



CHANGE DETECTION OF CHANDAKA FOREST AND ANALYSIS OF REMOTE SENSING DATA USING MACHINE LEARNING AND GEOGRAPHIC INFORMATION SYSTEM

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ARTICLE INFO

Article History

Received on: February 19, 2026

Reviewed on: March 20, 2026

Accepted on: May 10, 2026

Published on: June 30, 2026

Keywords:

Change Detection, Geographic Information System (GIS), Google Earth Engine (GEE), Land Use Land Cover (LULC), Machine Learning (ML), Random Forest (RF), Support Vector Machine (SVM).

ABSTRACT

Change detection is a challenging and significant task in satellite applications due to the unavailability of satellite photos of a given geographic area acquired at various times. This study employs remote sensing data to analyze the changes in the area by utilizing machine learning methods alongside a geographic information system. The satellite images are pre-processed, gathered from multiple sources, and classified according to features. Two of the most significant and efficient factors underlying many ecological systems are land use and land cover maps, and change detection. The integration of remote sensing, Geographic Information System (GIS), and machine learning techniques offers a promising approach for studying and monitoring forest ecosystems. Remote sensing offers a means of collecting large-scale data on forest cover and land use change, while GIS technology enables the analysis and visualization of this data. Machine learning algorithms can be used to classify and analyze the data, allowing researchers to analyze the changes occurring in forest ecosystems on the Google Earth Engine framework. Built-up planning, ecosystems, land resources, crop patterns, agriculture, and natural resources depend on land use and land cover assessment and analysis. Change detection mapping is done by Geographic Information System software. For accuracy assessment, identify the classes of land cover and land use that have changed in the area. This study area, Chandaka Forest, merely uses the Landsat 8-9 OLI/TIRS imageries for land use and land cover mapping. Using the proposed algorithm, the historical images of Chandaka Forest were obtained, and seven different class values were stored in the cloud. Using the data, the change detection has been obtained with an accuracy of 95.1%. A system for cloud computing named GEE implements Support Vector Machine and random forest as its primary classification algorithm models to make two-year interval land use land cover maps for 2014, 2016, 2018, 2020, and 2022. This research is based on machine learning classification plus geographic information system techniques for change detection of satellite images. Analyses of both satellite images captured at two distinct times in a specific geographical region demonstrate the effectiveness of the method. The effectiveness is verified using change detection accuracy, and the results are superior to those of the currently used approaches. This paper contributes to environmental monitoring, such as deforestation of Chandaka Forest, Odisha, using GIS and machine learning classification applied to remote sensing data.



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I. INTRODUCTION

The Google Earth Engine (GEE) is a cloud-based platform where remote sensing data are streamlined for processing and analysis to produce results. This developed system quickly and accurately identified the land use maps using Landsat-8 imagery using a machine learning approach.

The established 30-m four-year LULC maps were developed to provide crucial information on monitoring and understanding the changes in many LULC classes and alterations that have taken up residence in the Chandaka Forest. The study's main objective was to analyse environmental reliability and change detection from 2014 to 2022. To comprehend the trend of change, it also sought to identify the areas of effective change, quantify the scale of change, and evaluate the state of land cover for different years. The primary goal of the change detection approach is to recognise the major change that has evolved throughout a collection of images, given a set of images of the same place taken at various intervals. These key developments influence the creation of the change map [1]. Unwanted artefacts and noise components in the source photos may also affect the accuracy of the change map. The concept of significant change varies with application. Fusing these techniques enables a more comprehensive and accurate assessment of the LULC's extent at a nominal 30-meter resolution. Ecosystems and biodiversity can be severely affected by changes in land use and land cover in the Chandaka Forest in Odisha, India. Among the impacts are soil erosion, biodiversity loss, modified microclimate, habitat fragmentation, and effects on indigenous communities. Forest clearing for improvement, infrastructure, or agriculture can fragment environments, hinder wildlife corridors, and diminish genetic diversity. In addition to increasing soil erosion and reducing the soil's holding capacity, deforestation may disrupt the local ecology and hinder water utilisation for both wildlife and human settlements. Changes in land use may impact local economies and ways of life by disrupting norms and restricting access to natural resources.

Mineral resources are identified, differentiated, and improved in features and structures by using remote sensing data and image processing approaches [2]. Change detection, classification or segmentation, feature extraction, and fusion are different methods used for image processing on satellite images. Satellite image analysis uses several mathematical algorithms to extract essential information [3]. A Geographic Information System (GIS) provides a broader overview of the image under study and integrates different coverage of the area for change detection. The most significant advantages of using GIS are visualization and comparison of images for change detection. However, the results of change detection are influenced by the availability of multiple sources of information with various levels of accuracy. Remote sensing and GIS, a change detection technique, are used to assess the typical changes brought on by natural disasters [4]. Statistics on Chandaka Wildlife Sanctuary's use of GIS and remote sensing data, the technique to detect changes in vegetation cover is illustrated utilizing forest land use classifications obtained in 2006. Later, Normalized Difference Vegetation Index (NDVI) was developed in 2015 to monitor changes in forest LULC [5]. The following part explains the method that employs GIS and remote sensing to monitor land cover changes. Cost is reduced, change detection is made less complicated, and accuracy is enhanced with the aid of this technology [6]. Researcher workstations are now equipped with methodologies thanks to online platforms like Google Earth Engine (GEE), resulting in workflows and eliminate extraneous data downloads. The study on northern Iran uses Landsat satellite images for the analysis of LULC and change detection using machine learning algorithms [7]. LULC in Beijing uses Landsat satellite images from 2015 with a 30-m resolution. In this study, the input data were selected with the least cloud cover for orthorectification and calibration.

Because of the higher performance of its multi-dimensional characteristics, the Random Forest algorithm was selected as a classifier [8]. According to statistics on Chandaka Wildlife Sanctuary's Forest land use classes that utilizes GIS and image processing, the following areas were identified in the sanctuary area in 2006 with 3917.96 ha of dense mixed forest, 6024.56 ha of open mixed forest, 3181.74 ha of degraded mixed forest, 55.81 ha of dense Sal Forest, open Sal Forest, and degraded Sal Forest [9]. The open mixed forest occupies the maximum area of the sanctuary. Eupatorium or Lantana grows on 2131.29 ha, bamboo covers 1501.91 hectares, teak covers 270.97 ha, wastelands cover 140.28 ha, mining and research areas cover. Within the sanctuary, the village and settlement areas total 28.66 ha and 15.82 ha, respectively. In the sanctuary area, there are approximately 140.85 ha of water bodies and 1623.16 ha of agricultural land. The change detection of forest land use between the years 2003 and 2006 of the Chandaka-Dampara Wildlife division, the study found that the population increased due to the demand for crops and food for the people [10].

LULC in Chandaka Forest from 1980-2020 combines with remote sensing and GIS, which create maps to analyse the changes over a different period [11]. In this domain, we will present a hybrid model utilizing a machine learning methodology with better accuracy. Comparing the accuracy of three ML algorithms, Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Tree (CART), using Landsat-8 and Sentinel-2 images. To identify the LULC classification results with the highest accuracy, dataset comparison ratios were also investigated [12].

