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Research Article

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Posted Date: October 7th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11106454/v1>

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Additional Declarations: No competing interests reported.

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Abstract

As cities expand, surface urban heat islands intensify, yet how planning context shapes the cooling benefit of vegetation remains poorly understood. This study compares NDVI–LST cooling dynamics in two neighbouring cities within one conurbation: Islamabad, built to a master plan, and Rawalpindi, which grew organically. Multi-temporal Landsat imagery (2011–2024) was processed in Google Earth Engine to retrieve land surface temperature (LST), the Normalised Difference Vegetation Index (NDVI), and the Normalised Difference Built-up Index (NDBI) at 30 m resolution. Per-city ordinary least-squares regression, Fisher r-to-Z and slope z-tests, Global Moran’s I, Getis-Ord Gi* hotspot mapping, and a multivariate NDVI–NDBI–elevation model were used to compare the two cities. Both cooled modestly and greened over the study period, but their thermal behaviour diverged sharply. Rawalpindi’s intra-urban thermal heterogeneity was roughly double that of Islamabad, and it carried a persistent surface UHI of about 0.9°C, six times that of near-neutral Islamabad (about 0.1°C). Its NDVI–LST cooling slope was also consistently about twice as steep as Islamabad’s (slope z = 27–39, $p < 0.0001$), meaning each unit of vegetation cooled more where impervious cover was densest. Yet the multivariate model pointed to built-up density, not average greenness, as the dominant control on LST in both cities. Together, these results suggest that planning context and land-cover configuration, rather than vegetation abundance alone, govern how efficiently a city’s surface cools.

Keywords: urban heat island; NDVI–LST regression; land surface temperature; planned versus unplanned cities; Getis-Ord Gi*; spatial autocorrelation; Islamabad–Rawalpindi

1. Introduction

1.1 Global Urban Heat Island Context

Densely built-up areas consistently run warmer than their rural surroundings, a pattern known as the urban heat island (UHI) effect, and it has become one of the most widespread side effects of modern urbanisation. Global urban populations are projected to reach roughly 70% of humanity by 2050, so this thermal intensification is a growing environmental problem with direct consequences for public health, energy demand, and ecological sustainability (Yuan et al. 2025).

The mechanisms driving UHI are well established the substitution of permeable, vegetated land cover with heat-retaining materials such as concrete, asphalt, and steel alters surface energy balances by reducing latent heat flux, increasing sensible heat storage, and suppressing evapotranspirative cooling. Cities in low- and middle-income countries are disproportionately exposed to this phenomenon, as unplanned urban expansion (proceeding without adequate green infrastructure or land use regulation) drives significantly greater SUHI increases than planned urban growth (Yuan et al. 2025). This disparity between planned and unplanned urbanisation pathways makes comparative thermal analysis within conurbations that straddle both city typologies a particularly urgent scientific priority.

1.2 Green Space Cooling Mechanisms

Vegetation cools cities through three main biophysical pathways: evapotranspiration, shading, and changes in surface albedo. Evapotranspiration converts sensible heat into latent heat, lowering surface and near-surface air temperatures directly, while canopy shading blocks incoming solar radiation before it reaches, and is absorbed by, the impervious surfaces below. Together these processes produce what is often called a “park cool island,” where green spaces stay measurably cooler than the built fabric around them. Work across multiple urban systems has found that cooling sensitivity in built-up land peaks within an NDVI range of roughly 0.15–0.35, whereas already-vegetated areas show diminishing returns as greenness increases further (Huang et al. 2025). Not all vegetation cools equally: trees, with their large canopies and deep roots, cool more effectively than grass or low shrubs simply because they shade and transpire more (Lu et al. 2025).

How green space is arranged in space matters just as much as how much of it there is. Getis-Ord G_i^* hotspot analyses repeatedly find that the strongest cooling effects sit within about 400 metres of urban parks, an effect most visible in compact, high-density local climate zones

where vegetated and impervious surfaces sit close together. Park size and vegetation density both scale with cooling reach and intensity, but the relationship is non-linear and depends on how built-up the surrounding area is. This spatial variability in the NDVI–LST relationship is one reason high-resolution, spatially explicit analysis is needed to identify where interventions would do the most good.

1.3 Remote Sensing for UHI Analysis: NDVI, LST, NDBI, and Gi* Statistics

Remote sensing has reshaped what is possible in urban climate research, offering spatially continuous, temporally consistent, and relatively low-cost monitoring of UHI dynamics across many cities at once. Land surface temperature (LST), derived mainly from the thermal infrared bands of Landsat 5, 7, 8, and 9 and from MODIS, is the primary quantitative measure of surface urban heat island intensity. The Normalised Difference Vegetation Index (NDVI), computed from near-infrared and red reflectance, remains the most widely validated proxy for green space density and cooling capacity, while the Normalised Difference Built-up Index (NDBI) captures the density of impervious materials that drive heat absorption. Studies consistently find a strong inverse relationship between NDVI and LST, with spatial regression coefficients typically falling between about -0.43 and -0.68 depending on season, resolution, and urban form (Anand et al. 2025). Partial correlation analyses that separate vegetation’s direct cooling effect from the warming effect of built-up surfaces confirm that this negative NDVI–LST relationship has strengthened over multi-decadal records (Altiner and Bingol 2025).

