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## Article

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## Research Article

## Examining and predicting land use change dynamics in Gandhinagar district, Gujarat, India

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## ABSTRACT

Urbanization is gaining pace worldwide and is the most elemental cause of global land transformation. This necessitates land use land cover change to be analyzed on various spatial and temporal scales to understand its potential impacts on the environment. This work focuses on the urbanization in the area of Gandhinagar district, Gujarat, India which encloses Gandhinagar, the capital city of Gujarat. Though a capital, the city has seen limited growth and development since its formation in 1961. Land use change was analyzed from 1995 to 2016 and land change modeling was attempted to generate future prediction scenarios in 2025 using the IDRISI TERRSET Land change modeler. The change analysis revealed vast growth in rural and urban built-up, majorly, at the expense of agriculture, slightly contributed by the decline in scrubland. There is much scope for urban densification as urban built-up occupies only about 5% of the total land cover as observed by the land use land cover map of 2016. The growth of the city has been very slow as compared to the other cities of its time due to a state-centric approach. But the projected scenario discovered a faster sprawl-like built-up growth towards the urban areas in the west and the south instead of an isodiametric aggregation around the capital city due to an arbitrary planning system. We recommend bringing all the talukas in Gandhinagar under one roof and considering the development of the whole district in scope for better policy and management.

## 1. Introduction

Urbanization is a central demographic phenomenon in an increasingly global and interconnected world. As per the 2014 report on world urbanization prospects by the United Nations, 54% of the world population resides in the urban areas and this figure is projected to rise to 66% by 2050. India is going to be among the top contributors to the urban population by adding about 404 million urban dwellers by 2050 (United Nations, 2015). To meet the demand for the growing population, the forests, fields and pastures are continually being transformed into cities at ever increasing pace (Dadashpoor et al., 2019; Pickett et al., 2011). Such human modifications of the earth's surface disrupt the ecosystems by affecting microclimatic conditions, biogeochemical cycles, biodiversity, and water resources of the region (Purswani et al., 2020; Roy et al., 2015). Urbanization also increases the land surface temperature which creates urban heat island effects in cities. Besides, land use change, landscape pattern, and urbanization are linked to each other

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(Dadashpoor et al., 2019). Therefore, data on land use change is crucial for the efficient use of natural resources and for setting policy priorities for an equitable urban and rural development (United Nations, 2015; Kafy et al., 2021).

Causative factors of land use/land cover change (LULCC) include an increase in population, economic and political conditions, cultural values, technology, and geological conditions of the land. All of them are spatially and temporally dynamic (Holzhauer et al., 2019; Roy et al., 2015; Vinayak et al., 2021). Remote Sensing and GIS are the indispensable tools which help to monitor the above-mentioned factors and the resulting changes on the Earth's surface at regular intervals. Rapid development in remote sensing technologies offer data of high temporal, spatial, and spectral resolution for every land parcel on earth for free or at low cost for research and non-commercial purposes. Thus, updated LULC information can be obtained at any time for any area which would help to compare the past and current trends and predict future scenarios.

However, there is no temporally continuous LULC data of medium to high spatial resolution for India (Naikoo et al., 2020; Roy et al., 2015). Such data is required for regional and national level programs of agricultural planning, river basin and watershed development, biodiversity conservation, urban planning, etc., (Roy et al., 2015). Reasonably many small scale to large scale studies have covered LULC

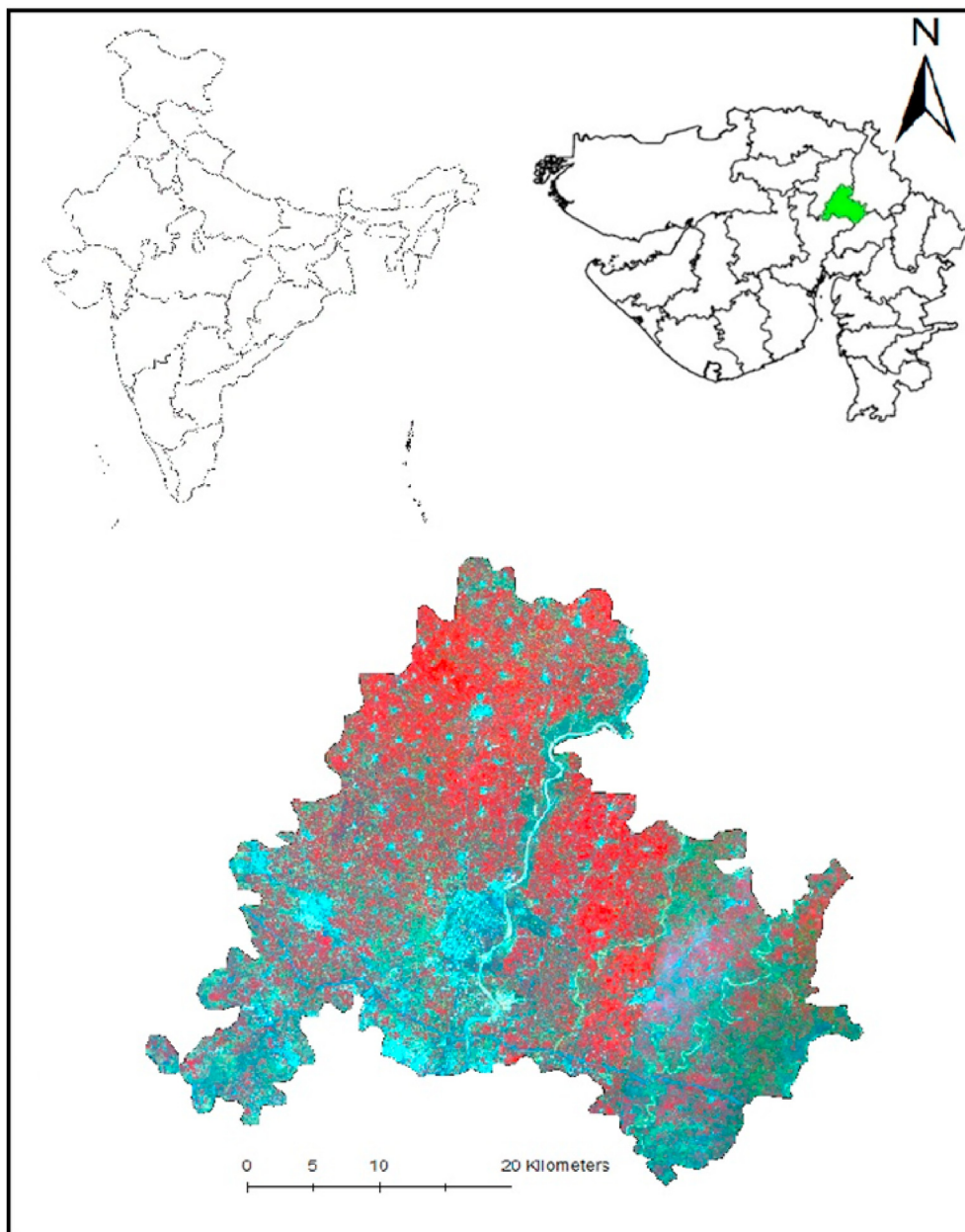


Fig. 1. Study area map.

change analysis using Landsat and IRS images of different cities and regions of India, nevertheless, a lot of them are yet to be studied (Aithal & Ramachandra, 2016; Dadhwal et al., 2011; Jain et al., 2016; Kantakumar et al., 2016; Mishra et al., 2018; Mondal et al., 2016; Nath and Acharjee, 2013; Nayak and Fulekar, 2017; Ramachandra et al., 2013; Roy et al., 2015; Vinayak et al., 2021; Yatoo et al., 2020, pp. 1–22).

