

Original Research

Urban Expansion, Thermal Transformation, and Ecological Stress in Chennai, India: A Multi-Temporal and Predictive Analysis Integrating Landsat and VIIRS

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Academic Editor: Yan-Fang Sang

Adv Environ Eng Res
2026, volume 7, issue 4
doi:10.21926/aeer.2604035

Received: August 01, 2026
Accepted: October 13, 2026
Published: October 23, 2026

Abstract

Rapid urban growth transforms land cover and alters surface thermal conditions, especially in fast-changing tropical coastal cities. This study examines the spatial and temporal relationships among land-use/land-cover (LULC) transformation, land surface temperature (LST), relative thermal stress, and nighttime illumination in Chennai, India. Landsat observations for 2005, 2015, and 2025 were processed in Google Earth Engine to derive LULC for 2005 and 2025 and seasonal LST and Urban Thermal Field Variance Index (UTFVI) measures for the thermal reference years, while annual VIIRS nighttime radiance was analysed for 2014-2025. We simulated future LULC using a Cellular Automata-Artificial Neural Network (CA-ANN) framework, then used Random Forest regression to estimate a conditional thermal response associated with the simulated 2045 land configuration. Between 2005 and 2025, built-up land increased from 258.83 to 305.69 km², whereas cropland and barren land declined by approximately 60% and 75%, respectively. Under the CA-ANN scenario, built-up land is projected to reach 352.55 km² by 2045, representing approximately 80.56% of the study area. Historical thermal analysis shows substantial redistribution among LST classes, with the 35-40°C class becoming increasingly dominant; however, the observed class redistribution is



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distinguished from a statistically significant temporal warming trend. The 2045 thermal surface is similarly concentrated within the 35-40°C range, while the highest-temperature classes contract under the modelled scenario. This redistribution is interpreted using fixed temperature thresholds and possible upper-tail attenuation in the Random Forest estimates and is not interpreted as evidence of future cooling. UTFVI analysis indicates substantial spatial redistribution of relative thermal stress, while mean absolute UTFVI (MAUTFVI) provides a more informative measure of interannual variation in stress magnitude. Annual VIIRS nighttime radiance increased significantly from 20.992 in 2014 to 28.990 in 2025, whereas the seasonal LST and MAUTFVI series did not show statistically significant linear temporal trends. The bivariate VIIRS relationships with seasonal LST and MAUTFVI were also not statistically significant at the 5% level, indicating that nighttime illumination alone does not adequately explain interannual thermal variability. Overall, the results indicate that nighttime illumination, land transformation, and thermal conditions represent related but non-synchronous dimensions of urban change. The integrated framework therefore provides a scenario-based basis for understanding Chennai's evolving thermal environment and for supporting climate-responsive and spatially targeted urban planning.

Keywords

Urban expansion; remote sensing; land surface temperature; thermal stress; UTFVI; VIIRS; CA-ANN; random forest; Chennai

1. Introduction

Urbanization is one of the most consequential forms of land transformation, with built-up areas progressively replacing cropland, wetlands, vegetation, and other permeable surfaces. These transformations alter surface albedo, roughness, moisture availability, and energy exchange, thereby influencing local surface-energy balance and broader environmental conditions [1]. Urban growth is shaped by interacting physical, demographic, socioeconomic, and infrastructural factors rather than occurring randomly [2]. Continued urban concentration is expected particularly across Asia and Africa [3, 4], while differences in urban form, including compact development and dispersed sprawl, produce contrasting spatial configurations and environmental consequences [5, 6]. The conversion and fragmentation of natural and semi-natural surfaces can reduce ecosystem services [7], increase exposure to environmental stress [8], and create challenges for sustainable land management and urban planning [9]. Global demographic projections further indicate continued urban concentration in the coming decades [10]. Understanding how these transformations modify urban thermal environments is therefore increasingly important for rapidly developing cities. Remote sensing provides a consistent spatial basis for examining long-term urban land transformation and its environmental consequences. Landsat imagery has been widely used for multi-temporal land-use and land-cover (LULC) mapping because its spatial resolution enables changes in urban, vegetated, agricultural, barren, and water-covered surfaces to be examined at intra-urban scales [11, 12]. Improvements in classification approaches have enhanced the accuracy and reproducibility of LULC mapping [13, 14], while multi-temporal analysis allows gradual land-

cover transitions to be identified [15]. Reliable radiometric calibration and quality screening are essential to maintain temporal consistency in remotely sensed observations [16, 17]. Spectral indicators such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) further help differentiate vegetated and built-up surfaces [18]. However, mapping land transformation alone does not explain its environmental consequences. An important question is how changes in surface composition alter the spatial distribution of land surface temperature (LST) and associated thermal conditions [19].

Urban land transformation can substantially modify the surface energy balance and contribute to urban heat island (UHI) conditions. Impervious surfaces generally absorb and store more solar energy, whereas the loss or fragmentation of vegetation can reduce evapotranspirative cooling [20-22]. Thermal remote sensing consequently provides an important means of examining the spatial expression of urban thermal conditions through LST [23]. Researchers have widely applied Landsat-based LST retrieval approaches to characterize urban surface-temperature patterns [24, 25]. Previous studies have repeatedly identified associations between urban expansion and increased LST, whereas vegetation generally exerts a cooling influence [26]. Reviews and comparative studies have established the value of LST for urban climate and environmental assessment [27, 28]. At the same time, investigations in Indian cities and other rapidly urbanizing regions have reported similar relationships between land transformation and surface warming [29-31]. These relationships, however, are neither spatially nor temporally uniform. Seasonal conditions can substantially modify thermal patterns, and the relationships between vegetation, built-up surfaces, and LST can vary across time and space [32, 33].

The thermal response of tropical coastal cities requires particular attention because surface heating depends not only on land-cover transformation but also on moisture availability, atmospheric humidity, coastal circulation, seasonal rainfall, vegetation, surface materials, and urban morphology. UHI conditions arise from changes in surface-energy balance associated with the replacement of natural or permeable surfaces by impervious materials, changes in evapotranspiration, heat storage, and radiative properties [20-23]. LST provides a spatially explicit measure of the thermal state of the land surface and is therefore widely used to characterize urban thermal environments [23-25]. It should not, however, be treated as a direct equivalent of near-surface air temperature or human thermal exposure because surface temperature is influenced by land-surface characteristics and atmospheric conditions at the time of observation. Seasonality further complicates these relationships. Recent research shows that the thermal environment's response to LULC and landscape configuration can differ substantially by season and depend on multiple environmental drivers. The Beijing-Tianjin-Hebei urban agglomeration study, for example, showed that summer and winter thermal environments differed in both magnitude and spatial configuration and that the effects of impervious surfaces, green space, terrain, vegetation, and other drivers varied seasonally [34]. Similarly, machine-learning research in the Pearl River Delta has demonstrated that LULC change can be linked explicitly with seasonal LST, UTFVI, and UHI and that future land-use scenarios can be used to examine potential changes in the urban thermal environment [35]. These studies reinforce the importance of considering seasonality, landscape configuration, and multiple environmental controls rather than interpreting thermal change only through the extent of built-up expansion.

This complexity matters especially in Indian metropolitan regions, where rapid urban transformation occurs alongside strong seasonal variability, heterogeneous urban morphology, and

substantial contrasts among vegetation, water bodies, open surfaces, and impervious development [29, 33]. In tropical coastal cities, humidity, sea-breeze circulation, wetlands, rivers, surface moisture, and seasonal rainfall can moderate or redistribute the thermal response to urban development [36-38]. Conversely, continued conversion and fragmentation of vegetated and moisture-retaining surfaces can reduce evaporative cooling and modify local heat storage. The resulting thermal environment therefore reflects interactions among land transformation, surface characteristics, seasonal conditions, and the regional coastal environment rather than a simple one-to-one relationship between built-up area and LST. Chennai provides a particularly relevant setting for examining these interactions [39, 40]. Located along the Bay of Bengal and characterized by low-lying terrain, high humidity, seasonal rainfall, wetlands, river systems, and extensive urban development, Chennai contains strong contrasts between densely built-up surfaces and areas influenced by vegetation and surface moisture. The coexistence of coastal, wetland, agricultural, open, and intensely urbanized surfaces within a relatively compact metropolitan region creates substantial spatial heterogeneity in thermal conditions. Coastal circulation and moisture can further modify surface heating, while dense urban development can alter heat storage and local ventilation. These characteristics make Chennai an appropriate case for investigating how LULC transformation, seasonal thermal conditions, and ecological thermal stress interact within a tropical coastal urban system.

LST provides information on the spatial distribution and magnitude of surface heating, but temperature patterns alone do not fully describe the ecological dimension of thermal stress. The Urban Thermal Field Variance Index (UTFVI) offers a complementary measure by linking local LST to the thermal conditions across the wider study area, thereby characterizing the spatial distribution of relative thermal stress [41]. UTFVI-based assessments have distinguished relatively favourable from unfavourable thermal conditions and identified locations requiring greater attention for mitigation [42, 43]. Previous studies integrating UTFVI with LULC have reported concentrations of higher thermal stress in densely built-up areas and areas characterized by reduced vegetation [44, 45]. These studies establish the usefulness of LULC-LST-UTFVI analysis but also demonstrate that the individual components are sufficiently well established that the present study should not claim novelty simply from combining the same indicators. The relevant question is instead how these components can be connected across historical, seasonal, and future spatial contexts within a common analytical framework. Future urban thermal conditions also depend on how the land system develops spatially. Machine-learning approaches can examine complex relationships between land characteristics and surface temperature [46-48], while spatial simulation approaches can project future land-use configurations [49]. CA-ANN models have been widely used to represent spatial transition processes and urban land-use change [50-53], while the MOLUSCE framework provides an operational GIS environment for such modelling. Regression and machine-learning techniques can subsequently be used to associate projected land configurations with thermal conditions [54, 55]. The existence of these approaches means that future LULC simulation or thermal modelling alone cannot be regarded as the principal novelty of the present study. Rather, the relevant contribution is the sequential connection of historical land transformation, future LULC simulation, and scenario-based thermal assessment. A further issue concerns temporal continuity. Landsat provides detailed spatial information on LULC, LST, and UTFVI, but studies based on selected observation years provide only a discontinuous view of changes in urban activity. VIIRS nighttime radiance provides an established annual record of nighttime illumination and an indirect indicator

of urban activity and development intensity [38-40]. The use of VIIRS itself is therefore not presented as a novel method, and radiance is not treated as a direct thermal measurement. Instead, its value in the present study lies in providing an independent temporal dimension that can be compared with the discrete Landsat-based observations. This allows us to examine whether increasing nighttime urban activity is accompanied by synchronous changes in seasonal LST and the magnitude of spatial thermal variability, while recognizing that these dimensions can be influenced by different environmental and temporal controls.

Against this background, three specific analytical gaps are addressed. First, a spatial-temporal integration gap remains. Previous studies have already established relationships among LULC, LST, and UTFVI, including applications that combine these indicators [44, 45]. The unresolved issue addressed here is therefore not the simple co-use of these variables, but their connection across multiple historical years and seasons within a common spatial framework. The study examines LULC transformation together with seasonal LST and pixel-level UTFVI to determine how changes in land composition correspond with changes in surface temperature and the spatial distribution of relative thermal stress. Second, a future thermal-translation gap remains. Previous studies have demonstrated that CA-ANN and related land-use simulation approaches can be combined with thermal modelling [56-60]. The present study does not claim that this methodological combination is unprecedented. Instead, it uses the simulated 2045 LULC configuration as the spatial basis for estimating potential future LST and interpreting its corresponding UTFVI pattern. This sequential framework connects the projected spatial land configuration with its potential thermal and ecological implications. Importantly, the 2045 results are treated as scenario-based estimates conditional on the projected land configuration and the modelled predictor relationships, not as deterministic forecasts of future climate or extreme temperature. Future thermal conditions will also depend on meteorological, atmospheric, socioeconomic, coastal, and other processes not fully represented in the land-use scenario. Third, a temporal urban-activity evidence gap remains. VIIRS nighttime radiance is already an established source for monitoring nighttime illumination and urban activity [38-40]. Its contribution here is therefore not the novelty of the dataset but its integration with the discontinuous Landsat observations. The annual 2014-2025 VIIRS record is combined with seasonal Landsat-derived LST and UTFVI measures to test statistically whether temporal changes in urban activity are associated with changes in thermal conditions. This design permits the study to distinguish between increasing nighttime urban intensity and changes in surface thermal conditions rather than assuming that the two must follow identical temporal trajectories. These three gaps are analytically distinct and map directly onto the five objectives of the study. Objective 1 establishes the 2005-2025 LULC baseline required to interpret subsequent thermal change rather than treating land-use mapping as an end in itself. Objective 2 links seasonal LST with pixel-level UTFVI to examine surface thermal response and ecological thermal stress jointly. Objective 3 uses CA-ANN to translate the observed land-transition structure into a 2045 spatial scenario, while Objective 4 translates this projected land configuration into potential seasonal LST and UTFVI responses through Random Forest modelling rather than treating future LULC as a direct thermal scenario projection. Objective 5 adds the continuous annual VIIRS dimension and tests whether changes in nighttime urban activity correspond temporally with seasonal LST and MAUTFVI. The contribution therefore lies in the linkage and interpretation of established approaches within a common Chennai framework, rather than in claiming novelty for any individual dataset or method.

The resulting framework provides complementary spatial and temporal perspectives on Chennai's thermal environment. LULC mapping establishes the trajectory of land transformation; seasonal LST characterizes the associated surface thermal response; UTFVI identifies the spatial distribution of relative thermal stress; CA-ANN provides the projected 2045 land-use configuration; Random Forest estimates the potential thermal response associated with that scenario; and annual VIIRS radiance provides an independent temporal indicator of nighttime urban activity. This framework also maintains a necessary distinction between observed historical conditions, statistical associations, and scenario-based projections. In particular, we do not assume that increasing nighttime radiance produces a proportional increase in LST or UTFVI, and we do not treat a projected future LULC configuration as a deterministic forecast of future thermal conditions. The study therefore examines Chennai's urban thermal transformation as a coupled but not necessarily synchronous process involving land change, seasonal surface temperature, spatial ecological thermal stress, future land-use configuration, and temporal urban activity. This integrated perspective is particularly relevant in tropical coastal environments where urban morphology, vegetation, moisture, atmospheric processes, and coastal influences shape surface thermal conditions. It also provides a basis for identifying whether apparent changes in urban activity correspond to changes in the thermal environment and for interpreting where future land transformation may generate greater thermal pressure.

The objectives of this study are:

1. To map land use and land cover changes in Chennai for 2005 and 2025 using multi-temporal Landsat data, thereby establishing the spatial and temporal baseline of urban land transformation.
2. To derive seasonal land surface temperature (LST) and Urban Thermal Field Variance Index (UTFVI) for 2005, 2015, and 2025 and examine the spatial thermal response associated with changing land-cover conditions.
3. To simulate the spatial configuration of LULC for 2045 using a Cellular Automata-Artificial Neural Network (CA-ANN) model implemented in MOLUSCE and use the resulting scenario as the basis for future thermal assessment.
4. To estimate the potential 2045 LST and UTFVI patterns associated with the projected land-use scenario using Random Forest regression, thereby translating simulated land transformation into a scenario-based assessment of future thermal conditions.
5. To analyse annual VIIRS nighttime radiance from 2014 to 2025 as an independent indicator of changing urban activity and examine whether its temporal variation is statistically associated with seasonal LST and MAUTFVI, thereby distinguishing changes in urban activity from changes in surface thermal conditions.

2. Materials and Methods

2.1 Study Area

Chennai is situated on the southeast coast of India along the Bay of Bengal. The study area lies between 12.8° N and 13.3° N latitude and 80.1° E and 80.3° E longitude (Figure 1). The city is part of Tamil Nadu and functions as a major metropolitan and economic center in southern India. The landscape is mainly flat, with elevation between 0 and 60 m above mean sea level. The Cooum, Adyar, and Kosasthalaiyar rivers form the principal drainage network of the coastal plain. The

metropolitan area contains several wetlands and marsh ecosystems, including the Pallikaranai marsh. The study area's coastal boundary extends over 15 km. The eastern boundary of the study area is directly influenced by the Bay of Bengal. Inland areas include previous agricultural and suburban lands that are changing rapidly due to urban development. This difference between coastal areas and the inland areas creates different surface conditions over short distances. The presence of wetlands, rivers, and densely built-up areas allows the comparison of different land cover types within the same urban area.

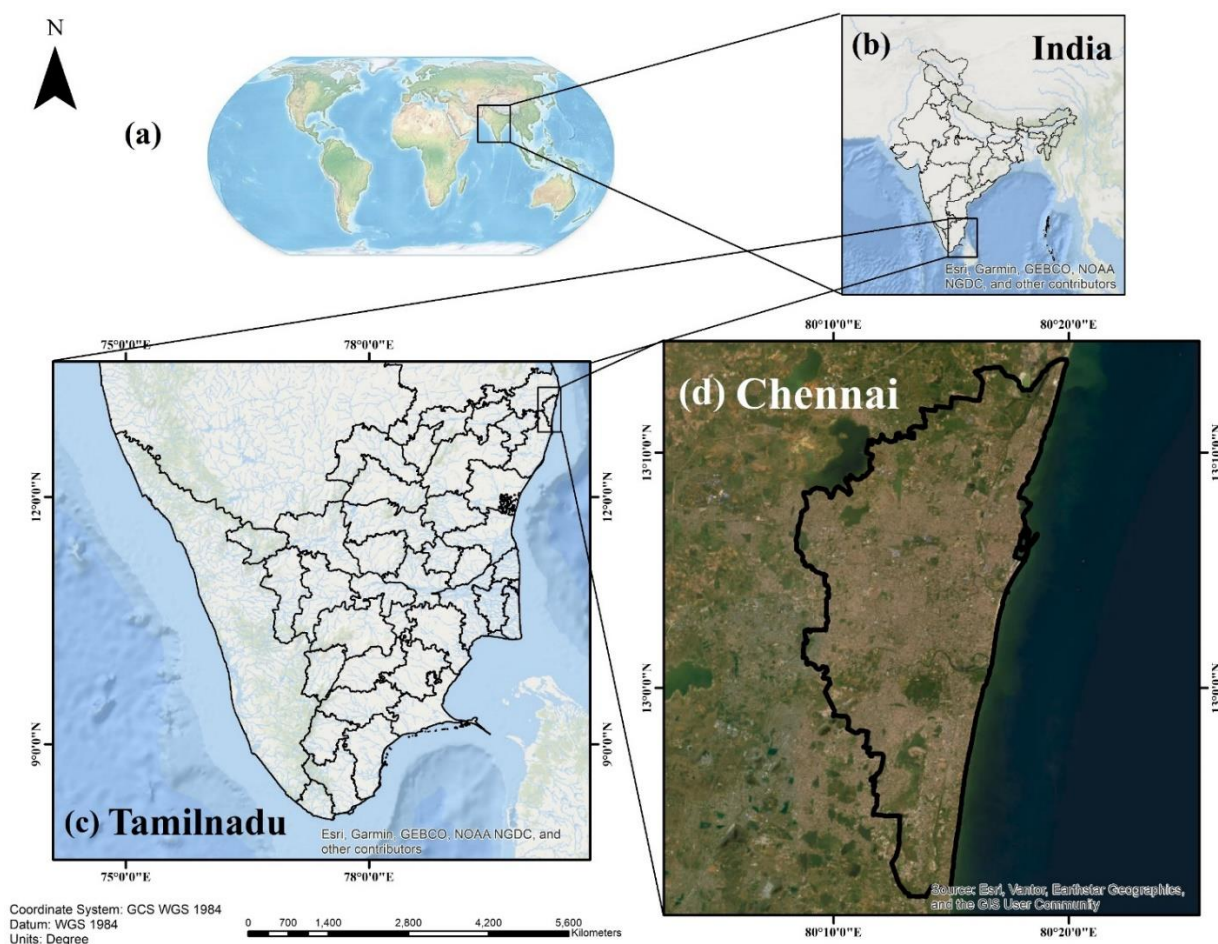


Figure 1 Location of the study area with (a) Global location of the Indian subcontinent; (b) Location of India within the Indian subcontinent; (c) Location of Tamil Nadu in India; and (d) Location and satellite image of Chennai.

These conditions make the study area suitable for analyzing the relationships between land use change and land surface temperature. Chennai has a tropical climate with consistently high temperatures. The hottest period is from April to June when daytime air temperature often exceeds 38°. The majority of rainfall occurs during the northeast monsoon from October to December. The city receives an average of about 1200 mm of rainfall each year, but its distribution is uneven and heavy rainfall events frequently occur. The city's coastal location keeps humidity levels high. Sea breezes help reduce temperatures in some parts of the city, whereas their effect is weaker in densely built-up areas where air movement is limited. Together, the climate and land surface characteristics shape the thermal environment. High temperatures, high humidity and dense urban development increase thermal stress. The region shows clear seasonal variation, but hot conditions

are not restricted to a single season. This makes it suitable for studying seasonal and long-term thermal changes.

2.1.1 Urban Growth Context

Urban expansion in Chennai has increased rapidly over the past two decades as the city has grown both by expanding into the surrounding areas and by developing the land within the existing urban boundary. Many settlements on the outskirts have gradually become part of the metropolitan area while agricultural land and open spaces have been converted into residential, commercial and industrial uses. The growth of transport infrastructure and IT development zones has accelerated this change and has increased the built-up density, especially in the central and southern parts of the city, although the pattern of urban expansion has not been the same across all parts of Chennai. Urban growth has largely followed transport networks and major economic corridors, which has created long and connected patterns of development across the city. As built-up areas expanded, impervious surfaces increased. At the same time, vegetated land became less continuous, and urban development gradually spread into floodplains and wetland edges, changing the natural drainage system and reducing its ability to store excess water. The loss of green space has also increased the variation in surface temperature across the city. The changes between 2005 and 2025 clearly show how Chennai has shifted from a landscape with mixed land cover to one dominated by built-up areas, making this period suitable for analyzing long-term land use change and projecting future conditions.

2.1.2 Environmental Sensitivity

Chennai is environmentally sensitive because of its coastal location and low elevation, which make the city vulnerable to cyclones, heavy rainfall, storm surges, and frequent flooding. Flood events have become more common in recent years, and land use changes have added to this problem by reducing wetlands and increasing built-up areas. Wetlands such as Pallikaranai play an important role by storing excess runoff and helping to maintain the local microclimate, but the loss of these wetlands increases both flood risk and surface temperature. Urban growth has also changed the river systems, as floodplains have become narrower and natural drainage channels have been modified, which has increased surface runoff as built-up areas continue to expand. At the same time, the loss of vegetation reduces evapotranspiration and weakens the natural cooling effect of the landscape. The thermal conditions in Chennai are shaped by all of these factors together because land cover, moisture availability, and atmospheric conditions interact with each other and these interactions become stronger as land conversion continues. This combination of high climatic exposure and rapid urban growth makes Chennai an ideal area for studying thermal stress under both present and future land use conditions.

