>
</table>

(b)

<table>
<thead>
<tr>
<th>2013 - 2016 (per hec)</th>
<th>Intact</th>
<th>Fragment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact</td>
<td>3363</td>
<td>352</td>
</tr>
<tr>
<td>Fragment</td>
<td>472</td>
<td>460</td>
</tr>
</tbody>
</table>
Figure 4. Representing TCI and VCI along with VHI for 2009 and VHI result for 2013, 2014 and 2016 respectively.

Figure 5. Change Detection of fragmentation between 2009 - 2013 and 2013 –2016.
This study helped to understand the health of mangroves over the Thane Creek. Various indices used to assess the health of mangroves using the time series satellite data. The AHP technique results show that ARVI, EVI is observed to have more weight than NDVI, NDII, and NDWI. We also considered other parameters for having a much better understanding of the growth and health of the mangroves. Hence, we used VHI which gave the overall health and fragmentation showed the region where the mangroves have degraded. These parameters were useful in assessing mangrove health at a higher level. The above indices and further indicators on plant diversity, sedimentation pattern would be an immense use for the effective management and conservation of mangrove forest.

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Matsushita, B., Yang, W., Chen, J., Onda, Y., & Qiu, G. (2007). Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: a case study in high-density cypress forest. *Sensors, 7*(11), 2636-2651.


SEASONAL VARIATION IN THE RESIDENCE TIME CHARACTERISTICS OF A TROPICAL ESTUARY  
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ABSTRACT
Lakes and estuaries are key components of biogeochemical processes and ecological sensitive systems, where residence time plays crucial role in modulating their properties and interactions. Anthropogenic interventions create disturbances and pressure on the estuarine system that results in eutrophication, declining of biodiversity and finally deteriorations of water quality. The natural way of self-purification of estuarine system strongly depends upon its hydrodynamic conditions such as tides, waves, currents and freshwater influx. Estuaries with poor flushing and long residence time tends to retain effluents and pollutants within the system leading to high primary productivity rates. Sedimentation, advection and diffusion can be considered to be the main physical processes that influence the cleaning capacity of an estuarine ecosystem. The residence time of the water particle inside the estuary gives an idea of the efficiency of the flushing process. Thus the understanding of the hydrodynamic behavior is of major interest in the environmental management of the estuaries and lakes. Cochin estuary (CE) is under the threat of nutrient enrichment, which is mainly contributed by the anthropogenic interventions and terrestrial inputs from seven rivers. In Kerala about 70% of chemical industries are located along the banks of the rivers Periyar and Chitrapuruzha in the Ernakulam district, which receives high concentrations of industrial effluents (10^4 x 10^3 m^3 per day) and untreated domestic waste delineated the importance of the present study.

In this study, Finite Volume Community Ocean Model hydrodynamic model coupled with Lagrangian particle module (passive tracer) is used for the estimation of residence time, delineation of site specific transport processes and its flow trajectory in the Cochin estuary. Spatial and temporal patterns of the particle distribution are concurrent in monsoon and post-monsoon periods. Residence time of the Cochin estuary varied from 25days in monsoon to 30days in post-monsoon period. Approximately 50% of the evenly distributed particles flushed out of the system within 15 days (fast decay phase); beyond this time period particle trajectory curves become steady (slow decay phase) during the monsoon and post-monsoon period. During pre-monsoon period, around 20% of the initial particles were flushed out from the system and the remaining particles resides within in the estuary showed that the mean residence time is about 90 days. The study reveals that water exchange capacity of the Cochin estuary was very low during the pre-monsoon period compared to the monsoon and post-monsoon period. Results from this study is an effective tool for resolving the emerging coastal environmental problems and can be a benefit for the environmental policy makers for the better management of industrial effluent dispersal plans.

KEYWORDS: Cochin estuary, Hydrodynamic model, Lagrangian trajectory, Residence time, Pollution dispersal

1. INTRODUCTION
Estuarine environments are one of the most exclusive productive system on the Earth, supporting unique communities of species specially adapted for life in estuaries. Estuaries are often situated at the vicinities of highly populated and industrialised areas, which results into massive inputs of pollutants (Liu et al. 2003). Anthropogenic interventions in estuarine system significantly creates disturbances and pressure on the system that results in eutrophication of water bodies, declining of biodiversity, deteriorations of water quality etc. Estuaries serves as a nutrient trap due to salt and fresh water possessing different densities. Water quality of the system greatly influences the physical, chemical, biological characteristics of the estuary and it adversely affects the living organisms and reduces economical wealth. The self-purification capacity of estuarine system strongly depends on its hydrodynamic conditions such as topographic features, tides, waves, currents and freshwater influx. Estuaries with poor flushing and long residence time tends to retain nutrients within the system leading to high primary productivity rates (Lancelot and Billen 1984). In contrast, well-flushed estuaries are more resilient to nutrient loading due to reduced residence time and greater exchange with less impacted coastal waters. The rate of exchange is generally determined by three time scales, viz, flushing time, age, and residence time (Monsen et al. 2002). The flushing time characteristics of an estuary can be computed by two approaches, viz, classical approach of tidal prism and freshwater fraction method. Age of the estuarine water body represents the time taken for a dissolved or suspended material at any location to be transported from its source to its current location (Delhez et al. 1999). One primary physical control on eutrophication is estuarine flushing and ultimately residence time (González et al. 2008), which is defined as the time elapsed until a water parcel leaves a water body through its outlets. Estuarine residence time is a major driver of eutrophication and water quality which results into the impairment of ecological function of estuaries in terms of biodiversity, habitat quality, and trophic structure. The calculation of residence time for particles in natural reservoirs was described by Bolin and Rodhe 1973; the concept was later extended and modified for coastal sea applications (Zimmerman 1976; Takeoka 1984). Although the terminology and precise definition tend to vary between studies, residence time and similar analyses are useful tools in estimating the mixing and renewal of estuarine and coastal waters (Zhang et al. 2010). Spreading of industrialisation around the globe is one of the major contributor of the effluents to the estuary apart from the other factors of water pollution. In Kerala about 70% of its chemical industries are located in Ernakulam district dotted along the banks of the rivers Periyar and Chitrapuruzha. Angamali to Kochi occupies the most industrialized zone.

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which is at northern part of the CE. There are more than 50 large and medium industries and 2500 small scale industries situated in this region. These industries dump high concentrations of effluents of $104 \times 10^3$ m$^3$ per day and untreated domestic waste of $0.26 \times 10^3$ m$^3$ per day (CPCB, 1996) to the CE. The industries located in Edayar – Eloor area consumes about 189343 m$^3$ per day water from the river and discharges about 75% of it as used water along with large quantity of effluents and pollutants. The major types of these industries are fertilizers, pesticides, chemicals, and allied industries, petroleum refining and heavy metal processing, radioactive mineral processing, rubber processing units, animal bone processing units, battery manufacturers, acid manufacturers, pigment and latex producers etc. Levels of Fe, Mn, Zn, Cu, Cd, Pd, Cr, Co and Ni in the surficial sediments of the estuary rendered significantly high concentration in northern parts of the estuary (Nair and Balchand 1993; Balachandran et al. 2005; Martin et al. 2012; Nair and Sujatha 2013). The wide spectra of pollutants that adversely affect the natural environmental quality of the water from the river include toxic and hazardous materials such as heavy metals, phenolics, hydrocarbons, pesticides, radionuclides, ammonia, phosphates, domestic and untreated waste water. Thus anthropogenic and terrestrial inputs results in nutrient enrichment, which deleteriously affect estuarine ecosystem.

There are 604 houseboats being operated in the district by 18 companies, in addition to 308 private motorboats and 33 speedboats. These houseboats discharge a total of 230160 litre of waste water into CE per day, slowly killing the estuary. Houseboats in Panavally dump 1,600 litre of waste water; those in Mannancherry and Kayamkulam dump 520 litre and 400 litre, respectively (Times of India, Kochi edition, 29th April 2012). Studies of coastal and large lake environments close to the river outlets have conceded, densely populated urban environments become an important source of microplastics. Low density plastic particles normally float on freshwater such as polyethylene and polypropylene, which become incorporated into the channel bed as a result of biofouling or other processes. The presence of ubiquitous micro plastic particles in the lake not only have direct impact on the aquatic environment and habitats, but may also set off a cascade of perturbations to the entire food web. Evidence of microplastics in sediment of CE were recently reported by Sruthy and Ramasamy 2017. The abundance of microplastics from the sediment samples are in the range of 96-496 particles m$^{-2}$ and spotted with low density polyethylene. Hence the pollutants transport process in the estuarine system is more relevant. CE attributed with prolonged monsoon enhances the complexity of residence time. It is very relevant to identify the retaining capacity of the CE.

Previous efforts have focused on estimating the flushing characteristics of the CE using a single value based on the ratio of the estuary volume to the out flow rate (tidal prism method, flushing time calculation using estuarine volume, freshwater flush methods). This method may not be appropriate for the systems like CE, owing highly complex hydrodynamic conditions (Lallu et al. 2014; Vinita et al. 2015). Field experiments to infer the residence time is expensive and require vast human resources; hence it is highly appropriate to use a validated 3D hydrodynamic model to investigate on resident time. In this study, we use a three-dimensional hydrodynamic model of CE to identify the mechanisms controlling circulation and residence time. Even though CE has experienced several decades of declining water quality due to heavy eutrophication, the spatial and temporal variability in circulation and residence/flushing time is understudied. An application of the 3D hydrodynamic model is used to identify the mechanism controlling the circulation and residence time in CE which is demonstrated in this paper. The paper discusses the hydrodynamic setting of CE, followed by description of the modelling system, skill assessment, particle tracking, and modelling scenarios.