While land use analysis provides a window to observe and juxtapose past and present land use change patterns and growth trends, LULCC models try to seek insights into the future settings (Eastman, 2016; Halmy et al., 2015; Veldkamp & Lambin, 2001). The prerequisite step for developing models is to identify the critical drivers affecting land use in the area and find a way to quantify them. Multiple variables are considered in modelling which can be the potential drivers of land use change. These variables include distance from roads, proximity to urban centers, elevation, slope, distance from waterbodies, space from a riverbed, topography and so on. The cumulative impact of such proxy variables on prediction of the location of the change and the type of change is assessed. These proxy variables represent the socio-economic and political factors that are difficult to combine directly with biophysical variables. Thus, they are necessary and useful to resource managers and land use planners in making appropriate policies and decisions for land use planning (Guan et al., 2011; Mohamed & Worku, 2019). They are applicable in modeling rural development and urban growth, prioritizing conservation areas, and studying dynamics of shifting cultivation. They help to prevent and mitigate impacts of natural disasters and climate change and to study rangeland dynamics under different climate change scenarios. They are also required for urban planning in infrastructure setup, meeting transport and utility demand, and identifying risk prone areas.

With advancements in geomatics, a variety of land use change models are available and a good review of these approaches is done by Baker (1989), Veldkamp and Lambin (2001), Agarwal, 2002, Overmars et al. (2003) and Mohamed & Worku (2019). Land use models are classified as regression-based statistical models such as Markov chains, dynamic and spatially explicit models which are spatially referenced like cellular automata model, models based on agents and system dynamic model, and the integrated models such as Markov chain-cellular automata (MC-CA) (Yatoo et al., 2020, pp. 1–22) and CLUE (Conversion of Land use and its effects) (Guan et al., 2011), SLEUTH (Zhou et al., 2019). Statistical models are often spatially non-explicit while dynamic models like cellular automata are incapable of accounting for actual change on their own. Thus, integrated models work well by complementing each other. Although many artificial neural network (ANN) models have been developed, multilayer perceptron neural network (MLPNN) based model are commonly used in land use modelling around the world (Kafy et al., 2020; Losiri et al., 2016; Rahnama & Wyatt, 2021; Singh 2020; Vinayak et al., 2021; Yonaba et al., 2021).

Gandhinagar is the second planned city in India after Chandigarh and is currently under the list of smart cities mission of the Indian government. The city has 54% tree cover which is the highest of all the capital cities of India and hence it is also nicknamed ‘Tree Capital of India’ (Badlani et al., 2017). Since the construction of the Dharoi dam in 1978, the portion of the river Sabarmati upstream of the Narmada canal got dried up as all the water was diverted to the canal. The agriculture largely became irrigated and hence, a major land-use change was observed. Being at a very short distance of 23 km from Ahmedabad, Gandhinagar is seen as a potential market by investors and various private companies and hence numerous projects like Info-City, Gujarat International Finance Tech (GIFT) city, and Ahmedabad-Gandhinagar METRO rail project (MEGA) were envisioned. The peri-urban areas also started developing around Kalol in the west which is a notified industrial area under Gujarat Industrial Development Corporation (GIDC). This brought in more employment in the non-agricultural sector. Sprawl-like development and urban outgrowths in the southern region of the district, close to Ahmedabad, have led to more changes in the landscape. Urban areas have densified inside the city (Badlani et al., 2017) but the urban expansion and overall development of the surroundings have been restricted due to the rigid bylaws within the city boundaries (Byahut, 2020). Thus, the city of Gandhinagar is still in the nascent stage and has a huge scope for planned development. Hence, it can become a model city for other budding capital cities in India. All these factors drew our attention to study the land use dynamics in the district.

This article has tried to understand and analyze the pattern of land-use change for the past 2 decades from 1995 to 2016. The land use/land cover change was mapped and future land use/land cover patterns of the district were simulated. The main objectives of the current study were to 1) analyze LULC in the region between 1995 and 2016, and predict future LULC scenario for 2025 2) Compare the observed changes with other metropolitan cities and discuss the factors affecting the same.

## 2. Study area

The study area (Fig. 1) is Gandhinagar district of Gujarat state of India, an administrative division of Gujarat, whose headquarters are at Gandhinagar city, the state capital since 1970. The current areal extent of the district is 2140 km<sup>2</sup> which forms 1.09% area of the Gujarat state. Of the population of 1,391,753, 16%, was found to be urban (Directorate of Census Operations, 2011). The district is divided into four tehsils or talukas Gandhinagar, Kalol, Dehgam, and Mansa, consisting of 15 towns and 252 villages.

It is situated between latitude 22°56′ and 23°36′ and longitude 72°23′ to 73°05′. A major portion of the district falls under the Sabarmati basin. The entire district is a part of North Gujarat alluvial plain with neither the hill features nor any prominent natural water bodies. The Sabarmati, the Khari, and the Meshwo are the important rivers of the district but are dry for most of the year except monsoon. The climate is tropical and semi-arid with an annual average rainfall of 823 mm. The soils in the district are generally sandy loam type to alkaline sandy loam with decreasing permeability towards the west.

## 3. Material and methods

### 3.1. Data collection and LULC classification

The data utilized for the study included satellite data and supportive data which consisted of information on groundwater and population (Table 2). Landsat (L) images (paths 148 and 149/row 44) were obtained for four different years 1995 (L5 TM), 2003 (L7

ETM+), 2010 (L5 TM), and 2016 (L8 OLI) for the months between January to March, whichever available. The aim of the study was to understand how the landscape had changed in the previous 30 years and how it will change in the next decade. Scenes of the years 1995, 2003, and 2010 were used to test and validate the 2016 prediction with actual map of 2016. The ancillary data included the District Census data from the District Census Handbook, Shuttle Radar Topographic Mission (SRTM) 90 m grid spacing DEM data, and the road network created using Google Earth and projected to WGS 84 Datum. LULC maps were prepared for the years 1995, 2003, 2010, and 2016 (Fig. 3) at 1:50,000 scale considering 30 m resolution of Landsat images. The study area was categorized into nine LULC categories which included built-up urban, built-up rural, agriculture, vegetation, scrub, barren, waterbody, river-canal, and others. The others was a miscellaneous class which included industries, resorts, golf club, offices, and quarters of security bodies like the army, air force, etc. These classes were made by making some additions to level II of Anderson et al. (1976) LULC classification system (Table 1). The latest year data was ground verified by the field surveys, selectively, in all four directions – north, east, west, and south. A manual interpretation technique was adopted for classification as supervised classification of the area could not show greater than 70% accuracy.

Stratified random sampling was conducted by laying the plots measuring an area of 0.1 ha. The accuracy of classification and the change detection was assessed by verifying a certain number of points on the map and identifying those locations on the ground. A contingency matrix was created by calculating the commission and omission errors, the Cohen's kappa, and overall accuracy of the maps. The complete process adopted is shown in a flow-chart (Fig. 2).

