Digital Twin for Climate-Resilient Urban Planning: Modeling and Mitigation of Urban Heat Islands

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Abstract

Urbanization and climate change are rapidly transforming metropolitan environments, posing serious challenges to sustainable development, climate resilience, and disaster risk management, Among these challenges, concern, where built up areas experiences higher temperatures than surrounding rural regions due to increased impervious surfaces, vegetation loss and altered urban morphology. As UHI intensifies heatwave impacts and public health risks, advanced tools are required to monitor, simulate and mitigate urban heat dynamics. This Study analyses the spatio-temporal evolution of Land Surface temperature (LST) and UHI intensity in Bengaluru for 2004 to 2024 using multi-temporal Landsat data. Key surface indicators include, NDVI, NDBI, NDWI, albedo ad LULC were derived to assess thermal behaviour. Results indicate rapid built-up expansion and declining vegetation, leading to the regression predicts 1-2 °C increases in LST by 2023 in highly urbanized areas.
To support urban climate decision making, a 3D Digital Twin platform was developed using CesiumJS, integrating geospatial analysis, remote sensing, and predictive simulations. The framework demonstrates the potential of Digital Twins as an effective decision-supportive tool for climate-adaptive and sustainable urban planning.

1. Introduction

Rapid urbanization coupled with climate change is transforming metropolitan environments, creating complex challenges for urban sustainability, environmental management, and public health. One of the most critical consequences of accelerated urban growth is the Urban Heat Island (UHI) effect, wherein urban areas exhibit significantly higher temperatures than their rural surroundings (Renard *et al.*, 2019).This phenomenon arises due to the expansion of impervious surfaces, reduction in vegetation cover, dense built structures, and modifications in urban morphology, all of which disrupt the natural urban energy balance(Lin Liu and Yuanzhi Zhang, 2011) . As a result, UHI intensifies heat related hazards, increases disaster vulnerability, and exacerbates public health risks particularly in rapidly growing cities(Mohammad *et al.*, 2025).

Urban growth in India has contributed to a substantial rise in near-surface temperatures across many cities. The expansion and increasing scale of urban areas significantly alter local climate patterns and their long-term evolution. Research conducted in major metropolitan centres such as Chennai, Bengaluru, Delhi and Pune consistently demonstrates marked temperatures increases linked to urban development(Yadav and Singh, 2024).

1.1 Urban Heat Island

Urban Heat Island (UHI) refers to the climatic condition in which urban areas exhibit significantly higher temperatures than their surrounding rural regions, with the contrast often being more pronounced during night time(Lin Liu and Yuanzhi Zhang, 2011). Rural landscapes dominated by vegetation and exposed soil promotes heat dissipation through evapotranspiration, whereas the loss of urban green spaces significantly reduces this cooling effect. Dense high-rise developments create urban canyon effects that trap heat and restrict airflow(Yang *et al.*, 2016).
This phenomenon results from a combination of anthropogenic activities and environmental modifications associated with urbanization(Yadav and Singh, 2024). Heat emission from transportation, industry and air-conditioning further intensifying urban warming. Urban Surfaces such as asphalt, concrete, rooftop and building materials possess high thermal inertia, enabling them to absorb substantial solar ration during daytime and gradually releases the stored heat at night, thereby inhibiting effective nocturnal cooling(Agnihotri, 2018).

Land Surface Temperature (LST) is widely used indicator for assessing UHI intensity using remote sensing techniques(Omrany and Al-Obaidi, 2024). Satellite data from platforms such as Landsat and Sentinel provide spatio-temporal information on thermal patterns and surface characteristics including vegetation, built-up areas waterbodies, and albedo. Strong correlation between impervious surfaces and elevated temperatures highlight the need for advanced, predictive, and scenario-based approaches for urban heat mitigation(Lin Liu and Yuanzhi Zhang, 2011).

