RESEARCH ARTICLE

Monitoring of land use land cover dynamics and prediction of urban growth using Land Change Modeler in Delhi and its environs, India

Bhavna Singh[1] · Veluswamy Venkatramanan[1] · Benidhar Deshmukh[2]

© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

In the recent decades, cities have been expanding at a great pace which changes the landscape rapidly as a result of inflow of people from rural areas and economic progression. Therefore, understanding spatiotemporal dynamics of human induced land use land cover changes has become an important issue to deal with the challenges for making sustainable cities. This study aims to determine the rate of landscape transformations along with its causes and consequences as well as predicting urban growth pattern in Delhi and its environs. Landsat satellite images of 1989, 2000, 2010 and 2020 were used to determine the changes in land use land cover using supervised maximum likelihood classification. Subsequently, Land Change Modeler (LCM) module of TerrSet software was used to generate future urban growth for the year 2030 based on 2010 and 2020 dataset. Validation was carried out by overlaying the actual and simulated 2020 maps. The change detection results showed that urban and open areas increased by 13.44% and 2.40%, respectively, with a substantial decrease in crop land (10.88%) from 1989 to 2020 and forest area increased by 3.48% in 2020 due to restoration programmes. Furthermore, the simulated output of 2030 predicted an increase of 24.30% in urban area and kappa coefficient 0.96. Thus, knowledge of the present and predicted changes will help decision-makers and planners during the process of formulating new sustainable policies, master plans and economic strategies for rapidly growing cities with urban blue-green infrastructures.

Keywords Land use land cover · Change detection · Urban growth · Predictive modelling · Land Change Modeler · Cellular automata · Markov chain

Introduction

The world is being metamorphosed into urbanisable area progressively where 3.5 billion people inhabits in the cities today which is going to increase 60% by 2030 (Sustainable Development Goal 2021). According to World Urbanization Prospects (2018), 95% of urban extension will occur in the developing world in the next decades. Cities are the centres of positive force for technological innovation, human development, poverty reduction and development of economic

growth which shares about 60% of global gross domestic product (Sustainable Development Goal 2021; UN 2019). However, these urbanisable areas also account for 70% global carbon emissions, 60% of resource use and 60–70% of energy consumption (UN-Habitat 2019).

Urban growth is a dynamic and complex socio-economic process that changes cities in terms of both size and pattern, i.e. population demography (Kafi et al. 2014; UN 2019). The urban transition and economic growth have been linked closely to modernization, industrialization and globalization that fuels the urbanization (Mallupattu and Reddy 2013; Hasan et al. 2020). People migrate from rural to urban areas due to availability of increased opportunities and facilities such as employment, education, health care and other recreational activities (Hasan et al. 2020; Liping et al. 2018; Sarkar and Chouhan 2019). Consequently, this leads to rapid transformation and alteration of land use and land cover features that are mainly induced by anthropogenic activities than natural phenomenon (Hamad et al. 2018; Mahmoud and Alazba 2016). There are several studies that have shown

✉ Bhavna Singh
  bhavna7singh@gmail.com

[1] School of Inter-Disciplinary and Trans-Disciplinary Studies, Indira Gandhi National Open University Maidan Garhi, Delhi 110068, India

[2] School of Sciences, Indira Gandhi National Open University, Maidan Garhi, Delhi 110068, India

only few remote locations are still remaining in their natural and pristine state (Alawamy et al. 2020).

Rapid urbanization and urban growth in combination with unsustainable way of using natural resources resulted in the development of slums, insufficient infrastructure, air pollution, increased pressure on fresh water supplies, forest deterioration, biodiversity loss, global warming, transformation of arable land to urban construction, increase in natural disaster events, climate change, urban heat island and desertification (Kumar et al. 2019; Reis 2008; Aliani et al. 2019; Koko et al. 2020). Increase in the urban clusters with increase in the urban population has significantly changed the land surface which is the most important natural resource at the expense of destruction of natural landscape, decline in open spaces and reduction in the capacity of providing ecosystem services and goods (Gharbia et al. 2016; Hamad et al. 2018).

As a capital, Delhi has experienced congestion, problem in providing civic amenities adequately and increased land rent values with increasing population pressure (NCRPB 2021; Naikoo et al. 2020). Therefore, the Master Plan of Delhi (1962) proposed the concept of National Capital Region (NCR) to disperse the pressure of population towards the surrounding areas (DDA 2021). The NCR is a rural–urban planning region, also known as Delhi Extended Urban Agglomeration and its major cities are Delhi, Faridabad, Ghaziabad, Gurugram and Noida (NCRPB 2021). People started moving out from Delhi to look for comparatively cheaper land for residential or commercial purposes and creation of special economic zones (SEZ) also attracted them (Naikoo et al. 2020; Hasnine and Rukhsana 2020). It resulted in a mixed land use pattern and gave rise to many small urban centres which have now become big cities.

The uncontrolled rate of changes in the land use land cover (LULC) of the city especially the transformation of natural to artificial land cover in the cities has become the major concern around the world at global level (Gharbia et al. 2016; Keshtkar and Voigt 2016). These changes need to be continuously monitored and assessed at different spatial and temporal scales in order to understand what, where and when the changes occurred and at which rate they occurred (Mengistu and Salami 2007; Kumar et al. 2016). Regional mapping of LULC is essential to consider positive and negative changes, to evaluate the impacts of "from-to", to detect driving forces for those changes and to understand the interconnection between people and environment (Kafi et al. 2014; Alipbeki et al. 2020; Mengistu and Salami 2007). Remote sensing and geographic information systems (GIS) are powerful tools and advance means to derive LULC information because they are real time, highly reliable and accurate, cost-effective, and time saving with wide spatial coverage (Maina et al. 2020; Lu et al. 2019). Remote sensing data from Landsat series of satellites have been broadly used in LULC studies as data is easily and freely accessible with comparatively better spatial resolution (Lu et al. 2019).

Urban growth dynamics has become a matter of interest and concern as it changes the basic structure and function of ecosystems (Keshtkar and Voigt 2016). Thus, simulation of urban growth is necessary to examine the future trends in land use and landscape structure (Al-Shaar et al. 2021). Land change modelling is an important tool that allows space–time predictions, i.e. in what way it is likely to change in the coming years (Lu et al. 2019; Al-sharif and Pradhan 2014). It enables city planners, policy makers and environmentalists to make better planning for future sustainable urbanization and mitigation strategy in order to achieve Sustainable Development Goal 11, i.e. sustainable cities and communities (Sustainable Development Goal 2021; Sarkar and Chouhan 2019). Recent advancements in the geospatial technology enable researchers to predict future LULC changes more realistically and effectively (Devendran and Lakshmanan 2019). In this study, Land Change Modeler (LCM) of TerrSet software is used, which comprises of cellular automata — Markov chain process (CA–Markov) to predict the future urbanization (Kumar et al. 2016; Hasan et al. 2020). This model is widely accepted as it integrates historical LULC data with driving factors of urbanization and produces improved spatial patterns of LULC (Hamad et al. 2018; Liping et al. 2018).

Background model description

Markov chain

In 1906, Andrey Andreyevich Markov a Russian mathematician developed a technique known as Markov chain that gives new direction to predictive probability theory (Seneta 1996; Mohamed and El-Raey 2019). Markov chain is a random process used to model the change over a specified time period from one state to another, i.e. from one LULC class to another and is expressed as (Gidey et al. 2017; Mohamed and El-Raey 2019)

$$X_n = i \qquad (1)$$

where i = state, n = time.

In this model, changes from one state to another are according to a given set of probabilistic rules. The predicted future states depend only on the present states and not upon the past states. Probability of going from present state (i) to future state (j) is given by following mathematical expression (Shawul and Chakma 2019):

$$P_{ij} = P\{X_{n+1} = j | X_n = i\} \rightarrow, i.e. P = \{future | present\} \quad (2)$$

It produces a transition probability matrix having information of probability of conversion.

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix} \qquad (3)$$

where P_{ij} is the transition probability matrix, and m is class number.

P_{ij} must satisfy two conditions:

$$\leq P_{ij} < 1 \text{ for all } i \text{ and } j; i, j = 0, 1, 2 \cdots m$$

$$\sum P_{ij} = 1 (\text{rowwise})$$

It results in probabilities of the future state for decision making. The following formula is used to predict the state (Lu et al. 2019):

$$P(\text{Future period}) = P(\text{Present period}) \times \text{Transition Probability}(P_{ij}) \qquad (4)$$

where P is land use land cover conditions.

The basic principle of the Markov chain in Terrset software is that it forecasts the future LULC change from present time (n) to future time ($n+1$) (Gidey et al. 2017). In order to model LULC changes using Markov chain, first, the two input images of different dates are compared on a class-by-class basis and then estimate the replacement rate of one class to other for predicting the third date (Yagoub and Bizreh 2014). Markov chain modelling is appropriate to predict the transition trends of LULC system.

Markov chain is a useful tool for simulating LULC dynamics which predicts the future dimensions and trends (Muller and Middleton 1994; Al-sharif and Pradhan 2014). However, it does not provide scientific explanation of projected changes and spatial distribution of LULC categories (Koko et al. 2020; Gidey et al. 2017). The spatial distribution is highly significant in understanding the patterns and potential impact of certain factors such as socio-economic, political and biophysical that changes over the time (Lambin et al. 2000; Kamusoko 2012). To address this problem, the cellular automata is used to give spatial dimension to LULC (Wang et al. 2019).

Cellular automata

The CA is based on the principle that repeats the interaction of simple rules may results in complex phenomena with time. It is a bottom-up, abstract, spatially and temporally discrete dynamic model (Sarkar and Chouhan 2019; Gidey et al. 2017) and composed of following four elements:

(i) Grid of cells – cell is a fundamental and smallest unit. Each cell carries data of only one state at any one time from a defined set of states (Kumar et al. 2016). Cell size represents the land area that each cell covers. In this study, Landsat data having 30 m × 30-m cell size has been used.

(ii) State – it allocates possibilities to the cell which is typically finite (Virtriana et al. 2014), e.g. 0 and 1 or urban and non-urban for a given time step. These states either change into a new state or remain in their present state at every discrete time step (Keshtkar and Voigt, 2016).

(iii) Neighbourhood – each cell has a local neighbourhood, representing a set of cells or adjacent cells that have direct interaction/relationship with the centrally located cell (Kumar et al., 2016). At every iteration, the state of each cell is decided by the states of its local neighbourhood (Gidey et al., 2017). The effect of neighbourhood cells is inversely related to the distance from the central cell (Gharbia et al. 2016; Wolfram 2002; Barredo et al. 2003).

(iv) Transition rules – the changes occurred in the cell state is due to simple and logical rules applied on the states of neighbourhood cells iteratively through a number of discrete time steps defined prior to the execution (Keshtkar and Voigt 2016; Al-Shaar et al. 2021). The formula for calculating cell's state at any given time t + 1 is as follows (Gidey et al. 2017):

$$C_{t+1} = R(C_t, O_t) \qquad (5)$$

where C is the cell state at time t and $t+1$, O is the state of cells in its neighbourhood and R is the transition rules.

Transition rules are the most essential element in order to simulate real world LULC changes (Gharbia et al. 2016). In relation with urban growth, rules consider various driving factors such as socio-economic, biophysical, accessibility and disturbances which have significant impact on LULC (Arsanjani et al. 2013; White and Engelen 1993; Liu et al. 2008). So, the probability of transitions to forecast LULC changes in the state of neighbourhood cells is not completely random decision (Liping et al. 2018). CA has a strong capability for modelling LULC dynamics because it considers time–space interactions and urban expansion as it uses proximity concept, i.e. cells that are nearer to current class have higher probability of changing into another class (Yang et al. 2014; Nguyen et al. 2019).

Objectives

The objectives of the study are to (i) evaluate the changes in LULC using satellite imagery for the period from 1989 to 2020, and (ii) model and predict future LULC changes,

particularly growth in urban area for the year 2030. The findings will help policy makers in improving the land use policies that will safeguard the local environment and sustainable development.

