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ORIGINAL PAPER

Assessing land surface temperature and land use change through spatio-temporal analysis: a case study of select major cities of India

Bharath H. Aithal[1] · Chandan M C[1] · Nimish G[1]

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Abstract
Globalisation and opening up of markets has seen large-scale unplanned urbanisation in previous decade especially in developing countries like India. Dynamic changing policies influenced by global entities to set up profitable, industry-oriented cities have powered extensive migration with population upwelling contributing to the fast-growing urban expansion that needs monitoring and planning to design urban cities of the future. Research agenda here is to understand the change in land use (LU) temporally and model the land use change based on cellular automata through slope, land use, excluded, urban, transport and hillshade (SLEUTH) approach. Scientific studies carried out to address LU, its linkage with rising surface temperature and prediction of urban growth are limited or conducted only for smaller geographical extents and lack study especially in the most active and diverse country like India. This paper proposes implementation of integrated method of LU, land surface temperature dynamics, and urban modelling for four major cities: Delhi, Mumbai, Kolkata and Hyderabad. Of the four cities, Delhi, the capital of India, has shown enormous change in terms of increasing paved surface from 21.63% in 2003 to 31.56% in 2017 with corresponding mean surface temperature surge of 25.93 °C and 36.51 °C, respectively, suggesting one of the worst affected cities. Predicted LU envisions the possibility of a spurt in unplanned growth across the city boundary that would hinder developing basic amenities and would cause increased thermal discomfort amongst residents. This was understood through analysis of land surface temperature in relation to changing land use, indicating a need for sustainable development strategies to be implemented to avoid business-as-usual scenario. The analysis aims to help planners and city managers to understand region-specific issues in urban growth and to improve the cityscape with specific interventions.

Keywords Urban growth model · Sleuth modelling · Pattern analysis · Cellular automata · Surface temperature

Introduction

Climate change initially in the start of the nineteenth century was deliberated imperative for academic knowledge, but from past few decades, it is one of the most researched topic across the globe (Lal 2017). It is now a known fact that climate change is one of the challenging aspects for human survival (United Nations 2018). This has been established well with the fourth assessment report of IPCC (2014) that states the role of human activities in emission of greenhouse gases (GHGs) and their increasing concentration altering the balance of atmospheric processes causing seasonal shifts in terms of climate change. India being one of fastest growing developing countries is vulnerable to climate change due to its large population and its dependence on climate-sensitive sectors such as agrarian, forestry, fisheries and natural resources for their livelihood (Majra and Gur 2009). The country faces various climatic extremes every year affecting several lives due to various allied effects of climate extremes such as heat strokes, flooding, water scarcity, landslides, changing rainfall pattern,

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✉ Bharath H. Aithal
bharath@infra.iitkgp.ac.in

[1] Ranbir and Chitra Gupta School of Infrastructure Design and Management, Indian Institute of Technology Kharagpur, Kharagpur 721302, India

droughts and rise in farmer suicides due to crop failure. Urbanisation has been supplemented by urban land expansion, shortage of housing (Huang and Du 2018) with increased thermal discomfort due to increased temperature, seasonal shifts and altered rainfall patterns. Rapid urbanisation in India can also be attributed to urban migration, reclassification of cities, improved economic opportunities etc. The Indian government has launched various schemes such as Smart Cities Mission, Housing for All (by 2022), Jawaharlal Nehru National Urban Renewal Mission (JNNURM), Atal Mission for Rejuvenation and Urban transformation (AMRUT) and National Heritage City Development and Augmentation Yojana (HRIDAY) (Proptiger 2018) emphasising mainly on sustainable urban development. This established the need to understand the current spatio-temporal land use (LU) pattern of Indian cities and to visualise the change in pattern. Several studies throughout the globe have taken the advantage of geo-informatics in solving issues related to land use and land cover changes and land surface temperature (LST) quantification, its impact on urban environment and their solution individually (Deng et al. 2009; Petrisor et al. 2010; Wu et al. 2013; Rojas et al. 2013). Similar efforts in Indian context are reported by Zhao et al. (2006), Raj and Azeez (2010), Dutta (2012) and Tian et al. (2014). This research article therefore attempts to integrate aforementioned aspects together and aim at providing a more realistic scenario of present land use along with LST and modelling. Thus, the objectives of this study include the following: (1) analysing land use change pattern of four major cities of India, (2) understanding LST as metric to establish the effects of unplanned urban growth and (3) modelling land use dynamics. The paper is organised as sections of literature review, study area, detailed method, results, discussion and conclusion.

Background study

Urbanisation and its impacts on climate

Urbanisation can be referred to as the physical growth of impervious surface with an increased demographic pressure due to migration or amalgamation of peri-urban areas into cities (Ramachandra et al. 2012). Numerous agents of climate change include undue usage of fossil fuels, natural resources, increased agricultural activities and rise in land, water and air pollution. But irrevocable, haphazard and unplanned urbanisation in Indian cities is identified as the major factor that leads to alteration of the natural climate regime (Patra et al. 2018) and indirectly increases the rate of depletion of natural resources creating an unstainable future. Though there are various green energy sources such as geothermal energy, wind energy, hydro-electric power and biofuels that can be used to retaliate the climate change, these being non-conventional sources to date does not help. Rapid influx of population to cities for better standards of living is considered one of the reasons of unplanned growth and it eventually leads to mismanagement of basic amenities and with service sustainability not being met due to failure in maintaining quality of life, providing potable water, increased pollution levels etc. (Alcamo et al. 2005; McDonald et al. 2009, 2011; Seto et al. 2012). Various studies across Indian cities have highlighted aforementioned issues (Sudhira et al. 2004; Bhatta 2009; Taubenbock et al. 2009; Ramachandra et al. 2012, 2015, 2017; Bharath et al. 2018a; Nimish et al. 2018) and have stressed on the need for understanding urban growth patterns with operational, developmental and restorative strategies essentially for ensuring the sustainable development agenda that encompasses directives to ensure cities are inclusive, are resilient and have sufficient natural resources to support the urban ecosystem (Rasul 2016). Unplanned rapid urbanisation not only alters the structure of the landscape but also increases pressure on naturally available resources affecting both humans and the environment. Cities have grown denser and more huddled spreading beyond the boundaries of central core (Chaise 2009; Ramachandra et al. 2016). The expansion of cities into peri-urban areas—a process that is commonly referred to as sprawl—leads to changes in land use patterns in such environments (Owusu 2008). These areas are under a tremendous transformation pressure through physical, social and economic factors relating them in the developing world (Bharath et al. 2018b). Urbanisation can be explained and studied by understanding the land use dynamics.

Land use change and land surface temperature

Land use denotes the human alterations of bio-physical features present on earth's surface for associated economic activities (Cihlar and Jansen 2001). LU changes affect the rate of evaporation, surface albedo, storage of heat and moisture content of the soil, wind turbulence, solar radiation and surface temperature (Pal and Ziaul 2017). Alterations in land use pattern also affect the evapotranspiration rates thereby changing the latent heat and sensible heat patterns (Mojolaoluwa et al. 2018). Also with increasing demographic pressure, construction activities, unmanaged transportation sector and with shortfall of renewable energy generation to satisfy the needs of the population has been affecting human lives through climate variability. This would also in turn escalate concentration of pollutants in the atmosphere in the form of particulate matter (PM10, PM2.5, PM1 and suspended PM) and GHGs such as CO_2, CO, NO_X, SO_X, O_3, CH_4 amongst others, sourcing increment in skin temperature of the earth's surface (Ministry of Statistic and Programme Implementation 2015). As per the fourth assessment report of Intergovernmental Panel for Climate Change, anthropogenic activities have instigated rise in global concentration of atmospheric GHGs (CO_2

concentration increased from 280 to 419 ppm; methane has increased twofold, etc. within past 300 years). India being one of the fastest developing countries is vulnerable to climate change and contributes more than 4% of emissions across the globe (Lok Sabha Secretariat 2013).