2. METHODOLOGY

Lagrangian particle module coupled with 3D hydrodynamic model (FVCOM) was used to simulate the transport mechanism of water parcel in the CE. Several steps followed by particle tracking module was coded with lagrangian random-walk technique to track the spatial distributions of water particles in time, and draw the transport trajectory (Fig.1.a). The Finite Volume Community Ocean Model (FVCOM, v. 3.2) is an unstructured grid, finite-volume, free surface, three-dimensional primitive equation coastal ocean model that solves the momentum, continuity, temperature, salinity, and density equations (Chen et al. 2003). The model decomposes primitive equations over unstructured triangular grids having spatial resolution varying from 10m to 600m over 15479 nodes and 22520 elements of the study area. The uniform sigma-coordinate system was applied with 10 levels for vertical grid resolution. The base map was digitized using IRS LISS-III data and the corresponding grid was generated with Gmsh (version 2.5) developed by Geuzaine and Remacle 2009. The bathymetry data (Fig.1.b) for the model was derived from digitizing Inland water Authority Plan Chart-2006 (IWAI, NW-3) using QGIS. The bottom roughness parameter was set to 0.035 with minimum value 0.015 for the model drag co-efficient with initial conditions provided by the simulation from the previous year, and produced hourly output of three-dimensional currents, water temperature, turbulent diffusivity, and 2-D water level fluctuations.
Figure 1.a Flow chart for hydrodynamic model (Cochin Estuary)

Figure 1.b Model domain with unstructured grid and bathymetry
2.1 Observations

One month long time series observations of water level and currents were conducted in CE from 20th September to 20th October 2009. Water levels were recorded at 10 minutes interval at 6 different locations (Fig.1.b) using SBE- 26 plus water level recorder having an accuracy of 0.1% of full-scale (Strain Gauge Pressure). Aanderaa RCM-9 current meters were used to record speed and direction at 10 minutes interval with an accuracy of ±0.15 cms⁻¹;±2°. Surface currents & Salinity were measured at Arookutty and Thanneermukkom, while surface & bottom currents and salinity were measured at Fort Kochi. The daily river discharge at the respective gauging stations were sourced from Central water commission (CWC), Government of India.

2.2 Validation of the model

The reliability of the model were expressed using Taylor diagram and Index of agreement (d). Willmott 1981 proposed new approach in model skill Index of agreement (d), which can be defined as

\[
    d = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} (P_i - \bar{O})^2 + \sum_{i=1}^{N} (O_i - \bar{O})^2} \tag{1}
\]

where \(P\) and \(O\) represents model predicted and observed values respectively, \(\bar{O}\) is time mean of \(O\), and \(N\) is the size of the data set. Perfect agreement between model results and observations yields a skill value of one and complete disagreement gives a skill value of zero.

2.2.1. Tide

The model predicted tidal elevation was compared with observed water level data in the CE and computed the statistical significance of the model (Fig.2) to predict the estuarine dynamics (Table 1). Quantitative comparisons based on regression analyses (0.89) and index of agreement (skill value 0.92) revealed high reliability of the model to predict the lake dynamics. The maximum error of 0.07 m (lowest index agreement 0.84) was observed at Thanneermukkom, which was dominated by the freshwater influx. The model achieved average correlation of 0.8 with observed value

2.2.2. Currents

Comparison between the model and observed currents (U and V components) at 3 stations showed significant correlation with maximum (0.88) index of agreement at Arookutty and minimum (0.62) at Thanneermukkom. Bi-directional flow at Fortkochi inlet during the flood period (surface layer flow towards sea while bottom layer to the lake) had been captured by the model vividly, where the index of agreement with the observed data at surface and bottom were 0.81 and 0.80 respectively.

2.2.3. Salinity

Comparison between the model and observed salinity of the Arookutty were scrutinized which is 20 km apart from the Cochin inlet and achieved the 0.7 skill value. Taylor diagram of salinity is shown in the Figure.2.d and the model data was well corroborated with the observed value of correlation 0.87.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Index of agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tide</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Munambam</td>
<td>0.94</td>
</tr>
<tr>
<td>Cherai</td>
<td>0.95</td>
</tr>
<tr>
<td>Fortkochi</td>
<td>0.97</td>
</tr>
<tr>
<td>Arookutty</td>
<td>0.95</td>
</tr>
<tr>
<td>Makeyilkadavu</td>
<td>0.89</td>
</tr>
<tr>
<td>Thanneermukkom</td>
<td>0.84</td>
</tr>
</tbody>
</table>
2.3 Lagrangian Particle Tracking Model

Lagrangian Particle-tracking technique has been widely used to estimate the transport time scales in variety of water bodies. Lagrangian particle tracking was accomplished using a Fortran program developed previously to study transport of larval code in the Gulf of Maine (Huret et al. 2007; Churchill et al. 2011) and has previously been applied in the Great Lakes (Anderson and Phanikumar, 2011). In this study, FVCOM hydrodynamic model coupled with Lagrangian Particle model were applied to estimate the residence time and the site specific transport trajectory of CE. The Mean residence time of the estuary is estimated by the e-folding time, which is the time when the average of conservative particles in the estuary is decreased to 1/e (37%, e-folding) of the initial particle numbers. We preformed seasonal (Pre-monsoon, Monsoon and Post-monsoon) simulations for estimating the residence time of CE separately. The flushing accomplished by each inlet of the CE was quantified by the percentage of particles removed through each inlet by the end of the simulation period. The residence time for each particle was defined as days elapsed upon exit after the initial release. We compared different methods to determine the system wide mean residence time for the CE. Mean residence time was calculated by ensemble averaging individual particle’s residence time in the domain over all releases (Defne and Ganju 2015).

\[
T_{re} = \frac{1}{R} \sum_{i=1}^{N} (t_{ri})
\]

where \(T_{re}\) is the mean residence time based on the ensemble averaging, \(R\) is the total number of release, \(N\) is the total number of particles, and \((t_{ri})\) is the residence time for the \(i^{th}\) particle in \(j^{th}\) release.

3. RESULTS

Flow characteristics have a significant influence on the distribution and transport mechanism of the pollutants in the estuarine system. CE classified as monsoonal estuary that receives 73% of the freshwater inputs (discharge and sediment loading) during summer monsoon (June-September) and have a great impact on hydrographic and transport mechanism of the estuary. Rivers Periyar and Muvattupuzha contribute major part of the discharge compared to the other rivers feeding into the system. Seventy percentage of the chemical factories of the Kerala is located at the vicinity of the CE and the present level of the pollution in the northern arm of the CE is due to the direct release of industrial effluents into the Periyar River (Balachandran et al. 2008). Thus the understanding seasonal variations of transport mechanisms of pollutants have significant role in the management plan for the restoration program of CE. Particle tracking module was used to estimate the residence time of the CE and the initial particles in the model domain were evenly distributed with two resolutions (300m X 300m & 500m X 500m). The distribution of these particles were analysed for 60-90 days and the particles’ position during the model simulations were scrutinized for each time step (3600s). The following sections will demonstrate the spatial patterns of the flushing during monsoon, post-monsoon and pre-monsoon periods.

3.1. Spatial distribution of the particles during monsoon period

Spatial distribution of the particles during monsoon period according to the simulation of resident time has been illustrated on figure 2and 3. The initial percentage of the particles was set to 100% and the percentage of remaining particles in the estuary was computed for each time step (3600s). Approximately 50% of the particles were quickly flushed out from the system (fast decay phase); beyond this time particle trajectory become steady (slow decay phase). Over the 75% of the model domain, more than 90% of the particles were flushed out through Cochin inlet and the rest of the particles were flushed out through Munamabam inlet. A complete flushing was noticed at the adjacent regions of the inlet. 30% of the initial particles left the model domain within first 5days (Fig.3.b) and during this period particle residing in the main channel of the CE are flushed out from the model domain except at Nedungad region. After 15 days, 50% (fast decay phase) of the initial particles were flushed out from the estuary (Fig.3.c) and during this simulation period 80% of the particles residing in the main channel of the CE are flushed out from the model domain except at Nedungad. Almost 67% of the released particles were flushed out to the sea after 25 days (Fig.3.d). Hence the average mean residence time is 25 days for the CE during the monsoon (Fig.3). When the lateral movement of the particles were considered at southern side of the CE, the movement of the particles at the left side of the channel is faster than that of the right side, as the depth of the left side is more. Similarly, at Arookutty the speed of the particles at right side is more than that of the left side, as depth is more. The speed of the particles that come from the southern side of the CEincreases from Murinjapuzha onwards due to the
contribution of immense discharge from the Muvattupuzha River. When the fast decay phase completes, most of the initial particles get displaced from their initial position except at the Nedungad region. The particles at the Nedungad region starts displacing during the slow decay phase by the influence of freshwater at that time. As result of that, the particles from the Nedungad region were flushed out through the Cochin inlet during monsoon period. In previous studies, Nedungad region acts as null zone because tidal actions are nullified in all seasons (Ramamirtham and Muthusamy 1986; K. Balachandran et al. 2005). Modeling simulations also figure out the same effect of null zone.

