Semiconductor Optoelectronics, *Vol. 42 No. 2 (2023), 669-681*
https://bdtgd.cn/

Semiconductor Optoelectronics
ISSN: 1001-5868

LANDSLIDE INVENTORY MAPPING IN THE GHATS REGION OF KARNATAKA, INDIA

Anil D[1], Savitha Hiremath[2], S H Manjula[3] and Venugopal K R[4]
[1] Research Scholar, Bangalore University, Bengaluru
anilkumaratb@gmail.com
[2,3,4] Department of Computer Science and Engineering
University Visvesvaraya College of Engineering, Bengaluru, India.

Abstract— Landslide inventories are important application for analyzing the geospatial information for landslide hazards. A landslide-inventory map is one of the essential for identifying the past landslides using very high-resolution (VHR) satellite images. To mitigate the losses and damage resulting during landslides, it is very essential to analyze the past landslides which are more prone to landslides. This research aims to construct an accurate landslide inventory map for the section of ghats of Karnataka region using remote sensing and Geographical Information System (GIS). In this study, a comparison between existing landslide inventories and satellite landslides data are used for identifying the distribution of landslides. Existing inventories like NASA Landslides points and Bhuvan landslide data are used for preparing inventory maps which consists of 1532 landslide points. Google Earth Engine (GEE) provides access to a vast collection of satellite imagery, including historical datasets from satellites such as Landsat and Sentinel-2. These data are used for object-based image analysis to extract and prepare a landslide inventory map. Satellite data of high to very high resolution such as IMS-1(17 Bands), Resourcesat-2 and 2A LISS-III Ortho, Cartosat-1 and Aerial images were used in the mapping of landslides. Around 48 potential landslide points have been identified by the object-based image analysis. The Final inventory map consists of 1369 out of 1580 landslide points with 48 landslide points identified are confirmed and mapped by VHR Satellite images using Google Earth Engine.

Index Terms — Adaptive region, Inventory Map, Landslides, Satellite Images, Segmentation, very high-resolution Images

I. INTRODUCTION

Natural hazards are events caused by nature, like landslides or floods, earthquakes, tsunamis, and volcanic eruptions affecting human societies and ecosystems. Understanding these processes and their potential impacts is crucial for preparedness, response, and mitigation efforts to minimize the harm they can cause to communities and ecosystems [1]. Landslides are a type of natural hazard that can occur on both land and in water. They are widely spread globally and particularly very common in areas like the Himalayas and the Western Ghats in India. Landslides are downward and outward movement of soil or rock mass that will be set off by one or more causes under the influence of gravity. The occurrence of landslides is influenced by factors like the quality of rock, the shape of the slopes, and the overall geographical and environmental conditions. Remote sensing and geographic information systems (GIS) are the techniques used for the scientific study of landslides. Remote sensing involves using satellite imagery or aerial photography to gather data from a distance, aiding in the identification and monitoring of landslide-prone areas. GIS, on the other hand, provides a platform for storing, analyzing, and visualizing geographical data. By integrating data from various sources such as topography, soil type, rainfall patterns, and historical landslide occurrences, GIS enables researchers and planners to assess landslide susceptibility and develop effective mitigation strategies. These technologies collectively enhance our understanding of landslides, contributing to informed decision-making and hazard management. According to data from the Geological Survey of India around 12.6\% of India's land is prone to various degrees of landslide risk.

As per Emergency Response Coordination Centre (ERCC) provides a Global overview of landslides for the period 01 January 2022 to 27 June 2022. According to The Geological Survey of India, over 15 \% of India’s landmass is prone to landslides, 300 people losing lives every year. The landslide prone areas are the North-East Himalayas, North West Himalayas, Western Ghats and Konkan Hills and Eastern Ghats. Over 3,782 landslides have occurred between 2015 and 2022 in various states and Union Territories. Kerala has highest with 2,239 landslides and followed by West Bengal reported the second-highest number of landslides with 376. The Geospatial Landslide Inventory Database, mapped by NRSC/ISRO under the DMS program, covers a comprehensive collection of 80,000 landslides across India. This database spans the period from 1998 to 2022 and covers landslide-prone areas in 17 states and 2 union territories, primarily within the Himalayas and Western Ghats. The inventory is categorized into three types: seasonal, event-based, and route-wise, focusing on the specified time frame. The event-based inventory highlights significant triggers like the Kedarnath and Kerala disasters, the Sikkim earthquake, and substantial valley-blocking landslides. The route wise inventory details landslides along important tourist and pilgrimage routes. The mapping process involves utilizing satellite data of varying resolutions, including IRS-1D PAN+LISS-III, Resourcesat-1, 2, and 2A LISS-IV Mx, Cartosat-1 and 2S, alongside data from international satellites (Sentinel-1 \& 2, Pleiades, and Worldview) and aerial images to accurately pinpoint and categorize the landslides [2].

