Environ Monit Assess (2019) 191: 551
https://doi.org/10.1007/s10661-019-7645-3

Changing pattern of urban landscape and its effect on land surface temperature in and around Delhi

Dipanwita Dutta · Atiqur Rahman · S. K. Paul · Arnab Kundu

Received: 10 April 2019 / Accepted: 10 July 2019 / Published online: 9 August 2019

Abstract The last couple of decades have seen remarkable spatial growth in the urban areas of developing countries. The process of urbanization is directly linked with land transformation which can be an effective way to monitor the spatio-temporal pattern of urban growth. New Delhi, the capital city of India has experienced a large-scale urban growth during the last decade. In order to identify the pattern of urban expansion in and around Delhi, the present study aims to assess the process of land transformation using multi-temporal Landsat datasets (1977–2014). The areas under various land use and land cover (LULC) extracted by support vector machine (SVM) hybrid classifier reveal asignificant change in the LULC pattern of the area. A good agreement was found between field-based information and maps generated using satellite images (kappa ≥ 0.84). Land transformation maps indicate rapid growth of few urban centres located outside Delhi National Capital Territory (NCT), like Gurgaon, Gautam Buddha Nagar, Faridabad and Ghaziabad. These centres have been remarkably expanded because of transformation of agricultural and vegetated lands. However, green patches within the city have not been affected by the consequences of urbanization. In tune with the rapid urbanization in the periurban centres of Delhi, the Moderate Resolution Imaging Spectro-radiometer (MODIS)-derived land surface temperature (LST) images revealed significant change in the level of LST. The interrelationship of impervious surface fraction (ISF) and LST proves a good agreement between them. The increasing trend observed in the long-term (1987–2011) summer temperature data obtained from India Meteorological Department (IMD) indicates the rise of mean summer temperature in the last few decades. Land transformation along with rapid urbanization especially in the periurban areas of Delhi NCT played a key role in the increasing trend of surface temperature.

Keywords Land transformation · LST · Periurban remote sensing · Urban growth

D. Dutta
Department of Remote Sensing and GIS, Vidyasagar University, Midnapore, West Bengal, India

A. Rahman
Department of Geography, Faculty of Natural Sciences, Jamia Millia Islamia, New Delhi, India

S. K. Paul
Department of Architecture and Regional Planning, Indian Institute of Technology-Kharagpur, Kharagpur, West Bengal, India

A. Kundu (✉)
DST-Mahamana Centre of Excellence in Climate Change Research, Institute of Environment and Sustainable Development, Banaras Hindu University, Varanasi, Uttar Pradesh, India
e-mail: arnknd@gmail.com

Introduction

The term 'urbanization' indicates a complex process of socio-economic and ecological transformation of an area which is mainly driven by anthropogenic activities. According to Davis and Golden (1954), it is a cyclic process through which a traditional agriculture-based society transforms into a mechanized industrial society. Although the characteristics of urban areas are almost same in different countries, the criteria for defining a region as urban are not similar across the countries. However, urban areas can be distinguished by their distinct physical and cultural characteristics. The characteristics of urban centres as well the pace of urbanization have altered with time. During 1980–2010, developing countries have witnessed massive increase in urban dwellers as compared to the developed countries (Grauman 1976).

The last century has experienced a large-scale growth in urban population followed by excessive demand of land both within and outside cities. It is estimated that urban population of Asia and Africa will be double within 2030 and developing countries will have 80% of the World's urban population (UN-Habitat 2006). India, being one of the fast growing countries of the world, experienced a massive growth in urban areas. The number of total population has increased 4.3 times, whereas the number of urban population has increased more than 11 times during 1991–2001 (Census of India 2001) which is mainly due to natural increase of population, rural to urban migration and reclassification of rural areas as urban. Urban population in India is mainly confined in class 1 cities, especially in the megacities where urban population has concentrated and increased steadily over the last few decades (Kundu 2006). It is also worthy to mention that percentage share of urban population has increased from 17.97% in 1961 to 31.16% in 2011 (Census of India 2011). The major reason behind the increasing trend of urban population of the country was natural increase of population. Beside this, rural to urban migration and emergence of new cities have also played a significant role in the past decades. The contribution of natural increase in urban population was 59.4%, whereas it was 21% and 6.2% respectively in rural to urban migration and emergence of new cities during the last century (Kundu 2006).

Although the process of urbanization in Delhi has been continuing from the Mughal era, it was accelerated after being designated as the capital of India in 1901. The city experienced sharp increase in population density after the independence and partition of the country in 1947 which led a huge number of refugees to migrate in the city. In order to provide land for development of new industries and accommodating the growing population, peri-urban area of Delhi city has undergone a rapid change by converting the agricultural and other lands into built up area. Periurban area indicates the active areas between urban and rural landscape with new industries, housing and commercial places. With increasing burden of population and growing demand of land in a city, the periurban areas experience a process of transformation from agro-based economy to a fully developed industry based economy which known as peri-urbanization.

After the concept of sustainable urbanization has come to the fore, it has emerged that urban spaces need to be planned with the understanding of ecological planning in order to provide environmentally sensitive urban development. Urban landscape planning means making decisions about the future situation of urban land, and it has many benefits in terms of the environment. It is necessary to predict how the land has changed over time and the effects of natural factors and human activities on the land. In this way, successful and sustainable landscape planning studies can be achieved (Cetin 2015a, b, c, d; Cetin and Sevik 2016a, b; Cetin 2016a, b; Cetin et al. 2018a, b, c, d; Cetin et al. 2019; Yucedag et al. 2018; Kaya et al. 2018). Land cover is one of the most important data used to demonstrate the effects of land use changes, especially human activities.

A precise and suitable information system plays vital role for sustainable development and future urban planning. In this context, geo-spatial techniques are being considered as a robust and efficient method for monitoring the land transformation and urban growth quantitatively with good accuracy. The satellite-based multi-spectral and multi-temporal images have become essential for assessing spatio-temporal changes in LULC of urban areas. The last three decades have seen extensive research in the field of urban change detection using remotely sensed images (Gomarasca et al. 1993; Yang and Lo 2003; Haack and Rafter 2006; Rahman et al. 2012; Dutta et al. 2015). Remote sensing technique coupled with geographic information systems (GIS) has been proven to be a useful and cost-effective tool for determining LULC change and identifying the pattern of land transformation. Urban growth and industrial development especially in the developing countries play a key role in changing micro-climate in any area. It is estimated that there is an increase of 0.94 °C in global mean surface temperature (IPCC 2007) and further estimated that it will increase 0.3 to 0.7 °C during 1916–1935 (IPCC 2013). Urban growth in and around the major cities affects the micro-climate of core cities and its periphery as a whole. Although it is a localized phenomenon, the impact of urban heat island effect is vast due to the high density of population in cities. So, understanding the inter-relationship between urban growth and changing micro-climate is crucial for studying urban environment. In this context, the present study attempts to find out the changing pattern of urban landscape in and around Delhi NCT and its impact on surface temperature using multi-temporal satellite datasets. Here, long-term effects of urban growth have been analysed using 8 day composite MODIS LST datasets and in situ climatic datasets from IMD. Beside this, variation in ISF and population density of different administrative units has been examined with satellite-derived LST data.

Study area

The National Capital Territory (NCT) of Delhi and its periurban areas has been chosen for the present study (Fig. 1). 'Periurban' area refers to a transition or interaction zone, where urban and rural activities are juxtaposed, and landscape features are subject to rapid modifications mainly induced by human activities (Douglas 2006).

Since the periurban area is a transitional zone between rural and urban centres, demarcation of its boundary is a difficult task. Generally, periurban area is demarcated by a buffering zone surrounding urban centre but the extension of outer boundary may vary according to the type of urban centre. Here, periurban area of Delhi NCT has been defined by 15 km. buffer area from the outer boundary of NCT region and covering all periurban centres like Gurgaon, Faridabad, Ghaziabad and Goutam Buddha Nagar. With a total area of 2618 km^2, the periurban area contains parts of Ghaziabad and Baghpat districts of Uttar Pradesh and parts of Sonepat, Jhajjar, Gurgaon and Faridabad districts of Hariyana. There are nine districts under Delhi NCT and cover an area of total 1483 km^2.

