

ISSN: 0973-4929, Vol. 20, No. (1) 2025, Pg. 206-220

Current World Environment

www.cwejournal.org

Land Use and Land Cover Prediction in Tamilnadu of India, Using Random Forest Machine Learning Technique

AKILA RAJAMANICKAM* and CHANDIRASEKAR KAMALAKANNAN

Department of Mathematics, Anna University, Chennai, Tamilnadu, India.

Abstract

Land Use and Land Cover (LULC) dynamics have a major impact on environmental sustainability, resource management, and urban development. Effective decision-making depends on correct forecasting of these changes. This research predicts LULC changes with the Random Forest (RF) machine learning technique using satellite-derived data from the Na-tional Remote Sensing Centre (NRSC) for the years from 2005 to 2023. The dataset includes various LULC categories such as built-up land, agricultural lands, plantation/ orchards, forests, wetlands, grasslands, wastelands, and water bodies. This study focuses on an area of Ta-milnadu, India, covered by NRSC's LULC datasets from 2005 to 2023. The Random Forest model was first trained on data for the years from 2005 to 2017 to predict LULC for the next consecutive years 2018–2023, with validated against actual LULC values for Tamilnadu, In-dia from the year 2018 to 2023, achieving high accuracy with a correlation coefficient (R ≥ 0.97 in later years) and decreasing Mean Absolute Error. Based on the complete historical da-taset from 2005 to 2023, the trained model is then applied to predict LULC changes for the years from 2024 to 2028. The results indicate a significant increase in urban development of 0.001 hectare annually and a consistent decrease in double/triple cropping areas of approximately 1.5 hectare between 2024 and 2028, stable but slightly declining forest cover, and wa-ter body spread oscillations. The steady increase in built-up land underscores the importance of controlled urban expansion and the decline in double/triple cropping areas calls for policies that support sustainable farming practices. With forest cover slightly declining, policymakers should strengthen conservation initiatives, afforestation efforts, and enforce stricter land-use regulations to prevent degradation. The oscillating spread of water bodies highlights the need for improved watershed management strategies.



Article History Received: 12 March 2025 Accepted: 26 April 2025

Keywords

Correlation Coefficient; Land Use and Land Cover (LULC) Machine Learning; National Remote Sensing Centre (NRSC) Satellite Data; Random Forest Regression.

CONTACT Akila Rajamanickam **k** akilarajamanickam@yahoo.com **Q** Department of Mathematics, Anna University, Chennai, Tamilnadu, India.



© 2025 The Author(s). Published by Enviro Research Publishers.

This is an Open Access article licensed under a Creative Commons license: Attribution 4.0 International (CC-BY). Doi: https://dx.doi.org/10.12944/CWE.20.1.16

Introduction

Environmental and socio-economic growth are greatly influenced by changes in land use and land cover (LULC). Among other factors, population increase, urban expansion, deforestation, climate change, and agricultural intensification influence LULC changes. While land use re-lates to human activities and changes on the land, such as agriculture, forestry, and urbaniza-tion, land cover reflects the physical and biological traits of the ground surface.^{1,2} Rapid ur-banization in many developing countries, for example, transforms agricultural and forested areas into built-up zones, therefore affecting biodiversity, water supplies, and climate adapta-tion measures.³⁻⁵ Researches shows that sustainable land management and disaster risk reduction depend on correct LULC forecasts.6,7 Changes in Land Use and Land Cover (LULC) greatly influence environmental management, urban planning, and sustainable development.

LULC changes have well-documented effects on natural resources as well. Spatial LULC dy-namics, for example, are directly related to groundwater recharge as well as levels. Research in the Hat Yai Basin demonstrates how tools like QGIS-based MOLUSCE software provide critical insights for sustainable water resource management.⁸ Similarly, the impact of LULC on soil properties and carbon sequestration has been evaluated in the upper Himalayan region, underlining the interplay between land cover variations and ecosystem carbon storage.^{9,10} Additionally, sustainable land resource use amidst changing LULC patterns highlights the need for tailored strategies in diverse geographical contexts.^{11,12}

Much research shows how policies influence LULC alterations. Land regulation policies have played a critical role in restricting agricultural land conversion to construction land. By em-ploying advanced remote sensing data (30 m resolution) and analytical methods, the study provides valuable insights for enhancing farmland protection programs and ecological land planning to address growing construction land demands in the Beijing Tianjin Hebei region. This findings contribute to informed policymaking for sustainable land management in regions experiencing rapid urbanization.^{13,14} In a similar context, comparative analyses of classification

algorithms in detecting LULC changes have revealed the utility of advanced techniques like machine learning in improving classification accuracy and understanding climatic impacts of land transformations.^{15,16}

