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ORIGINAL ARTICLE

Assessing Land Use–Land Cover Change and Its Impact on Land Surface Temperature Using LANDSAT Data: A Comparison of Two Urban Areas in India

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Abstract

The purpose of this study is to investigate the spatial and temporal changes in land use and patterns of vegetation and its impacts on land surface temperature (LST) in two Indian cities. Specifically the motivation behind this study is to examine whether a correlation exists between these parameters for the two cities. Indian cities are facing tremendous pressures of rapid urbanization altering the country's land use patterns. This in turn has significantly altered the country's land surface temperature over the years. This study investigates the changes in the land use, land cover and surface temperature in two Indian cities of Surat and Bharuch over a period of 2 decades using Landsat 5 Thematic Mapper and Landsat 8 OLI/TIRS datasets. The study also examines changes in vegetation pattern during this period using a normalized difference vegetation index (NDVI) and investigates the correlation between LST and NDVI. Additionally, the study examines the spatial patterns of LST by mapping the directional profiles of LST. Results of the study reveal that over time both the cities have witnessed a dramatic growth in built-up area, systematic reduction in green space and increase in LST. There is 85% increase in built-up area in Surat in the past 2 decades and 31% increase in built-up area in Bharuch during the same period. At the same time, mean surface temperature in Surat has shown an increase of 2.42 °C per decade while in Bharuch the mean surface temperature has increased by 2.13 °C per decade. Moreover, examination of correlation between LST and NDVI showed a negative relation between the two parameters. Directional profiles showed a continued increase in temperature from 2008 to 2016 from North to South direction Surat indicating an increased urbanization in that direction. Also, new peaks were observed in the profile of Surat for 2008 and 2016 in the north–south direction indicating urban expansion particularly in the southern part of the city. Moreover, substantial growth has taken place in the central part of the city and along the banks of the rivers Tapi and Narmada. This study will be helpful in investigations that address the challenges of urbanization in Surat and Bharuch by assisting local government officials, land management professionals and planners to determine areas where growth must be curbed to avoid further environmental degradation thereby assisting in systematic urban planning practices.

Keywords LULC · LST · NDVI · LANDSAT · India

1 Introduction

Countries all over the world are undergoing rapid urbanization, and urban areas are expanding at a pace never witnessed before, transforming the urban landscape. A recent United Nations report estimates that 55% of the total world population are urban dwellers and projects that by 2050 the urban population will increase to 68% (United Nations 2018). This would mean an additional 2.5 billion urban dwellers by 2050, and the 2018 UN report estimates that 90% of this increase would occur in Asia and Africa. Thus, the problem is more pronounced in developing countries that have witnessed an emergence of large urban agglomerations (UA) coupled with a rapid urban expansion. This process of urbanization has put a massive strain on the built and natural ecosystem and services of urban areas with far reaching demographic and environmental repercussions. Urban areas in the developing world bear the most consequences of the impacts of environmental degradation and unplanned urbanization coupled with global warming and climate

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change. This rapid and unplanned urbanization has posed new challenges for planning and governance of urban areas. Urban planners, policy makers and urban residents are thus compelled to find novel and innovative means to adapt to the changing environment and plan urban settlements (Alankar 2015; Hoelscher and Aijaz 2016). One of the biggest impacts of urbanization is the irreversible loss of greenery and an increase in built-up areas (Scolozzi and Geneletti 2012; Ng et al. 2011; Sharma et al. 2013). This alters the local climate affecting the health of the urban environment.

An important parameter to measure the status of urban health is land surface temperature (LST) (Chaudhuri and Mishra 2016; Govind and Ramesh 2019). LST patterns provide useful information regarding the climate and can hence aid in understanding urban climate (Bendib et al. 2017; Govind and Ramesh 2019). It is influenced by a number of factors, viz. vegetation, soil content, construction material used in roads and buildings, presence of pervious and impervious surfaces, etc. (Weng and Lu 2008; Raynolds et al. 2008). LST is inversely influenced by vegetation and green cover as vegetation can significantly reduce LST in urban environments and make urban areas less vulnerable to impacts of climate change (Dewan and Corner 2013; Rogan et al. 2013; Ali et al. 2017; Guha et al. 2018; Nandkeolyar and Kiran 2018; Zhou et al. 2019). LST is, hence, a good indicator of climate variability and urban expansion (Weng et al. 2004; Huang et al. 2010; Bhattacharya et al. 2010; Farina 2011) since urban expansion comes at the cost of urban green cover (Rogan et al. 2013). Several studies have examined the co-relation between LST and urban expansion (Weng 2001; Weng et al. 2004; Sheng et al. 2015; Chaudhuri and Mishra 2016; Wang et al. 2016; Ali et al. 2017; Nandkeolyar and Kiran 2018; Sahana et al. 2018). For instance, studies by Yuan and Bauer (2007) and Xiong et al. (2012) have demonstrated a positive correlation between LST and dense built-up areas with high population. Others (Yokohari et al. 2001; Yue et al. 2007; Petropoulos et al. 2014) have noted a positive relation between LST and land transformation.

Another important variable used in studying the relation between urbanization and its impacts on climate is land use/land cover changes (LULC). One of the major causes for alteration in LULC is conversion of vegetation and green cover into impervious surfaces fueled by anthropogenic activities (Weng and Lo 2001; Xiao and Weng 2007; Tan et al. 2010). As noted by past studies, LULC changes have the potential to have significant environmental impact altering the urban climate (Owen et al. 1998; Wilson et al. 2003; Sahana et al. 2018). Several studies have demonstrated the environmental impacts of LULC changes (Kalnay and Cai 2003; Hahs et al. 2009; Nagendra et al. 2012; Ahmed et al. 2013; Dewan 2015; Heinl et al. 2015; Chaudhuri and Mishra 2016). A burgeoning body of literature exists where LST has been used to examine the impacts of LULC change (Gallo and Tarpley 1996; Chen et al. 2006; Tan et al. 2010; Liu and Zhang 2011; Xiong et al. 2012; Feizizadeha et al. 2013; Zhang et al. 2013; Adams and Smith 2014; Sahana et al. 2016; Tran et al. 2017). Few studies have also examined the relation between LULC and LST using normalized difference vegetation index (NDVI) (Xiao and Weng 2007; Yue et al. 2007; Zhang et al. 2009; Sun and Chen 2012; Grover and Singh 2015; Nandkeolyar and Kiran 2018; Guha et al. 2018).

Thus, an expansive body of literature (Wilson et al. 2003; Weng et al. 2004; Alam and Rabbani 2007; Dewan and Corner 2013; Rogan et al. 2013; Adams and Smith 2014; Heinl et al. 2015; Almazroui et al. 2017; Tran et al. 2017; Guha et al. 2018; Nandkeolyar and Kiran 2018; Hamoodi et al. 2019; Ullah et al. 2019; Zhou et al. 2019; Yamamoto and Ishikawa 2020) exists that have examined the relationship between LST and LULC and vegetation patterns in western and non-western contexts. For instance, Ullah et al. (2019) have examined LULC patterns and its impacts on LST in the lower Himalayan regions of Pakistan while Zhou et al. (2019)'s investigation of the relationship between LST and physical variables in Washington DC showed that LST is impacted by land cover composition as well as its spatial geometric configuration. In another study, Yamamoto and Ishikawa (2020) explore the relationship between urban space, atmospheric condition and LST in an urban area in Osaka. Their study results showed that LST change was higher in high-density areas rather than in the low-density areas of low buildings, suggesting that higher building density leads to higher LST during daytime. Almazroui et al. (2017) examined the impact of urban growth on temperature variations in Jeddah and their study showed that urban sprawl has a minimal impact on land surface temperature in the city. However, majority of the studies have focused their attention on large urban areas, mega cities and big urban agglomerations. Very few studies have focused on small urban agglomerations, particularly in India to investigate these patterns. This study aims to address this gap by examining the case of Surat and Bharuch cities in the western part of India.

India is going through a massive process of urbanization. One in every three Indian today dwells in an urban area. As per the latest census, for the first time since independence the growth in population was more in urban areas in India than in rural areas (India Census, 2011). As per the 2011 census, urban population in India was approximately 380 million and it is projected that by 2030 the Indian population will grow to over 600 million and to almost 900 million by 2050 (Ahluwalia et al. 2014; Hoelscher and Aijaz 2016). The latest census in India also recorded 475 cities or urban agglomerations (UA) in India. Thus, urban areas/cities are expanding at a rapid pace in India. This process is not limited to mega cities.[1] Infact urban agglomerations such as Surat, Jaipur, Pune, Kanpur etc. have been impacted greatly by this process witnessing a rapid expansion of their urban areas in order to accommodate the tremendous growth in their population. LST and LULC studies based in India have primarily focused on mega cities and large urban agglomerations (Dhorde et al. 2009; Ogawa et al. 2012; Singh et al. 2014; Franco et al. 2015; Grover and Singh 2015; Joshi and Bhatt 2012; Chaudhuri and Mishra 2016; Sahana et al. 2018; Govind and Ramesh 2019). Very few studies have examined LST and LULC patterns for smaller urban agglomerations in India where enormous pressures of urbanization are being felt (Jalan and Sharma 2014; Kotharkar and Surawar 2015; Ali et al. 2017; Nandkeolyar and Kiran 2018). Some of these urban agglomerations such as Surat, Bharuch etc. are growing at a very fast pace and have the potential of transforming into a megacity in a decade or so.

Surat is the ninth largest urban agglomeration in India. With a population of approximately 4.6 million, it is the second largest city in the western state of Gujarat and the eight largest city of India. Surat has witnessed unprecedented growth and expansion in the past decade making it one of the fastest growing cities in the country. Similarly, Bharuch is a rapidly expanding urban agglomeration also located in the state of Gujarat. Both Surat and Bharuch are located in south Gujarat, a region known as the Golden Corridor owing to its large reserves of hydrocarbons and massive industrial agglomerations spread throughout the region. Bharuch is the largest urban agglomeration in the most industrialized area of India surrounded by large chemical, petrochemical, engineering, textile and pharmaceutical industries. The region is regarded as the chemical capital of India. Industrial growth in Bharuch has been further facilitated by Dahej Port operated by Gujarat Maritime Board (GMB). Bharuch has also witnessed unparalleled growth in the past decade fueled by industrial development in the region. In light of this, we examine the case of Surat and Bharuch cities to understand the changes in the spatial characteristics of the city's urban landscape and if and how those changes have influenced the land surface temperature in both the cities.

The main goal of this study is to compute the changes in land use patterns and land surface temperature in Surat and Bharuch over a period of 2 decades. To address this objective, multi-temporal satellite images were used to,

(1) assess urban change by calculating LULC for 1998, 2008 and 2016
(2) examine vegetation change by calculating Normalized Difference Vegetation Index (NDVI) from 1998 to 2016
(3) calculate Land Surface Temperature (LST) and asses the correlation between LST and NDVI for 1998, 2008 to 2016
(4) examine the spatial patterns of LST by mapping the directional profiles of LST from 1998 to 2016

LULC and LST calculations were further validated to establish the accuracy of their assessments from the calculations.

The study presented in this paper is part of a larger study that will examine the impacts of LULC and changing vegetation patterns on LST of several other small urban agglomerations in different parts of India to conduct a comparative analysis.

2 Study Area

Surat and Bharuch cities are located in the Indian state of Gujarat, one of the fastest urbanizing states in India. More specifically both the cities are located in south Gujarat, part of the Delhi–Mumbai industrial corridor and the region is referred as the Golden Corridor of India. Surat and Bharuch are the largest urban agglomerations in south Gujarat. The region along Surat and Bharuch is home to several chemical, petrochemical, textiles and pharmaceutical industrial conglomerates.

