

GEOSPATIAL AND MACHINE LEARNING TECHNIQUES FOR SPATIOTEMPORAL ANALYSES OF URBAN DYNAMICS IN THE COIMBATORE CITY, SOUTH INDIA

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Highlights:

- Study of urban expansion of Coimbatore city during 2001 to 2023 using multi-temporal Landsat imagery;
- Quantification of environmental impacts of urbanization by integrated analyses of LULC, LST, NDVI, NDWI, and NDBI;
- ANN-CA modelling was used to forecast the future land use/land cover changes and urban expansion for 2031;
- The findings are useful to promote sustainable urban planning and climate-resilient urban development in Coimbatore.

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Abstract. Rapid urbanization has drastically changed the land use and environmental conditions in Indian cities and need to be monitored continuously for sustainable urban planning. The study used Landsat satellite images of the years 2001, 2013 and 2023 to examine the spatiotemporal urban dynamics of the Coimbatore city of South India. The impacts of urban sprawl on the environment were evaluated from Land Use/Land Cover (LULC), Land Surface Temperature (LST) and spectral indices (NDVI, NDWI and NDBI). The built-up land increased by 1.21% (2001–2013) and 1.67% (2013–2023) and agricultural land decreased by 1.62% (2013–2023). The LULC classification had an Overall Accuracy of 95.76% with a Kappa coefficient of 0.95. The Kappa coefficient of 0.96 indicates that the ANN-CA model has high predictive reliability in predicting the LULC scenario in 2031. The results show that the continued expansion of cities leads to an increase in land surface temperature and a decrease in vegetation cover. This has major implications for sustainable urban development and contributes to SDG 11 and SDG 13.

Keywords: urban dynamics, Land Surface Temperature (LST), Land Use/Land Cover (LULC), spatiotemporal analysis, geospatial technology, spectral indices, ANN-CA model, Coimbatore city.

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1. Introduction

The urban population of the world has increased from 751 million in 1950 to 4.2 billion in 2018, posing great challenges and opportunities for environmental sustainability, urban planning and climate resilience. Rapid growth is more significant in developing countries like India, where urban growth can be very high without strategic planning (Singh et al., 2017). Urbanization is a complex business, and requires sophisticated methods of analysis and intervention. Geospatial technologies such as remote sensing and Geographic Information Systems (GIS) are indispensable tools to address these issues, monitoring urban sprawl, land use change and their environmental impacts. These technologies provide a comprehensive understanding of the spatial and temporal dimensions of urbanization and thus provide opportunities for specific and targeted actions towards sustainable urban development (Du et al., 2017). LST is one important variable in urban

climate study reflecting the complex interaction of urban structures, land cover and atmospheric conditions. LST is higher over urban areas, dry soils, roads, infrastructure and relatively lower over water bodies, wetlands, forests, grasslands, scrublands and cultivated lands (Guha & Govil, 2025). Accurate estimation of Land Surface Temperature (LST) and useful information on Urban Heat Island (UHI) effect and its relation to land cover change can be obtained from multispectral and thermal infrared bands of Landsat imagery (Chen et al., 2013). Spectral indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI) have also been proven to be useful for urban mapping (Zha et al., 2003). In addition, NDVI is a good indicator for the cooling effect of vegetation cover on urban temperature (Bouhennache et al., 2019). NDWI is very useful for the quick and correct classification of surface features from the satellite data (Pandey et al., 2024a). Urban heat is generated by built-up surfaces

and NDBI is positively correlated with LST (Pandey et al., 2024b). These indices are used as proxies for vegetation, water bodies and urban build-up (Ambrose et al., 2019; Mallupattu & Sreenivasula Reddy, 2013). Therefore, they help in understanding the effect of these factors on Land Surface Temperature (LST) and urban thermal behaviour.

While the urban environment of large metropolitan cities has been studied in detail, medium-sized cities such as Coimbatore, Tamil Nadu are still underexplored, exposing a critical research gap in the understanding of the urban dynamics and thermal environment of medium-sized cities. Coimbatore, with its unique pattern of urbanization resulting from its rapid development as an industrial city and a mix of planned and unplanned development (Prabu & Dar, 2018) makes a perfect case to study urban environmental changes (Jothimani et al., 2021).

The present study fills this gap by providing a comprehensive spatiotemporal analysis of urban dynamics in Coimbatore through (1) assessment of urban growth patterns and land-use changes by using remote sensing and GIS techniques and (2) analysis of urban growth trends for different time periods and their implications for urban planning (Weng et al., 2004; Xu et al., 2016). The present study has been conducted to analyse the changes in LST and its relationship with NDVI, NDWI, and NDBI using geospatial technology over two periods (2001–2013 and 2013–2023).

Previous studies have mainly focused on retrospective analysis of LULC change; this research extends the investigation by incorporating an Artificial Neural Network-Cellular Automata (ANN-CA) model to forecast future urban growth scenarios. Simulation-based prediction can forecast spatial patterns of urban sprawl and this is of considerable value for policy formulation and planning for sustainable development. Such methodology not only helps in the comprehension of urban environmental dynamics but also enables the formulation of informed urban planning and sustainability strategies for other similarly situated urban environments (Dimiyati et al., 1996; Ghouri et al., 2022).

Unlike previous studies that primarily focused on historical LULC change detection or individual relationships between LST and spectral indices, this study integrates spatiotemporal LULC analysis, LST retrieval, NDVI, NDWI, and NDBI assessment, and ANN-CA-based future urban growth prediction within a unified framework. Furthermore, Coimbatore represents a rapidly expanding industrial city in South India where comprehensive integration of historical urban dynamics with predictive urban growth modelling remains limited. The study therefore provides a practical framework for sustainable urban planning and climate-resilient urban development (Guha et al., 2020; Guha & Govil, 2021)

2. Study area

Coimbatore is a busy city situated in the heart of Tamil Nadu in Southern India. It is well known for its industry, education, and technology. This city is affectionately called as located on the banks of the Noyyal River, surrounded

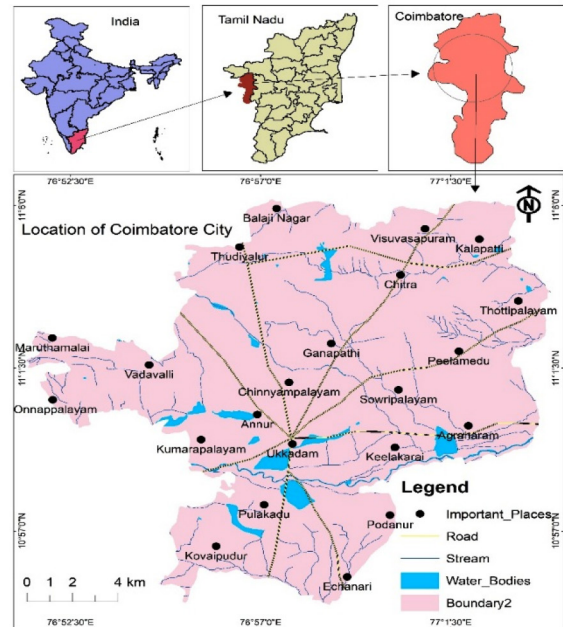


Figure 1. Location of Coimbatore Smart City

by the mighty Western Ghats, which give a picturesque setting to the bustling city life. Coimbatore is the second largest city of Tamil Nadu State after the capital city Chennai. Coimbatore has a big and fast-growing population with a steady growth rate annually. The population of Coimbatore is estimated to reach around 3,084,000 in 2024. Figure 1 illustrates the study area of the Coimbatore city.

