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Prediction of future Land Use/Land Cover (LULC) changes using random forest model in google earth engine (2035–2045)

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Abstract

This study analyzes past and future Land Use/Land Cover (LULC) dynamics of the Morna watershed using geospatial techniques and machine learning approaches. A Random Forest (RF) model was employed for LULC classification, achieving an overall accuracy of 71.6% and a Kappa coefficient of 0.61, indicating moderate to good classification performance. Future LULC scenarios for 2035 and 2045 were projected using a hybrid modeling framework integrating machine learning techniques. The results reveal that forest land remains the dominant and most stable class, increasing from 31.69% (2025–2035) to 34.10% (2035–2045), indicating strong ecological resilience. Urban expansion is identified as the most significant transformation process, with built-up areas increasing from 6.12% to 6.53%, primarily driven by the conversion of agricultural land (3.08% to 2.65%). Agricultural land shows moderate stability (11.13% to 12.80%) but faces continuous pressure due to urban encroachment. Barren land remains persistently high, increasing from 20.85% to 22.24%, highlighting ongoing land degradation and poor land management practices. Water bodies remain relatively stable (~1.75%), indicating minimal hydrological changes. The findings suggest that while the watershed exhibits partial landscape stability, increasing anthropogenic activities are significantly influencing land transformation. The study highlights the need for sustainable land use planning, particularly to control urban expansion, conserve agricultural land, and rehabilitate degraded areas. These insights provide valuable support for policymakers and environmental managers in developing effective strategies for sustainable watershed management.

Keywords: ML, RF, GEE, LULC

1. Introduction

Land Use/Land Cover (LULC) changes play a major role in global environmental change, affecting local weather, water systems, and ecosystem health (Gaur and Singh, 2023; Zafar *et al.*, 2025) [8, 25]. These changes are mainly driven by rapid urban growth and increased agricultural activities, which directly impact surface runoff and water quality in watersheds (Amini *et al.*, 2022; Loukika *et al.*, 2023) [2, 12]. In regions like Maharashtra, India, monitoring these changes is essential for sustainable land use planning and protecting important water resources (Patil *et al.*, 2025) [17]. Satellite remote sensing programs such as Landsat and Sentinel provide reliable, long-term data that help track changes in land use over time (Alshehri *et al.*, 2025; Wulder *et al.*, 2016; Shinde and Nandgude, 2024) [1, 24, 21]. However, traditional methods of analyzing this data can be time-consuming and require high computational power, making them difficult to use on standard computers (Gorelick *et al.*, 2017; Alshehri *et al.*, 2025) [9, 1]. Google Earth Engine (GEE) has transformed this process by offering a cloud-based platform that allows large-scale analysis of satellite data quickly and efficiently (Gorelick *et al.*, 2017; Tassi and Vizzari, 2020) [9, 22].

Machine learning techniques like Random Forest (RF) and Support Vector Machines (SVM) are more effective than traditional methods because they can handle complex patterns and noisy data (Breiman, 2001; Kipterer *et al.*,

2025) [6, 11]. Among these, RF is widely used in GEE due to its reliability and high accuracy across different landscapes (Alshehri *et al.*, 2025; Bhungeni *et al.*, 2025) [1, 4]. For predicting future land use changes, models such as Cellular Automata-Markov (CA-Markov) are useful as they simulate both spatial and temporal changes, helping in planning and decision-making (Osman *et al.*, 2023; Vahid and Aly, 2025) [16, 23].

The Morna watershed in Satara is experiencing increasing human pressure, but there is limited research that combines long-term machine learning-based analysis with future predictions (Ingle, 2022) [10]. Using LULC maps from 1995, 2005, 2015, and 2025, this study uses GEE to predict future scenarios for 2035 and 2045. The main objectives of this study are,

- To analyze past LULC changes in the Morna watershed (1995–2025) using machine learning models in GEE.
- To predict future LULC patterns for 2035 and 2045 using the Supervised ML-based temporal prediction.
- To evaluate the accuracy and reliability of the classification and prediction results.

Despite existing studies on LULC change, several gaps remain. There is limited integration of historical analysis with future prediction in a single framework, and few studies combine machine learning approaches like Random Forest in GEE with Supervised ML-based temporal

prediction. Additionally, the role of key biophysical and socioeconomic drivers is often not fully explored. The potential of Google Earth Engine for large-scale analysis is underutilized, and there is a lack of long-term, region-specific research on the Morna watershed. Furthermore, accuracy assessment of both classification and prediction models is often insufficient.