Database and methodology

Database

The multi-temporal Landsat datasets of 1977, 2003 and 2014 were collected from three different sensors of Landsat satellite series, i.e. Multi-spectral Scanner (MSS), Enhanced Thematic Mapper plus (ETM+), and Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) respectively (Table 1). Considering the seasonal phenological effects and availability of good quality images, the aforesaid years were selected. The Landsat datasets have been popularly used by the urban researchers since its launch in 1972 (Yuan et al. 2005; Lu et al. 2011a). Many researchers have chosen this data over high-resolution optical datasets for its better spectral resolution. Although high-resolution datasets are good for micro level in depth studies, utility of these datasets is limited by the high degree of spectral variance within same land cover and shadow problems (Zhou et al. 2009; Lu et al. 2011b). Along with satellite datasets, the study area was surveyed with a Trimble GPS.

The long-term effects of rapid urban growth in Delhi NCT and its periurban areas were analysed using in situ climatic datasets from IMD as well as satellite-based LST datasets. Long-term IMD dataset of 37 years (1974–2011) was used in the study as per the availability of data. Apart from this, satellite-based temperature product (8 day composite LST of June and December) of MODIS data (1 km spatial resolution) was collected from https://daac.ornl.gov/MODIS/ for the years 2003 and 2014. Four LST images for each months June and December were used for computing mean LST. Population density plays an important role in urban growth, and there is a close association between growth of population and built-up areas. Here, population density datasets of each municipality ward of Delhi NCT were collected for two census years, 2001 and 2011, from the Census of India and compared with satellite-derived mean temperature.

Methodology

The multi-temporal images of Landsat sensors were calibrated and then corrected by using FLAASH atmospheric correction model. After removing noises, the corrected images were co-registered using the base image of 2014. In order to extract different LULC classes, the multi-temporal Landsat images (1977, 2003 and 2014) were classified using SVM classifier. It is a hybrid classifier in which the vectors are separated through a hyperplane in feature space. This algorithm has been

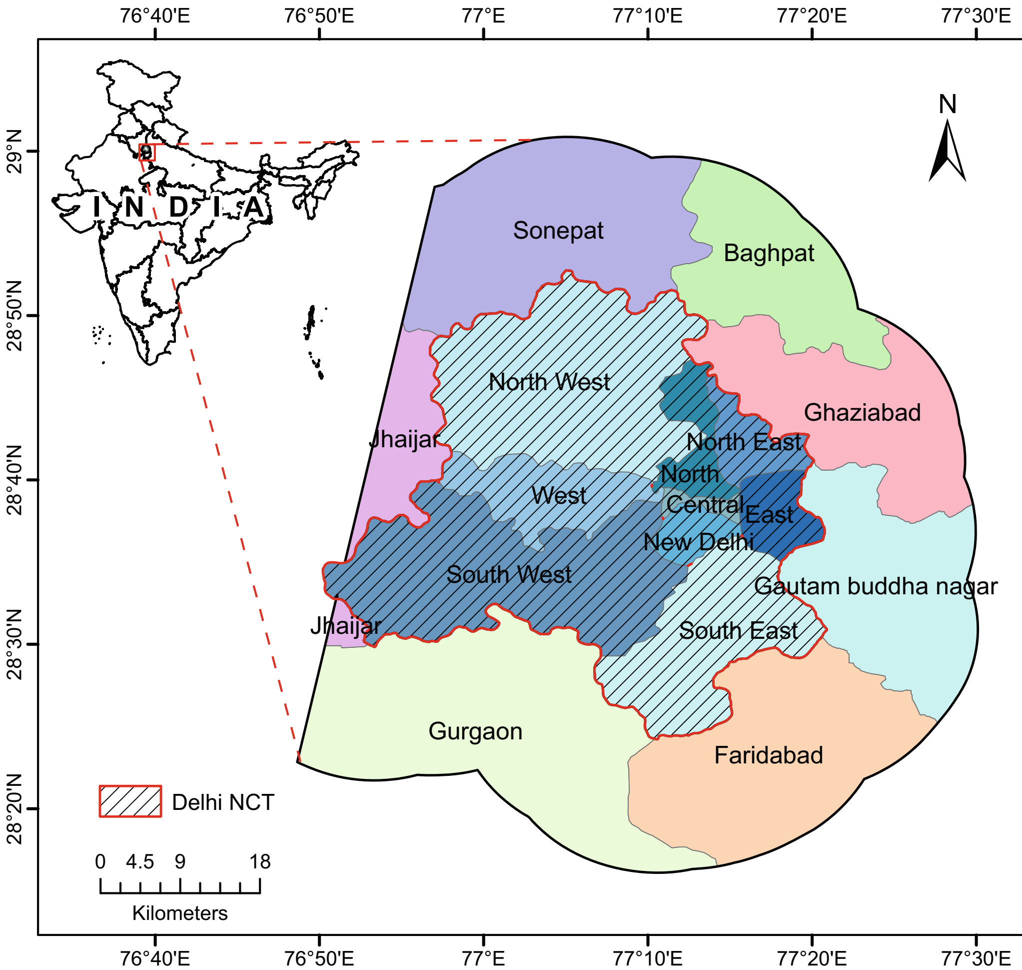


Fig. 1 Study area

popularly used by several researchers for separating LULC features in a robust manner (Guo et al. 2005; Huang et al. 2007; Mountrakis et al. 2011; Nooni et al. 2014). Seven broad LULC classes, i.e. high-density and low-density built-up, agricultural land, sparse vegetation, dense vegetation, wasteland and waterbody, were identified and extracted by using SVM classifier. Accuracy of the classifier was assessed by the field based ground truth information. The post classification change detection method was applied for quantifying the changes occurred in the areal coverage of each class. Except this, the spatio-temporal pattern of LULC conversion was mapped for analysing the land transformation process.

The 8 day composite MODIS LST datasets were georeferenced and rescaled using a scale factor value (0.02). Further, the unit of temperature was converted into degree Celsius and the images were classified as per the level of temperature. In order to assess the impact of urbanization on land surface temperature, the abundance of impervious surface was estimated through linear spectral unmixing (LSU) technique. The endmembers used in the model were extracted through minimum noise fraction (MNF) and pixel purity index (PPI). MNF transforms the raw image and separates the bands into two subspaces, signal and noise (Uhrin and Townsend 2016). The first three MNF components with high signal quality were used as input in PPI. Finally, the endmembers were extracted from the PPI image and used as input in LSU model. The resulted fractional images of impervious surface of 2003 and 2014 were used in the study and compared with MODIS-LST datasets.

