Modeling Earth Systems and Environment
https://doi.org/10.1007/s40808-018-0506-1

ORIGINAL ARTICLE

Simulating urban growth by two state modelling and connected network

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Received: 30 April 2018 / Accepted: 11 August 2018

Abstract

Unmanaged and uncontrolled urbanisation has led to chaotic growth causing extensive fragmentation altering the local land use dynamics and the environment in and around many cities across the globe and has reached crucial thresholds. Quantifying these spatiotemporal urban growth patterns and visualisation is essential to understand the dynamics of urbanization and landscape dynamics. In this study, we use remotely sensed data to understand and visualise the urban growth patterns of Bangalore-Silicon hub of India. It has been stated that population growth and huge investments from the global markets are driving the change in land-use in Bangalore with the influx of population increased by 200% in the last decade. Considering this aspect in this study, Cellular Automata based model with the integration of socioeconomic factors was calibrated using historical urban growth extracted from classified data. This is used to forecast three scenarios of urban growth to 2020 with constraints as per the City Development Plan. Time series analysis of land use change exhibited an extensive outgrowth and urban sprawl in Bangalore: there has been leapfrog development in core regions of the city, whereas the buffer zones had ribbon development and cluster-based development. Urban sprawl was more along the major roads and places with better connectivity. Modelled land use results indicated an increase in the paved surface by 170% in the scenario, as usual, is considered. Because of models highly explicit nature of prediction, it was able to capture both linear and non-linear behaviour and a phase transition that happens in the urban landscape.

Keywords Urban growth · Pattern analysis · Spatial metrics · Cellular automata

Introduction

Urbanisation is attributed as one of the major factors for the global land use pattern change and loss of biodiversity (Lambin and Geist 2006; Ramachandra and Bharath 2012). Urbanisation can be termed because of land use alteration by humans to completely paved surface. It has been established that it is considered as an extreme form of land use change that is influencing biodiversity and ecosystem services (Grimm et al. 2008; Ramachandra and Bharath 2012). The process of urban growth is very much associated with the development through factors such as socio-economic, development of infrastructure (Ji et al. 2006). This development has become a challenge due to unplanned growth and a shortage of basic amenities in developing countries across the globe. Hence, it is imperative to understand and visualise the land use change in these metropolitans to plan the basic infrastructural necessities for sustainable development and natural resource management (Wu et al. 2008; Ramachandra and Bharath 2012; Bharath et al. 2012a, b). As explained urbanisation has also some underlying effects and causes a natural spillover of urban growth in the periphery of the cities termed as Sprawl. Urban sprawl is as scattered development of a city in its close vicinity or the outskirts, that increases stream of traffic, depletes natural resources, and destroys lung spaces and have impacts on ecology of the area, hydrology, and vegetation etc., (Peiser 2001; Bharath and Ramachandra 2016; Bharath et al. 2018).

Researchers across the globe have studied urban growth and sprawl around the globe for many developing countries (Sudhira et al. 2004; Jat et al. 2008; Fenglei et al. 2008; Ramachandra and Bharath 2012, Ramachandra et al. 2017; Bharath et al. 2014, 2017a, b). Urban sprawl is often

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estimated based on broad indicators such as socio-economic factors, for example, population growth and density, basic daily liveability costs, settlements density etc., (Brueckner 2000; Lucy and Phillips 2001). However, these data lack the spatial context and lack as effective tools to visualise growth in various scenarios. Urban Municipal corporations use more survey-based data for planning the basic amenities. If the data is developed both in spatial and non-spatial context with the temporal ability it would reduce the manual labour, cost and time and would help in devoting more time, attention and effort in the management of land use resources and amending policies to cater the needs of the growing population. This also helps by serving for a balanced and sustainable development and planning at a longer timescale.

This gap can be filled using remote sensing as it can provide both spatial and temporal data and the analysed effective tools to visualise analyse the current land use and base data in predicting future changes in the landscape through modern mapping and modelling techniques (Epstein et al. 2002). Remote sensing is a technology that makes spatial analysis time integrated multi-view, resource integrated and cost-effective due to availability of open data and open source software technologies. These data have a synoptic view, multi-temporal one can analyse the existing land use, monitor changes in landscape (Pathan et al. 2004; Taubenbock et al. 2010; Fenglei et al. 2008; Ramachandra et al. 2013). The study of urban pattern change using available spatial data mapping associated land use change is independent of all experiments on the ground except a collection of validation points (Verburg et al. 2006). Hence can be an effective unbiased estimator of land use change. Bangalore being a hub of development is now attracting huge migration and from all over the country due to increased job opportunities, better education, and better provision of necessities in the city with the periphery and the buffer zones having almost no access to basic amenities for survival. This leads to pressure on city resources and planning the urban growth. Increasing pressure on both the city resource and the natural resources will lead to the extensive problem to human community and environmental issues. This necessitates a planned growth and requirement of visualisation of the future urban development both in the city and periphery and balancing it with available resources for sustainable development of urban areas and preservation of land use in rural regions. Thus, to acquire a better information and visualization of the dynamically growing urban system, researchers around the globe have developed different models for modelling such phenomena. Simulation-based modelling can provide basic and valuable site based insights into possible future developments; this includes understanding the pockets of current growth, understanding the development corridors due to various improving infrastructural facilities, and developmental activities due to policy decisions. Applying various rational simulation models can help in understanding the complex dynamical process of land use change and to visualise the future changes in the land use (Zhao and Murayama 2011). Implementing modelling methods to visualise the specific pockets of urban growth or sprawl (Al-shalabi et al. 2013) especially in developing nations of the world (Arsanjani 2011) like India is essential for effective decision-based plans.

