Poll Res. 40 (4) : 1322-1326 (2021)

ISSN 0257–8050

URBAN GROWTH ASSESSMENT AND MODELLING USING CELLULAR AUTOMATA AND GEOSPATIAL TECHNIQUES - A CASE STUDY OF PUNE CITY, INDIA

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(Received 25 January, 2021; accepted 4 May, 2021)

ABSTRACT

A spatio-temporal understanding of urban growth is vital for planners and policymakers for future urban development planning. In the present study, the spatio-temporal urban growth pattern (during 1991-2014) is assessed and predicted for 2028 for Pune city of Maharashtra, India, using remote sensing and GIS techniques. The results show enormous land cover transformation in the city during the analysis, where open land and open scrublands were the dominant classes in 1991 and 2000 respectively but were taken over by urban in 2014. The urban area has shown consistent area gain from 40.87 sq. km in 1991 to 57.46 sq. km in 2000 and 101.77 sq. km in 2014 with an overall growth rate of 149% across 1991-2014. While all other classes suffered area loss, agriculture experiencing the highest loss (67%) during the same period. Significant changes in the land cover are observed in the time interval (2000-2014) with 12% loss in vegetation, 29% in open scrubland, and 64% in agriculture, while an area gain of 77% in urban. The predicted map for 2028 depicts massive urban expansion and an equal reduction in agriculture and urban scrubland. These findings provide valuable information on landscape transformation in Pune city and will aid further landscape and urban development planning for the city.

KEY WORD : Urban growth, Change detection, GIS, Remote sensing, Cellular automata

INTRODUCTION

World has been urbanizing rapidly in recent decades. Only 30 percent of the world's population lived in urban areas in 1950, which grew to 55 percent by 2018. (United nation, 2018). Primarily due to voluntary and forced migration to avail better living conditions rise in urban dwellers is observed (Ji *et al*., 2006; Chikowore and Willemse, 2017). Today the speed of urbanization in developing countries is five times faster than that of the developed countries (López *et al*., 2001). Due to an exponential increase in population in countries like India, urban centers are expanding haphazardly (Fazal, 2000), causing the transformation of land parcels from agriculture and natural landscapes to urban (Taubenböck *et al.,* 2009). In this scenario, knowledge of the spatial effects of urban growth is crucial. (RS) Remote sensing and (GIS) Geographic Information System together seem to be a proper and effective tool (Maktav, 2002) in this endeavor. Accessibility and availability of spatio-temporal remote sensing data with cost efficiency and advanced analytical methods makes assessment and monitoring urban growth studies possible (Huang *et al*., 2009; Wu *et al*., 2011). Extensive research has been carried out for development, even in dynamic modelling, to serve this purpose (Batty and Xie, 1994b). Cellular Automata (CA) based Models are the most promising in terms of their technological development concerning urban applications (Yang and Lo, 2003). CA models for land use are usually constructed by integrating geographic information systems (GIS), intelligent algorithms, and statistical methods. (Liu *et al.,* 2018). CA-based urban models have made significant progress in transition rules, cell structure, scale effect, neighborhood configuration, and model evaluation (Barreira-

González and Barros, 2016). Therefore, this work focuses on determining urban growth in Pune City over three decades (1991, 2000, and 2014) using a GIS environment and simulating the CA algorithm to predict potential urban growth in 2028.

STUDY AREA

Pune is the second-largest city in the state of Maharashtra and the ninth most populous city in the country. It is situated between 180 32 'North latitude and 720 51' East longitudes in Pune District. The city has a total area being 243.96 Sq.km and a population of 3.11 million. Pune It is at an altitude of 560 m above mean sea level and has a wet and dry tropical climate with three seasons' rain, mild winter and summer. Pune City is well connected to most of India's major metropolitans such as Mumbai, Bangalore, Hyderabad, Kolkata, Delhi, and Chenna, as well as to all major cities and towns in Maharashtra State.

MATERIALS AND METHODS

Hardware/Software

The software used in the current study is Arc Map 10.1, image processing software ERDAS 2013, and Global Positioning System (GPS).

Satellite Data

LANDSAT 4-5 satellite images at 30 m resolution for the year 1991, 2000 and 2014 has been procured for the study.

METHODS

Digital Image Classification and Change Detection

The Landsat Images were first processed and then classified into six feature classes: Urban, Water, and Vegetation, Agriculture, open land, and open scrubland in ERDAS IMAGINE 2103 using Maximum Likelihood supervised classification method for all three years (Figure.4). The Kappa statistics were evaluated to verify the accuracy of these classified maps using 120 Ground control points (GCP). Finally, a pixel-based post-classification comparison was conducted to detect changes in all the feature classes for two time intervals (1991-2000) and (2000-2014).