LST serves as one of the most important parameters in the land surface processes at local, regional and global levels and can define climate change (Li et al. 2013). It serves as a vital indicator of the energy balance of composition of atmosphere and earth's surface and serves as a key component controlling biogeochemical interactions between surface and atmosphere (Tang et al. 2008). LST plays a dynamic role as a primary indicator in climate change study, vegetation monitoring (healthy or stressed), hydrological modelling, environmental and climate studies for an urban area, ecological study, biogeochemical study and estimation of GHGs (Schmugge and Becker 1991; Running et al. 1994; Khandelwal et al. 2018). Researchers have developed various computation techniques to derive LST through algorithms such as single-window approach, split window approach and radiative transfer equation from the radiance obtained from remotely present sensors which have a strong spatio-temporal variations with a large spectral variation (Labed and Stoll 1991; Salisbury and D'Aria 1994; Qin et al. 2001). Single-window method estimates the surface temperature using only one thermal band while split window takes into account two thermal bands and their difference is proportional to atmospheric attenuation. This study incorporates single-window algorithm that is easy yet an efficient method for estimation of LST and also is most suitable in this case as this study involves temporal analysis, and availability of multiple thermal bands was a constraint before the launch of Landsat 8. Understanding these effects with business-as-usual scenario, the study also predicts the land use.

Modelling future urban land expansion

Evaluating the changing land use impacts and understanding the process of complex connected systems involve extensive land use modelling and simulation that require innovative analytical methods and vigorous techniques. Sustainable cities can be developed only in terms of basic amenities that are lacking in current scenario. Analysis based on scenarios of change using various aspects of a city has emerged as an effective tool in attempting to blend social and environmental factors (Raskin et al. 2010) with quantitative modelling. Remote sensing data are useful for modelling urban growth as they provide spatially detailed observations and mapping capabilities at different temporal scales (Potere et al. 2009; Angel et al. 2011). Cellular automata (CA) is one such model having applications in various fields and successfully used in modelling urban growth (Shafizadeh and Helbich 2013; Fu et al. 2018). CA defines the state of a cell based on the previous state of the cells within a neighbourhood, using a set of transition rules. Over the years, CA has been coupled with Markov chain (MC) to define the transition probability of each cell in an image more evidently based on cell interactions. Although CA-Markov gives promising results, it fails to achieve accurate results since the driving forces or multi-agent systems are not accounted in this model (Torrens and Benenson 2005; Spencer 2009). CA model has certain limitations as reported by various researchers such as the following: CA is dependent on quality of data, inability to identify growth in different directions, no calibration procedure is involved in CA as such (Beigzadeh et al. 2013; Eastman 2009). Recognising these research gaps, further then, there has been devolvement of CA-based improved models such as SLEUTH (Clarke and Gaydos 1998; Candau et al. 2000). It is capable to predict urban/non-urban land use dynamics based on two submodels: urban growth model (UGM) and Deltron land model (DLM) (Dietzel and Clarke 2004). SLEUTH uses ancillary layers such as slope, land use, exclusion, urban, transportation and hill shade to improve visualisation of background data with cellular automata as a base to perform the prediction. SLEUTH model considers five factors: diffusion, breed, spread, slope resistance and road gravity (Sakieh et al. 2015). Apart from these factors, it also considers growth rules categorised into four broad types: spontaneous growth, new spreading centre growth, edge growth and road-influenced growth. Overall, the current research across the globe on urbanisation, future urban expansions and its relation with surface temperature have not yet reached consensus. There have been few contradictions as some researchers does not consider urbanisation, a factor for changing surface temperature, while other researchers believe that unplanned urbanisation leads to expansion of cities on the cost of vegetative lands and waterbodies, that in turn damages the natural ecosystem causing increased thermal discomfort (surface temperature).

Study area

Cities were chosen based on population, area, city's contribution to national GDP, infrastructure and social, economic and financial aspects. Literature has suggested potential of a city growing from stages like urban field to metropolitan area and then to conurbation, megacity and finally a megalopolis can be visualised and modelled. Keeping this factor intact, four major urban agglomerations of India, i.e. Delhi, Mumbai, Kolkata and Hyderabad, were chosen for analysis to determine present urban extents and that of future (Fig. 1).

Delhi Delhi officially known as the National Capital Territory is a city and a union territory of India. Delhi as a city has the second largest population, being the eighth biggest

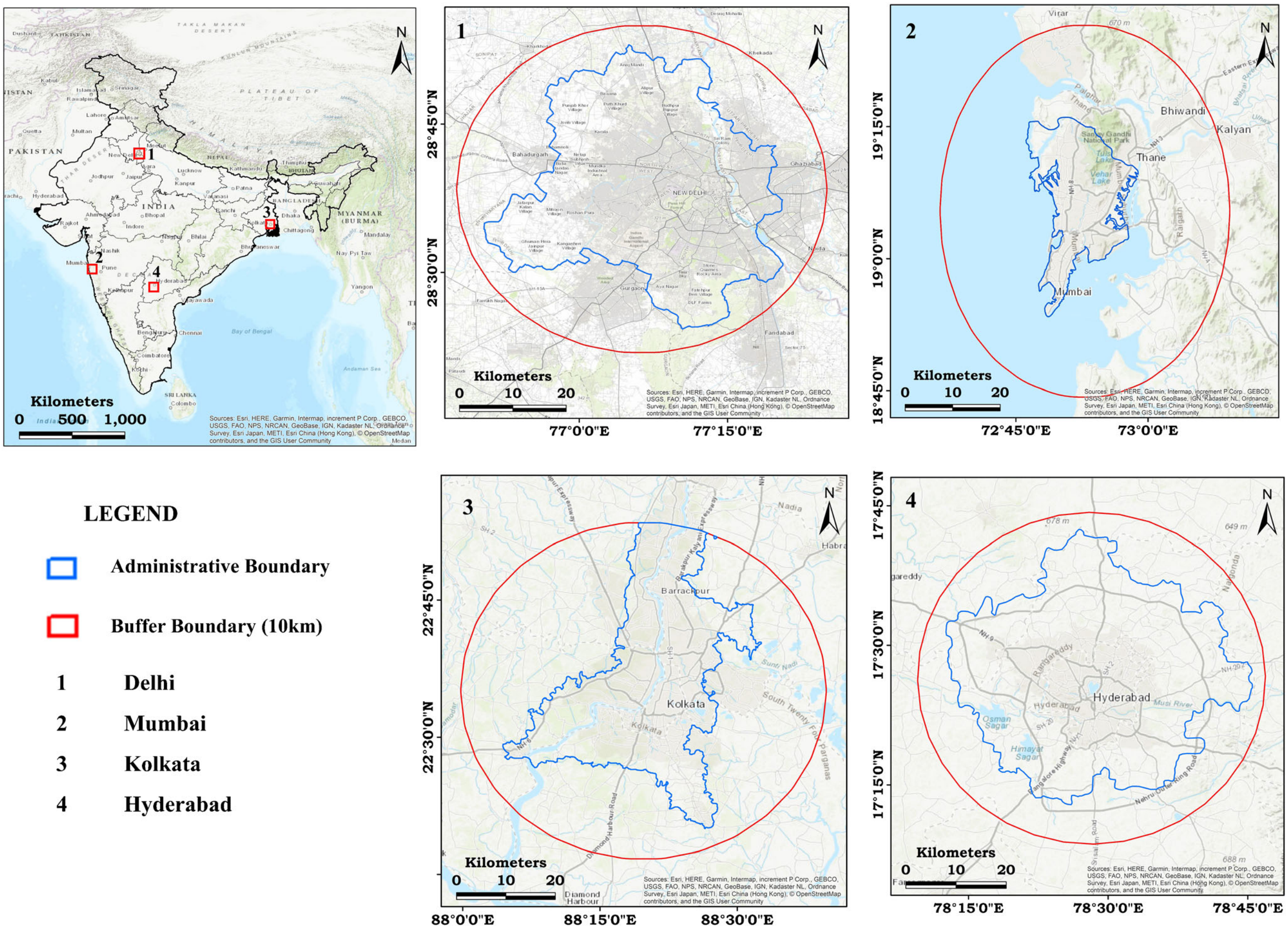


Fig. 1 Location of study sites and its spatial description

conurbation by population and largest metropolitan by area with 16.75 million population in the territory and nearly 22.2 million residents in the national capital urban agglomeration. National Capital Territory (NCT) has a widespread area of 1483 km^2.