Urban growth models provide an effective insight to planners and decision makers. These can be used these to plan the requirement of the future urban growth and trends of various developments and explore the potential impacts of various policies before implementation. Prominent ones to list are cellular automata (CA), which are widely used to simulate urban growth (White and Engelen 1993; Clarke et al. 1997). CA models are implemented based on user-defined transition rules based on an understanding of various processes (e.g., Jenerette and Wu 2001). Additionally, researchers also have used CA derived CA-Markov, Sleuth etc., along with GIS models such as land change modeller and Geomod (Bergen et al. 1998; Bharath et al. 2013) to understand the future landscape change based on the current trend and influencing factors (Mondal and Southworth 2010).

In this study, geographic modeller is used to model land use. Geographic modeller (GeoMod) is a cellular automata based spatial model that integrates geographic information system (GIS) technology for analysis of socio-economic and biophysical layers to well proven CA-Markov model. GeoMod model has been used in various modelling studies and was first demonstrated to model the biodiversity of the Western Ghats in India (Menon and Bawa 1997). GeoMod modelling yields quantitative validation measures and hence been used in several studies to model the land use change phenomena (Pontius et al. 2001; Menon et al. 2000; Pontius and Schneider 2001; Hall and Fagre 2003). Model is built on various spatial GIS layers that are integrated and weights are assigned based on the influence that they have to the neighbouring pixels. These weights assigned is used by GeoMod to predict land use change with time creating a pattern of development that closely parodists reality. Geomod adheres to certain principles (1) neighbourhood adjacency, tendency to change land use due to the influence of adjacent land use (2) dispersion choose a favourable location to grow and (3) regional heterogeneity to account for various factorial growth such as influencing factors of urbanisation like population, economic and political factors. Hence, this study uses Geomod to further visualise the developments.

Study area

Bangalore is geographically located at the south-eastern part of India and capital of Karnataka state is considered as a study area along with a circular buffer of 10 km, (Fig. 1) with spatial extents from 12°49′5″N to 13°8′32″N latitude

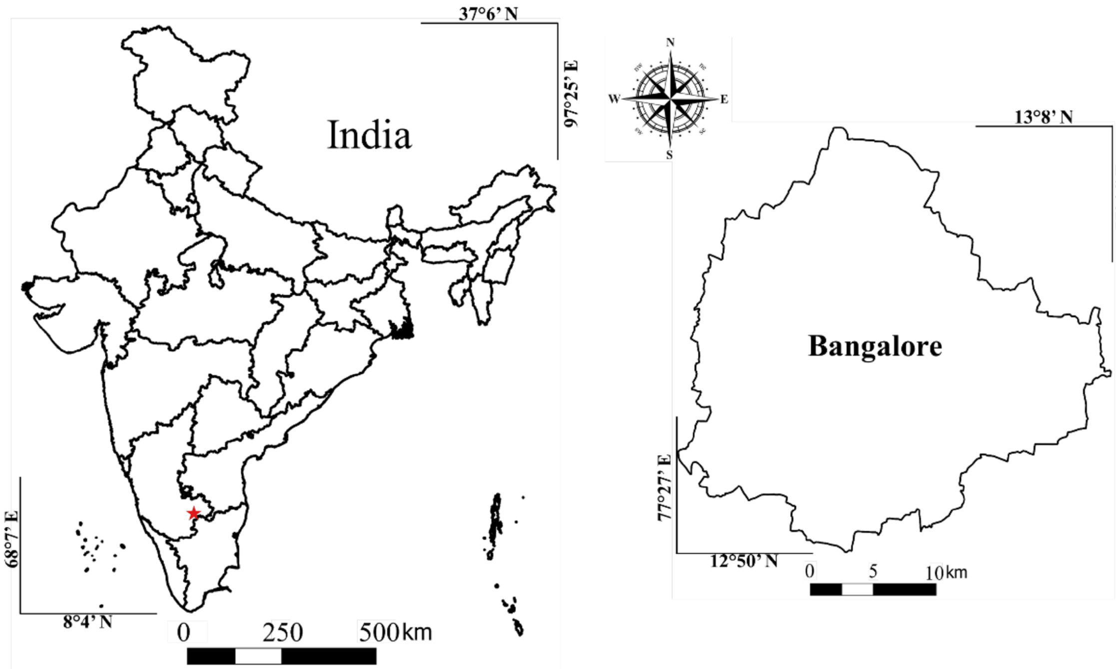

Fig. 1 Study area

and 77°27′29″ E to 77°47′2″E in longitude encompassing an area of 741 km^2. Ten km buffer from the administrative boundary was considered (with a gross area of 2290 km^2) to account for developments in the peri-urban regions. Population as per the census of Govt. of India has increased by 44% in a decade from 5.8 million in 2001 to 8.5 in 2011 at a rate of 4.4% annually, higher than the national average of 2.5%.

Data used

Remotely sensed data for a specific period of Landsat TM were used to analyse Land use changes. This data was supplemented with the toposheets and Bhuvan data to generate base layers including drainage network, road network etc. Training data was collected using the pre calibrated global positioning system (GPS) for classification, and validation of the classified results. Google earth was used as a digitising tool to extract the location of socio economic amenities and road network. This was verified with sampling field visits using Handheld calibrated GPS (Table 1).