One-third of the population of India lives in cities.17 To look for work and create their life in cities, people from the Tamil Nadu state and other neighboring states, as well as millions of North Indian states, have moved from rural Urbanization in India rose from 27.7% to 31.1%, a 3.3% increase between 2001 and 2011.18,19 Urbanization causes Indian cities to suffer un-clean health conditions and environmental degradation.²⁰ Among the fifteen main states mentioned by India, Tamil Nadu came first in urbanization. Based on the 2001 census, the state has reached the highest degree of urbanization at 43.86% in the nation.²¹ Approximately 27 million people call the metropolitan city of Tamil Nadu home.²² Tamil Nadu's urbanization pattern is scattered with towns in practically every district.23 Rapid urbanization in Tamil Nadu creates several problems, including deforestation, water shortage, floods, pollution, and other environmental damage.24

Remote sensing and GIS tools enable researchers to assess changes and guide sustainable management strategies effectively.^{25,26} The evolution of Geographic Information Systems (GIS) and remote sensing has significantly improved LULC research. Satellite pictures from sources such as Landsat, Sentinel, and MODIS offer multi-temporal data sets, allowing schol-ars to categorize land cover kinds and study temporal changes.²⁷⁻³⁰

By combining satellite-based LULC data from the National Remote Sensing Centre (NRSC) with machine learning techniques, this research enhances understanding of LULC trends in Tamil Nadu, a state known for its diverse geographical and land-use characteristics.

Though machine learning (ML) techniques have demonstrated better performance in capturing complex patterns in large datasets, traditional statistical models have been extensively used for LULC classification. LULC studies make extensive use of algorithms, including Random Forest (RF), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Con-volutional Neural Networks (CNN).^{31,32} Particularly the RF algorithm has become more well-known for its strength in managing high dimensional data, lowering overfitting, and generating precise forecasts.^{33,34}

Urban planning, resource management, and environmental sustainability are all significantly impacted by changes in land use and land cover (LULC). Over the past few decades, Tamil Nadu, an area in India that is rapidly becoming more urbanized, has seen significant changes in land use. Uses CA Markov models and remote sensing and to analyze urban growth and LULC changes over 140 years in the Coastal Districts of Northern Tamil Nadu. This study highlights the impact of urbanization on coastal ecosystems.35 Examines LULC data from 2005 to 2016, focusing on urbanization, agricultural decline, and forest cover reduction in Tamilnadu. This study emphasizes the need for sustainable land management.³⁶ Using Random Forest algorithms, a study maps LULC changes over two decades, analyzing vegetation and land surface temperature impacts in Tamilnadu.37 Employing QGIS MOLUSCE plugin and MLP-ANN models, this research forecasts LULC changes for 2025 and 2030 at Bhavani Basin in Tamilnadu, showing significant increases in cropland and built-up areas.38 The study uses geospatial techniques to monitor LULC changes, revealing shifts in agricultural and urban areas over several years in Salem District.39

There aren't many predictive models that use sophisticated Al-driven techniques to evaluate LULC changes over several years in Tamilnadu, despite the fact that many studies concentrate on retrospective LULC analysis and short-term projections of some areas in Tamilnadu. These papers emphasize the increasing need for including sophisticated computational methods for precise LULC prediction in Tamilnadu.

This paper aims to examine the LULC changes using machine learning for spatial analysis, therefore guaranteeing that data-driven insights direct land development policies.

An indepth analysis of Tamil Nadu, a state in southern India renowned for its diverse land use and

geography, Random Forest (RF) machine learning model is used in this study to forecast future land cover changes for the years 2024 to 2028 by analyzing historical LULC trends using NRSC satellite data from 2005 to 2023. The findings of this research will aid in sustain-able land management, environmental conservation, and urban planning across Tamil Nadu. The correlation coefficient evaluates the performance of the model.

Materials and Methods Study Area

This study was carried out in Tamil Nadu, research was conducted in Tamil Nadu, a southern Indian state with a seashore bordered by one dimension and a variety of landforms including hilly terrain, marshes, and forests.^{40,41} This paper offers a thorough examination of Tamil Nadu, a southern Indian state famous for its varied topographical and land use traits. Geographically located between latitudes 8°04' N and 13°35' N and longitudes 76°14' E and 80°21' E, Tamil Nadu covers 130.06 lakh hectare.⁴² Andhra Pradesh and Telangana border it to the north; Karnataka to the northwest, Kerala to the west; the Bay of Bengal to the east; the Indi-an Ocean to the south.⁴³

Data Collection

The dataset is obtained from the National Remote Sensing Centre (NRSC) is used in this study. and covers the period from 2005 to 2023.⁴⁴ Among the many land use and land cover (LULC) categories included are built-up areas, agricultural land (Kharif, Rabi, Zaid crops, double/triple annual crops, current fallow), plantations, various kinds of woodlands (evergreen, semi-evergreen, deciduous, degraded), wetlands, grasslands, wastelands, and water bodies (maximum and minimum spread).