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.* 2019, Shinde *et al.* 2024) [5, 20].

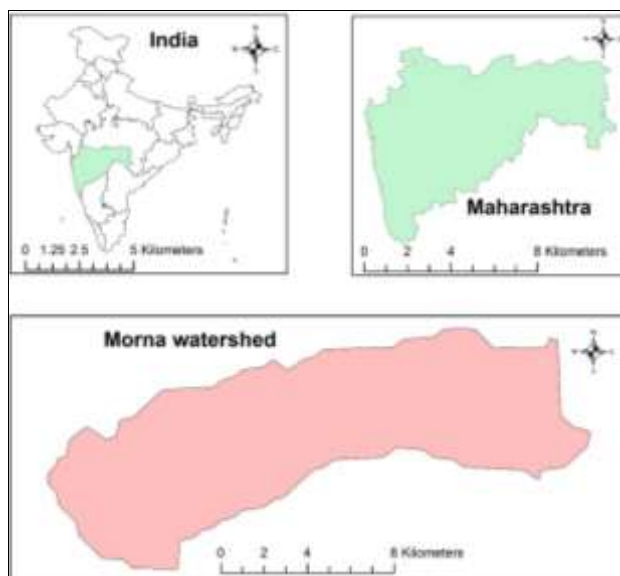


Fig 1: Location of Study Area

2.2 Data Sources

In this study, multiple satellite datasets were combined using the Google Earth Engine (GEE) platform. Landsat 5 TM and Landsat 8 OLI Surface Reflectance images were used for the years 1995, 2005, 2015, and 2025, all with a consistent spatial resolution of 30 meters (Zafar *et al.*, 2025; Loukika *et al.*, 2021) [25, 13]. Topographic information, such as elevation and slope, was obtained from the SRTM Digital Elevation Model (DEM) (Zafar *et al.*, 2025; Vahid and Aly, 2025) [25, 23]. Additional supporting data, including distance to roads and drainage networks, were collected from OpenStreetMap (OSM) and Survey of India (SOI) toposheets (Loukika *et al.*, 2023; Sankarrao *et al.*, 2021) [12, 19].

2.3 Image Pre-processing

All image pre-processing was carried out within the Google Earth Engine (GEE) platform to maintain consistency over time. Satellite images were filtered to remove those with high cloud cover (less than 10%) and were corrected for atmospheric effects (Nigar *et al.*, 2024; Kipterer *et al.*, 2025) [15, 11]. A median reduction method was then used to create clear, cloud-free composite images for each year (Tassi and Vizzari, 2020; Nigar *et al.*, 2024) [22, 15]. In addition, spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) were calculated and added to the dataset to improve the identification of vegetation and urban areas (Kipterer *et al.*, 2025; Loukika *et al.*, 2021) [11, 13].

2.4 LULC Classification

LULC classification was carried out using the Random Forest (RF) algorithm (ee.Classifier.smileRandomForest) (Alshehri *et al.*, 2025; Bhungeni *et al.*, 2025) [1, 4]. RF is widely used because it can handle large and complex datasets efficiently and reduces the risk of overfitting (Breiman, 2001; Belgiu and Drăguț, 2016) [6, 3]. The study area was classified into five categories: Agriculture, Forest, Waterbodies, Built-up, and Barren land. Training and validation data were prepared using a 70/30 split, with around 350 sample points verified using high-resolution images from Google Earth Pro (Nandgude *et al.* 2026) [14].

2.5 Accuracy Assessment

The accuracy of both classification and prediction results was assessed using a confusion matrix (Zafar *et al.*, 2025; Foody, 2002) [25, 7]. Key evaluation metrics included Overall Accuracy (OA), which shows the proportion of correctly classified pixels, and the Kappa Coefficient (κ), which measures the level of agreement while accounting for random chance (Zafar *et al.*, 2025; Pontius and Millones, 2011) [25, 18]. In addition, Producer's Accuracy and User's Accuracy were calculated to identify errors related to missing or misclassified land cover classes (Osman *et al.*, 2023; Foody, 2002) [16, 7].

2.6 Model Prediction

The future LULC prediction was carried out using a data-driven machine learning approach, where past land use patterns were used to simulate future scenarios. Unlike traditional methods, this approach does not rely on predefined transition rules but learns directly from historical data (Zafar *et al.*, 2025) [25]. The prediction for 2035 represents a short-term projection, primarily influenced by recent land use trends (2015–2025). In contrast, the prediction for 2045 represents a long-term projection, influenced by cumulative changes propagated through the recursive modeling process.

