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Halimjon Khujamatov
Gachon University
Doston Khasanov
Tashkent University of Information Technology
K. Mohaideen Pitchai
National Engineering College
Salar Sefati
salar.sefati@elcom.pub.ro

Universitatea Națională de Știință și Tehnologie Politehnica București

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Urban Spatial Growth Modeling and Prediction using an Inte-grated Model of Artificial Neural Network and Cellular Au-tomata

Halimjon Khujamatov [1], Doston Khasanov [2], K. Mohaideen Pitchai [3,*], and Seyed Salar Sefati [4,*]

1. Department of Computer Engineering, Gachon University, Sujeong-gu, Seongnam-si 13120, Korea; kh.khujamatov@tuit.uz (H.K.)
2. Department of Data Communication Networks and Systems, Tashkent University of Information Technologies, Tashkent, Uzbekistan; dhasanov@tuit.uz (D.K.)
3. Department of Computer Science and Engineering, National Engineering College, Kovilpatti, Tamilnadu, India; kmpcse@nec.edu.in (M.P.)
4. National University of Science and Technology POLITEHNICA Bucharest, Romania; salar.sefati@elcom.pub.ro (S.S.)

* Correspondence: kmpcse@nec.edu.in; salar.sefati@elcom.pub.ro

Abstract: The fast urbanisation and dynamic urban transformations resulting from population growth and migration require the identification and detection of such changes for effective urban management and sustainable development. Urban growth modelling is an important analytical tool to understand and address the complex challenges of urbanisation. A review of existing literature shows several research gaps. Most of the existing urban growth prediction models consider only geographical, topographical or socio-economic factors separately. Existing Cellular Automata (CA)-based models usually take into account only the current state of the neighbouring cells and the accuracy of their predictions is mainly based on the accessibility index or suitability index of the cells. To address these limitations, this paper proposes an integrated model that combines the strengths of CA and ANN to predict urban growth. The developed model first generates four-class LULC maps consisting of vegetation cover, surface water, bare soil, and urban land from the corrected imagery. These classes are then reclassified into two categories namely urban and non-urban. Geographical factors such as proximity from the urban center, roads, railways, water resources, and town centres, along with neighbourhood development intensity, estimates accessibility. Topographical factors like aspect, soil type, groundwater quality, and flood inundation determines suitability and socio-economic factors including population density, proximity to economic centres, and land value defines zoning. The model performance is evaluated using Percent Correct Match, Moran's I, and Shannon's Entropy. A confusion matrix, overall accuracy, and kappa statistics were used to evaluate classification accuracy. In addition, the model assessed land-use transitions through a transition matrix, conducted sensitivity analysis, and quantified urban area changes using statistical measures. Satellite images of Thoothukudi District, Tamil Nadu, India were pre-processed and classified into LULC (land use land cover) categories using the developed integrated model. Change detection techniques were used to identify changes such as urbanisation, loss of vegetation and changes in water bodies over time. These patterns are used to predict future LULC distribution for the year 2030 to help sustainable planning and environmental conservation.

Keywords: ANN, CA, Geographical factors, Topographical factors, Socio-economic factors, Urban growth.

1. Introduction

Urbanization is an important global challenge of the 21st century, reshaping landscapes, economies, and societies at an unprecedented pace. Cities are continuously expanding due to population increase, economic development, and migration, resulting in rapid and often unplanned land use changes. Understanding, monitoring, and predicting these spatial transformations have become vital for effective urban planning, infrastructure development, and sustainable resource management. Urban growth modelling provides a systematic approach to analyse the dynamics of city expansion and to forecast future growth patterns under varying environmental and socio-economic conditions.

Various modelling techniques have been proposed over the years to simulate the spatial dynamics of urban expansion. These include the statistical methods, machine learning models and CA-based approaches. But those models often come with big limitations. Much of the work is narrowly focused on one dimension such as geographical, topographical or socio-economic, neglecting the complex interrelationships between these factors which shape urban development. In addition, traditional CA models usually only consider the current state of adjacent neighbourhood cells and only consider either the accessibility index or the suitability index to predict urban transitions. These simplifications reduce the accuracy and reliability of urban growth predictions, especially in diverse urban environments. This work proposes an integrated urban growth prediction model which combines the adaptive learning capacity of Artificial Neural Networks (ANN) and the computing efficiency of CA to solve these encounters. The novelty and contribution of this works as follows:

- The pre-processed imagery is classified into four different Land Use Land Cover (LULC) classes namely urban land, surface water, vegetation cover and bare soil using Maximum Likelihood Classification (MLC) techniques. These classes are then reclassified into a binary scheme of urban and non-urban categories, where vegetation cover, surface water, and bare soil are merged into the non-urban class.
- The ANN model estimates the transition probability from a non-urban to an urban state by simultaneously incorporating geographical, topographical, and socio-economic factors. This approach allows to simulate urban expansion in a more detailed and accurate manner.
- The CA model simulates urban growth pattern by transition rules derived from multiple inputs such as geographical factors based on ANN outputs, topographical factors based on weighted average outputs and socio-economic factors based on logistic regression outputs.
- The models are evaluated using well-established spatial and statistical metrics like Moran's Spatial Autocorrelation Index, Percent Correct Match (PCM), and Shannon's Entropy.
- Thoothukudi District in Tamil Nadu, India is the model application. It is trained by data of 2016-2020 and then used to predict land-use pattern of 2021-2025. For validation, the predicted results are compared with the actual maps of the same period. The calibrated model is then applied to generate the urban growth projections for 2030. These projections reveal the actual and predicted growth patterns and are an appreciated tool for urban forecasting and development.

The method of the proposed hybrid model for predicting urban expansion, including the construction of the CA and ANN models, is explained in Section 3. It also explains the training and testing phases of the ANN, as well as its role in calibrating the CA model. The results of the proposed hybrid model are shown in Section 4, along with a detailed review of the results. Section 5 finishes up the paper by summarizing the key findings.

2. Related Works

Early CA models in urban studies were formulated using basic methodological approaches such as neighbourhood coherence constraints and Boolean rules for transition functions. These functions have evolved through the integration of dynamic transition rules, heuristic methods, fuzzy set theory, and multi-criteria evaluation techniques. Studies that integrate ANN with CA models for urban analysis, while incorporating geographical, topographical, and socio-economic factors, are relatively limited. The existing works, which are closely relevant to the proposed work, are covered in this section.

