

Temporal Analysis of Land Surface Temperature Dynamics and Urban Heat Islands in Chennai using Geo-Spatial Technology

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Abstract This study examines Chennai's Urban Heat Islands (UHIs) using advanced thermal remote sensing and an Autoregressive Integrated Moving Average (ARIMA) model. The research predicts Land Surface Temperature (LST) and its relationship with factors influencing UHIs by analyzing historical observations, Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Land Use/Land Cover (LULC) changes between 2012 and February 2023. Analyzing satellite imagery from Landsat 7 ETM+ and Landsat 8 OLI alongside NASA's LST dataset reveals an increase in urban areas and decrease in vegetation, leading to rising LST. The ARIMA-based model forecasts a continual temperature rise from 2012 to March 2023, primarily due to urbanization. Recommendations include integrating LST, LULC, and vegetation indices in urban planning to mitigate UHI expansion. This research emphasizes the importance of predictive models in understanding and addressing UHI impacts, despite limitations posed by cloud cover in remote sensing data.

Keywords: ARIMA model, Urban Heat Islands Impacts in Chennai, Land Surface Temperature (LST) Prediction

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1. Introduction

Urban Heat Islands (UHIs) represent a concerning consequence of increasing heat storage capacities in urban landscapes, resulting in elevated temperatures within built-up areas compared to their surrounding rural counterparts [1,2,3]. The ramifications of UHIs manifest in various detrimental impacts on both the environment and human health, encompassing compromised air quality, escalated energy consumption, disrupted ecological balance, and adverse health effects [4]. Particularly, the derivation of Land Surface Temperature (LST) from remote sensing data has emerged as a pivotal tool in characterizing and understanding the dynamics of UHI [5,6]. However, despite the extensive research conducted on UHI analysis, challenges persist in quantifying UHI spatial patterns over time due to the limitations associated with absolute LST values. To address this, the normalization of LST has been proposed as a means to compare LST spatial distributions effectively [7]. Nevertheless, issues such as spatial autocorrelation in normalized LST values warrant further consideration when assessing UHI patterns temporally [8].

In light of these challenges, this research aims to

employ an ARIMA (Autoregressive Integrated Moving Average) model to predict Land Surface Temperature (LST) and discern its relationship with various factors impacting Urban Heat Islands (UHIs). The objectives of this study encompass predicting LST using the ARIMA model based on historical observations, detecting changes in NDVI (Normalized Difference Vegetation Index) and NDBI (Normalized Difference Built-up Index) between 2012 and February 2023, analyzing Land Use/Land Cover (LULC) changes during the same period, and identifying the parameters influencing LST.

2. Study Area

Chennai is very large metropolitan city in the southern part of India in Tamil Nadu state. The geographical position of Chennai city is 13.04° N latitude and 80.17° E longitude with elevation ranging from 6 to 60 m above mean sea level. The area of the city is 426sq.km. In this study, the surrounding area of Chennai city within 10km buffer covering part of Tiruvallur (North Chennai) and Kanchipuram (South Chennai) district has also been considered for analyzing LST emergence (Figure 1). Chennai city is the main industrial hub in south India, currently home of 8,233,084 people. The two rivers flowing

through Chennai, the Cooum which flows through the centre and the Adyar River to the south, are linked by the Buckingham Canal which runs parallel to the coast. While the third river, the Kortalaiyar, flows through the outside boundary of the city before draining into the sea of Ennore.

Besides these, there are many lakes of different sizes located on the western fringes of the city. The city has somewhat ungenerously described as having three seasons - hot, hotter and hottest. Indeed, except for four pleasant months, November to February, the weather is uniformly hot and humid. May is the hottest season with the mercury sometimes touching 42 °C and the mean temperature about 33°C. December and January are the coolest months with a mean temperature of 24°C. However, the cool sea breeze (which sets in shortly after 3 PM daily) makes even the warmest of evenings bearable. But venturing out in between noon and 3 PM during April-August is best

avoided. The Chennai monsoon is from October to mid-December - and in a good year (from the point of view of water-short citizens) the rain on some days during this period can be quite heavy.

Chennai has a mix of tropical Wet and Dry Climate. For most of the year, the weather is hot and humid. The hottest part of the year is late May and early June, known locally as Agni Nakshatram or Kathiri Veyyil, with maximum temperatures around 38–42 °C . The coolest part of the year is January, with minimum temperatures around 18–20 °C. Chennai receives generous amount of rainfall, in the months of June to September. The winds that manipulate the weather, during this period are the South –Westerly winds and during the rest of the year, it is swayed by the North-easterly winds. The average annual rainfall is about 1,400 mm.