Coimbatore is located at an average elevation of about 411 m above mean sea level and lies adjacent to the Western Ghats. The regional topography affects the local climate, wind flow, distribution of rainfall, and surface temperature, which in turn affects the distribution of vegetation, urban sprawl, and thermal characteristics in the study area.

The expansion of the metropolitan area of Coimbatore, including the city and its suburbs, is also an index of the energetic growth and expansion of the city, and therefore an important area of study for urban dynamics in Tamil Nadu. The city's elevation from the sea level coupled with its proximity to the Western Ghats leads to its unique climate and ecology, factors that are critical to the understanding of the spatial-temporal urban dynamics studied here.

3. Methodology

Figure 2 shows the methodological framework used in this study. Urban growth dynamics of coimbatore city using geospatial and machine learning algorithms. The USGS Earth Explorer portal provided multi-temporal Landsat satellite images from Landsat 7 ETM+ (2001) and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) (2013 and 2023). These datasets offer multispectral data at 30 m spatial resolution that allows for a consistent analysis of urban land-use changes over time.

Initially, the respective spectral bands were combined to create false-colour composite images. Then, the

boundary of the study area was extracted by using the clipping tool in ArcGIS. LULC maps for the selected years were generated using the Supervised Maximum Likelihood Classification (MLC) algorithm in ENVI 4.7. The MLC algorithm was chosen as it is one of the most popular supervised classification techniques for medium-resolution Landsat imagery and provides reliable classification performance when representative training samples are available. The classified images of built-up land, agricultural land, forest cover, fallow land, and water bodies were used to assess the spatial and temporal patterns of urban expansion.

The accuracy of the classified LULC maps was assessed by a confusion matrix approach using an independent set of reference samples. Prior to further analysis, ground truth and high-resolution reference images were used to evaluate the classification performance and validate the reliability of the produced LULC maps.

The Land Surface Temperature (LST) was estimated from Landsat thermal infrared bands applying the standard radiative transfer method. Digital numbers were converted to spectral radiance and the brightness temperature was computed. Thereafter, the land surface emissivity was calculated based on the Normalized Difference Vegetation Index (NDVI) to estimate LST for each of the study years.

To evaluate environmental features associated with urban expansion, three spectral indices were calculated: the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI), and the Normalized Difference Built-up Index (NDBI). NDVI was used to measure vegetation cover, NDWI was used to detect the distribution of surface water and NDBI was used to

delineate built-up areas. These indices were selected based on the fact that they collectively represent the dominant land surface characteristics influencing the urban thermal environment.

The spatial relationships between LST and the derived spectral indices were analysed using GIS-based spatial analysis to evaluate the influence of vegetation, water bodies and built-up surfaces on the thermal characteristics of the study area.

To simulate future urban growth, an Artificial Neural Network-Cellular Automata (ANN-CA) model was used. The ANN component was used to predict land-use transition potential from the historical LULC patterns, and the Cellular Automata component simulated neighbourhood interaction governing urban expansion. Historical LULC maps were used for model calibration and validation, and the calibrated model was used to project future LULC scenarios for the study area. Predicted patterns of urban growth were further analyzed to support sustainable urban planning and land-resource management.

3.1 Land Use/Land Cover (LULC)

Understanding the Land Use/Land Cover (LULC) patterns is important for analyzing the urban growth and environmental dynamics in Coimbatore. The quantitative data from the satellite imagery were obtained by supervised classification using the Maximum Likelihood Estimation (MLE) method; LULC). The area statistics of each LULC in square kilometers were noted in the attribute table, and the area was determined using ENVI 4.7 software. In ad-

