



Delineating Urban Growth Boundary Using Remote sensing, ANN-MLP and CA model: A Case Study of Thiruvananthapuram Urban Agglomeration, India

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Abstract

This research paper investigates urban sprawl in Thiruvananthapuram Urban Agglomeration (UA) and attempts to delineate Urban Growth Boundary (UGB) for promoting urban sustenance. A 112% rise in the spatial expanse of Thiruvananthapuram UA from 256.22 km² in 2001 to 542.57 km² in 2011 might induce urban sprawl in the peripheral areas. The Landsat satellite imagery for the years 1987, 1997, 2007, and 2017 were extracted to examine the spatiotemporal urban growth pattern. Shannon's entropy index was employed to detect urban sprawl in Thiruvananthapuram UA. The UGB delineation process involved future urban growth prediction using the MOLUSCE (Modules for Land Use Change Simulations) plug-in of QGIS software. ANN-MLP (Artificial Neural Network-Multi Layer Perceptron) and CA (Cellular Automata) model was preferred in MOLUSCE to predict future urban growth for the year 2027. Thereafter, hexagons of one square kilometer were used to demarcate the Contiguous built-up Growth Boundary (CGB), and later, sub-administrative units were selected to delineate UGB. The results revealed a rise in the built-up areas from 36.04 km² in 1987 to 140.69 km² in 2017. Shannon's entropy index indicated the prevalence of urban sprawl in Thiruvananthapuram UA. The future growth prediction by 2027 exhibited a further rise in built-up areas to 173.31 km². The total area within CGB is 213.58 km², while UGB accounted for 355.59 km², which included 16 sub-administrative units. This study exhibited a unique methodology to delineate the urban growth boundary, which optimizes the future land requirements in developing nations.

Keywords Urban growth boundary · RS and GIS · ANN-MLP · CA · Urban sprawl · Thiruvananthapuram

Introduction

The world's population is expected to rise 10% by 2030 and a further 26% by 2050, wherein such growth will predominantly occur in the urban areas and their surroundings (United Nations, 2019). The saturation of large cities has shifted the hotspot of future urban growth to mid-sized cities with a population between 0.5–5 million (Perez et al., 2019). However, due to the lack of proper urban planning strategies in India, urban sprawl is likely to occur in mid-sized cities (Chetty & Surawar, 2020). Such a

pattern of urban growth marks a significant hurdle toward promoting safe, resilient, inclusive, and sustainable cities as per the 11th Sustainable Development Goal framed by the United Nations.

The rapid urban growth in Indian cities has accelerated peripheral urban growth and negatively affected the natural environment (Kumar & Pandey, 2013; Aithal & Ramachandra, 2016; Diksha and Kumar, 2017). Urban sprawl is a complex and dynamic phenomenon, and hence it has become challenging to achieve a consensus on the definition and measurement methods (Bhatta, 2012; Maitani, 2020). The significant characteristics of urban sprawl observed in Indian cities are rapid land cover changes (Mandal et al., 2019), low-density development (Alsharif & Pradhan, 2014), haphazard and unplanned growth (Aithal & Ramachandra, 2016; Sudhira et al., 2003), decrease in agricultural land and open spaces (Sahana

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et al., 2018; Singh & Singh, 2020), and increase in urban heat island (Singh & Kalota, 2019). Urban sprawl has been assessed using remote sensing (RS) and geographic information system (GIS) in combination with Shannon's entropy index, landscape metrics, expansion metrics, and spatial metrics (Saini & Tiwari, 2020).

There are multiple strategies aimed to contain and regulate urban sprawl, such as adequate public facilities ordinances, annexation, development priority zoning (DPZ), exclusive agricultural zoning, green belt, infill growth, infrastructure concurrency requirements, land purchase by the government, mitigation ordinance, urban service boundary (USB), urban growth boundary (UGB), transfer of development rights (TDR), and zoning (Bengston & Youn, 2006; Bhatta, 2010; Elson et al., 1993; Nelson & Moore, 1993; Wang et al., 2017). Comparatively, UGB is widely reviewed in academia and is also the most successful urban containment tool (Ding et al., 1999; Easley, 1992; Tayyebi et al., 2011; Yang et al., 2019).

UGB, by definition, is a line drawn to distinguish urban from rural areas, wherein compact, contiguous growth is promoted within the boundary, while agricultural lands, open spaces, forests, and ecologically fragile regions are protected outside the boundary (Carter, 2009; Meck, 2002). The advantages of UGB are its ability to curtail urban sprawl (Mubarak, 2004), shifts urban growth from greenfield sites (Morrissey et al., 2018), restricts the radius of a city (He et al., 2018), and lowers the cost of infrastructure provision and maintenance (Jain et al., 2019). In India, the concept of UGB is mainly inclined toward British green belts and was incorporated in the master plan of Indian cities such as Chandigarh in 1952 (Chalana, 2015), subsequently Ahmedabad in 1967 (Mell, 2017), Bengaluru in 1972 (Venkataraman, 2013), and Delhi in 1987 (Jain & Siedentop, 2014). However, the green belts were found to have limited success in India; therefore, UGB has been suggested as the potential substitute planning tool to contain future urban growth and limit urban sprawl (Jain et al., 2019).

Most of the UGBs implemented in the cities worldwide adopt traditional methods, such as statistical projection of the future urban population and land demand, stakeholder discussions, and a primary survey of the city (Al-Hathloul & Mughal, 2004; State of Victoria, 2002; Yang et al., 2020). Due to scientific advancements in recent years, the UGB delineation process has started to utilize landscape metrics for Wuhan, China (He et al., 2018) and a combination of the SLEUTH (slope, land use, exclusion, urban extent, transportation, and hill shade) model with the land regulation policies for Changzhou, China (Jiang et al., 2016). In India, IURP (Ideal Urban Radial Proximity), based on the concept of the circular city for Kolkata (Bhatta, 2009) and the ANN model for Siliguri

(Chakraborti et al., 2018) were attempted to delineate UGB. However, most of the simulated UGBs are tedious to implement in India due to issues related to administrative jurisdictions. In developing countries, flexible UGB is required to cater to existing and future land demands for development (Jain et al., 2019). The National Urban Policy Framework of India in 2018 prioritized the implementation of UGB for the sustainable development of urban agglomerations (MoHUA Govt. of India, 2018). Nevertheless, the research related to UGB delineation using modern scientific methods is at the very initial stages in India.