2.2 Satellite Data and Other Data Sources

The multispectral and thermal datasets from Landsat were used to characterize land transformation and seasonal surface thermal conditions in Chennai. For LULC classification, Landsat 7 ETM+ imagery was used for 2005 and Landsat 8 OLI imagery for 2025. In contrast, the thermal analysis used Landsat 5 TM for 2005, Landsat 8 OLI/TIRS for 2015, and Landsat 9 OLI/TIRS for 2025 (Table 1 and Table 2) [11, 12, 17, 18]. This distinction reflects the availability and suitability of the

sensor datasets for the separate classification and thermal-analysis tasks and should not be interpreted as use of a single sensor across the entire study period. We derived all thermal observations from Landsat Collection 2 Level-2 products using the sensor-specific surface-temperature bands provided for each platform. Landsat 5 TM and Landsat 7 ETM+ thermal observations use the sensor-specific thermal products associated with those missions, while Landsat 8 and Landsat 9 use the ST_{B10} product. The corresponding Collection 2 scale factors and offsets were applied before conversion to physical temperature, and a common LST retrieval framework was used across the reference years. The use of Collection 2 Level-2 products provides a consistent product-level radiometric basis; however, this does not imply complete removal of residual sensor-specific differences in thermal response. Accordingly, we interpret long-term LST comparisons are interpreted primarily in terms of broad spatial and categorical thermal patterns, while treating small absolute interannual differences cautiously [31, 39, 46].

Table 1 Satellite data used specifically for LULC classification.

Satellite	Collection Period	Resolution	Description
Landsat 7 ETM+	01/01/2005-31/12/2005	30 m	Collection 2 Tier 1 calibrated reflectance
Landsat 8 OLI	01/01/2025-31/12/2025	30 m	Collection 2 Level 2 surface reflectance

Note: The sensor sequence in this table refers to the LULC classification workflow and is distinct from the thermal sensor sequence used for LST/UTFVI analysis in Table 2.

Table 2 Satellite data used for LST and UTFVI estimation.

Year	Satellite & Sensor	Bands Used	Spatial Resolution
2005	Landsat 5 TM	SR _{B1-B7} , ST _{B6}	30 m
2015	Landsat 8 OLI/TIRS	SR _{B1-B7} , ST _{B10}	30 m
2025	Landsat 9 OLI/TIRS	SR _{B1-B7} , ST _{B10}	30 m

Note: Sensor-specific thermal bands were processed using the corresponding Landsat Collection 2 Level-2 scale factors and a common LST retrieval framework. No empirical inter-sensor thermal bias correction was applied; residual sensor-specific differences are acknowledged as a limitation of long-term absolute LST comparison. The sensor sequence in Table 2 refers specifically to the thermal/LST analysis. LULC classification used a separate imagery sequence described in Table 1. Landsat 5 TM was used for the 2005 thermal reference year, Landsat 8 OLI/TIRS for 2015, and Landsat 9 OLI/TIRS for 2025.

2.3 Image Processing and Preparation

For the analyses, Google Earth Engine was used to acquire and preprocess satellite imagery. The Chennai metropolitan boundary shapefile was used to clip all datasets. For the continuous 2014-2025 analysis, Landsat Collection 2 Level-2 scenes intersecting the study area were selected by acquisition date and spatial extent. Instead of applying a fixed scene-level cloud threshold as a hard exclusion criterion, pixel-level quality screening was applied using the Landsat QA_{PIXEL} and QA_{RADSAT} bands to remove fill, dilated cloud, cirrus, cloud, cloud-shadow, snow, and saturated pixels. This approach retained usable clear pixels while reducing the influence of cloud-contaminated observations. We generated seasonal median composites separately for summer (April-June) and

winter (November-December) to reduce short-term variability and maintain consistency with the historical seasonal analysis. We converted surface temperature values to Kelvin before calculating UTFVI. Annual VIIRS radiance composites were generated for 2014-2025 from the monthly VIIRS nighttime-radiance product. Seasonal LST and pixel-level UTFVI statistics were then calculated from the available quality-controlled Landsat observations.

For radiometric preprocessing, the standard USGS Landsat Collection 2 Level-2 scale factors and offsets were applied to the relevant surface-reflectance and surface-temperature products before index and thermal calculations. Surface-reflectance bands were converted to unitless reflectance using the corresponding Collection 2 scaling relationship. The sensor-specific surface-temperature bands were converted to physical temperature in Kelvin using the corresponding Collection 2 Level-2 scaling parameters, after which 273.15 K was subtracted to express LST in degrees Celsius. Thermal processing therefore used sensor-specific Landsat products rather than applying a single unmodified digital-number-to-temperature conversion across sensors. The same computational sequence was maintained across the thermal reference years: acquisition of the Collection 2 Level-2 product, quality screening, application of the sensor-specific scale factors and offsets, generation of the seasonal composite, conversion to Kelvin, and subsequent UTFVI calculation. This common processing structure reduces differences introduced by inconsistent preprocessing and preserves the sensor-specific calibration implemented in the Landsat Collection 2 products. The present study applied no additional empirical cross-sensor thermal bias correction. In particular, the analysis did not perform overlap-based inter-sensor regression, pseudo-invariant target adjustment, or an independent empirical calibration between Landsat thermal observations. Consequently, the processing should be understood as product-level radiometric standardisation and methodological harmonisation rather than complete removal of sensor-specific systematic differences. Residual differences in thermal response among Landsat generations may therefore remain and could contribute to small differences in absolute LST between reference years. For this reason, the interpretation places greater emphasis on broad spatial patterns, seasonal contrasts, thermal-class redistribution, and multi-indicator consistency than on attributing small absolute interannual LST changes solely to physical warming.

2.4 Land Use and Land Cover Classification

To procure LULC maps for the years 2005 and 2025, supervised classification was employed. Five classes were defined for the study: built-up land, vegetation, water bodies, cropland, and barren land (Table 3). The training samples were selected through visual interpretation supported by high-resolution imagery in GEE. A 30 m spatial buffer was applied to match Landsat resolution. The Random Forest classification with 50 decision trees was implemented. This method is robust to overfitting and performs well in heterogeneous urban landscapes [38]. Independent validation samples were used to assess classification accuracy. The evaluation included overall accuracy, producer accuracy, user accuracy, and the Kappa coefficient. These metrics quantify classification reliability and agreement with the reference data.

Table 3 LULC Classification Scheme.

LULC Type	Description
Built-up Land	Residential, commercial, infrastructure
Water Body	Rivers, lakes, ponds
Vegetation	Forest and green cover
Crop Land	Agricultural land
Barren Land	Exposed and unused land

2.5 Simulation of Future LULC

This study used the MOLUSCE plugin in QGIS to simulate land-use changes for 2045. The model integrates Cellular Automata (CA) and Artificial Neural Network (ANN) algorithms to represent spatial transition processes [47, 57]. The LULC maps for 2005 and 2025 were used to establish the historical land-transition structure and generate the transition probability matrix. Spatial transition potential was estimated using eight spatial driving variables: DEM/elevation, aspect, slope, hill shade, contour, curvature, distance to stream, and railway distance. The predictor set displayed in Figure S1 was selected to represent complementary geographical conditions that can influence the spatial suitability and direction of land-use transition. Rather than relying on a single measure of terrain or accessibility, the predictor set combines terrain configuration, hydrological proximity, and transportation-related accessibility. This allows the CA-ANN model to account for spatial heterogeneity in the landscape when estimating transition potential. DEM/elevation was included to represent the vertical position of the terrain and broad elevation-related differences in land suitability. Aspect was included to represent the directional orientation of terrain surfaces, which can be associated with differences in solar exposure, moisture conditions, and local environmental characteristics. Slope represents terrain steepness and therefore provides information relevant to the physical suitability and development constraints of different locations. Hill shade was included as a terrain-relief representation that captures spatial variation in surface illumination and relief configuration. Contour information represents the spatial organisation and gradient of elevation and provides an additional description of the terrain structure. Curvature represents local convexity and concavity and can distinguish relatively different terrain forms and local drainage or surface-form conditions. Together, these six terrain-derived variables provide complementary descriptions of the physical configuration of the landscape. We included distance to stream to represent the spatial relationship between potential land transformation and the drainage network. Proximity to streams can distinguish locations with different hydrological conditions and development constraints, particularly in a low-lying and environmentally sensitive urban area such as Chennai. Distance to the railway was included to represent proximity to transportation infrastructure and associated accessibility to established development corridors. It therefore provides a spatial representation of the infrastructure-related context within which urban expansion may occur.

The eight predictors were supplied jointly to the ANN for transition-potential estimation and were subsequently incorporated within the CA framework for spatial allocation of future land-use transitions. The predictors were treated as complementary spatial descriptors rather than as statistically independent explanatory variables, consistent with the scenario-based purpose of the CA-ANN component. The variables were therefore treated as complementary spatial descriptors

rather than as statistically independent causal determinants. In particular, aspect, slope, hill shade, contour, and curvature are derived from the same DEM and may contain related information. Their joint use is intended to represent different characteristics of terrain configuration, while acknowledging that some spatial dependence may exist among them. All predictor layers were derived or prepared at a common spatial resolution and harmonised to the coordinate reference system, spatial extent, and raster alignment of the LULC datasets. This ensured that each predictor corresponded to the same modelling cells and could be jointly incorporated into transition-potential estimation. The ANN component was used to estimate spatial transition-potential surfaces from the selected predictor set, while the CA component incorporated neighbourhood effects to spatially allocate future land-use transitions. We then applied the calibrated model to simulate the 2045 LULC configuration. The resulting 2045 map represents a scenario conditioned on the observed 2005-2025 transition structure and the selected spatial driving variables. The LULC classification accuracy and the CA-ANN simulation performance were treated as separate aspects of model assessment. The Overall Accuracy and Kappa coefficients reported for the 2005 and 2025 LULC maps assess the reliability of the classified LULC products and are not equivalent to independent validation of the CA-ANN simulation itself. The present study used CA-ANN as a spatial scenario-generation framework based on the observed 2005-2025 land-transition structure and the selected spatial predictors. A historical hindcast in which an earlier period was used to simulate a known subsequent year was beyond the original analytical scope and was therefore not performed. Consequently, we do not report simulation-specific validation measures such as Figure of Merit (FoM), simulation-specific Overall Accuracy, Kappa, or a simulated-versus-observed confusion matrix. This limitation is explicitly acknowledged because the absence of an independent hindcast constrains quantitative assessment of the spatial accuracy and uncertainty of the 2045 land-use scenario. The 2045 CA-ANN output is therefore interpreted as a scenario-based spatial projection conditional on the observed transition structure and selected predictors, rather than as a deterministic or independently validated prediction of future land use.

2.5.1 Predictor Selection and Multicollinearity Limitation

The spatial driving variables for the CA-ANN simulation were selected a priori according to their geographical relevance to land-transition processes and their ability to represent complementary aspects of terrain configuration, hydrological proximity, and transportation accessibility. The final predictor set comprised DEM/elevation, aspect, slope, hill shade, contour, curvature, distance to stream, and railway distance. Their individual spatial representations and methodological rationale are provided in Table S1. We therefore selected variables based on each variable's intended spatial-simulation role rather than on the assumption that each predictor represents an independent statistical determinant of land-use change. The six terrain-derived variables provide different descriptions of the physical configuration of the landscape. DEM/elevation represents vertical terrain position; aspect represents terrain orientation; slope represents terrain steepness; hill shade represents terrain-relief and illumination characteristics; contour represents the spatial organisation and gradient of elevation; and curvature represents local terrain form. Distance to stream represents hydrological proximity and potential drainage-related constraints, while railway distance represents transportation accessibility and development connectivity. The predictors were

therefore selected to provide complementary spatial information relevant to the location and suitability of land transformation.

A potential limitation of this predictor set is spatial redundancy among variables derived from the same underlying DEM. In particular, aspect, slope, hill shade, contour, and curvature are mathematically or spatially related terrain descriptors and may contain overlapping information. The predictors were nevertheless retained because the purpose of the ANN component was to estimate spatial transition potential from a combined set of environmental and accessibility descriptors rather than to estimate independent regression coefficients or causal effects for individual variables. The original CA-ANN workflow did not apply formal predictor-screening diagnostics, such as pairwise correlation thresholds or variance inflation factor (VIF). Consequently, the present study does not claim that the eight predictors are statistically independent, nor does it interpret the relative contribution of an individual predictor as an independent causal effect on land-use transition. The ANN was supplied with the predictor layers jointly, and the resulting transition-potential surface is therefore interpreted as a combined spatial suitability representation rather than as evidence of independent effects attributable to particular predictors.

This limitation may introduce redundancy in the predictor space and may influence the relative contribution assigned internally by the ANN to terrain-derived variables. However, because the objective of the CA-ANN component was scenario-based spatial allocation rather than causal inference from individual predictors, the principal interpretation of the 2045 output remains the spatial configuration generated by the combined predictor set and historical transition structure. The absence of formal collinearity screening consequently limits interpretation of individual predictor contributions and represents an uncertainty of the scenario-modelling framework. Future implementations should incorporate pairwise correlation analysis, VIF assessment, and predictor-sensitivity testing to identify potentially redundant variables and determine whether a reduced predictor set produces comparable transition potential and future LULC patterns. This would provide a stronger assessment of predictor stability and model robustness without changing the scenario-based purpose of the present analysis.

2.6 Derivation of Spectral Indices

The spectral indices were derived to represent key land surface characteristics influencing thermal behavior across the region. NDVI was used to quantify vegetation density, while NDBI was used to identify built-up surfaces. These indices help distinguish vegetated and impervious surfaces because these land-cover types have contrasting thermal properties. Built-up areas tend to retain and radiate heat, whereas vegetated surfaces promote evapotranspiration and surface cooling.

The Normalized Difference Vegetation Index (NDVI) was calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

The Normalized Difference Built-up Index (NDBI) was calculated as:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$

where:

NIR = near-infrared band

RED = red band

SWIR = shortwave infrared band

NDVI values range from negative (-ve) to positive (+ve), with higher values indicating dense vegetation. NDBI values highlight built-up features, with higher values corresponding to impervious surfaces. These indices were used as key inputs for analyzing land-temperature relationships and for subsequent modelling steps [61-63].

2.7 Land Surface Temperature Retrieval

This study calculated land surface temperature (LST) from the thermal infrared bands of the Landsat images using an emissivity-corrected method. The method accounts for surface characteristics by incorporating vegetation cover into emissivity estimation. This improves temperature retrieval accuracy, especially in heterogeneous urban environments.

Fractional vegetation cover was estimated using NDVI:

$$F_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2$$

Surface emissivity was then calculated as:

$$\varepsilon = 0.986 + 0.004 \cdot F_v$$

Finally, land surface temperature was derived using:

$$LST = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho} \right) \ln(\varepsilon)} - 273.15$$

where:

T_B = brightness temperature (Kelvin)

λ = wavelength of emitted radiance

$$\rho = \frac{h \cdot c}{\sigma}$$

where:

h = Planck constant

c = speed of light

σ = Boltzmann constant

The derived LST values were classified into five temperature classes to analyze the spatial distribution of thermal conditions across the study area (Table 4).

Table 4 LST class intervals.

Class	Temperature (°C)	Interpretation
1	<30	Low
2	30-35	Moderate
3	35-40	High
4	40-45	Very high
5	>45	Extreme

2.8 Urban Thermal Field Variance Index

We assessed ecological thermal stress using the Urban Thermal Field Variance Index (UTFVI), calculated from the spatial distribution of land surface temperature (LST). To avoid unit inconsistency, the retrieved LST values were first expressed in Kelvin before calculating UTFVI. For each pixel, UTFVI was calculated as the deviation of pixel-level LST from the corresponding study-area mean LST divided by the study-area mean LST:

UTFVI was calculated using the following equation:

$$UTFVI_i = \frac{LST_i - \overline{LST}}{\overline{LST}}$$

where $UTFVI_i$ is the UTFVI value for pixel i , LST_i is the pixel-level land surface temperature in Kelvin, and $\overline{LST}$ is the mean LST of all valid pixels within the study area in Kelvin.

Using Kelvin is essential because the numerator and denominator represent absolute temperature values. The formula produces a normalized dimensionless deviation from the study-area mean. Consequently, when you arithmetically average the UTFVI surface over the same valid pixels used to calculate the mean LST, positive deviations above the spatial mean and negative deviations below the spatial mean largely cancel. The arithmetic spatial mean of UTFVI is therefore expected to be numerically close to zero. A near-zero mean UTFVI should not be interpreted as an absence of thermal stress or as evidence of a unit-conversion error. The magnitude and spatial distribution of thermal variability were therefore evaluated from the pixel-level UTFVI distribution, including its standard deviation, range, percentile statistics, and classified spatial pattern. For the continuous 2014-2025 analysis, mean absolute UTFVI (MAUTFVI) was additionally calculated as the spatial mean of the absolute pixel-level UTFVI values. MAUTFVI removes cancellation between positive and negative deviations and therefore provides a direct summary of the magnitude of spatial thermal variability. This formulation also explains why annual mean UTFVI values in the VIIRS-LST time series can be numerically very close to zero. Such values result from spatial centering around the mean LST and are not indicative of a unit-conversion error. We then applied the UTFVI classification to the pixel-level UTFVI surface to identify areas experiencing different levels of ecological thermal stress (Table 5).

Table 5 UTFVI classification categories.

UTFVI Range	UHI Presence	Ecological Meaning
<0.005	Weak	Good
0.005-0.010	Middle	Normal
0.010-0.015	Strong	Bad
0.015-0.020	Stronger	Worse
>0.020	Strongest	Worst

Note: UTFVI classes were assigned using the pixel-level UTFVI values. The near-zero spatial mean of UTFVI is a mathematical consequence of normalization against the study-area mean LST and does not imply that all pixels have UTFVI values close to zero.

2.9 Integrated Machine Learning-Based Projection for 2045

A Random Forest regression framework was used to translate the simulated 2045 land-use configuration into a scenario-conditioned land surface temperature (LST) response. We selected NDVI, NDBI, and NDWI as predictor variables because they represent vegetation condition, built-up surface characteristics, and surface-water or moisture-related conditions, respectively. We considered separate seasonal models for summer and winter to account for differences in seasonal thermal behaviour. We calibrated the regression relationship using spatially distributed pixel observations from available Landsat-based thermal and spectral datasets for 2005, 2015, and 2025. These years represent the available temporal reference points for the thermal modelling, while the model fitting uses spatial observations from the corresponding study-area pixels rather than treating the three years as three individual observations. We then generated the 2045 predictor surfaces from the simulated 2045 land-use configuration and supplied them to the corresponding Random Forest model. The resulting LST surface represents a model-estimated thermal response conditional on the projected land configuration and the predictor relationships represented in the historical reference data. Thus, the Random Forest component functions primarily as a scenario-translation step, linking the simulated future land surface to a potential thermal response, rather than as an independently validated operational LST forecasting system.

An independent train-test validation framework, cross-validation procedure, and predictor-importance analysis were not included in the original analytical design. Consequently, training-versus-validation performance statistics such as independent validation R^2 , RMSE, and MAE, as well as formal predictor-importance rankings, are not reported. These statistics were therefore not used to claim predictive superiority of the model or to infer that NDVI, NDBI, or NDWI independently controls future LST. No independently observed 2045 thermal surface is available against which future predictive accuracy can be tested. This limitation is particularly relevant because only three temporal Landsat reference years (2005, 2015, and 2025) were available for the historical thermal modelling. Although the model fitting incorporates spatially distributed observations within these years, the temporal coverage remains limited and may constrain generalisation to predictor and thermal conditions outside the historical range. Overfitting, reduced extrapolation performance, and uncertainty in the upper tail of the projected LST distribution therefore cannot be excluded.

The 2045 Random Forest output is consequently interpreted as a conditional scenario estimate rather than a quantitatively validated future LST forecast. The results indicate the thermal response

generated by applying the learned historical relationships to the predictor surfaces associated with the CA-ANN 2045 land-use scenario. The absence of independent validation and predictor-importance diagnostics limits the extent to which the magnitude of the projected LST response or the contribution of individual predictors can be quantitatively established. Future studies using longer thermal time series, independent hold-out observations, explicit cross-validation, additional meteorological and urban-morphological predictors, and formal predictor-importance analysis would provide a stronger basis for evaluating model generalisation and predictive uncertainty.

2.10 VIIRS-Based Continuous Thermal Assessment (2014-2025)

We conducted continuous temporal analysis using annual VIIRS nighttime radiance alongside seasonal Landsat-derived LST and UTFVI metrics for 2014-2025. VIIRS nighttime radiance was used as an indirect indicator of nighttime illumination and urban activity, while Landsat-derived LST and UTFVI were used to characterize surface thermal conditions and spatial thermal variability, respectively. Annual mean VIIRS radiance values were extracted for the study area using Google Earth Engine. We generated seasonal Landsat datasets separately for summer (April-June) and winter (November-December) to match the seasonal thermal analysis. Mean seasonal LST was calculated for each year and season. We calculated UTFVI from the corresponding spatial LST surface using the formulation described in Section 2.8, with LST expressed in Kelvin before normalization. Because UTFVI is normalized relative to the corresponding study-area mean LST, the arithmetic spatial mean of the pixel-level UTFVI surface is expected to be approximately zero. Accordingly, the spatial mean UTFVI was retained as a diagnostic measure of the mathematical centering of the normalized index rather than as a measure of thermal-stress magnitude. To quantify the magnitude of spatial thermal variability in the continuous series, MAUTFVI was calculated for each year and season as the mean absolute value of the valid pixel-level UTFVI observations. Annual MAUTFVI was therefore used as the principal continuous measure of UTFVI magnitude. At the same time, the pixel-level UTFVI surfaces and classified UTFVI categories remained the basis for spatial thermal-stress interpretation.

2.10.1 Descriptive Statistical Analysis

We calculated basic statistical measures to summarize temporal variation in the thermal and nighttime-radiance indicators. These measures included the mean and standard deviation of LST and the mean, standard deviation, minimum, maximum, and 95th percentile of pixel-level UTFVI. Because the arithmetic spatial mean of UTFVI is mathematically centred close to zero when the index is normalized relative to the corresponding study-area mean LST, this mean was retained as a diagnostic statistic rather than interpreted as a measure of ecological thermal-stress magnitude.