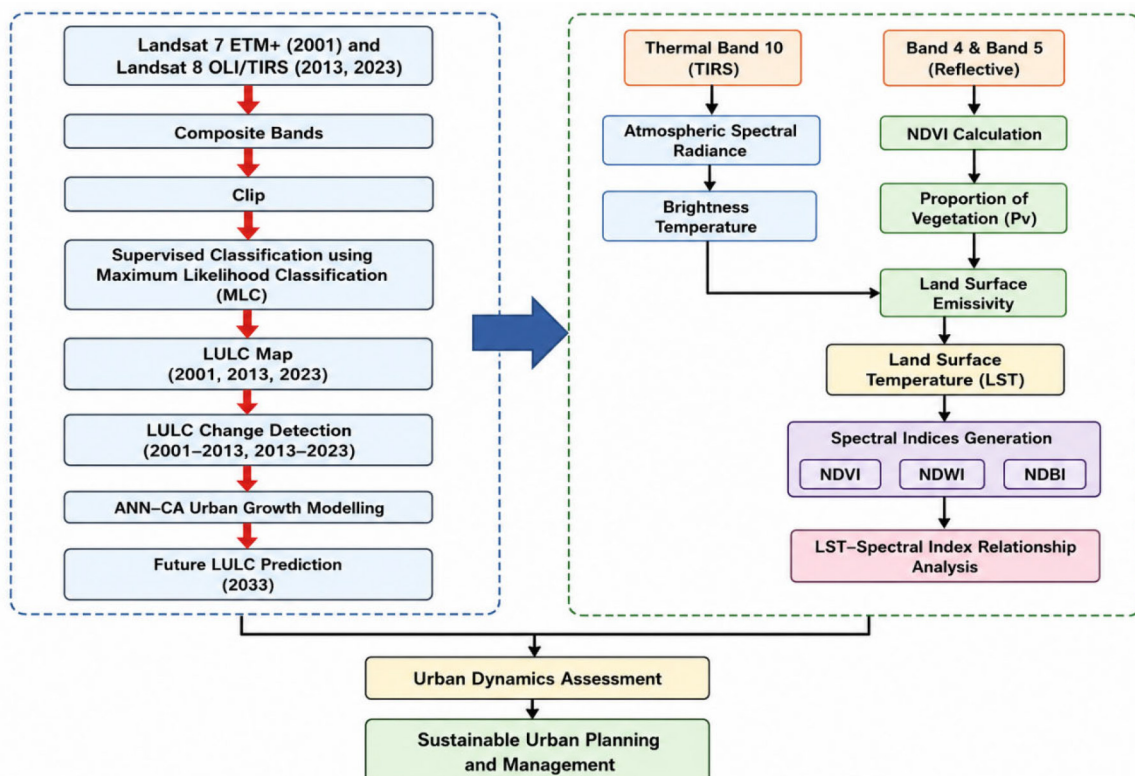


Figure 2. Methodology

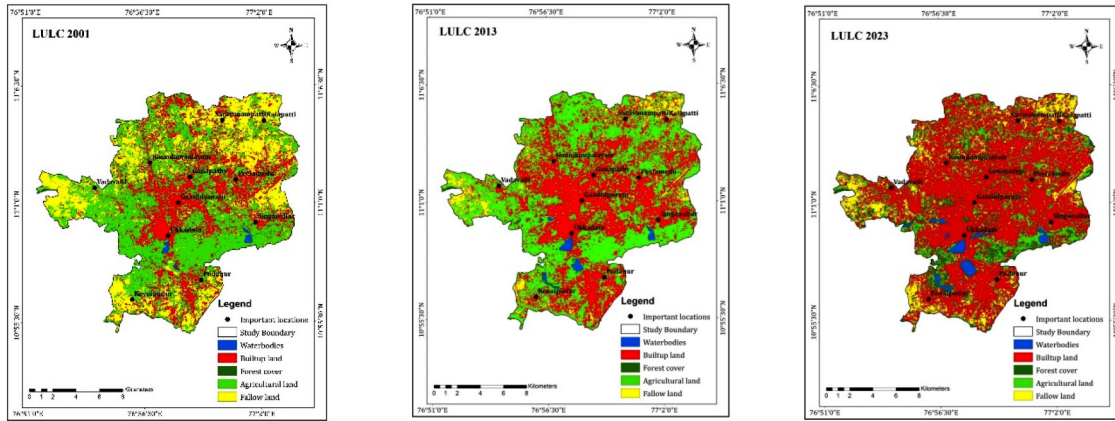


Figure 3. LULC map of the study area showing the land use and land cover distribution

dition, the ground truth verification method was used to ensure the accuracy of classification.

The Land Use and Land Cover (LULC) of the city in this study were classified into five classes, namely built-up land, agricultural land, forest cover, fallow land, and water bodies, as shown in Figure 3. The figure shows that built-up areas cover around 55% of the city, and agricultural land constitutes approximately 24% of the total area, reflecting the ongoing urbanization process and land-use changes in the region.

This temporal analysis was carefully checked in the field to validate the land use obtained from satellite images with the real land use observed. The concordance confirmed the reliability of the remote sensing analysis and showed a significant level of accuracy in the representation of LULC patterns of the study area.

3.1.1. Evaluation of performance

The supervised LULC classification was validated through accuracy assessment based on ground reference observations and high-resolution satellite imagery. The classified

land use categories were compared with the reference data using a confusion matrix. The overall accuracy of the classification was 95.76%, indicating a good agreement between the classified map and the reference observations. The Kappa coefficient was 0.95, indicating excellent performance of the classification and confirming the suitability of the classified LULC maps for further analyses such as LST estimation, spectral index analysis, and ANN-CA based urban growth prediction.

3.2. Derivation of NDVI

The NDVI is a crucial index for separating land cover types since it is responsive to changes in vegetation density and health (Kriegler et al., 1969). NDVI values range from -1.0 to 1.0. A value of -1.0 corresponds to bare surfaces and 1.0 corresponds to dense vegetation cover. The NDVI maps generated for the study area are shown in Figure 4.

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

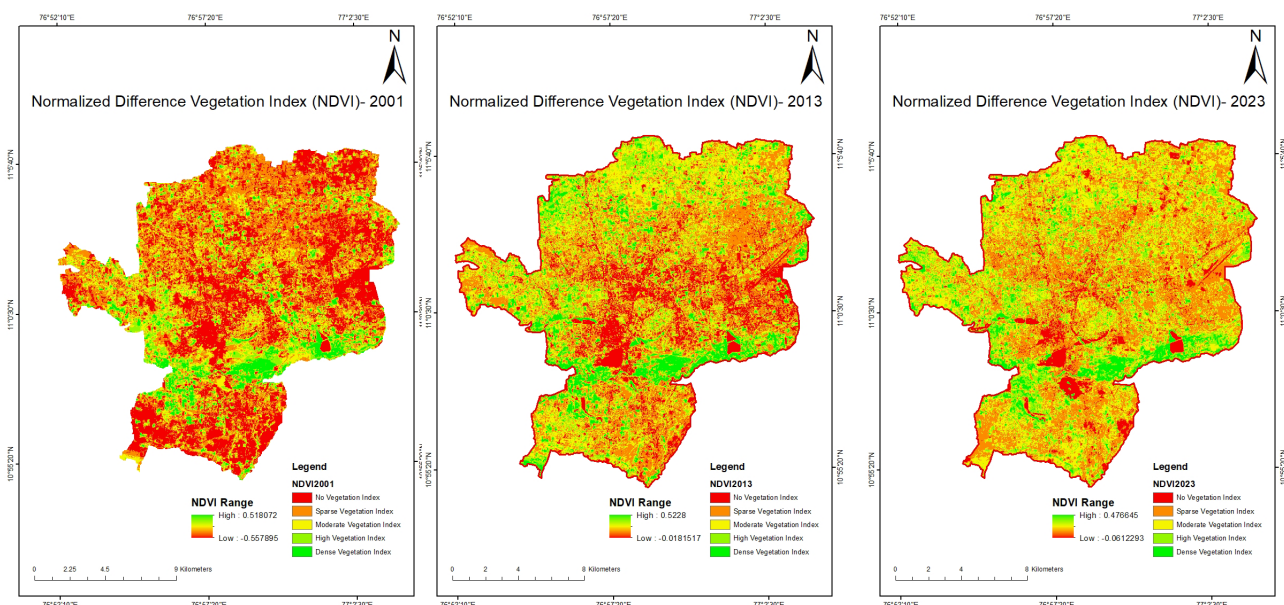


Figure 4. Normalized Difference Vegetation Index (NDVI) map of the study area showing vegetation distribution

where, 'NIR' refers to the near-infrared band (0.85–0.88 μm) and 'RED' refers to the red band (0.64–0.67 μm) of the Landsat image. The index is a good indicator of the vegetation health and coverage in the study area because it computes the normalized difference between the reflectance of the two bands on a per-pixel basis.

3.3. NDBI

In the analysis of urban growth and delineation of developed land, a variety of spectral indices are used extensively, as they can distinguish the various urban land uses. Urban research uses NDBI as an important indicator. Each index has its own formula and method to differentiate between the different land uses, i.e., built-up and barren land from vegetated and aquatic land.