Satellite photos, GIS-based land use maps, and supplementary data from government reports and research papers provide the basis for the data gathering.⁴⁵ The analysis emphasizes a terri-tory covered by NRSC's LULC datasets spanning 2005 to 2023. The dataset includes several different land cover kinds, as shown in the Table 1.

Built-Up Areas	Urban and rural settlements encompassing residential, commercial, and industrial areas that have experienced notable growth throughout time.
Agricultural Land	It encompasses a variety of cropping pat-terns, including Kharif (monsoon crops like rice and maize), Rabi (winter crops like wheat and mustard), and Zaid (summer crops like watermelon and cucumber). Addi-tionally, double/ triple annual cropping sys-tems indicate regions with intensive farming practices.
Plantations and	The area is cultivated with tree plantations such as rubber, coconut, tea,
orchards	coffee, and orchards producing fruits like mango, apple, and citrus varieties.
Woodland categories	Evergreen/Semi-Evergreen woodlands. Forests with dense canopy cover are found in areas receiving high rainfall
	Deciduous woodlands. Found in moderate to dry climate zones, trees that shed leaves annually.
	Degraded woodlands. These are places where human encroachment, overgrazing, or deforestation have caused forests to decline.
Wetlands and	Mangroves, swamps, and littoral Biodiversi-ty and climate control depend on
water bodies	coastal and interior wetland areas. And inland wetland regions are crucial for biodiversity and cli-mate regulation.
Water bodies (maximum and minimum spread)	All of which show changes in water avail-ability, this category includes seasonal and perennial lakes, reservoirs, and rivers.
Grasslands and wastelands	Grasslands . Often utilized for grazing and ecological preservation, open land ruled by natural or cultivated grasses.
	Wastelands. Wastelands are deteriorated lands that are unfit for farming, including rocky, sandy, or barren places with scarce vegetation.

Table 1: Different Land Cover Kinds

Preprocessing of Data

Data cleaning was done first to eliminate duplicate and missing records and to handle missing data using interpolation techniques like forward-fill and linear interpolation. Moving average techniques were used to smooth the variability in satellite derived data in order to improve the visualization of LULC patterns.

Random Forest Regression

Operating as an ensemble of decision trees, A method of machine learning is random forest regression. A many tree trained on several dataset components, their forecasts aggregated to generate a final output, decision tree regression was extended by Random Forest Regression. Using the "wisdom of crowds" method, this strategy increases generalization and decreases overfitting. Every tree in the forest was constructed from a random choice of data points and features, hence guaranteeing variation in the model. Averaging the outputs of all trees produces the last prediction; hence Random Forest Regression was very accurate and robust for forecasting continuous numerical values, such land use and land cover changes over time.

Random Forest Prediction (Final Output)

Each tree in the forest made a prediction \hat{y}_{i} , and equation (1) used to find the final prediction was the average of all tree outputs.

$$\widehat{y_{\text{final}}} = \frac{1}{T} \sum_{i=1}^{T} \widehat{y_i} \qquad \dots (1)$$

Where T = Number of decision trees in the forest and $\hat{y}i$ = Prediction from each tree.

Predicting continuous values is done using a nonparametric supervised learning technique called Decision Tree Regression. At every stage, it recursively divides the dataset into smaller areas, hence reducing the Mean Squared Error (MSE). The last forecast is based on the average of the target values in every area.

Equation (2) gives the mean value of the target variable y as

$$\overline{y} = \frac{1}{N} \sum_{i=1}^{N} y_i \qquad \dots (2)$$

yi= Target value for each data point, N = Total number of data points

Equation (3) measures the Mean Squared Error (MSE) gives the variance within a region before and after splitting

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2 \qquad ...(3)$$

Yi = Actual target value, y⁻ = Mean of target values in the region. To evaluate a potential split, equation (4) computes the weighted MSE as

$$MSE_{split} = \frac{N_{left}}{N}MSE_{left} + \frac{N_{right}}{N}MSE_{right} \qquad ...(4)$$

 N_{left} , N_{right} = Number of data points in left and right nodes, MSE_{left}, MSE_{right} = MSE of left and right child nodes

Rolling Prediction Approach Using Random Forest Regression.

Predicting land use and land cover (LULC) changes in Tamilnadu, India, throughout the years from 2018 to 2028, this paper used Random Forest Regression's recursive rolling prediction technique. Initially trained on historical data from 2005 to 2017 in Tamilnadu, India, the model forecasts LULC for 2018 in Tamilnadu, India. The dataset is then filled with the projected LULC values for the year 2018, and the model is retrained to forecast LULC for the year 2020 in Tamilnadu, India. Ensuring a progressive estimation of future land cover changes, this iterative procedure carries on using both real historical data and prior forecasts. Figure 1 shows a schematic depiction of the methodological framework applied in this investigation.

