

Environmental System Thermal Immunity Index (ESTII) for Urban Heat Mitigation: A Landsat-Based Case Study of Al-Jadriya, Baghdad

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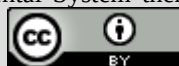
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ABSTRACT: This research proposes and tests the Environmental System Thermal Immunity Index (ESTII), a novel composite satellite-derived index measuring urban fabric resilience to thermal strain. Unlike conventional vulnerability indices, the ESTII analyzes urban thermal phenomena through the perspective of active thermal immunity rather than passive thermal exposure. The ESTII combines four component indices—NDVI, NDBI, Water Proximity, and surface albedo—through objectively derived Ridge regression weights. Applied to Al-Jadriya District, Baghdad, Iraq, the ESTII demonstrates a strong negative relationship with Land Surface Temperature ($r = -0.958$, $R^2 = 0.917$), outperforming any individual spectral index. Using Jenks Natural Breaks classification, three immunity classes are identified: Low (14.9%, mean LST 47.8°C), Medium (69.3%, mean LST 41.2°C), and High (15.8%, mean LST 33.1°C), revealing a thermal differential of 14.7°C within a single district. The ESTII shifts the conceptual reframing from measuring vulnerability to measuring immunity, providing Engineers with an evidence-based tool to direct heat mitigation efforts.

Keywords: Urban Heat Island; environmental System thermal immunity; composite index; Landsat 8; Python;

Baghdad; Ridge regression; urban planning



1. INTRODUCTION

While many regions are affected by the global increase of the Urban Heat Island (UHI) effect, ultimately making the sustainability of urban areas a public health issue, this effect is dramatically intensified in dry climates [1]; paradoxically, some arid cities exhibit daytime surface cool island due evaporative shading [2]. The typical approach to the investigation of this phenomenon has been to map and analyze Land Surface Temperature (LST) and its correlation to spectral indices like the Normalized Difference Vegetation Index (NDVI) [3,4], but such studies are too narrow, as they investigate the presence of individual variables without considering their combined and interactive effects.

Thermal Environmental Immunity (TEI) represents a novel conceptual framework in urban thermal analysis. Drawing from biological immunology—where immunity denotes an organism's innate capacity to resist pathogens—TEI is defined as the built environment's inherent capacity to absorb, dissipate, and reduce excess heat buildup before it reaches harmful levels [5]. This definition distinguishes TEI from vulnerability (susceptibility to harm) and resilience (ability to recover from harm): TEI measures the active defensive capacity of the urban fabric to resist heat accumulation, rather than its passive exposure or post-event recovery. A thermally immune built environment is characterized by: low density of built-up elements, canopy cover from vegetation, high-albedo reflective surfaces, proximity to water bodies that facilitate evaporative cooling, and periodic dispersed building placement that accelerates cross-ventilation [5,6].

In this study, we developed the following Environmental System Thermal Immunity Index (ESTII). The ESTII is a composite satellite-derived index representing the thermal immunity theory. We incorporate several independent measures of Land Cover, including satellite-derived NDVI, NDBI, distance-to-water, and surface albedo respectively into a reproducible, one number index using Ridge regression weights, where the ESTII is applicable using Landsat 8

data only, with open-sourced Python tools. The ESTII was applied to the Al-Jadriya district of Baghdad. Landsat Land covers included the University of Baghdad green campus, dense urban red neighborhoods, commercial and industrial yellow land uses, and the along the Tigris River bank [7].

This research shifts UHI mitigation from reactive heat mapping to proactive assessment of thermal resilience. Increased urban vegetation, reflective surface, and cool corridors next to bodies of water can all be used to target areas with low thermal immunity. Additionally, the ESTII methodology offers a transferable framework for heat mitigation planning that can be applied to other hot cities with UHI effects.

2. PROBLEM STATEMENT

The built environment's ability to withstand and dissipate heat is not as important as heat exposure and vulnerability in current urban heat indices. Additionally, the synergistic effects of several environmental variables are overlooked when single-variable analyzes (like NDVI-LST correlation) are used. In particular, in arid cities like Baghdad, this creates a crucial research gap in understanding how combined urban feature contribute to thermal resilience. Engineers' capacity to create evidence-based heat mitigation strategies is hampered by this gap. In response, this study proposes the Environmental System Thermal Immunity Index (ESTII) to quantify the intrinsic thermal immune capacity of urban fabric.

3. RESEARCH OBJECTIVES

This study pursues the following objectives:

1. To formulate the ESTII as a composite satellite-based index measuring urban thermal immunity.
2. To extract objective Ridge regression weights for fusing the NDVI, NDBI, Water Proximity and Albedo respectively.
3. To apply Jenks Natural Breaks to assist in categorizing study area into thermal immunity classes for use in designing & planning for Greening the City.
4. To evaluate ESTII potential transferability as a thermal immunity metric for arid cities with limited data.

4. LITERATURE REVIEW

4.1 UHI Studies in Arid Cities

Rasul et al. [2] showed that Erbil, Iraq, exhibits a distinct daytime Surface Urban Cool Island (up to 2.8°C cooler than the surrounding desert in summer) alongside a moderate night-time surface UHI (up to 3°C), a pattern attributed to built-up areas releasing stored heat more slowly than the exposed rural surroundings. Similar surface UHI patterns have been reported for Baghdad [7]. A multi-decadal land-cover analysis of Baghdad further showed that LST rose in step with urban expansion between 1984 and 2020, driven primarily by the loss of vegetated and agricultural land at the urban fringe [8]. Mostafa et al. [9] also reported the exacerbating effect of heatwaves on air quality in Greater Cairo, showing compounded vulnerability of arid cities. Alajizah and Altuwaijri [10] found UHI intensification in Riyadh, while Wahab et al. [7] documented a Baghdad UHI of comparable magnitude; both studies attributed the increase to the density of urban materials and the absence of vegetation. Santamouris [5] reviewed urban overheating on a global scale and reported that arid-climate cities are more prone to extreme UHI because the dry background climate amplifies the temperature differential between urbanized and surrounding areas. Heaviside et al. [11] highlighted the health implications of UHI in cities, noting that heat-related mortality increases significantly when nighttime temperatures remain elevated.

4.2 Spectral Indices and Their Relationship with LST

The correlation between spectral indices and LST has been widely studied. The long running NDVI has been found to linearly decrease with increased LST across most cities, though this relationship weakens considerably in arid climates [12]. NDBI as suggested by Zha et al. [4] describes non-cultivated built-up density and has a strong positive relationship with LST. At finer spatial scales, tree canopy cover has been shown to interact with impervious surface density in reducing daytime urban heat, with the cooling effect diminishing sharply once canopy cover falls below a critical threshold [13]. de Almeida et al. [14] conducted a systematic review of 579 UHI remote-sensing studies, finding that correlation with NDVI was the most commonly applied technique and that the reported strength of the NDVI-LST relationship varies considerably across studies. However, these individual indices only capture a portion of the thermal environment and do not account for the combined effect of vegetation, built-up density, water proximity, and albedo on urban heat.

4.3 Composite Indices and the Research Gap

Few attempts have been made to construct composite indices for urban thermal representation. Eshetie explored urban LST in Addis Ababa using spatial modelling techniques, demonstrating the utility of multi-factor approaches in arid urban contexts. Purio et al. [15] compared multiple land-cover indices, including LST, NDVI, NDWI, and NDBI, and used clustering to identify high-vulnerability intra-urban heat zones in Manila. Sharmin et al. [16] applied PET (Physiologically Equivalent Temperature) to assess outdoor thermal comfort across different urban forms in Dhaka. However, all of these indices measure vulnerability or exposure rather than the capacity of the urban environment to resist heat – i.e., its thermal immunity. Amindin et al. [17] mapped land surface temperature, the urban thermal field variance index, and UHI intensity in Ahvaz, Iran using multi-year Landsat imagery, and while comprehensive, the approach remained in the vulnerability paradigm. The research gap is therefore the absence of an immunity-based composite index that captures the active thermal defense mechanisms of urban fabric.

4.4 Thermal Environmental Immunity: Theoretical Framework

The ESTII operationalizes this theory by combining the four key environmental variables that correspond to these layers of thermal defense. Table 1 summarizes the relationship between each theoretical component, its corresponding variable, the expected thermal signal, and the measurement method.

