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Spatio-Temporal Assessment of Urban Heat Stress Using the Urban Heat Hazard Identification Model (UHHIM): A GIS-Based Study of Greater Chennai

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ABSTRACT

A study has been proposed to estimate Land Surface Temperature (LST) for Greater Chennai district, Tamil Nadu, India, using LANDSAT 8 satellite data incorporated with ARC GIS techniques. LST is an essential factor of various fields, including heat balance research, urban land use and cover, climate change, and climate models. The study utilizes LST-based spatial analysis to map and forecast urban heat hotspots in Greater Chennai using an Urban Heat Hazard Identification Model (UHHIM). UHHIM is a composite spatial index model developed to quantify, map, and classify urban heat hazard intensity by integrating thermal, built-up, and vegetation cover variables within a GIS framework. This model identifies heat-hazard-prone urban zones by combining Land Surface Temperature (LST). This may help urban planners and policymakers in implementing sustainable development strategies and climate resilient infrastructure in the study area.

Keywords: Remote sensing, GIS, Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Urban Heat Hazard Identification Model (UHHIM).

1.1 INTRODUCTION

The City of Chennai is one of the rapidly expanding urban area in the world. Chennai the capital of Tamil Nadu, one of the famous business hubs in India, and fourth largest city, with a total population of 4.68 million according to the 2011 India census, which has doubled during in the last two decades, according to 2024, estimated population of Greater Chennai Corporation is 7.1 million with an area of about 426 sq.km with 15 zones Recently it is notable that areas in the city are observed to be significantly hotter than when compared to fringes of the city, particularly in the built-up neighbourhoods.

As stated by the study from Anna University, Chennai has experienced a rise in residential, commercial and industrial areas. Built up areas increased from 17.7 % in 1988 to 48% in 2017. Agricultural lands and forest land also decreased from 42.2% 1988 to 19.6% in 2017. Land

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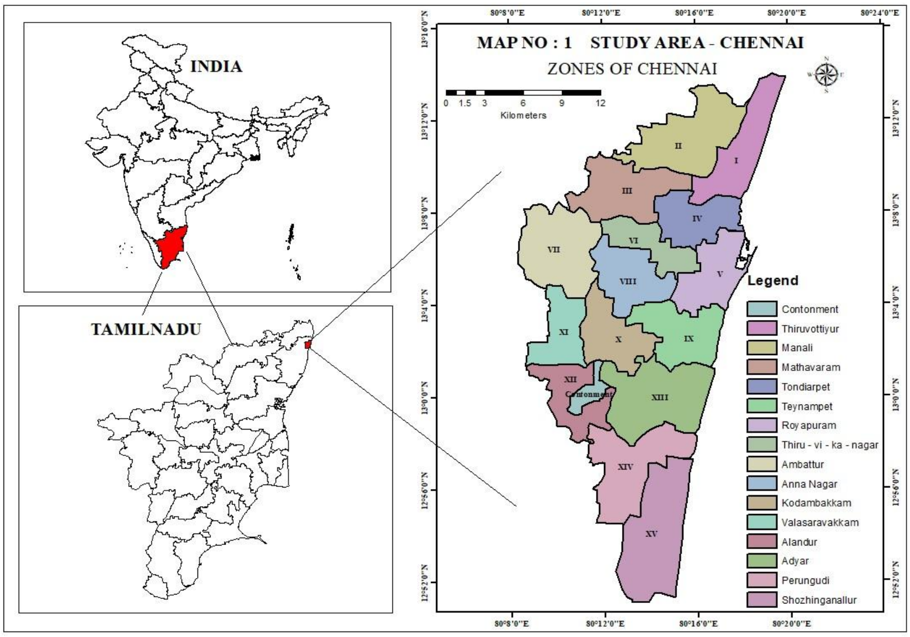
surface temperature (LST) studies conducted by the GCC show a rising trend in minimum and maximum values over the years – the recorded values were 27.12 degree C and 36.62 degree C in 2018; 26.73 and 40.75 in 2020; and 31.66 and 43.45 in 2022 (source: Indian Journal of Science and Technology, Jan 2024).

MAP NO : 1 STUDY AREA



1.2 AIM

The primary aim of this study is to assess Spatio-temporal changes in urban thermal patterns, identify urban heat hotspots, and forecast future urban heat trends for the year 2030 through the development of an Urban Heat Hazard Identification Model (UHHIM) in Greater Chennai.

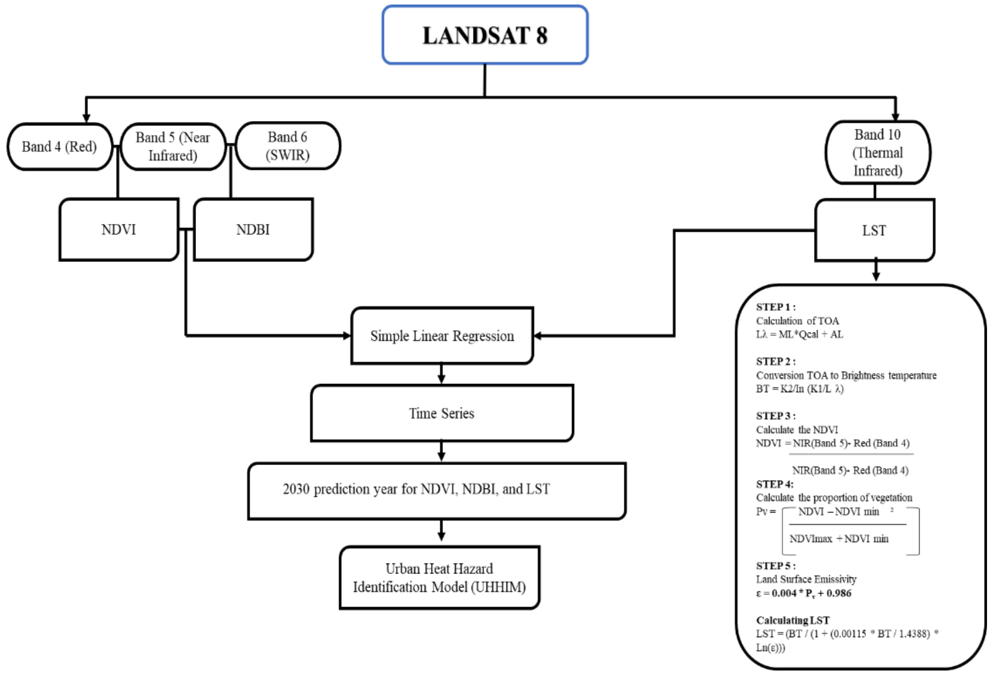
OBJECTIVES

i. To analyse the decadal growth and development of urbanisation in Greater Chennai for the years 2015, 2020, and 2025 using the Land Surface Temperature (LST) approach.
ii. To identify and delineate urban heat hotspots through spatial analysis of high-temperature zones, and predict future urban heat trends for the year 2030 based on observed spatio-temporal LST patterns and urbanisation dynamics.
iii. To create and validate an Urban Heat Hazard Identification Model (UHHIM) to evaluate the danger of urban heat and promote climate-resilient city development and Planning for urban sustainability.

