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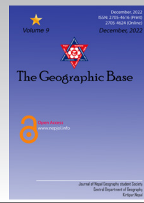

Effect of Urbanization on Land Surface Temperature: A Case Study of Kathmandu Valley

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Abstract

Growth in the population over time is bound to increase the expansion of densely populated areas which will change the dynamics of land use and land cover (LULC) directly or indirectly. The objective of this study is to analyze the effect of urban growth on the land surface temperature (LST) in Kathmandu. We used the maximum likelihood classification method for LULC classification and change detection of pre-monsoon satellite data for the years 2000, 2005, 2010, 2015 and 2020. LST was then calculated using the thermal infrared band from the satellite imagery. Finally, the relationship between urban growth and LST was assessed by correlation and regression analysis. The result shows an increase in urban areas by 241.61% of the total area between 2000 and 2020. The analysis of thermal patterns shows that there is a gradual increase in temperature in the urban area. With an overall accuracy of 89.96% and a Kappa coefficient of 0.86, the study shows high agreement between classified data from images. This study shows that urbanization has a significant positive impact on average land surface temperature. Sustainable city

planning and strict adherence to the Land Use Act and regulations will assist to make the urbanization process more sustainable in the future.

Introduction

Over time areas around the world have seen a concentration of population as people choose to reside in areas that offer better opportunities, better jobs, quality education, and healthcare (Feng et al., 2019; Shukla and Jain, 2019). As a result of this, there is a growth in the urban population. To address the demands of a growing population one type of land use has to inevitability be converted to another. For additional urban infrastructure brought on by population expansion, non-vegetated surfaces are replacing natural ones like vegetation. These non-vegetated surfaces can absorb heat and then release it. The land surface temperature is observed to rise as a result of this shift in land cover. The degree to which the soil surface is hot or cold is known as the land surface temperature (LST) (Latif, 2014). It is dependent on the amount of sunlight as well as the composition of the surface or object. Wet soil, vegetation, and water bodies are cooler than bare dirt, sand, metal, and built-up areas. Consequently, there is a connection between LST and urbanization.

Globally, 55% of people live in urban areas as of 2018, and 68% are predicted to live in urban areas by 2050 (Ritchie & Roser, 2018). According to the projection made in 2021 by the United Nations Department of Economic and Social Affairs made, 68.4% of the world's population will reside in urban areas by the year 2050 which was 56.2% in 2020. The dynamics of land use and land cover (LULC) have dramatically changed as a result of this growth in built-up metropolitan regions due to urban population growth (Feng et al., 2019; Wang et al., 2016). Nepal is one of the top ten fastest-urbanizing countries. There were 5,130,000 people living in cities in 2014, and the rate of urbanization was 3% while the degree of urbanization was 18.2% (UNDESA, 2014). Studies on the Kathmandu Valley between 1978 and 2000 AD indicated that urban areas there grew by almost 450% (Ishtiaque & Shrestha, 2017). Additionally, the Kathmandu Valley's average maximum temperature was 30°C in 2005, 31°C in 2012, and 35°C in 2015 (Magar et al., 2021). Urbanization has thus been recognized as a crucial factor in the valley. Population growth, environmental degradation, urban fragmentation, unplanned landscape development, stress on ecosystem structure, and changes to land use patterns are the results of it (Chauhan et al., 2021; Thapa, 2009).

Using data from thermal infrared remote sensing, the LST is determined. Thermal emission at infrared or microwave wavelengths, or "atmospheric windows," can be used to calculate the land surface temperature for satellites. The extraction of LST from radiance, which is directly recorded by onboard sensors, is fraught with numerous errors. Because the range of variation in surface emissivity in the thermal infrared (TIR) domain is lower and the reliance of the radiance on temperature is stronger, TIR-based LST retrievals are less uncertain than microwave-based ones. As recommended by UNHABITAT (2015), Kathmandu is susceptible to the impact of climate change.

In this context, this study aims to analyze the effect of urban growth on the LST in Kathmandu Valley.