To characterize the magnitude of spatial UTFVI variability in the continuous 2014-2025 series, mean absolute UTFVI (MAUTFVI) was calculated as:

$$MAUTFVI_t = \frac{1}{N_t} \sum_{i=1}^{N_t} |UTFVI_{i,t}|$$

where: $MAUTFVI_t$ is the mean absolute UTFVI for year and season t , $UTFVI_{i,t}$ is the pixel-level UTFVI value for valid pixel i , and N_t is the number of valid pixels for that year-season observation. MAUTFVI

retains the magnitude of both positive and negative thermal deviations and therefore provides a more informative temporal measure of spatial thermal variability than the arithmetic mean UTFVI.

Percentage-change verification: For all LULC, LST, and UTFVI area-change tables, percentage change was independently recalculated from the reported area values using $\% \Delta A = [(A_2 - A_1)/A_1] \times 100$, where A_1 is the initial area, and A_2 is the comparison-year area. Negative values indicate a reduction and positive values indicate an increase. Percentage values were calculated from the underlying unrounded area measurements and rounded to two decimal places for presentation. We checked each reported percentage against the corresponding area difference before tabulation.

2.10.2 Trend Analysis

We used linear regression models to analyze temporal trends in LST, annual VIIRS nighttime radiance, and MAUTFVI. The spatial mean UTFVI was not treated as the principal magnitude variable in temporal trend analysis because its near-zero value is a mathematical consequence of normalization around the study-area mean LST. Instead, MAUTFVI was used to describe temporal changes in the magnitude of the pixel-level normalized thermal deviation. Trend analysis was conducted separately for summer and winter, while the VIIRS radiance series was analyzed annually for 2014-2025.

The regression model is expressed as:

$$Y_t = \beta_0 + \beta_1 t + \epsilon_t$$

where Y_t represents the temporal variable of interest (LST, MAUTFVI, or VIIRS radiance), β_0 is the intercept, β_1 is the temporal slope, t is the year, and ϵ_t is the residual error.

The coefficient of determination (R^2) was used to evaluate the strength of the trend:

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$$

Higher R^2 values indicate stronger explanatory power.

2.10.3 Correlation Analysis

The temporal relationship between annual VIIRS nighttime radiance and the seasonal thermal indicators was examined using Pearson's correlation coefficient. The analysis was designed to assess the direction and strength of the temporal association between nighttime radiance and surface thermal conditions rather than to establish causality.

Pearson's correlation coefficient was calculated as:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \cdot \sum(Y - \bar{Y})^2}}$$

where:

X_i = annual VIIRS nighttime radiance

Y_i = corresponding seasonal thermal indicator

r = Pearson's correlation coefficient

The coefficient ranges from -1 to +1, indicating the direction and strength of the linear association. Positive values indicate that both variables tend to increase together, whereas negative values indicate an inverse temporal association. Pearson's correlation has been widely used to examine relationships between nighttime lights and urban thermal patterns [64-68]. Four temporal relationships were evaluated separately: VIIRS-summer LST, VIIRS-winter LST, VIIRS-summer MAUTFVI, and VIIRS-winter MAUTFVI. MAUTFVI (mean absolute UTFVI) was used for the inferential UTFVI analysis because the arithmetic spatial mean of UTFVI is mathematically centred close to zero when UTFVI is calculated relative to the study-area mean LST. MAUTFVI instead represents the mean magnitude of the absolute pixel-level UTFVI deviations and therefore provides a more informative measure of the temporal variation in spatial thermal-stress magnitude. The summer relationships were based on 12 annual observations covering 2014-2025. The winter relationships were based on 12 annual observations [69-72].

The statistical significance of each correlation coefficient was assessed using a two-tailed t-test:

$$t = r \sqrt{\frac{n - 2}{1 - r^2}}$$

where t is the test statistic, r is the Pearson correlation coefficient, and n is the number of paired observations. Thus, the degrees of freedom were 10 for both the summer and winter relationships ($n = 12$). A significance level of $p < 0.05$ was adopted.

The correlation results were interpreted as temporal bivariate statistical associations rather than evidence of a direct causal effect of nighttime radiance on land surface temperature or ecological thermal stress. In particular, VIIRS nighttime radiance represents an indirect indicator of nighttime illumination and aspects of urban activity, whereas LST and MAUTFVI represent different thermal characteristics influenced by land-cover composition, vegetation, moisture conditions, surface properties, atmospheric variability, and coastal processes.

2.10.4 Regression Analysis Between VIIRS and Thermal Indicators

Simple linear regression models were used to quantify the temporal association between annual VIIRS nighttime radiance and the selected seasonal thermal indicators. Four models were fitted separately:

- VIIRS vs Summer LST
- VIIRS vs Winter LST
- VIIRS vs Summer MAUTFVI
- VIIRS vs Winter MAUTFVI

Annual VIIRS radiance was treated as the explanatory variable (X), whereas the corresponding seasonal LST or MAUTFVI was treated as the dependent variable (Y). Summer models contained 12 annual observations, whereas winter models contained 12. For each model, the regression coefficient (β), standard error, t-statistic, coefficient of determination (R^2), p-value, and 95% confidence interval for the VIIRS coefficient were calculated. The slope represents the expected change in the dependent thermal indicator associated with a one-unit increase in annual VIIRS nighttime radiance. The regression models were interpreted as bivariate temporal associations and not as estimates of the independent or causal contribution of nighttime human activity to thermal

conditions. Because the annual spatial mean UTFVI is centred close to zero by mathematical construction, MAUTFVI was used instead of the spatial mean UTFVI in the inferential regression models involving ecological thermal stress. We retained the spatial mean UTFVI for diagnostic interpretation and to demonstrate the index's normalization property.

The regression analysis was intentionally specified as a bivariate temporal assessment. It was designed to determine whether annual changes in nighttime radiance were linearly associated with corresponding annual seasonal LST and MAUTFVI values, rather than to estimate the independent effect of nighttime illumination after controlling for other environmental or urban variables. Accordingly, the regression coefficients and R^2 values should be interpreted as measures of bivariate temporal association. They cannot be used to identify a dominant thermal control or to establish that changes in nighttime radiance cause changes in LST or thermal-stress magnitude. Potential influences not represented by the bivariate models include land-surface composition, vegetation and moisture conditions, surface materials, urban morphology, atmospheric variability, anthropogenic heat timing, and coastal processes. A multivariate framework incorporating these additional predictors would be required to estimate their independent or relative contributions, which is beyond the present study's analytical scope.

2.10.5 Statistical Interpretation

The statistical analyses were interpreted jointly rather than based on a single coefficient. Pearson's r was used to describe the direction and strength of association, while the regression coefficient and R^2 were used to assess the direction and explanatory strength of the fitted relationship. The p -value was used to evaluate whether the observed association differed statistically from zero at the 5% significance level. Given the relatively small annual sample and the use of a single explanatory variable, both significant and non-significant relationships were interpreted cautiously. A statistically significant relationship was considered evidence of temporal association within the observed series, but not evidence of causality. Conversely, a non-significant relationship was interpreted as indicating that the observed temporal association could not be distinguished statistically from random variation at the selected significance level. The results were interpreted alongside the spatial LULC, LST, and UTFVI analyses and the physical distinctions among nighttime radiance, surface temperature, and normalized thermal stress.

2.10.6 Seasonal Comparison

Seasonal variation in thermal behavior was assessed by comparing summer and winter LST and MAUTFVI values, together with the corresponding temporal trends and VIIRS associations.

2.10.7 Spatial Cross-Analysis of LULC and LST Transitions

To test whether the observed redistribution of thermal conditions was spatially associated with land-use transformation, the 2005 and 2025 LULC maps were cross-referenced with the corresponding summer and winter LST-class maps. The categorical rasters were spatially aligned to a common 30 m grid using nearest-neighbour resampling to preserve class identities, and only pixels with valid observations in all required layers were retained. The common valid analysis area comprised 485,706 pixels, corresponding to approximately 437.14 km². The five LULC classes were

retained according to the classification scheme described in Table 3, while the LST classes were retained according to the fixed intervals described in Table 4. We represented LULC transitions as 2005 class → 2025 class. To specifically identify movement toward the thermal range highlighted in the results, two thermal-transition indicators were calculated. A pixel was classified as having transitioned into the 35-40°C class when its 2005 LST class was below 35°C and its 2025 LST class was 35-40°C. A pixel was classified as having transitioned into the ≥40°C range when its 2005 LST class was below 40°C and its 2025 LST class was either 40-45°C or >45°C.

We cross-tabulated these thermal-transition indicators with LULC transitions to quantify the area and proportion of each land-use transition associated with movement toward warmer thermal classes. We conducted the analysis separately for summer and winter. The resulting cross-tabulation was used to distinguish areas undergoing land transformation from areas that retained their original land-cover class and to determine whether urbanizing transitions were disproportionately associated with movement toward the 35-40°C and ≥40°C thermal ranges. The analysis was interpreted as spatial correspondence rather than direct causation.

2.11 Ethical Statement

This study used only publicly available satellite and geospatial data and involved no human participants or personal information. Ethical approval was not required because all the data used in this study were openly available. The datasets were used according to the guidelines provided by the respective data sources and followed standard research ethics.

3. Results

3.1 Changes in Land Use and Land Cover in Chennai from 2005 To 2025

Land-use land-cover analysis shows substantial restructuring in Chennai between 2005 and 2025. During this period, Built-up land expanded consistently. The built-up area covered 258.83 km², accounting for 59.15% of the total area in 2005. By 2025, built-up area increased to 305.69 km², representing 69.86 percent, an absolute growth of 46.86 km² and a relative increase of 18.1 percent (Table 6; Figure 2 and Figure 3). In the same period, water bodies recorded a moderate overall increase. Surface water extent expanded from 6.82 km² in 2005 to 12.37 km² in 2025, reflecting an increase of 5.55 km². The percentage share rose from 1.56% to 2.83%. During the study period, vegetation increased. Vegetated area increased from 61.18 km² in 2005 to 86.81 km² in 2025. This corresponds to a gain of 25.63 km², or 41.88 percent. Its share increased from 13.98 percent to 19.84 percent of the total area.

Table 6 Total area and percentage share of each LULC class in Chennai for 2005 and 2025.

Class	2005 (km ²)	2005 (%)	2025 (km ²)	2025 (%)
Built-up land	258.83	59.15	305.69	69.86
Waterbody	6.82	1.56	12.37	2.83
Vegetation	61.18	13.98	86.81	19.84
Crop land	43.50	9.94	17.60	4.02
Barren land	67.25	15.37	15.11	3.45

Note: The percentage share was independently checked against the corresponding total area and rounded to two decimal places.

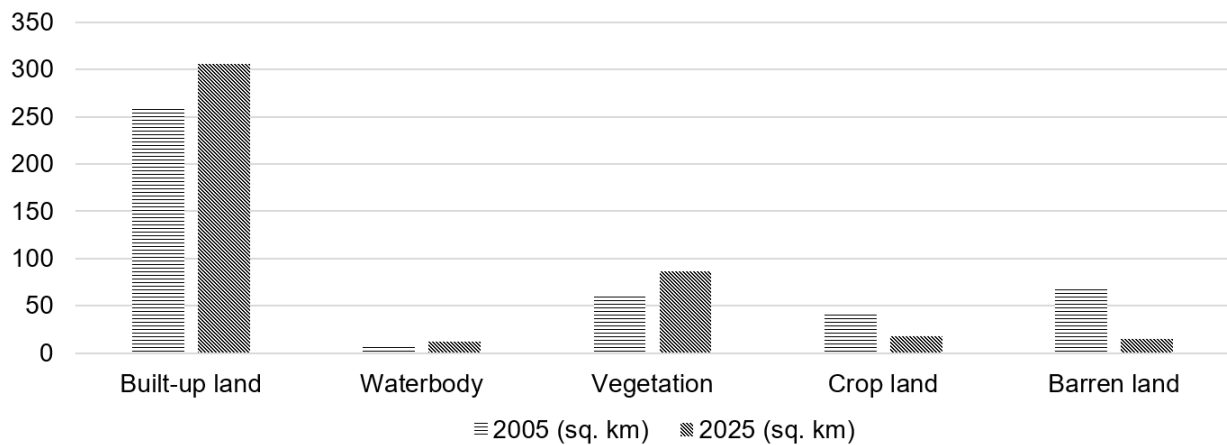


Figure 2 Land-use land-cover classes from 2005 to 2025 in Chennai.

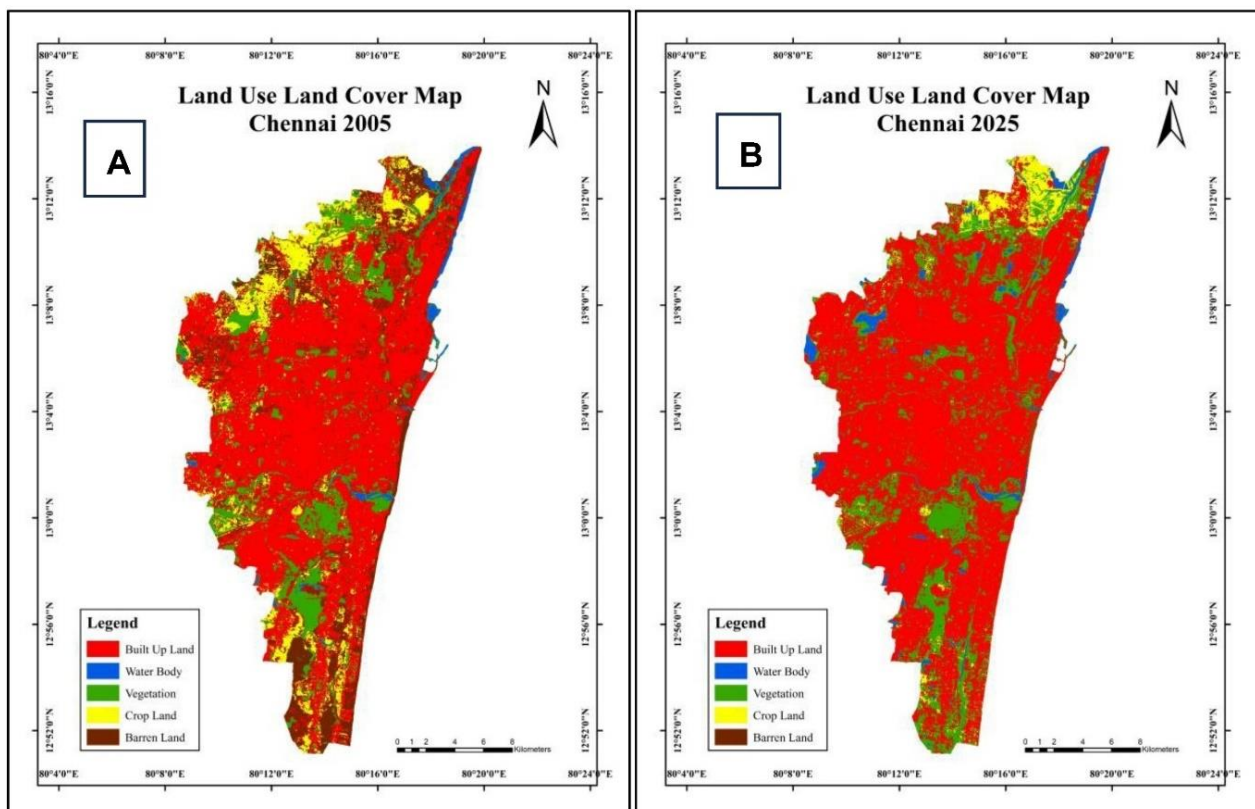


Figure 3 Land-use Land-cover Map of Chennai (A) 2005, (B) 2025.

In contrast, cropland has declined sharply during the study. Agricultural land reduced from 43.50 km² in 2005 to 17.60 km² in 2025. This shows a decline of 25.90 km² or 59.54 percent. The percentage share fell from 9.94% to 4.02%. Barren land also declined significantly. The area covered by barren land decreased from 67.25 km² in 2005 to 15.11 km² in 2025. Overall, barren land decreased by 52.14 km² (77.5%), while its percentage share fell from 15.37% to 3.45%. Comparison of the 2005 and 2025 spatial distribution maps indicates the expansion of urban built-up areas and the reduction of cropland and barren land. Overall, the results indicate that built-up land is increasing, there is a moderate increase in vegetation and water bodies, and agricultural and barren land decreased between 2005 and 2025.

3.1.1 Accuracy Assessment of LULC Maps

The classification results for both 2005 and 2025 show high accuracy. The overall accuracy was 89.6% in 2005, with a Kappa coefficient of 0.824, and increased to 95.1% in 2025, with a Kappa coefficient of 0.887 (Table 7). These values indicate strong agreement between the classified maps and the reference data. The built-up class in 2005 showed a user's accuracy of 92.8% and producer's accuracy of 88.6%. Water bodies recorded an accuracy of 96.2 percent and 94.1 percent producer accuracy. Vegetation had lower classification accuracy, with 70.4% user accuracy and 77.9% producer accuracy. Cropland showed 79.5 percent user accuracy and 82.3 percent producer accuracy. Among all classes, barren land recorded the lowest accuracy, with user's accuracy of 61.7% and a producer accuracy of 67.5%.

Table 7 Accuracy assessment of LULC maps for 2005 and 2025.

LULC Classes	User Accuracy (%) 2005	Producer Accuracy (%) 2005	User Accuracy (%) 2025	Producer Accuracy (%) 2025
Built-Up Land	92.8	88.6	99.5	94.3
Water Body	96.2	94.1	98.9	97.8
Vegetation	70.4	77.9	76.8	85.4
Crop Land	79.5	82.3	84.2	89.1
Barren Land	61.7	67.5	68.5	74.8
Overall Accuracy (%)	89.6		95.1	
Kappa Coefficient	0.824		0.887	

Most categories' classification performance improved in 2025. Built-up land reached 99.5 percent user accuracy and 94.3 percent producer accuracy. Water bodies recorded 98.9% and 97.8%, respectively. Vegetation recorded a user's accuracy of 76.8 percent and a producer accuracy of 85.4 percent. The cropland class achieved a user's accuracy of 84.2 percent and 89.1 percent producer's accuracy. The barren land class remained at the lowest, with 68.5 percent user accuracy and 74.8 percent producer accuracy. The classification results for both years were verified using high-resolution Google Earth imagery. A visual comparison confirmed strong correspondence between the built-up and water categories. Overall, the results confirm that the LULC maps for 2005 and 2025 provide a reliable basis for change analysis and simulation. These accuracy statistics evaluate the quality of the classified LULC products and should be distinguished from CA-ANN simulation accuracy. In particular, the 2025 Overall Accuracy of 95.1% and Kappa coefficient of 0.887 indicate

strong agreement between the classified LULC map and the reference data, but they do not measure the ability of the CA-ANN model to reproduce a subsequent observed LULC configuration.

3.1.2 Transition Dynamics in ANN Modelling

The CA-ANN model was used to simulate LULC conditions for 2045. The Artificial Neural Network was trained using 1000 iterations with a 1×1 pixel neighbourhood configuration. The learning rate was set to 0.100, the number of hidden layers to 10, and the momentum to 0.050 (Table 8). These parameters were used to estimate transition potential and spatially allocate future land-use changes. The ANN transition-potential estimation incorporated eight spatial driving variables: DEM/elevation, aspect, slope, hill shade, contour, curvature, distance to stream, and distance to railway. The first six variables represent terrain configuration, while distance to stream and distance to railway represent hydrological and transportation-accessibility conditions, respectively. The 2005 and 2025 LULC maps provided the historical land-change information used to establish the transition structure for the simulation.

Table 8 The ANN parameter settings used for LULC simulation.

Parameter	Value
Neighbourhood	1×1 pixel
Learning Rate	0.100
Maximum Iterations	1000
Hidden Layers	10
Momentum	0.050

The predictor variables were supplied jointly to the ANN rather than being interpreted as independent causal variables. In particular, the terrain predictors are derived from a common DEM and may therefore contain related spatial information. The model was consequently interpreted as estimating spatial transition suitability from the combined predictor set. The classification accuracy of the 2025 LULC map was high, with an Overall Accuracy of 95.1% and a Kappa coefficient of 0.887; however, these statistics assess the Random Forest classification and do not represent independent CA-ANN simulation accuracy. Because an independently simulated historical validation map was not generated, the present study does not report simulation-specific Overall Accuracy, Kappa, confusion matrix, or Figure of Merit. We therefore interpret the 2045 output as a scenario-based spatial projection conditioned on the observed historical transition structure and the selected spatial driving variables.

The eight predictor variables were incorporated jointly into the ANN transition-potential estimation to represent complementary spatial characteristics of land transformation. DEM/elevation, aspect, slope, hill shade, contour, and curvature describe different aspects of terrain configuration, while distance to stream represents hydrological proximity and distance to railway represents transportation accessibility. We did not interpret the predictors as independent causal determinants of land-use change. Instead, their combined spatial information was used to estimate transition suitability within the CA-ANN framework. The six terrain-derived predictors were retained because they represent different characteristics of the same physical landscape, although some degree of spatial redundancy is possible because they originate from a common

DEM. Distance to stream and distance to railway were retained to represent hydrological proximity and transportation accessibility, respectively. Consequently, the model results are interpreted in terms of combined spatial transition suitability rather than independent variable effects. The absence of formal VIF or correlation-based exclusion of predictors is acknowledged as a limitation and may introduce redundancy into the ANN input space.

3.2 Seasonal Changes in Land Surface Temperature in Chennai from 2005 to 2025

The seasonal analysis of land surface temperature in Chennai shows a clear increase in surface temperature between 2005 and 2025. The results show that both summer and winter shifted from lower to higher temperature classes (Table 9; Figure 4 and Figure 5). In summer 2005, most of Chennai was distributed across the lower and moderate temperature classes. Areas below 30°C covered 44.07 km². The 30-35°C class dominated the landscape with 243.95 km². Moderately high temperatures between 35-40°C extended across 137.66 km². High temperature zones between 40-45°C were limited to 12.07 km², and areas above 45°C were negligible at 0.11 km². By summer 2015, a major thermal shift was identified. The area under the <30°C class reduced sharply to 4.60 km², a decline of 39.47 km², or 89.56 percent. The 30-35°C class also declined to 60.06 km². Compared with 2005, the 35-40°C class grew by 183.69 km² (133.44%), reaching a total area of 321.35 km². The 40-45°C class increased to 51.07 km², while the area above 45°C increased to 0.78 km². Because the historical thermal series combines sensor-specific Landsat surface-temperature products, the observed LST differences are interpreted with the residual possibility of cross-sensor systematic variation in mind; the principal emphasis is therefore placed on broad seasonal and categorical patterns rather than on attributing small absolute temperature differences exclusively to temporal physical change.