Ahmad et al. [1] developed a hybrid framework of Cellular Automata-Artificial Neural Network (CA-ANN) to study spatiotemporal changes in the Sundarbans Delta, India. The research used the multi-temporal satellite derived LULC datasets to document past land transformation patterns. ANN was trained on spatial variables to predict transition probabilities for various land-use classes. These probabilities were integrated into a CA model, which simulated spatial dynamics based on neighbourhood influence rules. The absence of high-resolution remote sensing data limits their research. Moreover, it lacks a more detailed LULC classification and an integrated simulation framework based on neural networks.

Farhan et al. [2] presented a CA-Markov chain based model to predict the change in land surface temperature (LST) and LULC in Islamabad. The study used historical LULC data from 1992–2022 to compute transition proba-

bility matrices using Markov analysis. These probabilities were spatially allocated using CA rules. The model produced predictions up to 2042, highlighting rapid urban expansion and corresponding increases in LST. The low-resolution Landsat images used in this study may have made it more difficult to identify small-scale features, especially in heterogeneous landscapes.

A Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) hybrid network model was constructed by Varma et al. [3] to predict LULC changes. The study used satellite imagery as input to identify both temporal and spatial patterns. CNN extracted spatial features, while LSTM captured temporal dependencies. The simulations were not performed using high-quality LULC data, which may limit their ability to effectively detect LULC change patterns and produce accurate predictions. WetNet, a spatial-temporal ensemble deep learning system that combines Sentinel-1 and Sentinel-2 data for wetland categorisation, was proposed by Hosseiny et al. [4]. The study used multi-source satellite imagery as input. Their approach comprised three sub models, each integrating multiple recurrent and convolutional layers to capture spatial and temporal features.

An ANN-based approach for investigating the association between land surface temperature and land use-dependent carbon patterns was introduced by Sarkar et al. [5]. The inputs were LULC data and environmental variables. The ANN was used to model the complex relationship of land use changes and associated temperature variations. Their results showed the effects of anthropogenic land-use changes on the environment. The forest cover change detection effectiveness may have been limited due to the limited availability of cloud-free remote sensing imagery used as input to this study. Jianxin Yang et al. [6] proposed a spatiotemporally explicit CA model to simulate urban expansion. In their study, urban demand factors and historical LULC maps were used to increase the accuracy of predictions. The CA model dynamically simulated the urban growth. This model is constrained by intensive calibration of high parameter sensitivity for urban growth.

Yuehui Qian et al. [7] proposed a hybrid method of CA and spatiotemporal convolution techniques for dynamic land use simulation. They used multi-temporal LULC datasets as input to their study and proposed convolution-based methods to capture spatial dependencies. This approach ignores the mixed land-use realities of high-density urban environments. Yan Zhou et al. [8] analysed the effectiveness of land use planning policies in controlling the growth of construction land in China. Their study analysed the policy impacts with long-term LULC datasets. The study uses mathematical and econometric modelling to measure the intensity of growth management. But it does treat the real process of enforcement as a black box.

Haoran Zeng et al. [9] proposed a state-of-the-art CA framework which integrates economic development zones and land-use policies into the urban growth modelling. The model took LULC datasets, policy constraints and economic indicators as inputs. Their work emphasizes the identification of urban growth patterns. However, it frequently underrepresents the influence of urban policy and planning on urban development. The spatial limitations and classifiers in CA-based urban growth models were systematically compared by Cassiano Bastos Moroz et al. [10]. The study evaluated different input datasets and classification techniques to identify optimal modelling strategies. The results emphasized the role of spatial constraints in improving the accuracy of predictive models. Although the study compared the most commonly used classifiers, its scope remained limited. Furthermore, several machine learning and additional calibration techniques for spatial restrictions in CA models are still being investigated.

Najib Ansari et al. [11] proposed a CA–ANN hybrid model for urban expansion analysis in Kolkata. The model used historical LULC maps along with spatial drivers such as road proximity and population density. ANN estimated transition probabilities, while CA simulated spatial growth patterns. The model cannot reproduce unprecedented non-linear changes of urban development. Gopal Kumar et al. [12] developed a CA-ANN model for modelling and prediction of urban growth of Indore. Variables studied included spatial variables such as elevation, road networks and land suitability. The model generated future LULC maps that are useful for sustainable urban planning and policy development. The model does not forecast abrupt disturbances such as new economic corridors, industrial parks or significant changes to Indore city.

Tania Yeasmin et al. [13] developed an ANN model of CA for predicting the land cover dynamics in the urban areas of Bangladesh. The study used multi-temporal satellite datasets and spatial drivers as inputs. The model's generalisation ability is limited as the study does not consider the use of transfer learning and data augmentation techniques that could enhance the performance and reduce the dependence on large training datasets. A hybrid

model of ANN–CA with Bayesian Weight of Evidence has been proposed by Muhamad Iqbal Januadi Putra et al. [14]. LULC maps and spatial drivers (slope and distance to infrastructure) were used in the study. The model avoids overfitting and underfitting by not using additional spatial variables, and does not use modelling frameworks to capture non-linear and exponential urban growth.

Anthony Yeh et al. [15] reviewed a detailed study of CA models for urban and regional planning. The study described principles of CA, transition rules and spatial simulation techniques. The model does not integrate CA with big data or social media data, which restricts its predictive power. Mehrez Marzougui et al. [16] proposed a deep learning model for LULC classification using satellite imagery. In the study, convolutional neural networks were used to extract spatial features. The applicability of the model to a wide variety of satellite datasets with different spectral and spatial characteristics is limited because the model generalisation and computational efficiency are not considered.

Shazada Ahmad et al. [17] studied the relation between LULC changes and atmospheric pollution with the help of ANN models. The study used environmental and satellite data as input. The approach is limited by overtraining and the assumption of static driving variables, which reduces the accuracy of localised analyses. For analysis of post-earthquake urban changes in Turkey, ANN–Markov model was proposed by Fatih Sunbul et al. [18]. LULC datasets for simulating future urban growth in disaster scenarios. The results showed significant land-use changes due to seismic events. This framework has several limitations such as poor integration of socio-economic data, satellite image misclassification and lack of real-time validation.

