MAPPING AND QUANTIFYING SURFACE URBAN HEAT ISLANDS IN INDIA'S MOST DENSE CITIES

Abstract

Rapid urbanization and climate change are intensifying the Urban Heat Island (UHI) effect. In many dense tropical and subtropical cities of the world, land surface temperatures of 140°F (60°C) and air temperatures above 100°F (40°C) regularly occur during summer days and persist during the night as air conditioners reject heat to the outdoors. Today, 54% of the world's population resides in urban areas and that percentage is projected to increase to 66% in future decades, with India being the greatest contributor to this growth. Nascent research on the use of building design and urban planning to mitigate anthropogenic heat release in India's developing, super-dense cities is emerging, but substantial work is still needed to characterize existing conditions and reliably predict the urban microclimate in such heat islands. This research uses remote sensing data to map Land Surface Temperature (LST) and quantify urban heat islands in several Indian and US cities. This work is part of a broader research goal of analyzing microclimatic interactions with buildings and outdoor occupancy in India's cities.

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Keywords

Urban Heat Island, remote sensing, Land Surface Temperature, India, urban development

Introduction

For those who study building performance and urban design, understanding Urban Heat Islands (UHI) can be a means to understand the impact of building designs and ways to improve their environmental performance. Urban Heat Island studies date from at least the 1800s when Luke Howard compared temperatures in London to those outside the city and concluded that London temperatures represented an "artificial warmth, induced by [the city's] structure, by a crowded population, and by the consumption of great quantities of fuels in fires" (Howard). Since that time, UHI has commonly been defined as the higher temperatures in urban areas when compared to rural surroundings. More recent research has shown that in a city with at least one million people, (currently about 25% of urban areas globally [Demographia, April 2018]), the annual average ambient air temperature can be 1–3°C higher compared to the surrounding rural areas (Oke, 1997). In addition, exposed surfaces of the built environment in peak summers can be 30°C to 40°C (86°F to 104°F) hotter than the urban ambient air dry bulb temperature (Akbari, Pomerantz, & Taha, 2001).

Now, 200 years after Howard's London research, when for the first time in history more than half the world's population is urban (Demographia, April 2018) and when all of the first seventeen years of the 21st century rank among the 18 warmest on record (Dahlman, 2017; NOAA, 2018) understanding UHI dynamics and how to mitigate them might be considered essential education for designers of buildings and urban environments.

If population density is a key factor in the creation of UHI as Howard suggested, then Asian cities are important areas to study. A 2018 study of world urban areas states that 58% of the large urban areas are in Asia (Demographia, April 2018). A 2016 United Nations report (United Nations, 2016) states that, of 31 megacities in the world, i.e., cities with more than 10 million inhabitants, six are in China and five are in India. By 2030, China and India are each projected to have seven megacities (17%) of a total of 41 globally.

Current reviews of UHI research, however, show a limited number of studies in these areas, especially for Indian cities and some of the other hottest cities in the world (Deilami, Kamruzzaman, & Liu, 2018; Giridharan & Emmanuel, 2018; Tzavali, Paravantis, Mihalakakou, Fotiadi, & Stigka, 2015). One of the primary objectives of this research, therefore, is to add to the characterization and understanding of UHIs in areas that are currently poorly characterized—India's developing cities—as a means to understand the impact of design of the built environment and how to improve it, with a broader goal of analyzing the interaction between built environment, UHIs and microclimates. To address that objective, LSTs across cities in India and US were mapped and UHIs were quantified. The LST maps can be used to examine the existing urban landscape and the range of temperatures across urban and rural areas, and to identify hot spots within these areas.

Methodology

UHI DEFINITION AND DATA

One of the essential decisions in UHI research is determining how to define and study the UHI phenomenon. Urban Heat Islands can be defined and studied in different ways (Erell, 2012), mostly influenced by the scale of study: Surface Urban Heat Island (SUHI), canopy level UHI, and boundary layer UHI. Surface Urban Heat Islands are defined by Land Surface Temperatures (LSTs) and the SUHI is computed by comparing the LST of urban and rural areas. LST data come from remote sensing or other forms of aerial imagery (digital data and corresponding earth's images). A canopy level UHI is a micro-scale study defined by air temperatures measured closest to the city surfaces, generally at 6.5 feet above the ground surface, and is quantified as the difference between rural and urban air temperatures. A canopy level UHI analysis provides most information about the urban microclimate, i.e, what urban dwellers experience. A boundary layer UHI represents the air temperatures of the city as a whole measured above the city's vertical boundary or the virtual dome of the city (commonly referred to as the boundary layer). It is computed as the difference between atmospheric air temperatures above the city and rural areas, showing the meso-scale UHI.

For this research, LSTs were used to define Urban Heat Islands. Surface UHIs provide flexibility in terms of spatial scale, local through global. LST is the most important parameter to understand the surface energy balance of an area because the impact of radiation can be computed. A recent literature review (Deilami et al., 2018) shows that there are at least 75 prior studies that use LST to measure the UHI intensity and analyze the spatial and temporal factors that impact UHI formation. Of those studies, approximately 5% were done for cities in India.