In recent times, object-based image analysis (OBIA) has gained prominence as a new standard in remote sensing and GIS. OBIA offers strong potential for precise identification of landslides and change detection in satellite imagery. This method has been increasingly utilized for the extraction of landslides and satellite-based change analysis. OBIA is an approach in remote sensing and geographic information systems (GIS) that focuses on analyzing images based on objects or segments rather than individual pixels. Unlike traditional pixel-based methods, OBIA groups pixels into meaningful objects that share similar characteristics, such as color, texture, shape, and spatial arrangement. This approach takes into account both spectral and contextual information, allowing for more accurate and contextually relevant analysis [3]. In landslide mapping using Object-Based Image Analysis (OBIA), various Machine Learning and AI techniques are harnessed for effective results. Algorithms like Random Forest and Support Vector Machine enable the classification of segmented objects into landslide and non-landslide categories based on spectral, textural, and contextual attributes. Image differencing and

Convolutional Neural Networks (CNNs) aid in change detection, identifying altered areas. Fuzzy Logic and Logistic Regression are used for landslide susceptibility mapping, integrating diverse criteria for assessment. Autoencoders and Mask R-CNN facilitate feature extraction and object segmentation, respectively. Multi-temporal high-resolution satellite images, digital elevation models (DEMs), geological maps, and land use data play vital roles in enhancing algorithms for landslide mapping through Object-Based Image Analysis (OBIA). These datasets empower various techniques: satellite images aid in detection and change analysis; DEMs contribute to susceptibility mapping; geological maps inform geological factors; and land use data influences susceptibility. The integration of these datasets enables algorithms like Random Forest, Support Vector Machine, CNNs, Fuzzy Logic, and Logistic Regression to better learn patterns and relationships, resulting in accurate and comprehensive landslide mapping. The Landslide Prone Zone Mapping relies on data obtained through Remote Sensing and GIS Techniques. Remote Sensing and GIS are prominent methods for mapping and categorizing landslides. Commonly, detection approaches employ pixel-based techniques for mapping using very high-resolution (VHR) satellite imagery before and after an event. Due to the advancements in Earth observation technology have led to the availability of bitemporal satellite images and Sentinel-2 optical images. These resources have proven invaluable in accurately identifying and extracting landslide occurrences. The increased accessibility of multi-temporal high-resolution satellite images (HRSI) has facilitated the acquisition of pre- and post-landslide event imagery. This has enabled the visual interpretation of these images from different time periods using tools like Google Earth, resulting in the creation of maps that highlight specific features. Google Earth Engine is a cloud-based platform that allows users to analyze and visualize geospatial data at scale [4].

II. LITERATURE REVIEW

Landslide inventory can be prepared through various methods such as detailed geomorphologic studies, mapping from remote sensing data and topographic maps, historical archive studies. In this research, existing inventories and satellite images were used as the main source for obtaining a multi-temporal landslide inventory. Niraj et al., [5] explained the influence of the Normalized Difference Vegetation Index (NDVI) in the creation of Landslide Susceptibility Maps (LSMs) through GIS-based bivariate and multivariate statistical models. These models encompass techniques such as frequency ratio (FR), information value (IoV), multiple linear regression (MLR), and logistic regression (LR), utilizing a dataset of 108 training and 56 testing landslide points along with ten causative factors. The accuracy of the resulting LSMs was notably highest in the case of the IoV model, both when NDVI was included and when it was omitted as a causative factor. This emphasizes NDVI's significant role in improving the predictive performance of LSMs, ultimately enhancing our ability to assess and manage landslide susceptibility effectively.

