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IMPACTS OF LAND USE/LAND COVER CHANGES ON SURFACE URBAN HEAT ISLANDS: A CASE STUDY OF COIMBATORE, INDIA

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ABSTRACT

Urban Heat Island (UHI) is a major urban environmental issue throughout the world. UHI is a climatic phenomenon where anthropogenic modification leads to increased air temperature in urban areas when compared to that of the surrounding rural areas. Over urbanisation leads to an increase in UHI, resulting in the decrease of human health and a healthy environment. Remote sensing plays a major role in mapping the UHI as it can sense the top of the atmosphere radiances. From brightness, temperatures can be derived using Planck's constant. In this study, UHI of Coimbatore was determined by using the single channel algorithm during winter season. Landsat data of TM, ETM+ and OLI/TIRS were used. Thus, LST helps to identify the increase in heat due to expansion urban areas. Supervised classification with maximum likelihood technique was used to classify the imageries into five landuse classes.Based on this study, the result emphasies that the land use changes was observed to be 14.55 per cent, where as vegetation reduction was 11.6 per cent.Thus, by correlating all these scenario from the year 1990 to 2015 with a five-year interval, the rapid development that took place in the Coimbatore region led to decrease in vegetation and increase in built-up land and temperature. This study reveals that there was an increase of 3.8°C in land surface temperature during in the study periods. Also, the result indicates that there is a strong linearly negative correlation between land surface temperature and vegetation.

Keywords: GIS, LST, Landsat, Urbanisation and UHI.

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Introduction

Urbanisation has become a universal problem and the most important social and economic phenomenon which is occurring almost all around the world. One of the most crucial issues of global change in the 21st century is the rapid urbanisation,taking place in the developing world, will continue to affect the human dimensions (Sui and Zeng, 2001). Surface heat fluxes, govern the interaction of urban land surfaces with the atmosphere, thus its distribution is significantly modified by change in LULC. The main factors that impact the heat fluxes from urban areas are changes in the physical properties of the thermal capacity, surface albedo and heat conductivity. Converting the vegetation/natural surfaces to the asphalt and concrete surface buildings (i.e. pervious to impervious surfaces), the complicated geometry of streets, anthropogenic heat and tall buildings, decrease the surface moisture available for evapotranspiration and the near surface flow which results in a profound impact on radiative fluxes. This results in increased difference of temperature in urban areas when compared to the non-urban i.e. rural areas, this is called Urban Heat Island (UHI) (Mallick et al, 2013; Stathopoulou and Cartalis, 2007;Feizizadeh and Blaschke, 2012; Sobrino et al., 2013).

The magnitude of UHI is drastically affected by the changes in land use-land cover pattern, topographical location size and urban sprawl pattern, ecological context and seasonal variation of the temperature. (Singh et al., 2014). Various main reasons for urban climate change can be industrialisation, population increase and urban growth (Hu and Jia, 2010). The magnitude of UHI effect is proportional to the size of the urbanised area and its variation is high in summer time. As per the definition, the Urban Heat Island is a high temperature zone of hot air layer, formed at top of the buildings, paved surface, concrete structures and industries. Land surface temperature (LST) is the skin temperature of earth surface i.e. on the surface, it shows to what extent the earth is hot on its surface. Mainly, the parameters like different LULC categories and topography are some of the features that influence it greatly (Kayet et al., 2016). People are concerned about LST because, increase in surface temperature has a horrifying impact on the global climate. Hence, there is a need to study the impact of human activities and change in LST.

In general, three different methods were used to determine LST (1) Single Channel (SC) method, (2) Split Window (SW) algorithm and (3)Mono-window and the radiative transfer equation-based method. Zhang et al., (2011) developed a tool using C++ language for retrieving LST from Landsat TM/ ETM+ data using SC and SW approaches. Sekertekin et al., (2016) studied the spatiotemporal variation of UHI in Zonguldak city from 1986 to 2015, using the Landsat 5 TM and Landsat 8 OLI/TIRS imageries. In this study, thermal band 10 of Landsat 8 TIRS are used with the Mono-window algorithm for estimating the LST. A new method called Improved Mono-window (IMW) algorithm for LST extraction from Landsat 8 TIRS band 10 was developed by Wang et al. (2015). From their analysis, it was found that the IMW algorithm showed less errors than the SC algorithm.

