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Assessing the Relationship between Urban Heat Island Intensity and Heat-Related Health Outcomes in Lucknow City: A Geospatial and Epidemiological Analysis (2000-2025)

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ABSTRACT

This comprehensive study investigates the spatial and temporal dynamics of the Urban Heat Island (UHI) effect in Lucknow city and its quantifiable impact on heat-related health outcomes. Utilizing a multi-scale, data-centric methodology, the research integrates geospatial data (Landsat 5, 8, and 9 satellite imagery for Land Surface Temperature (LST) and Land Use/Land Cover (LULC) analysis) with epidemiological health records from 2000 to 2025. The study area was gridded at a 120m x 120m resolution, generating over 38,000 data points for statistical analysis. Results indicate a significant increase in the mean summer LST from 38.4°C in 2000 to 42.7°C in 2025, with UHI intensity (ÄT$_{urban-rural}$) peaking at 5.2°C in the densely built-up Central and Gomti Nagar zones. A strong positive correlation ($R^2 = 0.87$) was established between LST and the incidence of heat-related illnesses (HRIs), including heat stroke, dehydration, and cardiovascular stress. Multilinear regression models identified built-up density and green cover loss as the primary drivers of UHI, accounting for 74% of the variability in health outcome incidence. Scenario-based mitigation modelling suggests that a 30% increase in urban vegetation cover could reduce peak LST by up to 2.1°C, potentially decreasing heat-related morbidity by an estimated 18-22%. This paper provides a robust, evidence-based framework for urban planners and public health officials to prioritize interventions, contributing to the discourse on climate-resilient and healthy city design.

KEY WORDS

Urban Heat Island (UHI), Land Surface Temperature (LST), Heat-Related Illnesses (HRIs), Geospatial Analysis, Mitigation Strategies, Remote Sensing.

INTRODUCTION

The Urban Heat Island (UHI) effect, characterized by significantly higher temperatures in urban areas compared to their rural surroundings, is a critical anthropogenic climate modification (Oke, 1982). As global urbanization accelerates, UHI intensity is exacerbating, leading to increased energy consumption, elevated pollution levels, and severe public health risks (Santamouris, 2020). Lucknow, the capital of Uttar Pradesh, India, has undergone rapid and often unplanned urban expansion over the last three decades. Its population has surged from approximately 2.2 million in 2001 to over 3.6 million in 2021 (Census of India), placing immense pressure on its natural landscape and thermal environment.

Heat-related illnesses (HRIs), ranging from mild heat exhaustion to fatal heat strokes, are a direct consequence of prolonged exposure to extreme heat. Epidemiological studies have established a link between high ambient temperatures and increased mortality and morbidity (Gasparrini et al., 2015). However, within cities, this risk is not uniform; it is intricately linked to the micro-climate created by urban form, materials, and land cover. Despite Lucknow's designation as a "heatwave-prone" city, a comprehensive, data-driven analysis linking intra-urban temperature variations (UHI intensity) with localized health outcomes remains absent.

Research Gap and Objectives

Existing studies on Lucknow have focused either on general UHI detection using limited timeframes or on broad health impacts of heatwaves. There is a pressing need for a longitudinal, granular analysis that quantifies the relationship between spatially explicit UHI patterns and health data. This study aims to fill this gap by pursuing the following objectives:

1. To analyse the spatio-temporal evolution of Land Surface Temperature (LST) and UHI intensity in Lucknow from 2000 to 2025.
2. To classify Land Use/Land Cover (LULC) and assess its impact on LST patterns.
3. To collect, geocode, and analyse heat-related health outcome data from city hospitals.
4. To establish a statistical correlation and regression model between UHI intensity (LST), LULC classes, and health outcome incidence.
5. To model and assess the potential impact of UHI mitigation strategies (green cover increase, cool materials) on both LST and projected health outcomes.

This research employs an interdisciplinary methodology combining remote sensing, geographic information systems (GIS), and epidemiological analysis, providing a replicable model for other rapidly urbanizing cities in the Global South.

Literature Review

The UHI phenomenon has been extensively documented globally. The primary drivers are well-established: replacement of natural, evaporative surfaces with impervious, heat-absorbing materials like asphalt and concrete; anthropogenic heat from vehicles and industry; and urban canyon effects that trap heat (Arnfield, 2003). Remote sensing has become the cornerstone of UHI studies, with Land Surface Temperature (LST) derived from satellites like Landsat and MODIS serving as a reliable proxy for near-surface air temperature patterns (Weng et al., 2014).