Sangeeta et al., [6] discussed the combined influence of parameters linked to both rainfall and earthquake triggers on Landslide Susceptibility Zones (LSZ) was examined using a Geographic Information System (GIS)-based relative frequency ratio (RFR) approach. This methodology allowed for the assessment of how both rainfall and earthquake-related factors collectively contribute to the susceptibility of specific areas to landslides. Chen et al., [7] introduces full convolution networks with focus loss (FCN-FL) for mapping historical landslides in regions with imbalanced samples. This approach employs an improved symmetrically connected full convolution network and focus loss function to enhance feature analysis and minimize background loss impact, aiming to provide a robust solution for accurate landslide mapping. Thambidurai et al., [8] prepared landslide inventory map using a frequency ratio model, which involved establishing correlations between factors influencing landslides and historical landslide occurrences. Subsequently, the LSZ map was divided into five distinct susceptibility zones: very low, low, medium, high, and very high, representing varying levels of susceptibility to landslides. This classification provides a valuable visual representation of the regions' relative vulnerability to landslides based on the identified influencing factors and historical patterns. Sivakumar et al., [9] integrated various methods contributed to the accurate identification and mapping of landslide occurrences within the specified time frame. Creation of a landslide inventory from Sentinel-2 imagery specifically for the year 2020 utilizing the capabilities of Sentinel-2 imagery to provide a detailed inventory for the designated year using image processing techniques, mainly band ratio, Principal Component Analysis, and image classification techniques. Ghorbanzadeh et al., [10] introduced the rule-based approach to object-based image analysis (OBIA) was developed, utilizing probabilities generated by the ResU-Net model for accurate landslide detection. The ResU-Net model was trained using a diverse landslide dataset that incorporated inventories from multiple geographical regions, including the study area. Subsequently, the trained model was evaluated using a distinct testing area that wasn't part of the training dataset. During the OBIA phase, initial steps involved calculating land cover and image difference indices using multi-temporal images before and after the landslide events. This multi-step approach, combining machine learning with OBIA, aims to enhance the precision of landslide detection, ultimately contributing to improved hazard assessment and mitigation strategies. Jose et al., [11] presented a hybrid approach for landslide detection is presented, combining semi-automated techniques of Object-Based Image Analysis (OBIA) and a machine learning algorithm, specifically the Support Vector Machine (SVM). This method is applied to identify landslides in Eastern Hiroshima, Japan following the aftermath of the 2018 Typhoon Prapiroon which led to significant devastation. By synergizing OBIA and SVM, this approach aims to accurately delineate the landslide-affected regions. The combination of spatial analysis through OBIA and machine learning-driven classification with SVM is anticipated to offer improved accuracy in identifying landslides post-disaster, thus contributing to efficient disaster response and recovery efforts in the studied area.

III. STUDY AREA

The state of Karnataka, it starts from Dandeli in the north to Mangalore in the south and from the edge of the western coastline they go as far as Coorg and Madikeri. Karnataka is located in the south western region of India covering an area of 191,791 sq km approximately situated between 11.5° North and 18.5°' North latitudes and 74° East and 78.5°' East longitude. There are more than a dozen peaks whose heights is greater than 1,500m, among those Mullayanagiri is one of the tallest peaks in Karnataka with the height of 1923m. The Western Ghats region in Karnataka stretches across the southwestern part of the state, covering portions of multiple districts. It spans approximately 600 kilometres (370 miles) from north to south and varies in width from about 48 to 190 kilometres (30 to 118 miles). The region encompasses hilly and forested landscapes, valleys, rivers, and diverse ecosystems [12]. In Karnataka, the landslide studies have been mainly focused in the Western Ghats region. The Western Ghats extend from Coorg (now Kodagu) District in the South to Uttar Kannada district in the north in Karnataka state covering an area of about 27855.45 sq. km. Landslide studies in the area have been carried out mostly along transportation corridors (National Highway \& State Highways) in the Western Ghats. The temporal data for most of these slides are not available as far as the study area is concerned. The study area is located on the eastern side of the Western Ghats and It has been generated using ArcGIS mapping software as shown in Figure 1.