This study uses Landsat 8 data. The Landsat program launched its first satellite in 1972 and is the world's longest running program to collect satellite images of the earth. The Landsat satellite captures data images called scenes that are typically sized 115 miles (north-south) by 115 miles (east-west) every 16 days (US Department of the Interior, 2018).

Atmospheric disturbances that exist while these images are captured require mathematical processing to extract the LSTs. The satellite data is in digital numbers (DN—a binary integer assigned to each pixel of the image) that must be converted to temperatures. DNs include atmospheric effects between the earth's surface and the satellite. To convert these DNs to LSTs, several methods have been developed by prior researchers (Weng, 2009; Deilami et al., 2018; Jimenez-Munoz et al., 2009; Zhang, Wang, & Li, 2006). One of these methods, the radiative transfer equation (Barsi, Schott, Palluconi, & Hook, August 2005), was used for computing LSTs in this study.

CHOICE OF URBAN AREAS

The strategy for choosing Indian cities for this research was to identify at least one densely populated city from each of the five climate zones classified by India's Energy Conservation Building Code (Bureau of Energy Efficiency, Government of India, Energy Conservation Building Code, 2007). Based on this and the availability of cloud-free data, a total of seven cities were studied. Populous US cities in which UHIs are well-documented (New York, Chicago, Houston) were also included in this study to provide comparisons of urban landscapes and to help validate the methodology used in this study. Phoenix, a US desert climate, was included for comparison to hot, dry Indian locations, and Pittsburgh, the city from which the research is being conducted, was included in case future work permits the exploration of air temperatures and other local built environment characteristics to serve as validation of the methodology applied elsewhere. Table 1 shows the cities chosen for this analysis with their Köppen climatic zones, population densities (Demographia, April 2018), and cooling and heating degree day data (Bhatnagar, Mathur, & Garg, 2018).

As seen in the table, the Indian cities are heavily cooling dominated compared to the US cities. Even more noticeable are the differences in population density; the Indian cities are 3–15 times more dense than New York City, the most densely populated city in the US. Although CCDs in Houston and Phoenix are comparable or higher than those in India, the HDDs in those cities and far lower population densities suggest reduced impact from high temperatures.

City	Köppen Zone*	Urban Density (ppl/sq mile)	CCD (65F/18C)	HDD (65F 18C)
Mumbai	Aw	68,400	3,457	0
Chennai		26,100	3,992	0
Bengaluru		24,300	2,342	0
Hyderabad		20,200	3,154	0
Ahmedabad	Bsh	58,400	3,587	6
New Delhi		32,100	2,926	248
Guwahati	Cwa	14,600	2,325	61
New York City	Dfb	4,500	1,429	3,996
Pittsburgh		1,900	849	4,915
Chicago	Dfa	3,400	992	5,433
Houston	Cfa	2,800	3,532	807
Phoenix	Bwh	3,100	5,210	608

Aw= wet-dry tropical, Bsh=dry tropical, Cwa & Cfa= humid mid-latitude, Dfa & Dfb=humid continental, Bwh=dry mid-latitude

Table 1: Cities chosen for analysis, Köppen Climate Classification, Urban Population Densities, and Cooling and Heating Degree Days (base temp: 65°F).

Landsat data from 2016 was used. Data from the summer months was reviewed to identify scenes that covered the metropolitan region of the city and surrounding rural areas with the least land cloud cover on days when the air temperatures were highest or close to highest. Based on these selection criteria, the dates for which data were downloaded and their respective air temperature and cloud cover details are provided in Table 2.

Location	Date	Max Temp (°F)	Land Cloud Cover (%)	Acquisition Time (local time, am)
New Delhi	05/21/2016	111	1.32	10:45
Mumbai	05/03/2016	93	5.15	11:00
Hyderabad	05/23/2016	104	0.04	10:40
Chennai	05/25/2016	106	16.77	10.30
Bengaluru	05/23/2016	100	2.58	10:40
Ahmedabad	05/10/2016	113	5.36	11:00
Guwahati	08/03/2016	100	5.95	09:45
New York City	08/12/2016	93	7.82	10:30
Houston	05/05/2016	57	0.06	10:45
Chicago	06/24/2016	82	22.05	10:30
Pittsburgh	06/14/2016	79	3.98	11:00
Phoenix	07/12/2016	102	0.00	11:00

Table 2: Date of analysis, maximum air temperature, cloud cover, and data acquisition for different locations.

Due to extensive cloud cover in data of summer months for Guwahati and Houston, non-summer data was used. Images from all the cities were captured in the mornings between 9 am–11:30 am local times. Use of morning data was necessary because the satellite path is fixed and these are the daytime hours at which the satellite passes through most of the Indian and US cities. Nighttime data is also available for some of the US cities, but this study chose to analyze the daytime LSTs while the impact of radiation is visible. The restriction on time of data capture is a limitation of this study, the Landsat data in particular. Availability of data across the temporal scale of a day would provide more accurate information about UHI at different times of the day. Although the results in this study do not reflect the peak LSTs of the day, because they reflect similar times of the day in summer months, they are still useful for calculating the surface UHI.