Table 9 Summary of summer and winter LST in Chennai for 2005, 2015, and 2025.

LST (°C)	Area (km ²)			Net Change (km ²)			Change (Percentage)		
	2005	2015	2025	2005-15	2015-25	2005-25	2005-15	2015-25	2005-25
Summer Season									
Less than 30	44.07	4.6	1.86	-39.47	-2.74	-42.21	-89.56	-59.57	-95.78
30-35	243.95	60.06	52.77	-183.89	-7.29	-191.18	-75.38	-12.14	-78.37
35-40	137.66	321.35	308.42	183.69	-12.93	170.76	133.44	-4.02	124.08
40-45	12.07	51.07	73.18	39	22.11	61.11	323.03	43.3	506.3
Above 45	0.11	0.78	1.63	0.67	0.85	1.52	609.09	108.97	1381.82
Winter Season									
Less than 30	46.8	5.69	4.95	-41.11	-0.74	-41.85	-87.84	-13.00	-89.42
30-35	274.31	122.89	95.51	-151.42	-27.38	-178.80	-55.20	-22.28	-65.18
35-40	107.52	294.63	316.96	187.11	22.33	209.44	173.99	7.58	194.77
40-45	9.19	14.34	19.5	5.15	5.16	10.31	56.04	35.98	112.21
Above 45	0.05	0.31	0.94	0.26	0.63	0.89	520	203.23	1780

Note: Percentage changes were independently recalculated from the corresponding area values using $\% \Delta A = [(A_2 - A_1)/A_1] \times 100$.

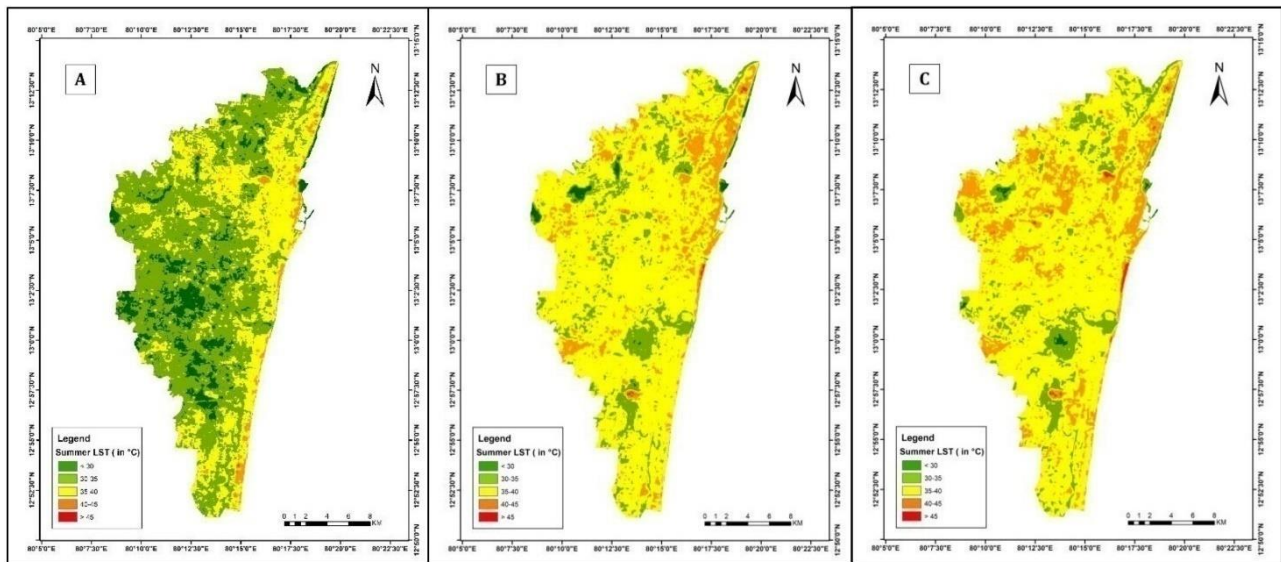


Figure 4 Summer season LST distribution in Chennai (A) 2005, (B) 2015, (C) 2025.

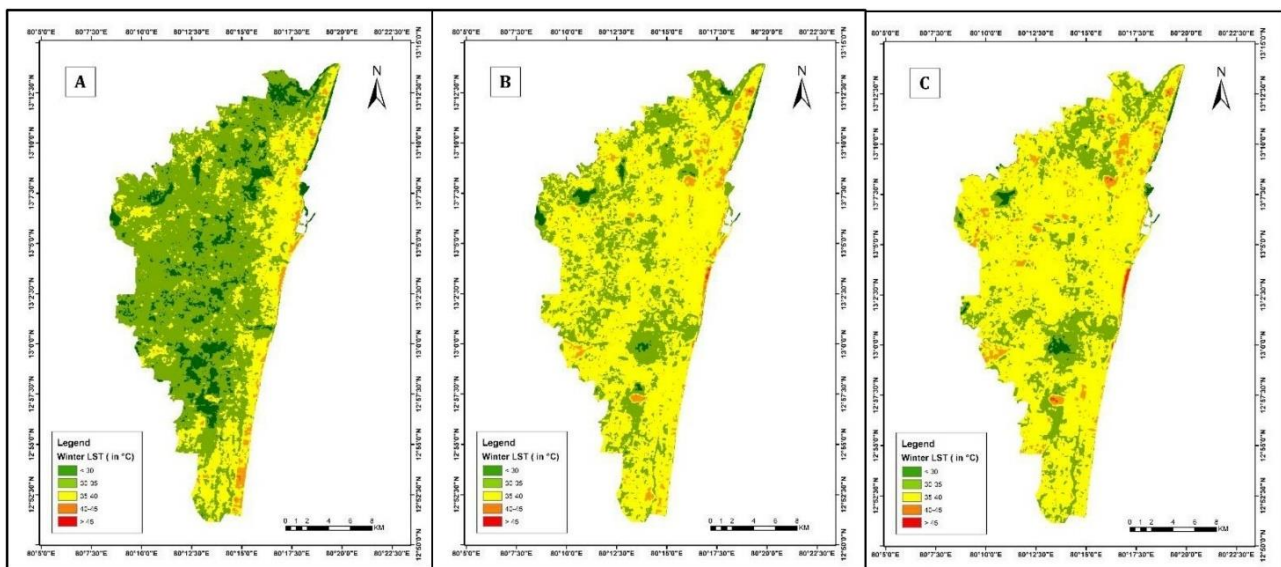


Figure 5 Winter season LST distribution in Chennai (A) 2005, (B) 2015, (C) 2025.

In summer 2025, high-temperature classes became more dominant. The class $<30^{\circ}\text{C}$ further declined to 1.86 km^2 . The $30\text{--}35^{\circ}\text{C}$ class declined to 52.77 km^2 . The $35\text{--}40^{\circ}\text{C}$ class covered a large area of 308.42 km^2 . The $40\text{--}45^{\circ}\text{C}$ class increased further to 73.18 km^2 . Areas above 45°C increased to 1.63 km^2 . Between 2005 and 2025, the $40\text{--}45^{\circ}\text{C}$ class increased by 61.11 km^2 , while the $>45^{\circ}\text{C}$ class increased by 1.52 km^2 , indicating a substantial expansion of the upper-temperature tail but a much smaller spatial increase in the extreme-temperature category. Areas below 30°C covered 46.80 km^2 in winter 2005, whereas the $30\text{--}35^{\circ}\text{C}$ class dominated with 274.31 km^2 . The $35\text{--}40^{\circ}\text{C}$ class covered an area of 107.52 km^2 . High-temperature classes above 40°C were rare.

By 2015, the winter LST pattern changed noticeably as the area below 30°C decreased sharply to 5.69 km^2 and the $30\text{--}35^{\circ}\text{C}$ class also declined to 122.89 km^2 . At the same time, the $35\text{--}40^{\circ}\text{C}$ class increased to 294.63 km^2 , with a gain of 187.11 km^2 or 173.99 percent, while the $40\text{--}45^{\circ}\text{C}$ class increased to 14.34 km^2 and the area above 45°C reached 0.31 km^2 . In winter 2025, the $35\text{--}40^{\circ}\text{C}$ class

became more dominated, covering 316.96 km². The 30-35°C class was further reduced to 95.51 km². The 40-45°C category expanded to 19.50 km², and areas above 45°C increased to 0.94 km². From 2005 to 2025, the 35-40°C class increased by 209.44 km², while the 40-45°C class grew by 10.31 km². Overall, both seasons show a clear contraction of lower-temperature classes and an expansion of higher-temperature categories.

A quantitative comparison of the annual 2014-2025 seasonal series further highlights the persistent thermal contrast between summer and winter. Across the 12 annual observations, the mean summer LST was 42.55°C, compared with 33.57°C in winter, giving an average summer-winter difference of 8.98°C. The annual seasonal difference varied from 4.50°C in 2017 to 12.89°C in 2022, showing that seasonal separation varied by year. Summer mean LST also showed substantial interannual variability, ranging from 39.47°C in 2024 to 46.42°C in 2022, while winter mean LST ranged from 30.16°C in 2018 to 36.73°C in 2017. The persistent positive summer-winter difference, together with year-to-year variation in its magnitude, indicates that seasonal thermal conditions in Chennai are governed by the combined effects of solar forcing, atmospheric moisture, vegetation and surface-water availability, urban surface properties, and coastal atmospheric processes rather than by a single directional effect of urban expansion.

3.2.1 Spatial Correspondence between LULC Transition and LST Change

The spatial cross-analysis demonstrates that the redistribution of thermal conditions was associated with specific land-use transitions rather than occurring uniformly across the study area (Table 10). Between 2005 and 2025, 80.09 km² of the common analysis area underwent conversion from non-built-up classes to built-up land. Of this urbanizing area, 37.51 km² (46.83%) in summer transitioned from LST classes below 35°C into the 35-40°C range, while 16.48 km² (20.57%) moved from below 40°C into the ≥40°C range. The corresponding winter values were 41.46 km² (51.77%) entering the 35-40°C range and 6.18 km² (7.71%) entering the ≥40°C range. The source of the urbanizing transition also influenced the magnitude of the thermal correspondence. Vegetation → built-up conversion showed the highest proportion of within-transition movement into the 35-40°C class in summer, with 69.96% of the transition area entering this temperature range, followed by cropland → built-up (51.55%) and barren land → built-up (33.39%). In winter, the corresponding proportions were 57.16%, 62.58%, and 43.43%, respectively. Although barren-land conversion showed a lower proportion entering the 35-40°C class than vegetation conversion, it represented the largest individual non-built-up source of built-up expansion at 38.87 km². It was also associated with the largest area entering the ≥40°C range among non-built-up-to-built-up transitions, particularly in summer (10.81 km²).

Table 10 Spatial correspondence between major LULC transitions and transitions into warmer LST classes in Chennai, 2005-2025.

LULC transition, 2005 → 2025	Transition Area (km ²)	Summer <35 → 35-40°C (km ²)	Summer within- transition (%)	Summer <40 → ≥40°C (km ²)	Winter <35 → 35-40°C (km ²)	Winter within- transition (%)	Winter <40 → ≥40°C (km ²)
Cropland → Built-up	22.19	11.44	51.55	3.52	13.89	62.58	0.73
Barren land → Built-up	38.87	12.98	33.39	10.81	16.88	43.43	4.38
Vegetation → Built-up	18.55	12.97	69.96	2.09	10.60	57.16	1.02
Waterbody → Built-up	0.48	0.11	23.78	0.05	0.09	19.48	0.05
All non-built-up → Built-up	80.09	37.51	46.83	16.48	41.46	51.77	6.18
Stable Built-up	225.42	122.15	54.19	40.87	140.10	62.15	6.77
Stable Vegetation	33.32	11.52	34.58	0.43	6.48	19.45	0.14
Other transitions	98.31	38.09	38.75	8.25	33.43	34.01	3.68

Note: The analysis was conducted on 485,706 common valid 30 m pixels (approximately 437.14 km²) after spatial alignment and masking of invalid observations. “<35 → 35-40°C” identifies pixels with an LST class below 35°C in 2005 and 35-40°C in 2025. “<40 → ≥40°C” identifies pixels with an LST class below 40°C in 2005 and ≥40°C in 2025. The percentage columns represent the proportion of the respective LULC-transition area that entered the indicated thermal range. “All non-built-up → Built-up” aggregates cropland, barren land, vegetation, and waterbody conversions to built-up land. The analysis demonstrates spatial correspondence and does not imply direct causation. Percentages were calculated from the underlying unrounded raster-derived transition areas; therefore, they may differ slightly from percentages recalculated using the rounded areas displayed in the table.

The analysis also indicates that thermal transition was not restricted to newly urbanized pixels. Stable built-up areas accounted for a large amount of movement into the 35-40°C range, reflecting the influence of temporal changes in surface thermal conditions even where the categorical LULC class remained unchanged. However, stable vegetation showed substantially smaller proportions of movement into the ≥40°C range, with only 1.30% in summer and 0.43% in winter of the stable-vegetation area entering the ≥40°C category. This contrast supports the interpretation that both land transformation and the persistence of non-built surfaces contribute to the spatial organization of thermal conditions. The spatial correspondence is particularly relevant to the expansion of the 35-40°C class identified in the preceding analysis. The cross-tabulation shows that a substantial portion of the land undergoing conversion to built-up surfaces also moved from lower thermal classes into the 35-40°C range. Thus, the large increase in the 35-40°C category between 2005 and 2025 is spatially consistent with the restructuring of the land-surface, especially through conversion of vegetation, cropland, and barren land to built-up areas. This result provides a spatial basis for interpreting thermal redistribution alongside LULC changes rather than treating the two patterns independently.

Spatially, the concentration of non-built-up to built-up transitions is most evident in the northern and central-western portions of the Chennai study area, with additional clusters in the southern urbanizing corridor. The associated thermal transitions toward 35-40°C occur within these same broad areas of land transformation, providing spatial correspondence between urban expansion and warming of previously lower-temperature surfaces. The pattern is therefore more consistent with concentrated land-surface restructuring than with a spatially uniform increase in temperature across the study area.

3.3 Seasonal Dynamics of UTFVI in Chennai (2005-2025)

The Urban Thermal Field Variance Index (UTFVI) was used to assess seasonal ecological thermal stress in Chennai for 2005, 2015, and 2025 (Table 11; Figure 6 and Figure 7). The results show a gradual shift in thermal stress from weaker to stronger categories in both summer and winter. In summer 2005, the Weak category covered 234.81 km² while the strongest class occupied 174.04 km². The intermediate stress categories covered comparatively smaller areas. By 2015, a clear shift had occurred. The weak category covered 226.71 km², reflecting a slight decline. The strongest category declined to 165.33 km², down 8.71 km². Meanwhile, the Middle, Strong, and Stronger categories expanded noticeably. The Middle class rose from 9.41 km² to 15.78 km² and the Strong class increased from 9.86 km² to 15.29 km². Summer stress patterns intensified in higher categories in 2025. The Strongest category increased to 178.05 km², surpassing its 2005 level by 4.01 km². The Stronger class increased to 15.28 km². Over the two decades, the Weak category declined by 19.67 km² to 215.14 km². The Middle and Strong categories increased substantially between 2005 and 2015 but declined slightly by 2025, whereas the Stronger category continued to increase. The Strongest category also fluctuated, declining in 2015 before reaching 178.05 km² in 2025. Overall, the summer results indicate a net decline in weak-stress area and a redistribution toward several higher-stress categories, but not a monotonic increase in every intermediate category at every observation year.

Table 11 Summer and winter UTFVI in Chennai for 2005, 2015, and 2025.

UTFVI	Area (km ²)			Net Change (km ²)			Change (Percentage)		
	2005	2015	2025	2005-15	2015-25	2005-25	2005-15	2015-25	2005-25
Summer Season									
Weak	234.81	226.71	215.14	-8.10	-11.57	-19.67	-3.45	-5.10	-8.38
Middle	9.41	15.78	14.55	6.37	-1.23	5.14	67.69	-7.80	54.62
Strong	9.86	15.29	14.83	5.43	-0.46	4.97	55.07	-3.01	50.41
Stronger	9.75	14.74	15.28	4.99	0.54	5.53	51.18	3.66	56.72
Strongest	174.04	165.33	178.05	-8.71	12.72	4.01	-5.00	7.69	2.3
Winter Season									
Weak	243.75	238.11	223.12	-5.64	-14.99	-20.63	-2.31	-6.30	-8.47
Middle	10.7	16.39	16.82	5.69	0.43	6.12	53.18	2.62	57.2
Strong	10.13	15.7	16.83	5.57	1.13	6.7	54.99	7.2	66.14
Stronger	9.99	15.03	16.54	5.04	1.51	6.55	50.45	10.05	65.57
Strongest	163.3	152.64	164.55	-10.66	11.91	1.25	-6.53	7.8	0.77

Note: Percentage changes were independently verified from the corresponding UTFVI area values using $\% \Delta A = [(A_2 - A_1)/A_1] \times 100$.

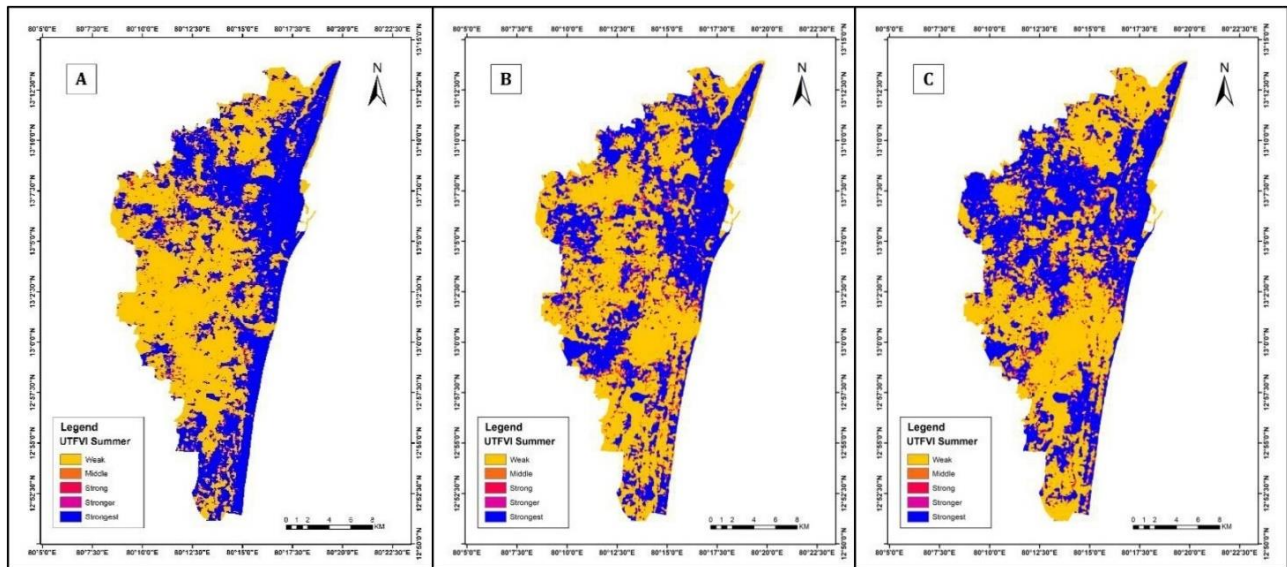


Figure 6 Summer season UTFVI distribution in Chennai (A) 2005, (B) 2015, (C) 2025.

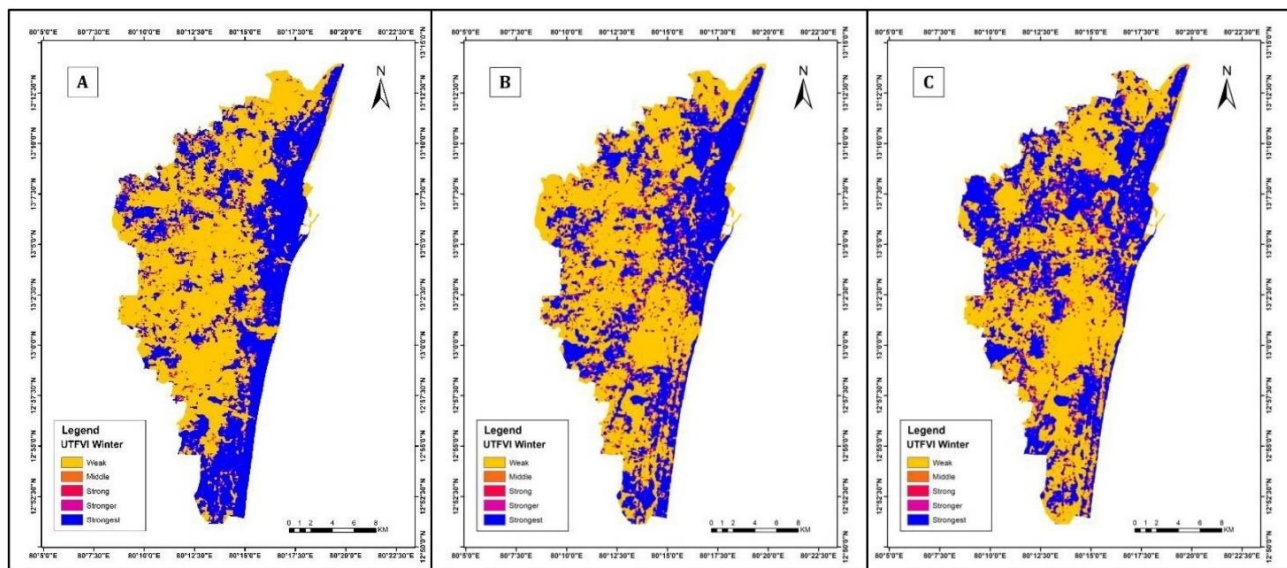


Figure 7 Winter season UTFVI distribution in Chennai (A) 2005, (B) 2015, (C) 2025.

A similar but more moderate trend was observed in the winter UTFVI patterns. The 2005 results show that the Weak category covered 243.75 km² whereas the Strongest category covered 163.30 km². By 2015, the Weak class declined to 238.11 km² the Strongest class reduced to 152.64 km². Middle categories expanded during this period. The Middle class increased from 10.70 km² to 16.39 km², and the Strong class rose from 10.13 km² to 15.70 km². Winter stress intensified again in higher categories during 2025. The Strongest category increased to 164.55 km², slightly higher than its 2005 level. The Stronger category increased to 16.54 km². The Weak class declined to 223.12 km², showing a total reduction of 20.63 km² between the year 2005 and 2025. In both seasons, the area under the Middle, Strong, and Stronger categories increased continuously. The Weak category showed a gradual decline, whereas the Strongest category fluctuated and remained high by 2025. The results show a gradual increase in ecological thermal stress between 2005 and 2025 as more areas moved into the higher stress categories across Chennai.

