ORIGINAL RESEARCH PAPER

Earth Science

UHI SPATIO-TEMPORAL ANALYSIS WITH GEOSPATIAL TECHNIQUES: A CASE OF AHMEDABAD CITY.

KEY WORDS: Land Surface Temperature (LST), Normalize Vegetation Index (NDVI), Particulate Matter10 (PM10), Particulate Matter2.5 (PM2.5), Land Use Land Cover (LULC)

Ms. Darshana Rawal*	PhD Students. *Corresponding Author
Dr. Vishal Gupta	Associate Professor.

ABSTRACT

Spatio-temporal changes in land use land cover (LULC) have been relevant factors in causing the changes in Urban Heat Island (UHI) pattern across rural and urban areas all over the world. Studies conducted have shown that the relation between LULC on scale of the UHI can be an important factor assessing the condition not only for a country but for environment of a city also. Over the years it is reflected in health of vegetation and urbanization pattern of cities. As the thermal remote sensing has been evolved, the measurement of the temperature through satellite products has become possible. Thermal data derived through remote sensing gives us birds-eye-view to see how the thermal data varies in the entire city.

In this study such relations are shown over Ahmedabad city of India for the period of 2007 to 2020 using Landsat series satellite data. Land Surface Temperature (LST) is calculated using Google Earth Engine Platform Surface Brightness Temperature for Landsat data and using Radiative Transfer Equation for Landsat data. LST is correlated with land use land cover mainly Built-up, Vegetation, Barren land, Water & Other and corresponding Land Use and Land Cover respectively, and it is found that LST is positively related with all indices except for Normalize Difference Vegetation Index (NDVI) with strong negative correlation and R 2 of 0.51.

INTRODUCTION

In recent years urban heat waves, extreme droughts and forest fires have been reported with increasing frequency, disturbing the environmental dynamics and the quality of life in the affected cities. These changes affect the absorption of solar radiation, surface temperature, evaporation rates, storage of heat, wind turbulence and can drastically alter the conditions of the near-surface atmosphere over the cities (Mallick et al., 2008).

Urban Heat Island (UHI) term was coined in the year 1940 which refers to the atmospheric warmth of the city as compared to the countryside. Traditionally, UHI is measured at the standard screen height which is 1-2 meter above the ground below the mean roof height of the city. The structures and the land covers of the urban and rural areas are different which causes the UHI effect. The city's structure is rough attributed to the high raised buildings and the soil is impervious because of the construction material spread across the soil and vegetation cover of the city. The human induced release of moisture and heat also contribute to the UHI effect of the city (Stewart and Oke, 2012). The natural surface energy and radiation balance gets disturbed by such activities making the cities warmer (Oke, 1982, Lowry and Lowry, 2001).

The asphalt roads and highways, being black, absorb significant amount of electromagnetic radiations and hence heat up which later radiates heat into the relatively cold night sky (Berdahl and Bretz, 1997). The geometric effects such as the height of the buildings which provide multiple surfaces for reflection and absorption of sunlight- "the urban canyon effect", the blocking of wind are the other reasons for formation of UHI. Many forms of pollution also tend to alter the radiative properties of the atmosphere (Oke, 1982). These are a few reasons that cause difference in temperature between the rural and urban areas. The main cause of the urban heat island is modification of LULC. Urbanization has been significant during the last half-century and is expected to continue in the next decades (Alberti et al. 2007). Certain land use classes have a significant impact on the climate of a city. Weng et al. (2007) used landscape metrics and assessed the impact of LULC pattern on LST, and found that LST is positively correlated with the impervious surface but negatively correlated with green vegetation fraction. Same way Katpatal et al. (2008) investigated the influence of LULC of an urban area on air temperatures and found that the presence of a specific LULC class in the city may be related to the formation of surface heat island and canopy layer heat island within the urban area.

It has been observed in numerous studies that vegetation class in a city has an inverse relationship with the land surface temperature. As the total vegetation area in the city decreases over the decades, there is an increase in the temperature. Similar way, there is a strong correlation between the built- up area and land surface temperature. Yue and Xu (2008) found that urban buildings and population density, a location of industries, types of underlying surfaces, and diversity of urban landscape were the leading factors contributing to the urban thermal environment in the metropolitan area.

Variation in the Vegetation area, built-up area are the main factors of LULC, which influence the temperature in the city. As the urban sprawl has been increasing and it's leading to change in the LULC classes, it has become of utmost essential to understand how it is affecting the regional climate. More anthropological activities have consumed the space of fallow land and barrow land. This process of occupying the barren land, and, using it for various human activities have created a vicious cycle, which is keep affecting the temperature of a city.

While characterization and monitoring of ongoing urbanization processes is important, equally important is the ability to predict the local and regional environmental effects and feedbacks associated with expanding urban centers(Grimm et al. 2000).

