

Land Use and Land Cover Change (LULC) Analysis and Prediction Using Cellular Automata - Artificial Neural Network (CA-ANN) Approach: A Case Study of Sriperumbudur Taluk, Tamil Nadu, India

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ABSTRACT

India's major metropolitan centres are changing quickly, Sriperumbudur Taluk a peri-urban landscapes are a good example of this shift. It includes industrial growth, expanding transport networks, and residential development are all taking place alongside continuing agricultural activity. This study examines land use and land cover (LULC) change in the taluk between 2016 and 2020 and forecasts future LULC for 2024 and 2028 using a Cellular Automata–Artificial Neural Network (CA-ANN) approach. Sentinel-2A data was classified through supervised maximum likelihood algorithm into five categories: agricultural land, built-up area, sparse vegetation, water bodies, and barren land. The resulting maps obtained an overall accuracy of 84.20%, 86.52%, and 87.12% for 2016, 2020, and 2024 respectively, with corresponding Kappa coefficients of 0.826, 0.847, and 0.861. The MOLUSCE plugin was used to model transition potentials based on the change observed between 2016 and 2020. The elevation, distance from roads, population density, and geomorphology are taken as spatial driving variables. When compared against an independently classified 2024 reference map, the simulated 2024 map achieved a prediction accuracy of 83.72%, and the validated model was subsequently used to project LULC for 2028. Between 2016 and 2028, agricultural land in the study area shows a consistent and substantial decline, while built-up land steadily expands, reflecting sustained urbanization pressure. Water bodies remain relatively stable with minor fluctuation. Spatially, this growth is concentrated along existing transport corridors and around established industrial zones. These findings suggest that CA-ANN-based geospatial modelling can offer useful evidence for urban growth management, land use zoning, and the protection of productive agricultural land in fast-developing peri-urban regions.

Keywords: Land Use/Land Cover Change, Cellular Automata, Artificial Neural Network, Geospatial Modelling, Urbanization

INTRODUCTION

Land use and land cover (LULC) shows how human activity interacts with the natural environment. Shifts in LULC tend to track closely with population growth, infrastructure expansion, economic activity, and changing patterns of resource use. Geospatial studies have repeatedly shown that LULC change can reshape the spatial structure of a landscape and add further pressure on environmental resources [1,3,6]. This is especially true in peri-urban regions, where agricultural land and natural cover are directly exposed to the pace of development.

Remote sensing combined with Geographic Information Systems (GIS) has considerably improved how LULC is monitored across large areas. Satellite imagery gives repeated views of the Earth's surface and supports consistent classification of agricultural land, vegetation, water bodies, built-up areas, and barren land. More recent work has also highlighted how well Sentinel imagery performs alongside machine-learning-based

classification for generating reliable LULC information [2,8]. Multi-temporal satellite data adds a further advantage, helping to reveal both the direction and the magnitude of landscape change over time.

Predicting future LULC matters just as much as tracking past change, since historical trends alone cannot indicate where new development is likely to occur. Cellular Automata models are well suited to representing spatial growth because they allow neighbouring land cells to influence the transitions that follow. Coupling these models with neural networks further strengthens their ability to capture complex relationships between land transitions and their spatial drivers. Baghel et al. [1] applied MOLUSCE for LULC change detection and future prediction, while Devendran and Gnanappazham [4] demonstrated the value of neural-network-coupled Cellular Automata modelling for urban growth specifically in Sriperumbudur Taluk. Several other studies have used CA-based or related predictive frameworks to examine future land transformation under shifting demographic and spatial conditions [5,7,10,11].

This study focuses on Sriperumbudur Taluk, a fast-growing peri-urban and industrial region of Tamil Nadu. The specific aims are to assess LULC change between 2016 and 2020, identify the main spatial drivers behind these transitions, validate a CA-ANN prediction for 2024, and project the likely LULC pattern for 2028. The study also considers what continued built-up expansion could mean for agricultural land and for sustainable land management going forward.

Study Area

The study area lies within Sriperumbudur Taluk, Kancheepuram District, Tamil Nadu, India, situated roughly between 12.8° N - 13.1° N latitude and 79.8° E - 80.1° E longitude (Figure 1). The region experiences a tropical climate, with hot, humid summers and rainfall concentrated in the monsoon season. Agriculture continues to play an important role here, with millets, groundnut, and sugarcane among the main crops grown. Because the taluk sits close to Chennai, it has also benefited from and been shaped by considerable industrial and infrastructure investment. Automobile manufacturing units, technology parks, transport corridors, and the residential growth that follows them have all added to the development pressure on the region. This combination of active agriculture and fast industrialization makes Sriperumbudur Taluk a fitting setting for examining peri-urban LULC change.