Statistical analyses consistently document strong inverse correlations between NDVI and LST, with spatial regression coefficients routinely ranging from approximately -0.43 to -0.68 depending on season, spatial resolution, and urban form (Anand et al. 2025). Partial correlation analyses that isolate the independent contribution of each index have confirmed the direct cooling influence of vegetation against the warming contribution of built-up surfaces, with the negative NDVI–LST relationship strengthening over multi-decadal observation periods (Altiner and Bingöl, 2025). Within multivariate frameworks, NDVI frequently registers the strongest negative (cooling) regression coefficient among urban morphological predictors, and the multiscale geographically weighted regression (MGWR) approach has demonstrated particular utility in capturing the spatial non-stationarity of this relationship, achieving R^2 values exceeding 0.72 across heterogeneous intra-urban environments (Huang et al. 2025). The Getis-Ord G_i^* statistic complements

1 regression-based approaches by identifying statistically significant spatial clusters of thermal
2 extremity, thereby delineating the geographic boundaries of heat hotspots and vegetation-driven
3 cool islands with inferential rigour (Getis and Ord 1992).

4 These tools are increasingly deployed in combination within Google Earth Engine (GEE),
5 which provides the cloud computing infrastructure necessary to process multi-decadal Landsat
6 archives at regional scales. The integration of supervised machine learning classification
7 (particularly Random Forest) for land use and land cover (LULC) mapping with thermal analysis
8 pipelines has become the methodological standard for high-accuracy, temporally comparative UHI
9 studies.

10 **1.4 South Asia and Pakistan Context**

11 South Asia hosts some of the world's most rapidly urbanising landscapes, with Pakistan
12 now the most urbanised country in the region, where urban areas are projected to accommodate
13 half the national population within this decade (Azhar et al. 2024). Pakistani cities are characterised
14 by the concurrent operation of two radically different urban development models, formally planned
15 cities governed by master plans and statutory development authorities, and organically evolved,
16 unplanned urban centres shaped by informal land markets, population pressure, and institutional
17 fragmentation. This planned/unplanned duality creates intra-conurbation thermal gradients that
18 have received insufficient rigorous quantification.

19 Within this national picture, the Islamabad–Rawalpindi conurbation offers an
20 internationally relevant case study. Islamabad, Pakistan's federal capital, was masterplanned from
21 its inception in the 1960s and still retains substantial green infrastructure: forested margins, urban
22 parks, and vegetated residential sectors. Its built-up area grew from roughly 5.7% (52 km²) in 1990
23 to 25.7% (233 km²) by 2021. Rawalpindi, by contrast, is an older city that grew organically and
24 has densified relentlessly, its built-up share rising from 3.7% (60 km²) to 14.1% (228 km²) over
25 the same period (Kamran et al. 2023). A machine-learning analysis of the conurbation found a
26 roughly 22% increase in built-up area between 1990 and 2020, alongside a corresponding loss of
27 vegetation and bare soil, and showed that planned areas achieve markedly better temperature
28 control through green space than their unplanned counterparts (Waleed and Sajjad 2022). Most
29 notably, Rawalpindi's mean LST rose by 3.04°C over the three decades to 2020, an annual increase
30 of 0.12°C, directly tied to a 22.3% expansion of impervious surfaces (Nawaz 2025). These trends

place both cities among the most thermally stressed urban environments in South Asia, in line with national estimates that UHI intensity across Pakistan's major cities ranges from 2.9 to 5.0°C depending on time of day and season (Khan and Shahid 2024).

1.5 Research Gap

Despite a growing literature on UHI dynamics in South Asian cities, a real analytical gap remains for the Islamabad–Rawalpindi conurbation.

1.6 Research Objectives

This study was designed to close that gap through a multi-scale framework combining per-city NDVI–LST regression, surface UHI quantification, and Global Moran's I / Getis-Ord Gi* spatial-clustering analysis of the LST surface across the conurbation for 2011–2024.

This study is guided by the following four principal objectives:

- quantify the spatiotemporal dynamics of land surface temperature (LST) and vegetation cover (NDVI) across the Islamabad–Rawalpindi conurbation for 2011, 2016, 2021, and 2024, using multi-temporal Landsat imagery processed in Google Earth Engine;
- establish city-specific NDVI–LST regression relationships for planned Islamabad and unplanned Rawalpindi, and statistically compare both the strength (Fisher's r-to-Z) and the magnitude (slope difference) of vegetation cooling between the two planning contexts;
- identify and map statistically significant clusters of thermal intensity and vegetation-sustained cool islands across the conurbation using Global Moran's I and the Getis-Ord Gi* hotspot statistic over the study period;
- To assess the relative explanatory contribution of NDVI versus NDBI in predicting intra-urban LST variation, and to derive evidence-based recommendations for targeted green infrastructure interventions in each planning context.

1.7 Significance of the Study

The significance of this research operates at multiple scales. At the local scale, it delivers the first per-city, formally-compared NDVI–LST regression framework for the Islamabad–Rawalpindi conurbation, a metropolitan system operating under two fundamentally different planning regimes.

1 By quantifying the comparative cooling deficit of unplanned Rawalpindi relative to planned
2 Islamabad, the study provides urban planners, the Capital Development Authority (CDA), and the
3 Rawalpindi Development Authority (RDA) with spatially precise, evidence-grounded targets for
4 green space restoration and urban forestry investment.

5 At the national scale, the findings contribute to the Pakistani urban climate knowledge base at a
6 critical juncture, as the country's urban heat exposure is projected to intensify under ongoing
7 demographic growth and climate change. The analytical framework developed (integrating Google
8 Earth Engine-based LULC classification, thermal band processing, spatial autocorrelation analysis,
9 and comparative regression modelling) is directly transferable to other Pakistani cities and to the
10 broader category of conurbations where planned and unplanned urban forms coexist in proximate
11 spatial configurations.