![Residence time of CE during monsoon](image1.png)

![Spatial distribution of particles during monsoon](image2.png)

### 3.2. Spatial distribution of the particles during post-monsoon period

Figure 4 & 5 illustrate the simulation results of the residence time and spatial distribution of the particles during the post-monsoon period. Spatial distribution of the particles during the post-monsoon periods are similar to that of the monsoon period with longer residence time than the monsoon. Most of the particles were flushed out through Cochin inlet and complete flushing was noticed in the close vicinity of the inlets. Residence time attained the fast and slow decay phase with slight difference in the days than that of the monsoon. 30% of the initial particle were flushed out from the model domain within 7 days (Fig.5.a), during this period particles residing in the region from Munambam to Arookutty were completely flushed out except at Nedungad region. After 17 days, 50% (fast decay phase) of the initial particles were flushed out from the estuary (Fig.5.b) and during this simulation period (post-monsoon) 80% of the particle resided in the main channel of the CE are flushed out from the model domain except at Nedungad. Almost 67% of the released particles were flushed out to the sea after 30 days (Fig.5.c), hence the average mean residence time is 30 days for the CE during the post-monsoon (Fig.4). Lateral difference of the particle movements were also similar to that of the monsoon. The speed of the particles that come from the southern side of the CE increases from Murinjapuzha onwards due to influx from the Muvattupuzha river. When the fast decay phase completes, most of the initial particles get displaced from their initial position except for Nedungad.
region. The particles at the Nedungad region starts displacing during the slow decay phase and eventually flushed out through Munambam inlet during this period.

![Figure 4. Residence time of CE during post-monsoon](image)

Figure 4. Residence time of CE during post-monsoon

![Figure 5. Spatial distribution of particles during post-monsoon.](image)

Figure 5. Spatial distribution of particles during post-monsoon.

3.3. Spatial distribution of the particles during pre-monsoon period (Thanneermukkom Barrage closure period)

During the pre-monsoon period the tidal interactions was obstructed at the Thanneermukkom barrage for preventing the salt intrusion towards the upper reaches of the CE. Hence the evaluation of the residence time during this period were limited to Thanneermukkom barrage. Compared to the other seasons, the particle trajectories during the pre-monsoon period has drastic variations. Less than 20% of the initial particles were flushed out from the system and the remaining particles resides within the estuary which shows that the mean residence time is about 90 days (Fig.6). The result reveals that water exchange capacity of the CE was very low during the pre-monsoon period compared to the monsoon and post-monsoon periods. Even though there is significant movement for particles, due to the strong tidal interactions there is a tendency for them to retain their initial positions which leads to the long residence time in the system. During the pre-monsoon time the particles from Munambam to Arookutty took 20 days to flush out and comparatively lesser amount were flushed out than the other two seasons. It is clear from the figure 7 that the particles at Nedungad and branches of the Periyar river have negligible movement. During the pre-monsoon period the particles from Arookutty to Vaikom were completely flushed out due to the moderate discharge from the Muvattupuzha river. Most of the particles from Vaikom to Thanneermukkom remains in the system after 20 days of simulation and 60% of these particles still reside throughout the simulation because of the presence of standing waves generated from the southern upstream boundary(Srinivas et al. 2003). A distinct path can be observed for
the lateral movement of the particles in the southern part of the estuary. The particles resides at the left side of the channel shows the tendency to quickly flush out from the system than that in the right side of the channel.

![Image of data distribution](image1.png)

**Figure 6. Residence time of CE during Pre-monsoon**

4. **DISCUSSION**

The study emphasizes the influence of residence time in the estuarine ecosystem according to the physical, chemical and biological changes. The coupling of unstructured 3D hydrodynamic model with Lagrangian particle module depicts comprehensive behaviour of the seasonal transport variability of the CE, which corroborates with previous studies (Balachandran et al. 2008; Shivaprasad et al. 2013; Janardanan et al. 2015). The flushing efficiency calculation by traditional approach have a limitation to label water masses and to monitor their position from the origin in space and time, whereas in the Lagrangian approach, particles can be labelled with information about their releasing point or origin (Braunschweig et al. 2003). Thus knowledge of the origin will be helpful in understanding where water masses are coming from, as they are transported among different regions and it can be used as a potential decision support tool to manage the environmental problems.

Pollutants from different sectors are discharged into the CE throughout the season and the dense population (1250 per km²) in the banks of the CE tempt to deposit untreated sewage waste. According to Remani et al. 2010, sewage waste will increase to double (~428mld) the volume of present value (~227.2 mld) in the projected population of Ernakulum, Alappuzha & Kottayam by the year 2034. In the present study the fast and slow flushing zones in the CE are demarcated (Fig.3, 5 &7). CE shows resemblance in the spatial movement of the particles during monsoon and post monsoon periods,
and a longer residence time was attained in the post monsoon. During the pre-monsoon period, a long-lasting movements of particles were observed due to the strong tidal interactions and a lesser amount of particles were flushed from the system. These seasonal behaviour of the residence time in CE provide an insight into the relationship between the tides and freshwater influx. According to modeling study, freshets from the seven rivers are the major components contributing in the active flushing mechanism of the CE. The particles from Munambam to Arookutty were completely flushed out from the system in all seasons except at Nedungad region. These particles took 5days in monsoon, 8days in post monsoon and 20days in pre monsoon to flush out. The fast flushing zones were identified in the branches of Periyar and Chalakudy during monsoon & post monsoon periods. However during the lean discharge period these places were identified as a slow flushing zone. Anas et al. 2015 reported that the levels of dissolved heavy metals in the branches of Periyar are higher in the pre monsoon period which corroborates with the present study. The transport trajectories simulation shows that the particles released from the Nedungad region remain in Nedungad itself, indicating that this area is a slow flushing zone, which inhibits the diffusion of pollutants throughout the seasons (Balachandran et al. 2005; Balachandran et al. 2006). Compared to the southern part, the movement of the particles is slightly higher at Muninjapuzha throughout the season due to the steady freshets from Muvattupuzha river. The particles from TV Puram to Thanneermukkom maintained a longer residence time in pre monsoon when compared to the other two seasons. Hence the study is imperative to understand the seasonal residence time, transport trajectory and flushing efficiency of the CE, which is very essential to document the contamination area by pollutants that reaches in to the estuary.

5. CONCLUSIONS

Estuaries with high population density and industrial activity are always important in terms of pollutant transport and dispersal mechanisms. Cochin estuary is one of the most densely populated region, where most of the industries in Kerala are located and also have high consumption of fertilizers. Understanding the hydrodynamic behavior in connection with transport trajectory and residence time of the CE by the application of GIS and Coastal model has not yet been done so far. An integrated hydrodynamic model (FVCOM) coupled with particle tracking module was subjected to study the seasonal transport and dispersal capabilities of the CE. The mean residence time of the pollutants was estimated during monsoon, post-monsoon, and pre-monsoon periods. Residence time of the CE varied from 25days in monsoon to 30days in post monsoon period. Approximately 50% of the evenly distributed particles flushed out of the system within the first 15 days (fast decay phase); beyond this time period particle trajectory curves become steady (slow decay phase) during the monsoon and post monsoon period. In pre-monsoon period, less than 20% of the initial particles were flushed out from the system and the reaming particles resides within the estuary which shows that the mean residence time is about 90 days. The results from the particle tracking reveals that water exchange in the CE is significantly influenced by the freshwater influx driven by monsoon. Study concludes slow flushing zones at southmost part and at Nedungad (Null zone) in the northern part of the CE, while the opening area of both inlets were identified as the fast flushing zones. This will be a crucial information for multiple stakeholders in planning and adaptive management of developmental activities in the CE that supports healthy, sustainable estuarine environment.

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REFERENCES


ESTIMATION OF ABOVE GROUND BIOMASS USING HIGH RESOLUTION MULTISPECTRAL WORLDVIEW-2 IMAGE

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ABSTRACT

In this study, we have estimated the above ground biomass in mangrove forest of Bhitarkanika National Park, Odisha, India by using very high resolution optical remote sensing data, WorldView-2. Since the destructive sampling for plot biomass estimation was not possible, it was calculated using available species specific and common allometric equations which relate biomass with structural properties such as tree height, diameter at breast height, wood density, etc. After the pre-processing, image parameters from 8 spectral reflectance bands, 28 simple band ratios, and 12 vegetation indices were derived and their relation with the plot biomass was investigated. Then, the textural parameters using Grey Level Co-occurrence Matrix method were derived from reflectance bands, band ratios, and vegetation indices to investigate the relation with plot biomass using multiple regression modeling. From the results, it is found that the textural parameters has given better results than the simple reflectance bands and band ratios where as in the case of vegetation indices there was no such improvement observed. The textural analysis of band ratio has the combined information from band ratio as well as the textural analysis and helps in the improvement of biomass estimation.