1.2 Digital Twin

A Digital Twin (DT) is a virtual representation of a physical system that integrates multi-source data to replicate its real world sate and behaviour, originating form product life-cycle management application(Jones *et al.*, 2020). By combining sensor data, analytics and simulation capabilities, DTs enable real-time monitoring, analysis and decision support(Sukma, Koeva and Reckien, 2024). While initially applied in manufacturing, Digital Twin technology has expanded into geospatial and urban domains, where it represents not only the geometry but also the dynamic behaviour and temporal evolution of complex environments. An Urban Digital Twin provides a virtual replica of city component, enabling the simulation and evolution of scenario-based urban processes(Cárdenas-león *et al.*, 2024).

Digital Twin Technology is widely adopted across multiple sectors, including aerospace and automotive engineering for performance optimization and predictive maintenance, healthcare for personalized treatment and system testing, and infrastructure management, and citizen engagement. By integrating GIS, IoT, artificial intelligence, and immersive visualization technologies, Digital Twins offer a data-driven framework for analysis, forecasting and optimization(Omrany and Al-Obaidi, 2024).

For urban climate applications, digital twins provide a transformative platform by inegrating remote sensing data, geospatial analytics, machine learning predictions, and 3D visualization environmnets. Unlike static GIS models, DTs are dynamic and interactive, alowing simulation of future development scenarios and assessment of mitigation stratgies(Luo and He, 2024). In the contect of urban Heat island studies, a DT-based framework enables continous thermal monitoring, identification of vulnerable zones, evaluation of planning alternative, and informed decsion-making for climate-adaptive and sustainable urban development(Afzalinezhad, 2024).

This study aims to develop a Digital twin based framework for climate-resilient urban planning by modeling the spatial and temporal dynamics of Urban Heat Island (UHI), identifying heat hotspots, and evaluating mitigation strategies to reduce urban heat stress and support sustainable, climate-adaptive city development. The objective is to identify factors contributing to urban heat stress and quantify them, then identify hotspot using DT model and understand distribution of heat pattern later predict future LST and UHI hotspots using Machine Learning for the next 10^{th} (2034) year.

2. Study Area

Bengaluru is one of the fastest growing metropolitan cities in India and has experiences rapid transformation in past two decades, transition from a relatively cooler “Garden City” to a densely built, heat retaining region due to significant reduction in green cover and water bodies, altered land surface morphology, and intensified local temperatures(Ambinakudige, 2011). The resulting heterogeneous urban fabric exhibits pronounced spatial thermal contrasts, making Bengaluru a critical case study for urban heat stress analysis.

Bengaluru, the capital of Karnataka is situated in Deccan Plateau at an elevation exceeding 900m above mean sea level, the city historically experienced a moderate climate supported by extensive green space. Bengaluru cover approximately 741 km^2 and had a population of about 10.46 million as per the 2001 census. Despite ranking highly in national liability and economic productivity indices, rapid and largely unplanned urban expansion has placed increasing pressure on the city’s thermal environment, underscoring the need for advanced geospatial and predictive approaches to support climate-resilient urban planning.