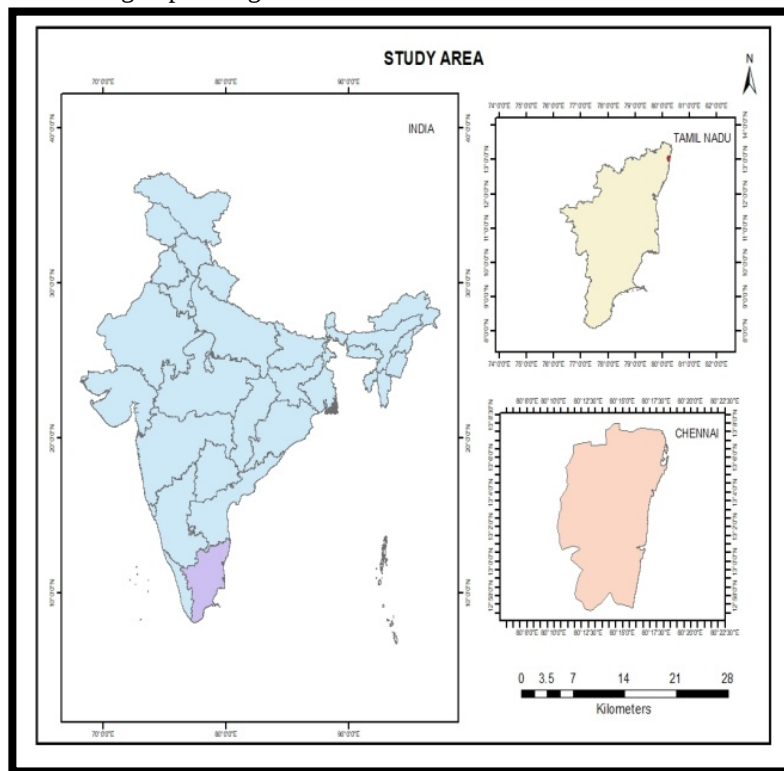


Figure 1. Study Area: Chennai

Table 1. Satellite Dataset

SL.NO.	SATELLITE IMAGE	SPATIAL RESOLUTION	LULC	NDVI	NDBI
1.	17-05-2012 (Landsat 7 ETM+)	15m	Band 3(RED) Band 4(NIR) Band 2 (GREEN)	Band 4(NIR) Band 3 (RED)	Band 5 (SWIR) Band 4 (NIR)
2.	22-02-2023 (Landsat 8+ OLI)	15m	Band 5(NIR) Band 4(RED) Band 3 (GREEN)	Band 5 (NIR) Band 4 (RED)	Band 6 (SWIR) Band 5 (NIR)
3.	02-04-2020 (Landsat 8+ OLI)	15m	Band 5(NIR) Band 4(RED) Band 3 (GREEN)	Band 5 (NIR) Band 4 (RED)	Band 6 (SWIR) Band 5 (NIR)
4.	23-04-2016 (Landsat 8+ OLI)	15m	Band 5(NIR) Band 4(RED) Band 3 (GREEN)	Band 5 (NIR) Band 4 (RED)	Band 6 (SWIR) Band 5 (NIR)

3. Data Sources and Methodology

This study implies the use of Landsat 7 ETM+ and Landsat 8 OLI satellite images for the year of 2012 and 2023 of February, April and May month which has been downloaded from “Earth Explorer” website of United States Geological Survey (USGS). And the Land Surface Temperature dataset “NASA-Power (Prediction Of Worldwide Energy Resources)” has been taken from National Aeronautics and Space Administration (NASA).

Table 2. Land Surface Temperature Dataset

COMMUNITY	PARAMETERS	MODEL NAME
Renewable Energy	Temperature at 2 meters Maximum (01.01.2012-31.03.2023)	MERRA 2

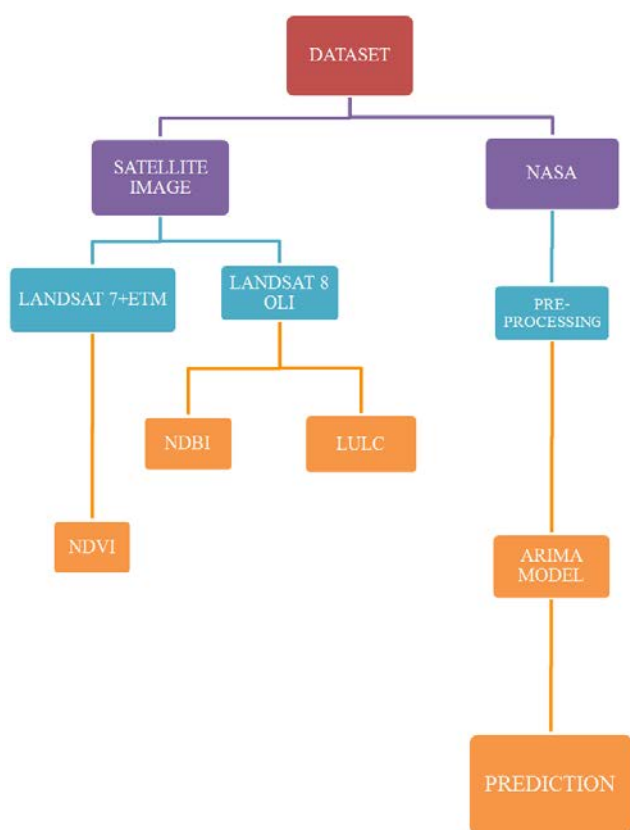


Figure 2. Flow Chart of Methodology

Once the pre-processing of the satellite data was over the ERDAS Imagine software has been used for the generation of land use and land cover (LULC) overlay images by performing the supervised classification along with recoding process. The land matrix table as well as source and sink maps has been derived from the prepared LULC maps. For calculating the NDVI and NDBI we have again use the ERDAS Imagine software to perform the process on Landsat 7 ETM+, Landsat 8 OLI images and further reclassified in Arc GIS software.