Surat, a port city is the eighth largest city and the ninth biggest urban agglomeration in India. It is the second largest city in the state of Gujarat and is the commercial and economic capital of the state and also one of the most prosperous cities of India. The city has witnessed unprecedented growth in recent years and is considered to be one of the fastest growing cities in the world. The primary economic base of this city is textiles and diamond industries which has given Surat the title of Diamond City of India. In recent times, the city has also witnessed an emergence of information and communication technology (ICT)-based industries. Surat is at the forefront as the pioneering city in the Indian government's push toward the use of ICTs for urban governance (Mukherjee 2018). Surat was one of the twenty cities that were selected to be developed as a smart city under the Smart Cities Mission of the Indian Government. The present study focuses on Surat inner city (Fig. 1) covering approximately 309.12 km2 area.

Bharuch, another port city, is one of the biggest industrial areas in India and is also referred to as the chemical capital of India. The region surrounding Bharuch is rich with hydrocarbon reserves with the largest land-based petroleum reserve in India. This has led to a number of engineering, chemical, petrochemical, textile and pharmaceutical

[1] A megacity is defined by the United Nations as a city which has a population of 10 million or more people. Accordingly, India has three megacities, 40 cities with over a million population and 396 cities with a population between 100,000 and 1 million.

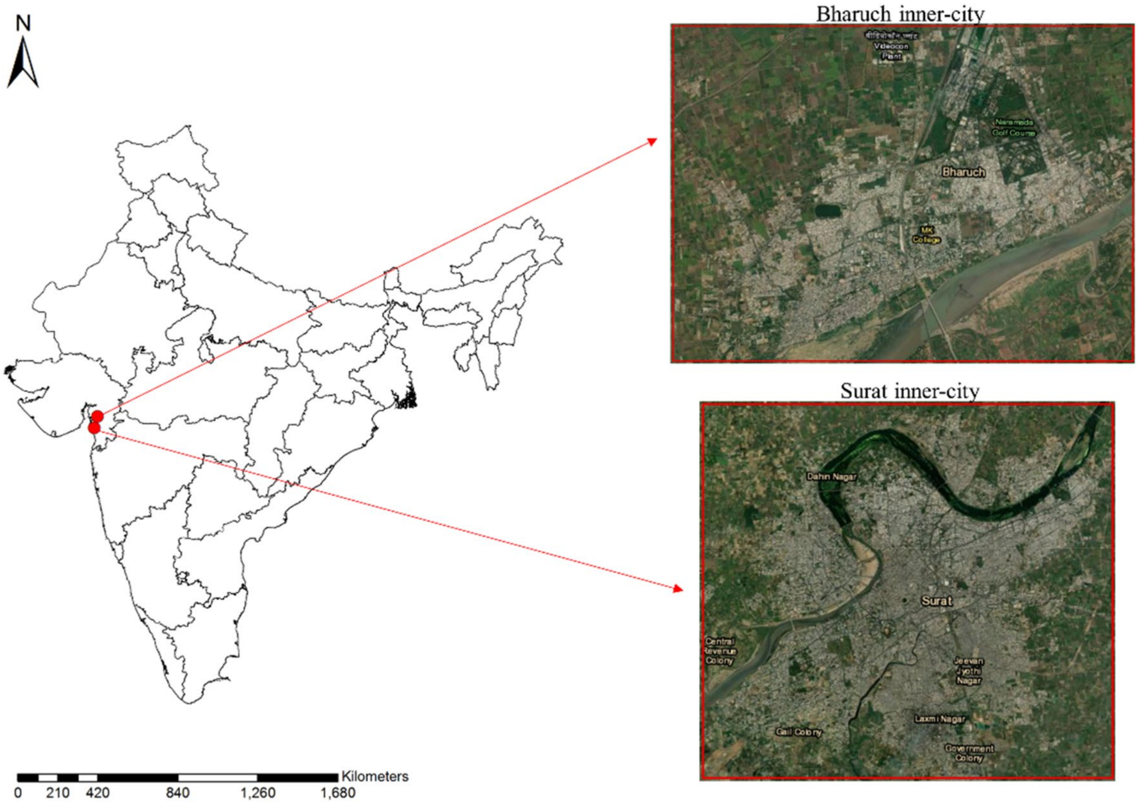

Fig. 1 Study area

industries in the areas surrounding Bharuch. Bharuch is the largest urban area in this industrialized region. Moreover, the city is also home to many metallurgical and port-based industries and houses the only liquid bulk port and chemical terminal in India. Bharuch is one of the major cities along the Delhi–Mumbai industrial corridor.

3 Data and Methods

3.1 Data

In this study, Landsat 5 TM (1998 and 2008) and Landsat 8 OLI/TIRS (2016) satellite images for Surat inner city and Bharuch city were used. Details regarding the data used and methodology are shown in Table 1 and Fig. 2, respectively.

3.2 Method for Land Use/Land Cover Classification

A variety of methods are used for image classification (Lu and Weng 2007; Abdullah et al. 2019). These methods can be divided into four categories; supervised and unsupervised classification, fuzzy classification, parametric and non-parametric classification and per-pixel and sub-pixel classification methods (Jensen 2016; Abdullah et al. 2019). Traditionally, classification methods have used ISODATA, K-means, minimum distance and maximum likelihood (Tso and Mather 2001; Jensen 2016) algorithms. Recent studies have utilized advanced classification algorithms such as artificial neural networks (ANN), Support Vector Machines (SVM), Random Forest (RF) and Classification and Regression Trees (CART) (Mountrakis et al. 2011; Adam et al. 2014; Belgiu and Dragut 2016; Rahman et al. 2017; Abdullah et al. 2019). In this study, unsupervised classification using ISODATA clustering method was used. Future studies will examine LULC for the two study areas discussed in this paper using advanced classification algorithms recommended by the above studies.

Unsupervised classification method does not require prior knowledge of the study area's landscape. Hence, human errors are minimized. The method produces classes based on spectral information and are hence not as subjective as visual

Table 1 Details of Landsat data used in the study

Date of acquisition	Satellite	Sensor	Source
26 November, 1998	Landsat 5	TM	USGS Earth Explorer
20 October, 2008	Landsat 5	TM	USGS Earth Explorer
26 October, 2016	Landsat 8	OLI/TIRS	USGS Earth Explorer

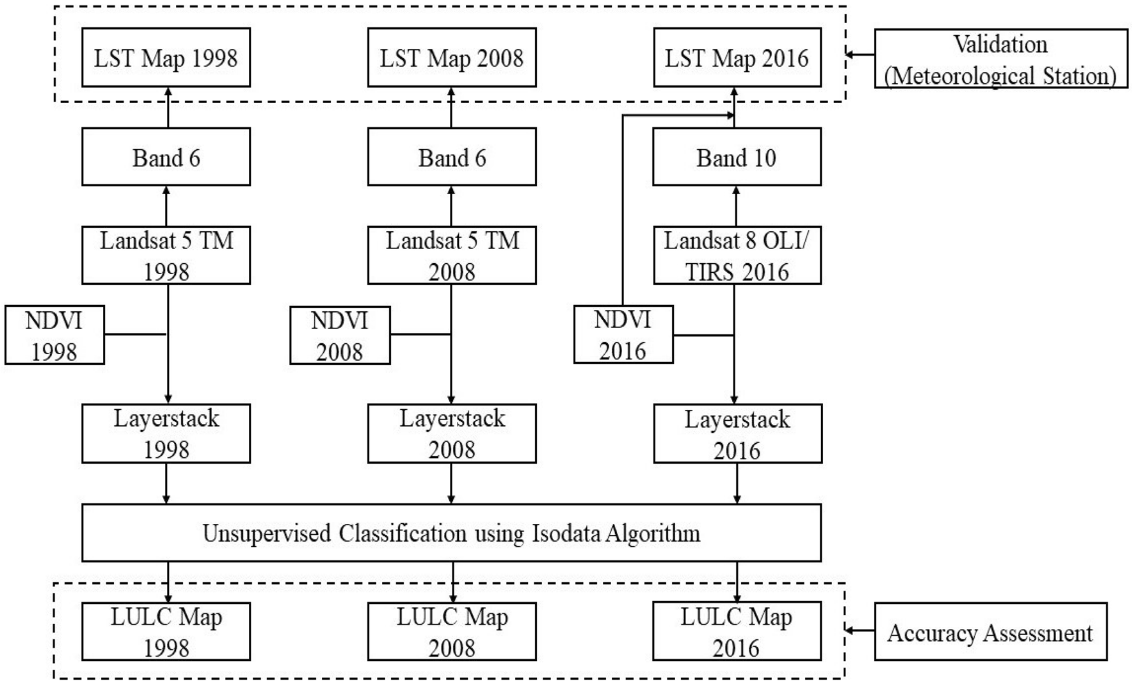

Fig. 2 Methodology

interpretation. Unsupervised classification works well for uncomplicated, broad land cover classes such as water, vegetation, built-up area (Tso and Mather 2001; Jensen 2016). Both the urban areas that were examined in this paper do not have a very complicated terrain with normal land cover species. The main focus of this paper was to examine broad land cover classes in the two urban areas and how those classes have changed over 2 decades. Therefore, unsupervised classification was utilized in this study.

Additionally, this study is part of a larger examination that will evaluate the impacts of LULC and vegetation patterns on LST for several small urban agglomerations in different parts of India for the purpose of comparative analysis. The present study first started with unsupervised classification in order to establish that LULC patterns are changing at an alarming rate for small urban agglomerations in India. Ultimately, the long-term goal is to utilize one or more of the advanced classification algorithms discussed in recent studies (Abdullah et al. 2019) to examine LULC patterns of the study areas in future investigations.

A thematic raster layer using ISODATA algorithm was generated in ArcGIS. Four land cover classes were identified using the unsupervised classification method that included water, vegetation, built-up and bare soil.

3.3 Method for NDVI Extraction from Landsat Data

NDVI is widely utilized in studies examining presence of green cover and status and health of vegetation. The index is used based on the rationale that vegetation reacts to the absorption and reflection of red and near-infrared lights. NDVI values range from − 1 to 1. A value of zero indicates the presence of urban areas while a negative value is an indication of a water body. A positive value closer to one indicates the presence of green cover (Sahana et al. 2016; Tan et al. 2010; Babalola and Akinsanola 2016). NDVI is calculated using the following formula,

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})} \quad (1)$$

Red and NIR represents spectral reflectance measurements in the red and near-infrared bands, respectively.

3.4 Method for Extracting LST from Thermal Band of Landsat Data

Spectral radiance method (Sahana et al. 2016) was used to recover surface temperature from the Landsat data. For 1998 and 2008 band 6 of Landsat 5TM was utilized whereas for 2016 band 10 of Landsat 8 TIRS was used.

Spectral radiance was retrieved from Landsat TM 5 image by using the following formula

$$L = M_{\mathrm{L}} * Q_{\mathrm{cal}} + \mathrm{AL} \quad (2)$$

Here L represents spectral radiance, M_{L} is band-specific multiplicative rescaling factor, AL is band-specific additive rescaling factor, Q_{cal} is thermal band.

After the extraction process, the retrieved spectral radiance was converted to surface temperature using the following formula

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L} + 1\right)} - 273.15 \tag{3}$$

Here T_B is surface temperature, K_1 and K_2 are thermal conversion constants.

In order to convert the temperature units to Celsius, absolute zero (approx. -273.15) is added to the above formula (Xu and Chen 2004).

In order to retrieve surface temperature from band 10 of the Landsat 8 TIRS data, values from the above two equations, vegetation fraction and land surface emissivity were used. Vegetation fraction F_V was computed using the following formula (Carlson and Ripley 1997):

$$F_v = \frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}}^{2} \tag{4}$$

Here $\text{NDVI}_{\min}$ represents minimum NDVI value indicating the presence of bare soil and $\text{NDVI}_{\max}$ is maximum NDVI value indicating the presence of healthy vegetation (Guha et al. 2018).