1.1 STUDY AREA

Chandaka Forest, also known as Chandaka-Dampara Wildlife Sanctuary. It is a protected forest area located in the Khordha and Cuttack districts of Odisha, India, near the state capital city Bhubaneswar, since August 1982. It is listed in the Survey of India toposheet No.73H/11, 12, and 15, study area map is shown in Figure 1 [13]. It is located between 85° 34' 42" E to 85° 49' 27" E longitude and 20° 12' 29" N to 20° 26' 18" N latitudes. It represents the northeastern limits of the Eastern Ghats. In 2006, land use classes of the sanctuary were gathered, implementing image processing techniques and GIS [14], [15]. The major attractions for the tourists are watch towers and restrooms to observe the birds and animals. Deras Dam and Jhumka Dam are two water reservoirs situated within the forest. In 2005, the sanctuary's total forest area, which included dense, open, and scrub forests, had significantly decreased to just 62.72% of the original area [16].

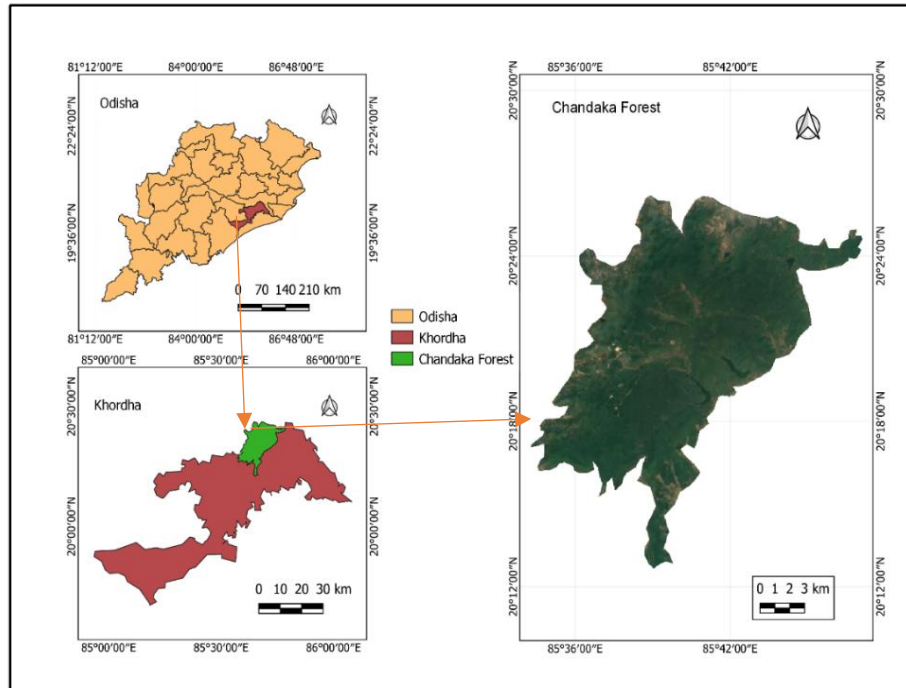


Figure 1: Boundary map of Odisha with the Study area, and Satellite map of Chandaka Forest.
Source: Authors, (2026).

II. MATERIALS AND METHODS

Wide-ranging usages for remote sensing data include change detection, which involves finding significant variances between two sets of images. Two distinct periods are used to collect the images. A change map is made up of the identified changes. This research employed an amalgamation of Geographic Information Systems and Machine Learning technologies to detect the change in Chandaka Wildlife Sanctuary. This research shows a novel and integrated technique to employ machine learning algorithms in a cloud-based geospatial framework, such as GEE with GIS analysis, to discover changes in LULC. For a better understanding, the flow of process is represented in Figure 2, which shows the architecture of the proposed work to analyse the change detection. The process starts with the Data Collection, then follows Pre-processing, Feature Extraction, Feature Selection, Classification, Post-processing, and Accuracy Assessment.

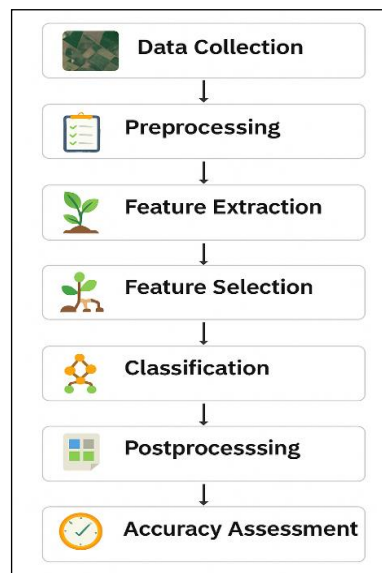


Figure 2: Change Detection Architecture.
Source: Authors, (2026).

II.1 DATA COLLECTION

To analyse the change detection, the Landsat satellite image was loaded from the United States Geological Survey (USGS) authoritative website (earthexplorer.usgs.gov). Every satellite image serves as a dry season image, and Landsat sensor data were taken into account in Table [17]. The Landsat-8 Operational Land Imager (OLI) or Thermal Infrared Sensor (TIRS) images were obtained in LANDSAT/LC08/C01/T1_SR through Google Earth Engine [18]. The details of the satellite data used in the study are shown in Table 1.

The Landsat 8 satellite, equipped with the Operational Land Imager (OLI), provides multispectral imagery useful for monitoring environmental changes. The data used in this study spans two time periods: January to December 2014 and January to December 2022. Each band, labelled SR_B1 to SR_B7, shows different sections of the electromagnetic spectrum, measured in micrometers (μm), whereas SR_B1 is called as surface reflectance band 1.

Table 1: Details Of Satellite Data.

Satellite id	Period	Sensor id	Spatial Resolution	Path	Quality
Landsat 8	Period 1: January – December, 2014 Period 2: January – December, 2016 Period 3: January – December, 2018 Period 4: January – December, 2020 Period 5: January – December, 2022	OLI/TIRS	30m	140/46	9

Source: Authors, (2026).

The reflectance values range from covering the interval from 1 to 65,455, scaled by a factor of $2.75\text{e-}05$ with an offset of -0.2 to convert raw digital numbers to reflectance values. Every band has a spatial resolution that is defined in meter. Specifically, SR_B1 captures coastal aerosol reflectance ($0.435\text{--}0.451\ \mu\text{m}$), useful in atmospheric correction near water bodies. SR_B2 to SR_B4 cover the visible spectrum (blue, green, red), aiding in vegetation and water analysis. SR_B5 corresponds to the near-infrared region ($0.851\text{--}0.879\ \mu\text{m}$), which is particularly sensitive to vegetation. SR_B6 and SR_B7 represent shortwave infrared bands ($1.566\text{--}2.294\ \mu\text{m}$), which are valuable for analyzing moisture content, burned areas, and soil properties. Additionally, the SR_QA_AEROSOL band provides aerosol quality information, important for atmospheric correction and improving data reliability. These bands are crucial for understanding different land topography features and robustness of the vegetation. From the Red and Near Infrared bands, the Normalized Difference Vegetation Index (NDVI) was derived to evaluate the presence and condition of vegetation. All imagery was obtained in Top of Atmosphere (TOA) reflectance from the USGS, ensuring consistency and quality in the remote sensing data. The image has a spatial resolution of 30 meters, meaning each pixel represents a 30 by 30-meter area on the ground, allowing for detailed land surface analysis. It corresponds to Path 140 and Row 46 of the Worldwide Reference System-2 (WRS-2), identifying the specific geographic location of the scene. The image has a quality level of 9, indicating excellent clarity with minimal cloud cover or distortions, making it highly suitable for accurate remote sensing applications.