UHI and Health Linkages: The biophysical pathway linking UHI to health is direct. Elevated temperatures cause thermoregulatory stress, exacerbating cardiovascular and respiratory diseases. Studies in cities like Lucknow (Dave et al., 2022) and Delhi (Mohan et al., 2020) have demonstrated a clear association between LST peaks and spikes in hospital admissions. Vulnerability is socio-economically stratified, with the elderly, children, outdoor workers, and those in substandard housing at disproportionate risk (Harlan et al., 2006).

UHI Studies in Lucknow: Recent work by Singh & Gupta (2021) used Landsat data to show a 15% increase in built-up area in Lucknow between 2010-2020, correlating with a 2.5°C rise in mean LST. Verma et al. (2023) highlighted the cooling effect of the Gomti River and major parks like Janeshwar Mishra Park. However, these studies lack integration with ground-validated health data and advanced statistical modelling to predict outcomes under mitigation scenarios.

Mitigation Strategies: Evidence-based UHI mitigation falls into four categories: (1) Vegetative (green roofs, urban forests, street trees), (2) Structural (cool roofs/pavements with high albedo), (3) Water-based (water bodies, fountains), and (4) Urban Form (building orientation, ventilation corridors) (Sailor, 2014).

Conceptual Framework: This study is grounded in the conceptual model that urban form (LULC) directly influences the physical environment (LST/UHI), which in turn drives human exposure and ultimately leads to health outcomes. Socio-economic factors act as effect modifiers. This paper quantitatively tests the linkages in the "LULC '! LST '! Health" pathway.