Zhiyong Lv et al. [19] proposed a land-cover change detection neural network model based on cross-attention. The model used satellite imagery and state-of-the-art deep learning to improve the accuracy of detection. When used for geographic areas at regional or global scale, the model is computationally expensive and demands expensive hardware resources. Md. Namzur Rahman et al. [20] analysed the impacts of urban expansion on land surface temperature and carbon emissions using machine learning techniques. It used LULC maps and environmental data as input. The results do not translate into an overall land-use prioritisation strategy to effectively counter urban expansion, surface warming and rising greenhouse gas emissions. Previous studies integrating LULC analysis with ANN and CA have shown a high capability to forecast future urban growth by modelling the land-use transition probabilities and realistic spatial expansion patterns. These hybrid CA-ANN frameworks outperform many conventional methods in learning complex behaviours of urban conversions from historical satellite-derived LULC maps and simulating neighbourhood-driven urban expansion over time. Thus, the generated prospective LULC maps offer useful assistance for sustainable urban planning, infrastructure development and environmental management.

While the existing methods offer various advantages, they also have some limitations that require further attention. Many current models are based mainly on a few driving factors such as proximity to roads and slope, and neglect important socio-economic, accessibility, land suitability and regulatory zoning influences. Moreover, simplified CA transition rules may not be able to capture the complexity of irregular urban sprawl dynamics. Moreover, the black-box nature of ANN based prediction models limits the interpretability of their decision-making process. Many studies also depend on moderate-resolution datasets that constrain the detection of fine-scale land-use changes in rapidly urbanising regions. In addition, model validation is often limited to conventional accuracy metrics, with little attention paid to sophisticated performance metrics, uncertainty quantification and scenario-based forecasting. Likewise, the majority of reported approaches have been evaluated only in specific regional settings, limiting their wider applicability and scalability.

To tackle these encounters, the proposed work proposes a more inclusive LULC prediction framework that incorporates accessibility, land suitability and zoning constraints into a single transition function. This allows a more realistic simulation of urban growth processes. The framework is developed to improve the prediction accuracy by improved CA simulation strategies and ANN-based learning, and to show better performance compared with conventional CA-only and Multi-Criteria Evaluation (MCE)-CA baseline models. In addition, the work emphasizes policy-relevant urban zonation supported by quantified uncertainty analysis, thereby providing more reliable and useful information for future land-use management and sustainable urban planning. These contributions are expected to produce more accurate, interpretable, and policy-oriented urban expansion maps for long-term decision-making.

3. Methodology

The developed urban growth model includes several key steps to predict and analyze how cities expand. It begins with data pre-processing, where raw geographical, topographical, and socio-economic datasets are collected, cleaned, normalized, and prepared for analysis. This is followed by the design of the CA model, in which transition rules are defined based on the geographic, topographic, and socio-economic characteristics of each cell. These factors are used to estimate the accessibility index, suitability index, and zoning index, respectively. The next step, CA calibration, involves ANN training, where the ANN is employed to generate the accessibility index for the CA-based model. The weighted average and logistic regression methods are used to estimate the suitability and zoning indexes for the CA-based model. Furthermore, the efficiency of the designed ANN will be evaluated by comparing it with the conventional MCE integrated CA model. The prediction phase of CA after the calibration, the model is applied to predict the probability of land conversion from non-urban to urban land and analyse the effects of different neighbourhood sizes on the prediction accuracy. The CA evaluation process then assesses the model accuracy and performance through spatial and statistical metrics such as Shannon's Entropy [21], Percent Correct Match [22] and Moran's Spatial Autocorrelation Index [23]. Lastly, the generation of urban expansion zonation maps visualizes the predicted urban expansion, highlighting distinct zones of potential development and offering valuable insights to support efficient urban planning and sustainable land-use management.

3.1 Data Pre-processing

Figure 1 shows the pre-processing of collected remote sensing data into a format of data that is suitable for training and testing of the ANN based CA model.



Figure 1. Data Pre-Processing

Satellite images for the periods 2016–2020 and 2021–2025 of Thoothukudi, located in Thoothukudi District, Tamil Nadu, India were obtained from the Sentinel-2 satellite under the Copernicus Programme dataset. This was used for the analysis of urban growth patterns. Images having cloud cover below 10% were chosen, primarily from the dry season (16th February 2016, 21st January 2018, 7th February 2023 and 5th August 2025) to ensure temporal

consistency. Annual median composites were generated to reduce atmospheric noise and residual cloud contamination. Pre-processing was performed in QGIS and included atmospheric correction, radiometric correction, geometric correction, layer stacking, clipping to the study area, and cloud masking.

Sentinel-2 channels B2, B3, B4, and B8, each having a spatial accuracy of 10 m, were used for classification. Then, the corrected satellite imageries were first classified into four LULC classes, namely urban land, vegetation cover, surface water, and bare soil, using the Maximum Likelihood Classification technique, after which the non-urban classes were merged into a single non-urban category for urban growth modelling. Reference samples were generated using Google Earth historical imagery. 100 urban and 300 non-urban samples were randomly divided into training and testing datasets. Accuracy of classification was evaluated using an error matrix, kappa statistics, and overall classification accuracy. This study employs six spatial variables to characterize the urban growth parameters of each cell in the urban development simulation. They are

- proximity from the urban center (S1)
- proximity from road networks (S2)
- proximity from the closest railways (S3)
- proximity from the nearest water resource (S4)
- proximity from the nearest town centre (S5)
- degree of development in the neighbourhood cells (S6)

The distance variables are obtained by the Euclidean distance tool of QGIS software. The degree of development in the neighbourhood was measured using the Von Neumann neighbourhood, which considers the four cells adjacent to the central cell.

3.2 Cellular Automata (CA) Design

Three crucial elements of sustainable urban design must be taken into account, specifically, geographical factors (accessibility), topographical factors (suitability) and demographical factors (zoning). To address these issues, this work uses a hybrid type of CA for modelling the urban growth. The hybrid CA Model includes the Standard, Suitability and Constrained type of CA models to increase the accuracy and reproducibility of urban land usage pattern predictions. The designed hybrid CA model uses the accessibility index ($AI^t(x,y)$), suitability index ($SI^t(x,y)$) and zoning index ($ZI^t(x,y)$) of the pixel (x,y) during t^{th} time to simulate future land-use maps of that cell.

$AI^t(x,y)$ denotes the accessibility index of the pixel (x,y) during t^{th} time for transition to urban cell. The geographical parameters mentioned above (S1, S2, S3, S4, S5) are used to calculate the accessibility index by using ANN. $SI^t(x,y)$ denotes the suitability index of the pixel (x,y) during t^{th} time for transition to urban cell. Suitability index is essential for determining appropriate land use in urban planning, thereby promoting efficient and sustainable land-use management. The topographical factors such as aspect, soil type, ground water quality and flood inundation are also considered to calculate the suitability index. Here the parameter 'aspect' represents the physical factor of the land and the other parameters belong to the environmental factors. The aspect map is calculated from Digital Elevation Model (DEM) using the QGIS tool. Therefore, land suitability shows an important role in influencing the state transitions of a cell within an idealized urban development pattern. It is computed as follows.

$$SI^t(x,y) = \sum_i W_i X_i \quad (1)$$

Here W_i is the weight factor of the i^{th} parameter (aspect, soil type, ground water quality and flood inundation) and X_i is the criterion score of the i^{th} parameter.