Developed and barren areas tend to have more reflectance in the Short-Wave Infrared (SWIR) spectrum than the Near-Infrared (NIR) spectrum. This special reflective characteristic is important for urban object detection, because these regions tend to absorb more IR radiation. But water bodies have low reflectance in these infrared bands. This helps to separate water from urban and vegetated areas, which have higher NIR reflectance than SWIR reflectance. Spectral variations are important for mapping and analysis of urban regions, giving insight into their growth, density, and related environmental implications (Figure 5). Their relevance to urban studies lies in their capacity to offer quantitative assessments to support sustainable urban planning and management strategies.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (2)$$

where 'SWIR' refers to the shortwave-infrared band (1.57–1.65 μm) and 'NIR' refers to the near-infrared band (0.85–0.88 μm) of the Landsat image.

3.4. NDWI

NDWI is an important indicator to evaluate water bodies using Green and Near-Infrared (NIR) bands of remote sensing images. This index effectively enhances the detection of water features in different scenarios and the information thereof. However, its sensitivity to urbanized areas can sometimes lead to an overestimation of water bodies. The NDWI is derived from the following equation. The NDWI enhances the contrast between water and other land use categories and thus allows accurate mapping and analysis of water features. Figure 6 illustrates the NDWI of the study area.

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \quad (3)$$

where 'GREEN' refers to the green band (0.53–0.59 μm) and 'NIR' refers to the near-infrared band (0.85–0.88 μm) of the Landsat image.

3.5. Land Surface Temperature (LST)

The Land Surface Temperature (LST) was calculated from Landsat thermal infrared bands by the conventional radiative transfer method. The Digital Numbers (DN) of the thermal band were converted to Top of Atmosphere (TOA) spectral radiance using the radiometric rescaling coefficients given in the Landsat metadata. The TOA spectral radiance was converted to brightness temperature using the thermal conversion constants (K1 and K2) provided with the satellite data. The Normalized Difference Vegetation Index (NDVI) was also calculated for the red band (Band 4) and near-infrared band (Band 5) to assess the effect of land surface features on thermal emission. The NDVI values were then used to calculate the Proportion of vegetation (Pv), which was used to estimate the land surface emissivity. Finally, the Land Surface Temperature

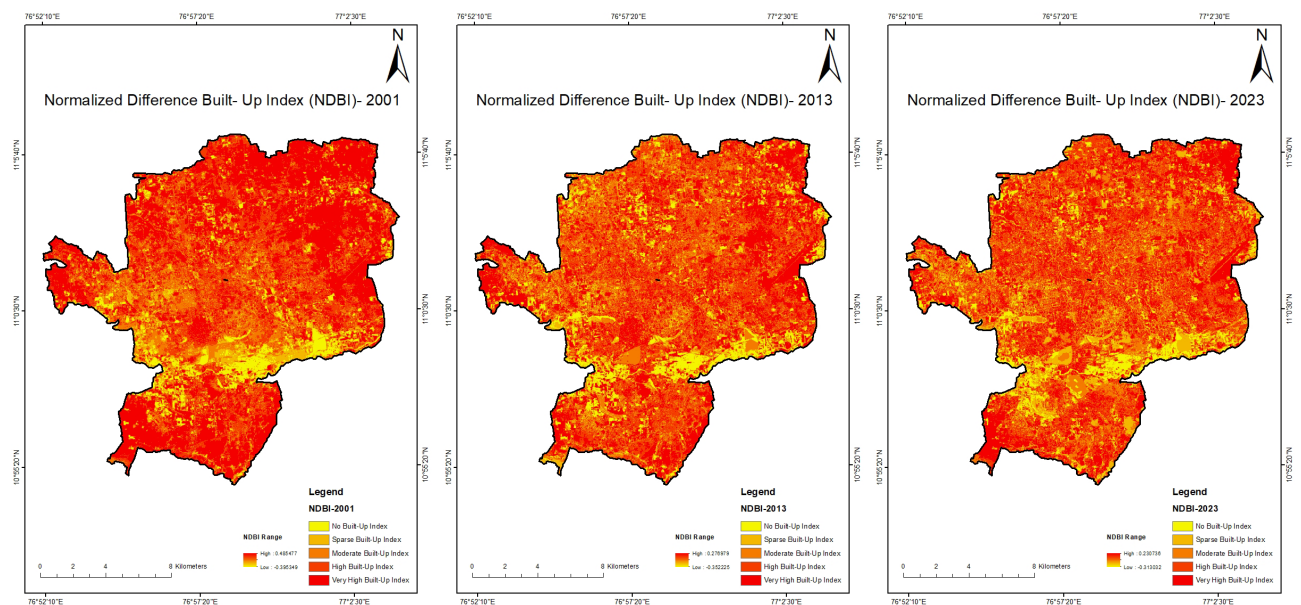


Figure 5. Normalized Difference Built-up Index (NDVI) map of the study area showing built-up area distribution

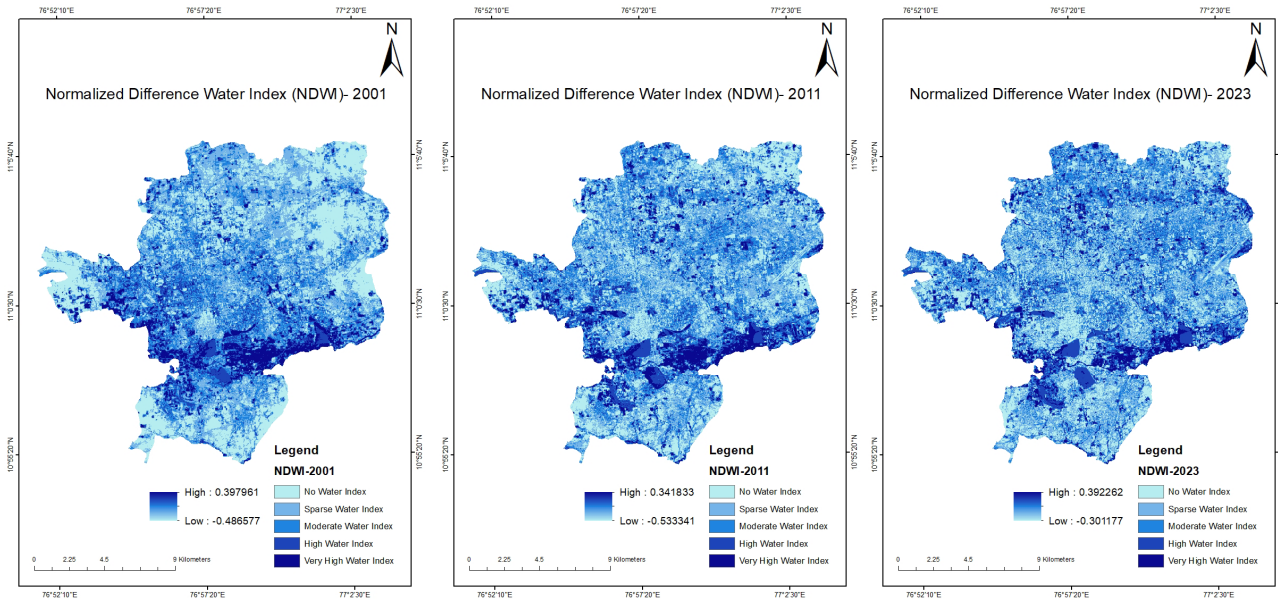


Figure 6. Normalized Difference Water Index (NDWI) map of the study area showing the distribution of water bodies