Method

Analysis can be delineated into five major steps (1) data acquisition from public repositories such as USGS, land use classification and accuracy assessment using open source software GRASS. (2) Land use analysis and baseline validation. (3) Developing data for three scenarios based on urban growth. (4) Calibrating the model to find out the best weights based on the influence on the neighbourhood pixels. (5) Development of model and validation of the model

Table 1 Materials used in analysis

Data	Year/scale	Description
Landsat thematic mapper (30 m)	2008, 2010, 2012	Land use analysis
ASTER (30 m)	2012	Slope map
SOI toposheets	1:250,000 and 1:50,000	Delineating administrative boundary and geometric correction
Bhuvan and google earth		Support data for site data, delineation of road network
GPS		Data classification and validation
Census	1991, 2001, 2011	Population census data

with predicting of future scenario based on validated data and calculation of spatial metric for analysis of landscape configuration in various scenarios.

1. *Image pre-processing* Remote sensing data were acquired for specific years from USGS earth explorer (http://www.usgs.gov/). Remotely sensing data obtained were geo-referenced, rectified and cropped pertaining to the study area.
2. *Land use analysis* Land use analysis was performed using supervised pattern classifier—Gaussian maximum likelihood classifier (GMLC). GMLC has been already proved as one of the superior classification techniques due to use of cost function and probability determination techniques employed (Duda et al. 2000; Bharath et al. 2018). Land use classification was performed and the classified data is categorised into four major classes built-up area, vegetation, open area, and water body as described in Table 2.

   Essentially land use analysis is performed in four broad steps as follows.

   a. Stacking as image composite-false colour composite to identify various classes of patches (bands–near infrared, green and red green).
   b. Collection of training data as training polygons using pre-calibrated GPS AND and using google earth (validated and corrected with a shift in position). Training data was collected in order to classify and also to validate the results of the classification. 70% of the training data collected were used to derive the user-classified map. 30% of exact ground truth was used to validate it.
   c. Land use classification using GMLC using GRASS GIS (Geographical Analysis Support System) an open source software has been used for the analysis, which has the robust support for processing both vector and raster files.
   d. Validation of land use by performing accuracy assessment and kappa statistics: accuracy assessments helps the data generators to determine the quality of the information. The test samples from user classified map and validation ground truth maps generated is use to generate well-known methods in validation of land use using error matrix and calculate kappa (κ) statistics.
3. Population growth rate has been a major influencing factor of urban growth in Bangalore. Hence using this as a factor three scenario was designed as per the suitability map. The first scenario considered current growth population rate of Bangalore (approach. 5% per annum) as business as usual scenario, further with the national growth rate at 2–3%, were considered as deviations for designing the next two scenarios. The second scenario was designed based on a decreased growth rate of 3% matching the national average and the third scenario was based on increased growth rate of 7%.
4. *Modelling land use scenarios* GeoMod was used for modelling the land use pattern and to predict the future scenarios. GeoMod is built on a grid-based model that persists the maps as grids of data to simulate the urban pattern of land use change and has a capability to predict both as time forward or time backwards (Pontius and Schneider 2001; Pontius et al. 2001; Dushku and Brown 2003). GeoMod works on a binary map and simulates the land use change based on this binary map as two categories (binary images are first created as urban and non-urban). Map considered as a base to predict is supplied by the user and map to be used as validation is also used (in case of validation) else only the grid cells are mentioned, along with the land use change driver's associated with weights. This grid are assigned as one of the two categories for the ending time based on the various decision rules.

   a. *Map-persistence* GeoMod can simulate two change but in different transitions. In a single transition, it simulates only a single way change.
   b. *Grid based differentiation or stratification* It would simulate land use change within a strata or specific region.
   c. *Neighborhood constraint* It is based on a nearest neighbor principle and treats cells restrictions for one time change with the edge between two portions A&B in the land use
   d. *Site suitability* This is generated empirically using several maps and the land-use transition map from the beginning time.

   Site suitability of each cell is calculated using the equation below

Table 2 Land use categories

Land use class	Land use included in class
Urban	Any paved surface and mixed pixels with built-up area
Water	Any water dominated surface, drainages etc.
Vegetation	Forest dominated land use including plantations and standing crop in agricultural croplands
Others	open area, unpaved roads, croplands with no crop, bare land, quarries etc.

$$R(i) = \sum\nolimits_{a=1}^{A} \{Wa * P_a(i)\} / \sum\nolimits_{a=1}^{A} Wa, \qquad (1)$$

where: R(i) = suitability value in cell (i), a = particular driver map, A = the number of driver maps, Wa = the weight of driver map a, and Pa (i) = percent-developed in category ak of attribute map a, where cell (i) is a member of category ak.

Figure 2 describes the identified drivers that have a weighing influence on urbanization and process of modelling and validation. Weightages were derived based on the influence of each driver (Road, availability of public transport etc.,) in urbanizing the neighbourhood pixels through a multi criteria evaluation to derive a transition suitability map.

5. Developed suitability map along in conjunction with land use maps of the year 2008 and 2010 was considered as base data to simulate urban growth in the year 2012. The model performance was assessed by comparing the simulated year 2012 urban map to the actual year 2012 classified map. Accuracy is calculated for each analysis. This process is reiterated until the simulation reaches the threshold accuracy by changing the driver behaviour and influence characteristics. Once the model is trained to land use of 2010 and 2012 is used as base data to predict urban pattern growth for the year 2014 to the year 2020 in a time step of 2 years and land use is quantified.