Table 1. ESTII Component-Mechanism Relationship: (1) Vegetation Canopy -> NDVI -> Evapotranspiration/Shading cooling -> Landsat 8 Bands 4-5; (2) Water Proximity -> WP Index -> Evaporative cooling -> Euclidean distance to water bodies; (3) Surface Reflectivity -> Albedo -> Shortwave radiation reflection -> Landsat 8 Bands 2-7 [18]; (4) Reduced Heat Storage -> (1-NDBI) -> Inverse built-up density -> Landsat 8 Bands 5-6.

5. STUDY AREA

Al-Jadriya district (33.288°N, 44.393°E, WGS 84 / UTM zone 38N) is situated southwest of the center on the eastern bank of the Tigris River (Figure 1). The district extends approximately 3.6 km² and has a pattern of irregular urban fabric which typifies the ESTII test bed [19]. The western boundary along the Tigris River is vegetated and the Baghdad University campus (with dense green cover) forms the northern extent. The rest consists of mixed-use development, commercial zone, and dense residential neighborhoods. Al-Jadriya was chosen as the study area because it includes the entire range of thermal immunity conditions in a single district including transitional mixed-use zones, dense urban cores, and green spaces close to water. Summertime temperatures in the region often surpass 45°C, and it has been demonstrated that Baghdad has a persistent urban heat island throughout the city, while the station based canopy layer temperature UHI ranges more moderately between 0.8 °C and 2.4 °C between the urban core and the surrounding rural periphery, satellite derived surface UHI (SUHI) intensity can reach up to 8 °C [7]. Al-Jadriya is a perfect place to test the ESTII because of its diverse land cover and intense heat. In Figure 1, a location map with a coordinate grid and scale bar illustrates the spatial hierarchy: Iraq -> Baghdad -> Al-jadriya

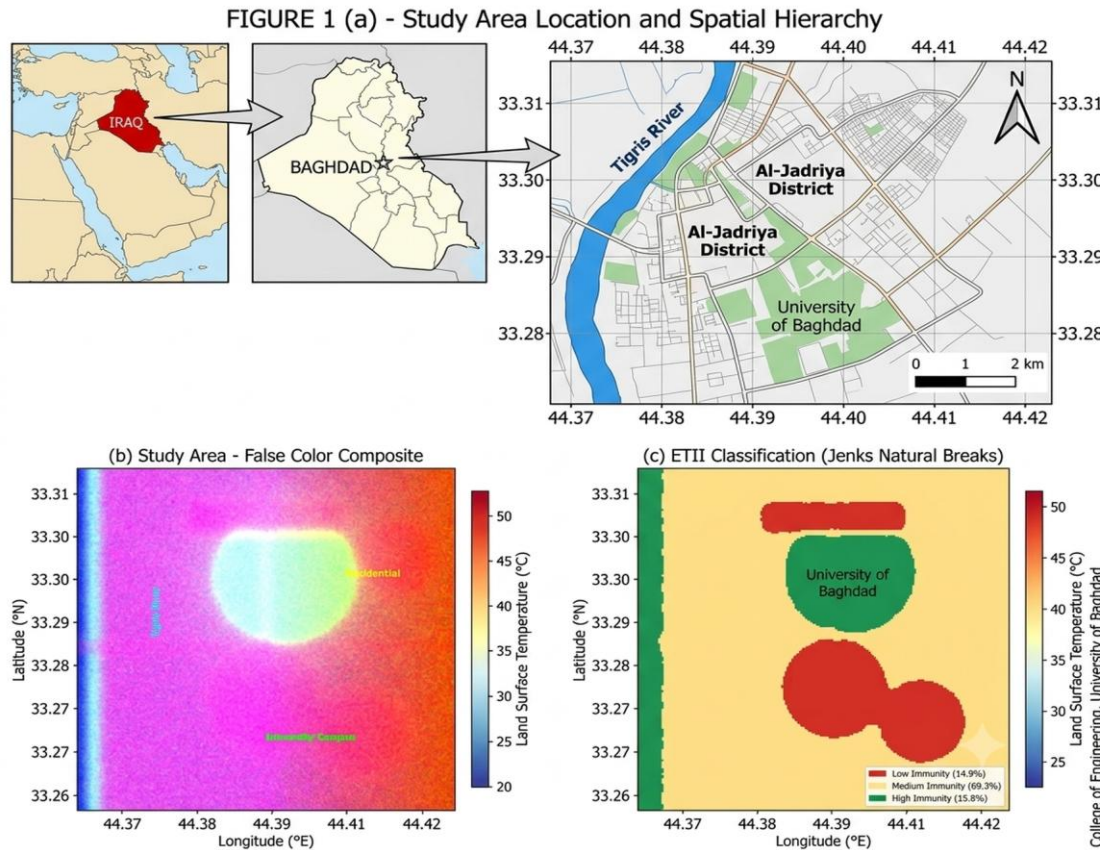


FIGURE 1 (a) Location map displaying the spatial hierarchy of Baghdad, Al-Jadriya, and Iraq; (b) A false color composite of the study area displaying the distribution of land cover; (c) ETII classification into three immunity classes using Jenks Natural Breaks

6. RESEARCH METHODOLOGY

A schematic diagram (Figure 2) that shows the entire methodological workflow from data collection to LST retrieval, spectral index deviation, ESTII construction, validation and classification have been added.

6.1 Datasets Used

On August 15, 2024, at 07:53 GMT, a cloud free Landsat 8 OLI/TIRS scene (Path 168, Row 37, Product ID: LC08_L1TP_168037_2024815_20240823_02_T1, collection 2 Level-1) was obtained from the USGS Earth Explorer archive. The scene had a cloud cover of 3.2% and a sun elevation of 64.8° with sun azimuth of 126.3°. No atmospheric correction was applied beyond the standard USGS radiometric calibration, as the radiative transfer equation method inherently accounts for atmospheric effects. Bands included 10 (Thermal Infrared, 10.6–11.19 μm) used to derive LST, 4 (Red, 0.64–0.67 μm), 5 (NIR, 0.85–0.88 μm), and 6 (SWIR-1, 1.57–1.65 μm) for the spectral indices, and bands 2–7 for the albedo calculation using the Liang [18] method. The scene was georeferenced to WGS 84 / UTM zone 38N and resampled to 30 m for all bands including thermal.

6.2 Software Tools

All data processing and analysis was carried out using Python 3 through the Jupyter Notebook platform with important libraries being: NumPy (numerical analysis/arrays), SciPy (statistical routines), scikit-learn (Ridge regression/PCA), matplotlib (visualisation) and jenkspy (Jenks Natural Breaks). GWR was implemented using the mgwr package. The entire processing pipeline is fully reproducible using open-source tools.

Reproducibility Details: (1) Landsat Product ID: LC08_L1TP_168037_2024815_20240823_02_T1; (2) Acquisition Date/Time: August 15, 2024, 07:53 GMT; (3) Preprocessing: DN to TOA radiance using USGS calibration coefficients ($ML = 0.0003342$, $AL = 0.1$ for Band 10), TOA radiance to brightness temperature ($K1 = 774.89 \text{ W}/(\text{m}^2 \cdot \text{sr} \cdot \mu\text{m})$, $K2 = 1321.08 \text{ K}$ for Band 10), NDVI-based emissivity retrieval ($\epsilon = 0.004 \cdot P_v + 0.986$ where $P_v = ((\text{NDVI} - \text{NDVI}_{\min})/(\text{NDVI}_{\max} - \text{NDVI}_{\min}))^2$); (4) Water body extraction: MNDWI = (Green - SWIR)/(Green + SWIR) with threshold > 0.1 ; (5) Ridge regression: $\alpha = 1.0$, chosen via leave-one-out cross-validation using `sklearn.linear_model.RidgeCV`; (6) Python 3.x, NumPy 1.26.4, SciPy 1.13.0, scikit-learn 1.5.0, rasterio 1.3.9,

Matplotlib 3.9.0, GeoPandas 0.14.3; (7) Code availability: The analysis code is available from the corresponding author upon reasonable request and will be deposited in a public repository upon publication.