Mumbai Previously known as Bombay is the capital city of Maharashtra state. Mumbai is known as the financial capital of India. The population has rapidly increased from approximately 5.9 million in 1971 to more than 12 million in 2011. The availability of basic infrastructure and support from government and local authorities have facilitated the region's economic prosperity and severe land use changes in last two decades. Mumbai Metropolitan Region Development Authority (MMRDA) is responsible for infrastructure development in the region consisting of five districts: Mumbai city, Mumbai suburban, Thane, Palghar and Raigad. Area encompassing MMRDA is 4355 km^2.

Kolkata The gateway city of the eastern region and capital state of West Bengal is the third most populous city in India with a population of 14.11 million in 2011 (Government of India 2011). Kolkata is one of the major commercial and financial hubs of northeastern India. Total area under Kolkata Metropolitan Development Authority (KMDA) is 1886 km^2.

Hyderabad Hyderabad is the joint capital of Telangana and Andhra Pradesh. The city is located along the banks of river Musi while Hyderabad Urban Development Authority (HUDA) was expanded in 2008 to form Hyderabad Metropolitan Development Area (HMDA) covering 7257 km^2 and a population of 7.74 million (2011).

Data acquisition

Temporal data of Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI-TIRS) satellites and digital elevation model (DEM) data were downloaded from the public archive of USGS Earth Explorer. Data collection also involved obtaining ground control points (GCPs) using Global Positioning System (GPS). Bhuvan and Google Earth interfaces were used to demarcate remote and restricted areas where manual GPS data collection was not possible. The raw satellite data was geo-corrected using GCPs by using secondary data along with handheld GPS data. Details of various datasets used and source are listed in Table 1.

Method

Pre-processing

Remote sensing data obtained were georeferenced and data pertaining to study regions were cropped along with 10-km buffer. Contrast stretching was performed wherever necessary to maintain the dynamic range. Satellite data were registered to world geodetic system (WGS) 84, and universal transverse Mercator (UTM) Zone numbers 43 (Delhi and Mumbai), 44 (Hyderabad) and 45 (Kolkata).

Land use analysis

False colour composite was generated using bands green and red and near-infrared bands to understand the heterogeneity of land use classes (Ramachandra et al. 2016). Ground truth data supplemented with data from virtual data observatories such as Google earth were used to train the classifier. Supervised classification was performed using Gaussian maximum likelihood classification algorithm to understand the land use mix and to classify into four broad categories: urban—consisting of all paved surfaces; vegetation—consisting of primary/secondary forest, plantations and trees; water—waterbodies in the form of ponds, lakes, rivers and ocean; others—bare land, barren land, quarry, mining area and agriculture land. Likelihood classifier is considered to be efficient since it evaluates both variance and covariance of training data to classify a pixel under investigation (Lillesand 2015). Accuracy assessment was performed by developing confusion matrix, estimating overall accuracy and kappa coefficient.

Quantification of land surface temperature

- In the acquired remotely sensed data, every pixel has a digital number (DN) value corresponding to the reflectance/emitted values by the features under consideration as acquired by the sensor. For obtaining quantitative information, these values should be converted to spectral radiance and top-of-atmosphere temperature. Presence of atmosphere between the features and sensor leads to distortions that need to be corrected before estimating LST (Giannini et al. 2015). The study incorporates the most common but efficient method for measurement of surface temperature—single-window algorithm that takes a single thermal band ranging from 10.4 to 12.5 μm into account. The steps involved in estimation of LST are as detailed below:
- Calculation of at-satellite brightness temperature: band 6 of Landsat 5 and Landsat 7 and band 10 of Landsat 8 were used to extract the LST. These DN values can be converted into at-satellite brightness temperature in a two-step process (Kayet et al. 2016; USGS 2019).
- Quantification of emissivity: LSE for water, soil and vegetation were considered directly based on various literature, while others were based on comparison with land use data. For example, for pixels with a combination of soil and vegetation, emissivity was calculated using Eq. 1 (Avdan and Jovanovska 2016; Yu et al. 2014).

$$\varepsilon_{SV} = \varepsilon_V P_V + \varepsilon_S (1 - P_V) + C \quad (1)$$

where ε_{SV} = emissivity of (soil + vegetation), ε_S = emissivity of soil, ε_V = emissivity of vegetation and P_V = proportion of vegetation or fractional vegetation cover which can be calculated as shown in Eq. 2 (Avdan and Jovanovska 2016; Yu et al. 2014).

C = term that takes into account cavity effect due to surface roughness (C = 0 for flat surfaces) and is calculated as shown

Table 1 Various dataset used for the analysis and its description

S. no.	Layer name	Source	Description/year/satellite data details
1	Slope and hillshade	Processed from ASTER DEM (raster)	Data taken for the year 2010 for all cities Spatial resolution, 30 m
2	Land use and urban extent	Classified from Landsat series images (raster)	Spatial resolution, 30 m
3	Land surface temperature	Quantified from thermal bands in Landsat series (Landsat 5, 7 and 8)	City: years considered (path/row) Delhi: 2003, 2010 and 2017 (146/40 and 147/40)
4	Transportation (roads)	Street data (OSM, Bhuvan and Google maps) updated with classified images (originally vector, rasterised)	Mumbai: 1992, 1998, 2009 and 2017 (148/47) Kolkata: 1990, 1999, 2009 and 2017 (138/44 and 138/45) Hyderabad: 1989, 1999, 2009 and 2016 (144/48)
5	Excluded map	City development plan (CDP), toposheets and other plans (originally vector, rasterised)	Binary map

in Eq. 3. (Avdan and Jovanovska 2016; Yu et al. 2014).

$$P_V = \left(\frac{\mathrm{NDVI}-\mathrm{NDVI_S}}{\mathrm{NDVI_V}-\mathrm{NDVI_S}}\right)^2 \quad (2)$$

NDVI = NDVI of the pixel under consideration (DN), $\mathrm{NDVI_S}$ = NDVI of soil and $\mathrm{NDVI_V}$ = NDVI of vegetation.

$$C = (1-\varepsilon_S)\varepsilon_V F(1-P_V) \quad (3)$$

F = geometrical factor ranging from 0 to 1 depending on surface geometry (usually F = 0.55).

- Quantification of LST: emissivity values for each class (soil, vegetation and water) were considered along with at-satellite brightness temperature as input and LST was estimated using Eq. 4. (Avdan and Jovanovska 2016).

$$\mathrm{LST} = \frac{T_B}{1+\left(\frac{\lambda T_B}{\rho} X \ln(\varepsilon)\right)} \quad (4)$$

where λ (m) denotes the wavelength at which maximum relative response is observed; $\rho = \frac{hc}{\sigma} = 1.438 \times 10^{-2}$ m·K)where h is Plank's constant = 6.626×10^{-34} J·s; c is the speed of light = 3×10^8 m s^{-1}; σ is Stefan Boltzmann constant = 1.38×10^{-23} J·K

Calculation of coefficient of variation

Coefficient of variation (COV) is a statistical parameter used to understand how distributed the observations are from the mean of a particular category. Intra-class variation of surface temperature was estimated as shown in Eq. 5.

$$\mathrm{COV} = \frac{\sigma}{\mu} \times 100 \quad (5)$$

where COV = coefficient of variation (%), σ = standard deviation and μ = mean.