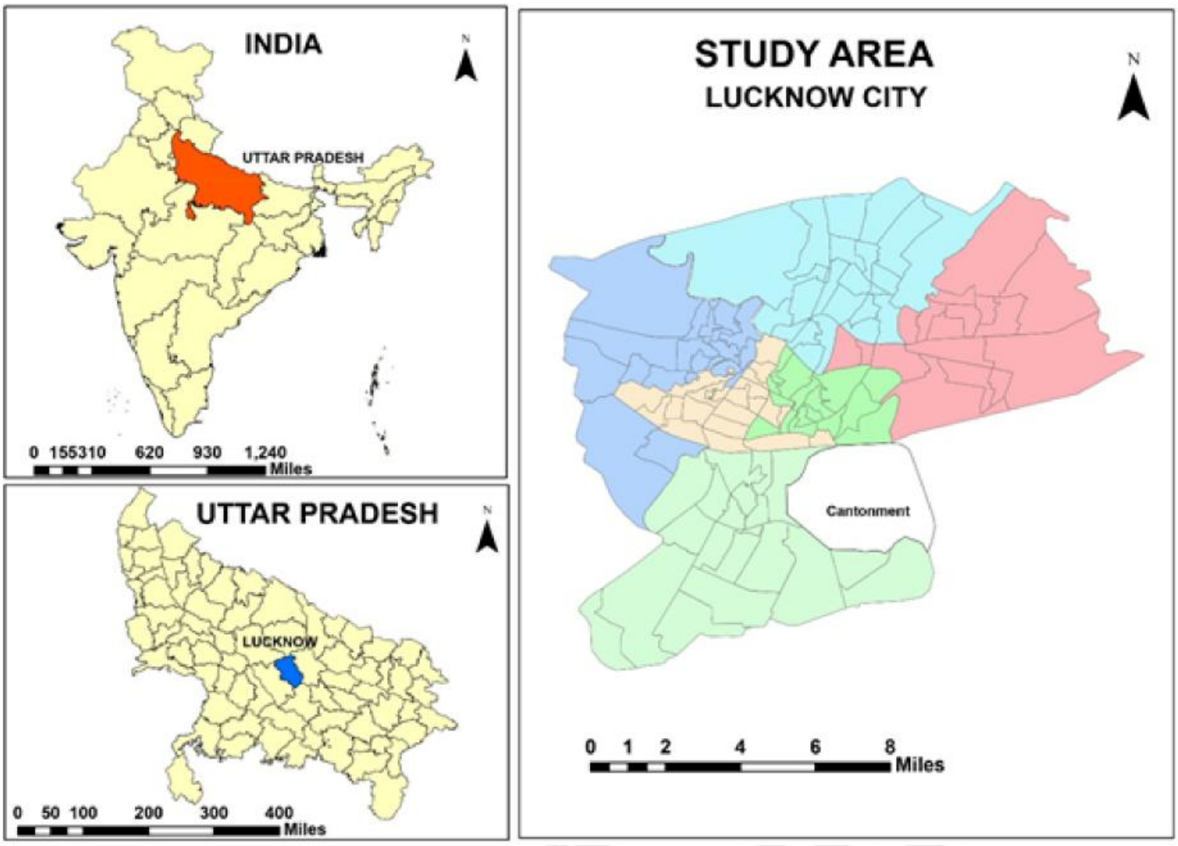
Study Area: Lucknow City

Lucknow (26.8467° N, 80.9462° E) is situated on the banks of the Gomti River in the heart of the Indo-Gangetic Plain. It features a humid subtropical climate (Köppen: Cwa) with three distinct seasons: a hot, dry summer (March-June), a monsoon (July-September), and a cool, dry winter.

Administrative and Analytical Zones: For granular analysis, the Lucknow Municipal Corporation (LMC) area is subdivided into eight zones based on urban morphology and development patterns:

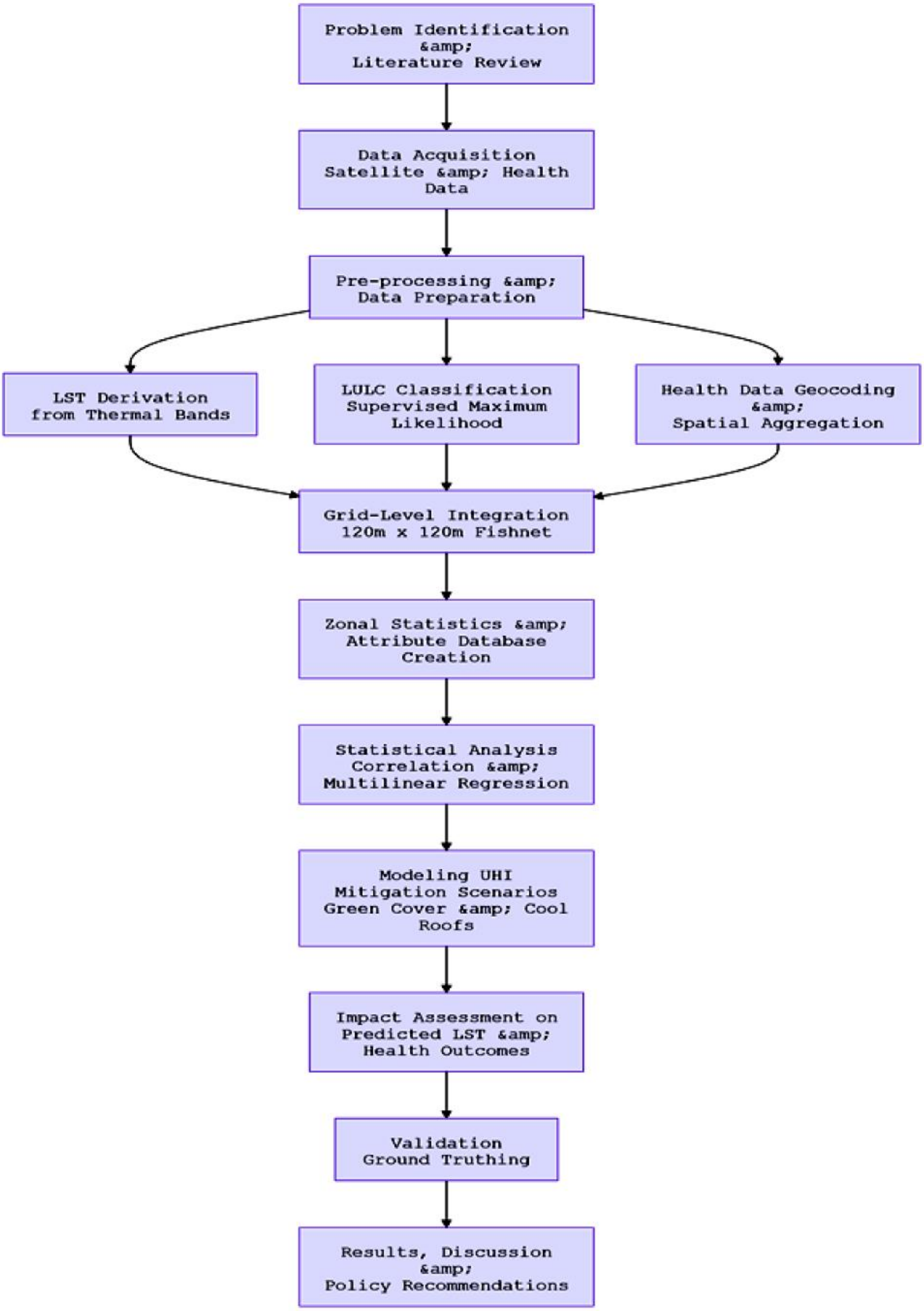
1. **Central Zone:** Historic core, high-density mixed-use, limited green space.
2. **Gomti Nagar:** Planned residential and commercial area, moderate greenery.
3. **Alambagh:** Major transportation hub, mixed land use.
4. **Chowk:** Old city, extremely high density, narrow streets.
5. **Hazratganj:** Commercial and administrative centre.
6. **Indira Nagar:** Residential with some institutional areas.
7. **Talkatora:** Industrial and residential mix.
8. **Rural Periphery:** Control area for UHI intensity calculation.