II.2 PRE-PROCESSING

Image pre-processing is the set of steps applied to raw images to make them high-quality, consistent, and ready for analysis or modelling. The Landsat-8 QA_PIXEL (Quality Assessment) layer is a FMASK (Cloud mask algorithm) derived bitmask that encodes per-pixel data quality. The algorithm for cloud and shadow detection and details how it is applied as a preprocessing step for Landsat imagery are introduced and expanded [19-21].

Algorithm Fmask: Cloud/Shadow Mask from QA_PIXEL

Input: Landsat-8 SR image I with band QA_PIXEL and bands SR_B1..SR_B7

Output: Masked SR image I' (only clear pixels kept), with SR bands renamed

Constants (bit masks):

DILATED = 1 << 1 (2)

CIRRUS = 1 << 2 (4)

CLOUD = 1 << 3 (8)

SHADOW = 1 << 4 (16)

Procedure:

1. $qa \leftarrow I.\text{select}("QA_PIXEL")$

2. Compute boolean "clear" mask:

$M \leftarrow (qa \& DILATED == 0) \wedge (qa \& CIRRUS == 0) \wedge (qa \& CLOUD == 0) \wedge (qa \& SHADOW == 0)$

3. Select SR bands with a regex and rename:

$SR \leftarrow I.\text{select}("SR_B.*", ["SR_B1", "SR_B2", "SR_B3", "SR_B4", "SR_B5", "SR_B6", "SR_B7"])$

4. Apply mask: $I' \leftarrow SR.\text{updateMask}(M)$

5. Return I'.

Source: Authors, (2026).

The Fmask algorithm for cloud and shadow detection and details how it is applied as a preprocessing step for Landsat imagery are introduced and expanded. Individual bits flag conditions: fill (no data), dilated cloud fringe, high-confidence cirrus, cloud, cloud shadow, snow, a "clear" flag (set only when neither cloud nor dilated cloud is present), and water. In addition, four 2-bit confidence fields report the likelihood of cloud, cloud shadow, snow/ice, and cirrus, each graded as none, low, medium, or high. Together, these flags let you reliably screen out clouds, shadows, snow, and water or keep only clear land pixels before computing indices or running classification. It is a rule-based algorithm used in Landsat surface reflectance products to filter pixels before analysis. It applies a decision-tree approach that combines spectral thresholds, such as brightness in blue, cirrus, and thermal bands, with geometric tests that match clouds and their shadows based on solar angles.

II.3 FEATURE EXTRACTION

Feature extraction from satellite imagery is the process of transforming raw pixel values into compact, informative variables that facilitate the differentiation of land-cover classes. Typical ingredients include spectral features (original bands) plus spectral indices such as NDVI, NDWI, NDBI, EVI. Combining pixel-based and object-based approaches is a valid strategy to address the salt-and-pepper effect, particularly in applications like image classification. The normalized difference vegetation index (NDVI), the normalized difference water index (NDWI), and the normalized difference built-up index (NDBI) are three band indices that are often extracted because of their value to researchers [22-25]. Calculating the above indices requires the following formulas:

Normalized Difference Vegetation Index

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (1)$$

Whereas NIR is near infrared and Red is red band.

Normalized Difference Water Index

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)} \quad (2)$$

Whereas Green is green band.

Normalized Difference Built-up Index

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \quad (3)$$

Whereas short-wave infrared is the waves that are invisible to human eyes. The pre-processed imagery from satellites is applied to generate spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), which are then employed for assessing changes in the vegetation cover [26].

Enhanced Vegetation Index

$$EVI = G \frac{NIR - Red}{NIR + C1Red - C2Blue + L} \quad (4)$$

Whereas NIR is near infrared, Red is red band, and Blue is blue band, with standard coefficients $G=2.5, C1=6, C2=7.5, L=1$. Equations (1), (2), (3), (4) are Spectral Indices used as features. On Landsat-8, this is represented as NIR is SR_B5, red band is SR_B4, and blue band is SR_B2. These indices act as proxies for the density and health of the vegetation, which enables the detection of temporal modifications in the cover of the vegetation. The next step is to apply regression analysis in order to describe the link between spectral indices and ground-based vegetation observations. This makes it easier to estimate how the density of vegetation has changed over time. Normalized Difference Water Index (NDWI) and other water indices are computed from satellite imagery to perform the Water Body Dynamics Assessment. Pixel-based features: These methods operate on individual pixels and are good at capturing the spectral (color) characteristics of the image. However, they can lead to a scattered "salt-and-pepper" appearance in the final result because each pixel is classified independently. Object-based features: These methods first segment the image into meaningful objects or regions. They then analyze the features of these whole objects, such as their shape, texture, and spectral values, rather than individual pixels.

II.4 FEATURE SELECTION

Feature selection (FS) is the process of keeping a small, informative set of predictors while dropping redundant or noisy ones so the Change Detection model stays accurate and stable. In practice, start with a broad stack (bands, key indices, terrain, textures), then do quick filters: remove near-constant features and one of any pair with very high correlation. If the classifier is scale-sensitive, standardize features. Next, use embedded signals to rank importance e.g., Random Forest/XGBoost (Gini or permutation importance) or L1-regularised models that shrink weak features toward zero and, when the feature count is modest, a wrapper like RFE (Recursive Feature Elimination) can fine-tune the subset [27].

II.5 LAND USE LAND COVER (LULC) CLASSIFICATION

The classification of the land use land cover scheme is divided into different classes [28]. The model learns $f(\kappa)$ from the training dataset and implements to predict classes of the given image in supervised classification.

LULC Classification

$$\hat{y} = \sum_{j=0}^n f(\kappa_j) \quad (5)$$

The above equation (5) represents the function of LULC. Whereas $\hat{y}$ is predicted classes (e.g., dense forest, open forest, water bodies, waste land, urban areas), κ_j is the spectral features, and $f(\kappa)$ is the classification function (e.g., SVM, RF).