Study area

The study area covers Delhi (capital of India) and neighbouring four important NCR districts namely Ghaziabad, Faridabad, Gurugram and Gautam Buddha Nagar lies between longitudes 77°21′12.36″E to 77°25′16.78″E and 28°14′15.59″N to 28°55′52.05″N latitudes (Fig. 1). It spreads over an area of 5955 km². The climatic conditions of the area are characterized by hot semi-arid summers with maximum temperature 48 °C and fairly cold subtropical

winters with minimum temperature 4 °C. As per the Indian Meteorological Department, the average annual rainfall is approximately 886 mm.

Materials and methods

Satellite data

Satellite imageries are helpful in mapping and representing the spatial distribution of LULC information (Rawat and Kumar 2015). The LULC data used in this study were prepared from the Landsat images for the years 1989, 2000, 2010 and 2020. These satellite images were obtained from the US Geological Survey (USGS) data portal (http://earth

Fig. 1 Location map of the study area
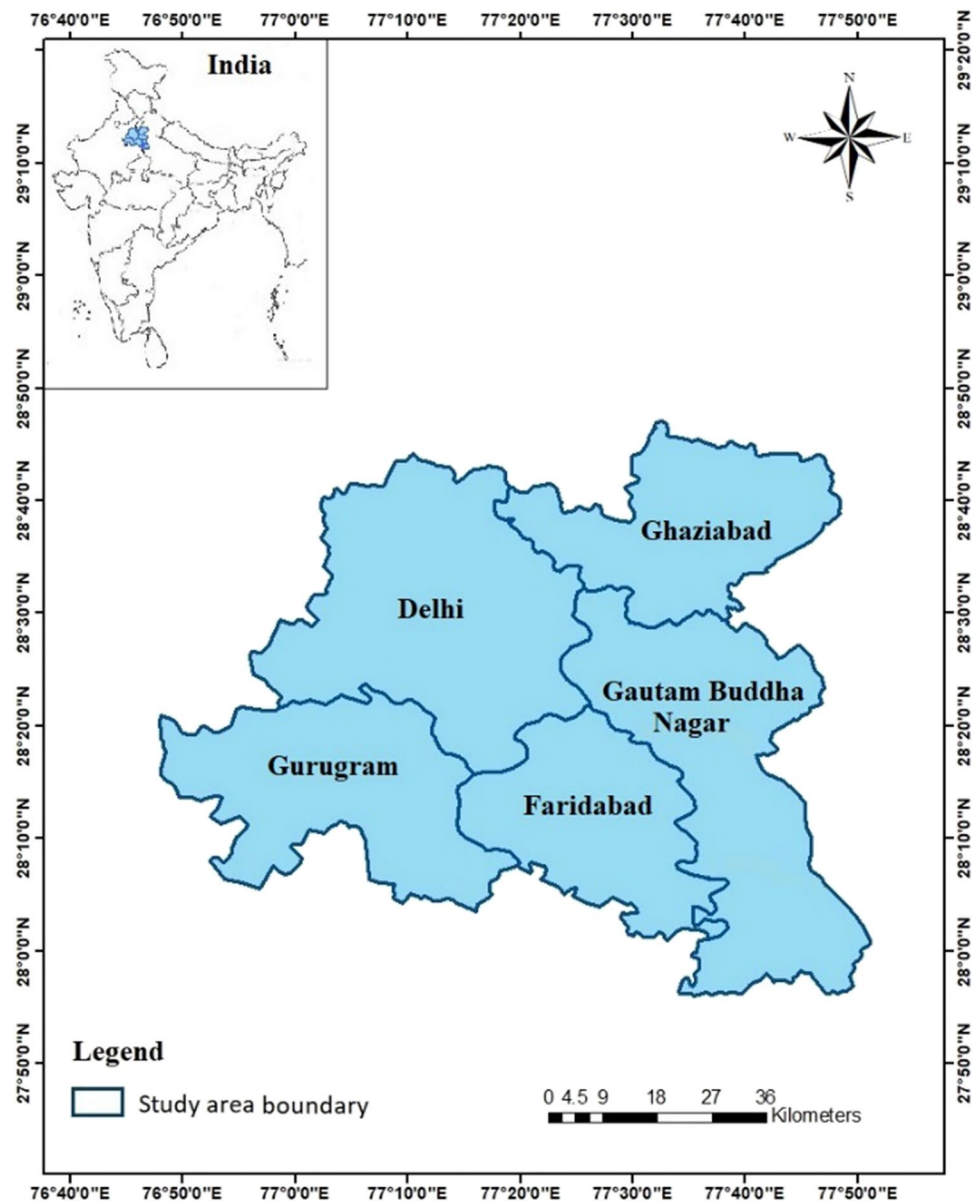
explorer.usgs.gov/). The images were selected from the same season to reduce the effect of seasonal variation. The details of satellite data are given in Table 1.

Ancillary data

This study considered the biophysical and socioeconomic driving factors that exert direct effect on the urban growth pattern. The following five factors were selected for running the model to predict the urban expansion:

(i) Proximity from roads – road network is an important factor in expanding as well as stimulating urban growth. It increases the accessibility of land and decreases the cost of getting common facilities as all the urban land use categories such as residential, commercial and institutional places are interconnected to each other (Abdullahi and Pradhan, 2018). Road network data was extracted from the Open Street Map (https://www.openstreetmap.org/) dated 15 March 2021. In this study, it was assumed that the road network data remained unchanged. Therefore, this data was entered for the year 2010 assuming that network was similar during that period. Both major roads and minor roads were considered in this study. The Euclidean distance tool was applied to calculate the distance from roads based on the closest cell (Gharbia et al. 2016).

(ii) Elevation – elevation map was generated from Digital Elevation Model (DEM) to represent topography. DEM was obtained from Shuttle Radar Topographic Mission (SRTM) which was downloaded from USGS Earth Explorer.

(iii) Slope – slope map was derived from the DEM using slope tool.

(iv) Land use and land cover – LULC maps are the most crucial input for urban growth projection. These data can be used to extract the trend of changes in the landscape.

(v) Distance from urban disturbance – it is most likely that the beginning of new urban areas usually spread close to the existing urban areas, i.e. there are high chances for urban growth in nearby places due to neighbourhood effect (Gharbia et al. 2016). To estimate distance from urban disturbance, Euclidean distance tool was used.

Method

The workflow that was carried out in this study consists of the following: (1) image pre-processing, (2) image classification and accuracy assessment, (3) change detection and (4) urban growth prediction using LCM for the year 2030. Flowchart illustrating the methodology used in the study is given in Fig. 2.

Image pre-processing

Pre-processing of satellite images is a vital step as it enhances the quality and visibility of images by minimizing the errors (Alawamy et al. 2020). The foremost step is layer stacking, i.e. combining different bands into a standard False colour composite (FCC) image used to determine the colour tone of a specific class (Mohamed and El-Raey 2019). The area of interest (AOI) was masked and extracted from the FCC image.

Image classification and accuracy assessment

The goal of the image classification procedure is to classify image's pixels into several LULC classes based on their different spectral signatures or reflectance values (Alawamy et al. 2020). To categorize the images, supervised classification technique was performed with the maximum likelihood classifier algorithm which aggregates the pixels having similar spectral properties of the image (Mahmoud and Alazba 2016; Maina et al. 2020). For this study, NRSC classification scheme was adopted and images were classified into 12 LULC classes, namely forest, scrub, grass, urban, rural, crop land, fallow land, barren area, open area, waterbody, riverbed and mining. The LULC maps for the years 1989,

Table 1 Details of satellite data used in the study

Satellite	Sensor	Path/row	Acquisition date	Cloud cover	Resolution
Landsat 5	TM	146/40	05–12-1989	0%	30
		147/40	12–12-1989	0%	
Landsat 7	ETM+	146/40	25–11-2000	0%	30
		147/40	02–12-2000	0%	
Landsat 5	TM	146/40	29–11-2010	0%	30
		147/40	06–12-2010	7%*	
Landsat 8	OLI/TIRS	146/40	10–12-2020	8.77%*	30
		147/40	01–12-2020	12.62%*	

*Not present in study area

Fig. 2 Flowchart of Methodology adopted in the study for change detection and prediction of urban growth
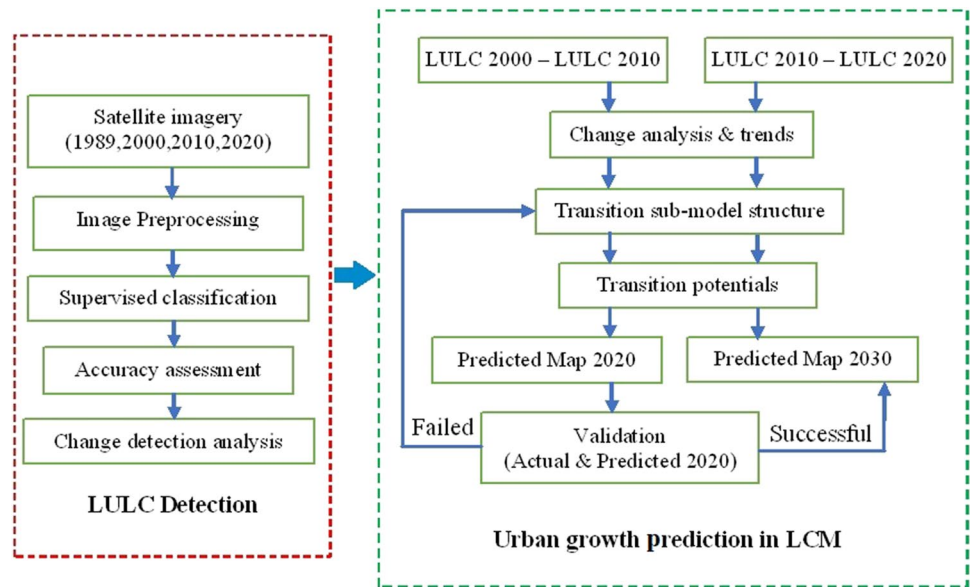
2000, 2010 and 2020 have been prepared. Description of these LULC classes is presented in Table 2.

Due to the high spatial heterogeneity in the study area, recoding was done on the basis of local knowledge, familiarity with the study area, field observations and Google earth images for improving the classification results considerably (Sarkar and Chouhan 2019). Accuracy assessment was performed on the classified images as it quantitatively evaluates how accurately pixels are classified into different LULC classes and examines the reliability of classified image (Alipbeki et al. 2020). High-resolution imagery from Google Earth Pro and field visits were used as reference data of corresponding time periods (Luo et al. 2015) and 610 randomly distributed ground control points (GCPs) were generated across each across each LULC categories. After comparing the classified images with reference, it gives final

result in the form of overall accuracy and kappa coefficient for the years 1989, 2000, 2010 and 2020 (Table 3). The overall accuracy is the ratio of total number of pixels classified correctly to the total number of pixels (Aliani et al. 2019). Value of kappa coefficient ranges from + 1 to –1 which indicates the accuracy between the ground reality classes and the classified classes (Duric et al. 2014; Lillesand et al. 2015).