1.3 METHODOLOGICAL FRAMEWORK

In this Study, ArcGIS 10.8.1 and Landsat-8 OLI/TIRS Collection-2 Level-2 data to execute a spatiotemporal analysis of vegetation cover (NDVI), built-up density (NDBI), and land surface temperature (LST). Band 10 was used to calculate thermal radiance and brightness temperature, Bands 4 and 5 were used to calculate NDVI, and Bands 5 and 6 were used to calculate NDBI. Standard retrieval procedures were then used to estimate LST. The linest() function of Excel is used to infer the NDVI, NDBI, and LST value of each point for the year 2030 by calculating its respective slope and intercept values using previous three time periods. The regressed values are spatially joined with their respective points and interpolated to produce raster of Chennai city for the year 2030 as prediction Index.

METHODOLOGICAL FRAMEWORK



Source: Generated by the scholar

The spatial distribution of LST was mapped and analyzed to identify high-temperature zones and their correlation with the built-up areas in the field of study were assessed to develop the Urban Heat Hazard Identification Model (UHHIM). The findings provide valuable information about appropriate accuracy of the thermal environment of Greater Chennai.

1.4 DISCUSSION AND RESULTS

The spatio- temporal analysis of 15 zones of Greater Chennai shows a distinct and steady changes in the city between the years of 2015 to 2025. Using data from the NDVI and NDBI indices, the study examines the geographical and temporal dynamics of land surface temperature (LST) in Greater Chennai in connection to variations in vegetation cover and built-up intensity. The discussion analyzes, the results of the study, especially land use changes and the rapid development of urbanization due to the growth IT sector, has changed the city's surface thermal environment by including multi-temporal satellite-based indicators. The found correlations between NDVI, NDBI, and LST provide insight on how vegetation loss and the growth of impermeable surfaces contribute to the intensification of urban heat trends in the Greater Chennai zones.

1.5 NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)

NDVI (Rouse et al.1973) is among the most reliable and widely used Vegetation indices in Remote sensing studies due to its simplicity and accuracy in detecting the density of vegetation.

NDVI is a ratio-based index (Braun & Herald 2004) that involves two different wavelength bands namely the Near Infrared (NIR) and Red. It produces a normalized value that ranges between -1 and + 1 proportionate to the quantity of vegetation present in a pixel of an Imagery.

$$NDVI = NIR - RED / NIR + RED$$

The value range can be broadly classified into three categories based to the presence of vegetation.

-1 to 0 = Nil or very less vegetation (Eg. Waterbodies, Barren lands)

0 to 0.5 = Moderate vegetation (Eg. Sparse vegetation, Grasslands, Fallow lands)

0.5 to 1 = Dense vegetation (Eg. Agricultural lands, Forests)

In order to understand the urbanization trend of Chennai city, a temporal study of Vegetation from 2015 to 2025 accomplished by calculating the NDVI data for the years 2015, 2020 and 2025 respectively at 5 year periodic intervals.

Landsat 8,9 OLI sensor's Near Infrared and Red wavelength bands were downloaded for the years 2015, 2020 and 2025 that were captured on October 14th, April 2nd and March 7th respectively to derive corresponding NDVI using Raster calculator of ArcGIS Desktop 10.8 software. The value range obtained for the three time periods were observed to be within the prescribed range and were found to reflect the reality.

1.5.1 Forecasting NDVI for the year 2030

It is imperative to predict the vegetation trend of Chennai in the coming years to ascertain whether rapid urbanization will have an impact on them. In order to do that, a Simple Linear Regression (SLR) method was adopted to extrapolate the NDVI values for the year 2030.

The Create Fishnet tool of ArcGIS Desktop 10.8 software was used to create a set of random points spaced at an interval of 500 meters therein covering the entire study area. By doing so, 1704 points were generated at regular intervals spanning the entire city. The Extract multi values from raster tool was used to extract NDVI values at each point for the years 2015, 2020 and 2025. The table containing the extracted values was stored as an excel file for further analysis.

1.5.2 Simple Linear Regression (SLR)

Simple Linear Regression technique (Kaps & Lamberson 2004) is applied to determine the value of a dependent variable (y) using an independent variable (x) using an equation as follow

$$y = a + bx$$

where y is dependent variable, x is independent variable, a is the intercept and b is the slope NDVI values are influenced by time, thus they depend or rely on it. In keeping with that, NDVI variable is considered as the dependent variable and time variable as the independent variable. While a represents intercept, which is the initial value of y without a change in x, b represents slope, that is how much y increases or decreases with an increase in x.

The linest() function of Excel is used to infer the NDVI value of each point for the year 2030 by calculating its respective slope and intercept values using previous three time periods. The regressed values are spatially joined with their respective points and interpolated to produce an NDVI raster of Chennai city for the year 2030.

1.5.3 Inverse Distance Weightage (IDW) Interpolation

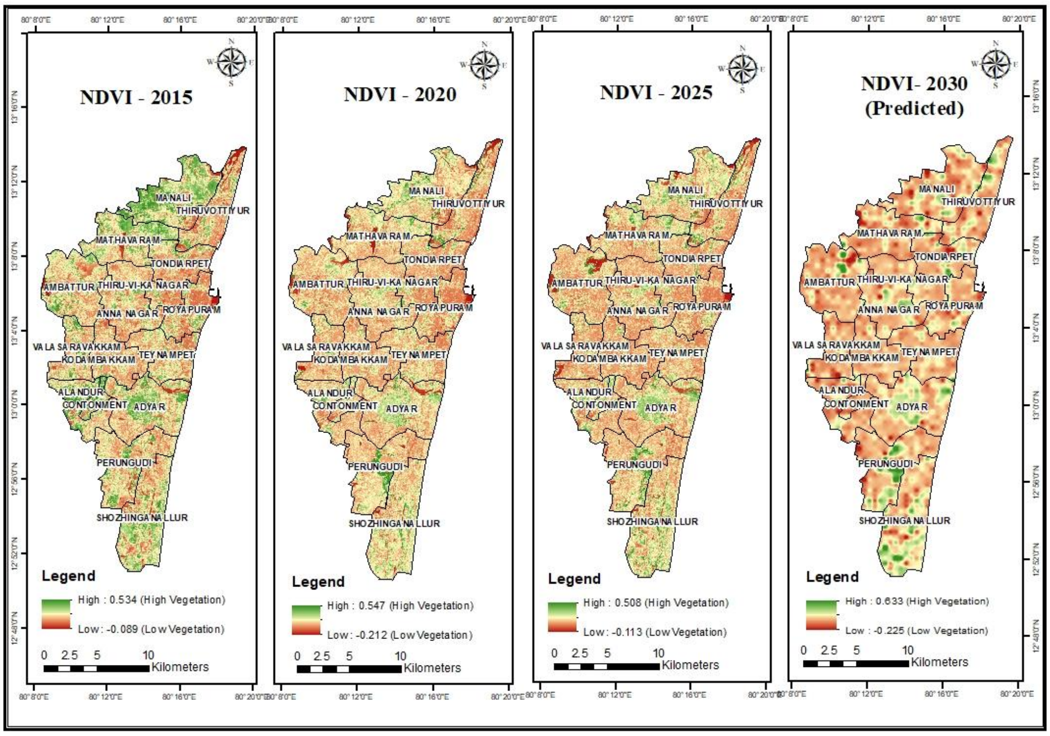
Interpolation (Li & Heap,2008) is the process of converting discretely varying point features into a continuously varying raster surface. Despite the fact that there are various methods of doing it, IDW is commonly used and widely accepted due its simple calculation.