KEYWORDS: Mangrove biomass, Texture analysis, Worldview-2, Allometric equations, Vegetative indices

1. INTRODUCTION

Mangroves represent vegetation ecosystem commonly thriving in silt or clay soil in the intertidal zone of tropical and subtropical coastlines (Tomlinson, 1994). In total, about 110 known plant species were identified as mangroves. Out of them, 54 species belonging to 20 genera of 16 families were categorised as true mangrove species living in the core zone (Kuenzer et al., 2011) and remaining species were represented as associated species as they found associated with mangroves and often occur in transition zone between mangrove ecosystem and terrestrial ecosystems. Mangroves form a natural barrier along the coast and act as a shield for coastal community against natural calamities such as cyclones, storm surges and tsunamis (Alongi, 2008). Mangrove ecosystem sequestreates the atmospheric carbon and store in their biomass thus plays a critical role in ensuring the stability of the climate change. The accurate estimation of the above ground biomass and carbon stored in the vegetation is one of the important objectives in the resolutions of the Bali Action Plan (2007) approved by United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol (2005). In 2010, the Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD+) strategy was conceived for the conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries. The restoration of forest to halt biodiversity loss and to improve global vegetation biomass has been one of the targets of Sustainable Development Goals (SDG’s) framed during the Rio+20 Summit held in June 2012 (Eckert, 2012; Mayers, 2014). Conference of the Parties to the UNFCCC (COP21/CMP11) held at Paris in December 2015 also insisted on the two global challenges: tropical deforestation and climate change. COP21 aims at international cooperation for the protection and conservation of tropical forest to sustain global vegetation biomass by reducing the deforestation of tropical forest (Vina and Leon, 2014). One of the most important functions of wetlands including mangroves is that they play a crucial role in trapping atmospheric carbon dioxide, fix in their biomass through photosynthesis, and so often credited as “carbon sinks.” Mangrove deforestation generates 10% of carbon emission due to global deforestation per year despite their global tropical forest cover of just 0.7% (Donato et al., 2011). The “Blue Carbon Initiative” project, funded by United Nations Environmental Programme (UNEP), aims to restore and protect mangroves and other vegetated coastal habitats in order to improve carbon sequestration (Ellenbogen, 2012; Nellemann et al., 2009).

Remote sensing based biomass estimation usually involves field data collection about biophysical properties such as diameter at breast height (DBH), tree height, number of individuals of a particular species, leaf area index (LAI), etc. Using these biophysical parameters, plot biomass are calculated with the help of species specific and common allometric equations which would be then correlated with remote sensing image to develop biomass models (Hirata et al., 2014; Patil et al., 2014). Green et al., (1997) predicted the Leaf Area Index (LAI) values with the help of Normalized Difference Vegetation Index (NDVI) parameter derived from mangroves growing on the Caicos Bank, Turks and Caicos Islands. Kovacs et al., (2004) used Simple Ratio (SR) in addition to NDVI derived from IKONOS data to regress with LAI of degraded mangroves forest of the Agua Brava Lagoon System of Nayarit (Mexico) and found that there is a strong correlation of LAI versus NDVI and SR at 8m and 15m plot sizes. Similar methodology was applied on high-spatial resolution QuickBird multispectral imagery and estimated LAI value of 2.71 for areas excluding dead mangroves using NDVI model (Kovacs et al., 2009). Fatoyinbo et al., (2008) used Landsat multispectral data and Shuttle Radar Topography Mission (SRTM) elevation data to determine the spatial distribution of mean tree height and biomass of Mozambique’s mangrove forests by making use of field biomass calculated using allometric equations.

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In another study, high-resolution multispectral QuickBird data of Beilun Estuary, China was used to quantify per-pixel biomass information using sub-pixel analysis. The results obtained from the model were verified using the QuickBird panchromatic data derived from the same acquisition (Ji et al., 2010). Mutanga et al., (2012) stated that the saturation problem associated with use of NDVI for biomass estimation of high canopy density wetland vegetation. They used random forest regression and stepwise multiple linear regression models for predicting the biomass using NDVI derived from WorldView-2 data and found that random forest model performed better in biomass estimation. Zhu et al., (2015) used Back Propagation Artificial Neural Network (BP ANN) model to estimate AGB with and without the consideration of species types using vegetation indices derived from WorldView-2 image and field survey. They concluded that the Red edge band and the associated vegetation indices such as Red edge Normalized Difference Vegetation Index (Re-NDVI), Red edge Simple Ratio Index (Re-SRI), and modified Red edge Simple Ratio Index (mRe-SRI) derived from WorldView-2 images are more efficient than other bands in predicting the biomass of high-density mangrove forests.

In this study, we attempted to analyse the potentiality of the high resolution multispectral WorldView-2 data in estimating the above ground biomass of mangroves of Bhitarkanika National Park, Odisha, India. Image derived parameters such as reflectance bands, band ratios, vegetation indices, and their respective textural parameters derived from Grey Level Co-occurrence Matrix are regressed with the actual plot biomass calculated using allometric equations which utilizes field inventory biophysical parameters. Statistical multiple regression analyses were used to estimate the plot biomass from various image derived information.

2. MATERIALS AND METHODOLOGY

2.1 Study Area

Bhitarkanika National Park is situated in north-eastern part of the state, Odisha in Indian east coast. It is located in the combined estuarine region of rivers Brahmani, Baitrani and Dhamra and has rich alluvial deposits with gently sloping topography. The total area of Bhitarkanika wildlife sanctuary is 672 sq. km., of which core area of 145 sq. km. covered by mangrove forest was declared as National park in 1998. In the year 2002, Bhitarkanika mangrove ecosystem was declared as ‘Ramsar’ site – A wetland of International importance by Ramsar Convention of Wetlands. The study area lies between 20°38'19'' N - 20°47'27'' N latitudes and 86°49'26'' E - 87°05'48'' E longitudes. This area experiences semi diurnal high and low tides twice a day with the tidal amplitude ranges between 2 m – 3.5 m in upstream and 3.5 m – 6 m near to river mouths (Ravishankar et al., 2004). In Bhitarkanika, 76 mangrove species were identified. In which 30 are true species and 46 are associated species.

2.2 Remote Sensing Data

WorldView-2 sensor data was used for our study. World View-2 was launched by Digital Globe Corporation on 08th October 2009. It operates at an altitude of 770km and provides data in eight multispectral bands with a high spatial resolution of 0.46m for the panchromatic band and 1.84m for the multispectral band. WorldView-2 is the only new-age commercial and high resolution multispectral sensor to provide data in unique spectral bands such as coastal, yellow, red-edge, and NIR-2 (Tarantino et al., 2012). The red-edge band is more related to the mangrove vegetation health, and also sensitive to biomass at high densities (Zhu et al., 2015).

2.3 Field Biomass Data

Field data collection was carried out in Bhitarkanika National Park, to record field biomass variables from sample plots during the year 2012 and 2013 (Winter and Summer). Biophysical parameters such as diameter at breast height (DBH), tree height, number of trees in each species, etc. were collected from 40 stratified sample plots selected based on the reference mangrove distribution at community level as mapped by Space Application Centre, Ahmedabad, India.

Figure 1.False Colour Composite image of the study area derived from WorldView-2 sensor showing the locations of sample plots

We designed the sample plots as of size 10m x 10m based on the image resolution of WorldView-2. All sample plots were selected carefully based on the criteria that they are covered with vegetation canopy and without any intervention like roads, creeks, or other features within a buffer of 10m (Refer Figure 1). Tree height was measured using Leica Disto D8 laser distometer, and DBH was recorded at a height of 1.3m from the ground for individual trees. In the case of multi-stemmed mangrove species such as...
Rhizophora, DBH was measured for each stem (Zhu et al., 2015). However, those trees with DBH less than 4cm are not considered in this study but were recorded. Number of trees in each species within the plot and canopy dominant species were recorded with the inputs of field experts from the Forest Department, State Government of Odisha, India. Since Bhitarkanika is one of the National Parks, the marine wetland is highly protected from cutting of mangroves. So we restricted ourselves from destructive sampling method and adopted non-destructive sampling method for field biomass estimation. Species specific and common allometric equations from literatures on mangrove species were used for plot biomass estimation.

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Mangrove Species</th>
<th>Species Specific Allometric Equation</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Avicennia marina</td>
<td>$B = 0.308 \times \text{DBH}^{1.14}$</td>
<td>(Comley and McGinness, 2005)</td>
</tr>
<tr>
<td>2</td>
<td>Bruguiera parviflora</td>
<td>$B = 0.168 \times \text{DBH}^{2.42}$</td>
<td>(Clough and Scott, 1989)</td>
</tr>
<tr>
<td>3</td>
<td>Pongamia pinnata</td>
<td>$B = \exp[-2.409 + 0.9522 \ln (\text{DBH}^2 \times H \times \rho)]$</td>
<td>(Ahmedin et al., 2013)</td>
</tr>
<tr>
<td>4</td>
<td>Xylocarpus granatum</td>
<td>$B = 0.0823 \times \text{DBH}^{2.59}$</td>
<td>(Clough and Scott, 1989)</td>
</tr>
</tbody>
</table>

$H$ – Tree Height, $\text{DBH}$ – Diameter at breast height, $\rho$ – wood density.

Table 1. Species-specific allometric equations used for the calculation of plot biomass

Since species specific allometric equations were not available for other species, the common allometric equation modelled for mangroves provided by Komiyama et al. (2005) $B = 0.251 \times \text{DBH}^{2.46}$ was used in our analysis. We made use of global wood density data for tropical vegetation provided by different researchers (Chave et al., 2009; Joshi and Ghose, 2014).