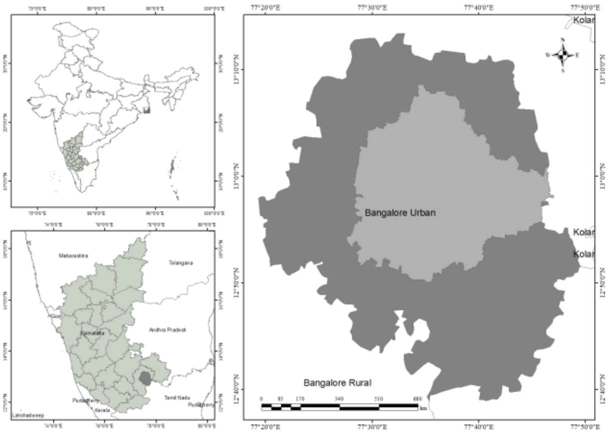

Figure 1. Location of the study area - Bengaluru

3. Materials and Methodology

3.1 Materials

This research utilizes two categories of datasets: spatial data and non-spatial data. The spatial datasets comprise satellite imagery and city boundary layers, while the non-spatial datasets include meteorological variables and urban morphological information. Multi-temporal satellite imagery from Landsat 8-9 OLI/TIRS Level-1 was employed at five-year intervals covering the period 2004-2024, along with Digital Elevation Model (SRTM - DEM) obtained from the USGS repository. Administrative and urban boundary shapefiles were sourced from official government portals ad open-access geospatial database. The non-spatial components consists of atmospheric parameters, including air temperature, relative humidity and wind speed at 2 meter, retrieved form the NASA POWER database. In addition, urban fabric characteristics were collected through field –based site surveys to capture local morphological features. Together, these integrated datasets support a comprehensive spatial-temporal assessment of urban thermal dynamics.

Table 1 Data sets

Category	Data Set	Data	Source
Spatial Data	Satellite Data	Landsat (5, 8, 9)	USGS Earth Explorer https://www.usgs.gov/
		DEM (30 meter resolution)	
	City Shapefile	Building Footprints & Road Network	Open source / Digitization
Non-Spatial Data	Meteorological data	Temperature (at 2 meter)	NASA POWER https://power.larc.nasa.gov/
		Humidity (at 2 meter)	
		Wind Speed (at 2 meter)	
	Urban Morphology	Urban Fabric Components	Open source

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3.2 Methodology

The objective of this research is to identify hotspots using DT model and predict future LST and UHI hotspots using Machine Learning for the next 10th year. This research is grounded in a comprehensive review of existing research to identify the key factors influencing Urban Heat Island(UHI) formation and to evaluate datasets and analytical methods used to examine relationships among urban, environmental and climate variables. Building on this foundation, the study integrates multi-source spatial data and non-spatial data to analyse IHI dynamics and project future Land Surface Temperature (LST). A digital Twin based framework combined with machine learning techniques is employed to model present conditions, validate inert-variable relationships, and simulate future urban thermal scenarios. This integrated approach demonstrates how digital Twin technology can be effectively coupled with predictive analytics to support long-term, climate-responsive urban planning.

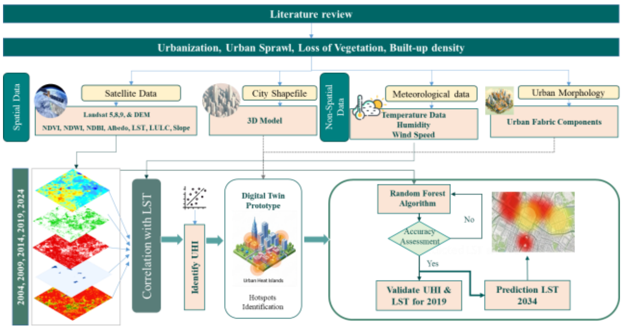

Figure 2 Methodological flowchart

3.3 Pre-processing and Variable Generation

3.3.1 *Land Use Land Cover (LULC)*

Land Use and Land Cover (LULC) describes both how land is utilized for human activities such as residential, industrial, or agricultural purposes and the physical features present on the surface. LULC is a fundamental indicator for analysing land transformation, patterns of urban growth, and environment change over time. In this study, LUC information is derived from multi-temporal Landsat imagery using Google Earth engine and a supervised classification approach. The study area was categorized into vegetation, waterbodies, built-up areas, agricultural land and barren land. Classification accuracy was evaluated 2004-2024 with five-year intervals, and the Kappa statistic was calculated to assess the reliability and performance of the land cover map.