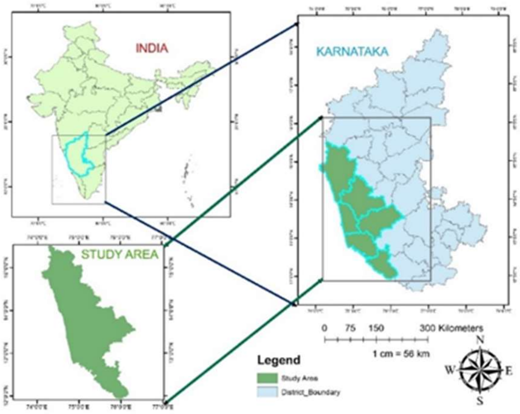

Figure-1: Study Area Map

IV. DATA ACQUISITION AND IT'S SOURCES

In Most recent studies, a wide variety of techniques have been used for extracting the spatial data for landslide inventory mapping. Listed out a few techniques to get aerial photographs to predict areas prone to landslides. This section lists and describes the datasets used for analysis in this research and is depicted in Table 1.

A. NASA Global Landslide Catalog (GLC): The Global Landslide Catalog (GLC) serves as a comprehensive repository of landslide occurrences, sourced from news reports, academic articles, and existing inventories. It encompasses a substantial collection of approximately 60,000 landslides spanning the years 2007 to 2018. This valuable dataset is accessible to the public and is presented in either geospatial point or tabular data formats, offering a valuable resource for researchers, policymakers, and the general public to better understand and analyse the distribution and characteristics of landslides across various regions and time periods. The NASA Landslide contains Catalog for both points and polygon shape file which contains around 60,000 landslide points across the world. Among these 39,623-landslide mapped are from points shape file and 20,055 were from polygon shape file [13]. These points and polygons shape files are used to map landslide points using GEE and ArcMap. Among these landslide Catalog, around 272 landslide points were mapped and visually interpreted through the map using ArcMap for our study area.

TABLE 1: Data descriptions and source information

Sl No	Input Data	Datatype	Source
1	Global Landslide Catalog	NASA Cooperative Open Online Landslide Repository (COOLR) points and polygons	https://gpm.nasa.gov/landslides/data.html
2	Geological Survey of India (GSI) with Bhukosh	Multi-temporal images with Polygon and Points Shapefile	https://bhukosh.gsi.gov.in/Bhukosh/Public

3	Resourcesat-1 LISS-III	24-meter spatial resolution and a swath of 141 km.	https://bhuvan-app3.nrsc.gov.in/data/download/index.php
4	IMS-1: Hyperspectral Imagery	500-meter spatial resolution and swath of 128 kms	
5	Cartosat-1 (All Versions)	stereo data with a spatial resolution of 2.5m and 10bit quantization	
6	Resourcesat-1 AWiFS	56-meter spatial resolution and a combined swath of 730 km achieved through two AWiFS cameras	

B. Geological Survey of India (GSI) with Bhukosh: Geological Survey of India has an enterprise portal with rich geo-scientific content, 'Bhukosh'-the spatial data portal and a geophysical data repository. This multi temporal images acquired are the information of historical landslides and this is resulting in 1260 landslide polygons for our study area. The Landslide dataset can be obtained as a shapefile(polygon) and then it was converted to Keyhole Markup Language (KML) Layer for visualization in Google Earth Engine. This information includes longitude, latitude, location, type of landslides, toposheet and so on. The Geological Survey of India (GSI) landslide data spanned seven districts within our study area. A total of 1260 landslide occurrences were processed and transformed into a point shapefile including all attributes. This conversion process was facilitated using ArcGIS 10.3 software [14].

C. Satellite Images: Mapping of landslide points based on Satellite images like IMS-1(17 Bands), Resourcesat-2 and 2A LISS-III Ortho, Cartosat-1 DEM. These landslides are polygon shape file and then it is converted to points and digitized using ArcGIS. Validation of landslide inventory using points based on post-landslide images can be performed. The very high-resolution images were obtained from the above Satellites using the coordinates points (longitude and latitude) for our study area. These data acquired in NRSC/ISRO Open data and product using Satellite Products at Bhuvan NOEDA Data Products [15].

