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## Land use land cover change detection using machine learning in google earth engine of Morna Watershed

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### Abstract

Land Use/Land Cover (LULC) change is a key factor influencing environmental conditions and resource management in rapidly developing regions. This study focuses on the Morna watershed in Akola district, Maharashtra, India, to analyze LULC dynamics over a 30-year period (1995–2025). Multi-temporal Landsat data (1995, 2005, 2015, and 2025) with 30 m spatial resolution were processed using the Google Earth Engine (GEE) platform. Supervised machine learning techniques, including Random Forest (RF), CART, and Support Vector Machine (SVM), were applied to classify the area into Agriculture, Forest, Waterbodies, Barren, and Built-up classes. The results indicate that RF outperformed other models, achieving accuracy between 97.32% and 98.56% and Kappa values from 0.948 to 0.973, making it the most reliable classifier. Change detection analysis reveals that forest remained the dominant class, with stability increasing from 27.47% (3625.52 ha) during 1995–2005 to 31.07% (4100.28 ha) during 2015–2025. Barren land also showed high stability, ranging from 24.02% to 21.59%. Significant land transformations were observed, including forest loss to agriculture (661.84 ha; 5.01%) and barren land (579.95 ha; 4.39%). Agricultural expansion occurred mainly through conversion of barren land (688.04 ha; 5.21%), while urban growth increased due to conversion of agricultural (424.27 ha; 3.21%) and barren land (152.56 ha; 1.15%) into built-up areas. The study highlights increasing human influence on land use, with RF proving to be the most efficient model for accurate LULC mapping.

**Keywords:** RF, CART, SVM, LULC, GEE

### 1. Introduction

Land use and land cover (LULC) dynamics are critical indicators of environmental change, reflecting complex interactions between natural processes and human activities (Osman *et al.*, 2023) <sup>[14]</sup>. Rapid population growth, urban expansion, agricultural intensification, and climate variability have accelerated landscape transformation, significantly impacting ecosystem services, hydrology, and biodiversity (Sun and Zhang, 2025) <sup>[21]</sup>. Consequently, accurate and timely monitoring of LULC is essential for sustainable land management and effective environmental planning (Tahmi *et al.*, 2026) <sup>[22]</sup>.

Remote sensing has emerged as a powerful tool for LULC mapping due to its synoptic coverage and temporal consistency (Loukika *et al.*, 2021) <sup>[11]</sup>. The availability of multi-temporal satellite data such as Landsat and Sentinel, combined with advancements in cloud-based platforms like Google Earth Engine (GEE), has greatly improved large-scale environmental monitoring capabilities (Pande *et al.*, 2023) <sup>[16]</sup>. GEE enables efficient processing of vast geospatial datasets by utilizing parallel processing and Map Reduce architecture, facilitating advanced analyses without the need for high-end local computing resources (Ahmed *et al.*, 2024) <sup>[2]</sup>.

The integration of machine learning (ML) algorithms, including Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART), has further enhanced classification accuracy (Basheer *et al.*, 2022) <sup>[4]</sup>. These models effectively handle complex, nonlinear data and have demonstrated high performance in diverse landscapes (Belay *et al.*, 2024; Tesfaye *et al.*, 2024) <sup>[5, 23]</sup>. Studies indicate that RF frequently outperforms other classifiers in terms of overall accuracy and robustness, particularly in agriculturally dominant regions (Pande *et al.*, 2024) <sup>[17]</sup>. However, challenges remain in selecting optimal training data, integrating auxiliary variables, and ensuring consistent performance across regions (Alshehri *et*

*al.*, 2025; Loukika *et al.*, 2021) [3, 11].

In India, particularly in Maharashtra, watershed systems are increasingly affected by land transformation driven by rainfed agriculture and limited water management (Pande, 2022) [15]. The Morna watershed exemplifies such vulnerability, characterized by steep slopes and high erosion potential (Ingle, 2022) [10]. Despite its hydro-ecological importance, previous studies have largely focused on morphometry rather than advanced LULC analysis (Chavhan, 2015, Shinde *et al.*, 2024) [7, 19]. Furthermore, a specific challenge in this region is the spectral confusion between urban impervious surfaces and the region's characteristic black cotton soils, which necessitates sophisticated feature-engineering.