(LST) was retrieved by integrating the brightness temperature, surface emissivity and vegetation fraction, and a map of the spatial distribution of the surface temperature was generated for the study area. This methodology correctly captures the thermal response of different land cover types and allows the assessment of the urban heat variations associated with land-use and land-cover changes. Below Figure 7 shows that land surface temperature of the study area.

IST was derived from Landsat thermal data using the radiative transfer method. The DN values were initially converted to Top of Atmosphere (TOA) spectral radiance using sensor-specific rescaling factors. Then the TOA radiance was converted into brightness temperature in Kelvin. Later, the Proportion of vegetation (Pv) and surface emissivity (ϵ) were estimated from NDVI values to account for

the changes in land cover.

$$LST = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho} \right) \ln \epsilon} \quad (4)$$

The LST equation was computed for each pixel using the brightness temperature, emissivity (ϵ), radiative constant (ρ), and vegetation proportion as defined in Eq. (4) to produce a complete thermal map of the study area.

3.6. ANN-CA modelling of cellular automata and artificial neural networks

Future Land Use/Land Cover (LULC) changes were modeled using the Artificial Neural Network-Cellular Automata

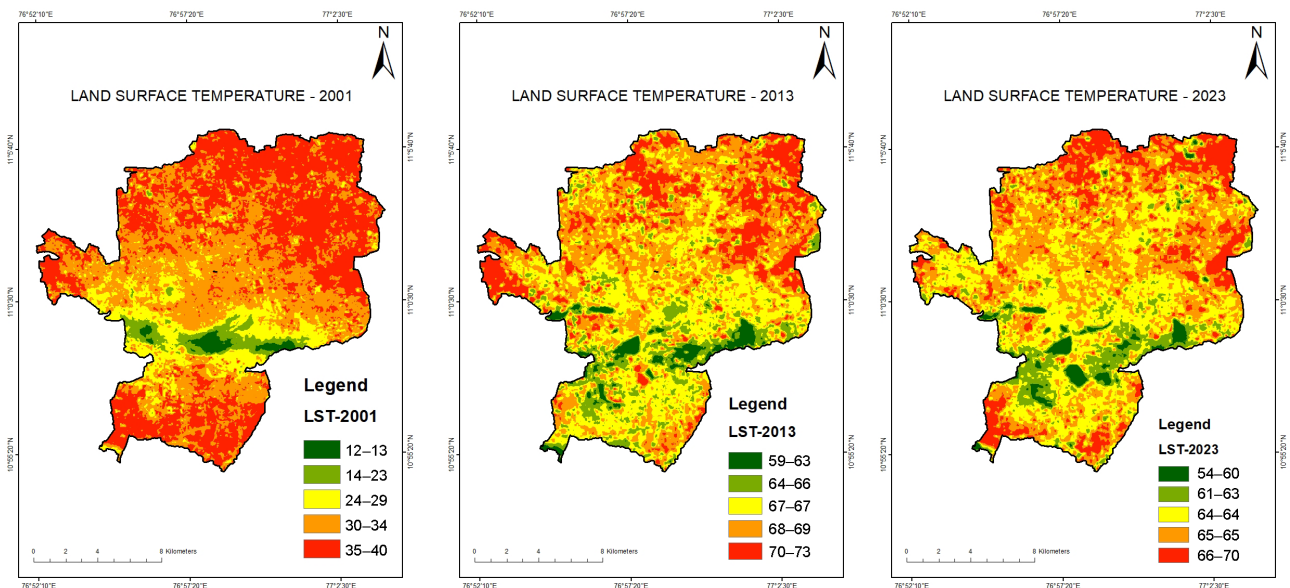


Figure 7. Land Surface Temperature (LST) of the study area showing the spatial distribution of temperature

(ANN-CA) framework, with the MOLUSCE (Modules for Land Use Change Simulation) plugin in QGIS. The ANN-CA model was chosen because of the combination of the Artificial Neural Networks' ability to identify complex non-linear associations between the past land-use changes and their driving factors, and the spatial neighborhood simulation characteristics of the Cellular Automata, which makes it suitable for modeling the urban growth dynamics. Historical land-use/land-cover maps were used to estimate transition potentials between different land-use categories, and spatial explanatory variables were incorporated to detect the factors driving land-use transitions. All input datasets were converted to a raster format with a spatial resolution of 30 meters to maintain uniformity across the modeling process.

Transition probability matrices were initially developed by analyzing multi-temporal land use/land cover maps which helped to identify the land-use conversion patterns in different time periods. The artificial neural network was then trained to evaluate the transition potential for each land-use category as a function of the normalized input variables. The transition potentials were subsequently integrated into the Cellular Automata model, which uses neighbourhood transition rules to simulate the spatial distribution of future land-use changes. Historical land use and land cover datasets were used to calibrate and validate the model. The predictive capability of the model was evaluated by comparing the simulated land-use map and the corresponding observed map using the Kappa coefficient and Overall Accuracy. Subsequently, the trained ANN-CA model was used to forecast the future Land Use/Land Cover (LULC) scenario for 2031 based on the existing urban growth trends and land-use transition patterns under similar environmental and anthropogenic conditions after successful calibration and validation.

4. Results and discussion

The research focuses on landscape dynamics with digital change detection methods on multi-temporal satellite images. In this study, the spatiotemporal variation of Land Use/Land Cover (LULC) along with NDVI, NDBI, NDWI and

LST are investigated. While these indices are used to characterise different surface properties, their combined use provides essential information on environmental change. The study integrates these parameters to provide a holistic insight into the process of urban transformation and its subsequent impact on local climatic dynamics.