Change detection

Change detection is a comparative analysis used to identify the changes in the nature and extent of different LULC features between different periods (Alawamy et al. 2020). In order to detect LULC changes over three decades from 1989 to 2020, the classified images were compared which estimates the net changes, gains and losses in the LULC

Table 2 Description of the land use land covers classes identified in the study area

LULC categories	Description
Forest	Dense and open forest, plantation forest, continuous stand of trees, many of which may attain a height of 50 m
Scrub	Areas less dense than forest and have short vegetation such as small trees, bushes and shrubs
Grass	Areas covered by grasses, golf course, lawns
Urban	Industrial, residential, commercial, transportation and facilities
Rural	Villages, clustered settlements having rural characteristics
Crop land	Irrigated areas and crop fields
Fallow land	Uncultivated agricultural land
Barren area	Areas with exposed soils, stony area, unvegetated lands
Water	River, ponds, lakes, canal, drains, wetlands
Open area	Areas used for upcoming construction sites and going to have human settlements, area influenced by humans
Riverbed	Sandy area along river
Mining	Rock, sand, silica mining

Table 3 Estimation of LULC changes and accuracy assessment for 1989, 2000, 2010 and 2020

LULC categories	Area								Differences		
	1989		2000		2010		2020		1989–2000	2000–2010	2010–2020
	Km²	%	Km²	%	Km²	%	Km²	%	%	%	%
Forest	492.65	8.27	323.95	5.44	270.25	4.54	477.64	8.02	−2.83	−0.90	3.48
Scrub	1092	18.34	911.88	15.31	817.72	13.73	840.55	14.11	−3.02	−1.58	0.38
Grass	60.07	1.01	84.06	1.41	80.91	1.36	122.17	2.05	0.40	−0.05	0.69
Urban	407.06	6.84	682.51	11.46	993.53	16.68	1207.59	20.28	4.63	5.22	3.59
Rural	131.2	2.20	172.84	2.90	196.31	3.30	218.22	3.66	0.70	0.39	0.37
Crop land	2504.74	42.06	2654.87	44.58	2452.3	41.18	1856.82	31.18	2.52	−3.40	−10.00
Fallow land	493.2	8.28	354.43	5.95	313.87	5.27	383.55	6.44	−2.33	−0.68	1.17
Waterbody	104.95	1.76	99.37	1.67	132.32	2.22	89.48	1.50	−0.09	0.55	−0.72
Riverbed	35.65	0.60	23.45	0.39	15.48	0.26	8.97	0.15	−0.20	−0.13	−0.11
Open area	355.63	5.97	414.23	6.96	490.65	8.24	498.3	8.37	0.98	1.28	0.13
Barren area	253.3	4.25	213.91	3.59	192.17	3.23	252.22	4.24	−0.66	−0.37	1.01
Mining	25.06	0.42	20.01	0.34	0	0.00	0	0.00	−0.08	−0.34	0.00
Total	5955.51		5955.51		5955.51		5955.51				
Overall accuracy	88%		91%		93%		89%				
Kappa coefficient	0.85		0.89		0.91		0.87				

categories and to understand the dynamics of changes (Singh 1989). The magnitude of change is a rate of expansion or reduction in the area of each class. A negative value indicates loss in the area while a positive value indicates gain in the area (Kafi et al. 2014).

Urban growth prediction using LCM

LCM is an innovative and vertical application in the Terrset software used to predict future urban growth with better spatiotemporal pattern (Hyandye and Martz 2017; Keshtkar and Voigt 2016; Sayemuzzaman and Jha 2014). The following steps were involved:

(i) Images of both earlier and later LULC maps, i.e. 2000–2010 and 2010–2020 were used as an input into the change analysis panel to estimate the change between two different LULC that help in predicting changes in 2020 and 2030, respectively (Eastman 2016). The images were reclassified into five LULC classes which are important to predict urban growth namely-scrub, urban, agriculture, open area and other lands. There is a spatial trend analysis tool that gives output of pattern of changes. Trends of 3rd and 4th order were calculated.

(ii) The transition potential panel displays a list of transition sub models that consist of a group of transitions existed between two LULC classes and filtered out the specific sub models required for the urban growth prediction (Lu et al. 2019). The transition probability

matrix was computed based on the later LULC image set as starting point for change simulation by Markov chain which compares all pixels and their transition for each LULC class (Kumar et al. 2016; Eastman 2016). This reflects the probability and quantity of expected LULC change from one class to another (Al-sharif and Pradhan 2014).

(iii) Some of the driving factors that act as agents of urbanization are responsible for the cause of dynamics of LULC events (Eastman 2016). Cramer's V coefficient has been used to assess association of each of the driving factor towards urban growth. Higher the Cramer's V coefficient value indicates that the driver has higher relationship with urban growth (Eastman 2016; Eastman and Toledano 2018). In this study, we have considered major variables based on literature, i.e. elevation, slope, distance from roads, distance from urban disturbances and trends of 3rd or 4th order.

(iv) Transitions are modelled using multi-layer perceptron (MLP) neural network method as it allows multiple transitions at one time and equal sample size per class (Devendran and Lakshmanan 2019; Eastman and Toledano 2018). This empirical method operated in automatic mode as it decides on its own how parameters should be used and changed to get better output data (Gidey et al. 2017). The dynamic learning procedure initiates with start learning rate and lowers down successively as it approaches to end learning rate and with this number of iterations com-

pleted (Kumar et al. 2016; Eastman and Toledano 2018). During each time step, pixels with higher transition probability changed to new land type class and others remain unchanged to generate a new land map at the end of each iteration (Wang et al. 2019). Once the training process is completed, it gives transition potential images (Eastman 2016).

(v) Based on the proximity concept of CA, spatial reallocation of each land class is estimated and overlaid to produce output (Kamusoko 2012). For predicting the future scenario for a specific period, previous rates of change and transition potentials were used. We have chosen the hard prediction mapping which is based on multi-objective land allocation (MOLA) module of LCM (Abuelaish 2018; Kumar et al. 2016).

(vi) Model validation is a decisive part as it examines the predictive power of any model and dependability of outcome (Gidey et al. 2017; Kamusoko 2012). For this purpose, a comparison is done between actual and predicted maps of the year 2020 (Singh et al. 2015).

Results and discussion

LULC change detection

LULC change is a continual process influenced by socioeconomic, political, cultural, demographic and environmental factors (Rahman et al. 2012). It needs a comprehensive understanding and monitoring of all the factors which are important for establishing association between the policy decisions, driving forces of the process and to overcome the problems (Mahmoud and Alazba 2016; Mallupattu and Reddy 2013). The change analysis is carried out to understand the land transformation and trends in the LULC. Positive and negative changes are noticed over 31 years in the area under the LULC categories. The coverage percentage of each land use class in the years 1989–2020 is presented in Fig. 3. The LULC classification results which are summarized for the 1989–2020 period are shown in Table 3. The LULC maps for the years 1989, 2000, 2010 and 2020 are depicted in Fig. 4. Results of gains and losses of different LULC classes are presented in Fig. 5.

Green cover (forest, scrub and grass)

The green cover areas are sanctuary, ridge, biodiversity parks, botanical gardens, protected and reserved forests, city forest, recreational areas and parks. Green cover area is observed to have declined from 1989 (1644.72 km^2) to 2000 (1319.89 km^2) and also further significant decline is observed from 2000 (1319.89 km^2) to 2010 (1168.88 km^2). This is attributed to conversion of forest into scrub and green cover into built-up and crop land classes prominently. The study area comprises of Aravalli range which was an active mining site with stone crushing zone. This left the area highly deteriorated and deprive of green cover. Other anthropogenic activities such as illegal tree cutting, continuous expansion of settlement and roads traverse through green cover reduce the natural vegetation. These human-induced changes caused fragmentation of green cover, tremendous loss of habitat for native flora and fauna, decline in air quality, adversely affect

Fig. 3 Graphical representation of LULC change for selected time periods in the years 1989–2020
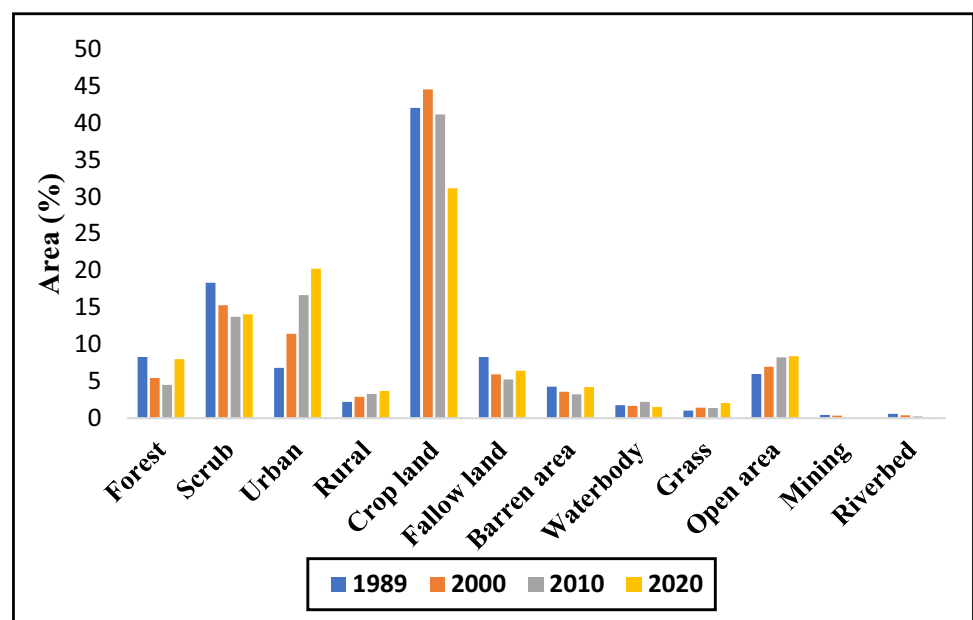
Fig. 4 Classified maps of the study area of **a** 1989, **b** 2000, **c** 2010 and **d** 2020
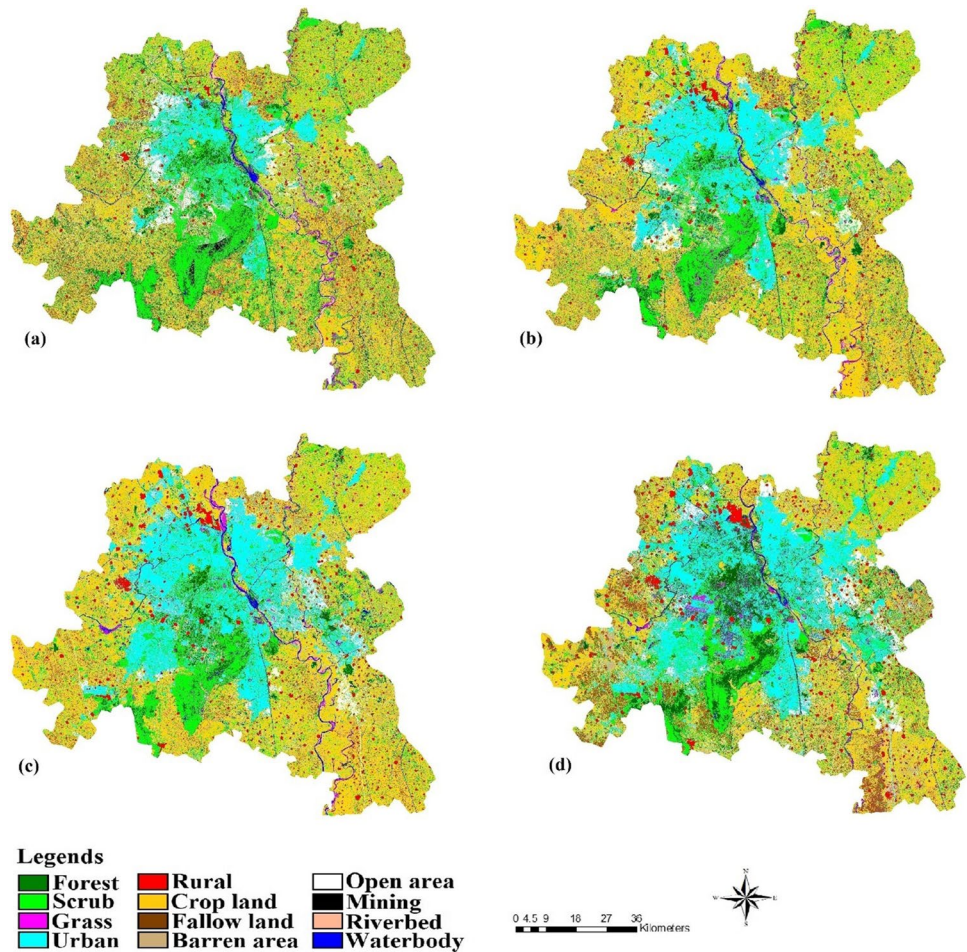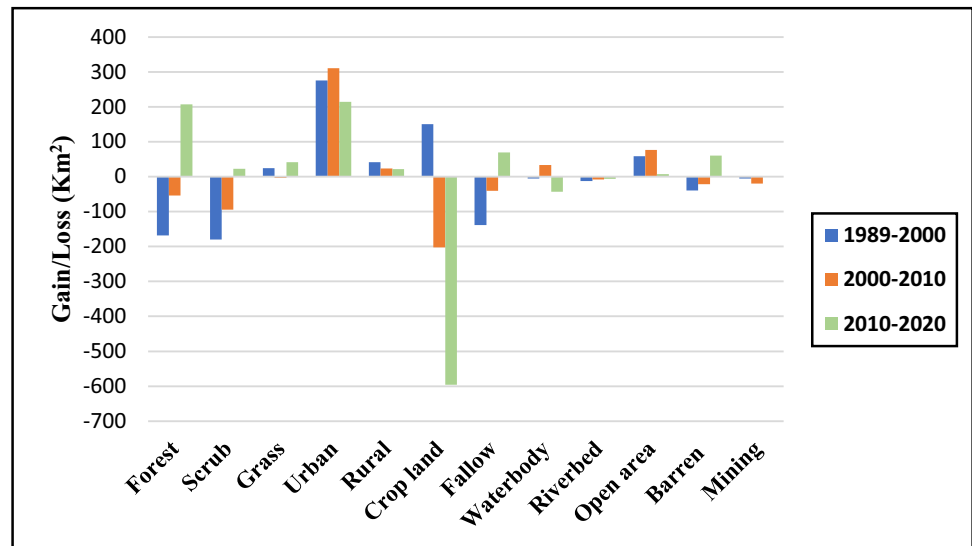