Thiruvananthapuram UA had experienced an increase (112%) in the spatial expanse from 256.22 km² in 2001 to 542.57 km² in 2011, which might induce urban sprawl in the peripheral areas. Moreover, the city is surrounded by the fragile ecology of the coastal plains region, wherein rapid urban sprawl poses a major threat (Arulbalaji et al., 2020). Therefore, this study attempts to exhibit a unique UGB delineation method for Thiruvananthapuram UA by utilizing hexagon cells of one square kilometer and sub-administrative boundaries. The major objectives of this paper are to: (1) conduct land cover change detection of Thiruvananthapuram UA during 1987, 1997, 2007, and 2017; (2) simulate future urban growth through ANN-MLP and CA model; and (3) delineate CGB and UGB based on the combination of hexagon cells and administrative boundaries of the study area.

Study Area

Thiruvananthapuram is the capital city of Kerala state of India (Fig. 1). It is one of the extremely urbanized cities in the state and is located in the coastal plains along the Lakshadweep sea. Thiruvananthapuram UA includes 30 sub-administrative units within its boundary, i.e., one Municipal Corporation (M.Corp.), three Municipalities (M), twenty-four Census Towns (CT), and two Outgrowths (OG). As per the Census of India 2011, Thiruvananthapuram UA has a total population of 1.687 million within an area of 542.57 km². It has an undulating terrain, and the elevation varies from 0 to 257 m from mean sea level. Earlier the city was an educational and research hotspot, but after the economic liberalization of the Indian economy, it has evolved as an IT hub in the state.

Research Methods

The flowchart of this research is shown in Fig. 2. The details of the Landsat satellite images for the years 1987, 1997, 2007, and 2017 are presented in Table 1. The total

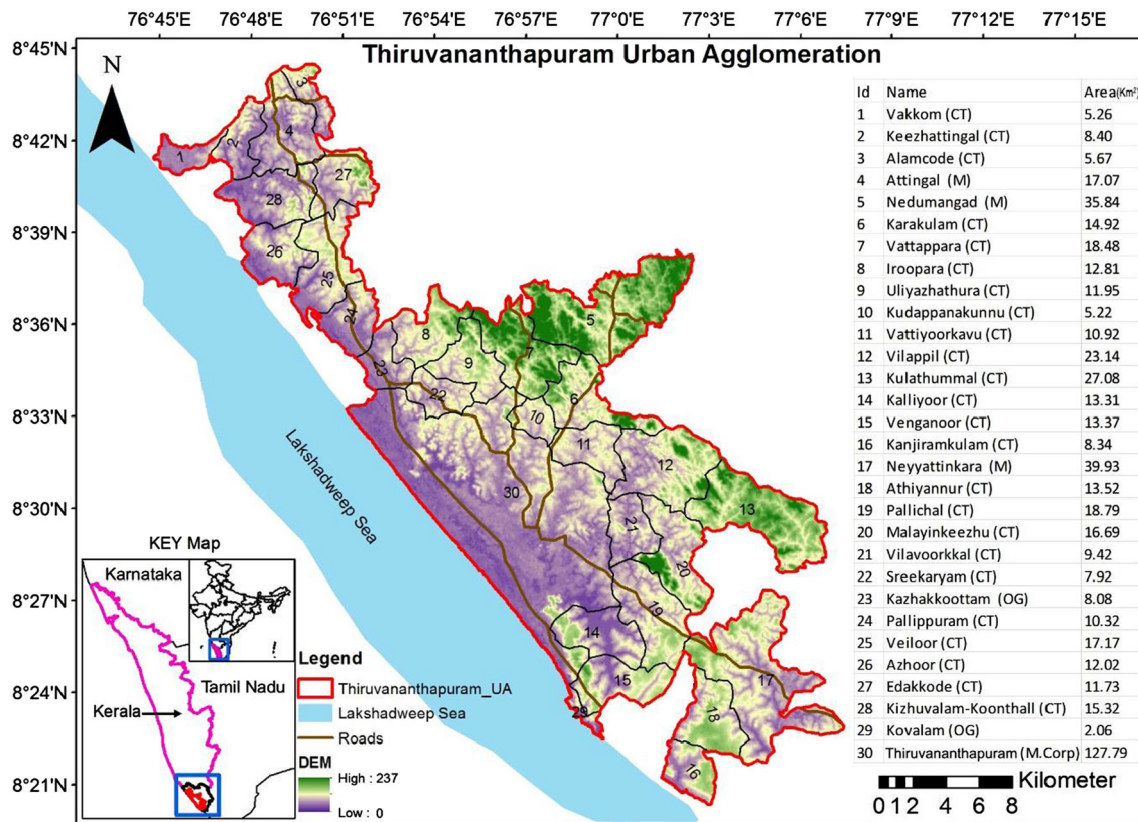


Fig. 1 Location map of Thiruvananthapuram Urban Agglomeration

population, UA boundary, and the constituents of Thiruvananthapuram UA were availed from the Census of India 2011 website. Other essential data, such as state boundary and district boundary, were obtained from the administrative atlas of India. The nearest neighbor assignment technique was adopted for resampling the 1987 Landsat image to 30 m resolution. The downloaded satellite images were used to conduct land cover change detection through the maximum likelihood supervised classification (MLC) tool in ArcGIS 10.3. Shannon's entropy index was used to detect urban sprawl. Further, in QGIS 2.8.4, the MOLUSCE plug-in was employed to predict land cover for the year 2027. However, before utilizing the model for prediction, the accuracy of the model was determined by comparing the 2017 MLC land cover map with the simulated land cover map of 2017. Thereafter, one sq. km hexagon cells combined with administrative boundary were used to delineate contiguous built-up growth boundary and urban growth boundary.

Land Cover Classification

The downloaded Landsat satellite images were georeferenced to Universal Transverse Mercator (UTM) Zone 43 N. Dark-Object Subtraction (DOS) method was

employed for the atmospheric correction of the satellite images (Dutta & Das, 2019). The study area was clipped using the vector file of the Thiruvananthapuram UA boundary in ArcGIS 10.3. All the required layers of satellite images were merged, and a composite image was obtained before proceeding with the land cover classification process. The accuracy and precision of the classification process were enhanced by increasing the texture of the composite images and preparing a false-color composite using the optimum index factor for each period (Kalkhajah & Jamali, 2019). After thorough visual image interpretation, land cover maps were obtained using the MLC tool (Bharath et al., 2014). Despite these measures, a few mixed pixels observed during the classification process were removed through the reclassification process. The MLC tool predicts the probability of pixels belonging to a land cover class based on the Bayes' theorem, as

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

where A and B are events and $P(B) \neq 0$; $P(A|B)$ is the likelihood of event A occurring given that B is true, $P(B|A)$ is the likelihood of event B occurring given that A is true, $P(A)$ and $P(B)$ are the probabilities of observing A and B independently of each other.