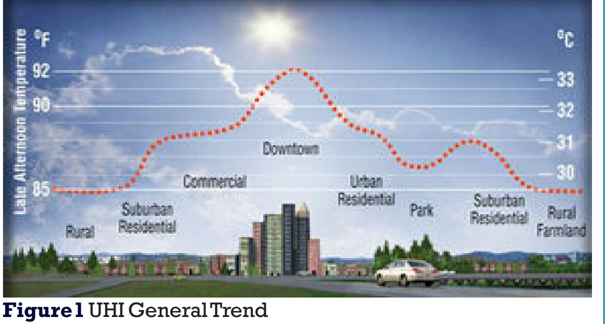

Figure 1 UHI General Trend

Using remote sensing techniques, it is possible to analyze the thermal and environmental information gathered by earth observation satellites to produce maps of the urban surface temperature, land use and vegetation index, which can help identifying areas that are susceptible to greater risk in case of occurrence of these weather anomalies. The purpose of this study is to analyze the spatial and temporal variation of land surface temperature with respect to the changing land cover, of Ahmedabad city.

Study Area

This study aims at analyzing and understanding why the urban heat islands are formed in a city. And by inferring which parameters are affecting urban heat island, and to infer the associated parameters affecting urban heat island. The study also aims to use a suitable model.

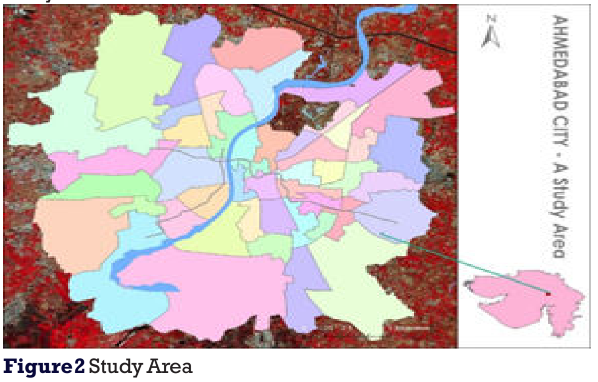

Figure 2 Study Area

Ahmedabad is located at 23.03°N 72.58°E in western India at an elevation of 53 meters (174 ft) from sea level on the banks of the Sabarmati River, in north-central Gujarat. It covers an area of 464 km2. Ahmedabad is the administrative headquarters of the Ahmedabad district with a population of more than 5.8 million and an extended population of 6.3 million; it is the fifth largest city and seventh largest metropolitan area of India. Ahmedabad is located on the banks of the River Sabarmati, 32 km from the state capital Gandhinagar. Ahmedabad is one of the fastest-growing metropolitan cities in India. 2.5 km. boundary has been created around the city for better analysis. Ahmedabad is located on the banks of the Sabarmati River, situated 30 km from the state capital Gandhinagar.

DATA USED AND METHODOLOGY

Table 1 Data Used

Satellite Sensors	Years
LISS-IV	2007,2011,2015,2017,2020
LandSat -5	2077,2011
LandSat – 8	2015,2017,2020

The LISS-IV data is used to carry out Land Use and Land Cover (LULC) with SVM Classification. Thermal Band of the Landsat data is used to carry out the analysis of the LST. NDVI also calculated from the Landsat Images.

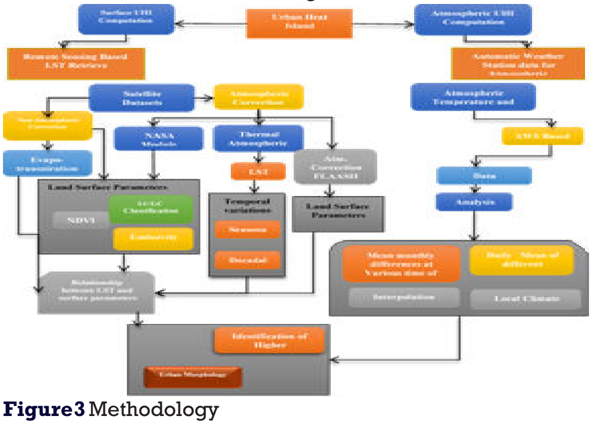

Figure 3 Methodology

The Methodology is consisting of two parts, one is the analysis of the Satellite image and another is an analysis of the Insitu data.

Image Processing

The LANDSAT-5 and Landsat 8 TM data was processed with layer stacking and the LST and other related parameters like NDVI and LISS- IV for LULC were retrieved in order to study the spatio-temporal UHI effect surrounding Ahmedabad city.