V. METHODOLOGY

This research aims to construct landslide inventory map using satellite images including the existing inventories. The object-based image analysis was performed for the extraction of landslides for inventory mapping. In this section, the framework of the proposed Landslide Inventory Mapping using VHR remote sensing images is presented in detail as shown in Figure 2. The Framework consist of three Phases: 1) Image Segmentation 2) landslide detection 3) Visual Interpretation

The guidelines for automating the extraction of landslides were formulated following the Standard Operation Procedure (SOP) declared by the National Remote Sensing Centre (NRSC) [16]. These guidelines were customized for implementation within the eCognition software platform. The NRSC developed a dedicated ruleset within the eCognition environment, utilizing satellite imagery as the foundational data source for this extraction process.

1. Image Segmentation

Satellite image preprocessing using Google Earth Engine (GEE) involves preparing raw satellite data for analysis by removing noise, correcting atmospheric effects, and converting the data to appropriate formats. GEE provides a powerful platform to preprocess and analyze VHR remote sensing data [17]. The Preprocessing steps include the following in GEE:

- Import the image collection: Load the satellite imagery as an image collection from the GEE catalog. You can filter the collection based on time, region of interest, and other parameters.

• Cloud masking: Clouds can obscure the satellite images and affect the analysis. Apply cloud masking algorithms to remove or minimize the impact of clouds. GEE has built-in cloud masking functions for various datasets.

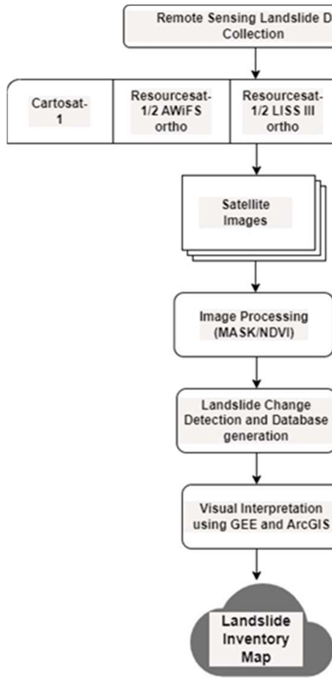

Figure-2: Architecture Diagram

• Radiometric calibration: Some satellite images need radiometric calibration to convert digital numbers to radiance or reflectance values. The calibration depends on the sensor used in the satellite.

• Atmospheric correction: Correct for atmospheric effects, such as scattering and absorption, which can distort the satellite data. GEE provides tools like the "ee.Algorithms.Landsat.TOA" for Top of Atmosphere reflectance correction.

• Mosaicing and clipping: If your study area is large and covered by multiple satellite images, mosaic them together into a single image. Additionally, you can clip the image to your area of interest for efficient processing.

• Band selection and indices calculation: Select relevant bands and compute spectral indices (e.g., NDVI, NDWI) for vegetation and water monitoring.

• Data export: Once the preprocessing is complete, you can export the processed data for further analysis or visualization outside GEE.

Once the cloud mask is derived for each image, the subsequent step involves computing the time series of the Normalized Difference Vegetation Index (NDVI). This is achieved by calculating the ratio of specific bands, enabling the extraction of meaningful vegetation information from the satellite imagery.

NDVI ={NIR-R} / {NIR + R}

The Normalized Difference Vegetation Index (NDVI) is a standardized metric ranging from -1.0 to 1.0, calculated by comparing the near-infrared (NIR) and red (R) bands of satellite imagery. Elevated NDVI values, typically within the range of 0.6 to 0.9, signify lush and dense vegetation [18]. Intermediate NDVI values, around 0.2 to 0.5, may indicate sparse vegetation or aging crops. Conversely, an NDVI