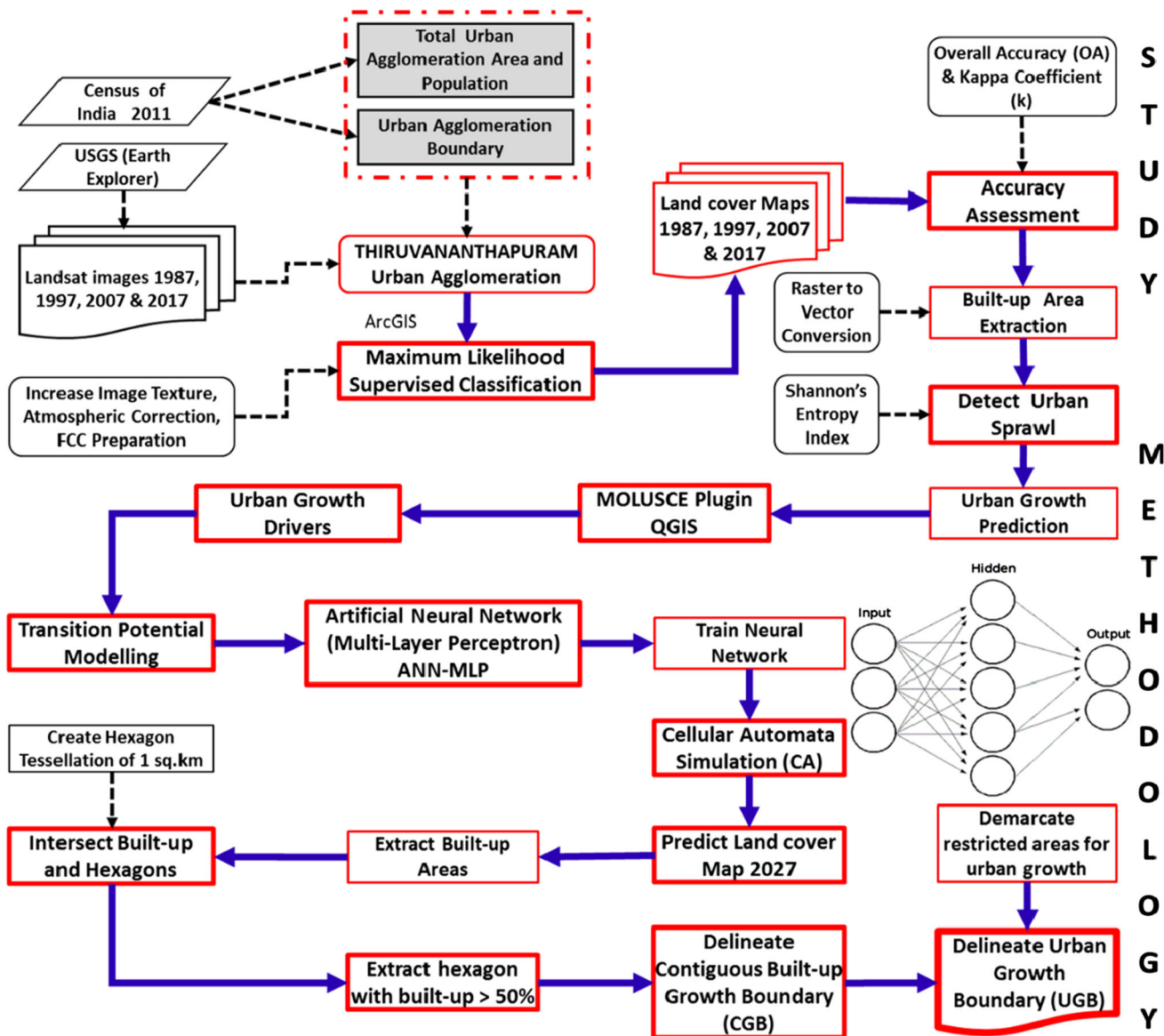


Fig. 2 Flowchart of the methodology adopted in the study

Table 1 Descriptions of Landsat satellite images used in the study

Landsat sensor	Thiruvananthapuram UA				
	Scene ID/Tile number	Path/Row	No. of bands	Acquisition date	Resolution (m)
4–5 TM Mosaics	MTN-43-05_LOC		03	19 February 1987	28.5
5 TM	LT51440541997043SGI00	144/54	07	12 February 1997	30
7 ETM +	LE71440542007047SGS00	144/54	08	16 February 2007	
8 OLI_TIRS	LC81440542017002LGN01	144/54	11	02 January 2017	

shown in Eq. 1 (Alkaradaghi et al., 2019).

The images were classified into five major land cover classes, i.e., vegetation, built-up, water body, agriculture, and fallow land (John et al., 2020; Prasad & Ramesh, 2019;

Xu et al., 2010). The accuracy of the obtained land cover maps was assessed through the ground truth data collected from the Google Earth archives (Shooshtari et al., 2019). For each land cover class, 50 ground truth points, i.e., a

total of 250 random samples, were collected (Girma et al., 2019; M and M, 2019). Overall accuracy (OA) and kappa coefficients (k_i) were determined for each land cover map as shown in Eq. 2 and 3 (Congalton, 1991; Setturu, 2013).

$$OA = \frac{\sum_{i=1}^k n_{ij}}{n} \quad (2)$$

$$k_i = \frac{P_{(o)} - P_{(e)}}{1 - P_{(e)}} \quad (3)$$

where n_{ij} = diagonal elements in the error matrix, k = total number of classes, n = total number of samples in the error matrix, $P_{(o)}$ = observed proportion of agreement, $P_{(e)}$ = proportion expected by chance.

Shannon's Entropy Index

After obtaining the required accuracy standards, the built-up land cover was extracted to analyse the urban growth pattern. Shannon's entropy index was used to detect urban sprawl (Sudhira et al., 2003). In this method, the index value approaching zero indicates concentrated urban development, while the values nearer to $\log_e(n)$ indicate

$$H_n = - \sum_{i=1}^n P_i \log_e(P_i) \quad (4)$$

$$P_i = X_i / \sum_{i=1}^n X_i \quad (5)$$

where P_i is the probability or the proportion of the variable occurring in the zone i . In this research, the study area is divided into eight cardinal direction therefore, the value of n is 8.

the occurrence of urban sprawl. Shannon's entropy H_n is calculated, as shown in Eq. 4 and 5.