For calculating the LST values, the DN values of the imageries were converted into the Radiance values. The calculation as done in the Google Earth Engine webpage that provides values for Transmittance, Upwelling

Radiance, and Downwelling Radiance, for Landsat data. (http://atmcorr.gsfc.nasa.gov/).

$$CV_{R2} = \frac{CV_{R1} - L\uparrow}{\varepsilon\tau} - \frac{1-\varepsilon}{\varepsilon} L\downarrow \qquad (1).$$

Where,
CVR2 = atmospherically corrected cell value as radiance
CVR1 = Cell value as radiance
L↑ = Upwelling Radiance
L↓ = Downwelling Radiance
τ = Transmittance
ε = Emissivity (typically 0.95)
Next, the radiance values hence obtained were converted into Kelvin values (At Sensor Brightness Temperature-TB). By applying the inverse of the Planck function, the temperature values can be derived as :

TB = K2 / ln (K1 / Lλ + 1) (2)

Where,
TB = at sensor brightness temperature, K1 = 607.76 W/m2 .Sr μm,
K2 = 1260.56 K

Derivation of LST from Landsat 5 TM imagery

Urban heat island effect studies with LST derived from Landsat TM 5 data have been widely conducted. In 2001, Qin et al. proposed the mono-window algorithm for retrieving LST from Landsat TM 5 data. Based on thermal radiance transfer equation, the mono- window algorithm only requires three parameters - emissivity, transmittance and effective mean atmospheric temperature - to retrieve LST from Landsat TM 5 and 8.

The formula used is:
TS = [a(1-C-D) + (b(1-C-D) + C + D)TB – D*Ta]/C (3)

Where,
C = ετ, D = (1-τ) [1 + (1-ε)τ], a = 67.355351, b = 0.458606,
τ = the total atmospheric transmissivity of the thermal band
ε (Emissivity)= 1.0094 + 0.047 ln (for NDVI ranging from 0.157 to 0.8)
Derivation of NDVI from Landsat 5 TM imagery

NDVI from Landsat-5 TM and and Landsat TM 8 is calculated from reflectance measurements in the red and near infrared (NIR) portion of the spectrum. The formula for NDVI is given by:

NDVI = NIR–Red/NIR+Red (4)

The Normalized Difference Vegetation Index (NDVI) is one of the most widely applied vegetation indices. Normalized difference vegetation index [NDVI] is used to measure and monitor plant growth, vegetation cover and biomass production. Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1. A dense vegetation canopy (0.3 to 0.8), Soils (0.1 to 0.2) Reflects near-infrared spectral somewhat larger than the red spectral, Clear Water (very low positive or even slightly negative) low reflectance in both spectral bands.

Second phase comprises of collection and interpolation of in-situ data from the Municipal Corporation. Then regression has been done with the whole parameter for identification of the relationship between LST, NDVI, PM10, PM2.5.

DATA ANALYSIS AND INFERENCES

Spatiotemporal changes in LST: The thermal products have been derived for years 2007, 2011, 2015, 2017 and 2020 through Landsat-5 and Landsat8 thermal bodies. Daily temperature has been evaluated from 2001 – 2020 through MODIS11 A1. The Daily temperature collection of MODIS11A1 had been done through google earth engine.

Trend analysis gives information on series with respect to time. This is a statistical technique that processes the data relative to the time intervals.

In the case of LST, two seasons; summer and winter of the year 2007 to 2020, where 2007, 2011, 2015, 2017 and 2020 is selected for trend analysis. The computed LST is divided into beaches for the summer and winter seasons, so the symbology can be preserved for visualization.

Table 2 Values Of LST In °C For Summer And Winter Seasons

Year	Mean	Max	Min	Year	Mean	Max	Min
2007	40.26	45.85	26.68	2008	25.30	30.43	20.18
2011	30.60	36.98	24.23	2015	21.05	26.78	15.32
2015	35.35	43.95	26.65	2016	24.33	29.66	18.94
2017	41.95	43.41	29.39	2017	25.89	31.24	20.54
2020	35.77	44.16	27.39	2018	22.95	28.06	17.85
For Summer				For Winter			

Statistics shows that, for Summer and Winter season, For Summer, in 2008 temperature recorded was 40.26 °C, it increased to 41.95°C in 2017 and in 35.77°C temperature was recorded in 2020. The maps below show temporal changes of LST for the summer season.

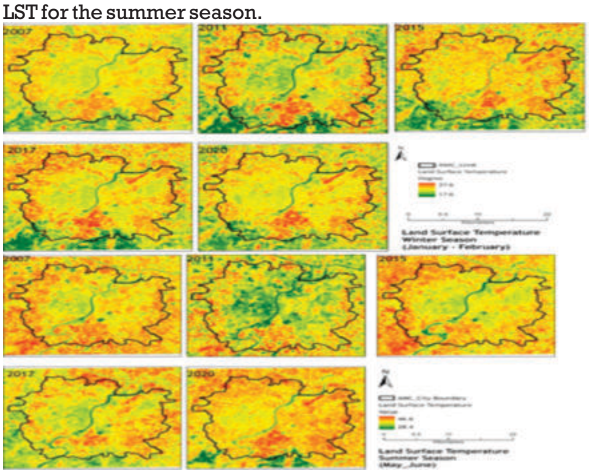

Figure 4 Average Mean Of The Temperature- Summer And Winter

Also, during winter, in 2007, temperature recorded was 25.30 °C, it increased little in 2017 25.89°C and in 22.95°C temperature was recorded in 2020. Maps below show temporal changes in LST for the winter season. Temperatures went up in 2017. The mean temperature for the summer and winter of 2007 to 2020 is 36°C and 23°C respectively.