Inverse Distance Weightage (Wong, 2017) as the name implies, assigns value to an unknown point location using the values of know locations with closer points exerting more influence on the unknown than the farther ones. The weightage of a known point decreases as its distance to the interpolated point increases and vice versa.

$$\textit{Weightage} \propto 1/\,\textit{Distance}$$

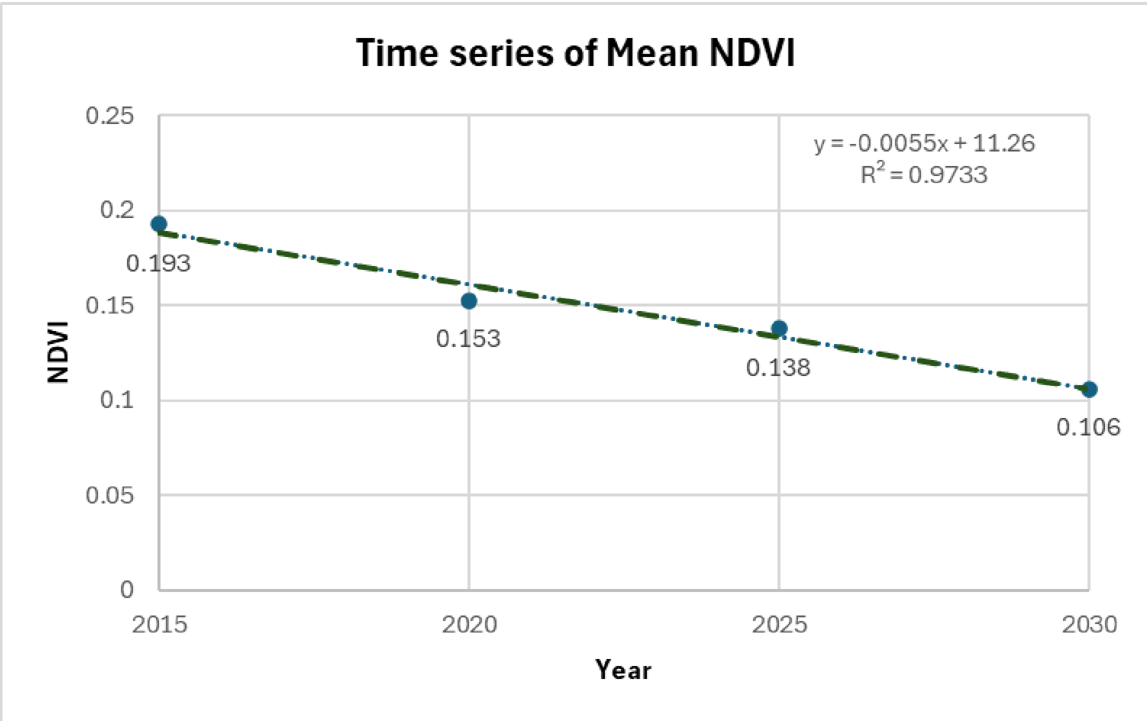
The Variable radius approach of IDW interpolation method was used with the number of points to be considered for interpolating an unknown point as 3. This enables the software to create circles of different radius around each unknown location until the said number of points (3) fall within them. The rationale behind choosing this approach is due to the randomness of points unlike a stratified or systematic one. To ensure data standardization, the output raster's cell size was set as 30 meters and was clipped as per the study area's spatial extent.

MAP NO 2: NORMALIZED DIFFERENCE VEGETATION INDEX FOR GREATER CHENNAI



Map no 2 shows the Significant changes in Chennai's vegetation cover is revealed by the spatio temporal study of NDVI for 2015, 2020, 2025, and the predicted year of 2030. A portion of the Northern central, and southern zones had moderate vegetation cover in 2015, with NDVI values ranging from 0.534 (high vegetation) to −0.089 (poor vegetation). With NDVI values ranging from 0.547 to −0.212 in 2020 and 0.508 to −0.225 in 2025, the city's vegetation was gradually declining. Nearly every zone showed indices of vegetation decline by 2025. The Pallikaranai wetlands, the Adyar region, and portions of the northern and southern zones witnessed localized vegetation degradation in 2030, with NDVI values ranging from 0.633 to −0.225. In spite of this, a slight increase in maximum NDVI from 0.534 (2015) to 0.633 (2030) indicates partial vegetation recovery. To corroborate this further, a scatter plot was generated to compare the average NDVI at four time periods for the entire study area to analyze if there is a trend that is evident. This uneven growth is attributed to government-mandated green space policies, urban forestry initiatives, wetland restoration, and green infrastructure development. However, rapid urban expansion persisted in Perungudi, Sholinganallur, Manali, Ambattur, and Madhavaram, where NDVI values remained negative or near zero due to intensive built-up growth.

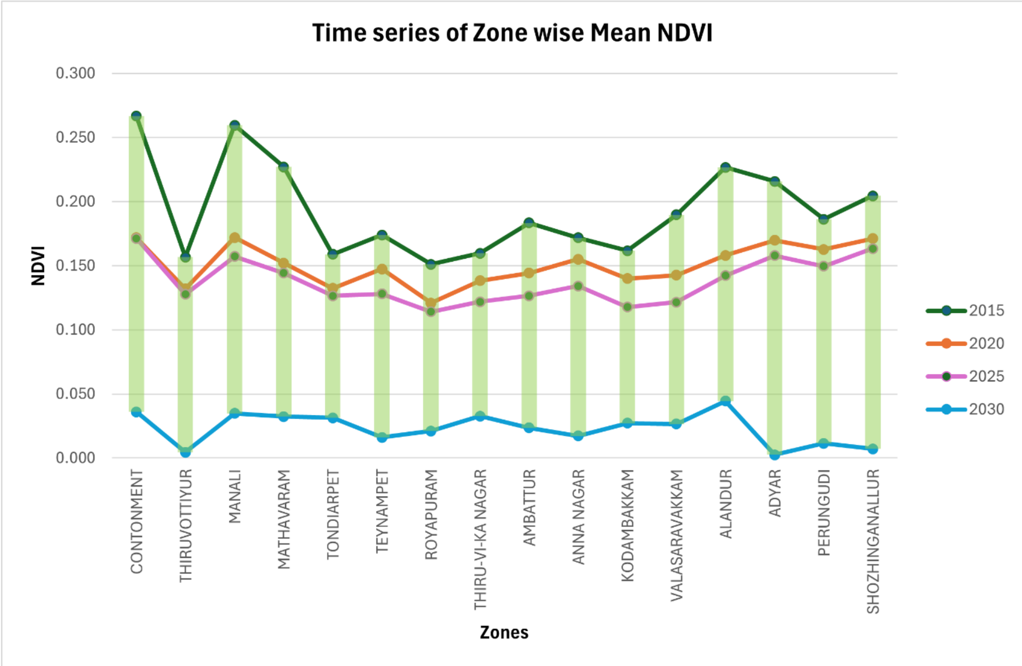
FIG 1: TIME SERIES PLOT OF MEAN NDVI FOR THE STUDY AREA



As observed in Fig 1, there is an evident downward trend with a gradual decrease in overall NDVI of the City with a strong positive coefficient of determination (R^2) value of 0.97 therein explaining 97% of variability in the dependent variable. The intercept (a) is -0.0055 which explicitly states there is a decline in NDVI of the said value for every 5 year progress in time.