MOLUSCE

MOLUSCE (Module for Land use change evaluation) plug-in, programmed jointly by Asia Air Survey Co. Ltd. and NEXTGIS for QGIS 2.8.4 software, was used to forecast land cover change within an area. The interface of the MOLUSCE plug-in is easy to use and includes basic modules such as input variables, area change analysis, transition potential modeling, simulation, and validation (Asia Air Survey & Next GIS, 2012). The model was trained by producing a 2017 simulated land cover map based on the actual land cover maps of 1987, 1997, and 2007. Since the gap between each consecutive study period is ten years, the future land cover was predicted for the year 2027. The input variables contain raster land cover maps of 1987, 1997, and 2007 and spatial variables as driving factors. The prominent urban growth drivers (Fig. 3)

gathered from the literature to simulate future built-up growth includes slope, hill shade, DEM, distance from the urban core, suburban centers, waterbody, railways, major roads, airport, and future urban centers (Long et al., 2012, 2013; Liu et al., 2016; Wang et al., 2018; Jamali and Kalkhajah, 2019).

The slope and hill shade maps were extracted from DEM, while other raster maps of growth drivers were obtained by calculating Euclidean distances from the respective vector datasets. The DEM of the study area ranges from 0 to 237 m from the mean sea level. The slope map exhibited the presence of hills within the city. The distance from the urban core revealed an occurrence of high urban growth in the core and gradual decline toward the periphery, especially toward the north-west direction of Thiruvananthapuram UA. The suburban centers included three municipalities, i.e., Attingal, Nedumangad, and Neyyattinkara. The distance from the waterbody is another essential factor to be considered for future urban growth prediction. The location of the railway line, major roads, and airports is major contributing factors to the land cover change of an area. Thus, the Euclidean distances from these vector datasets were determined to forecast urban growth. Before proceeding with the simulation, the raster image of all the drivers was scaled between -1 to 1 using the raster calculator function in ArcGIS 10.3 to avoid inconsistency in datasets. After that, the area change analysis produces a land cover change map and land cover class statistics of each year to display 'from-to' changes during the period. To conduct transition potential modeling in MOLUSCE, the ANN-MLP model is preferred due to its higher computing performance (El-tantawi et al., 2019; Tayyebi et al., 2011). It is a nonlinear data analysis algorithm that trains urban growth drivers and considers complex underlying features during modeling (Maithani, 2009; Yang et al., 2016). This model creates a transition probability map through input, hidden, an output layers, which altogether forms a multilayer perceptron (Pijanowski et al., 2002). The training parameters adopted to customize the MOLUSCE model are shown in Table 2.

The training of neurons involves the feed-forward of the weighted input neuron, the backpropagation of the associated error, and the adjustment of the weights using a standard delta rule. Thereafter, Cellular Automata (CA) was used to predict future urban growth within Thiruvananthapuram UA; it is considered highly accurate in such studies (Santé et al., 2010). An urban CA model involves a disconnected cell space characterized by its function, qualitative data (land uses), and quantitative urban data. In the CA model, the previous state of each cell and the state of neighboring cells affect the current state of each cell. For the validation of the model, the reference pixels from the 2017 simulated map obtained through