Formulas:

a) NDVI:

The normalized difference vegetation index (NDVI) is a simple graphical indicator that can be used to analyze remote sensing measurements and assess whether the

target being observed contains live green vegetation or non vegetation. The NDVI values basically range from -1 to +1. The positive values shows vegetation landscapes and negative values shows non – vegetation landscapes.

$$NDVI = (NIR - Red) / (NIR + Red)$$

Where, NDVI = Normalized Differential Vegetation Index

NIR = Near Infra-Red band and RED = Red band

For Landsat 7 ETM + satellite images,

$$NDVI = (band\ 4 - band\ 3) / (band\ 4 + band\ 3)$$

For Landsat 8 OLI satellite images,

$$NDVI = (band\ 5 - band\ 4) / (band\ 5 + band\ 4)$$

b) NDBI:

The normalized difference built up index (NDBI) is a simple graphical indicator that can be used to analyze remote sensing measurements and assess whether the target being observed contains. The NDVI values basically range from -1 to +1. The positive values shows built up landscapes and negative values shows non – built up landscapes.

$$NDBI = (SWIR - NIR) / (SWIR + NIR)$$

Where, NDBI = Normalized Differential Built up Index
SWIR= Short wave Infra-Red band and NIR = Near Infra-Red band

For Landsat 7 ETM + satellite images,

$$NDBI = (band\ 5 - band\ 4) / (band\ 5 + band\ 4)$$

For Landsat 8 OLI satellite images,

$$NDBI = (band\ 6 - band\ 5) / (band\ 6 + band\ 5)$$

c) Time series model

The past behaviour of the time series is examined to infer something about the future behaviour instead of searching for effect of one or more variables on the forecast variables.

ARIMA (Autoregressive integrated moving average) is an extension of ARMA when AR means Autoregressive and MA means Moving average. ARMA has an extra function for different time series. If the dataset exhibits long-term variations such trend, seasonally and cyclic components, differencing a datasets in ARIMA allows the model to deal with them. ARIMA model was introduced by Box and Jenkins (1970), was frequently use for discovering the pattern and predicting the future values of the time series data. The ARIMA orders can be explained below:

- Autoregressive (p): The number of autoregressive orders in the model. Autoregressive order specifies which previous value from the series is used to predict the current values.
- Difference (d): Specifies the orders of differencing applied to the series before estimating the models. Differencing is necessary when trends are present and is used to remove their effect.
- Moving average (q): The number of moving average orders in the model. Moving average order specifies how deviation from the series means for various values are used to predict the current values.

The periods involves in ARIMA are Estimation and forecast period:

- Estimation period: The estimation period defines the set of cases used to determine the model. Depending on available data, the estimation period

Used by the procedure may vary by dependent variable and thus differ from the displayed value.

- Forecast period The forecast period begins at the first case after the end of the estimation period. The forecast period can also be set.

ARIMA Parameter

- Model parameters were estimated using the Statistical package for social sciences (SPSS) package to fit the ARIMA models.

Autoregressive Models

In the autoregressive (AR) time series model, an observation Y_t is directly related to P previous observations equation 4.2.1

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} \dots + \Phi_p Y_{t-p} + \varepsilon_t \quad 4.2.1 \text{ (Eq.1)}$$

This is Autoregressive series of order p , AR (P). In this model, ε_t is called the error. When the errors are independent, have the normal distributions with mean zero and constant variances.

Moving Average Models

Another common model is the Moving average series of order q , MA (q), defined equation 4.2.2

$$Y_t = \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-p} + \varepsilon_t \dots 4.2.2 \text{ (Eq.2)}$$

Where, θ_1 , the parameters of the model, μ is the expectation of Y_t , (often assumed to equal 0), and ε_t is white noise terms.

ARIMA Model

The model is generally referred to as an ARIMA (p, d, q) model where p , d , and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively.

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p} + \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-p} + \varepsilon_t \quad (\text{Eq.3})$$

Where Y_t is predict the value; ε_t , independently and normally distributed with zero-mean constant variance for $t=1, 2, \dots, n$; d is the fraction differenced while interpreting AR and MA; Φ_p , and θ_q , are coefficients to be estimated.