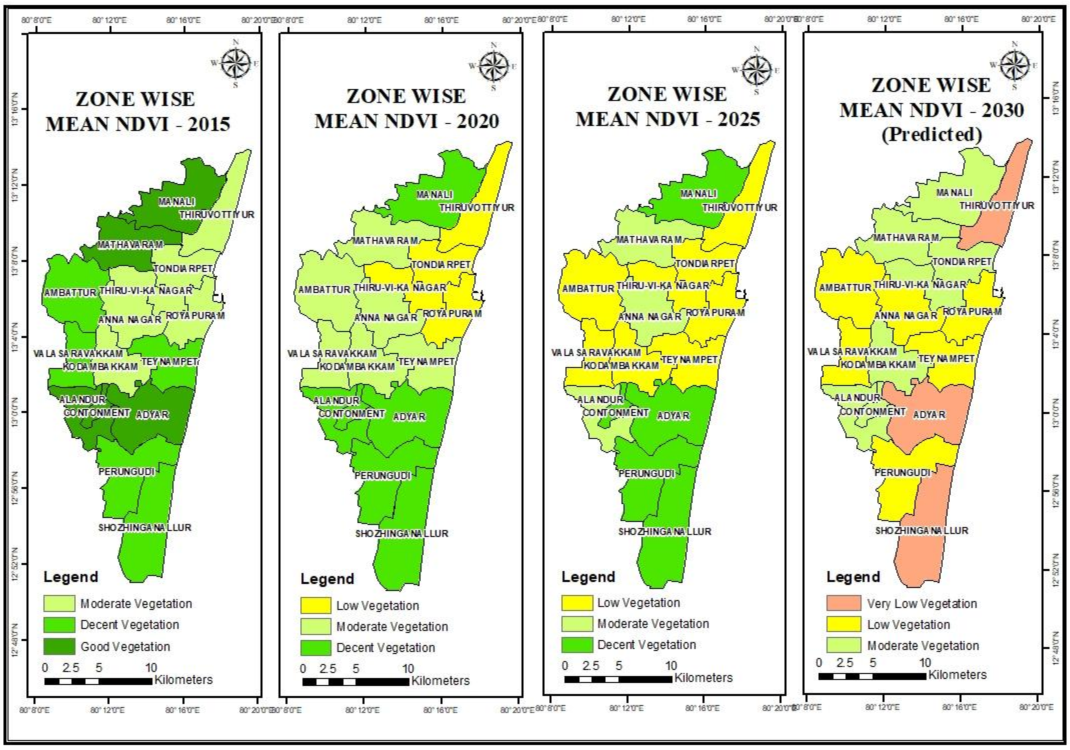
Since analyzing the mean NDVI for the entire study area is generic and vague, it is important to extract the mean NDVI of each of the 15 zones to get a detailed view.

FIG 2: TIME SERIES PLOT OF ZONE WISE MEAN NDVI



A scatter plot of NDVI for 2015,2020, 2025 and 2030 was created as shown in Fig 2 and It is evident that Zones like Manali, Madhavaram, Alandur, Adyar, Perungudi and Sholinganallur have exhibited enormous variations in NDVI on a temporal basis. Their NDVI values have dropped significantly over the course of 5 year intervals.

MAP NO 3: SPATIAL REPRESENTATION OF ZONE WISE MEAN NDVI FOR GREATER CHENNAI



Map 3 indicates the estimated mean NDVI of each zone was spatially plotted to prepare a thematic layout with categorical classifications with a range of Very Low to Good vegetation in accordance to their respective values.

The findings indicate a steady decrease of vegetation, especially in the Southern regions. Several Northern and Central zones had modest vegetation in 2015, although Manali, Madhavaram, Alandur, Adyar, and areas of the south had comparatively higher cover. By 2020, there was little stability in the centre regions and a reduction in vegetation in the majority of the Northern and Southern zones. Widespread deterioration was visible throughout the city in 2025, with large drops in Ambattur, Kodambakkam, Teynampet, Valasaravakkam, and Alandur. Due to growing development, particularly along IT corridors, projections for 2030 show very little vegetation in Thiruvotriyur, Adyar, and Sholinganallur, with only slight improvements or stability in a few zones.

1.6 NORMALIZED DIFFERENCE BUILTUP INDEX (NDBI)

NDBI (Xu, 2005) is used to map built up density in an area with higher values implying more built up and vice versa. Its value range is similar to NDVI ranging between -1 and +1. It is also a ratio based index considering two wavelength bands namely, the Shortwave Infrared (SWIR) and Near Infrared Red (NIR). Its formula is as follow

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

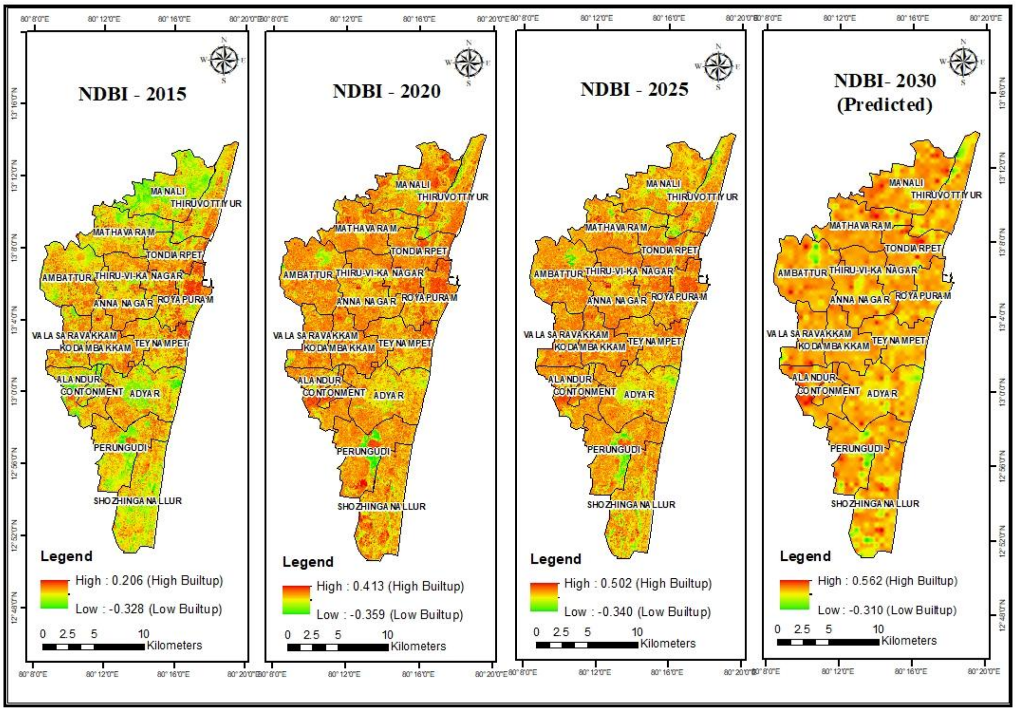
Since the scope of this study is to gauge the impacts of urbanization, The significance of NDBI cannot be underestimated in any aspect. SWIR and NIR bands of Landsat 8,9 OLI sensor were downloaded for 2015, 2020 and 2025 on October 14th, April 2nd and March 7th respectively to create respective NDBI data. The value range was as expected for the three time periods with a gradual increase observed in many parts of city over the years.

