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Article *in* GeoJournal · June 2022

DOI: 10.1007/s10708-021-10374-w

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GeoJournal
https://doi.org/10.1007/s10708-021-10374-w

Land use/land cover (LU/LC) change dynamics using indices overlay method in Gautam Buddha Nagar District-India

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Accepted: 7 January 2021

Abstract This study is aimed to analyze the dynamics of land use/ land cover (LU/LC) change in a newly created special economic zone, Gautam Buddha Nagar district during 2003–2015. The Landsat satellite data has been used to map the LU/LC pattern of 2003 and 2015 of the study area, using indices overlay method. Consequently, the indices overlay have been created using three land-use indices, i.e. modified normalized difference water index (MNDWI), soil adjusted vegetation index (SAVI), and enhanced built-up and bareness index (EBBI), and then the maximum likelihood classifier (MLC) has been used for the LU/LC classification. The result illustrates that the built-up area (419.35%) and open land (388.36%) have increased during 2003–2015 while the cropland (− 34.38%), scrubland (− 73.25%), and water bodies (− 58.37%) have declined. Further, northern parts of the district have experienced maximum change in the LU/LC while the southern parts have experienced comparatively low change. The study also reveals that

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the increase in the built-up area occurred mostly at the cost of cropland and scrubland. The statistical analysis shows that the EBBI and SAVI have high relationships with LU/LC while the MNDWI has a comparatively low relationship. The study concludes that cropland and scrubland are the main LU/LC types that get transformed due into the built-up area the study area and the SAVI, MNDWI, and EBBI are the good indicators in the study of LU/LC classification and change analysis.

Keywords Land use/land cover (LU/LC) · Land use indices · Indices overlay method (IOM) · Special economic zone (SEZ)

Introduction

In an agrarian economy like India, land is the most important source of livelihood, but various developmental activities are causing vast changes in the utilization of the landscape (Nguyen et al. 2019). In past few decades, the productive agricultural land and forested lands are being converted into non-agricultural land use type such as urban areas, industrial land and are being converted for some other economic activities like special economic zones (SEZ) by the government and people (Dutta et al. 2020; Chavanavesskul and Cirella 2020; Barau and Qureshi 2015). This process of conversion of agrarian land into commercial, industrial and residential land is taking place in the periphery of most of the metropolitan cities in India (Naikoo et al. 2020; Dutta and Das 2019; Levien 2012). Therefore, it is important for the researchers and planners to quantify the changes in landscape pattern and their drivers in the urban and peri-urban areas (Berihun et al. 2019; Rahman et al. 2012).

To have a good understanding of the dynamics of landscape changes in a particular time frame, land use/land cover (LU/LC) change analysis is a most essential component to figure out that how different activities are coming up especially on the agrarian land (Dutta et al. 2019; Rahman et al. 2012). The LU/LC changes occurs as a consequence of both natural as well as anthropogenic factors and there exists a dynamic relationships between the LU/LC change and its driving factors (Yesuph and Dagnew 2019; Wentz, et al. 2014; Lambin et al. 2001). Several potential factors of LU/LC change and landscape transformation have been identified during the recent past such as population growth (Shahfahad et al. 2020; Lambin and Meyfroidt 2011), urban expansion (Naikoo et al. 2020; Rahman et al. 2012; Xiao et al. 2006), economic development (Berihun et al. 2019; Long et al. 2007), hydrological changes (Talukdar and Pal 2020) and natural environment changes (Tran et al. 2015) etc. The expressions land use and land cover are used to denote the surface of the earth, in which the former is the type of earth's surface with human influence and modifications while later is the natural surfaces without any human interference (Hu et al. 2016). The land use and land cover affect each other simultaneously (Hansen and Loveland 2012). Nevertheless, the changing pattern of landscape caused by various anthropogenic activities lead to change in LU/LC and in return affect biodiversity, water and climate (Ganaie et al. 2020; Yesuph and Dagnew 2019; Patra et al. 2018). Even a little increase in impervious surfaces and change in LU/LC may lead to an increase in the land surface temperature (Mallick et al. 2013). Further, in urban areas the changing LU/LC pattern leads to decline in the public open spaces (POS) and landscape quality (Shahfahad et al. 2019).

During recent past, the earth observation satellite data have been proved to be very relevant and valuable source for the LU/LC change analysis (Tong et al. 2020; Pandey et al. 2019; Gessner et al. 2015). The anthropogenic changes such as encroachments, haphazard urban growth and urban induced expansion of built-up surfaces are being mapped using the satellite data (Kamga et al. 2020; de Arruda et al. 2019; Mallick et al. 2014; Dewan et al. 2012; Rahman et al. 2011). The application of remote sensing techniques in the field of LU/LC change analysis is found to be incredibly effective and inexpensive in terms of both time and money (Verburg 2006). In this direction, the freely accessible Landsat data series have provided precious and incessant information sequence to identify and monitor the variation in anthropogenic and natural settings of the globe for nearly four decades (Chander et al. 2009).

With the advancement of remote sensing technology, several advance techniques and approaches have been applied for the LU/LC mapping like expert classification system (Wentz et al. 2008), sub-pixel based linear spectral unmixing (LSU) technique (Dutta et al. 2015), urban sprawl matrix (Sahana et al. 2018), neural network and landscape matrix approach (Chakarborti et al. 2018). A number of studies used indices like normalized difference vegetation index (NDVI), normalized difference built-up index, normalized difference bareness index (NDBaI), etc. for the analysis of LU/LC change (Bazan et al. 2019; Rasul et al. 2018; As-syakur et al. 2012; Glenn et al. 2008; Zha et al. 2003). Further, the application of machine learning techniques like support vector machine (SVM) and artificial neural network (ANN), random forest and decision tree algorithms have been employed for the LU/LC mapping during past few years (Talukdar et al. 2020; Xie et al. 2019). However, anyone can not say that which technique or algorithm is best for the LU/LC classification and is unlikely that one could yet be identified. In the present study, new indices overlay method (IOM) has been proposed for the LU/LC classification, in which we used three thematic land use indices, i.e. enhanced built-up and bareness index (EBBI), modified normalized difference water index (MNDWI) and soil adjusted vegetation index (SAVI).

Numerous studies have been done to analyze the pattern of LU/LC changes in the urban and peri-urban areas of the Indian cities (Ganaie et al. 2020; Sahana et al. 2018; Patra et al. 2018; Gupta 2014; Rahman et al. 2011). However, none of the studies have been done for the analysis of LU/LC changes due to the development of special economic zones (SEZs). The LU/LC change in India and other developing countries occurs as a consequence of the population growth and economic development (Alam et al. 2019; Rahman et al. 2012). The development of SEZs in these developing countries has further accelerated the rate of LU/LC change due to land acquisition for the development of industries, infrastructure and other economic units (Chavanavesskul and Cirella 2020; Parwez and Sen 2016). Land acquisition for the development of SEZs leads to the large scale transformation of forested areas and water bodies into agricultural and residential areas and the agricultural areas gets transformed into industrial, residential and commercial areas (Chavanavesskul and Cirella 2020). Hence, the mapping and quantification of LU/LC changes has been regarded as an important aspect of the spatial planning and policy making as any changes in the LU/LC pattern affects biodiversity, ecosystems, landscape quality, environment and society (Pal and Talukdar 2020; Nguyen et al. 2019; Lin et al. 2018).