12 At the international scale, the study addresses a recognised gap in the global UHI literature
13 concerning the planned/unplanned cooling efficiency differential. Cities in low- and middle-
14 income countries across South Asia, Sub-Saharan Africa, and South-East Asia share structural
15 analogies with the Islamabad–Rawalpindi case, and the empirical relationships derived here will
16 inform the growing evidence base on vegetation-based UHI mitigation in the Global South. The
17 study also responds to calls in the recent bibliometric literature for greater representation of small
18 and medium-sized cities, and of socio-institutional dimensions of urban heat, in mainstream
19 remote sensing and urban climate research (Duymuş, 2025). In sum, by combining methodological
20 rigour with policy relevance, this research advances scientific understanding of how planning
21 context mediates the cooling efficiency of urban vegetation, and how that understanding can be
22 translated into actionable climate adaptation strategies for rapidly urbanising regions.

23 **3. Materials and Methods**

24 This study integrates multi-sensor satellite imagery, terrain data, and administrative boundaries
25 within the Google Earth Engine (GEE) cloud-computing platform (Gorelick et al. 2017). The
26 principal thermal and optical data were drawn from the Landsat archive across four reference years
27 (2011, 2016, 2021, 2024), supplemented by Sentinel-2 imagery for independent NDVI validation,
28 the SRTM digital elevation model (DEM) as a topographic covariate, and CDA/RDA
29 administrative boundaries for delineating the study area and the urban–rural classification required

1 for UHI computation. For each reference year, an annual cloud-free median composite was
2 generated within GEE to maximise spatial coverage and minimise atmospheric and seasonal
3 artefacts, an approach widely adopted in multi-temporal LST analyses (Ermida et al. 2020). A
4 complete inventory of datasets is provided in Table 1. Pixel sample sizes for the regression
5 analyses differ between the two cities ($n = 1,140$ for Islamabad; $n = 6,860$ for Rawalpindi in the
6 multivariate model; $n = 1,119$ and $6,251$ respectively in the bivariate regressions after removing
7 pixels with missing data) because Rawalpindi's administrative boundary encompasses a
8 substantially larger spatial extent than Islamabad's, reflecting the respective administrative
9 footprints of the CDA and RDA boundaries used for delineation. Sample sizes are thus
10 proportional to administrative area rather than chosen by design.

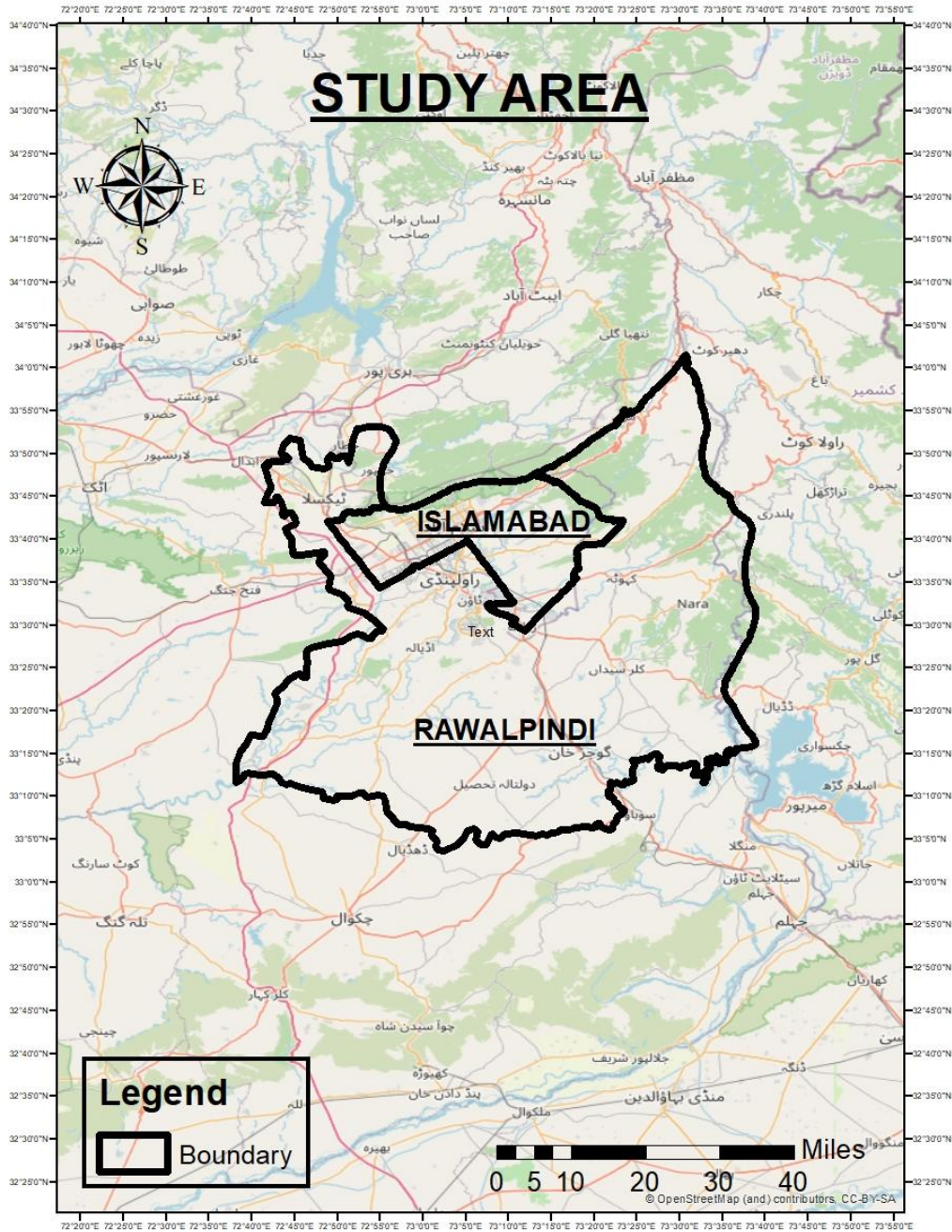


Fig. 1 Location of the study area showing the Islamabad–Rawalpindi conurbation, with the administrative boundaries of Islamabad (planned) and Rawalpindi (unplanned) delineated within the wider regional context.