Emissivity ε was calculated using the formula

$$\varepsilon = 0.004 * F_v + 0.986 \tag{5}$$

Finally, Land Surface Temperature (LST) was calculated using the following equation (Weng et al. 2004; Guha et al. 2018).

$$\text{LST} = \frac{T_B}{1 + \left(\frac{\lambda \sigma T_B}{hc}\right) \ln \varepsilon} \tag{6}$$

Here h is Plank's constant ($6.626 \times 10-34$ Js), c is the velocity of light in vacuum ($2.998 \times 10-8$ m/s), λ is effective wavelength (10.9 mm for band 10 in Landsat 8 data), σ is Boltzmann constant ($1.38 \times 10-23$ J/K).

3.5 Correlation Analysis

After computing NDVI and LST, zonal statistics was calculated for each LULC class to summarize NDVI and LST values. Regression analysis was employed to compute the correlation between LST and NDVI.

4 Accuracy Assessment

4.1 Accuracy Assessment of Land Use Classification

After calculating the above values, accuracy assessment was conducted to determine how close the computed values are to the true values on ground.

To assess the accuracy of the classified image a confusion matrix (Table 2) was generated. This matrix provides values for overall accuracy, producer's accuracy, user's accuracy, omission error, commission error and Kappa coefficient. A total of 885 sample sites were selected from Google Earth and matched with the LULC map produced (Rwanga and Ndambuki 2017; Choudhury et al. 2018).

Overall accuracy measures the accuracy of the classification process by determining whether all reference sites are correctly classified and mapped. Overall accuracy is calculated using the following equation (Rwanga and Ndambuki 2017; Choudhury et al. 2018)

$$\text{Overall Accuracy} = \frac{\sum \text{Diagonal Value}}{N} \tag{7}$$

Accuracy of individual LULC classes is determined using user's accuracy and producer's accuracy. User's accuracy is calculated by dividing the matched number of sites for individual LULC class by the total number of sites of the same class and multiplying that number with 100 (Story and Congalton 1986). Commission error of user's accuracy measures how closely a classified pixel matches the land use–land cover type on ground (Congalton 1991; Jensen 1996; Campbell 2007). User's accuracy and commission error are calculated using the following equations,

$$\text{User's Accuracy}(\%) = \frac{\sum \text{Diagonal value of Row}}{\text{Row Total}} \times 100 \tag{8}$$

$$\text{Commission Error} = \frac{\sum \text{off Diagonal element of Row}}{\text{Row Total}} \times 100 \tag{9}$$

Producer's accuracy measures how effectively the classification process was conducted and it is calculated by dividing the number of matched sites by the total number of sites from the georeferenced data and multiplying that number with hundred. Omission error of producer's accuracy determines the percentage of sites that were not classified. Producer's accuracy and omission error are calculated using the following formula (Choudhury et al. 2018; Rwanga and Ndambuki 2017).

$$\text{Producers Accuracy } (\%) = \frac{\sum \text{Diagonal value of Column}}{\text{Column Total}} \times 100 \tag{10}$$

Table 2 Confusion matrix for Surat city

Reference data								
Year	LULC	Water	Vegetation	Built-up	Bare soil	Total	UA (%)	Kappa
Classified data								
1998	Water	31	0	1	2	34	91.17	0.85
	Vegetation	0	88	2	5	95	92.63	
	Built-up	3	2	74	7	86	86.04	
	Bare soil	2	3	4	71	80		
	Total	36	93	81	85	295		
	PA (%)	86.11	94.62	91.35	83.52			
	OA (%)	89.49						
2008	Water	27	3	2	0	32	84.38	0.88
	Vegetation	0	75	2	4	81	92.59	
	Built-up	2	0	61	3	66	92.42	
	Bare soil	3	1	0	66	70	94.29	
	Total	32	79	65	73	249		
	PA (%)	84.38	94.94	93.85	90.41			
	OA (%)	91.96						
2016	Water	57	2	0	2	61	93.44	0.92
	Vegetation	0	75	3	1	79	94.94	
	Built-up	0	2	104	3	109	95.41	
	Bare soil	1	4	2	90	97	92.78	
	Total	58	83	109	96	346		
	PA (%)	98.28	90.36	95.41	93.75			
	OA (%)	94.20						

PA Producer's accuracy, *UA* User's accuracy, *OA* overall accuracy

$$\text{Omission Error} = \frac{\sum \text{off diagonal element of Column}}{\text{Column Total}} \times 100 \tag{11}$$

Another method for measuring the accuracy of a classification process is the Kappa coefficient (K) (Foody 1992; Ma and Redmond 1995). Kappa coefficient is a discrete multivariate technique for measuring accuracy as compared to random values. The coefficient value varies between negative one and one where a negative value indicates that the classification process performed is worse than the random assigned values, a value of zero indicates the process is no better and a value closer to one indicates the classification process conducted is significantly better (Jensen 1996; Congalton 1991; Rwanga and Ndambuki 2017). Kappa coefficient (K) is calculated using the following equation:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_i + Xx_{+1}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{ii}Xx_{+1}\right)} \tag{12}$$

Here r is number of rows and columns in error matrix, N is total number of observations (pixels), x_{ii} is observation in row i and column i, $Xi+$ is marginal total of row i, $X+i$ is marginal total of column i.

4.2 LST Validation

A widely used method for validating LST is by using/comparing near-surface air temperature (Srivastava et al. 2009; Li et al. 2013) data measured at meteorological stations. In this study, the calculated LST values were validated by comparing with the mean near-surface air temperature and the actual air temperature at the study site (Table 12) at the time of the satellite passing over the meteorological station. Real-time surface air temperature data were derived from National Oceanic and Atmospheric Administration (NOAA) website for the meteorological station in the study area.

5 Results

5.1 LULC Change

In this study, four LULC classes were assigned viz. vegetation, water body, built-up area and bare soil (Figs. 3 and 4). Accuracy assessment of the classified images was conducted to create a confusion matrix (Tables 2 and 3). As shown in the matrix, the overall accuracy of the classified images for Surat city was 89.49%, 91.96% and 94.20% for 1998, 2008 and 2016, respectively. The Kappa coefficient was 0.85, 0.88

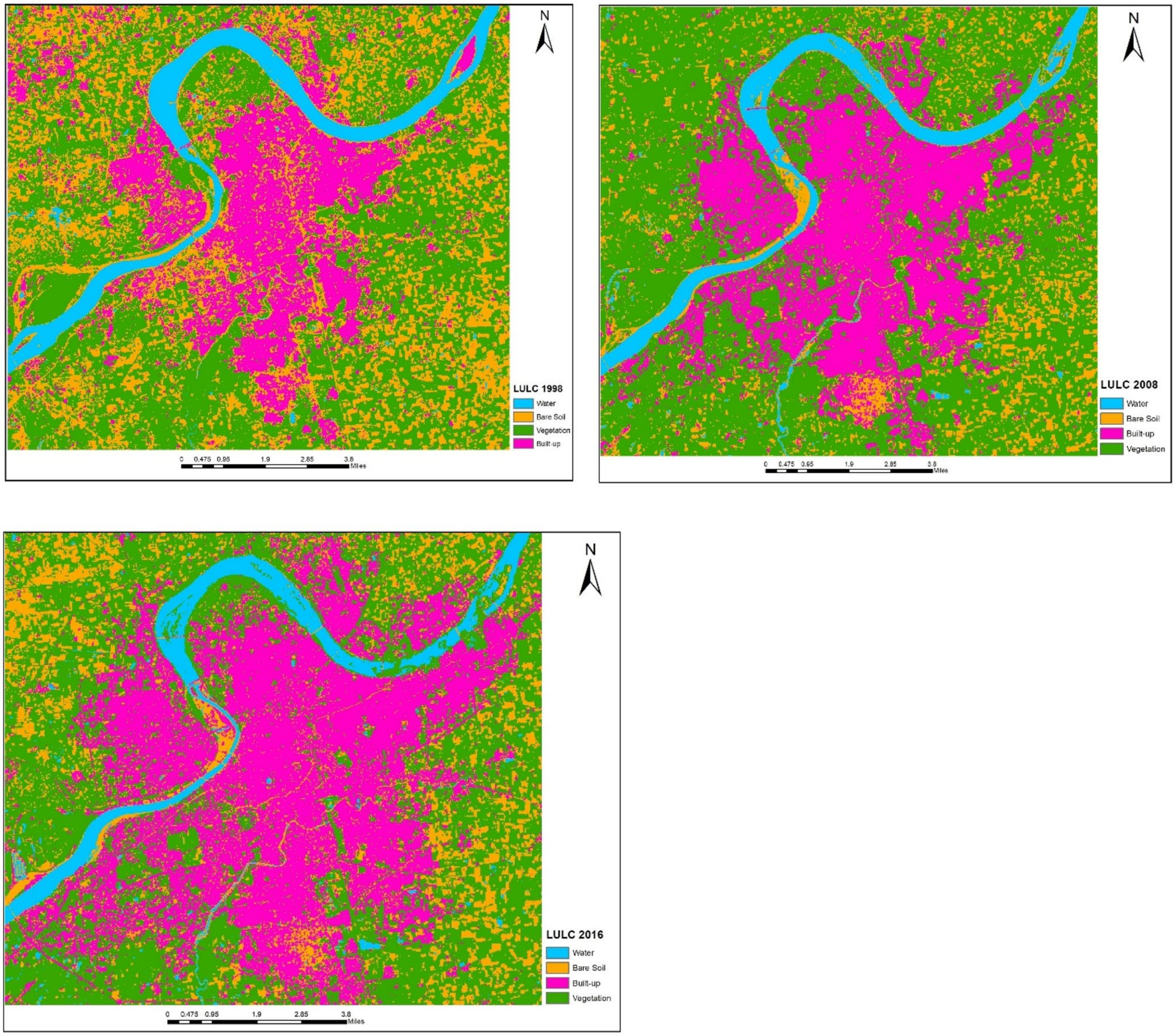

Fig. 3 Classified images of Surat city for 1998, 2008 and 2016

and 0.92 for the 3 years (Table 2). In case of Bharuch, the overall accuracy of the classified images was 95%, 96% and 98% for 1998, 2008 and 2016, respectively. The Kappa coefficient was 0.92, 0.95 and 0.97 for the 3 years (Table 3).

The total area of each LULC class and percentage from 1998 to 2016 for both the cities was computed (Tables 4 and 5). As depicted in Table 4, Surat has witnessed a considerable increase in built-up area in 16 years and a systematic decrease in water body, vegetation and bare soil. A visible increase in built-up from 19.10 to 26.41% was observed from 1998 to 2008 and from 26.41 to 35.45% from 2008 to 2016. Thus built-up area has increased at the rate of 38.28% from 1998 to 2008 and at the rate of 34.23% from 2008 to 2016. Similarly, water body exhibited a decrease in area (0.36% during 1998–2008 and 0.21 during 2008–2016). While, vegetation and bare soil showed increase in one phase and decrease in other phase of study. In case of vegetation, first phase of study showed increase by 10.19% during 1998–2008 and decrease in second phase of 12.92% during 2008–2016. Likewise, bare soil showed decrease in first phase (17.14% during 1998–2008) and increase in the second phase of study (4.08% during 2008–2016).

