Predictive Modeling of Urban Heat Islands in Indian Cities: A Case Study of Jaipur city, Rajasthan, India

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Abstract

Rapid urbanization and the loss of vegetative cover in Indian cities have raised serious concerns about environmental sustainability and public health. This study focuses on analysing and forecasting Urban Heat Island (UHI) patterns in *Jaipur, India*, by examining both Surface UHI (SUHI) and Atmospheric UHI (AUHI). Using Google Earth Engine, the research integrates diverse spatio-temporal datasets—including Landsat-derived indices (such as LULC, NDVI, NDWI, NDBI, NDMI, albedo, and emissivity), geospatial features (building density, sky view factor, and population density), and meteorological data (air temperature, humidity, wind speed, and solar radiation) from 2000 to 2024—to train a Random Forest Regression model. The model demonstrated strong performance ($R^2 = 0.806$; RMSE = 0.059), surpassing linear and generalized additive models by effectively capturing complex, non-linear relationships. It also helped identify high-risk areas like Transport Nagar and Budhsinghpura. Projections for 2030 and 2035 indicate increasing heat stress, particularly in *Jaipur’s* expanding urban periphery. This GIS-integrated machine learning framework presents a replicable approach for UHI prediction in other fast-growing Indian cities.

1. Introduction

Urban Heat Islands (UHIs) represent one of the most pervasive microclimatic phenomena impacting contemporary cities worldwide. Characterized by elevated temperatures in densely built-up areas compared to their rural surroundings, UHIs arise from multiple interacting factors: extensive impervious surfaces (asphalt, concrete), reduced vegetation and soil moisture, heat emitted by buildings and transportation, and altered radiative balance due to low surface albedo (Oke, 1982; EPA, 2008). These localized warming effects not only exacerbate thermal discomfort and heat-related illnesses among urban residents but also drive-up energy consumption for cooling, worsen air pollution episodes, and undermine overall urban sustainability and resilience. Jaipur, the capital city of Rajasthan, exemplifies this trend: its expanding built environment and declining green cover have contributed to pronounced daytime and nocturnal UHI intensities, aggravating heat exposure for vulnerable populations (Joshi et al., 2019).

Despite an increasing number of descriptive studies mapping UHI hotspots using satellite-derived Land Surface Temperature (LST) and indices such as NDVI (Normalized Difference Vegetation Index) or NDBI (Normalized Difference Built-up Index), there remain critical gaps. Most analyses provide retrospective, seasonal, or annual snapshots, lacking the predictive capabilities needed for forward-looking urban planning. Moreover, few investigations incorporate the full suite of biophysical and meteorological drivers—such as building density, sky view factor, surface emissivity, solar radiation, wind speed, and humidity—that modulate both Surface UHI (SUHI) and Atmospheric UHI (AUHI) dynamics.

To address these shortcomings, this study develops an integrated predictive framework for UHI in Jaipur, leveraging Google Earth Engine for data processing and Random Forest Regression to capture complex, non-linear relationships among multi-source variables from 2000 to2024. Inputs include Landsat-derived LULC, NDVI, NDWI, NDBI, NDMI, albedo, emissivity, building density, sky view factor, population density, alongside meteorological records (air temperature, humidity, wind speed, solar radiation). The proposed model not only quantifies historical SUHI and AUHI patterns at the Municipal Ward level (Municipal Wards are the lowest level administrative boundary in Indian cities) but also forecasts intensities for 2030 and 2035, revealing emerging hotspots on the urban fringe. By providing high-resolution, actionable predictions, this approach equips policymakers and planners with early-warning insights to prioritize targeted mitigation—such as green infrastructure, reflective materials, and updated development regulations—and contributes a transferable methodology for evidence-based UHI management in rapidly urbanizing contexts.

2. Literature Review

A critical component of predictive modeling Urban Heat Island (UHI) is the identification of candidate variables that influence surface and atmospheric heating in urban environments. Past studies have widely recognized land surface temperature (LST) as the primary dependent variable for evaluating SUHI intensity Oke (1982), while a diverse array of explanatory variables has been employed across different geographies. Key among these are vegetation indices such as NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), and NDMI (Normalized Difference Moisture Index), which serve as proxies for green and water coverage and surface moisture (Kumar & Goyal, 2018; Pandey, Tiwari, & Jain, 2021). In parallel, built-up indices like NDBI (Normalized Difference Built-up Index) and metrics such as albedo, emissivity, sky view factor (SVF), and building density are used to characterize surface energy balance and morphological features (Gadgil & Padmakar, 2020; Suresh, Rao, & Mehta, 2022). Meteorological variables, including air temperature, wind speed, relative humidity, and solar radiation, are frequently integrated into atmospheric UHI (AUHI) models (EPA, 2008). These variables collectively capture the thermodynamic, radiative, and geometric aspects of urban environments, establishing a robust foundation for data-driven UHI modeling.