Table 1. Data sources and their analytical roles.

Dataset	Sensor / Source	Year(s)	Spatial resolution	Analytical role
Landsat 5 TM	USGS / GEE	2011	30 m (TIR 120 m, resampled 30 m)	LST, NDVI, NDBI

Landsat 8 OLI/TIRS	USGS / GEE	2016	30 m (TIR 100 m, Band 10)	LST, NDVI, NDBI
Landsat 8 OLI/TIRS	USGS / GEE	2021	30 m (TIR 100 m, Band 10)	LST, NDVI, NDBI
Landsat 9 OLI-2/TIRS-2	USGS / GEE	2024	30 m (TIR 100 m, Band 10)	LST, NDVI, NDBI
Sentinel-2 MSI (L2A)	ESA Copernicus / GEE	2018–2024	10 m	NDVI validation
SRTM DEM v3	NASA / USGS	2000	30 m	Elevation covariate (ELEV)
Administrative boundaries	CDA / RDA / GADM		Vector	Study area clip; urban/rural mask

Sensor band designations differ across the Landsat series. The near-infrared (NIR), red, and short-wave infrared (SWIR) bands correspond to B4/B3/B5 in Landsat 5 TM, and to B5/B4/B6 in Landsat 8 OLI and Landsat 9 OLI-2. Thermal infrared (TIR) data were drawn from Band 6 (L5) and Band 10 (L8/L9), respectively.

All scenes underwent radiometric calibration to top-of-atmosphere reflectance followed by atmospheric correction. For the Tier-1 Landsat collections, surface reflectance products corrected via the LEDAPS (L5/L7) and LaSRC (L8/L9) algorithms were used; where image-based correction was required for consistency checks, the improved Dark Object Subtraction (DOS) method of Chavez (1988) and the 6S radiative-transfer routine of Vermote et al. (1997) were applied. Cloud, cloud-shadow, and cirrus contamination were removed using the CFMask QA_PIXEL bitmask for Landsat (Foga et al. 2017) and the Scene Classification Layer (SCL) for Sentinel-2 (Main-Knorn et al. 2017). After masking, the per-year median composite was clipped to the study-area boundary extended by a 5 km buffer, ensuring that edge pixels and the rural reference zone required for UHI estimation were fully captured.

The Normalised Difference Vegetation Index (Rouse et al. 1974; Tucker 1979) was computed for each composite as:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

NDVI was subsequently reclassified into five vegetation-density classes (water/non-vegetated, sparse, low, moderate, and dense vegetation) following established thresholds, providing the vegetation gradient used in subsequent correlation and regression analyses. Sentinel-2-derived NDVI (10 m) for the overlapping 2018–2024 period was used to cross-validate the Landsat-derived NDVI surfaces.

The Normalised Difference Built-up Index (Zha et al. 2003) was computed to quantify impervious surface density as:

$$\text{NDBI} = (\text{SWIR} - \text{NIR}) / (\text{SWIR} + \text{NIR})$$

NDBI was used to derive a Built-Up Area Fraction (BUAF), which entered the regression models as a control variable isolating the effect of impervious surface density from the vegetation-cooling signal. The inclusion of NDBI as an explicit covariate, rather than as the primary predictor, reflects the analytical priority of this study on quantifying vegetation-mediated cooling while statistically accounting for built-up density.

Land surface temperature was retrieved from the thermal infrared band (Band 6 for L5; Band 10 for L8/L9) using the single-channel / mono-window family of algorithms (Qin et al. 2001; Jiménez-Muñoz and Sobrino 2003). Land surface emissivity (ϵ) was estimated via the NDVI-threshold method (Sobrino et al. 2008; Sobrino and Raissouni 2000), in which fractional vegetation cover derived from NDVI is used to assign emissivity to vegetated, mixed, and bare/built surfaces (Carlson and Ripley 1997). At-sensor brightness temperature was converted to LST using the retrieved emissivity, and all temperatures were expressed in degrees Celsius. Band 10 was preferred over Band 11 for Landsat 8/9 owing to its lower calibration uncertainty and higher agreement with ground measurements (Yu et al. 2014).

Surface UHI intensity was computed as the difference between mean urban and mean rural land surface temperature:

$$\text{UHI} = \bar{T}_{\text{urban}} - \bar{T}_{\text{rural}}$$

where urban and rural zones were defined from the administrative mask and the NDBI/NDVI-based land cover, with the rural reference drawn from the vegetated peri-urban belt within the 5 km buffer. To identify statistically significant spatial clustering of thermal extremity, the Getis-Ord *Gi local statistic* (Getis and Ord 1992; Ord and Getis 1995) was applied directly to the LST surface*, not to urban-growth pixels, yielding z-scores and p-values that delineate statistically significant hot spots (clustered high LST) and cold spots (clustered low LST). Significance was classified at the 90%, 95%, and 99% confidence levels, ensuring that vegetation-sustained cool islands were rendered visible alongside thermal hot spots.

As a first-order assessment of the vegetation–temperature relationship, the Pearson product-moment correlation coefficient was computed between NDVI and LST, and between NDBI and LST, for each city and reference year. This provided a non-spatial baseline against which the subsequent spatial-regression coefficients could be interpreted, and confirmed the expected inverse NDVI–LST and positive NDBI–LST associations.