3.3.2 *Spectral Indices*

Normalized Differential Vegetation Index (NDVI)
NDVI reflects vegetation health by comparing how much red and near-infrared light a surface absorbs and reflects. Hgher NDVI values indicate healthier, denser vegetation.

$$NDVI = \frac{NIR - RED}{NIR + RED}, \qquad (1)$$

Normalized Differential Built-up Index (NDBI)
NDBI highlights built-up urban areas by measuring the reflectance difference between short-wave infrared and near-infrared light. Higher NDBI values corresponds to stronger urbanization and impervious surfaces.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}, \qquad (2)$$

Normalized Differential Water Index (NDWI)
NDWI detects surface water by analysing the difference between green and near-infrared reflectance. Positive NDWI values typically represents water rich or moisture areas

$$NDWI = \frac{GREEN - NIR}{GREEN - NIR}, \qquad (3)$$

3.3.3 *Albedo*

Albedo refers to the fraction of incoming solar radiation reflected by a surface. Surface with low albedo absorb more heat, contributing to higher Urban Heat Island intensity.

$$\alpha = \frac{(0.356 * B2 + 0.130 * B4 + 0.373 * B5 + 0.085 * B6 + 0.072 * B7 - 0.018)}{1.016}, \qquad (4)$$

3.3.4 *Land Surface Temperature (LST)*

Land Surface temperature refers to the radiative temperature of the Earth's surface as measured by satellite materials add indicates how different land-cover types such as vegetation, water bodies, and built-up areas absorb, store and release heat. As a key indicator in urban climate studies, LST is widely used to assess spatial thermal variations and to qualify the intensity of Urban Heat Island (UHI) effects. LST was computed using following step;

1. Top-of-Atmosphere (TOA) radiance

$$TOA\ (L) = ML * Qcal + AL, \qquad (5)$$

Where,
ML = Band-specific multiplicative
Qcal = corresponds to band 10.
AL = Additive rescaling factor

2. Brightness Temperature (BT)

$$BT = (K2 / (\ln (K1 / L) + 1)) - 273.15, \qquad (6)$$

Where,
K1 = Band-specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x, where x is the thermal band number).
K2 = Band-specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x, where x is the thermal band number).
L = TOA

3. NDVI

$$NDVI = \frac{NIR - RED}{NIR + RED}, \qquad (1)$$

4. Proportion of Vegetation (P_v)

$$NDVI = \left(\frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{\min})}\right)^2, \qquad (7)$$

5. Emissivity

$$\varepsilon = 0.004 * P_v + 0.986, \qquad (8)$$

Where,

P_v – Proportion of Vegetation

Land Surface Temperature

$$LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon))), \quad (9)$$

Where,

BT – Brightness Temperature

ε - Emissivity

3.3.5 *Slope and Elevation*

Slope and Elevation derived from the SRTM DEM taken from USGS, which represent terrain variability and height above mean sea level.

3.4 Limitations

This research has few limitations that should be acknowledged. The analysis primarily focuses on outdoor Land Surface Temperature and urban heat patterns and therefore does not account for indoor thermal comfort, in addition the study does not incorporate demographic, socio-economic factors.

4. Results and Discussion

4.1 LULC Classification

Land Use-Land Cover (LULC) classification was carried out using a supervised approach with manually generated training samples for five classes: vegetation, cropland, built-up areas, water bodies, and barren land. Spectral signatures were extracted from Landsat imagery, and the datasets was divided into 70% training and 30% validation samples. A Random Forest classifier with 300 trees was implemented to generate LULC maps for the year 2004, 2009, 2014, 2019, and 2024.
Classification accuracy was evaluated using a independent validation set through confusion matrices, overall accuracy, producer's and user's accuracy and the Kappa statistic to ensure classification reliability. Pixel-Based area estimation was performed to quantify land-cover extent.