Thus, the main objective of this study is to analyze the changes in LU/LC during 2003 to 2015 in Gautam Buddha Nagar district using indices overlay method (IOM) proposed by Xu, (2008). The Gautam Buddha Nagar district was selected for this study because it is one of the fastest urbanizing districts of India and has experienced large scale transformation both in terms of physical as well as economic aspects since it was declared as SEZ (Singh and Hussian 2016). In 1985, the Noida SEZ was setup by the Government of India and in 1997, the Gautam Buddha Nagar district came into existence which became the home of Noida SEZ, after that the economic development and population growth has increased many fold in the district (Singh and Singh 2011). Due to its proximity to the capital city of India i.e. New Delhi as well as its special economic status, the district has experienced large scale transformation of LU/LC during past two decades (Avtar et al. 2019).

Study area

Gautam Buddh Nagar is a largely suburban district of the state of Uttar Pradesh and comes in the National Capital Region (NCR). The district was created in 1997 by carving out some part of Bulandshaher and Ghaziabad districts. The district is subdivided into 3 *tehsil*s (sub-division of a district) in the district namely Dadri, Jewar and Dhankaur and 4 blocks i.e. Bisarakh, Dadri, Dankaur and Jewar (Fig. 1). The district has an area of about 1442 sq. km and its head quarter is the industrial city of Greater Noida. The total population of the district is 16, 48,115 among them 890,214 (54%) are male and 757,901 (46%) are female and the population density was 1282 persons per sq. km (Census of India 2011). As per 2011 Census, the district has 13 urban settlements among which NOIDA is the largest. The climate of Gautam Buddha Nagar as well as whole of the NCR comes under the sub-tropical moist type (*Koppen Cfa*) with evenly

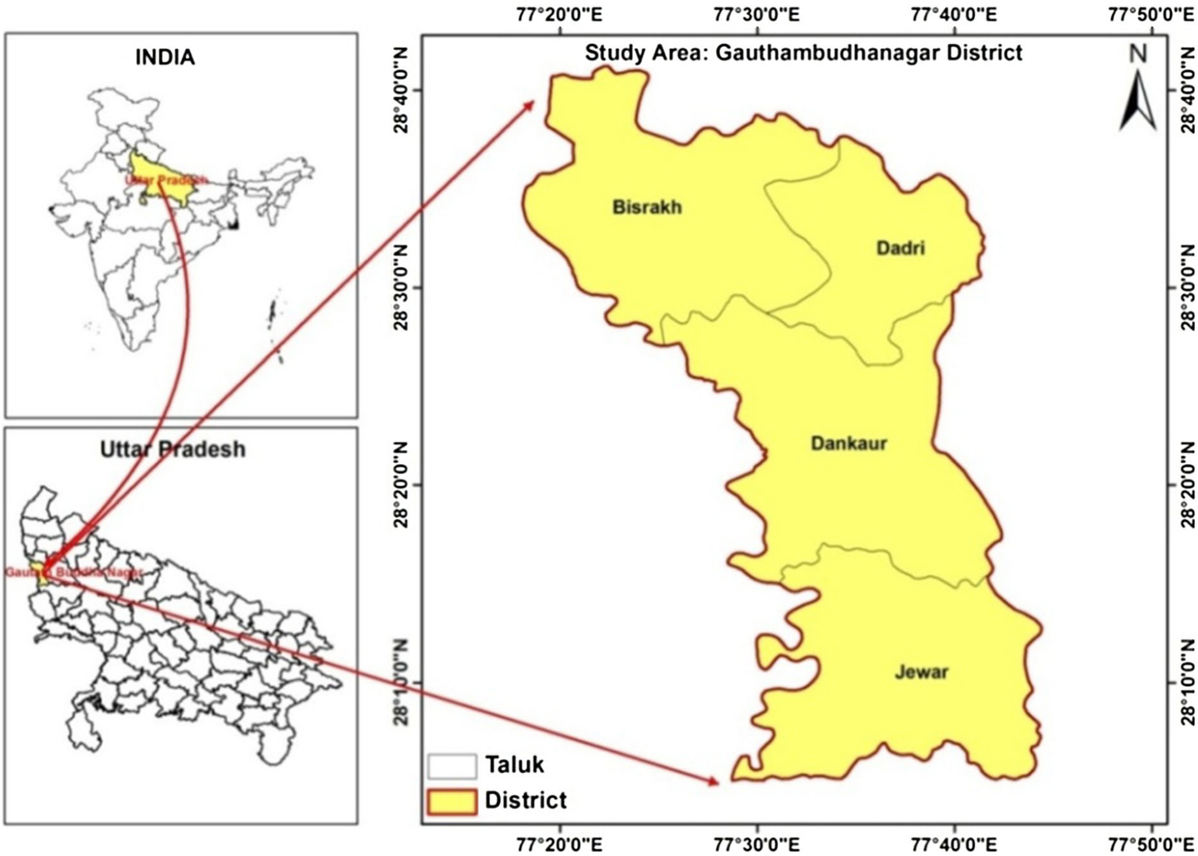


Fig. 1 Location of study area

distributed temperature and precipitation. In the whole of NCR maximum temperature is about 45 °C during May–June and the minimum temperature reaches to about 2–4 °C during December–January. The district statistics 2011 shows that out of the rural area of 124,164 hectares, 42.6% is under cultivation, 1.6% under forest, 16.2% area is under fallow land and 28.7% is under non-agricultural land use. The district recorded 51.52% decade growth rate (Census of India 2011) and is one of the fastest-growing districts of India.

Materials and methods

Materials used

Landsat 7 (ETM + SLC) data of 2003 and Landsat 8 (OLI/TIRS) satellite data of 2015 (Table 1; Fig. 2) is used for driving the various indices, LU/LC and transformation. The toposheet from Survey of India at a scale of 1:50,000 have been used to extract the map of Gautam Buddha Nagar district. Firstly the pre-processing (atmospheric and radiometric corrections) were done for the data downloaded from USGS Earth

Table 1 Details of satellite data sets used in the study

S. No	Satellite/ sensor	Date of acquisition	No. of spectral bands	Spatial resolution	Path/ row
1	Landsat 7 (ETM + SLC)	07 March 2003	7	30 m	146/40
2	Landsat 8 (OLI + TIRS)	28 February 2015	11	30 m	146/40