Table 1 Characteristics of the Landsat archive, NASA, MSS, TM, and OLI/TIRS sensors

Sensors	Spectral bands (μm)	Spatial resolution (m)	Spectral region	Time of acquisition
Landsat-MSS	Band 1: 0.50–0.60 Band 2: 0.60–0.70	60	Green Red	1977, February
	Band 3: 0.70–0.80 Band 4: 0.80–1.11		Reflected IR	
Landsat-TM	Band 1: 0.45–0.52 Band 2: 0.53–0.60	30	VNIR	2003, February
	Band 3: 0.63–0.69			
	Band 4: 0.75–0.90			
	Band 5: 1.55–1.75		SWIR	
	Band 6: 1.04–12.5	120	TIR	
	Band 7: 2.09–2.35	30	SWIR	
Landsat- OLI	Band 1: 0.45–0.52 Band 2: 0.52–0.60	30	Visible Visible	2014, February
	Band 3: 0.63–0.69		Visible	
	Band 4: 0.77–0.90		Near-infrared	
	Band 5: 1.55–1.75		Near-infrared	
	Band 6: 10.40–12.50		Thermal	
	Band 7: 2.09–2.35	60 (30)	Mid-infrared	
	Band 8: 0.52–0.90	15	Panchromatic	

Results and discussions

LULC extracted from multi-temporal images

The LULC information extracted by SVM–supervised classifier has been used to analyse the spatial distribution of different LULC classes. The proportional distribution of different LULC classes reveals that percentage of high density built-up areas was distinctly low in 1977 (Table 2). More than 50% of the total area was under agricultural land. It indicates the involvement of people in agricultural activities and dominance of agro-based economy. The second dominant land cover, sparse vegetation, occupied one-fourth of the total area. This is mainly evident over the Delhi ridges. The pattern of urban landscape has undergone significant change in 2003 mainly due to growth of low density built-up areas. As a result, this class was ranked second highest from 2003 onwards. It was estimated from the classified images that both high and low density built-up areas have experienced remarkable increase during the period, 1977–2014. Estimated areas under agriculture, sparse vegetation and wasteland reveal a decreasing trend. Significant decrease in the areas under those classes certainly indicates transformation of lands into other LULC classes. Overall classification accuracy and kappa statistics of the classified images were found > 0.86 and > 0.84, proving a good agreement between LULC extracted from SVM classification and ground truths.

Spatio-temporal change detection (1977–2003)

In order to assess the contribution of different LULC in the spatio-temporal growth of built-up areas, the proportions of converted area were estimated for each LULC classes (Fig. 2a, b). The quantitative analysis shows that only 4% and 16.8% of the total area (including both NCT and periurban region) were under high and low density built-up classes in 2003. The area under high density built-up class experienced more than six times increase during 1977–2003, whereas the low density built-up areas increased about three times during that period. The change detection analysis reveals that most of the areas under high density built-up class was converted from low density built-up and sparse vegetation class which together accounts for more than 50% of newly grown high density built-up area. On the other hand, low density built-up area has expanded mainly due to

Table 2 Spatial statistics of LULC in 1977, 2003 and 2014

Land use and land cover classes	1977		2003		2014	
	Area in km^2	Percentage	Area in km^2	Percentage	Area in km^2	Percentage
High density built-up	25.45	0.62	162.43	3.97	636.22	15.53
Low density built-up	235.67	5.75	688.02	16.80	839.48	20.50
Dense vegetation	198.48	4.85	253.44	6.19	266.16	6.50
Agricultural land	2048.72	50.02	2001.26	48.86	1598.22	39.02
Sparse vegetation	1069.88	26.12	636.19	15.53	412.42	10.07
Waterbody	51.75	1.26	43.22	1.06	43.51	1.06
Wasteland	465.95	11.38	311.33	7.60	299.88	7.32
Total	4095.90	100.00	4095.90	100.00	4095.90	100.00

transformation of sparse vegetation and agricultural land. It is also noteworthy that about one-third of total low density built-up area remained unchanged during the period 1977–2003. As a whole, this area experienced a transition from agro-based rural area to an urbanized area. The spatial pattern of contributors to net change of built-up land shows that vast area under agricultural land was converted into low density built-up land along the western boundary of the city (Fig. 4a). This type of conversion is also evident in south western part, near Gurgaon. Except this, the map also indicates huge conversion of sparse vegetation along the outskirt of the core city.

Spatio-temporal change detection (2003–2014)

The spatio-temporal growth of high and low density built-up areas and conversion of different LULC were analysed through estimating the percentage of each class converted into built-up land (Fig. 3a, b). The study shows that about 15.5% and 20.5% of the total area (including NCT and peri-urban) were under high and low density built-up class. It was estimated from the spatio-temporal change detection study (2003–2014) that more than half of the total high-density built-up area was come up due to conversion of low density built-up area (Fig. 3a). The area under low density built-up land (20.5%) was mainly contributed from the conversion of agricultural land (Fig. 3b), wasteland and sparse and densely vegetated land. It can be observed (Fig. 4b) that a large portion of area in central Delhi (shown by orange patches) has been converted from low density to high density built-up during the period, 2003–2014.

The study also depicts that conversion of agricultural land into low density built-up (shown by yellow patches) was occurred mainly in the south-eastern and eastern part of the periurban area. Apart from this,

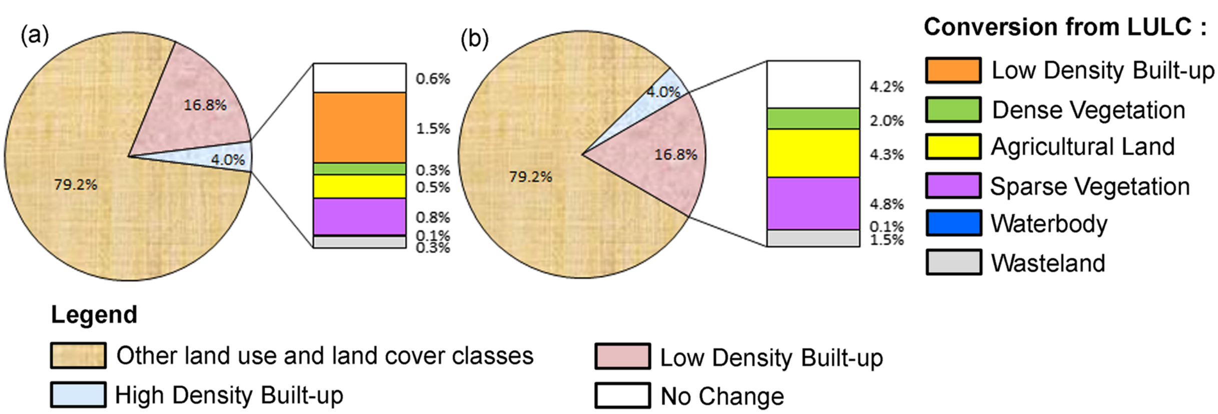


Fig. 2 Proportion of contributors in net increase of high density (**a**) and low density (**b**) built-up areas during 1977–2003

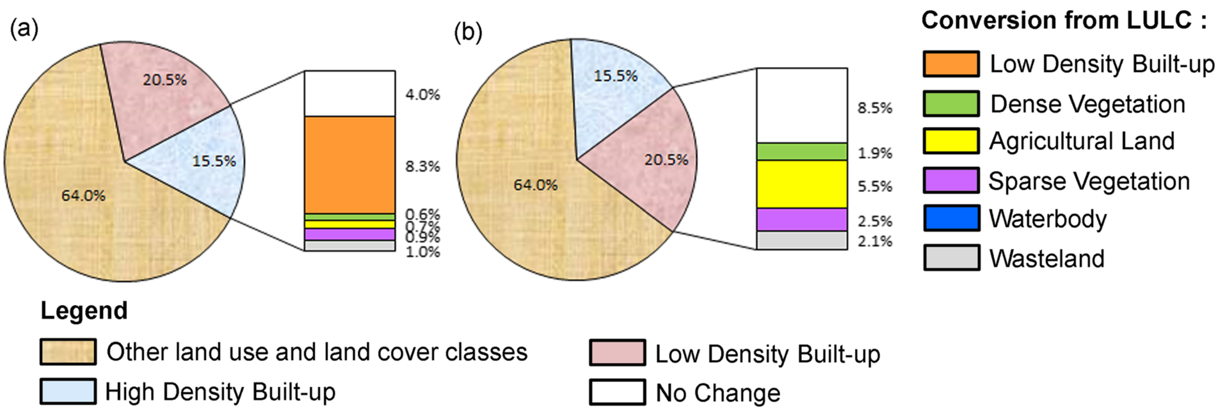


Fig. 3 Proportion of contributors in net increase of high density (**a**) and low density (**b**) built-up areas during 2003–2014

numerous small pockets of low density built-up land evident in the northeastern and northwestern part of periurban area were come up due to conversion of sparsely vegetated areas.