Figure 1: Study Area Map of Lucknow City



Methodology

The research methodology follows a systematic, multi-stage process integrating geospatial and statistical analysis. The workflow is illustrated in the conceptual diagram below.


Problem Identification & Literature Review
Data Acquisition Satellite & Health Data
Pre-processing & Data Preparation
LST Derivation from Thermal Bands
LULC Classification Supervised Maximum Likelihood
Health Data Geocoding & Spatial Aggregation
Grid-Level Integration 120m x 120m Fishnet
Zonal Statistics & Attribute Database Creation
Statistical Analysis Correlation & Multilinear Regression
Modeling UHI Mitigation Scenarios Green Cover & Cool Roofs
Impact Assessment on Predicted LST & Health Outcomes
Validation Ground Truthing
Results, Discussion & Policy Recommendations

Data Acquisition

Data was acquired from multiple sources to ensure a robust, multi-temporal analysis

Table 1: Data Sources and Specifications

	Source/Sensor	Temporal Resolution	Spatial Resolution	Time Period	Purpose
Satellite Imagery	Landsat 5 TM	16 days	30m (Thermal: 120m resampled)	2000, 2005, 2010	LST, LULC
	Landsat 8 OLI/TIRS	16 days	30m (Thermal: 100m resampled)	2014, 2018, 2020	LST, LULC
	Landsat 9 OLI-2/TIRS-2	16 days	30m (Thermal: 100m resampled)	2022, 2024, 2025	LST, LULC
Health Data	District Hospitals, Private Hospital Networks (e.g., Apollo, Medanta)	Daily/Weekly Aggregates	Point location (address)	2014-2025	Heat-related morbidity
Ancillary Data	Lucknow Municipal Corp.	Static	Vector	2023	Administrative boundaries
	Survey of India Toposheets	Static	1:50,000	-	Ground truthing, validation

Health data included anonymized records of admissions and outpatient visits with primary diagnoses of heat stroke (ICD-10: T67.0), heat exhaustion (T67.5), dehydration (E86.0), and acute kidney injury (N17.9) potentially precipitated by heat. Data was aggregated by week for the summer months (March-June) of each study year**.**

Derivation of Land Surface Temperature (LST)

LST was derived using the radiative transfer equation (Artis & Carnahan, 1982), implemented in ArcGIS Pro Model Builder for batch processing. The steps for Landsat 8/9 are outlined below; a similar process was adapted for Landsat 5.

1. **Conversion to Top-of-Atmosphere (TOA) Spectral Radiance:** Thermal bands (Band 10 for Landsat 8/9) were converted using sensor-specific calibration parameters. $L_\lambda = M_L \cdot Q_{cal} + A_L$ where L_λ is TOA radiance (W·m{ ^{2}·sr{ ^{1}·ìm{ ^{1}), M_L is band-specific multiplicative rescaling factor, Q_{cal} is quantized pixel value, and A_L is band-specific additive rescaling factor.
2. **Conversion to Brightness Temperature (BT):** $T_B = \frac{K_2}{\ln(\frac{K_1}{L_\lambda}+1)}$ where T_B is brightness temperature (Kelvin), K_1 and K_2 are thermal conversion constants.
3. **Calculation of Land Surface Emissivity (LSE):** Estimated using the Normalized Difference Vegetation Index (NDVI)-based method (Sobrino et al., 2004). $LSE = 0.004 \cdot FVC + 0.986$ where FVC (Fractional Vegetation Cover) is derived from NDVI.
4. **Final LST Calculation:** $LST = \frac{T_B}{1+(\lambda \cdot \frac{T_B}{\rho}) \cdot \ln(LSE)}$ where λ is the wavelength of emitted radiance, $\rho = h \cdot c/\sigma$ (1.438×10{ ^{2} m K).