3.4 Simulation of the Year 2045

The CA-ANN model was applied to generate a potential LULC configuration for Chennai in 2045 based on the historical transition structure and the eight spatial driving variables comprising DEM/elevation, aspect, slope, hill shade, contour, curvature, distance to stream, and railway distance. These variables represent complementary terrain, hydrological, and transportation-accessibility characteristics within the study area. The resulting spatial pattern indicates continued expansion of built-up land and contraction of several non-urban classes. Because the model was not independently hindcast against an observed intermediate-year LULC map, the 2045 output is interpreted as a scenario-based spatial projection rather than a deterministic and independently validated prediction.

3.4.1 Projected Land Use and Land Cover for 2045

Under the CA-ANN 2045 scenario, built-up land becomes increasingly dominant, increasing from 305.69 km² in 2025 to 352.55 km² in the simulated 2045 configuration (Figure 8). This represents an increase of 46.86 km², with built-up land accounting for more than 80% of the study area. The projected pattern reflects the spatial outcome of the calibrated CA-ANN scenario and should therefore be interpreted as conditional on continuation of the historical land-transition relationships (Table 12).

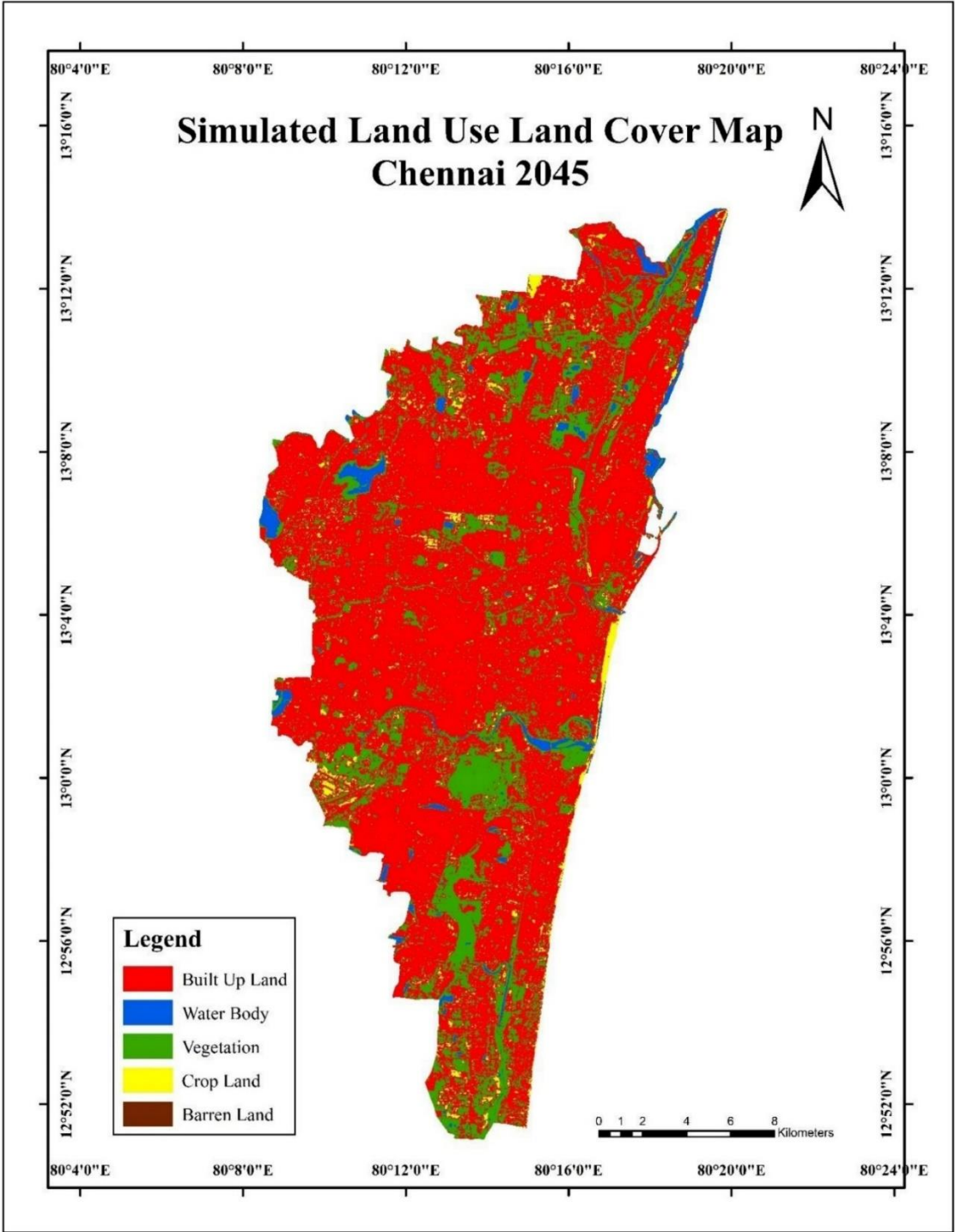


Figure 8 Simulated 2045 land-use and land-cover configuration of Chennai under the CA-ANN scenario.

Table 12 Area coverage of different LULC classes in Chennai under the observed 2005-2025 conditions and the simulated 2045 CA-ANN scenario.

Class	2005 (km ²)	2025 (km ²)	2045 (km ²)
Built-up land	258.83	305.69	352.55
Waterbody	6.82	12.37	14.92
Vegetation	61.18	86.81	56.45
Crop land	43.5	17.6	8.3
Barren land	67.25	15.11	5.36

Note: The 2045 values represent the spatial configuration generated by the CA-ANN scenario and are conditional on the observed 2005-2025 transition structure and selected spatial predictors. They should not be interpreted as independently validated deterministic forecasts of actual future land-cover extent.

Under the CA-ANN 2045 scenario, vegetation is projected to decline from 86.81 km² in 2025 to 56.45 km² in the simulated 2045 configuration, representing a reduction of 30.36 km² or 34.97%. This scenario outcome is consistent with the continuation of the land-transition relationships represented in the model and indicates potential pressure on green-space extent under the assumed development pathway. Cropland is projected to decline from 17.60 km² to 8.30 km², a reduction of 9.30 km² or 52.84%, while barren land is projected to decrease from 15.11 km² to 5.36 km², a reduction of 9.75 km² or 64.50%. Waterbody area is projected to increase from 12.37 km² to 14.92 km², a gain of 2.55 km² or 20.61%. These values describe the spatial configuration generated by the CA-ANN scenario and should not be interpreted as deterministic estimates of the actual future extent of individual land-cover classes. Overall, the simulated 2045 configuration represents a highly urbanized land-use scenario in which built-up surfaces become increasingly dominant while several non-urban categories contract under continuation of the historical transition structure.

3.4.2 Projected Land Surface Temperature for 2045

The machine learning-based projection indicates a substantial redistribution of Chennai's projected thermal environment by 2045 (Table 13; Figure 9A, 9B). The projected LST surface is conditioned on the CA-ANN-based 2045 land-use configuration and therefore represents a scenario-based thermal response rather than an independently observed future condition. The interpretation of the projected temperature distribution consequently focuses on the spatial redistribution among temperature classes rather than treating individual extreme-temperature classes as deterministic forecasts. Because the Random Forest component was not independently validated against a hold-out thermal dataset, the projected values are interpreted as conditional model estimates associated with the CA-ANN land-use scenario, and not as estimates with independently quantified predictive accuracy.

Table 13 Changes in seasonal LST from 2005 to 2045 in Chennai.

LST (°C)	Area (km ²)				Net Change (km ²)			Change (Percentage)		
	2005	2015	2025	2045	2005-45	2015-45	2025-45	2005-45	2015-45	2025-45
Summer Season										
Less than 30	44.07	4.6	1.86	0.29	-43.78	-4.31	-1.57	-99.34	-93.70	-84.41
30-35	243.95	60.06	52.77	59.29	-184.66	-0.77	6.52	-75.70	-1.28	12.36
35-40	137.66	321.35	308.42	375.49	237.83	54.14	67.07	172.76	16.85	21.75
40-45	12.07	51.07	73.18	2.72	-9.35	-48.35	-70.46	-77.47	-94.67	-96.28
Above 45	0.11	0.78	1.63	0.06	-0.05	-0.72	-1.57	-45.45	-92.31	-96.32
Winter Season										
Less than 30	46.8	5.69	4.95	0.3	-46.50	-5.39	-4.65	-99.36	-94.73	-93.94
30-35	274.31	122.89	95.51	56.5	-217.81	-66.39	-39.01	-79.41	-54.02	-40.84
35-40	107.52	294.63	316.96	377.52	270	82.89	60.56	251.16	28.13	19.11
40-45	9.19	14.34	19.5	3.48	-5.71	-10.86	-16.02	-62.13	-75.73	-82.15
Above 45	0.05	0.31	0.94	0.06	0.01	-0.25	-0.88	20	-80.65	-93.62

Note: LST classes were defined using fixed temperature thresholds (<30, 30-35, 35-40, 40-45, and >45°C) and were applied consistently across all historical and projected years. The 2045 values represent model-estimated thermal conditions associated with the CA-ANN land-use scenario and should not be interpreted as independently observed future temperatures. Percentage changes in Table 13 were independently recalculated from the corresponding area values using $\% \Delta A = [(A_2 - A_1)/A_1] \times 100$. The 2045 thermal values are conditional outputs of the Random Forest scenario-translation framework and are not accompanied by independently estimated future-prediction accuracy because no observed 2045 thermal reference surface is available.

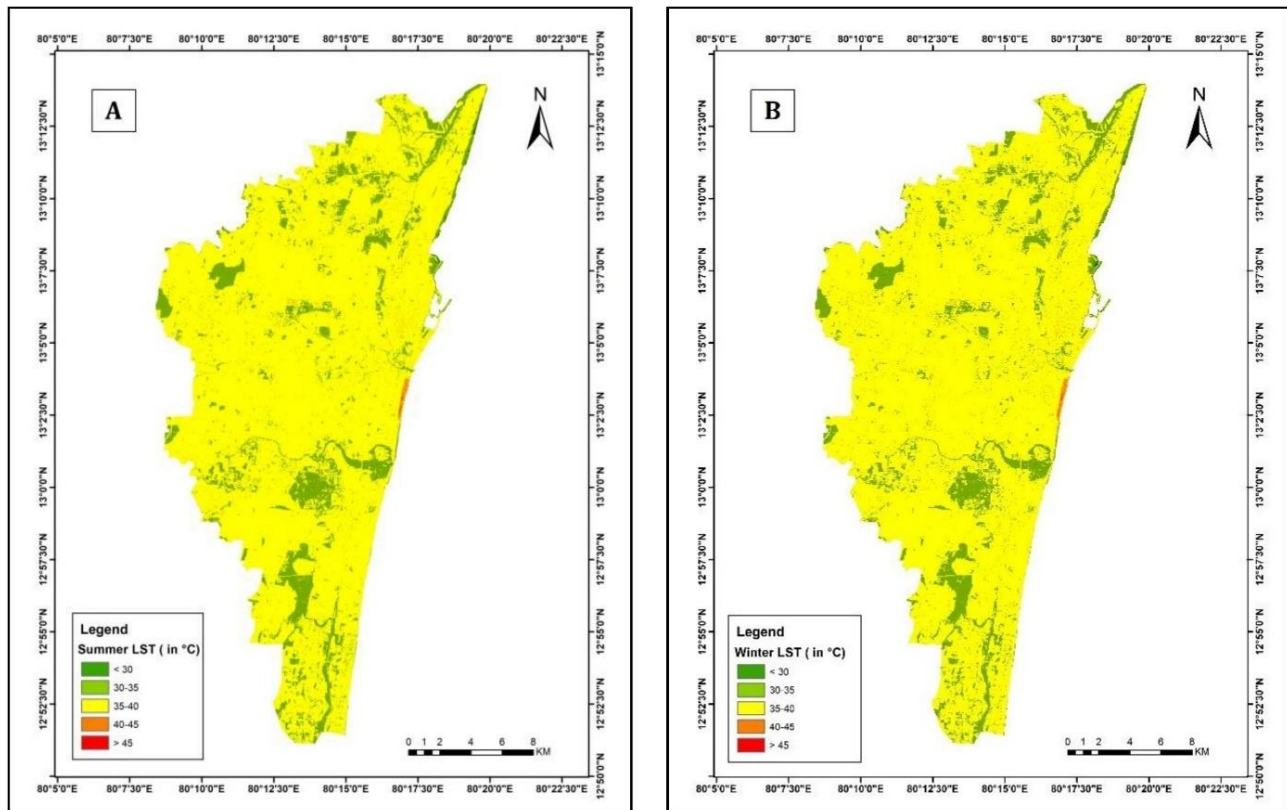


Figure 9 Scenario-based simulated LST maps for Chennai in 2045: (A) summer and (B) winter. Note: The maps represent model-estimated thermal conditions associated with the CA-ANN land-use scenario. They should be interpreted together with Table 13 as a redistribution of the projected temperature classes rather than as independently validated future observations.

The LST classes in Table 13 were defined using fixed temperature thresholds of <30, 30-35, 35-40, 40-45, and >45°C. These thresholds were applied identically to the historical and projected LST surfaces and were not changed or recalibrated for 2045. The reduction in the highest temperature classes is therefore not an artefact of using different classification criteria for the future scenario. The same thresholds allow the direction and magnitude of class redistribution to be compared consistently across 2005, 2015, 2025, and 2045.

In summer, the projected distribution shows a pronounced reduction in cooler classes together with a strong expansion of the 35-40°C category. The area below 30°C decreases from 44.07 km² in 2005 to 0.29 km² in 2045, representing a reduction of 43.78 km² or 99.34%. Relative to 2025, the same class declines from 1.86 km² to 0.29 km². The 30-35°C category decreases from 243.95 km² in 2005 to 59.29 km² in 2045, although it increases slightly by 6.52 km² relative to 2025. In contrast, the 35-40°C class expands from 137.66 km² in 2005 to 375.49 km² in 2045, representing a net increase of 237.83 km² or 172.76%. Relative to 2025, the class increases by 67.07 km² and becomes the dominant projected summer thermal category. Thus, the principal projected change is a redistribution of a large proportion of the study area toward the 35-40°C range rather than a uniform expansion of the >45°C category.

The upper-temperature classes show the opposite change. The 40-45°C class decreases from 73.18 km² in 2025 to 2.72 km² in 2045, while the >45°C class decreases from 1.63 km² to 0.06 km².

Importantly, these reductions occur alongside the near disappearance of the $<30^{\circ}\text{C}$ class and a strong expansion of the $35\text{--}40^{\circ}\text{C}$ category. The result therefore represents a redistribution and concentration of projected values within the moderate-to-high temperature range, rather than a transition from a warmer to a cooler thermal environment. A comparable pattern is projected for winter. The area below 30°C decreases from 46.80 km^2 in 2005 to 0.30 km^2 in 2045, representing a 99.36% reduction. The $30\text{--}35^{\circ}\text{C}$ category decreases from 274.31 km^2 to 56.50 km^2 . In contrast, the $35\text{--}40^{\circ}\text{C}$ class expands from 107.52 km^2 in 2005 to 377.52 km^2 in 2045, an increase of 270.00 km^2 or 251.16%. Relative to 2025, this category increases by 60.56 km^2 . At the same time, the $40\text{--}45^{\circ}\text{C}$ category decreases to 3.48 km^2 and the $>45^{\circ}\text{C}$ category decreases from 0.94 km^2 in 2025 to 0.06 km^2 in 2045. Thus, the winter scenario exhibits the same broad redistribution as summer: lower-temperature surfaces become increasingly limited, while the $35\text{--}40^{\circ}\text{C}$ range becomes spatially dominant. The apparent reduction in the $40\text{--}45^{\circ}\text{C}$ and $>45^{\circ}\text{C}$ classes requires careful interpretation. The LST classification used in Table 13 is based on fixed temperature thresholds of <30 , $30\text{--}35$, $35\text{--}40$, $40\text{--}45$, and $>45^{\circ}\text{C}$, which are applied consistently to all historical and projected surfaces. Consequently, the reduction in the highest temperature classes is not attributable to a change in the classification criteria. Rather, it reflects the redistribution of the model-estimated 2045 LST values across the same predefined temperature intervals. In summer, the $35\text{--}40^{\circ}\text{C}$ class expands from 308.42 km^2 in 2025 to 375.49 km^2 in 2045, while the $40\text{--}45^{\circ}\text{C}$ and $>45^{\circ}\text{C}$ classes contract from 73.18 km^2 and 1.63 km^2 to 2.72 km^2 and 0.06 km^2 , respectively. A similar pattern occurs in winter, where the $35\text{--}40^{\circ}\text{C}$ class increases from 316.96 km^2 to 377.52 km^2 , whereas the $40\text{--}45^{\circ}\text{C}$ and $>45^{\circ}\text{C}$ classes decrease from 19.50 km^2 and 0.94 km^2 to 3.48 km^2 and 0.06 km^2 , respectively.

This redistribution should not be interpreted as evidence of an overall cooling tendency. In both seasons, the decline in the highest temperature classes occurs together with a substantial reduction in cooler surfaces and a pronounced expansion of the $35\text{--}40^{\circ}\text{C}$ category. The dominant projected signal is therefore a concentration of the modelled thermal distribution within a widespread moderate-to-high temperature regime, rather than a uniform reduction in temperature across the study area. The apparent contradiction between the overall expansion of warmer conditions overall and the reduction of the $>45^{\circ}\text{C}$ class arises because the projected change concerns the distribution of temperature values among fixed classes rather than a uniform upward displacement of every pixel. A further consideration is the possibility of upper-tail attenuation associated with the Random Forest model. The 2045 LST surface was estimated from relationships between LST and NDVI, NDBI, and NDWI and applied to predictor surfaces derived from the simulated 2045 land-use configuration. Because the model is learned from the predictor and thermal ranges represented in the historical observations, it may reproduce the dominant range of the learned relationships more strongly than isolated extreme observations. The contraction of the $40\text{--}45^{\circ}\text{C}$ and $>45^{\circ}\text{C}$ classes is therefore considered compatible with some attenuation of the upper thermal tail in the model-estimated surface. However, this remains a methodological interpretation rather than a directly measured model error.

The magnitude of any such upper-tail attenuation cannot be independently verified because an observed 2045 LST surface does not exist for direct comparison. The present study therefore cannot determine whether the reduction in extreme-temperature area represents the actual future evolution of extreme surface temperatures, some degree of model-related compression, or a combination of both. Accordingly, the reduction in the $>45^{\circ}\text{C}$ and $40\text{--}45^{\circ}\text{C}$ classes is interpreted as a characteristic of the scenario-based modelled thermal distribution and not as evidence that future

extreme heat will disappear. The 2045 LST results should consequently be interpreted as conditional thermal responses to the simulated CA-ANN land-use pathway. They provide an internally consistent scenario for examining the potential thermal implications of future land transformation, but they should not be regarded as independently validated scenario projections of absolute future LST or extreme-heat occurrence. This uncertainty is particularly important for the tails of the temperature distribution, where model sensitivity and limited historical calibration may have a greater influence on the projected spatial extent of extreme classes.

3.4.3 Projected UTFVI for 2045

The 2045 UTFVI distribution is derived from the projected thermal environment associated with the CA-ANN land-use scenario. The resulting UTFVI classes should therefore be interpreted as potential future ecological thermal-stress conditions under the simulated land-transition pathway rather than as independently validated future observations. The 2045 projected UTFVI pattern shows increasing ecological thermal stress across Chennai (Table 14; Figure 10A, 10B). The results suggest a reduction of weak-stress zones, whereas intermediate-stress categories expand notably across both summer and winter. The Weak category declines continuously in summer from 234.81 km² in 2005 to 198.96 km² in 2045. Over the four-decade period, the area decreased by 35.85 km² or 15.27 percent. The area decreased by 16.18 km² compared to 2025. The Middle category shows strong growth. It increased from 9.41 km² in 2005 to 29.84 km² in 2045. The net increase from 2005 is 20.43 km², reflecting 217.11 percent growth. Similarly, the Strong class rose from 9.86 km² in 2005 to 29.32 km² in 2045, an increase of 19.46 km² or 197.40 percent. Over four decades, the Stronger category increased from 9.75 km² to 28.67 km², reflecting an overall increase of 194.05 percent.

Table 14 Seasonal UTFVI changes in Chennai during summer and winter from 2005 to 2045.

UTFVI	Area (km ²)				Net Change (km ²)			Change (Percentage)		
	2005	2015	2025	2045	2005-45	2015-45	2025-45	2005-45	2015-45	2025-45
Summer Season										
Weak	234.81	226.71	215.14	198.96	-35.85	-27.75	-16.18	-15.27	-12.24	-7.52
Middle	9.41	15.78	14.55	29.84	20.43	14.06	15.29	217.11	89.1	105.09
Strong	9.86	15.29	14.83	29.32	19.46	14.03	14.49	197.4	91.76	97.71
Stronger	9.75	14.74	15.28	28.67	18.92	13.93	13.39	194.05	94.5	87.64
Strongest	174.04	165.33	178.05	151.06	-22.98	-14.27	-26.99	-13.20	-8.63	-15.16
Winter Season										
Weak	243.75	238.11	223.12	195.96	-47.79	-42.15	-27.16	-19.60	-17.70	-12.17
Middle	10.7	16.39	16.82	27.41	16.71	11.02	10.59	156.17	67.23	62.96
Strong	10.13	15.7	16.83	28.43	18.3	12.73	11.6	180.65	81.08	68.93
Stronger	9.99	15.03	16.54	28.07	18.08	13.04	11.53	180.98	86.77	69.71
Strongest	163.3	152.64	164.55	157.99	-5.31	5.35	-6.56	-3.25	3.51	-3.99

Note: Percentage changes were independently recalculated from the corresponding UTFVI area values using $\% \Delta A = [(A_2 - A_1)/A_1] \times 100$.