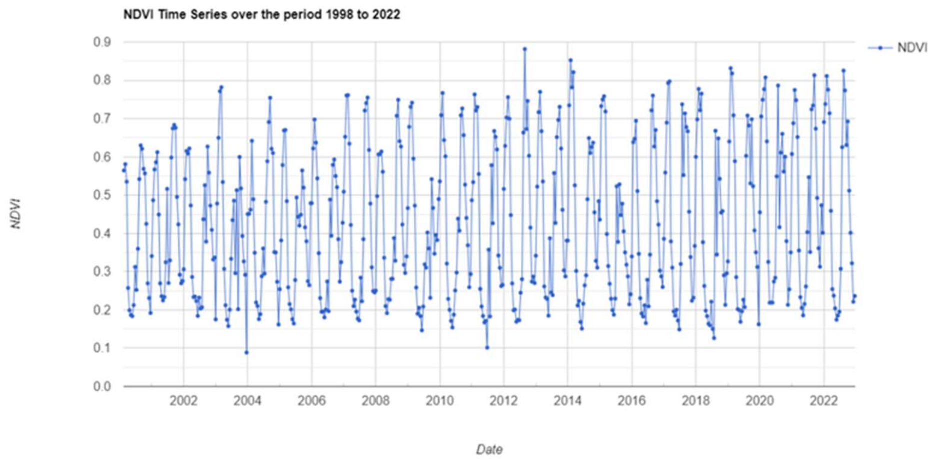

Figure-3: NDVI Time Series for the Period 1998-2022

below 0.1 might indicate exposed soil or rocky terrain. By analyzing these the NDVI time series for the period 1998 to 2022 is plotted with different NDVI values as shown in Figure 3, it becomes possible to differentiate between areas with and without landslides. The process of eliminating false positives or inaccurate landslide identifications can be enhanced through the utilization of NDVI (Normalized Difference Vegetation Index) values. NDVI serves as a valuable tool to distinguish between actual landslides and potential misclassifications, particularly in regions with vegetation.

2. Landslide Detection

This algorithm is used for change-detection with VHR satellite images for detection of landslides to construct LIM. This is a basic image processing technique that can be used for land use change detection with VHR remote sensing images. This Algorithm has three steps includes constructing adaptive region around a pixel, describing the shape of the region with direction lines and calculating the change-detection using discrete Fréchet distance

A. Adaptive Region: The algorithm takes greyscale image (VHR) as input with some threshold parameters. This threshold determines the allowed variation in pixel values within the region. We iterate over each pixel in the image and generate an adaptive region around it using a sliding window approach. We start with the pixel at coordinates (1, 1) and generate the adaptive region around it. The process is repeated for all pixels in the image to generate adaptive regions around each pixel.

B. Defining the Shape using Direction Lines: Defining the shape of an adaptive region by direction lines involves specifying the directions or orientations along which the region will extend from a central pixel. Assuming we want to define the shape of the adaptive region by horizontal and vertical direction lines, we can extend the region along these lines from a central pixel. By defining the shape of the adaptive region using horizontal and vertical direction lines, we ensure that the region extends in a consistent manner along these directions. The resulting adaptive region captures the surrounding pixels in both the horizontal and vertical directions relative to the central pixel.

C. Change-Detection using discrete Fréchet distance: The Adaptive Region Size Selection (ARSS) algorithm is used to calculate the change magnitude by measuring the distance between histogram curves and selecting an appropriate adaptive region size for each pixel. Calculate the distance between the histogram curves of Image 1 and Image 2 using a suitable metric, such as the discrete Fréchet distance (DFD). The DFD captures the similarity between the two curves, considering both shape and magnitude differences. Based on the calculated histogram curve distance, determine the appropriate adaptive region size for each pixel. The adaptive region size is typically chosen dynamically based on the magnitude of change.