Modelling urban land use change

CA-based SLEUTH was used as a modelling framework in visualising the urban growth. Layer of exclusion was created by referring to city development plans (CDPs) and existing and proposed land use plans to digitise areas that restrict land use conversion. Layers were compiled, re-classed, cropped, resampled and exported as greyscale 8-bit GIFs in three different resolutions: coarse (120 m), fine (60 m) and full (30 m) for the purpose of three modes of calibration.

- Model test and calibration phase: Datasets were verified for each city using test mode with a single run, before calibration to examine the compatibility of layers and changes to be modified in the scenario file. Random values were assigned to each coefficient such as diffusion, breed spread, road gravity and slope resistance, until the model stabilises with a range of values as dataset. Followed by the test mode, the calibration mode is performed to locate the exact range of possible growth coefficients and therefore achieve the best-fit values. Each growth coefficient can have any value ranging between 0 and 100. The output of this mode provides best-fit coefficient values based on the brute force method. Similarly, the second phase of calibration or fine calibration and third phase or final calibration is conducted to determine the optimum combination suitable for all five coefficients.
- Model prediction phase: Results of the final calibration phase provide the optimum start value for each coefficient. The start values tend to alter during the model run due to self-modification rules incorporated in SLEUTH. After each run, the model returns a total number of 13 metrics to evaluate the goodness of fit. These metrics are a product, compare, population, edges, clusters, cluster size, Lee-Salee, slope, percent urban, *X*-mean, *Y*-mean, the radius of urban distribution and *F*-match. Based on the literature reviewed, five important metrics signifying the model fit measure (Dietzel and Clarke 2007) were used in this study; details are listed in Table 2.

Result

Land use analysis

Temporal land use analysis for Delhi, Mumbai, Kolkata and Hyderabad was assessed for the last three decades and results show rapid increase in built-up area due to increased demographic pressure. Each of the city land use pattern is discussed in the following section.

Delhi and buffer zone Delhi land use pattern shows an extreme increase in urban built-up both in city region and the buffer region as shown in Fig. 2a and tabulated in Table 3. Previous studies by Ramachandra et al. (2015) considered for 1980–2000 show that the built-up area has increased by 325% between 1980 (9.72%) and 2017 (31.56%), whereas vegetation cover has decreased from 38.1 to 5.93% respectively. In the core city, only central ridge reserve forest retains vegetation intact. Urbanisation in Delhi has increased from 0.5% per annum (1980–2003) to 0.72% per annum (2010–2017). Delhi, New Delhi, Shahdara, Dwarka, Gurgaon, Noida and

Table 2 Metrics used for model fit measurement

S. no.	Metric	Description
1	Compare	Modelled population for final year/actual population for final year, or if $P_{\text{modelled}} > P_{\text{actual}}$ {1 − (modelled population for final year/actual population for final year)}
2	Population	Least-squares regression score for modelled urbanisation versus actual urbanisation for the control years
3	Edges	Least-squares regression score for modelled urban edge count versus actual urban edge count for the control years
4	Cluster size	Least-squares regression score for modelled average urban cluster size versus known average urban cluster size for the control years
5	Lee-Salee	A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years

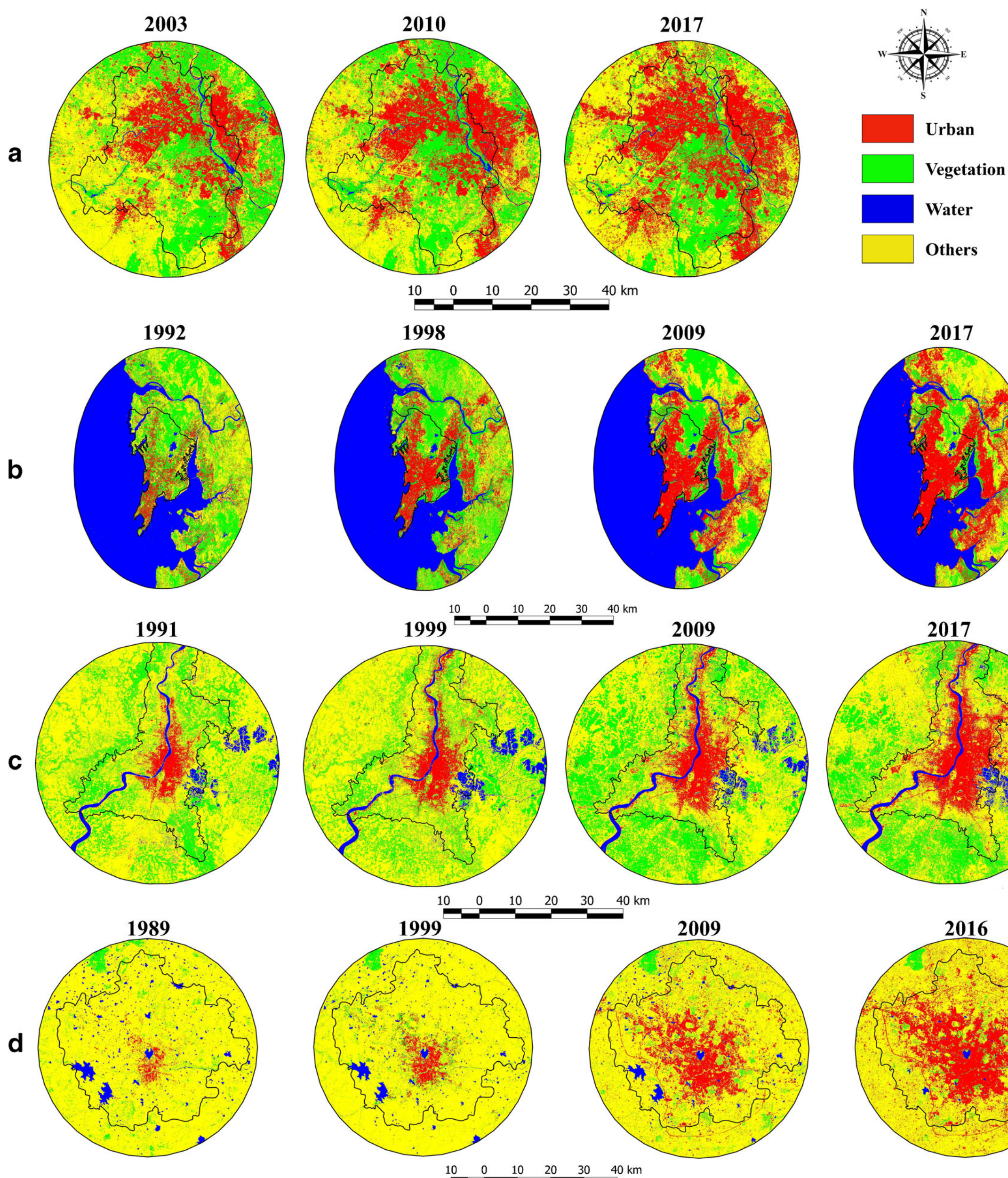


Fig. 2 Land use dynamics of (**a**) Delhi, (**b**) Mumbai, (**c**) Kolkata and (**d**) Hyderabad

Table 3 Land use statistics (in percentage)—Delhi, Mumbai, Kolkata and Hyderabad

City	Delhi				Mumbai			
Year	2003	2010	2017		1992	1998	2009	2017
Urban	21.63	26.52	31.56		7.37	13.80	20.21	24.14
Vegetation	30.15	29.00	5.93		21.92	23.55	15.27	10.02
Water	1.24	1.15	1.12		45.82	44.66	44.52	43.75
Others	46.97	43.32	61.39		24.89	17.99	20.00	22.08
City	Kolkata				Hyderabad			
Year	1991	1999	2009	2017	1989	1999	2009	2016
Urban	4.1	6.5	9.0	12.5	1.75	3.39	14.21	24.18
Vegetation	68.6	67.7	58.0	59.2	4.0	3.53	3.83	2.43
Water	4.2	4.7	4.7	6.2	3.75	2.89	2.46	0.64
Others	23.1	21.2	28.2	22.1	90.5	90.19	79.5	72.76

all connecting highways have exhilarated higher urbanisation. Waterbodies do not show much of a variability across time.