### 3.2. LULC change prediction

We have utilized the land change modeler embedded in Idrisi TERRSET. It provides an easy and robust alternative for forecasting the land-use change. We chose Multi-Layer Perceptron (MLP) for transition potential analysis and Markov Chain analysis (MCA) for generating a soft prediction of future (2025) LULC distribution. MLP is a type of artificial neural network (ANN) requiring minimum user intervention. It is extremely potent at handling multiple transitions and is widely used in LULC analysis (Kafy et al., 2020). In this study, we estimated the LULC changes during the two-decade interval (1995–2016) based on the transition sub-models. To calculate its training error and adjust the weight, MLP forms a neuron network with weights. As the weights are adjusted, the RMS error decreases, and the accuracy is improved which should be a minimum of 80% (Eastman, 2016; Vinayak et al., 2021). For simulating a spatially explicit scenario, a multi-objective land allocation module (MOLA) was used which operates on the principle of the multi-objective decision process. The model predicts the future LULC change in four steps: i) Change analysis ii) Creating Transition potential maps and matrices iii) Data Validation iv) Future Prediction.

The LULC classification maps of different periods viz., 1995, 2003, 2010, and 2016 were used to account for the change that happened in the two-decade period (Fig. 3). The spatial and quantitative distribution of the change in the area of each LULC class for each year was calculated using ArcGIS ver. 10.2 (Table 3). Change matrices were prepared using the change detection function of ERDAS Imagine ver. 2014. The percentage change in each land use/land cover class for all the transition periods including the net change from 1995 to 2016 was calculated (Table 4). The net gains and losses in each land use category were measured (Fig. 4) and the net change was calculated. The classes contributing majorly to built-up were analyzed with the help of LCM (Fig. 5).

The next step was to identify the potential drivers causing land use change. Cramer's V test is available as a non-parametric statistical tool in the software TERRSET to measure the efficiency of the drivers. Variables with Cramer's V value greater than 0.15 and above are suggested to be efficient. Higher values towards 1 indicate higher explanatory power of the variable (Eastman, 2016). The values for the drivers used are given in Table 5 and the maps of the variables are shown in Fig. 6. The variables distance to road, distance to urban centers, distance to river-canal, slope and elevation were tested (Fig. 6). The Cramer's V values of all the driver variables were close (Table 5). However, backward step forcing showed that the 'distance to urban centers' was the most influential factor. 'Distance to roads' and 'elevation' were other factors affecting the transitions. Gandhinagar notified area (GNA), Ahmedabad, and Kalol are the major areas surrounding which most of the urbanization has occurred. The development surrounding roads happened majorly on the highways between Gandhinagar and Ahmedabad and hence, the 'distance to roads' did not prove a good driver.

The selected transitions were included in transition sub-models to get more accurate results from MLP (Eastman, 2016). The results

**Table 1**  
Description of Land use classes mapped in the study (Halmy et al., 2015).

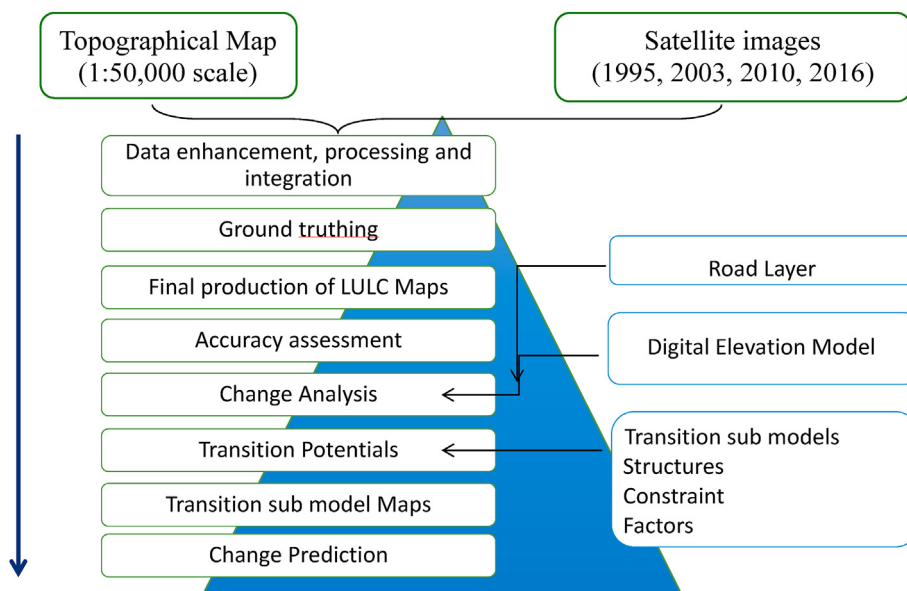
Anderson (1976) LULC classes	Anderson (1976) Code	LULC Class referred to in this study	Class Code	Description
Residential	11	Built-up rural	BR	Small towns, villages
Residential	11	Built-up urban	BU	Cities
Another built-up land	17	Resorts, Industries, and other building complexes	O	Areas occupied by construction or remote industrial facilities and highways or used for recreation and villas
Croplands	21	Agriculture	A	Irrigated areas and those used primarily for the production of crops.
Orchards and other agriculture	22	Plantation/Vegetation	V	Areas planted with fig or olive trees and areas plowed and used for growing barley and wheat depending on rain.
Rangelands	3	Scrub	S	Areas covered with natural vegetation (shrubs and grasses) nearby rivers,
Water	5	Waterbody	Wb	Areas covered by water ponds, lakes,
Barren mixed areas	74	Barren areas with very little or no vegetation	B	Rocky areas with thin soil layer and low or no vegetation.
Water	5	River/canal	R	Areas covered by river, riverine and rivers



**Table 2**

Data utilized in the study.

Type of Data	Source	Year	Dataset
Satellite images	USGS	1995, 2003, 2010 and 2016	Landsat TM (1995, 2010), Landsat ETM+ (2003), Landsat OLI (2016)
SRTM	USGS	2016	Digital Elevation Model (DEM)
Ancillary data	Directorate of Census Operations	2001, 2011	District Census Handbook
a. Population	Central Ground Water Board	2014	Ground Water Brochure
b. Groundwater data			

**Fig. 2.** Flow-chart of adopted methodology.

generated by the MLP were used for generating the transition probability matrices of the LULC classes. Transition potential maps created from the matrices quantify the potential of the conversion of each *pixel* to a land-use class. The *pixel* values of a class vary between 0 and 255 where 0 represents the minimum suitability and 255 signifies the maximum suitability for conversion to a certain LULC class. The transition rules are set using a threshold value of the pixels or the area, beyond which the conversions that have ensued among the LULC classes are considered for creating the transition potential maps. Here, transitions in categories with less than 10 ha were ignored to account for only significant land-use conversions. All the transitions accounting for more than 10 ha of change were mapped and accounted for the prediction of future land use. The transition potential maps were used in the consequent step for validating the model by predicting LULC distribution in 2016 (Fig. 7) and simulating the distribution in 2025 (Fig. 8).

Markov chain analysis (MCA) works on the principle that the future LULC distribution of a land parcel ( $M_t$ ) at time 't' depends on its earlier state at time t-1 ( $M_{t-1}$ ). Thus, the distribution of each LULC class is predicted using the transition probability matrix P by the formula:

$$P \times M_{t-1} = M_t$$

MCA utilizes the transition probability metrics generated thereby, to project the future configuration of a land parcel whose previous state is known (Kafy et al., 2020). MCA is based on a random probability distribution pattern which may be statistically analyzed. It does not provide a spatially explicit LULC distribution when used alone (Moghadam & Helbich, 2013). Hence, GIS-based models like the cellular automata are required to convert the soft predictions generated by the MCA into spatially explicit hard prediction. However, MCA has a potential to statistically quantify the LULC changes effectively (Yang et al., 2012). It overcomes the inadequacies of the regression model by utilizing spatially dependent land use data. Numerous studies have depicted and validated the use of Markov chain analysis to simulate the future land use trends and matrices. These matrices are based on the land transition between the previous and the consequent period. They then estimate the probability of conversion of each pixel of a certain LULC class to a pixel of future LULC class (Eastman, 2016; Vinayak et al., 2021).