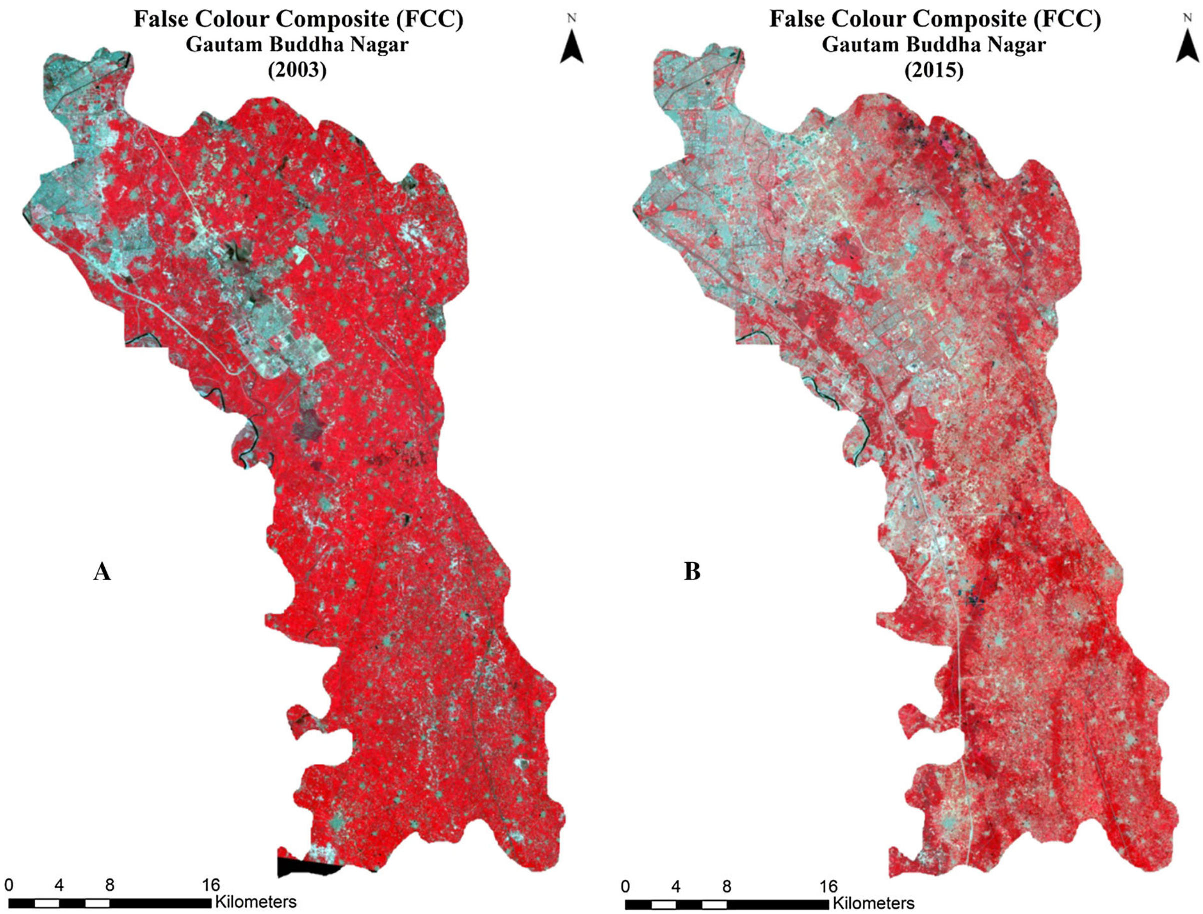


Fig. 2 FCC of Gautam Buddha Nagar. **a** 2003 and **b** 2015

Explorer website and then the image processing work (deriving of SAVI, MNDWI and EBBI, LU/LC maps and LU/LC change detection) has been done using Erdas Imagine software version 14, while the statistical analysis such as correlation and regression analysis are done using IBM SPSS software version 20.

Methods

Several techniques have been used for the LU/LC change but none of them have been proved to be best technique for LU/LC classification since the accuracy of each classification techniques varies with time and space (Pal et al. 2021; Shishir and Tsuyuzaki 2018; Hütt et al. 2016). For the preparation of LU/LC maps, the indices overlay method proposed by Xu (2008) has been used, in which three land-use indices, i.e. SAVI, MNDWI, and EBBI were used. These indices have been used because the Gautam Buddha Nagar district is a suburban district of Delhi where vegetation cover (scrublands, forested areas or crop land), built-up surfaces, water bodies and barren land are the main LU/LC typology in the district (Somvanshi et al. 2020). The land use indices were derived using the Landsat images and then a composite layer of SAVI, MNDWI, and EBBI was created for 2003 and 2015. Further, the supervised classification technique has been applied over the composite image to prepare LU/LC maps and to assess the changes with a view that this will produce better classified LU/LC of the area. Five LU/LC classes have been identified in the study area based on Level-1 classification scheme the National Remote Sensing Centre (NRSC 1995). The LU/LC classes identified in the study area includes water bodies (which includes rivers, lakes, ponds, canals and wetlands), open land (barren land, waste land and all other surfaces without any green cover or artificial structure), croplands, scrubland (grasslands and bushes), vegetation cover (forested and plantation areas) and built-up area.

To analyse the LU/LC change, the change detection technique has been applied to the classified LU/LC maps. For the validation of output change map of 2003, sample points were taken from Google Earth while for 2015; the points were taken from ground observation as well as from Google earth. These sample points were analyzed along with sample points from classified maps using Kappa Coefficient technique for accuracy assessment. Further, to analyze which element i.e. vegetation, water and built-up of LU/LC the Pearson correlation and multiple linear regression analyses are done between SAVI, MNDWI, EBBI, and LU/LC. The detailed methodology is shown in Fig. 3.

Calculation of soil adjusted vegetation index (SAVI)

The SAVI is calculated using near-infrared (NIR) and Red band of Landsat data based on Huete (1988), using Eq. 1.

$$SAVI = \frac{(NIR - Red)(1 + l)}{NIR + Red + 1} \quad (1)$$

where l is correction factor which ranges from 0 (which depict very high density) to 1 (which is very low density). In this study value of 0.5 is used to generate the SAVI because the study area has sparse to moderate vegetation cover.

Calculation of modified normalized difference water index (MNDWI)

The MNDWI has been calculated based on Xu (2006) by using green and middle infrared (MIR) band, using Eq. 2.

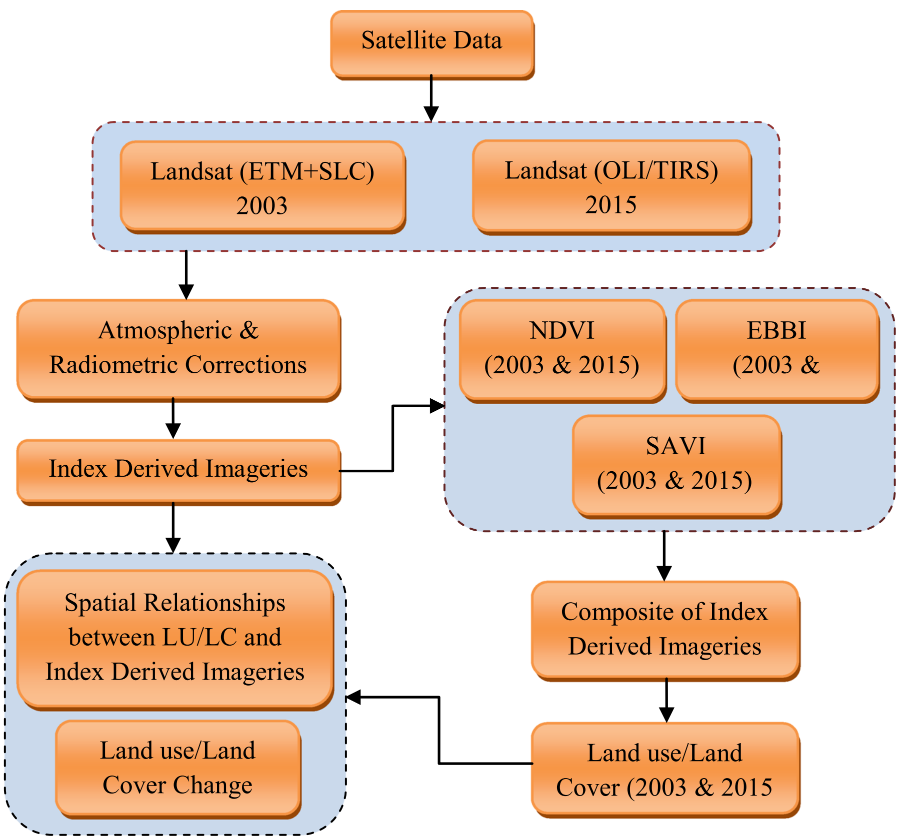


Fig. 3 Flow chart of the methodology

$$MNDWI = \frac{GREEN - MIR}{GREEN + MIR} \quad (2)$$

Calculation of enhanced built-up and bareness index (EBBI)