Mumbai indicated a swift increase in urban area between 1992 and 2002 reaching saturation (Fig. 2b, Table 3), whereas Navi Mumbai since its formation showed an increase in urban areas with concentrated growth. On a whole, Mumbai along with a buffer of 10 km showed an increase in built-up which is between 7.3 and 24.1% between 1992 and 2017; meanwhile, vegetation has declined from 21.9 to 10.02%, and the presence of Sanjay Gandhi National Park is one of the factors retaining vegetation cover in the region.

Kolkata exhibited an increase in urban area between 4.1% (1991) and 12.5% (2017). Kolkata City, Howrah, Dumdum and others have experienced concentrated growth (Fig. 2c, Table 3). Vegetation has fairly decreased from 68.6 to 59.2%; a total of 2% increase in waterbodies during the last two and a half decades can be observed due to rise in aquaculture occupation towards eastern and northeastern direction from the city.

Hyderabad exhibited an increase in built-up area by 93% during 1989–1999, 319% (during 1999–2009) and 70% (2009–2016) (Fig. 2d, Table 3) with the emergence of various industrial sectors such as an automobile and hardware manufacturing as well as information technology parks. Waterbodies of Hyderabad show a very critical decrease, indicating either these land uses are converted or they have been dried up. A decline from 3.75 to 0.64% during 1989–2016 highlights the grave situation in the region and the need to restore and rejuvenate waterbodies, which aid as a lifeline of the society. With this knowledge of altering land use pattern, changes in surface temperature were estimated to understand its effect on climate.

Validation of land use maps Land use change was validated using kappa statistics and overall accuracy. The results for all cities show a good accuracy of land use classification with ground truth with overall accuracy in the range of 85–97% and kappa in the range of 0.73–0.94.

Land surface temperature analysis

LST was quantified (for summers—March–May) for the four megacities considering buffer area for three decades as illustrated in Fig. 3a–d. Bright red tone in the map represents region with high temperature and as the tone shifts towards blue, the temperature reduces. Temperature statistics for each city with buffer region was found and is shown in Table 4.

The mean surface temperature of Delhi with buffer region was observed to be 28–32 °C. The minimum and maximum temperature has experienced a rise of 9–11 °C when compared with 2003 levels. Due to significant rise in urban and others category, the mean surface temperatures of both the classes have shown a rise of 11–12 °C. Vegetation has declined/converted from one type to other drastically and has led to increased surface temperature for vegetation class by 11.5 °C. For 2017, maximum surface temperature was observed at Indira Gandhi International airport and minimum was observed for Yamuna River and Okhala bird sanctuary. Coefficient of variation was calculated to find the variation of temperature in various classes due to the change in construction material or land use type within each class. In 2017, the waterbody shows the maximum value of COV illustrating that the presence of shallow ponds and the deep waterbody has variation in temperature. Urban area shows less variation in COV (compared to other classes) signifying majorly the building material in the region is equally reflecting and emitting the energy.

Mean surface temperature of Mumbai region was found to be 28–32 °C. A rise of 4 °C was observed in minimum and maximum temperature from 1992 levels. Urban area in the region has increased by 227.68% since 1992 that can be referred to rise in mean surface temperature of urban class by 2.11 °C. Due to the presence of high density and high-rise buildings along with large slum, highest surface temperature was observed in city centre and Chhatrapati Shivaji International Airport for 2017. Minimum surface temperature was observed in various lakes such as Tulsi lake, Vihar lake and Powai Lake and regions in the vicinity of the sea. The coefficient of variation was calculated to understand the diversity of temperature amongst the individual class and it was observed that in 1992 and 1998, others and vegetation class have a maximum COV. In 2017, the coefficient of variation for urban class shows a value of 8.91 that signifies the materials used for construction have a direct impact on the surface temperature.

Mean LST of Kolkata was observed to be 30–32 °C. The minimum and maximum temperature of the region has increased by 8 °C during the study period. Due to rise in urban

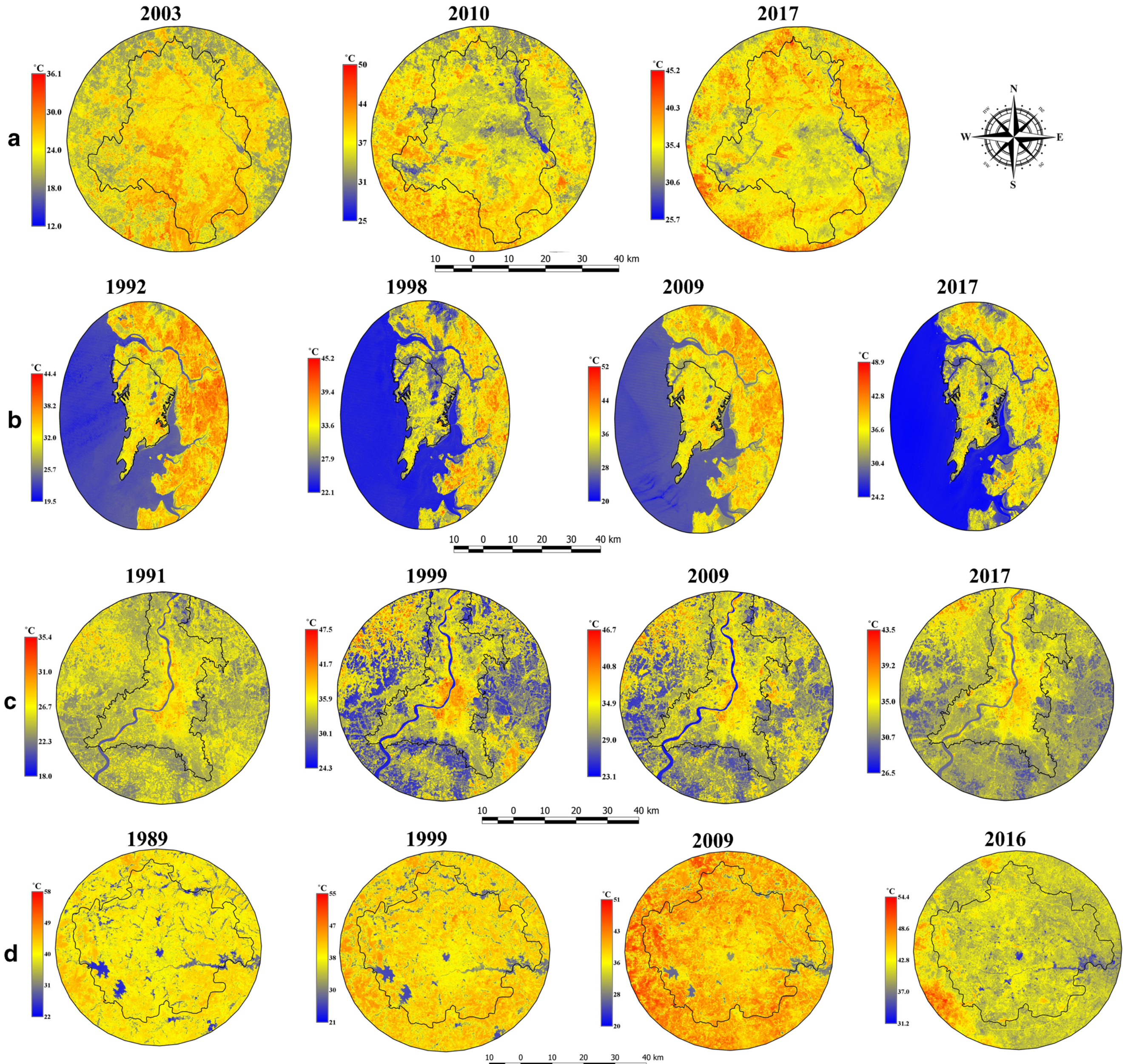


Fig. 3 Temporal land surface temperature of (**s**) Delhi, (**b**) Mumbai, (**c**) Kolkata and (**d**) Hyderabad

area by 205% since 1992, mean surface temperature of urban class has seen a rise from 27.70 to 34.96 °C. As per 2017 LST, maximum temperature was observed at Netaji Subhash Chandra Bose International Airport while minimum was observed for river Hooghly and wetlands. Vegetation in the region shows moderate temperature. Presence of river Hooghly helps to moderate the surface temperature of the regions in its vicinity. COV was estimated for looking at intra-class variability of temperature and it was found that waterbodies have highest value inferring that there is a variation in depth and pollutant concentration in waterbodies. Urban area shows low value indicating not much variation in construction materials used in the city.