Various studies have been conducted by several researchers on the assessment of LST and vegetation correlation.They investigated the use and explored the relationship between land use type and LST magnitudes. Kayet et al. (2016) studied spatial impact of land use/land cover change on surface temperature distribution in Saranda forest, Jharkhand.The study concluded that the decrease in the vegetation areas is mainly due to the growth of rapid mining industrial areas which also significantly increased the surface temperature. Weng et al. (2004), studied LST–vegetation abundance relationship u sing a Landsat ETM+ imagery of Indianapolis, IN, USA. Linear spectral mixture analysis was used to estimate urban vegetation abundance. Li et al. (2009) assessed the impact of rapid urban growth of Shanghai during 1997– 2004, developing UHI using remote sensing and GIS techniques. Chen et al. (2006) studied, UHI for Pearl River Delta (PRD) in Guangdong province, southern China using Landsat TM and ETM+ images from 1990 to 2000. To extract bare land from the satellite images, a new index called Normalised Difference Bareness Index (NDBaI), was proposed. Analysis results showed that due to a certain land use and land cover type, higher temperature in the UHI was located in a scattered pattern.The relationship between UHI and land cover changes was correlated with various index.

In this study, an effort is made to estimate the UHI by calculating the LST values, of Coimbatore region. Landsat TM, ETM+ and Landsat 8 data were downloaded between the periods of 1995 to 2015. ArcGIS 10.4 was used to prepare land use land cover classification. Also ArcGIS model builder was used to create a new tool to estimate LST using SC algorithm. It helps in deriving the relationship between land use and surface temperature of the region.

Study Area

The study area, Coimbatore is the second largest city in the State after Chennai and 16th largest city in India. It is located on the banks of Noyyal River, surrounded by the Western Ghats. The corporation consists of 452.2 square kilometre area with 100 wards, extended from latitude 10°53′ to 11o7′ and longitude of 76°48′ to 77°11′ (Figure 1). It is divided into five zones namely, North, South, East, West and Central with a population of 1,601,438 individuals as per the 2001 census. Now the city's population has almost doubled since the year 1981 which points at a steady increase in population and is represented in Table 1 and Figure 3. The study area has four distinct seasons, South-West monsoon from June to September, North-East monsoon from October to December, the winter season from January to February and summer from March to May.The highest temperature ever recorded is 40.4 °C on May 5, 1983, while the lowest is 11.7 °C on January 8, 1912.The annual average rainfall is 670 mm and the city gets rain during both the monsoon periods. Rapid industrial developments in textiles and automobiles sectors between 1990 and 2010 attracted more number of people towards the city. which resulted in an increase in the urban built-up area and consequently a decrease in the forest and agriculture lands in and around the city (Table 3, Figures 2 and 3).

Table 1: Demographic Data for Coimbatore

Year	1911	1921	1931	1941	1951	1961	1971	1981	1991	2001	2011
Population (Lakhs)	0.47	0.68	0.95	1.3	1.98	2.86	3.563	7.04	8.16	9.3	11.2