Bharuch too has witnessed a visible increase in built-up areas and systematic reduction in water body and bare soil. However, vegetation has increased slightly. Built-up area initially decreased by 1.97% from 1998 to 2008 and then increased by 6.23% from 2008 to 2016. Water body has shown a very slight reduction in area by 0.01% from 1998 to 2008 and by 1.86% from 2008 to 2016. Areas covered by

Fig. 4 Classified images of Bharuch inner city for 1998, 2008 and 2016

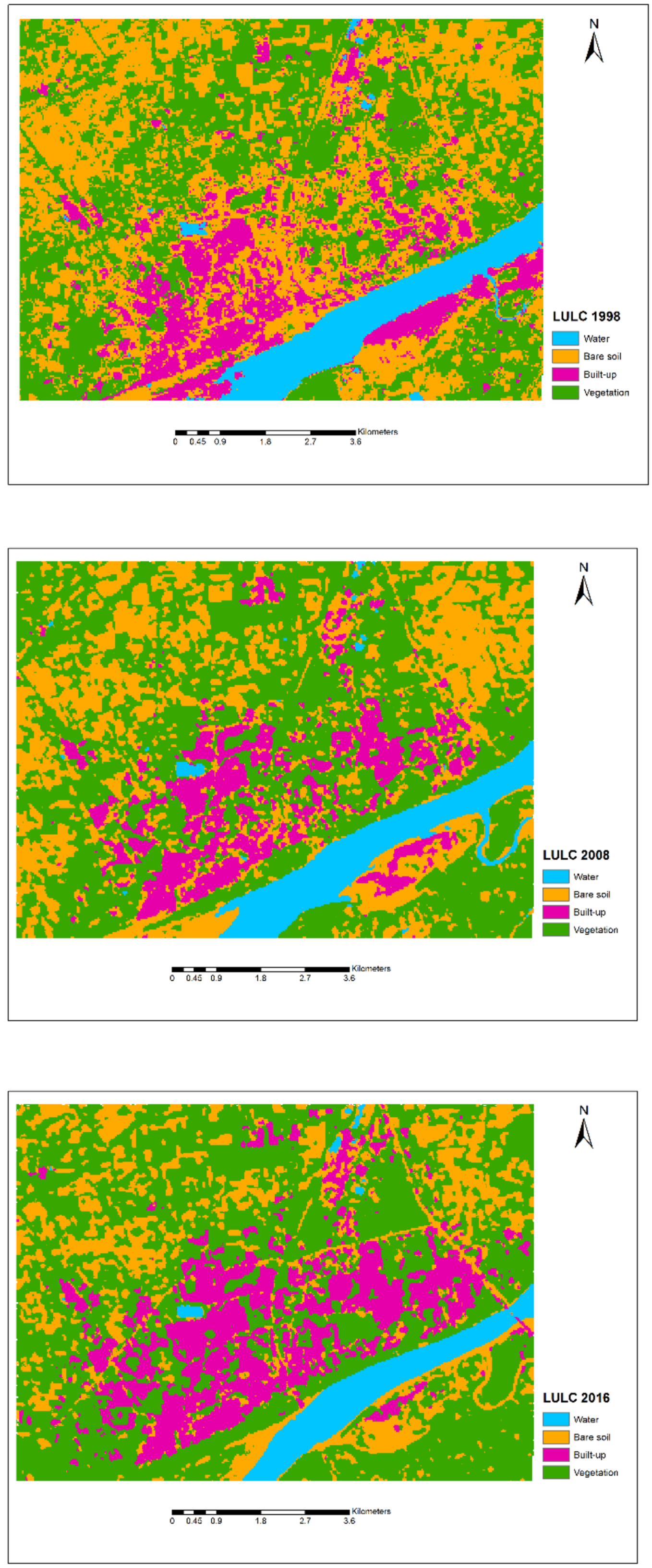

Table 3 Confusion matrix for Bharuch

Reference data								
Year	LULC	Water	Bare soil	Built-up	Vegetation	Total	UA (%)	Kappa
Classified data								
1998	Water	30	0	0	0	30	100	0.92
	Bare soil	0	26	0	0	26	100	
	Built-up	0	7	30	0	37	81.08	
	Vegetation	0	1	1	86	88	97.73	
	Total	30	34	31	86	181		
	PA (%)	100	76.47	96.77	100			
	OA (%)	95%						
2008	Water	35	0	0	0	35	100	0.95
	Bare soil	0	55	0	0	55	100	
	Built-up	0	9	64	0	73	87.67	
	Vegetation	0	0	0	127	127	100	
	Total	35	64	64	127	290		
	PA (%)	100	85.93	100	100			
	OA (%)	96%						
2016	Water	39	0	0	0	39	100	0.97
	Bare soil	1	82	0	0	83	98.80	
	Built-up	0	7	89	0	96	92.71	
	Vegetation	0	0	0	211	211	100	
	Total	40	89	89	211	429		
	PA (%)	97.5	92.13	100	100			
	OA (%)	98%						

PA Producer's accuracy, *UA* User's accuracy, *OA* Overall accuracy

Table 4 Land use–land cover distribution for Surat city

LULC	Area in hectares			Area in percentage			Change in area		Change in percentage	
	1998	2008	2016	1998	2008	2016	1998–2008	2008–2016	1998–2008	2008–2016
Water	1837.89	1728.09	1664.1	5.95	5.59	5.39	− 109.8	− 63.99	− 0.36	− 0.21
Vegetation	14,094	17,241.84	13,250.52	45.62	55.81	42.89	3147.84	− 3991.32	10.19	− 12.92
Built-up	5899.95	8158.41	10,951.83	19.10	26.41	35.45	2258.46	2793.42	7.31	9.04
Bare Soil	9063.36	3766.86	5028.75	29.34	12.19	16.28	− 5296.5	1261.89	− 17.14	4.08

Table 5 Land use–land cover distribution for Bharuch

LULC	Area in hectares			Area in percentage			Change in area		Change in percentage	
	1998	2008	2016	1998	2008	2016	1998–2008	2008–2016	1998–2008	2008–2016
Water	558.54	558	410.22	7.02	7.02	5.16	− 0.54	− 147.78	− 0.01	− 1.86
Bare soil	3245.58	2655.45	1917.18	40.81	33.39	24.10	− 590.13	− 738.27	− 7.42	− 9.28
Built-up	1084.59	928.26	1423.98	13.64	11.67	17.90	− 156.33	495.72	− 1.97	6.23
Vegetation	3065.04	3812.04	4202.37	38.54	47.93	52.84	747	390.33	9.39	4.91

vegetation have increased by 9.39% from 1998 to 2008 and by 4.91% from 2008 to 2016.

5.2 NDVI Change

Spatial variation of NDVI depends on various factors such as slope, topography, radiation availability etc. (Liu et al. 2004). NDVI was calculated and maps showcasing the

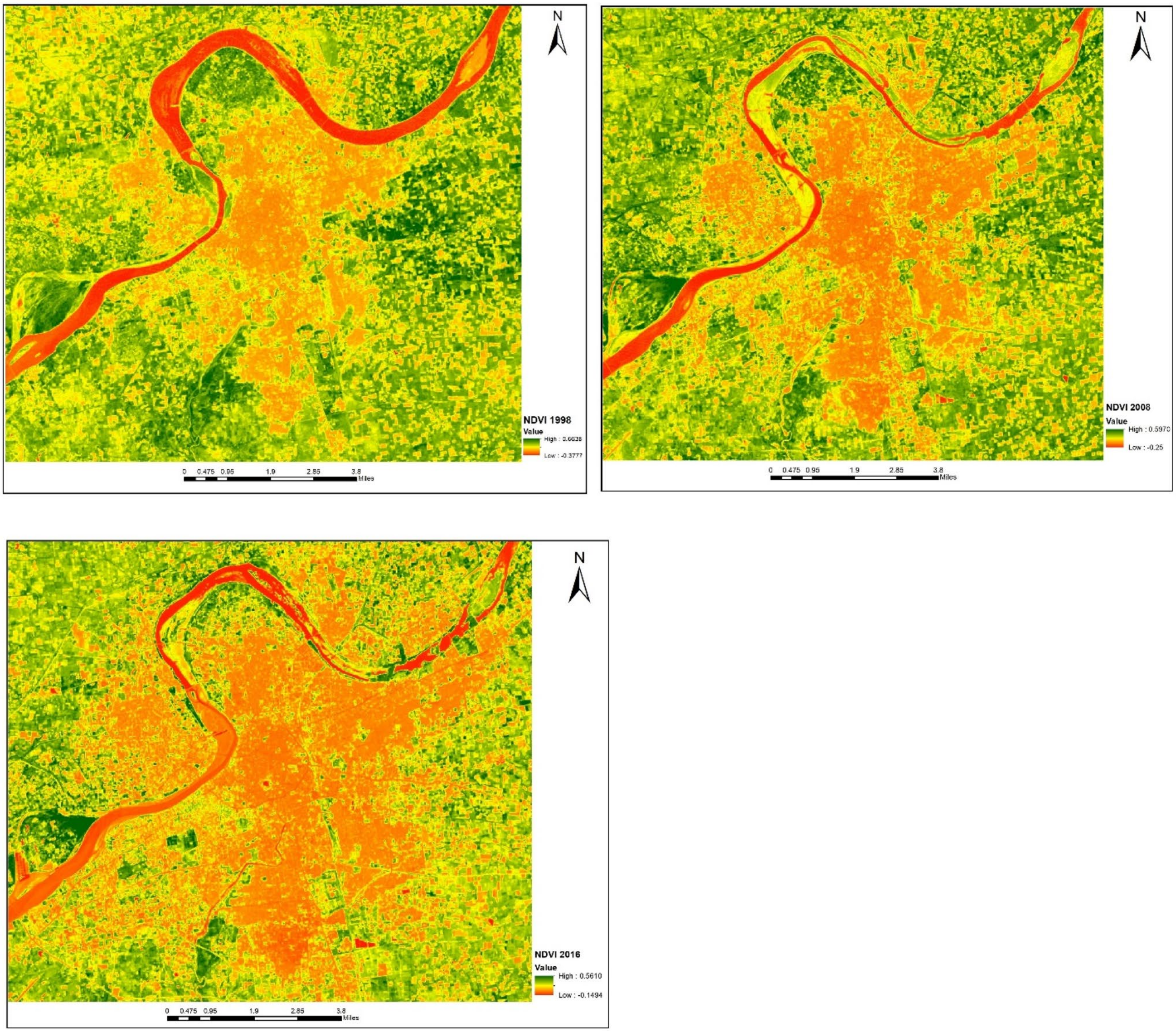

Fig. 5 Spatial distribution of NDVI for Surat for 1998, 2008 and 2016

distribution of NDVI for Surat and Bharuch were generated for 1998, 2008 and 2016 (Figs. 5 and 6).

Figure 5 shows the distribution of NDVI in Surat city, and Table 6 shows the NDVI values for the four LULC classes. As shown in Table 6 in case of Surat, in 1998 the NDVI values varied between − 0.37 and 0.66, which gradually reduced in 2008 ranging between − 0.25 and 0.59 and further reduced in 2016 ranging between − 0.14 and 0.56. Vegetation exhibited the highest value of mean NDVI in 1998 and the value sharply reduced in 2008 and 2016. Whereas built-up areas exhibited a sharp increase in NDVI values from 1998 to 2016. This clearly demonstrates a systematic reduction in vegetation and a sharp increase in built-up areas in Surat.

Figure 6 shows the distribution of NDVI in Bharuch, and Table 7 shows the NDVI values for the four LULC classes. As shown in Table 7 in 1998, the NDVI values varied between − 0.03 and 0.64, which reduced slightly in 2008 ranging between − 0.15 and 0.59 and further reduced in 2016 ranging between − 0.04 and 0.55. Vegetation exhibited the highest mean NDVI value in 1998 which reduced in 2008 and 2016 demonstrating a decline in vegetation.