$ZI^t(x,y)$ denotes the zoning index of the pixel (x,y) during t^{th} time for transition to urban cell. The demographical factors such as population density, distance from economical centres and land value are used to estimate the zoning index. The parameter 'population density' is the social factor and the remaining parameters are the economic factors. The zoning index is calculated by the following stepwise logistic regression.

$$\ln\left(\frac{ZI^t(x,y)}{1-ZI^t(x,y))}\right)=\sum_i \beta_i Y_i(x,y)\ (2)$$

Where Y_i are demographical factors and β_i denotes the coefficient associated with the i^{th} factor in the logistic regression model.

To calculate this equation, projected population growth is required. Based on historical population data, future population growth can be estimated using the geometric progression method as follows.

$$P(t)=P(0)\ (1+k)^d (3)$$

Here *P(t)* denotes the projected data of population at upcoming period '*t*'. *P(0)* is the initial population. '*k*' represents the average percentage growth rate (geometric mean) and '*d*' denotes the projection period, expressed in decades. Finally, the calculated development probability of a cell is compared with the pre-defined threshold value. If the calculated value exceeds the predefined threshold, the cell undergoes a state transition from the non-urban class to the urban class. Thus the calculation of the development probability of a cell includes the geographical, physical, environmental, social and economic factors for transition to urbanized state.

3.3 Artificial Neural Network (ANN) Design

In this work, an ANN is used to calibrate the CA. Figure 2 shows the design of ANN which generates the Mean Accessibility Value for a sample of cells. The designed ANN generates accessibility index of the pixel *(x,y)* from the extracted urban growth attributes. A multilayer feedforward neural network trained using the backpropagation algorithm was employed for urban growth prediction. The network architecture consists of two hidden layers, an output layer, and an input layer. Each urban growth parameter associated with the pixel *(x,y)* was represented by a neuron in the input layer. As these parameters represent various proximity measures, all input values were transformed to the interval [0,1] to ensure compatibility using the function of sigmoid activation. Eight neurons made up the input layer, which was followed by two hidden layers of sixteen neurons each and an output layer. The Rectified Linear Unit (ReLU) activation mechanism was used by the hidden layers to improve learning performance and decrease gradient vanishing problems.

The output layer comprised one neuron employing a sigmoid activation function to generate the accessibility index for pixel *(x,y)*, which was used to estimate its transition probability from the non-urban class to the urban class. The Adam optimization technique was used to train the ANN at a learning rate of 0.001. Additionally, it uses binary cross-entropy to reduce prediction error. Training, verification, and testing categories covering 70%, 15%, and 15% of the samples in the dataset, respectively. To avoid overfitting, the model underwent training for a maximum of 100 iterations. Training was stopped early when the validation loss stopped improving. Dropout regularization was incorporated into the hidden layers at a rate of 0.2 to improve generalization performance.

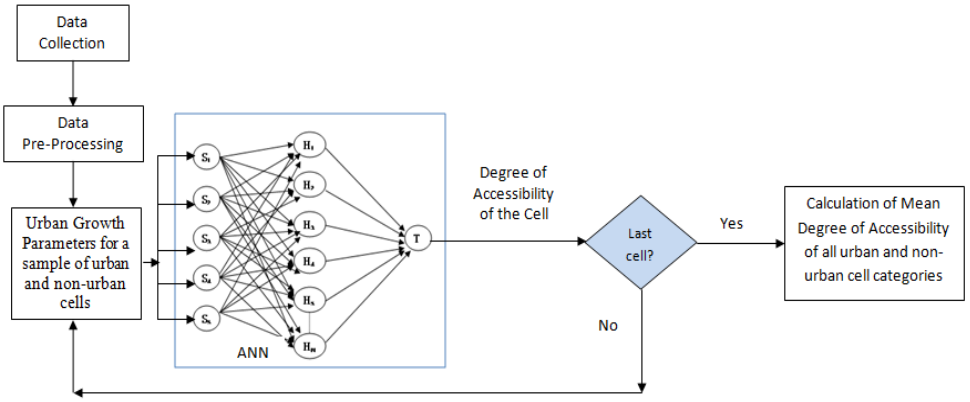


Figure 2. Accessibility Index Calculation

The pre-processed training data is sampled into a group of urban and non-urban cells. The urban growth parameters of each urban cell are feed into the ANN which produces the accessibility index of the cell. Similarly, the accessibility index of all the cells in the non-urban category is generated using the ANN. Then the mean accessibility value of the urban and non-urban category is calculated which can be used as a threshold value of accessibility index for ANN training.

3.3.1 ANN Training

Figure 3 shows the training of the ANN which can be used for CA calibration. The urban growth parameters of urban and non-urban cells are feed into the ANN and get the accessibility index. The input from the i^{th} neuron in the input layer to the j^{th} neuron in the hidden layer for cell (x,y) is calculated as follows.

$$H_j = \sum w_{ij} S_i(x,y) \quad (4)$$

Where H_j denotes the aggregated input to the j^{th} hidden neuron for cell (x,y), and $S_i(x,y)$ represents the i^{th} urban growth parameter associated with that cell. w_{ij} represents the link weight between the j^{th} hidden neuron and the i^{th} input neuron in the ANN. Sigmoid activation function is used in the hidden layer. The hidden layer's activation for the signal is

$$\frac{1}{1+e^{-H_j}} \quad (5)$$

The output 'T' for cell (x,y) is calculated from

$$T = \sum w_j \frac{1}{1+e^{-H_j}} \quad (6)$$

Here, w_j represents the link weight between the output neuron and the j^{th} hidden neuron. Then the accessibility index 'T' is compared with the mean Accessibility Index (mAI) value. Based on this comparison, the conjugate gradient approach is used to update the network's weights and biases. This leads to minimising the discrepancy between network outputs (T) and the targets (mAI value). This procedure is repeated until the target is reached, based on the difference between the outputs and the targets. If the calculated result of urban cell is higher than the mAI parameter of urban category, then it is back propagated to the network through weight updating process. Otherwise the generated value is acceptable and then it is checked against whether it is the last cell. In the same way, the generated value of the non-urban cell is less than the mDA value of non-urban category, and then it is back propagated to the network through weight updating process. Otherwise the generated value is acceptable and then it is checked against whether it is the last cell. If that cell is the last cell, then the process of ANN training is finished. The network is sufficiently tuned to replicate urban expansion after training. The output of the trained neural network is the accessibility index of a cell.