Several studies have examined UHI dynamics in *Jaipur* city, highlighting the city's vulnerability due to its semi-arid climate, rapid urban expansion, and low vegetation cover. Joshi et al. (2019) conducted a temporal assessment of LST using Landsat data and reported increasing SUHI intensity in core city areas such as *Mansarovar*, and the *walled city* zone. Similarly, Pandey et al. (2021) investigated the spatial distribution of UHI in *Jaipur* city and found that built-up density and lack of vegetation were significant drivers of heat accumulation. Studies by Goyal and Kumar (2018) and Sharma et al. (2020) emphasized the role of land use change in exacerbating thermal stress, with peri-urban expansion zones showing emerging hotspots. While these studies provided important insights into UHI distribution, most relied on static or descriptive approaches and did not employ predictive modeling frameworks capable of simulating future scenarios.

In recent years, machine learning models particularly Random Forest (RF) regression have gained prominence in UHI research due to their ability to handle high-dimensional, non-linear data relationships and their robustness against multicollinearity. RF models, as demonstrated in studies by Weng et al. (2020) and Tan et al. (2022), outperform traditional linear and generalized additive models in predicting LST and identifying UHI hotspots. By employing RF regression in *Jaipur* city, this research aims to fill a critical methodological gap by not only identifying significant predictors of UHI but also forecasting its future spatial extent.

3. Study Area: *Jaipur Nagar Nigam* (*Jaipur Municipal Corporation*)

This study is undertaken within the jurisdiction of the *Jaipur Municipal Corporation (JMC)*, located at approximately 26.91°N latitude and 75.79°E longitude at the western part of India (fig. 1). Jaipur, a Tier 1 city and the capital of Rajasthan, covers an area of approximately 484.64 km² and is home to over 3.7 million people as per 2019 estimates, with an urban population density of around 7,635 persons per km² (Directorate of Local Bodies, Rajasthan, 2020). Administratively, the city is divided into 250 wards, with varied land use patterns ranging from high-density commercial zones in the core to rapidly expanding residential and mixed-use developments in peri-urban areas. The city is at an elevation of 442 m above sea-level and is in the semi-arid region of the state, experiencing a hot and dry climate through most months of the year.

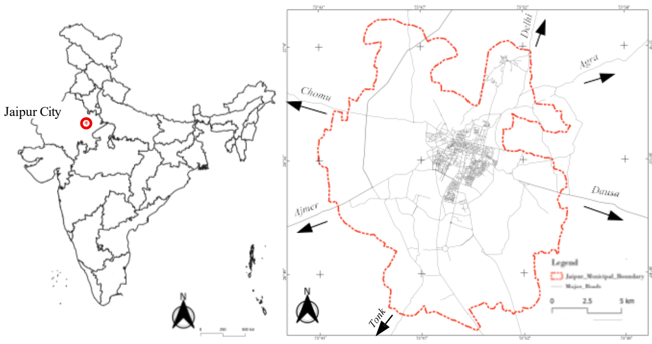

Figure 1. Location of the JMC in Rajasthan, India

Jaipur city was selected for this study due to its high vulnerability to Urban Heat Island (UHI) effects stemming from intense urbanization, reduced vegetation, and semi-arid climatic conditions. The city experiences extreme seasonal variation, with summer temperatures regularly exceeding 45°C and minimal rainfall averaging around 650 mm annually—conditions that exacerbate surface heating and reduce the natural cooling effect of vegetation and moisture. Moreover, the city's topography, characterized by a combination of flat plains and low-lying hillocks, influences local wind circulation patterns, which affect the dispersion of heat. Built-up areas such as *Transport Nagar, Sheopur,* and *Murlipura* exhibit dense construction, low sky view factors, and limited canopy cover, making them especially prone to heat accumulation.

The city's unique combination of arid climate, dense urban areas, and limited green spaces makes it an ideal case study for understanding UHI dynamics. Moreover, *Jaipur* city's diverse urban environment, ranging from historical heritage areas to modern urban sectors, presents an opportunity to explore the spatial variability of UHI and its mitigation strategies in a rapidly evolving context.
The declining green cover and growing expanse of impervious surfaces further contribute to the intensification of both Surface UHI (SUHI) and Atmospheric UHI (AUHI) effects. Given its diverse urban morphology and climatic extremes, *Jaipur* offers an ideal case to develop and test predictive models of UHI, assess spatio-temporal trends, and propose targeted mitigation strategies that are transferable to other rapidly urbanizing Indian cities.