Trend Fitting

The Box-Ljung Q statistics was used to transform the non stationary data in to stationary data and to check the adequacy for the residuals. For evaluating the adequacy of AR, MA and ARIMA processes, various reliability statistics like R , stationary R , Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Bayesian Information Criterion (BIC) were used. The reliability statistics viz. RMSE, MAPE, BIC and Q statistics were computed as below: Y_i

$$RMSE =$$

$$\sqrt{\frac{1}{N} \sum_{i=1}^n (Y_{i\text{actual}} - Y_{i\text{forecasted}})^2}$$

$$MAPE = \frac{1}{N} \left(\frac{\sum_{i=1}^n (Y_{i\text{actual}} - Y_{i\text{forecast}})}{Y_{i\text{actual}}} \right)$$

$$BIC(p, q) = \ln V^*(p, q) + (p + q) \left[\frac{\ln(n)}{n} \right]$$

$$Q = \frac{n(n+2) \sum_{i=1}^k k^2}{n-k}$$

4. Result and Discussion

4.1 Land Use Land Cover

Land use land cover (LULC) has been studied by the current study to understand the landscape distribution pattern. The study has been conducted for the period of 2012 and 2023.

Table 3. Land use Land cover

SL.NO	LULC CLASS	2012	2016	2020	2023
1.	BUILT UP	51.2	54	56.4	69.4
2.	VEGETATION	12.5	30.4	7.9	22.2
3.	BARREN LAND	34.2	14.2	38.6	6.3
4.	WATER BODIES	1.9	1.2	1.9	2.1

The Figure 4, shows land use land cover of the year 2012, the study area have four classes which includes Built up, Vegetation, Barren and Water bodies. The Built up in Chennai is 51.2% with vegetation 12.5%, Barren land 34.2% and Water 1.9%.

The Figure 5, shows land use land cover of the year 2016, the study area have four classes which includes Built up, vegetation, Barren and Water bodies. The Built up in Chennai has increased from 51.2% to 54%, vegetation from 12.5% to 30.6%, Barren land has decreased from 34.2% to 14.2% and Water bodies from 1.9% to 1.2%.

The Figure 6, shows land use land cover of the year 2020, the study area have four classes which includes Built up, vegetation, Barren and Water bodies. The Built up in Chennai has increased from 54% to 56.4%, Vegetation have decreased from 30.6% to 7.1%, Barren land have raised from 14.2% to 34.6% and Water Bodies from 1.2% to 1.9%.

The Figure 7, shows the Land use Land cover of the year 2023, the study area have four classes which includes Built up, vegetation, Barren and Water bodies. The Built up in Chennai has risen from 56.4% to 69.4%, Vegetation is 22.2%, Barren Land has reduced from 34.6% to 6.3% and Water Bodies has increased from 1.9% to 2.1%.