### 2.4 Derivation of Vegetation and Textural Parameters

After the pre-processing, reflectance values of eight spectral reflectance bands were obtained. From these 8 reflectance bands, 28 simple band ratios were calculated. Vegetation indices (VI’s) are defined as the mathematical transformation of the spectral bands designed to assess the spectral contribution of vegetation to multispectral observation (Elvidge and Chen, 1995). Since VI’s are nothing but combination of different spectral bands, it minimizes external effects such as sun angle, sensor angle, shadow, soil background, leaf, and canopy angle, terrain effect etc. (Kasawani et al., 2010). In the present study, 12 vegetation indices were calculated (Table 2) from the WorldView-2 multispectral image to model the biomass using multiple regression analysis.

<table>
<thead>
<tr>
<th>Vegetation Indices</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference Vegetation Index (DVI)</td>
<td>$2.5 \times \frac{\text{NIR1} - \text{Red}}{\text{NIR1} - (6 \times \text{Red} - (7.5 \times \text{Blue} + 1))}$</td>
</tr>
<tr>
<td>Enhanced Vegetation Index (EVI)</td>
<td>$((\text{Red edge} - \text{Red}) - 0.2 \times (\text{Red edge} - \text{Green})) \times (\text{Red edge} / \text{Red})$</td>
</tr>
<tr>
<td>Modified Chlorophyll Absorption Vegetation Index (MCARI)</td>
<td>$0.5 \times (2 \times \text{NIR1} + 1 - ((2 \times \text{NIR1} + 1)^2 - 8 \times (\text{NIR1} - \text{Red}))^{2/3})$</td>
</tr>
<tr>
<td>Modified Soil Adjusted Vegetation Index (MSAVI)</td>
<td>$(\text{NIR1} - \text{Red}) / (\text{NIR1} + \text{Red})$</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index (NDVI)</td>
<td>$(\text{NIR2} - \text{Red}) / (\text{NIR2} + \text{Red})$</td>
</tr>
<tr>
<td>Near Infra-Red NDVI (NIRNDVI)</td>
<td>$(1 + 0.16) \times (\text{NIR1} - \text{Red}) / (\text{NIR1} + \text{Red} + 0.16)$</td>
</tr>
<tr>
<td>Optimized Soil Adjusted Vegetation Index (OSAVI)</td>
<td>$(\text{NIR1} - \text{Red}) / (\text{NIR1} + \text{Red})^{1/2}$</td>
</tr>
<tr>
<td>Renormalized Difference Vegetation Index (RDVI)</td>
<td>$((1+0.5) \times (\text{NIR1} - \text{RB}) / (\text{NIR1} + \text{RB} + 0.5)$</td>
</tr>
<tr>
<td>Soil and Atmospherically Resistant Vegetation Index (SARVI)</td>
<td>where, $\text{RB} = \text{Red} - 1 \times (\text{Blue} - \text{Red})$</td>
</tr>
<tr>
<td>SoilAdjusted Vegetation Index (SAVI)</td>
<td>$((1+0.5) \times (\text{NIR1} - \text{Red}) / (\text{NIR1} + \text{Red} + 0.5)$</td>
</tr>
<tr>
<td>Triangular Vegetation Index (TVI)</td>
<td>$0.5 \times 120 \times (\text{NIR1} - \text{Green} - 200 \times (\text{Red} - \text{Green}))$</td>
</tr>
<tr>
<td>Yellow NDVI (YNVDVI)</td>
<td>$(\text{NIR2} - \text{Yellow}) / (\text{NIR2} + \text{Yellow})$</td>
</tr>
</tbody>
</table>

Table 2. Vegetation Indices derived from WorldView-2 used in biomass estimation

Of the available texture based statistical models, the Grey Level Co-occurrence Matrix (GLCM) method is widely acclaimed and hence we used. The selection of moving window size is one important factor to be concerned in GLCM method because the small window size exaggerates the local variance whereas the large window size may not extract textural information because of over-smoothing of the textural variation (Chen et al., 2004; Nichol and Sarker, 2011). So the textural analysis carried out in this study used small to medium moving window sizes of 3x3 to 5x5. The following GLCM textural parameters such as Mean, Variance,
Homogeneity, Contrast, Dissimilarity, Entropy, Angular Second Moment, and Correlation were derived from three sets of image inputs: (1) 8 reflectance bands, (2) 28 simple band ratios, and (3) 12 Vegetation Indices derived from WorldView-2 image.

### 2.5 Modelling Biomass

The relationship between field biomass and information derived from remote sensing data can be established using statistical methods. Though several statistical models are available, multiple regression model can perfectly establish the complex relationship between the field biomass and remote sensing derived information (Nichol and Sarker, 2011). So we used the multiple regression model in this study to measure the linear association between the dependent variable and at least two independent variables. Total biomass of each of the 40 sample plots calculated using allometric equations was used as the dependent variable whereas the parameters extracted using the 3x3 and 5x5 pixel AOI masks from the image derived data were used as independent variables in the multiple regression analysis at a confidence interval of 95%. Prior to the multiple regression analysis, the Pearson’s correlation was calculated between independent variables in each of the model and dependent variable and those variables which had high correlation were selected for further analysis. The statistical model parameters such as coefficient of determination ($R^2$), Root Mean Square Error (RMSE), and significance value of the model (P-value) were calculated to avoid overfitting problem and to find best fit model for biomass estimation. In addition to that, beta coefficient value (B), standard error of B, significance value (p), and Tolerance and Value Inflation Factor (VIF) were also calculated for each independent variable in the model to understand the multicollinearity effect. The tolerance value of less than 0.10 and the VIF value of more than 10 were determined to indicate multicollinearity problem (Belsley, 2006).

### 3. RESULTS

The multiple regression analysis was carried out individually for six input independent variables extracted using 3x3 and 5x5 AOI mask from seven different input image derived datasets at a confidence interval of 95%. Two AOI masks were used to know the influence of mask size in achieving the relation between dependent and independent variables in multiple regression analysis.

#### 3.1. Relation between Spectral Reflectance and Biomass

From the results of multiple regression analysis, it is found that the relationship between the reflectance of WorldView-2 spectral bands and the estimated biomass of sample plots is not so significant. The coefficient of determination ($R^2$) value for 3x3 mask is found to be 0.20 which is slightly better than that of 5x5 mask for which the $R^2$ is of 0.17 (Figure 2a and 2b). Both these models exhibit high RMSE value of 195.67 and 198.98 respectively (Table 3) and found to be non-significant models with p-value more than 0.05. However, the multiple regression results in better prediction than that of linear regression results obtained for individual bands. Earlier studies also reported that the relationship between simple reflectance bands and the plot biomass is comparatively poor due to the strong intercorrelation among the reflectance bands and therefore fails in predicting the biomass (Nichol and Sarker, 2011).

#### 3.2. Relation between Spectral Reflectance Band Ratios and Biomass

The multiple regression results between the plot biomass and the simple ratio of the reflectance bands is found to be better from that of the simple reflectance bands. The $R^2$ value for the 3x3 mask while using simple band ratio is 0.52 and for the 5x5 mask, the $R^2$ value is 0.46. Meanwhile the RMSE found to be decreased for this model when compared with the earlier model and the values for 3x3 and 5x5 masks are 176.03 t/ha and 181.79 t/ha respectively (Figure 2c and 2d). Even though, this model is also found to be insignificant, it is comparatively better than the regression with reflectance bands with p-value of 0.17 and 0.23 for 3x3 and 5x5 mask size which validates the fact that for biomass estimation, band ratios perform better than simple reflectance bands. This is because the band ratios generally minimizes the attenuations in simple reflectance bands arises due to solar irradiance, soil background, and topographic effects meanwhile increasing the spectral response from the vegetation (Elvidge and Chen, 1995).

### 3.3. Relation between Vegetation Indices and Biomass

When plot biomass was regressed with 12 vegetation indices, it is found that they performed slightly better than simple reflectance bands but not significant as that of with band ratios. This could be evident from the $R^2$ value and RMSE value from the Table 3 and Figure 2e and 2f. From the p-value, these models are also found to be insignificant. This is due to the fact that the relation between vegetation indices and the biomass is asymptotic in tropical forest and also the vegetation indices cannot be used together as independent variables in the multiple regression for biomass modelling since they are highly correlated (Sarker and Nichol, 2011).

<table>
<thead>
<tr>
<th>Input Data</th>
<th>AOI mask</th>
<th>$R^2$ value</th>
<th>RMSE (t/ha)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Reflectance</td>
<td>3x3</td>
<td>0.20</td>
<td>195.67</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.17</td>
<td>198.98</td>
<td>0.61</td>
</tr>
<tr>
<td>Band Ratio</td>
<td>3x3</td>
<td>0.52</td>
<td>176.03</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.46</td>
<td>181.79</td>
<td>0.23</td>
</tr>
<tr>
<td>Vegetation Indices</td>
<td>3x3</td>
<td>0.23</td>
<td>194.62</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.31</td>
<td>184.80</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Table 3. Model fitting parameters derived from the results of biomass estimation using simple reflectance, band ratios and vegetation indices.
Figure 2. Relationship between the field biomass and the model predicted biomass using 8 spectral reflectance bands (a and b), 28 band ratios (c and d) and 12 vegetation indices (e and f) while using 3x3 and 5x5 masks respectively.