The transition weights derived from MLP were integrated into the MCA probability matrix for the prediction of LULC in 2025. The transition potential maps, and the transition probability matrix of the period 2016–2025 (Table 11), both, were used to prepare the future LULC change map for 2025 as shown in the Fig. 8. The analysis was conducted within the framework of IDRISI TERRSET©1987–2016 (Eastman, 2016).

The spatial trend of change can be seen through the LULC prediction tab where it generates a soft prediction using the transition

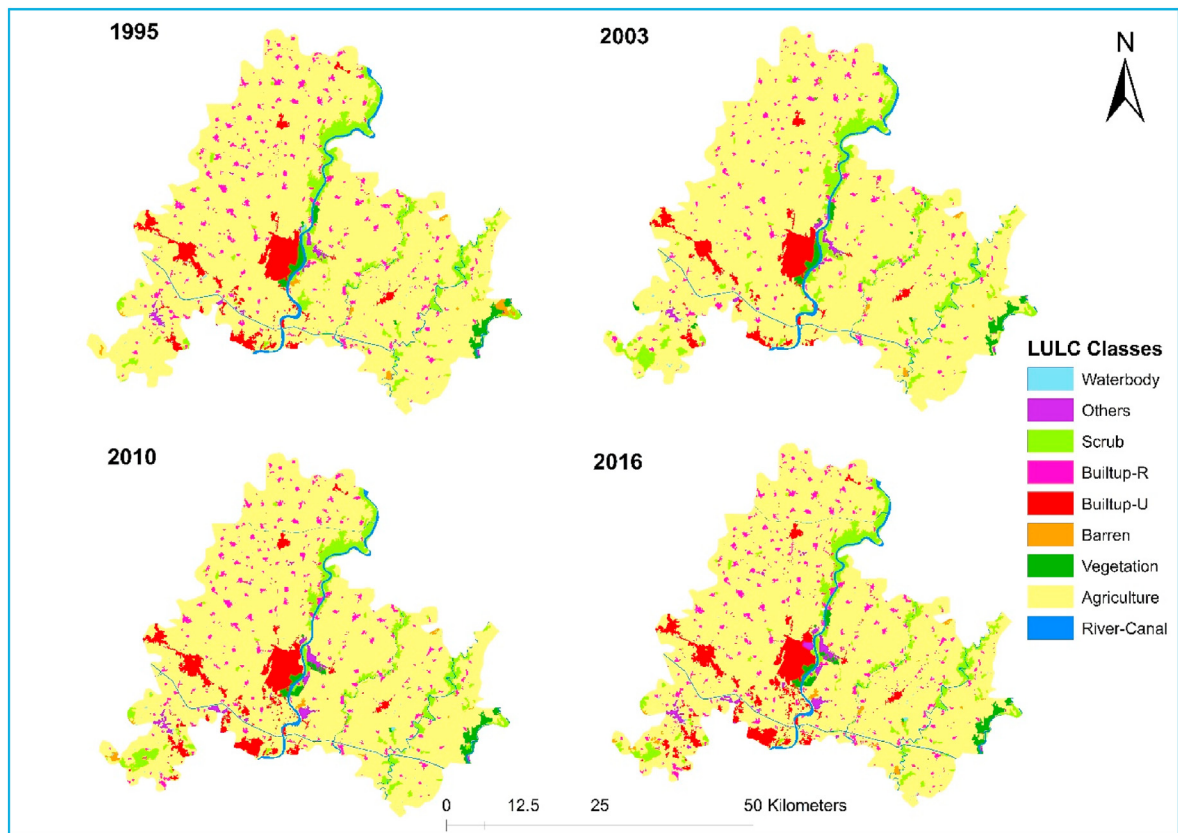


Fig. 3. LULC maps of years 1995, 2003, 2010 and 2016.

Table 3

Area (sq. km) in all land use classes from 1995 to 2025.

Class Name	1995	2003	2010	2016	2025
Agriculture	1825.36	1815.50	1754.49	1730.49	1676.70
Barren	3.42	3.18	4.99	7.80	13.98
Built-up-R	48.07	56.61	76.60	86.77	102.85
Built-up-U	62.33	67.03	102.30	111.11	128.46
Others	9.73	9.74	17.26	21.11	24.37
River-canal	35.28	35.29	37.53	37.55	37.70
Scrub	134.29	132.80	121.89	118.53	126.07
Vegetation	21.30	19.78	22.99	24.52	27.06
Waterbody	3.17	3.03	4.91	5.08	5.77
Total	2142.96	2142.96	2142.96	2142.96	2142.96

Table 4

Area (%) of each land use class & net change (%) in the intervals.

Period	1995	2003	2010	2016	2025	95–03	03–10	10–16	95–16	16–25	95–25
Agriculture	85.18	84.72	81.87	80.75	78.24	−0.54	−3.36	−1.37	−5.20	−3.11	−8.14
Barren	0.16	0.15	0.23	0.36	0.65	−7.03	56.85	56.38	128.03	79.14	302.65
Built-up-R	2.24	2.64	3.57	4.05	4.80	17.76	35.31	13.27	80.50	18.54	113.95
Built-up-U	2.91	3.13	4.77	5.19	5.99	7.54	52.61	8.61	78.25	15.62	106.08
Others	0.45	0.45	0.81	0.99	1.14	0.11	77.25	22.29	116.99	15.47	150.57
River-canal	1.65	1.65	1.75	1.75	1.76	0.03	6.35	0.05	6.43	0.41	6.87
Scrub	6.27	6.20	5.69	5.53	5.88	−1.11	−8.21	−2.76	−11.74	6.36	−6.12
Vegetation	0.99	0.92	1.07	1.14	1.26	−7.14	16.20	6.67	15.10	10.35	27.02
Waterbody	0.15	0.14	0.23	0.24	0.27	−4.35	61.94	3.54	60.38	13.62	82.22