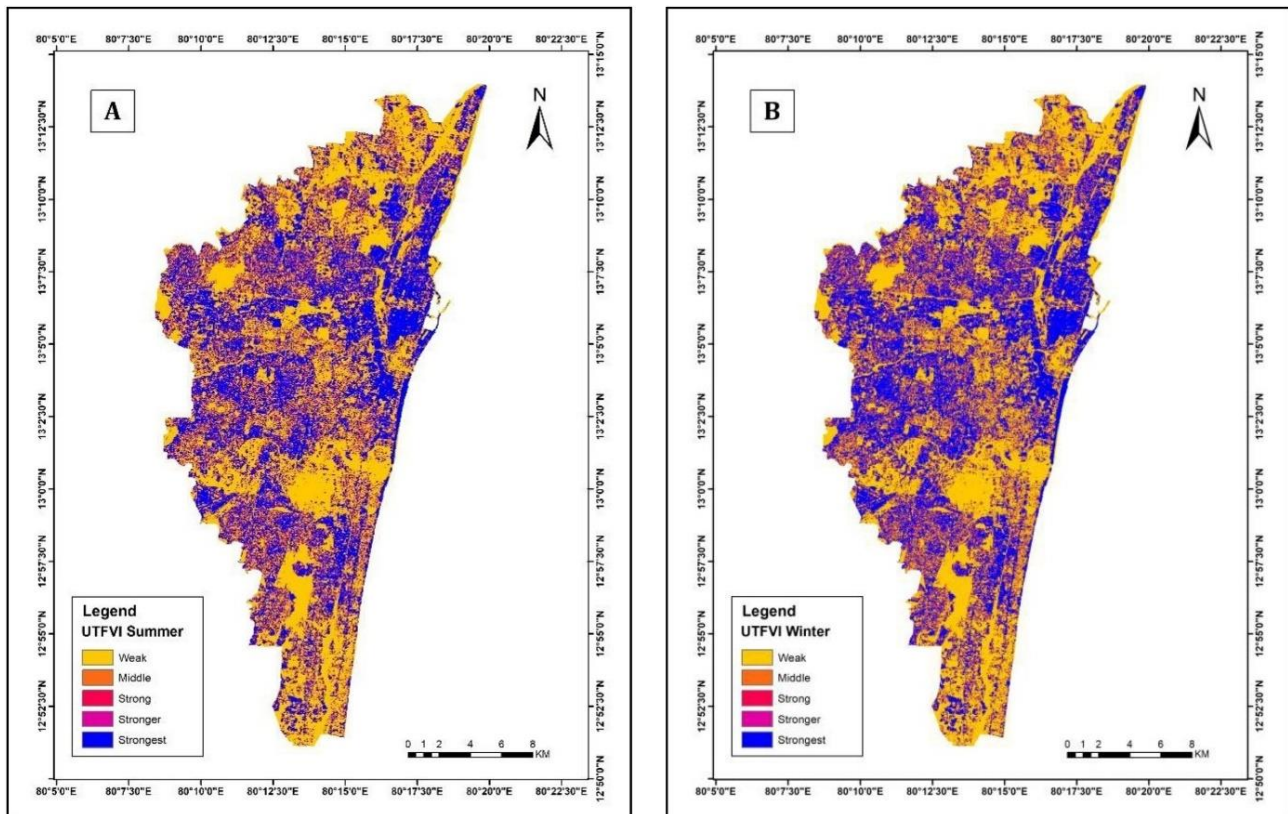


Figure 10 Simulated Maps of (A) summer and (B) winter UTFVI distribution for the year 2045 in Chennai.

Unlike the intermediate categories, the Strongest category declines from 174.04 km² in 2005 to 151.06 km² in 2045. This indicates an overall reduction of 22.98 km² or 13.20 percent. Compared to 2025, it has been reduced by 26.99 km². Extreme stress areas shrink, but they remain spatially important. The winter projections show a similar pattern. The Weak category class declines from 243.75 km² in 2005 to 195.96 km² in 2045. The Weak category is projected to decrease by 47.79 km² which is a reduction of 19.60 percent. The Middle category is expected to increase from 10.70 km² to 27.41 km² with a growth of 156.17 percent. The Strong category is also projected to increase from 10.13 km² to 28.43 km² with a gain of 18.30 km² or 180.65 percent. The Stronger category is expected to grow from 9.99 km² to 28.07 km², an increase of 180.98 percent. The Strongest category shows a small decline from 163.30 km² in 2005 to 157.99 km² in 2045, with a reduction of 5.31 km² or 3.25 percent. These results show that by 2045 thermal stress in Chennai is likely to become more common in the Middle, Strong, and Stronger categories while the Weak category continues to shrink. Although the Strongest category decreases slightly, it still covers a large part of the study area. This suggests that future thermal stress in Chennai will spread across a larger part of the urban landscape instead of remaining limited to a few isolated areas.

3.5 Continuous Thermal Behavior (VIIRS, 2014-2025)

Continuous thermal behavior was assessed using annual VIIRS nighttime radiance together with seasonal Landsat-derived LST and spatial UTFVI statistics for the period 2014-2025 (Table 15). The regenerated series provides a year-to-year temporal record that complements the discrete spatial analyses for 2005, 2015, and 2025. Because the arithmetic spatial mean of UTFVI is mathematically

centered close to zero, MAUTFVI was used as the principal indicator of the magnitude of spatial UTFVI variability in the continuous analysis, while the spatial mean UTFVI was retained as a diagnostic measure (Figure 11).

Table 15 Annual VIIRS nighttime radiance, seasonal LST, and UTFVI magnitude indicators in Chennai, 2014-2025.

Year	Summer LST (°C)	Winter LST (°C)	VIIRS radiance	Summer mean UTFVI	Winter mean UTFVI	Summer MAUTFVI	Winter MAUTFVI
2014	40.496	31.439	20.992	6.91×10^{-15}	8.05×10^{-15}	0.006798	0.004599
2015	42.983	34.822	22.527	-8.21×10^{-15}	6.35×10^{-15}	0.007576	0.005598
2016	42.794	34.488	23.436	3.27×10^{-15}	8.63×10^{-15}	0.006312	0.004886
2017	41.225	36.725	24.459	-5.29×10^{-16}	-2.02×10^{-15}	0.007609	0.008245
2018	41.648	30.164	26.187	-1.85×10^{-15}	9.17×10^{-15}	0.008002	0.006681
2019	44.524	36.145	25.391	3.46×10^{-14}	-9.09×10^{-15}	0.006729	0.007446
2020	43.419	31.615	22.775	3.08×10^{-14}	4.15×10^{-15}	0.007219	0.005950
2021	41.325	34.238	25.133	1.83×10^{-14}	1.73×10^{-14}	0.009891	0.004709
2022	46.421	33.536	26.268	1.41×10^{-14}	-9.70×10^{-15}	0.018193	0.007505
2023	43.277	32.415	28.993	2.36×10^{-14}	-6.27×10^{-15}	0.006669	0.007094
2024	39.465	33.584	27.397	-6.61×10^{-15}	1.45×10^{-14}	0.008315	0.005745
2025	43.056	33.673	28.990	7.48×10^{-15}	1.62×10^{-14}	0.006529	0.007715

Note: Mean UTFVI represents the arithmetic spatial mean of the pixel-level normalized UTFVI surface and is expected to be numerically close to zero because UTFVI is calculated relative to the corresponding study-area mean LST. These values therefore represent the mathematical centering of the index and should not be interpreted as indicating the absence of thermal stress. MAUTFVI (mean absolute UTFVI) represents the mean magnitude of absolute pixel-level UTFVI deviations and is used as the principal measure of UTFVI magnitude in the continuous 2014-2025 analysis. Across the study period, MAUTFVI remains within the expected small magnitude range of the normalized UTFVI distribution. LST was converted to Kelvin before UTFVI calculation to maintain consistency between numerator and denominator. Trend, correlation and regression statistics were calculated using the unrounded annual values; values displayed in Table 15 are rounded for presentation. Quality-controlled verification statistics for the revised 2025 Landsat-derived LST and UTFVI surfaces used to verify the UTFVI formulation is displayed in Table S2.



Figure 11 Annual VIIRS radiance (2014-2025).

Distinguishing the arithmetic spatial mean UTFVI from MAUTFVI is essential for interpreting the continuous series. Because UTFVI is calculated as the normalized deviation of each pixel from the

corresponding study-area mean LST, the spatial average of the numerator ($LST_i - \overline{LST}$) is mathematically centred on zero when the same valid pixels are used to derive both quantities. Consequently, the annual mean UTFVI values in Table 15 are near machine zero, ranging from about -9.70×10^{-15} to 3.46×10^{-14} across the 2014-2025 observations. These values represent numerical residuals of the normalization and should not be interpreted as the magnitude of thermal stress. MAUTFVI avoids the cancellation of positive and negative pixel-level deviations and therefore provides an appropriate measure of the magnitude of spatial UTFVI variability. For example, in 2025 the mean LST was 43.056°C (316.206 K) in summer and 33.673°C (306.823 K) in winter, while MAUTFVI was 0.006529 and 0.007715, respectively. The corresponding UTFVI standard deviations were 0.009125 and 0.010301, and the 95th-percentile values were 0.011469 and 0.017820. These magnitude-based statistics demonstrate that the near-zero arithmetic mean results from the mathematical centering of UTFVI rather than from a Kelvin-conversion, unit, or formula error.

VIIRS nighttime radiance shows a clear and sustained increase throughout the study period. Annual mean radiance increased from 20.992 in 2014 to 28.990 in 2025, corresponding to a positive linear slope of 0.608 radiance units per year. The temporal regression explained approximately 75.5% of the variation in annual radiance ($R^2 = 0.755$, $p < 0.001$). Although intermediate-year fluctuations occurred, the overall trajectory indicates sustained growth in nighttime illumination intensity across Chennai (Figure 11 and Figure 12). The VIIRS trajectory therefore provides continuous evidence of increasing nighttime urban intensity during the study period.

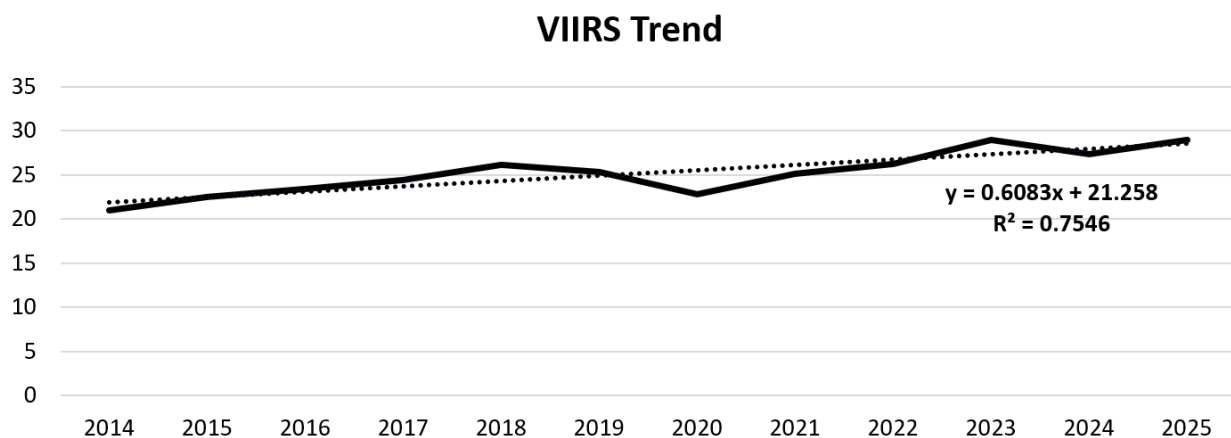


Figure 12 Temporal trend of VIIRS radiance (2014-2025).

The seasonal LST series shows substantially greater interannual variability than the VIIRS series. Summer mean LST varied from 39.465°C in 2024 to 46.421°C in 2022, while the 2014 and 2025 values were 40.496°C and 43.056°C, respectively. Despite the higher endpoint value in 2025, the linear summer trend was weak and statistically non-significant, with a slope of 0.083°C per year and $R^2 = 0.026$ ($p = 0.619$). Thus, the increase between selected endpoint years should not be interpreted as evidence of a consistent annual warming trend. The pronounced year-to-year variability indicates that factors beyond the gradual increase in nighttime urban activity influence summer surface temperature (Figure 13).

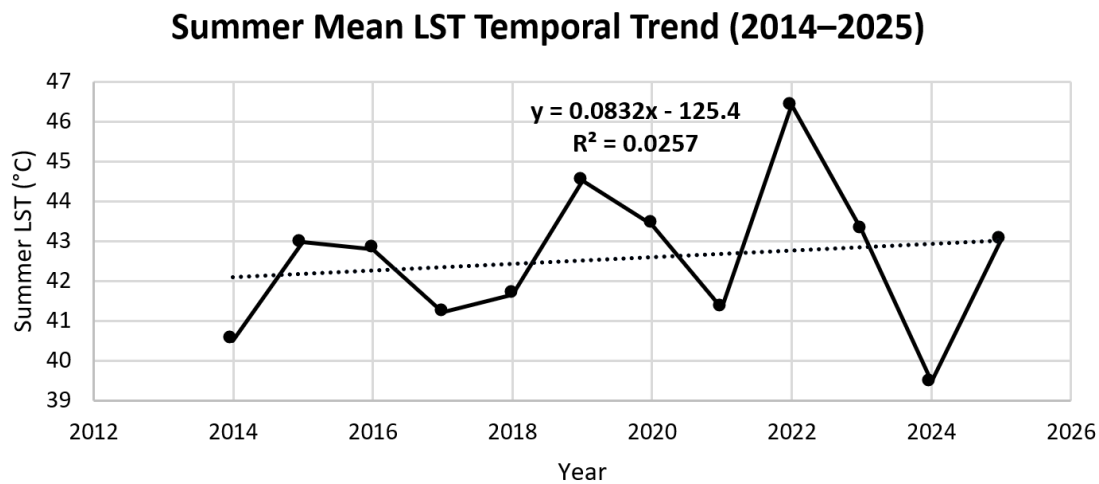


Figure 13 Temporal trend of summer mean land surface temperature (LST) in Chennai, 2014-2025.

Winter LST also showed substantial interannual variability. The winter series contained 12 valid observations. Mean winter LST was 31.439°C in 2014 and 33.673°C in 2025, while higher values occurred in several intermediate years. The fitted temporal trend was very weak and slightly negative, with a slope of -0.0326°C per year and $R^2 = 0.0037$ ($p = 0.8503$). Consequently, no statistically significant linear winter LST trend was identified during 2014-2025 (Figure 14).

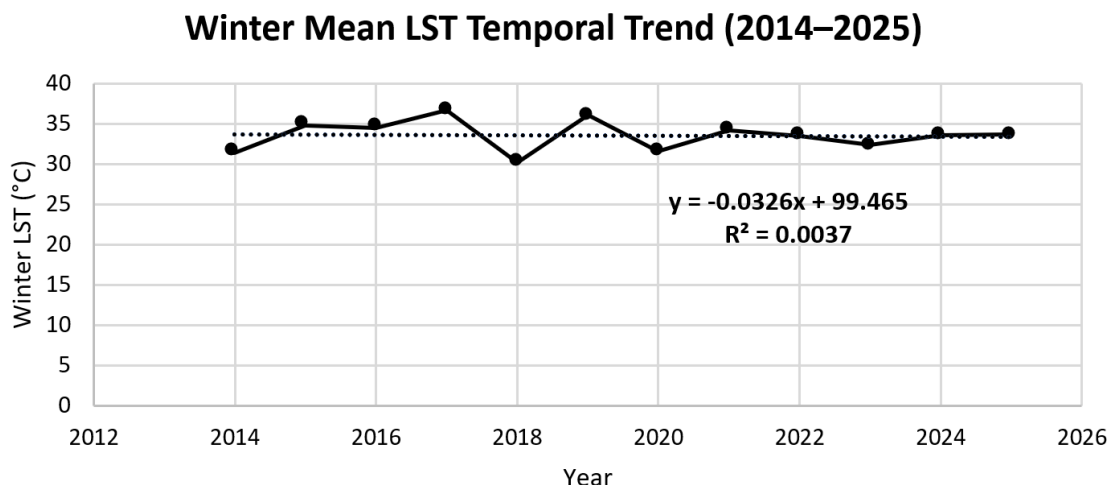


Figure 14 Temporal trend of winter mean land surface temperature (LST) in Chennai, 2014-2025.

The annual spatial mean UTFVI remained numerically close to zero throughout the continuous series because UTFVI is normalized relative to the corresponding study-area mean LST. This near-zero arithmetic mean represents the mathematical centering of the index and does not indicate an absence of spatial thermal variability. MAUTFVI was therefore used to quantify the magnitude of spatial normalized thermal variability. Summer MAUTFVI ranged from 0.006312 to 0.018193, with the highest value recorded in 2022, while winter MAUTFVI ranged from 0.004599 to 0.008245 across the 12 annual observations. The corresponding UTFVI distributions demonstrate measurable pixel-level spatial variability despite the near-zero arithmetic mean. Thus, the very small arithmetic mean UTFVI values should not be interpreted as evidence of an error in Kelvin conversion or UTFVI

formulation; rather, they arise from the averaging of positive and negative normalized deviations around the spatial mean (Figure 15 and Figure 16).

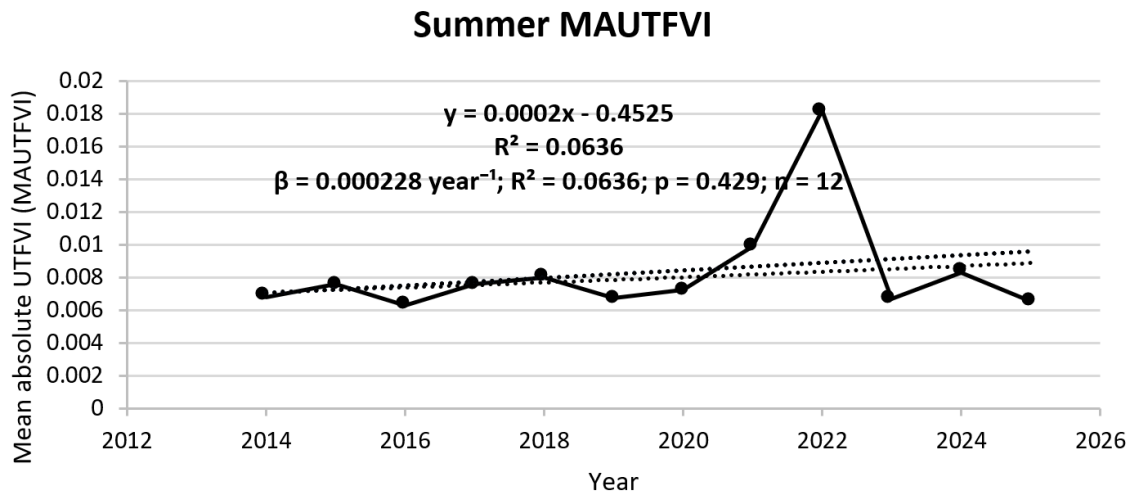


Figure 15 Temporal trend of summer mean absolute UTFVI (MAUTFVI) in Chennai, 2014-2025.

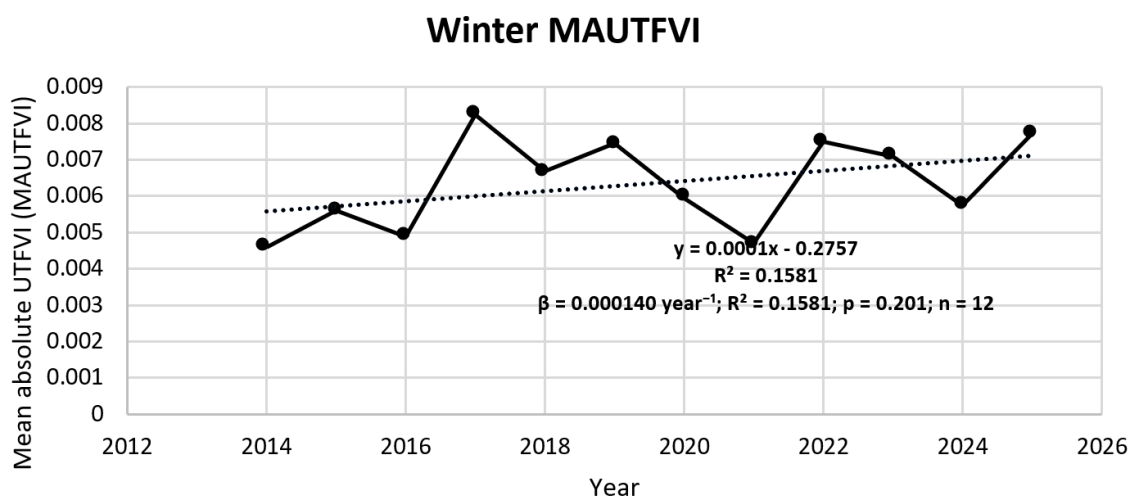


Figure 16 Temporal trend of winter mean absolute UTFVI (MAUTFVI) in Chennai, 2014-2025.

The distinction between mean UTFVI and MAUTFVI is particularly important for interpreting the continuous series. The near-zero mean UTFVI is a mathematical consequence of the normalization procedure, whereas MAUTFVI retains the magnitude of both positive and negative pixel-level deviations. The regenerated data show that MAUTFVI remains within the expected magnitude range of the normalized UTFVI distribution. For example, summer MAUTFVI was 0.006529 and winter MAUTFVI was 0.007715, while the corresponding UTFVI standard deviations were 0.009125 and 0.010301 and the 95th-percentile values were 0.011469 and 0.017820, respectively. These statistics demonstrate measurable spatial thermal variability despite the near-zero arithmetic mean. Overall, the continuous record reveals a clear divergence between the temporal behaviour of nighttime radiance and the seasonal thermal indicators. VIIRS radiance increased strongly and consistently, whereas summer and winter LST did not show statistically significant linear trends, and MAUTFVI

also showed no statistically significant temporal trend. This divergence indicates that nighttime radiance captures a dimension of urban intensification that does not translate into a simple one-to-one annual response in land surface temperature or the magnitude of normalized thermal variability.

3.6 Relationship between VIIRS Radiance and Thermal Indicators

The correlation and regression analyses examined the temporal relationship between annual VIIRS nighttime radiance and the seasonal thermal indicators during 2014-2025. Because the spatial mean UTFVI is mathematically centred close to zero, MAUTFVI was used as the principal UTFVI magnitude indicator for inferential analysis. Summer relationships were based on 12 annual observations, and winter relationships were based on 12 observations. Table 15 and Table 16 present the results. The relationship between VIIRS radiance and winter LST was effectively absent in the regenerated 12-year series ($r = -0.009$, $p = 0.977$). The corresponding regression coefficient was $\beta = -0.00722$, with $R^2 = 0.00009$ and $p = 0.977$. The 95% confidence interval for the coefficient ranged from -0.5443 to 0.5299. Thus, annual VIIRS nighttime radiance provided essentially no linear explanatory power for winter LST during 2014-2025 (Table 16).

Table 16 Correlation between annual VIIRS nighttime radiance and seasonal LST and MAUTFVI, 2014-2025.