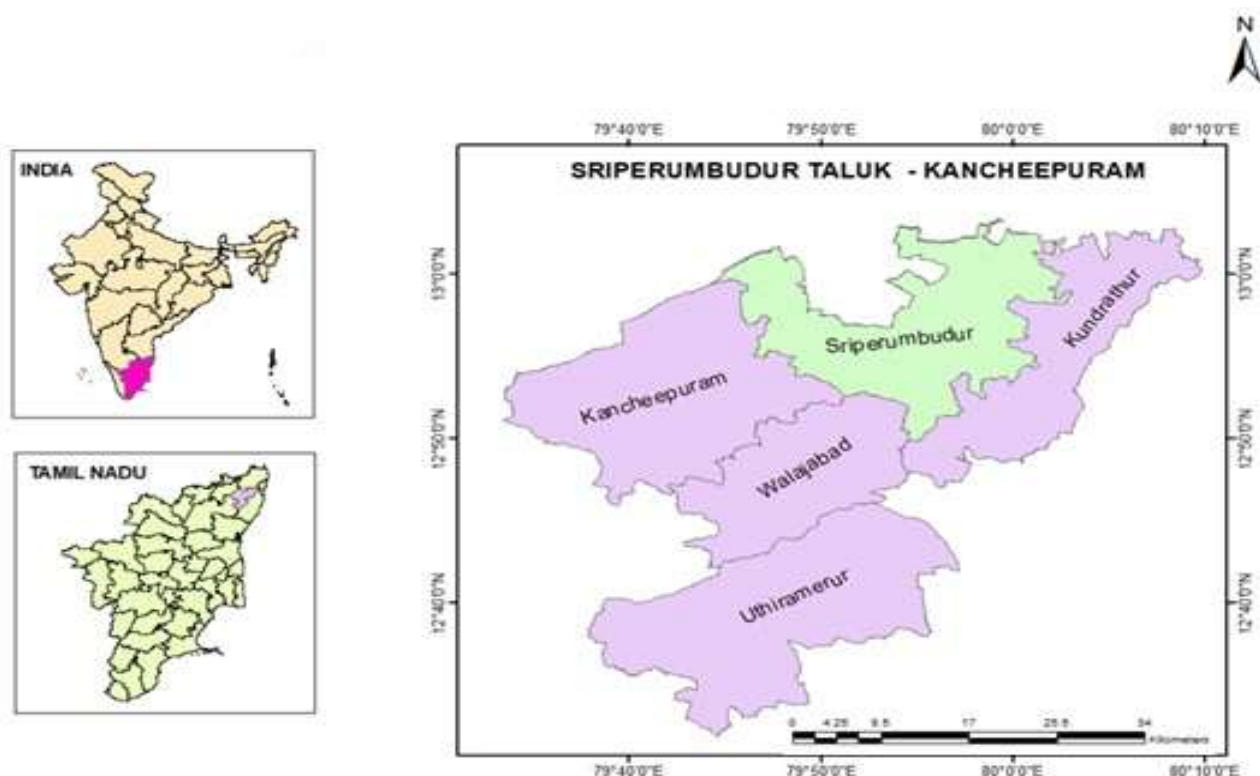


Figure 1: Study area

Data Used

Satellite imagery and supporting spatial datasets were used together to prepare the LULC maps and the driving variables needed for CA-ANN modelling; Table 1 lists the datasets used and where each was sourced from.

Table 1: Data sources used for LULC classification and prediction

Data	Thematic layer	Source
SRTM GL1	Elevation and terrain information	Open Topography
Sentinel 2A	LULC maps	Copernicus

METHODOLOGY

The overall workflow followed in this study from data collection is summarized in Figure 2, and each stage is described in detail in the subsections below.