Fig. 5 Gains and losses of LULC classes for each time period

the ecological settings of the region and unfavourable hydrological changes (Mengistu and Salami 2007). This raised the concern at global and national level through the United Nations Environment Programme, Convention on Biological Diversity, the Earth Summits, Biodiversity Act 2002, setting up of protected areas and so on in order to save the natural heritage and maintaining the environmental qualities.

The area of green cover increased by 4.55% in 2020. The transformation of land from scrub to forest and expansion of the green zone can be attributed to the implementation of reforestation, afforestation and restoration programmes initiated by government, academic institution and local communities (CPCB 2020; Sinha 2014). A ban was imposed on mining in 2004 (Iamgurgaon 2020) and conservative as well as innovative concept of biodiversity park and city forest were evolved to rewild the area and revive the nearly extinct biodiversity (DBF 2016). In Delhi, there are 4 ridges (Northern ridge, Central Ridge, South Central ridge and Southern ridge), 7 biodiversity parks (Yamuna Biodiversity park, Aravalli Biodiversity park, Neela Hauz Biodiversity Park, Tilpath Valley Biodiversity Park, Kamla Nehru Ridge, Tughlaqabad Biodiversity Park and Kalindi Biodiversity Park), Asola-Bhatti Wildlife Sanctuary and 26 notified protected and reserved forests such as Sanjay Van, Jahanpana forest, Rajokri forest and Mitraon forest (Forest Department 2015). However, there are only a few notified green areas — 5 in Gurugram (Sultanpur bird sanctuary, Sarbasirpur reserve forest, Eco restoration Chakkarpur Bundh, Badshahpur Forest corridor, Sikanderpur forest area), 5 in Gautam Buddha Nagar (Okhla bird sanctuary, Surajpur bird sanctuary, Night safari, Miyawaki forest, biodiversity park sec-91), 1 in Faridabad (Magar Bani forest) and 1 in Ghaziabad (City forest). So, these areas must focus on increasing the green breathing space which are self-sustained and healthy ecosystems that act as green lung to metropolitan cities. The green cover in the study area needs more protection as they are still under threat and more disturbed due to encroachment, unsustainable development, illegal construction, illegal tree cutting, proximity to densely populated urban centres, construction of highways and expressway bisect them. These green areas help in combating the local climate change and boost the quality of urban environment as they act as sink for urban pollutants, improve local weather conditions and mitigate the urban heating (Singh 2017). The grass area witnessed an increase in its size from the initial 60.07 km^2 in 1989 to 122.17 km^2 in 2020 as the riverbed, farm house lawns and abandoned land got covered by grass with the time.

Waterbody

The waterbody area shows a trend of decreasing first to 5.58 km^2 during the period 1989–2000, then increasing 32.95 km^2 (2000–2010) and again decreasing status 42.84 km^2 (2010–2020). The rapid decrease in waterbodies is occurred due to their conversion into agricultural areas, filling them up for creating human settlements, dumping of solid waste materials, discharge of untreated sewage causes biomagnification and construction of embankments for preventing flood water entry. This causes shrinking, degrading, vanishing and drying up of waterbodies. In fact, many of waterbodies have

become open drains and lost their self-purification abilities due to human disturbances. Presently, the study area depends on the Yamuna river, Hindon river and groundwater sources for its water supply which are contaminated and water table level has been dropping from 1 to 3 m every year at different places (CGWB 2015; Dev et al. 2020). These water-stressed cities are largely urbanized with a huge and growing population required to accomplish the accelerating fresh water demand which is becoming more difficult with every passing day. To address this semi-critical situation, rejuvenation of the city's water networks becomes necessary. The concept of constructed wetlands is adopted which work similarly to the natural ones; absorb the impurities in water through natural processes at low-cost, ensures the original ecological integrity and recharging the groundwater (Gorgoglione and Torretta 2018). Some successful cases of the restored lakes or wetlands in the study area are Neela hauz, Hauz khas lake, Surajpur wetland, Rajokri lake, Old Fort lake and Najafgarh Jheel (Saxena 2017). The noticeable change observed is that deep pits of mines within the green cover area have filled up with water and converted into healthy functional lakes gradually. But the current rate of population and its demand growing is higher than that of rate of reviving waterbodies which is at slow pace. There is need of quick initiatives and speedy participation with careful balancing between development and environment.

There are obstacles in conserving and preserving the waterbodies present in the study area. For example, encroachment, construction of skyscrapers looming nearby, large amount of domestic and industrial effluents released into them, appearance of unusual white foam, concretization around waterbodies, and waste dumping have (i) drastically degraded the quality of water, (ii) blocked the rain water absorption, and (iii) affected the aquatic organisms. Some of the practices can be adopted for reviving and improving the health of waterbodies such as Phytorid-Scientific Wetland with Active Biodegradation technology developed by NEERI, establishment of porous pavements, installation of rain water harvesting systems for residential and commercial buildings as well as flyovers and roads, removal of encroachments, creating awareness about the waterbodies and their potential, and active water resources management (Saxena 2017; Ritter 2019).

The waterbodies showed a maximum increment in the area 132.32 km^2 in 2010. This happened because of the cloudburst incident taken place at Leh which also affects the study area. The area received highest rainfalls and Yamuna river overflows (Guhathakurta et al., 2020).

Urban area

During the 1989–2020 period, the level of urbanization in the area increased remarkably from 407.06 to 1207.59

km^2. It indicates that urban area is experiencing continuous growth in the last 31 years. On the contrary, the crop land, open area and green cover reduced during the same time. At present, the study area is characterized by intensive growth in the population (Figs. 6 and 7) and high inflow of migrants resulting in the accelerated demand for housing and facilities that can be attributed to the change in land use pattern. Table 4 shows total migrants and their socio-economic reasons for migration.

There are certain factors that are responsible for attracting the population and evident for the changes in the urban cluster level are as follows:

(i) Transportation infrastructure plays a crucial role in providing mobility to people, goods and services (Aljoufie et al. 2011). It tends to stimulate an active urban growth, land use changes and enhances the level of economic activity through the accessibility it provides to the region (Marovic et al. 2018). In the study area, road network and metro rail are the

main drivers of urbanization as well as expansion of fringe zones of Delhi due to the fast and good connectivity providing links to various places and close proximity. Road network serves as a skeleton for urban development and dominant transport asset used on a daily basis by millions of commuters (Shi et al., 2019). Table 5 shows major roads in the study area and their expansion with the time to bring different regions closer together. The increase in the total road length from 36,248 (2012) to 38,716 km (2019) (DES 2019a; DESH 2019; DESUP 2019), aided in linking the cities (NCRPB, 2021). In the study area, these expressways and highways act as catalyst behind the rising of numerous commercial and residential complexes. It attracts both buyers and investors which offers a lot of scope for future townships. Metro rail is a mass rapid transit system connects all five main metropolitan areas of study with each other having 12 operational lines covering total length of 391 km (Metro 2022). The metro rail
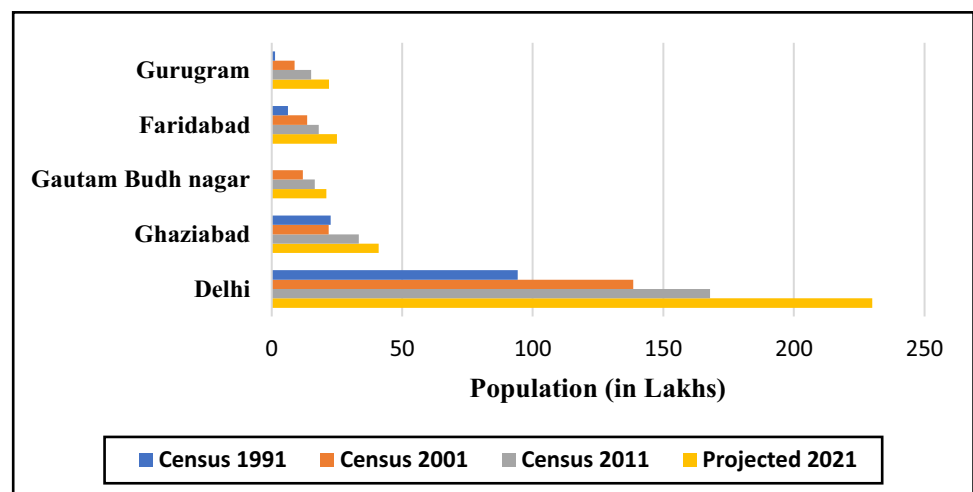

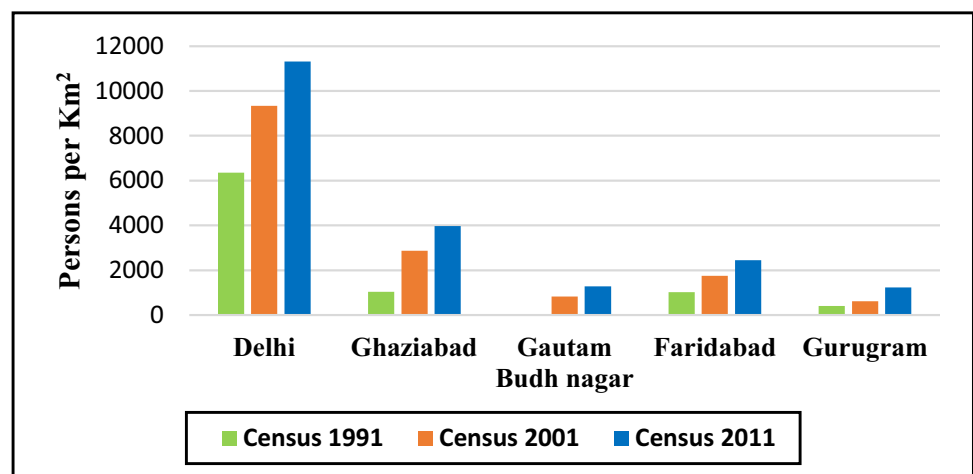**Fig. 6** Decadal population growth

Fig. 7 Decadal population density

Table 4 Socio economic factors for migration and total migrants

Reason of migration	Ghaziabad			Faridabad			Gurugram			Gautam Buddha nagar		Delhi		
	1991	2001	2011	1991	2001	2011	1991	2001	2011	2001	2011	1991	2001	2011
Employment	13,560	104,079	410,181	101,609	174,775	224,581	9320	26,551	220,107	61,320	183,627	1,083,597	2,011,796	2,029,489
Business	1780	3879	24,077	16,370	4116	9409	2630	811	6632	3006	9157	163,863	41,298	51,426
Education	480	2457	18,118	4750	2254	6108	900	572	4724	1472	8555	50,405	81,521	101,963
Marriage	55,186	73,687	325,345	68,155	82,527	227,357	19,443	23,813	234,543	18,277	223,463	708,949	917,680	1,330,756
Moved with household	26,526	171,960	731,631	119,989	213,325	338,648	21,821	38,521	304,019	86,677	272,107	1,424,463	2,024,838	2,545,234
Moved after birth	-	5979	75,486	-	12,408	56,182	-	1660	18,147	2733	23,130	-	129,237	183,077
Others	7850	110,085	395,842	28,590	93,456	219,378	9834	20,630	88,452	39,204	128,431	292,185	808,088	982,569
Total migrants	105,382	472,126	1,980,680	339,463	582,861	1,081,663	63,948	112,558	876,624	212,689	848,470	3,723,462	6,014,458	7,224,514

Source: Census 1991, 2001, 2011

stretches have been witnessing rapid development. There is a continuous increase in ridership, i.e. average daily ridership was 80,000 (2002), 12.59 lakhs (2010) and 57 lakhs (2020) (ESI 2020).