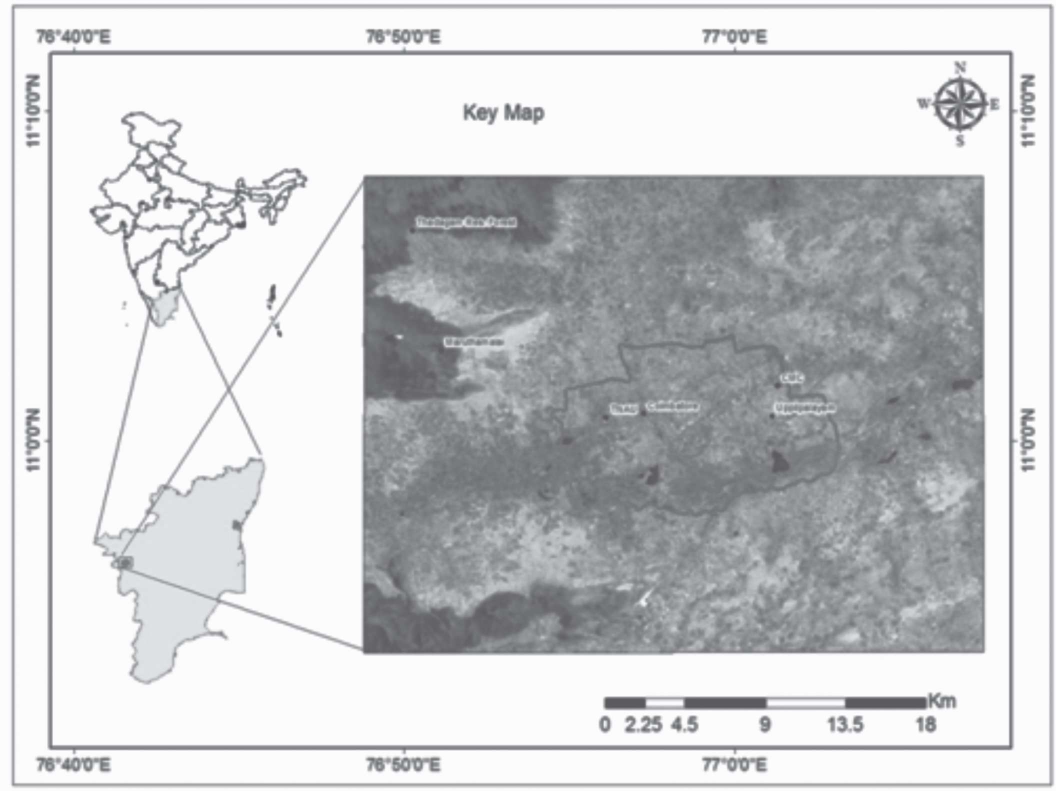

Figure 1: Map Showing the Study Area

Data Used

Depending on the availability of maps for the study area, features for the Base Map and availability of other resources of such data products are derived and extracted through various sources which are given in the following Table 2. Imh off et al. (2010) have reported that magnitude of UHI was higher in the summer during and almost all the images were downloaded in summer.

Table 2: Data and Products Used

Different data sources	Date	Resolution(m)	Path	Row
Landsat 5TM	31 May, 1995	30	144	52
Landsat 7TM	26 March,2000	30	144	52
Landsat 7TM	9 May, 2005	30	144	52
Landsat 7 ETM+	9 Nov, 2009	30	144	52
OLI/TIRS L8	3 April, 2015	30	144	52

Methodology

Three main steps are involved basically in this study, they are (1) Pre-processing which is atmospheric and radiometric correction (2) LU/LC classification using supervised classification and (3) LST calculation and UHI effect using Landsat thermal imagery. Zero cloud cover satellite dataset of Landsat TM, Landsat-7 ETM+ and Landsat OLI data of the study area are downloaded and the first step is to convert the DN values to at-sensor radiance,

$$L_\lambda = \frac{L\max_\lambda - L\min_\lambda}{QCAL\max - QCAL\min} * (DN - QCAL\min) + L\min_\lambda \quad (1)$$

L_λ= Spectral radiance at the sensor (watts/meter squared* Ster* μm)

DN = The quantised calibrated pixel value in DN

$L\min_\lambda$= The spectral radiance that is scaled to QCALMIN (watts/meter squared* Ster* μm)

$L\mathrm{man}_\lambda$= The spectral radiance that is scaled to QCALMAX (watts/meter squared* Ster* μm)

*QCAL*min=The minimum quantised calibrated pixel value in DN = 1

QCALmax=The maximum quantised calibrated pixel value in DN = 255

L_{MAX} and L_{MIN} are obtained from the meta data file available with the Landsat image.

NDVI Map Generation: The Normalised Difference Vegetation Index (NDVI), is an indicator for the vegetation that uses the visible and near-infrared bands of the electromagnetic spectrum. This is adopted to analyse measurement in remote sensing and to assess whether the target that is observed contains live green vegetation. Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1. NDVI values can be obtained by the following Eq. 2:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (2)$$

In this equation, Band 4 and Band 3 define the NIR and RED band of electromagnetic spectrum in Landsat TM and ETM+ whereas it is Band 5 and Band 4 define the NIR and RED band of electromagnetic spectrum in Land sat 8 OLI/TIRS. In this study, NDVI maps are generated in ArcGIS 10.4 software.

Land Use and Land Cover Classification: The land use and land cover categories are classified using the supervised classification method. For this classification, it involves two steps, one is to collect the data from the field survey as well as the local people in order to acquire local knowledge of the area. Second step involves making use of the collected data and assigning the training classes to classify the images for the study. The maximum likelihood classification algorithm is used for the study. Thus, this classification depicts a good fit with the field data. Thus, the area was classified accordingly into five classes: forest, agricultural land, built-up area, water body and wasteland. The classification process accuracy is usually assessed by comparing the results of classification with mentioned data from field visits.

Estimation of LST: The thermal infrared band (Landsat band 6 for Landsat 5 & 6 and band 10 & 11 for Landsat 8) was used to record the reflectance from the earth surface usually for the wavelength range between 10.4 and 12.5 µm. In an electromagnetic spectrum, this band is referred as the thermal band. Land surface temperature plays an important role in assessing many environmental processes. It can also provide basic primary information on the physical properties taking place on the surface of earth and climatic condition that is evolving. For example, the TM TIR data are very much helpful in observing the temperature difference between urban and non-urban areas in some States of the U.S. (Weng 2001). In most studies, LST is generated using the image processing software followed by processing in GIS software. In this study, ArcGIS 10.4 software is used to develop an automated tool for analysis of the LST. The overall methodology used to develop the LST mapping is given in Figure 2.