Hyderabad region shows a mean surface temperature of 39–41 °C. The lower bound of the temperature has increased from 22 °C (1989) to 31.2 °C (2016) for the city. Hyderabad has experienced the highest change in urban area (1308%) amongst all the other cities considered. The region is dominated by others category and that is the reason for its higher temperature ranges. The region has experienced a tremendous loss/reduction in waterbodies that can be inferred as second factor for rise in the overall temperature. LST for 2017 shows that the highest temperature was observed in few unsown agricultural fields in the southwestern part while minimum temperature was observed for the lakes present in the city. COV was

Table 4 Temperature statistics for (a) Mumbai, (b) Kolkata, (c) Delhi and (d) Hyderabad

Year	Land use class	Temperature (°C)		COV (%)	Year	Temperature (°C)		COV (%)
		Min–max	Mean ± std. dev			Min–max	Mean ± std. dev	
a. Mumbai					b. Kolkata			
1992	Urban	22.17-42.52	33.35 ± 2.21	6.62	1991	18.62-35.38	27.70 ± 1.47	5.31
	Vegetation	22.17-43.68	33.59 ± 2.83	8.43		18.00-31.66	24.31 ± 1.04	4.29
	Water	19.51-40.57	23.39 ± 1.46	6.24		18.00-31.66	22.80 ± 1.59	6.96
	Others	21.73-44.44	34.05 ± 3.31	9.72		18.00-33.74	25.11 ± 1.54	6.12
1998	Urban	23.05-43.68	32.76 ± 2.58	7.86	1999	24.69-47.47	37.31 ± 3.16	8.47
	Vegetation	22.06-45.21	30.52 ± 3.58	11.73		24.69-44.83	31.70 ± 2.72	8.56
	Water	22.61-36.19	23.77 ± 0.6	2.52		24.78-45.21	28.70 ± 2.44	8.5
	Others	22.5-44.83	34.31 ± 2.93	8.53		24.26-46.72	32.49 ± 3.52	10.85
2009	Urban	23.05-51.54	36.84 ± 3.29	8.92	2009	23.49-46.72	35.42 ± 2.50	7.07
	Vegetation	26.49-48.22	34.39 ± 3.22	9.36		24.69-41.35	29.12 ± 1.90	6.52
	Water	20.41-43.68	25.69 ± 1.26	4.89		23.05-44.06	27.86 ± 2.94	10.56
	Others	25.21-50.44	38.76 ± 3.37	8.68		24.35-44.44	32.99 ± 2.55	7.73
2017	Urban	24.67-48.19	35.62 ± 3.1	8.69	2017	27.24-43.49	34.96 ± 1.74	4.96
	Vegetation	26.15-43.26	31.33 ± 2.34	7.48		27.30-40.04	30.06 ± 1.49	4.95
	Water	24.25-38.59	25.3 ± 1.1	4.36		26.49-39.58	29.68 ± 1.81	6.08
	Others	24.63-48.94	36.63 ± 3.26	8.91		26.74-42.12	32.23 ± 1.89	5.85
c. Delhi					d. Hyderabad			
2003	Urban	11.99-36.06	25.93 ± 1.55	5.98	1999	26.06-51.17	38.89 ± 1.80	4.62
	Vegetation	17.07-36.06	23.07 ± 3.01	13.06		22.51-46.72	37.21 ± 3.67	9.86
	Water	15.98-34.62	21.51 ± 2.95	13.72		25.21-47.85	31.28 ± 5.16	16.5
	Others	13.71-34.62	24.32 ± 2.76	11.38		21.18-55.15	39.74 ± 3.34	8.41
2010	Urban	25.21-49.7	36.53 ± 2.05	5.62	2009	19.96-51.17	38.51 ± 2.32	6.03
	Vegetation	24.71-48.96	35.05 ± 3.08	8.81		26.41-48.59	37.99 ± 3.22	8.47
	Water	24.78-49.7	31.63 ± 3.54	11.21		27.77-47.47	32.42 ± 4.99	15.38
	Others	25.97-50.07	38.66 ± 2.64	6.84		26.06-50.81	39.72 ± 3.32	8.35
2017	Urban	26.85-44.71	36.51 ± 1.79	4.92	2016	31.21-54.36	41.17 ± 1.68	4.09
	Vegetation	26.12-45.03	34.5 ± 1.9	5.52		33.24-49.80	39.09 ± 1.66	4.24
	Water	25.69-45.19	31.84 ± 3.03	9.54		32.15-49.99	36.33 ± 2.80	7.72
	Others	27.64-44.81	36.05 ± 2.09	5.8		32.48-52.91	41.05 ± 2.18	5.32

calculated and it gave the temperature variations amongst individual classes. Water throughout the study period provided a high value of COV, indicating a huge heterogeneity in the type of waterbodies in the region. Vegetation shows lower values for COV indicating the presence of similar vegetation type. Buildings with various materials influence the temperature and it can be seen from the COV of urban class, but a lower value amongst all indicates that most of the materials used in buildings have equivalent absorption and emittance capabilities.

Variability of LST with LU

Temperature profile graphs were used as a tool to understand how each class contributes to LST alterations. Transacts were considered for each city for the year 2017/2016 and temperature profile graphs were generated as shown in Fig. 4a–d. The change in LST can be inferred to changes in LULC in the given time period. It was observed that higher temperature pixels represent urban and others category while lower temperature ranges were observed for waterbody and vegetation. It was observed that waterbodies and vegetation in the vicinity act as heat sinks and helps to moderate the microclimate of the region by providing thermal comfort. Liu et al. (2016) performed a similar study for Nanjing Metropolitan Region, China, and observed similar class-wise variation of surface temperature with altering land use. Figure 5 shows the temperature values with transects on land use map for each city.

Modelling urban growth to next decade

Input layers used for the SLEUTH model were in standard grey scale and 8-bit GIF data format. A total of 5, 8, 10 and 100 numbers of Monte Carlo iterations were used for coarse, fine, final and prediction mode respectively for all the cities. Table 5 shows calibration coefficients of SLEUTH model. The values obtained after the final calibration mode were used in the prediction phase. Land use prediction for all the cities was performed for the year 2025, depicted in Fig. 5a–d and as tabulated in Table 6. The figure also shows the visualisation of urban growth trajectory for the year 2025 compared against 2016/2017. While Delhi shows 20.06% of increase in urban growth (least of all four cities) from 2017 to 2025, Mumbai (45.16%) and Kolkata (53.19) showed marginal increase, whereas Hyderabad (113.01%) depicted tremendous change in urban footprint by the year 2025. Further, city level modelling details are discussed below.

Delhi Only diffusion has shown lower values suggesting no chance of dispersive growth at the outskirts of the city limits majorly due to strict restrictions on urban development imposed and considered excluded layer. Topography setting in and around Delhi region is controlled and justified by very high slope resistance value allowing restricted growth outward the metropolitan limits.