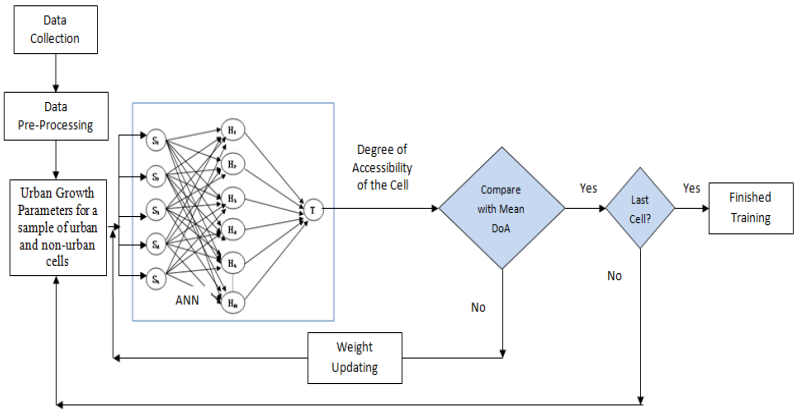


Figure 3. ANN Training

3.3.2 ANN Testing

Figure 4 shows the ANN testing process. The predicting data is given as input to the suitable ANN and the accessibility index is calculated. Then it is used along with suitability index and zoning index to identify whether the cell is transited to urban cell or remains in the non-urban cell using the developed CA Model. This process is repeated until the last pixel of the input dataset. The CA transition rules are framed with the cells geographical factors defined by the ANN outputs, topographical factors defined by weighted average output and the socio-economic factors defined by logistic regression method outputs. If the target cell is urban, it stays urban, otherwise, for non-urban cells, the decision for converting it to urban is taken with the help of the designed CA transition rule.

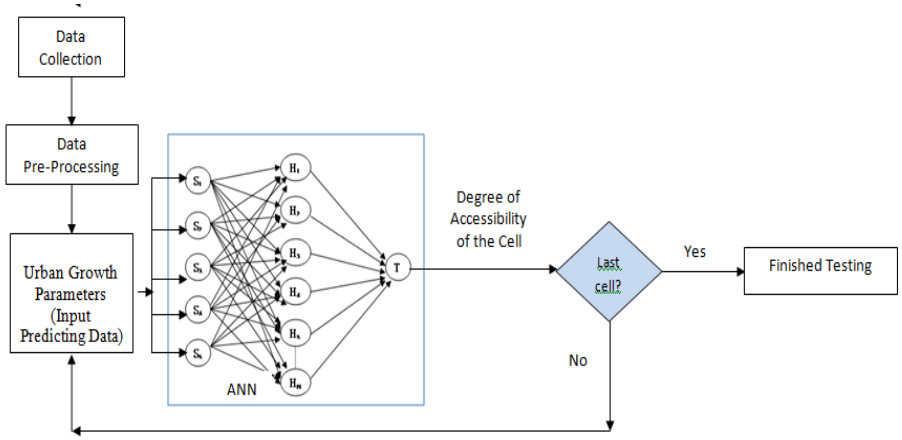


Figure 4. ANN testing

3.4 ANN-CA Integration

The CA model uses the accessibility index, suitability index, and zoning index of each cell as transition rules and applies them across the grid to simulate future land-use maps. Standard cellular automata is used to calculate the development probability $(d^t_{\{x,y\}})$ of a cell at position *(x,y)* over time '*t*' depending on its surrounding states.

$$P(d^t_{\{x,y\}}) = f(CS_t\{x,y\}, nc) (7)$$

Here $S_t\{x,y\}$is the current state of the cell *(x,y)* and *'f'* is a transition function that determines how the cell changes based on its state and its neighbors. *'N'* denotes the neighbourhood of a cell, representing the surrounding cells in the grid. The transition function *'f'* is defined in equation (8)

$$f(CS_t\{x,y\}, N) = SDT\ X\ (AI^t(x,y) + SI^t(x,y) + ZI^t(x,y) + NB_N(x,y)) (8)$$

Where '*SDT*' is a stochastic disturbance term represents denotes unidentified simulation mistakes. This may result in more realistic patterns. It is defined as

$$SDT = 1 + (-\ln \gamma)^{\alpha} (9)$$

Here 'γ' is a standard random variable between 0 and 1, and 'α' is the parameter that controls the amount of the stochastic variation. In this study, the value of 'α' was experimentally calibrated as 2.0 based on iterative simulations to balance compact and dispersed urban growth patterns while minimizing prediction error.

$NB_N(x,y)$ denotes the neighborhood influence on the cell *(x,y)* from '*N*' neighbors. In this study, N=4 corresponds to the Von Neumann neighbourhood is used. The transition rules for N=4 is defined as

$$N_{dev}(x,y) = (UDP_{x-1,y} + UDP_{x+1,y} + UDP_{x,y-1} + UDP_{x,y+1})/4 (10)$$

The urban development potential ($UDP(x,y)$) of a cell (x,y) is modelled as a combination of the accessibility, suitability, and zoning factors. It is defined as

$$UDP(x,y) = w_1 AI(x,y) + w_2 SI(x,y) + w_3 ZI(x,y) \quad (11)$$

The weights (w_1, w_2 and w_3) were calibrated through iterative comparison between simulated and observed urban growth patterns using historical land-use data from 2016–2020. The transition threshold value of accessibility index (T) was experimentally determined as 0.5 after multiple simulation trials to achieve the highest Percent Correct Match (PCM) and spatial agreement with actual urban growth. If the development probability is greater than T, then the transition state of that cell is urban. Otherwise it remains in non-urban state. The calibration procedure involved repeated adjustment of the transition threshold, stochastic dispersion parameter, and neighbourhood influence settings until the simulated urban growth pattern closely matched the observed land-use changes. Shannon's entropy, Moran's spatial autocorrelation index, and Percent Correct Match (PCM) were used to assess the model's performance. To further validate the effectiveness of the developed CA-ANN framework, the results were compared with a conventional Multi-Criteria Evaluation (MCE) based urban growth model. While the MCE model relies on fixed weighted overlays of spatial factors, the CA-ANN approach dynamically captures nonlinear spatial interactions and neighbourhood-driven urban transitions.