Methods and Materials

Study area

The study area is Kathmandu Valley of Nepal which is located at Latitude: 27°34’33"N to 27°49’4" N and Longitude: 85° 11' 19" E to 85° 34' 57" E (Figure 1). Kathmandu Valley consists of Kathmandu, Lalitpur and Bhaktapur districts. The average elevation is 1300 meters above mean sea level (Pant & Dongol, 2009). It is surrounded by four high hills: Shivapuri in the northwest, Chandragiri in the southwest, Nagarjun in the northeast and Phulchoki in the southeast. Their altitude ranges from 1500 m to 2800 m.

Nepal's most populated and developed region is the Kathmandu Valley. The valley serves as the nation's economic center because it is home to the majority of the government's offices, corporate headquarters, and commercial hubs. The valley is also significant historically because it is home to seven world heritage sites. The Kathmandu Valley, which makes up less than 1% of the country's total land area, is home to 31% of the nation's urban residents (CBS, 2020). Since the 1980s, urban growth in the valley has intensified, and the growth rate was very high during the 1990s (Sharma, 2003).

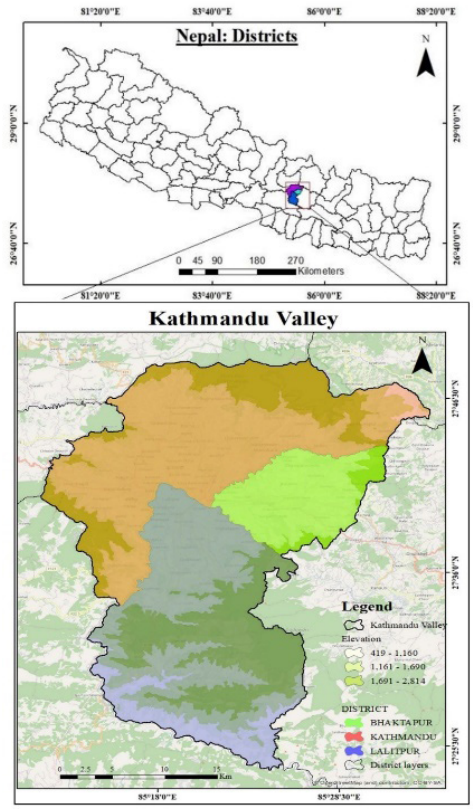

Figure 1. Location map of the study area

The Kathmandu Valley experiences subtropical chilly temperate weather. In April, the temperature reaches a high of 35.6 °C and a low of -3 °C. The average temperature ranges from 2°C to 20°C in the winter and from 19°C to 27°C in the summer. Southeast tropical monsoon influences the climate, which receives 1400 mm of rain on average from June to August. There are three distinct seasons: winter, which lasts from November to February, summer, which lasts from March to May, and rainy season, which lasts from June to October (Pant & Dongol, 2009).

Data

LULC data were based on the images of the pre-monsoon season of the different years (2000, 2005, 2010, 2015 and 2020) from Landsat satellites retrieved from the USGS website (https://earthexplorer.usgs.gov) (Table 1). These satellite data were also used to create LST based on the thermal band and NDVI based on red and near infra-red bands.

Table 1. Description of the Landsat datasets used for the study area

Sensor	Path/Row	Resolution	Acquisition date	Constants of thermal conversion		Source
				K1	K2	
Landsat 4-5 TM	141/41	30 m	4-Apr-2000	(Band 6)	(Band 6)	USGS
Landsat 4-5 TM		30 m	18-Apr2005	607.76	1260.56	
Landsat 4-5 TM		30 m	31-March2010			
Landsat 8 OLI/TIRS		30 m	1-June-2015	(Band 10)	(Band 10)	
Landsat 8 OLI/TIRS		30 m	7-Apr-2020	774.8853	1321.0789	

Methods

Figure 2 shows the methods applied in the spatiotemporal analysis for LULC change detection. For LST change analysis, first, the radiometric correction was performed to reduce or correct errors that arise in the digital numbers of satellite images. The raster was then clipped into the region of interest i.e. Kathmandu Valley. Secondly, Land Surface Temperature was estimated for the selected five years (2000, 2005, 2010, 2015 and 2020) from the brightness temperature using a thermal infrared band of Landsat using equations (i) and (ii) (Jiménez-Muñoz et al., 2014; Reddy & Manikiam, 2017).