(ii) The 7th 5-year plan (1985–1990) and 8th 5-year plan (1992–1997) of the Government of India proposed the development of small and medium towns around large cities. These towns aimed as key centres of attraction to the migrants by providing availability to economic activities and employment opportunities that could further help in reducing immigration into the large cities (Chachra, 1993). Accordingly, the National Capital Region Planning Board was established in 1985 and new district Gautam Budh Nagar is created in 1997 to minimize the pressure of population in Delhi. In the study area, the diversion of population influx towards Ghaziabad, Noida, Greater Noida, Faridabad and Gurugram is observed.

(iii) The New Economic Policy (1991) opened the doors for globalization that gave entry to private and foreign players, lowered the import duties and allowed the international flow of goods, services and technology with few restrictions (Madaan and Madan 1995). This raised the economic growth centres in the study area related to various fields such as automobiles, banking, pharmaceutical, information technology, food processing, telecommunications and pesticide that generates more employment opportunities (Dev et al. 2020). With the entry of multinational companies (MNC's), the number of industries within the study area had increased from 11,836 in 2011 to 13,038 in 2018 (Table 6). It implies large-scale infrastructure construction with more residential spaces for working people. Therefore, it can be noted that changing pattern of economy had a considerable role in LULC dynamics in the national capital and urban fringe zones. In Delhi, there is a decrease in the industries due to strict environmental norms and sealing of small-scale industries caused the shifting to nearby outskirt area while increase the corporate sector simultaneously (DES 2019a, 2019b).

The Special Economic Zone Act (2005) created free trade zones that have more liberal economic laws, efficient transport system, uninterrupted power supply and global telecommunication network for enhancing foreign investment. Noida and Gurugram are Special Economic Zones present in the study area. The maximum extension of urban area has been observed from Noida than Gurugram. The government is launching policies time to time for creating an ecosystem for doing business with ease such as Enterprise Promotion Policy 2015 and Invest India

Table 5 Changes and expansion of major roads in the study area

Name of major roads	Length	Connects	Widening with time	Constructed
Outer Ring Road	47 km	With all National Highways passing through Delhi	6 lane	1984
Inner Ring Road	55 km	Northern, Western, Southern, Eastern areas in Delhi	6 lane 8 lane	1992
NH 24* (Delhi-Meerut Expressway)	34 km	Delhi-Ghaziabad-Noida	2 lane 4 lane 14 lane	1972 2021
NH 2*, NH 44#	36 km	Delhi-Faridabad	2 lane 4 lane	-
Delhi Noida Direct Flyway (DND)	9.2 km	Delhi-Noida	8 lane	2001
Noida- Greater Noida Expressway	24.53 km	Noida-Greater Noida	6 lane	2002
NH 8*, NH 48# (Delhi-Gurugram Expressway)	28 km	Delhi-Gurugram	2 lane 6–8 lane	2008
Delhi Faridabad Skyway	4.4 km	Delhi-Faridabad	6 lane	2010
Taj Highway	4.3 km	Ghaziabad-Greater Noida	4–6 lane	2012
Hindon Elevated Road	10.3 km	Ghaziabad-Delhi	4 lane	2018

*Old numbering, #new numbering. Source: ESI 2005, TCPO 2007, DSC 2022, Jica 2022, Wayback 2022a,Wayback 2022b

that attracts investors and large number of employees towards Delhi-NCR.

(iv) The study area is the home to many educational institutions and renowned universities which bring people from all over India. Other infrastructure facilities also are getting available with urban development such as malls, hospitals, community and sports facilities and water supply which further attract people to have a good standard of living (Qadir et al. 2020).

The study area is subjected to intensive human influence and to meet its daily needs has its direct impacts on the resources of the region. The transformation of land into urban areas leads to increase in impervious surfaces that decrease the percolation of water into the soil as a result decrease in the ground water recharge (GWYB 2019). Land use changes effect the biodiversity of the region and a constant intrusion into green cover. The study area witnessed haphazard growth of construction area which do not follow local laws as a consequence the area suffered from different types of pollution (air, water, noise and light pollutions).

The World Air Quality Report (2019) highlighted the elevated PM 2.5 pollution level in the air and faces the environmental and human health risk issues gained from the rapid urbanization of metropolitan cities. The most polluted cities are from study area — Ghaziabad (110.2 $\mu g/m^3$), Delhi (98.6 $\mu g/m^3$), Noida (97.7 $\mu g/m^3$), Gurugram (93.1 $\mu g/m^3$) and Greater Noida (91.3 $\mu g/m^3$). During lockdown period of COVID-19, reduction in the air pollutant concentration is observed significantly from 55 to 67% due to temporary drop down in economic

activities (Greenpeace India 2020). Therefore, the government should focus in implementing the sustainable development along with green framework around the urban clusters to protect the human health and ensure a healthy planet for all.

Rural area

There is a gain in rural area from 131.2 (1989) to 218.22 km^2 (2020). It is observed that the number of villages and size of villages increases as the number of villagers also increases as well. It occurred because of the economic transformation takes place in the surrounding areas. But simultaneously, some of the rural areas have been occupied for urban development.

Crop land

The crop land which has an area of 2504.74 km^2 in 1989 has raised to 2654.87 km^2 in 2000. The expansion of crop land due to increased demand for food is the major factor that opens up an opportunity to bring green cover under cultivation.

The study has shown a sudden decrease in the available agricultural land from 2452.3 (2010) to 1856.82 km^2 (2020), with net decrease of 595.48 km^2 within the study area. The study area witnessed a large amount of crop land acquired by the government authorities for urban settlements and infrastructural development. There are many private real estate developers that take up the crop land for various upcoming

Table 6 Number of industries and number of employees in the study area

Cities	2011–12		2012–13		2013–14		2014–15		2015–16		2016–17		2017–18	
	No. of registered industries	No. of employees	No. of registered industries	No. of employees	No. of registered industries	No. of employees	No. of registered industries	No. of employees	No. of registered industries	No. of employees	No. of registered industries	No. of employees	No. of registered industries	No. of employees
Faridabad	2469	2,07,161	2491	2,11,804	2499	2,13,352	2,478	216,329	2588	2,15,896	2763	2,21,416	2783	2,24,307
Gurugram	1897	2,55,755	2019	2,65,061	2119	2,71,036	2200	2,79,625	2267	2,82,560	2378	2,86,670	2476	3,00,222
Gautam Buddha Nagar	2780	-	2953	-	3154	-	3329	-	3451	-	3474	-	3478	-
Ghaziabad	1714	-	1727	-	1637	-	1695	-	1819	-	1835	-	1845	-
Delhi	2976	1,18,778	3183	1,26,354	2980	1,15,731	2928	1,18,103	2852	1,13,782	2639	1,11,776	2456	1,05,146
Total	11,836	-	12,373	-	12,389	-	12,630	-	12,977	-	13,089	-	13,038	-

and ongoing projects and have changed its land use pattern of the area.

Fallow land

The fallow land is reduced in the study area from 493.2 (1989) to 354.43 km^2 (2000) and further decreased to 313.87 km^2 in 2010 as cultivation has resumed in some of the parts again and some of the areas has converted to built-up area. The net increase shown in the area is 69.68 km^2 in 2020 as they are not cultivated for one or more seasons.

Open area

The open area increased continuously during the 31 years from 355.63 (1989) to 498.3 km^2 (2020) as the area acquired by the government and private sector for the upcoming construction projects. The disturbed area of green cover is also represented by open area because of the human influence.

Barren area

The barren area reduced by 21.74 km^2 (2010) and moved to open area, crop land and recreation cover. During last one decade, the total barren area increased as the other land cover getting abandoned.

Riverbed

The study has revealed a constant decrease in the riverbed area as some of the portion has been occupied by crop land or build up while some part is naturally covered by grass or shrub with the time.

Mining

The Aravalli range in the study area was adversely affected by the mining activity which was banned in 2004 (iamgurgaon 2020) and area was reforested with the help of eco task force.

Urban growth Prediction

The study area consists of Ghaziabad, Gautam Buddha Nagar, Faridabad and Gurugram which no longer to be considered as satellite towns to Delhi. With the pace of time and accelerated development, they become large urban agglomerations and now can be classified as independent cities. But after the opening of the economic corridors and changes in policies, the study area experienced haphazard, unplanned and unauthorized colonization and development activities. The advancement in remote sensing and GIS technologies and large amount spatiotemporal

data availability helps in evaluating changes in the past and forecasting the future urban growth can provide assistance to decision-makers for developing a strategic sustainable plan (Fathizad et al. 2015). The results indicate that 20.28% of the entire study area has been occupied as urban area in 2020 which will be expected to increase by 24.30% in 2030 is explained by the decline in agriculture and open area. The change trajectories between the actual and predicted land use land cover classes for the year 2020–2030 are shown in Fig. 8. Figure 9 illustrates a

Fig. 8 Graphical representation of actual and predicted LULC classes for 2020–2030
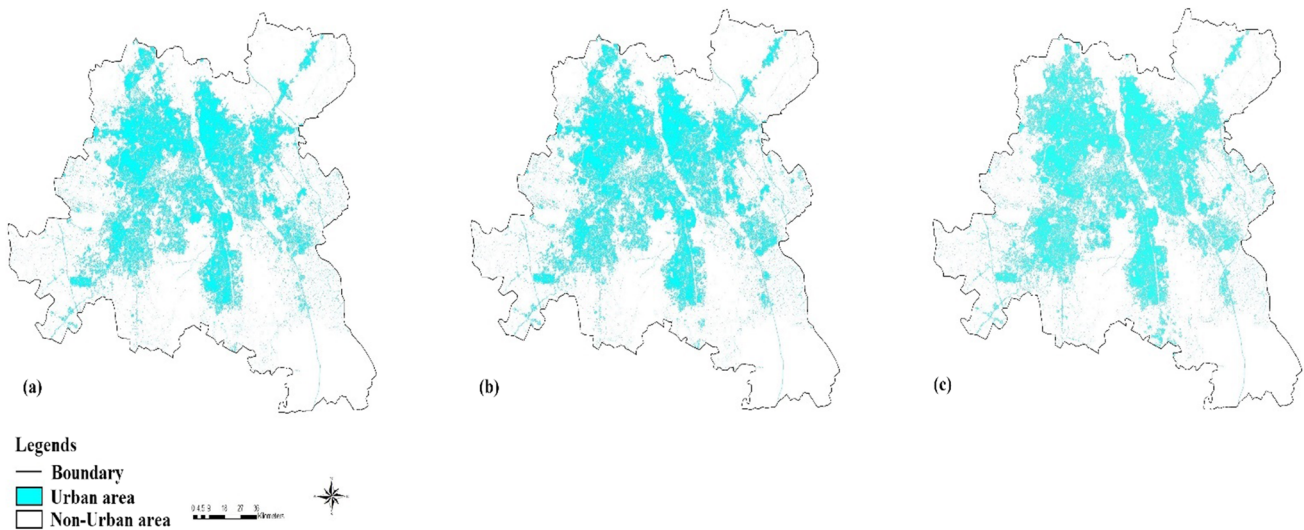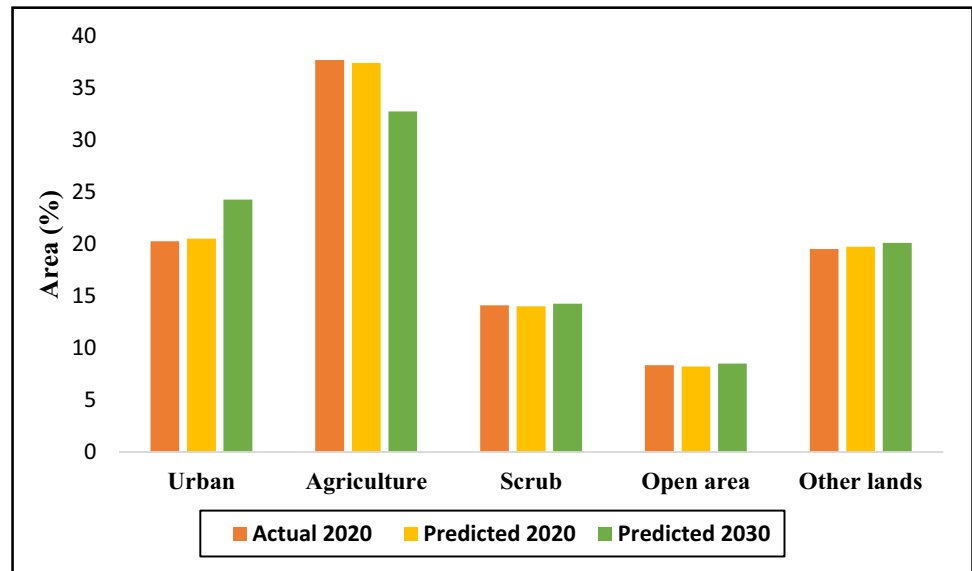
Fig. 9 Urban growth maps of the study area (**a**). Actual map 2020 (**b**). Predicted map 2020 (**c**). Predicted map 2030