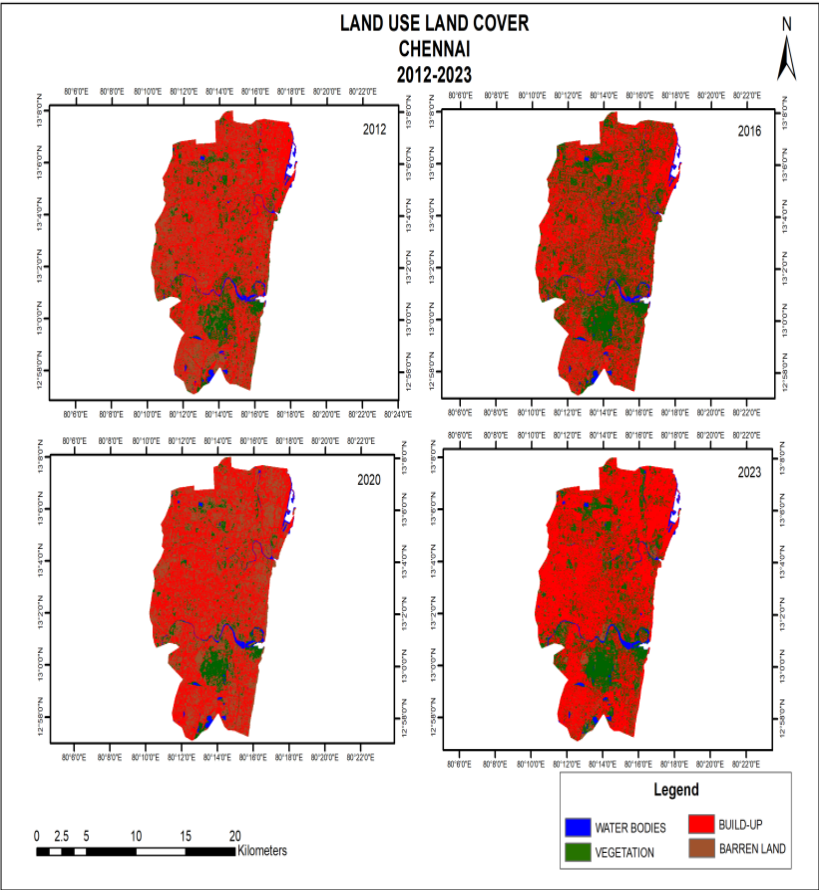


Figure 3. Land Use Land Cover

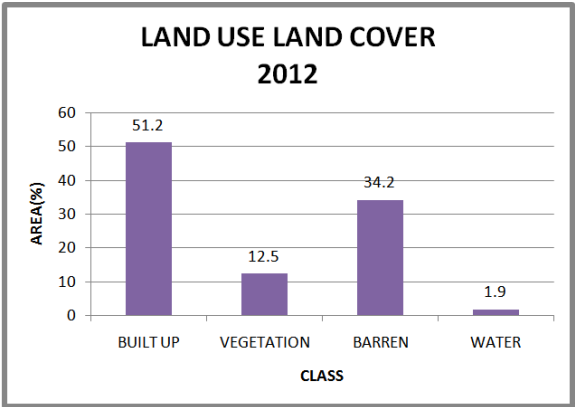


Figure 4. Land use Land Cover, 2012

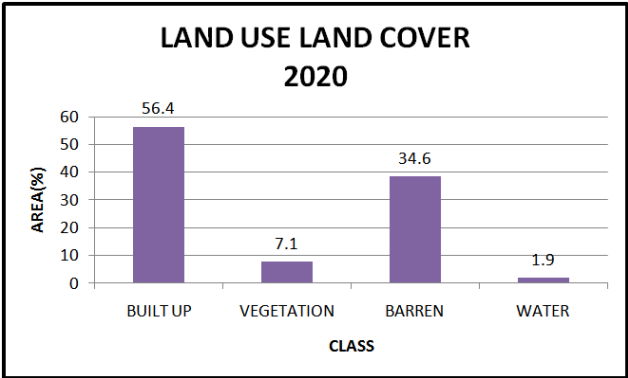


Figure 6. Land use Land Cover, 2020

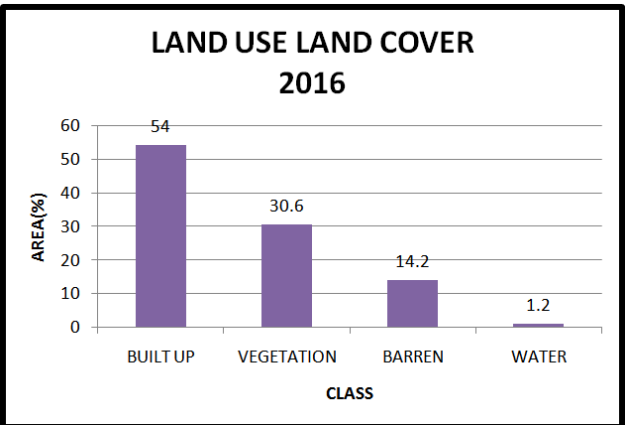


Figure 5. Land Use Land Cover, 2016

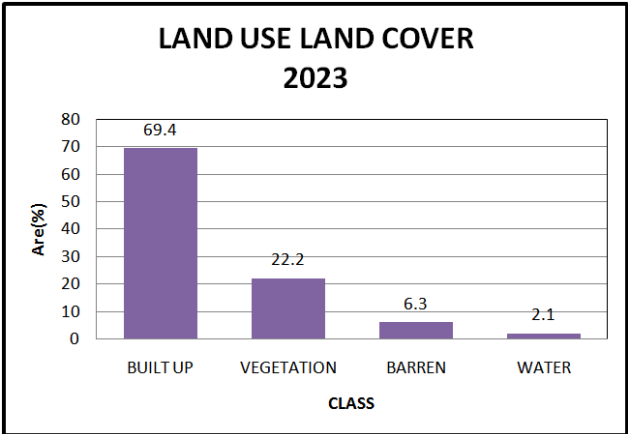


Figure 7. Land Use Land Cover, 2023

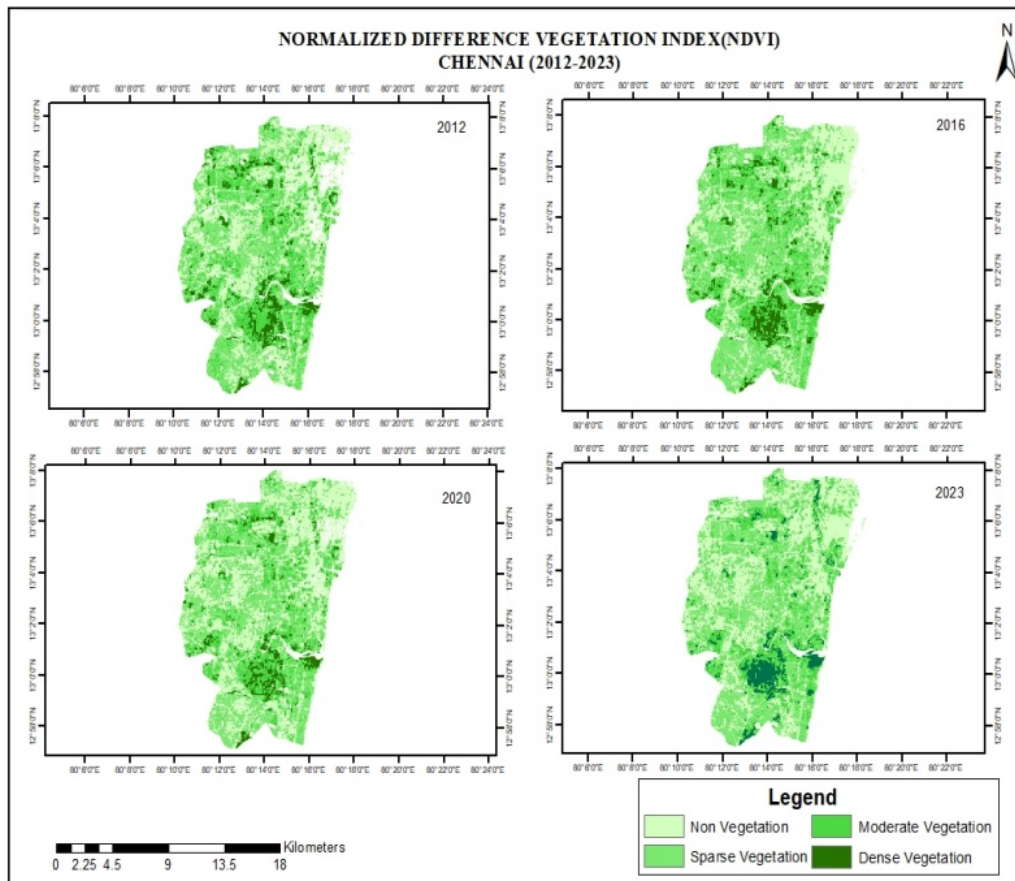


Figure 8. Normalized Difference Vegetation Index

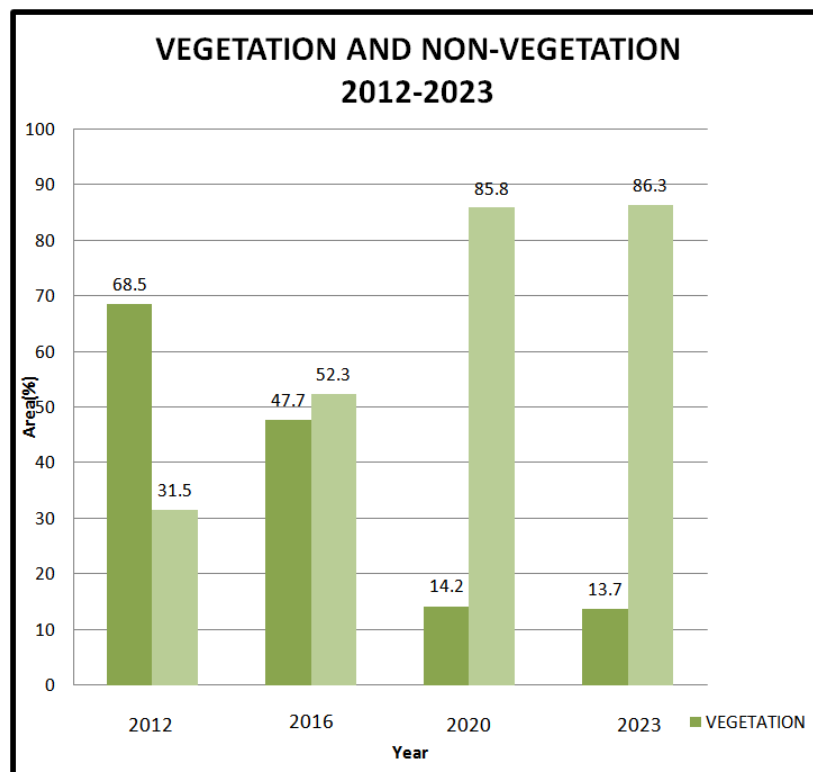


Figure 9. Vegetation and Non-Vegetation, 2012-2023

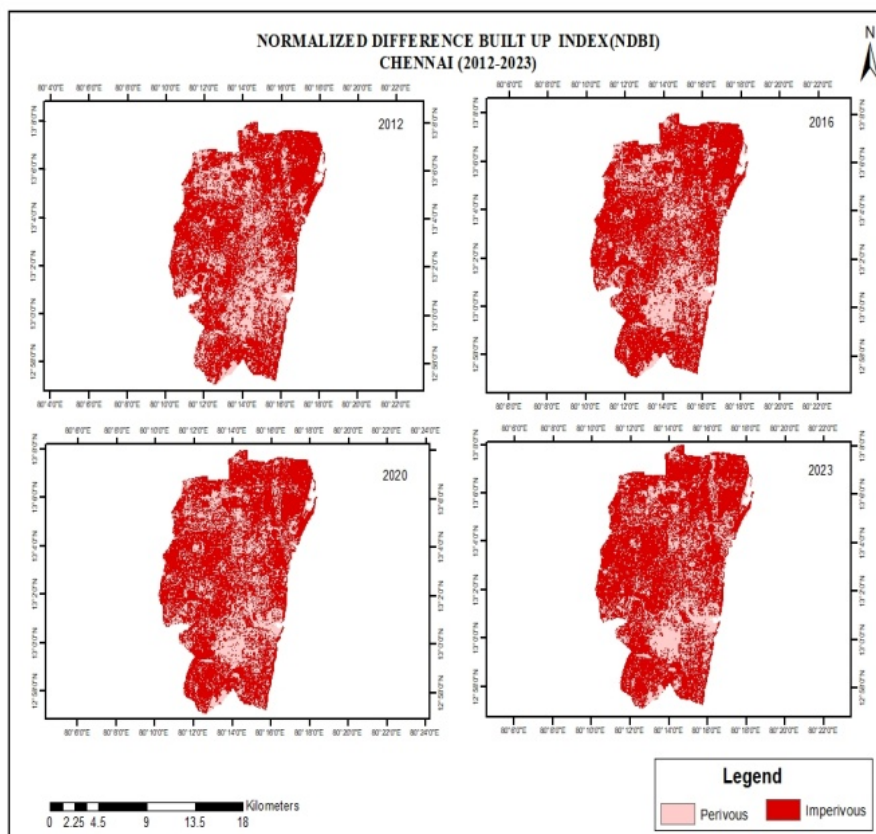


Figure 10. Normalized Difference Build Up Index

4.2. NDVI

Normalized Difference Vegetation Index (NDVI) has been studied by the current study to understand the Vegetation distribution pattern. The study has been conducted for the period of 2012 and 2023.