DEFINING URBAN AND RURAL BOUNDARIES, AND QUANTIFYING SUHI

The locations chosen for analysis are dense urban areas/cities expected to have high temperatures compared to the surrounding rural areas. However, there isn't any standardized way of defining the boundaries of a city/urban area. Rapid urbanization often extends built-up areas beyond original metropolitan boundaries. Prior research shows that researchers use different ways to define a city and/or calculate the UHI intensity (H. Liu & Weng, 2008; W. F. Li, Cao, Lang, & Wu, 2017; J.-j. Li, Wang, Wang, Ma, & Zhang, 2009; Mathew, Khandelwal, & Kaul, 2017; L. Liu & Zhang, 2011).

For this research, Land Use Land Cover (LULC) data (NRSC, 2018) for all the Indian cities was studied. Land cover provides information about the type of land, such as water, cropland, etc, while land use shows how the land is being used by the human population. LULC data are available for free from the National Remote Sensing Center of India and from the US National Oceanic and Atmospheric Administration for other global locations.

As seen in Figures 1 and 2, in Hyderabad and Ahmedabad, the district boundary includes large areas of agricultural and barren land, as well as urban built-up area, showing a blend of LULC urban and rural uses. The opposite is observed in Figures 3 and 4, for Mumbai and Chennai, where the district boundaries do not include all the urban built-up land use in that area.

In the chosen Indian cities, neither the city administrative boundary nor the district boundary effectively delineated urban and rural areas. Hence, the LULC data was visually analyzed and mapped, using Google Earth, to define the urban boundary. A perimeter was drawn around the urban built-up land use type and the area within that perimeter was considered to be urban. The UHI magnitude was calculated based on these classifications.

For the US locations, county boundaries were used to define the urban areas for every city except New York because the county boundary included all the urban built up areas. In New York, the urban area was defined using the LULC and Google satellite imagery. For both Indian and US cities, the rural boundary was considered to be 50% of the urban area added around the urban boundary.

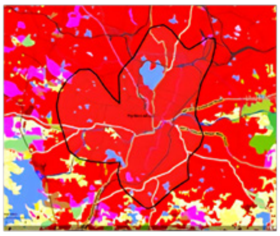
The UHI was quantified as the difference between urban mean LST and rural mean LST. Table 3 shows this information: the urban and rural mean LSTs for each city and the difference between those values, indicated as ΔT. Table 3 is discussed in the next section.

Results and Discussion

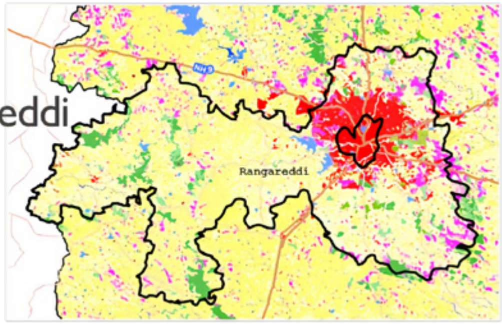
LSTs were mapped and analyzed for each city. Although, prior studies show a strong correlation between air temperatures andh LSTs (Gallo, Hale, Tarpley, & Yu, 2011; Kawashima, Ishida, Minomura, & Miwa, 2000; Mildrexler, Zhao, & Running, 2011; Mutiibwa, Strachan, & Albright, 2015), none of these studies examine Indian locations. Studies show that the relationship between LST and air temperature can vary highly with land cover. In this study, as seen in Figures 5–9, the LST ranges for cities in India and US look similar. The near surface air temperatures, however, are likely to be quite different based on the variations in population density and CDD shown in Table 1. And these near surface air temperatures affect building cooling energy needs and human comfort. Air temperatures are influenced many local factors such as infrared radiation, wind, anthropogenic heat rejection, cooling caused by vegetation, etc., rather than the more limited factors (solar radiation and surface properties) that influence LSTs. However, mapping LSTs provides interesting insights into the range of temperatures across regions, the urban landscapes, and potential means to mitigate UHIs in urban areas. Cool roofs, green roofs, and urban greenery are well-documented mitigation measures for UHI (Akbari, Levinson, & Rainer, 2005; Akbari, Menon, & Rosenfeld, 2009; Baik, Kwak, Park, & Ryu, 2012; Xu, Sathaye, Akbari, Garg, & Tetali, 2012). Exploring and mapping LSTs is an important first step to identify possible UHI mitigation measures related to built environment.

LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup Urban	202.5	Agriculture Crop land	1.12
Grass/Grazing	0.34	Barren/unculturable/ Wastelands, Scrub land	0.53
Wetlands/Water Bodies River/Stream/canals	2.6	Wetlands/Water Bodies, Reservoir/Lakes/Ponds	9.91
Total			217.00

Hyderabad

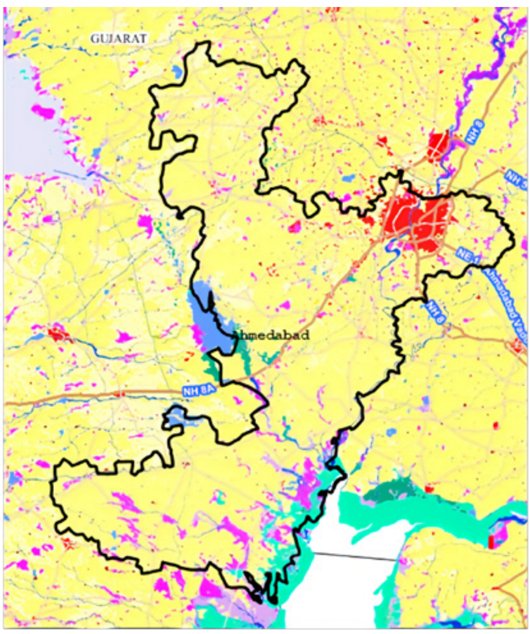


Rangareddi



LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup,Urban	826.18	Builtup,Rural	128.01
Builtup,Mining	62.2	Agriculture,Crop land	3844.4
Agriculture,Plantation	67.08	Agriculture,Fallow	1084.56
Forest,Deciduous	315.25	Forest,Forest Plantation	62.55
Forest,Scrub Forest	276.32	Grass/Grazing	30.47
Barren/unculturable/ Wastelands, Salt Affected land	0.02	Barren/unculturable/ Wastelands, Gullied/Ravinous Land	0.33
Barren/unculturable/ Wastelands, Scrub land	489.64	Barren/unculturable/ Wastelands, Barren rocky	58.41
Wetlands/Water Bodies, River/Stream/canals	28.35	Wetlands/Water Bodies, Reservoir/Lakes/Ponds	219.21
Total			7493.00

Figure 1: Land Use Land Cover data for Hyderabad and Rangareddi District (surrounding Hyderabad), showing urban areas beyond Hyderabad and extensive non-built-up land in Rangareddi District.

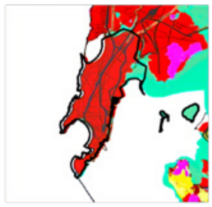


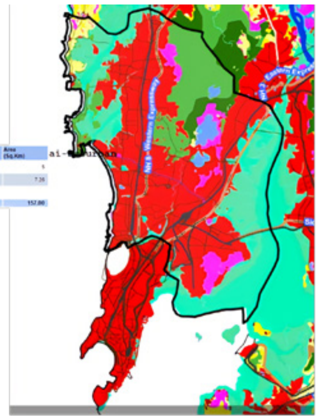
Ahmedabad District

LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup,Urban	325.46	Builtup,Rural	58.55
Agriculture,Crop land	6591.87	Agriculture,Plantation	11.2
Agriculture,Fallow	331.38	Forest,Swamp/ Mangroves	1.13
Barren/unculturable/ Wastelands, Salt Affected land	143.56	Barren/unculturable/ Wastelands, Scrub land	461.33
Barren/unculturable/ Wastelands, Sandy area	35.12	Wetlands/Water Bodies, Inland Wetland	394.35
Wetlands/Water Bodies, Coastal/Wetland	74.75	Wetlands/Water Bodies, River/Stream/canals	128.91
Wetlands/Water Bodies, Reservoir/Lakes/Ponds	149.39		
Total			8707.00

Figure 2: Land Use Land Cover data for Ahmedabad District, showing extensive non-built-up land in the district.

LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup Urban	144.12	Forest Swamp/ Mangroves	5
Barren/unculturable/ Wastelands, Barren rocky	0.5	Wetlands/Water Bodies Inland Wetland	7.28
Wetlands/Water Bodies Reservoir/Lakes/Ponds	0.32		
Total			157.00