Spatial metrics using open source software fragstat was then computed. This was performed for all scenarios to observe the change in urban land use by 2020 depending land use configuration. As suggested by Ramachandra and Bharath (2012) urban land use dynamics can be characterized by few spatial metrics as tabulated in Table 3 based on shape, edge, complexity criteria.

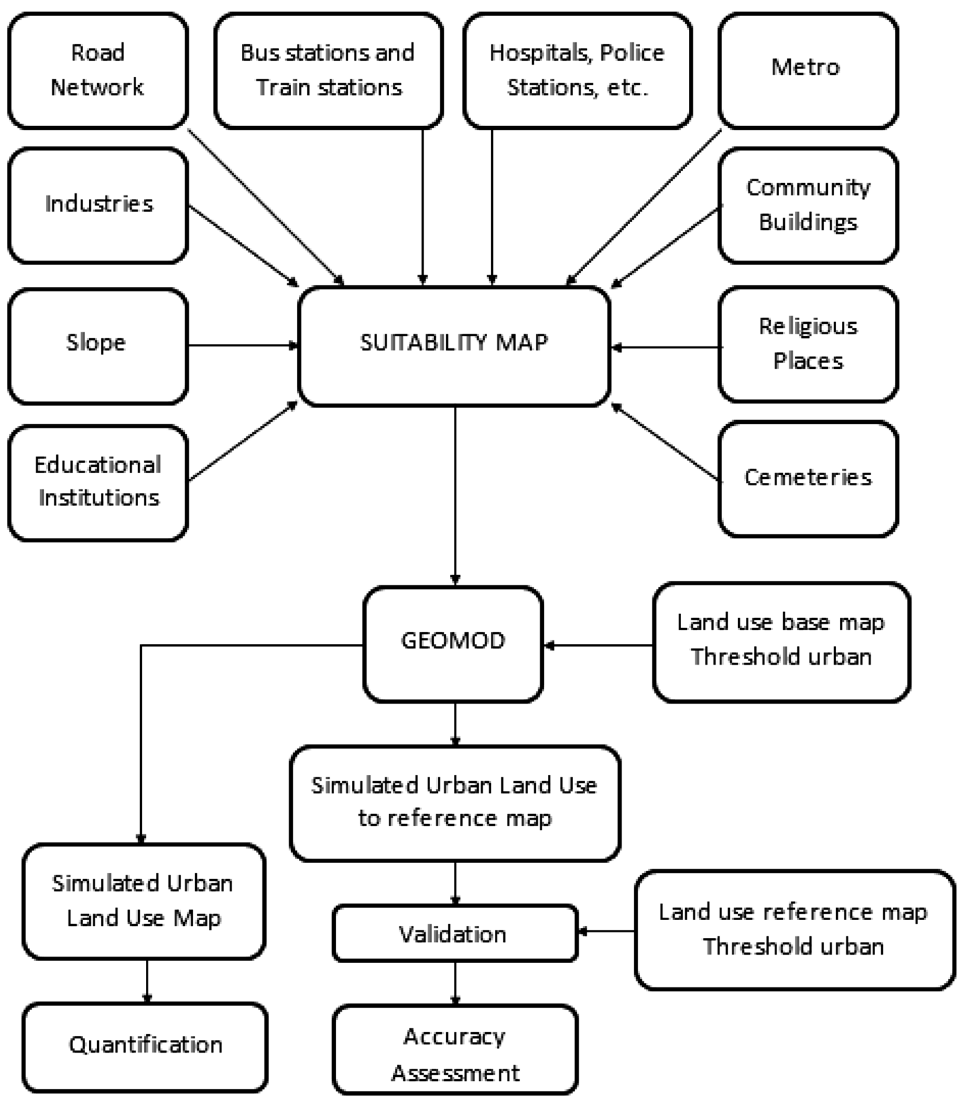

Fig. 2 Procedure for modelling

Results and discussion

Land use analysis

As explained land use analysis was performed using GMLC, with ground truth collected from various field surveys and supplemented by google earth. Land use analysis shows that urban area had phenomenally increased to 29.33% in 2012 of the entire region. Whereas, vegetation decreased drastically to about 33.68% for the entire area. Land use statistics are as tabulated in Table 4 below and the output of land use analysis is as described in Fig. 3. Urban land use change can be seen in form of clumped in filling growth in the city limits. Urban area mushrooms near the regions that have an urban class, and develops as a leapfrog along the highways and roads that connect the city with the periphery. Classically it can be observed that the urban land use spurt in the northeast. It can be attributed to developments of amenities such as International airport and satellite towns. Southeast defines the development based on connecting corridor to another mega city indicating that transport corridor plays an important part in urban sprawl. Land use analysis highlights that the percentage of urban land is increasing in all directions due to the policy decisions of (1) industrialization (2) boost to information technology and biotechnology sector in late 1990s and consequent housing developments in the periphery and unplanned outgrowth.

Accuracy assessment Accuracy assessment of the land use analysis was performed by generating the reference image through the 30% signatures developed using known ground truth data. The results of the accuracy assessment are tabulated in Table 5. Accuracy assessment indicated a good classification result with an overall accuracy of 80–90% and kappa close to 0.8. Land use data is then used as base layers for training the model, validation of model and prediction to the year 2020.