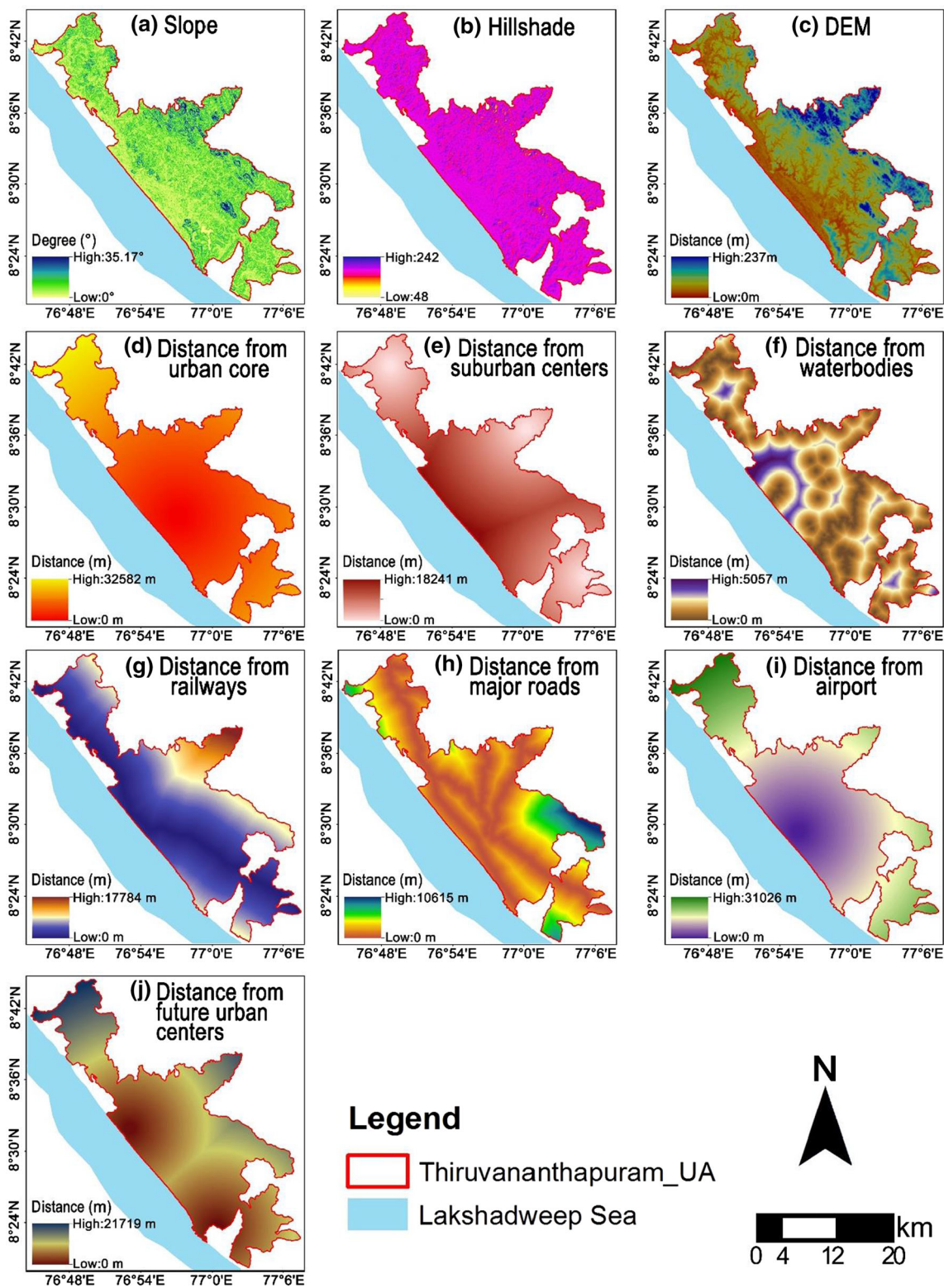


Fig. 3 Urban growth drivers used for future growth prediction of Thiruvananthapuram UA, **a** Slope, **b** Hill shade, **c** DEM, **d** Distance from urban core, **e** Distance from suburban centers, **f** Distance from

waterbody, **g** Distance from railways, **h** Distance from major roads, **i** Distance from airport, and **j** Distance from future urban centers

MOLUSCE were compared with the land cover map of 2017 obtained through the MLC process. The overall

accuracy and Kappa (overall) were determined to assess the accuracy of the model. After obtaining the desired

Table 2 Training parameters to customize the ANN-MLP model

S. No	Parameter setting	Value
1	Neighborhood	1 px
2	Learning Rate	0.001
3	Maximum iterations	10,000
4	Hidden layers	10
5	Momentum	.050

accuracy standards, the process was repeated to produce a simulated land cover map for the year 2027 (Ullah et al., 2019).

Urban Growth Boundary

Delineation of the Urban Growth Boundary (UGB) for the year 2027 involves a unique approach. The predicted raster land cover map was converted to vector data, and the built-up class was extracted for the delineation purpose. A hexagon mesh of one sq. km covering the whole study area was constructed in ArcGIS 10.3 and intersected with the built-up layer to obtain a Contiguous built-up Growth Boundary (CGB). For this purpose, hexagon cells of more than 50% built-up were extracted since this criterion is used in other studies to demarcate contiguous growth (Kantakumar et al., 2016; Sahana et al., 2018). The remaining built-up units were excluded as they are not suitable for future urban development (Tayyebi et al., 2014; Zhou et al., 2016). Moreover, as per environmental protection policies, the areas demarcated for conservation and no development were restricted for future development (Zhuang et al., 2017). Since CGB surpasses through multiple sub-administrative units within Thiruvananthapuram UA, it might challenge maintaining the recommended momentum of urban growth as per UGB policies. Hence, for practical delineation of UGB, the sub-administrative units within which the CGB surpasses were considered to decrease confusion among the concerned authorities.

Results and Discussion

Land Cover Change Detection

The land cover maps of Thiruvananthapuram UA during 1987, 1997, 2007, and 2017 obtained through the MLC tool are exhibited in Fig. 4.

As per the accuracy assessment (Table 3), the Overall Accuracy (OA) and kappa coefficients (k_i) were above 85% and found to be satisfactory for further analysis (Congalton, 1991; Fenta et al., 2017).

During the study period, the vegetation land cover had exhibited a decreasing trend from 349.83 km² in 1987 to 193.47 km² in 2017 (Fig. 5). The built-up area had increased from 36.04 km² in 1987 to 140.69 km² in 2017. There was a minimal increase in water body land cover from 4.19 km² in 1987 to 6.03 km² in 2017, agriculture land cover from 52.53 km² in 1987 to 86.24 km² in 2017, fallow land cover from 99.98 km² in 1987 to 116.14 km² in 2017. Overall, the reduction in vegetation land cover had resulted in the rapid built-up growth within Thiruvananthapuram UA. Such large-scale vegetation loss was also observed in other cities of Kerala (Veettil & Grondona, 2018).

Such urban growth patterns of the city can be attributed to the dominance of industrial units and the IT sector post-liberalization of the Indian economy, i.e., 1990. Earlier, Thiruvananthapuram was majorly a service town, wherein the local workforce was primarily involved with governmental and administrative operations. Multiple industries were established, such as Technopark at Kazhakootam in 1990, and KINFRA (Kerala Industrial Infrastructure Development Corporation) in 1993, set up a small industrial park at Thumba and film and video park at Kazhakootam (Thiruvananthapuram Corporation, 2012; Shaji, 2019). Gradually, an industrial estate at Pappanamcode, a mini-Industrial estate at Ulloor, and an Industrial Development Center at Kochuveli were developed. These recent developments have attracted rapid built-up growth in Thiruvananthapuram UA, as observed in the land cover change analysis (Arulbalaji et al., 2020).

Further, it was observed that many cities in Kerala, including Thiruvananthapuram, exhibited a rise in urban areas primarily through dispersion (Pandey et al., 2013; V et al., 2017). A similar land cover change pattern in areas surrounding Thiruvananthapuram, wherein growth in built-up areas and decline in vegetation, water bodies, and fallow land cover was also identified by other researchers (Arulbalaji et al., 2020). Few of the other mid-sized cities of India also exhibited rapid growth of built-up areas at the cost of natural land covers, such as Ranchi (Kumar et al., 2011), Dehradun (Deep & Kushwaha, 2020), Udaipur (Mondal et al., 2020), Lucknow (Shukla & Jain, 2019), and Ludhiana (Singh & Kalota, 2019).

Urban Sprawl Detection

Urban sprawl was detected using Shannon's entropy index (H_n), wherein during 1987, H_n was 1.92, which increased to 1.95 in 1997, 1.98 in 2007, and 2.02 in 2017. As per H_n values, urban sprawl exhibited an increasing trend in Thiruvananthapuram UA. Similar trends of Shannon's entropy index were observed in Kozhikode UA (Krishnaveni & Anilkumar, 2020). The major drivers of urban

Fig. 4 Land cover Map of Thiruvananthapuram Urban Agglomeration; **a** 1987, **b** 1997, **c** 2007, and **d** 2017