4.1. Land use/land cover detection and analysis

The Land Use and Cover (LULC) classification analysis was performed by supervised classification techniques, (maximum likelihood algorithm) in ENVI 4.7 software for the years 2001, 2013 and 2023. The evaluation of the classification outputs revealed important changes in the land use patterns between the two periods studied. Major decadal changes mainly occurred in agricultural and urban areas from 2001 to 2013, where the urban land area increased by 1.21% and the agricultural land area increased by 0.34%. The changes in water bodies were insignificant. However, forest cover and fallow land were decreased by 0.51% and 1.02%, respectively. The analysis indicates a 1.67% rise in built-up areas, a 1.62% decline in agricultural land, minor changes in water bodies and forest cover between 2013 and 2023.

Table 1. Attribute data from the unsupervised classification

S/N.	LULC	2001	%	2013	%	2023	%
1	Agricultural land (L1)	267216	26.82	270530	27.16	286746	28.78
2	Built-up land (L2)	212159	21.30	224246	22.51	240867	24.18
3	Fallow land (L3)	327368	32.86	317216	31.84	296475	29.76
4	Forest cover (L4)	182510	18.32	177390	17.81	165423	16.60
5	Water bodies (L5)	6987	0.70	6858	0.69	6729	0.68

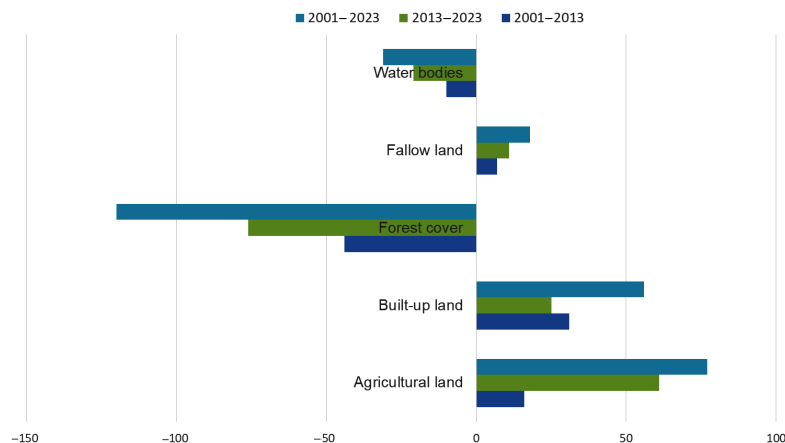


Figure 8. Land use/land cover changes of the study area

Table 2. Two-decadal changes of land use/land cover in pixels

S/N.	LULC	2001–2023
1	L1	19530
2	L2	28708
3	L3	–30893
4	L4	–17087
5	L5	–258

Fallow land, however, shows a significant increase of 3.5%. The change detection mapping of the comparative analysis (Figure 8) showed the land use change over the period of two decades with transition from forest cover to agricultural, built-up and fallow lands, agricultural lands to vegetated, fallow and urban lands and water bodies to vegetative land. This broad perspective demonstrates the dynamic characteristics of land use in the study area, emphasising the effects of urbanisation and land management strategies (Gupta et al., 2024). The attribute data obtained from the unsupervised classification is shown in Table 1 and the two-decadal changes of land use/land cover in terms of pixels is shown in Table 2.

4.2. NDVI change detection

NDVI was used in this paper to accurately monitor the spatio-temporal variation of vegetation cover in the study area from 2001 to 2023. The study recorded NDVI values ranging from –0.02 to 0.2. The area of sparse vegetation increased remarkably from 2001 to 2013. The increase was attributed to more rainfall and the adoption of water conservation measures. During this period, the mounting pressure of population on the land resource led to the conversion of barren lands into cultivated lands. Also, changes in vegetation density were identified in the fol-

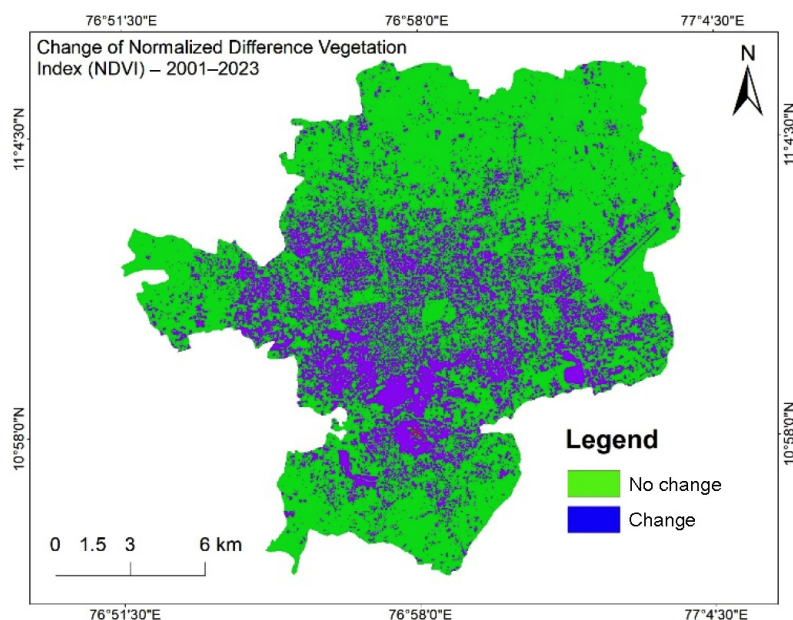
lowing decade (2013–2023). NDVI values vary from 0 (no vegetation) to 1 (dense vegetation). Maximum NDVI was 0.5, indicating dense vegetation.

NDVI values showed an increase in vegetation cover from 0.69 in 2013 to 0.74 in 2023. This increase is due to the beneficial impact of better rainfall patterns, improved irrigation facilities and specific forest conservation programmes. The study emphasizes the importance of NDVI in monitoring vegetation dynamics and shows significant change in land use land cover. In particular, the reserved forest areas remained more or less unchanged, but the low past vegetation cover areas improved in vegetation density, thus confirming the essential interrelation between environmental management and transformations in land use. Figure 9 shows NDVI changes over two decades representing significant temporal changes of vegetation cover. The figure shows the areas with loss, gain and stability of vegetation during the study period Sur et al. (2026).

Table 3. NDVI changes in percentages

NDVI	C (+2)	C (+1)	C (0)	C (–1)	C (–2)
Unclassified	0	0	0	0	0
C (+2)	0	0.002	0	0.043	10.638
C (+1)	70	88.492	0	58.344	40.426
C (0)	0	0	100	0	0
C (–1)	20	11.504	0	41.555	48.936
C (–2)	10	0.002	0	0.058	0
Class difference	100	11.508	0	58.445	100
Image difference	330	10.248	0	–27.544	8.511

The NDVI change matrix as shown in Table 3 depicts a high stability of the central class (C0) of 100% consistency and high changes for the extreme classes (C+2 and C–2) resulting from large vegetation gain and loss, respectively. Classes C+1 and C–1 exhibited moderate changes which

**Figure 9.** NDVI changes of the study area

suggest gradual changes in vegetation cover in the study period. The matrix depicts stability and dynamic changes in NDVI classifications across the landscape.