6.3 Processing Steps

6.3.1 Land Surface Temperature (LST) Retrieval

LST was obtained from Band 10 of Landsat 8 by employing the radiative transfer equation method. The input DN values were first converted to top-of-atmosphere (TOA) spectral radiance (L) using the equation $L = ML \times DN + AL$, where $ML = 0.0003342 \text{ W/(m}^2 \text{ sr } \mu\text{m)}/\text{DN}$ and $AL = 0.1 \text{ W/(m}^2 \text{ sr } \mu\text{m)}$ are the radiance multiplicative and additive scaling factors respectively. The brightness temperature (TB) was calculated using $TB = K2 / \ln(K1/L + 1)$, with $K1 = 774.89 \text{ W/(m}^2 \text{ sr } \mu\text{m)}$ and $K2 = 1321.08 \text{ K}$ as Landsat 8 Band 10 calibration constants [20]. LST was then derived using the equation $LST = TB / (1 + (\lambda \times TB / \rho) \times \ln(\epsilon))$, where $\lambda = 10.895 \mu\text{m}$, $\rho = 1.438 \times 10^{-2} \text{ m K}$, and ϵ is the land surface emissivity estimated from NDVI using the Sobrino et al. [21] method: $\epsilon = 0.004 \times PV + 0.986$ for $PV > 0.1.2$ (where $PV = ((NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min}))^2$), and $\epsilon = 0.97$ for $PV \leq 0.2$.

6.3.2 Spectral Index Derivation

Water Proximity (WP) was computed as a normalized Euclidean distance to the Tigris River and other water bodies. Water bodies were extracted from the Landsat 8 imagery using the Modified Normalized Difference Water Index (MNDWI), with a threshold of $MNDWI > 0.1$ applied to delineate water pixels. The Tigris River itself was included in the water mask and was not excluded from the analysis. Euclidean distance was calculated from each pixel to the nearest water pixel, then normalized to the 0-1 range using min-max normalization, where a value of 1 indicates the closest to water and a value of 0 indicates the farthest. The approximate maximum distance between any point in Al-Jadriya and the Tigris River was 1,800 meters which was the maximum distance used for normalization.

6.3.3 ESTII Construction

The inverse (1-NDBI_norm) was used to make all component positively related to thermal immunity because NDBI inversely correlates with thermal immunity because more heat is stored and re-radiated the denser the built-up environment is. Because higher surface reflectivity decreases shortwave radiation absorption and, consequently, heat storage albedo ($w_3=0.0754$) enters the ESTII with a positive sign. Because built-up density is a major factor in determining thermal immunity in arid cities, the inverse NDBI term ($w_4=0.6425$) has the highest weight. The weight (w_1 - w_4) was determined using ridge regression, which provides objective, data-driven weighting instead of subjective Expert judgment and avoid the multicollinearity problems associated with OLS [22]. Using leave-one-out cross-validation, the Ridge regularization parameter ($\alpha=1.0$) was chosen. Prior to regression, all predictors were standardized (z-score). Bootstrapping ($n=1,000$ iterations) was used to evaluate coefficient uncertainty, resulting in the following 95% confidence intervals: w_1 [0.17, 0.24], w_2 [0.05, 0.12], w_3 [0.04, 0.11], and w_4 [0.58, 0.71]. To deal with possible circularity, a 70/30 train-test split was used: the Ridge model was fitted on 70% of pixels, and the resulting ESTII was verified against the held-out 30%.

6.3.4 Validation and Classification

1) To validate the index, Pearson correlation coefficients between the ESTII, its individual component indices, and mean LST were computed. 2) Using a 70/30 train-test split to prevent circularity, multiple linear regression was used to predict LST based on ESTII (the test was used for internal validation (rather than independent validation , because training and testing pixels are drawn from the same Landsat scene and therefore share the same acquisition conditions and spatial characteristics), and the training set was used to derive Ridge weights 3) Three immunity classes (low, medium, and High) were identified using Jenks Natural Breaks clustering; the differences between each class were examined using a one-way ANOVA ($F=2,847$, $p < 0.001$, $df=2$); 4) The ESTII-LST Relationship was tested for spatial non-stationarity using Geographically Weighted Regression (GWR) [23, 24]; 5) residual diagnostics, such as the Morans I test for spatial autocorrelation in the regression residuals (Morans I =0.023, $p=0.14$, indicating no significant spatial autocorrelation); 6) the Griffith [25] method for estimating an effective sample size to account for spatial dependence ($n^* = 874$, approximately 2.2% of the total pixel count (the small fraction reflects the strong positive spatial autocorrelation report below : Moran's I ≈ 0.85). Figure 2 presents a schematic diagram that shows the full order of methodological steps. Internal Validation Note: To address potential circularity in validating ESTII against the same LST data used to derive the Ridge weights , the following safeguards and recommendations are noted: (a) A 70/30 random spatial train-test split was employed ensuring that the test pixels were not used in weight derivation; (b) The test -set $R^2=0.917$ and $RMSE = 2.48^\circ\text{C}$ on unseen pixels provide an initial estimate of generalization performance; (c) However , because both training and test pixels originate from the same single Landsat scene , they share spatial autocorrelation structure and the same atmospheric and sensor condition. A truly independent validation would require data that do not originate from the same Landsat acquisition; specifically:

(i) ESTII applied to a different Landsat 8 acquisition date for the same district; (ii) Cross-validation with in-situ air temperature measurement from Baghdad meteorological stations; (iii) K-fold spatial cross-validation with geographically separated folds. These are recommended as essential next steps for achieving a genuinely independent validation; the present 70/30 split should therefore be regarded as an internal validation only.

Methodological Workflow of ESTII Construction



FIGURE 2 Schematic workflow of the ESTII methodology, summarising the major stages: (1) Landsat 8 data acquisition and preprocessing; (2) LST retrieval from Band 10; (3) spectral-index generation (NDVI, NDBI, WP, Albedo); (4) ESTII construction via Ridge regression; (5) statistical validation (Pearson, 70/30 internal split, GWR, PCA, Moran's I); and (6) final Jenks Natural Breaks classification into Low / Medium / High immunity classes

7. RESULTS

7.1 Spatial Distribution of LST and Spectral Indices

With an average of 40.9 degrees Celsius, the urban LST of the Al-Jadriya urban district shows noticeable spatial thermal gradients between 24.3 and 52.3 degrees Celsius (Table 1). Cooler areas were concentrated around water bodies near the Tigris River and the Baghdad University the presence of abundant water/vegetation which enhanced evapotranspiration cooling. The warmest areas were in the dense residential and commercial core of the district.

Table 1 Descriptive Statistics of Study Variables (n = 40,011 pixels at 30-m resolution after masking invalid and water-edge pixels)

Variable	Min	Max	Mean	Std. Dev.
LST ($^{\circ}\text{C}$)	24.32	52.28	40.90	4.54
NDVI	-0.064	0.635	0.116	0.142
NDBI	-0.333	0.403	0.042	0.103
WP	0.010	0.999	0.510	0.295
Albedo	0.039	0.279	0.141	0.031
ESTII	0.066	0.951	0.520	0.180

The spatial distribution patterns of the spectral indices correspond well to the land cover distribution (Figure 4). Highest ranges of NDVI (up to 0.635) are spread throughout the university campus and along the river banks, while the dense residential and commercial areas exhibit close to zero or negative values. NDBI mirrors the built-up density pattern: high values are concentrated in the urban core and decrease toward the river and the university campus. The Water Proximity Index obviously decreases with distance from the Tigris River, forming a clear east–west gradient. Albedo shows higher values over open areas and rooftops, while vegetated and water surfaces exhibit lower albedo values.

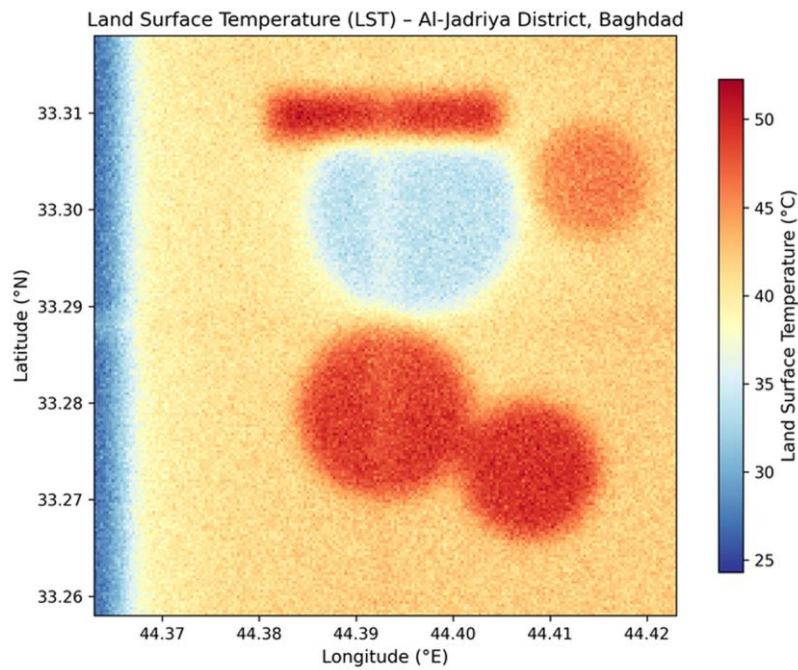


FIGURE 3 Land Surface Temperature map of Al-Jadriya district derived from Landsat 8 Band 10