Spatio-temporal change detection (1977–2014)

The change detection analysis for the period as a whole (1977–2014) reveals that growth of high density built-up land was high in Delhi NCT whereas the growth of low density built-up was high in the periurban areas (Fig. 4c). It was estimated that area under high density built-up was increased about 26.79% within Delhi NCT, but it was only 8.19% in the periurban areas (Table 3). The periurban area of NCT experienced a massive growth of low density built-up land (18.56%) as compared to NCT (7.99%). Densely vegetated lands have experienced positive increase in both areas which indicates aforestation and development of parks and city forests in the area. The positive growth in built-up and densely vegetated land was paid by the conversion

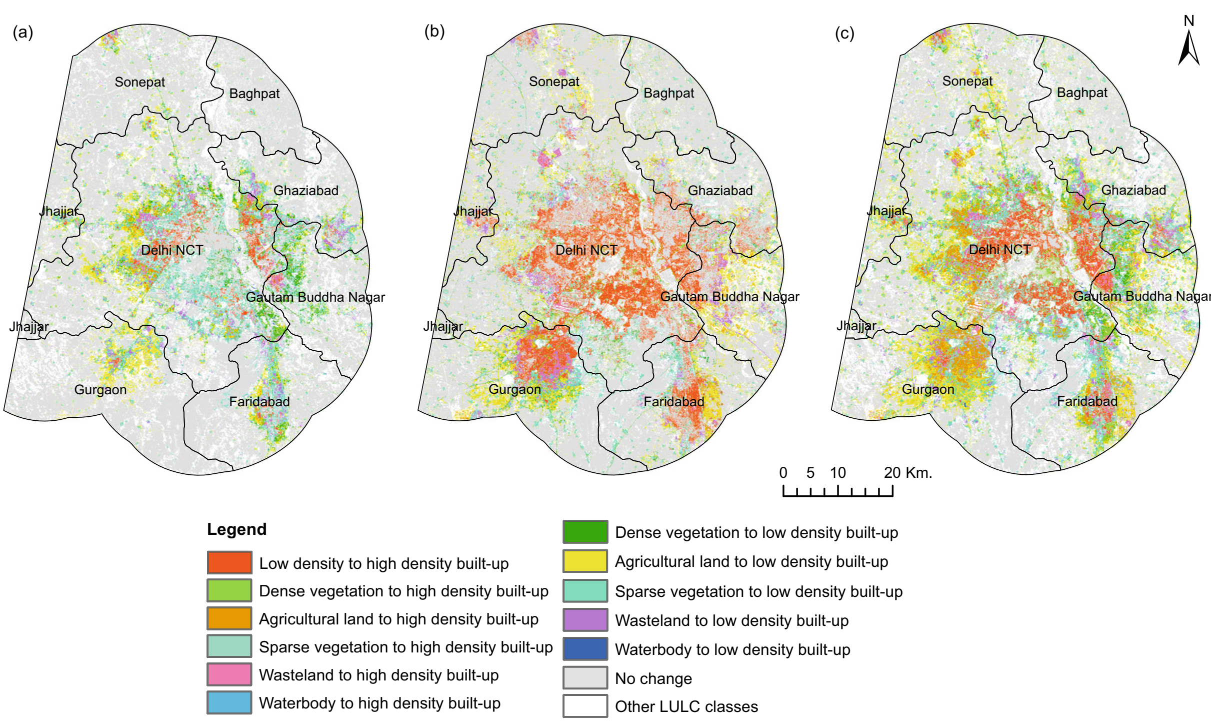


Fig. 4 Spatio-temporal pattern of land transformation during 1977–2003 (**a**), 2003–2014 (**b**) and 1977–2014 (**c**)

Table 3 Change statistics of LULC classes in Delhi NCT and its periurban area

LULC classes	Spatio-temporal change (%)					
	Delhi NCT			Periurban areas		
	1977–2003	2003–2014	1977–2014	1977–2003	2003–2014	1977–2014
High density built-up	7.16	19.63	26.79	1.19	7.01	8.19
Low density built-up	14.5	− 6.51	7.99	9.09	9.47	18.56
Dense vegetation	1.31	1.7	3.01	1.36	− 0.48	0.88
Agricultural land	− 6.81	− 4.46	− 11.27	2.04	− 12.88	− 10.84
Sparse vegetation	− 12.2	− 8.4	− 20.6	− 9.68	− 3.8	− 13.48
Waterbody	− 0.44	− 0.07	− 0.51	− 0.08	− 0.05	− 0.02
Wasteland	− 3.52	− 1.89	− 5.41	− 3.92	0.68	− 3.29

of areas under agricultural land, sparsely vegetated land, water bodies and wasteland.

It can be observed from the Fig. 5a, b that the proportion of high-density built-up land (15.5%) of the whole study area (2014) was mainly resulted from conversion of lands under sparse vegetation (4.4%), low density built-up (4.2%) and cultivation (3.5%). Only 0.6% of the total area was under high density built-up land which remained unchanged during 1977–2014. It was also found that area under low density built-up land (20.5%) was contributed from the conversion of areas under agriculture (9.3%), sparse vegetation (5.8%) and wasteland (2.5%).

The study depicts that the process of conversion of land within Delhi NCT and its peri-urban areas follows a distinct spatial pattern with three major zones of conversion (Fig. 4a–c). It can be seen that the process of conversion in the central part of the city is mainly confined by transformation of low density built-up land into high density built-up land. It is also noteworthy that the core of city remained unchanged as this area was already developed during 1977. However, some patches like the central ridge forest adjacent to the core city remained unchanged during the last 37 years. Surrounding this area, there is another zone of conversion identifiable in the map which indicates the conversion of sparsely vegetated area into built-up land (Fig. 4c). It was found from the change detection study that these unprotected areas were converted into fully developed built-up land during the last decades. The third zone of conversion depicted in the map by yellow colour denotes conversion of agricultural land into built-up areas. With the increasing pressure of population on land, a city grows vertically and horizontally. The horizontal growth of city takes place by spatio-temporal changes of surrounding areas of core city which involve transformation of LULC features into built-up land. In order to meet the demand for land, the agricultural lands surrounding the existing built-up areas of Delhi were altered for development of housing projects. The transformation of agricultural land is evident extensively in Gurgaon, Faridabad and towards the

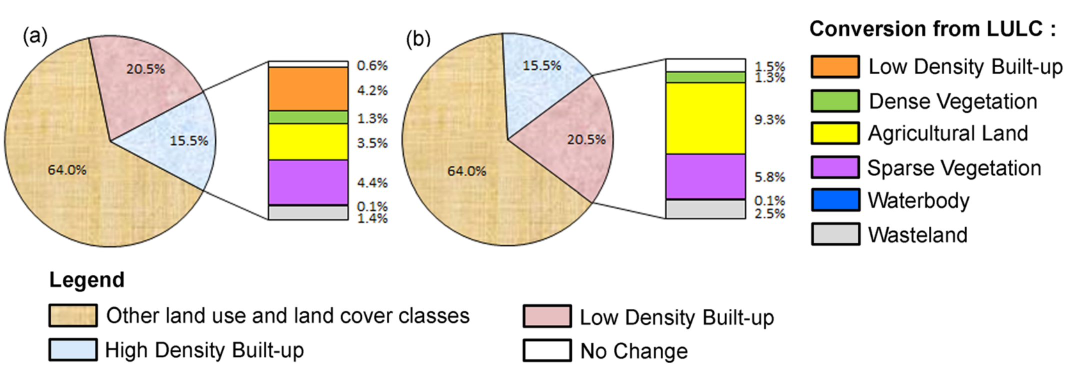


Fig. 5 Proportion of contributors in net increase of high density (a) and low density (b) built-up areas during 1977–2014

western part of the city. It is worthy to mention that the process of LULC conversion over time followed a distinct pattern. The urbanization in Fig. 6 a and b shows the spatial pattern of urbanization in and around Delhi during 1977–2014. It was found that high density built-up areas were mainly confined in the central-eastern part of Delhi NCT along the western part of Yamuna Riverin 1977 (Fig. 6a). Areas of low density built-up land were located surrounding the core city (Fig. 6b). During 1977–2003, these built-up areas expanded towards the outer direction and the areas under agriculture, sparse vegetation and wasteland were altered gradually as a consequence of rapid urbanization.