$BT = (k_2/\ln (k_1/ L_\lambda +1)) – 273.15$ ……(i)

Where,

BT = Brightness temperature

L_λ = TOA spectral radiance (Watts/m^2 * sr * µm)

K1 and K2 are the thermal constants

$LST = BT/ (1+ (\lambda * BT/ C2) * \ln(\varepsilon))$ .. (ii)

Where h is the Planck's constant (6.62 * 10^{-34} Js), c is the light's velocity (2.998 * 108 m/s), and is the Boltzmann constant

($1.38 * 10^{-23}$ J/K), and λ is the central band wavelength of the emitted radiance (10.8 m) $\rho = h * c / \sigma$ ($1.438*10^{-2}$ mK).

ε is the emissivity given by $\varepsilon = 0.004 * PV + 0.986$, where, PV is the portion of vegetation calculated from the NDVI $((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}))^2$ and 0.986 is the correction value of the equation.

Third, image classification was done using pixel-based supervised classification. For the five selected years, images were classified into four categories as water, vegetation, settlements and bare land with the help of the maximum livelihood classification tool. Among them, the settlement area indicates urban growth which was of particular importance for this study. The resulting classified imagery was subjected to accuracy validation using an error matrix, producer accuracy and overall accuracy. For water, vegetation, settlements, and bare terrain, the producer's accuracy was 87.50%, 94.32%, 86.36%, and 88.89%, respectively. For the aforementioned class categories, the user's accuracy was 87.50%, 91.21%, 96.61%, and 81.63%. The Kappa Coefficient was calculated to be 0.86, indicating an almost perfect agreement between frequencies of data from images captured in the years 2000 to 2020. The overall accuracy was achieved at 89.96%. A total of 109 random spots were generated, with each class receiving a minimum distance allowance of 30 meters.

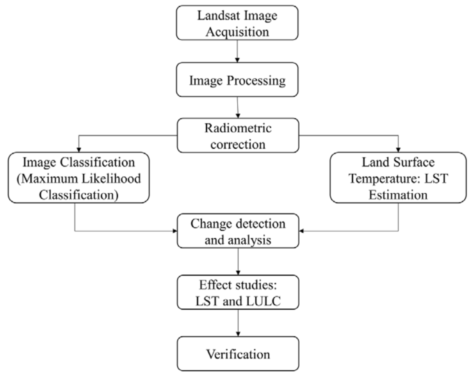

Figure 2. Methodological flow diagram

The Landsat 4-5 image from 2000 and the Landsat 8 image from 2020 with a 30 m resolution were used as the basis for the change detection approach. This was performed on a pixel-by-pixel level to create a different image. In the process, the pixel value was subtracted from the initial image and final image. Correlation and regression analyses were carried out to study the effect of urbanization on land surface temperature. The normality of the variables like LST, settlements, vegetation, bare land and water was checked using the R version 4.1.2 using Shapiro-Wilk Normality Test. And all the data follows a normal distribution.

Results and Discussion

Land use land cover change

The user and producer accuracy of the LULC classification was greater than 85% and overall accuracy was greater than 87%. Spatiotemporal analyses of LULC of Kathmandu Valley (Figure 3) show water, vegetation, settlements and bareland as major classes between the years 2000 and 2020. During this time settlements have increased in area by 241.61% of the total area. While vegetation, bare land, and water have decreased by 15.43%, 3.39% and 0.35 respectively (Figure 3).