The vegetation–temperature relationship was quantified at the pixel level separately for each city and reference year. First, the Pearson product-moment correlation coefficient was computed between NDVI and LST to establish the strength and direction of their association. An ordinary least squares (OLS) regression of LST on NDVI was then fitted for each city. It is acknowledged that the very high spatial autocorrelation observed in the LST surface (Global Moran's $I \approx 0.95$; see Section 4.5) technically violates the OLS independence assumption, which may inflate significance estimates. The OLS framework was nonetheless retained here to enable a transparent, replicable comparison of cooling slopes across planning regimes; future work should implement spatial lag or spatial error models (SLM/SEM) or geographically weighted regression (GWR) to fully account for spatial dependence:

$$LST_i = \beta_0 + \beta_1 \cdot NDVI_i + \varepsilon_i$$

where β_1 is the NDVI cooling coefficient, interpretable as the change in LST ($^{\circ}\text{C}$) per unit increase in NDVI, and ε_i is the error term. The slope β_1 , the intercept, the coefficient of determination (R^2), and the associated significance were extracted for Islamabad and Rawalpindi in each year, enabling a direct comparison of vegetation-cooling magnitude between the planned and unplanned urban forms. The analysis was conducted independently per city to preserve the planned/unplanned contrast that is central to the study. Regression analyses were implemented in Python using the statsmodels and SciPy libraries. The complementary Normalised Difference Built-up Index (NDBI) was retained as an additional predictor for the multivariate comparison of vegetation versus built-up controls on LST reported in Section 4.6.

To characterise the spatial clustering of the temperature field itself, Global Moran's I (Moran 1950; Cliff and Ord 1981) was computed on the LST surface, and the local Getis-Ord G_i^* statistic (Section 4.6) was used to delineate statistically significant thermal hot spots and cool islands. Spatial statistics were implemented in Python using the PySAL/esda library (Rey and Anselin 2007).

Rawalpindi. The difference in cooling magnitude between the two cities was tested with a z-test on their independent regression slopes, comparing β_1 for Islamabad against β_1 for Rawalpindi using their respective standard errors. Together, these tests underpin the study’s central comparative claim about differential cooling efficiency between the two planning regimes, with a two-tailed significance threshold of $p < 0.05$ applied throughout. Fig. 2 summarises the full analytical workflow, from data acquisition through to the final statistical comparison.

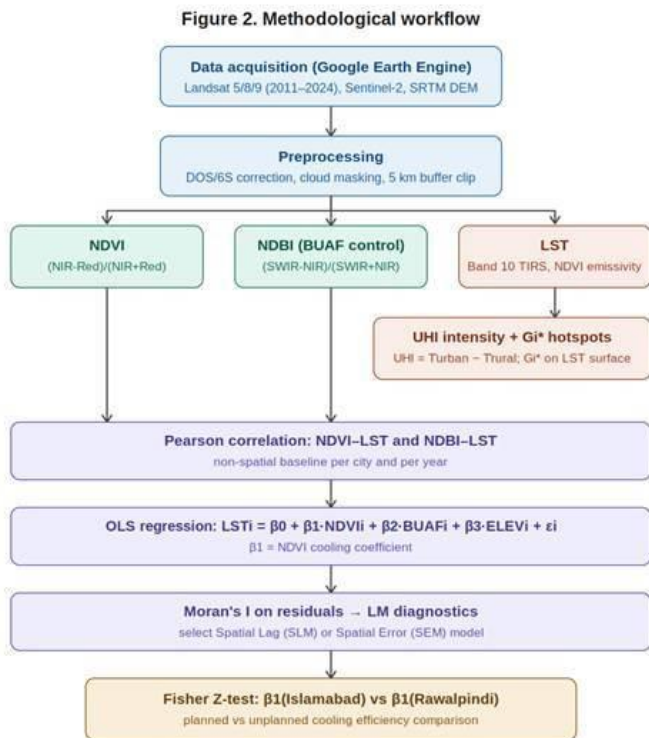


Fig. 2 Methodological workflow of the study.

4. Results

4.1 Spatiotemporal Dynamics of LST and NDVI

This section describes how land surface temperature (LST) and vegetation cover (NDVI) behaved in space and time across planned Islamabad and unplanned Rawalpindi over the four reference years, 2011, 2016, 2021, and 2024. Table 2 gives descriptive statistics for both indices by city, and their spatial distributions are mapped in Fig. 3 (LST) and Fig. 4 (NDVI).

4.1.1 Land surface temperature

Mean LST was broadly similar between the two cities in any given year, but they diverged sharply in how much that temperature varied internally. In Islamabad, mean LST stayed within a narrow band, from 27.54 °C in 2011 to a peak of 28.03 °C in 2016, then declining to 27.13 °C in 2021 and 26.25 °C in 2024. Rawalpindi followed a broadly similar path, from 27.97 °C in 2011 to 26.16 °C in 2024, so both cities cooled modestly overall, a pattern consistent with the multi-temporal land-cover trend Khalil et al. (2024) reported for this conurbation.

What really set the two cities apart was not their average temperature but its spread. Rawalpindi's LST standard deviation ran consistently higher, from 2.32 to 2.84 °C, roughly double Islamabad's 1.07–1.50 °C in every year studied. The same contrast showed up at the extremes: Rawalpindi's maximum LST reached 31.5–32.5 °C while its minimum fell as low as 16.9–18.2 °C, an intra-urban range exceeding 13 °C. Islamabad was far more thermally uniform by comparison, with maxima of 29.1–31.5 °C and noticeably warmer minima of 22.4–23.6 °C. Rawalpindi's wide range and hotter extremes fit the dense, fragmented, largely unvegetated fabric typical of an organically grown city, while Islamabad's narrower spread reflects the moderating effect of its planned green infrastructure and regulated plot coverage (Kamran et al. 2023).