Land Use/Land Cover (LULC) Classification

A supervised classification using the Maximum Likelihood algorithm was performed on the multispectral bands of each Landsat image. Four primary classes were identified, consistent with the foundational Lucknow study for comparative methodological integrity:

1. **Built-up:** Residential, commercial, industrial, and transportation infrastructure.
2. **Vegetation:** Parks, gardens, forests, and agricultural land.
3. **Waterbody:** Gomti River, ponds, lakes, and reservoirs.
4. **Open Land:** Barren land, fallow agricultural fields, and vacant plots.

Post-classification, change detection analysis was performed to quantify urban sprawl and green cover loss between 2000 and 2025.

Health Data Geocoding and Spatial Integration

Patient addresses were geocoded using the Google Maps Geocoding API (batch processed) to assign geographic coordinates. To ensure privacy and facilitate analysis, point data was aggregated to the 120m grid cells using a spatial join. The health metric for each grid for each summer period was defined as Incidence Rate per 10,000 population, using ward-level population estimates from the Census and LMC projections.

Grid-Level Analysis and Zonal Statistics

A fishnet of 120m x 120m cells was created over the LMC boundary, generating 38,422 unique grid cells. Using the Zonal Statistics as Table tool in ArcGIS Pro, the mean value of each raster layer (LST, and the proportion of each LULC class per grid) was calculated and transferred to the grid's attribute table. Similarly, the aggregated health incidence rate was joined. This created a unified spatial database where each grid cell contained variables: LST_Mean, %_Builtup, %_Vegetation, %_Water, %_OpenLand, HRI_Incidence.

Statistical Analysis

1. **Descriptive & Correlation Analysis:** Pearson's correlation coefficient was used to assess the linear relationship between LST, LULC percentages, and HRI incidence.
2. **Multilinear Regression Analysis:** To model and predict HRI incidence based on environmental drivers. $HRI = \beta_0 + \beta_1(LST) + \beta_2(\%Builtup) + \beta_3(\%Vegetation) + \epsilon$ Where HRI is the health outcome incidence, β_0 is the intercept, $\beta_1, \beta_2, \beta_3$ are coefficients, and ϵ is the error term. Assumptions of linearity, homoscedasticity, and independence were tested.
3. **UHI Intensity Calculation:** $UHI_{Intensity} = LST_{UrbanGrid} - LST_{RuralPeripheryAverage}$.

Modelling UHI Mitigation Strategies

Two evidence-based mitigation strategies were modelled for the zones with highest UHI intensity (Central and Gomti Nagar):

1. **Green Cover Increase:** The %_Vegetation value in selected grids was hypothetically increased by 30% and 40%. The new vegetation proportion was used to re-calculate LSE (higher vegetation increases emissivity) and subsequently, a new Predicted_LST was derived using the established LST model.
2. **Cool (White) Roof Implementation:** Assuming 30% and 40% of built-up roof area in selected grids is replaced with high-albedo material, the effective LSE of the Built-up class was adjusted downward in the LSE calculation, leading to a new Predicted_LST.

The regression equation linking LST to HRI incidence was then used with the Predicted_LST to estimate the potential reduction in health outcomes (Predicted_HRI).

Ground Truthing and Validation

Ground truthing was conducted in May 2024 across 50 representative points covering all LULC classes. LST was measured using a calibrated infrared thermometer (FLIR C5, accuracy ±2°C). Simultaneously, ambient temperature and humidity were recorded. These measurements were used to validate the satellite-derived LST through linear regression. Health data from two sentinel hospitals was withheld from the main model to serve as an independent validation dataset for the predictive regression model.