5.3 LST Change

LST was calculated for 1998, 2008 and 2016 for Surat and Bharuch. Figure 7 shows the spatial distribution of LST, Table 8 shows the LST values for the four LULC categories,

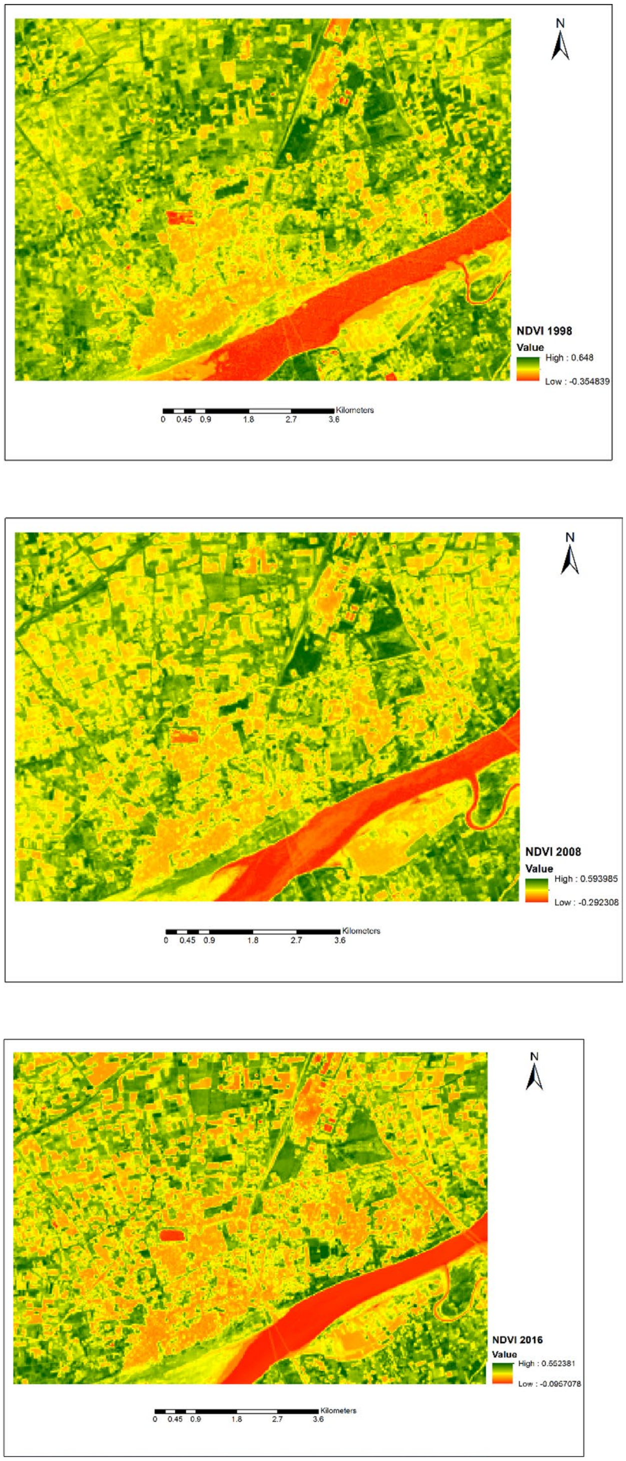

Fig. 6 Spatial distribution of NDVI for Bharuch for 1998, 2008 and 2016

and Table 9 shows the changes in LST values for the four categories in Surat for the study period. The mean surface temperature in Surat showed an increase of 2.42 °C per decade. Moreover, as shown in Tables 8 and 9 all the LULC categories in Surat exhibited an increase in surface temperature from 1998 to 2016. Built-up area showed the highest mean temperature of 28.46 °C in 1998 that systematically increased to 32.46 °C in 2008 and to 32.62 °C in 2016. Additionally, the highest LST in Surat was recorded in the central part of the city which is heavily urbanized and rapidly expanding indicating a positive correlation between built-up area and LST (Fig. 8).

Surat has only one water body, and it showed the lowest mean surface temperature of 23.42 °C in 1998, 27.23 °C in 2008 and 28.23 °C in 2016. Water body thus showed a low surface temperature but exhibited the highest rate of increase in surface temperature from 1998 to 2016. Satellite data of Surat were acquired during the months of October and November. That time period is winter season in India and during cold periods the radiance reflected from water bodies is lower than other objects, thereby leading to an overall higher rate of increase in surface temperature. Surface temperature in Surat increased from 1998 to 2016 at the rate of 4.81 °C for water body, followed by 4.33 °C for bare soil, 4.18 °C for vegetation and 4.16 °C for built-up areas (Table 9).

In case of Bharuch, the mean surface temperature increased by 2.13 °C per decade. As shown in Tables 10 and 11, all the LULC categories in Bharuch showed an increase in surface temperature from 1998 to 2016. Built-up area and bare soil showed the highest mean temperatures of 28.83 °C and 28.63 °C, respectively, in 1998. The values consistently increased in 2008 and 2016. Built-up area recorded the highest mean LST in 1998 and 2008 while bare soil recorded the highest meant LST in 2016. As witnessed in Surat, Bharuch too has only one water body that exhibited the lowest mean surface temperature of 23.58 °C in 1998, 26.80 °C in 2008 and 27.16 °C in 2016. Surface temperature in Bharuch increased at the rate of 4.46 °C for bare soil followed by 4.03 °C for vegetation, 3.58 °C for water body and 3.31 °C for built-up area.

In order to validate LST calculations, daily summary surface temperature collected at the meteorological station was compared with the calculated LST for 1998, 2008 and 2016. Table 12 shows a comparison of the calculated LST and actual LST readings for Surat and Bharuch derived from the meteorological station and the difference in the two LST readings for the study period varies between 4.06 and 6.87 °C.

5.4 LST and NDVI Correlation

To assess the correlation between LST and NDVI in both the cities, regression analysis and correlation analysis were conducted.

In case of Surat, linear regression showed a coefficient of determination (r^2) of 0.965 for 1998, 0.969 for 2008 and 0.88 for 2016 (Fig. 9). The correlation coefficient (r) was

Table 6 NDVI values for different LULC categories for Surat

LULC	NDVI								
	1998			2008			2016		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Water body	− 0.3778	0.2857	− 0.1747	− 0.2500	0.4615	0.0020	− 0.1495	0.3530	0.0627
Vegetation	0.0309	0.6639	0.3278	0.0213	0.5970	0.3046	0.1187	0.5611	0.2994
Built-up	− 0.1111	0.2444	0.0092	− 0.1053	0.3217	0.0318	− 0.1102	0.3889	0.0949
Bare soil	− 0.1642	0.3902	0.1155	− 0.1467	0.4348	0.1279	− 0.0666	0.4312	0.1626

Table 7 NDVI values for different LULC categories for Bharuch

LULC	NDVI								
	1998			2008			2016		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Water body	−0.3548	0.1000	−0.2136	−0.2923	0.1940	−0.1722	−0.0957	0.0750	−0.0532
Bare soil	−0.1515	0.4722	0.1967	−0.1733	0.4701	0.1321	−0.0795	0.2921	0.1454
Built-up	−0.1746	0.4717	0.0804	−0.1500	0.3451	0.0521	−0.0436	0.3969	0.1230
Vegetation	−0.0306	0.6480	0.3917	0.0638	0.5940	0.3276	0.1424	0.5524	0.3175

−0.982 for 1998, −0.984 for 2008 and −0.938 for 2016. This indicates a negative correlation between LST and NDVI for Surat.

In case of Bharuch, linear regression showed a coefficient of determination (r^2) of 0.989 for 1998, 0.9941 for 2008 and 0.966 for 2016 (Fig. 10). The correlation coefficient (r) was −0.994 for 1998, −0.997 for 2008 and −0.983 for 2016. This indicates a negative correlation between LST and NDVI for Bharuch.

5.5 Directional Profile

Four directional profiles were generated for the study areas, i.e., North–South (N–S), East–West (E–W), Northwest–Southeast (NW–SE) and Northeast–Southwest (NE–SW) to validate the spatial distribution of LST.

In case of Surat, N–S profile of LST for 1998, 2008 and 2016 showed an initial drop in temperature but then showed continued increase in temperature during 2008 and 2016 owing to the increased urbanization from North to South direction as shown in Fig. 11. Moreover, new peaks were observed in the profile for 2008 and 2016 which was absent in 1998. This can also be attributed to increased urbanization in the city toward the southern direction. E–W profile represented only one high peak for 1998 while the profile flattened with high temperatures in 2008 and 2016. In case of NW–SE profile, the temperature values were minimal at the beginning and end of the profile resulting in lowest peaks due to the presence of vegetation and bare soil areas. New peaks were also observed in 2016 due to growth of built-up areas while depression in the profile was detected at one place due to the presence of a water body Surat. Similar depression was identified for all the profiles owing to the presence of the water body. In NW–SE profile, a new peak was identified in 2008 and 2016 due to the escalated urbanization at the bank of the river but the peak was observed to be the highest in 2016.

In case of Bharuch, not much of a difference was observed in the LST values for different years in each of the four directional profile, i.e., E–W, NE–SW, N–S and NW–SE. Hence, the profile for 2016 is only highlighted in each of the four zones. Highest peak was observed in NW–SE directional profile (Fig. 12).

As shown in Fig. 13, Surat has developed and is growing in all the directions, particularly in the southern and western parts. Udhna, Piplod, Pal Gam, Mota Varacha and Punagam areas (encircled in Fig. 13) have seen the most growth. Also the central part of the city around Athwa Gate and Majura has enlarged considerably in the past 2 decades. Growth of built-up area is most pronounced along the banks of the main waterbody, river Tapi that flows along the northern part Surat with built-up areas actually infringing upon the river along both the sides of the banks. Not surprising surface temperature has also increased over the years in these areas particularly in the southern and south-eastern parts of Surat as shown in Fig. 13.

As shown in Fig. 14, Bharuch is growing and expanding, particularly in the northern part of the city. Most visible is the growth along the banks of the river Narmada