3. Visual interpretation using GEE and ArcGIS

The visual interpretation process was applied to the landslide inventory data obtained from National Remote Sensing Centre (NRSC), Indian Institute of Remote Sensing (IIRS) under the Indian Space Research Organization, Bhukosh, and Bhuvan Satellite Products. The process of Landslide inventory mapping was carried out using the visual interpretation method, integrating remote sensing and Geographic Information Systems (GIS). The utilization of Very High-Resolution (VHR) optical satellite imagery further enhances the capability to identify distinct landslide areas. The landslide inventory along National Highways and State Highways of Ghat Roads in Coorg, Dakshina Kannada, Udupi, Shimoga, and Chikkamagaluru Districts of Karnataka revealed that a significant portion of landslides were triggered by anthropogenic causes and heavy rainfall. The spatial distribution of these mapped landslides is presented in the final inventory map, resulting in a comprehensive and accurate representation of the impacted areas. According to the landslide inventory conducted along the National Highways and State Highways of Ghat Roads in Coorg, Dakshina Kannada, Udupi, Shimoga, and Chikkamagaluru Districts of Karnataka, a significant majority of the observed landslides appear to have been instigated by anthropogenic factors and intensified by heavy rainfall events. The resulting spatial distribution of these identified landslides has been consolidated and presented in the final landslide inventory map.

VI. RESULTING LANDSLIDE INVENTORY

Around 1532 landslides have occurred from last 24 years, most of the landslides are repeating or continuing every year, and out of 1532 landslides 366 landslides are still active from 1998 to 2022 which are mainly concentrated in the southern and Western ghats region of Karnataka. Accuracy and quality of landslides are gradually changed from 1998 to 2022. Figure-4 shows landslides triggered in various parts of our Study Area which includes Kodagu, Chikkamagaluru, Shivamogga and Uttara Kannada District.

Complete landslide inventory for Karnataka

The landslide inventory for the study area containing 1532 confirmed landslides. Out of these 1532 landslides 1260 were derived from the GSI and 272 landslides from the Global NASA Landslide Catalog points. Additionally, 48 new landslide points were identified using the VHR Satellite imagery available in Google Earth. Figure-5 shows the complete landslide inventory map of our Study Area.