Relationship	n	Pearson r	p-value	Statistical interpretation
VIIRS-Summer LST	12	0.144970	0.653048	Not significant; weak positive association
VIIRS-Winter LST	12	-0.009475	0.976687	Not significant; negligible association
VIIRS-Summer MAUTFVI	12	0.131219	0.684377	Not significant; weak positive association
VIIRS-Winter MAUTFVI	12	0.570612	0.052685	Not significant; comparatively strong positive association

Note: r represents Pearson's correlation coefficient. p -values are two-tailed and were evaluated at the 0.05 significance level. Both summer and winter relationships contain 12 annual observations covering 2014-2025. Correlations represent temporal bivariate associations and should not be interpreted as evidence of causality.

The relationship between VIIRS radiance and summer MAUTFVI was weak and positive ($r = 0.131$, $p = 0.684$). The regression coefficient was very small ($\beta = 0.000170$), reflecting the normalized scale of MAUTFVI, and the fitted model explained only 1.7% of the temporal variation ($R^2 = 0.017$, $p = 0.684$). The 95% confidence interval extended from -0.000733 to 0.001072 and included zero. The result therefore provides no evidence of a statistically significant summer association between nighttime radiance and the magnitude of spatial thermal variability. A comparatively stronger positive association was observed between annual VIIRS radiance and winter MAUTFVI. Using all 12 annual observations, Pearson's correlation coefficient was $r = 0.571$ with $p = 0.053$. The corresponding regression coefficient was $\beta = 0.000286$, with $R^2 = 0.326$ and $p = 0.053$. Although the model explained approximately 32.6% of the temporal variation in winter MAUTFVI, the relationship did not reach the adopted 5% significance threshold. The 95% confidence interval for the VIIRS coefficient ranged from approximately -0.000004 to 0.000577 and included zero. The result therefore indicates a comparatively strong positive temporal association, but not statistically significant evidence of a winter relationship at $p < 0.05$ (Table 17).

Table 17 Simple linear regression between annual VIIRS nighttime radiance and seasonal LST and MAUTFVI, 2014-2025.

Model	β	SE	T	R ²	p-value	Lower 95% CI for β	Upper 95% CI for β
VIIRS → Summer LST	0.107380	0.231758	0.4633	0.021016	0.653048	-0.409008	0.623768
VIIRS → Winter LST	-0.007223	0.241053	-0.0300	0.000090	0.976687	-0.544322	0.529877
VIIRS → Summer MAUTFVI	0.00017	0.000405	0.4186	0.017219	0.684377	-0.000733	0.001072
VIIRS → Winter MAUTFVI	0.000286	0.000130	2.1973	0.325598	0.052685	-0.000004	0.000577

Note: β represents the regression coefficient of annual VIIRS nighttime radiance. SE is the standard error of β , t is the corresponding t-statistic, and R² represents the proportion of variance explained by the bivariate linear model. p-values refer to the statistical significance of the VIIRS coefficient. Confidence intervals are 95% confidence intervals for β . Both summer and winter models use 12 annual observations covering 2014-2025. The models represent bivariate temporal associations and do not estimate the independent or causal contribution of nighttime human activity to thermal conditions. For Figures 17-20, the corresponding Pearson correlation coefficients, p-values, sample sizes, regression coefficients, R², and 95% confidence intervals are reported in the figure captions and Table 15 and 16 to ensure transparent statistical interpretation without overcrowding the graphical panels. The very small UTFVI regression coefficients arise because the dependent variable is the spatial mean of a normalized index whose arithmetic mean is mathematically centered close to zero. These coefficients should therefore be interpreted only as the slope of the annual bivariate association and not as a measure of the magnitude of spatial ecological thermal stress. We evaluate spatial thermal stress from pixel-level UTFVI distributions and their classified categories.

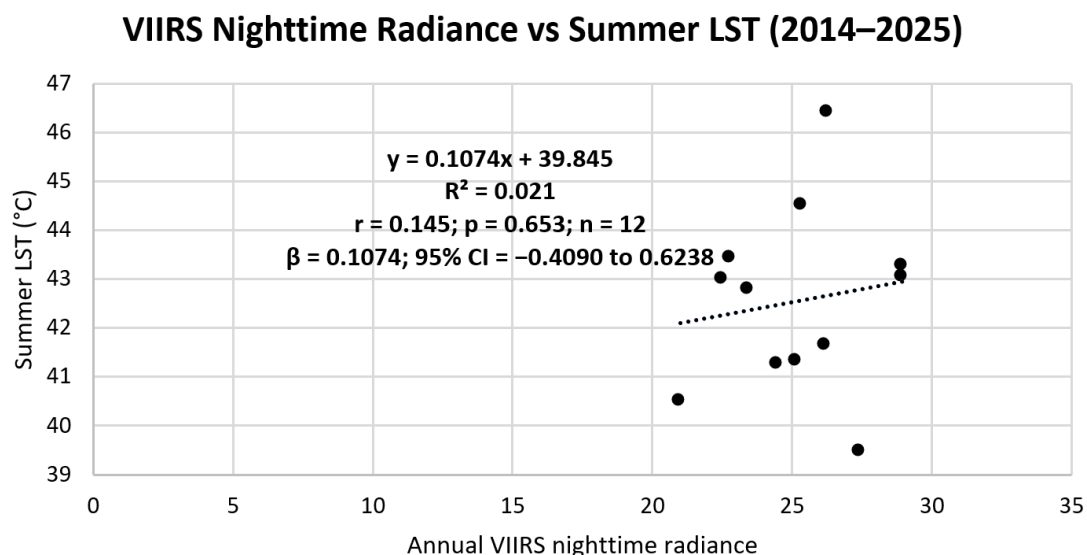


Figure 17 Relationship between annual VIIRS nighttime radiance and summer mean land surface temperature (LST) in Chennai, 2014-2025.

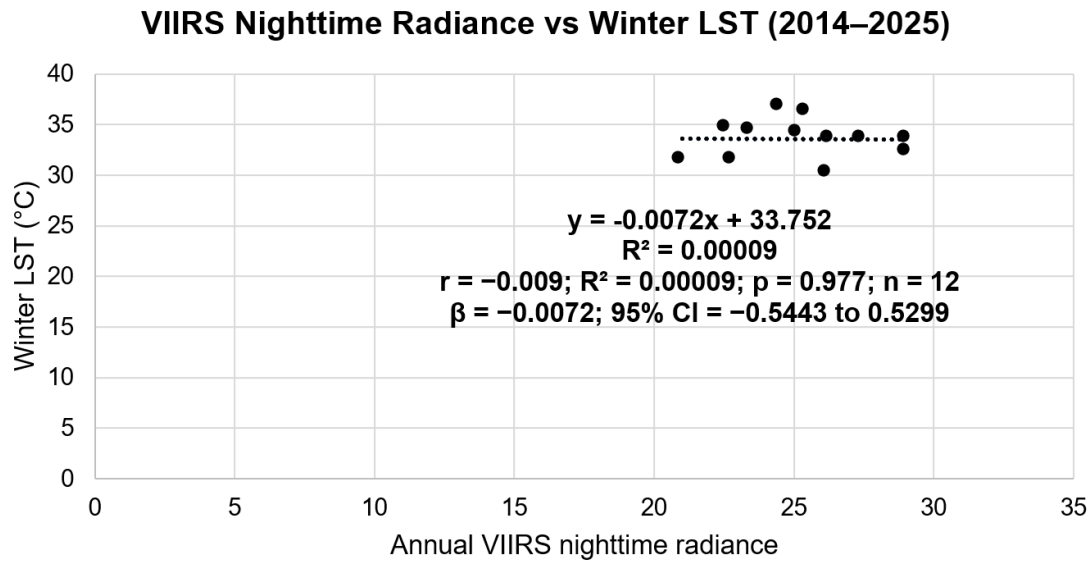


Figure 18 Relationship between annual VIIRS nighttime radiance and winter mean land surface temperature (LST) in Chennai, 2014-2025.

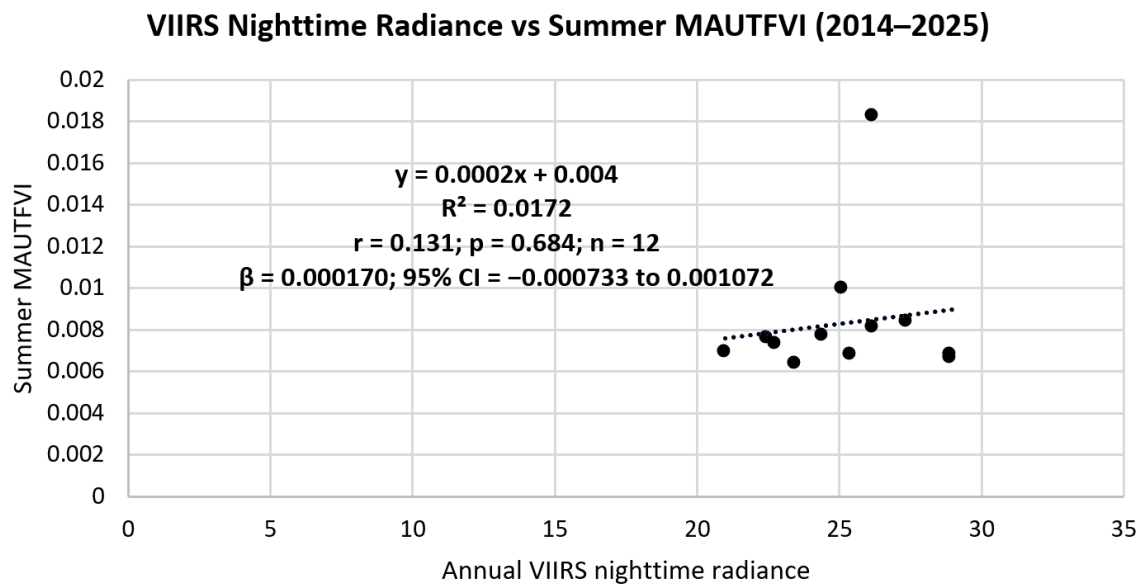


Figure 19 Relationship between annual VIIRS nighttime radiance and summer mean absolute UTFVI (MAUTFVI) in Chennai, 2014-2025.

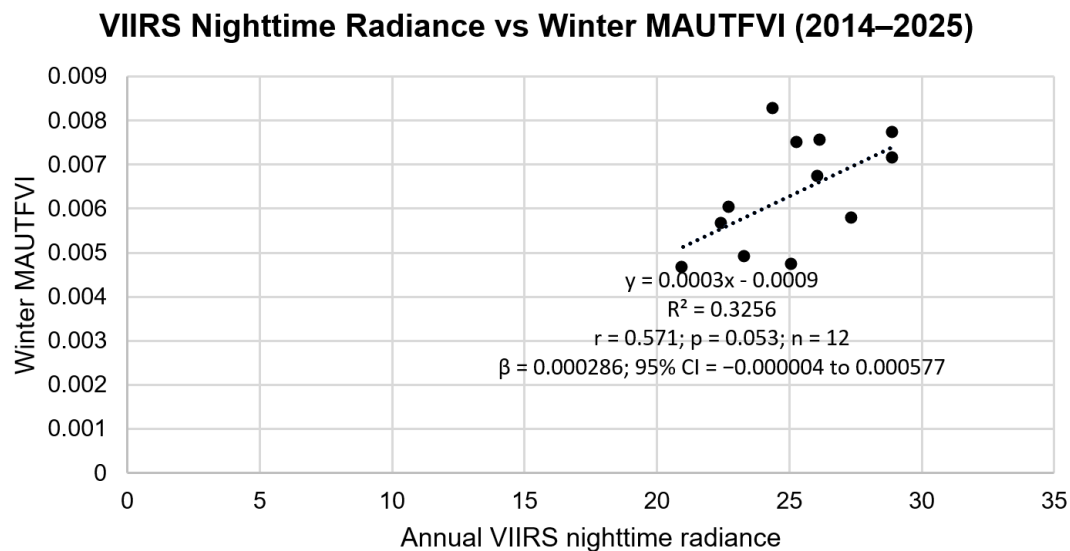


Figure 20 Relationship between annual VIIRS nighttime radiance and winter mean absolute UTFVI (MAUTFVI) in Chennai, 2014-2025.

The comparatively strong but non-significant winter MAUTFVI relationship requires careful interpretation. The positive coefficient indicates that years with greater nighttime radiance tended to coincide with greater magnitude of spatial thermal variability, but the association did not reach the adopted 5% significance level. VIIRS radiance is an indirect indicator of nighttime illumination and aspects of urban activity, whereas MAUTFVI reflects the spatial magnitude of LST deviations relative to the study-area mean. Seasonal atmospheric variability, vegetation and moisture conditions, surface materials, coastal processes, and interannual meteorological differences may influence the thermal response independently of nighttime radiance. The limited number of annual observations also restricts statistical power, so the results should be regarded as suggestive rather than conclusive evidence of a winter association. Taken together, the four bivariate models provide no statistically significant evidence of a linear temporal relationship between annual VIIRS nighttime radiance and the selected seasonal LST and MAUTFVI indicators at the 5% significance level. The summer LST association was weak and positive, while winter LST showed a stronger negative association that remained statistically non-significant. The summer and winter MAUTFVI relationships were positive, but both explained only a limited proportion of the observed interannual variation. These results should not be interpreted as evidence that nighttime illumination has little or no influence on thermal conditions, nor as evidence that any other single factor is the dominant control. Rather, they indicate that annual nighttime radiance considered alone does not adequately explain the interannual variability in the selected thermal indicators. The observed thermal response is likely to reflect the combined influence of land-surface composition, vegetation and moisture conditions, surface materials, urban morphology, atmospheric variability, seasonal processes, and coastal conditions. The present analysis therefore provides evidence of temporal association only and does not estimate independent effects or causal relationships. Associations with summer LST, winter LST, and summer MAUTFVI were statistically non-significant. Winter MAUTFVI showed the strongest positive association with VIIRS radiance among the four relationships, but the association remained marginally above the adopted 0.05 significance threshold ($r = 0.571$, $p = 0.053$). This pattern supports the interpretation that nighttime radiance represents a complementary dimension of urban intensification rather than a direct surrogate for

thermal conditions. The LULC, LST, and spatial UTFVI analyses therefore remain essential for understanding the physical distribution and future evolution of thermal stress across Chennai.

4. Discussion

4.1 Urban Expansion and Reformation of the Land System

The results confirm a clear restructuring of Chennai's land system between 2005 and 2025. Built-up land increased from 258.83 km² to 305.69 km², while cropland declined from 43.50 km² to 17.60 km², and barren land reduced from 67.25 km² to 15.11 km². The built-up land is projected to reach 352.55 km² by 2045 and is expected to cover more than 80 percent of the total land area. This shows that Chennai will continue to grow both by filling the remaining open spaces within the city and by expanding towards the surrounding areas. The same pattern has been reported in many rapidly growing Indian cities where agricultural land and open land have gradually been converted into residential areas and other urban infrastructure [30]. Cropland loss in Chennai is much higher, suggesting that pressure on peri-urban areas is likely to continue. The VIIRS time series provides a complementary temporal indicator of increasing nighttime illumination intensity. Mean radiance increased from 20.99 in 2014 to 28.99 in 2025, indicating a sustained increase in nighttime light intensity during the study period. This temporal pattern broadly coincides with the documented expansion of built-up land, but the two indicators represent different dimensions of urban change. The LULC results provide direct evidence of spatial land-cover transformation, whereas VIIRS radiance proxies nighttime illumination and aspects of urbanization and anthropogenic intensity. The observed correspondence should therefore be interpreted as consistency between two indicators rather than evidence that changes in radiance directly measure, cause, or quantify urban expansion.

The vegetation area is projected to decrease from 86.81 km² in 2025 to 56.45 km² in 2045. This suggests that the increase in vegetation seen in the earlier period is unlikely to continue as the city expands and land demand keeps rising. The same pattern has been reported in other studies where CA ANN models showed that future urban growth usually follows the existing pattern of development and is influenced by factors such as accessibility and urban density [52]. The LULC and VIIRS results together show that built-up areas are becoming more connected while vegetation is breaking into smaller patches. These land changes provide important spatial context for the observed thermal redistribution and the thermal conditions projected under the 2045 scenario, while by vegetation, moisture, surface properties, urban morphology, and seasonal environmental conditions.

The spatial configuration of the 2045 scenario was generated from the combined influence of terrain, hydrological proximity, and transportation accessibility represented by the eight CA-ANN predictors. Including DEM/elevation, aspect, slope, hill shade, contour, and curvature provides a multidimensional representation of terrain configuration, while distance to stream and distance to railway capture spatial relationships with drainage and transportation infrastructure. These variables allow the model to represent spatial heterogeneity in transition potential rather than allocating future development solely according to historical class quantities. The resulting spatial pattern should not be interpreted as evidence that any individual predictor independently caused the projected land-use transitions. Because several terrain variables are derived from the same DEM, some spatial redundancy is possible. We therefore interpret the predictors collectively as

descriptors of terrain configuration, hydrological proximity, and transportation accessibility. The resulting 2045 pattern should accordingly be understood as the spatial outcome of the combined predictor set within the CA-ANN scenario framework rather than as an estimate of the independent causal effect of any single variable. The interpretation of the CA-ANN scenario should also account for uncertainty associated with the predictor set. The terrain-related variables provide different representations of landscape configuration, but several are derived from the same DEM and may therefore contain overlapping spatial information. Because no formal VIF or pairwise-correlation screening was used to remove potentially redundant variables, the modelled transition potential should not be interpreted as evidence that any individual terrain variable independently drives urban expansion. Instead, the predictor set provides a combined spatial representation of terrain, hydrological proximity, and transportation accessibility. This limitation may influence the relative contribution of individual predictors within the ANN but does not alter the intended use of the 2045 output as a scenario-based spatial projection. A limitation of the present CA-ANN implementation is that the modelling workflow did not incorporate formal predictor-collinearity diagnostics. This is particularly relevant because aspect, slope, hill shade, contour, and curvature were derived from the same DEM and may contain related terrain information. We therefore interpreted the predictions collectively as spatial descriptors rather than as statistically independent explanatory variables. Future work should incorporate predictor-correlation analysis, variance inflation factor (VIF) assessment, and sensitivity testing to evaluate redundancy among the spatial drivers and determine whether a reduced predictor set produces comparable transition-potential patterns. Interpret the 2045 thermal implications with the temporal limitations of the machine-learning framework in mind. The Random Forest thermal model was calibrated from the available Landsat observations for 2005, 2015, and 2025 and therefore represents relationships learned from a limited number of temporal reference years. Although the model was fitted using spatially distributed observations within the three reference years, the limited temporal diversity of the calibration data may constrain generalization when the model is applied to the simulated 2045 predictor configuration. The projected thermal patterns are therefore best interpreted as conditional scenario-based estimates rather than as independently validated future temperature conditions.

4.2 Changes in Thermal Patterns Across Seasons

The seasonal LST differences reflect more than a simple contrast between a hotter summer and a cooler winter. Across the 2014-2025 annual series, summer LST averaged 42.55°C compared with 33.57°C in winter, producing a mean seasonal difference of 8.98°C. The magnitude of this difference varied considerably among years, from 4.50°C to 12.89°C, indicating that the seasonal thermal contrast is modulated by changing environmental conditions rather than being fixed. The summer distribution also contains a much larger concentration of pixels in the higher temperature classes, with the 35-40°C class becoming dominant over the historical period, while winter conditions remain more concentrated in the 30-40°C range. One important mechanism is seasonal solar forcing. Summer observations occur during a period of stronger incoming shortwave radiation and intense surface heating, which increases the energy available for sensible heat flux and raises the temperature of exposed impervious surfaces. Built-up materials such as concrete, asphalt, and masonry can store substantial daytime energy and later release some of it, strengthening the daytime surface-temperature response. In winter, weaker solar forcing and shorter-duration

heating generally reduce the amount of energy available for surface warming, contributing to lower LST. The magnitude of the response nevertheless depends on the thermal properties and spatial configuration of the urban surface, so the seasonal contrast is not uniform across Chennai. A second mechanism is moisture and evapotranspiration. Vegetated, moisture-retaining surfaces can partition available energy into latent rather than sensible heat, moderating surface temperature. Seasonal variation in rainfall, soil moisture, wetland conditions, and vegetation water availability can therefore modify the temperature response of the same land-cover class between summer and winter. In Chennai, this effect matters because wetlands, river corridors, water bodies, vegetated areas, and peri-urban moisture-retaining surfaces coexist with densely built-up areas. Where moisture availability is reduced, or vegetated surfaces are replaced by impervious materials, the potential for evaporative cooling is diminished, and a larger proportion of available energy can contribute to sensible heating.

Atmospheric conditions provide a third control. Air temperature, humidity, wind speed, atmospheric stability, and cloud conditions influence the partitioning and redistribution of surface energy and therefore affect the magnitude and persistence of LST. The large year-to-year variation in the summer-winter temperature difference is consistent with the influence of these background atmospheric conditions. Thus, even where the built-up footprint changes progressively, the thermal response in a given year can be amplified or moderated by the prevailing atmospheric state. This helps explain why the 2014-2025 LST series does not exhibit a simple monotonic response despite substantial land transformation. Chennai's coastal setting introduces an additional control through the Bay of Bengal and associated sea-breeze circulation. Coastal air exchange can influence near-surface temperature, humidity, ventilation, and sensible heat redistribution, while proximity to water and seasonally varying moisture can modify surface-energy partitioning. These effects may be especially important in differentiating the thermal response of locations with similar levels of urban development but different exposure to water, vegetation, ventilation, and coastal influence. Wetlands and river systems can further moderate local temperatures through moisture storage and evapotranspiration.

Urban morphology and surface composition also help explain why seasonal differences are spatially heterogeneous. The LULC-LST cross-analysis shows that non-built-up to built-up transitions were frequently associated with movement toward the 35-40°C range, with 46.83% of the summer transition area and 51.77% of the winter transition area moving from below 35°C into that range. This correspondence indicates that land transformation is an important spatial component of thermal redistribution. However, substantial thermal transitions also occurred within areas that retained their categorical LULC class indicates that building density, surface materials, vegetation condition, moisture, shading, and urban configuration can modify thermal behaviour without requiring a change in the categorical land-cover label. The summer and winter results should therefore be interpreted as seasonally differentiated expressions of the same urban thermal system rather than as two independent temperature regimes. Summer provides stronger solar forcing and generally greater surface-heating potential, while winter thermal conditions are moderated by weaker radiative forcing and different atmospheric and moisture conditions. The observed seasonal contrast therefore results from the interaction of land-surface transformation with meteorological background conditions, surface moisture, vegetation, urban morphology, and coastal processes. This interpretation also explains why increasing nighttime illumination and land transformation do not necessarily generate identical annual responses in summer and winter LST.