4.3. Urban dynamics

The variation in the area of NDVI, NDWI, and NDBI is illustrated in Figure 10a–c, respectively. The NDVI assessment shows an increase in areas with high vegetation, indicating a local increase in green cover, whereas areas with low vegetation and barren land show a downward trend due to urban sprawl. The NDWI maps show that the distribution of surface water was generally similar during the period of the study with some changes in space in some places. Results of the NDBI show a steady growth of developed areas from

2001 to 2023 indicating rapid urbanization and increase of impermeable surfaces. The study shows a slow conversion of farm and open land to built-up areas with little alteration in vegetation and water resources.

The detailed study of LULC, LST, NDVI, NDWI and NDBI indicates that the rapid urbanization has impacted the ecological condition of Coimbatore city to a great extent. The population increase and the rising demand for residential, commercial and industrial facilities have expedited the process of transformation of agricultural land and open areas into urban developments. This led to higher Land Surface Temperature (LST) in areas of high urbanization due to the heat retaining properties of impermeable materials such as concrete and asphalt, which consequently caused higher Land Surface Temperature

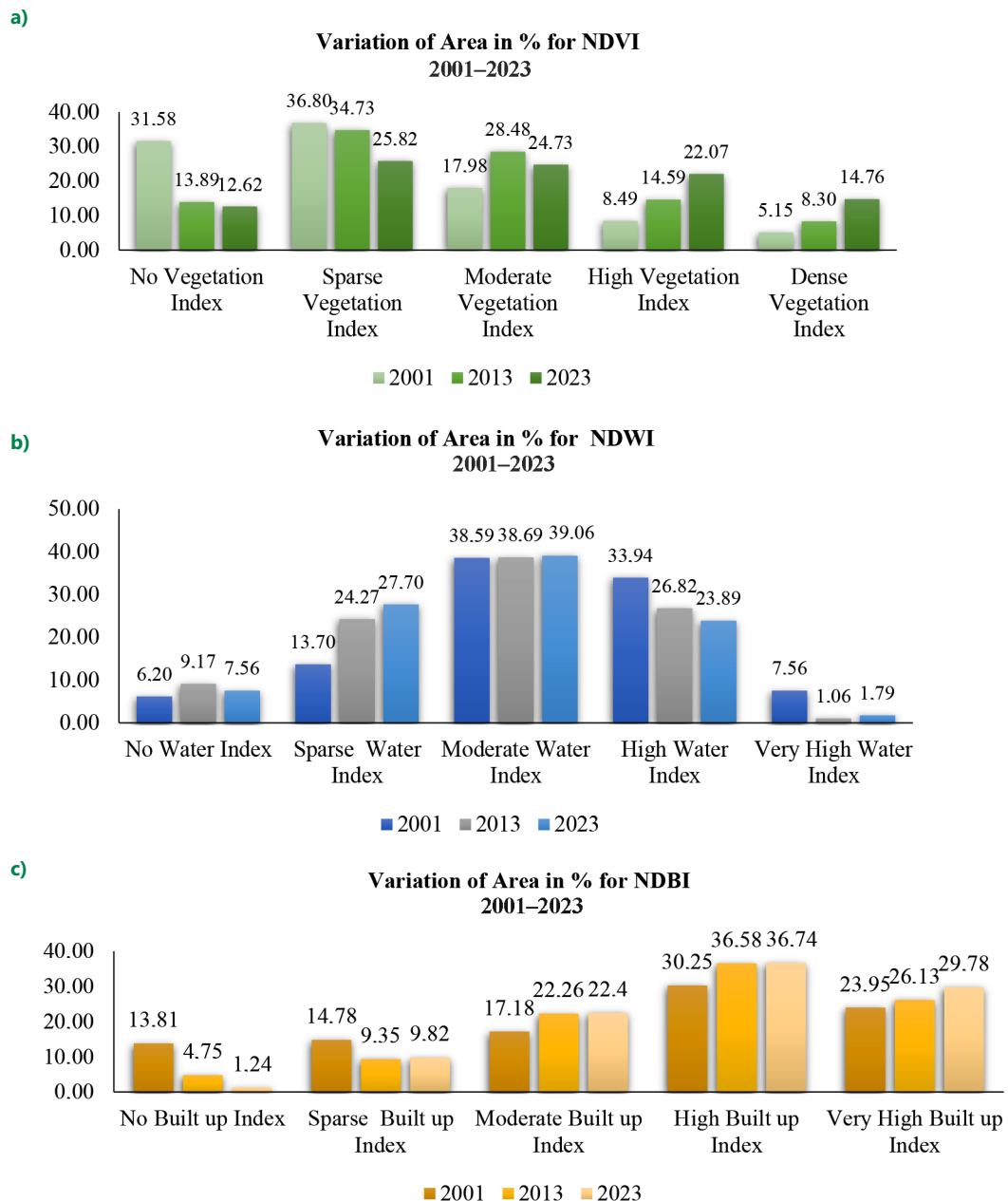


Figure 10. Urban dynamics of spectral indices: a) Variation of area for NDVI; b) Variation of Area for NDWI; c) Variation of Area for NDBI

(LST) in areas with high urbanization. In contrast, high values of NDVI and NDWI were generally related to lower land surface temperature, as vegetation and water bodies cool the air through evapotranspiration and ability to store water. The results show that vegetation and surface water bodies are important for reducing the urban heat, whereas the expansion of built-up environments further intensifies thermal stress.

The present results agree with the earlier observations which reported similar relation between urban sprawl and loss of vegetation and increasing land surface temperature in fast developing urban areas (Sur et al., 2026; Gupta et al., 2024). The environmental changes we are witnessing require the protection of urban green spaces, the safeguarding of water related ecosystems and the adoption of sustainable land use planning strategies for the improvement of climate resilience and sustainable urban development. Urban dynamics of NDVI, NDBI and NDWI statistics with LST are shown in Table 4.

Table 4. Urban dynamics of NDVI, NDBI, and NDWI Statistics with LST

Urban Indices	2001		2013		2023	
	Min	Max	Min	Max	Min	Max
NDVI	-0.557	0.518	-0.018	0.522	-0.0612	0.476
NDBI	-0.395	0.485	-0.352	0.276	-0.313	0.230
NDWI	-0.390	0.571	-0.485	0.134	-0.450	0.097
LST	12	40	59	73	54	70

4.5. Modelling and prediction of land use/land cover change

LULC map for 2031 is presented in Figure 11. From the map it is seen that there will be a significant rise in the built-up areas of Coimbatore mainly due to agricultural lands and forest lands. Gandhipuram, Podanur, Singanalur, etc. are examples of uncontrolled urban sprawl.