NDVI Analysis:

Normalized Difference Vegetation index is directly related with the land surface temperature, as vegetation covered area is cooler than area without vegetation cover, it is observed that as NDVI value increases, LST is decreased and vice versa.

NDVI is an important indicator of the volume and state of green vegetation. There was an increase in vegetation in the southwestern periphery of the city in 2007 compared to 2007 and 2020.

On the periphery of the southern portions, vegetation decreased in 2011 but increased slightly in 2015 compared to 2007. In the eastern part of the city as well as in the southeast, there is a great decrease in vegetation in 2020. This decrease is due to urbanization in the eastern part of the city.

Table 3 Comparison Of NDVI, Albedo And LST

	NDVI	ALBEDO	LST
2007	0.24	0.156	19.05
2011	0.27	0.159	24.92
2015	0.25	0.156	19.9
2017	0.27	0.159	24.92
2020	0.25	0.156	19.9

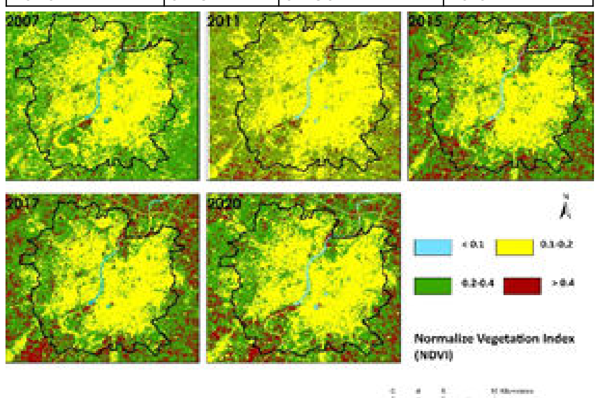

Figure 5 Temporal Analysis of NDVI

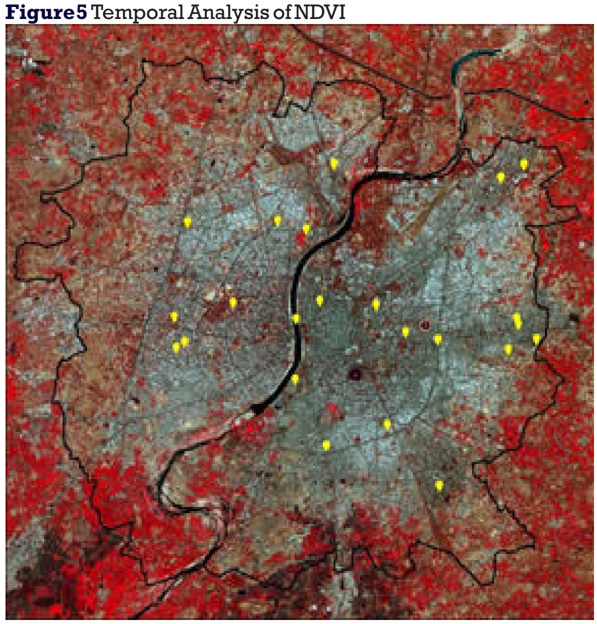

Figure 6 Location of the Weather Monitoring Station

Vegetation increased on the southwest edge of the city in 2011 relative to 2007 and 2011. On the periphery of the southern portions, vegetation decreased in 2020 but increased slightly in 2017 compared to 2007. In the eastern part of the city as well as in the southeast, there was a sharp decline in vegetation in 2011. This reduction is due to urbanisation in the eastern part of the city. In January 2007, the peripheral area south-west of the city has a low temperature due to the higher number of vegetation pixels in these areas. The entire south, east and north of the town has more temperature in 2011 because there was very little or no vegetation in these areas.

The albedo of open areas was found to be higher than built-up areas. The albedo is less than that of asphalt so their reflectivity is also inversely related. It was also noted that the warmer albedo areas were elevated. Urban areas also had more weather but less than open land, which was due to more Albedo of open land. The central area in the city is compactly built up and having more LST but less Albedo but the LST of these areas was found to be less than those of open areas.

SPATIAL INTERPOLATION FOR AIR QUALITY:

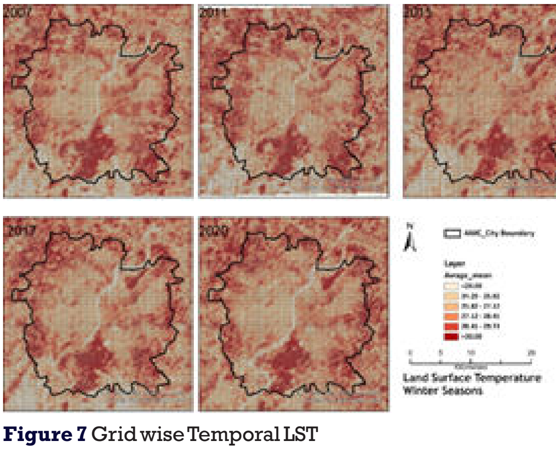

Figure 7 Grid wise Temporal LST

Spatial interpolation is the technique for estimating the value of unknown points by known points. It is used to predict unknown values by existing spatial values. For instance, we are having a data variable which has spatial value at each point (e.g. elevation, temperature etc.), but the data variable is not spatially distributed, so it is necessary to produce a continuous raster surface which can give the predicted value of other points based on existing points.