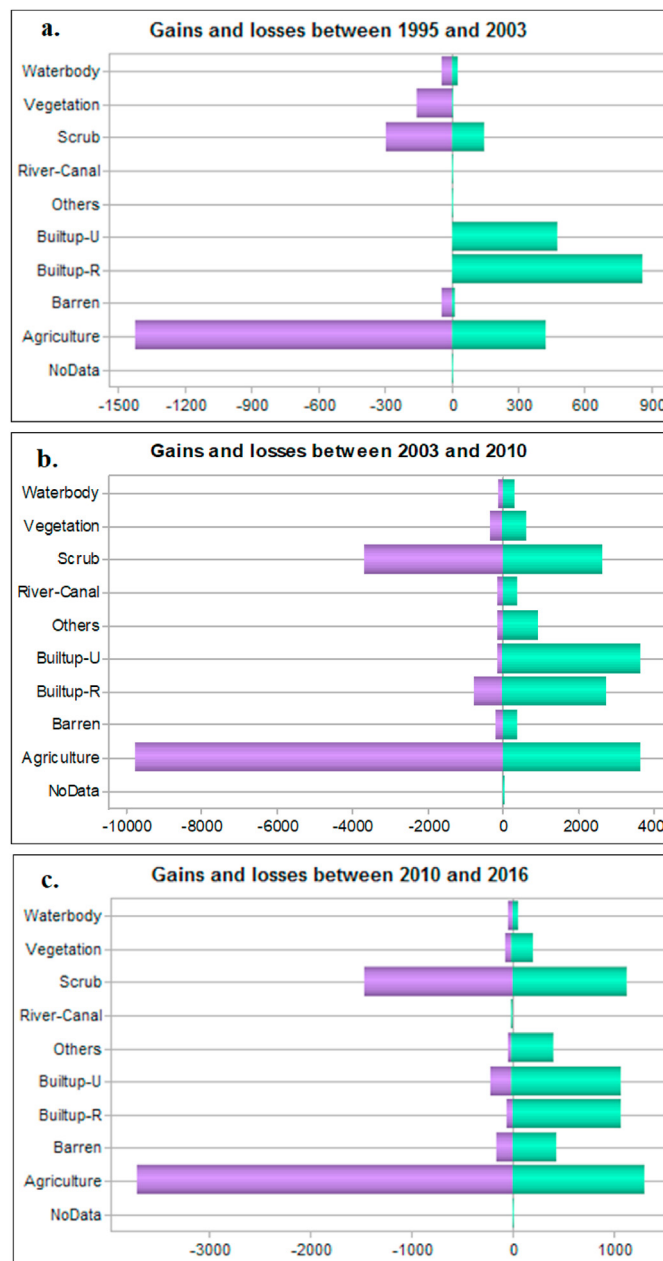


Fig. 4. Gains and losses in the three periods a) 1995–2003 b) 2003–2010 c) 2010–2016.

probability matrices. With the combination of the Markov chain and the multi-layer perceptron model, soft prediction maps were generated. This was followed by a hard prediction which is obtained through the inbuilt multilayer perceptron neural network (MLPNN) model and LULC images fed at the initial stage. The prediction scenario was created initially for the year 2016 and the model was validated with the actual LULC map of the year 2016 (Fig. 7). After the validation, the future scenario was simulated for the year 2025 (Fig. 8).

## 4. Results and discussion

### 4.1. LULC analysis

The time series maps were prepared for the following 9 classes viz., agriculture, barren, rural built-up, urban built-up, others (including commercial and industrial complexes), scrub, vegetation (including plantation areas), river/canals, and water bodies. The results suggest significant changes in land use land cover classes that were quantified by the change matrices. The accuracy assessment



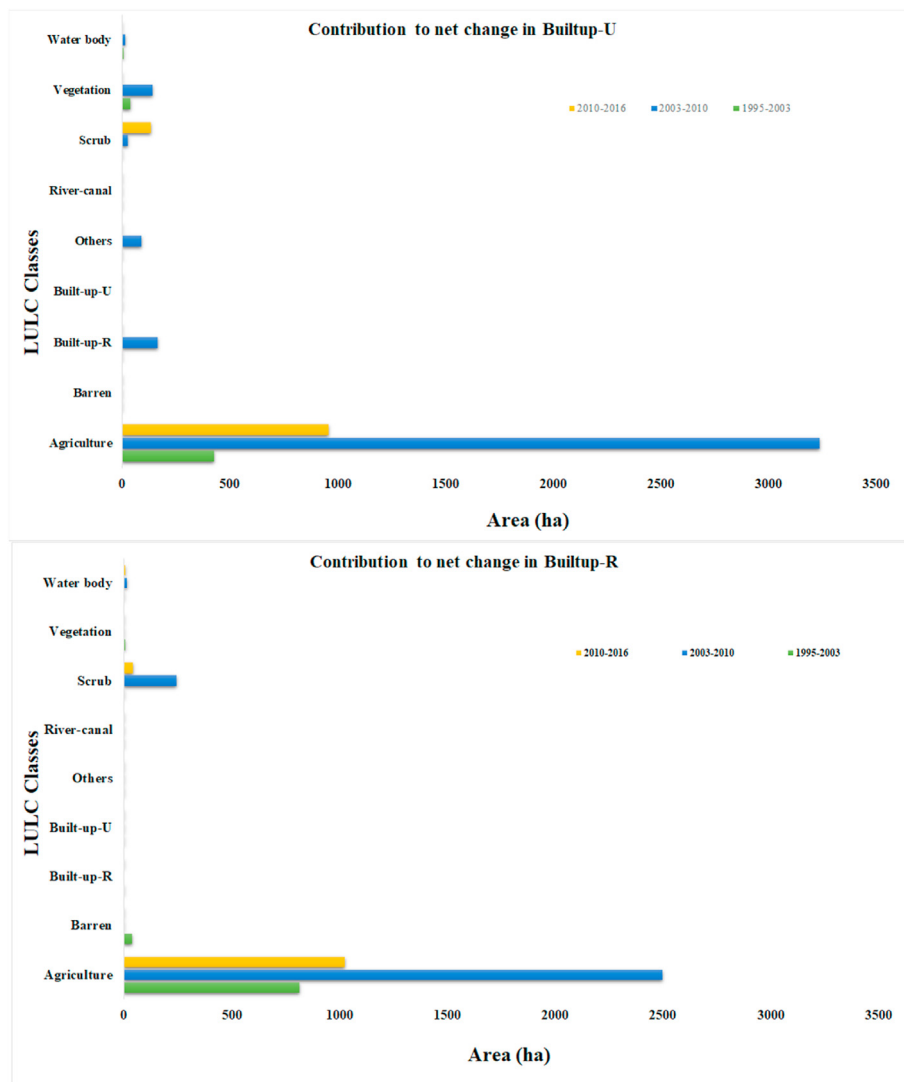


Fig. 5. Maps of driver variables used in the study.

**Table 5**

Evaluation and selection of spatial drivers.

Sr. No.	Variable	Cramer's V	P value
1	Distance to urban center	0.3481	0.0000
2	Distance to roads	0.2654	0.0000
3	Distance to river-canal	0.3333	0.0000
4	Elevation	0.34	0.0000
5	Slope	0.332	0.0000

of the classified images gave the kappa values as 0.91, 0.89, 0.89, and 0.90 for the years 1995, 2003, 2010, and 2016 respectively and overall classification accuracy for the classified images was found to be 91.74, 89.30, 89.52, and 90.65 respectively. The accuracy assessment of the predicted 2016 image was also done in a similar manner. It showed an overall accuracy of 96.07 and kappa value of 0.96 (Table 10). This result validated the model for its further use in future prediction.

The area of each land use class as a percentage of the total land cover and percent change in each land use class is displayed in Table 4. The LULC change during period 1, period 2, period 3, and net change from 1995 to 2016 was analyzed by generating change matrices in MS-Excel (Tables 6–9). The LULC changes were evaluated by the gains and the losses experienced by the different classes.