4.1.2 Vegetation cover (NDVI)

Rawalpindi's administrative extent, rather than any real densification of NDVI cover within the urban core itself. NDVI variability was similar in both cities and years ($SD \approx 0.11$ – 0.13), and the full range in both extended from near-bare or built-up values (≈ 0.2 – 0.3) to densely vegetated surfaces (≈ 0.68 – 0.77).

4.1.3 Coupled LST–NDVI behaviour

Taken together, the two indices moved in a coherent, inverse pattern at the aggregate scale: as mean NDVI rose over the study period, mean LST fell in both cities, a first descriptive hint of the vegetation-cooling relationship that Section 4.3 quantifies formally through correlation and spatial regression. Yet Rawalpindi's markedly greater thermal heterogeneity, despite NDVI levels comparable to, and by 2024 even exceeding, Islamabad's, points toward this study's central finding: that how green cover is arranged and the planning context it sits within, rather than how much of it there is on average, is what actually governs cooling efficiency.

1 **Table 2. Descriptive statistics of LST (°C) and NDVI by city and year.**

Year	City	LST Mean	LST Min	LST Max	LST SD	NDVI Mean	NDVI Min	NDVI Max	NDVI SD
2011	Islamabad	27.54	22.65	30.23	1.50	0.303	−0.235	0.694	0.119
2011	Rawalpindi	27.97	17.38	31.47	2.84	0.275	−0.214	0.765	0.119
2016	Islamabad	28.03	23.58	31.53	1.40	0.352	−0.200	0.699	0.124
2016	Rawalpindi	27.91	18.21	32.50	2.38	0.365	−0.191	0.721	0.111
2021	Islamabad	27.13	22.84	29.49	1.24	0.362	−0.086	0.681	0.118
2021	Rawalpindi	27.48	17.14	30.96	2.61	0.354	−0.160	0.708	0.107
2024	Islamabad	26.25	22.38	29.09	1.07	0.365	−0.166	0.715	0.129
2024	Rawalpindi	26.16	16.94	30.60	2.32	0.375	−0.296	0.762	0.121

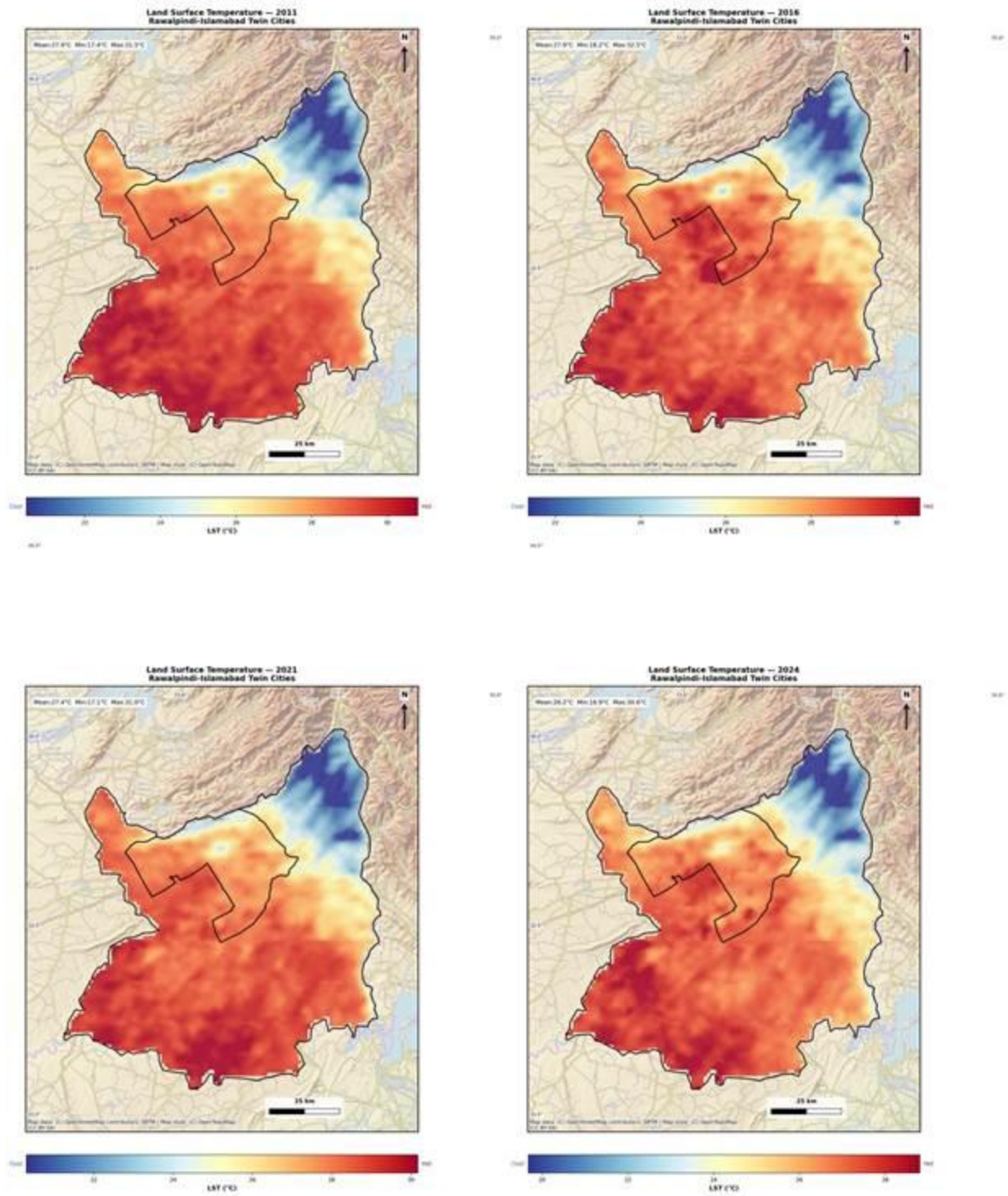


Fig. 3 Spatial distribution of land surface temperature (LST) across the Islamabad–Rawalpindi conurbation for 2011, 2016, 2021, and 2024.