Cellular Automata Prediction

CA based Land use modeling focuses on the transition from non-urban land to urban land, addressing the conflict between population growth and limited urban space (Feng *et al.*, 2018). CA is an iterative computing method. The future cell state is calculated on the basis of a neighborhood feature, which provides for the achievement of established transitional rules and specified constraints. Any CA system is composed of four components – cells, state, neighborhood, and transition rules. The process for validating the designed predictive CA model is described in (Fig. 2). The model is designed to predict a 14 years gap. The validation process

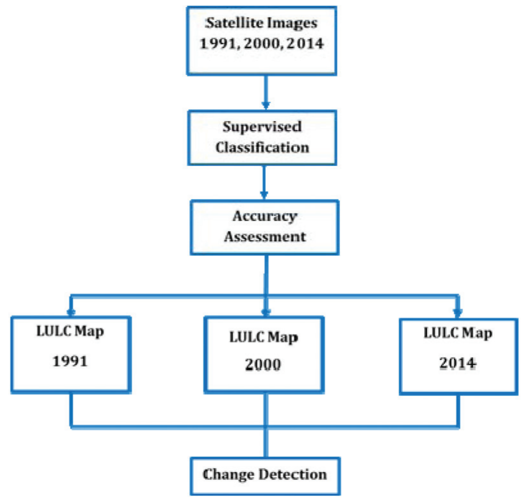

Fig. 1. Change Detection Flowchart

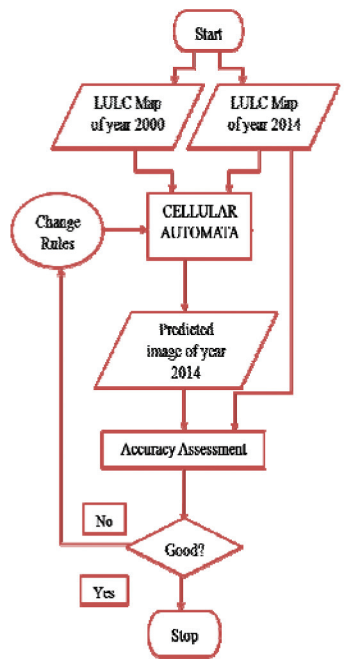

Fig. 2. Model validation Flowchart

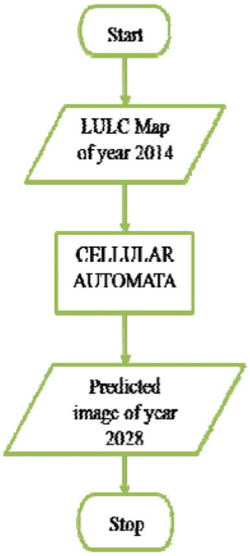

Fig. 3. Predictive model flowchart

takes the LULC image of the year 2000 as the first input to predict the LULC for the year 2014. The outcome is then compared with the classified image of 2014 for accuracy (Figure 6). If any discrepancies were found in the output, changes in transition rules were made accordingly to make the model robust. After the results obtained proved satisfactory, a prediction was made using the updated model (Figure 3) for 2028.

RESULTS AND DISCUSSION

The LULC maps (Figure 4) depict the spatio-temporal distribution of LULC classes in Pune city. The classification yielded a kappa accuracy of 75% in 1991, 72% for 2000, and 80% for 2014. It is observed that open land and open scrubland together form the background of the entire region; the agriculture class is seen dominant in the east and southeast zones, while the vegetation in the southwest and urban occupies the heart of the city and is seen expanding in all direction during the course of the analysis. The statistics (Table 1) reveal dramatic growth in the urban area- 40.87 sq. km in 1991 to 57.46 sq. km in 2000, further to 101.77 sq. km in 2014. On the contrary, agricultural land saw a drastic decrease in the area during the same period (47.18 sq. km to 15.43sq. km); other classes also experienced area loss during this period. The time interval (2000-2014) is the most dynamic period with extreme gains and losses in land cover classes. It is observed that all classes except urban have suffered losses with the highest loss in agriculture (64%). On the other hand, urban has shown a growth rate of 77% in this interval and a 149% growth during (1991-2014). The urban expansion from small clusters in 1991 is seen spreading widely in 2014, especially in the northwest and northeast zones. The emergence of industries and IT hubs in and around the city can be the reason for the observed growth pattern.

2014 has shown the most dramatic change among all the three years.

