Urban growth modelling using Cellular Automata coupled with land cover indices for Kolkata Metropolitan region

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Abstract. Urbanization is at a rapid pace in India since past two decades with severe increase in population and demand in the infrastructure service of the city along with environment degradation. This paper examines the urban growth pattern of Kolkata metropolitan area that includes Kolkata city for three consecutive decades. Urban pattern analysis is carried out along with modelling future developmental pockets using specific growth pattern of the city. Results indicate urban growth from 4.1% in 1990 to 11.58% in 2017 and mainly sprawling outward in the buffer region. Modelling using CA-Markov pointed out that urban growth may increase by 14.94% by 2025. The notable observation of our study is that urban growth would have an infill growth in the city completely and then starts sprawling outward and emphasises need for policy planners and urban managers to provide immediate interventions for infrastructure development necessary for sustainable growth of Indian urban agglomerations.

1. Introduction

Changing land use to complete paved surface is a matter of serious concern for the environment stability of a city, for planners and policy makers. This growth is due to a huge influx of population through sub-urbs and surrounding areas to cities in search of better jobs, facilities and availability of basic necessities without any dynamic visionary region specific planning resulting in disorganised and chaotic growth of the cities pose a great threat to the resources, environment and the sustenance of the cities. Today urban areas host 54 percent of the world population which is expected to rise to 66 percent by 2050 with 90% of the growth happening in Asia and Africa [1]. In India scenario urban growth has been phenomenal with growth from 31.14% in 2011 from 25.7% in 1991 [2]. India being one of the fastest growing economy and the second most populous country in the world with more than one sixth of the world’s population is has urban growth in a good proportion. In India, the attention to the economic liberalization, reforms in financial sector and the decentralization process since 1990 is the main driving force for the economic driven urban growth that enhances the economic role of cities development [3]. In theory it is said that urban growth majorly happens in the region of high economic value, opportunities and concentrated human activities which involves spatial and demographic changes [4,5,6].

Urbanization as nature has several underlying effects and one the major effect that it can cause to a city network is urban-sprawl, defined as a type of suburban development with low-density built-up, outward spread of sub divisions and land uses defined by activity [7]. Apart from affecting both air quality and health, which influences the human condition urban sprawl causes storm water runoff, soil degradation and rise in land surface temperature. This results in creating health issues for inner city...
occupants due to high level of emissions in the environment. It is very crucial to understand the trends of LULC changes in developing cities, especially in developing countries like India, where there is rapid economic growth. Remote Sensing and GIS is considered as an effective tool for spatial and environmental studies to generate a good decision support system [8,9]. Bharath and Ramachandra [10] analyzed land use and land cover of Karnataka tier 2 cities and revealed the increment in urban category and reduction in vegetation cover in last two decades. Sokhi et al. [11] visually interpreted the remote sensing imageries for four different times i.e. 1975, 1981, 1985 and 1987 to produce land use map. Jain et al. [12] analysed the spatiotemporal dynamics of the urbanization in New Delhi based on a period of 38 years in the form of satellite images. The study concluded that Delhi is experiencing three types of urban sprawl patterns: highly sprawled districts, medium sprawled districts and least sprawled districts whereas Delhi as a whole is experiencing medium level urban sprawl.

Modeling platforms based on the cellular automata (CA) are used in urban studies across the globe. CA based models have been used successfully in modeling urban development. Having said these CA models lack ability to interact with the current scenario criteria to account for change probability. This opens up opportunity to couple Markov-Chain and Cellular-Automata approaches. There has been a series of development in application of CA-MC models and the main difference is based on its neighborhood, state and transition rules [13]. There has been statistical development angle such as including regression to model the land use transition [14]. There has been large no of research across the globe in application of geospatial technologies but empirically substantial studies are very few. AllThus, modelling temporal land use changes would thus help in visualizing development scenarios aimed at decision making [15,16].

In this paper landsat-5 and landsat-8 data is used to quantify the degree of urbanization in the study for four time zones- 1990, 1999, 2009 and 2017 and also an attempt has been made to predict the degree of urbanization by the 2025 to provide a vision source for urban planners and administrators to provide specific interventions in specific pockets of the city.

2. Study Area
Figure 1 depicts administrative boundary of Kolkata (with circular boundary) and 10km buffer considered for the study.

![Figure 1. Administrative boundary along with 10 km buffer boundary of study area](image)

Metropolitan region of Kolkata also called as KMA has been chosen for study. Kolkata is a part of KMA and is the capital city of West Bengal and situated on the eastern bank of Hooghly river at 22.34° N and 88.24° E. According to 2011 census [17], Kolkata city has third highest population in
India and KMA is the eighth largest urban agglomeration in the world with a population of about 14.11 million. It is due to the fact that Kolkata has attracted majority of population all over the country with presence of vibrant trade and commerce, several tourist destinations and excellent employment opportunities. It is an important centre for many software and telecom firms across the country.