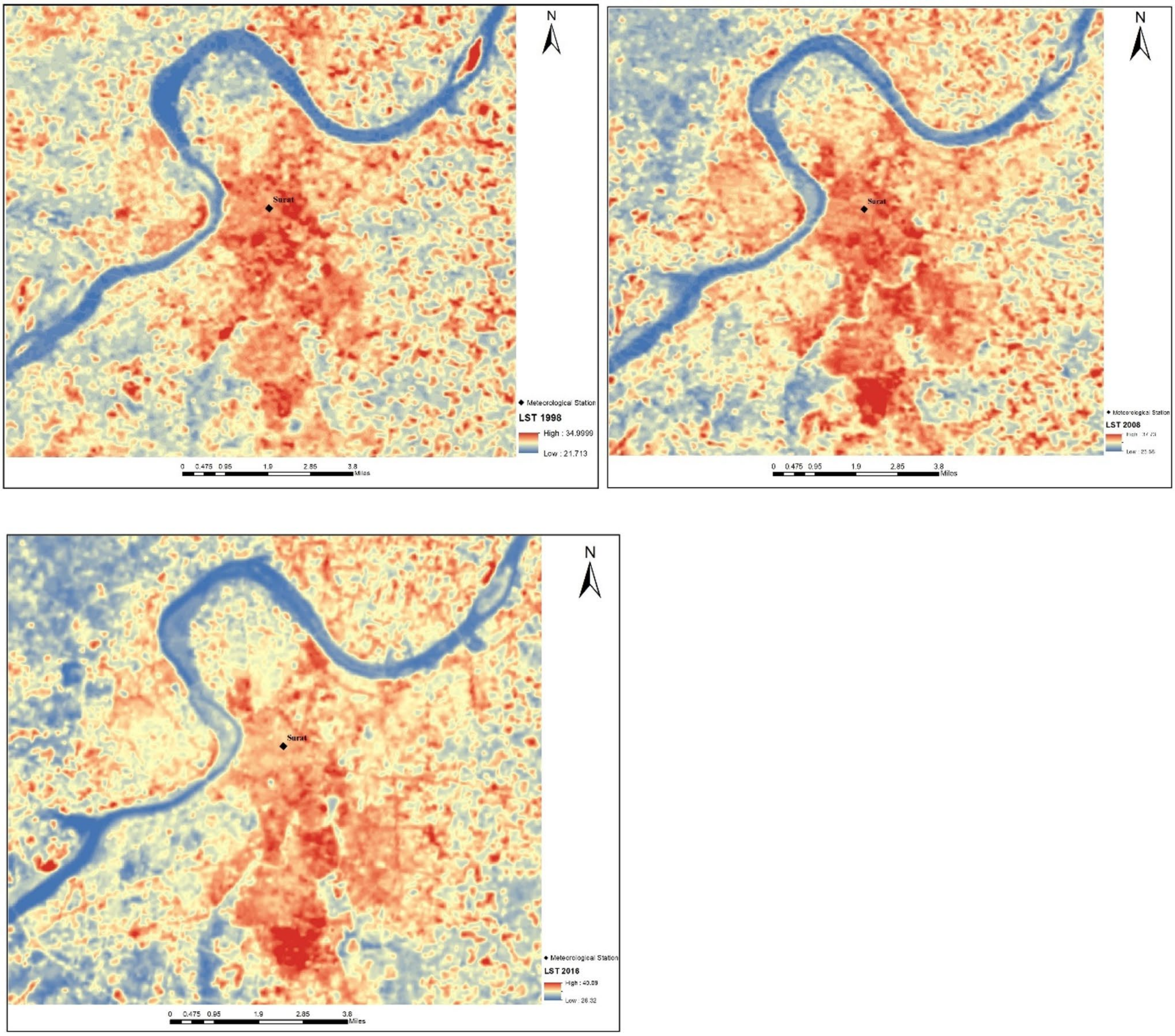

Fig. 7 Spatial distribution of LST for 1998, 2008 and 2016 in Surat

Table 8 LST values over different land use–land cover categories for Surat

LULC	Land surface temperature (°C)								
	1998			2008			2016		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Water body	21.71	28.94	23.42	25.59	34.60	27.23	26.49	36.36	28.23
Vegetation	22.58	33.01	26.56	26.44	35.79	30.33	26.32	37.21	30.74
Built-up	23.88	35.00	28.46	27.28	37.74	32.46	27.66	39.39	32.62
Bare soil	22.58	33.41	27.69	26.44	37.74	31.68	26.95	40.10	32.03

Table 9 Change in LST values over different land use–land cover categories for Surat

LULC	Change in LST (°C)				
	1998–2008	2008–2016	1998–2016	Yearly increase	Decadal increase
Water body	3.80	1.00	4.81	0.27	2.67
Vegetation	3.76	0.42	4.18	0.23	2.32
Built-up	3.99	0.17	4.16	0.23	2.31
Bare soil	3.98	0.35	4.33	0.24	2.41

that flows through the southern part of the city as seen in Fig. 14.

6 Discussion

Both Surat and Bharuch have witnessed unprecedented growth in the last 2 decades. While Surat has expanded in all the directions, Bharuch has expanded along the banks of the river. Along with urban expansion, both the cities have witnessed a systematic increase in their temperature. This in turn has exposed both the cities to a variety of infrastructural and climate-related problems.

Surat and Bharuch have undergone massive industrialization since 2000 due to the State Government's renewed political agenda of development that has pushed for urbanization and industrialization in the State (Ruparelia 2015; Mukherjee 2018). The State Government undertook several initiatives to attract global investment in the State and introduced policies and incentives to enable multinational corporations and industrialists to start their business in the State. The State introduced a Special Economic Zone (SEZ) policy followed by the Special Investment Region (SIR) Act to promote the establishment of industrial enclaves and promote industrialization (Shah 2013). Moreover, industries in Gujarat are also impacted by the Delhi Mumbai Industrial Corridor (DMIC), also called the Golden Corridor because of the large investment and income generated by the 150 km long corridor. Nearly 40% of this corridor is located within Gujarat and Bharuch and Surat are both located within the corridor. Additionally, Surat was the country's first and the only private sector SEZ (Surat Special Economic Zone). Surat has the largest number of SEZs in the state and Surat SEZ is the center of a highly industrialized belt that includes Bharuch city. Bharuch SEZ is also home to several industries. Both Surat and Bharuch have the largest operational SEZs in the state. This has attracted several chemicals, petrochemicals, textile industries and other related businesses in the region. Due to the State Government's economic policies, the State has witnessed high economic growth and development and accounts for nearly 8% of India's GDP (Nair et al. 2013). This has particularly impacted industrial and commercial centers like Surat and Bharuch. Both the cities have faced unprecedented growth in the past decade, and Surat is one of the fastest growing urban areas with the most rapid economic growth rates not only in the State but also in India (http://citymayors.com/statistics/urban_growth1.html; Bhat et al. 2013). This is accompanied by an exorbitant growth in population. As per the last census data, Surat has witnessed 63% growth in its population in a decade, while population in Bharuch has grown at 15% (Census of India 2011). Accordingly, local government authorities have been compelled to expand the city limits to accommodate the rising population (Savani and Bhatt 2016) and to incorporate urbanizing peri-urban and rural areas on the fringes putting a pressure on the infrastructure and service delivery by urban local bodies (Tewari and Godfrey 2016). Nonetheless, the unprecedented growth in both the cities in the last 2 decades has encroached upon the non-urbanized areas also.

The rapid growth and expansion has presented its own sets of problems for the cities. Urban expansion has come at the cost of agricultural land. Poor farmers who own small lands have been marginalized, further deepening rural poverty. The SEZs have acquired farmland and pastoral land for different industrial projects (Shah 2013). Farmlands have also been acquired in the outskirts of both the cities by developers for fancy real estate projects to accommodate the huge influx of population. A large number of shiny, high rise, multi-storey building projects have sprouted all over the city especially along the river banks. This in turn has led to an exorbitant increase in land and real estate prices. Expensive high rise residential projects and elaborate commercial building developments have pushed to the outer limits of both of the cities also clear in this study. This has led to increased commute time, higher number of vehicles on roads, traffic congestion and air pollution from vehicular emissions. Pollution is another negative result of the rapid urban expansion in both the cities. Both Surat and Bharuch lie in the DMIC and is concentrated with textiles, chemicals and petrochemical industries that emit extremely toxic pollutants that pollute water, air and soil. Infact both the cities lie in the country's most polluted industrial enclave.

Increase in surface temperature coupled with loss of vegetation to built-up area over the years has made both the cities more vulnerable to natural hazards, viz. flooding,

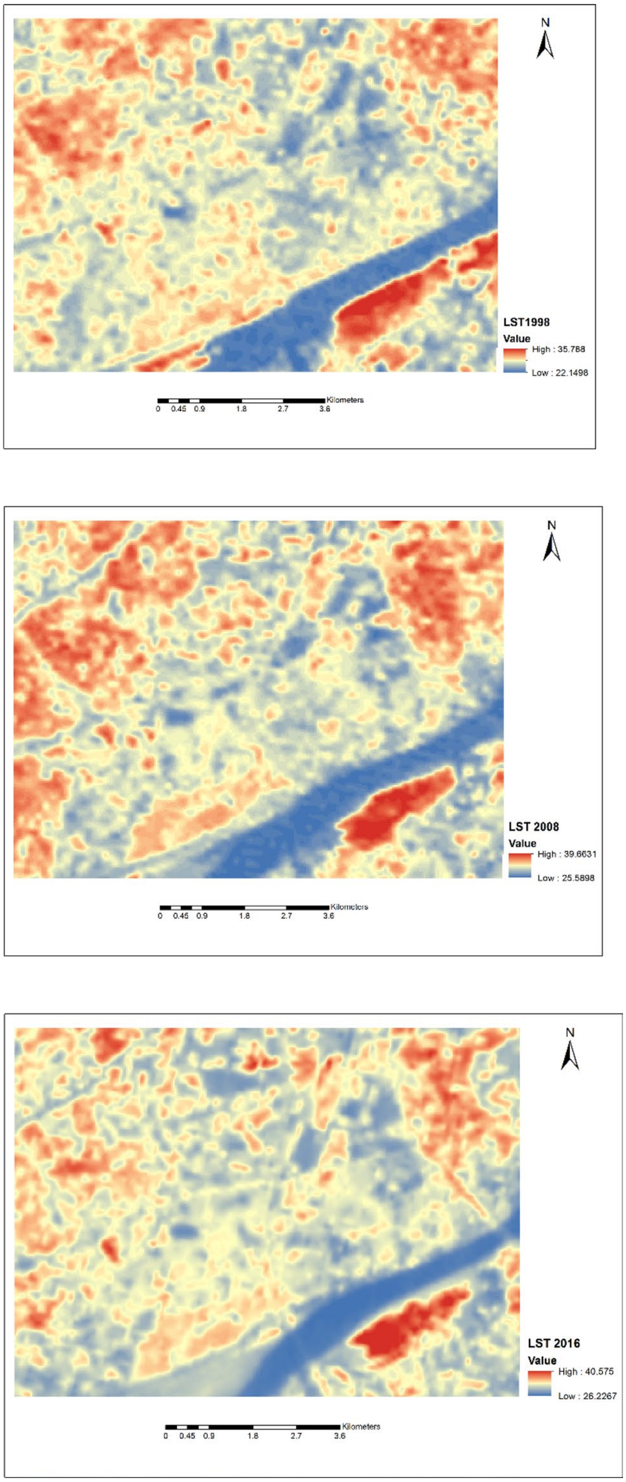

Fig. 8 Spatial distribution of LST for 1998, 2008 and 2016 in Bharuch

cyclones, etc. Flooding in particular has become a recurrent problem. In case of Surat, flooding is primarily caused by heavy rainfall in Tapi River's catchment area. This catchment area covers approximately 65,000 sq. kms and only 6% of this area lies in Gujarat. The remaining area lies in two neighboring states of Maharashtra and Madhya Pradesh. The Ukai multipurpose dam was built over Tapi river in the 1970s for the purpose of irrigation, power generation and flood control. The dam is located around 100 kms upstream from Surat. Heavy rainfall in the dam's catchment area in the neighboring state of Maharashtra leads to heavy inflow into the dam's reservoir which when discharged leads to flooding in Surat. Rapid urban expansion of Surat has further exacerbated the problem. Urban expansion in Surat along the banks of the river on both the sides has greatly modified the hydrology by increasing the built-up areas, encroachment of constructions in the floodplains adjacent to the river and construction of new bridges which has reduced the capacity of the river and the open space for the floodwaters to spread out. Additionally, Hazira industrial area located in Hazira SEZ downstream from Surat has grown exponentially over the years by reclaiming sections of the floodplain, reducing the mouth of Tapi River where it meets the sea ((Tewari and Godfrey 2016). Over the past 2 decades, there has been large-scale industrial development in the areas in and around the mouth of Tapi river causing a rise in water level and subsequent flooding with large economic and societal costs to the city.

Moreover, rise in surface temperature has led to hotter summers, shorter monsoon season and heavy rainfall further raising the risk of severe flooding events (Bouissou 2014; Tewari and Godfrey 2016). Besides, high temperature coupled with high humidity level increases human health risks owing to higher incidence of diseases like endemic malaria, dengue, filariasis and leptospirosis that are already prevalent in the region. Additionally, accumulation of stagnant water after a flooding event along with high surface temperature is a breeding ground for mosquitoes further worsening incidences of malaria and dengue. Thus, urban expansion with rising temperature has far reaching health impacts on both the cities. In addition to diseases, rising temperatures also have a negative impact on industrial productivity. As surface temperature keeps rising, it drives the industrial workforce away since slums, where majority of the factory workers dwell and factories, where they work are already very hot and air-conditioning is very expensive and higher temperatures only add to worsening their living and work environment. Low-income families who dwell in slum and shanties are also most vulnerable to the risks associated with disease, flooding and rising temperatures.