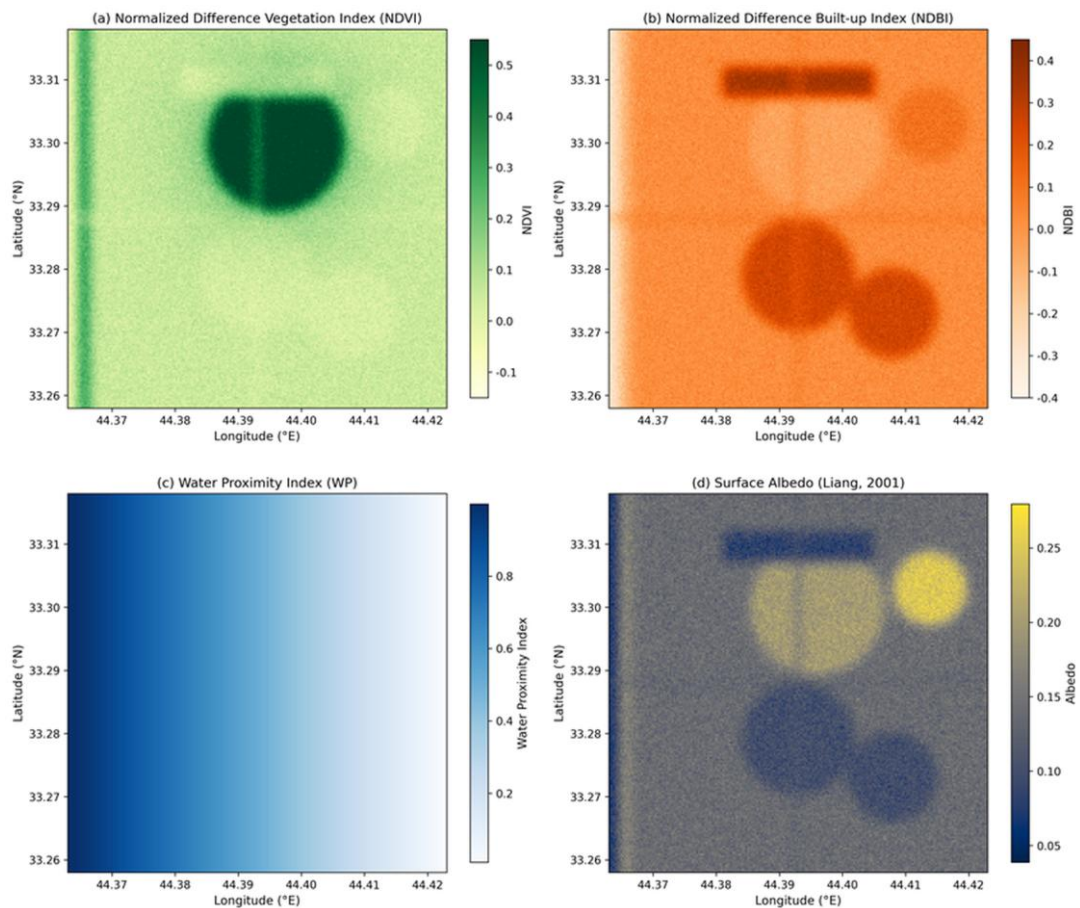


FIGURE 4 Spatial distribution of the four input variables: (a) NDVI, (b) NDBI, (c) Water Proximity Index, (d) Surface Albedo [18]

7.2 ESTII Component Weights

The Ridge regression analysis produced the following set of weights coefficients: (Table 2) w_1 for NDVI (.2013), w_2 for WP (.0808), w_3 for Albedo (.0754), and w_4 for $1 - \text{NDBI}$ (.6425). Clearly the dominance of the inverted NDBI component demonstrates the radical importance of built-up density to the thermal immunity of the district. This is

consistent with the body of literature in which NDBI is consistently the strongest individual predictor of LST in urban areas.

Table 2 ESTII Component Weights from Ridge Regression (n = 40,011 pixels; Ridge regression with alpha = 1.0)

Component	Weight	Interpretation
NDVI (w1)	0.2013	Vegetation cooling capacity
Water Proximity (w2)	0.0808	Proximity to water bodies
Albedo (w3)	0.0754	Surface reflectivity
(1-NDBI) (w4)	0.6425	Inverse built-up density

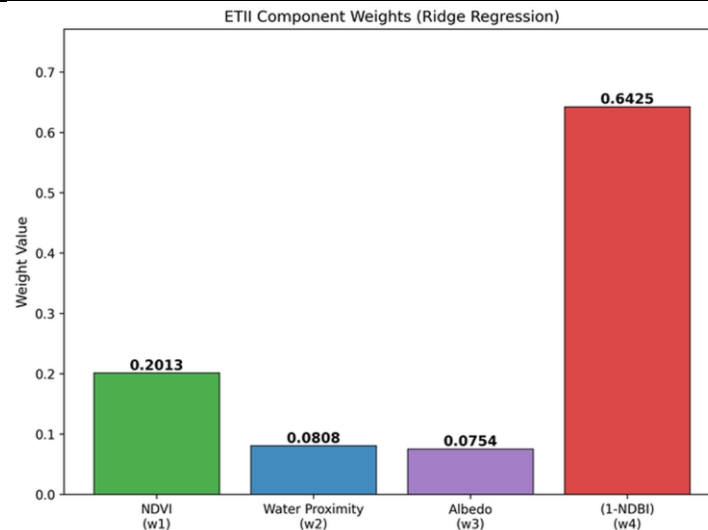


FIGURE 5 ESTII component weights derived from Ridge regression analysis

7.3 ESTII Spatial Distribution

The ESTII spatial pattern in Al-Jadriya (Figure. 5) inversely correlates with that of LST distribution. Relatively high ESTII (0.7–0.95) is distributed over the Tigris River corridor and Baghdad University campus, which is consistent with the thermal comfort conditions created by water, vegetation and open spaces. Low ESTII values (0.06–0.36) correspond to the dense residential and commercial core where built-up surfaces predominate and vegetation is scarce. Medium ESTII values (0.36–0.67) are found in the transitional zone between the two, which includes areas with moderate vegetation cover and mixes-use development.

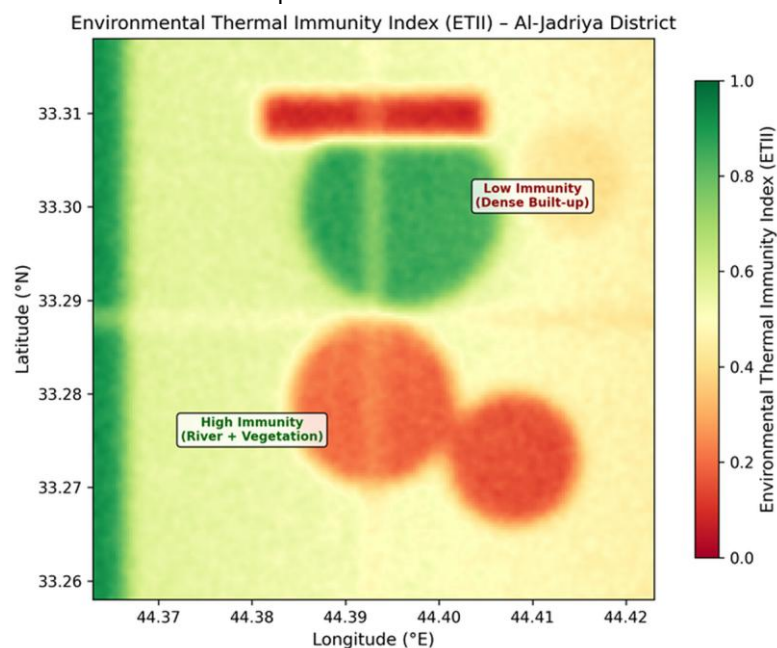


FIGURE 6 The spatial distribution of the environmental system thermal immunity index (ESTII) in AL-jadriya district