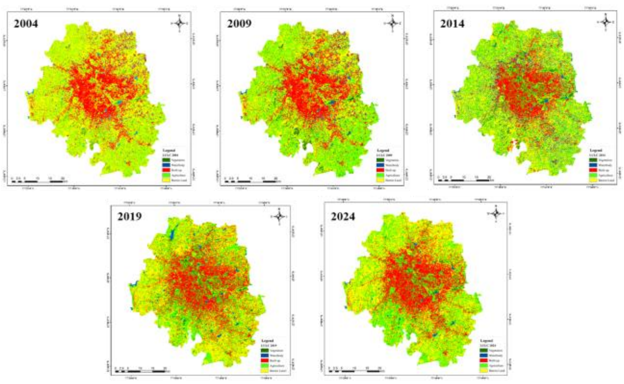

Figure 3 Land Use Land Cover Classification

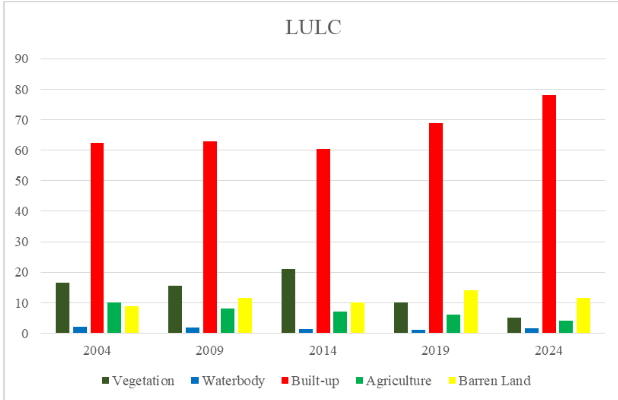

Figure 4 LULC

LULC analysis from 2004 to 2024 revels a study and accelerating expansion of built-up areas, increasing from approximately 62% to nearly 78% indicating sustained urban growth. This expansion is accompanied by a continuous decline in vegetation and agricultural land, reflecting the progressive loss of green cover and conversation of productive and open lands to urban uses. Waterbodies remain largely stable with minor pronounced changes occurred between 2014 and 2024, when built-up land increased sharply form 58.08% to 70.28% and vegetation and agricultural areas declined substantial, highlighting intensified urbanization and significant reduction of natural land-cover classes.

4.2 Spectral Indices

Spectral indices derived from satellite reflectance data were used to characterize surface conditions related to vegetation, built-up areas, water bodies, and surface reflectance. In this study, NDVI, NDWI, NDBI and Albedo were calculated from which a trend analysis of these indices indicates a substantial transformation of the urban surface environment over time. NDVI exhibits an overall declining trend, reflecting long-term vegetation loss associated with urban expansion, while NDWI shows a temporary decline followed by partial recovery, suggesting localized waterbodies and wetland restoration(CDD, 2023). Concurrent increases in built-up intensity and albedo confirm the expansion of impervious surfaces, which enhances heat storage and contribute to increase urban thermal accumulation