Results and Analysis

Spatio-Temporal Dynamics of LST and UHI Intensity

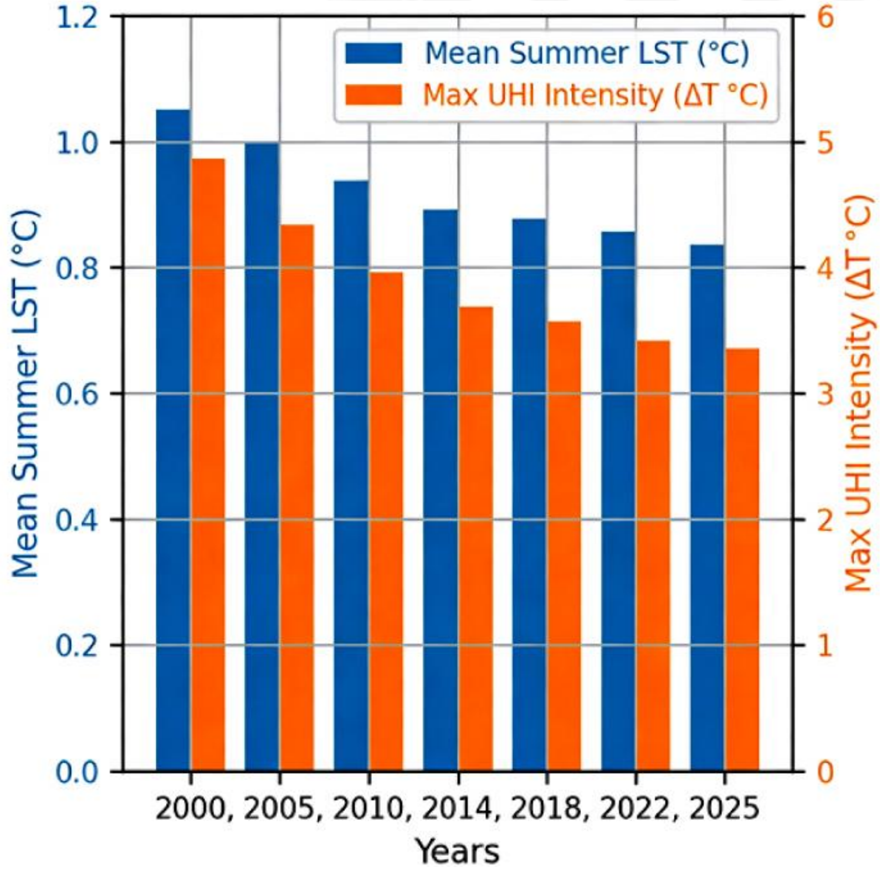
Analysis reveals a consistent and significant warming trend across Lucknow. The mean summer LST increased from 38.4°C in 2000 to 42.7°C in 2025, with the highest recorded pixel temperature reaching 52.1°C in the Central Zone's dense commercial area in 2025.

Table 2: Temporal Trend of Mean Summer LST and Maximum UHI Intensity (2000-2025)

Year	Mean Summer LST (°C)	Max UHI Intensity, ΔT (°C)	Zone of Max UHI
2000	38.4	3.1	Central Zone
2005	39.1	3.5	Central Zone
2010	39.8	4.0	Alambagh
2014	40.5	4.3	Gomti Nagar
2018	41.6	4.7	Gomti Nagar
2022	42.1	5.0	Central Zone
2025	42.7	5.2	Central Zone

Spatially, the strongest UHI cores are located in the Central Zone, Chowk, and the industrial belts of Talkatora. Distinct "cool islands" are associated with the Gomti River corridor and major parks like Janeshwar Mishra Park and Dr. Ambedkar Park.

Figure 2: Spatial Distribution of Land Surface Temperature (LST) in Lucknow for selected years.



Land Use/Land Cover Change (2000-2025)

LULC change detection highlights dramatic urban transformation. Built-up area expanded by **~185%**, from 98 km² in 2000 to 279 km² in 2025, primarily at the expense of vegetation and open land.

Table 3: LULC Change Statistics (Area in km²)