II.5.1 Support Vector Machine (Svm)

Support Vector Machine (SVM) is a supervised classifier that separates classes by finding the decision boundary (a hyperplane) with the largest possible margin to the nearest training points, called support vectors. Among all supervised machine learning algorithms, SVM is one of the most reliable classification algorithms. It can immediately identify the changing features and transform feature dimensions since it is based on the classification. To handle non-linear patterns, SVM maps features into a higher-dimensional space via a kernel, commonly the radial basis function (RBF), so the boundary in the original space can curve around complex class shapes [29]. It can immediately identify the changing features and transform feature dimensions since it is based on the classification. To deal with nonlinear data, the core of the SVM is the appropriate kernel function, which measures the similarity between input data [30]. The advantage is that it can be used for the classification of high-dimensional data like images. An image is analysed by a computer and is perceived as a two-dimensional array of pixels. The image's resolution determines the array's dimensions; for instance, an image 200 pixels wide and 200 pixels high will have dimensions of $200 * 200 * 3$. The image's width and height are represented by the first two dimensions, respectively, whereas the third dimension represents the RGB color. The array's values represent the pixel's intensity at each location, i.e. from 0 to 255. According to the metadata, the images of the forest have a geographic extent defined by coordinates in degrees and consist of 781 columns and 917 rows, which indicates its pixel dimensions of $781 * 917 * 3$. The image's values are texture, edge detection, and pixel color. We can utilize the retrieved features as input for the SVM algorithm after that. Finding the nearest points of the various classes is the fundamental concept underpinning support vector machines (SVMs).

$$(x) = \text{sign} \left(\sum_{j=1}^n \alpha_j y_j \cdot \exp(-\gamma \|x - x_j\|^2) + b \right) \quad (6)$$

The above equation (6) represents the function of SVM. Whereas x is the Input feature vector (e.g., spectral values of a pixel), x_j is the Support vector from the training data, α_j is Lagrange multipliers (learned during training), y_j is the Class label of x_j (+1 or -1), b is the Bias term, γ is the Kernel parameter (controls the width of the RBF function), $\|x - x_j\|^2$ is the Squared Euclidean distance between the input and the support vector, $\exp(\cdot)$ Exponential function used in RBF, $\text{sign}(\cdot)$ Output is either +1 or -1, determining the predicted class.

II.5.2 Random Forest (Rf)

Random Forest (RF) is an ensemble classifier that builds many decision trees on different random “views” of your data and then combines their votes. Each tree is trained on a bootstrap sample (a resampled subset) of the training set, and at every split, the tree considers only a random subset of features, which decorrelates the trees and reduces overfitting. For a new pixel, each tree predicts a class, and the forest returns the majority vote (for regression, it averages). The tree structure used by the decision tree (DT) is to select one feature and distribute it across different classes. The capability and effectiveness of isolating nonlinear features have been demonstrated. Overfitting, however, is subject to DT [31]. We used Landsat 8 pictures from different years for LULC classification with Random Forest (RF) in the GEE. These photos were normalized and filtered to top-of-atmosphere reflectance, with a cloud cover of less than 10 % serving as the primary input data. Except for the bands required for change detection, we used all bands with a resolution of 30 m. Additional textural features for categorization were retrieved, including color, intensity, contrast, and NDVI provided for that year [32].

$$\hat{y} = \sum_{k=0}^n \binom{n}{k} \kappa^k a^{n-k} \quad (7)$$

$$\hat{y} = \text{majority_vote} (T_1(\kappa), T_2(\kappa), \dots, T_N(\kappa))$$

The above equation (7) represents the function of RF. Whereas $\hat{y}$ is the predicted class label, $T_j(\kappa)$ is a prediction made by the j^{th} decision tree, x is the input feature vector (e.g., NDVI, NDBI, spectral bands), majority_vote is the final class is the one most trees agree on.

II.6 ACCURACY ASSESSMENT

The accuracy assessment is significant, which shows the extent to which the related categorized image accurately depicts reality. The overall accuracy (OA) of the image is used for the accuracy assessment of the classified image. We find it by dividing the total number of accurately recognized pixels by the overall pixel count [1]. The overall accuracy is calculated as:

$$OA = \frac{P_c}{P_n} \quad (8)$$

Whereas P_c is the total count of pixels classified precisely and P_n is the total of pixels in equation (8). To account for random agreement, Jacob Cohen invented Cohen's kappa in 1960, replacing the traditional method of using per cent agreement [33]. The accuracy of data presentations is assessed by interoperability, which is evaluated using the kappa statistic. Kappa values span from -1 to +1 [34]. It quantifies the improvement of the classification compared to randomly assigning pixels to their correct classes [35].

$$\text{kappa} = \frac{\text{Observed Agreement} - \text{Expected Agreement}}{1 - \text{Expected Agreement}} \quad (9)$$

The above equation (9) represents the accuracy assessment using kappa coefficient.

Algorithm: For two time periods and different bands magnitude of change detection. Given: The Study area is Chandaka Wildlife Sanctuary

```

1. StudyArea ← DelineateBoundaryFromMap ()
   Shapefile ← ExportAsShapefile (studyArea)
2. ImportShapefileToGEE (shapefile)
3. DataCollection ← ImageCollection ("Landsat")
4. filteredImages ← FilterByDateAndCloud (imageCollection, startDate, endDate,
   cloudThreshold)
5. samplePoints ← GenerateSamplePoints (filteredImages, classes)
6. labeledSamples ← LabelSamples (samplePoints, bands)
7. dataset ← CreateDataset (labeledSamples)
8. mergedTrainData ← MergeClasses (traindata)
9. rfModel ← TrainRandomForest (mergedTrainData)
   svmModel ← TrainSVM (mergedTrainData)
10. rfResult ← ClassifyImage (filteredImages, rfModel)
    svmResult ← ClassifyImage (filteredImages, svmModel)
11. rfAccuracy ← EvaluateAccuracy (rfResult, testData)
    svmAccuracy ← EvaluateAccuracy (svmResult, testData)
12. if (rfAccuracy > svmAccuracy)
        finalResult ← rfResult
    else
        finalResult ← svmResult
    endif
13. ExportImage (finalResult, "classifiedImage.tif")
14. rasterImage ← ImportToQGIS ("classifiedImage.tif")
15. colorImage ← ApplyColorSymbology (rasterImage)
16. clippedImage ← ClipRasterWithShapefile (colorImage, shapefile)
17. classAreas ← CalculateAreaByClass (clippedImage)
18. changeMap ← ChangeDetection (previousClassifiedImage, finalResult)
    return changeMap, classAreas

```

Source: Authors, (2026).

II.7 POST-PROCESSING

Monitoring of changes in land cover, the Pre-Classification Method and the Post-Classification Method are the two main categories of Change Detection Techniques. Without knowing the image's value, the pre-classification method analyses the change. The "Normalized Difference Vegetation Index" (NDVI) pre-classification approach is the most popular and extensively utilized. However, the most implemented change detection technique in use today is the post-classification method. An accurate, designated classification of land cover is the basis for post-classification, which assesses the change in land cover. Some of the popular post-classification Change detection techniques are post-classification comparison, Aerial Difference computation, Image Differencing, Image rationing, Image regression, etc [17].

III. RESULTS AND DISCUSSIONS

Google Earth Engine (GEE) is a cloud-based web application for the interpretation and mapping of geospatial data. It provides a complete dataset of remote sensing imagery and alternative metadata. Its application programming interface (API) with both JavaScript and Python front-ends allows for the analysis of the data available in the catalogue on the Google server [36]. The raster layer in QGIS uses the EPSG:4326 coordinate reference system, which is based on the WGS 84 datum and represents spatial data using latitude and longitude in degrees. The raster is in GeoTIFF format, a widely used file type that preserves georeferencing information. The coordinate units are in degrees, consistent with geographic coordinate systems, making the data suitable for global or regional-scale spatial analysis. A sample of the end-to-end methodology, which we have executed using the GEE for the Water Bodies class, is depicted in Figure 3. This area is the Deras reservoir in Chandaka-Dampara Wildlife Sanctuary. One of the most important parts of the process is deciding on the training points and polygon, which will enhance the level of accuracy of the concluded classification results [37]. All the data images taken have less than 10% cloud cover.