To check if the suggested Random Forest model is correct, we calculate prediction accuracy, mean absolute error (MAE), and correlation coefficient (R), accuracy percentage for the years where we have real data, like 2018, 2020, 2021, 2022, and 2023. This validation ensures reliability before making longterm predictions for 2024–2028. Before projecting long-term for 2024–2028, this validation guarantees dependability. Interpretation is helped by visualizations such projected LULC distributions, pie charts, and bar charts for actual vs. expected values. While reducing independent annual estimation errors, this stepwise prediction technique offers a systematic way to examine future LULC changes.



Fig. 1: Methodology for Predicting Land Use and Land Cover in Tamilnadu, India.

Mean Absolute Error

Ignoring direction, equation (5) gives the Mean Absolute Error (MAE) measures the average size of discrepancies between projected and actual values. It offers a clear way to gauge how near predictions are to actual observations. A lesser MAE indicates a more accurate model.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Y_{\text{actual},i} - Y_{\text{predicted},i}| \qquad \dots (5)$$

Where, n = Total number of observations , $Y_{predicted,I}$ = Predicted land cover value for the i-th observation and $Y_{actual,i}$ = Actual land cover value for the i-th observation.

Accuracy

Regarding land use and land cover forecasting, The accuracy provided by equation (6) is the percentage of valid model predictions for the actual data. It provides a broad evaluation of how well the model reflects the observed LULC trends. A high accuracy % shows that the projections of the model closely match the real land cover changes, hence enabling it to estimate future trends. On the other hand, low accuracy indicates notable forecast mistakes that call for model changes.

Accuracy =
$$(1 - \frac{\Sigma |Y_{actual} - Y_{predicted}|}{\Sigma Y_{actual}})X 100$$
 ...(6)

Where Y_{actual} = Actual land cover values and Ypredicted= $_{Predicted}$ land cover values

Kappa Coefficient

The Kappa coefficient is a statistical measure of agreement between the predicted land cover classes and the actual observed data in the context of land use and land cover (LULC) prediction; it also considers the agreement that could arise by chance. Unlike simple accuracy, which only considers the proportion of correct predictions, equation (8) gives the Kappa coefficient provides a more rigorous evaluation of model performance, particularly in cases where class distributions are imbalanced.

$$\kappa = \frac{P_o - P_e}{1 - P_e} \times 100 \qquad \dots (7)$$

Where

- P_o = Observed agreement (i.e., the proportion of correctly predicted land cover types)
- P_e = Expected agreement by chance (calculated

based on the distribution of predictions and actual values)

A high Kappa value shows a substantial agreement between the expected and actual classifications, signifying that the model performs well beyond random chance. On the other hand, a low or negative Kappa score indicates that the predictions of the model are not consistently better than random guessing, and improvements are needed to enhance classification quality.

Producer's Accuracy

Producer's Accuracy is calculated using Equation (8), which measures the classifier's ability to accurately identify instances in the real (ground truth) data belonging to a certain class. It computes the proportion of accurately forecasted cases for a particular class relative to the total number of cases of that class in the actual data.

"Producer's Accuracy= True Positives for Class /Total Actual Instances for Class ×100(8)

Where

- True Positives for Class: The number of data points that belong to a specific class and are correctly predicted as that class.
- Total Actual Instances for Class: The actual number of data points belonging to that class the ground truth.

User's Accuracy (for data)

User's Accuracy, as defined by Equation (9), is the capacity of the classifier to accurately forecast a particular class when it designates that class to a data point. It computes the proportion of correct predictions for a particular class relative to the total number of cases forecasted as that class.

User's Accuracy=True Positives for Class /Total Predicted Instances for Class" ×100 ...(9)

Where

- True Positives for Class: The amount of data points accurately forecasted to fit a certain class.
- Total Predicted Instances for Class: The total amount of data points the classifier predicted would belong to that class.

Implementation Using Python

Python was used for all data processing, model training, and visualization in this work. Data processing was done using Pandas, visualisation using Matplotlib and Seaborn, and machine learning-based forecasts using Scikit Learn. Python scripts streamlined the whole process from data preparation to accuracy assessment, hence guaranteeing consistency and reproducibility.

In order for machine learning algorithms to process LULC datasets efficiently, categorical labels like "Forest," "Urban," "Agriculture," or "Water Bodies" must be transformed into numerical values. Categorizing numerical values (for example, "Forest" \rightarrow 0 and "Urban" \rightarrow 1)

The class distributions in LULC datasets are frequently unbalanced, with some land categories (like urban areas) having an overrepresentation and others (like wetlands or forests) having an underrepresentation. Assign higher weighing to minority classes like forest and wetland to reduce bias toward majority land categories in LULC models

Results

Empirical Analysis of Land Use and Land Cover Comparing actual and projected Land Use and Land Cover (LULC) values for various land in Tamilnadu, India, for the years 2018, 2020, 2021, 2022, and 2023 is shown in Fig. 2

With projected values in most cases nearly matching actual values, the model efficiently reflects LULC distribution across several categories. The minor differences imply that the Random Forest Regression model is consistent in forecasting significant LULC changes.