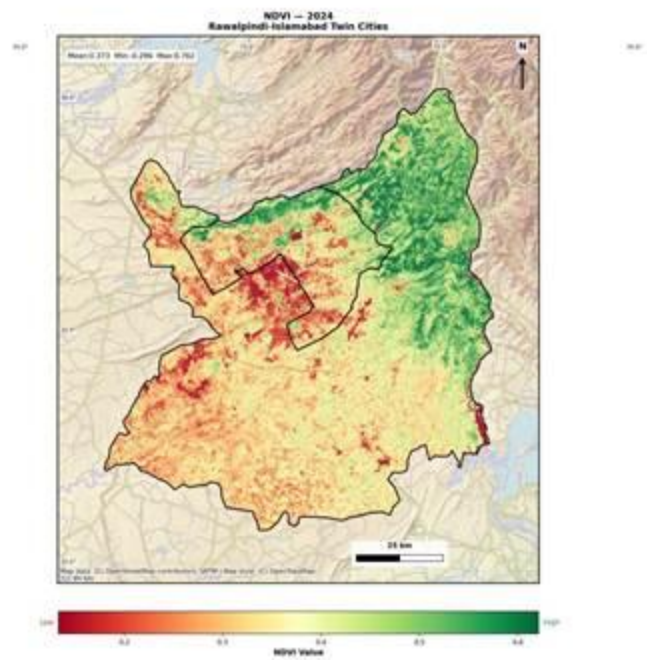
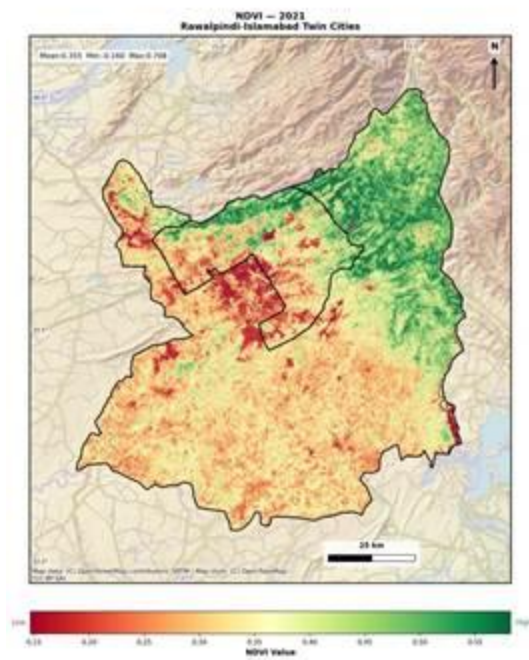
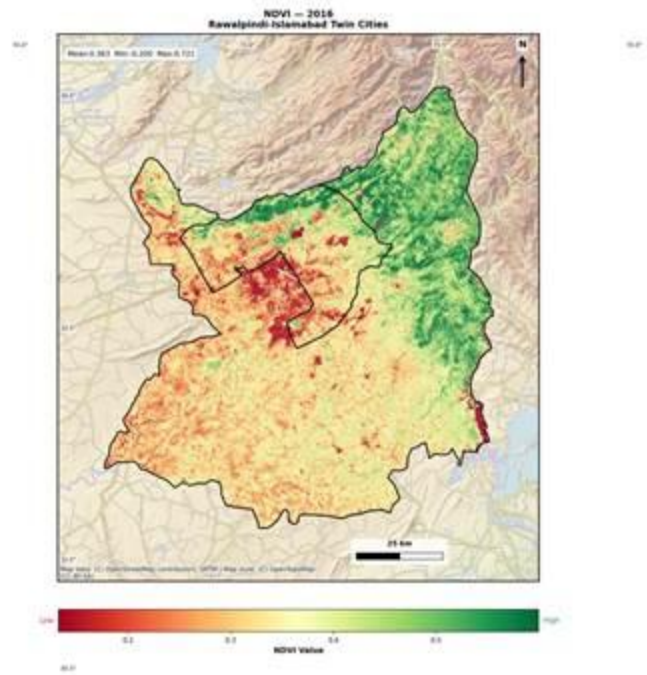
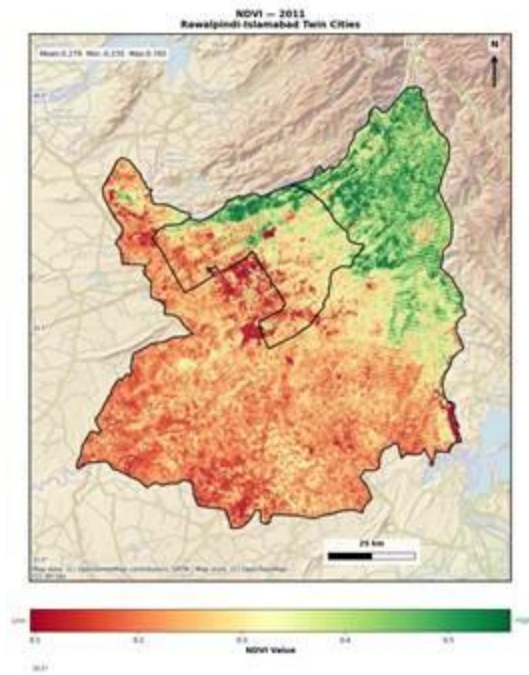


Fig. 4 Spatial distribution of NDVI across the Islamabad–Rawalpindi conurbation for 2011, 2016, 2021, and 2024.