3. Data Used
Primary data used was the time series spatial data as summarized in Table 1. Secondary data used are as follows:

- Ground truth data through GPS surveys,
- Virtual data banks such as Google Earth (http://earth.google.com),
- Survey of India topo sheets

| Satellite data                              |                                 |
|---------------------------------------------|---------------------------------|
| Landsat Series (30m): L-5(TM)               | 1990, 1999, 2009                |
| Landsat Series (30m): L-8(OLI)              | 2017                            |

4. Method
Spatio-temporal pattern of urbanization was analyzed from the year 1990 to 2017. The method has been delineated in Figure 2.

4.1. Data Pre-processing
Remote sensing imageries (Landsat series) for Kolkata, acquired for different time periods, were geo-corrected and cropped according to the study area. Secondary data acquired during field visit using ground pre calibrated GPS (Global Positioning System) was used for geo-registration of remote sensing data. Survey of India geo-referenced topographic maps were also used for the same for identifying known points like major road junctions, etc.

4.2. Land Cover analysis (LC)
LC depicts the natural cover present on the ground like forests, impervious surfaces, wetlands, agriculture, and other water and land types. A multi-fold approach of using Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) as described by He et al. [18] for extraction (Eq. 1) of built up form. Urban areas with a reflectance in the shortwave-infrared (SWIR) in comparison with Near-Infrared (NIR) region can be extracted using NDBI [19]. NDVI was obtained using equation (2). Both these land cover indicators range from -1 to 1.

\[
NDBI_c = \frac{SWIR\ (DN) - NIR\ (DN)}{SWIR\ (DN) + NIR\ (DN)} \quad (1)
\]

\[
NDVI_c = \frac{NIR\ (DN) - RED\ (DN)}{NIR\ (DN) + RED\ (DN)} \quad (2)
\]

The continuous built-up image \( BU_c \) was generated using equation (3). A larger value of a pixel in the \( BU_c \) image probability of built-up area. Finally, using an optimum threshold value, the \( BU_c \) image was reclassified into one binary image of built-up with value 1 and other cover by 0.

\[
BU_c = NDBI_c - NDVI_c \quad (3)
\]
4.3. Land Use Dynamics
Land use analysis to understand the human generated growth of urban areas in the city was computed. Training polygons were selected from heterogeneous patches in the landscape on the FCC image obtained. Table 2 describes all the land use types considered for generating the training signatures. Finally, supervised pattern classifier named Gaussian Maximum Likelihood Classifier (GMLC) was used to classify the satellite data (FCC) into a data including the desired land use classes. Accuracy assessment method such as overall accuracy, kappa statistics were used to determine the performance of the classifiers [20].

Table 2. Classes categorized under each land use

| Class          | Residential area, Industrial area, Paved surfaces, all built up areas |
|----------------|---------------------------------------------------------------------|
| Vegetation     | Forest, Cropland, Nurseries                                         |
| Water Bodies   | Tanks, Lakes, Rivers, Reservoirs                                    |
| Others         | Rocks, quarry pits, open ground at building sites, kuccha roads     |

4.4. Modelling
Land use was predicted for the year 2025 using CA Markov which takes into account the output from both Cellular Automata and Markov to produce best results based on the data of 1990, 1999, 2009 and 2017. Markov gives the information about the temporal changes occurring in the study region [21]. Cellular automata gives an account of spatial changes in the study region over the course of time [22]. It makes use of the reclassification rule which dictates the conversion of one land use to another with
respect to the state of neighbourhood cells of the previous state of the cell considered. CA Markov used the output of the Markov analysis as the input to the Cellular Automata to analyse both temporal and spatial changes occurring the study area.

Validation: Land use transition during 1990 to 1999 was used to predict the land use for 2009 considering 1999 as the base year. Predicted land use was verified using the classified land use of 2009. The same process was repeated for the year 2017 considering 2009 as the base year. To validate the results, Kappa was calculated for simulated and classified maps. Similarly land use 2025 was predicted using transition data during 2009 to 2017 taking 2017 as the base year.

5. Results and Discussions

5.1. Land Cover Analysis

Temporal built-up cover analysis was performed through the computation of NDBI generated for the period 1990-2017 as illustrated in Figure 3. Figure 4 depicts the continuous built-up images generated for the period 1990-2017 of the study region. This index aids in understanding the extent of changes in built-up and non-built-up areas in a study region of a period of time. Table 3 exhibits the proportion of urban area in the year 1990, 1999, 2009 and 2017. Kolkata has seen a tremendous growth in urban class from 4.7% in 1990 to 12.4% in 2017. This result can be directly linked with the fact that Kolkata ranks third in the list of cities having high population density in India.

| LAND COVER (%) | 1990 | 1999 | 2009 | 2017 |
|----------------|------|------|------|------|
| Built-Up       | 5.1  | 6.7  | 10.3 | 12.4 |
| Non-Built-Up   | 94.9 | 93.3 | 89.7 | 87.6 |

Figure 3. NDBI maps of the study region for the time period 1990-2017.