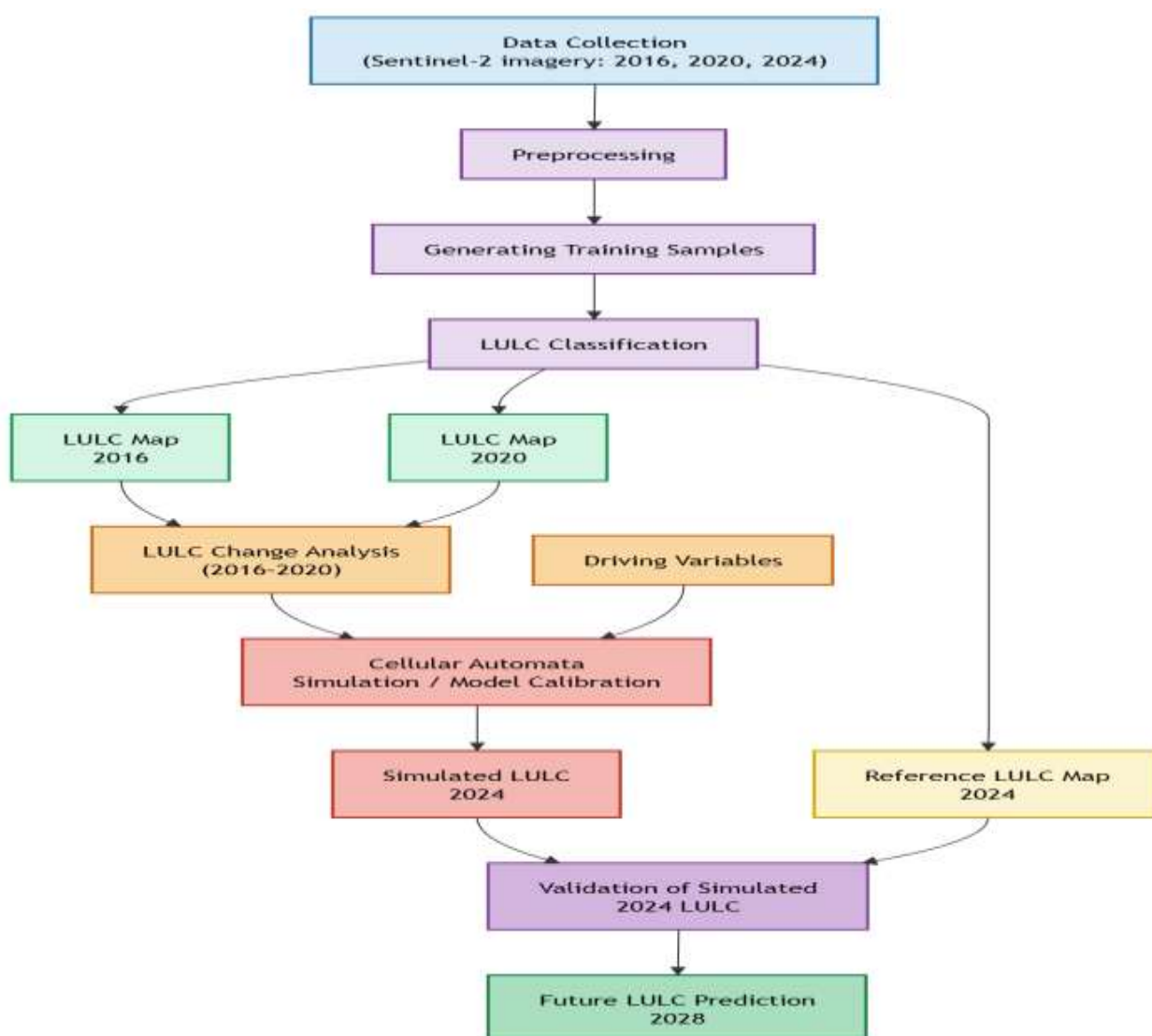


Figure 2: Methodology

Data acquisition and pre-processing

The two primary datasets: SRTM GL1 elevation data at a 30 m spatial resolution, and Sentinel-2A satellite imagery at 10 m resolution, together forming the core inputs for classification and terrain analysis. These were supplemented by road and geomorphology data, along with village-level population. This data provided the additional spatial and demographic context needed for the driving-variable analysis. All datasets were brought into a common geospatial environment and reprojected to ensure spatial consistency across layers of differing origin and resolution. The Sriperumbudur Taluk boundary was then used to clip each dataset to a common study extent, so that all subsequent processing and analysis were confined to a uniform spatial frame.

Image classification and accuracy assessment

The Sentinel-2A data for 2016, 2020, and 2024 was processed into false colour composite images using bands 8, 4, and 3. The study area was then classified into five LULC classes such as sparse vegetation, agricultural land, water body, settlements/built-up land, and barren land using supervised maximum likelihood algorithm. The accuracy was assessed using stratified random method. The reference points for each year, checked against high-resolution Google Earth imagery, and obtained overall accuracies of 84.20%, 86.52%, and 87.12% for 2016, 2020, and 2024 respectively, with Kappa coefficients of 0.826, 0.847, and 0.861.

LULC change detection (2016–2020)

The change in LULC was assessed by comparing the classified 2016 and 2020 maps. The area occupied by each class was calculated for both years, and the difference between the two data was used to identify where gains and losses had occurred. In order to understand which land covers were contributing most to urban expansion, the transition potentials of other classes to built-up class was analysed.

Spatial driving variables

To capture the physical and demographic factors influencing land transition four spatial variables were prepared. To align with the Sentinel-2A data, elevation derived from the SRTM DEM, was resampled to 10 m. The road and geomorphology shapefile were clipped to the study area and used to compute a continuous Euclidean distance-from-road surface. Population density was calculated for each village as the ratio of population to area and then converted into a continuous spatial layer, as shown in Figures 3 and 4.