The PCM compares cells that were anticipated to move to an urban area with those that actually did so within the same study period. The number of cells in each category divided by the actual number of cells that experienced transition yielded the PCM metric, as shown in equation (11).

$$PCM = (\#\ cells\ properly\ predicted\ for\ changing * 100) / (\#\ cells\ really\ converted) \quad (12)$$

The accuracy with which the model has predicted the urban spatial pattern or morphology is measured using the Moran spatial autocorrelation index. The similarity of objects within a region is measured by spatial correlation. There is a strong spatial correlation between two objects that are adjacent to one another and have very similar spatial characteristics. There is little spatial auto-correlation between two nearby objects with differing spatial characteristics. A regionalized, smooth, clustered pattern is indicated by a Moran spatial autocorrelation index greater than zero, whereas an uncorrelated, random pattern is shown by a Moran spatial autocorrelation value equal to zero.

A geographical variable (x_i) can have its degree of spatial concentration or dispersion among $'n'$ zones measured using Shannon's Entropy (SE_n). It is calculated by

$$SE_n = \sum_{i=1}^{n} p_i \ln\left(\frac{1}{p_i}\right) \quad (13)$$

Where 'p_i' denotes the likelihood that an event will occur in the i^{th} zone ($p_i = z_i / \sum_{i=1}^{n} z_i$), '$z_i$' represents the phenomenon's observed value in the i^{th} zone and 'n' represents all of the zones. Entropy has a value between 0 and ln(n). By analysing whether land development in a city or town is compact or spread, entropy can be utilized to determine the level of urban expansion.

3.5 Generation of urban growth zonation maps

In the conventional CA simulation, a unit problem is handled cell by cell. The fundamental building block of cellular automata, the cell, only has two binary values: 0 for no change and 1 for successful development. These "black or white" cells don't have any intermediate values. This creates an issue when it's necessary to distinguish growth rates between cells or for a cell over time. By assigning each cell a value between 0 and 1, the cell's "grey" state can be used to address this unit issue. It can be used for two things. First, a cell's degree or percentage of development can be correctly represented by the "grey" condition. Partially developed cells are called "grey" cells. However, if the resolution were raised, a "grey" cell may be split into several absolute "black" and "white" subcells. Second, the "grey" state can also be thought of as a helpful dummy variable to show the development likelihood or accumulation of development throughout the process of the CA model's iterations. The "grey" state $G_d^t(x,y)$ of a cell in this CA model indicates the developed (urbanized) percentage of the cell (x,y). First, using conventional

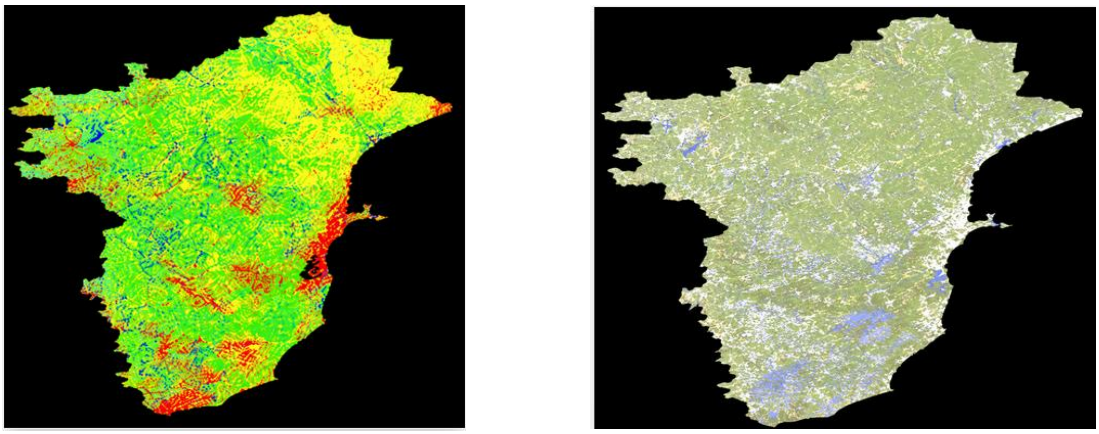
cellular automata, the development probability of a cell at time 't' can be computed based on its neighbouring states using equation (6). A cell's additional developed percentage or additional "grey" state $\Delta G_d^t(x,y)$ at time 't' is both dependent on the constraint score and proportional to the likelihood. The aggregate of the obtained percentages for each iteration step is the final "grey" state. The `grey' state is restricted to the range (0,1). Therefore, when $G_d^t(x,y)$ reaches 1, $\Delta G_d^t(x,y)$ is assigned a value of 0. In the constrained CA model, a cell's grey-state value is updated using the following iteration formula.

$$CS_{t+1}(x,y) = \begin{cases} urbanized\ if\ G_d^t(x,y) = 1 \\ partially\ urbanized\ if\ 0 < G_d^t(x,y) < 1 \\ CS_t(x,y)\ \ if\ G_d^t(x,y) = 0 \end{cases} \quad (14)$$

Thus, the grey cells whose $G_d^t(x,y)$ value is '1' represents the urban growth zonation maps using CA and ANN is generated.

4. Simulation and Results

In the present study, the prediction model was implemented for Thoothukudi District of Tamil Nadu, India (Figure 5a). Thoothukudi District is bounded by Tirunelveli District to the west, Ramanathapuram District to the northeast, the Gulf of Mannar to the east, and Virudhunagar District to the north. The Thamirabarani River is the major river flowing through the district, supporting irrigation and drinking water needs. Srivaikuntam, Koram-pallam, and Vagaikulam tanks and several other minor irrigation tanks are the important water bodies located within the study region. Agriculture and fishing are the major occupations of the people. However, in recent years, rapid industrialisation and urban growth have resulted in the conversion of land used for agriculture into industrial and residential areas. Apart from Thoothukudi city, areas such as Kovilpatti, Tiruchendur, Srivaikuntam, Ettayapu-ram, and Kayalpattinam have experienced significant growth in settlements over the past decade.