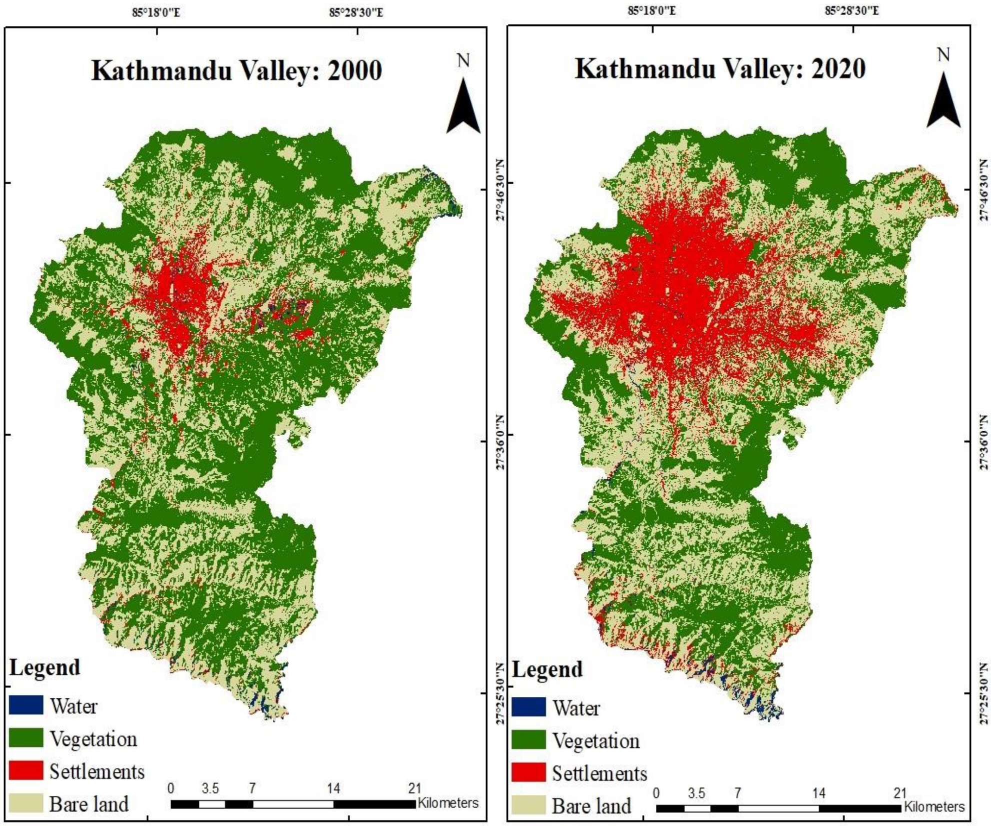

Figure 3. LULC of Kathmandu Valley in 2000 and 2020.

Figure 4 depicts summaries of the LULC change. Among all the classes obtained from the classification results, vegetation is dominant in the year 2000, 2005 and 2015 occupying 516.95 sq. km, 489.21 sq. km and 476.63 sq. km respectively. Settlements, on the other hand, have a substantial area expansion from 5.85% in 2000 to 19.98% in 2020. The temporal urban growth pattern is given in Figure 5. Water area is found to occupy a small portion and decreased slightly in the study period. The chart also depicts a trendline of average LST over the same time frame and a noticeable decrease is observed in the temperature. The LST however shows very low significance to the LULC classes.

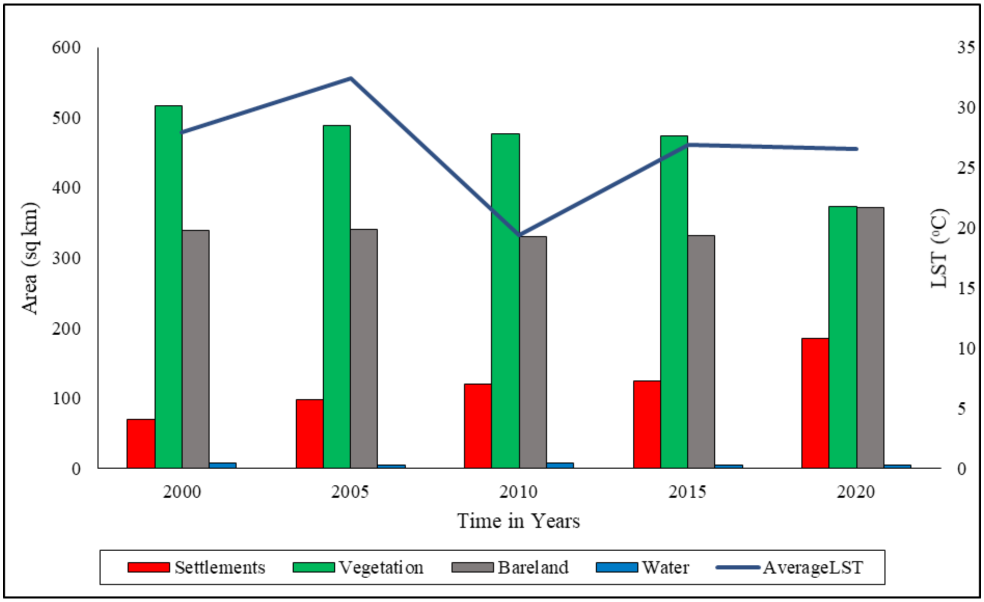

Figure 4. LULC change from 2000 to 2020 with the classification types

Figure 5 represents the trendlines of different land use classes. The figure shows an increase in the bare land and settlements. On the other hand, there is a decrease in vegetation and a very slight decrease in water. Trendlines relate the increase of bare land and settlements to cause a decline in vegetation.