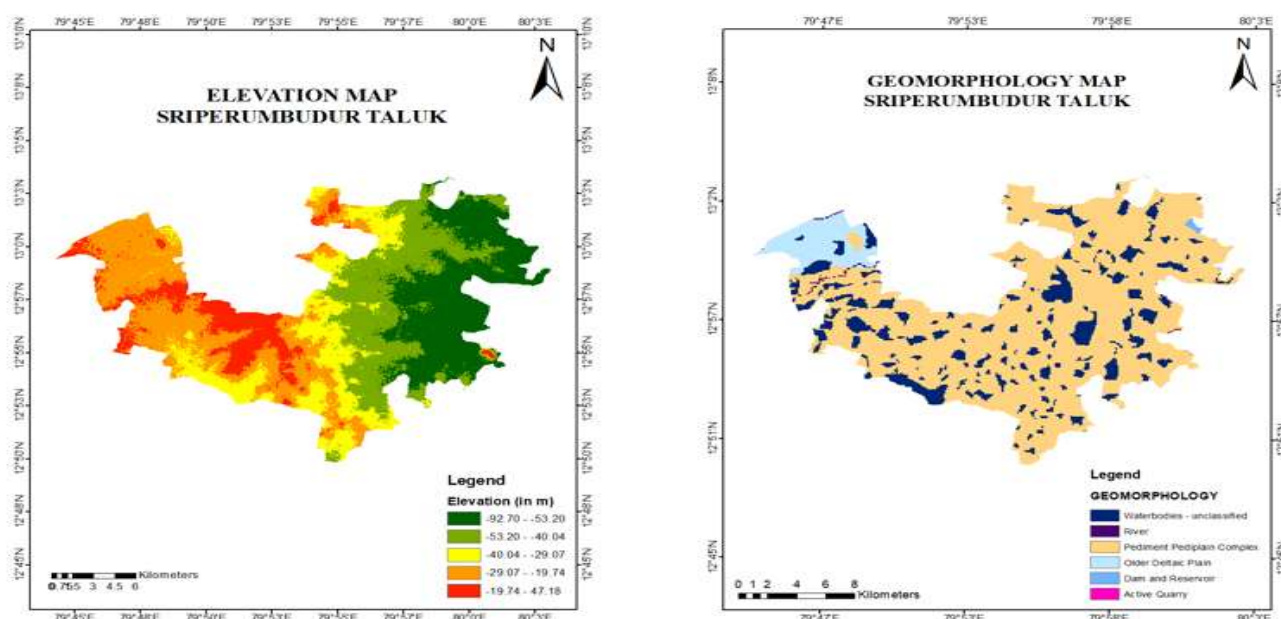


Figure 3: Elevation and geomorphology map

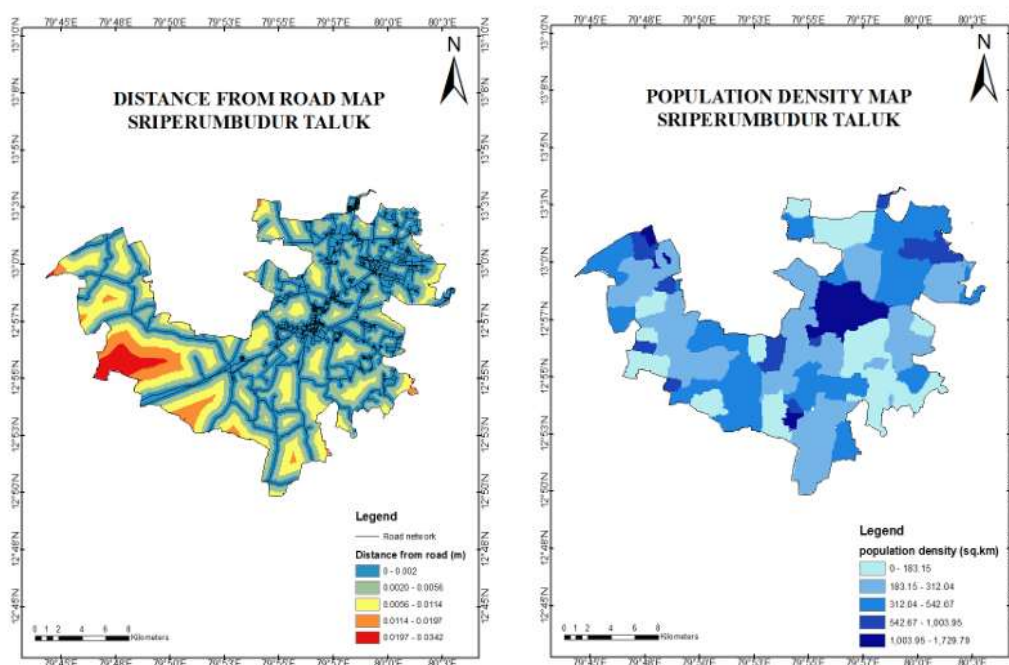


Figure 4: Distance from road and population density map

CA-ANN model development, validation, and future prediction

The MOLUSCE plugin in QGIS was used to develop a Cellular Automata–Artificial Neural Network (CA-ANN) model for LULC change prediction. The LULC maps for 2016 and 2020 were used as the historical input maps, while the four spatial driving variables elevation, slope, population density, and distance to built-up areas were provided as explanatory variables. A Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) was trained using the observed LULC transitions between 2016 and 2020 to estimate the transition potential of different land-use classes. The transition potential maps generated by the ANN were then integrated with the Cellular Automata (CA) model in MOLUSCE to simulate the spatial allocation of future LULC changes. Based on the transition probabilities and spatial suitability, the calibrated CA-ANN model was first used to predict the LULC map for 2024. The predicted 2024 LULC map was subsequently used as the base map for the next simulation period, and the model was further iterated to predict the future LULC map for 2028.

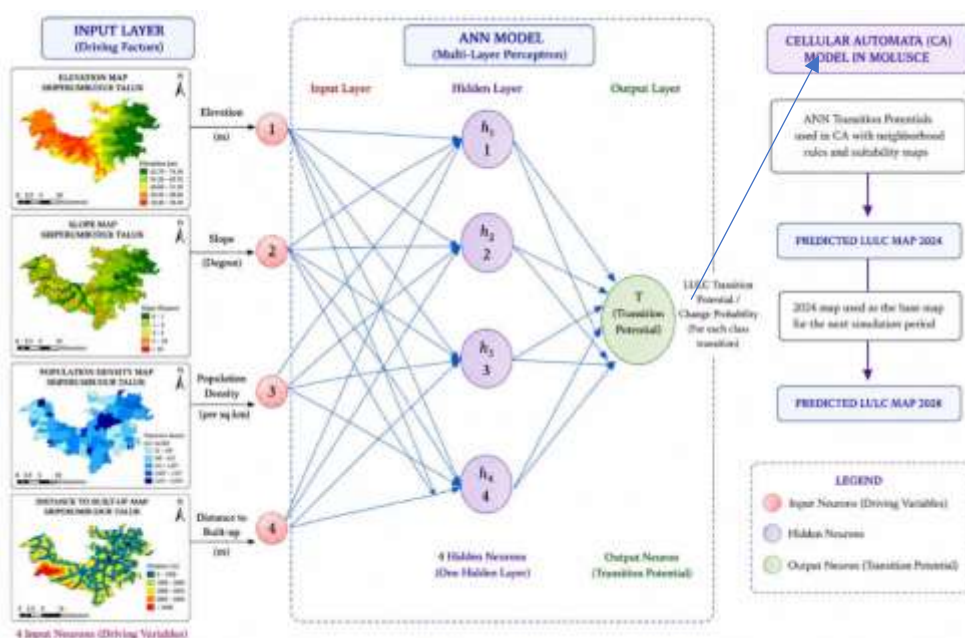


Figure 5: CA-ANN model

RESULTS AND DISCUSSION

The classified LULC maps shows the transformation of the landscape between 2016 and 2020. Built-up land expanded around existing settlement clusters, with growth particularly visible along the major road corridors, while agricultural land became increasingly fragmented near developed areas. The classified maps, with accuracies of 84.20% for 2016 and 86.52% for 2020, provided a base for change analysis between the two time periods. Agricultural areas were an important land source for urban expansion. The increase in built-up land was accompanied by a reduction in agricultural land.