4. Methodology

The methodology adopted in this research is structured around a multi-phase approach that aims to identify, understand, and predict Urban Heat Island (UHI) patterns in Jaipur. The process integrates satellite-based remote sensing data, meteorological datasets, geospatial analysis tools, and machine learning techniques to study both Surface UHI (SUHI) and Atmospheric UHI (AUHI). This comprehensive framework ensures that the study captures the complex interactions between climatic variables, urban morphology, and land surface dynamics that influence UHI intensities.

4.1 Identification of Candidate Variables

The first step in the methodology focuses on identifying the factors that contribute to the formation of Urban Heat Islands (UHI) in Jaipur city. Based on literature review on UHI, the key determinants influencing UHI intensity identified as land surface temperature (LST), Land Use and Land Cover (LULC), indices such as the Normalized Difference Vegetation Index (NDVI) and urban morphological characteristics. The identified variables serve as inputs for the modelling phase and ensure that the analysis captures the most significant contributors to UHI formation (table. 1).

Table 1. Identified Candidate Variables

Category	Variables	Description
LAND COVER	LULC	Urbanization increases heat retention,
	NDVI	Influencing natural cooling through
	NDWI	Highlights surface water availability.
	NDMI	Reflects soil and vegetation moisture.
	Albedo	Measures surface reflectivity.
	Emissivity	Ability to emit thermal radiation.
	LST	Direct indicator of the intensity of SUHI.
URBAN GEOMORPHOLOGY	Buildings	Determines Urban Compactness.
	Sky view factor	Quantifies Sky Openness.
	NDBI	Assesses built-up areas.
	Population Density	Population density measurement of population per unit land area.

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WEATHER STATIONS	Relative humidity	Affects thermal comfort and the intensity of heat stress.
	Wind speed	Affects natural cooling through wind flow.
	Wind direction	
	Incoming solar irradiation	Solar energy absorbed by urban surfaces.
	Air Temperature	Direct indicator of the intensity of AUHI.

4.2 Data Collection and Preparation

The data collection and preparation phase involved acquiring, processing, and organizing a wide range of spatial, climatic, and demographic variables essential for accurate UHI prediction in *Jaipur* city. Remotely sensed satellite data from Landsat 7 (2000–2012) and Landsat 8 (2013–2024) were used to derive key land surface indicators such as Land Use/Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Moisture Index (NDMI), Normalized Difference Built-up Index (NDBI), albedo, emissivity, and Land Surface Temperature (LST). Urban morphological variables including building density, sky view factor (SVF), and population density were collected from the Global Human Settlement Layer (GHSL), digital surface models, and Census data respectively (table. 2). All raster datasets were pre-processed using Google Earth Engine (GEE), which included atmospheric correction, cloud masking, temporal compositing, and standardization to a 30-meter spatial resolution. Climatic parameters such as air temperature, wind speed, relative humidity, and solar radiation for the period 2000–2024 were sourced from the Indian Meteorological Department (IMD) stations in *Jaipur* city. The tabular meteorological data was refined for outliers and missing values, and spatially interpolated using kriging interpolation to generate continuous raster surfaces aligned with the spatial resolution of satellite data (spatial resolution is of 30 meters).

Table 2 Data Checklist

Variables	Product	Time Period
LULC	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
NDVI	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
NDWI	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
NDMI	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
Albedo	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
Emissivity	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
LST	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
Buildings Density	GHSL	2000-2024
SVF	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
NDBI	Landsat 8 & Landsat 7	2000-2013 / 2013-2024
Population Density	GHSL	2000-2024
Air Temperature	IMD Jaipur	2000-2024
Relative humidity	IMD Jaipur	2000-2024
Wind speed	IMD Jaipur	2000-2024
Wind direction	IMD Jaipur	2000-2024
Solar Radiation	IMD Jaipur	2000-2024

4.3 Temporal Trend (2000-2024) of Surface and Air Temperature

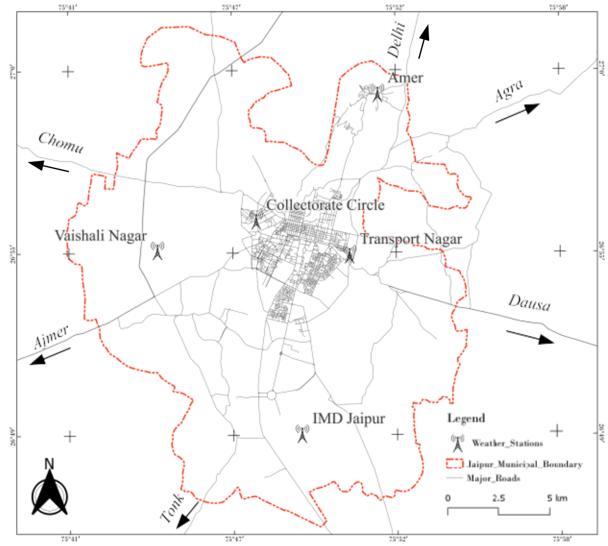

Figure 2 Weather Station Location within Jaipur city.