Model Performance Evaluation

The performance of the Random Forest Regression model was assessed using an empirical analysis of Land Use and Land Cover (LULC) data of Tamilnadu, India, from 2018 to 2023. Predictions' correctness was confirmed by means of the Correlation Coefficient (R), Mean Absolute Error (MAE), and correctness. Table 2 summarizes the predictive accuracy of the Random Forest model.

The model's performance, assessed using the Mean Absolute Error (MAE), Correlation Coefficient (R), and Accuracy (%), shows notable increases in prediction dependability. While the declining MAE implies improved accuracy, a greater R-value shows a significant correlation between actual and anticipated values. The rising accuracy rate emphasizes the model's increasing capacity to capture LULC trends.

Year	Correlation Coefficient (R)	Mean Absolute Error (MAE)	Accuracy (%)	Kappa Coefficient	Producer's Accuracy (%)	User's Accuracy (%)
2018	0.75	3.220	62.858	0.667	64.52	70.24
2020	0.96	1.864	78.502	0.833	87.32	96.41
2021	0.969	1.286	85.172	0.823	65.77	82.33
2022	0.986	1.201	86.144	0.919	81.5	98.32
2023	0.979	1.039	88.018	0.893	83.69	87.23

able 2: Random	Forest model's	predictive	accuracy
----------------	----------------	------------	----------

The accuracy for the year 2018 was relatively low and improved in later years by Rolling Forecast Method. Regularly revising the forecast as new data becomes available, the Rolling Forecast Method is a continuous forecasting technique that uses historical data to project fu-ture performance over a given period. User accuracy, producer accuracy, and the kappa coef-ficient calculated on referenced data were used to examine the accuracy of the identified LULC. The Kappa statistics shows that the strong agreement between the predicted LULC and the actual data of Tamilnadu, India, from 2018 to 2023. Producer's Accuracy (PA) shows that LULC categories (e.g., urban areas, wetland, forest) are correctly classified and User's Accuracy shows reliability of predicted LULC for each class.



Fig. 2: Comparing actual and predicted LULC values for different land categories in Tamilnadu, India, for the years 2018, 2020, 2021, 2022, and 2023.

The consistent improvement across these measures verifies the strength of the Python-based machine learning approach. The reduction in Mean Square Error and rise in Accuracy percentage indicate effective data preprocessing and model optimization.

These results validate the Random Forest model's reliability for LULC forecasting. Further enhancements, such as incorporating additional spatial and temporal data, could further im-prove prediction accuracy. The approach ensures a strong foundation for future land use analysis.

Future LULC Predictions in the years from 2024 to 2028

The future Land Use and Land Cover (LULC) forecasts in Tamilnadu, India, for the years from 2024 to 2028 have been generated by means of a Pythonbased machine learning ap-proach combining historical LULC patterns with advanced predictive modeling techniques. These forecasts provide critical insights into expected land cover transformations, aiding urban planning, environmental management, and sustainable land use strategies. Table 2 below pre-sents the predicted LULC values for different land categories of Tamilnadu, India, from the year 2024 to 2028.

These projections highlight possible changes in agricultural land, urban expansion, forest cover, and water bodies in Tamilnadu, India, supporting decision making for sustainable development and conservation efforts.

Future LULC Distribution

Pie charts for each projected year from 2024 to 2028 have been produced to help one see these LULC variations over time. Figure 3 shows the percentage contribution of every LULC category, hence enabling a better knowledge of land cover changes and possible future trends in Tamilnadu, India. These visualizations assist in spotting patterns and trends in land cover changes, which are vital for environmentalists, urban planners, and legislators in making educated choices. Predictive accuracy can be improved by further modifications, including remote sensing data, socio-economic considerations, and climatic variables, therefore offering more in-depth knowledge of future land use possibilities.

 Table 2: predicted LULC values (in hectares) for different land categories in Tamilnadu,

 India, from the years 2024 to 2028

LULC Category (L ha)	2024	2025	2026	2027	2028
Built-up	6.13	6.13	6.131	6.132	6.133
Kharif Crop	11.734	11.677	11.677	11.67	11.635
Rabi Crop	17.87	18.079	18.224	18.334	18.45
Zaid Crop	0.982	0.98	0.989	0.993	0.987
Double/Triple/Annual Crop	34.21	34.11	33.98	33.863	33.805
Current Fallow	15.623	15.62	15.61	15.61	15.59
Plantation/Orchard	10.08	10.071	10.076	10.081	10.079
Evergreen/Semi-Evergreen woodland	5.516	5.516	5.516	5.516	5.516
Deciduous woodland	15.389	15.385	15.38	15.38	15.39
Degraded woodland	1.307	1.305	1.303	1.303	1.303
Littoral/Swamp/ Man-groves	0.082	0.082	0.082	0.082	0.082
Grassland	0.649	0.648	0.646	0.645	0.64
Wasteland	4.043	4.038	4.037	4.039	4.045
Waterbodies max spread	5.256	5.271	5.266	5.264	5.278
Waterbodies min spread	1.186	1.15	1.13	1.121	1.119