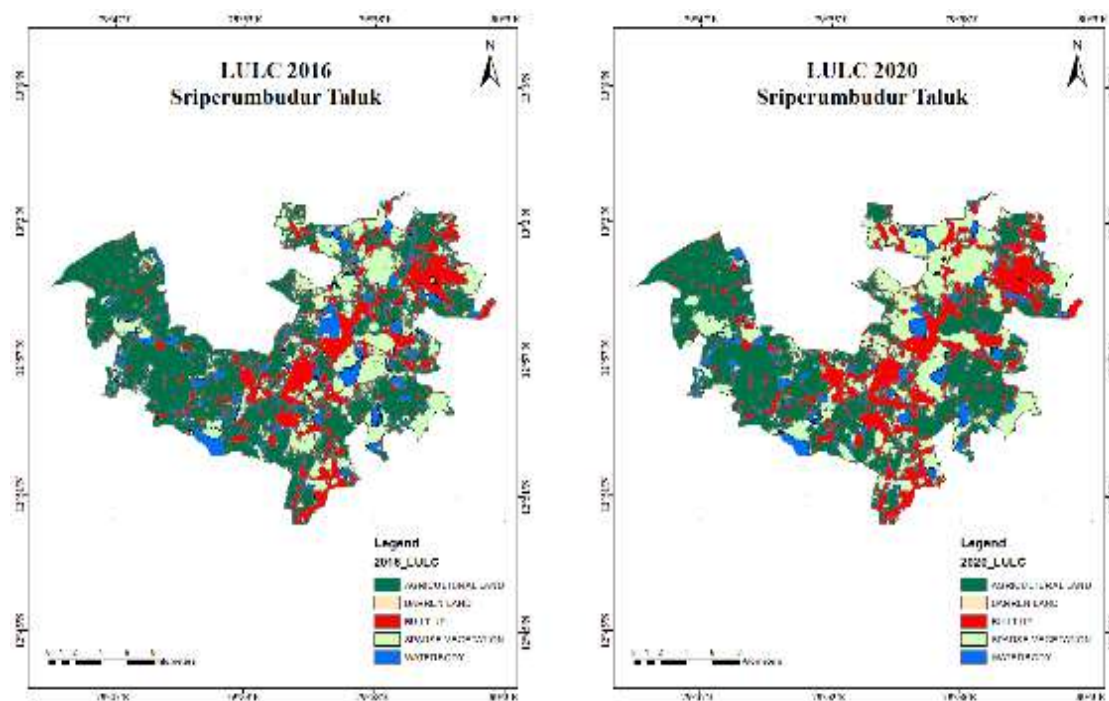


Figure 6: LULC classification map for 2016 and 2020

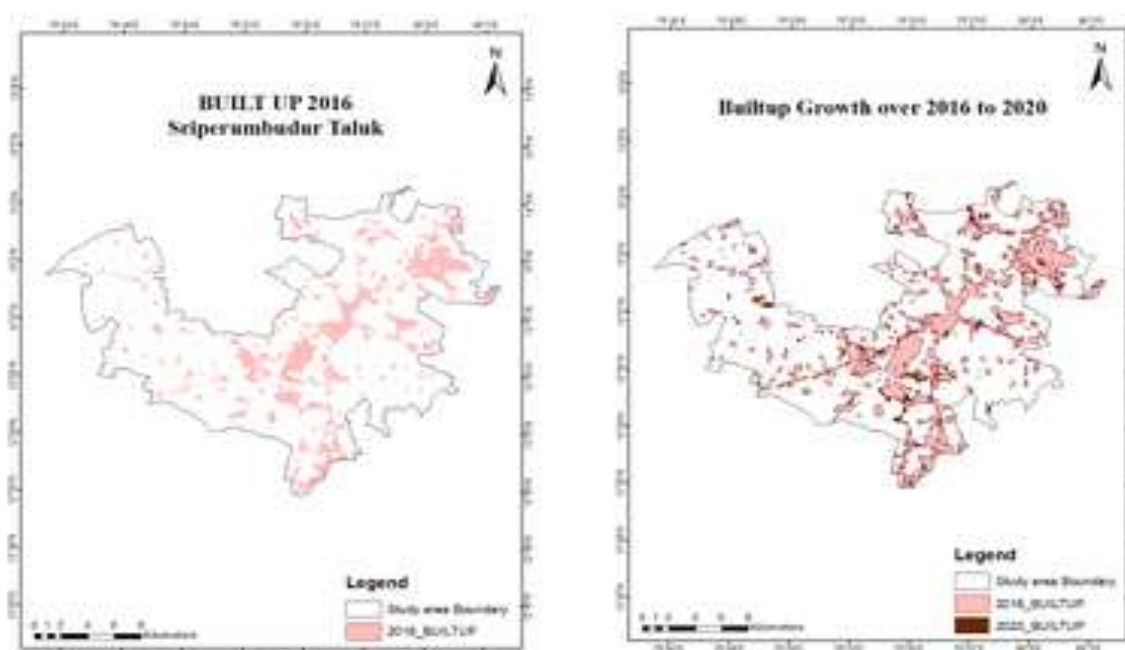


Figure 7: Built-up change map for 2016 and 2020

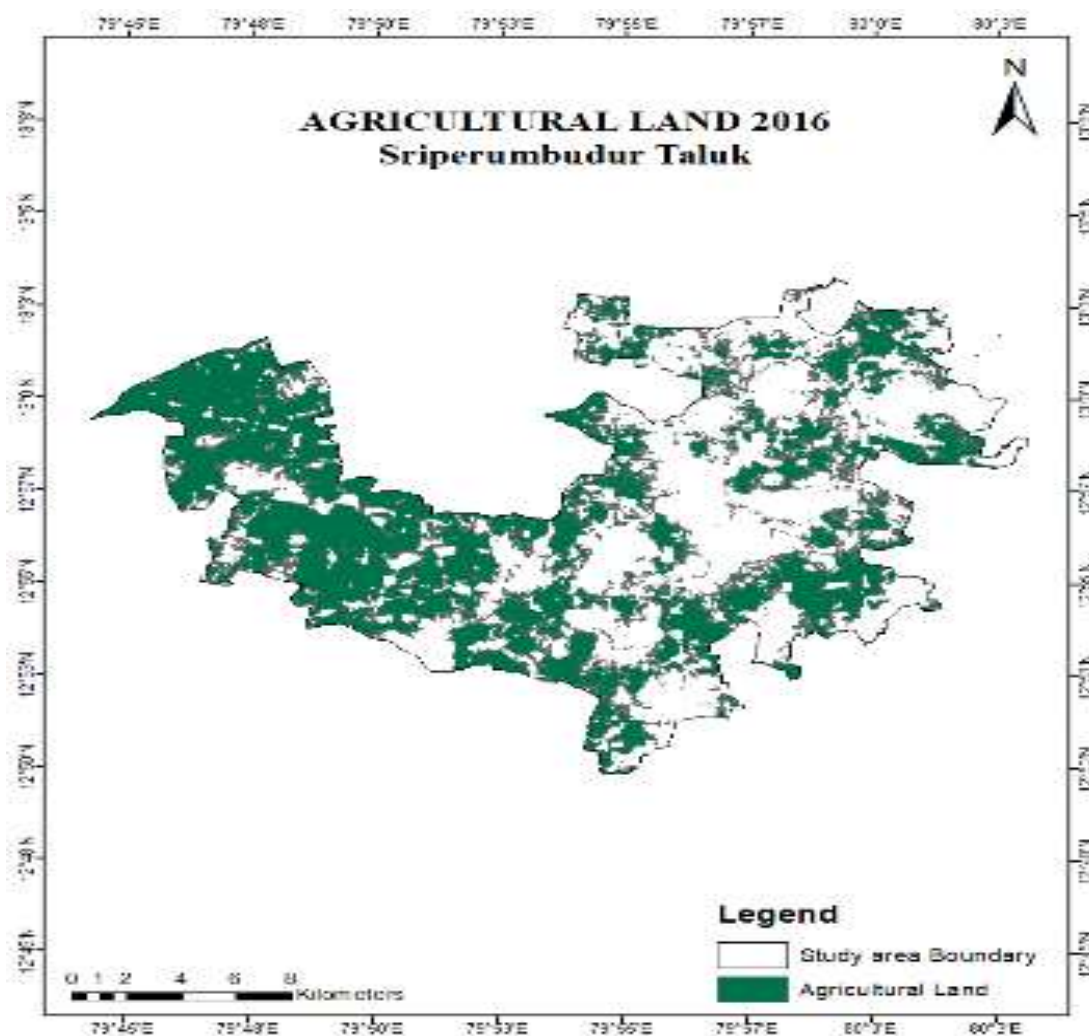


Figure 8: Spatial distribution of agricultural land

Table 2: LULC area distribution for 2016, 2020, 2024, and 2028

LULC class	2016 (km ²)	2020 (km ²)	2024 (km ²)	2028 (km ²)
Water body	30.04	24.25	24.05	24.78
Sparse vegetation	90.73	102.02	122.80	120.96
Agricultural land	172.79	154.23	132.18	116.79
Built up	63.33	76.56	77.08	92.18
Barren land	0.26	0.10	0.005	0.40

Table 3: LULC area change between 2016 and 2020

LULC class	2016 (km ²)	2020 (km ²)	Change (km ²)
Water body	30.04	24.25	-5.79
Sparse vegetation	90.73	102.02	+11.28
Agricultural land	172.79	154.23	-18.55
Built up	63.33	76.56	+13.23
Barren land	0.26	0.10	-0.16

Between 2016 and 2020, built-up land grew by 13.23 km², while agricultural land fell by 18.55 km² and sparse vegetation increased by 11.28 km². Water bodies also declined, by 5.79 km². The distribution of the changed areas is also important for understanding the nature of development. The new built-up areas were mainly associated with locations that already contained settlements or had good road accessibility. This indicates that development followed an existing spatial structure instead of occurring randomly across the taluk. The expansion of settlements around established developed areas can gradually increase the continuity of built-up patches.

Table 4: Major agricultural land transitions identified for 2016 to 2020

Transition	Area (km ²)
Agricultural land to water body	2.78
Agricultural land to sparse vegetation	32.15
Agricultural land to built up	9.34
Agricultural land to barren land	0.002