In Gandhinagar, the major land use class was found to be agricultural land. As the changes were analyzed for the three different time intervals, it was noted that all the categories gained at the expense of agriculture and scrubland. In 1995, the agricultural land area was

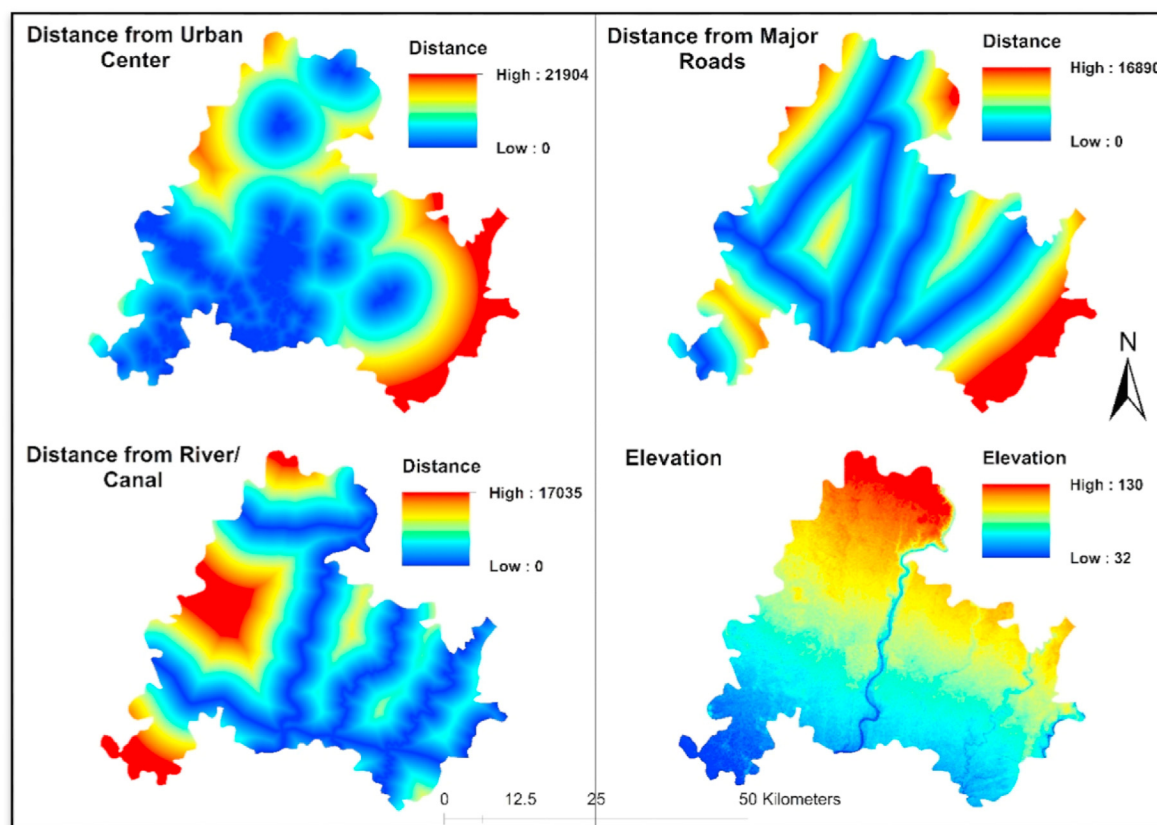


Fig. 6. Contributions to built-up class (4a Builtup-R and 4b Builtup-U) in the three periods between 1995 and 2016.

1825.37 km<sup>2</sup> (85.18% of total area); it decreased to 1815.50 km<sup>2</sup> in 2003, 1754.49 km<sup>2</sup> in 2010 and up to 1730.49 km<sup>2</sup> in 2016. Agriculture land contributed to the increase of built-up area, other classes contributing to the built-up were vegetation (4.85%), water body (3.31%), and rural built-up (2.07%). The areas under water bodies show maximum transition probability to rural built-up (5.76%). The growth in urban areas was understood through visual and quantitative maps of earlier and later years of the district (Figs. 4 and 5). The maximum growth rate of built-up urban was seen from 2003 to 2010 which was 52.61%. The total built-up, combining rural and urban areas, covered an area of 110.4 km<sup>2</sup> (5.15% of total land cover) in 1995, almost doubled, extending to 221.31 km<sup>2</sup> (10.79% of total land cover) in 2016.

A visual interpretation of the land-use change also revealed the increasing density of the sprawls and outgrowths in the south rather than an isodiametric expansion of the urban area around the urban center of Gandhinagar. This points to proximity to Ahmedabad as the driving factor of expansion. This accorded with the population data of urban outgrowths in the southern region of the district towards Ahmedabad (Directorate of Census Operations, 2011).

Vegetation class decreased by 7.14% between 1995 and 2003 following a constant increase from 2003 to 2016. The net growth in the area under vegetation cover was 15.10% making 1.14% of the total land cover in 2016 from 0.99% in 1995. This has been possible because of the plantations done on a large scale (GEER Foundation, 2014). Scrubs have seen a continuous decline with dynamic rates of 1.11% in the first period, 8.21% in the second period, and 2.76% in the third period.

A major increase in the area of river-canal class in 2003–2010 is observed due to the development of a new canal in the north region in that period. The area under the land use class of river-canal has recorded a net gain of 6.43% by 2016. A fluctuating trend is seen in the land use class of the water body. The number of water bodies declined initially (−4.35%) following a huge increase of 61.94% in 2003–2010 followed by a slight growth of about 3% between 2010 and 2016. This may be due to water conservation initiatives taken by the government or due to the intensive perusal of groundwater by the government in 2004, 2009, and 2011. But the groundwater brochure of the central groundwater board (2014) reports that all the groundwater resources in the district are overexploited. There is no further scope of development (Central Ground Water Board, 2014). This might be the reason for the decline observed in the growth of the number of water bodies. A significant amount of agricultural land is depicted as transit to water bodies for the burgeoning population (Fig. 4). An exponential increase was seen in the barren class in the period between 2003 and 2016. This is contributed mainly by the agriculture and the scrub areas.

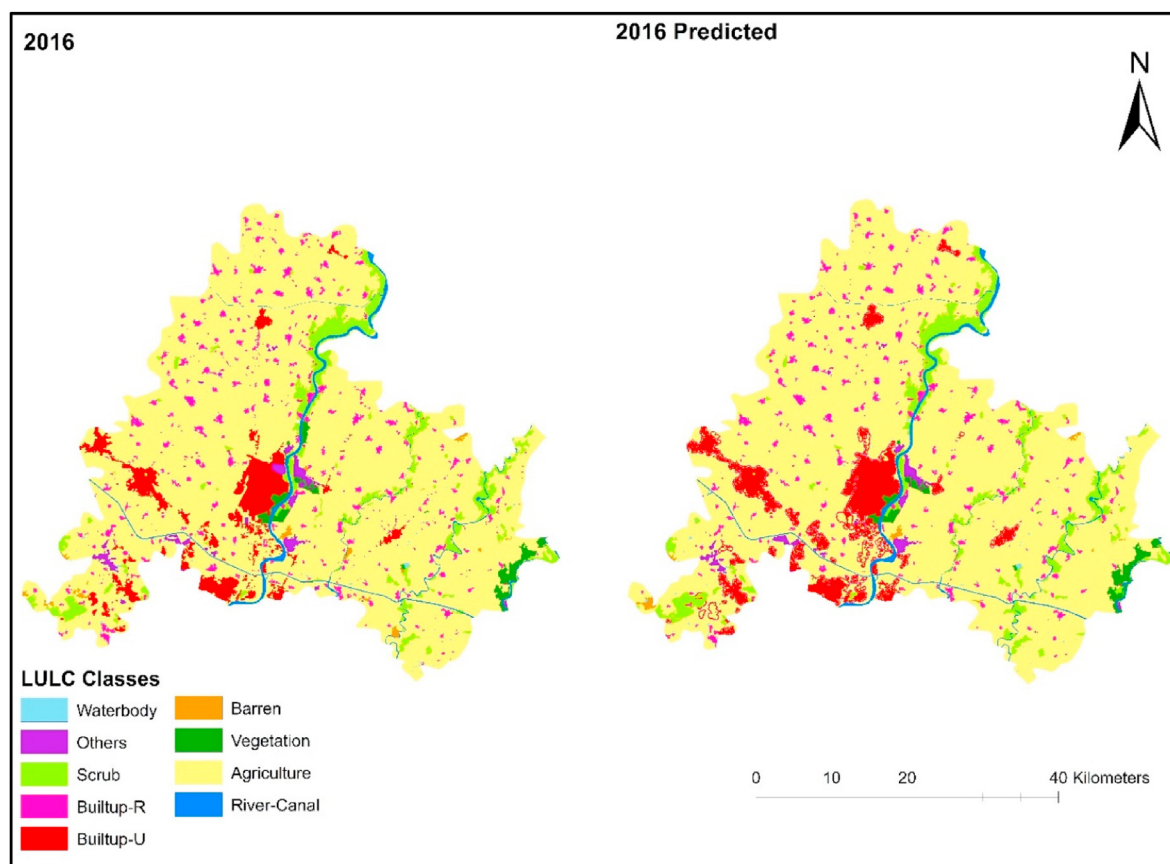


Fig. 7. Comparison between 2016 classified map and 2016 map predicted by the model.