Modelling the spatial change of the urban extent in 2020

Land use data was then recoded into built-up and non built-up class, using the module r.reclass and further recoded to two classes and a binary image was generated as output from the GRASS. The drivers that are responsible for urban growth were digitised from google earth and manual data collection. These drivers were then used to derive the site suitability maps based on influence and dependence values of each driver. Multi-criteria evaluation is considered to develop the allocation suitability for urban growth based of a variety of attributes such as urban growth etc., These criteria's are standardised to yield weight(s) for each of the

Table 3 Landscape metrics analysed

	Indicators	Formula
1	Number of urban patches (NUP)	$NPU = n$, NP equals the number of patches in the landscape
2	Normalized landscape shape index (NLSI)	$NLSI = \frac{\sum_{i=1}^{i=N} \frac{p_i}{s_i}}{N}$, where s_i and p_i are the area and perimeter of patch i, and N is the total number of patches
3	Total edge (TE)	$TE = \sum_{k=1}^{m} e_{ik}$, where, e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i
4	Clumpiness index (Clumpy)	$G_i = \left[\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - \mathrm{mine}_i}\right]$ $\mathrm{CLUMPY} = \left(\begin{array}{c} \left[\frac{G_i - P_i}{P_i}\right] \text{for } G_i < P_i\ P_i < 5;\ \textit{else} \\ \frac{G_i - P_i}{1 - P_i} \end{array} \right)$ Range: clumpiness ranges from − 1 to 1

Table 4 Land use class distribution in each year

Year	Class							
	Built-up area		Water		Vegetation		Others	
	Ha	%	Ha	%	Ha	%	Ha	%
2008	49915.42	24.85	1068.94	0.53	77036.96	38.35	72851.95	36.27
2010	57208.40	28.48	1571.41	0.78	73460.57	36.57	68,656.40	34.17
2012	59103.90	29.33	1169.82	0.58	67883.85	33.68	73385.73	36.41