In this context, the present study aims to address these gaps by employing machine learning algorithms within the GEE platform for LULC mapping and change detection in the Morna watershed. The specific objectives are, a) To generate accurate LULC maps using multi-temporal satellite imagery (Landsat 8/9 and Sentinel-2). b) To evaluate the performance of selected machine learning classifiers (RF, SVM, and CART). c) To analyze spatiotemporal LULC changes and land cover transitions within the watershed.

## 2. Materials and Methods

### 2.1 Study area

Morna is tributary of Koyna River, which is one of the major

tributaries of river Krishna in Maharashtra. As shown in Fig. 1, this catchment lies in Satara district of Maharashtra state in western India, between 17° 24' N to 17° 50' N latitude and 73° 46' E to 74° 0' E longitudes. The total area of watershed is 13,285.13 ha. Length of Morna river is 24.25 km. The average minimum and maximum temperatures are 7.50C to 38.50C, respectively and May is hottest month. The average annual rainfall is 2012 mm. The soil is laterite having dark reddish to yellowish red color. The textural class is clay-to clay loam and has pH value between 4 and 5.8. Cropping pattern of the watershed is dominated by cereals, paddy and millets which are major Kharif crops (Bowlekar *et al.* 2018, Shinde and Nandgude, 2024) [6, 18].

### 2.2 Data Types and Sources

Multi-temporal satellite imagery was acquired from the Landsat series (Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS) through the Google Earth Engine (GEE) platform. Landsat data were selected due to their long-term availability, moderate spatial resolution (30 m), and suitability for LULC classification. Satellite images corresponding to selected time periods (e.g., 1985, 1995, 2005, 2015, and 2025) were used to capture temporal changes. Images were selected based on minimal cloud cover and seasonal consistency, typically during the post-monsoon or early winter period to ensure optimal spectral separability of land cover classes.

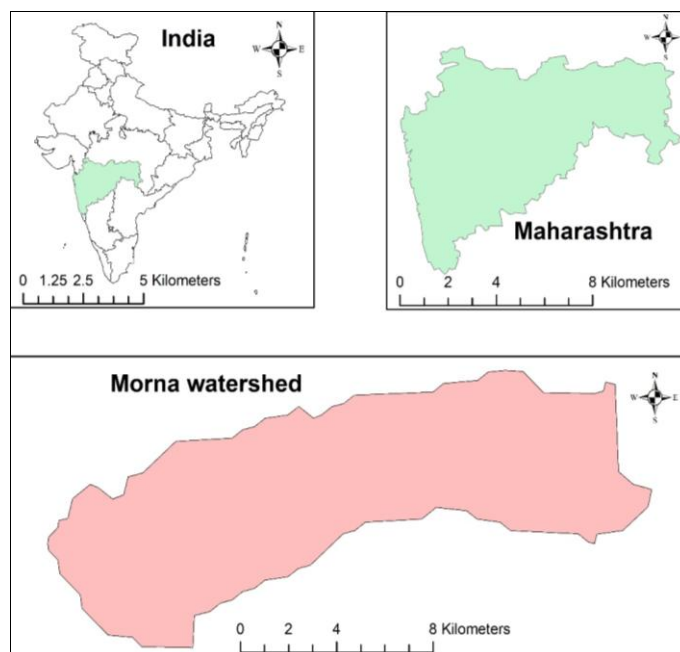


**Fig 1: Morna Watershed area**

### 2.3 Data Preprocessing

Preprocessing of satellite imagery was executed within the GEE environment to guarantee data uniformity and quality for the study area. Cloud and shadow masking utilized Quality Assessment (QA) bands and algorithms such as s2cloudless to effectively eliminate pixel contamination (Vyas *et al.*, 2025; Tesfaye *et al.*, 2024) [24, 23]. Surface reflectance products (Landsat Collection 2 Level 2 and Sentinel-2 Level-2A) were prioritized to minimize the influence of atmospheric interference on spectral values (Belay *et al.*, 2024) [5].

Images were precisely clipped to the Morna watershed boundary using predefined vector data to isolate the specific area of interest (Sultana *et al.*, 2024; Moharir *et al.*, 2024) [20, 12].

Temporal compositing, specifically employing median filtering, allowed for the generation of cloud-free, representative imagery for each study year by reducing variability in pixel values (Nasiri *et al.*, 2022) [13]. These comprehensive steps ensured the integrity of spectral information for accurate machine learning-based LULC classification (Osman *et al.*, 2023) [14].