7 Conclusion

This study has shown that since 1998–2016 both Surat and Bharuch have experienced a loss in vegetation while land surface temperature during that period has increased

Table 10 LST values over different land use–land cover categories for Bharuch

LULC	Land Surface Temperature (°C)								
	1998			2008			2016		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Water body	22.58	30.17	23.58	25.59	34.60	26.80	26.23	37.74	27.16
Bare soil	22.58	34.21	28.63	26.44	39.66	33.57	26.49	40.57	33.09
Built-up	22.58	35.79	28.83	26.44	39.66	32.58	27.46	40.31	32.14
Vegetation	22.15	33.81	27.18	26.01	38.51	31.22	27.20	40.19	31.21

Table 11 Change in LST values over different land use–land cover categories for Bharuch

LULC	Change in LST (°C)				
	1998–2008	2008–2016	1998–2016	Yearly increase	Decadal increase
Water body	3.22	0.36	3.58	0.20	1.99
Bare soil	4.94	−0.49	4.46	0.25	2.48
Built-up	3.74	−0.44	3.31	0.18	1.84
Vegetation	4.05	−0.01	4.03	0.22	2.24

Table 12 Details and difference between LST and air temperature for Surat and Bharuch

Station	Station ID	1998			2008			2018		
		LST	Data	Difference	LST	Data	Difference	LST	Data	Difference
Surat, India	42840099999	29.5	25.44	4.06	33.41	26.54	6.87	33.12	26.94	6.18

consistently rising from 1998 to 2016. Additionally during this period both the cities have also experienced an increase in its built-up area and a consistent reduction in water, vegetation and soil, indicating a rapid expansion of urban areas at the cost of its vegetation, soil and water bodies. Surat has expanded over an area of approximately 50.51 sq. kms while Bharuch has expanded slightly over an area of 3.4 sq. kms during this period in multi-directions. Surat has grown over a much larger area as compared to Bharuch during the study period. Nonetheless, both the cities have witnessed an increase in land surface temperature. In case of Surat, land surface temperature was particularly elevated in the central part of the city which is a heavily urbanized area, representing a strong correlation between urban expansion and land surface temperature. In case of both of the cities, growth along the water body was noticeable. However, the results from this study must be read with some caution. Firstly, Landsat data that have been used in this study generate imageries with low-to-moderate spectral resolution. Secondly, this study has utilized unsupervised classification for LULC analysis that imparts uncertainty in classified data (Abdullah et al. 2019) and may not be as effective in associating class membership. A methodological direction for future studies will utilize advanced classification algorithms as well as remotely sensed data of different resolutions.

Surat is one of the fastest growing cities of India with a rapidly increasing urban population while Bharuch is heavily industrialized area facing rapid urbanization. This has exerted an enormous pressure on the urban environment of both the cities. Rapid and chaotic urban expansion accompanied with high surface temperature has made both the cities vulnerable to diseases, natural hazards like flooding, increased pollution and reduced industrial productivity. This observed phenomena is very similar to other mega cities in India and across the globe and it is high time that cities like Surat and Bharuch start paying attention to the ramifications of industrialization, development and urbanization. Local Government officials in Surat for instance have started heeding the consequences of urban expansion. Surat was one the pioneering member cities of the Asian Cities Climate Change Resilience Network (ACCCRN) established by the Rockefeller Foundation. The main goals of the network focus on ameliorating Surat's flood risk management strategies, public health emergency preparedness and infrastructure (Anguelovski et al. 2016). In 2011, the city crafted a City Resilience strategy and institutionalized action plans as

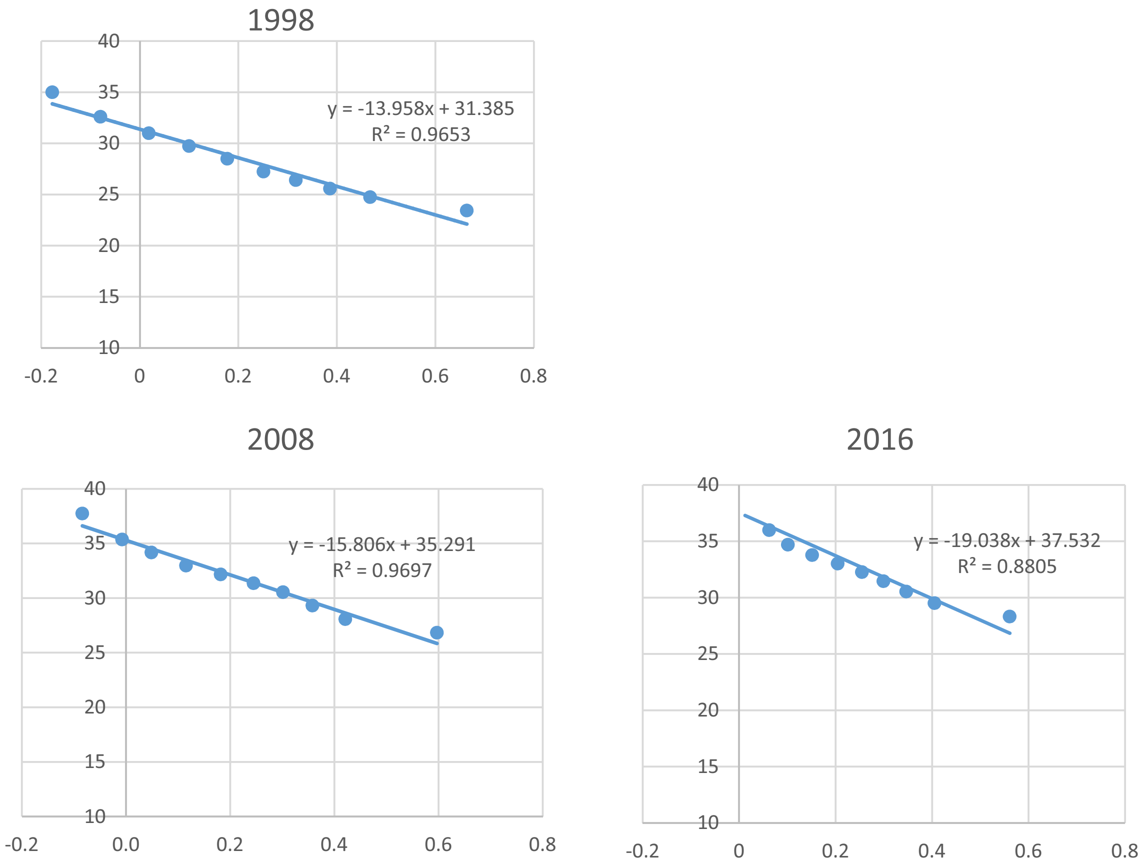

Fig. 9 Regression analysis showing the relationship between LST and NDVI for Surat in 1998, 2008 and 2016

part of Surat Climate Change Trust (Chu et al. 2016). The city has also established an Urban Health and Climate Resilience center with the goal of addressing epidemics associated with climate change. Surat is at the forefront trying to combat the consequences of urban expansion and serves as a model for other cities in India. Bharuch while it suffers from the consequences of industrialization and urbanization just like Surat has yet to take any action to combat the aftermath of these processes.

The present study has addressed an important issue by providing a detailed analysis of land transformation and surface temperature change in one of the fastest urbanizing areas of India. Medium and small urban agglomerations all over the world particularly in developing countries are facing tremendous pressures of urbanization and the process will continue for the next several decades. Urban areas continue to grow at the cost of green spaces, agricultural land and rural areas. In many parts of the world, urban areas are pushing into the most vulnerable parts of the environment as also witnessed in Surat and Bharuch. Coupled with this, issues of climate change and shifting weather patterns pose a challenging problem for environmental planning and urban and land management. Studies like the one conducted here can assist land use and land management professionals and policy makers in making policy decisions to manage urban areas and curb the impacts of rapid and haphazard urbanization.

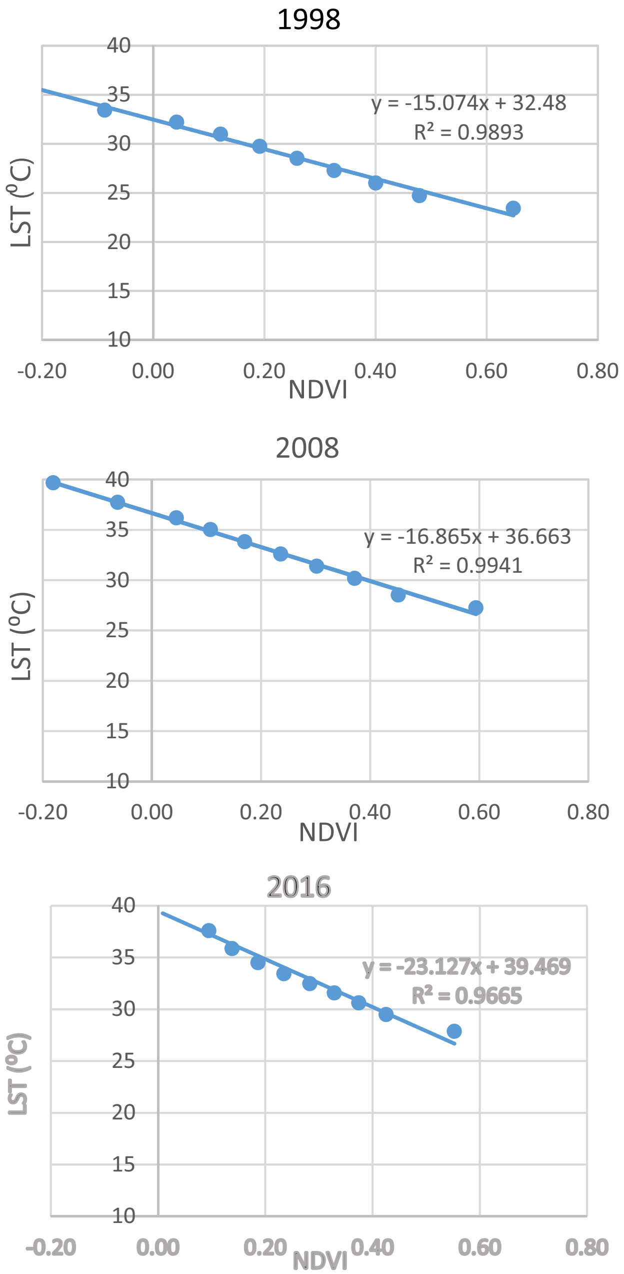

Fig. 10 Regression analysis showing the relationship between LST and NDVI for Bharuch in 1998, 2008 and 2016