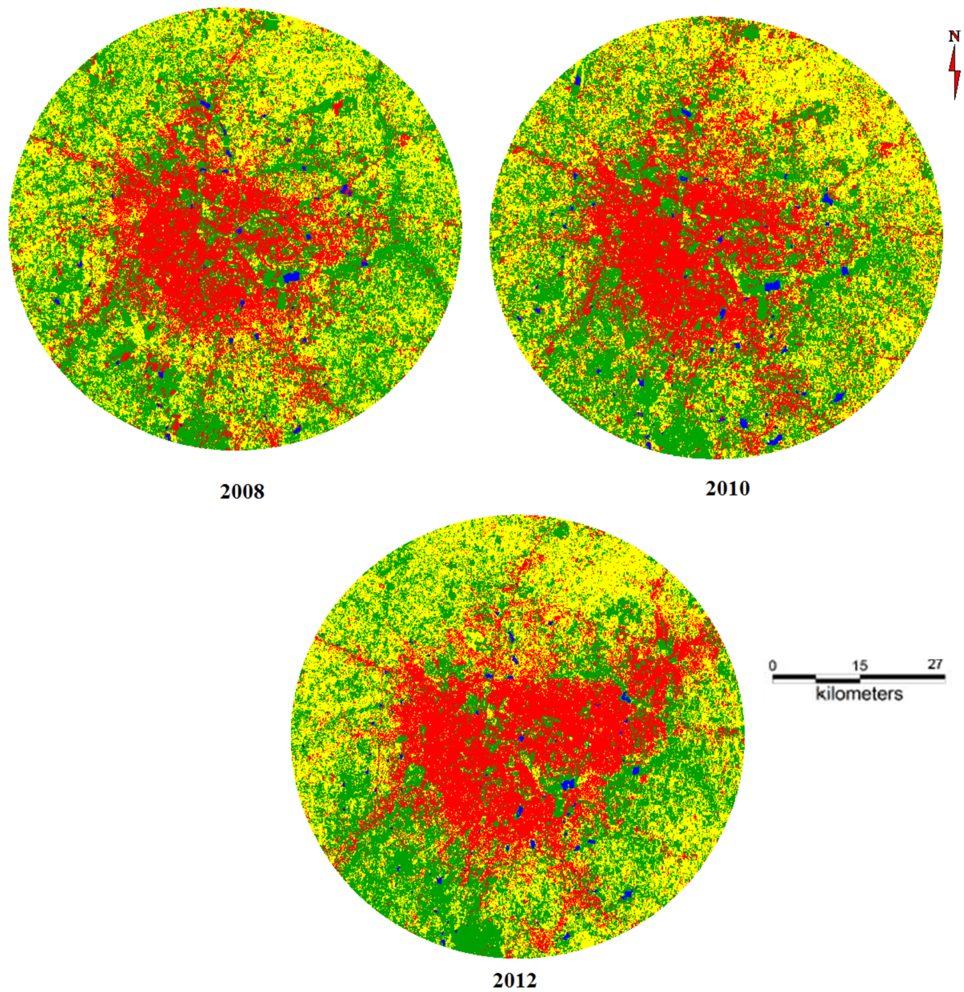

Fig. 3 Results of land use analysis

Table 5 Accuracy assessment

Year	Overall accuracy (%)	Kappa
2008	86.35	0.78
2010	91.62	0.86
2012	90.43	0.85

drivers. These weights act as input criteria for the influence of each driver on urban growth. Higher the weight rate of a particular driver urban growth is higher, lower the weight of a particular driver urban growth is lower. Further to obtain the realistic influence and weight characteristics the land use images were used as references. Based on recoded land use image of 2008, the influence of each driver in order to urbanise the area was tested keeping the reference images of 2010 and 2012. The condition was applied such that the spatial extents of current water bodies (2012) do not change during the modelling. The weights for each scenario was then obtained based on validation per pixel basis so that the developed semantics match the original land use. The land use supervised classified data and the generated simulated data for the years 2010 and 2012 is as shown in Fig. 4. The accuracy assessment was done using the land use classified data of 2012 as a reference and simulated data for 2012 as actual data. The accuracy assessment and Kappa values calculated are as tabulated in Table 6. Once the validation reaches a threshold overall accuracy and kappa. Then 2012 is used as a base image to predict 2014–2020 for business as usual scenario. Population is then changes to match the other two scenarios and prediction was performed for 2014–2020. The results of each scenario is as shown in Fig. 5 and quantified in Table 7.

Results of GEOMOD indicate that there would be an extensive growth along with various drivers across the study regions. Roads including the major highways such as state highway and national highway influence the majority of outgrowth or urban sprawl. Whereas there would be an extremely high growth density towards the International airport. Results also indicated by 2018, the city infilling would reach a threshold value and the growth would start spreading extensively from the centre towards the rural regions

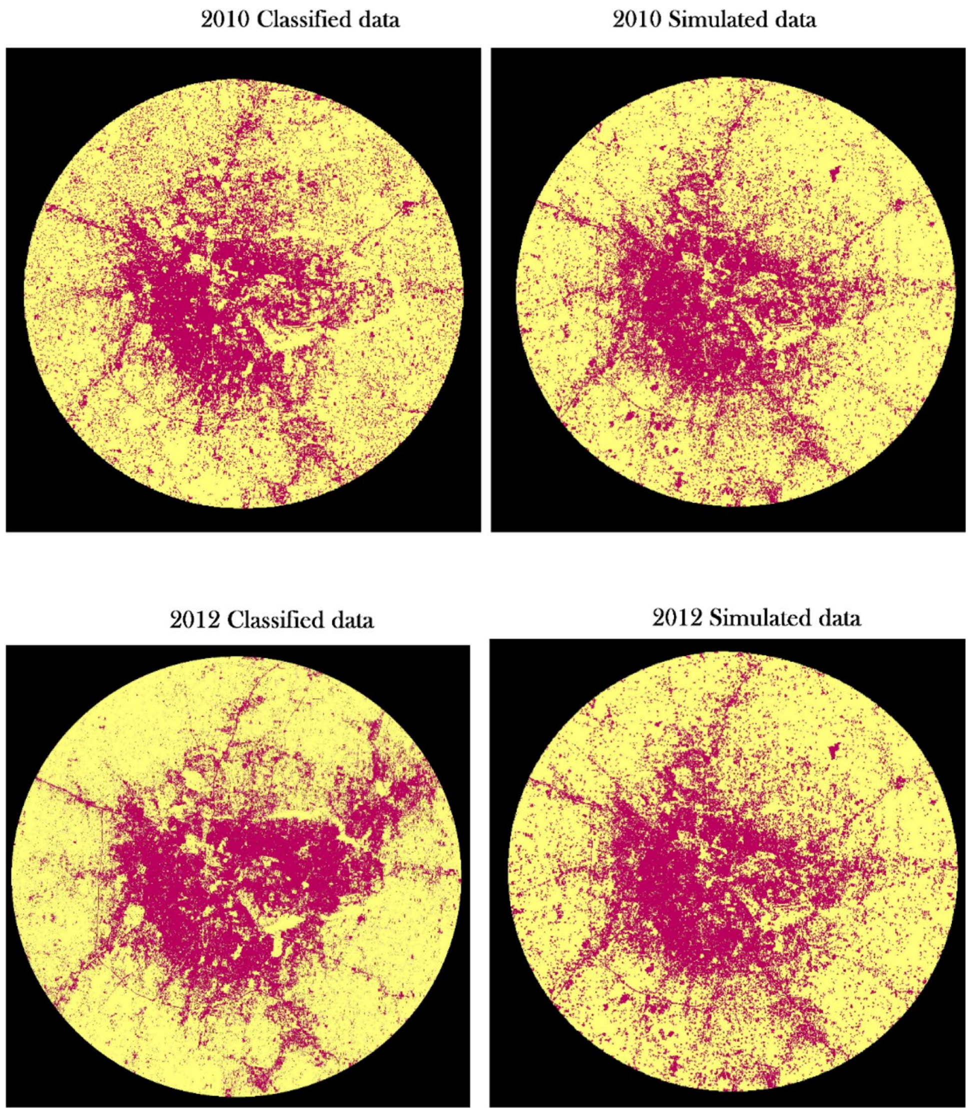

Fig. 4 Classified data and simulated data keeping 2008 as base layer

Table 6 Accuracy assessment

Year	Overall accuracy (%)	Kappa
2010	91.43	0.94
2012	87.68	0.843

adjoining its boundary. This would affect the rural dynamics considerably and provision of basic amenities such as potable water and sanitation would become a challenge by 2020. Further, to understand the spatial arrangement of growth spatial metrics as indicators were analysed.