Dataset: Samples = 356, Training = 299, Testing = 57

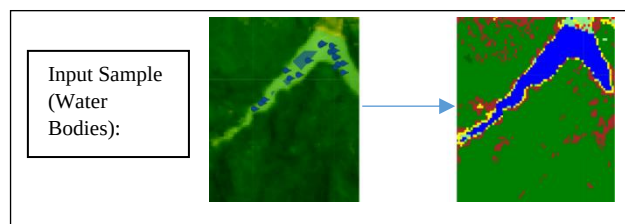


Figure 3: Example of a small region of Chandaka Forest, output after Random Forest Classification.

Source: Authors, (2026).

The GEE application provides a variety of classifiers. We evaluated the effectiveness of two of them in Land cover classification using random forest (RF), and support vector machine (SVM), and their overall use and dependability [38].

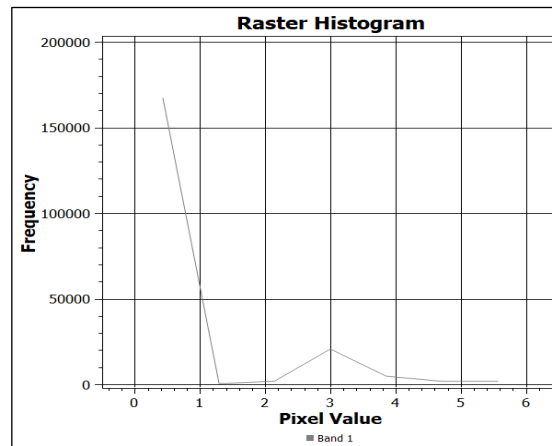


Figure 4: Histogram after the Classification of Chandaka Forest in the year 2022.
Source: Authors, (2026).

To prepare the input blocks for model training, auxiliary data such as feature vectors and edge information were first synchronized with Google Earth Engine (GEE) in shapefile format. These datasets were then utilized alongside external data sources to generate sample blocks using Support Vector Machine (SVM) and Random Forest (RF) classifiers. The resulting data was stored within Google Earth Engine's Assets. For model training, the input blocks were converted into TFRecord format and exported as GeoTIFF files to a Cloud Storage Bucket, a component of the Google Cloud Platform. The training process was carried out using the GPU capabilities provided by Google Collaboratory. Once training was completed, the model parameters were saved in the Cloud Storage Bucket. These parameters are essential for deploying the trained model in GEE and must be hosted within an AI network before they can be applied for inference [39]. They must be managed by an AI network, which we did by storing the trained parameters in a Cloud Storage Bucket. The GEE map area environment was used to collect a set of points (356 in total) for each class using numerous reference layers. For each class, a set was composed of training points 25% of the total and testing points 75 % of the total, for a total of 299 training points and 57 testing points for the years 2014, 2016, 2018, 2020 and 2022, respectively. All of the training points were gathered visually, and only for the forest classes were the validation points gathered visually supported by a thorough understanding of the area and Landsat 8 Bands and Band Combinations. Whereas Figure 4 shows the histogram after the Classification of Chandaka Forest in the year 2022. The histogram illustrates the frequency distribution of pixel values found in Band 1 of a classified raster image. On the horizontal axis, pixel values range from 0 to 6, each representing a distinct land cover category. The vertical axis shows the number of pixels corresponding to each class. Among these, class 1 has the highest count, with more than 150,000 pixels, indicating it is the most dominant land cover type in the area. In contrast, other classes like 3 and 4 have moderate pixel counts, while categories 5 and 6 are represented by a relatively small number of pixels. The graph reveals a clear imbalance in class representation, with a few classes covering most of the area. Overall, the histogram offers a concise overview of how different land cover types are distributed across the raster image.

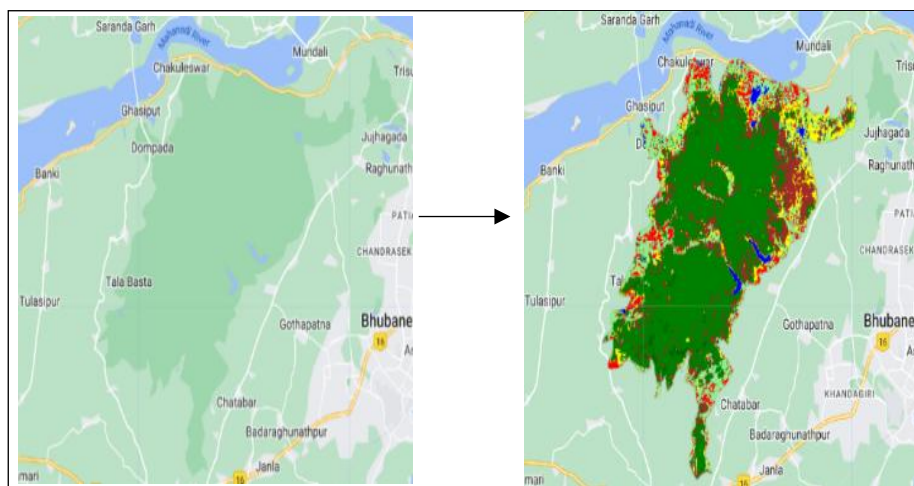


Figure 5: Classification of Chandaka Forest in GEE.
Source: Authors, (2026).

We chose the Random Forest algorithm as a classifier because of its better performance and its multi-dimensional characteristics. Multiple recent investigations have leveraged Google Earth Engine (GEE) combined with Random Forest (RF) classification, illustrated in table 2, to analyze land use and land cover dynamics across Ethiopia, Portugal, and Nepal.

Table 2: Comparative Analysis of Land Use Land Cover and Change Detection.