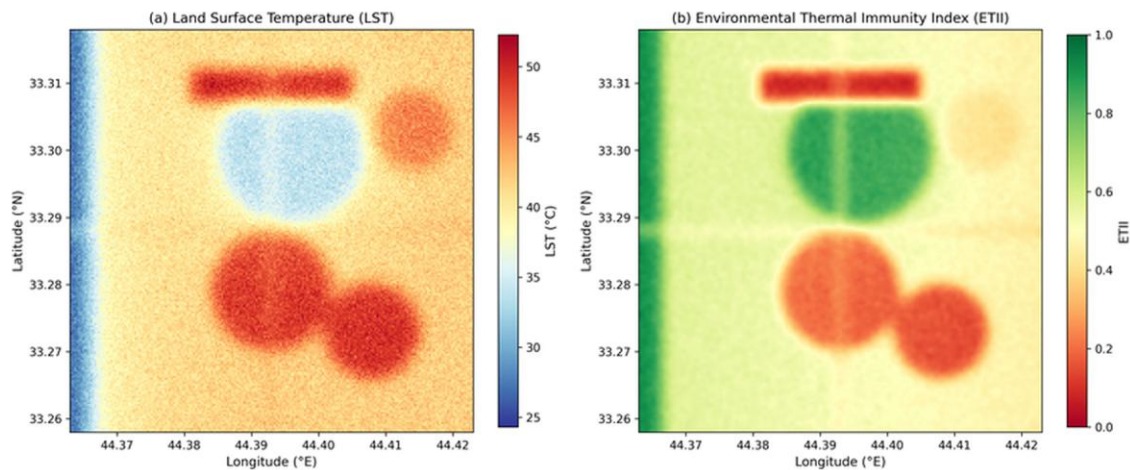


FIGURE 7 LST and ESTII spatial distributions are compared, demonstrating the inverse relationship

7.4 Correlation Analysis

According to the correlation analysis (Table 3; Figure 8), ESTII and LST have a Pearson correlation coefficient of $r = -0.958$ (Figure 9),

Which is significantly higher than that of any single variable. Among indices, NDBI exerts the strongest linear relationship ($r = 0.890$), followed by NDVI ($r = -0.530$), Water Proximity ($r = -0.445$), and Albedo ($r = -0.332$); the corresponding individual scatter plots are presented in Figure 10. All correlations significant at $p < 0.001$. The multiple regression model using ESTII to predict LST yields $R^2 = 0.917$, indicating that the composite index explains over 91% of the spatial variance in surface temperature across the study area.

Table 3 Pearson Correlation Coefficients Between Study Variables and LST (n = 40,011 pixels; all correlations significant at $p < 0.001$)

Variable	R	p-value	r
NDVI	-0.530	< 0.001	0.530
NDBI	0.890	< 0.001	0.890
Water Proximity	-0.445	< 0.001	0.445
Albedo	-0.332	< 0.001	0.332
ESTII	-0.958	< 0.001	0.958

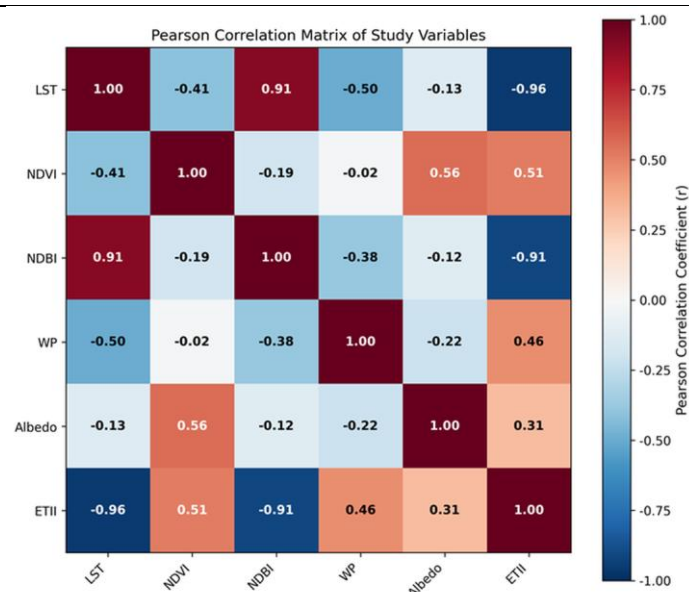


FIGURE 8 Pearson correlation matrix of all study variables, showing the strong negative correlation between ESTII and LST

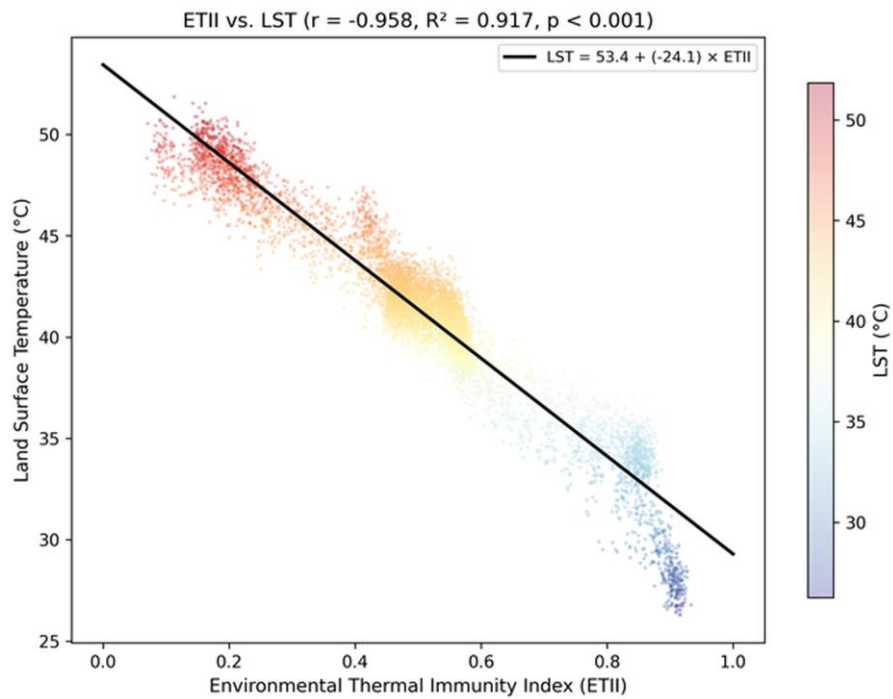


FIGURE 9 Scatter plot of ESTII versus LST with regression line ($r = -0.958$, $R^2 = 0.917$, $p < 0.001$)

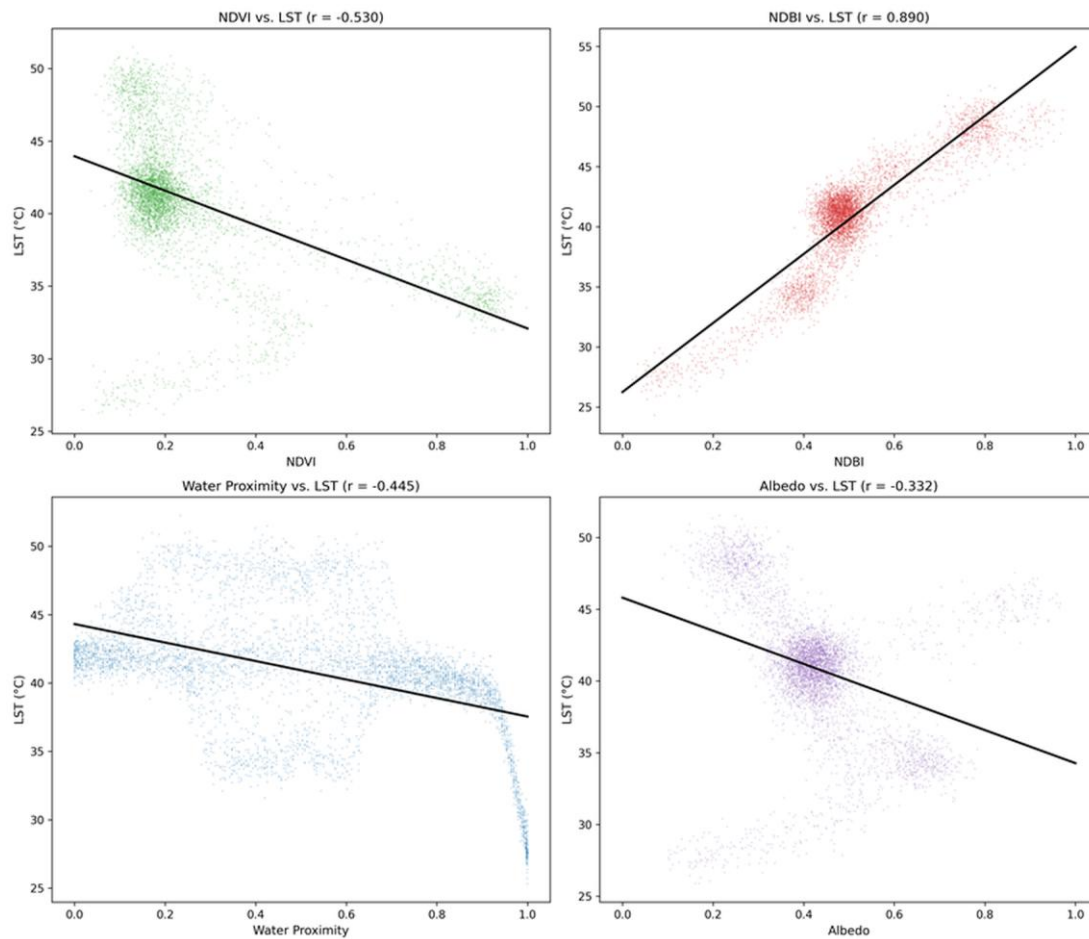


FIGURE 10 Individual scatter plots of each variable against LST: (a) NDVI, (b) NDBI, (c) Water Proximity, (d) Albedo