Predicted LULC Distribution for 2024





Predicted LULC Distribution for 2025





Predicted LULC Distribution for 2026





- Double/Triple/Annual Crop (L ha) 26.1%

Predicted LULC Distribution for 2027





Fig. 3: Predicted LULC Distribution in Tamilnadu, India for the years 2024, 2025, 2026, 2027 & 2028

Discussion

The LULC shift two-decade study in Tamil Nadu reveals notable urban area growth and fallow landscape monotonicity as well as a considerable drop in farmland and plantation agriculture landforms. Most of these changes result from individuals migrating from the rural areas to the towns in Tamil Nadu, particularly Chennai, Coimbatore, Trichy, and Madurai, seeking employment by abandoning their own estates, hence making agricultural lands barren and comparable owing to high demand. Urbanfringes are sold and mapped, therefore generating settlements that cause urbanization.⁴⁶ When compared to earlier studies. Liping *et.al*,¹ found the trends in Tamil Nadu

are in line with patterns of urbanization and land abandonment seen in China and Nepal, where land use is being reshaped by population increases, urbanization, agricultural expansion, and climate change. Effective land resource management and planning depend on monitoring and forecasting these shifts. Rapid urban expansion sometimes turns agricultural land and woods into built regions, consequently upsetting ecological balance and food supply. Sustainable land management policies so rely on exact projections of LULC trends. As remote sensing and machine learning techniques have advanced, predictive modeling has been a helpful tool for analyzing LULC trends. This paper aims to predict future LULC changes by ap-plying the RF model using historical LULC patterns in Tamil Nadu from the year 2005 to 2023. Classification accuracy is evaluated using Producer's Accuracy, User's Accuracy and Kappa coefficient, Comprising first forecasting LULC from the year 2018 to 2023 and verify-ing it against actual data, and second projecting LULC from the year 2024 to 2028 across Tamilnadu. GIS tools allow spatial data processing, hence allowing high accuracy display and modeling of LULC changes. This paper investigates how well the Random Forest (RF) classifies land cover in the Tamilnadu. By including satellite-based LULC data from the National Remote Sensing Centre (NRSC), this work serves to enhance land-use planning and environ-mental protection initiatives.

Conclusion

The findings show notable urban development, a steady drop in double/triple cropping areas, stable but slightly declining forest cover, and water body spread oscillations. A Random Forest Regression model for forecasting Land Use and Land Cover (LULC) changes in Tamil Nadu, India, was trained and validated using satellite data from the National Remote Sensing Centre (NRSC) between 2005 and 2023, therefore attaining great accuracy with a correlation coefficient (R > 0.97) and lowering Mean Absolute Error (MAE). Results indicated signifi-cant urban development, a decline in double/triple cropping areas, slightly diminishing forest cover, and fluctuating water body spread, reflecting the impacts of urbanization, agricultural practices, and environmental shifts in Tamilnadu. Strict governmental policies should be fol-lowed to minimize the consequences of landform change since it is beyond control in poor countries to convert agricultural or forest land into impermeable layers. Some initiatives, like the Conversion of Cropland to Forest Program (CCFP), can be implemented in line with this one; farmers who take part in these programs may get subsidies. These programs can benefit communities that are moving to urban areas for a variety of reasons and gaining more ecosys-tem values. These findings provide crucial insights for environmentalists, urban planners, and policymakers, supporting sustainable land management and climate adaptation strategies in Tamil Nadu. Future research should incorporate climate factors (rainfall, temperature) and socioeconomic data (population growth, economic development) to better capture human-driven LULC changes and improve predictive accuracy. Also, using deep learning techniques like CNN, LSTM, and ensemble learning, along with advanced GIS spatial analysis and heatmap visuals, can improve predictions and spot areas at high risk for urban growth or de-forestation, helping make better decisions for sustainable land use and protecting the environment.

Acknowledgement

This research was made possible by my student Chandirasekar Kamalakannan, Master of Mathematics, Anna University, Chennai, Tamilnadu, India. I would like to thank my student Chandrasekar. K., who worked and generously shared their ideas with me.

Funding Sources

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Conflict of Interest

The authors do not have any conflict of interest.

Data Availability Statement

satellite-derived data from the National Remote Sensing Centre (NRSC)

Ethics Statement

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not re-quired.