EBBI is calculated using near-infrared (NIR), mid-infrared (MIR) and thermal infrared (TIR) bands based on As-syakur et al. (2012), using Eq. 3.

$$EBBI = \frac{MIR - NIR}{10\sqrt{MIR - TIR}} \quad (3)$$

Analysis of spatial relationships between indices and LU/LC pattern

At 99% confidence level, 433 sample points were selected from the study area using online calculator with respect to the area of Gautam Buddha Nagar district for the analysis of relationships between land use indices (EBBI, MNDWI and SAVI) and LU/LC. To draw the relationship, the sample points were randomly selected in such a way that each LU/LC class can be covered. The points of the same location were then taken from the land use indices and LU/LC maps. A number of studies have used land use indices for the extraction and mapping of LU/LC pattern in different parts of the world (Acharya et al. 2018; He et al. 2010; Xu 2008; Zha et al. 2003). Following all these studies, the indices used in this study were classified into LU/LC classes based on their utility and each class was then given a code. In SAVI, the value above 0.15 was classified as vegetation and coded '0', the value between 0 and 0.15 were classified as open land and coded as '1' and value below '0' were classified as water and coded '2' as suggested by Sinha et al. (2015). In MNDWI the value above '0.10' were classified as water and coded 0 and below '0.10' were classified as other land-use types and coded as '1' based on Acharya et al. (2018). In EBBI, the value below '0.10' was classified as other land-use type and coded '0', between 0.10 and 0.35 classified as built-up and coded '1' and above 0.35 classified as open land and coded as '2' as classified by As-syakur et al. (2012). Similarly, in classified LU/LC maps, the LU/LC classes were coded with numeric values (0, 1, and 2) with the same code for the similar LU/LC class and then the correlation and regression analysis was performed.

Result

Spatio-temporal analysis of SAVI, MNDWI, and EBBI

The Spatio-temporal analysis of SAVI shows that the SAVI value ranges between − 0.16 to 0.33 in 2003 and − 0.05 to 0.27 in 2015 with a standard deviation of 0.06 for both the study years (Table 2). This implies that the vegetation density has declined in the Gautam Buddha Nagar district. Further, Fig. 4 shows that in 2003 the SAVI was high throughout the district except for north-eastern and north-central parts, but in 2015, the SAVI has declined throughout the district, especially northern and central parts. The small patches of low SAVI were distributed sparsely in 2003 in the districts which increased in 2015.

On the other hand, the Spatio-temporal analysis of MNDWI shows that the MNDWI value ranges between − 1 to 0.68 in 2003 and − 0.39 to 0.32 in 2015 with the standard deviation (SD) of 0.2 and 0.6, respectively (Table 2). Figure 5 shows that in 2003, the patches of low MNDWI were distributed in all parts of the district, especially in north-central parts but MNDWI was high in maximum parts. But in 2015, the area under high MNDWI declined in all parts of the district and the area under high MNDWI remains very less in comparison to 2003. Further, in 2003, the MNDWI was very low in the south-western part of the district but in 2015, the MNDWI has increased in this part of the district.

The Spatio-temporal analysis of EBBI shows that the value of EBBI ranges between − 1 to 0.89 in 2003 and − 0.98 to 0.91 in 2015 with the SD of 0.39 and 0.37, respectively (Table 2). Further, Fig. 6 shows that the EBBI was low in most parts of the district especially below the central district in 2003 and was high only in the extreme north-west and north-central parts. But in 2015, the EBBI has increased to moderate to high in most parts especially in southern parts and is low in few parts in small patches like western margins and extreme northern parts of the city.

In the next step of indices overlay preparation, all the indices were superimposed over each other to get the overlay index (Fig. 7). Hence, the SAVI, MNDWI,

Table 2 Descriptive statistics of the indices (2003 and 2015)

S. No	Indices	2003			2015		
		Minimum	Maximum	S.D	Minimum	Maximum	S.D
1	SAVI	− 0.16	0.33	0.06	-0.05	0.27	0.06
2	MNDWI	− 1	0.68	0.2	-0.39	0.32	0.6
3	EBBI	− 1	0.89	0.39	-0.98	0.91	0.37

Fig. 4 Soil Adjusted Vegetation index for **a** 2003 and **b** 2015

and EBBI of 2003 have been superimposed as one layer and the same was done for 2015 to get the overlay map for both years. The overlay indices have been used for the preparation of LU/LC maps of 2003 and 2015 using the maximum likelihood classifier.

Land use/land cover (LU/LC) classification

The LU/LC maps prepared using indices overlay method shows that the built-up area and open land has increased in the Gautam Buddha Nagar district during 2003–15, while the other land use classes have declined significantly during the same period (Fig. 8). In 2003, the built-up areas were mostly concentrated in the north-western and north-central parts of the district and the small patches of the built-up area were also present in southern and central parts. But in 2015, most of the northern and central parts have been converted into the built-up area while the patches in the southern part have been also increased. Further, the expansion of built-up area has occurred maximum in the areas where the SEZ units have been