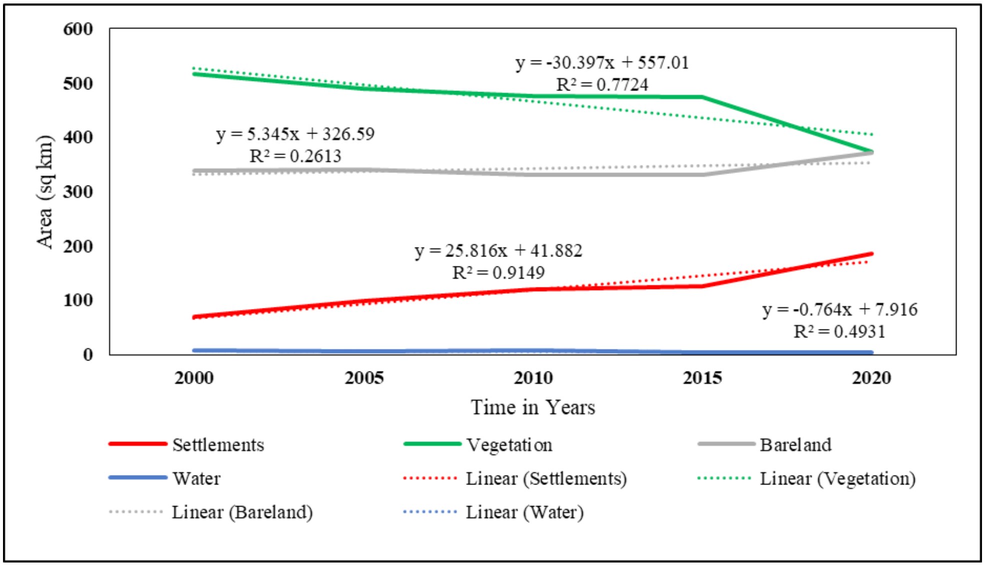

Figure 5. Trendlines of Different Land Use Classes

Figure 6 shows the most recent urban expansion on the northwest side of the valley. The other directions such as the eastern side, western side, and southern side have shown significant change in LULC too. Although the districts Lalitpur and Bhaktapur lie in the Kathmandu Valley, the rate of urbanization seems to be slower than in the Kathmandu district itself hence, the change in the other directions has been slow. Kathmandu Valley being the administrative capital of the country has opportunities to foster many lives with education, jobs and other amenities such that immigration to the valley is high every year. Hence to fulfill the different amenities that the valley has to offer, the building up of residential areas, parking lots, and shopping malls is on a rise and will tend to rise in the days to come.