### 2.4 Variables and Spectral Indices

To enhance class separability and improve classification accuracy, several spectral indices were derived from the satellite imagery. These includes, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), Bare Soil Index

(BSI). Additionally, topographic variables such as elevation and slope derived from the SRTM DEM were incorporated as auxiliary predictors, as these factors significantly influence land cover distribution and classification performance.

## 2.5 Training and Validation Data

Training and validation datasets were generated using a combination of field knowledge, high-resolution imagery, and visual interpretation. Representative samples for each LULC class were collected using a stratified random sampling approach to ensure adequate representation of all land cover types (Basheer *et al.*, 2022) [4]. The dataset was divided into training and validation subsets, typically following a 70:30 split. The training dataset was used to develop classification models, while the validation dataset was used to assess model performance (Feizizadeh *et al.*, 2023; Tesfaye *et al.*, 2024) [23].

## 2.6 Classification and Modelling Approach

Supervised machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART), were implemented within the GEE platform. These algorithms were selected due to their robustness, efficiency, and proven performance in LULC classification (Hasoba *et al.*, 2025; Ahmad *et al.*, 2026) [9, 1]. The classification workflow involved feature selection, model training, parameter tuning, and classification of the study area. Hyperparameter tuning was performed—often utilizing grid search methods and cross-validation—to optimize model performance and prevent overfitting. The classifiers were trained using a comprehensive set of spectral bands, indices (such as NDVI, NDWI, and NDBI), and topographic variables (elevation and slope) as input features (Fariz *et al.*, 2024; Waindeshkar *et al.*, 2025) [8, 25].

## 2.7 Accuracy Assessment

The accuracy of the classified LULC maps was evaluated using a confusion matrix approach. Performance metrics including Overall Accuracy (OA), Kappa Coefficient (K), Producer's Accuracy (PA), and User's Accuracy (UA) were computed.

$$\text{Overall Accuracy} = \frac{\text{Total number of pixels}}{\text{Number of correctly classified pixels}}$$

## Producers Accuracy

$$\text{Producers Accuracy} = \frac{C_{ii}}{\sum_{j=1}^n C_{ij}} \times 100$$

Where,

$C_{ii}$  is the number of correctly classified pixels for class

$\sum_{j=1}^n C_{ij}$  is the total number of actual pixels in class i (The sum of the row in the confusion matrix corresponding to class i)

## User's Accuracy

$$\text{User's Accuracy} = \frac{C_{ii}}{\sum_{j=1}^n C_{ji}} \times 100$$

Where,

$C_{ii}$  is the number of correctly classified pixels for class i.

$\sum_{j=1}^n C_{ji}$  is the total number of pixels classified as class i (the sum of the column in the confusion matrix corresponding to class i)

## Kappa Coefficient

$$\text{Kappa Coefficient}, k = \frac{P_o - P_e}{1 - P_e}$$

Where,

$P_o$  is the observed agreement (i.e., overall accuracy)

$P_e$  is the expected agreement by chance

Post-classification comparison was employed to analyze LULC changes over time. Classified maps from different years were compared to quantify transitions between land cover classes. Change matrices were generated to identify dominant trends such as agricultural expansion, deforestation, or urban growth.

## 3. Results and Discussion

### 3.1 Accuracy Assessment

The classification performance of Random Forest (RF), CART, and SVM models was evaluated using Accuracy (OA) and the Kappa coefficient for the years 1995, 2005, 2015, and 2025 as shown in Table 1. The results show that RF consistently outperformed the other models across all years. The accuracy of RF ranged from 97.32% (1995) to 98.56% (2015), which was higher than CART (96.06%–97.24%) and SVM (92.96%–97.77%). Similarly, the Kappa coefficient values for RF (0.948–0.973) were also higher compared to CART (0.927–0.949) and SVM (0.863–0.958), indicating stronger agreement and reliability. Finally, Random Forest proved to be the most accurate and stable classifier, making it the best model for LULC classification in this study.

**Title 1:** Accuracy assessment of models used for LULC change detection

| Year | Overall Accuracy |        |        | Kappa Coefficient |       |       |
|------|------------------|--------|--------|-------------------|-------|-------|
|      | RF               | CART   | SVM    | RF                | CART  | SVM   |
| 1995 | 97.32%           | 96.76% | 92.96% | 0.948             | 0.937 | 0.863 |
| 2005 | 97.55%           | 96.06% | 94.70% | 0.954             | 0.927 | 0.901 |
| 2015 | 98.56%           | 97.24% | 97.77% | 0.973             | 0.948 | 0.958 |
| 2025 | 97.89%           | 97.18% | 96.91% | 0.962             | 0.949 | 0.944 |

### 3.2 Coding of LULC

The land use/land cover (LULC) change classes are coded to represent transitions between different categories over time. Each code indicates the conversion from one land class to another, where the first digit represents the initial class and the second digit represents the final class.