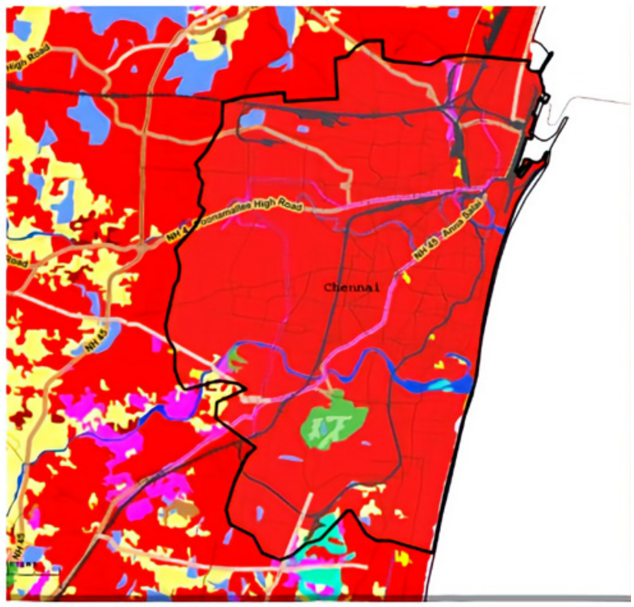




Mumbai city and Mumbai Suburban Districts

LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup,Urban	191.39	Builtup,Rural	0.7
Builtup,Mining	1.05	Agriculture,Crop land	32.63
Agriculture,Plantation	7.17	Agriculture,Fallow	0.01
Forest,Evergreen/ Semi evergreen	31.93	Forest,Deciduous	44.28
Forest,Scrub Forest	0.84	Forest,Swamp/ Mangroves	53.26
Barren/unculturable/ Wastelands, Salt Affected land	0.05	Barren/unculturable/ Wastelands, Scrub land	21.23
Barren/unculturable/ Wastelands, Barren rocky	0.25	Wetlands/Water Bodies, Inland Wetland	49.22
Wetlands/Water Bodies, River/Stream/canals	7.16	Wetlands/Water Bodies, Reservoir/Lakes/Ponds	4.82
Total			446.00

Figure 3: Land Use Land Cover data for Mumbai and Mumbai Suburban Districts, showing urban built-up area (in red) beyond district boundary line.



Chennai District

LULC Class	Area (Sq.Km)	LULC Class	Area (Sq.Km)
Builtup,Urban	157.39	Builtup,Rural	0.02
Agriculture,Crop land	1.34	Agriculture,Plantation	0.62
Forest,Deciduous	2.69	Forest,Scrub Forest	0.59
Barren/unculturable/ Wastelands, Scrub land	1.45	Barren/unculturable/ Wastelands, Sandy area	0.65
Wetlands/Water Bodies Coastal/Wetland	1.81	Wetlands/Water Bodies River/Stream/canals	3.51
Wetlands/Water Bodies, Reservoir/Lakes/Ponds	0.93		
Total			171.00

Figure 4: Land Use Land Cover data for Chennai showing urban built-up area (in red) beyond district boundary line (in black).

LST, LULC, AND URBAN DENSITIES

The LST maps were examined to see the temperature patterns across locations. In the maps for Indian locations, the core urban areas with high urban densities indicate lower LSTs than the suburban or rural areas for all cities except Chennai and Guwahati. Figure 5 shows the maps for Delhi and Guwahati. In dense urban areas, concrete buildings with some surrounding greenery, such as can be found in Delhi, can cause local shading, reducing the surface temperatures. By comparison, rural areas of Delhi are barren, fallow lands with no shading or moisture, and hence retain the heat from the short wave radiation that increases LST. A similar case is the US city of Phoenix, where the urban LSTs are lower than the surrounding desert lands (Figure 6).

For Chennai and Guwahati, however, the surrounding rural areas are densely vegetated, with more moisture, shading, and evapotranspiration, and hence lower temperatures compared to urban areas. This pattern is also observed for all the US cities except Phoenix. Figure 6 shows how LSTs taper away from the city center in Chicago, whereas the reverse is seen in Phoenix.

These maps do not clearly show the impact of population density on LSTs. Vertically rising buildings with no or minimal greenery are typical in dense Indian cities. Because the satellites read only the earth's skin temperatures, which may be roof and pavement temperatures, they may record lower temperatures within the city when compared to surrounding barren lands with no shading effect or moisture.

LST, LULC, AND HUMIDITY

Though LSTs are mainly influenced by surface properties, they can also vary with convective transfer that occur across surfaces, transferring heat from the surface to the lower atmosphere. This convective heat transfer process is highly dependent on the roughness of the surface and is also affected by humidity and heat rejection from human activities (Oke, 1982). This current work doesn't highlight or quantify the impact of human activity, but the SUHI patterns across humid climates were studied. A prior study (Zhao, Lee, Smith, & Oleson, 2014) reported that the SUHI is higher in humid climates where rural areas have higher moisture, greenery, and roughness. This phenomenon was also observed in this study, where the SUHIs are higher for humid climates.

Figure 7 shows examples of this. Chennai, a southern city in India on the Bay of Bengal, showed a ΔT of 3°F (see Table 3). This is the maximum DT observed among all the Indian locations and is the only case in which urban LSTs are greater than the rural. Similarly, Houston, a southern city in the US near the Gulf of Mexico, shows a DT of 12.8º F, the maximum among the US locations. As seen in the figure, the urban areas show higher temperatures compared to the surrounding areas. New York City, another humid location, follows this pattern with a higher ΔT (7.9°F) compared to the other cities in the US.