3.4. Relation between Textural Parameters and Biomass

As far as the textural parameters of spectral bands are concerned, the model fitting parameters such as $R^2$ value, RMSE and p-level have shown some improvement. In this particular case, the $R^2$ value increased from 0.20 to 0.35 (for 3x3 mask) and from 0.17 to 0.30 (for 5x5 mask) when compared with the simple reflectance band (Figure 3a and 3b). Considering the significance of the model, the p-value for the models are 0.07 and 0.23 for 3x3 and 5x5 masks exceeds the upper limit 0.05 to establish the significance (Table 4). While considering the case of texture of band ratios, even though the $R^2$ value decreases from 0.52 to 0.41 (for 3x3 mask) and from 0.46 to 0.35 (for 5x5 mask) (Table 3 and Table 4), from the RMSE value and p-value, it could be inferred that textural model is better than simple band ratio model developed earlier (Figure 3c and 3d). Furthermore, the p-value of 0.07 and 0.12 shows that the significance of the model is improved when textural parameters are used. And, the biomass estimation using textural parameters of vegetation indices found to have no improvement than using vegetation indices (Figure 3e and 3f). This is also evident from insignificant RMSE value and the p-value (Table 4). Except in the case of vegetation indices, the textural parameters have shown some improvement in biomass estimation when compared with their counterparts while used as it is. As mentioned earlier, the vegetation indices are asymptotically related to the biomass and the higher intercorrelation among the vegetation indices resulted in the textural parameters which also had similar relation with biomass. This could be explained by the fact that the textural properties are sensitive to the shadow effects in the mixed canopy structure and this difference contributes the improvement in the biomass estimation. Similar kind of improvement in biomass estimation while incorporating the textural parameters derived from the optical
remote sensing data in the regression model were earlier reported while applied in tropical evergreen forest (Lu, 2005), subtropical mountainous forest (Sarker and Nichol, 2011) and Siberian tundra forest (Fuchs et al., 2009).

![Figure 3. Relationship between the field biomass and the model predicted biomass using textural parameters derived from 8 reflectance bands (a and b), 28 band ratios (c and d) and 12 vegetation indices (e and f) using 3x3 and 5x5 masks respectively.](image)

<table>
<thead>
<tr>
<th>Input Data</th>
<th>AOI mask</th>
<th>R² value</th>
<th>RMSE (t/ha)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texture of Reflectance bands</td>
<td>3x3</td>
<td>0.35</td>
<td>176.42</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.30</td>
<td>186.33</td>
<td>0.23</td>
</tr>
<tr>
<td>Texture of Band Ratio</td>
<td>3x3</td>
<td>0.41</td>
<td>173.53</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.35</td>
<td>179.81</td>
<td>0.12</td>
</tr>
<tr>
<td>Texture of Vegetation Indices</td>
<td>3x3</td>
<td>0.20</td>
<td>195.09</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>5x5</td>
<td>0.28</td>
<td>187.88</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Table 4. Model fitting parameters derived from the results of biomass estimation using textural parameters of simple reflectance, band ratios and vegetation indices.

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In earlier studies, it has been proved that the textural properties could enhance the prediction of biomass and carbon stocks of different tropical and temperate forest ecosystems when compared with image parameters such as reflectance bands, vegetation indices etc. when modelled individually (Eckert, 2012; Fuchs et al., 2009; Nichol and Sarker, 2011; Zhu et al., 2015).

4. DISCUSSION

The objective of this study was to analyse the potential of high resolution WorldView-2 multispectral image to estimate biomass of dense heterogeneous mangrove ecosystem of Bhitarkanika, Odisha, India which is the first of its kind for the study area. However, there are some points need to be discussed regarding the moderate results obtained when compared to other studies using WorldView-2 data for improvement of biomass estimation using different image analysis methods (Eckert, 2012; Zhu et al., 2015). The number of sample location used in this particular study where the biomass variables collected is limited due to the hostile and inaccessible conditions in the swampy mangrove environment. Though the sample points are uniformly distributed over the study area, the sample points were less normally distributed for calculated field biomass. Since the mangroves in India are highly protected by law and the study area is a National Park (under the privilege of maximum conservation zone), the destructive sampling method to derive species specific and site specific allometric equations is not possible. Furthermore, the studies related to biomass estimation for Indian mangroves are very limited and there are no many established species specific allometric equations available for Indian mangroves. So the common allometric equations developed by Komiyama et al. (2005) for mangroves were used in which estimation for Indian mangroves are very limited and there are no many established species specific allometric equations available for Indian mangroves. So the common allometric equations developed by Komiyama et al. (2005) for mangroves were used in which.

Woodcock and Strahler, (1987) stated that in an image of a forested area of heterogeneous stand with high species diversity and when the spatial resolution increases to the size of the dominant tree crown in the pixel, the local variance obviously increases. Especially the differential growth of different stands, uneven canopy arrangement, difference in tree crown size and gaps, tree shadows, and most importantly spatial resolution of the image used improves the local variance in an image. This supports the scope of using the textural parameters in biomass estimation. Since the sample plots considered in this study area is found to be heterogeneous in forest canopy structure, the stronger correlation with the textural parameters is expected. It is stated that when biomass and canopy structure have strong correlation, the spectral reflectance would be a key parameter. On the other hand, in structurally complex ecosystem like mangroves, textural parameter would have strong correlation with biomass (Eckert, 2012). The model based on the textural parameters derived from band ratios outperformed than that of textural parameters derived from reflectance bands and vegetation indices. Among the textural parameters derived from different vegetation indices, textural parameters from Enhanced Vegetation Index (EVI), Modified Soil Adjusted Vegetation Index (MSAVI) and Renormalized Difference Vegetation Index (RDVI) were selected as fitting variables in the best biomass model. Among them, EVI outperformed other two with lower Tolerance and higher Value Inflation Factor (VIF) as this index was developed with the aim of increasing the sensitivity of high biomass region. This result is similar to the case studies of Huete et al. (2002) where they used MODIS data and Eckert (2012) in which WorldView-2 was used for vegetation biophysical characteristics assessment using different vegetation indices.

5. CONCLUSION

The potential of using high resolution WorldView-2 multispectral image with a spectral resolution of 8 bands and spatial resolution of 1.84m for predicting the above ground biomass of highly complex mangrove ecosystem was tested. Even though, the spectral reflectance bands and vegetation indices were not performing well, the band ratio gave acceptable result. But these models were found to be statistically insignificant. Textural analysis has given promising results since the study area is heterogeneous in forest structure and having mixed canopy structure. The textural parameter derived information from band ratio has taken the advantage of information from both band ratio and texture analysis and gave better results. Perhaps, the reason is lack of site specific wood density and species specific allometric equations since the drilling or cutting of trees in the forest is prohibited. So we used Global Wood Density Index and allometric equations from earlier studies for available species. For other species, we used common allometric equation derived by Komiyama et al. (2005). The current methodology would be extended and further investigated by combining the textural parameters, taking more number of stratified sample points to validate the site specific wood density and to derive species specific allometric equations to improve biomass estimation.
REFERENCES


SEMI AUTOMATED APPROACH FOR MAPPING PERIPHERAL AND BOUNDARY PLANTATIONS IN ARID REGION OF INDIA USING HIGH RESOLUTION SATELLITE DATA

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ABSTRACT

Arid region across the globe faces challenges due to both natural perturbations and human activities. In India alone about 69 percent of the country is dry land and further degradation has severe implications for livelihood and food security for the local communities. Several initiatives both at international and national levels have been launched to address these challenges under which watershed development through agroforestry is the most critically acclaimed. However, the progress in promoting agroforestry is held back due to the lack of awareness, appropriate monitoring tools and adequate decision making system. Though significant amount of research is available on various aspects of agroforestry using remote sensing and GIS, mapping of tree configuration on the bunds in a cultivated landscape has not been explored fully in spite of the huge potential. This study attempts to effectively map the bund occupation by peripheral and boundary plantations (PBP) in Barmer, district of Rajasthan comprising of two micro watersheds and a Macro Watershed (IWMP Project – XV, 2009-10) and falling in Dry Arid Hot Agroclimatic Zone. We used high resolution panchromatic Cartosat-1 Orthorectified (2.5 m) data in tandem with multispectral LISS-IV MX (5.8 m) acquired during November 2016. A semi-automated approach consisting Object Based Image Analysis (OBIA) followed by interactive classification PBP by overlaying on-screen visually interpreted bund boundaries has resulted in realistic mapping of the bund configuration and PBP. Results obtained shows that the total bund length of 912.047m exists in the 5766 ha of the project of which 13.51% is devoid of any PBP whereas remaining 86.49% of the bunds are under various degree of plantation including 100% PBP in 26.41% of the bunds mapped in the study. The approach is found to be viable for mapping PBP over a broad spatial extent and could be integrated with already existing IWMP Bhuvan portal for assessing the potential and monitoring the progress of schemes such as Har Med Par Ped (HMPP) that have been launched to encourage tree plantation on individual farms.