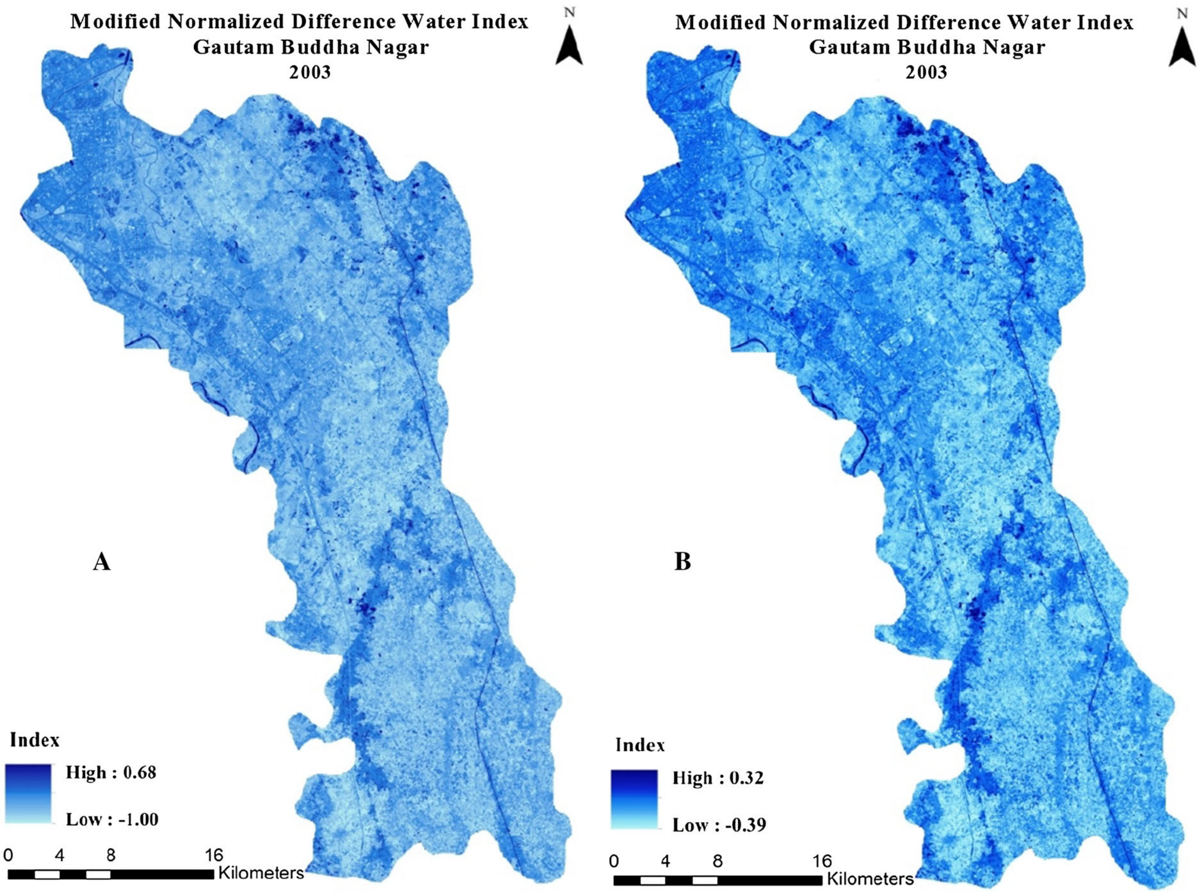


Fig. 5 Modified Normalized difference water index for **a** 2003 and **b** 2015

established (Fig. 8b). The open land was concentrated in small patches in northern and south-western margins of the city in 2003, but in 2015, the patches of open land can be easily seen in the northern and central parts of the district. On the other hand, the cropland, scrubland, and water bodies have significantly declined during the period, especially in northern and central parts of the city (Fig. 9).

Table 3 shows that the built-up area and open land have increased during the study period while scrubland, water bodies, and cropland has declined. In 2003, the open land and built-up areas were 650.88 (0.52% of the total area) hectares and 9933.93 hectares (7.89%), respectively, which in 2015 increased to 3178.64 hectares (2.52%) and 51,591.53 hectares (40.98%), respectively. The water bodies were 6207.57 hectares (4.93%) in 2003 which in 2015 declined to 2584.33 hectares (2.05%). The cropland and scrubland were 101,250.77 hectares (80.42%) and 7858.17 hectares (6.24%), respectively in 2003 which declined to 66,444.14 hectares (52.78%) and 2102.29 hectares (1.67%), respectively in 2015. Overall, the maximum increase has been noticed in the built-up area (419.35%) and the maximum decrease has been observed in scrubland (− 73.25%).

Dynamics of land use/land cover (LU/LC) change

The change detection technique has been used to analyze the LU/LC change dynamics. The analysis of change dynamics shows that the maximum change has been observed in cropland and scrubland. Figure 10 shows that the landscape transformation has occurred in all parts of the district in the form of the built-up increase during 2003–2015. The highest increase occurred as a consequence of the transformation of cropland, water bodies and scrubland into the built-up area and open land. Most of the area unchanged is

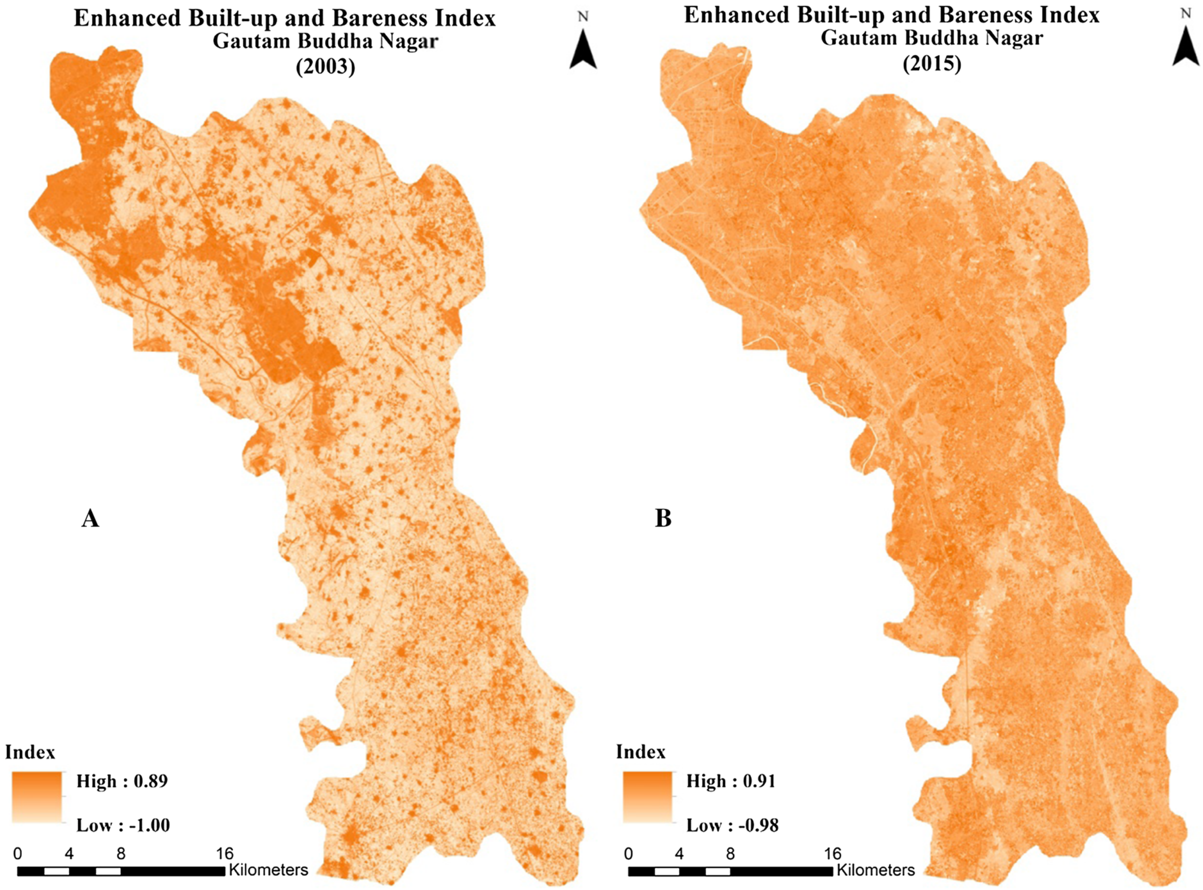


Fig. 6 Enhanced built-up and barren index for **a** 2003 and **b** 2015

either cropland or built-up area. The conversion to water bodies and scrubland was least during the study period in the district.

Table 4 shows the LU/LC change matrix of Gautam Buddha Nagar during 2003–2015. It clearly shows that the maximum transformation of each LU/LC class occurred in the built-up area. The scrubland is the highest contributor in the built-up increase (73.64%) followed by open land (53.81%) and cropland (33.67%) while water bodies have contributed least (23.54%). Further, the highest contributors to cropland are water bodies (31.12%) and open land (28.47%). Although percent-wise the open land has gained very less area from each land-use class (2.63% and 4.66% from cropland and scrubland), it is increased significantly during the 2003–2015. From Fig. 9 it is obvious that only the built-up area and open land have experienced an increase in their area while all rest land use classes have declined during 2003–15.

Analysis of classification accuracy

The overall accuracy for the classified LU/LC map using IOM of 2003 was 94.11% whereas for 2015 it was 93.07% (Table 5). User and producer accuracy are also calculated for LU/LC map of 2003 and 2015. In 2003 user's accuracy is highest in cropland i.e. 99.21% followed by water bodies (99.18%), built-up (98.33%), scrubland (91.17%) and open land (68.33%). Whereas in 2015 user's accuracy is highest in built-up i.e. 99.82% followed by cropland (94.01%), open land (93.79%), water bodies (88.75%) and scrubland (53.40%). In 2003 producer's accuracy is highest in cropland i.e. 99.54% followed by water bodies (98.10%), scrubland (97.11%), open land (94.25%) and built-up (88.47%). Whereas in 2015 producer's accuracy is highest in built-up i.e. 98.35% followed by water bodies (97.05%), open land (88.59%), scrubland (88.28%) and cropland (71.73%).