Air quality, PM2.5 and PM10 data collected from the Center Pollution Control Board(CPCB) are attribute data, which are presented in a point format file. Based upon available points, it was needed to generate surface for AMC study area so that Air Quality (PM2.5 and PM10) can also be predicted where collection point is not available.

To generate the mesh for the AMC area, the spatial extension is taken into account in accordance with the Study and the grid size is taken 120*120m. Landsat spatial resolution is 30m thus in order to get overall average scenario of LST, Air Quality and LULC in grid level, smallest grid size which contains 16 pixels is 120*120m. Total number of cells generated are 47,073.

Macro and mesoscale analysis are done once the most UHI prone zones were demarcated, a microlevel analysis based on LST and its relation with the causative Land Use, NDVI, and PM10 was done.

The spatial location wise, the southern eastern part and northern western part of the city and outside of the city have higher temperature, wherein for each grid, the mean temperature, PM10, NDVI and the major land use class was calculated using Zonal Statics method from GIS, for both Summer and Winter Seasons of Year 2007, 2011, 2015, 2017 and 2020.

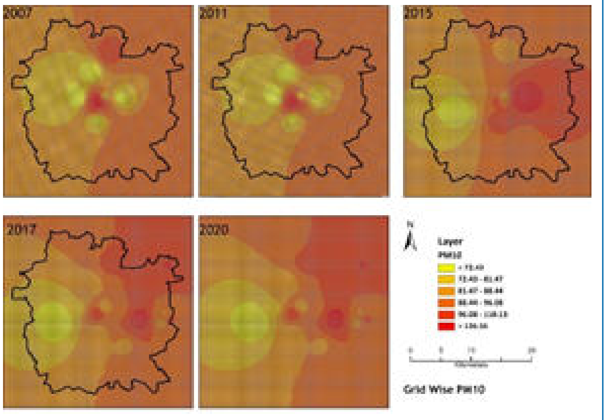

Figure 8 Grid wise Temporal Pm10

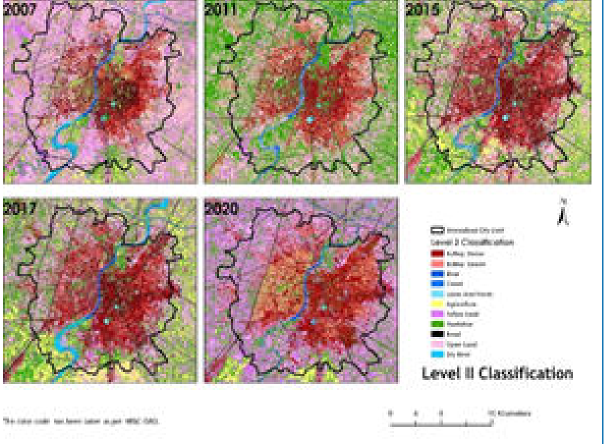

Figure 9 Temporal Land Use And Land Cover

It was observed that all networks whose main land use category was open land and urban areas, as well as the highest mean temperatures, were also recorded from the same networks. All grids with substantial land use as vegetation showed lower temperatures were also recorded from the same networks. All grids with substantial land use as vegetation showed lower temperatures. Further in the urban class, temperature range differences were observed around the town.

Major land use classes showed comparatively lower temperatures, due to the presence of water bodies like Kankaria Lake and Chandola Lake. In addition, the urban networks in the western zone showed lower temperatures compared to those in other parts of the city, due to the low accumulation density.

While, constantly high mean temperatures were observed in case of urban grids lying in the east, south and central zones due to high built up density, commercial activities, industrial development and existence of railway station, and type of building material. Thus, emissivity of features like cement, sand, soil, water, types of vegetation was also observed to play an important part in effecting the local temperature of that area.

On observing the above figures temporally, all the vegetation class grids that showed lower temperatures thereafter showed higher temperatures when replaced by built up or open lands. For example, all the grids towards the New West zone, and all grids towards the end of Sabarmati River, temporally showed higher temperatures in both the seasons, as the vegetation there was replaced by built up and open lands. In this way, a much clearer understanding of the effect of land use, it density at a given place, material emissivity could be observed. and material emissivity, could be its observed over the changing LST and the building of UHI zones in the city.