KEYWORDS: Peripheral Bund Plantations, Agro-Forestry, watershed, GIS, Remote Sensing, Image Segmentation

1. INTRODUCTION

The arid regions across the world represent some of the most complex natural ecosystems that are highly responsive to both natural perturbations and human activities (Brown et al, 1997). Due to its unique geographic setting and vast expanse, India harbors variety of landforms with climate ranging from tropical to temperate and from alpine to arid. According to the India’s 4th National Report to United Nations Convention to Combat Desertification (UNCCD) about 69 per cent of the country is dry land, arid, semi-arid and dry sub-humid and degradation has severe implications for livelihood and food security for millions of people living in these heavily populated areas. Thus, for the people inhabiting such regions, life is the constant struggle for survival. Appropriate measures backed by scientific justification are required at policy level to combat problems for food, water and basic livelihood needs in arid areas. The need to mainstream land degradation issues into national policies and frameworks has been supported by international mechanisms such as the United Nations Convention to Combat Desertification (UNCCD) and the Millennium Development Goals (MDG) 2000. The target 15.3 under the Sustainable Development Agenda (SGD) 2030 also aims to combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutrual world. For optimum use of resources, sustainable outcomes and to restore the ecological balance by harnessing and conserving natural resources such as soil, vegetation and water, the Department of Land Resources (DoLR) under Ministry of Rural Development (MoRD) in India also launched Integrated Watershed Management Programme (IWMP), a modified programme of erstwhile Drought Prone Areas Programme (DPAP), Desert Development Programme (DDP) and Integrated Wastelands Development Programme (IWDP) during the period 2009-10.

Developments of watersheds, micro catchments, protective bunds and planting of tested crops, bushes, shrubs and trees of economic value and high ecological significance are among some of the practical measures recommended for the ecological restoration and community development especially in the in Arid regions. Integration of trees into farms, through agroforestry diversifies and sustains smallholder production for increased social, economic, and environmental benefits (Leakey, 1996). Agro forestry is one of a wide range of approaches for restoring degraded forests and agricultural lands, thereby contributing to landscape restoration. Agroforestry has been identified as a climate change mitigation practice for its potential to sequester carbon (Rioux, 2012). An ultimate goal of agroforestry is the conservation of the soil and water resources of watersheds while satisfying the needs of rural people for food, fuel and income. The potential of agroforestry systems helps to restore land productivity, conserve biodiversity, increase the resilience of agro-ecosystems, alleviate

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poverty and contribute to food security and nutrition (Hillbrand et al., 2017). The recognition of benefits from agroforestry in rural set-up has resulted in development of small scale rural development forestry as compared to the conventional large scale industrial forestry with dual focus on environment protection and community development in the policies of many of the major international development agencies within the past decade (Schreckenberg, 1998). Current estimates show that about 65% of the timber requirement in India is met from the trees grown on farms (Shukla et al., 2018). The National Mission for Green India (GIM) is one of the eight Missions outlined under the National Action Plan on Climate Change (NAPCC) also adopts an integrated cross-sectoral approach as agroforestry is implemented on both public as well as private lands with a key role of the local communities in planning, decision making, implementation and monitoring. India is also the first country to have articulated and adopted a comprehensive national policy on Agro forestry -2014 which aims to increase the percentage of tree cover in India while increasing farm incomes and reducing climate risk. A Sub-Mission on Agro forestry (SMAF) under the framework of National Mission for Sustainable Agriculture (NMSA) has launched Har Med Par Ped Scheme (HMPPS) with an outlay of Rs.935 crore for a period of 4 years (2016-17 to 2019-20) to expand the tree coverage on farmland in complementary with agricultural crops. However, it is also recognized that success of any such ambitious programme would be guided by a suitable monitoring and evaluation mechanism in place.

Earth observation systems providing remote sensing data serves as an excellent tool for mapping and monitoring of natural resources on earth. Remote Sensing (RS) plays a significant role in providing geo-information in a spatial format and also in determining, enhancing and monitoring the overall capacity of the earth (Navalgund et al., 2007). Most widely used applications of remote sensing in agroforestry spread across aspects such as estimating spatial extent (Rizvi et al. 2009b), mapping crown density using bio-physical indices (Godinho et al., 2016) and site suitability assessment for agroforestry systems (Unnluh and Lefebvre 1995; Bydekerke et al. 1998; Bentrup and Leininger 2002; Ahmad and Goparaju, 2017), In the recent years however, agroforestry has received increased attention in the REDD+ context for measuring carbon sequestration and projecting climate change impacts (Kumar and Nair, 2011) and Rizvi et al.(2016); Luedeling et al., (2014) effectively used RS and Geographic Information System (GIS) for projecting the impacts that agroforestry can have on climate change. Determining the continuity of bund plantations is an essential component of for the management and maintenance of complete and stable shelterbelt systems. Assessment of connectivity index of shelterbelts using geospatial tools has been demonstrated in many studies (Kristensen and Caspersen, 2002; Shi et al., 2011). With the fast developments in the tools of computing, RS and GIS, methodological research in agroforestry have also gained significant developments. Karlson et al. (2016) used multi-seasonal WorldView-2 imagery to map five dominant tree species at the individual tree crown level in a parkland landscape in central Burkina Faso using Random Forest algorithm. Rizvi et al (2016) demonstrated the increased suitability of sub-pixel classifiers over the routine pixel classifiers with moderate resolution satellite data for better estimation of area under agroforestry. Deng et al (2013) established a waveform recognition model for belt continuity based on waveform recognition theory using SPOT 5 images with a 10 m spatial resolution using GIS. However, with the increased availability of the low cost high resolution data it is felt that approaches that utilize imagery sources with resolutions finer than, 5 m are needed (Liknes et al, 2010) for accurately mapping the bund plantations since they have inherent tendency to have lesser impact of sub-pixel effect and are better equipped with capacity to represent the fine details of the PBT.

Ironically, in spite of demonstrated role of RS and GIS tools in agroforestry for last more than three decades, most of current applications in this field are still restricted to specific case studies. Rigorous and consistent procedures for data collection and reporting at sub national and national scales are lacking. This has in turn resulted in missing the opportunity to capitalize on the environmental services of agroforestry and thus a serious setback to its potential development that could have been possible otherwise (Nair, 2012). There is a need to have reliable data sets and appropriate tools to accurately map and to have an adequate decision making system on wall to wall basis. In Indian context, wall to wall mapping and assessment of TOF is regularly carried out by Forest Survey of India (FSI) using a well-defined sampling design since 2002-03, however, the entire exercise and area estimates are available at a coarse scale of 1:50K which though give sufficiently fair estimates of block plantations but have limitation in terms of PBT. There is a need to have a monitoring mechanism using satellite based inputs at a much higher scale so that farm level assessments can be in terms of actual contribution of the Peripheral and Boundary Plantation (PBP)/ Border Tree plantation (BTP). Though the agroforestry lacks the large research foundation of its agriculture and forestry counterparts, development and use of computer-based tools in agroforestry have been substantial and are projected to increase as, the recognition of the productive and protective roles of these tree-based practices expands (Ellis et al, 2004). With this background, our study provides a novel approach for monitoring the PBP in terms of running meter length and percentage cover on the bund using high resolution satellite data.

2. STUDY AREA

The study area selected is IWMP-Barmer- 16 (2009-10) project having coordinates 25º 39’ 44” N & 72º 10’ 16” E. The total geographical area under the study is 5766.56 Ha and it forms a part of Jagsa Gram Panchayat in Balotra Block of Barmer district in the state of Rajasthan. It comprises of 2 micro watersheds including 1 Macro Watershed in Agroclimatic Zone Dry Arid Hot Zone. The average rainfall is 100-250 mm and about 80 percent of its annual rainfall is received in the month of July to September. The temperatures in the area range between 45ºC during summer and 10º-15ºC during winter. The soil texture is sandy to sandy loam and the area is severely affected by erosion with an average soil loss to the extent of 500-800 t/ha.
Major agroforestry crop in the area is *Prosopis cineraria*, *Tecomella undulate*, *Ziziphus nummularia*, *Capparis deciduas*. These trees are grown along with the pearl millet, mung bean and cluster bean. *L. sindicus* and *C ciliaris* are the dominant grasses that appear in the long fallows and form an important sylvipastoral system. The area is sparsely populated with only 30.32 ha (i.e., 1%) under habitation. 82% area is covered under the cropland, 7.5% is under barren rocky, and 3.52 are degraded having scrubs (Figure 1).