The classification used in this study is as follows, 0 = Agriculture, 1 = Forest, 2 = Water, 3 = Barren, and 4 = Built-up. For example, a code such as 11 represents Forest to Forest, indicating no change and stable forest area. Similarly, 14 represents Forest to Built-up, which indicates deforestation combined with urbanization. Another example is 33, which represents Barren to Barren, showing stable barren land with no change over time. This coding helps in clearly identifying and quantifying both stable areas and transitions between different land use classes.

### 3.3 LULC Change Detection (1995–2005)

The LULC change analysis between 1995 and 2005 shows that a large portion of the landscape remained stable as shown in table 2 and fig. 2. Forest areas showed strong persistence, with 3625.52 ha (27.47%). Similarly, barren land covered 3170.04 ha (24.02%), indicating a dominant and stable presence. Water bodies (930.58 ha; 7.05%) and agricultural land (933.97 ha;

7.07%) also remained relatively stable during this period. However, some important changes were observed. A notable transformation was the conversion of forest to barren land (724.07 ha; 5.49%), indicating deforestation and land degradation. At the same time, agricultural expansion into forest areas (365.16 ha; 2.76%) suggests vegetation regrowth in some

locations. Conversion of built-up areas to agriculture (435.94 ha; 3.30%) reflects land reuse practices. This period shows moderate land transformation, with forests largely stable but experiencing some degradation, while barren land remained a dominant feature of the landscape.

**Table 2:** LULC Change Detection from 1995–2005

| Change Type                    | Area, ha | %      | Meaning                     |
|--------------------------------|----------|--------|-----------------------------|
| Forest → Forest (11)           | 3625.52  | 27.47% | Stable forest (very strong) |
| Barren → Barren (33)           | 3170.04  | 24.02% | Large barren stability      |
| Water → Water (22)             | 930.58   | 7.05%  | Stable water bodies         |
| Agriculture → Agriculture (00) | 933.97   | 7.07%  | Stable agriculture          |
| Built up → Built up (44)       | 505.28   | 3.82%  | Stable Built up             |
| Forest → Barren (13)           | 724.07   | 5.49%  | Deforestation               |
| Built → Agriculture (40)       | 435.94   | 3.30%  | Land reuse                  |
| Agriculture → Forest (01)      | 365.16   | 2.76%  | Vegetation growth           |

### 3.4 LULC Change Detection (2005–2015)

Between 2005 and 2015, landscape stability slightly improved as shown in table 3 and fig. 2. Forest areas continued to dominate, with 3768.19 ha (28.55%), while barren land also showed high consistence at 3338.87 ha (25.30%). At the same time, significant land transformations occurred in Agricultural land, which was increasingly converted into built-up areas (689.74 ha;

5.23%), indicating strong urban expansion. Conversion of water bodies to forest (614.02 ha; 4.65%) suggests vegetation growth in certain areas, while barren land being converted to agriculture (588.89 ha; 4.46%) reflects increased cultivation activities. It highlights a clear trend of urban growth and agricultural expansion, while forest areas remained relatively stable and continued to play a dominant role in the watershed.

**Table 3:** LULC Change Detection from 2005–2015

| Change                         | Area, ha | %      | Interpretation              |
|--------------------------------|----------|--------|-----------------------------|
| Forest → Forest (11)           | 3768.19  | 28.55% | Stable forest (very strong) |
| Barren → Barren (33)           | 3338.87  | 25.30% | Large barren stability      |
| Water → Water (22)             | 240.31   | 1.82%  | Stable water bodies         |
| Agriculture → Agriculture (00) | 933.97   | 7.07%  | Stable agriculture          |
| Built up → Built up (44)       | 505.28   | 3.82%  | Stable Built up             |
| Agriculture → Built-up (04)    | 689.74   | 5.23%  | Urban expansion             |
| Water → Forest (21)            | 614.02   | 4.65%  | Vegetation growth           |
| Barren → Agriculture (30)      | 588.89   | 4.46%  | Land cultivation            |