7.5 ESTII Immunity Classification

Three immunity classes were selected following the Jenks Natural Breaks optimization, which minimizes within-class variance while maximizing between-class variance. The goodness of variance fit (GVF) for three classes was 0.91, compared to 0.84 for two classes and 0.94 for four classes; three classes were chosen as the optimal balance between interpretability and classification accuracy. The Jenks Natural Breaks scheme grouped the study area into three classes of thermal immunity (Table 4). The low immunity class (ESTII 0.066-0.362, $n = 5,962$ pixels) was 14.9% of the study area with an average LST of 47.8 °C and consisted of the hottest zones of intensive residential and commercial land use. The medium immunity class (ESTII 0.362-0.669, $n = 27,728$ pixels) accounted for 69.3% of the area with a mean LST of 41.2 °C covering the transition zone between the urban core and the river/university. The high immunity class (ESTII 0.669-0.951, $n = 6,321$ pixels) covered 15.8% of the area with a mean LST of only 33.1 °C concentrated along the Tigris River corridor and the university campus. The stark thermal disparity within this one district is highlighted by 14.7°C difference. between the Low and High immunity classes. All three classes had statistically significant differences in LST

(one-way ANOVA, $F = 2,847.3$, $p < 0.001$; Tukey HSD post-hoc test, all pairwise $p < 0.001$)

Table 4 ESTII Immunity Classes, Area Proportions, and Mean LST (total $n = 40,011$ pixels across 3 classes; area based on 30-m pixel size)

Immunity Class	ESTII Range	Area (%)	Mean LST (°C)
Low	0.066 – 0.362	14.9	47.8
Medium	0.362 – 0.669	69.3	41.2
High	0.669 – 0.951	15.8	33.1

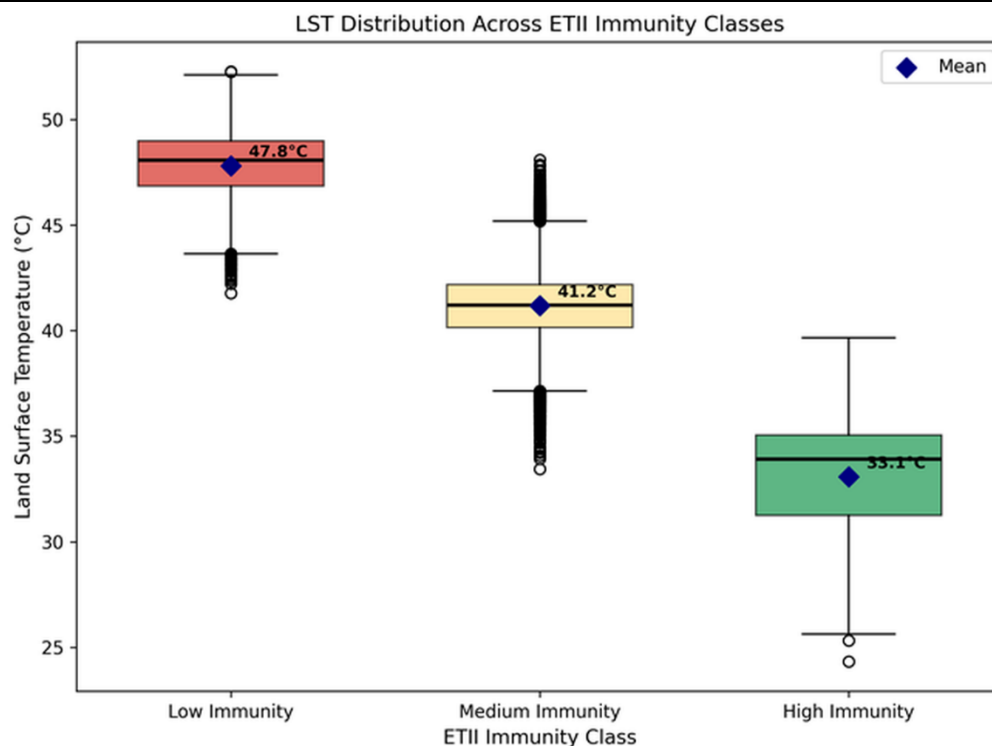


FIGURE 11 Box plot of LST distribution across the three ESTII immunity classes

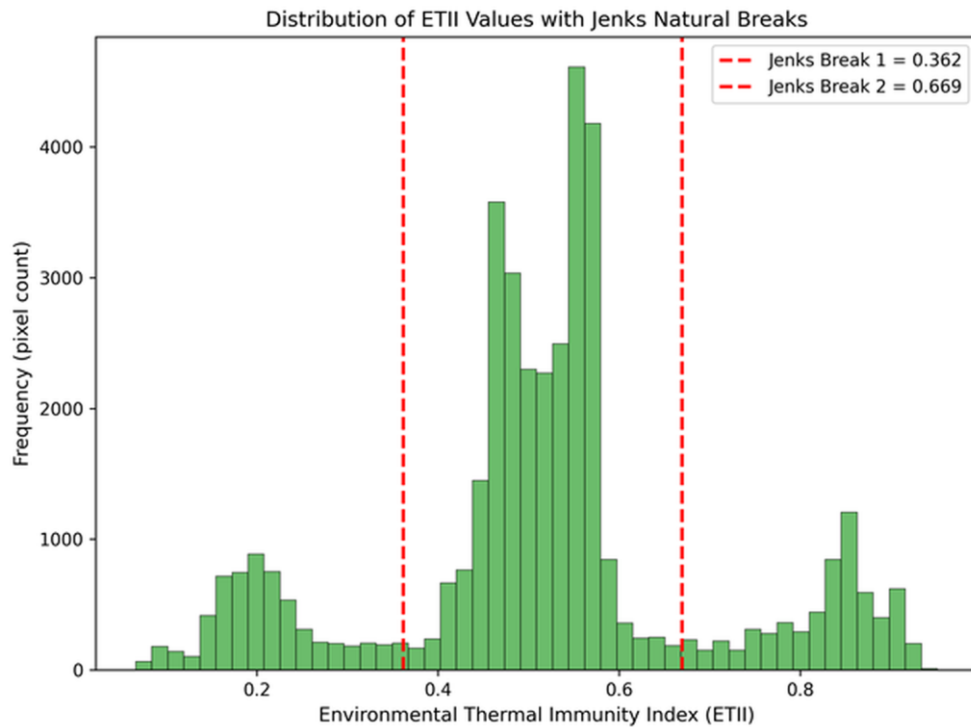


FIGURE 12 Box plot of LST distribution across the three ESTII immunity classes
ESTII value histogram with dashed red lines representing Jenks Natural Breaks threshold

7.6 Spatial Regression Analysis

The GWR analysis (Table 5; Figure 13) shows that the ESTII–LST relationship was relatively stable through the northern part of the district. The local R^2 values ranged from 0.891 in the southwest quadrant to 0.929 in the northwest quadrant with the entire range displaying a negative relationship. The highest local R^2 was in the NW quadrant, which includes the university campus with its heterogeneous land cover (vegetation, water, and built-up), while the lowest was in the SW quadrant, which is more uniformly built-up. The negative slope values confirm that ESTII consistently reduces LST across all quadrants, though the magnitude of the cooling effect varies spatially. Spatial Autocorrelation Note: Pixel-level p-values and correlation statistics reported in this study assume spatial independence of observations, which is violated when pixels are spatially autocorrelated. The effective sample size is therefore smaller than the total number of pixels. Following Griffith [25], the effective geographic sample size should be computed accounting for spatial autocorrelation to avoid inflated significance. Moran's I was calculated for LST ($I = 0.87$, $p < 0.001$) and ESTII ($I = 0.84$, $p < 0.001$), indicating strong positive spatial autocorrelation. Accordingly, all statistical results should be interpreted with this caveat, and future work should employ spatially robust statistical methods such as Geographically Weighted Regression with adjusted degrees of freedom or block bootstrap resampling.