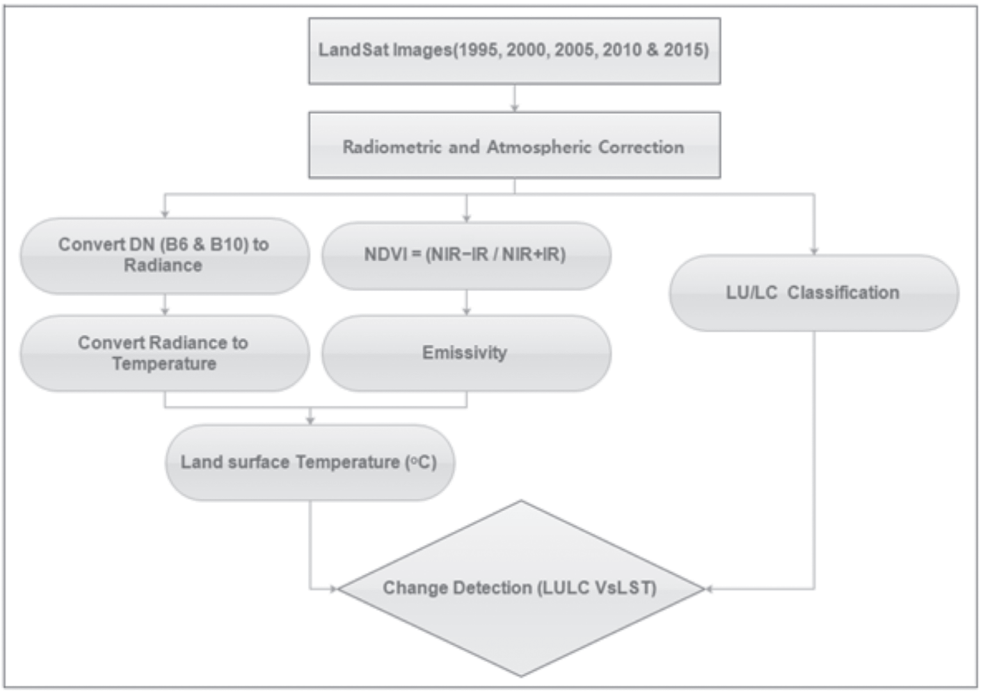

Figure 2: Flowchart Showing the Methodology for LST Mapping

Determination of LST: The LST is calculated by applying the following several steps.

(a) DN to Radiance

The DN values should be converted from Digital Number to radiance values using the equation (3)

$$Ls = Gain.\ DN + Bias \qquad (3)$$

(b) *Radiance to Brightness Temperature*

The Radiance value is now converted to Brightness Temperature using the equation (4)

$$T_s = \frac{k_2}{In\left[\frac{K_1}{L_s}+1\right]} \qquad (4)$$

(c) Proportion of Vegetation

It is used to identify the proportion of vegetation which is used to calculate the emissivity of the data. Thus, the proportion of vegetation is calculated by the equation (5)

$$T_s = \frac{NDVI - NDVI_{Min}}{NDVI_{Max} - NDVI_{Min}} \qquad (5)$$

(d) Emissivity

The emissivity were based on our land cover classification (Yuan et al., 2005). In this study emissivity values were adopted from Snyder et al. (1998). From the proportion of vegetation, the emissivity of the data could be analysed using the equation (6)

$$\in = 0.004P_v + 0.986 \qquad (6)$$

(e) Land Surface Temperature

Thus, by using the Thermal band, Brightness Temperature and Emissivity, the LST can be obtained using the equation (7)

$$LST = \frac{T_s}{1+\left(\lambda * \frac{T_s}{\rho} * In(\varepsilon)\right)} \qquad (7)$$

Where $\rho(1.438x10^{-2}mK) = h * \frac{c}{s}$

h = Planck's constant (6.626 x 10^{-34} JS)

c = Velocity of light (3 x 10^{8} m/s)

s = Boltzmann constant (1.38 x 10^{-23} J/K)

Model Builder: An automated tool was created to determine LST using ArcGIS model builder with Single Channel algorithm. Model Builder is a sequence of tools and data chained together where the output of one tool is fed to the input of another. Figure 4 shows the developed model builder and Figure 5 shows the tool in execution condition. Blue box indicates the input parameter, yellow box indicates the processing parameter and green box indicates the output parameter.