Spatial metrics as indicators of growth

Landscape metrics as described were calculated on a binary class land use data to understand the arrangements of urban class from 2008 to 2020. Landscape spatial metrics were selected based on its various properties, such as area, shape, contagion, edge. The results of each metric are discussed in the following sections:

A number of urban patches (NP) NP quantifies the number of patches of the corresponding class. It does mean that if the value of this metric is 1 the entire landscape has only one class, if not any higher number indicates fragmentation of landscape. NP quantified for the study region showed that during 2008 and 2010, there were relatively larger patches in the landscape, when visually examined it was mainly in the outskirts (Buffer) of the city about 5000 patches. Which increased to an extent of 25,000 patches and was dominated by patch urban land use in 2012. Further, towards 2020 number of patches consistently decreased indicative of the fact that the many urban patches in the neighbourhood expanded converting other land uses to urban land use, forming single urban patches, therefore reducing the count of the patches

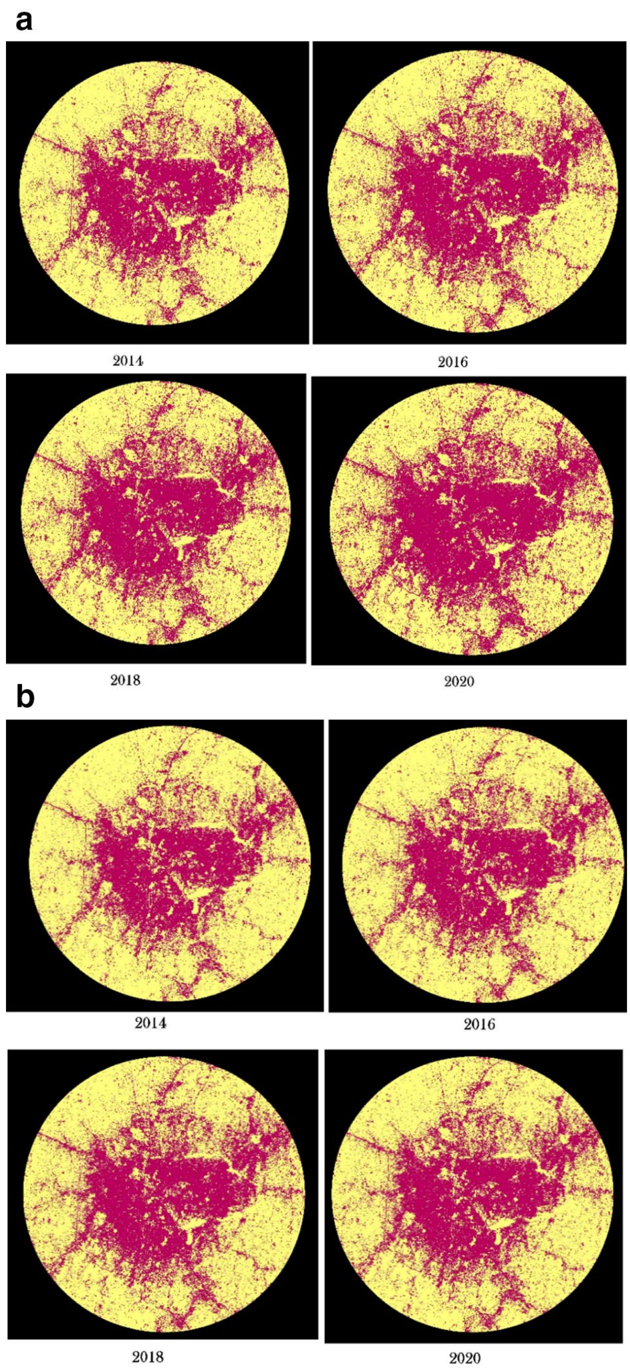

Fig. 5 **a** Results of analysis for the years 2012, 2014, 2016, 2020 considering the rate of growth as 5%. **b** Results of analysis for the years 2012, 2014, 2016, 2020 considering the rate of growth as 3%

as infilling increases between the patches. This growth can be visualised in various parts of the study area such as the northeast and the southern part. Some parts of the city that show extensive urban growth are near the International airport, the emergence of the taluks such as Hoskote and Doddaballapura as developed urban corridors and the close proximity to the IT Corridor of the Silicon Valley, compared to other areas of the city. This argument remains the same in all scenario though scenario with 3% shows lesser infilling between patches but higher sprawl. The scenario with 7% shows that the dominant class would be urban by 2020 (Fig. 6).

Normalised landscape shape index of urban class (NLSI)

NLSI metric signifies the shape of the class in the landscape. Simple shape implies that the land use class has become clumped and is the dominant urban class. Complex shape signifies the higher number of patches in the landscape of the particular class. Values close to 1 indicates that the class in fragmented and complex shape and have various land use in the neighbourhood. Values close to zero indicates simple shape with the dominant class under consideration. NLSI calculated results show that the 5% growth scenario resulted in a value of 0.1 signifying complete degradation of all other class and dominance of urban patch by 2020, and with 7% scenario it showed the worse value of 0.05. But in the scenario of 3%, the value was significantly lower of 0.15. The simulated land use output for 2020 clearly brings out the fact that if the green spaces, open spaces are not well managed, Bangalore would face the crisis of these by 2020.

Total edge present in urban class This metric signifies again the edges formed by the patches, as patches increase and again coagulate form a large number of edges. As the number of edges increases, the presence and dominance of the class under consideration also increases. It can be seen that by 2020 all scenarios project a huge number of edges in the landscape. This again points out the fact that the land use will be dominated by urban (Fig. 7).