MULTILINEAR REGRESSION ANALYSIS

Multilinear regression analysis is similar to liner regression analysis, but with a difference that two or many independent variables are taken in the model. Statistical representation of multilinear regression is:

$$Y = a + bX_1 + cX_2 + dX_3 + \epsilon$$

Equation1: Multilinear Regression

Where:
Y – dependent variable
x1, x2, x3 – independent variables
a – intercept
b, c, d – slope
ε – residual/error

In this study, there are four variables, LST, PM2.5, PM10 and LULC. In order to perform regression analysis, Multilinear regression method has been used. For predicting LST, it is taken as a dependent variable.

Table 4 Regression -1

Regression Statistics	
Multiple R	0.809074773
R Square	0.654601988
Adjusted R Square	0.654558728
Standard Error	9.022893242
Observations	40773

The value of R2 is 0.65, which is a positive correlation, which means that 65.45 percent of the variance of the dependent variable is explained by the independent variable.

The multiple linear regression is expressed here as,

LST= 32.86 + 0.09 * UrbanP + 0.13 * OpenP + 0.038 * VegP

Where,
LST= Land Surface Temperature
32.86= Intercept
UrbanP= Percentage of Urban
OpenP= Percentage of Open land
VegP= Percentage of Vegetation

In the equation, it was observed that WaterP (percentage of water) with the coefficient value being zero, the fact that only 10% of the total area of the MAC land use area has a land cover class of the water body. Attempts have been made to select only those systems where the water body belongs to the land cover category. Thus, grids with a water area percentage greater than 50% are selected per query and 679 grids were selected. For these 679 grids, the multilinear regression was calculated and the R2 value was calculated at 0.314, which is a negative correlation.

Moreover, it has been extended to the multi-linear regression equation that has derived before which has no significance due to the insufficient data of the water body class.

Table 5 Regression Analysis -2

Regression Statistics	
Multiple R	0.560449
R Square	0.314103
Adjusted R Square	0.310388
Standard Error	8.065898
Observations	679

Thus, the multi-linear regression equation with the value extracted from WaterP comes,

LST= 32.86 + 0.09 * UrbanP + 0.13 * OpenP + 0.038 * VegP - 0.035 WaterP

Where,
LST= Land Surface Temperature
32.86= Intercept

UrbanP= Percentage of Urban
OpenP= Percentage of Open land
VegP= Percentage of Vegetation
WaterP=Percentage of Water
3.1. Linear regression analysis for LST and PM2.5, Pm10.

In simple linear regression, the relation between the dependent variable and the independent variable is considered. The simple linear regression model use following equation:

Where:
y – dependent variable
x – independent variable
a – intercept
b – slope
ε – residual/error

Simple linear regression for the dependent variable PM2.5, PM10 with independent variable LST is considered for the summer and winter seasons. Results are shown below:
Summer Seasons:
Dependent variable: LST
Independent variable: PM2.5

Table 6 Regression Analysis Pm10

Regression Statistics	
Multiple R	0.975516681
R Square	0.951632794
Adjusted R Square	0.95161155

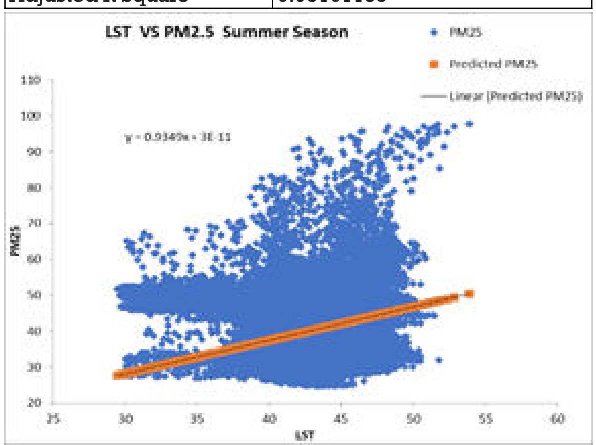

Figure 10 LST VS PM2.5

Now for, Dependent variable: LST Independent variable: Pm10.

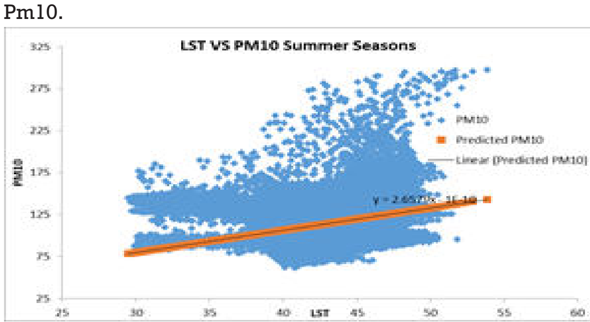

Table 7 Regression Analysis Pm10

Regression Statistics	
Multiple R	0.97882
R Square	0.958088
Adjusted R Square	0.958067

Regression statistics show strong positive correlation between PM2.5, PM10 and LST with R2 value of 0.95.