Permission to Reproduce Material from other sources

Not Applicable

Author Contributions

- Akila Rajamanickam: Funding Acquisition, Resources, Supervision, Review & Editing, Visualization, Supervision, Project Administration
- Chandirasekar Kamalakannan: Conceptualization, Methodology, Writing – Original Draft, Data Collection, Analysis, Writing.

References

- 1. Liping C., Yujun S., Saeed S. Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—a case study of a hilly area, Jiangle, *China. PLOS ONE.* 2018;13(7).
- Turner BL., Meyer WB., Skole DL. Global land-use/land-cover change: towards an inte-grated study. *Environmental Science*. 1994;1(2):123-145.
- Arfasa GF., Owusu-Sekyere E., Doke DA. Predictions of land use/land cover change, drivers, and their implications on water availability for irrigation in the Vea catchment, *Ghana. Geocarto Int.* 2023;38(1):1-23.
- 4. Long H., Tang G., Li X., Heilig GK. Socioeconomic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. *Journal of Environmental Management.* 2007;83(3):351-364.
- Mark M., Kudakwashe M. Rate of land-use/ land-cover changes in Shurugwi district, Zim-babwe: drivers for change. *Journal* of Sustainable Development in Africa. 2010;12(3):107-121.
- Mishra V., Rai P., Mohan K. Prediction of land use changes based on land change modeler (LCM) using remote sensing: A case study of Muzaffarpur (Bihar), India. *Journal of the Geographical Institute*. 2014;64(1):111-127.
- Prakasam C. Land use and land cover change detection through remote sensing approach: A case study of Kodaikanal taluk, Tamil Nadu. Advances in Remote Sensing. 2010;15(3):45-60.
- Ali D., Hussain A., Begum F. Assessing the impact of land use and land cover changes on soil properties and carbon sequestration in the upper Himalayan region of Gilgit, Pakistan. *Environmental Chemistry One World*. 2025;5:100038.
- Zhang L., Qu W., Li X., Du H. Effect of land use and land cover change on ecosystem service value of Northeast Sandy Land in China. Sustainability. 2025;17(1):167.
- Foley JA., DeFries R., Asner GP., Barford C., Bonan G., Carpenter SR. Global consequences of land use. *Ecosystem Studies*. 2005;12(4):570-574.

- 11. Jahanbakhsh M., Esmaeily A., Pour AB. Spatio-temporal assessment of land use and land cover dynamics in Urmia lake basin of Iran: A bi-directional approach using optical and radar data on the Google Earth Engine platform. *Advances in Space Research*. 2025;17(3):1299-1313.
- 12. Bisht BS., Kothyari BP. Land-cover change analysis of Garur Ganga watershed using GIS/remote sensing technique. *Indian Remote Sensing Journal.* 2001;29(3):137-141.
- 13. Zeng L., Yang L., Su L., Hu H., Feng C. The impact of policies on land use and land cov-er changes in the Beijing–Tianjin–Hebei region in China. *Environmental Impact Assessment Review.* 2025;110:107676.
- 14. Lambin EF., Turner BL., Geist HJ., Agbola SB., Angelsen A., Bruce JW. The causes of land-use and land-cover change: moving beyond the myths. Global *Environmental Change*. 2001;11(4):261-269.
- 15. Nuthammachot N., Ali MZ. Comparative study of multiple algorithms classification for land use and land cover change detection and its impact on local climate of Mardan dis-trict. *Environmental Challenges*. 2025;18:101069.
- Singh A. Review article digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing. 1989;10(6):989-1003.
- Ermida SL., Soares P., Mantas V., Göttsche FM., Trigo IF. Google earth engine opensource code for land surface temperature estimation from the landsat series. *Remote Sensing.* 2020;12:1471.
- Padmanban R., Painho M. Urban agentbased model of urban slum Dharavi, Mumbai, In-dia. *Journal of Earth System Science and Engineering*. 2017;2:1110.
- Dandona L., Dandona R., John RK., McCarty CA., Rao GN. Population-based assess-ment of uveitis in an urban population in southern India. *British Journal of Ophthalmology*. 2000;84:706-709.
- Anees MM., Shukla R., Punia M., Joshi PK. Assessment and visualization of inherent vul-nerability of urban population in India

to natural disasters. Climate Development. 2020;12(2):532-546.