Results and Discussion

Land cover data help in calculating the area or region covered by various land covers such as built-up land, forests, vegetative land, wasteland and waterbodies. Waterbodies include Rivers and lakes. Land use shows in which manner people are using the landscape for development, conservation, or mixed uses. Different types of land cover can be managed or used quite differently. The LU/LC map of the study area is prepared from satellite imagery using supervised classification in ArcGIS.

The LULC for Coimbatore region is processed and analysed from the year 1995 to 2015 in every five-year intervals, in which it has been classified as Level 1 classification of NRSC, where it has been classified into 5 classes namely settlements, reserved forest, agriculture, wasteland, water body. Classified LU/LC image of Coimbatore for the period of 1995-2015 is shown in Figure 3 and the corresponding statics are shown in Table. 3. Accuracy of this land use classification was use to collect ground truth values.

Table 3: LULC Statics for Coimbatore

Landuse	Area _1995 (Sq. Km)	Area_2000 (Sq. Km)	Area_2005 (Sq. Km)	Area_2010 (Sq. Km)	Area_2015 (Sq. Km)
Reserved forest	56.81	51.34	50.15	43.45	44.01
Agricultural land	216.58	206.14	196.46	190.05	161.70
Settlement	44.17	45.64	73.20	76.37	94.72
Wasteland	131.87	147.90	130.42	139.63	149.67
Water body	2.775	1.20	1.90	2.54	2.05

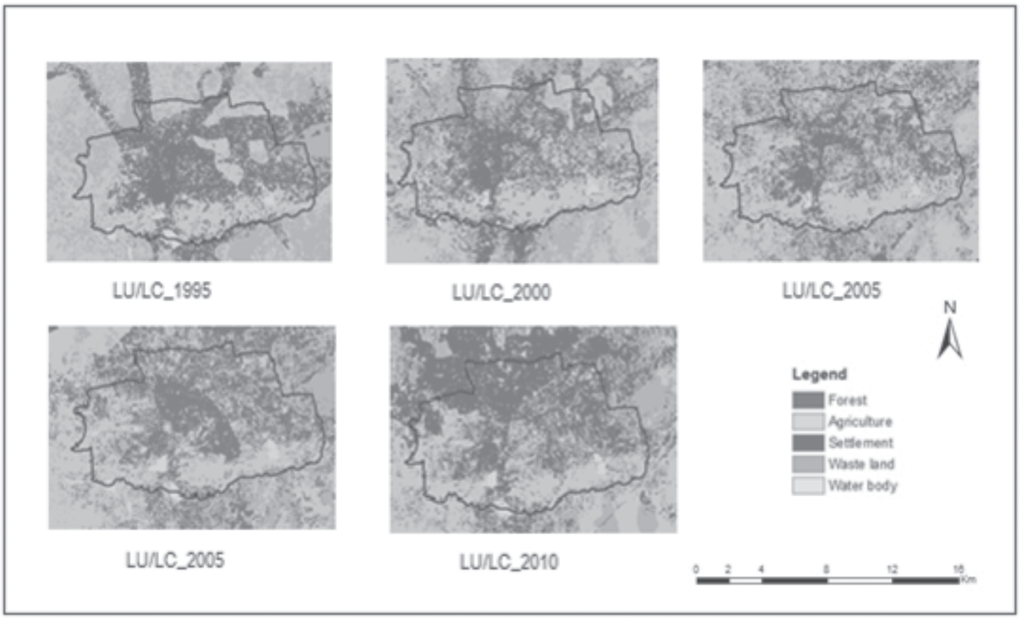

Figure 3: Land Use Land Cover Classified Map of the Study Area for the Periods of 1995-2015

The classified maps are displaying the incremental growth of built-up area (Figure 3). Within the time span of 20 years (1995– 2015), the build-up area has increased by 11.17 per cent point i.e. total 25.64 sq.km geographical land area. The maximum growth rate of build-up cover has been captured in 2000-2005 period with 50.64 per cent increase among other study periods (see Figure 3).