For Winter:
Dependent variable: LST
Independent variable: PM2.5

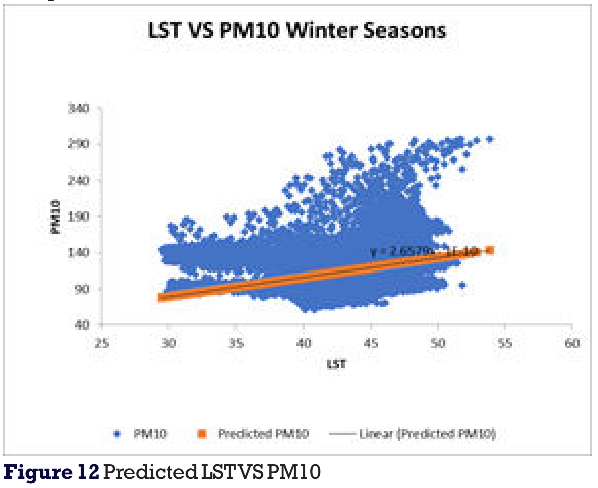

Figure 12 Predicted LST VS PM10

Table 8 Regression Analysis 2.5

Regression Statistics	
Multiple R	0.984914728
R Square	0.970057021
Adjusted R Square	0.970035777

Now for, Dependent variable: LST

Independent variable: Pm10

Table 9 Regression Analysis LST

Regression Statistics	
Multiple R	0.993962
R Square	0.98796
Adjusted R Square	0.987938

Analyzing the two results, we find that in winter correlation with PM2.5, MP10 with LST are stronger than the summer season. The reason could be a suspended particle like PM2.5 and PM10 having a higher concentration on the ground in winter than in summer due to low temperature.

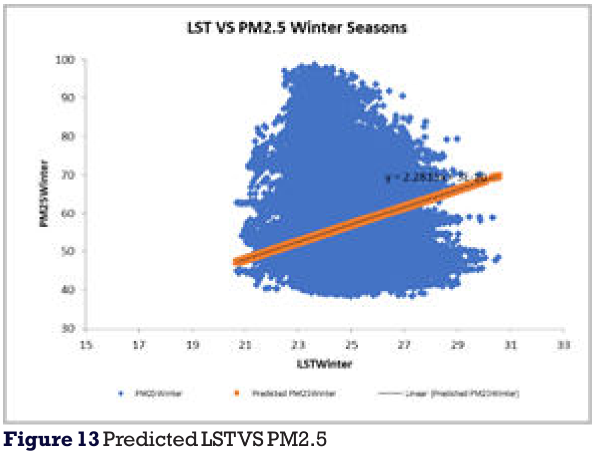

Figure 13 Predicted LST VS PM2.5

From the current study it was observed that Geospatial techniques in combination with ground-based analysis can greatly help in identifying the UHI effect from Macrolevel to Microlevel study, for any given scale of area.

In this study, the single-window algorithm was used to retrieve the surface temperatures in Ahmedabad using the Landsat5 TM and Landsat 8 TM data. From the temperature data obtained by satellite, it was found that the distribution of heat islands in the city of Ahmedabad was widely distributed among different parts of the city.

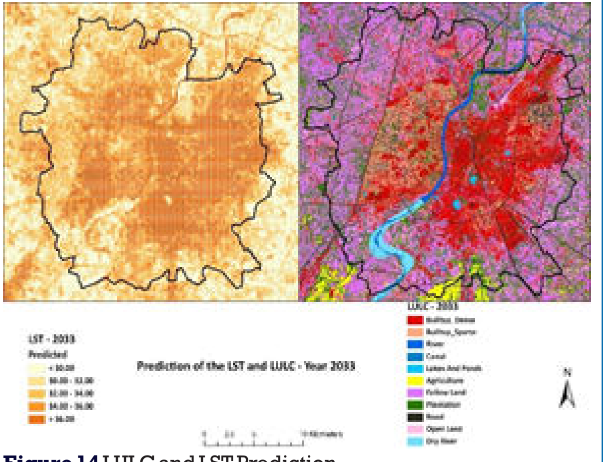

Figure 14 LULC and LST Prediction

An increasing trend of UHI phenomenon was observed temporally from 2007,2011,2015,2017 and 2020. Spatially the UHI phenomenon was more concentrated in the Eastern, Southern and peripheral parts of North West Ahmedabad. Changes in land cover/vegetation and material emissivity have had a significant impact on the surface temperature of a given area. Furthermore, within the urban class, variations in temperature were observed due to the accumulated density and emissivity of the construction materials used. Over time, even though not much variation was found in NDVI values, the overall vegetation cover was observed to convert to open land or urban, thus impacting the surface temperature of those areas.

Considering a longer duration (greater than 10 years) and more relative parameters, an extremely effective study on the effect of UHI and its impact on climate change could be conducted. In future studies several works need to be focused, i.e. considering the impact of other parameters such as NDBI, NDBI, Evapo-transpiration, diapers of Waterproof Fraction, etc.