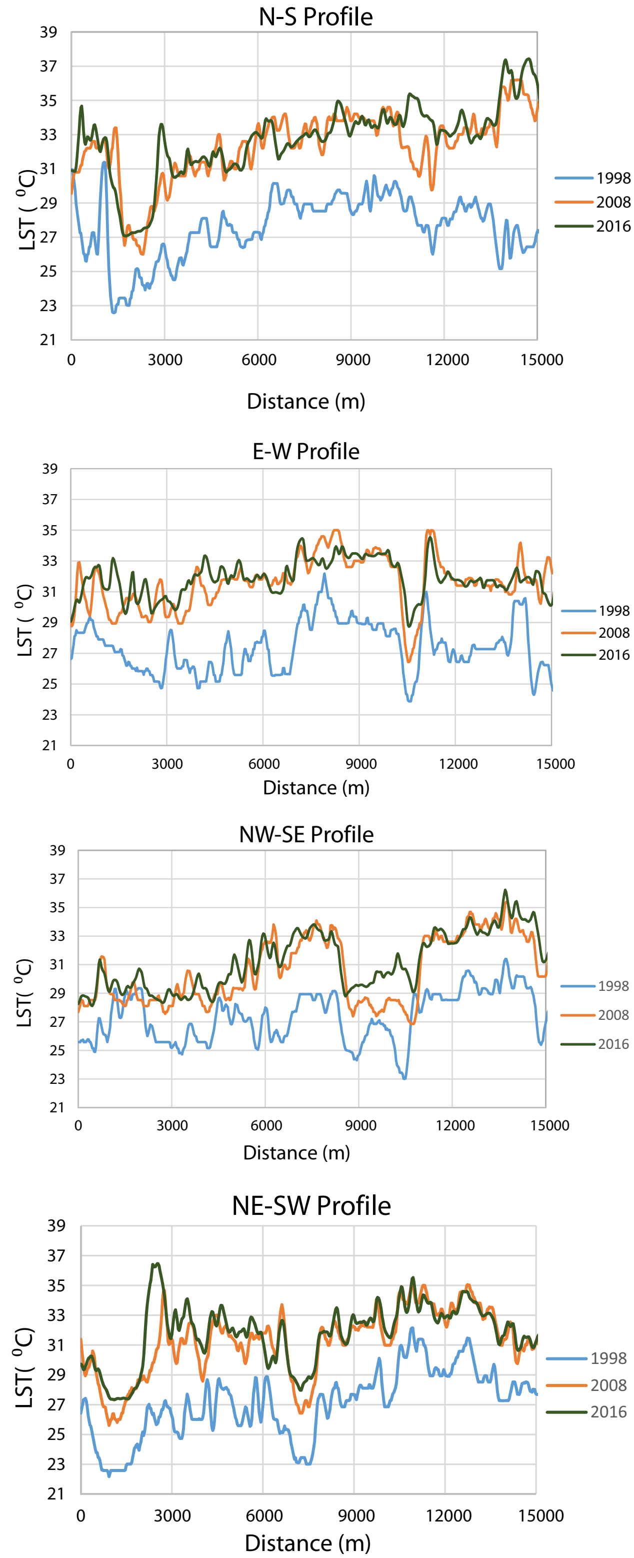

Fig. 11 Directional profiles for Surat in N–S, E–W, NW–SE and NE–SW directions

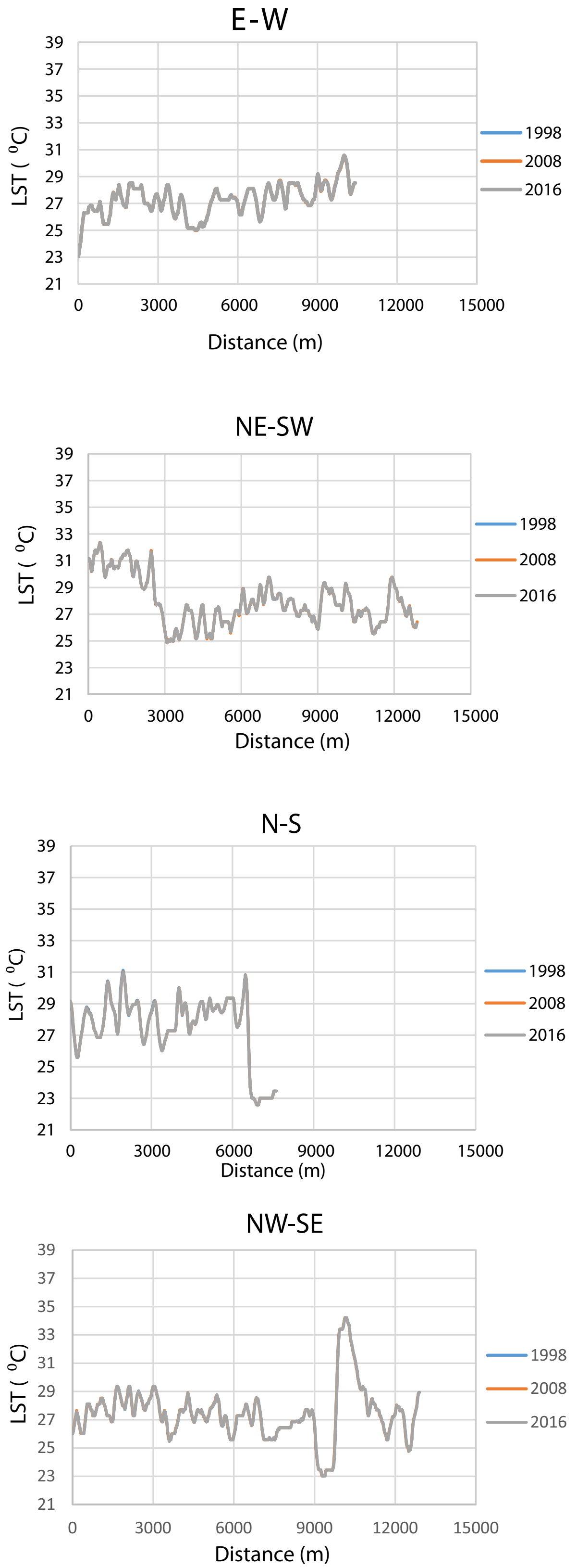

Fig. 12 Directional profiles for Bharuch in N–S, E–W, NW–SE and NE–SW directions

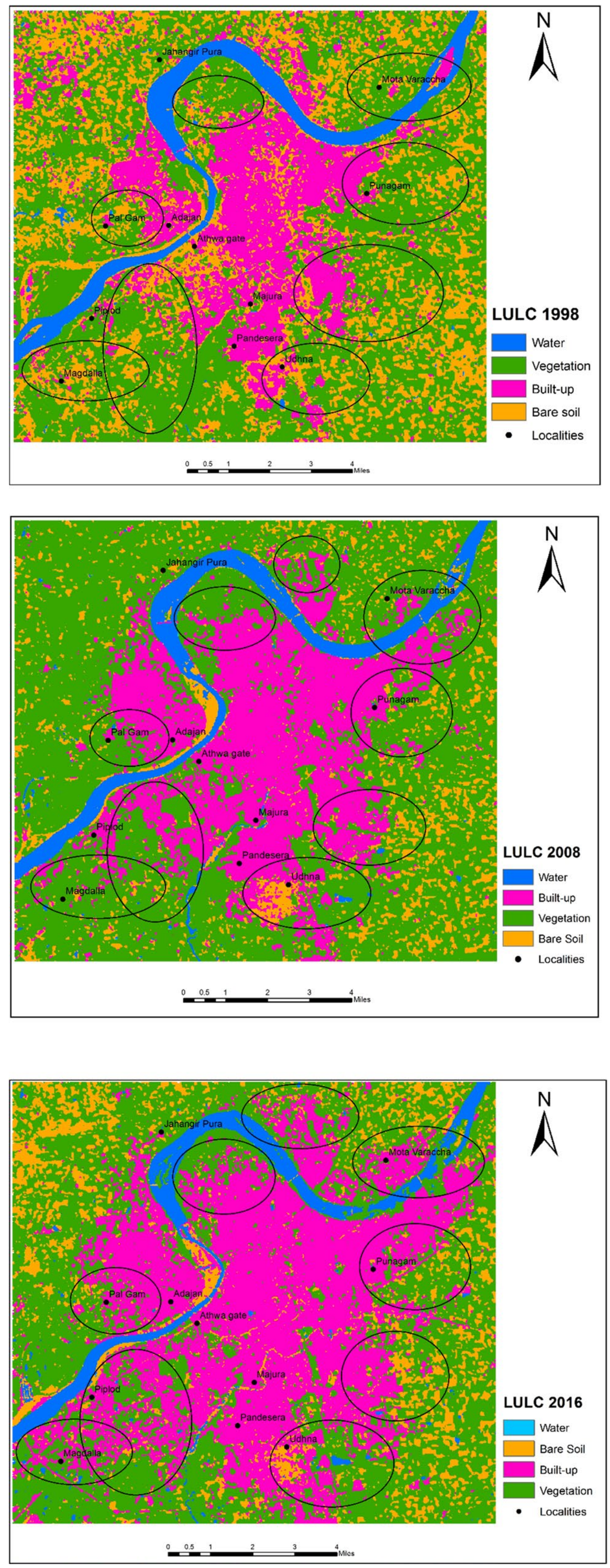

Fig. 13 Urban expansion in Surat from 1998 to 2016

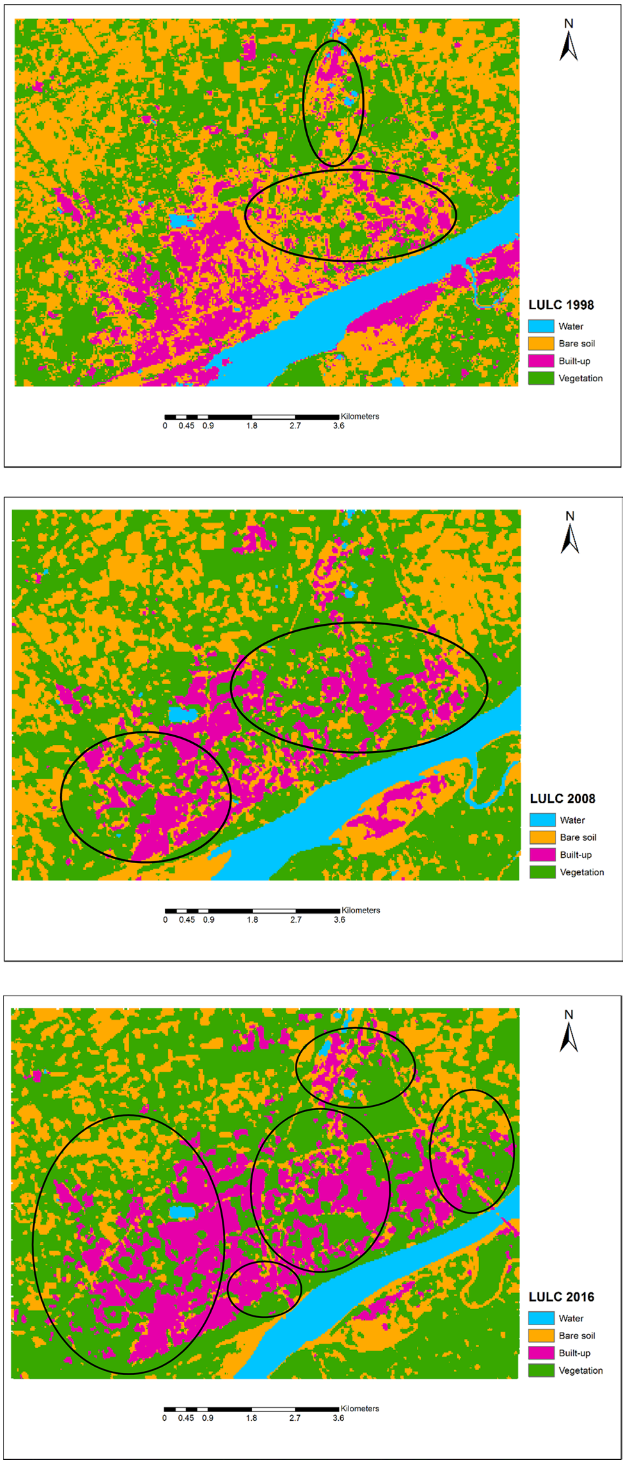

Fig. 14 Urban expansion in Bharuch from 1998 to 2016

Compliance with Ethical Standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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