It can be observed that there was a massive growth of built-up areas in Dwarka and Gurgaon, located in south-western part of the study area. Apart from this, patches of newly developed built-up land can be observed in the eastern part of the periurban area.

Spatio-temporal pattern of MODIS-LST

The LST maps of January show that there has been a significant change in the spatial pattern of temperature from 2003 to 2014 (Fig. 7a). The areas under > 9 °C temperature were mainly confined in the central part of the city in 2003 which has been visibly expanded in 2014. Beside this, the areas under < 5 °C covering mainly the periurban districts have been squeezed in this 11 years time span. The spatio-temporal pattern of temperature of June found coherent with such pattern. The LST map of June 2014 (Fig. 7b) shows increasing temperature in the periurban centres like Gurgaon, Noida and Faridabad. High temperature in the western part (Jhajjar district) does not represent the impervious land. Rather, these areas are agricultural land and high temperature can be explained by seasonal fallow lands present in the month of June. It is noteworthy that areas under relatively high temperature resembles with the pattern of impervious surface of the area. On the other hand, the areas with relatively low temperature mainly represent the vegetated lands. The contrasting temperature in the built-up areas and pervious lands of periurban districts definitely indicates the effect of urban heat island.

Urban growth and associated LULC change have an important role in controlling micro-climate of the study

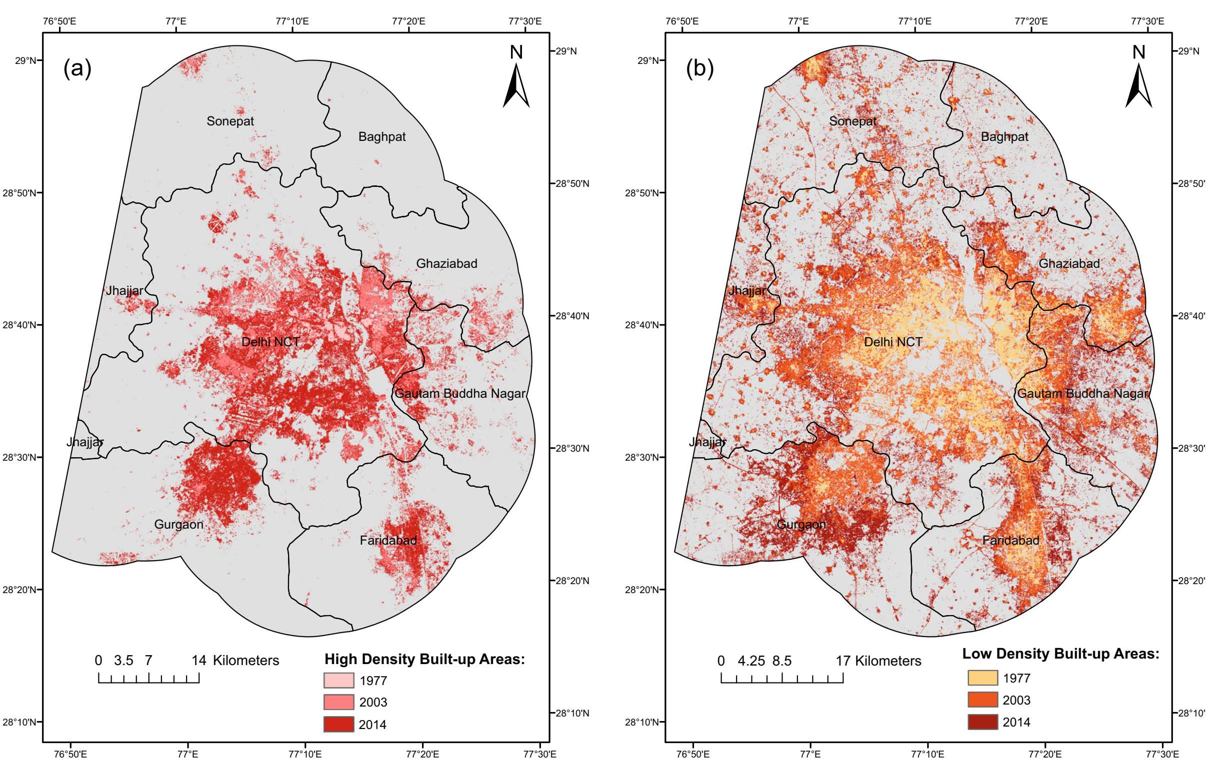


Fig. 6 High density (a) and low density (b) built-up over time (1977–2014)

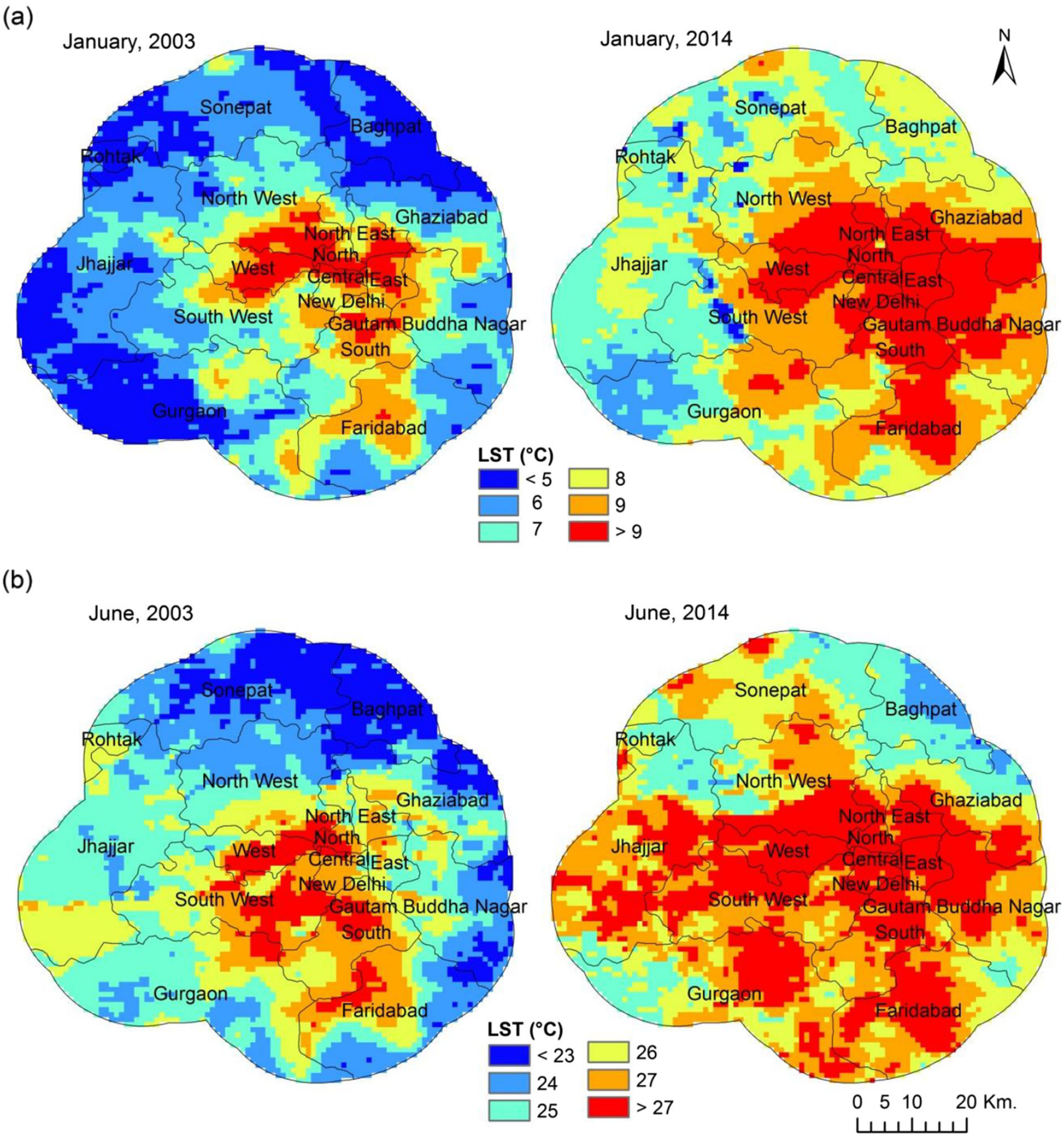


Fig. 7 Spatio-temporal pattern of LST (2003, 2014) in January (**a**) and June (**b**)