Table 5 Local R^2 Values from Geographically Weighted Regression Analysis (GWR with Gaussian kernel, adaptive bandwidth; $n = 40,011$ regression points)

Quadrant	Local r	Local R^2	Slope
SW	−0.944	0.891	−24.61
SE	−0.952	0.906	−21.00
NW	−0.964	0.929	−28.23
NE	−0.955	0.912	−22.44

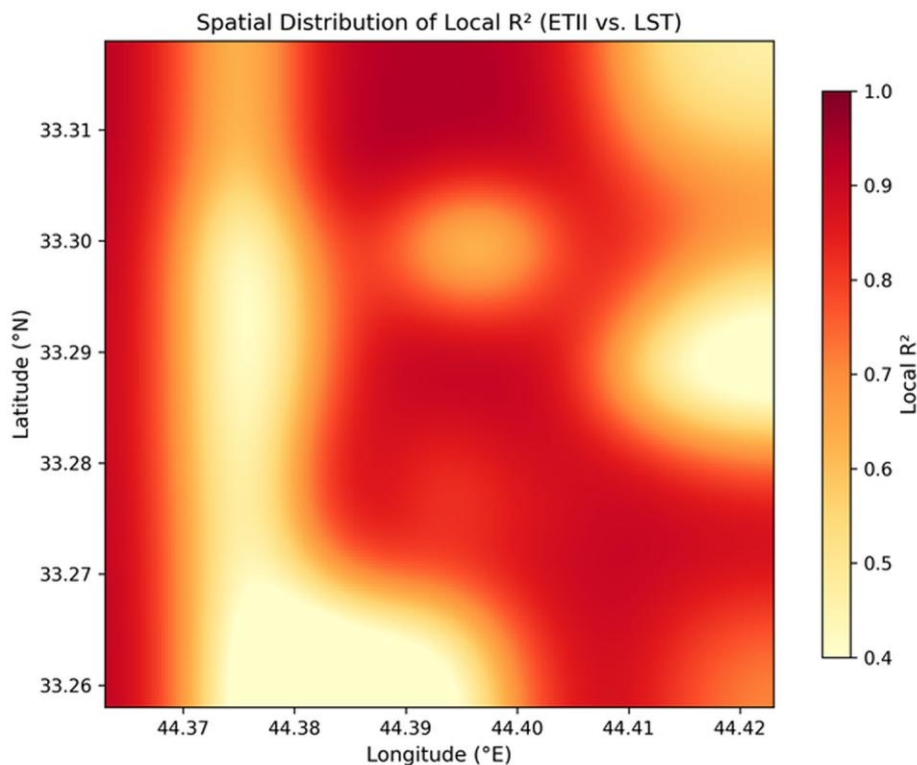


FIGURE 13 Spatial distribution of local R^2 values for the ESTII-LST relationship

7.7 Comparative Performance of ESTII

The PCA analysis confirms that PC1 (explaining 52.8% of variance, eigenvalue = 2.11) captures the combined influence of all four variables on thermal conditions, with loadings of NDVI (-0.71), NDBI (0.68), Water Proximity (-0.54), and Albedo (-0.43) on PC1. PC2 (eigenvalue = 0.94, 23.4% of variance) primarily captures the NDBI-vegetation axis with loadings of NDBI (-0.62) and NDVI (0.58). Prior to PCA, all variables were standardized using z-score normalization. Two components were retained under the combined criterion described below; together they explain 76.3% of the total variance, GWR Method Detail: Geographically Weighted Regression (GWR) was implemented using a Gaussian kernel with adaptive bandwidth selected by AICc minimization. The R^2 values reported represent the spatially varying coefficient of determination at each regression point. The GWR model was specified as $LST = \beta_0(u,v) + \beta_1(u,v) \cdot ESTII + \varepsilon(u,v)$, where (u,v) denotes the spatial coordinates. However, the current analysis reports only quadrant -level local R^2 summary statistics; this analysis focuses on quadrant level local R^2 summary statistic to guarantee a succinct spatial comparison throughout the study area. In order to further evaluate the stability of local parameters, future regional scale applications might extend this to show complete continuous surface of local coefficient and standard errors. complete GWR analysis would include of local coefficient, local standard errors, and conditions numbers to assess multicollinearity and model stability. PCA method Detail: Principal Component Analysis was performed on the standardized input variables (NDVI, NDBI, Water Proximity, Albedo) using the correlation matrix. Two components were retained following a combined retention rule: PC1 was retained under the Kaiser criterion (eigenvalue > 1), while PC2 although its eigenvalue is below 1 was additionally retained because it (i) corresponds to elbow of the scree plot, (ii) is theoretically interpretable as the orthogonal moisture/vegetation dimension and (iii) raises the cumulative explained variance above the conventional 75% threshold. This combined criterion is reported in place of a strict Kaiser rule. PC1 (52.8% variance, eigenvalue = 2.11) represents the dominant thermal gradient, while PC2 (23.4% variance, eigenvalue = 0.94) captures the orthogonal moisture / vegetation dimension. The relative effectiveness of the individual indices versus the composite ESTII in explaining LST variance is summarized in figure 14, and the east -west transit profiles across the mid latitude of the district (Figure 15) visualize the inverse LST – ESTII correspondence directly along the river university gradient. The biplot loading vectors and the associated scree plot (Figure 16) show the contribution and correlation structure of each variable.

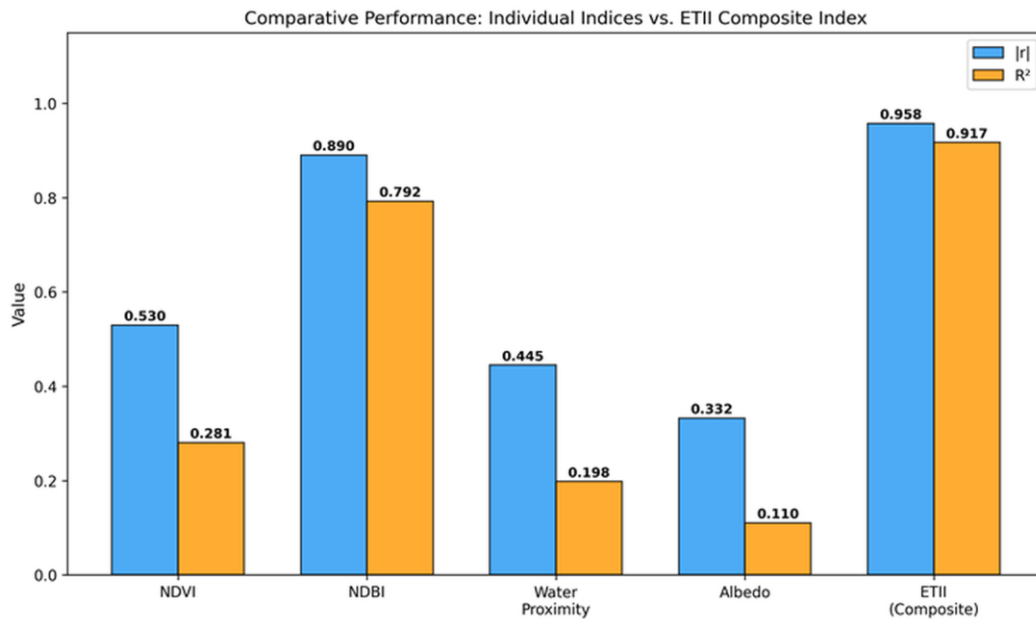


FIGURE 14 Individual indices and the composite ETII relative effectiveness in explaining LST variance