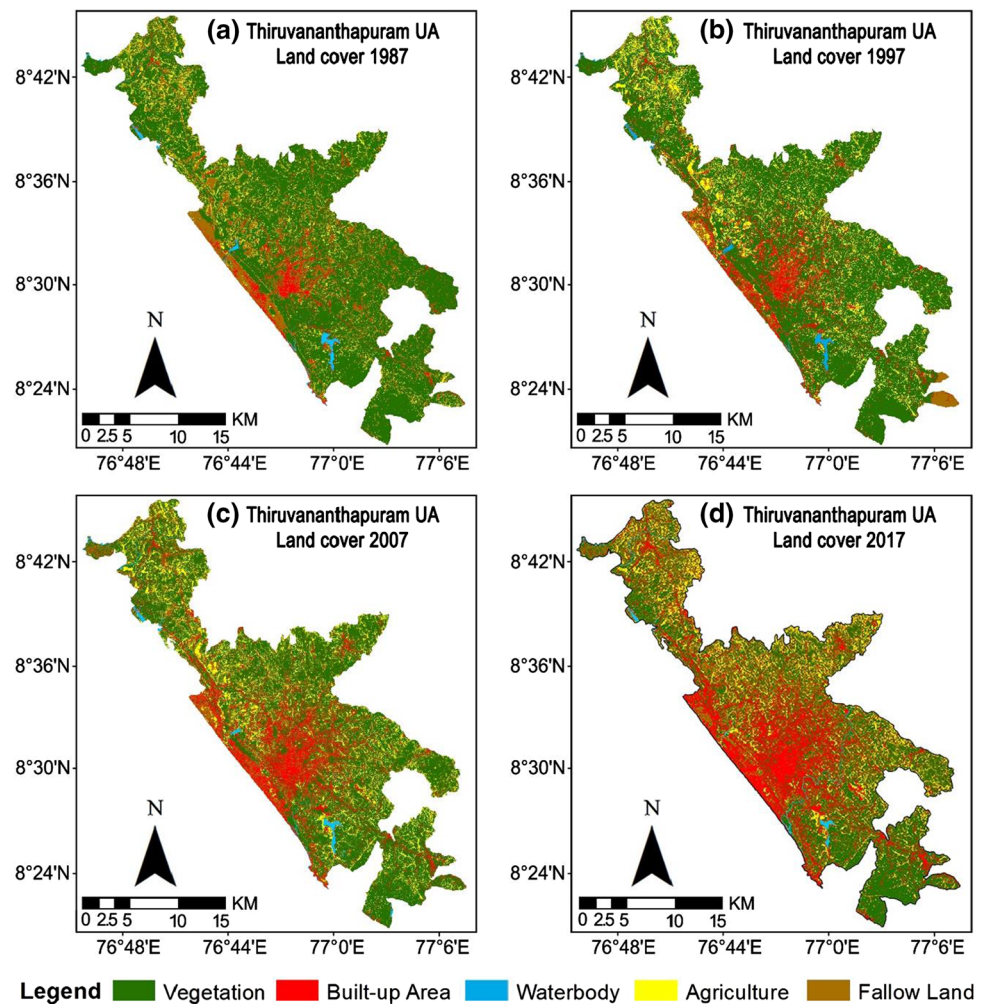


Table 3 Accuracy assessment of Landsat-based land cover maps (1987, 1997, 2007, and 2017)

S.No	Accuracy assessment	Thiruvananthapuram UA			
		1987 (%)	1997 (%)	2007 (%)	2017 (%)
1	Overall accuracy	86.39	88.53	90.78	92.18
2	Kappa coefficient	85.04	86.32	88.06	90.67

sprawl are the location of development projects in peripheral areas, mostly due to the rising real-estate market and land crunch in the core city. Comparatively, during the 2018 floods in Kerala state, Thiruvananthapuram UA was least affected due to its undulating terrain, but the people residing in encroached low-lying areas and wetlands were drastically affected. Although, for the planned and organized development of Thiruvananthapuram and its surrounding area (295.35 km²), TRIDA (Thiruvananthapuram Development Authority) was constituted. However, after the 74th CAA legislation in 1992, the power and functions of TRIDA were curtailed, and it remained as a small-scale project implementing agency within its limited jurisdictions. Therefore, UGB delineation is necessary for

Thiruvananthapuram UA combined with the formation of a metropolitan body, which would administer the urban growth holistically, monitor implementation of UGB, and enhance the coordination among multiple sub-administrative units.

Urban Growth Prediction

Future urban growth was predicted based on the combination of the ANN-MLP and CA model in the MOLUSCE plug-in of QGIS 2.8.4. As mentioned in MOLUSE Section, the model was calibrated by simulating land cover for 2017 based on 1987, 1997, and 2007 land cover maps. The geometry of all the selected urban growth drivers and land

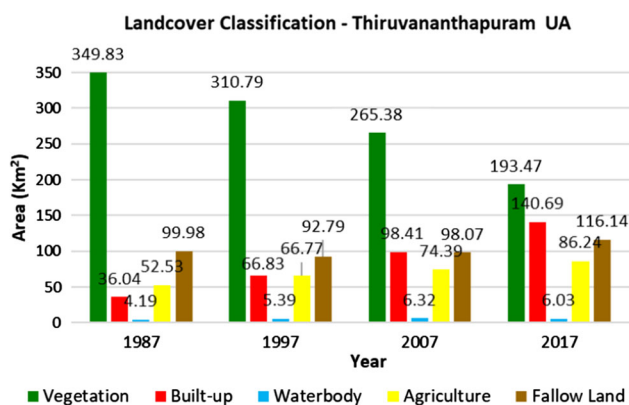


Fig. 5 Land cover classification of Thiruvananthapuram UA (1987, 1997, 2007, and 2017)

cover maps were checked, and later area change analysis was conducted. The transition matrix obtained from the tool highlights that vegetation land cover significantly contributed to the rise of built-up growth from 1987 to 2007.

After training the neural network through the ANN-MLP model and then obtaining a satisfactory kappa coefficient, the land cover map for 2017 was simulated. MOLUSCE displayed the delta overall accuracy as -0.00249 (the difference between the minimum reached error and current error), minimum validation overall error as 0.01047 (the minimum reached error after validating the sample set). The kappa value represented by the current validation kappa was 0.91354. Thereafter, the CA model produced a simulated land cover map for the year 2017 (Fig. 6). The accuracy of the model was assessed by comparing the reference pixels from the 2017 MLC land cover map of Thiruvananthapuram UA (Fig. 4d) with the

simulated 2017 land cover map. As per the simulated map of 2017, the built-up land cover was 146.85 km², while the actual built-up (MLC) was 140.69 km². The comparison between the actual and simulated land cover maps exhibited that the built-up land cover occupied the most over-estimated area, i.e., 6.16 km², followed by agriculture (3.03 km²), water body (0.36 km²). However, the simulated vegetation land cover exhibited less occupied areas (4.86 km²), followed by the fallow land cover (4.69 km²) than the actual land cover. Comparatively, the growth pattern of the core city areas was predicted more accurately than the distant peripheral areas. The simulated built-up land cover was excessively predicted in some parts of Thiruvananthapuram UA, such as Nedumangad, Sreekarayam, Kudappanakunnu, and Neyyattinkara. The overall accuracy and kappa value obtained after validating the simulated land cover with the actual land cover were 90.89% and 88.17%. Thus, after obtaining satisfactory results from the calibration of the MOLUSCE model, the future land cover map for the year 2027 was predicted, as shown in Fig. 7.