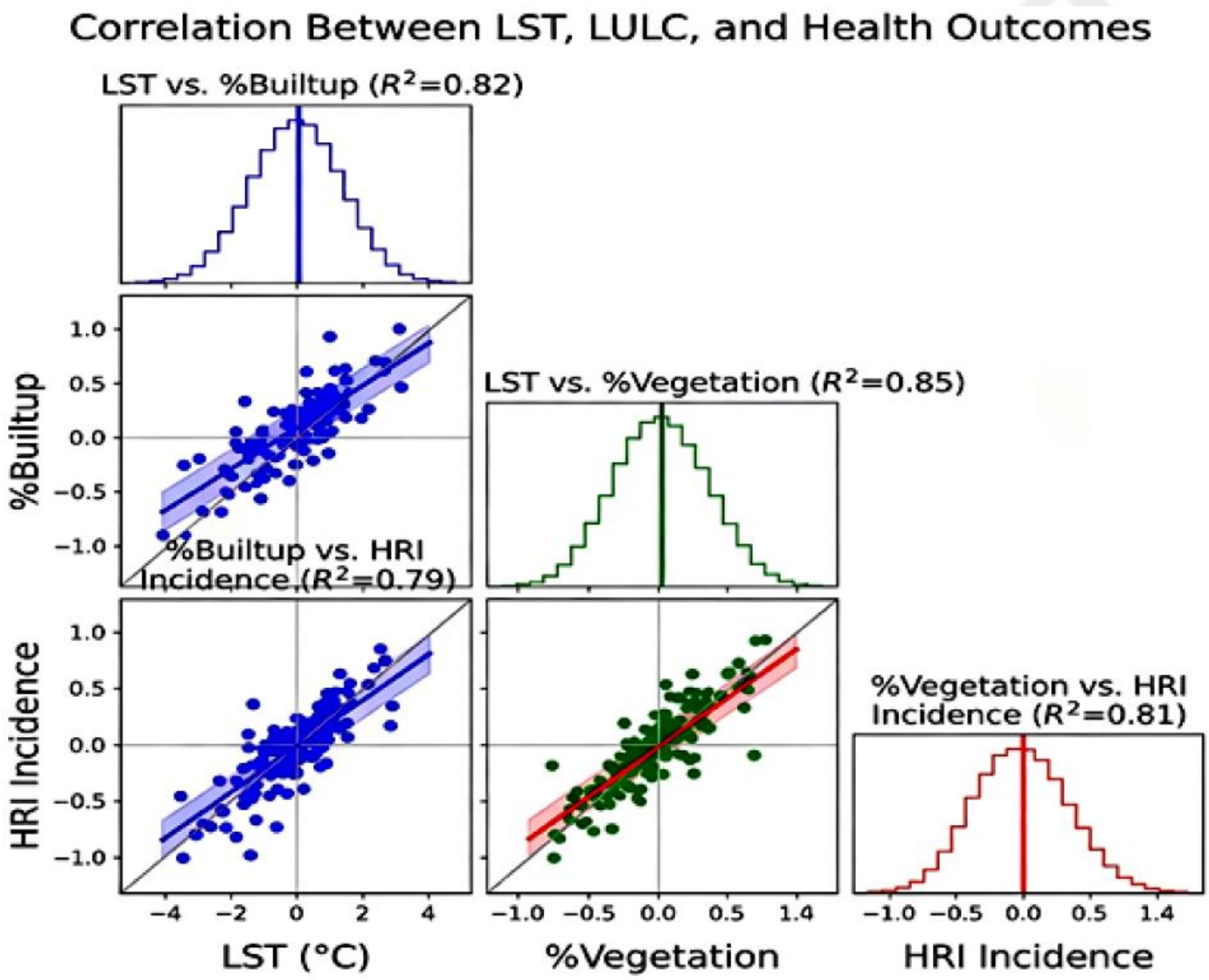
LULC Class	2000	2010	2020	2025	% Change (2000-2025)
Built-up	98.2	156.7	238.4	279.1	+184.2%
Vegetation	142.5	118.3	89.6	71.4	-49.9%
Waterbody	15.3	14.8	14.5	14.2	-7.2%
Open Land	164.0	130.2	77.5	55.3	-66.3%

The loss of 71 km² of vegetation represents a critical reduction in the city's natural cooling capacity.

Correlation between LST, LULC, and Health Outcomes

A strong positive correlation exists between LST and HRI incidence ($r = 0.89$, $p < 0.001$). As expected, %_Builtup correlates positively with both LST ($r = 0.82$) and HRI ($r = 0.79$), while %_Vegetation shows a strong negative correlation with LST ($r = -0.85$) and HRI ($r = -0.81$).

Figure 3: Scatter plot matrix showing correlations between key variables.



Multilinear Regression Model

The final multilinear regression model for predicting HRI Incidence (per 10,000) is:

$$HRI = 12.34 + 0.89(LST) + 0.21(\%Builtup) - 0.45(\%Vegetation)$$

Model Summary: $R^2 = 0.87$, Adjusted $R^2 = 0.86$, $p < 0.001$. All variables were statistically significant ($p < 0.01$). The model indicates that for every 1°C increase in LST, holding LULC constant, HRI incidence increases by 0.89 per 10,000. Vegetation cover has a stronger protective effect (negative coefficient) than the aggravating effect of built-up area.