Forecasting NDBI for the year 2030

Similar to NDVI, the SLR method was used to estimate values at random locations in the study area and the regressed values are interpolated to get an NDBI raster for 2030 using IDW method.

Map no 4 reveals a rapid increase of built up can be observed during past years, from 2015 to 2025 specifically in the Northern and Southern parts of Chennai as seen in The zone-wise NDBI analysis reveals a steady increase in built-up intensity across all 15 zones of Chennai from 2015 to the projected year 2030. While core zones like Tondiarpet, Royapuram, Thiru-Vi-Ka Nagar, Kodambakkam, Teynampet, and Anna Nagar showed moderate to high urban density in 2015, outlying zones including Manali, Madhavaram, Thiruvottiyur, Perungudi, and Sholinganallur showed low built-up levels (−0.032 to 0.206). NDBI values increased (−0.359 to 0.413) by 2020 due to increased residential, commercial, and industrial growth, especially in Ambattur, Alandur, and Valasaravakkam. By 2025, there was additional growth (−0.340 to 0.502), particularly along the Southern IT corridor in Perungudi and Sholinganallur. According to the 2030 prediction, built-up dominance is uniformly high in both core and outlying zones (−0.310 to 0.562), which reflects Chennai's development into an extremely compact metropolitan city, broad urban saturation, and declining open areas.

MAP NO 4 : NORMALIZED DIFFERENCE BUILT – UP INDEX FOR GREATER CHENNAI



In keeping with the trend, the regressed data for 2030 has predicted sizeable built up density in the same regions. A time series plot of overall Mean NDBI was created to know the at which the city's built up density increases for each time step.

FIG 3: TIME SERIES PLOT OF MEAN NDBI FOR THE STUDY AREA

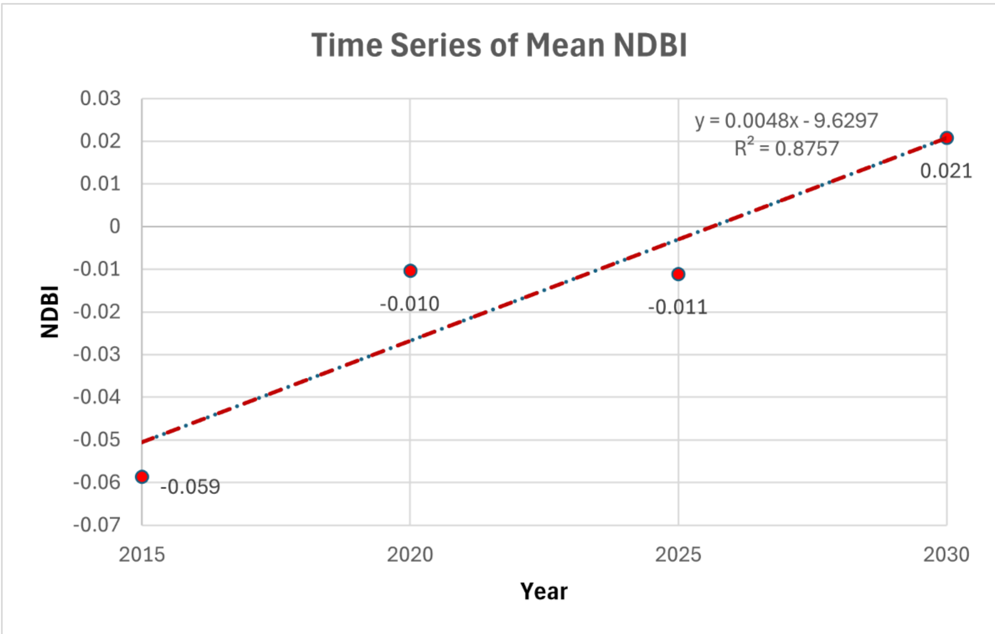
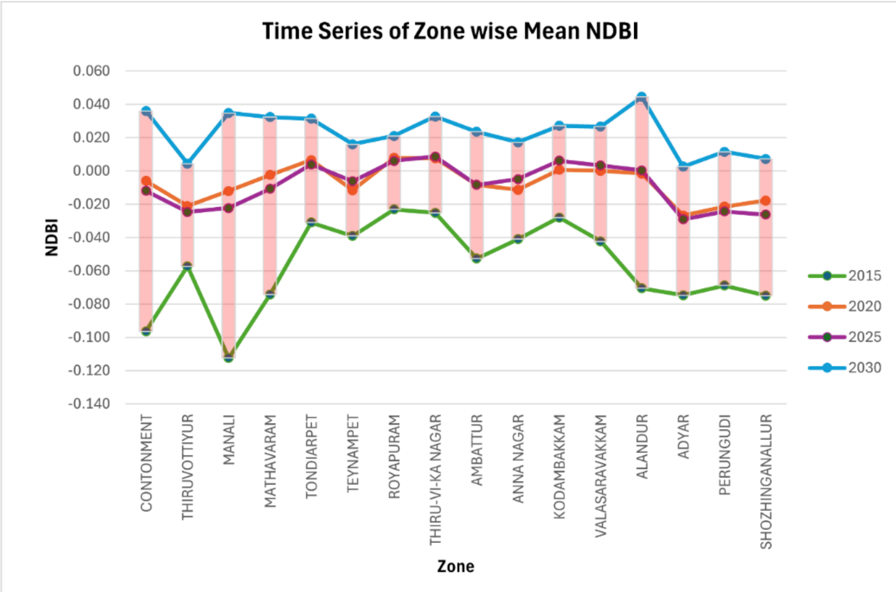