N o.	Study Title	Authors and Year	Study Area	Time Period	Methods	Key Findings	Novelty
1	Integrating Google Earth Engine and Random Forest for LULC Change Detection and Analysis in the Upper Tekeze Basin	Alelgn Ewunetu and Gebeyehu Abebe, 2025	Upper Tekeze Basin, Ethiopia	1986, 1998, 2010, 2022	GEE + Random Forest with Landsat 5/7/8 imagery; household surveys	Over 62% of the landscape experienced change; forest and shrubland declined; cultivated land and settlement expanded; local drivers include population growth and agricultural expansion.	Combines multi-temporal Landsat data with local knowledge (surveys) for enhanced LULC transition understanding in arid highlands.
2	Comparative Study of RF and SVM for Land Cover Classification and Post-Wildfire Change Detection	Yan-Cheng Tan et al., 2024	Serra da Estrela Natural Park, Portugal	Pre/post 2022 wildfire + Summer 2023	GEE with Sentinel-2A; RF vs. SVM; OBIA vs. PBIA	RF + OBIA produced highest classification accuracy; SVM + PBIA better resembled official LULC maps; OBIA enhances spatial detail in burnt area analysis.	First to compare OBIA and PBIA using GEE in a post-wildfire environment for detailed vegetation recovery mapping.
3	Modeling LULC Changes Using GEE and ML: Implications for Landscape Management	Weynshet Tesfaye et al., 2024	Robit Watershed, Ethiopia	1993, 2003, 2013, 2023	GEE + RF, SVM, CART with Landsat and auxiliary data	RF outperformed SVM and CART; agricultural land and shrubland declined; built-up and grazing land increased; drivers include settlement, fuelwood, and population growth.	Integrates multiple classifiers with auxiliary data in GEE for robust long-term LULC modelling in Ethiopian watershed context.
4	Mapping Forest Loss and Encroachment Drivers Using Remote Sensing and RF	Bhoj Raj Ghimire et al., 2025	Sudurpaschim Province, Nepal	1990-2020	Remote Sensing + RF with field data and Landsat	RF achieved >81% accuracy; 1,634 km ² of forest lost; agriculture (78.21%) and settlement (15.97%) were primary encroachment drivers.	Links RF-based classification with field-surveyed driver attribution to identify encroachment hotspots over three decades.
5	Analyzing LULC Changes Using GEE and RF: Implications for Land Degradation	Alemu Eshetu Fentaw and Assefa Abegaz, 2024	Upper Tekeze Basin, Ethiopia	1990, 2000, 2010, 2021	GEE + RF with Landsat imagery + OpenLand R package	Forest, shrubland, and bareland decreased; water, farmland, and settlements increased; supports use of afforestation and land management to mitigate degradation.	Integrates post-classification land transition matrix with GEE to quantify degradation-linked landscape changes.

Source: Authors, (2026).

In Ethiopia's Upper Tekeze Basin, temporal data from Landsat (1986, 1998, 2010, 2022) calibrated with local surveys and study indicated that nearly 63% of the region underwent at least one LULC transition, with expansion of cultivation and settlements consuming grassland and shrubland [40]. The LULC dynamics in Ethiopia's Upper Tekeze Basin from 1990 to 2021 using Google Earth Engine (GEE) with the Random Forest (RF) classifier and incorporating the OpenLand R toolkit to generate transition intensity maps. Landsat TM (1990, 2000, 2010) and Landsat 8 OLI (2021) imagery, combined with auxiliary datasets, supported classification. The RF model achieved strong performance, with around 83% accuracy and a Kappa score of 0.75 despite the region's complex terrain and climate [41]. An additional Ethiopian study extended this analysis (1990–2021) using OpenLand R packages, quantifying degradation-driven transitions and revealing declines in forest, bushland, shrubland, and bareland. In Portugal's Serra da Estrela Natural Park, comparisons between RF and SVM classifiers tied to object-based (OBIA) and pixel-based (PBIA) approaches on Sentinel-2A data showed the RF + OBIA workflow delivered the highest accuracy, while SVM + PBIA corresponded more closely to official land use maps [42]. In Nepal, field-validated RF classification of Landsat imagery from 1990 to 2020 identified approximately 1,634 km² of deforestation, primarily linked to agricultural and settlement expansion (~78% and ~16%, respectively) [43]. This research explores three decades of land use and land cover transitions (1993–2023) in the Robit Watershed (Northern Ethiopia), utilizing Landsat imagery processed within Google Earth Engine (GEE) alongside machine learning classifiers: Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART). Topographic and spectral indices were included as auxiliary variables to enhance classification accuracy. Focus group discussions and interviews supplemented remote sensing data with socio-environmental context. RF consistently outperformed SVM and CART, achieving exceptionally high accuracies ranging from 93 % to 97 % and Kappa values between 0.93 and 0.95 across all four time points (1993, 2003, 2013, 2023). Land-use analysis revealed notable declines in forest cover (28.3 % decrease from 1993 to 2003) and shrubland (21.6 % loss from 1993 to 2013), while grazing land expanded by over 50 % in the same period. Overall, this study underscores the efficacy of GEE RF workflows enhanced with auxiliary data and community validation for producing highly accurate LULC maps and transition trends. The insights derived support sustainable watershed planning and resource management interventions tailored to local socioecological realities [44].

Across these diverse landscapes, RF consistently proved a reliable, adaptable classification tool when paired with auxiliary ground truth data, advanced image segmentation methods, or post-classification analysis, demonstrating its strength in interpreting both ecological changes and human-driven land transformation.

Table 3: Accuracy Results of Chandaka Forest for 2014, 2016, 2018, 2020 and 2022.

Year	SVM		RF	
	OA	Kappa	OA	Kappa
2014	0.919	0.884	0.947	0.928
2016	0.924	0.904	0.932	0.913
2018	0.907	0.892	0.921	0.897
2020	0.925	0.898	0.937	0.913
2022	0.885	0.854	0.951	0.923

Source: Authors, (2026).

The overall accuracy and kappa coefficient accuracy results displayed in Table 3 show that random forest is better for classification than SVM. Between 2014 and 2022, Random Forest (RF) consistently outperformed Support Vector Machine (SVM) in overall accuracy (OA) and Kappa coefficient across the dataset. In 2014, RF achieved an OA of 94.7% with a Kappa of 0.928, compared to SVM's 91.9% and 0.884. Although SVM slightly narrowed the gap in 2016 (OA: 92.4%, Kappa: 0.904), RF still maintained higher performance (OA: 93.2%, Kappa: 0.913). For both classifiers, a minor decline occurred in 2018—SVM dropped to OA 90.7% (Kappa 0.892) and RF to 92.1% (Kappa 0.897). In 2020, performance improved again; SVM returned to 92.5% (Kappa 0.898), while RF reached 93.7% (Kappa 0.913). By 2022, RF achieved its peak metrics (OA 95.1%, Kappa 0.923), while SVM fell to its lowest values in the series (OA 88.5%, Kappa 0.854). This trend suggests RF delivered higher and more stable classification reliability, with smoother fluctuations across years. While SVM performance varied more significantly, RF sustained accuracy levels above 92% and Kappa values above 0.90 in most years. With the help of GPS, we gathered 356 training samples, and we used GE to evaluate 75 validation samples. The number of samples for each kind was calculated based on the percentage of the individual area. Google Fusion Tables were used to upload the training data and validation samples to the GEE.

Table 4: Description of Land Cover Classes Used in this Research.

Class ID	LULC Classes	Satellite Images
0	Dense Forest	
1	Open Forest	
2	Water	
3	Scrub Forest	
4	Urban Areas	

5	Waste Land	
6	Crop Land	

Source: Authors, (2026).