The recursive nature of prediction introduces slight uncertainty but is essential for simulating realistic future dynamics. It allows the model to account for feedback effects, such as, expansion of built-up areas, persistence of barren land and stability of forest regions etc. The results indicate that land use changes are not random but follow systematic transition patterns, which can be effectively captured using machine learning techniques.

3. Results and Discussion

3.1 Accuracy assessment

The accuracy assessment of the Random Forest (RF) model for the Morna watershed for the year 2025 shows an Overall Accuracy (OA) of 71.6% and a Kappa coefficient of 0.61 (Nandgude *et al.* 2026) ^[14]. These results indicate that the model performs at a moderate to good level in classifying land use and land cover (LULC) classes. An overall accuracy of 71.6% means that the model correctly classified approximately seven out of every ten pixels, suggesting a reasonably reliable representation of the actual ground conditions. Meanwhile, the Kappa coefficient of 0.61 reflects a substantial level of agreement between the predicted and reference data beyond chance, reinforcing the consistency of the model's performance. Together, these metrics suggest that the RF model is effective for LULC mapping in the Morna watershed, though there is still room for improvement.

3.2. LULC change prediction of 2035

The projected LULC changes for the Morna watershed between 2025 and 2035 reveal a landscape that is partially stable but undergoing noticeable anthropogenic

transformations, which is shown in fig. 2. Forest land exhibits the highest stability (31.69%), indicating strong ecological resilience and confirming its dominance in the region. Barren land also shows significant persistence (20.85%), which reflects ongoing land degradation or limited land productivity. Agricultural land demonstrates moderate stability (11.13%), suggesting that while farming remains important, it is vulnerable to change.

A key finding during this period is the continuous expansion of built-up areas. The transition from agriculture to built-up land (3.08%) and from barren land to built-up land (1.16%), along with the persistence of existing built-up areas (6.12%), clearly indicates steady urban growth. This trend highlights increasing developmental pressure, particularly on agricultural land, which is gradually being converted for urban uses.

Forest degradation is present but relatively controlled, as seen in the transitions from forest to agriculture (1.35%) and forest to barren land (2.10%). This suggests localized disturbances rather than widespread deforestation. Meanwhile, water bodies remain largely stable (1.75%), indicating minimal changes in the hydrological system during this period.

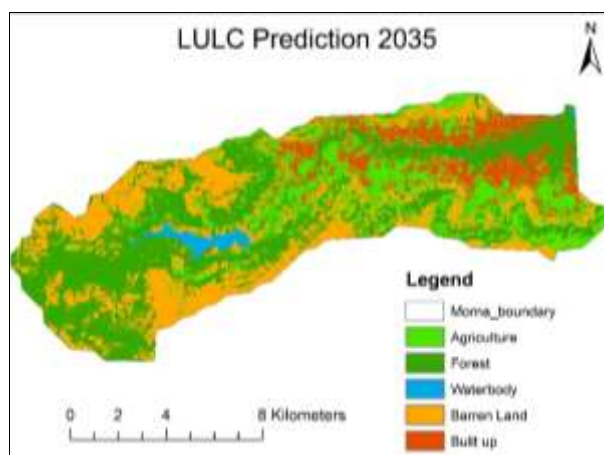


Fig 2: LULC change prediction of Morna watershed for 2035

3.3 LULC change prediction of 2045

The LULC projections for 2035–2045 indicate a trend toward increased landscape stability in the Morna watershed. Forest land stability rises to 34.10%, barren land to 22.24%, and agricultural land to 12.80%, suggesting that land use patterns become more consolidated over time. This stabilization may reflect the establishment of dominant land-use practices and reduced rates of abrupt transitions. LULC change prediction for year 2045 is as shown in fig. 3.

Despite this stabilization, urban growth continues as a persistent trend. Built-up land remains stable at 6.53%, and the conversion of agricultural land to built-up areas (2.65%) indicates ongoing urban expansion. Although slightly reduced compared to the previous decade, this trend confirms that urbanization remains a key driver of land transformation.

A major concern during this period is the continued persistence of barren land (22.24%). This highlights significant environmental challenges such as soil degradation, reduced land productivity, and possibly inadequate land management practices. The increasing stability of barren land suggests that degraded areas are not

being effectively restored.