Mumbai Majority of the sloped areas within Mumbai region is considered excluded areas, since it consists of national park and reserved forest. Therefore, the calibration results fetched extremely less values for slope, breed and diffusion. These parameters also suggest there is no chance of dispersive outward growth and likelihood of new urban settlements on its own. This statement can be defended by understanding the geographical location of Mumbai as it stands right next to Arabian Sea on to the west and also Thane, Vasal and Panvel creek which gives absolutely no scope for future urban development.

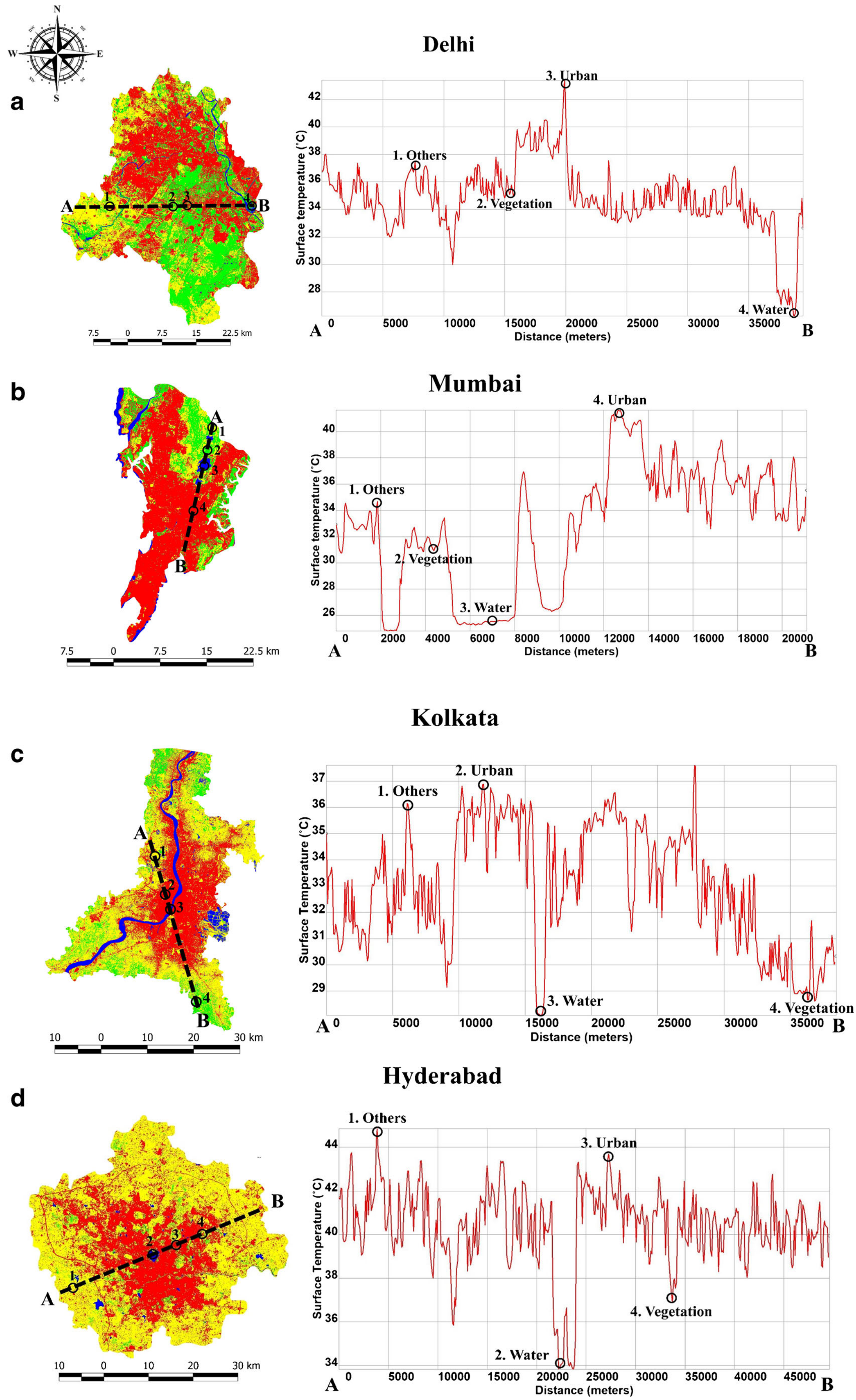
Kolkata Geographically located on Indo-Gangetic plain substantiates the argument and hence the lower slope coefficient of value 8. It is important to notice that the hill shade map and slope map for the region also depicts generally flat terrain throughout. Diffusion and breed parameters also pose less value in all three phases of calibration and therefore prediction has lower overall dispersiveness, comparatively slow outward distribution and lower chances of new urban pocket to be formed. Medium values of road gravity (52) reflect the road as the chief urban attraction factor (major roads for instance Grand trunk road or AH1, AH 45, NH 34 etc.)

Hyderabad Of the five parameters, except spread coefficient, all the other parameters show low- and medium-range values. The spread coefficient with a value of 73 (based on Lee-Salee metric) and 70 (based on average log file) clearly demonstrates the dominance of diffused urban areas from existing built-up region.

Discussion

In this research paper, we employ a novel idea of integrated method to highlight the link between land use change and LST considering four major metropolis of India. We use supervised classification technique to quantify land use for nearly three decades. The technique has proved to be apt for all the four regions considered for analysis since the overall accuracy and kappa ranged from 84 to 99% and 0.73 to 0.96 respectively. The general trend observed for all four cities is that they have experienced rapid urban growth during the period 2000 and 2015. However, trends of urbanisation in megacities like Kolkata, Mumbai and Delhi have reached saturation or threshold in terms of both population and resource availability and urban growth rate seem to be slowing down post 2010, whereas newer urban agglomerations in India, for instance, Ahmedabad, Hyderabad and Pune, are picking up the pace of urban expansion. Transition has already begun in major cities and tier II cities from traditional model of industrial development with new spatial forms of urban growth interspersed and juxtaposed (Jain et al. 2011; Ramachandra et al. 2012). As in the case of Delhi and Mumbai, development would go overboard the city and spread into extensively the rural neighbourhood creating a natural imbalance. Being one of the biggest and oldest city in Eastern India, Kolkata as major metropolis is yet now very intensive due to the different approach of agglomeration and city growth. Kolkata would be a classic example of city development but not on urban agglomeration that is being and would face the unplanned urbanisation in the near future as predicted. With information technology and manufacturing sectors, Hyderabad would transform and is predicted to be unstable in terms of urban-rural development with reforms such as special economic zones and other entities promoted by governing agencies.

Furthermore, results of land use insisted vegetation or green cover and waterbodies have been lost dramatically, causing alterations in urban surface temperature. An attempt of adopting supervised land use classification technique and single-window algorithm for LST also confirm that there is a strong correlation between increasing urban structure and temperature rise, being one of the key findings of the study. As demonstrated in the results, the worst affected city amongst the four is Delhi, with an urban cover of 21.63% (2003) and 31.56% (2017) which has led to rise in average mean temperature of 25.93 °C (2003) to 36.51 (2017). Results of LU and LST also sends an alarming signal to authorities to


a
b
c
d
N
E
S
W
Delhi
Mumbai
Kolkata
Hyderabad
A
B
1. Others
2. Vegetation
3. Urban
4. Water
4. Urban
3. Water
2. Urban
3. Water
4. Vegetation
2. Water
3. Urban
4. Vegetation
Surface temperature (°C)
Surface Temperature (°C)
Distance (meters)
7.5 0 7.5 15 22.5 km
10 0 10 20 30 km

◀ **Fig. 4** Temperature profile graphs for (**s**) Delhi, (**b**) Mumbai, (**c**) Kolkata and (**d**) Hyderabad

immediately intervene and taking unbiased decisions towards restricting unplanned or unauthorised growth. The study also focused on capturing dynamic growth in the near future with the aid of SLEUTH. Obtained statistical fit measures are all in acceptable range (Silva and Clarke 2002; Jafarnezhad et al. 2012) and mimics exactly the historical trends of expansion. As argued earlier, Hyderabad, an upcoming megalopolis, has shown 113% increase in urban cover in just over a period of nine years (2016–2025). Researchers, government panellists and scientists have already started to draft policies in the direction of achieving and monitoring sustainable initiatives (VNRR 2017).