A temporal trend analysis of both Surface Temperature and Air Temperature was conducted at five representative locations within *Jaipur* city which are *IMD Jaipur (Airport)*, *Transport Nagar, Collectorate Circle, Vaishali Nagar,* and *Amer* (Fig. 3). Surface temperature data was derived using Google Earth Engine (GEE) from Landsat imagery, while air temperature records were obtained from the Indian Meteorological Department (IMD). The analysis revealed a consistent upward trend in surface temperatures across all sites, with the steepest increases observed in highly urbanized areas such as Transport Nagar and IMD Jaipur, indicating intense Surface Urban Heat Island (SUHI) effects. Comparatively, less urbanized, or peripheral zones like *Amer* exhibited relatively moderate increases, although air temperatures also rose in these regions, highlighting the spatial spread of Atmospheric Urban Heat Island (AUHI) effects. Notably, the gap between surface and air temperatures widened over the years, particularly in core city areas, emphasizing the role of urban morphology, impervious surfaces, and vegetation loss in intensifying localized heating (fig. 4).

These findings support the expansion of UHI phenomena across Jaipur and underscore the need for localized predictive modelling and mitigation strategies to address heat-related urban challenges.

4.4 Spatio-Temporal Analysis

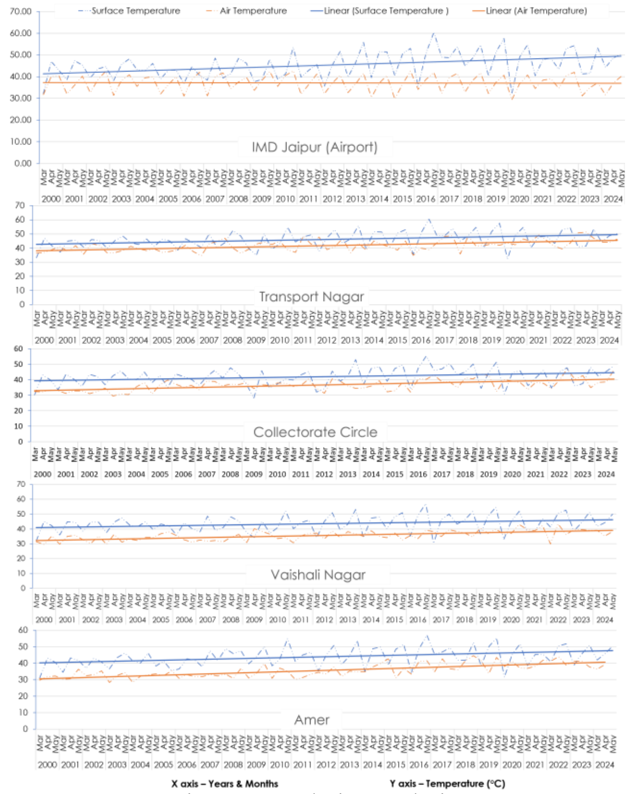

Figure 3 Trend Line Analysis

The spatio-temporal analysis provides an in-depth understanding of the spatial distribution and temporal evolution of key variables influencing Urban Heat Island (UHI) formation in *Jaipur* city between 2000 and 2024. This analysis was carried out for both land cover and climate variables using satellite imagery, meteorological data, and derived geospatial indicators. The land cover analysis reveals significant changes over time: built-up areas expanded considerably from 2000 to 2024, as evident in the LULC layers, while vegetation cover—measured by the Normalized Difference Vegetation Index (NDVI)—declined, the Land Surface Temperature (LST) showed a consistent upward trend, with Surface Urban Heat Island (SUHI) intensities becoming more pronounced in high-density zones.

These intensifying hotspots aligned spatially with areas experiencing rapid urban expansion and vegetation loss (fig. 4). In addition to land cover changes, the study examined several driving factors influencing UHI. Variables such as NDVI, NDMI, albedo, emissivity, sky view factor (SVF), NDBI, building density, and population density were mapped for the year 2024 to visualize their influence on heat accumulation. Low NDVI and high NDBI and Building Density were found to be associated with higher SUHI values. The sky view factor maps indicated lower openness (legend should be there showing low to high openness) in denser areas, reducing thermal dissipation and contributing to heat retention (fig. 5).