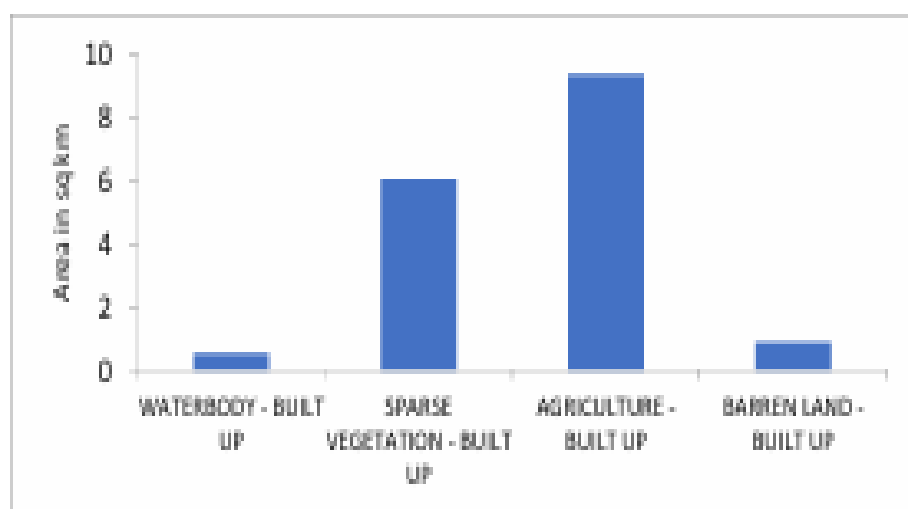


Figure 9: LULC transitions to built-up land during 2016 to 2020

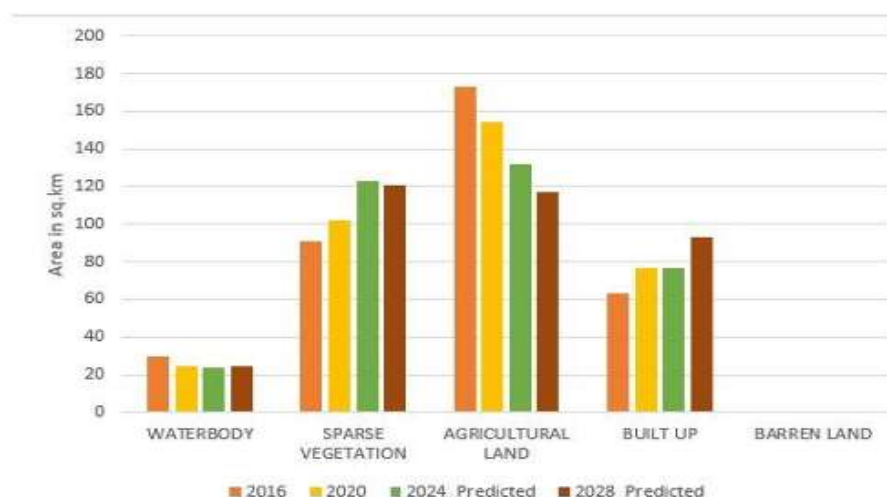


Figure 10: Comparison of LULC class areas for 2016, 2020, 2024, and 2028

The CA-ANN model was trained on the 2016–2020 transition pattern together with the selected spatial variables, and the resulting simulated 2024 map closely matches the spatial pattern of the independently classified reference map, achieving an overall prediction accuracy of 83.72%. This suggests the model was able to reproduce much

of the observed spatial transition pattern, this support for the 2028 prediction, although some small local differences between the predicted and reference maps do remain.

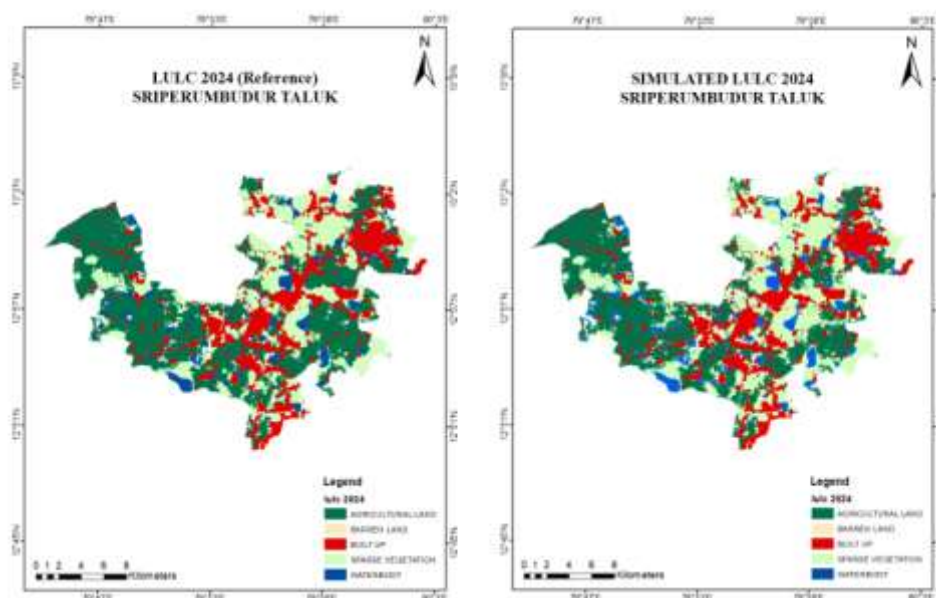


Figure 11: Reference and simulated LULC maps

Table 5: Comparison of 2024 reference and predicted LULC areas

LULC class	2024 reference (km ²)	2024 predicted (km ²)	Difference (km ²)
Water body	24.07	24.05	0.01
Sparse vegetation	120.46	122.80	2.34
Agricultural land	134.10	132.18	1.92
Built up	77.49	77.08	0.41
Barren land	0.003586	0.005496	0.0001

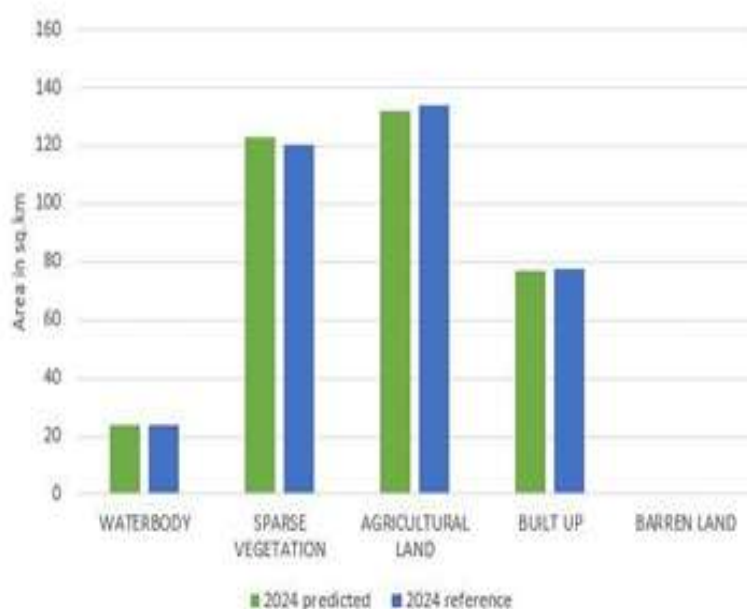


Figure 12: Comparison of predicted and reference LULC class areas for 2024

The 2028 simulation points to continued urban expansion, with built-up land predicted to reach 92.18 km² and agricultural land expected to fall to 116.79 km². Relative to 2016, this amounts to roughly 28.85 km² of additional built-up land and a loss of about 56.00 km² of agricultural land. Sparse vegetation is predicted to remain the largest non-agricultural cover after agricultural land itself, while water bodies stay comparatively stable. The predicted pattern shows development concentrated around existing transport corridors and established industrial areas, echoing earlier work on Sriperumbudur that linked transportation, industrial activity, and other urban growth factors to the spatial expansion of developed land [4]. The continuing conversion of agricultural land is also consistent with broader findings from LULC prediction studies in other rapidly developing regions [1,5,7,11].