#### 4.2. Projected land use land cover

As suggested in land use land cover analysis, the projected LULC of 2025 showed that the rural and urban built-up, others, river-canal and vegetation classes gained at the expense of agriculture and scrubland. Agriculture is projected to reduce to 1676.70 km<sup>2</sup> in 2025 which would be a 8.14% change from 1995. The expansion of the urban built-up area from 2016 to 2025 was 15.62%. Urban built-up forms only 5.99% of the total land cover in 2025 which was far less in comparison to the older Indian cities. However, the urban growth rate is seen to be around 106% from 1995 to 2025. The scope of the dense urban growth indicates the nascent stage of urban development as compared to the megacities like Mumbai, Delhi, and the other urban agglomerations which are nearly saturated (Aithal & Ramachandra, 2016; Jain et al., 2016; Taubenböck et al., 2009). Extended sprawling and outgrowth towards the south west of the city would merge it with Ahmedabad. This would make it a suburban part to Ahmedabad and destroy its individual identity as against the original plan laid at its foundation (Apte, 2012). Also, unidirectional expansion would draw inflow of population towards these areas making them concentrated. This would also create additional demand for resources like groundwater calling upon more diversion of the river water towards cities hampering agriculture.

The vegetation-covered area is forecasted to increase from 24.50 km<sup>2</sup> in 2016 to 27.02 km<sup>2</sup> in 2025. This transition is predicted by the model in the northeastern part of the district. Additionally, the regeneration rates of plants have to be monitored and maintained to realize the predicted increase in vegetation (GEER Foundation 2014). However, the main city area would possibly lose some green patches in the course of development.

The scrub class is projected to gain slightly by 2025 (5.88%). It is projected to have a net decline of 6.12% from 1995 to 2025. The area under scrub would increase from 118.53 to 126.07 km<sup>2</sup> between 2016 and 2025. River/canal class is predicted to show a slight gain in 2025.

Besides the above results, there were certain limitations of the study. There are several different models currently available for better land use simulations. Older satellite images of years earlier to 1995 could also prove beneficial. A more accurate prediction of future could be observed by analyzing more factors affecting socio-economic and natural conditions of the area. Along with the accessibility to urban areas and topography, factors like land use policies and potential productivity could be considered (Zhao et al., 2018). Overall, we can say that this study can act as a baseline study for further research in this area.

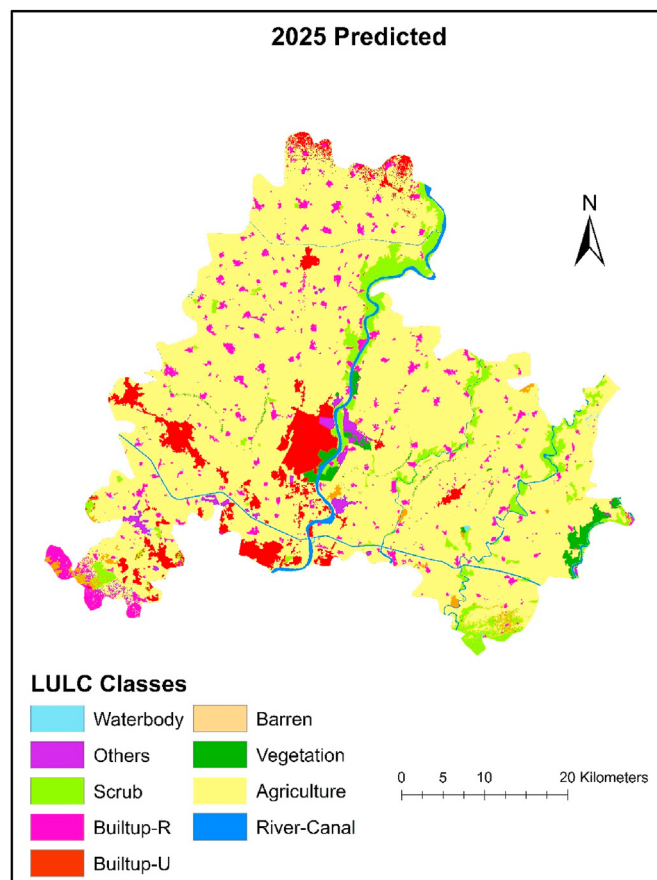


Fig. 8. Future Prediction LULC map of the year 2025.

Table 6

Change Matrix table for period 1 (1995–2003).

1995	2003								
	A	B	BR	BU	O	R	S	V	W
A	181126	0	812.7	427.68	0	0	147.15	0	32.76
B	0	302.67	39.87	0	0	0	0	0	0
BR	0	0	4801.77	0	0	0	0	0	0
BU	0	0	0	6228.36	0	0	0	0	0
O	0	0	0	0	973.71	0	0	0	0
R	0	0	0	0	0	3528.72	0	0	0
S	280.44	15.39	0	0	0	0	13132.4	0	0
V	106.65	0	6.75	39.87	0	0	0	1978.11	0
W	36.72	0	0	7.56	0	0	0	0	270.36

#### 4.3. Comparison and analysis of urban growth

In a comparison of the growth rate among cities, Gandhinagar ranked on the lower side (Table 12). It has been observed that the urban growth rate of cities which were brought up as new townships in the past half century like Chandigarh (7.21%), Jaipur (11.8%), Pune (13.77%) has been faster than Gandhinagar. Chandigarh which was the model for Gandhinagar showed a faster growth rate (Chandan et al., 2020). It is nearly equal to the growth-rates of old, saturated cities like Delhi and Mumbai. State-led master plan has been the key reason due to which Gandhinagar has not responded to urban growth pressures (Byahut, 2020). The strict regulations and rigid laws have caused a lack of vibrancy and enthusiasm of an urban life in the capital city. Also, the total area under Gandhinagar district is controlled by multiple agencies like Gandhinagar notified area committee (GNAC), Gandhinagar Urban Development Authority (GUDA), Gandhinagar Capitals Project Division (GCPD) (Byahut & Mittal, 2020). This has caused overlapping of areas and functions. Therefore, functions and jurisdictions of multiple agencies and state-led departments should be clearly distinguished and separated from each other to ensure a smooth operation of the development measures to be adopted (Byahut, 2020). Kalol and Dehgam

**Table 7**

Change matrix analysis for 2003–2010.