- Wu DCN., Banzon EP., Gelband H., Chin B., Malhotra V/, Khetrapal S. Healthcare in-vestments for the urban populations, Bangladesh and India. *Bulletin of the World Health Organization*. 2020;98(1):19-29.
- Anuradha B., Iyappan L., Partheeban P., Jaganmogan K., Hariharasudan C., Palanikumar K. Statistical study on area cultivated in peri-urban and rural tanks during pre and post re-habilitation. *International Journal of Agricultural Statistics Science*. 2020;16:883-888.
- 23. Mohanraj R., Sathishkumar M., Azeez PA., Sivakumar R. Pollution status of wetlands in urban Coimbatore, Tamil Nadu, India. *Bulletin of Environmental Contamination and Toxicology.* 2000;64:638-643.
- 24. Kiruthiga K., Thirumaran K. Effects of urbanization on historical heritage buildings in Kumbakonam, Tamil Nadu, India. *Frontiers* of Architectural Research. 2019;8(2):94-105.
- Ologunde OH., Kelani MO., Biru MK., Olayemi AB. Land use and land cover changes: A case study in Nigeria. *Land.* 2025;14(2):389.
- Sala OE., Chapin FS., Armesto JJ., Berlow E., Bloomfield J., Dirzo R. Global biodiversity scenarios for the year 2100. *Biodiversity Studies*. 2000;287(5459):1770-1774.
- Raguraman N., Bhardwaj A. Spatial analysis of land use land cover dynamics in the Madurai District using Sentinel-2 Data and supervised learning algorithms. International Ar-chives of Photogrammetry, *Remote Sensing, and Spatial Information Sciences*. 2024;4:367-372.
- Adeniyi PO., Omojola A. Landuse/landcover change evaluation in Sokoto-Rima basin of NW Nigeria based on archival remote sensing and GIS techniques. *Remote Sensing and GIS Applications*. 1999;8(2):87-93.
- 29. Dhinwa PS., Pathan SK., Sastry SVC. Land use change analysis of Bharatpur district using GIS. *Indian Society of Remote Sensing Journal.* 1992;20(4):237-250.
- Xiaomei Y., RongQing LQY. Change detection based on remote sensing information model and its application to the Yellow River Delta's coastal line. *Earth Observation*. 1999;5(1):77-85.

- 31. Pal M. Random forest classifier for remote sensing classification. *International Journal of Remote Sensing*. 2005;26(1):217-222.
- 32. Javed A., Khan I. Land use/land cover change due to mining activities in Singrauli indus-trial belt, Madhya Pradesh using remote sensing and GIS. *Journal of Environmental Re-search and Development*. 2012;6(3A):122-134.
- Vinayak B., Lee HS/, Gedem S. Prediction of land use and land cover changes in Mumbai City, India, using remote sensing data and a multilayer perceptron neural networkbased Markov chain model. *Sustainability*. 2021;13(2):471.
- Turner BL.;, Lambin EF., Reenberg A. The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences.* 2007;104(52):20666-20671.
- 35. Abijith D., Saravanan S. Assessment of land use and land cover change detection and prediction using remote sensing and CA Markov in the northern coastal districts of Tamil Nadu, India. *Environmental Science and Pollution Research*. 2022;29:86055-86067.
- Sushmitha S., Chandrashekara B. Temporal evolution of land use patterns in Tamil Nadu: A satellite-based analysis. *GEO-EYE*. 2023;12(2):49-53.
- Shamsudeen M., Padmanaban R., Cabral P., Morgado P. Spatio-temporal analysis of the impact of landscape changes on vegetation and land surface temperature over Tamil Nadu. *Earth.* 2022;3(2):614-638.
- Kamaraj M., Rangarajan S. Predicting the future land use and land cover changes for Bha-vani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin. *Environmental Science and Pollution Research*. 2022;29:86337-86348.
- Arulbalaji P. Analysis of land use/land cover changes using geospatial techniques in Salem district, Tamil Nadu, South India. SN Appl Sci. 2019;1:462.
- 40. Tariq A., Shu H. CA-Markov chain analysis of seasonal land surface temperature and land use/land cover change using optical multi-temporal satellite data of Faisalabad, Pakistan. *Remote Sens.* 2020;12:3402.

- 41. Cabral P., Feger C., Levrel H., Chambolle M., Basque D. Assessing the impact of landcover changes on ecosystem services: A first step toward integrative planning in Bordeaux, France. *Ecosyst Serv.* 2016;22:318–327.
- Kiruthiga K., Thirumaran K. Effects of urbanization on historical heritage buildings in Kumbakonam, Tamil Nadu, India. *Front Archit Res.* 2019;8:94–105.
- GEE EarthEngine Data Catalog. Available online: https://developers.google.com/earthengine/datasets/catalog/ (accessed on 4 January 2020).
- 44. Geist H., McConnell W., Lambin EF., Moran E., Alves D/, Rudel T. Land-Use and Land-Cover Change. Springer. 2006;Berlin Heidelberg, Germany.
- 45. Indian Geo Platform of ISRO. Available online: https://bhuvan-app1.nrsc.gov.in. Pub-lished February 21, 2025. Accessed February 21, 2025.
- Balk D., Montgomery MR, Engin H., Lin N, Major E., Jones B. Urbanization in India: Population and urban classification grids for 2011. *Data*. 2019;4:35.