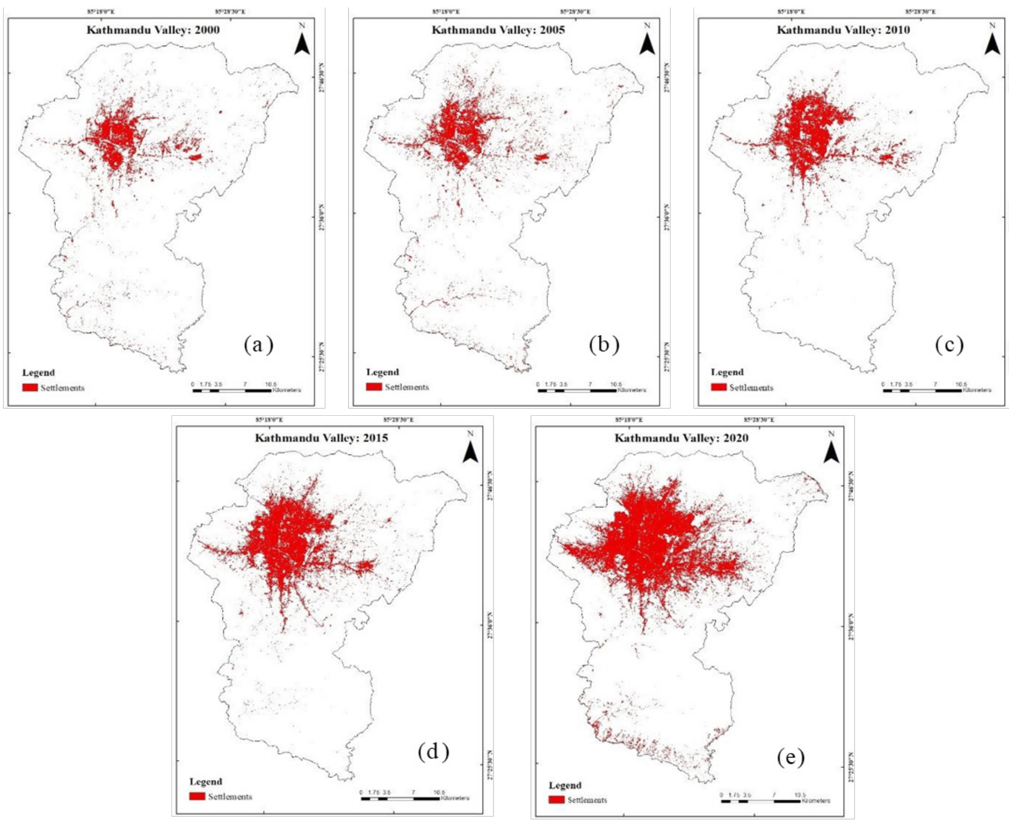

Figure 6. The urban growth pattern of Kathmandu Valley in a. 2000, b. 2005, c. 2010, d. 2015 and e. 2020

Kathmandu, Nepal's capital, is one of Southeast Asia's cities that is growing the fastest. It is located in the increasingly urbanizing Bagmati province in the country's center. This area is becoming more urbanized due to its religious and tourist attractions (Ishtiaque et al. 2017; Rimal et al. 2018). Losses of LULC classes, particularly barren areas and vegetation, have been caused by the rapid expansion of built-up zones in the form of transportation networks, residential, commercial, and industrial infrastructures, as well as associated buildups. Rapid population growth and migration for better facilities have boosted built-up areas and urban expansion dramatically. Many other cities throughout the world, most notably Chennai in India, have seen tremendous population increase and urban expansion. Many other cities around the world have experienced similar levels of rapid population growth and associated urban expansion, such as Xuzhou in China (Xi et al., 2018), Kandy City in Sri Lanka (Ranagalage, 2018), Chennai in India (Padmanaban, 2017), Tokyo in Japan (Wand et al., 2018), Istanbul in Turkey (Nigussie, 2016), Baguio in the Philippines (Estoque, 2017), Tehran in Iran (Rousta 2018).

Land surface temperature change

The pattern of LST of the urban area of Kathmandu is given in Figure 7. With the increase in urban areas, the urban heat island is also increasing.