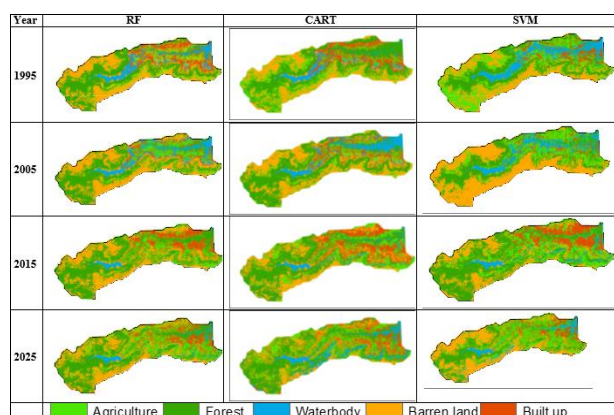


**Fig 2:** Estimated change in land use land cover from 1995 to 2025 using RF, CART and SVM

### 3.4 LULC Change Detection (2015–2025)

The analysis from 2015 to 2025 shows further improvement in forest stability, with 4100.28 ha (31.07%). Barren land, although still significant, decreased slightly in stability to 2849.75 ha (21.59%). Built-up areas also showed strong endurance, with 879.35 ha (6.66%), indicating consolidation of urban regions. Details of LULC change from 2015 to 2025 is shown in table 4. Key transformations during this period include the conversion of barren land to agriculture (692.11 ha; 5.24%), showing continued land development and expansion of farming. However, forest conversion to agriculture (469.22 ha; 3.55%) indicates ongoing deforestation pressure. This period reflects increased agricultural expansion, improved forest stability, and the strengthening of built-up areas.

**Table 4:** LULC Change Detection from 2015–2025

| Change                         | Area, ha | %      | Meaning                     |
|--------------------------------|----------|--------|-----------------------------|
| Forest → Forest (11)           | 4100.28  | 31.07% | Stable forest (very strong) |
| Barren → Barren (33)           | 2849.75  | 21.59% | Large barren stability      |
| Water → Water (22)             | 237.97   | 1.80%  | Stable water bodies         |
| Agriculture → Agriculture (00) | 1186.26  | 8.98%  | Stable agriculture          |
| Built up → Built up (44)       | 879.35   | 6.66%  | Stable Built up             |
| Barren → Agriculture (30)      | 692.11   | 5.24%  | Land development            |
| Forest → Agriculture (10)      | 469.22   | 3.55%  | Deforestation               |

### 3.5 Discussion

The change detection analysis from 1995 to 2025 shows a dynamic yet gradually stabilizing landscape. A large portion of the watershed remained unchanged over time, with forest stability ranging from 27.47% (3625.52 ha) in 1995–2005 to 31.07% (4100.28 ha) in 2015–2025. Similarly, barren land showed strong persistence, covering 24.02% (3170.04 ha) in 1995–2005 and 21.59% (2849.75 ha) in 2015–2025, indicating its dominant presence in the region.

Human activities have significantly influenced land use patterns across all periods. Agricultural expansion is clearly visible, particularly through the conversion of barren land to agriculture (688.04 ha; 5.21%) and forest to agriculture (661.84 ha; 5.01%) over the long term. Urban growth also increased, especially during 2005–2015, where 689.74 ha (5.23%) of agricultural land was converted into built-up areas, along with additional contributions from barren land (152.56 ha; 1.15%).

Although forests remained the dominant land cover, they experienced notable losses due to conversion into agriculture (661.84 ha; 5.01%) and barren land (579.95 ha; 4.39%), with a smaller portion converted into built-up areas (103.34 ha; 0.78%). These changes highlight ongoing pressure on forest resources and raise concerns about environmental sustainability.

At the same time, some positive trends were observed, such as vegetation growth (e.g., water to forest: 614.02 ha; 4.65%) and improved forest stability in later years. Overall, the watershed reflects a balance between stability and change, with increasing human influence driving agricultural expansion and urbanization, while forest conservation remains a critical environmental concern.

### 4. Conclusion

The LULC change analysis from 1995 to 2025 reveals that forest and barren land are the dominant and relatively stable land cover classes in the study area. However, significant transitions such as forest to agriculture and barren to agriculture indicate increasing anthropogenic pressure and agricultural expansion. Additionally, the growth of built-up areas highlights ongoing urbanization. These changes suggest a gradual transformation of natural landscapes into human-dominated land uses, emphasizing the need for sustainable land management strategies.

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