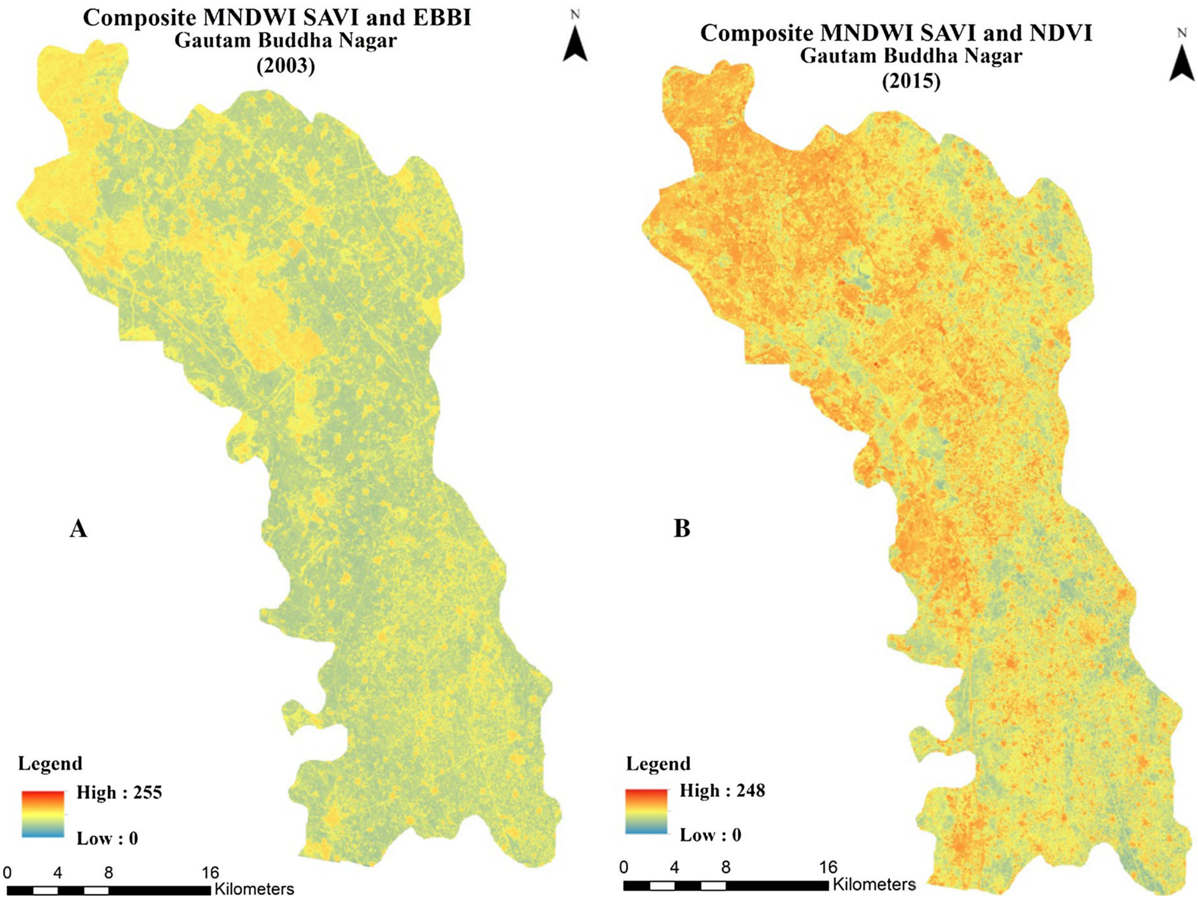


Fig. 7 Composite MNDWI SAVI and EBBI for **a** 2003 and **b** 2015

Statistical analysis of SAVI, MNDWI, EBBI and LU/LC

To analyze the spatial analysis between indices used and LU/LC, the Pearson correlation and multiple leaner regression technique has been applied. The correlation analysis shows that in 2003, the relationship of LU/LC with SAVI was high-negative (− 0.63) while with EBBI it was high-positive (0.601). The correlation coefficient shows that the relationship between LU/LC and MNDWI is negative but weak (0.128) for 2003. This is because the proportion of water bodies is very low in the Gautam Buddha Nagar district. Further, the relationships between LU/LC and indices for 2015 show the same pattern as 2003, as the correlation coefficient shows a relationship between LU/LC and SAVI is strong-negative (− 0.571), and the relationship between LU/LC and EBBI is strong-positive (0.546). The relationship between LU/LC and MNDWI is weak but positive for 2015 (Table 6).

The multiple linear regression analysis shows that the association between indices and LU/LC is high for both 2003 and 2015, but the coefficient of determination (R^2) shows that in 2003 (0.413) the association was more in comparison to 2015 (0.35) (Table 7). Further, the standardized coefficient (Beta) shows that the association between EBBI and LU/LC (0.342 and 0.903 for 2003 and 2015, respectively) is positive for both 2003 and 2015 but negative between SAVI and LU/LC (− 0.369 and − 1.507 for 2003 and 2015, respectively) as well as MNDWI and LU/LC (− 0.19 and − 0.239 for 2003 and 2015, respectively). Further, the standard error in regression analysis is maximum for SAVI and minimum for EBBI for both the time periods (Table 8).