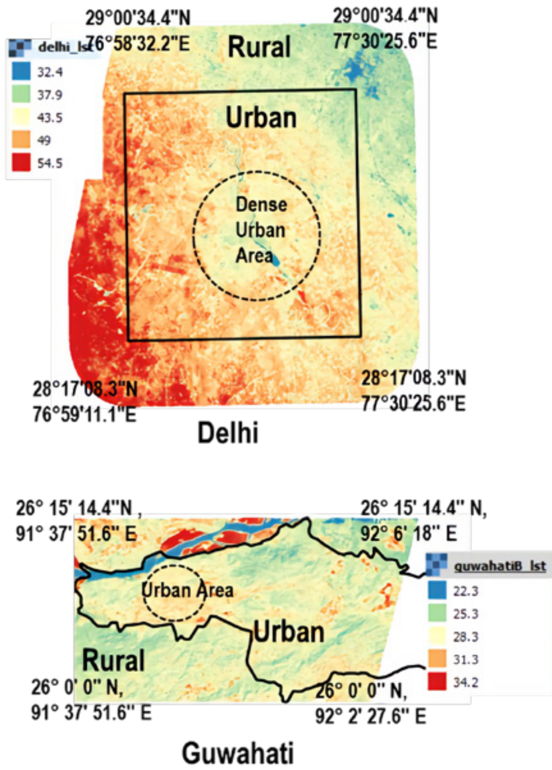


Figure 5: LST maps for Delhi and Guwahati showing urban and the surrounding areas. Delhi shows higher LSTs in rural barren lands compared to dense urban areas. Guwahati has higher LSTs in urban areas compared to surrounding vegetated rural areas.

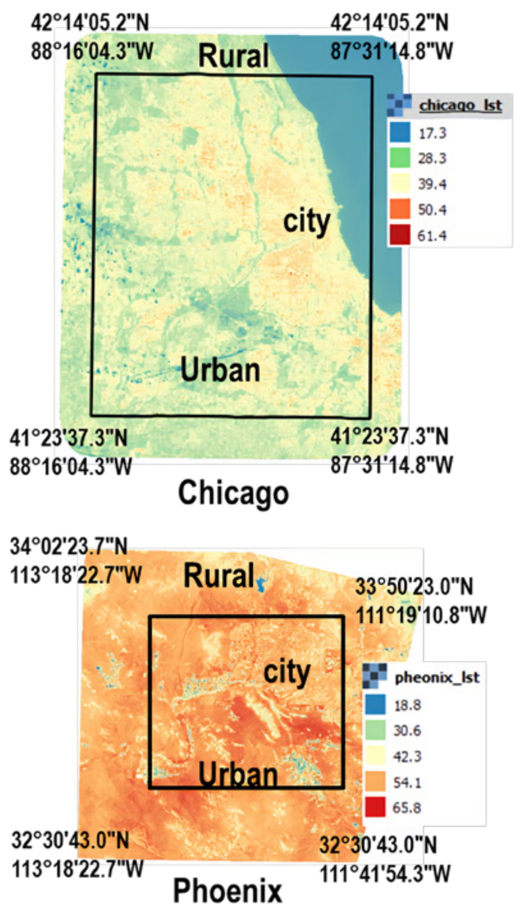


Figure 6: LST maps for Chicago and Phoenix showing areas. Chicago has higher LSTs in urban areas compared to surrounding vegetated rural areas. Phoenix shows higher LSTs in rural barren lands compared to dense urban areas.

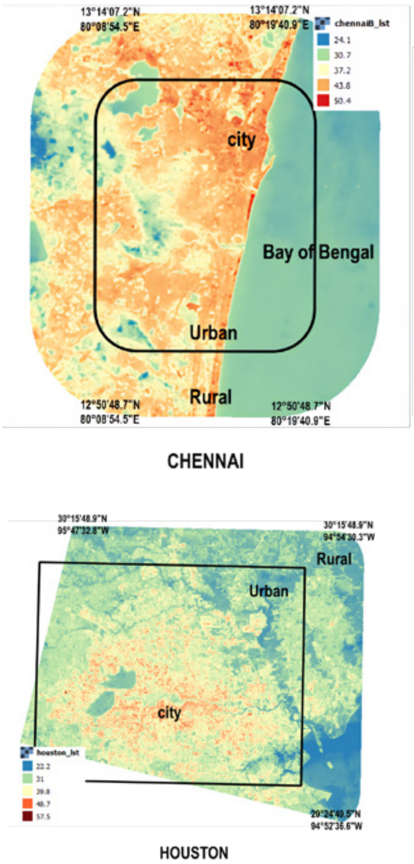


Figure 7: LST maps for Chennai and Houston showing warmer urban areas compared to the surrounding rural areas.