2003	2010								
	A	B	BR	BU	O	R	S	V	W
<b>A</b>	171803	113.22	2500.11	3236.04	699.12	337.23	2361.6	245.43	254.34
<b>B</b>	31.95	115.38	1.89	0	0	0	164.25	0	4.59
<b>BR</b>	562.14	0	4896.54	166.68	12.78	0	15.48	0	7.47
<b>BU</b>	128.52	0	1.53	6554.43	0	0	10.89	0	8.1
<b>O</b>	56.97	0	2.7	89.82	814.59	0	8.1	0	1.53
<b>R</b>	123.66	0	0	0.09	8.73	3373.02	19.98	3.24	0
<b>S</b>	2525.76	261.27	242.28	27	177.57	29.16	9568.71	425.79	21.96
<b>V</b>	144.27	9	0	142.47	12.15	13.5	32.58	1624.14	0
<b>W</b>	72.99	0	14.94	13.68	0.99	0	7.65	0	192.87

**Table 8**

Change matrix analysis for 2010–2016.

2010	2016								
	A	B	BR	BU	O	R	S	V	W
<b>A</b>	171746	184.14	1024.11	957.15	170.46	13.68	1074.24	226.89	53.01
<b>B</b>	145.35	339.39	0	0	0	0	14.13	0	0
<b>BR</b>	52.83	0	7605.18	0	0	0	0	0	0
<b>BU</b>	0	0	0	10018.5	211.68	0	0	0	0
<b>O</b>	30.51	0	0	0	1690.47	0	0	0	4.95
<b>R</b>	11.97	0	0	0	0	3740.94	0	0	0
<b>S</b>	1028.07	256.59	41.94	135.27	0	0	10726	0	0
<b>V</b>	0	0	0	0	37.98	0	35.55	2225.07	0
<b>W</b>	35.1	0	5.58	0	0	0	3.24	0	446.94

**Table 9**

Change matrix table for net change from 1995 to 2016.

1995	2016								
	A	B	BR	BU	O	R	S	V	W
<b>A</b>	170327	24.54	3758.76	4676.22	752.58	335.79	1843.11	243	285.84
<b>B</b>	12.96	284.13	0.99	39.87	0	0	0	0	4.59
<b>BR</b>	115.56	0	4585.23	71.1	15.75	0	7.92	0	6.21
<b>BU</b>	92.7	0	1.53	6032.61	86.31	0	10.89	0	4.32
<b>O</b>	31.41	0	2.7	1.08	26.55	0	8.1	0	3.87
<b>R</b>	116.46	0	1.08	0	8.82	3376.17	22.95	3.24	0
<b>S</b>	2125.26	162.45	305.37	116.28	275.22	29.16	9822.69	581.58	10.17
<b>V</b>	151.56	9	6.75	149.94	45.36	13.5	131.13	1624.14	0
<b>W</b>	76.77	0	14.4	23.85	0	0	6.39	0	193.23

**Table 10**

Accuracy assessment of 2016 predicted image.

Sr. No.	LULC Classes	Producers Accuracy	Users Accuracy
1	<b>Agriculture</b>	96.00	94.12
2	<b>Barren</b>	96.00	97.96
3	<b>Builtup-R</b>	92.00	97.87
4	<b>Builtup-U</b>	97.92	95.92
5	<b>Others</b>	95.65	93.62
6	<b>River/Canal</b>	95.83	97.87
7	<b>Scrub</b>	95.56	93.48
8	<b>Vegetation</b>	96.08	96.08
9	<b>Waterbody</b>	100.00	97.67
	<b>Total Accuracy</b>		<b>96.05</b>
	<b>Kappa Coefficient</b>		<b>0.96</b>

municipalities are yet under Ahmedabad Development Authority (AUDA) though they are situated inside the Gandhinagar district. This puts a hindrance on the development of Gandhinagar from a broader perspective.

Gandhinagar city leads all the major capital cities in the country in green cover by having 416 trees per 100 persons, followed by

**Table 11**  
Transition probability matrix 2016–2025.

2016	2025								
	A	B	BR	BU	O	R	S	V	W
A	96.88	0.15	0.87	0.81	0.15	0.01	0.89	0.19	0.04
B	40.47	55.48	0.06	0.06	0.01	0	3.89	0.01	0
BR	1.03	0	98.93	0	0	0	0	0	0.04
BU	0.01	0	0	96.91	03.07	0	0	0	0
O	02.63	0	0	0	96.93	0	0	0	0.42
R	0.48	0	0	0	0	99.52	0	0	0
S	12.43	2.85	0.52	1.63	0.01	0	82.53	0	0.02
V	0.06	0.01	0	0.01	2.45	0	2.24	95.24	0
W	10.47	0.01	1.68	0.02	0	0	0.96	0	86.86

**Table 12**  
Comparison of urban growth among capital cities.

City	Annual rate of change	Annual rate of predicted change	Model used	Reference
Jaipur (89–00–05–11)	11.80	–	–	Dadhich and Hanaoka (2011)
Mumbai MMR (92–02–11–50)	4.56	1.13	MLPNN	Vinayak et al. (2021)
Chandigarh (90–99–08–17)	7.21	3.16	SLEUTH	Chandan, Nimish, Bharat, 2020
Pune (92–00–10–13)–22–25	13.77	2.54	MC-CA	Aithal and Ramachandra, 2016
Gandhinagar (95–03–10–16)–25	4.12	1.73	MLPNN	Current study
Delhi (89–2019)	10.88	2.63	MC-CA	Tripathi and Kumar, 2019

Bengaluru 17 trees per head. However, the tree density per hectare (15.2) is surpassed by many other cities including Bengaluru (19.9), Brihan Mumbai or Greater Mumbai (43.2), Nagpur (98.9) and other cities of Gujarat like Vadodara (45.9) and Bhavnagar (91.3) (Ramachandra et al., 2014). The per capita green space in units of meter square per capita for Gandhinagar is the second highest in India (29.77 m<sup>2</sup>), just behind Chandigarh (38 m<sup>2</sup>) (Ramaiah and Avtar, 2019). The smart city proposal (released versions) and urban development plan do not incorporate details on the mechanism to sustain and increase green cover. The further action plan for smart city must discuss in detail how its 2027 target of 1400 ha of green cover per 100000 people would be achieved with expanding urbanization (MoUD, n.d). The increase in green cover is to be discussed with various case scenarios of expanding population and built-up areas to prevent its replacement by built-ups. Moreover, just like other capital cities, urbanization would slowly occupy the whole tehsil further covering the entire district. Therefore, accounting the land-use of the whole district will help make better policies for a planned urban development.

## 5. Conclusion

A majority of the districts occupying the capital cities in India are already saturated with the urban growth. Gandhinagar, being a planned city and the district being at a nascent stage of development, sustainable urban development is still very much possible. This study focused on studying the land change pattern in Gandhinagar district in a two-decade period of 1995–2016 by using geospatial methods and predicting the land use pattern for the next decade, 2016–2025. It provided an insight into the spatial and quantitative results of the amount and location of changes with pixel-by-pixel transition. Areas under the agriculture and the scrub classes are predicted to face the maximum loss. The predicted increase in the vegetation area would be possible if measures for the maintenance of the green cover are taken in urban and others class which includes industries, resorts, and the like. The proximity to Ahmedabad at the south and development of industrial areas in the west (Kalol) seem to be major driving factors towards the urban outgrowths and the sprawl development in those locations. An extension of the study can include an analysis of the landscape metrics to analyze the details of spatial and temporal growth pattern in the region. This scenario can help the planners and policy makers to visualize and plan the systematic development of the whole region including the peri-urban areas surrounding Gandhinagar. This would be an inclusive approach for future as the urban development surrounding the city would eventually engulf the entire jurisdiction of the district.

## Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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