The Figure 9 shows the vegetation and non vegetation areas of year 2012-2023. In the above figure in the year 2012, the vegetation areas is 68.5% comparing with non vegetation is 31.5%. In the year 2016, the vegetation area is 47.7% comparing with non vegetation which slightly increased is 52.3%. In the year 2020, the vegetation reduced from 47.7 % to 14.2% comparing with non vegetation which have increased from 52.3% to 85.8%. In the year 2023, the vegetation decreased to 13.7% comparing with non vegetation which has increased to 86.3%. The conversion of vegetation into non vegetation and Built up area are the reason for LST.

4.3. NDBI

Normalized Difference Built-Up Index (NDBI) has been studied by the current study to understand the Vegetation distribution pattern. The study has been conducted for the period of 2012 and 2023.

The Figure 11 shows the Imperious and Pervious surface of 2012. Imperious Surface is 65.2 % compare with the pervious is 34.8%. In the year 2016, the Imperious surface has increased to 74.2 % compare with the pervious surface which have decreased to 25.8%. In the year 2020, the Imperious surface has increased from 74.2 % to 80.7 % and pervious surface has decreased from 25.8% to 19.3 %. In the year 2023, the Imperious

surface has raised to 91.3 % compared to the Pervious surface has reduced to 8.7%. The Barren land and vegetation are converting into Urban area are the reason for LST in Chennai.

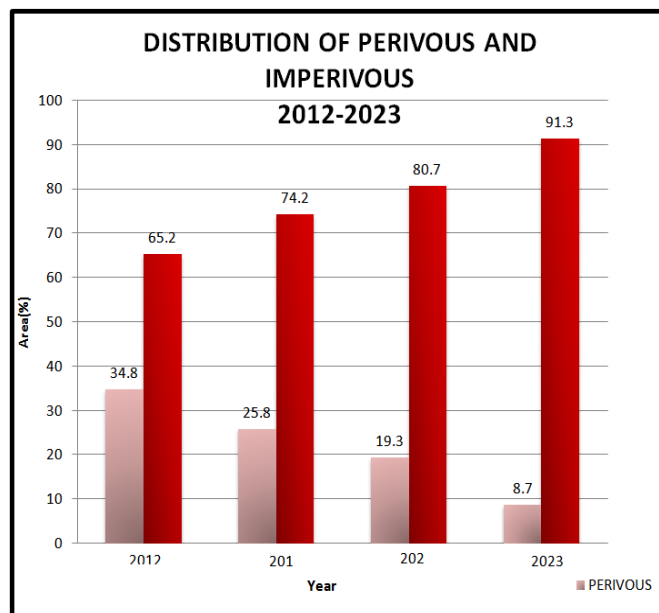


Figure 11. Distribution of Pervious and Imperious surface, 2012-2023

4.4. LST Using ARIMA Model

Land Surface Temperature has been studied for the current study to understand the Vegetation distribution pattern. The study has been conducted for the period of 2012 and March 2023.