Table 1. LULC area for three years

Years	**1991-2000**	**2000-2014**	**1991- 2014**
Feature Classes		**(%) Area**	
Vegetation	**2%**	**-12%**	**-10%**
Water	**-25%**	**-7%**	**-30%**
Open Land	**-16%**	**5%**	**-12%**
Open Scrub Land	**-1%**	**-29%**	**-29%**
Agriculture	**-10%**	**-64%**	**-67%**
Urban	**41%**	**77%**	**149%**

Table 2. LULC Change Detection for three time-intervals

Years Feature Classes	1991-2000	2000-2014 (%) Area	1991-2014
Vegetation	2%	-12%	-10%
Water	-25%	-7%	30%
Open Land	-16%	5%	-12%
Open Scrub Land	-1%	-29%	-29%
Agriculture	-10%	-64%	-67%
Urban	41%	77%	149%

The validation of the CA model yielded 76% accuracy for the predicted 2014 LULC image. The predicted LULC map of 2028 (Fig.5) shows enormous growth in urban built-up (169.36 sq. km) in all directions. The area statistics (Table 3) suggest the extensive conversion of open land, open scrubland, and agriculture to urban with a decrease in the area to 18.54 sq. km, 29.57 sq. km, and 4.14 sq. km, respectively. This urban growth is consistent with the growth pattern from 1991 to 2014.

CONCLUSION

The study spans over 24 years from 1991 to 2014 and a prediction for another 14 years. As observed in the results, it can be concluded that urbanization at the start of the study period was quite subtle, being clustered in the heart of the city with a 1.6 Million population. The year 2000 saw a drastic

Table 3. Predicted LULC area for 2028

Feature Classes	Vegetation	Water	Open Land	Open Scrub Land	Agriculture	Urban
Area (sq.km)	19.68	2.68	18.54	29.57	4.14	169.36

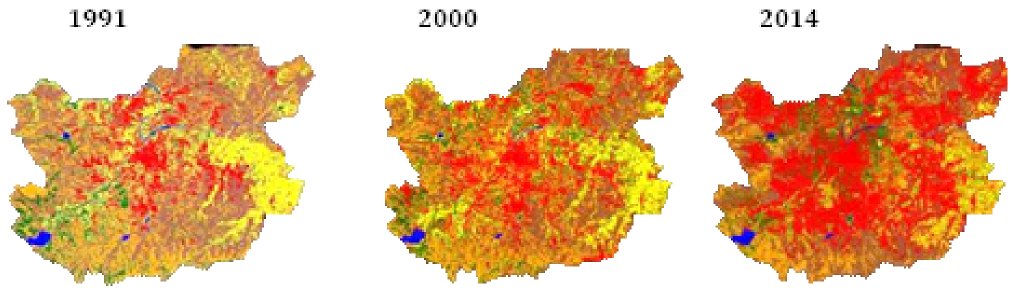

Fig. 4. LULC Maps for 1991, 2000, and 2014 respectively

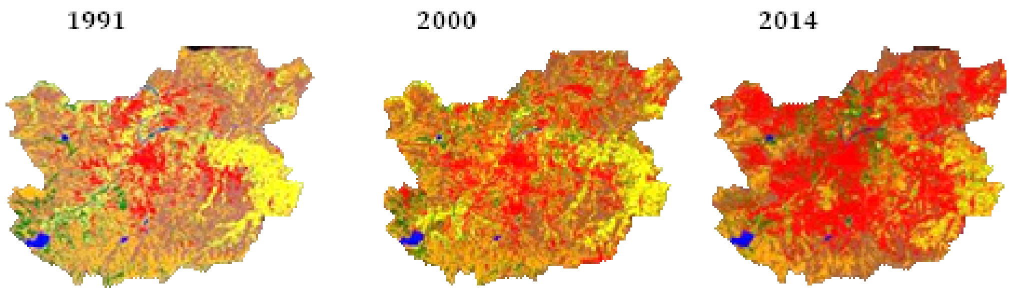

Fig. 5. Predicted Image 2028

change in the scenario with industrialization on the rise; also, the population grew to 2.5 million with a record of 50.08% decadal growth rate. Thus resultant urban growth is observed in the south and west region of the city, rendering its proximity to the industrial areas. It can be further concluded that the urban growth in 2014 in the western region of the city is influenced by the Hinjewadi IT park while in the northeast by the Viman Nagar IT Hub. The study also predicts the urban growth for the year 2028 with the help of the Cellular Automata model. From the results, it can be concluded that the smart city plan for Pune may bring more opportunities, leading to extensive migration in the city, and thus growth depicted in the prediction in all directions of the city will be observed. The study also reveals that Geospatial technology aids in implementing growth simulation models, evaluating the results, and presenting them in a visually interpretable environment. The use of a cellular automata algorithm has proved to be very useful in the predictive modelling of the urban growth of Pune city. The use of programming language and its integration with ArcGIS makes our algorithm robust. Finally, it can be concluded that urbanization is having an extensive impact on the environment and especially on the agricultural land in the study area. Thus it is crucial to adopt better planning and environmental policies to subside the effect on natural landscapes.

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