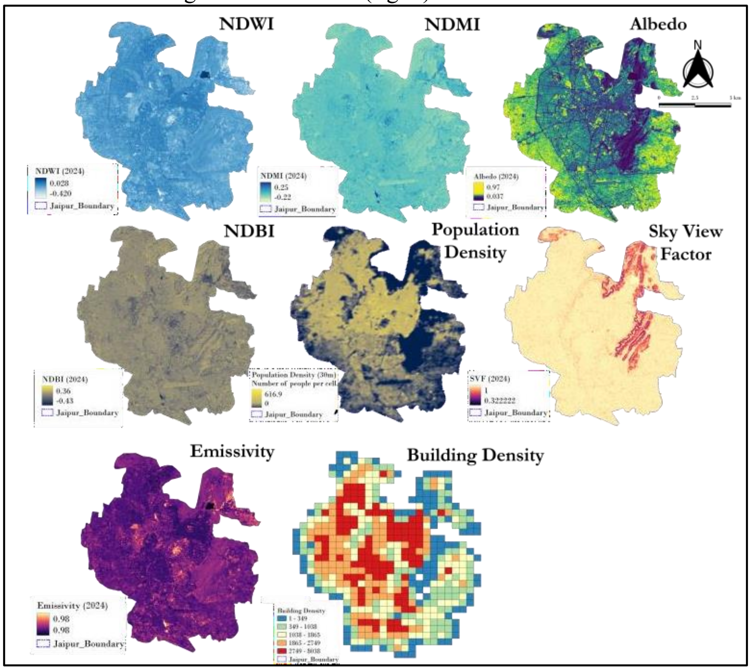

Figure 5 Mapping of Driving Factors (2024)

Climate variables—air temperature, wind speed, relative humidity, and solar radiation—were also analysed across the same time frame. Air temperatures have steadily increased, particularly in central and western zones, while wind speed and relative humidity showed spatial and temporal fluctuations. Solar radiation remained consistently high across *Jaipur* city, amplifying surface heating (fig. 6).

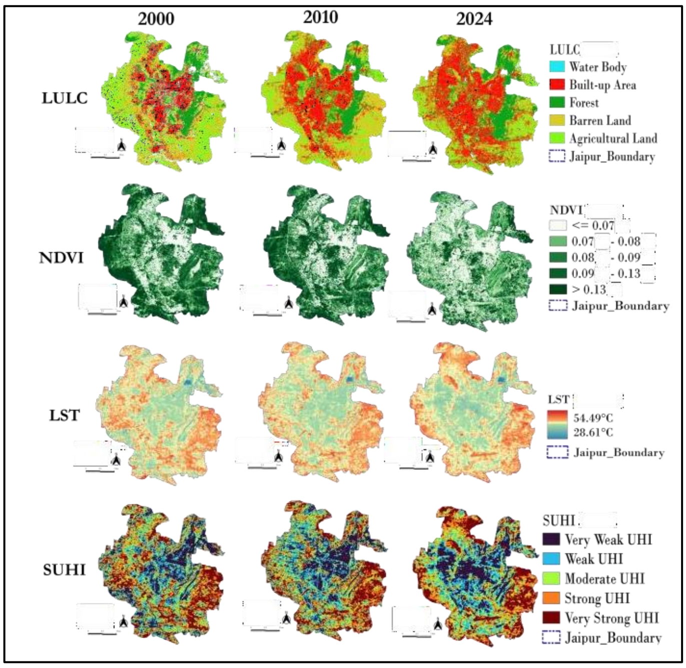

Figure 4 Spatio-temporal analysis of Land Cover Variables

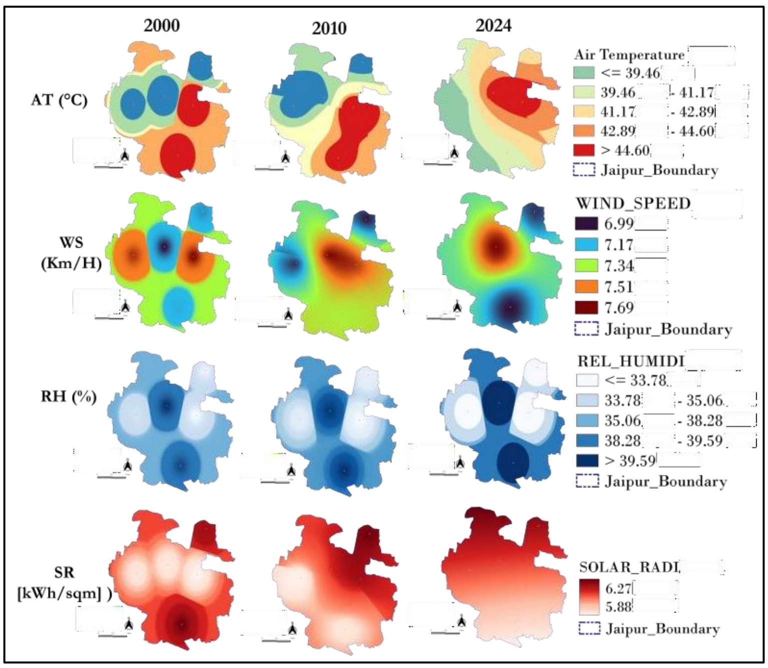

Figure 6 Spatio-temporal analysis of Climate Variables (Weather Stations)