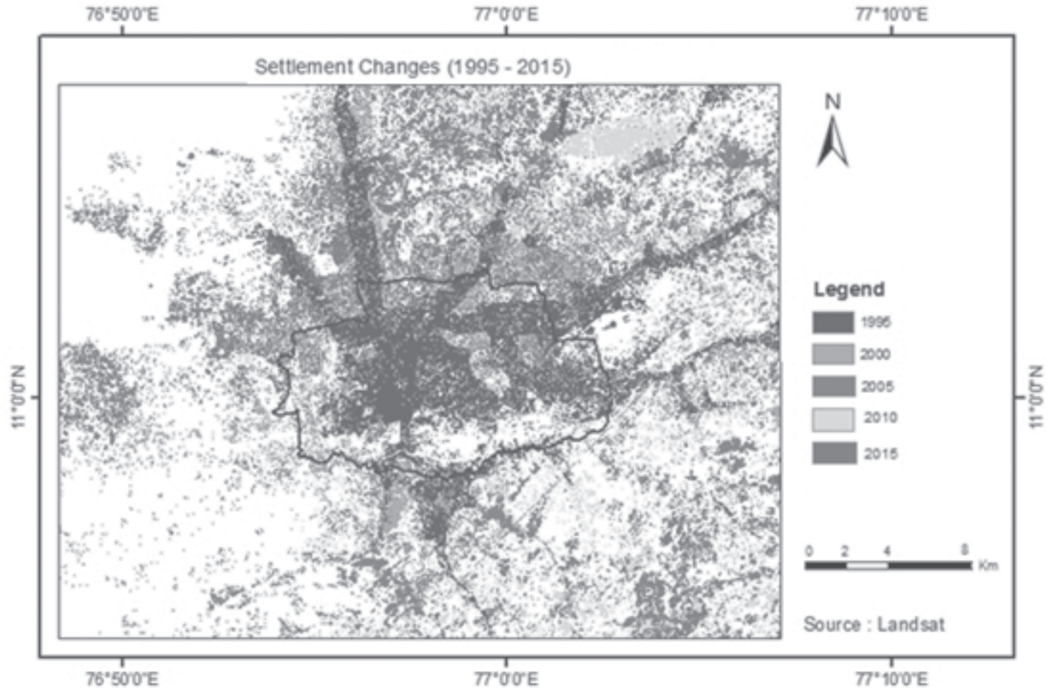

Figure 4: Expansion of Built-up Area During1995-2015

The pattern of changes in land use and land cover is heterogeneous in this study as the land cover categories other than the residential land use have experienced asymmetric fluctuation in growth. But, most of the growth was along the major road corridors.The growth of build-up area in each time span is shown in Figure 4. On the other hand, forest and agriculture area were reduced drastically. The maximum reduction rate of agriculture has been captured in 2010-2015 period with 14.94 per cent decrease among other study periods (see Figure 3). Also, water bodies have constantly shrunk with the rate of 0.16 sq.km within an interval of 16 years and 6.87 sq.km within 20 years. Overall, the water body shrinks nearly two per cent of the total area. Therefore, based on the land use classified maps, it is clear that in 2015 waste barren land and settlement area have increased and forest, agriculture and water body significantly gone down.