This scheme, shown in Table 4 assigns integer IDs 0–6 to the seven-land use/land cover types you map: 0 = Dense Forest, 1 = Open Forest, 2 = Water, 3 = Scrub Forest, 4 = Urban Areas, 5 = Wasteland, and 6 = Cropland. The IDs serve as labels attached to training/validation samples, becoming the legend keys in your classified maps and confusion matrices, ensuring consistent encoding across years and models. The “Satellite Images” column can store representative chips (or links to VHR references) for each class to aid in labelling and QA, which is useful for photo-keys, teaching assistants, or reproducibility notes. Finally, we divided the study region into seven categories: dense forest, open forest, shrub forest, water bodies, urban areas, wasteland, and cropland. The LULC change map showed that dense forests changed to open forests, shrub forests, water bodies, urban areas, wasteland, and cropland. The statistics of Land use and Land cover maps are given in Table 5 for the years 2014 and 2022.

Table 5: Land Use Land Cover of the Chandaka Forest Area in 2014 and 2022.

LULC Classes	2014			2022		
	Area (Pixel Sum)	Area (%)	Area (km ²)	Area (Pixel Sum)	Area (%)	Area (km ²)
Dense Forest	155738	56.27003024	130.755873	127528	46.07741	107.070052
Open Forest	2958	1.068761314	2.484245	20587	7.05145	25.681695
Water Bodies	4185	1.512091311	3.513076	4462	1.612175	3.745685
Scrub Forest	37811	13.66157337	31.743526	47853	17.288996	40.172053
Urban Areas	18539	6.698365785	15.562266	35300	12.755191	29.635530
Waste Land	16909	6.109426995	14.194728	30362	11.357038	17.093658
Crop Land	40629	14.67975098	34.107956	10677	3.85773	8.962997

Source: Authors, (2026).

It reveals a 10.2% decrease in dense forest coverage between 2014 and 2022. There was also an increase in open forest coverage from 2014 and 2022 by 5.98%. There was also an increase in urban area coverage in the study area from 2014 and 2022 by 6.05% documented. Similarly, the open forest is also changed into dense forest, shrub forest, water bodies, urban areas, wasteland, and cropland, as shown in Figure 6 in the change detection graph. This classification is done in GEE using the Random Forest algorithm and further visualized in QGIS 3.20.2. This is a known, accurate method for visualization and analysis in GIS. The map is generated for 2014, 2016, 2018, 2020, and 2022, as shown in Figure 7 below. This image also provides details about the areas covered by various classes, according to the classification method. The first level of the FROM-GLC (Finer Resolution Observation and Monitoring of Global Land Cover) categorization scheme is consistent with the classification system [40]. After classification, the results from GEE for the year 2022 are shown in Figure 5 for reference. Deforestation in this forest during the past few years has been studied. Reviewing images collected in the same area throughout a period of four years to evaluate change detection [45]. Improved satellite imagery and novel algorithms have made significant progress in change detection. Yet, data integration, flexibility, validation, scalability, and specific to the environment impact evaluation remain areas for improvement. Rectifying these shortcomings will be essential for converting change detection methodologies from mostly academic studies into flexible, practical mechanisms that can guide practical problems and preservation efforts. Further, it creates decision trees for the classification and visualization of categorical predictor variables and constant dependent components, with the goal of producing accurate LULC simulations in GEE data. The GIS approach integrates geographical and geological information with historical and present-day land use maps. The binary masking and image overlaying approaches are beneficial for quantitatively exposing the changing dynamics in each category [46]. The major LULC change map within the Chandaka Forest area is presented in Figure 8. The map illustrates land use and land cover changes in Chandaka Forest from 2014 to 2022. It presents a detailed spatial analysis showing various transformations among land cover classes over time. Each category of change is colour-coded, as indicated in the legend, to represent specific transitions such as open forest converting to dense forest, scrub forest shifting to crop land, or urban areas expanding into forest zones. Areas where no significant change occurred are also highlighted for each land cover type. The map is georeferenced with latitude and longitude labels along the borders and includes a scale bar indicating distances in kilometres. This visual representation helps in identifying regions affected by urbanization, deforestation, and land conversion, providing a clear overview of environmental dynamics within the Chandaka region. It is a thematic change detection map that helps to visually interpret how different land categories have transformed over time. Each type of land cover change is represented by a unique colour, as defined in the legend on the right side of the map.

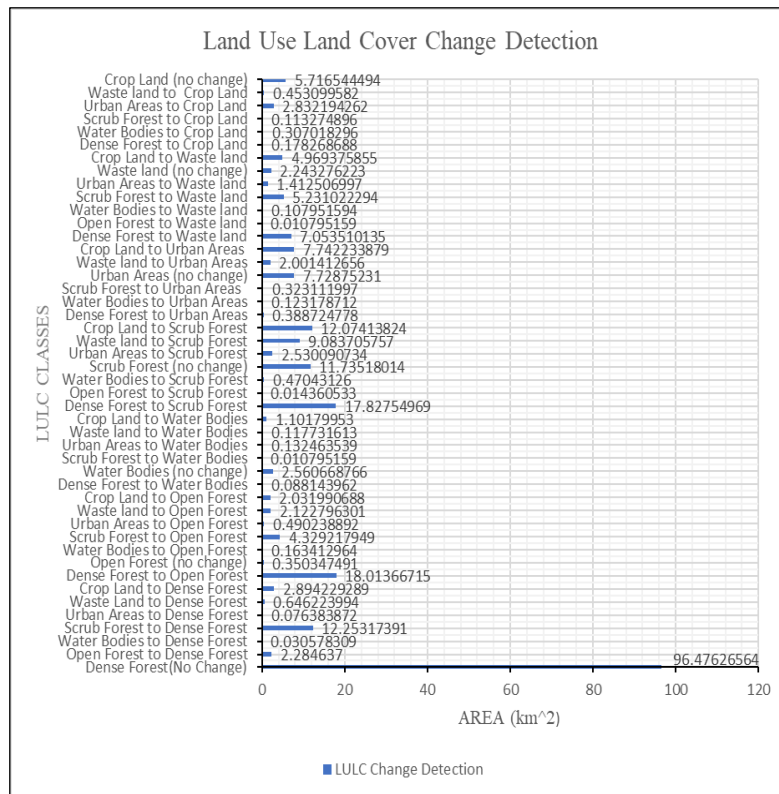


Figure 6: Change Detection Graph of Chandaka Forest (2014-2022).

Source: Authors, (2026).

The legend contains a comprehensive list of all possible changes between land cover types. For example, green shades indicate areas where no change occurred, such as Dense Forest (No Change), Scrub Forest (No Change), or Urban Areas (No Change). Blue and cyan shades generally represent forest-related transformations, such as the shift from Open Forest to Dense Forest, Scrub Forest to Open Forest, or Forest to Urban/Crop Land. Orange to red shades highlight urban expansion and agricultural conversions, such as Urban Areas to Crop Land, Water Bodies to Urban Areas, or Waste Land to Scrub Forest. Dark brown or maroon signifies Crop Land (No Change), marking the areas consistently used for agriculture throughout the study period. The central and southern regions of the map display a large concentration of dark blue and cyan tones, suggesting dominant forest classes, possibly areas where open or dense forest was either preserved or changed in type. Overall, this map serves as a crucial tool for forest management, conservation planning, and monitoring anthropogenic impact. It highlights how significant land cover shifts, such as urban sprawl, deforestation, water body reduction, and cropland expansion, have reshaped the Chandaka Forest landscape over time.