5. Model Framework for SUHI Prediction Using Random Forest Regression

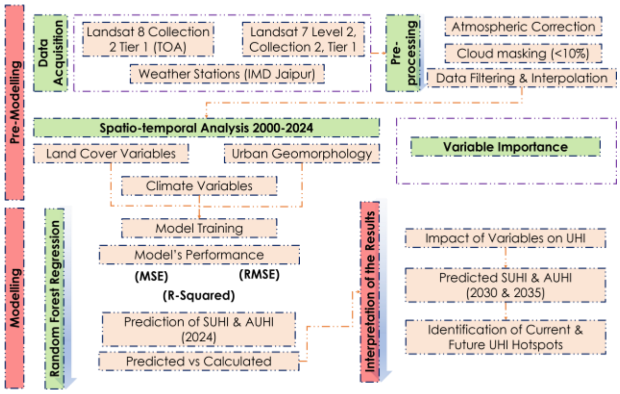

Figure 7 Schematic diagram of the workflow of the prediction model.

The workflow illustrated in fig. 7, represents the machine learning model architecture employed to predict future Surface Urban Heat Island (SUHI) patterns in Jaipur. A Random Forest (RF) regression approach was adopted due to its ability to handle nonlinear relationships, manage large and high-dimensional datasets, and deliver robust predictive performance even in the presence of multicollinearity among input features.

The first step in the model development involved the preparation of the training dataset, which was composed of a comprehensive set of explanatory variables derived from remote sensing products, climate data, and urban morphology indicators. These included Land Use/Land Cover (LULC), Land Surface Temperature (LST), vegetation indices (NDVI, PVI, EVI), water indices (NDWI, NDMI), albedo (AL), surface emissivity (Emiss), Surface Roughness Index (SRI), and Built-Up Density (BD). In addition, terrain, and climate-related parameters such as Elevation (Eliv), Sky View Factor (SVF), Normalized Difference Built-up Index (NDBI), Relative Humidity (RH), wind speed (WS), Incoming Solar Radiation (ISR), Air Temperature (AT), and population density (Pop) were incorporated. This multi-dimensional dataset ensured a holistic representation of both natural and anthropogenic influences on SUHI patterns.

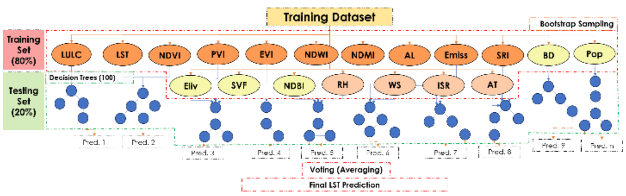

Figure 8 Prediction Model (Random Forest Regression).

The dataset was split into two subsets: 80% for model training and 20% for model testing. The training set was used to develop a Random Forest regression model consisting of 100 decision trees. Each tree was constructed using a bootstrap sample of the data, and the final prediction was obtained by averaging the outputs of all individual trees, thereby reducing overfitting and enhancing generalization capability. The tree-based structure allows the model to iteratively partition the input space based on the most informative features, resulting in a strong ensemble model capable of capturing intricate patterns in SUHI variation. During the training phase, each input feature was evaluated for its contribution to the model's predictive performance. Variables like LST, NDVI, NDBI, and BD typically emerged as influential predictors due to their direct relationship with surface temperature and urban morphology. The model captured spatial and temporal heterogeneity in urban environments, accounting for the varying roles of vegetation cover, impervious surfaces, terrain structure, and demographic stressors.

Once trained, the model was applied to the testing dataset, which constituted the remaining 20% of the samples. This phase served as a validation step to assess the model's generalizability and predictive accuracy. The performance of the model, as previously discussed, was evaluated using key regression metrics such as Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the R-squared (R^2) value, with results demonstrating high reliability and low error margins (table. 3).

Overall, this machine learning-based modeling framework presents a scalable and adaptable approach for predicting urban thermal patterns. By integrating multisource geospatial data and leveraging the strengths of Random Forest regression, the model provides a powerful decision-support tool for urban planners and policymakers aiming to assess future UHI risks and design mitigation strategies tailored to vulnerable urban neighborhoods.