Table 7 Variation in LULC area of actual 2020 and predicted 2020 and area statistics of predicted 2030

Class name	Urban	Agriculture	Open area	Scrub	Other land	Total
Actual area 2020 (km^2)	1207.59	2245.37	498.3	840.55	1163.7	5955.51
Predicted area 2020 (km^2)	1223.71	2229.54	490.62	835.73	1175.91	5955.51
Area difference (km^2)	16.12	− 15.83	− 7.68	− 4.82	12.21	-
Area difference (%)	1.33	− 0.71	− 1.56	− 0.57	1.04	-
Predicted area 2030 (km^2)	1447.74	1951.25	507.22	850.69	1198.61	5955.51

Table 8 Factors considered and their Cramer's V values for predicting urban growth

Explanatory variables	Cramer's V coefficient	
	Overall	Urban
Elevation	0.1978	0.2629
Slope	0.0742	0.0618
Distance from roads	0.1450	0.1067
Distance from urban disturbance	0.1052	0.1001
Agriculture to urban 3rd order	0.2178	0.4588
Open area to urban 4th order	0.2292	0.4428
Scrub to urban 3rd order	0.2054	0.4390

comparison of the variations in urban area between 2020 and 2030. The changes in the area for years 2020 and 2030 are presented in Table 7. Table 8 represents the potential explanatory power of each driving force, calculated by Cramer's V.

To a large extent, there are consequences of urban growth as it puts pressure on the natural resources which requires a necessary consideration and effective measures towards them such as shortage of water resources, landscape fragmentation, loss of arable land, deforestation, land degradation, mitigating local climatic conditions and pollution (Gidey et al. 2017; Lu et al. 2019). Therefore, in order to balance the growth of urban areas, economic benefits, protection of arable land and conservation of the natural environment, a holistic approach with harmonizing way is essential (Koko et al. 2020).

Model validation

Validation of model was performed by comparing the predicted map of 2020 with the actual map of 2020 (Gidey et al. 2017). The overall accuracy and kappa coefficient of the predicted output of 2020 are found to be 98.63% and 0.96 respectively. This reveals that LCM model is capable of forecasting the future changes successfully. Although the model used in this study is an effective technique for performing the simulation, there are several uncertainties in the prediction of land type classes in the future, which are described as follows: First, the future changes made by the government in the land development policies and master plans as well as natural processes that effect the land use pattern cannot be estimated through model. As the model predicts, the future changes on the basis of present LULC patterns identified (Keshtkar and Voigt 2016). Second, the driving factors keep on changing with the time. For example, change in the transportation system directly influences the direction and shape of growth in the city as settlement locations and density shifts. Thus, the selection of most favourable set of driving

forces is important to improve the model prediction accuracy; otherwise, it may result in error in estimating changes correctly (Arsanjani et al. 2013; Wang et al. 2019).

Land use and planning

There is a complex relationship between land use land cover changes, human activities and sustainable use. The gaps in the present land use planning (Master Plans) of the study area that needs to be filled are as follows.

(i) We should construct regularly updated databases that include population economics, population density and environmental issues which help in framing strategic plans. The lower the density per square kilometre of a region makes things to be managed in a better way. For example, the Ghaziabad Municipal Corporation is not taking the necessary steps to address solid waste remediation (NGT 2020) as its the population density is high, i.e. 3971 persons per sq.km (Census 2011).

(ii) To mitigate immigration and excessive load on natural resources, the government should take decisions and efforts for sustainable development by uniform distribution of economic zones, services and facilities throughout the country instead of creating infrastructure at particular places.

(iii) The master plans of different areas in the study excluding Delhi have mentioned the recreational or open space land use category which is generally used in the form of public parks, playgrounds, golf course and amusement park but this will not cope up the air pollution problem. Proper planning is required to deal with pollution and provide healthy life to the resident people. There should be conscious efforts for increasing green cover with the creation of healthy dense green areas or biodiversity parks to mitigate local environmental problems.

(iv) After the establishment of Delhi Development Authority (DDA), it has prepared only three master plans for the years 1962, 2001 and 2021, Ghaziabad Development Authority (GDA) master plans 2001 and 2021 (interval of 20 years), and NOIDA master plan 2021 and 2031 (interval of 10 years). This prolonged time interval between the master plans could be the origin of haphazard growth in the study area. There is a need to amend the duration of master plan updation to meet with the pace of fast-growing urban cities. This will help the planners and authorities effectively monitor and manage land uses and also formulation of integrated systematic master plans which can be modified according to the ground feedback.

(v)   During the preparation process of Master Plan, there is a lack of public and stakeholder's participation which helps in understanding and resolving local level issues and improving social infrastructure. In this direction, DDA is taking suggestions from the public for preparing master plan for 2041. Other regions may also follow bottom-up approach.

(vi)   To adopt nature-based solutions and sustainable urban designs such as walkability principle. To make the city walkable, it should meet certain conditions — safety, continuity, comfort, accessibility and attractiveness. It would help in health, environment and socio-economic benefits (Shafray and Kim 2017).

(vii)   Now a days, plantation of ornamental plants is more on roadsides, sidewalks and parks. It should be mixed type of plantation which includes native species, medicinal species, air purifying species, ornamental species and fruit species. It could help in reconnecting people with local vegetation, improvement in quality of environment, increases attractiveness, provide fruits to homeless people and welcoming back the birds to cities.

Conclusion

The study demonstrates that the integration of remote sensing, GIS and LCM with multi-temporal data helps in understanding and assessing the LULC dynamics and future trends of urban growth. LULC changes serves as a scientific basis to understand the implications of cause–effect relationship between humans and environment that studied area is experiencing, such as poor drainage, waterlogging, imperious surfaces, ecological problems, over exploitation of natural resources and unauthorized constructions. This is the result of weaker policy implementation and less responsive behaviour.

The study revealed a significant expansion of urban area from 1989 to 2020 due to government policies, population growth, infrastructure facilities and also close proximity to capital. There is an improvement in the green cover area which may benefit the local climatic conditions, provide valuable ecosystem services and enhance the quality of life. The decrease in the waterbody may contribute to irregularity in water supply and water scarcity. It is required to maintain equilibrium with the nature by creating sustainable cities as land is limited and its utilization should be judicious and well managed. In the view of tomorrow, sustainable cities should offer healthy environment, more green spaces, zero waste, carbon neutrality with progressive and green economy. To strengthen this process, it is imperative

to actively engage local communities in planning and monitoring activities.

The study shows that there are number of drivers that challenges the future development of sustainable cities. Therefore, urban simulation studies can help in understanding the effects of future changes and drawbacks of current planning policies to safeguard the adverse effects. The prediction results indicate that the model has good potential and accuracy to stimulate the future trends. Such database is very useful for multi-criteria decision making, environmentally sound management and future urban planning to harmonize the demand and reduce the impacts arises from land use pattern.

Furthermore, the study offers the policy-makers and planners to improve the policies and formulate new master plans with integrated multidisciplinary framework. Considering the difference between current situation and projected changes in urban growth, the study area needs to take short-term action plans with long-term vision to achieve urban green–blue network. There must be strict building by-laws on all construction activities which restricts haphazard growth within the cities, introduction of urban regeneration projects at all levels (economic, socio-cultural and environmental) and redevelopment of urban riverfronts of Yamuna and Hindon.

Author contribution BS: conceptualization, data curation, methodology, processing and analysis of the data, simulation, writing — original draft. VV: conceptualization, methodology, supervision, writing — review and editing. BD: conceptualization, methodology, supervision, writing — review and editing.

Data availability All data generated or analysed during this study are included in this manuscript.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication All of the authors consented to publish this manuscript.

Conflict of interest The authors declare no competing interests.

References

Abdullahi S, Pradhan B (2018) Land use change modeling and the effect of compact city paradigms: integration of GIS-based cellular automata and weights-of-evidence techniques. Environ Earth Sci 77:251. https://doi.org/10.1007/s12665-018-7429-z

Abuelaish B (2018) Urban land use change analysis and modeling: a case study of the Gaza Strip. In: MT Camacho Olmedo, M Paegelow, JF Mas, F Escobar (Eds.) Geomatic approaches for modeling land change scenarios. Springer, Cham. pp 271–291. https://doi.org/10.1007/978-3-319-60801-3_13

Akin A, Aliffi S, Sunar F (2014) Spatio-temporal urban change analysis and the ecological threats concerning the third bridge in Istanbul City. The Int Arch Photogramm Remote Sens Spat Inf Sci XL7:9-14. https://doi.org/10.5194/isprsarchives-XL-7-9-2014

Alawamy JS, Balasundram SK, Mohd. Hanif AH, Boon Sung CT, (2020) Detecting and analyzing land use and land cover changes in the Region of Al-Jabal Al-Akhdar, Libya using Time-Series Landsat data from 1985 to 2017. Sustainability 12(11):4490. https://doi.org/10.3390/su12114490

Aliani H, Malmir M, Sourodi M, Sourodi M, Kafaky SB (2019) Change detection and prediction of urban land use changes by CA–Markov model (case study: Talesh County). Environ Earth Sci 78:546. https://doi.org/10.1007/s12665-019-8557-9

Alipbeki O, Alipbekova C, Sterenharz A, Toleubekova Z, Aliyev M, Mineyev N, Amangaliyev K (2020) A spatiotemporal assessment of land use and land cover changes in Peri-Urban areas: a case study of Arshaly District. Kazakhstan Sustainability 12(4):1556. https://doi.org/10.3390/su12041556

Aljoufie M, Zuidgeest M, Brussel M, Maarseveen MV (2011) Urban growth and transport: understanding the spatial temporal relationship. WIT Transactions on The Built Environment 116:315–328. Retrieved 3 Mar 2022. https://www.witpress.com/Secure/elibrary/papers/UT11/UT11027FU1.pdf

Al-Shaar W, Gerard JA, Nehme N, Lakiss H, Barakat LB (2021) Application of modified cellular automata Markov chain model: forecasting land use pattern in Lebanon. Model Earth Syst Environ 7:1321–1335. https://doi.org/10.1007/s40808-020-00971-y