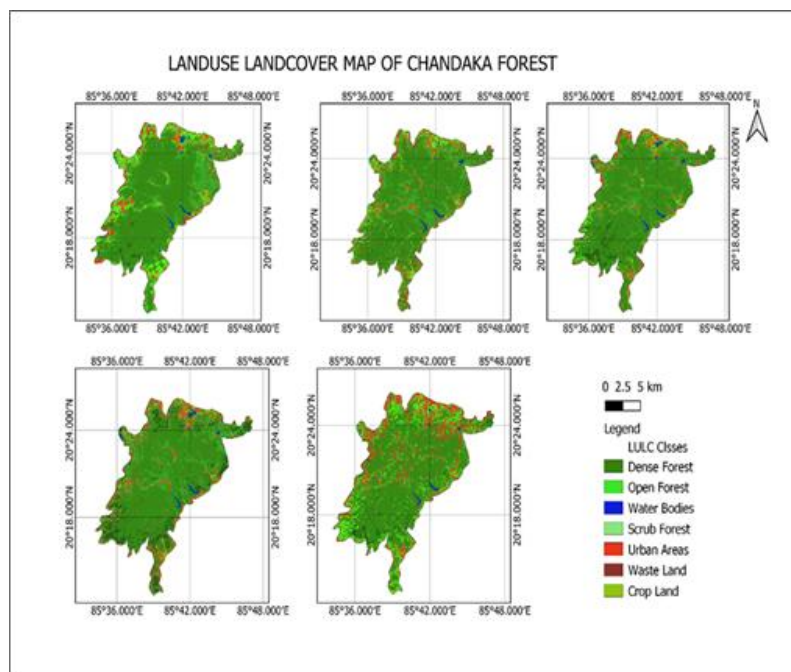


Figure 7: Land Use Land Cover (LULC) map of Chandaka Forest for years 2014, 2016, 2018, 2020 and 2022.

Source: Authors, (2026).

IV. CONCLUSIONS

Remote sensing has recently improved earth observation technology, which requires an effective, proficient, and accessible analytics approach. As a result, combining various analytics approaches, the state of the art regarding methods, and evaluating their effectiveness might be deemed to create geomatics, which is the focus of the current study. This is an analysis of the effectiveness of machine learning algorithms that served as the initial step in the research for using the GEE platform for LULC mapping. To analyse the LULC map in Chandaka Forest, SVM and RF were used as two algorithms for machine learning. As a result of our findings, RF was the most effective and, in the GEE context, a reliable data classifier. The goal of this work is to generate a map for various years using remote sensing, GIS, and machine learning techniques that identify, quantify, and evaluate changes in the LULC. The specific goal is to recognise changes that occurred across different periods. The result comes as a decrease in forest regions in Chandaka Forest in the year 2022 with respect to 2014 due to natural calamities and social interaction. Dense forest decreased by 10.2% between 2014 and 2022, and continued to decline in coverage by 7.33% from 2016 to 2022, and from the year 2014 to 2022, it declined by 7.22%. In the study area, open forest coverage increased by 5.98% from 2014 to 2022, while forest cover rose by 5.78% from 2016 to 2022 and by an additional 4.06% from 2018 to 2022. There was also an increase in urban area coverage in the study area between 2014 and 2022 by 6.05%. The change detection has been obtained with an accuracy of 95.1%. GIS is implemented for change detection and better visualisation. The hybrid framework of change detection improves accuracy. Sentinel satellite images can be used in the future, and deep learning can be used for classification in other areas. A critical analysis of misclassification factors includes the limitations of the current study.

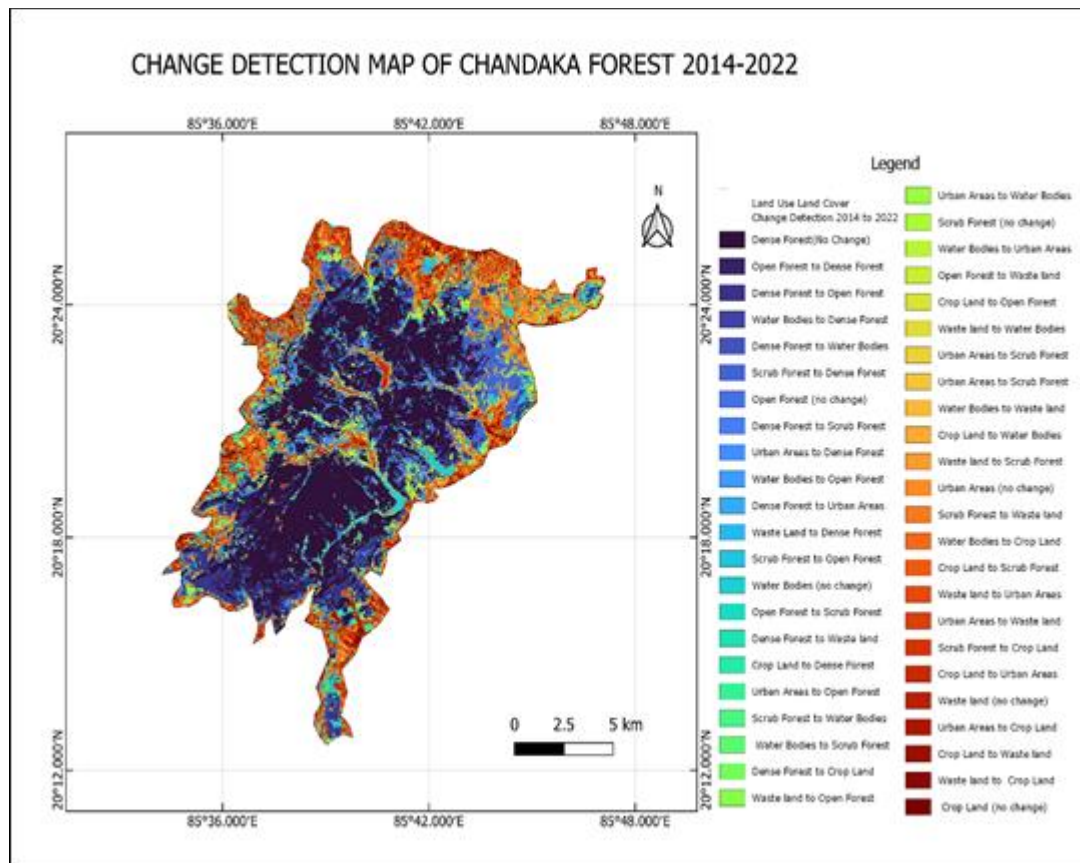


Figure 8: Change Detection Map of Chandaka Forest (2014-2022).

V. AUTHOR'S CONTRIBUTION

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Methodology: Arpita Majhi and Mrutyunjaya Panda

Investigation: Kabir Mohan Sethy

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VI. ACKNOWLEDGMENTS

I express my deepest gratitude to my supervisors, Prof. Mrutyunjaya Panda, and Prof. Kabir Mohan Sethy for their constant guidance, encouragement, and support throughout the course of this research work. Their insightful suggestions, patience, and constructive criticism have been invaluable in shaping this paper and helping me to overcome many challenges.

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