A different pattern can be seen when these results are compared with the VIIRS data. Annual nighttime radiance increased steadily over the study period, but summer LST did not increase in the same way. The summer LST showed only a weak temporal trend ($R^2 = 0.0257$, $p = 0.619$) and substantial year-to-year variability. This indicates that factors beyond the gradual increase in nighttime urban activity influence surface temperature, including the spatial arrangement of built-up areas, surface materials, vegetation and moisture conditions, and seasonal atmospheric variability. The projected decrease in the summer area under the 40-45°C and >45°C classes should likewise not be interpreted as evidence that Chennai will become cooler; rather, the projected thermal distribution shifts toward a more spatially extensive 35-40°C regime.

The spatial cross-analysis further supports the relationship between land transformation and thermal redistribution. Of the 80.09 km² undergoing non-built-up to built-up conversion in the common analysis area, 46.83% of the summer transition area and 51.77% of the winter transition area moved from below 35°C into the 35-40°C thermal range. The correspondence was particularly pronounced for vegetation-to-built-up and cropland-to-built-up transitions. In contrast, barren-to-built-up conversion produced the largest area of transition into the ≥40°C range because of its larger spatial extent. These findings suggest that the expansion of the 35-40°C class was linked spatially with urban restructuring, while also demonstrating that unchanged built-up areas can undergo thermal reorganization over time. The result should nevertheless not be interpreted as evidence that LULC transition alone determines LST. Surface moisture, vegetation condition, urban morphology, surface materials, seasonal atmospheric conditions, and coastal processes can modify the thermal response of any land-cover transition. The cross-analysis therefore strengthens the spatial interpretation of the LST results by showing where land transformation and thermal transition coincide, while retaining the distinction between spatial correspondence and causal attribution.

The VIIRS record provides an additional temporal context for the seasonal contrast, but the two datasets represent different physical dimensions of urban change. Nighttime radiance increased during 2014-2025, whereas the seasonal LST series showed substantial interannual variability and no statistically significant linear temporal trend. These differences reflect seasonal atmospheric conditions, moisture availability, surface properties, coastal circulation, and the timing of heat storage and release. Annual nighttime illumination therefore cannot be expected to translate directly into a proportional daytime LST response. The contrast between summer and winter further demonstrates that the relationship between nighttime illumination and surface thermal conditions is seasonally mediated rather than uniform across the year. The projected contraction of the extreme-temperature classes requires a distinction between thermal redistribution and overall thermal change. The >45°C class declines to 0.06 km² in both seasons by 2045, while the 35-40°C class becomes the dominant projected thermal regime and cooler classes contract substantially. Therefore, the result is therefore not interpreted as future cooling, but as a redistribution of the modelled temperature frequency distribution toward a widespread moderate-to-high thermal range. The fixed thresholds used throughout the analysis ensure that different classification criteria between observed and projected years do not drive this interpretation.

The modelling framework provides a second important qualification. Random Forest regression estimates the 2045 thermal surface from relationships learned from the historical predictor space and applies them to the CA-ANN-derived future land configuration. This estimation can represent the central portion of the learned thermal response more strongly than isolated extreme values, so

some attenuation of the upper thermal tail is plausible. However, the available data do not allow independent quantification of this potential effect because no observed 2045 thermal surface is available for validation. The apparent decline in extreme-temperature area is therefore best regarded as a characteristic of the scenario-based modelled distribution rather than as a definitive scenario projection of future extreme heat. The VIIRS results also require careful interpretation. Nighttime radiance increased continuously during 2014-2025, indicating sustained growth in urban activity and development intensity. However, this temporal increase was not accompanied by statistically significant linear changes in the selected seasonal LST and UTFVI indicators. The absence of a significant bivariate relationship should not be interpreted as evidence that urban activity is thermally unimportant. VIIRS represents nighttime radiance and is therefore an indirect proxy for human activity rather than a direct measure of built-up density, surface materials, anthropogenic heat release, or energy consumption. In addition, surface temperature responds simultaneously to vegetation, moisture, land-cover composition, atmospheric conditions and coastal processes. The relatively small annual sample further limits statistical power. The VIIRS analysis is consequently most useful for identifying whether a simple temporal correspondence exists between nighttime urban intensity and thermal indicators, rather than for isolating the independent causal contribution of human activity.

When interpreting the projected thermal patterns, also consider the uncertainty associated with the CA-ANN land scenario. The 2045 LST distribution is estimated from the simulated future land configuration and therefore represents a conditional thermal scenario rather than an independently validated scenario projection. The projected dominance of the 35-40°C class should consequently be interpreted as the thermal response associated with the modelled land-transition pathway. The use of multiple Landsat thermal sensors also introduces an important comparability consideration. Collection 2 Level-2 processing provides calibrated sensor-specific products and a consistent scaling framework, but it does not eliminate every difference in the spectral response and thermal characteristics of Landsat 5, Landsat 8, and Landsat 9. Because we did not apply an additional empirical inter-sensor thermal bias correction, small differences in absolute LST among observation years may partly reflect sensor characteristics. The principal interpretation therefore focuses on the magnitude and spatial distribution of broad thermal changes rather than assuming that every small interannual difference represents a purely physical change in surface temperature.

4.3 Changes in Ecological Thermal Stress and UTFVI

The spatial UTFVI results demonstrate that ecological thermal stress in Chennai is distributed across a broad range of categories and changes substantially with land transformation. The 2005-2045 comparison shows a decline in the Weak category and expansion of several intermediate stress categories, indicating a broader spatial distribution of relative thermal stress rather than a simple increase restricted to a small number of extreme hotspots. The Strongest category remains spatially important even as its projected area decreases, indicating that a reduction in the highest category does not necessarily represent an improvement in overall thermal conditions.

The continuous 2014-2025 analysis requires a distinction between the arithmetic spatial mean UTFVI and the magnitude of the pixel-level UTFVI distribution. Because UTFVI is normalized around the study-area mean LST, the arithmetic spatial mean is mathematically expected to remain close to zero. The regenerated annual values confirm this behaviour, with mean UTFVI values generally

around 10^{-15} to 10^{-14} . These values therefore do not indicate negligible thermal stress. Instead, MAUTFVI, standard deviation, range and percentile statistics provide more meaningful measures of the magnitude of spatial thermal variability. In the regenerated series, MAUTFVI ranged approximately from 4.6×10^{-3} to 1.82×10^{-2} , demonstrating that the underlying pixel-level UTFVI distribution was consistently non-zero. The 2025 quality-controlled results further demonstrate this distinction. Summer mean LST was 43.056°C (316.206 K), with a UTFVI standard deviation of 0.009125, a 95th-percentile UTFVI value of 0.011469, and MAUTFVI of 0.006529. Winter mean LST was 33.673°C (306.823 K), with a UTFVI standard deviation of 0.010301, a 95th-percentile UTFVI value of 0.017820, and MAUTFVI of 0.007715. These values are consistent with the expected small normalized range of UTFVI and demonstrate that the near-zero arithmetic mean results from spatial centering rather than from a temperature-unit or formula error. The relationship between nighttime radiance and thermal conditions further supports the spatial UTFVI interpretation. VIIRS radiance increased strongly during 2014-2025, but the seasonal LST series did not show statistically significant linear trends. The summer and winter MAUTFVI trends were also not statistically significant. Winter MAUTFVI showed the strongest positive association with VIIRS radiance among the four tested relationships ($r = 0.571$, $p = 0.053$; $R^2 = 0.326$), but the association did not reach the adopted 5% significance threshold. Thus, the result suggests a potentially meaningful seasonal relationship that requires further investigation but does not provide statistically significant evidence of a VIIRS-winter MAUTFVI association at the selected significance level. The divergence between VIIRS and the thermal indicators should therefore be interpreted in relation to differences in dataset meaning, spatial and temporal scale, vegetation and moisture conditions, atmospheric variability, coastal processes, and the limited number of annual observations. We therefore interpret the divergence between VIIRS and the thermal indicators as meaningful rather than contradictory. VIIRS provides an annual indicator of nighttime illumination and aspects of urban activity, whereas LST and MAUTFVI represent surface thermal conditions and the spatial magnitude of normalized thermal variability. Their different physical meanings, spatial supports, observation periods, and sensitivity to land-cover, moisture, atmospheric, coastal, and urban-morphological conditions mean that the indicators are not expected to respond identically. The mechanisms underlying this divergence are discussed in greater detail in Section 4.4.

4.4 Interpreting the Asynchronous Relationship between Urban Activity and Thermal Dynamics

The divergence between the strong increase in nighttime radiance and the lack of statistically significant temporal trends in seasonal LST and MAUTFVI is an important finding of this study rather than an inconsistency among the datasets. The results indicate that urban intensification and surface thermal behaviour represent related but non-equivalent dimensions of urban change. The spatial LULC analysis and the LULC-LST transition cross-analysis demonstrate that land transformation is associated with thermal redistribution, whereas the annual VIIRS series indicates a broader and more continuous increase in nighttime urban activity. The absence of a synchronous temporal response therefore suggests that the thermal environment is mediated through several processes that are not represented directly by nighttime radiance.

One important factor is urban canopy structure and surface composition. VIIRS nighttime radiance records the intensity of artificial illumination and aspects of human activity. Still, it does not directly measure building height, street-canyon geometry, roof and wall materials, impervious-

surface properties, vegetation structure, shading, or local ventilation. These characteristics can strongly influence how the land surface absorbs, stores, redistributes, and releases incoming energy. Two locations with similar nighttime radiance can therefore exhibit different LST responses if their urban morphology, surface materials, vegetation cover, or moisture conditions differ. The spatial cross-analysis provides evidence that thermal redistribution coincides with land-surface restructuring, while the bivariate VIIRS analysis indicates that radiance intensity alone does not explain the interannual variation in the selected thermal indicators. Seasonal differences in anthropogenic activity and heat exchange provide a second possible explanation. VIIRS in this analysis represents annual nighttime illumination intensity, whereas LST represents the thermal state of the land surface during the Landsat observation period. Anthropogenic heat associated with buildings, transport, commercial activity, industry, and electricity use can vary substantially between day and night and between seasons. Nighttime illumination may therefore provide a useful indicator of urban activity without producing a proportional daytime LST response. In addition, the amount of heat stored in urban materials and its subsequent release depend on surface properties, atmospheric stability, wind conditions, and the duration and timing of solar heating. Consequently, increased nighttime radiance does not necessarily imply an equivalent increase in the daytime surface temperature measured by Landsat [20-23].

The regional climate and coastal background of Chennai further control the thermal response. Chennai is influenced by the Bay of Bengal, high humidity, seasonal rainfall, sea-breeze circulation, surface moisture, and great seasonal changes in atmospheric conditions. These processes can modify surface heating independently of long-term changes in nighttime illumination. In particular, coastal circulation can influence heat removal and redistribution, while moisture availability can alter the partitioning of available energy between sensible and latent heat. Vegetation and wetland conditions can further moderate LST through evapotranspiration and moisture storage. Thus, even as urban activity increases, interannual and seasonal atmospheric and surface-moisture variability can obscure a simple linear relationship between nighttime radiance and LST. A fourth consideration is the difference in spatial and temporal scale between the datasets. Landsat-derived LST is generated at a fine spatial resolution and captures detailed intra-urban thermal heterogeneity, whereas VIIRS nighttime radiance represents illumination over a substantially coarser spatial support. Local hot and cool surfaces clearly differentiated in Landsat imagery can therefore be aggregated into the broader spatial response represented by VIIRS. The temporal aggregation also differs: the present VIIRS series represents annual nighttime radiance, whereas the LST measures are seasonal composites. Consequently, a local or seasonal thermal response can occur without producing a corresponding change in the annual city-scale radiance series.

The spatial organization of land transformation provides another reason for the apparent temporal divergence. The LULC-LST cross-analysis showed that conversion to built-up land was frequently associated with movement toward the 35-40°C range, demonstrating a spatial relationship between land transformation and thermal redistribution. However, the same analysis also showed substantial thermal transitions in areas where the LULC class remained unchanged. This indicates that thermal conditions depend not only on whether a pixel changes category but also on the configuration, density, material properties, vegetation condition, and moisture characteristics of the surrounding urban landscape. Urban consolidation can therefore modify the thermal environment even when the categorical LULC class remains unchanged. These considerations also explain why the statistical results should not be interpreted as evidence that

nighttime urban activity is thermally irrelevant. The VIIRS series demonstrates sustained urban intensification, while the thermal indicators reflect the combined influence of land-surface properties, morphology, seasonal atmospheric conditions, moisture availability, and coastal processes. The non-significant VIIRS-thermal relationships consequently indicate that nighttime radiance alone is insufficient to explain interannual thermal variability, rather than demonstrating an absence of interaction between urban development and thermal conditions.

The strongest positive association in the present analysis occurred between VIIRS radiance and winter MAUTFVI, but the relationship remained non-significant at the 5% level. This result may nevertheless be informative because spatial thermal variability can respond differently from mean LST, and winter conditions may be more sensitive to the interaction among urban form, surface moisture, atmospheric stability, and coastal circulation. The relationship should therefore be regarded as a season-specific empirical pattern requiring further investigation rather than as a general causal mechanism. Overall, the apparent mismatch between urban activity and thermal indicators is therefore best understood as a consequence of different physical meanings, spatial supports, temporal aggregation, seasonal controls, and surface processes represented by the datasets. VIIRS contributes an important continuous measure of nighttime urban intensity, while Landsat-derived LST and UTFVI provide spatially detailed information on the thermal environment. Their divergence is consequently analytically useful: it demonstrates why urban thermal assessment cannot rely on nighttime illumination alone and why land-surface composition, urban morphology, environmental background conditions, and seasonal processes must be considered jointly.

4.5 Limitations of the 2045 Land-Use and Thermal Projections

A primary limitation of the 2045 projection concerns the absence of an independent historical hindcast validation of the CA-ANN land-use simulation. The model was calibrated from the observed 2005-2025 land-transition structure and the selected spatial predictor variables, then applied to generate the 2045 scenario. An earlier-period simulation, such as using an initial historical interval to reproduce a known subsequent LULC map, was not part of the original analytical design. Consequently, simulation-specific measures such as Figure of Merit, simulation-specific Overall Accuracy, Kappa, and simulated-versus-observed confusion matrices are unavailable for independently quantifying the spatial accuracy of the 2045 LULC configuration. The 2045 map should therefore be interpreted as a conditional scenario generated by continuing the observed transition relationships and predictor structure. This limitation means the spatial location and magnitude of future land-cover transitions should not be regarded as deterministic outcomes, and uncertainty associated with model specification, predictor redundancy, transition assumptions, and unrepresented socioeconomic or policy changes remains. A further source of uncertainty in the historical thermal calibration is residual cross-sensor variation among the Landsat generations used for the reference years, because the present workflow applied Collection 2 product-level standardization but did not perform an independent empirical inter-sensor bias adjustment.

A key limitation of the 2045 thermal projection is the absence of an independently observed future LST surface against which the modelled temperature distribution can be validated. The Random Forest thermal model was calibrated from the available historical observations and subsequently applied to predictor surfaces associated with the CA-ANN land-use scenario. Consequently, uncertainty is expected to be greater for projected conditions that differ from the

historical predictor and thermal ranges, particularly at the upper tail of the temperature distribution. The observed contraction of the $>45^{\circ}\text{C}$ and $40\text{--}45^{\circ}\text{C}$ classes should therefore not be interpreted as a verified reduction in future extreme heat. Instead, it represents the response of the specified modelling framework under the assumed land-use pathway. Future validation using observed thermal data and, where available, additional meteorological and urban-morphological predictors would be required to determine the magnitude and robustness of projected changes in extreme surface-temperature conditions.

A related limitation concerns the predictive assessment of the Random Forest thermal component. The model was developed within the scope of the present study as a scenario-translation framework linking the simulated 2045 land configuration with potential seasonal LST, rather than as an independently validated operational forecasting model. Accordingly, we did not use an independent train-test framework, cross-validation procedure, or hold-out thermal dataset to quantify predictive performance. Training and validation R^2 , RMSE, MAE, and formal predictor-importance rankings are therefore not available for demonstrating independent model generalisation or the relative contribution of NDVI, NDBI, and NDWI. This limitation matters because the thermal relationship was learned from only three historical reference years (2005, 2015, and 2025), despite the use of spatially distributed pixel observations within those years. The 2045 thermal surfaces should consequently be interpreted as conditional scenario estimates whose uncertainty may increase where the projected predictor configuration differs from the historical range. Future work incorporating longer thermal time series, independent hold-out observations, explicit cross-validation, additional meteorological and urban-morphological predictors, and formal predictor-importance assessment would provide a stronger basis for evaluating predictive accuracy and uncertainty.

5. Conclusion

This study examined Chennai's urban transformation and its thermal consequences by integrating historical land-use/land-cover (LULC) change, seasonal land surface temperature (LST), spatial ecological thermal stress, future land-use simulation, and continuous nighttime radiance. The results demonstrate that urban growth and thermal change are closely connected spatially but do not necessarily evolve synchronously in time. This distinction is central to understanding the thermal implications of continued urbanisation in a tropical coastal metropolitan environment. The historical analysis shows substantial restructuring of Chennai's land system between 2005 and 2025, characterised by the expansion and increasing continuity of built-up surfaces and contraction of cropland and barren land. The LULC-LST cross-analysis further shows that many areas undergoing non-built-up to built-up conversion simultaneously moved from lower thermal classes toward the $35\text{--}40^{\circ}\text{C}$ range. The strongest correspondence occurred for vegetation- and cropland-to-built-up transitions, while substantial thermal reorganisation was also observed within areas where the categorical LULC class remained unchanged. These findings indicate that land transformation contributes to thermal redistribution, but LULC conversion alone does not determine the thermal response. The seasonal thermal analysis indicates a broader redistribution toward moderate-to-high temperature conditions. In the 2045 scenario, the $35\text{--}40^{\circ}\text{C}$ class becomes spatially dominant in both summer and winter, while cooler classes contract substantially. The concurrent reduction in the $40\text{--}45^{\circ}\text{C}$ and $>45^{\circ}\text{C}$ classes should not be interpreted as evidence of future cooling. Rather, the

projected thermal field reflects a model-estimated response to the simulated land configuration, and the Random Forest modelling framework may attenuate the upper temperature tail. The projected UTFVI pattern similarly indicates a broader distribution of intermediate thermal-stress categories rather than a future landscape defined only by isolated extreme hotspots [71].

The continuous 2014-2025 VIIRS analysis provides an important temporal qualification to these spatial findings. Nighttime radiance increased strongly and consistently, whereas neither summer nor winter LST showed a statistically significant linear temporal trend, and neither summer nor winter MAUTFVI exhibited a statistically significant trend. Among the four tested VIIRS-thermal relationships, winter MAUTFVI showed the strongest positive association, but the relationship remained above the adopted 0.05 significance threshold. These results indicate that nighttime radiance is a useful complementary indicator of urban activity, but it should not be regarded as a direct surrogate for surface thermal conditions [72, 73]. Differences in urban morphology, surface materials, vegetation, moisture, atmospheric conditions, coastal processes, and the spatial and temporal supports of VIIRS and Landsat can produce asynchronous trajectories. From a planning perspective, the findings support a place-specific approach to thermal-risk management in Chennai. Remaining vegetation and moisture-retaining landscapes should be protected where land transformation coincides with movement toward the 35-40°C thermal range. Particular attention should be given to wetland and river-associated landscapes, including the Pallikaranai marsh system and the corridors of the Cooum, Adyar and Kosasthalaiyar rivers, because these areas provide both thermal-regulation and hydrological functions. New and redeveloped built-up areas should incorporate heat-mitigation measures such as higher-reflectance and permeable materials, shading, and tree canopy where spatially feasible. Thermal-transition maps and UTFVI stress categories can also support land-use regulation, green-infrastructure targeting, and development screening in rapidly urbanising areas. Planning should consider thermal exposure alongside vegetation, drainage and coastal sensitivity rather than relying on built-up extent or nighttime illumination alone. Overall, the study demonstrates the value of integrating spatial land transformation with seasonal thermal indicators, scenario-based land-use modelling, and continuous nighttime urban-activity observations. LULC provides the spatial context for thermal redistribution; seasonal LST characterises the surface thermal response; UTFVI identifies the spatial distribution of relative thermal stress; MAUTFVI provides a continuous measure of its magnitude; CA-ANN provides a plausible future land-use scenario; Random Forest translates that scenario into a conditional thermal response; and VIIRS provides an independent temporal perspective on nighttime urban intensity. Together, these components provide a more comprehensive basis for understanding Chennai's evolving thermal environment and for supporting climate-responsive urban planning [74].

Acknowledgments

The authors acknowledges the open access geospatial datasets provided by the Survey of India, the National Aeronautics and Space Administration (NASA), the United States Geological Survey (USGS), the Indian Space Research Organisation (ISRO), and Google Earth. These datasets were used to process the data and support the analysis and interpretation carried out in this study.

Author Contributions

R.K.G. developed the initial concept for this article and provided comprehensive editing and oversight throughout the process. Y.K.T. was responsible for data acquisition, Google Earth Engine scripting, data processing, statistical analysis, and ensuring accuracy and relevance. G.Y. & A.G. prepared the initial draft and executed the necessary computations while validating the analytical methods employed in this research. S.G. explored specific approaches and reviewed and approved the final version of the manuscript.

Funding

No funding was received for this study.

Competing Interests

The authors have declared that no competing interests exist.

Data Availability Statement

All the data used in this study are publicly available. The Landsat Collection 2 Level-2 data were obtained from the United States Geological Survey (USGS). The VIIRS Day/Night Band monthly radiance data were obtained from the National Oceanic and Atmospheric Administration (NOAA). All image processing was carried out using Google Earth Engine, and the statistical analysis was performed using SPSS.

AI-Assisted Technologies Statement

Grammarly was used only for language editing to improve grammar and clarity. It was not used for the research design, data processing, analysis, interpretation, or scientific writing. All aspects of the study, including the methodology, coding, statistical analysis, interpretation of the results, and manuscript preparation, were carried out independently by the author. The author accepts full responsibility for the accuracy and integrity of the work.

Additional Materials

The following additional materials are uploaded at the page of this paper.

1. Figure S1: Spatial predictor variables used in the CA–ANN simulation of future LULC in Chennai: (a) DEM/elevation, (b) aspect, (c) slope, (d) hill shade, (e) contour, (f) curvature, (g) distance to stream, and (h) distance to railway.
2. Table S1: Spatial predictor variables used in the CA–ANN simulation.
3. Table S2: Quality-controlled verification statistics for the revised 2025 Landsat-derived LST and UTFVI surfaces used to verify the UTFVI formulation.

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