![Figure 1. Location Map of Study Area](image1)

<table>
<thead>
<tr>
<th>LULC-SIS DP THIRD ORDER (2013)</th>
<th>AREA in HA</th>
<th>AREA in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barren rocky</td>
<td>508.78</td>
<td>7.95</td>
</tr>
<tr>
<td>Crop land</td>
<td>5242.23</td>
<td>81.91</td>
</tr>
<tr>
<td>Grassland &amp; grazing land</td>
<td>91.07</td>
<td>1.42</td>
</tr>
<tr>
<td>Gullied/ravine areas</td>
<td>235.49</td>
<td>3.68</td>
</tr>
<tr>
<td>Hamlets &amp; Dispersed household</td>
<td>24.99</td>
<td>0.39</td>
</tr>
<tr>
<td>Lakes/Ponds</td>
<td>5.5</td>
<td>0.09</td>
</tr>
<tr>
<td>Mixed settlements</td>
<td>5.33</td>
<td>0.08</td>
</tr>
<tr>
<td>Rain/Stream/Drain</td>
<td>114.19</td>
<td>1.78</td>
</tr>
<tr>
<td>Sandy areas</td>
<td>11.7</td>
<td>0.18</td>
</tr>
<tr>
<td>Scrub land dense</td>
<td>2.18</td>
<td>0.03</td>
</tr>
<tr>
<td>Scrub land open</td>
<td>119.72</td>
<td>1.87</td>
</tr>
<tr>
<td>Village</td>
<td>38.57</td>
<td>0.60</td>
</tr>
<tr>
<td>Grand Total</td>
<td>6399.8*</td>
<td>100.00</td>
</tr>
</tbody>
</table>

![Figure 2. Land Use Land Cover Map of Study Area](image2)

3. METHODOLOGY

A semi-automated approach has been used to delineate the PBT using IRS high resolution panchromatic 2.5 m data (Cartosat-1 Orthorectified; path 502; row 79; dated 21 Oct, 2013) in tandem with 5.8 m multispectral LISS IV data to discern the tree crown lines at a detailed scale over the bunds. In the first step, farm bunds were visually interpreted on Cartosat-1 data in ArcGIS at 1:5k scale. The second step consisted of Object Based Image Analysis (OBIA) approach as implemented in commercial suite of e-Cognition (Ver. 8.9) that offers segmentation at user defined scale followed by application of wide range of spectral, textural and object geometry to discern the linear tree clad segments (Pujar et al., 2014). Methodology has incorporated the ability of segmentation algorithm to delineate the PBP harnessing the spectral distinction and contrast of the image elements. Segmentation algorithm exploits the shape and compacters limits put as constraints on pixel aggregation at particular scale specified by user. Scale is an empirical parameter defined by user to correspond to the detail of the entities in the given landscape. Segments were developed iteratively using 1:50k, 1:30 k and 1:10k scale and the 1:30 was found to be most suitable. Other parameters (shape / compactness) were interactively selected using appropriate tools available in e-cognition. These segments were interactively/manually classified into PBT by overlaying with the farm bunds boundaries digitized in the previous step and a poly vector having these linear PBT was obtained. Segments with excessive non tree cover fraction were carefully avoided during selection. Running length of the PBP and percentage length of the bunds under PBP were computed using ArcGIS overlay function. There were instances of bunds not falling in the crown lines due to the
differences in scale; this was taken care by taking a buffer of the crown lines so that such error of omission due to scale is taken care and final statistics were computed.

4. RESULTS

Results obtained in the exercise shows that study area supports total bund length of 912,047 m in spread over the area of 5766 ha. Length of individual bunds was found to range from 5m to 546 m (Figure 3). These were classified further to generate number of bund under various %PBP Classes: Length of bunds (in Km) under various %PBP Classes. Spatial variability of PBP density using Grid wise approach was also computed to give an overall representation.

4.1. Bund under levels of % PBP Occupancy

Number of Bund under various %PBP Classes was categorised in to 10 categories to understand the variability in the spread. Total bund units that are occupied by tree crowns in each category of occupancy shows highest units in completely covered category (100% occupancy) at 3390 units. Interestingly, this was followed by 1463 number of bunds with no tree cover at all. 1561 units consisted PBP of < 25 %, while 1295 units were under occupancy of > 90%. Therefore in all, 4685 bund units were covered with > 90% crown occupancy (46% of total bunds). Least number of units was found in 40-50 percent.
occupancy category. The trend evident from the shape of the distribution indicates that as a crop in the entire landscape, tree presence is matured and there is enough regeneration to sustain the future stock. Intermediate stages are also well represented with a typical j-shaped distribution characteristic of well balanced population.

4.2. Length of bunds under various % PBP Classes

Analysis was carried out considering the fraction of occupancy in each occupancy category of bunds in terms of length. This showed that 100 percent occupancy bunds contributed 240.9 km PBPs followed closely by 137.2 Km by >90 percent occupancy bunds. Least occupancy bunds at < 25% occupancy contributed 20.1 km. It is interesting to note that if bunds with more than 50% occupancy were considered in all, up to 100%, total contribution accounted for 90% of the PBP (501.8 Km) witnessed in the study watershed project (551.7 Km). Pattern of contribution in terms of stock also confirms to well distributed occupancy, if least occupied bunds can be considered as equivalent to regenerating stock. An assumption of 5 m diameter crown on an average yields 275 ha of vegetation in the area, which is a sizeable fraction of complete geographic extent of 5500 ha.

4.3. Spatial variability of PBP

The farmland shelterbelt network is set scientifically to minimize the occurrence of wind erosion and sand damage as much as possible during the wind-affected season for farmland (Zuo et al, 2018). We carried out a grid wise assessment of spatial variability of PBP existing in each 100 ha of the area, which can be used to further model the role of PBP as shelterbelts in minimizing the soil erosion by integrating with the other spatial datasets and field based inputs. It was found length of PBP ranged from 0-16094 m/100ha in the study area. Higher values occurred in the densely populated grids whereas lowest values were found in the area with rocky terrain and uncultivable land. The study areas show a fairly good distribution of PBP which shows the acceptance of the agroforestry practices by the rural population which is also acclaimed and accepted globally.

Figure 5. Graph showing distribution of Number of Bunds under % PBT classes; Figure 6: Graph showing distribution of length of bunds (in m) under % PBP Classes

Figure 7. Map showing PBP percentage of Bunds planted in PBP in IWMP-Barmer- 16 (2009-10) project, Jagsa Gram Panchayat, Balotra Block, Barmer district, Rajasthan.
5. DISCUSSION

Agroforestry systems have received increased focus during the last few decades due to their capability as multifunctional systems providing a wide range of economic, socio-cultural and environmental benefits. Linkages of agroforestry with the sustainable development goals qualify them to be priority area of research. These systems can be of great benefit to the smallholder farmers by means of generating diverse products and services on a limited land area and at the same time meeting the ecological balance. However, agroforestry systems also have limitations, and a careful analysis should be carried out before their introduction (FAO, 2018). Spatially explicit information derived from satellite images forms an important component of any planning and development of natural resources. There has been a significance development in the techniques of mapping and monitoring natural resources using remote sensing and GIS in agroforestry also during the last few decades. Agroforestry has witnessed application of wide range of methodologies in mapping its various aspects such as area, yield, carbon sequestration potential, site suitability etc. as explained in the earlier section of this paper. There is an increased use of Computer Based Decision Support Tools (DST) in integrating information to facilitate the decision-making process that directs development, acceptance, adoption, and management aspects in agroforestry (Ellis et al, 2004). GIS based models are increasingly being used to address the issues related to agro-forestry and study the impact on socio-economic and ecological aspects. This study is a step forward toward prototype development for the effective mapping and monitoring of PBP in agroforestry systems of arid region in India using high resolution satellite data and geo-spatial tools. Overall, it was found the approach presented in this paper demonstrates a viable solution/ prototype for mapping PBP over a broad spatial extent. Up scaling of the methodology through ISRO’s geo-web portal Bhuvan that hosts vast archive of high resolution satellite data of the whole country and also supports various programme of the ministry of rural development, ministry of agriculture and farmer welfare and also the ministry of environment and forest and climate change may serve as an effective tool in mainstreaming the mapping and monitoring the micro-level agroforestry efforts in the country. Under the Digital India Land Record Modernisation Programme (DILRMP) high resolution satellite data is being effectively used for generating the Digital Cadastral maps of villages and land parcels which largely coincide with the bunds in majority of the cases. These maps can be monitored for the presence of PBP and effectiveness of the agro-forestry initiatives as envisaged in the HMPP programme of the Ministry of Rural Development that have been launched to encourage tree plantation on individual farms. Geotagging of the plantation related activities capturing its various stages and their monitoring using high resolution satellite data and further classification of these stages using object based image analysis as presented in this paper provides a viable tool for management of agro-forestry and modeling the impacts in the long run. Several studies demonstrate the use of cadastral dataset in assessing the potential tree belt functions in rural landscapes (Nowak and Pędziwiatr, 2018). However, to achieve large scale national level coverage and implementation of the project with the existing portal and efforts would also need strengthening of technical and institutional capacities of the stakeholders along with the integration of field measurements and observations using mobile applications and capacity building of the field functionaries. The utility of the existing and future tools for decision-support in agroforestry must take into account the limits of our current scientific, information, the diversity of aspects (i.e. economic, social, and biophysical) that must be incorporated into the, planning and design process and most importantly the end users. Once available, information derived from PBP in agroforestry systems would enhance the current understanding of impact of ecological restoration programs on dust concentrations (Long et al, 2018) at local and regional scales, impact of wind speed and surface wind erosion.
characteristics in a farm-shelter forest network (Zuo et al., 2018), and spatial modeling of impacts of conservation bunds on crop yields (Tilahun et al., 1999) etc. Thus, incorporating digital tools into the design and planning process will enhance the capability of agroforestry to simultaneously achieve, environmental protection and agricultural production goals in a long run (Ellis et al., 2004).

6. CONCLUSION

Satellite based inputs and decision support systems provides an excellent tool in planning and designing ecological restoration projects based on agroforestry and monitoring them. However, for a country like India with vast expanse and rural spread, consistency between flight paths is an operational challenge to use indigenous satellite data for PBP and cadastral mapping at a national level. With these challenges taken care, the semi automated approach in this paper could be a viable operational and cost effective tool for mapping and monitoring of PBP on a regular basis.

REFERENCES