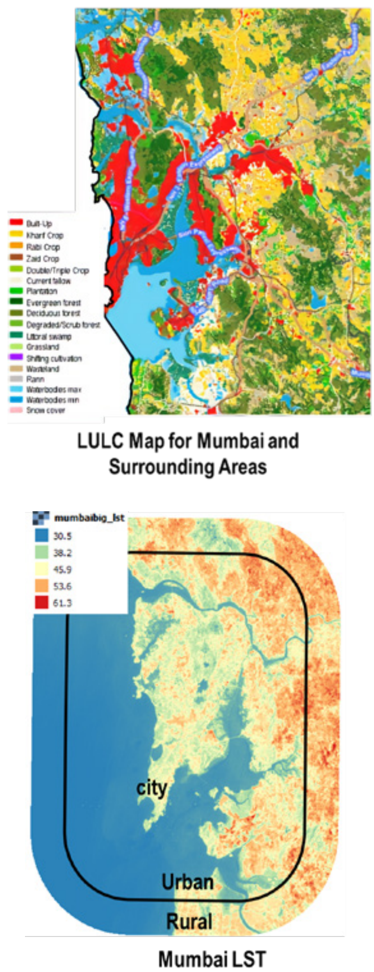


Figure 8: Land Use Land Cover Map (2016-17) of Mumbai and |surrounding areas in comparison with the LSTs across the area.

However, this wasn't true in the case of Mumbai, a western city along the Arabian Ocean in India, seen in Figure 8. The pattern in Mumbai is the opposite. The rural mean LST is 6.1°F greater than urban mean LST. Figure 8 shows the LULC maps for Mumbai and its surrounding areas, and the LST map. As seen in the figure, the majority of the rural surrounding of Mumbai are forests or croplands (rainy and winter crops) that lack greenery and moisture during summers, which may be the reason for the higher LSTs.

COMMON HOT SPOTS ACROSS URBAN AREAS

For all the locations in India and the US, the maximum LSTs are noted at either airports or black roofs on industrial or manufacturing buildings, and the minimum LSTs are observed in vegetated forest lands or water bodies. An example of this is shown in Figure 9, showing the maximum LST areas for Ahmedabad and New York City mapped with respective Google satellite imagery.

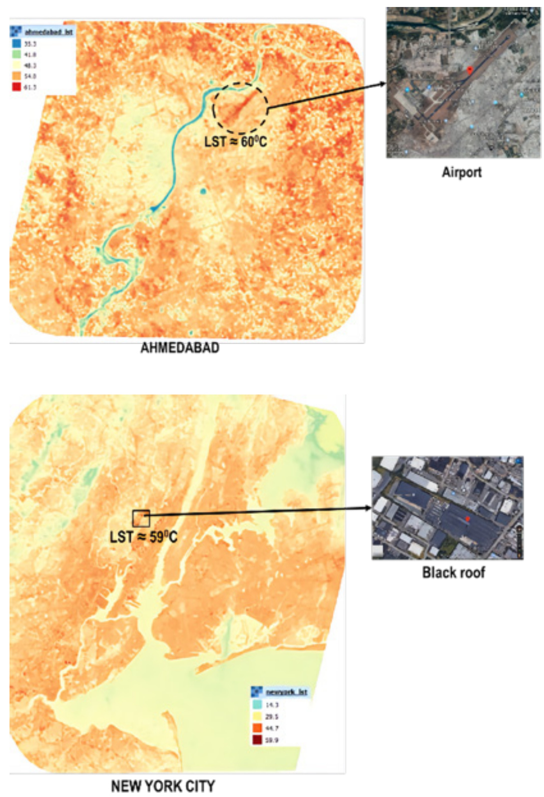


Figure 9: Ahmedabad and New York City LST maps highlighting example pixels with close to maximum LST values shown for an airport runway in the case of Ahmedabad, and for a black roof of a commercial building in New York City.

These results suggest the importance of albedo and evapotranspiration. Both of these factors have been identified by other authors as important factors in creating lower LSTs (Chen, Zhao, Li, & Yin, 2006; J. X. Li et al., 2011; Xu et al., 2012).

SUHI QUANTIFICATION AND RESULTS VALIDATION

The DTs ($T_{LSTurbanMean} - T_{LSTruralMean}$) calculated for all cities are shown in Table 3 and are consistent with the LST patterns mapped. For the Indian cities, the urban mean LSTs range from a low of 82°F in Guwahati, to a high of 114°F in Ahmedabad. The rural mean LSTs for the Indian cities are all slightly higher than the urban mean LSTs, ranging from 82.3°F in Guwahati to 120°F in Mumbai. This results in a negative number for the DT values in each Indian city. The greatest difference occurs in Mumbai, when the rural mean LST exceeds the urban mean LST by 6°F. These results appear to contradict the conventional definition of an Urban Heat Island, where urban temperatures exceed rural temperatures. While this trend of warmer rural temperatures in Indian locations was previously reported, there are no studies that have computed the intensities across several urban locations of India.

For the US cities, the urban mean LST range is similar to that of the Indian cities, ranging from a low of 83°F in Pittsburgh to a high of 131°F in Phoenix. However, for all the US cities except Phoenix, the rural mean LSTs are lower than the urban mean LSTs, a pattern consistent with the conventional UHI definition. Under these conditions, the DT is a positive number for each city except Phoenix. The largest difference occurs in Houston, where the urban mean LST exceed the rural mean by 11.4°F. In Phoenix, the DT is negative, but the difference is less than 1°F. These LSTs and the DTs computed for US locations are comparable with existing research (Liu & Weng, 2009; Li et al., 2016; Zhao et al., 2014; Imhoff, Zhang, Wolfe, & Bounoua, 2010). Hence, inclusion of US locations in this study not only helped in drawing comparisons across different climates and surface characteristics, but also helped in validating the methodology of this study. During the analysis, it was also noticed that the DT value, i.e., SUHI quantification, is highly dependent on how the urban and rural areas are defined. Alternative approaches to boundary definitions will be explored in future research.