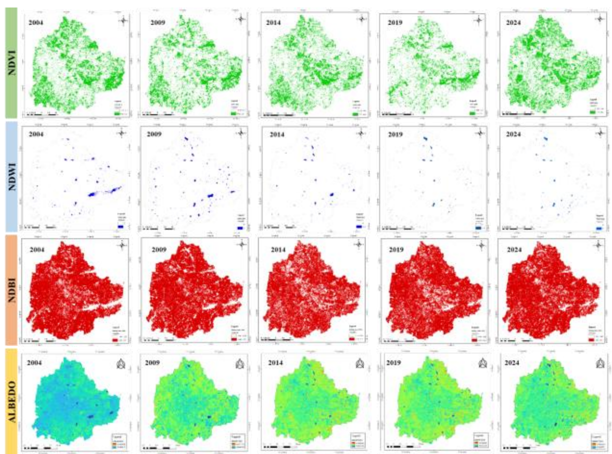

Figure 5 NDVI, NDWI, NDBI and Albedo changes from 2004-2024

4.3 Land Surface Temperature (LST)

Lad Surface Temperature analysis indicates a strong link between urban expansion and rising thermal intensity across the study area. The increase in built-up surfaces, particularly along major transport and development corridors, has enhanced heat absorption and storage, while the loss of vegetation and water bodies has reduced natural cooling through reduction in LST was observed in 2014, a sharp rise of nearly 10°C occurred by 2019, corresponding with rapid urban growth and extensive surface sealing. By 2024, a moderate decline in temperatures was evident, likely reflecting the positive impact of lake restoration, increased green cover, and urban cooling initiatives. These findings underscore the critical role of land cover composition in regulating urban thermal environments and highlight the effectiveness of green and blue infrastructure in mitigating urban heat stress.

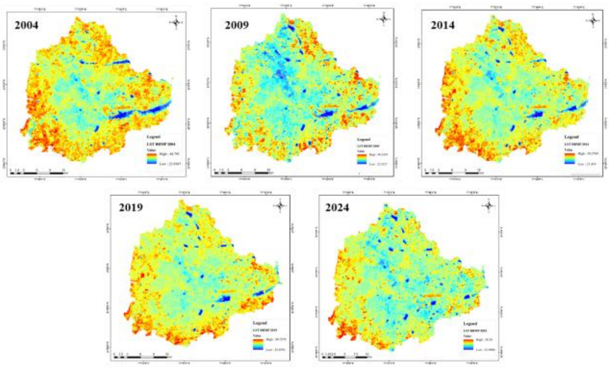

Figure 6 Land Surface Temperature

4.4 Multi-Linear Regression

Linear Regression was used to examine how Land Surface Temperature (LST) responds to variations in land surface characteristics. Random samples (n=1470) collected across the BBMP region were analysed for multiple years between 2004 and 2024 using NDVI, NDBI, NDWI and albedo as explanatory variables. The results indicate a moderately strong relationships, with R2 values ranging from 0.59 to 0.66. NDVI and NDWI show negative coefficients, confirming the cooling influence of vegetation and surface moisture, while NDBI and albedo exhibit positive relationships with LST, indicating increased temperatures over built-up and reflective surfaces. These trends are consistently supported by regression plots and spatial sample distributions.

Table 2 Multi Liner Regression

Year	R^2	Coefficients			
		NDVI	NDBI	NDWI	Albedo
2004	0.664	-25.17	16.25	-33.00	3.33
2009	0.587	-13.00	19.21	-19.86	7.46
2014	0.606	-21.36	12.02	-27.68	3.51
2019	0.638	-16.39	17.89	-25.31	2.61
2024	0.636	-17.35	16.14	-23.59	5.96