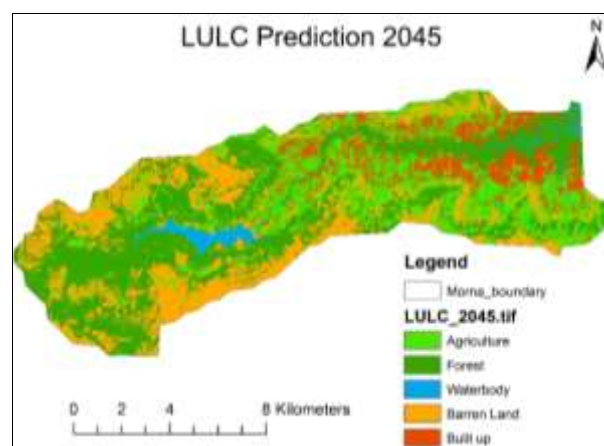


Fig 3: LULC change prediction of Morna Watershed for 2045

3.4 LULC change prediction from 1995 to 2045

The long-term analysis (1995–2045) for the Morna watershed shows consistent and clear land use trends supported by observed values. Forest land remains the

dominant and most stable class, increasing from about 31.69% (2025–2035) to 34.10% (2035–2045), indicating strong ecological resilience.

Urban expansion is the most prominent and continuous change, with built-up stability rising from 6.12% to 6.53%, along with ongoing conversion from agriculture (3.08% to 2.65%). This reflects sustained development pressure driven by population growth and infrastructure expansion.

Agricultural land shows moderate stability (11.13% to 12.80%) but faces continuous pressure due to conversion into built-up areas, raising concerns about its long-term sustainability.

Barren land remains consistently high, increasing from 20.85% to 22.24%, highlighting persistent land degradation, possibly due to poor land management and environmental stress.

Water bodies show minimal variation, with stability around 1.75%, indicating that the hydrological system of the watershed remains largely stable over time.

4. Conclusion

The study successfully demonstrates the effectiveness of machine learning models in predicting future LULC changes in the Morna watershed. The projected scenarios for 2035 and 2045 clearly indicate continuous urban expansion, with built-up land increasing from 6.12% to 6.53%, along with notable conversion from agriculture (3.08% to 2.65%), reflecting growing developmental pressure.

Agricultural land shows moderate stability (11.13% to 12.80%) but is gradually declining due to urban encroachment, raising concerns about its long-term sustainability. In contrast, forest areas remain relatively stable and dominant, increasing from 31.69% to 34.10%, which highlights strong ecological resilience within the watershed.

However, the persistent and increasing extent of barren land (20.85% to 22.24%) indicates ongoing land degradation and emphasizes the urgent need for sustainable land management and restoration strategies. Water bodies remain largely stable (~1.75%), suggesting minimal impact on the hydrological system.