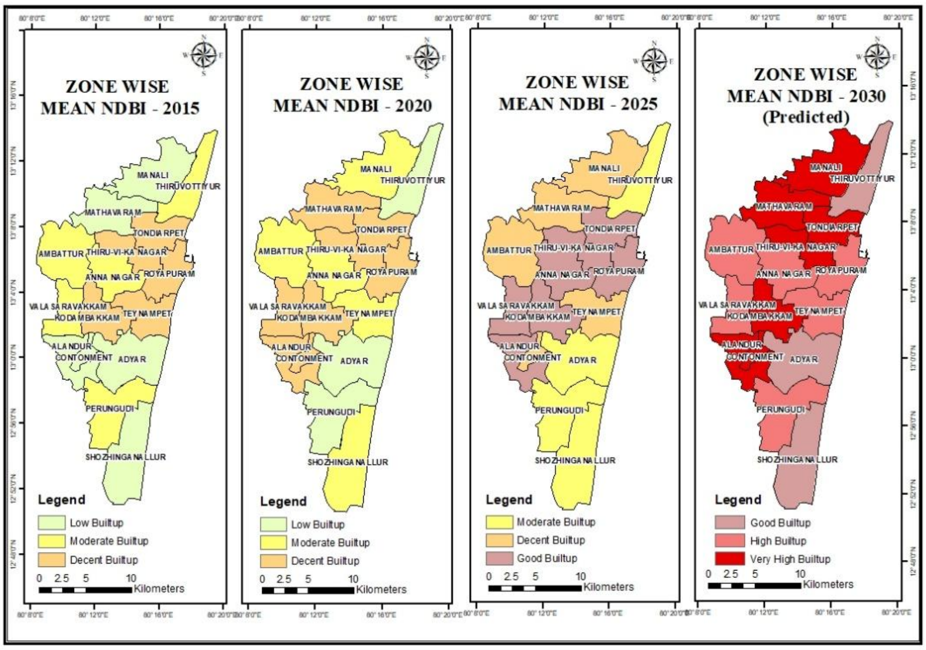
Fig 6 stating that a positive Slope(b) value of 0.0048 is noted for every time interval.there is an increase in built up. The Coefficient of determination(R^2) is 0.8757 therein explaining the dependent variable's (NDBI) variability in accordance to independent variable (Year) by up to 87.5%.

FIG 4: TIME SERIES PLOT OF ZONE WISE MEAN NDBI



To ascertain the changes underwent by each zone, Their corresponding averages were calculated.and plotted to observe their range variance over the years. As evident in Fig 4, Zones like Manali, Madhavaram and Alandur has experiencing an intensive urbanization in 2030. NDBI value of Manali rose from -0.110 to 0.039 in 2030. Hence the range of urbanization and building index is very dynamic. In the past 10 years as their range variance are significantly higher than their counterparts.

MAP NO 5: SPATIAL REPRESENTATION OF ZONE WISE MEAN NDBI FOR GREATER CHENNAI



Map 5 shows the average NDBI values of each zone is used to spatially plot representing the concentration of Built up. Since the values significantly varied over the years, the same color symbology was not used to avoid misinterpretation of them. Nearly all the Zones have undergone a gradual urbanization process over the years with prominent ones like Sholinganallur, Manali and Alandur. All 15 of Chennai's zones show a steady rise in built-up intensity from 2015 to the predicted year 2030, according to the zone-by-zone NDBI analysis. In 2015, Tondiarpet, Royapuram, Kodambakkam, Teynampet, Thiru-Vi-Ka Nagar, and Anna Nagar showed moderate urban density, while peripheral areas including Manali, Madhavaram, Thiruvottiyur, Perungudi, and Sholinganallur showed low to moderate built-up levels.

By 2020, built-up levels in areas like Ambattur, Valasaravakkam, Alandur, and Adyar had increased due to increased residential, commercial, and transportation development. Rapid land conversion is indicated by the 2025 scenario, which shows widespread of high built-up intensity. According to the 2030 estimate, almost every zone in Greater Chennai falls into the high to very high built-up classes, creating a cohesive and compact urban structure.

1.7 LAND SURFACE TEMPERATURE (LST)

Land Surface Temperature is a primary indicator of a Urban heat island phenomena which states considerable amount of built up in an area can correspondingly increase that area's land surface temperature due to Albedo effect. (Galodha & Gupta, 2021)

Albedo effect (Oke, T. R. 1987). is a process of how much a material irrespective of whether it is natural or anthropogenic reflects off the incoming solar radiation. As for natural features, snow and ice in particular due to whitish appearance reflect enormous amounts of insolation therein having higher albedo with values nearing 1 while waterbodies and dense forests have less albedo as they reflect less due to their much darker appearance. As for manmade features, concrete materials and asphalt which are employed in the construction buildings and paving roads respectively have very less albedo nearing 0 therein creating Urban heat islands characterized by drastic increase of temperatures within small patches of land.

It is with respect to this, LST is considered to analyze the thermal effects of rapid urbanization in some parts of study area. For estimating LST for the three time periods, the Thermal band (Band 10) of Landsat 8 OLI Sensor was downloaded for 2015, 2020 and 2025 on October 14th, April 2nd and March 7th respectively.

1.7.1 Computation of LST

In order to determine the Land surface Temperature (Anandababu et al. 2018), the downloaded Thermal bands along with appropriate rescaling factors were used to compute the Top of Atmosphere (TOA) Radiance which indicates the total amount of insolation that is reflected off the land surface and the atmosphere on top of it.

$$\mathbf{TOA\ (L) = M_L * Q_{cal} + A_L}$$

where:

M_L = Thermal band's multiplicative rescaling factor

Q_{cal} = Thermal band

A_L = Thermal band's additive rescaling factor

TOA radiance was used to compute the Brightness temperature (BT) using appropriate temperature constants as follow

$$\mathbf{BT = (K_2 / (\ln (K_1 / L) + 1)) - 273.15}$$

where:

K_1, K_2 = Thermal band's thermal conversion constants

L = TOA Radiance

Now, NDVI was calculated using NIR and Red wavelength bands as discussed above and the same information along with its lowest and highest values were used to calculate the Proportion of Vegetation which indicates the fractional cover of an area by vegetation.

$$\mathbf{P_v = Square ((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}))}$$

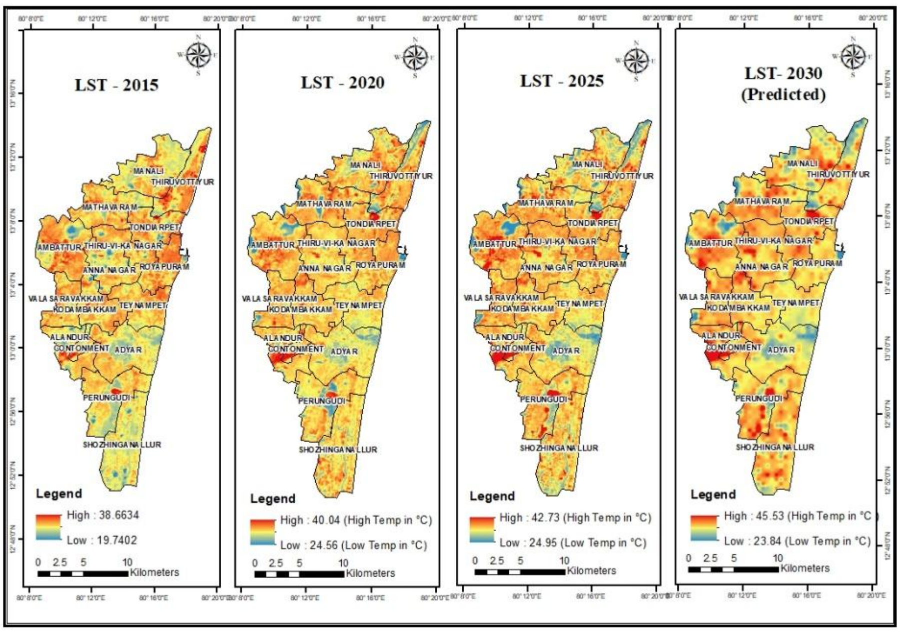
Emissivity **(ε)** is calculated using Proportion of vegetation to estimate the ground object's efficiency in emitting thermal radiation. It is a dimensionless value with 0 representing a perfect reflector where only instant reflection occurs with no emission occurs and 1 representing full emission with nil reflection like a black body.