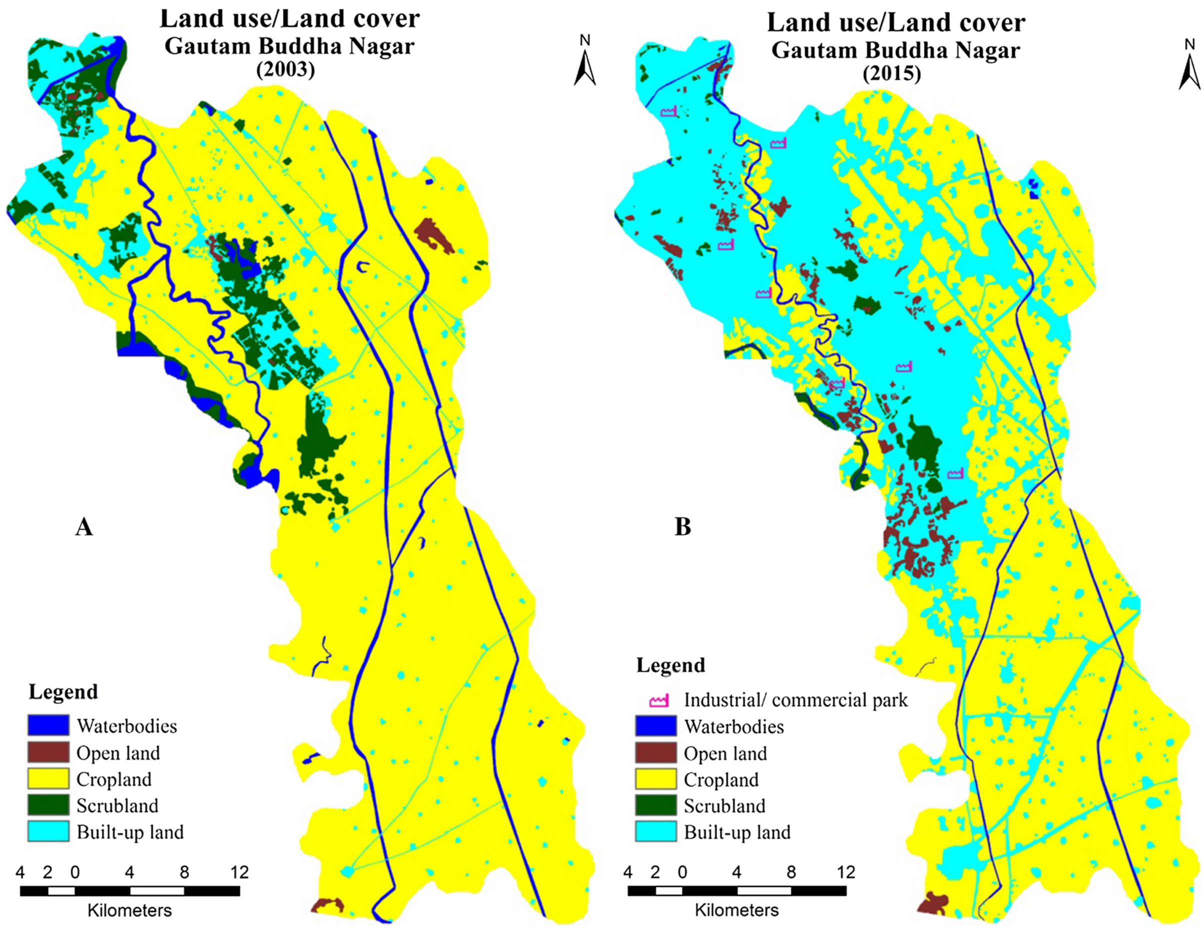
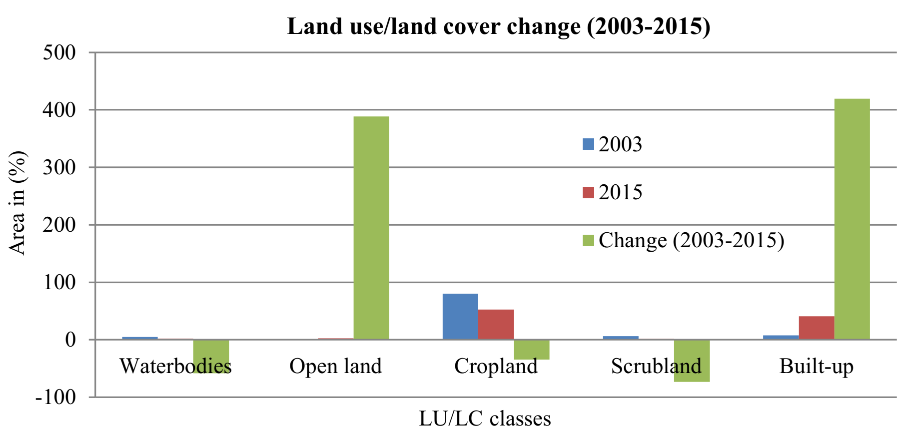


Fig. 8 Land use/land cover map of **a** 2003 and **b** 2015

Fig. 9 Graph showing dynamics of land use/land cover change during 2003–2015



Discussion

Urban areas are quite heterogeneous, dynamic and complex systems with some generalization in terms of LU/LC (Das et al. 2019; Dou and Chen 2017; Healey 2007). The urban land-use system is generally classified into three classes, viz. the built-up area and open land, vegetation cover and the water bodies (Ridd

Table 3 Land use/land cover change (2003–2015)

S. No	LU/LC classes	Area (2003)		Area (2015)		Change (%)
		In (hectare)	%	In (hectare)	%	
	Water bodies	6207.57	4.93	2584.33	2.05	− 58.37
	Open land	650.88	0.52	3178.64	2.52	388.36
	Cropland	101,250.77	80.42	66,444.14	52.78	− 34.38
	Scrubland	7858.17	6.24	2102.29	1.67	− 73.25
	Built-up	9933.93	7.89	51,591.53	40.98	419.35
	Total	125,901.32	100.00	125,900.93	100.00	–

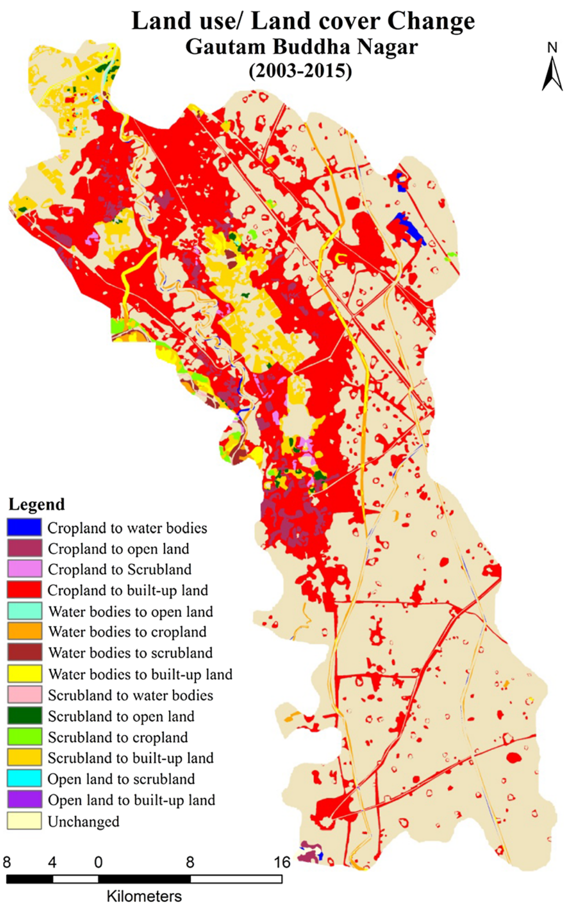


Fig. 10 LU/LC change pattern during 2003–2015

1995). Hence, the composite of three land-use indices has been used for the LU/LC classification in this study, i.e. EBBI for built-up and open land, soil adjusted vegetation index (SAVI) for vegetation and cropland and the normalized difference water index (NDWI) for water bodies. The SAVI gives better accuracy than normalized difference vegetation index (NDVI) in the region having moderate vegetation cover (Kayet et al. 2016), therefore, the SAVI has been used in this study instead of NDVI. Further, the MNDWI is a modified version of the MNDWI and gives more accurate results in mapping water bodies (Xu 2006); hence the MNDWI is used in this study. The EBBI is technique is used to map both built-up land and bare soil, mostly of an urban area (As-syakur et al. 2012); consequently, it has been applied in this study.

The overall accuracy using the maximum likelihood classifier (MLC) was 90.41% for 2003 and 88.01% for 2015, but it increased to 94.11% for 2003 and 93.07% for 2015, when integrated with the IOM i.e. composite image of SAVI, EBBI and MNDWI. The supervised classification technique using the maximum likelihood classifier (MLC) has been used for LU/LC classification on the composite image of SAVI, MNDWI, and EBBI. Numerous studies have noted that the MLC has better classification accuracy for LU/LC classification using Landsat data (Sannigrahi et al. 2019; Hütt et al. 2016; Rahman et al. 2011). Furthermore, studies have also noted that the natural-pervious land cover typologies such as water bodies, open land, cropland, and vegetation cover declines with the expansion of urban areas (Kumari et al. 2018; Dou and Chen 2017) due to growth in built-infrastructure. The variation in the maximum and minimum values of SAVI, EBBI, and MNDWI shows the maximum value of EBBI has increased while MNDWI and SAVI increased during 2003–2015.