Figure 4. Built-up maps extracted for the study region for the time period 1990-2017.
5.2. Land Use Analysis

Further land use analysis was done to differentiate between the impervious layer of urban area and non-urban areas. Temporal land use analysis done using GMLC method as illustrated in Figure 5.

![Temporal Land Use Analysis](image)

**Figure 5.** Temporal Land Use in the study region for the time period 1990-2017.

It depicts land use of the study region during the period 1990-2017. Accuracy assessment obtained using overall accuracy and kappa statistics is as presented in Table 4. Temporal analyses indicates increase in urban areas like buildings, roads and other infrastructure facilities by 202.67% for the period 1990-2017 in Kolkata region. Table 5 indicates the statistics of the land use classes considered, highlighting the urban growth in the city.

**Table 4.** Overall accuracy and Kappa value obtained

| Accuracy Assessment | 1990 | 1999 | 2009 | 2017 |
|---------------------|------|------|------|------|
| OA                  | 88   | 93   | 91   | 91   |
| K                   | 0.94 | 0.96 | 0.85 | 0.89 |

**Table 5.** Land use statistics of the classified images

| YEAR     | 1990 | 1999 | 2009 | 2017 |
|----------|------|------|------|------|
| LAND USE | Area (%) | Area (Ha) | Area (%) | Area (Ha) | Area (%) | Area (Ha) | Area (%) | Area (Ha) |
| Urban    | 4.11 | 14,988 | 6.45 | 23,467 | 9.04 | 32,903 | 11.58 | 45,363 |
| Vegetation | 23 | 83,957 | 21.17 | 76,999 | 28.23 | 102,702 | 22.17 | 80,547 |
| Water    | 4.19 | 15,266 | 4.7 | 17,095 | 4.73 | 17,213 | 6.24 | 22,589 |
| Others   | 68.62 | 249,610 | 67.68 | 246,135 | 58 | 210,990 | 60 | 215,206 |
5.3. Land use modelling

Land use data of the year 2009 and 2017 were used as input to the CA-Markov to study the temporal as well as spatial changes happening in the study area by 2025. Markov is used to generate the transitional area and probability matrix to understand the likelihood of change in land use. The output of the Markov analysis served as the input to the cellular automata to generate spatial allocation of various land use based on rules and its neighbourhood. The results of CA Markov analysis is as shown in Figure 6 and is as tabulated in Table 6.

Figure 6. Predicted land use map for 2025

To validate the model urban growth for 2017 was predicted using 2009 as base year and then kappa statistics were computed as shown in Table 7. Predicted land use of the year 2025 shows trends of urban growth similar to last decade which is continuous in nature. Urban area is expected to rise to 14.94% (54,345 Ha.) in 2025. The main concentration of settlements can be seen mainly near primary roads, airport, industrial areas, salt lake and surroundings. Also there is a lot of predicted growth outside the KMA boundary which can be attributed to the low cost of land near the sub urban areas.

Table 6. Predicted land use statistics for 2025

| Predicted Land use (2025) | Urban | Vegetation | Water | Others |
|--------------------------|-------|------------|-------|--------|
| Area (%)                 | 14.94 | 25.96      | 6.67  | 52.42  |

Table 7. Land use statistics of predicted and classified maps of 2017.

| Land use (%) | Predicted land use, 2017 | Classified land use, 2017 |
|--------------|--------------------------|---------------------------|
| Urban        | 10.22                    | 11.58                     |
| Vegetation   | 36.87                    | 22.17                     |
| Water        | 4.49                     | 6.24                      |
| Urban        | 48.42                    | 60                         |

(kloc=.8, kno=.71, kstandard=.67)
6. Conclusion
Rapid urbanization is posing serious environmental challenges in many cities hindering the goals of sustainable development including natural resource management, maintenance of infrastructure facilities available, etc. In this backdrop, urban growth in the study region has also has stimulated concerns over the degradation of living, health and environmental conditions of its people and their surroundings. In this study, an attempt was made to understand the changing dynamics of land cover and land use in Kolkata city, quantified by NDBI and GMLC and modelling the same for the future. CA Markov was used for modeling and predicting future urban growth in the Kolkata region which would act as a prototype for various other analysis in the region. Remote sensing data and GIS techniques were used as major tools in the study for extraction, monitoring and modeling the dynamics of rapid urbanization.

Temporal land cover analysis depicts an increase in urban area in the study region by 143%. Growth in urban footprints has been visualized majorly in the city centre with the expansion of major centers of trade and commerce. A large number of new infrastructure facilities in form of office buildings, roads, rail and metro stations, commercials space, etc. have been constructed in the region. These results were further confirmed with land use analysis which indicated an increase in urban footprint by 57% from 1990-1999, 40% from 1999-2009 and 38% from 2009-2017 in the study region. Further, the modelled land use map predicted the extent of urban area in the Kolkata region to be 14.94% in 2025. It is in accordance with the urban growth trend with an increase of 29% from 2017-2025. This communication provides a detailed insight of the urban dynamics in the study region which would act as a vital reference for the urban planners and developers in efficient planning and management of the Kolkata region.

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