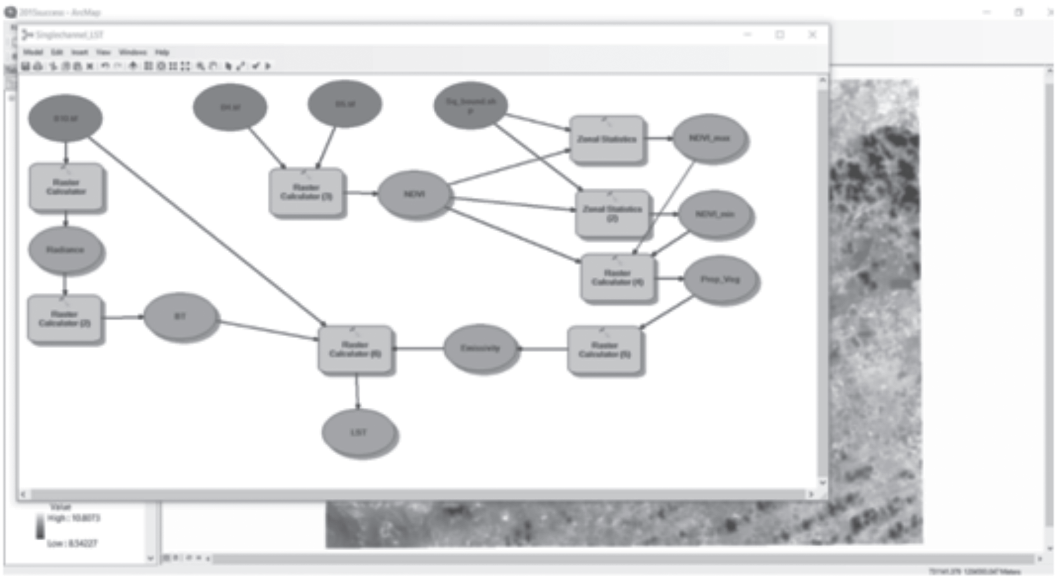

Figure 5: Model Builder Interface

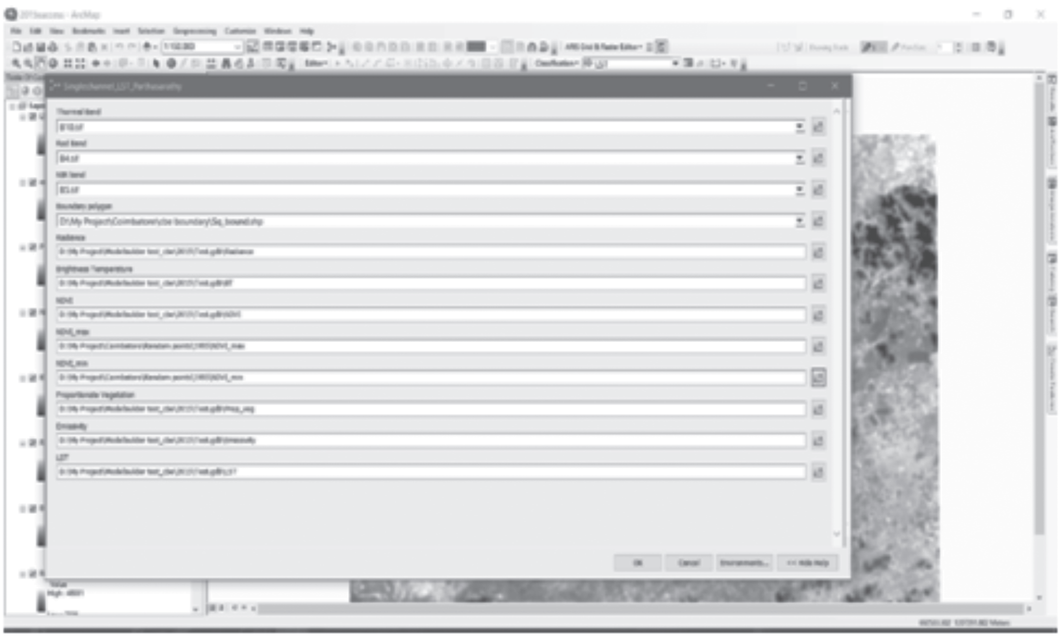

Figure 6: Snapshot of GUI of LST Tool in ArcGIS 10.4

Using the above interface (Figure 5), the model has been created to simplify the steps involved in deriving the LST within few clicks. This GUI model with assigned parameter value is presented in Figure 6.

Spatial Distribution and Changes of LST: The spatially varying LST for Coimbatore region is derived and analysed from the year 1995 to 2015, in every five-year intervals using the developed tool. In the year 2000, the LST (Figure 7) value ranges from 280°C to 300°C within the city corporation and slightly higher than 300°C where shown at periphery of the corporation boundary. Whereas, southern and south west region had less brightness temperature and less temperature.