Al-sharif AAA, Pradhan B (2014) Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. Arab J Geosci 7:4291–4301. https://doi.org/10.1007/s12517-013-1119-7

Arsanjani JJ, Helbich M, Kainz W, Boloorani AD (2013) Integration of logistic regression, markov chain and cellular automata models to simulate urban expansion. Int J Appl Earth Obs Geoinf 21:265–275. https://doi.org/10.1016/j.jag.2011.12.014

Barredo JI, Kasanko M, McCormick N, Lavalle C (2003) Modelling dynamic spatial processes: Simulation of urban future scenarios through cellular automata. Landsc Urban Plan 64(3):145–160. https://doi.org/10.1016/S0169-2046(02)00218-9

Basharin GP, Langville AN, Naumov VA (2004) The life and work of A.A. Markov Linear Algebra and Its Applications 386:3–26. https://doi.org/10.1016/j.laa.2003.12.041

Census (1991) Census of India. https://censusindia.gov.in/digitallibrary/Archive_home.aspx. Retrieved 15 Mar 2022

Census (2001) Census of India. https://censusindia.gov.in/2011-common/census_data_2001.html. Retrieved 15 Mar 2022

Census (2011) Census of India. https://censusindia.gov.in/2011-Common/Archive.html. Retrieved 22 Apr 2021

CGWB (2015) Aquifer mapping and formulation of aquifer management plan in NCR, UP. Central Ground Water Board, Ministry of Water Resources, River Development and Ganga Rejuvenation, Government of India, UP. Retrieved 15 Apr 2021. http://cgwb.gov.in/AQM/NAQUIM_REPORT/UP/NCR,%20U.P.pdf

Chachra S (1993) Government policies and rural-urban migration. Indian Anthropologist 23(1):73–81. Retrieved 15 Mar 2022. https://www.jstor.org/stable/41921808

Chen Q, Mynett AE (2003) Effects of cell size and configuration in cellular automata based prey–predator modelling. Simul Model Pract Theory 11:609–625. https://doi.org/10.1016/j.simpat.2003.08.006

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ 37:35–46. https://doi.org/10.1016/0034-4257(91)90048-B

CPCB (2020) Guidelines for setting up of biodiversity parks in floodplains of rivers of India, including River Ganga. Central Pollution Control Board, Ministry of Environment, Forest and Climate Change, India. Retrieved 6 Mar 2021. https://cpcb.nic.in/openpdffile.php?id=UmVwb3J0RmlsZXMvMTE1M18xNjA3NDI3NjkxX21lZGlhcGhvdG8xMTYxMi5wZGY=

DBF (2016) Delhi Biodiversity Foundation- origin and concept. Retrieved Apr 16, 2021 from https://www.delhibiodiversityparks.org/origin-concept.html

DDA (2021) Delhi Development Authority. https://dda.org.in/planning.aspx Retrieved 25 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2011) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2012) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2013) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2014) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2015) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2016) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

Department of Economics and Statistical Analysis, Haryana (2017) https://esaharyana.gov.in/state-statistical-abstract-of-haryana/ Retrieved 26 Apr 2021

DES (2019a) Statistical abstract of Delhi. Directorate of Economics and Statistics, Delhi. Retrieved 15 Mar 2021. http://des.delhigovt.nic.in/wps/wcm/connect/9e42f900409730e68a0abea50c073453/StatisticalAbstarct2019a.pdf?MOD=AJPERES&lmod=108608480&CACHEID=9e42f900409730e68a0abea50c073453&StatisticalAbstarct2019a

DES (2019b) Delhi Statistical Hand Book. Directorate of Economics and Statistics, Delhi. Retrieved 15 Mar 2021. http://des.delhigovt.nic.in/wps/wcm/connect/be7414004f2f3c28b3cfb7a50c073453/handbook_1408.pdf?MOD=AJPERES&lmod=-328276286&CACHEID=be7414004f2f3c28b3cfb7a50c073453

DESH (2019) Statistical abstract of Haryana. Department of Economics and Statistical Analysis, Haryana. Retrieved 15 Mar 2021. https://cdnbbsr.s3waas.gov.in/s32b0f658cbffd284984fb11d90254081f/uploads/2021/07/2021072372.pdf

DESUP (2019) Statistical abstract of Uttar Pradesh. Directorate of Economics and Statistics, Uttar Pradesh http://updes.up.nic.in/esd/reports_publication_Elib_public.htm. Retrieved 16 Mar 2022

Deutsch A, Dormann S (2017) Cellular automaton modeling of biological pattern formation: characterization, applications, and analysis. Springer Science and Business Media, New York. https://doi.org/10.1007/978-1-4899-7980-3

Dev M, Veerabhadrappa SM, Jha MK (2020) GIS based temporal analysis of land use pattern and its impact - proposed Gurgaon Manesar urban complex. Int Mech Prod Eng Res Dev 10(3):6941–6952

Devendran AA, Lakshmanan G (2019) Analysis and prediction of urban growth using neural-network-coupled agent-based cellular automata model for Chennai Metropolitan area, Tamil Nadu India. J Indian Soc Remote Sens 47:1515–1526. https://doi.org/10.1007/s12524-019-01003-8

Directorate of Economics and Statistics, Delhi (2019) http://des.delhigovt.nic.in/wps/wcm/connect/DOIT_DES/des/home/. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2011) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2012) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2013) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2014) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2015) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

Directorate of Economics and Statistics, Uttar Pradesh (2016) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 April 2021

Directorate of Economics and Statistics, Uttar Pradesh. (2017) http://updes.up.nic.in/esd/Industrial_Statistics/ASI/Industrial%20Statistics(a).htm. Retrieved 26 Apr 2021

DSC (2022) http://dsclimited.com/dev/index.php?modepage=18&m=8&c=9. Retrieved 10 Mar 2022

Duric N, Pehani P, Oštir K (2014) Application of in-segment multiple sampling in object-based classification. RemoteSensing 6(12):12138–12165. https://doi.org/10.3390/rs61212138

Eastman JR (2016) TerrSet Manual. Clark labs, Clark University, Worcester, USA. Retrieved 15 Feb 2021. https://clarklabs.org/wp-content/uploads/2016/10/Terrset-Manual.pdf

Eastman JR, Toledano J (2018) A short presentation of the Land Change Modeler (LCM). In: MT Camacho Olmedo, M Paegelow, JF Mas, F Escobar (Eds.) Geomatic Approaches for Modeling Land Change Scenarios. Springer, Cham. pp 499–505. https://doi.org/10.1007/978-3-319-60801-3_36

El-Hallaq MA, Habboub MO (2015) Using cellular automata-markov analysis and multi criteria evaluation for predicting the shape of the Dead Sea. Advances in Remote Sensing 4:83–95. https://doi.org/10.4236/ars.2015.41008

ESI (2005) Economic survey of Delhi. Planning Department, Delhi. http://delhiplanning.nic.in/content/economic-survey. Retrieved 10 Mar 2022

ESI (2020) Economic survey of Delhi. Planning Department, Delhi. http://delhiplanning.nic.in/content/economic-survey. Retrieved 10 Mar 2022

Fathizad H, Rostami N, Faramarzi M (2015) Detection and prediction of land cover changes using Markov chain model in semi-arid rangeland in western Iran. Environ Monit Assess 187:629. https://doi.org/10.1007/s10661-015-4805-y

Forest Department (2015) Forest & tree cover of Delhi as per India SFR – 2015. http://forest.delhigovt.nic.in/wps/wcm/connect/doit_forest/Forest/Home/Forests+of+Delhi/. Retrieved 18 Apr 2021

Gashaw T, Tulu T, Argaw M, Worqlul AW (2017) Evaluation and prediction of land use/land cover changes in the Andassa watershed, Blue Nile Basin. Ethiopia Environ Syst Res 6:17. https://doi.org/10.1186/s40068-017-0094-5

Gharbia SS, Alfatah SA, Gill L, Johnston P, Pilla F (2016) Land use scenarios and projections simulation using an integrated GIS cellular automato algorithms. Model Earth Syst Environ 2:151. https://doi.org/10.1007/s40808-016-0210-y

Gidey E, Dikinya O, Sebego R, Segosebe E, Zenebe A (2017) Cellular automata and markov chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. Model Earth Syst Environ 3:1245–1262. https://doi.org/10.1007/s40808-017-0397-6

Gorgoglione A, Torretta V (2018) Sustainable management and successful application of constructed wetlands: a critical review. Sustainability 10(11):3910. https://doi.org/10.3390/su10113910

Greenpeace India (2020) Air Quality in the world's top ten polluted Indian cities improves drastically, still more than 25 μg/m3 WHO prescribed standards. https://www.greenpeace.org/india/en/press/4871/air-quality-in-the-worlds-top-ten-polluted-indian-cities-improves-drastically-still-more-than-25-%ce%bcg-m3-who-prescribed-standards/. Retrieved 24 Apr 2021

Guhathakurta P, Narkhede N, Preetha Menon P, Prasad AK, Sable ST (2020) Observed rainfall variability and changes over Delhi state. Climate Research and Services, India Meteorological Department, Ministry of Earth Sciences, Pune. Retrieved 19 Mar 2021. https://imdpune.gov.in/hydrology/rainfall%20variability%20page/delhi_final.pdf

GWYB (2019) Ground water year book of states. Central Ground Water Board, Delhi. http://cgwb.gov.in/GW-Year-Book-State.html Retrieved 26 Apr 2021

Hamad R, Balzter H, Kolo K (2018) Predicting land use/land cover changes using a CA-Markov model under two different scenarios. Sustainability 10(10):3421. https://doi.org/10.3390/su10103421

Hasan S, Shi W, Zhu X, Abbas S, Khan HUA (2020) Future simulation of land use changes in rapidly urbanizing South China based on Land Change Modeler and remote sensing data. Sustainability 12(11):4350. https://doi.org/10.3390/su12114350

Hasnine M, Rukhsana, (2020) An analysis of urban sprawl and prediction of future urban town in urban area of developing nation: case study in India. J Indian Soc Remote Sens 48:909–920. https://doi.org/10.1007/s12524-020-01123-6

Hyandye C, Martz LW (2017) A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. Int J Remote Sens 38:64–81. https://doi.org/10.1080/01431161.2016.1259675

Iamgurgaon (2020) Aravali Biodiversity Park, Gurugram 2010–2020 Making of a city forest- a ten-year report. iamgurgaon, Gurugram. Retrieved 12 Mar 2021. https://iamgurgaon.org/wp-content/uploads/2020/09/Aravali-Bio-Diversity_-Making-of-a-City-Forest.pdf

Jica (2022) https://www.jica.go.jp/english/our_work/evaluation/oda_loan/post/2005/index.html. Retrieved 11 Mar 2022

Kafi KM, Shafri HZM, Shariff ABM (2014) An analysis of LULC change detection using remotely sensed data; a case study of Bauchi City. IOP Conf Ser Earth Environ Sci 20:012056. https://doi.org/10.1088/1755-1315/20/1/012056

Kamusoko C (2012) Markov–cellular automata in geospatial analysis. In: Y Murayama (Ed.) Progress in Geospatial Analysis. Springer, Tokyo, pp 107–124. https://doi.org/10.1007/978-4-431-54000-7_8

Keshtkar H, Voigt W (2016) A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. Model Earth Syst Environ 2:10. https://doi.org/10.1007/s40808-015-0068-4

Koko AF, Yue W, Abubakar GA, Hamed R, Alabsi AAN (2020) Monitoring and predicting spatio-temporal land use/land cover

changes in Zaria City, Nigeria, through an integrated cellular automato and markov chain model (CA-Markov). Sustainability 12(24):10452. https://doi.org/10.3390/su122410452

Kumar KS, Kumari KP, Bhaskar PU (2016) Application of Markov chain & cellular automata based model for prediction of Urban transitions. 2016 International Conference on Electrical, Electronics, and Optimization Techniques 4007–4012. https://doi.org/10.1109/ICEEOT.2016.7755466

Kumar S, Ghosh S, Hooda RS, Singh S (2019) Monitoring and prediction of land use land cover changes and its impact on land surface temperature in the Central Part of Hisar District, Haryana under semi-arid zone of India. J Landsc Ecol 12(3):117–140. https://doi.org/10.2478/jlecol-2019-0020