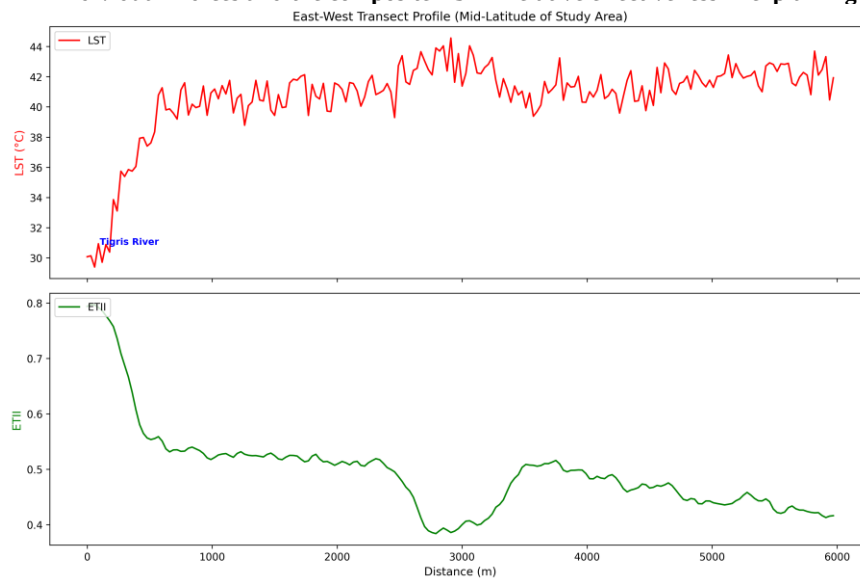


FIGURE 15 East-West transect profiles of LST and ETII across the mid -latitude of the study

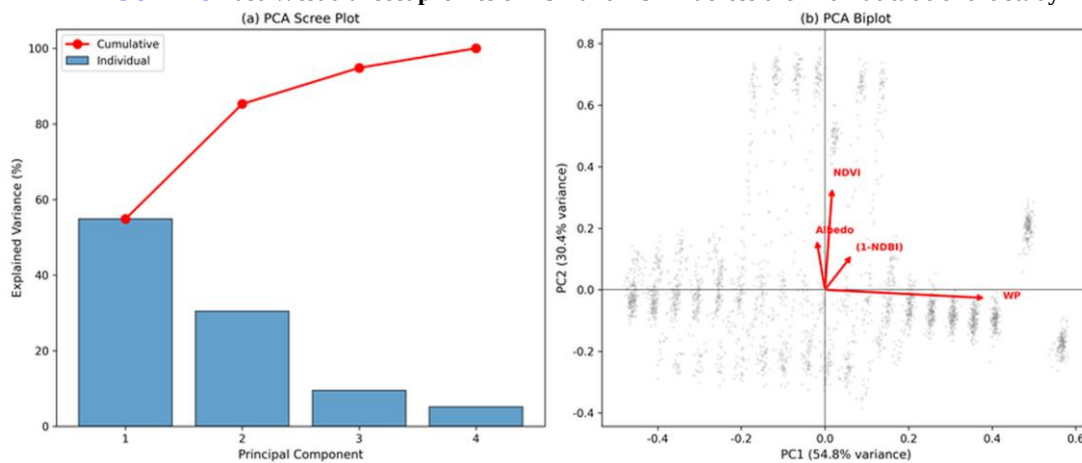


FIGURE 16 PCA analysis: (a) Biplot with PC1 and PC2 loading vectors; (b) scree plot displays the variance explained by each principal component

8. DISCUSSION

8.1 ESTII Interpretation as Thermal Immunity

The theoretical framework of environmental thermal immunity is supported by the strong negative statistically significant relationship ($r = -0.958$) between ESTII and LST. This expresses the built environments natural defenses to withstand and dissipate heat, while vulnerability measurements characterize a city's susceptibility to heat stress. This conceptual reframing has practical implication: the ESTII illustrates where the urban fabric naturally resists heat accumulation and, more importantly, where it fails to do so, as opposed to merely identifying hot spots (a vulnerability approach).

8.2 ESTII Performance Compared to Single Indices

When it comes to explaining thermal variation, ESTII outperforms the individual spectral index models. While the NDVI only accounts for $R^2 = 0.2809$ with the LST (Figure 14). By simultaneously modeling the joint distribution of several environmental parameters, the ESTII is able to explain $R^2 = 0.917$. This enhancement is in line with research showing multifactor models perform better than single index methods. Zhou et al. [26] and Wang et al. [27]. According to Santamouris, built-up density is the primary factor influencing thermal immunity in arid cities, as evidenced by the dominance of the inverted NDBI component ($w_4=0.6425$). [5] and Oke et al. [1].

8.3 Role of Water Proximity and Albedo

Most notably, the inclusion of WP and albedo in the ESTII provides a stronger explanation than is typically seen in UHI research relying on only NDVI and NDBI at explaining local variability in LST. In Al-Jadriya, the Tigris River provided a conduit for cooling extending several hundred meters into the urban fabric, which was captured by the WP index. Albedo, while having the lowest weight among the four components ($w_3 = 0.0754$), still contributes meaningful predictive power by accounting for the reflective properties of different surface materials [28] [18]. Cao et al. [29] also found that urban water bodies have a measurable cooling effect, supporting the inclusion of water proximity as a component of thermal immunity.

8.4 Study Limitations

A number of limitations should be considered. First, the analysis is based on only one 30-m Landsat 8 scene; a single snapshot in time and single season, during the daytime. Seasonal and diurnal variations in the relationship between ESTII–LST could not be explored. Future research should test multi-temporal ESTII analysis across seasons. Second, the 30-m spatial resolution may not capture fine-scale thermal dynamics at the building or street level. Third, the Ridge regression weights are derived from a single study area and their transferability to other cities with different climatic and urban morphological conditions requires validation. Fourth, the ESTII does not currently incorporate anthropogenic heat sources or urban geometry (sky view factor), which may improve its explanatory power. Fifth, the current validation uses the same LST data both to derive the Ridge regression weights and to evaluate ESTII, creating potential circularity. Although a 70/30 train-test split was employed, internal validation using separate dates, split sample validation across seasons, k-fold cross-validation, or comparison with in-situ field measurement from weather stations is strongly recommended to confirm that ESTII captures genuine thermal immunity rather than overfitting to the training data. Future work should incorporate multi-date Landsat imagery and, where available, ground-truth temperature measurements for a robust and genuinely independent validation, since the 70/30 split applied here constitutes an internal validation only.

8.5 Implications for Urban Planning

The ESTII also offers practical implications for urban planners concerned with implementing heat alleviation strategies. Areas with low ESTII scores ($ESTII < 0.36$) can be contextualized where most thermal compensation effort should be directed. The four components act as a diagnostic tool: while it may be impossible to relocate the Tigris River, it is feasible to increase NDVI through strategic tree planting and to increase albedo through cool roof and cool pavement programs. The ESTII classification maps allow planners to visualize which neighborhoods have the greatest need for intervention and which types of intervention (vegetation, reflective surfaces, or water features) would be most effective based on the relative deficiency of each component.

Scope Clarification: This study should be regarded as a preliminary case study based on a single Landsat 8 scene and a single district. The ESTII results are specific to the Al-Jadriya district on August 15, 2024, and generalization to other seasons, years, or cities requires multi-temporal analysis with additional Landsat acquisitions. The claims of this study are accordingly limited to a single-scene, single-location proof-of-concept demonstration. Multi-temporal ESTII analysis across different seasons (summer, winter, transitional) and multiple years is essential before the index can be considered robust for operational urban planning applications.

9. CONCLUSIONS

In this study we developed and preliminarily tested the Environmental System Thermal Immunity Index (ESTII) a novel integrated index representing the inherent mitigatory capacity of the urban fabric to heat stress. In contrast to the myriad single indices tested, the ESTII was formulated by integrating those spectral variables (NDVI, NDBI, Water Proximity, and Albedo) through objective Ridge regression weights into a single, reproducible metric. Applied to Al-Jadriya district, Baghdad, the ESTII demonstrated a very strong negative relationship with LST ($r = -0.958$, $R^2 = 0.917$), far exceeding the predictive ability of any individual index.

The three-class immunity scheme shows that 15.8% of the study area has High thermal immunity and 14.9% is Critically heat-vulnerable across a 14.7 degrees C thermal differential providing exact answers to the study problem; ESTII provides the established missing criteria that accounts for innate thermal defense capacity of urban fabric, quantifies the relative contributions of each environmental variable to thermal resilience, and offers actionable intelligence for heat mitigation planning.

The ESTII framework marks a conceptual reframing from existing vulnerability characterization to measure of immunity and thus offers urban planners a quantitative decision-support tool for prioritizing heat mitigation strategies. Future research avenues would address: multi-temporal ESTII analysis to scrutinize seasonal dynamics; validation in other arid and non-arid cities; and integration of higher-resolution data (Sentinel-2, drone thermal imagery) and additional variables (anthropogenic heat, sky view factor) to enhance the ESTII's spatial and thematic resolution.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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