In 2027, the built-up land cover exhibited a further increase to 173.31 km², followed by agriculture 99.05 km². Other land covers presented a declining trend, such as vegetation (161.84 km²), fallow land (102.51 km²), and water body (5.86 km²). Overall, there was a significant rise in built-up land cover from 1987 to 2027 in Thiruvananthapuram UA (Fig. 8). The rise in built-up growth had followed the previous trend, i.e., through the conversion of vegetation and fallow land. Such a pattern of urban growth will primarily occur in the northern direction, i.e., the areas surrounding Technopark Phase II and Phase III at Attinkuzhi. In the southern direction, considerable built-up

Fig. 6 Simulated land cover map of Thiruvananthapuram UA for the year 2017

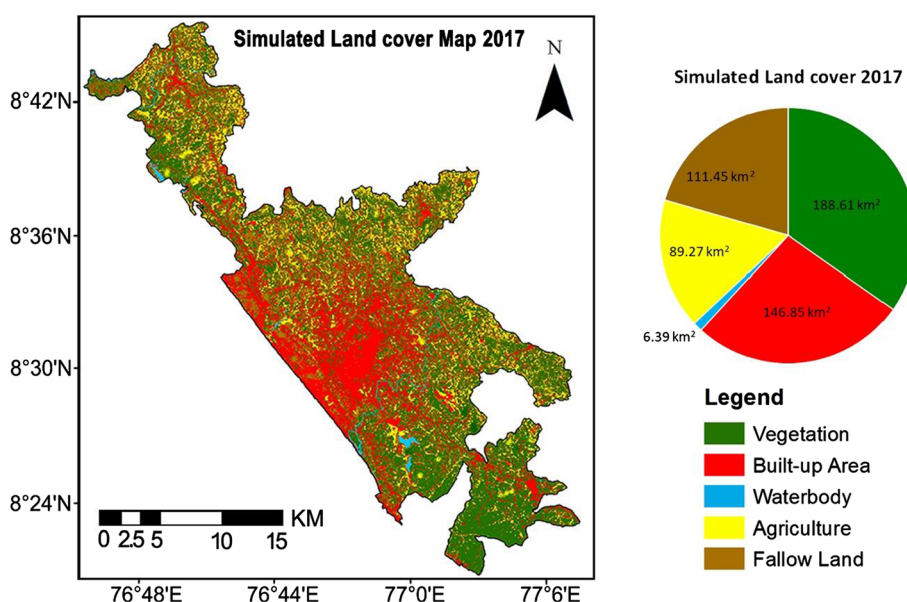


Fig. 7 Predicted land cover map of Thiruvananthapuram UA for the year 2027

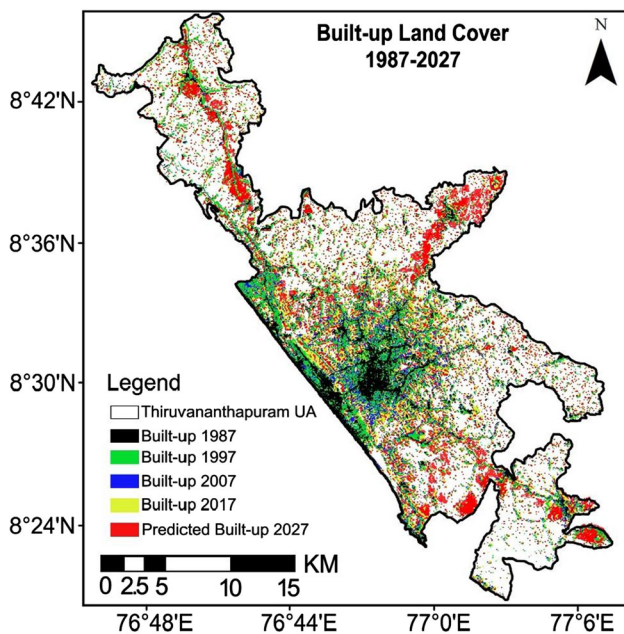
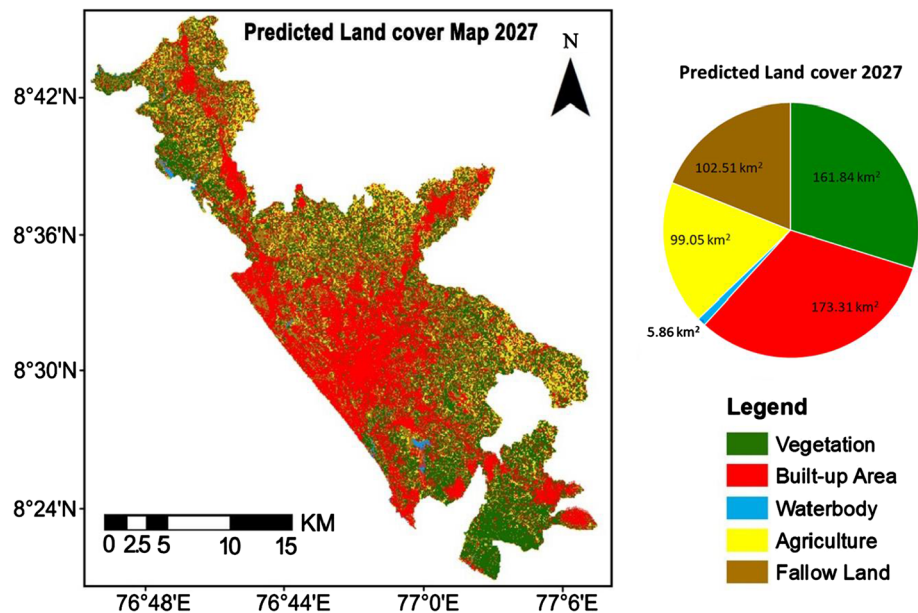


Fig. 8 Built-up land cover map of Thiruvananthapuram UA from 1987–2027

growth is expected to occur due to the Vizhinjam International Deepwater Multipurpose Seaport at Vizhinjam. Moreover, the availability of a better quality of life due to capital city favoritism by the politicians and policymakers has also triggered urban growth (Abhishek et al., 2017).