Location	Urban Mean LST (0F)	Rural Mean LST (0F)	DT (0F)
Delhi	113.8	114.2	-0.4
Mumbai	114.4	120.6	-6.1
Chennai	104.3	101.3	3.0
Bengaluru	97.4	98.6	-1.2
Hyderabad	102.4	105.8	-3.4
Ahmedabad	124.8	127.2	-2.5
Guwahati	82.0	82.3	-0.3
New York City	103.8	95.9	7.9
Chicago	97.2	93.1	4.2
Houston	96.2	83.5	12.8
Pittsburgh	82.8	79.7	3.1
Phoenix	130.9	131.8	-0.8

Table 3: Surface Urban Heat Island intensities across all the locations in India and the United States.

LIMITATIONS

There are prior studies of Indian urban areas that identify the impact of urbanization on LSTs and vegetation cover over time (Sharma, Ghosh, & Joshi, 2013; Jalan & Sharma, 2014; P. Singh, Kikon, & Verma, 2017). These studies indicate that LSTs in urban areas in India increased with time due to a decrease in vegetation. These studies also showed increased LSTs over more land area due to urban sprawl, a finding somewhat different from that observed here. One of the limitations of this study is the temporal scale. The analysis was conducted using data from a single summer day. Hence, future work will include analysis across different seasons and years. It will also attempt to understand the interrelationship over time between urban development and the barren land within and around Indian cities.

Remote sensing data is commonly used for UHI studies because of its easy availability at no cost. However, LSTs may be quite different than the UHI as experienced by the human population. Consideration must be given for means to compare LST data with the urban microclimate, assuming that canopy level studies of each of these cities is not feasible for this research project.

The current research is a first step in achieving the broader goal of identifying the impact of the built environment, specifically building design and urban configurations, on UHIs across urban areas in India. The work, therefore, focuses on understanding the potential reasons for the UHI patterns and magnitudes and does not discuss the impacts—environmental, social, or economic—of the observed results. This will be a part of future work.

Conclusion

One of the primary objectives of this research was to add to the characterization and understanding of UHIs in areas that are currently poorly characterized—India's developing, super-dense cities—as a means to understand the impact of design of the built environment and how to improve it. While the results to date do not yet provide extensive insights into urban and building design strategies, they do provide useful information about the use of remote sensing data to map UHIs in rapidly developing places like India and reveal patterns in UHI that suggest the need for further exploration.

Remote sensing data is free and readily available, and as such provides the opportunity for UHI research almost anywhere. The mapping analysis in this research yields several insights, some of the most important include the LST maps for Indian locations that do not represent a traditional UHI pattern and that administrative boundaries are likely to be different from actual urban boundaries, so a UHI analysis must consider carefully how urban and rural boundaries are defined. Currently, researchers use a variety of methods and this can make the interpretation and comparison of results across studies difficult. The search for new and effective methods to define boundaries is important, however, and perhaps could become more standardized in the future.

As seen in this work to date, single point-in-time summer LSTs may be similar in very different climates. They do ot reflect the duration of heat (CDDs) and do not appear to indicate the impact of humidity. As such, comparing LSTs and the UHI ΔTs across locations may not reveal a great deal about the intensity or human impact of the UHI in a given location.

The SUHI quantification (ΔT) in this study revealed a pattern of consistently negative DT values for the Indian cities, except for Chennai, and for one US, Phoenix. The occurrence of negative ΔT values has been noted in other studies, but to date, very few researchers seem to have suggested that the definition of Urban Heat Islands may need to be revisited. Reconsidering the definition seems warranted and may lead to new insights into effective development of both urban areas and surrounding rural lands.

LSTs do not seem to reflect much impact of population density. As such, they may not be useful in looking at the combined impact of high pop density in already hot climate and climate change. A study of LSTs in a single area across multiple years, however, may be useful in evaluating those impacts and their magnitude based on the pace of change over time.

One clear design insight the study did provide was that, regardless of climate and the characteristics of natural land surfaces, dark building roofs and pavements will be hotter. In hot climates, those surface temperatures can exceed 140°F, even during morning hours. Design and engineering strategies that provide alternatives to dark roofs and pavements, and to their total surface area, will reduce LSTs. Because LSTs do not represent the air temperatures or the extent to which UHIs can impact building energy consumption and human comfort, it may be necessary to integrate LST research with a microclimate analysis of the built environment and canopy level UHIs to characterize UHI sufficiently to propose mitigation measures that address building and urban design.

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