LST extracted from the remote sensing data with land use change modelled to the year 2025 have pointed out the implication of extensive unplanned urbanisation and need to mitigate the urban heat islands. These cities in India are important areas due to its geographical, political and economic importance with better transportation networks, but also due to its location; it serves as an advantage for the hub of cities across the region to develop and sustain. With a broad perspective, the factors driving LST is vegetation cover reduction and unplanned unmanaged urban expansion. Our research indicates that visualising and managing the urban growth, planning strategies such as urban parcels with predefined vegetation and amenities for people, is the feasible solution to reduce the effects of heat islands, thus improving the quality of life through environmental quality and enhancing the urban systems' functioning with reduction in effects on humans. Thus, this communication successfully demonstrates the role of geoinformatics in assessing and quantifying LU, LST, and future growth poles, its effects on urban environment and its need to attain sustainable development goals in Indian perspective, as

Table 5 Summary of calibration results and fit statistics

Value based on Lee-Salee (for prediction mode)				
Parameters/ cities	Delhi	Mumbai	Kolkata	Hyderabad
Diffusion	1	1	1	1
Breed	50	1	1	10
Spread	75	40	27	73
Slope	100	1	8	16
Road gravity	35	94	52	25
Model fit measures (final calibration mode)				
Compare	0.580	0.846	0.657	0.631
Population	0.993	0.999	0.999	0.999
Edges	0.990	0.997	0.909	0.999
Cluster size	0.848	0.999	0.582	0.790
Lee-Salee	0.446	0.530	0.520	0.355

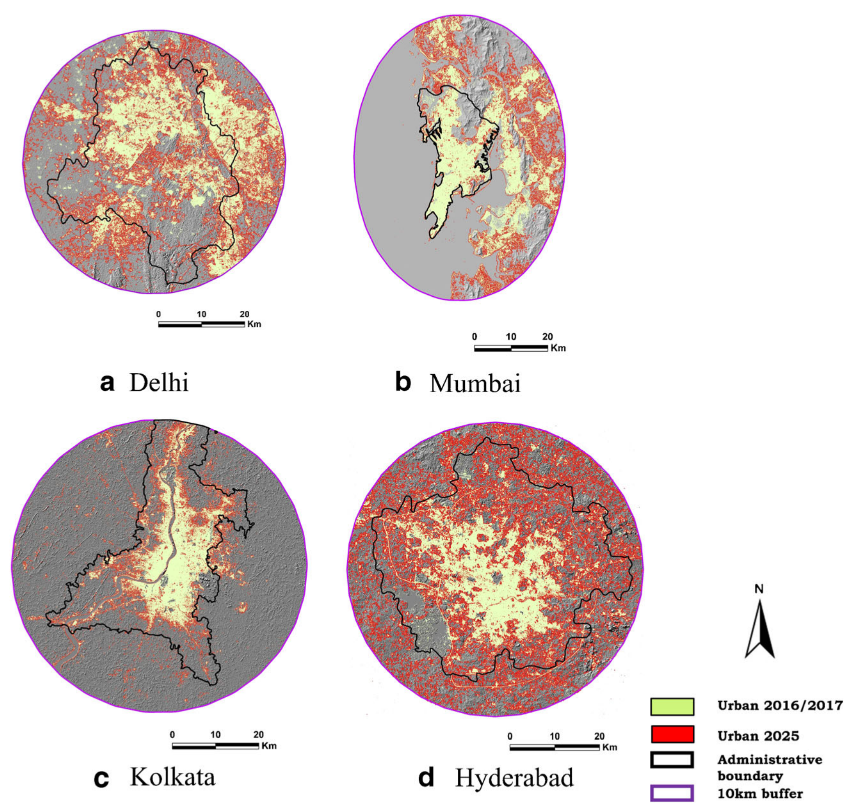


Fig. 5 (**a**–**d**) Modelled urban growth using SLEUTH for the year 2025

Table 6 Predicted urban land use statistics

	Year	% urban cover	Urban area in km^2	Percent increase
Delhi	2017	44.35	1297.51	20.06
	2025	53.24	1557.80	
Hyderabad	2016	24.63	840.93	113.01
	2025	52.46	1791.29	
Kolkata	2017	13.60	494.73	53.19
	2025	20.83	757.91	
Mumbai	2017	24.12	861.99	45.16
	2025	35.01	1251.34	

it has been successfully practiced by scholars around the world (Almeida et al. 2018; Koch and Krellenberg 2018; Jaeger et al. 2019)

Findings to global connections through the case study

This paper employs data derived from various sensors of Landsat series of satellite to extract the pattern of land use and to derive land surface temperature in order to understand the spatio-temporal relation that exists between land use change and LST. With cases of 4 cities, we found that the impervious built-up has higher temperature than that of regions that have thick tree cover or waterbodies in general. Therefore, urban expansion exacerbates the effects of urban heat island. Urban growth and land surface temperature change is highly variable in both time and space. It is described that on an average, the urban area temperatures may be 1–3 °C warmer under meteorological conditions and can go up to 10 °C warmer air temperatures than surrounding rural environments (Oke 1973). This global scenario also matches the urban growth and rising temperatures in India as per the finding. This is also attributed by various research on LST analysis for example in Nanjing Metropolitan Region, China, which also describes a similar situation in China and extends that the scenario can be applied to India and other Asian cities due to similar land use pattern change to urban region (Liu et al. 2016). Importantly, the heating of the surface is due to anthropogenic emissions and land use change over the city region that is responsible to heat the air above the ground.

Compared to all studies performed over the Indian region, this study analysed the change over the city and its surrounding to account for change the agents of change and to develop the next set of routines that may be needed for the local planners and the city managers. This method explained here could also be used in other regions of the Earth. In addition to the data that has been used in this analysis, the can be well utilised to improve the theoretical work to establish the daily/monthly data retrieval and analysis for satellite data for real-time data dissemination.

Conclusion

In the past three decades, Indian cities have undergone a dynamic urban transition. The country is emerging as a market-based global hub, encouraged by central and state government through various schemes. However, though there is an impressive rate of urban growth and land use change, the cities have not met the minimum standards of the requirement in terms of availability of basic amenities such as air, water and shelter (Vij and Narain 2016). The cities selected for integrated analysis in this study are facing critical issues of environmental degradation due to extensive irreversible urban growth coupled with resource-intensive unplanned development strategy. Therefore, an attempt has been made to explore the link between historical land use change and its effect on surface temperature. Moreover, the increasing trend of LSTs leads to urban climate complexity and related risks. LST extraction has improved with specific emissivity; however, it makes more sense with data-intensive and specific methods of calibration. Another major observation of this study is urban growth modelling using SLEUTH that could stimulate the growth close to real urban form; it needs further integration of various factors that can simulate the realistic and unplanned growth through drivers influencing change scenarios from business-as-usual trends. However, there is a lack of agent-based models and generalising the urban complexity has to be counter developed that can realistically visualise the urban growth. Based on the model and urban effects, priority has to be more on the development of agent-based models that supports sustainable development for better future. These models aim at modelling different spatial scales and numerous scenarios based on economic, social, policy-based etc., and enhancing the parametric adaptability for various spatial forms helping model and implement sustainable development 2030 agenda in a more realistic sense to achieve goals set by the United Nations. The findings of this research on various climate and environmental variables can be great help in taking mitigation measures against the impact of climate change on Indian cities towards realisation in agenda of goals 11 and 13 in United Nations Sustainable Development Goals to make cities and human settlements inclusive, resilient and sustainable.

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