area. The increasing summer temperature is actually caused by the increasing built-up surface and industrial growth which exaggerated the green house effect. The combustion of fossil fuels has been increased with the rising population pressure, and it has a major contribution in the increasing amount of green house gases in the area. The increasing temperature in both summer and winter months clearly indicates the UHI effects.

Trend in mean annual temperature (1974–2011)

In order to study the trend of temperature in Delhi NCT, the long-term mean maximum and minimum temperatures of June (Fig. 8a, b) were analysed. Although having several fluctuations in the temporal profile, it reflects an upward rise in both mean minimum and maximum temperature. The ranges of mean maximum

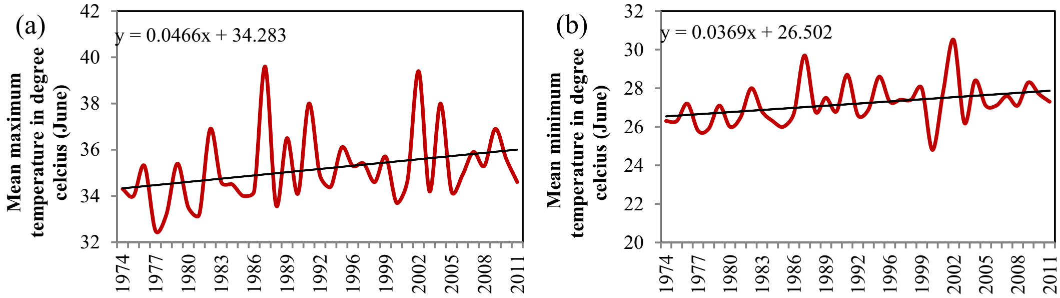


Fig. 8 Mean maximum (**a**) and minimum (**b**) temperatures of June

and minimum temperatures of the month were found 32.5 to 39.6 °C and 24.8 to 30.5 °C respectively. It is worthy to mention that average maximum temperature of June was highest in the years 1987 and 2002 which were drought years with very low rainfall.

Inter-relationship between LST, population density and urban growth

The present study clearly shows that Delhi NCT and its periurban areas experienced rapid urban growth during 2003–2014. The expansion of urban areas was found closely related to the conversion of LULC. The major cause behind such growth attributed to the increasing population density especially in the periurban centres. It was revealed that increasing population in Delhi and NCR is not resulted from natural increase, but there is a significant role of migration in the increasing trend of population that plays a vital role in the expansion of built-up areas. The demand for shelter fuels the growth of residential apartments, individual houses and infrastructure like concrete roads which cumulatively play a

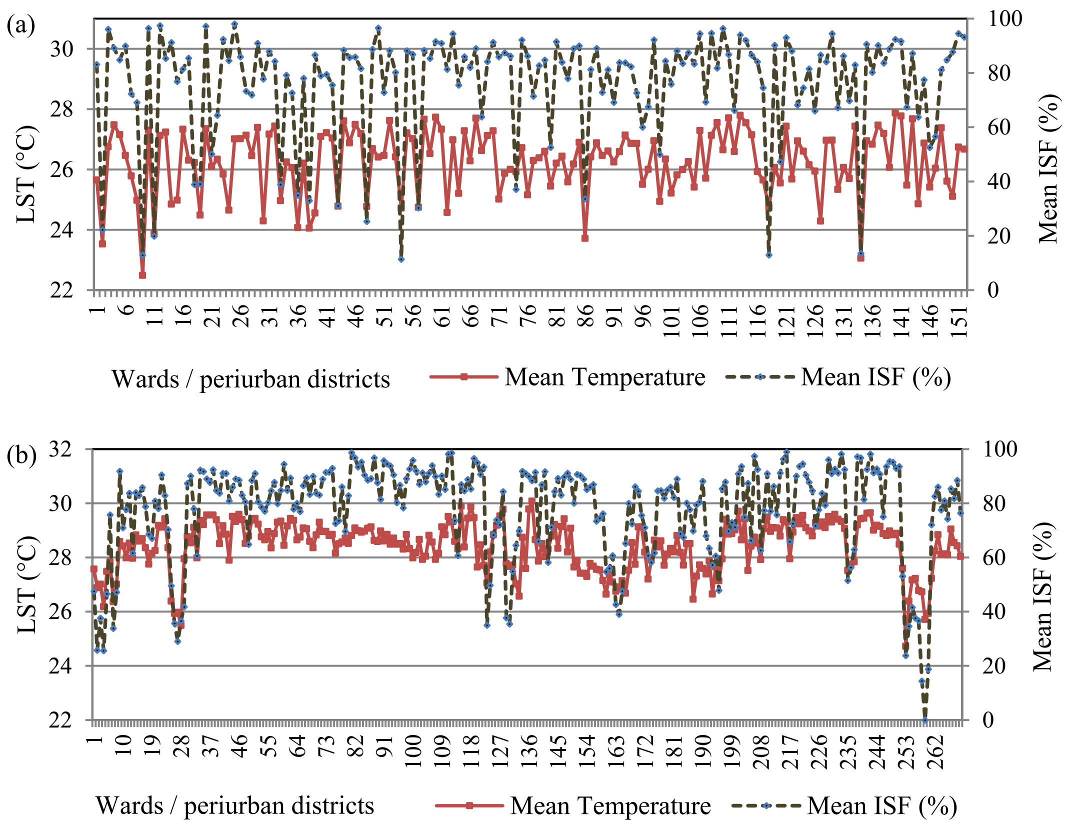
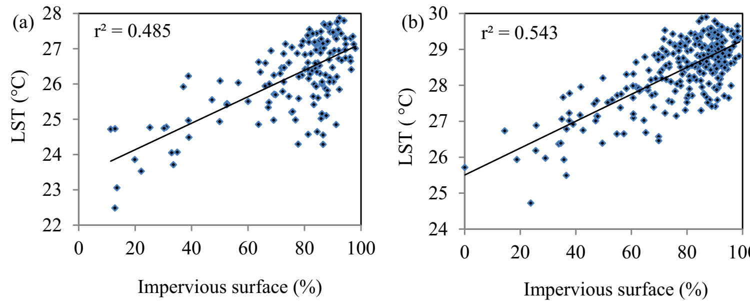


Fig. 9 Comparison between mean LST and ISF observed during 2003 (**a**) and 2014 (**b**)

Fig. 10 Correlation between mean LST and ISF in 2003 (**a**) and 2014 (**b**)



key role in controlling the micro-climate of the whole area.