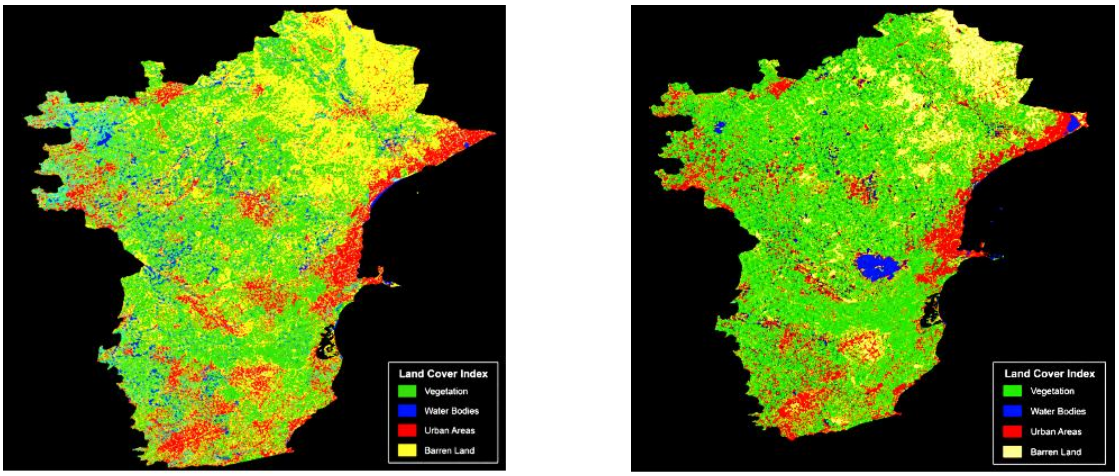
(a) (b)

Figure 5. Pre-processed image represents the satellite data: (a) Map of the Study Area. (b) Pre-processed Image

The pre-processed image of the satellite data after applying necessary image enhancement and correction tech-niques is shown in Figure 5b. These processes include, removal of noise, resizing, normalisation and conversion into a suitable format for further analysis. These pre-processing steps improve the image clarity and quality, which ena-ble effective extraction of meaningful features. This processed image is further used as input for the next LULC classification and prediction modules which in turn improves the accuracy and reliability of the outputs in the pro-cess.

Figure 6a presents the LULC classification map for the period 2021–2025, describing the distribution and extent of the different land-use and land-cover classifications in the area of investigation. The map was created by an inte-grated ANN-CA model using pre-processed Sentinel-2 satellite data. Spectral features of each pixel in the image were used to classify them into specific land-use classes such as bare soil, vegetation cover, urban and surface water. The land-cover classes were represented with different colours for the purpose of improving visual clarity and in-terpretation of the LULC classification map. Classification results show significant change in urban growth, surface

water and vegetation cover during the study period. A confusion matrix-based evaluation of accuracy was carried out utilising independent validation samples to test the dependability of the categorizing results.

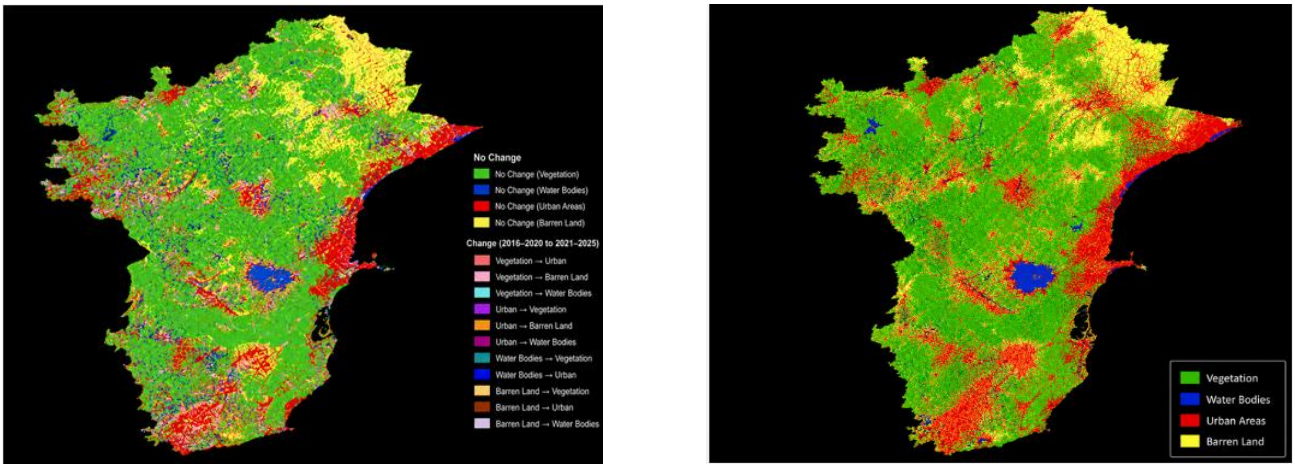


(a) (b)

Figure 6. LULC Classification Maps over the time: (a) LULC Classification Map for 2021-2025. (b) LULC Classification Map for 2016-2020.

The distribution of various land-use and land-cover classifications throughout the investigation region is shown on the LULC classification map for the years 2016–2020 in Figure 6b. The map was generated using the trained integrated model by classifying the Sentinel-2 pre-processed satellite imagery into different land use categories such as surface water, urban land, bare soil, and vegetation cover. Each class is represented using distinct colours to improve visualisation and interpretation. When compared with the 2021–2025 period, this map helps identify changes such as urban expansion, reduction in vegetation cover, and variations in water bodies. The CA–ANN model was compared with a traditional MCE-based urban growth model to evaluate the effectiveness of the proposed approach.

The change detection map, which shows the variations in land use and land cover between the years 2016–2020 and 2021–2025, is shown in Figure 7a. The map was generated by comparing the two classified LULC maps on a per-pixel basis to identify areas where changes have occurred. The changes such as urbanisation, reduction of vegetation cover and changes in water bodies are marked with different colours for easy visualisation. This comparison allows one to understand the spatial distribution and extent of land cover changes over time. Constant and large transition areas are clearly marked for easy interpretation and zero change areas are shown. This change detection map can be useful to analyse the land use trends, monitoring the environmental impacts and supporting the future land use planning and decision making.



(a) (b)

Figure 7. Predicted LULC Map based on Change Detection: a) Change Detection Map b) Predicted LULC Map for the year 2030

Figure 7b shows the predicted LULC map of 2030, which represents the expected land-use and land-cover properties of the research area. The prediction was generated by the ANN model trained using the historical and recent LULC raster datasets. During this training process the model learns the relationship between the pixel values and corresponding land cover classes which allows it to predict future land use patterns. In this approach, the pre-processed raster data are input to the trained integrated model, which analyses the spatial patterns and produces predictions for each pixel. The outcome is a classified map with each pixel assigned to a specific land cover type (e.g. bare soil, vegetation, urban land, surface water). Distinct colour codes are used for each class to facilitate interpretation of the spatial distribution. The predicted 2030 map shows possible trends of expansion of urban areas, reduction of vegetation cover and changes of water bodies based on changes observed in the past. This projected map is a useful tool for understanding future land use possibilities and supports planning and environmental monitoring. Additionally, this map helps in decision-making by clearly estimating the potential evolution of the research region.