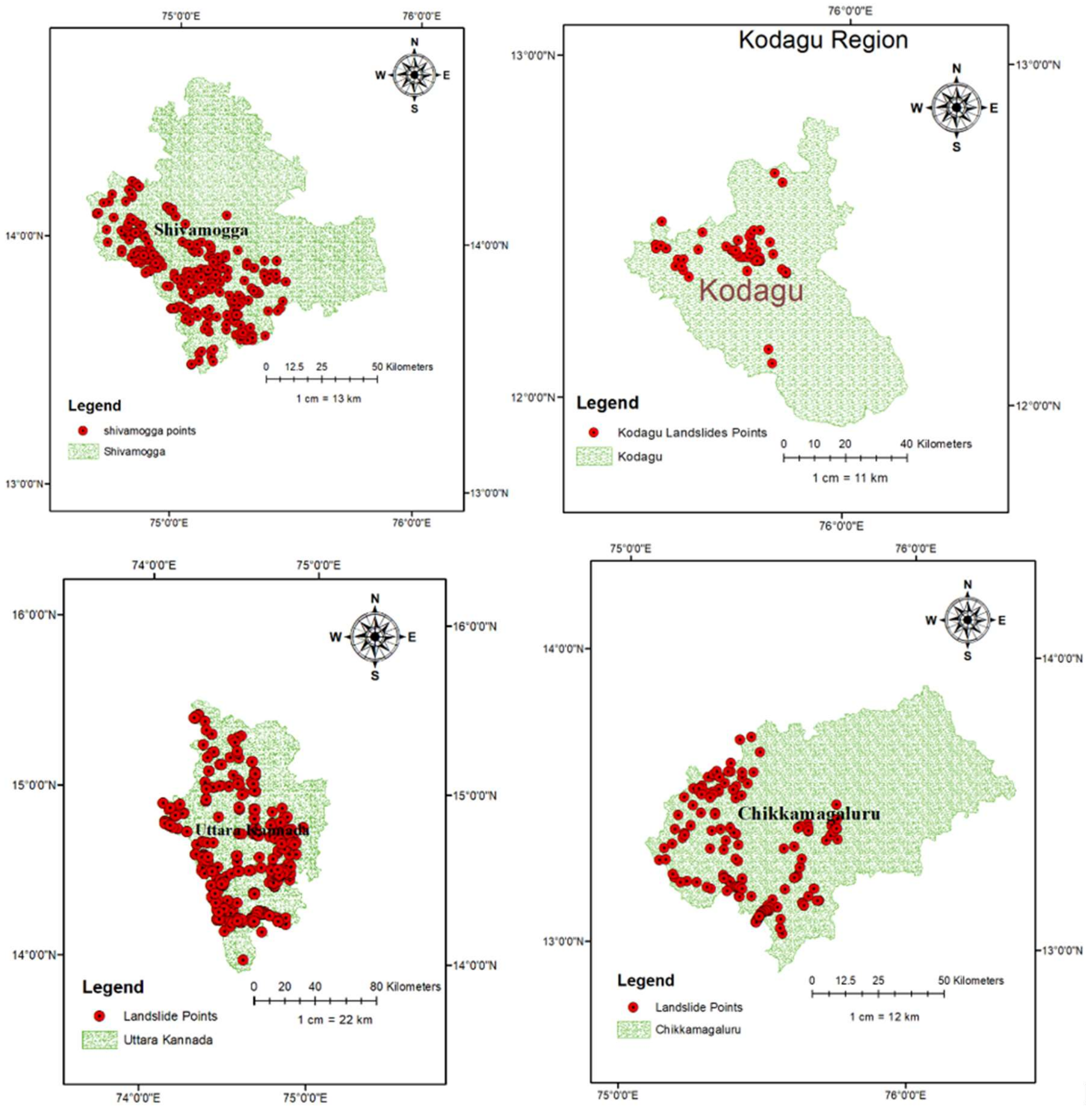

Figure-4: Landslides triggered in various parts of our Study Area

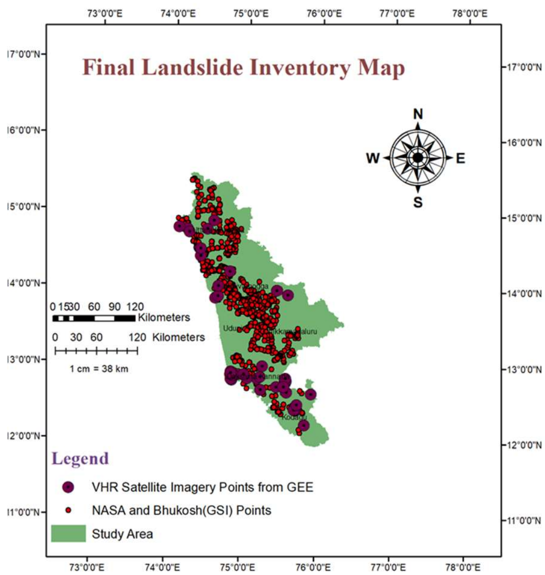

Figure-5: Complete landslide inventory map of our Study Area

Comparison of inventories

The final landslide point dataset, 1580 were confirmed by two existing landslide inventories. 163 landslide points were without an estimation for which no area could be determined in the images because the landslides were too small. It couldn't be identified in Google Earth or Resourcesat-2 LISS III satellite images due to the small size less than 3 m. Only 1369 out of 1532 landslides were confirmed and mapped by GSI using automatic classifications. The remaining 48 landslide points were identified and confirmed by multi-temporal Google Earth images. However, it is not possible to obtain the correctness of the inventories due to various lack of independent features and confirmed inventory completeness of data.

VII. CONCLUSIONS

In this article, proposed landslide inventory mapping with VHR remote sensing images. These multi-temporal images are covered with dense vegetation and other objects which make very difficult to detect them using automatic image classification. Around 163 landslides were detected which can't be identified using HRSIs. The automatic classification method can be depended on the resolution of images. The collaborating approach of mapping requires consistent results and several satellite images obtained from different sources images were interpreted by using Google Earth images. This study shows that 1369 (86\%) out of 1580 landslide points are confirmed and mapped as the final inventory mapping for the study area. So far, the final inventory can be seen in various satellite images, can be considered relatively complete for the entire study area using multi-temporal visual interpretation using GEE and ARCGIS tools. However, few landslide points are still missing in the final inventory for various reasons like poor resolution less than 3 m, dense vegetation and not possible to quantify the completeness of inventory map.

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