Due to establishment of the SEZ, a larger population moved to the Gautam Buddha Nagar district and also several industrial and economic units have come up in the district which has affected both physical as well as demographic structure of the district (Singh and Hussian 2016). Chavanavesskul and Cirella (2020) noted that the LU/LC pattern is an important influencing factor of the SEZs because it influences

Table 4 Land use/land cover change matrix (2003–2015) in per cent

Area change in per cent							
S. No	LU/LC classes (2003–2015)	Cropland	Water bodies	Open land	Scrubland	Built-up	Total
1	Water bodies	31.12	37.74	0.67	6.93	23.54	100
2	Open land	28.47	0.00	14.62	3.11	53.81	100
3	Cropland	63.07	0.20	2.63	0.44	33.67	100
4	Scrubland	5.85	0.49	4.66	15.35	73.64	100
5	Built-up	0.00	0.00	0.00	0.00	100.00	100

Table 5 Accuracy assessments for classified image of (2003 and 2015) in per cent

S. No	LU/LC classes	2003		2015	
		User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy
1	Water bodies	99.18	98.10	88.75	97.05
2	Open land	68.33	94.25	93.79	88.59
3	Cropland	99.21	99.54	94.01	71.73
4	Scrubland	91.17	97.11	53.40	88.28
5	Built-up	98.33	88.47	99.82	98.35

Table 6 Relationship between LU/LC, EBBI, MNDWI and SAVI (2003 and 2015)

	2003				2015			
Variables	*LU/LC*	*EBBI*	*MNDWI*	*SAVI*	*LU/LC*	*EBBI*	*MNDWI*	*SAVI*
LU/LC	1	–	–	–	1	–	–	–
EBBI	0.601**	1	–	–	0.546**	1	–	–
MNDWI	− 0.128**	− 0.526**	1	–	0.069	0.063	1	–
SAVI	− 0.630**	− 0.972**	0.374**	1	− 0.571**	− 0.972**	− 0.242**	1

**Correlation is significant at the 0.01 level (2-tailed)

Table 7 Summary statistics of the regression analysis (2003 and 2015)

Model year	R	R^2	Adjusted R^2	Std. error of the estimate	Durbin-Watson
2003	0.643[a]	0.413	0.409	0.822	0.866
2015	0.591[a]	0.35	0.345	1.416	1.029

several basic needs of the SEZs such as infrastructural facilities, raw materials etc. Further, most of the SEZs get established in either peri-urban or agrarian areas because of availability of land and labour at cheap prices in these areas and thus the pace of land transformation has been noted higher in the SEZs

Table 8 Detailed regression analysis (2003 and 2015)

Model year	Variables	Un-standardized coefficients		Standardized coefficients	Sig
		B	Std. Error	Beta	
2003	(Constant)	7.032	0.113	–	0
	SAVI	− 3.843	2.228	− 0.369	0.005
	MNDWI	− 3.687	1.157	− 0.19	0.002
	EBBI	1.857	1.265	0.342	0.014
2015	(Constant)	17.989	1.835	–	0
	SAVI	− 8.883	8.501	− 1.507	0
	MNDWI	− 8.161	2.101	− 0.239	0
	EBBI	6.447	1.818	0.903	0

than the other urban areas (Parwez and Sen 2016; Tiwari et al. 2015; Levien 2012).

The analysis of LU/LC pattern and change dynamics shows that the built-up area and open land has increased significantly in the Gautam Buddha Nagar district, while on the other hand, the scrubland and cropland have experienced a rapid decline. Similar results were found in the previous researches on impact of SEZs on landscape transformation in different parts of the world (Nguyen et al. 2019; Parwez and Sen 2016; Barau and Qureshi 2015). Thitawadee and Yoshihisa (2018) pointed that the residential and commercial areas are the main growing areas of an SEZ which expands over the croplands and range lands. In Gautam Buddha Nagar SEZ, the maximum expansion of built-up areas has occurred over the croplands and scrublands followed by vegetation cover and open land. Furthermore, the maximum expansion of built-up surface has been noted from the central and north-western parts of the district, because this part of the district has large urban cluster like Noida and Greater Noida and having a number of industrial and commercial firms as well as a dense population (Singh and Hussian 2016; Singh and Singh 2011). In this study the dynamics of LU/LC change due to establishment of special economic zone (SEZ) is studied, but the contribution of economic and industrial development has not been analysed. Therefore, the future research may be focussed on quantify the role of economic and industrial development in the transformation of LU/LC.

Studies also shows that the water bodies, croplands and scrublands are the main LU/LC types that get replaced by built-up surfaces and open land in the process of urban expansion and economic development (Alqurashi and Kumar 2019; Rahimi 2016). Although, the water bodies have seen a significant but low decline in the study area because most of the water bodies are in the form of the river (Hindon River) and canals (East Yamuna Canal), and those in the form of wetlands have been transformed. The croplands and scrublands also show comparatively low decline in the Gautam Buddha Nagar SEZ during 2003–2015. The decline in water bodies has occurred in the form of disappearance of wetlands, ponds and lakes in Gautam Buddha Nagar because the declining trend of rainfall in this part of the northern India (Kharol et al. 2013; Rana et al. 2012). Furthermore, studies have also noted declining trend in the monsoon rainfall in the Gautam Buddha Nagar and other parts of Delhi NCR (Praveen et al. 2020; Kumar et al. 2010). Several studies have noted the declining pattern of surface water resources due to decline in rainfall and its variability in different parts of the globe (Sapriza–Azuri et al. 2015; Whitehead et al. 2009). The croplands and water bodies have also declined in the Gautam Buddha Nagar due to encroachment by the real estate and industrial firms during past two decades. In SEZs, the encroachment for the expansion of industrial parks and residential colonies has also been noted by Chavanavesskul and Cirella, (2020).

Conclusion

The study has applied maximum likelihood classifier (MLC) scheme on the composite data which is made by overlaying indices i.e. EBBI, MNDWI and SAVI to assess the LU/LC change after the inception of SEZs in the Gautam Buddha Nagar. A major change has been observed in LU/LC with respect to built-up and open land during 2003 to 2015 which is to the tune of about 400% in both the classes. The area under other LU/LC class i.e. cropland, vegetation cover and water bodies have declined to about 34%, 73%, and 58% respectively. The decrease in the area under green cover and surface water bodies has adverse impact of the urban environment as well as the entire Gautam Buddha Nagar district. The study shows that these changes in LU/LC are the resultant impact of establishment of SEZs, which is at the cost of fertile crop land and scrubland. Further it may be safely concluded that such changes in the LU/LC is because of the establishment of industries now called as industrial parks several residential apartments, institutional establishments and other infrastructure development projects come up. The overall classification accuracy is 90.41 in 2003 and 88.01 in 2015 by using maximum likelihood classifier (MLC). But when we applied the MLC on the integrated land use indices i.e. EBBI, MNDWI and SAVI the overall classification accuracy come to 94.11 in 2003 and 93.07 in 2015. Therefore, it can be concluded that overlay indices method (IOM) is better over the maximum likelihood classifier (MLC) for making LC/LC classes and to assess the changes over certain period of time.

Acknowledgements The first and second authors of this study are thankful to University Grant Commission (UGC) for providing the Junior Research Fellowship (JRF) during this research work. The authors also thank USGS for making the Landsat data freely accessible. The authors are highly indebted to the learned reviewer(s) for making the scholarly comments which lead to significant improvement of the MS.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest on any financial or other issues.

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