References

1. Alshehri B, Zhang Z, Liu X. A review of Google Earth Engine for land use and land cover change analysis: trends, applications, and challenges. *ISPRS Int J Geo Inf.* 2025;14:416. <https://doi.org/10.3390/ijgi14110416>
2. Amini S, Saber M, Rabiei-Dastjerdi H, Homayouni S. Urban land use and land cover change analysis using random forest classification of Landsat time series. *Remote Sensing.* 2022;14(11):2654. <https://doi.org/10.3390/rs14112654>
3. Belgiu M, Drăguț L. Random Forest in remote sensing: a review of applications and future directions. *ISPRS J Photogramm Remote Sens.* 2016;114:24-31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>
4. Bhungeni O, Gebreslasie M, Ramjatan A. LULC change detection and future LULC modelling using RF and MLPNN-Markov algorithms in the uMngeni catchment, KwaZulu-Natal, South Africa. *Front Environ Sci.* 2025;13:1543524. <https://doi.org/10.3389/fenvs.2025.1543524>
5. Bowlekar A, Sawant H, Nandgude S, Mahale D, Scholar B. Morphometric analysis of Morna River catchment using geographic information system. *Agric Eng Today.* 2019;43(1):54-61.
6. Breiman L. Random forests. *Mach Learn.* 2001;45:5-32. <https://doi.org/10.1023/A:1010933404324>
7. Foody GM. Status of land cover classification accuracy assessment. *Remote Sens Environ.* 2002;80(1):185-201.
8. Gaur S, Singh R. A comprehensive review on land use/land cover (LULC) change modeling for urban development: current status and future prospects. *Sustainability.* 2023;15(2):903. <https://doi.org/10.3390/su15020903>
9. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sens Environ.* 2017;202:18-27. <https://doi.org/10.1016/j.rse.2017.06.031>
10. Ingle NB. Morphometric analysis of Morna River sub basin using geospatial approach. *Int J Multidiscip Res Dev.* 2022;9(1):71-78.
11. Kipterer JK, Boitt MK, Mundia CN. Comparative analysis of machine learning algorithms for optimal land use and land cover classification: guiding method selection for resource-limited settings in Tiaty, Baringo County, Kenya. *J Geosci Environ Prot.* 2025;13:393-414. <https://doi.org/10.4236/gep.2025.134021>
12. Loukika KN, Keesara VR, Buri ES, Sridhar V. Future prediction of scenario based land use land cover (LU&LC) using DynaCLUE model for a river basin. *Ecol Inform.* 2023;77:102223. <https://doi.org/10.1016/j.ecoinf.2023.102223>
13. Loukika KN, Keesara VR, Sridhar V. Analysis of land use and land cover using machine learning algorithms on Google Earth Engine for Munneru River Basin, India. *Sustainability.* 2021;13(24):13758. <https://doi.org/10.3390/su132413758>
14. Nandgude SB, Desai AV, Ganachari HS, Shinde SS, Wankhede PS. Land use land cover change detection using machine learning in Google Earth Engine of Morna Watershed. *Int J Res Agron.* 2026;SP-9(4):163-168. <https://doi.org/10.33545/2618060X.2026.v9.i4Sb.5386>
15. Nigar A, Li Y, Jat Baloch MY, Alrefaei AF, Almutairi MH. Comparison of machine and deep learning algorithms using Google Earth Engine and Python for land classifications. *Front Environ Sci.* 2024;12:1378443. <https://doi.org/10.3389/fenvs.2024.1378443>
16. Osman MA, Abdel-Rahman EM, Onono JO, Olaka LA, Elhag MM, Adan M, et al. Mapping, intensities and future prediction of land use/land cover dynamics using Google Earth Engine and CA-artificial neural network model. *PLoS One.* 2023;18(7):e0288694. <https://doi.org/10.1371/journal.pone.0288694>
17. Patil SS, Wandre SS, Patil MA, Gadakh S, Bansude SN, Gavit BK, Dhekale JS. Land use and land cover change detection using geospatial techniques in the Warana River Basin (WRB), Western Maharashtra, India. *J Geogr Environ Earth Sci Int.* 2025;29(11):49-63. <https://doi.org/10.9734/jgeesi/2025/v29i11967>

18. Pontius RG, Millones M. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *Int J Remote Sens.* 2011;32(15):4407-4429.
<https://doi.org/10.1080/01431161.2011.552923>
19. Sankarrao L, Ghose DK, Rathinsamy M. Predicting land-use change: intercomparison of different hybrid machine learning models. *Environ Model Softw.* 2021;145:105207.
<https://doi.org/10.1016/j.envsoft.2021.105207>
20. Shinde S, Nandgude S. Soil organic carbon stocks assessment under different land use land cover in Morna Watershed, India using GIS technique. *Mysore J Agric Sci.* 2024;58(3).
21. Shinde SS, More DD, Shendkar DA, Dahiphale MS, Thange AB, Nandgude SB. Temporal and spatial dynamics of land use and land cover in Shirur Kasar Tehsil, Maharashtra using geospatial technology. *Int J Agric Invent.* 2024;9(1):193-204.
<https://doi.org/10.46492/IJAI/2024.9.1.25>
22. Tassi A, Vizzari M. Object-oriented LULC classification in Google Earth Engine combining SNIC, GLCM, and machine learning algorithms. *Remote Sensing.* 2020;12(22):3776.
<https://doi.org/10.3390/rs12223776>
23. Vahid R, Aly MH. An integrated CA-Markov modeling framework for forecasting land use and land cover dynamics in Arkansas, USA. *Geomatics.* 2025;5(4):62.
<https://doi.org/10.3390/geomatics5040062>
24. Wulder MA, White JC, Loveland TR, Woodcock CE, Belward AS, Cohen WB, *et al.* The global Landsat archive: status, consolidation, and direction. *Remote Sens Environ.* 2016;185:271-283.
<https://doi.org/10.1016/j.rse.2015.11.032>
25. Zafar SM, Khan JA, Mobeen A, Jaafar WSWM, Kemarau RA. Estimating the plausible projections of land use/land cover dynamics in Jhelum and Chenab River basins using satellite imageries and machine learning models in Google Earth Engine. *Geocarto Int.* 2025;40(1):2491640.
<https://doi.org/10.1080/10106049.2025.2491640>