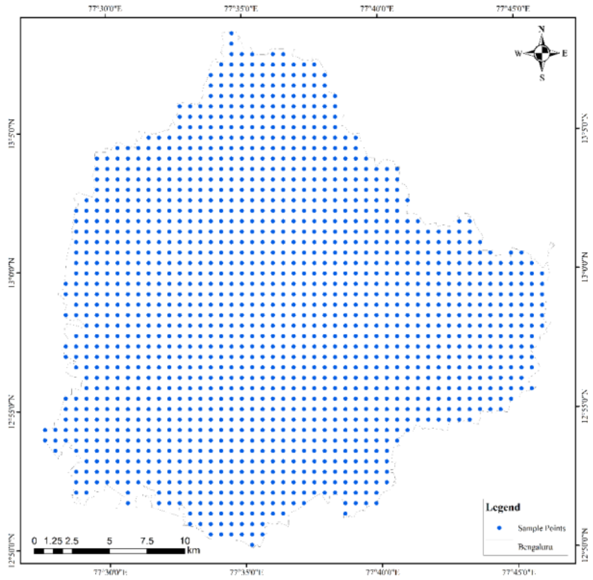

Figure 7 Sample Points used to perform Multi-linear regression

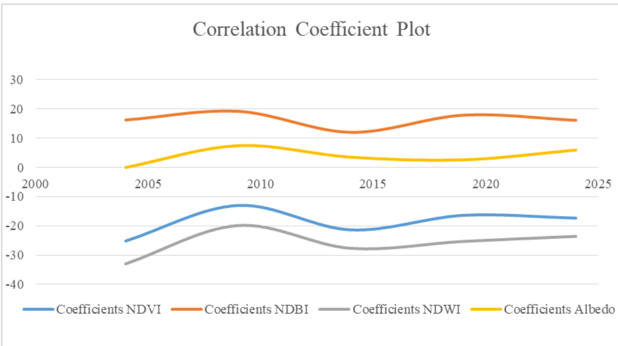

Figure 8 Correlation Coefficient Plot

4.5 Hotspot Detection

Hotspot detection was based on LST, four locations were identified Hotspot 1 – HAL – Industrial Area, Hotspot 2 – Singasandra – Urban Sprawl and IT zone, Hotspot 3 – Nagarbavi – Developing transport corridor, Hotspot 4 - Venkatapura Kushal Nagar – Core city. The hotspot detection was supported by the Digital Twin model of the Bengaluru city to understand the Built form and examining spatial variations of surface temperature across these locations.

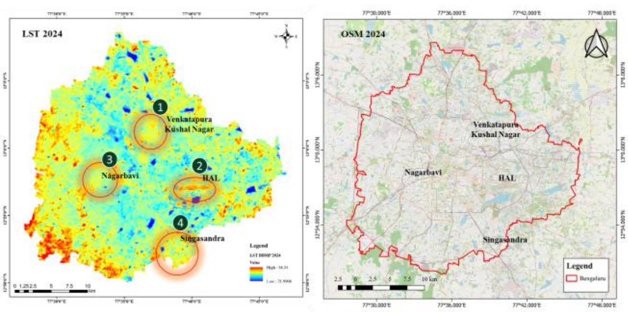

Figure 9 Identified Hotspots in the study area

4.6 Digital twin Platform

A Digital Twin System was developed using CesiumJS by combining three dimensional urban models with time-series Land Surface Temperature (LST) data. The Cesium viewer was configured with global terrain and camera settings to focus on the Bengaluru metropolitan area. Building footprints obtained from OpenStreetMap were imported and rendered as extruded 3D structures to represent the city's built environment. Multi-temporal LST layers spanning 2004-2024 were uploaded to Cesium Ion, assigned asset IDs, and integrated as selected raster overlays within the platform.
A user-friendly interface designed using HTML and CSS enables interactive control of map layers, 3D buildings, and temperature information. Temporal dynamics were visualized through an animation module that cycles through LST layers, allowing users to observe heat evolution over time, pause the sequence, and examine specific years. The developed platform facilities interactive exploration of urban thermal patterns, hotspot visualization, and long-term comparison of surface temperatures, functioning as a geospatial Digital Twin to support urban environmental analysis and planning.