$$\mathbf{\varepsilon = 0.004 * P_v + 0.986}$$

Finally, the Land Surface Temperature (LST) was calculated using the Brightness Temperature (BT) and Emissivity **(ε)** data as follow with correction factors

$$\mathbf{LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon)))}$$

MAP NO 6: TEMPORAL COMPARISON OF LST



The procedure followed to estimate regressed NDVI and NDBI used to derive the LST data for 2030. Map no 6 shows the surface temperature variations from 2015 to 2030. The values obtained for 2015, 2020 and 2025 were used to predict the values for the year 2030 using Simple Linear Regression (SLR) method. The temperature is estimated to escalate in Northern, Western and Southern zones in the near future with some places recording a value of around 45° C.

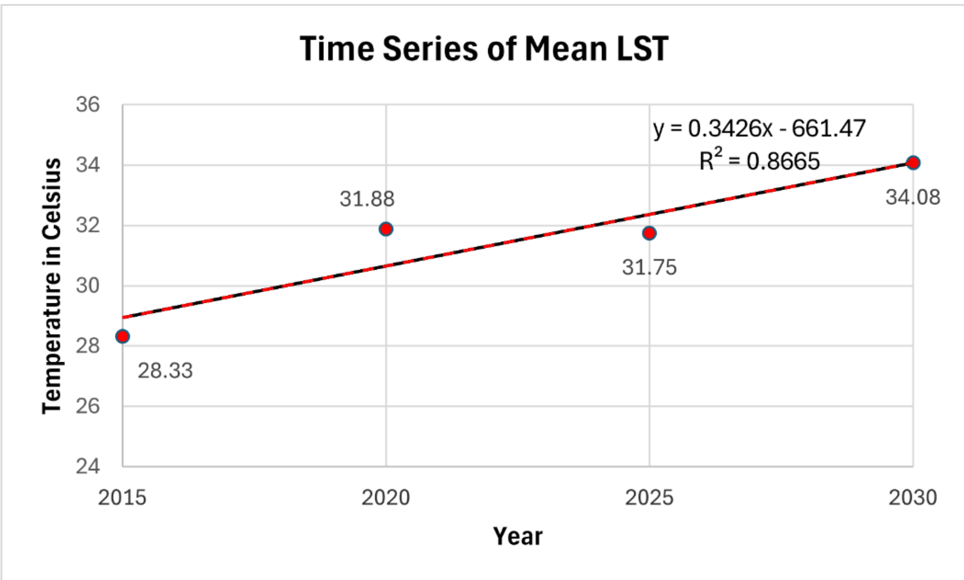
To ascertain the impact of urbanization on soaring surface temperature levels, the Pearson's correlation coefficient (r) was done between NDBI and LST variables to analyze the relationship between them.

TABLE 1: NDBI AND LST CORRELATION

NDBI & LST 2015	NDBI & LST 2020	NDBI & LST 2025	NDBI & LST 2030
0.412	0.475	0.492	0.513

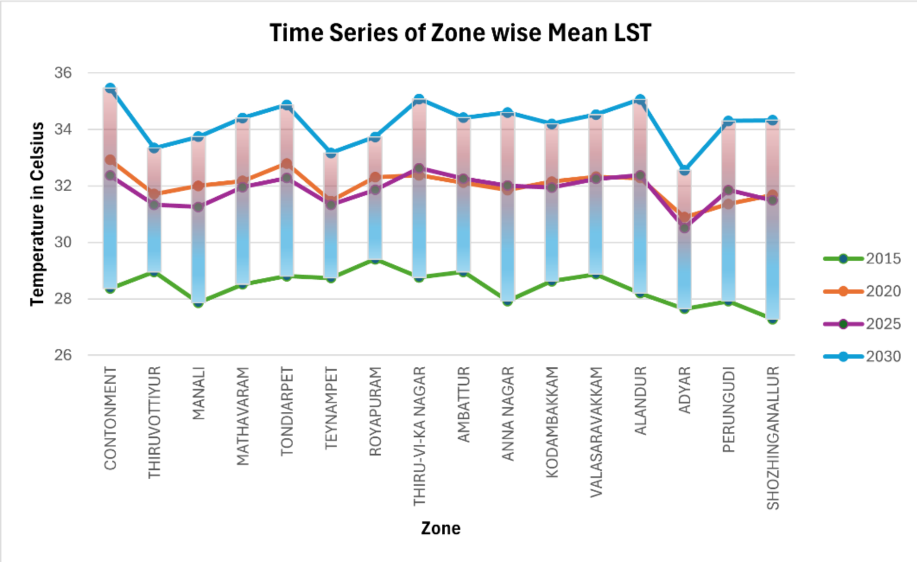
Table 1 shows the r value between NDBI and LST at respective time periods. It is observed that, the correlation is positive and is found to gradually increase from moderate to good as time progresses. The rationale behind the absence of a strong correlation can be attributed to cloud cover presence in the satellite imageries especially in the year 2015 which has the tendency to skew up the results as clouds can exhibit unusually higher NDBI values due to more reflectance in the Shortwave Infrared (SWIR) wavelength band of the Electromagnetic spectrum. Average LST of the study area for each time interval is calculated and plotted to analyze the trend in which they progress with each time step.