6. Predicted Surface Urban Heat Island (SUHI) Distribution: 2030 and 2035

The spatial projections of Surface Urban Heat Island (SUHI) intensity for the years 2030 and 2035, as illustrated it (fig. 10), offer a comprehensive outlook on the evolving urban thermal environment in *Jaipur* city. These maps were generated using the trained Random Forest regression model, incorporating key land surface, climate, and urban morphological variables derived from remote sensing and meteorological datasets. The classification of SUHI intensity into five categories—Very Low (< -2.0 °C), Low (-2.0 °C to -0.5 °C), Moderate (-0.5 °C to 0.5 °C), High (0.5 °C to 2.0 °C), and Very High (> 2.0 °C) —allows for a granular interpretation of intra-urban thermal variation.

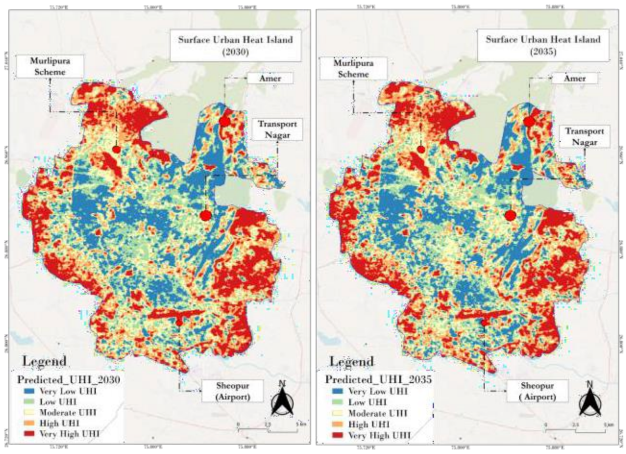

Figure 9 Predicted SUHI Maps (2030, 2035)

The 2030 prediction reveals a pronounced spatial concentration of high and very high SUHI intensity zones predominantly in the southern, central, and northwestern regions of *Jaipur* city. Notable hotspots include *Transport Nagar, Murlipura Scheme, Amer,* and the *Sheopur (Airport) area (fig.9)*. These zones correspond to areas with high built-up density, limited vegetation, and extensive impervious surfaces. The classification of *Transport Nagar (Ward 88)* under Local Climate Zone (defined as the regions that possess similar characteristics like surface cover, material, structure, and population activity) (EPA, 2008) (LCZ) 3 (Compact Low Rise) and *Sheopur (Ward 111)* under LCZs 5 and F (Open Mid-Rise and Bare/Open land) provides a morphological explanation for their elevated SUHI values. Such LCZs are typically associated with higher surface temperatures due to reduced evapotranspiration and increased anthropogenic heat emissions.

The projections for 2035 suggest an escalation in the spatial extent and intensity of UHI effects. Compared to 2030, there is a visible expansion of high to very high SUHI zones, particularly in the peripheral and semi-urban southern parts of the city. This spatial trend underscores the compounding impact of continued urban expansion and inadequate green cover on local microclimates (Fig. 10). The persistence of hotspots such as *Sheopur* and *Transport Nagar* over the five-year interval highlights the potential for chronic exposure to thermal stress in these wards unless mitigation measures are implemented.

Table 3 Regression Metrics

Name	Value	Results
MSE	0.00352	Very Low Error
RMSE	0.0594	Low Error
R-Squared	0.8059	Strong Correlation

The robustness of the predictive model is supported by the accompanying regression metrics. The model achieved a Mean Squared Error (MSE) of 0.00352 and a Root Mean Square Error (RMSE) of 0.0594, both indicating a low prediction error (table 3). Moreover, the R-squared value of 0.8059 reflects a strong correlation between observed and predicted values, affirming the model’s suitability for capturing complex spatial patterns of urban heat dynamics.

To inform targeted interventions, specific criteria were used to identify and prioritize vulnerable wards. Ward 88 (*Transport Nagar*) and Ward 111 (*Sheopur*) were selected based on their consistent exposure to high SUHI and AUHI intensities as well as their morphological characteristics. Additionally, Wards 18 and 20 in the *Murlipura Scheme* and Wards 1 and 2 in *Amer* have been flagged due to their susceptibility to increasing thermal stress (fig. 10). These insights can be leveraged by urban planners and policymakers for designing location-specific UHI mitigation strategies, including greening initiatives, land use zoning, and climate-sensitive urban design.

7. Variable Importance

The variable importance (Fig. 10) illustrates the relative contribution of each input feature in predicting the Surface Urban Heat Island (SUHI) intensity using the Random Forest regression model. The model incorporated a diverse set of predictors, categorized broadly into three thematic domains: climatic variables, land surface characteristics, and urban morphological parameters. The importance values have been normalized between 0 and 1, with higher values indicating greater predictive relevance in the model (fig. 10).