In order to identify the role of built-up surface on micro-climate, the relationship between ISF and LST was analysed (Fig. 9a, b). The results shows a good agreement between micro-climate and impervious surface of the area. It is worthy to mention that the number of spatial units in 2014 has been increased due to formation of new municipal wards. The pattern of impervious surface percentage shows remarkable increase during the period. In most of the areas, the percentage of ISF was less than 60% in 2003 but it was comparatively higher in 2014. In tune with the changing pattern of ISF, the study reveals that mean LST of June 2003 was relatively lower than 2014 in all spatial units. Mean LST of 2003 was less than 28 °C in all wards/spatial units of the study area. However, there was a significant increase as mean LST of most of the areas were found more than 28 °C in 2014. The correlation coefficient proves a good agreement between them both in the years 2003 and 2014 (Fig. 10a, b). The significant interrelationship between these two variables indicates that

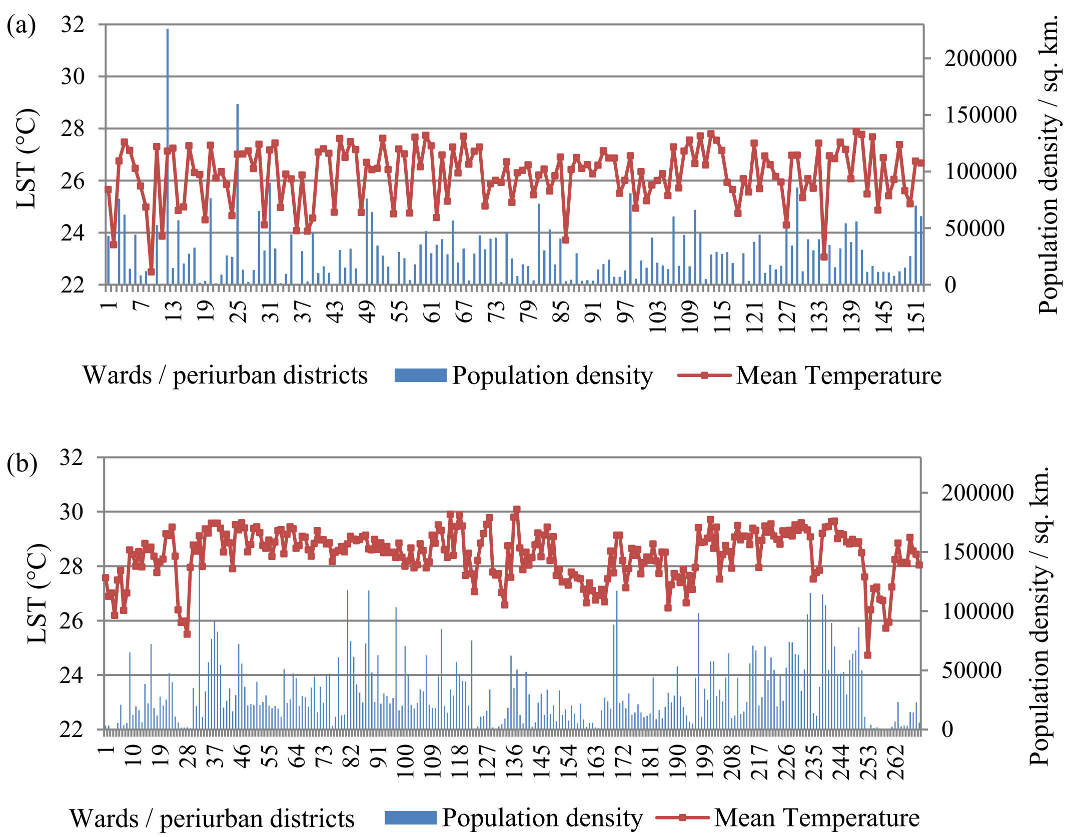


Fig. 11 Comparison between population density and mean temperature in 2003 (**a**) and 2014 (**b**)

with the increasing impervious surface cover of Delhi and surroundings, LST of the area has followed an upward trend.

In order to identify the role of population density in increasing micro-climate, it was compared with mean LST of municipality wards and periurban districts (Fig. 11a, b). The study shows a close association between population density and LST. Actually, population density has an indirect impact on LST. It is noteworthy that areas with high population density are characterized by abundant impervious surface which plays a vital role in controlling micro-climate. Apart from built-up surface, population density is also inter-linked with the number of vehicles that has a significant impact on air quality and temperature. So, the areas with high population density are characterized by high LST and vice-versa. Good agreement of LST with ISF and population density proves the effect of urbanization on its micro-climate. The changing pattern of LULC specifically the increasing impervious lands in Delhi and its periurban centre is causing alteration in durinal temperature and fuelling the heat island effects.

Conclusions

This study deals with the spatio-temporal pattern of LULC dynamics and urban growth through post classification change detection technique. It reveals that the area experienced significant change especially during 2003–2014. The percentage of high density built-up area was increased about five times, from 0.62 to 3.67% during 1977–2003, whereas it took only 11 years (2003–2014) to grow high density built-up area from 3.67 to 15.5%. It was found that high density built-up areas mainly increased in the NCT region through the conversion of low density built-up and agricultural lands. The periurban districts experienced growth in low density built-up area mainly at the cost of agricultural lands. It is noteworthy that inspite of remarkable urban growth in both NCT and its periurban districts, the vegetated areas, i.e. reserve forests, parks and other greeneries, have not been affected much during the period (Rahman et al. 2012; Dutta and Rahman 2017). The accuracy of all LULC maps was in acceptable range (overall accuracy ≥ 0.86 and kappa ≥ 0.84), proving the robustness of support vector machine classifier. The micro-climatic pattern of the area reveals good agreement with the ISF and population density. It is also significant that on an average, the mean LST of the whole area remarkably increased during 2003–2014. This increasing pattern of LST can be explained by the growth of impervious area especially in the periurban areas of Delhi NCT. One of the major fuelling factors behind such large-scale change in the urban landscape of Delhi is rural to urban migration. Although there are many pulling factors of migration present in the urban areas like Delhi, the regional imbalance in economic growth and rural poverty in the neighbouring states acted as a push factor in rural to urban migration. Since the capital city offers a lot of job opportunities, it has been a favourite destination for the unemployed as well as landless people of surrounding districts. The poverty led migration has a chain of consequences like unplanned and scattered growth of settlements, increasing number of slums, overexploitation of land and as a whole decreasing quality of environment.

Acknowledgements The authors would like to thank the Department of Geography, Jamia Millia Islamia University and Department of Remote Sensing and GIS, Vidyasagar University for providing necessary infrastructural facility to carry out the research.

References

Census of India. (2001). Govt. of India, http://censusindia.gov.in/2001. Accessed 12-01-2018.

Census of India. (2011). Govt. of India, http://censusindia.gov.in/2011. Accessed 12-01-2018.

Cetin, M. (2015a). Determining the bioclimatic comfort in Kastamonu City. *Environmental Monitoring and Assessment, 187*(10), 1–10. https://doi.org/10.1007/s10661-015-4861-3.

Cetin, M. (2015b). Evaluation of the sustainable tourism potential of a protected area for landscape planning: a case study of the ancient city of Pompeipolis in Kastamonu. *International Journal of Sustainable Development & World Ecology, 22*(6), 490–495. https://doi.org/10.1080/13504509.2015.1081651.

Cetin, M. (2015c). Using GIS analysis to assess urban green space in terms of accessibility: case study in Kutahya. *International Journal of Sustainable Development & World Ecology, 22*(5), 420–424. https://doi.org/10.1080/13504509.2015.1061066.

Cetin, M. (2015d). Consideration of permeable pavement in landscape architecture. *Journal of Environmental Protection and Ecology, 16*(1), 385–392.

Cetin, M. (2016a). Determination of bioclimatic comfort areas in landscape planning: a case study of Cide Coastline. *Turkish Journal of Agriculture-Food Science and Technology, 4*(9), 800–804. https://doi.org/10.24925/turjaf.v4i9.800-804.872.

Cetin, M. (2016b). Sustainability of urban coastal area management: a case study on Cide. *Journal of Sustainable Forestry, 35*(7), 527–541. https://doi.org/10.1080/10549811.2016.1228072.