Further for predicting the LST Generalized Liner Regression Model(s) (GLMs) can be considered as a generalization of the multiple linear regression model. There are also three components of GLMs, which are similar to the components of a linear regression model, but slightly different. More precisely, GLM consists of:

An output variable, Y, where all observations of this variable are assumed to be taken regardless of an exponential family distribution;

An input variable vector k, X1, X2, ..., Xk; and.

A vector of k 1 parameters, b0, b1,..., bk, and a g() link function, which let us write g(E(Y)) as a linear combination of our input variables.

That is: where m = E(Y).

For the prediction of the Land Surface Temperature (LST), current LST has taken as a Y Dependent value and Normalized Vegetation Index (NDVI), PM10 are taken has an explanatory variable.

As result is Comparison of result indicates that by the year 2033, the Eastern, Western and South-Eastern part of Ahmedabad will witness a substantial increase of Dense-Built-up area resulting into the increase in the LST.

CONCLUSION:

The bundle of measures which is adopted adopted worldwide varies in terms of measurement, scales and its applications. In India, studies of Urban Heat Island have remained by and large an academic exercise with no practical implication. However, we can see a glimpse of applicability of such studies in the Urban Planning's of Jodhpur Municipality, which impose the color of the walls and roofs in the old town. Therefore, such measures may be taken in respect of cold roofs and green roofs, consistent with the financial and other viability of the Authority. The measures must be incorporated into urban planning policy, building control regulations, zoning level. At the micro level, mitigation measures, citizen awareness and short-term awareness programmes are advocated.

REFERENCES

1. Gill, S., Forest, T. M., & Ennos, R. (2007). Adapting Cities for Climate Change: The Role of the Green Infrastructure, (April 2014). https://doi.org/10.2148/benv.33.1.115.
2. UN-Habitat. (2007). World Urbanization Prospects The 2007 Revision Highlights. New York. https://doi.org/10.2307/2808041
3. Liu, W., You, H., & Dou, J. (2009). Urban-rural humidity and temperature differences in the Beijing area, 201–207. https://doi.org/10.1007/s00704-008-0024-6
4. Golden, J. S., & Golden, J. S. (2010). The Built Environment Induced Urban Heat Island Effect in Rapidly Urbanizing Arid Regions – A Sustainable Urban Engineering Complexity Island Effect in Rapidly Urbanizing Arid Regions – A Sustainable Urban Engineering Complexity, 3430. https://doi.org/10.1080/15693430412331291698
5. Heat, U., & Basics, I. (n.d.). Reducing Urban Heat Islands : Compendium of Strategies Urban Heat Island Basics.
6. Imhoff, M. L., Zhang, P., Wolfe, R. E., & Bounoua, L. (2010). Remote Sensing of Environment Remote sensing of the urban heat island effect across biomes in the continental USA, 114, 504–513. https://doi.org/10.1016/j.rse.2009.10.008
7. Li, Z., Tang, B., Wu, H., Ren, H., Yan, G., Wan, Z., … Sobrino, J. A. (2013). Remote Sensing of Environment Satellite-derived land surface temperature : Current status and perspectives, 131, 14–37.
8. Devadas, M. D., & Amirtham, L. R. (2014). Urban Factors and the intensity of Heat Island in the City of Chennai Urban Factors and The Intensity of Heat Island In The City OF, (June), 2–6.
9. Taylor, P., Stathopoulou, M., & Cartalis, C. (n.d.)(2015) . Use of Satellite Remote Sensing in Support of Urban Heat Island Studies Use of Satellite Remote Sensing in Support of Urban Heat Island Studies, (January 2015), 37–41. https://doi.org/10.1080/17512549.2007.9687275
10. Estoque, R. C., Murayama, Y., & Myint, S. W. (2017). Science of the Total Environment Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the megacities of Southeast Asia, 577, 349–359.
11. Fortuniak, K. (n.d.). Global environmental change and urban climate in Central European cities.
12. Kotharkar, R., Ramesh, A., Bagade, A., & Asia, S. (2018). Urban Climate Urban Heat Island studies in South Asia : A critical review. Urban Climate, (July 2017), 1–16. https://doi.org/10.1016/j.uclim.2017.12.006
13. Li, H., Meier, F., Lee, X., Chakraborty, T., & Liu, J. (2018). Interaction between urban heat island and urban pollution island during summer in Berlin Science of the Total Environment Interaction between urban heat island and urban pollution island during summer in Berlin, (May). https://doi.org/10.1016/j.scitotenv.2018.04.254
14. Rawal D., Gupta V., "Land Use Land Cover Change Modeling using Multi-Layer Perceptron-Markov Chain; A case Study of Ahmedabad City", International Journal of Science and Research (IJSR), https://www.ijsr.net/search_index_results_paperid.php?id=SR21309194442, Volume 10 Issue 3, March 2021, 641 – 652.
15. Rawal, D., Chhabra, A., Pandya, M., and Vyas, A.: LAND USE AND LAND COVER MAPPING – A CASE STUDY OF AHMEDABAD DISTRICT, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B3-2020, 189–193, https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-189-2020, 2020.