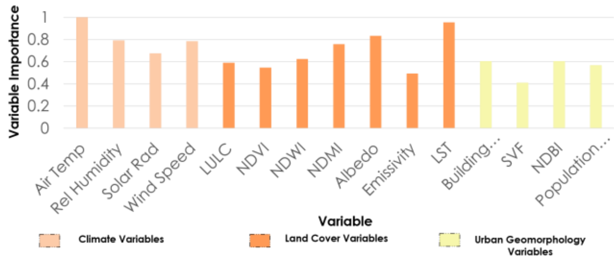

Figure 10 Variable Importance

Among all the variables, air temperature (AT) emerged as the most influential predictor with a normalized importance score of 1. This result is intuitive, as air temperature is directly related to the formation and intensity of SUHI phenomena. It strongly correlates with localized heat retention in urban areas, particularly during the late afternoon and nighttime periods. The other climatic variables—Relative Humidity (RH), Incoming Solar Radiation (ISR), and Wind Speed (WS)—also ranked high, with importance values close to or above 0.7. These variables influence heat exchange processes at the urban surface, affecting evapotranspiration rates, convective cooling, and atmospheric mixing, which are critical to urban heat dynamics.

In the second group, land cover variables such as land surface temperature (LST), NDMI, albedo, NDWI, and NDVI showed substantial importance. Notably, LST had a normalized importance score very close to 1, indicating its strong predictive power—given that it directly represents the spatial heat distribution on the surface and acts as a strong proxy for SUHI intensity. Albedo also demonstrated high relevance, underscoring the role of surface reflectivity in modulating absorbed solar radiation. Vegetation indices such as NDVI, NDWI, and NDMI contributed meaningfully, reflecting the cooling effects of vegetation and water availability through evapotranspiration and shading.

Variables related to urban morphology formed the third cluster. Here, Building Density (BD), sky view factor (SVF), Normalized Difference Built-up Index (NDBI), and population density exhibited moderate to strong importance. NDBI and building density scored similarly to land surface indices, emphasizing the contribution of impervious surfaces and compact urban forms in heat retention. SVF, with a lower importance value, still holds relevance due to its connection with the ability of urban canyons to radiate longwave energy at night. Population density, although slightly lower in importance than building density, signifies the anthropogenic influence on heat generation due to human activities and energy consumption.

Overall, the variable importance Fig. 11 underscores the multifactorial nature of SUHI formation, where both physical landscape characteristics and human-induced factors contribute jointly. The results also validate the utility of integrating multispectral remote sensing indices with socio-environmental datasets in machine learning-based predictive models. These insights not only improve model interpretability but also aid urban planners in identifying priority variables for mitigation strategies, such as increasing vegetation cover, modifying built form design, or implementing reflective surface materials.

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8. Conclusion and Wider Implications

This study presents a comprehensive assessment and predictive modeling framework for understanding the dynamics of Urban Heat Islands (UHI) in Jaipur, integrating multi-source spatial and climatic data with machine learning techniques. Through detailed spatio-temporal analysis across the years 2000 to 2024, the study has identified a consistent rise in both Surface Urban Heat Island (SUHI) and Atmospheric Urban Heat Island (AUHI) intensities, especially in high-density, low-vegetation zones such as *Transport Nagar, Sheopur* (Airport), and parts of the Walled City. The correlation between rapid urbanization, declining green cover, and increasing land surface temperatures was clearly established using variables such as LULC, NDVI, building density, and air temperature. The Random Forest Regression model employed for prediction showed high accuracy ($R^2 = 0.806$), validating its robustness in handling non-linear and multi-dimensional datasets.

The predictive modelling component of the study effectively forecasted future UHI intensities for 2030 and 2035, revealing spatial expansion of hotspots toward peri-urban zones. This highlights the urgent need for urban planners and policymakers to incorporate heat resilience into development plans. ENVI-met microclimate simulations further demonstrated the potential of mitigation strategies like increased urban vegetation, green roofs, and reflective surfaces in reducing both daytime and nighttime temperatures at the neighborhood scale.

Wider implications of this research extend to sustainable urban governance across Indian cities. The integrated use of GIS, remote sensing, and machine learning provides a scalable and replicable framework for UHI prediction and mitigation, especially in rapidly urbanizing regions. By identifying localized hotspots and quantifying the influence of physical and atmospheric variables, this study offers actionable insights for climate adaptation, public health protection, and energy efficiency. Furthermore, the methodology can be adapted to other climatic zones and urban typologies, supporting India's broader climate resilience and smart city initiatives.

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