Lambin EF, Rounsevell M, Geist H (2000) Are agricultural land-use models able to predict changes in land use intensity? Agr Ecosyst Environ 82(1–3):321–331. https://doi.org/10.1016/S0167-8809(00)00235-8

Lillesand T, Kiefer RW, Chipman J (2015) Remote Sensing and Image Interpretation, 7th edn. John Wiley & Sons, Hoboken

Liping C, Yujun S, Saeed S (2018) Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—a case study of a hilly area, Jiangle China. Plos ONE 13(7):e0200493. https://doi.org/10.1371/journal.pone.0200493

Liu X, Li X, Liu L, He J, Ai B (2008) A bottom-up approach to discover transition rules of cellular automata using ant intelligence. Int J Geogr Inf Sci 22:1247–1269. https://doi.org/10.1080/13658810701757510

Lu Y, Wu P, Ma X, Li X (2019) Detection and prediction of land use/land cover change using spatiotemporal data fusion and the cellular automata–Markov model. Environ. Monit. Assess. 191:68. https://doi.org/10.1007/s10661-019-7200-2

Luo G, Amuti T, Zhu L, Mambetov BT, Maisupova B, Zhang C (2015) Dynamics of landscape patterns in an inland river delta of Central Asia based on a cellular automata-Markov model. Reg Environ Change 15:277–289. https://doi.org/10.1007/s10113-014-0638-4

Madaan DK, Madan DK (1995) India's new economic policy - a macro study. Indian Journal of Asian Affairs 8/9(1/2):104–113. http://www.jstor.org/stable/41950393

Mahmoud SH, Alazba AA (2016) Land cover change dynamics mapping and predictions using EO data and a GIS-cellular automata model: the case of Al-Baha region, Kingdom of Saudi Arabia. Arab J Geosci 9:419. https://doi.org/10.1007/s12517-016-2439-1

Maina J, Wandiga S, Gyampoh B, Charles KKG (2020) Assessment of land use and land cover change using GIS and remote sensing: a case study of Kieni Central Kenya. J Remote Sens GIS 9:270. https://doi.org/10.35248/2469-4134.20.9.270

Mallupattu PK, Reddy JRS (2013) Analysis of land use/land cover changes using remote sensing data and GIS at an Urban Area, Tirupati India. Sci World J 2013:268623. https://doi.org/10.1155/2013/268623

Marovic I, Androjic I, Jajac N, Hanak T (2018) Urban road infrastructure maintenance planning with application of neural networks. Complexity 2018:5160417. https://doi.org/10.1155/2018/5160417

Mengistu DA, Salami AT (2007) Application of remote sensing and GIS in land use/land cover mapping and change detection in a part of south western Nigeria. Afr J Environ Sci Technol 1(5):99–109

Metro (2022) Delhi metro. https://www.delhimetrorail.com/. Retrieved 10 Mar 2022

Mohamed SA, El-Raey ME (2019) Land cover classification and change detection analysis of Qaroun and Wadi El-Rayyan lakes using multi-temporal remotely sensed imagery. Environ Monit Assess 191:229. https://doi.org/10.1007/s10661-019-7339-x

Muller MR, Middleton JA (1994) Markov model of land-use change dynamics in the Niagara Region, Ontario Canada. Landsc Ecol 9:151–157

Naikoo MW, Rihan M, Ishtiaque M, Shahfahad, (2020) Analyses of land use land cover (LULC) change and built-upexpansion in the suburb of a metropolitan city: spatio-temporalanalysis of Delhi NCR using landsat datasets. J Urban Manag 9(3):347–359. https://doi.org/10.1016/j.jum.2020.05.004

NCRPB (2021) National Capital Region Planning Board. http://ncrpb.nic.in/ .Retrieved 25 Apr 2021

NGT (2020) National Green Tribunal- order of Original Application No. 909/2018. https://greentribunal.gov.in/caseDetails/DELHI/0701109002082018. Retrieved 15 Apr 2021

Nguyen TA, Le PMT, Pham TM, Hoang HTT, Nguyen MQ, Ta HQ, Phung HTM, Le HTT, Hens L (2019) Toward a sustainable city of tomorrow: a hybrid Markov–cellular automata modeling for urban landscape evolution in the Hanoi city (Vietnam) during 1990–2030. Environ Dev Sustain 21:429–446. https://doi.org/10.1007/s10668-017-0046-2

Qadir A, Tahir M, Abir IA, Hwee LS, Akhtar N (2020) Land change detection of Delhi area, India: a GIS approach. PalArch's Journal of Archaeology of Egypt / Egyptology 17(9):7769–7780

Rahman A, Kumar S, Fazal S, Siddiqui MA (2012) Assessment of land use/land cover change in the North-West District of Delhi using remote sensing and GIS techniques. J Indian Soc Remote Sens 40:689–697. https://doi.org/10.1007/s12524-011-0165-4

Rawat JS, Kumar M (2015) Monitoring land use/cover change using remote sensing and GIS technique: a case study of Hawalbagh block, district Almora, Uttarakhand, India. Egypt J Remote Sens Space Sci 18:77–84. https://doi.org/10.1016/j.ejrs.2015.02.002

Reis S (2008) Analyzing land use/land cover changes using remote sensing and GIS in Rize. North-East Turkey Sensors 8(10):6188–6202. https://doi.org/10.3390/s8106188

Ritter K (2019) Groundwater plummets in Delhi, City of 29 million. https://www.circleofblue.org/2019/india/groundwater-plummets-in-delhi-city-of-29-million/. Retrieved 19 April 2021

Sarkar A, Chouhan P (2019) Dynamic simulation of urban expansion based on cellular automata and markov chain model: a case study in Siliguri Metropolitan Area. West Bengal Model Earth Syst Environ 5:1723–1732. https://doi.org/10.1007/s40808-019-00626-7

Saxena N (2017) Status, revival and greening of water bodies in Delhi. Delhi Parks and Gardens Society, Department of Environment & Forest, Govt. of NCT of Delhi. Retrieved 16 Mar 2021. http://pwd.delhigovt.nic.in/wps/wcm/connect/7e8d0a0049b7df8da347bb26edbf4824/Water+Bodies+Presentation.pdf?MOD=AJPERES&lmod=1827942602&CACHEID=7e8d0a0049b7df8da347bb26edbf4824

Sayemuzzaman M, Jha MK (2014) Modeling of future land cover land use change in North Carolina using markov chain and cellular automata model. Am J Eng Appl Sci 7(3):295–306. https://doi.org/10.3844/ajeassp.2014.295.306

Seneta E (1996) Markov and the birth of chain dependence theory. Int Stat Rev 64(3):255–263. https://doi.org/10.2307/1403785

Shafray E, Kim S (2017) A Study of walkable spaces with natural elements for urban regeneration: a focus on cases in Seoul South Korea. Sustainability 9(4):587. https://doi.org/10.3390/su9040587

Shawul AA, Chakma S (2019) Spatiotemporal detection of land use/land cover change in the large basin using integrated approaches of remote sensing and GIS in the Upper Awash basin. Ethiopia Environ Earth Sci 78:141. https://doi.org/10.1007/s12665-019-8154-y

Shi G, Shan J, Ding L, Ye P, Li Y, Jiang N (2019) Urban road network expansion and its driving variables: a case study of Nanjing City.

Int J Environ Res Public Health 16(13):2318. https://doi.org/10.3390/ijerph16132318

Singh A (1989) Digital change detection techniques using remotely-sensed data. Int J Remote Sens 10(6):989–1003. https://doi.org/10.1080/01431168908903939

Singh AK (2017) Biodiversity Park: an innovative approach for green environment. Rai Journal of Technology Research & Innovation 5:9–11. Retrieved 11 Mar 2021. http://www.jru.edu.in/wp-content/uploads/RTJ/vol5/BIODIVERSITY%20PARK%20AN%20INNOVATIVE%20APPROACH.pdf

Singh SK, Mustak S, Srivastava PK, Szabo S, Islam T (2015) Predicting spatial and decadal LULC changes through cellular automata Markov chain models using Earth observation datasets and geo-information. Environ Process 2:61–78. https://doi.org/10.1007/s40710-015-0062-x

Sinha GN (Ed.) (2014) An introduction to the Delhi Ridge. Department of Forests & Wildlife, Govt. of NCT of Delhi, New Delhi. Retrieved 12 Mar 2021. http://forest.delhigovt.nic.in/wps/wcm/connect/1e22578043fa6dcba014e23e3c4139c7/Delhi_Ridge_Book-Sinha%2C+G.N.+%28Ed.%29+%282014.pdf?MOD=AJPERES&lmod=804673140&CACHEID=1e22578043fa6dcba014e23e3c4139c7

Sustainable Development Goal (2021) Sustainable development goals-goal 11: make cities inclusive, safe, resilient and sustainable. https://www.un.org/sustainabledevelopment/cities/ Retrieved 25 Apr 2021

TCPO (2007) Evaluation study of DMA towns in National Capital Region (NCR). Town and Country Planning Organisation, Ministry of Urban Development, Government of India. Retrieved 6 Mar 2022. http://www.tcpo.gov.in/sites/default/files/TCPO/REPORTS/MUTP%20REPORTS/FinalDMAreport.pdf

Twisa S, Buchroithner MF (2019) Land-use and land-cover (LULC) change detection in Wami River Basin. Tanzania Land 8(9):136. https://doi.org/10.3390/land8090136

UN-Habitat (2019) The strategic plan 2020–2023. UN-Habitat for a better urban future, Kenya. Retrieved 24 Mar 2021. https://unhabitat.org/sites/default/files/documents/2019-09/strategic_plan_2020-2023.pdf

UN (2019) World Urbanization Prospects:The 2018 Revision. United Nations, Department of Economic and Social Affairs, New York. Retrieved 24 Mar 2021. https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf

Virtriana R, Sumarto I, Deliar A, Harto AB, Taufik M, Pasaribu US (2014) The integration method of cellular automata (CA)-Markov chain(MC), West Java's Northern part characteristics for land cover change prediction study. 2014 2nd International Conference on Technology, Informatics, Management, Engineering & Environment. 80–85. https://doi.org/10.1109/TIME-E.2014.7011596

Wang M, Cai L, Xu H, Zhao S (2019) Predicting land use changes in northern China using logistic regression, cellular automata, and a Markov model. Arab J Geosci 12:790. https://doi.org/10.1007/s12517-019-4985-9

Wayback (2022a) Internet Archive Wayback Machine https://web.archive.org/web/20111002234008/http://www.dndflyway.com/. Retrieved 10 Mar 2022

Wayback (2022b) Internet Archive Wayback Machine. https://web.archive.org/web/20160101032537/http://www.hccinfrastructure.com/projects/delhifaridabad_expressway.aspx Retrieved 10 Mar 2022

White R, Engelen G (1993) Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ Plan Econ Space 25(8):1175–1199. https://doi.org/10.1068/a251175

Wolfram S (1983) Statistical mechanics of cellular automata. Rev Mod Phys 55(3):601. https://doi.org/10.1103/RevModPhys.55.601

Wolfram S (1984) Universality and complexity in cellular automata. Physica D 10:1–35. https://doi.org/10.1016/0167-2789(84)90245-8

Wolfram S (2002) A new kind of science. Wolfram Media, Champaign, IL

World Air Quality Report (2019) World air quality report region & city PM2.5 ranking. IQAir, Switzerland. Retrieved 21 Mar 2021. https://www.iqair.com/world-most-polluted-cities/world-air-quality-report-2019-en.pdf

Yagoub MM, Al Bizreh AA (2014) Prediction of land cover change using markov and cellular automata models: case of Al-Ain, UAE, 1992–2030. J Indian Soc Remote Sens 42:665–671. https://doi.org/10.1007/s12524-013-0353-5

Yang X, Zheng XQ, Chen R (2014) A land use change model: integrating landscape pattern indexes and Markov-CA. Ecol Modell 283:1–7. https://doi.org/10.1016/j.ecolmodel.2014.03.011