FIG 5: TIME SERIES PLOT OF MEAN LST FOR THE STUDY AREA



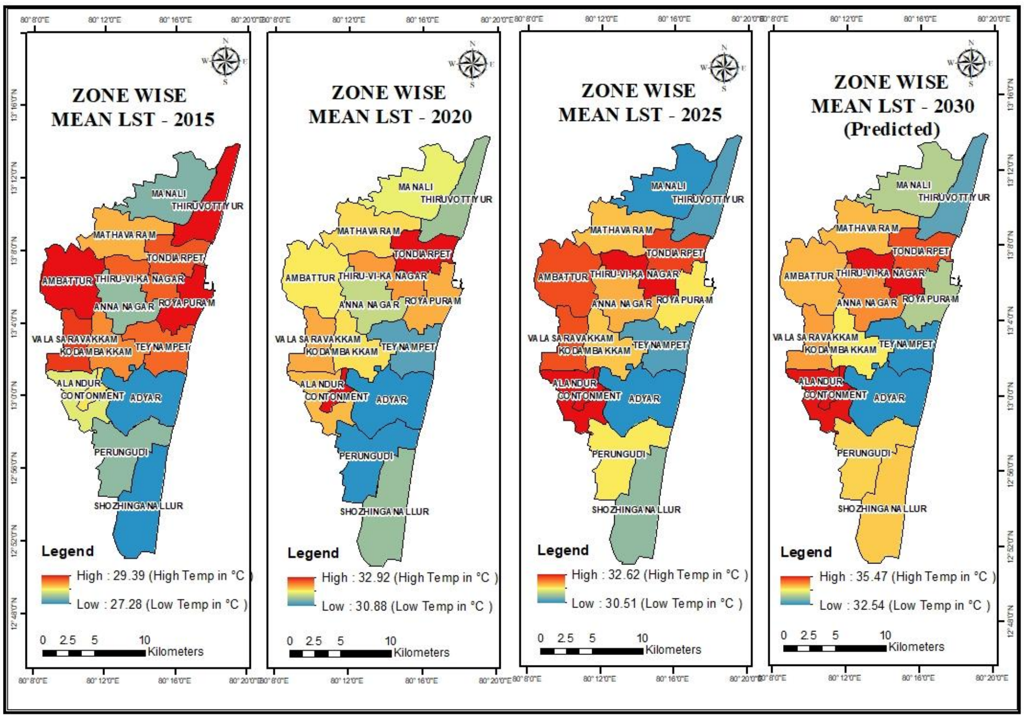
The average surface temperature of Chennai for the year 2030 is estimated to be 34.08° C. The R^2 value is 0.86 and the Slope(b) is on the positive side with an increase of 0.3426° C with every 5 years time progression.

FIG 6: TIME SERIES PLOT OF ZONE WISE LST



The temperature range is pronounced for Zones line Alandur, Thiru-Vi-Ka nagar and Sholinganallur with an increase of approximately 7°C from 2015 to 2030. Temperature recorded 27 degree in 2015 to 34.3 in 2030. Adyar is expected to change the least of them due to the sizeable presence of vegetation cover which act as coolants due to their reduced thermal conductivity and increased transpiration.

MAP NO 7: SPATIAL REPRESENTATION OF ZONE WISE MEAN LST FOR GREATER CHENNAI



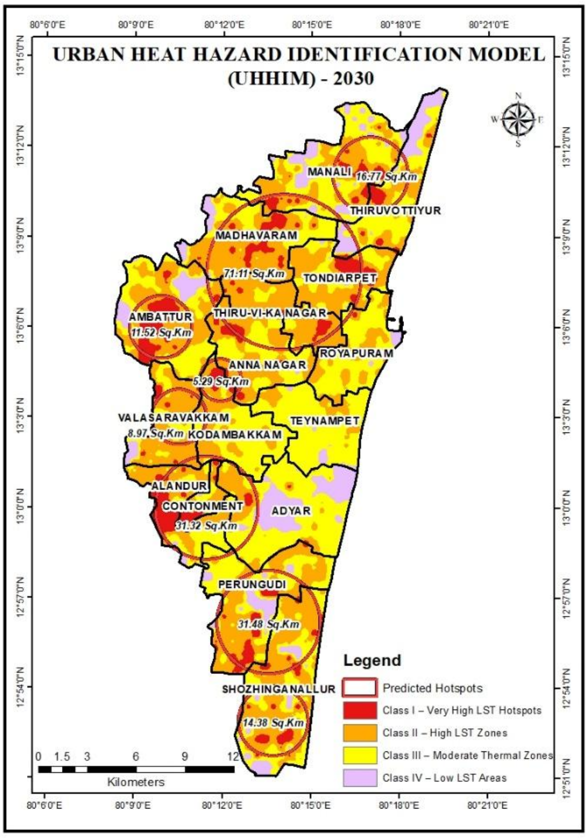
Map no 7 shows the average LST recorded at each zone that are quantitatively classified. Since the temperature range of each time period was recorded to be miniscule, a uniform color symbology was used with low values in blue and high values in red. It should be mentioned that zones which have decent vegetation canopy like Anna Nagar and Adyar have remained relatively cooler over the course of time, zones that experience rapid urbanization like Alandur, Perungudi and Sholinganallur have bore the brunt with pronounced increase.

1.8 URBAN HEAT HAZARD IDENTIFICATION MODEL (UHHIM)

There is no single person who "invented" a specific, universal "urban heat hotspot identification model" for urban planning; Instead, these models have developed over time through the contributions of many researchers using various methods. The phenomenon itself was first identified by Luke Howard in the early 19th century (Carrasco, Rebecca S.,2024)

Recent research has demonstrated the potential of combining methods for machine learning with geostatistical methods to improve the spatial accuracy of UHI models.

MAP NO : 8 URBAN HEAT HAZARD IDENTIFICATION MODEL (UHHIM)



Urban Heat Hazard Identification Model (UHHIM) for 2030 reveals that Greater Chennai is expected to experience significant intensification of thermal hotspots, particularly across the Northern and Western zones such as Manali, Madhavaram, Ambattur, Anna Nagar, Kodambakkam, Teynampet, and Perungudi, where large extents fall under Class I (very high LST) and Class II (high LST) due to dense built-up growth, industrial activity, and reduced vegetation. Tondiarpet, Thiru-Vi-Ka Nagar, Royapuram, and Valasaravakkam are examples of places with moderate thermal conditions (Class III), although only a few small portions in Adyar and Sholinganallur remain in Class IV (low LST) due to coastal influence and residual green cover. Overall, the model predicts that by 2030, about 190/ 426 sq.km area will be under class I and class II categories of very high and high LST zones. The progressive increase in LST demonstrates that the reduction in vegetation and the increase in built-up surfaces is directly contributing to the warming of the city's surface. The combined NDVI, NDBI, and LST results show the effects of fast urbanization, especially in areas impacted by infrastructure development and the growth of the IT sector.

The suggested model estimates the almost 50% of the total of 426 sq.km of greater Chennai. While NDBI and LST indicate an upward pattern, indicating increasing construction activity and rising temperatures. Urban growth, dwindling vegetation, and heat-retaining surfaces will cause widespread thermal stress throughout the city, highlighting the critical need for green infrastructure, sustainable land-use planning, and UHI mitigation techniques to stop further temperature increases.

1.9 CONCLUSION

This chapter provides a comprehensive analysis of how the land surface features of Chennai have evolved over time by evaluating NDVI, NDBI, and LST to assess urbanization during the period 2015, 2020 to 2025, along with a prediction for 2030. UHHIM constructed to evaluate the heat clusters of the city in 2030. The results demonstrate a constant and evident transformation throughout all 15 zones, indicating the city's continuous fast phase of urban expansion. The amount of impervious surfaces in the city has increased.as a result of new construction, road network expansion, commercial corridors, and IT-related initiatives. LST results strengthen this observation by demonstrating a continuous rise in Land surface temperatures from 2015 to 2025. In order to prevent urban growth from affecting the city's long-term ecological stability, these findings highlight the necessity of balanced and sustainable planning, green space preservation, and enhanced environmental management techniques.
Chennai's urbanization is characterized by rapid, sprawling growth, transforming agricultural land into built- up areas, especially south and west of the core, driven by economic hubs (IT, healthcare) and population influx, leading to pressures on significant climate risk like heatwaves , necessitating focused green infrastructure and smart planning initiatives like singara Chennai 2.0 for sustainable management.

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