Clumpiness index Clumpiness index is a measure of aggregation or disaggregation. Values of this index range from 0 to 1. Higher the values higher the clumped patch. Lower the values indicate the presence of other land use class. The quantified results point out the fact that the entire landscape will have a dominant paved urban patch by 2020. The values close to 1 in all scenario (0.91 in a scenario with 7% growth, 0.83 in scenario 5% growth and 0.79 in the scenario of 3% growth) show a clumped urban growth in 2020. The discussion highlights that the development during 2008 to 2020 was phenomenal in North East and South West of the city due to Industrial development, planning of new infrastructure such as airport and due to setting up of Information technology and biotechnology arena in this regions that attracts the rural–urban migration for jobs from across the state and country and consequent spurt in housing colonies in the nearby localities.

Table 7 Results of prediction for 2020

Year	Non-urban	Urban	Non-urban	Urban	Non-urban	Urban
2014	138,497.58	63,045.72	135,384.48	66,158.82	131,827.50	69,715.80
2016	134,555.76	66,987.54	121,215.60	80,327.70	119,205.60	82,337.70
2018	130,614.03	70,929.27	114,274.73	87,268.57	111,274.73	90,268.61
2020	126,672.21	74,871.09	99,991.80	101,551.50	97,991.80	103,551.50
Land use statistics considering the rate of growth as 3% (in hectares)			Land use statistics considering the rate of growth as 5% (in hectares)		Land use statistics considering the rate of growth as 7% (in hectares)	

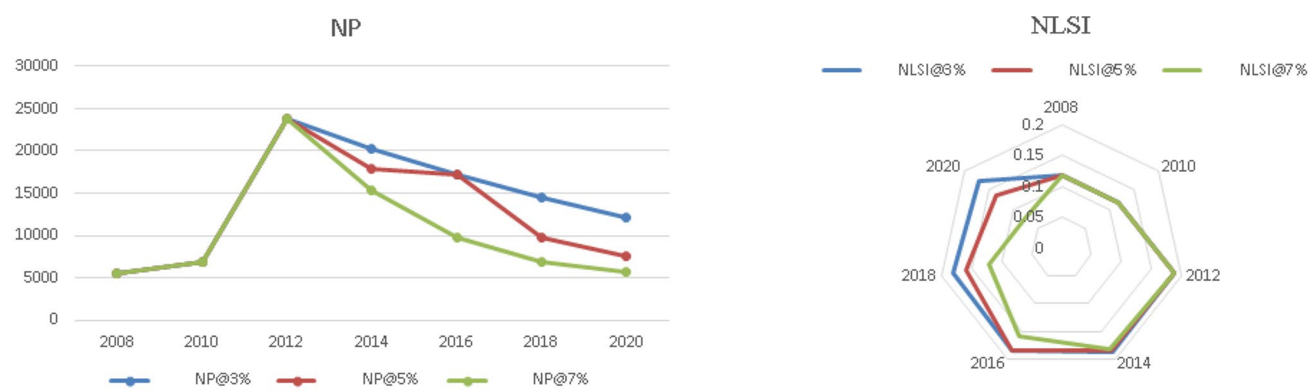

Fig. 6 Number of patch and NLSI metric

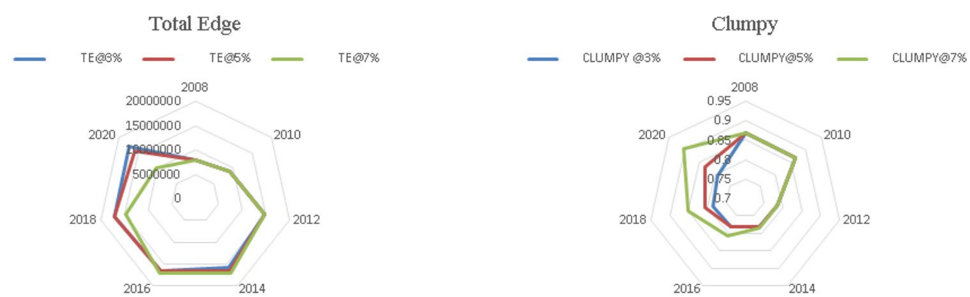

Fig. 7 Total edge and clumpyness metric

Conclusion

GeoMod was applied to the model and simulate the processes of urban development of a Bangalore considering a 10 km buffer. The expansion of urban impervious areas contributed to changes in other land use categories within the metropolitan area. This situation was exhibited by urban growth from 2008 to 2012, with additional patches of the urban area coming up in the peri-urban and buffer zones. This analysis helps the planners and institution enforcers of Bangalore to plan and develop the city and maintain the balance of all land use necessary in the system. Advantages for modelling urban development with help of GIS layers that was introduced by various authors were effectively utilised in this study improved the prediction capability of Geomod. The application of GeoMod produced land use maps with intermittent of time change of 2 years from 2008 to 2020 showed unprecedented growth of urban extent and points out the challenge to the planners and managers to effectively tackle the menace. Landscape metrics quantified also made the argument stronger for effective planning, with all metrics indicating the clumped and a simply shaped growth. The loss in of all other categories of land use for development of urban needs may have unfavourable penalties. The results from this study encourage and policymakers to explore various spatial models as effective tools for planning further developments.

Acknowledgements We are grateful to (1) Science and Engineering Research Board, India (2) the Sponsored Research Cell Indian Institute of Technology Kharagpur (3) Department of Science and Technology, Government of India and West Bengal for the financial support to carryout research and (4) Indian Institute of Science for infrastructural support.

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