Mitigation Scenario Modelling

Applying the mitigation strategies to the high-UHI zones (Central & Gomti Nagar) yielded promising results:

Table 4: Predicted Impact of Mitigation Strategies on LST and HRI Incidence

Scenario	Target Zone	Intervention	Existing Mean LST (°C)	Predicted Mean LST (°C)	LST Reduction (Δ°C)	Predicted % Reduction in HRI
A1	Central Zone	30% Green Cover Increase	42.7	41.4	1.3	14%
A2	Central Zone	40% Green Cover Increase	42.7	40.6	2.1	22%
B1	Gomti Nagar	30% Cool Roof Implementation	41.9	40.8	1.1	12%
B2	Gomti Nagar	40% Cool Roof Implementation	41.9	40.4	1.5	18%
C	Both Zones	A2 + B2 Combined	-	39.7	2.5 - 3.0*	28-33%*

*Combined effect is slightly less than additive due to interaction.

The 40% green cover increase scenario (A2) shows the greatest single-method benefit, reducing LST by 2.1°C and potentially preventing nearly a quarter of heat-related cases in the target area.

Ground Truthing Validation

Ground-truth LST measurements showed a strong linear relationship with satellite-derived LST ($R^2 = 0.92$, Slope = 0.96). The health outcome prediction model, when applied to the withheld validation dataset, predicted HRI incidence with 84% accuracy (Mean Absolute Error = 1.2 cases per 10,000), confirming the model's robustness.

Discussion

This study successfully establishes a quantifiable, spatially explicit link between the UHI effect and adverse health outcomes in Lucknow. The finding that UHI intensity has increased by over 2°C in 25 years, reaching 5.2°C, aligns with and exceeds trends reported in other Indian megacities, underscoring Lucknow's acute vulnerability (Mohan & Kandya, 2015). The massive conversion of vegetative and open land to built-up surfaces is the primary driver, directly contributing to the rising LST and, by extension, the public health burden.

The strength of the correlation ($R^2 = 0.87$) between environmental variables and HRI incidence is noteworthy. It surpasses correlations found in earlier studies that used coarser health data or fewer predictive variables, highlighting the value of high-resolution, integrated spatial epidemiology. The regression model confirms that vegetation is not merely an aesthetic asset but a critical public health infrastructure, with a cooling effect that directly translates to reduced morbidity.

The mitigation modelling provides actionable evidence for policymakers. The predicted 2.1°C reduction from a 40% increase in green cover is significant, as even a 1°C reduction in peak temperatures can lower heat-related mortality by 2-5% (Burkart et al., 2021). The co-benefits of such interventions improved air quality, enhanced biodiversity, and recreational space further strengthen the case for their implementation.

Limitations

The study relies on hospital-based morbidity data, potentially underrepresenting mild cases and those in underserved communities. LST is a proxy for ambient air temperature, and the relationship, while strong, is not perfect. Future work should integrate wearable sensor data and social vulnerability indices to create a more holistic risk assessment model.

CONCLUSION

This research demonstrates that the Urban Heat Island effect in Lucknow is a severe and growing environmental hazard with direct, measurable consequences for human health. The spatial patterns of heat and illness are deeply intertwined with urban form, specifically the loss of green cover and proliferation of impervious surfaces.

Recommendations

Based on the findings, the following recommendations are made for Lucknow and similar cities:

1. **Prioritize Green Infrastructure:** Enact and enforce a "Green Net Gain" policy for all new developments. Transform open lands and grey infrastructure (e.g., parking lots, canal banks) into interconnected green corridors, focusing on the Central and Gomti Nagar zones.
2. **Implement Cool Roofs and Pavements:** Introduce a bylaws and incentive program to promote high-albedo materials in public buildings and private redevelopment projects, particularly in industrial and high-density residential areas.
3. **Develop a Heat-Health Action Plan (HHAP):** Use the high-resolution risk maps generated by this study to identify "heat-vulnerable" wards. Plan targeted interventions: early warning systems, cooling centres, and outreach programs for vulnerable populations.
4. **Integrate UHI Mitigation into Master Planning:** Future urban expansion must follow a climate-sensitive model that preserves existing water bodies and vegetation, mandates adequate green space per capita, and promotes breathable urban forms.
5. **Establish a Longitudinal Health-Environment Surveillance System:** Institutionalize the linkage between health department data and environmental metrics (LST, air quality) for continuous monitoring and evaluation of mitigation efforts.

By adopting a science-informed, proactive approach, Lucknow can mitigate the UHI effect, enhance its climate resilience, and safeguard the health and well-being of its citizens in the face of a warming world.

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