4.1. Classification Performance

The LULC classification performance was assessed by Kappa coefficient [25,26], user accuracy, producer accuracy, and total classification accuracy [24]. The confusion matrix (Table 1) shows the accuracy assessment of LULC classification. Table 1 shows that 91.00% of the urban pixels and 91.33% of the non-urban pixels were correctly classified. The overall classification accuracy was 91.25% with Kappa coefficient of 0.88.

Table 1. Confusion Matrix for Classification Accuracy Assessment

Land Use Class	Urban Area	Vegetation	Water Bodies	Barren Land	Total	User's Accuracy (%)
Urban Area	91	3	2	4	100	91.00
Vegetation	4	93	1	2	100	93.00
Water Bodies	2	3	90	5	100	90.00
Barren Land	3	2	4	91	100	91.00
Total	100	101	97	102	400	0
Producer's Accuracy (%)	91.00	92.08	92.78	89.22	0	91.25

4.2. Prediction Performance

The PCM, Moran's spatial autocorrelation index, Shannon's entropy and land use transition matrices were used to assess prediction performance. The results of the comparison of prediction performance are shown in Table 2. The CA-ANN model performed better than the conventional MCE model in all the evaluation metrics because it can mimic the nonlinear dynamics of urban growth and neighbourhood interactions. The performance of CA predictions was evaluated based on the Moran's spatial autocorrelation index, Percent Correct Match (PCM) and Shannon's Entropy, which demonstrated that the model captured the spatial urban morphology and urban growth dynamics accurately. The PCM value of 91.4% obtained for the proposed model indicates a high level of agreement between the actual observed urban growth and the predicted urban transition cells. The simulated urban growth pattern showed a strong spatial clustering (Moran's Index value of 0.81) and realistic urban morphology. Shannon's Entropy increased from 1.42 (2016–2020) to 1.67 (2021–2025) showing increasing spatial dispersion and urban sprawl in the study area. Such results confirm the effectiveness of the proposed CA-ANN model in capturing the magnitude and the spatial characteristics of urban expansion.

Table 2. MCE Versus Proposed CA-ANN Model

Model	Overall Accuracy (%)	Kappa Coefficient	PCM (%)	Moran's Index
MCE Model	84.6	0.74	82.1	0.69
Proposed CA–ANN Model	95.5	0.88	91.4	0.81

From the classified LULC maps in Table 3, there is a significant urban expansion during the periods of 2016–2020 and 2021–2025. Urban land coverage increased from 18.4 to 27.9% of total study area indicating significant urban expansion. Vegetation cover decreased from 46.2% to 38.5%. Bare soil and surface water bodies experienced moderate reductions. The results show that the major cause of the urbanisation was the conversion of bare soil and vegetation cover to built-up areas. The land-use transition matrix was used to quantify changes among different LULC classes during the study period. The transition matrix shows that the greatest conversion to urban was from vegetation cover (7.1%) and then from bare soil (4.8%) which confirms the impact of urbanisation on the decline of the natural land cover. Table 4 quantifies the change matrix between the different classes of LULC for the study period.

Table 3. Urban land change statistics

Land Use Class	2016–2020 (%)	2021–2025 (%)	Change (%)
Urban Land	18.4	27.9	+9.5
Vegetation Cover	46.2	38.5	−7.7
Surface Water	12.8	10.6	−2.2
Bare Soil	22.6	23.0	+0.4

Table 4. Land-use transition matrix

From / To	Urban Area	Vegetation	Water Bodies	Barren Land
Urban Land	15.8	0.6	0.2	1.8
Vegetation Cover	7.1	34.4	1.5	3.2
Surface Water	1.2	1.0	9.3	1.3
Bare Soil	4.8	2.5	0.4	14.9

4.3 Sensitivity Analysis

The stability and reliability of the proposed model were assessed through sensitivity analysis [27]. The analysis is to investigate the effects of transition threshold (T) and stochastic dispersion parameter (α) on the prediction results. The analysis showed that lower threshold values caused too much urban expansion, and higher values led to an overestimation of urban growth. The best predictive performance was achieved for a threshold value T = 0.5 and a dispersion parameter α = 2.0. With these parameter settings, the model achieved maximum spatial agreement with the observed pattern of urban growth. The analysis also reaffirmed the importance of neighbourhood effect in controlling the compact and dispersed urban development patterns.

5. Conclusions

The proposed integrated urban growth prediction model overcomes the drawbacks of existing models that consider geographical, topographical and socio-economic factors independently. The proposed approach considers these factors simultaneously to improve the prediction accuracy of land use change and urban growth. Input data was pre-processed to have high quality for Thoothukudi District, Tamil Nadu. The processed images were classified into land use and land cover classes such as vegetation cover, surface water bodies, urban land and bare soil using the proposed model. Analysis of LULC maps of different time periods was conducted to understand the spatial distribution and land use patterns. The change detection analysis showed some major changes, such as urban growth, reduction of vegetation cover and change of surface water bodies. Future land use (2030) was predicted by the integrated model using both historical and recent data.

The performance of the proposed CA-ANN model in prediction and LULC classification was evaluated. The Kappa coefficient and the overall classification accuracy were used to assess the classification performance. The predictive ability of the model was evaluated through Percent Correct Match, Shannon's entropy, Moran's spatial autocorrelation index and land use transition matrices. Collectively, these measures quantify the degree of agreement of the actual and the predicted LULC maps. Sensitivity analysis was also performed to evaluate the effect of key model parameters on the predicted results, in order to assure the robustness of the proposed model. The results

imply possible urban sprawl and associated environmental changes in the study area. In general, the proposed combined CA-ANN model is an effective tool for sustainable land management, urban planning and environmental monitoring.

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Data availability: The satellite imagery used for the urban growth analysis of Thoothukudi, Tamil Nadu, India, was obtained from the Copernicus Sentinel-2 mission. The Sentinel-2 data are openly and freely accessible through the Copernicus Data Space Ecosystem (CDSE), which provides facilities for searching, visualizing, and downloading Sentinel satellite products. The dataset can be accessed through the following official repository: Copernicus Data Space Ecosystem: https://dataspace.copernicus.eu/ Sentinel-2 data collection: https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-missions/sentinel-2 Data source: Copernicus Sentinel-2, Data repository: Copernicus Data Space Ecosystem (CDSE), Access: Open and free.

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