4.5.1. ANN-CA model validation

The ANN-CA model was calibrated using historical LULC maps of 2001 and 2011, and the simulated 2021 LULC map was validated against the observed 2021 LULC map. The

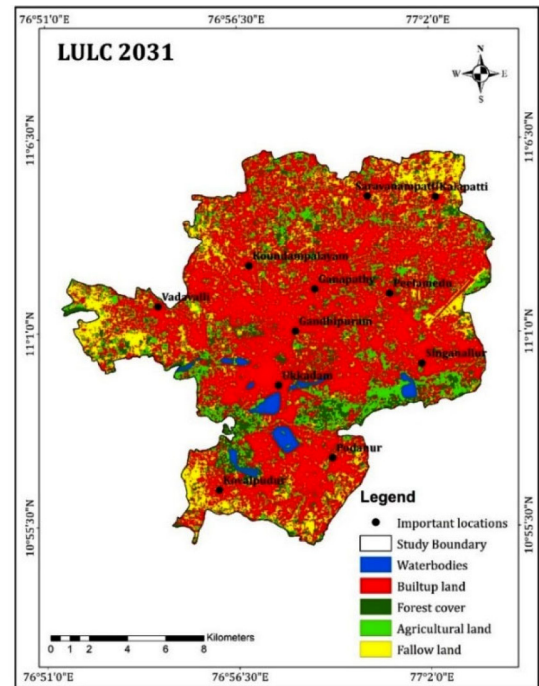


Figure 11. LULC Prediction of the study area in 2031

validation results showed a Kappa coefficient of 0.95 and an overall simulation accuracy of 95.76%, which confirms the robustness of the predictive model. The calibrated model, after successful validation, was used to simulate future LULC conditions for 2031. The ANN-CA model demonstrated an excellent predictive ability and reliability for urban growth simulation with a projected simulation for 2031 with a Kappa coefficient of 0.96. Table 5 shows that the Validation of ANN-CA model.

Table 5. Validation of ANN-CA model

Validation parameter	Value
Calibration period	2001–2011
Validation year	2021
Overall accuracy	95.76%
Kappa coefficient	0.95
Predicted year	2031
Prediction Kappa	0.96

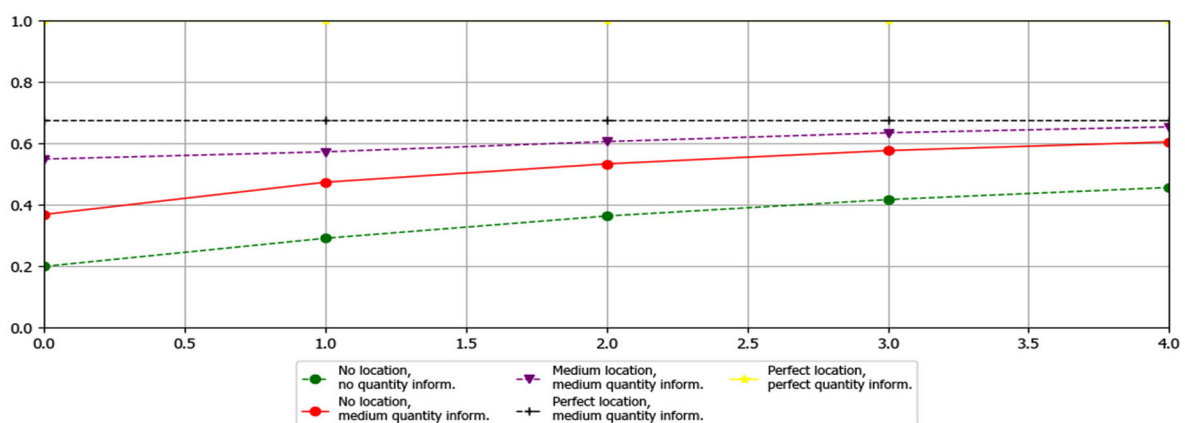


Figure 12. LULC Validation graph 2031

The accuracy assessment graph (Figure 12) indicates that the predictive models can be more accurate with better spatial and quantitative data and would reach maximum accuracy if both are known perfectly. The results underline the importance of sustainable urban planning and data-driven policy making to improve land use.

The ANN-CA simulation suggests the continuous process of urban expansion until 2031, mainly at the expense of agricultural land and open spaces surrounding the existing urban core. Overall Accuracy = 95.76%; Kappa = 0.95, achieved by the calibrated model, shows that the model can predict future urban growth patterns with reasonable reliability, and the projected Kappa coefficient of 0.96 again proves the robustness of the prediction model. Similar predictive performance was also reported by Ganeshmoorthi and Nagarathinam (2018).

5. Conclusions

The spatio-temporal dynamics of urban growth in Coimbatore City were studied using geospatial techniques and the Artificial Neural Network-Cellular Automata (ANN-CA) model using multi-temporal Landsat images of 2001, 2013, and 2023. Analysis shows a steady increase of urban land during the study period. Built-up land increased by 1.21% between 2001 and 2013 and by 1.67% between 2013 and 2023. In contrast, agricultural land showed reverse trends during the same period, with a small increase of 0.34% in the first decade and a decrease of –1.62% in the second decade, which indicated gradual conversion of productive land to urban uses. During 2001–2013, the fallow land (1.02%) and forest cover (0.51%) decrease was observed. Between 2013 and 2023, forest cover has risen by 3.50%. These changes indicate changing land management practices and urbanization pressures in the former period. Detailed analysis of Land Surface Temperature (LST) and spectral indices (NDVI, NDWI, and NDBI) shows that the urban expansion has impacted the thermal characteristics of the city. High urban density generally correlates with high Land Surface Temperature (LST). Vegetation and water bodies affect the control of surface temperature. The findings suggest that the continuing replacement of natural land cover by impervious surfaces will likely exacerbate urban heat stress and reduce environmental resilience if not mitigated. The ANN-CA model predicted the urban growth well. The model validation showed an Overall Accuracy of 95.76% and a Kappa coefficient of 0.95. The Kappa coefficient for 2031 projection was 0.96 indicating the good predictive capability of model. The projected urban sprawl (mostly on agricultural and forest land) necessitates anticipatory land use planning strategies to balance conservation of the environment and urban development. Our study provides a valuable geospatial framework to track urban dynamics in the past and predict future land use change in rapidly urbanizing cities. The results provide evidence-based urban planning and sound land management directly contributing to SDG 11: Sustainable Cities

and Communities. Also, the findings highlight the need to protect vegetation and water bodies to reduce urban heat and improve climate resilience, which contributes to SDG 13: Climate Action. Higher resolution satellite data, more socio-economic and infrastructural variables, and advanced deep learning approaches are able to achieve better prediction of urban growth and environmental assessment for future developments.

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