Urban Growth Boundary Delineation

The predicted land cover raster data of 2027 were converted to vector format, containing multiple polygons.

Hexagon cells of one square kilometer were intersected with the built-up layer in ArcGIS 10.3 to extract the contiguous built-up area. The current UGB delineation method considers the amount of land proposed for conservation under the SMART city scheme (Smart City Thiruvananthapuram Limited, 2018). The restricted areas for future urban growth were highlighted within the UGB, such as airports, railways, CRZ (Coastal Regulation Zone), and wetlands. Such steps are necessary to be considered while delineating UGB for its effective implementation in future without harming the local ecology (Tayyebi et al., 2011). Finally, the sub-administrative units of Thiruvananthapuram UA within which the CGB passes were selected for the delineation of UGB. Figure 9 displays the CGB and UGB of Thiruvananthapuram UA for 2027.

The total area within CGB is 213.58 km², while UGB accounted for 355.59 km², which included 16 sub-administrative units (one Municipal Corporation, three Municipalities, 10 Census Towns, and two Outgrowths). After excluding restricted land for future development, the areas within UGB would be planned for high-intensity development. The areas outside UGB are proposed for low-intensity development, which includes rural uses, such as agriculture, forests, water bodies, orchards, and open lands.

Despite the various benefits of UGB, it has often been associated with higher housing and land prices and might lower the rate of economic development (Dempsey & Plantinga, 2013; Sinclair-Smith, 2014). Since India is a developing country, there is a regular requirement of land supply for development purposes in urban areas. Moreover, there is a capacity constraint and weak coordination among the concerned authorities, which creates complexities while implementing a growth containment strategy (Jain et al.,

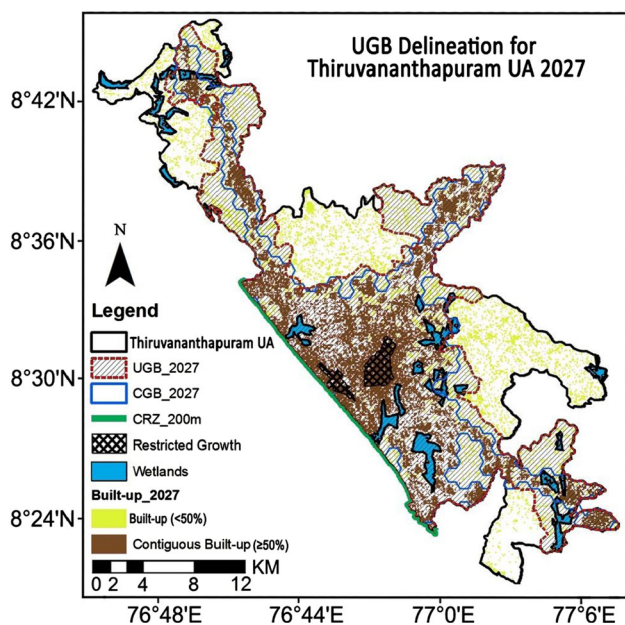


Fig. 9 Urban growth boundary of Thiruvananthapuram UA 2027

2019). Cumulatively these issues are responsible for uncontrolled urban growth and environmental degradation. Hence, researchers recommended a combination of flexible and rigid boundaries to ensure the success of UGB implementation (Jiang et al., 2016; Zhuang et al., 2017). These measures would balance the supply and demand for land in future for development. The delineation of CGB and UGB in this study serves the purpose in this context. CGB was delineated based on the contiguous urban growth by 2027 and can act as a flexible boundary. The urban growth within CGB will be strictly regulated, and only after achieving the level of proposed urban growth, the boundary can be expanded toward rigid UGB. The ultimate expansion of urban growth in Thiruvananthapuram UA can be extended only till the delineated UGB.

Conclusion

This paper utilized the machine learning approach and local area information to delineate UGB for Thiruvananthapuram city. The UGB was delineated through simple yet effective methods and can be implemented in knowledge and resource constraint developing countries. A hybrid model that combines ANN-MLP and CA with environmental protection policies was adopted in this study. Such a combination of multiple tools captures urban growth dynamics and thus assists decision-makers and urban planners prepare a better urban growth containment strategy. Furthermore, to trade off the drawbacks of UGB, especially in developing countries, this study incorporated

the use of a flexible and rigid UGB boundary. The MOLUSCE model used in this study was calibrated by producing a simulated land cover map of 2017 based on the actual land cover maps of 1987, 1997, and 2007. For the validation of the model, the 2017 land cover map obtained through the MLC process was compared with the simulated land cover map of 2017. The overall accuracy achieved was more than 85%, thus allowing the further use of the model to predict land cover of 2027, and thereafter UGB was delineated. UGB delineation is a complex process, so models that solely depend on scientific programming may not capture real-world externalities. Therefore, the local area information such as restricted areas, ecologically sensitive areas, and areas designated for conservation was considered while delineating UGB. Such a process altogether enhances the accuracy and precision of the model and avoids the prevalence of arbitrary growth and damage to natural resources in future. Compared to other studies, this paper exhibits the combination of ANN-MLP and CA models for the urban growth prediction and delineation of UGB. Unlike other studies where complex tools are used to delineate the contiguous built-up area, this paper utilized hexagon cells of one square kilometer. Such easy and effective techniques are required in developing countries due to capacity constraints and limited resource availability. Moreover, using a sub-administrative boundary to delineate UGB was attempted for better governance within the UGB and lower the confusion among the stakeholders.

The major conclusion derived from this study exhibits rapid built-up growth in Thiruvananthapuram UA, primarily at the cost of vegetation and fallow land cover. The city has been affected by urban sprawl; moreover, the future land cover prediction indicated a further rise in the built-up areas and a decrease in vegetation land cover. Such a pattern of urban growth tends to disturb the sensitive ecology of the coastal plains region, and hence for effective land utilization within the city, UGB was delineated. The future scope of work includes the formulation of detailed growth containment policies to be implemented within CGB and UGB. Further, an investigation of urban sprawl factors, such as socio-economy and demography, on the future growth pattern of Thiruvananthapuram UA could be analyzed. Such practical UGB delineation models can be implemented in developing countries to promote urban sustenance.

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Declarations

Conflicts of interest The authors declare that they have no competing interests.

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