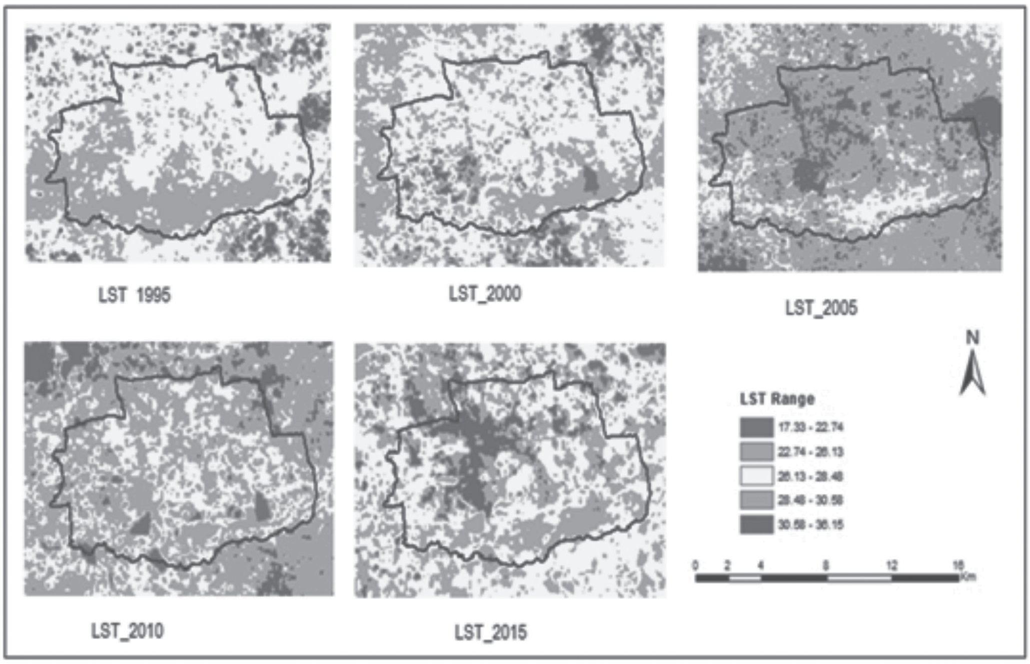

Figure 7: Land Use Surface Temperature Map of the Study Area for the Periods of 1995-2015

In the year 1995, the LST (Figure 7 a) value ranges from 260°C to 280°C within city corporation, due to the flow of Noyyal river on the south of the city and also as because of the high altitude. Thus, the temperature when analysed from the year 1995 to 2015, we come to know that UHI has increased where the temperature rise is up to 3.60°C at the hotspot region of the city, where the development is taking place in rapid rate. In the year 2015 the LST (Figure7e) value ranged from 300°C to 360 °Cn on an average within the city corporation limit. But, still there are few parameters like altitude and surrounding hills that have control over the increase in temperature, holding it back to the rise in temperature.

Relationship between LST and land use/ cover type: The land surface temperature patterns are associated distinctly with that of thermal characteristics of land cover classes (Weng, 2001). For the better understanding of the relationship of urban development on land surface temperatures, each land cover had been overlayed by a land surface temperature image with a land-use/land-cover map in the same year to obtain the thermal values. The land surface temperature mean values for various land-cover type for each of the multi-temporal images is summarised in Table 4. It is noticed that LST values were high in urban, bare land areas, followed by wasteland. On the other hand the LST values were low in vegetation areas, forest and water bodies (Table 4 and Figure 7). The LST values have increased for almost all areas from 2005 to 2015. For dense settlement area, industrial area and wasteland, increment in temperature is 3.6°C, 3.4 °C, and 3.3°C respectively. Similarly, for forest, vegetation and waterbody, it was slightly increased at 1.2°C, 1.3°C and 1.4°C. This increment may be an attributed result of less agriculture activities in this study area due to less amount of monsoon rainfall. The rise in temperature may be explained by the increase in percentages of sealed surfaces associated with extensive construction, road paving and higher building densities. In general, lower albedo values are referred to more heat absorption.

Table 4: LST for Each LULC Categories

LU/LC	1995_LST Value (°C)	2000_LST Value (°C)	2005_LST Value (°C)	2010_LST Value (°C)	2015_LST Value (°C)
Built-up	32.37	33.59	37.63	39.91	36.15
Water body	17.47	18.410	22.41	19.39	17.62
Dense forest	27.56	29.78	28.66	31.27	31.92
Agricultural land	28.40	29.63	28.26	31.12	31.77
Wastedland	30.56	32.71	31.42	33.36	35.89

Conclusion

This study is carried out to identify the spatially varying land surface temperature for the rapidly urbanising Coimbatore city in Tamil Nadu. Landsat data of TM, ETM+ and OLI/TIRS are used for the period of 1995 to 2015. Supervised classification technique was adopted to classify the satellite images. The LULC for Coimbatore region is processed and analysed from the year 1995 to 2015 in every five-year intervals based on Level 1 classification of NRSC. Accuracy assessment was made using observed field verification data. An automated tool was developed using model builder tool of ArcGIS software based on a single channel algorithm.

Thus, the LST helps to identify the increase in heat due to urbanisation and increase in impervious area. LU/LC classification data help to determine reduction of vegetative area fractions and increase in built-up land as well as the impervious surface variation in the region. Based on this study, there is a rapid growth in urbanisation of Coimbatore, the result emphasises that the land use changes was observed with 14.55 per cent vegetation reduction by year 2015. Thus, by correlating all these scenario from the year 1990 to 2015 with a five-years interval time, the rapid development that taking place in the Coimbatore region has lead to decrease in vegetation and increase in built-up land and temperature. This study reveals that an increase of 3.8° in land surface temperature occurs during the study periods. Also, the result indicates that there is a strong and linearly negative correlation between land surface temperature and vegetation. From the LST, it is clearly understood that the temperature surrounding the urban land is more than that of its periphery. Moreover, for a clear comparison and discussion the data should be in same month for all the year, preferably same period, but this is not possible as the data available may vary for even 2 or 3 months.

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