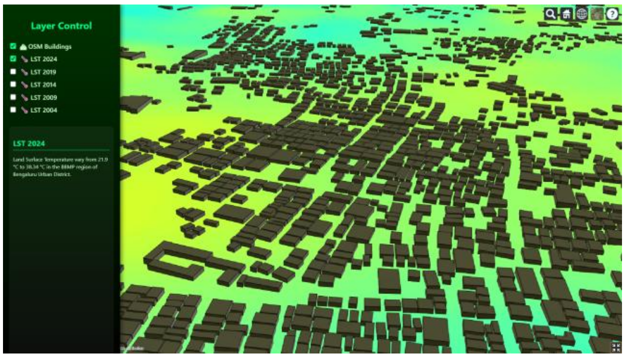

Figure 10 Digital Twin Platform

4.7 Prediction of Land Surface Temperature for 2034

To understand how changing temperatures can extensively impact urban environments in the future due to the changing urban factors there is a need to predict the changes in temperature. The random forest model has been adapted to predict the LST for the next 10th year i.e. 2034. Required libraries are imported then all the raster files are read, aligned and stored as a dataset. Pixel samples are extracted from the stacked raster layers and converted into training arrays. The Random Forest regression model is trained using these samples, with surface parameters which include NDVI, NDBI, NDWI, Albedo, LULC, DEM, Slope and Road Network are the predictor variables whereas observed LST as the target variable. Once trained, the model is applied across the entire raster grid to generate spatially continuous LST predicted LST raster files, enabling spatial analysis and visualization of future thermal patterns.

Based on the results of this study, future Land surface Temperature (LST) projections indicate a clear intensification of urban thermal conditions across the study area. Existing heat hotspots are expected to experience further temperature increase, reinforcing their vulnerability to heat stress. At the same time, areas that currently exhibit relatively lower temperatures are also projected to warm by approximately 1-2 °C, indicating a spatial expansion of heat stress beyond present-day hotspots.

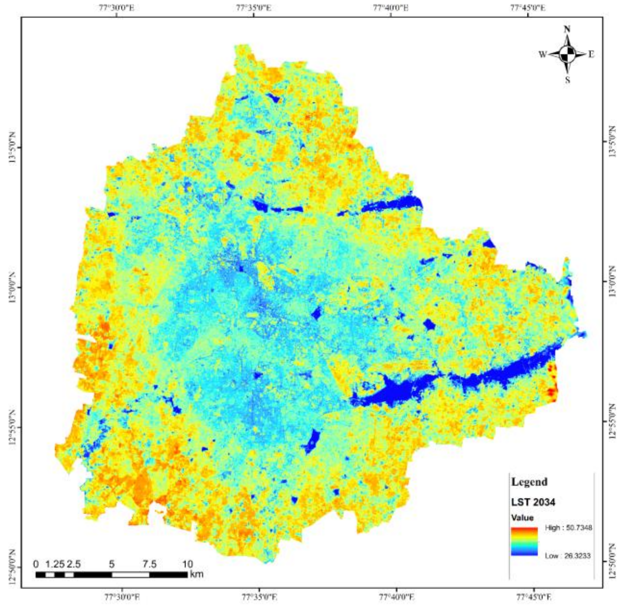

Figure 11 Land Surface Temperature of 2034

This widespread warming reflects continued urban expansion, increased impervious surface coverage, and reduce effectiveness of natural cooling mechanisms. The findings suggest that without targeted mitigation measures, thermal discomfort and heat related risks are likely to intensify across both high and moderate temperature zones, emphasizing the need for proactive climate-adaptive urban planning.

5. Conclusion

This study highlights the significant impact of rapid urbanization on the intensification of Urban Heat Island (UHI) effects in Bengaluru. Multi-temporal analysis reveals that the expansion of impervious surface and the decline in vegetation have disrupted the city's surface energy balance, leading to a steady rise in Land surface temperature (LST) and the formation of distinct urban heat hotspots. The strong relationships observed between LST and Land-cover indicators confirm the cooling role of vegetation and waterbodies and the warming influence of dense built-up areas.
The integration of a Digital Twin platform with machine learning based LST prediction provides an advanced and interactive framework for understanding both current and future urban thermal conditions. Projection for 2034 indicate an expansion and intensification of heat stress across the city, extending beyond existing hotspots. These findings emphasize the urgent need for climate-responsive urban planning that promotes green and blue infrastructure and informed land-use management to enhance urban thermal resilience and long term sustainability. Future research can incorporate socio-economic and demographic factors to better capture population vulnerability, and can be further extended to evaluate indoor thermal comforts. The study could also extended on addressing the indoor thermal comforts of specific neighbourhoods for a more holistic understanding of urban heat impacts.

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