Cetin, M., & Sevik, H. (2016a). Evaluating the recreation potential of Ilgaz Mountain National Park in Turkey. *Environmental Monitoring and Assessment, 188*(1), 1–10. https://doi.org/10.1007/s10661-015-5064-7.

Cetin, M., & Sevik, H. (2016b). Assessing potential areas of ecotourism through a case study in Ilgaz Mountain National Park. In L. Butowski (Ed.), *Tourism from empirical research towards practical application* (Vol. 190, pp. 81–110) http://www.intechopen.com/books/tourism-from-empirical-research-towards-practical-application/assessing-potential-areas-of-ecotourism-through-a-case-study-in-ilgaz-mountain-national-park. Accessed 16-06-2019.

Cetin, M., Onac, A. K., Sevik, H., Canturk, U., & Akpinar, H. (2018a). Chronicles and geoheritage of the ancient Roman city of Pompeiopolis: a landscape plan. *Arabian Journal of Geosciences, 11*, 798 https://doi.org/10.1007/s12517-018-4170-6.

Cetin, M., Adiguzel, F., Kaya, O., & Sahap, A. (2018b). Mapping of bioclimatic comfort for potential planning using GIS in Aydin. *Environment, Development and Sustainability, 20*(1), 361–375. https://doi.org/10.1007/s10668-016-9885-5.

Cetin, M., Sevik, H., Canturk, U., & Cakir, C. (2018c). Evaluation of the recreational potential of Kutahya Urban Forest. *Fresenius Environmental Bulletin, 27*(5), 2629–2634.

Cetin, M., Zeren, I., Sevik, H., Cakir, C., & Akpinar, H. (2018d). A study on the determination of the natural park's sustainable tourism potential. *Environmental Monitoring and Assessment, 190*(3), 1–8. https://doi.org/10.1007/s10661-018-6534-5.

Cetin, M., Kalayci Onac, A., Sevik, H., & Sen, B. (2019). Temporal and regional change of some air pollution parameters in Bursa. *Air Quality, Atmosphere & Health, 12*(3), 311–316. https://doi.org/10.1007/s11869-018-00657-6.

Davis, K., & Golden, H. H. (1954). Urbanization and the development of pre-industrial areas. *Economic Development and Cultural Change, 3*(1), 6–26 https://www.jstor.org/stable/1151656. Accessed 12-01-2018.

Douglas, I. (2006). Peri-urban ecosystems and societies transitional zones and contrasting values. In D. McGregor, D. Simon, & D. Thompson (Eds.), *Peri-urban Interface: approaches to sustainable natural and human resource use* (pp. 18–29). London: Earthscan Publications Ltd..

Dutta, D., & Rahman, A. (2017). Assessing pattern of spatio-temporal change in NCT of Delhi and its peri-urban areas using geospatial techniques. In P. Sharma & S. Rajput (Eds.), *Sustainable smart cities in India* (pp. 145–160). Cham: The Urban Book Series. Springer. https://doi.org/10.1007/978-3-319-47145-7_9.

Dutta, D., Rahman, A., & Kundu, A. (2015). Growth of Dehradun city: an application of linear spectral unmixing (LSU) technique using multi-temporal Landsat satellite data sets. *Remote Sensing Applications: Society and Environment, 1*(1), 98–111. https://doi.org/10.1016/j.rsase.2015.07.001.

Gomarasca, M. A., Brivio, P. A., Pagnoni, F., & Galli, A. (1993). One century of land-use changes in the metropolitan-area of Milan (Italy). *International Journal of Remote Sensing, 14*(2), 211–223. https://doi.org/10.1080/01431169308904333.

Grauman, J. V. (1976). Orders of magnitude of the world's urban population in history. *Population Bulletin of the United Nations, 8*, 16–33.

Guo, Q., Kelly, M., & Graham, C. H. (2005). Support vector machines for predicting distribution of Sudden Oak Death in California. *Ecological Modelling, 182*(1), 75–90. https://doi.org/10.1016/j.ecolmodel.2004.07.012.

Haack, B. N., & Rafter, A. (2006). Urban growth analysis and modelling in the Kathmandu valley, Nepal. *Habitat International, 30*(4), 1056–1065. https://doi.org/10.1016/j.habitatint.2005.12.001.

Huang, J., Lu, X., & Sellers, J. (2007). A global comparative analysis of urban form: applying spatial metrics and remote sensing. *Landscape and Urban Planning, 82*(4), 184–197. https://doi.org/10.1016/j.landurbplan.2007.02.010.

IPCC (2007) Inter-governmental Panel on Climate Change. Fourth Assessment Report (AR4), Climate Change 2007: Synthesis Report. *Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. Geneva, Switzerland, pp. 104

IPCC (2013) Inter-governmental Panel on Climate Change, The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. *Cambridge University Press*, Cambridge, United Kingdom and New York, NY, USA, pp. 1535.

Kaya, E., Agca, M., Adiguzel, F., & Cetin, M. (2018). Spatial data analysis with R programming for environment. *Human and Ecological Risk Assessment: An International Journal*. https://doi.org/10.1080/10807039.2018.1470896.

Kundu, A. (2006). Globalization and the emerging urban structure: regional inequality and population mobility, India. *Social Development Report* Oxford, New Delhi.

Lu, D., Li, G., Moran, E., Batistella, M., & Freitas, C. (2011a). Mapping impervious surfaces with the integrated use of Landsat Thematic Mapper and radar data: a case study in an urban–rural landscape in the Brazilian Amazon. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*(6), 798–808. https://doi.org/10.1016/j.isprsjprs.2011.08.004.

Lu, D., Moran, E., & Hetrick, S. (2011b). Detection of impervious surface change with multitemporal Landsat images in an urban-rural frontier. *ISPRS Journal of Photogrammetry and Remote Sensing, 66*(3), 298–306. https://doi.org/10.1016/j.isprsjprs.2010.10.010.

Mountrakis, G., .Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: a review. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001.

Nooni, I. K., Duker, A. A., Van Duren, I., Addae-Wireko, L., & Osei, E. M., Jr. (2014). Support vector machine to map oil palm in a heterogeneous environment. *International Journal of Remote Sensing, 35*(13), 4778–4794. https://doi.org/10.1080/01431161.2014.930201.

Rahman, A., Kumar, S., Fazal, S., & Siddiqui, M. A. (2012). Assessing land use/land cover change in the North-West District of Delhi using remote sensing and GIS techniques.

Journal of the Indian Society of Remote Sensing, 40(4), 689–697. https://doi.org/10.1007/s12524-011-0165-4.

Uhrin, A. V., & Townsend, P. A. (2016). Improved seagrass mapping using linear spectral unmixing of aerial photographs. *Estuarine,Coastal and Shelf Science, 171*(4), 11–22. https://doi.org/10.1016/j.ecss.2016.01.021.

United Nations Human Settlements Programme (UN-HABITAT) (2006). State of the World's Cities 2006/2007.

Yang, X., & Lo, C. P. (2003). Modelling urban growth and landscape changes in the Atlanta metropolitan area. *International Journal of Geographical Information Science, 17*(5), 463–488. https://doi.org/10.1080/13658810310000086965.

Yuan, F., Sawaya, K. E., Loeffelholz, B. C., & Bauer, M. E. (2005). Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multi-temporal Landsat remote sensing. *Remote Sensing of Environment, 98*(2–3), 317–328. https://doi.org/10.1016/j.rse.2005.08.006.

Yucedag, C., Kaya, L. G., & Cetin, M. (2018). Identifying and assessing environmental awareness of hotel and restaurant employees' attitudes in the Amasra District of Bartin. *Environmental Monitoring and Assessment, 190*(2), 1–8. https://doi.org/10.1007/s10661-017-6456-7.

Zhou, W., Huang, G., Troy, A., & Cadenasso, M. L. (2009). Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: a comparison study. *Remote Sensing of Environment, 113*(8), 1769–1777. https://doi.org/10.1016/j.rse.2009.04.007.