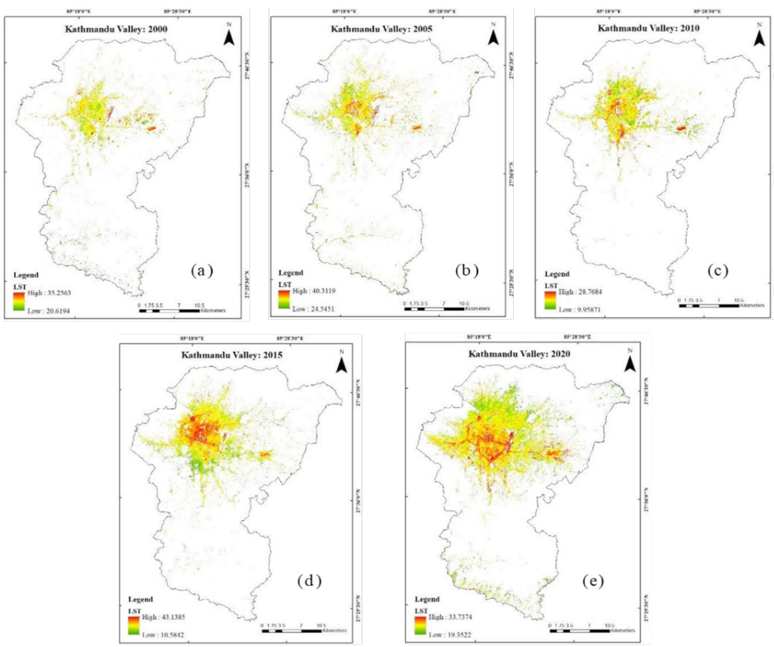

Figure 7. LST of urban areas of Kathmandu Valley from 2000 (a) to 2020 (e)

Figure 7 shows the LST in the years 2000, 2005, 2010, 2015 and 2020 respectively. LST ranged from 20.61ºC to 35.25 in 2000, 25.54ºC to 40.31ºC in 2005, 9.95ºC to 28.76ºC in 2010, 10.58 ºC to 43.13ºC in 2015, and 19.35ºC to 33.73ºC in 2020. The minimum temperature was observed to be increasing in the subsequent years. The maximum temperature decreased from 2005 to 2010 and from 2015 to 2020. Even if urban heating is an inescapable phenomenon brought on by population growth over time, the days can nevertheless get hotter. The red and yellowish patches in the figure corresponds to the urban settlements and the edges represent the other features like vegetation and bare land.

Relationship between LULC and land surface temperature

The effect of the spatiotemporal change of LULC on LST is presented in Table 2 and Table 3. There is a positive relationship between average LST and settlement. Since the p-value for all variables is greater than 0.05, the data follows a normal distribution. The relation between average LST and urban land use class was significant ($p<0.05$). For all other land used and land cover classes, p value for the significant test of correclation were greater than 0.05 (insignificant)

Table 2. Shapiro-Wilk normality test for different Variables

Variables	Shapiro.test (p-value)
LST	0.54
Settlements	0.76
Vegetation	0.13
Bare land	0.058
Water	0.47
Urban	0.06

The association between LST and bare land appears weak, but that between LST and vegetation is very poor. Water and LST have a weak correlation, as indicated by their negative correlation value (Table 3). Similar cases can be observed when settlements have a weakly negative association with LST. The findings imply a greater connection between bare land and settlement, i.e., that bare land decreases as settlement increases. The relationship between LST and Settlement is not discernible. This might be because the study only considered a small number of years and LST samples. A more precise cause-and-effect relationship might be revealed via the analysis of huge temporal data.

Table 3. Correlation (*r-value)* between urban growth and land surface temperature

LST	Max LST	Min LST	Avg. LST
Urban	-0.004	-0.087	0.075
All LULC	-0.479	-0.421	-0.105

The result also suggests a good association between bare land and settlements while the association of water and settlements is fair. McKinney (2006) suggest that the total vegetation in urban and suburban areas is a vital indicator of urbanization pressure on biodiversity because plants can be lost during either the initial habitat transformation or the topography fragmentation processes.

The mean LST increased from year 200 to 2005 from 27°C to 33 °C then greatly dropped in the year 2010 to 19°C, however the temperature increased in the years 2015 and 2020 to 27°C. The sudden drop in the year 2010 has slight to no effect on the LULC change.

Conclusion

Population growth over time will inevitably lead to unprecedented changes in land use and land cover patterns in cities. The study found that the Kathmandu Valley is experiencing rapid urban expansion. The main causes of this increase are an excessive population influx brought on by several pull factors and an inadequate land use plan. As a result, concrete structures are taking the place of open spaces and productive agricultural land. The trend is anticipated to worsen in the future due to the city's constantly expanding population. It has been determined that there has been a progressive rise in temperature in urban areas based on the analysis of the thermal pattern of the study region over the indicated time. One land use type will inevitably give way to another over time, but because urban growth in the Kathmandu Valley is rapid, the appropriate authorities must take the necessary action to buck this tendency.

The study has a few limitations. The images' resolution was just adequate (30 m) for purposes of categorization and change detection. The result could be improved by using high-resolution imagery data. It is also necessary to evaluate other geomorphic factors to better understand the urban growth and temperature relationship.

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