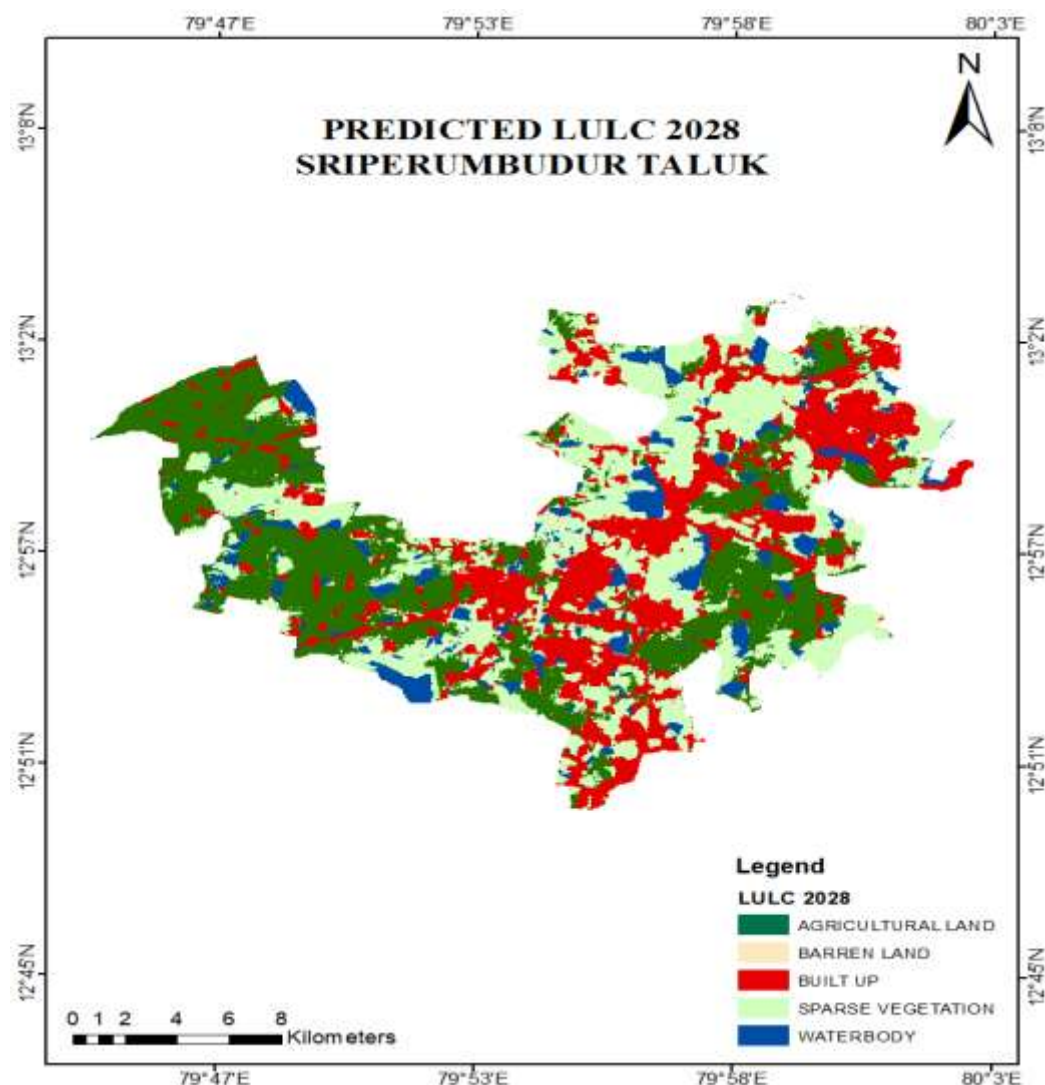


Figure 13: Predicted LULC map for 2028

These results directly help in planning, urban growth management, land use zoning, and the protection of productive agricultural land. Growth corridors already under high development pressure can be monitored more closely, and agricultural land near major roads and industrial areas are suggested for stronger land use controls. The resulted outputs support evidence based urban growth management while emphasizing the need to maintain a balance between industrial development, settlement expansion, agricultural productivity, and sustainable land resource management.



Figure 14: Comparative accuracy assessment of LULC classification and CA-ANN prediction for 2016, 2020, and 2024, showing confusion matrices, producer's accuracy, user's accuracy, and overall accuracy.

CONCLUSION

This study focuses on both LULC change and future land transformation in Sriperumbudur Taluk, using Sentinel-2A data, GIS-based spatial analysis, and a CA-ANN modelling approach. The classified maps for 2016 and 2020 show a clear increase in built-up land alongside a corresponding decline in agricultural land, with overall classification accuracies of 84.20% and 86.52% and Kappa coefficients of 0.826 and 0.847 indicating acceptable classification performance.

The CA-ANN model achieved an overall prediction accuracy of 83.72% for 2024 when checked against the independently classified reference map. The 2028 prediction suggests that built-up land could reach 92.18 km², while agricultural land may fall to 116.79 km². Relative to 2016, this represents an increase of about 28.85 km² in built-up land and a loss of roughly 56.00 km² of agricultural land.

Overall, the findings indicate that transport accessibility and existing development patterns are important spatial factors shaping future urban growth in the taluk, and they support the case for coordinated land use zoning, agricultural land protection, and infrastructure planning. The study also illustrates the broader value of combining remote sensing, GIS, and CA-ANN modelling for spatially explicit land management in rapidly peri-urbanizing regions.

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