Table 4. LST Data

DATE	LAST YEAR	PREDICTION	ORIGINAL
01-04-2022	34.57	34.72	35.03
02-04-2022	35.82	34.72	33.32
03-04-2022	35.4	35.72	33.13
04-04-2022	35.66	34.72	34.07
05-04-2022	36.2	34.72	32.42
06-04-2022	35.02	34.72	33.67
07-04-2022	35.59	35.73	34.65
08-04-2022	34.76	34.73	34.31
09-04-2022	34.7	34.73	34.47
10-04-2022	35.03	35.73	34.96
11-04-2022	34.1	38.73	36.52
12-04-2022	32.16	35.73	36.9
13-04-2022	32.76	38.73	38.21
14-04-2022	35.34	34.73	37.95
15-04-2022	37.09	37.74	37.44
16-04-2022	37.12	34.74	35.93
17-04-2022	36.58	39.74	36.19
18-04-2022	34.15	32.74	37.75
19-04-2022	35.9	34.74	38.43
20-04-2022	35.98	38.74	38.5
21-04-2022	34.93	34.74	38.23
22-04-2022	36.4	38.75	37.48
23-04-2022	34.02	34.75	36.21
24-04-2022	38.31	32.75	35.26
25-04-2022	37.4	34.75	34.02
26-04-2022	36.8	34.75	35.54
27-04-2022	37	34.75	35.6
28-04-2022	37.27	34.75	36.01
29-04-2022	37.44	34.75	35.07
30-04-2022	38.69	34.76	34.54

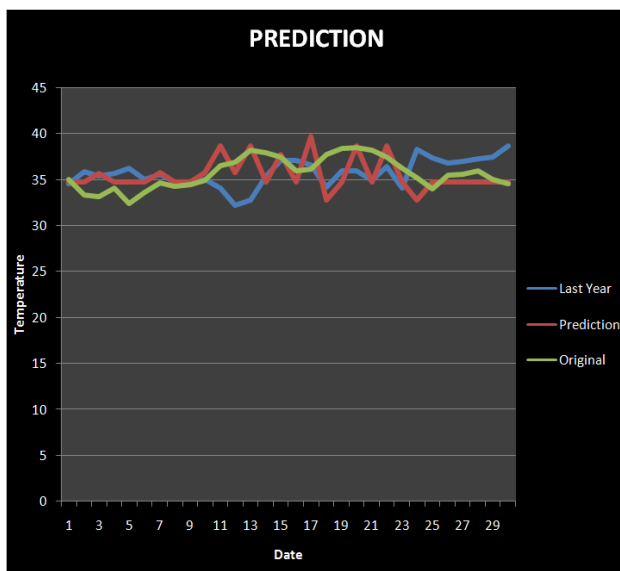


Figure 12. Land Surface Temperature Prediction

The Figure 12 shows the Land Surface Temperature of Last year, Prediction and Original values of Chennai. The Blue shows the Last year, Red as Prediction and Green as Original values. The highest temperature recorded in the year 2022 was 38.6°C on 30 April, 2022 and lowest temperature recorded was 32.1°C on 12th April, 2022. The

highest temperature is 39.7°C on 17th April, 2023 and lowest temperature is 32.7°C on 18th April, 2023 predicted in the model. The highest temperature recorded is 38.5°C on 20th April, 2023 and lowest temperature recorded is 32.4°C on 5th April, 2023. The fast expansion of urban areas and decrease in the vegetation is the reason for increase in temperature.

5. Conclusion

Thus, the research study conducted involves the assessment of different variables as LULC, NDVI and NDBI which are highly influential parameters determining the growth of LST and UHI. The LULC is prepared in order to analyze the significant changes with respect to each land use classes and analyze its impact on the growing LST. The LULC depicts a tremendous growth of urban areas and barren land as well as current fallow in the plain topography and coastal topography that has increased the potential for developing LST.

Moreover, the indices such as NDVI, NDBI and LULC as well as recoding processes were performed to identify various, pervious and impervious landscapes and vegetation and non-vegetation landscapes. It has been observed that the pervious and impervious landscapes derived from NDBI shows an increase in the impervious landscape and decrease in pervious landscapes increasing the possibility of development of LST. Likewise the vegetation and non-vegetation factors derived from NDVI depict the decrease in the vegetation in 2016 and similar parameter as 2020 and 2023 which contributing towards the development of LST.

The research study also emphasize on the spatio temporal variation of land surface temperature prediction using previous observations in different years between 2012 and March 2023.

ARIMA-based LST forecasting model was devised using Landsat-7 ETM and Landsat-8 OLI, LULC and SAVI data to study the emergence of UHI in metropolitan city Chennai, India. The predicted LST indicates that the prediction accuracy of the ARIMA forecast model is promising with a RMSE of 1.11°C. Comparative analysis reveals that there is continues steady rise in the LST from 2012 to March 2023 due to fast urbanization and land use changes. It also indicates that the fast expansion of urban areas has drastically diminished the evaporative cooling, resulting in urban areas in Chennai being much warmer than the surrounding region. Subsequently, the study recommends that during urban planning LST, LULC and vegetation index should be considered to mitigate the expansion of LST and UHI. This research work proves that effective implementation of model can examine the landscape dynamics and predict enduring environmental impacts in the urban area associated with climate and vegetation. Although, advent remote sensing offers time series satellite data product across the globe for different studies about the earth's surface, still high percentage of cloud covers is the primary limitation in deriving the NDVI, NDBI and land use land cover map which needs more substantial mechanism for better prediction.

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