4.2 Urban Heat Island Intensity

Surface UHI intensity was computed for each city and reference year as the difference between mean urban and mean rural land surface temperature ($\text{UHI} = \bar{T}_{\text{urban}} - \bar{T}_{\text{rural}}$), with urban and rural zones delineated within each administrative unit as described in Section 4.6. The resulting values, together with the underlying urban and rural mean temperatures and pixel counts, are reported in Table 3 and summarised in Fig. 5

The two cities exhibited a pronounced and consistent divergence in surface UHI intensity that constitutes one of the central comparative findings of this study. The unplanned city of Rawalpindi recorded a substantial positive UHI in every reference year, rising from 0.61 °C in 2011 to a peak of 1.23 °C in 2016, and remaining elevated at 0.97 °C in 2021 and 1.00 °C in 2024. In sharp contrast, the planned city of Islamabad displayed a negligible, and in one year slightly negative, surface UHI throughout: −0.09 °C in 2011, 0.31 °C in 2016, 0.03 °C in 2021, and 0.16 °C in 2024. Across the study period, Rawalpindi's mean UHI intensity (≈ 0.90 °C) was approximately six to seven times that of Islamabad (≈ 0.10 °C).

unplanned counterparts (Waleed and Sajjad 2022), and that rapid, unregulated urban expansion with limited green infrastructure intensifies surface heating in lower-income-country cities generally (npj Sustainability 2025).

The surface UHI magnitudes reported here, about 1 °C for Rawalpindi, are lower than the 2.9–5.0 °C range Khan and Shahid (2024) reported for major Pakistani cities. As noted earlier, this is because the present values come from annual, cloud-free median LST composites, which smooth over the diurnal and seasonal extremes that single-time-point measurements capture. What stands out is that the sharp contrast between the two cities persisted even as their mean NDVI converged over time, and by 2024 Rawalpindi's mean NDVI had even edged past Islamabad's. This decoupling of UHI intensity from mean greenness reinforces the study's central argument: it is the planning context and spatial arrangement of vegetation, not simply how much of it exists on average, that determines how effectively it mitigates surface heat.

Table 3. Surface UHI intensity (°C) by city and year.

Year	City	Urban mean LST	Rural mean LST	UHI intensity	Urban pixels	Rural pixels
2011	Islamabad	27.88	27.96	-0.09	79	815
2011	Rawalpindi	28.55	27.94	0.61	341	6013
2016	Islamabad	28.72	28.41	0.31	77	817
2016	Rawalpindi	29.04	27.80	1.23	569	5785
2021	Islamabad	27.47	27.44	0.03	131	763
2021	Rawalpindi	28.37	27.40	0.97	498	5855
2024	Islamabad	26.70	26.55	0.16	151	743
2024	Rawalpindi	27.07	26.06	1.00	652	5702

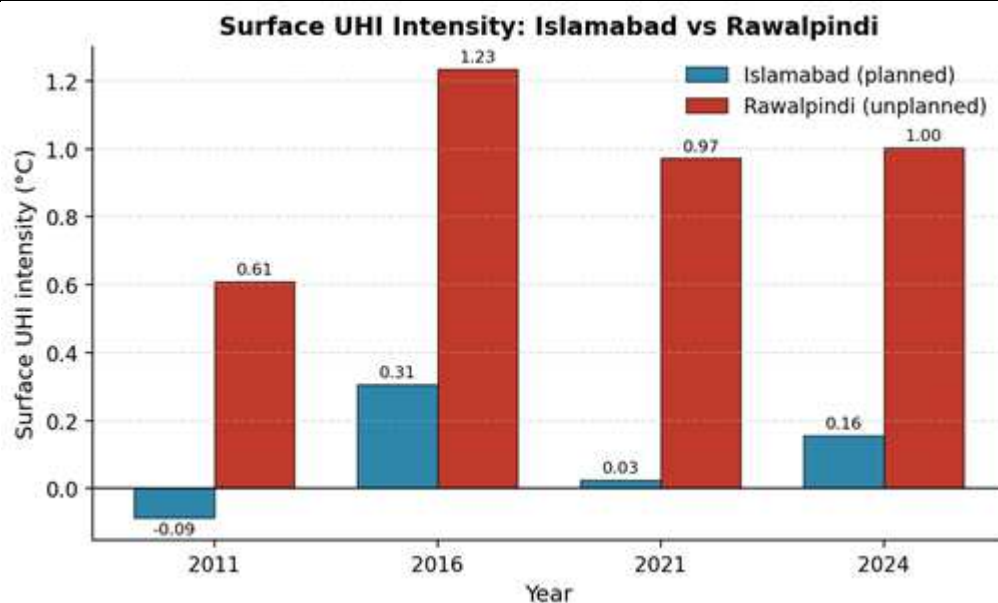


Fig. 5 Surface UHI intensity (°C) for Islamabad (planned) and Rawalpindi (unplanned) across the four reference years.

4.3 NDVI–LST Relationship: Correlation and Regression

To quantify the vegetation-cooling relationship and compare its strength between the two cities, pixel-level Pearson correlation and ordinary least squares (OLS) regression of LST on NDVI were computed separately for Islamabad and Rawalpindi in each reference year. The per-city results are reported in Table 5 and visualised in Fig. 6

4.3.1 Correlation strength

Both cities exhibited strong and statistically significant negative correlations between NDVI and LST in every reference year (all $p < 0.001$), confirming that vegetated surfaces are systematically cooler than non-vegetated surfaces throughout the conurbation. The Pearson correlation coefficient

ranged from -0.674 to -0.778 in Islamabad and from -0.712 to -0.847 in Rawalpindi. The strongest single correlation was recorded in Rawalpindi in 2011 ($r = -0.847$), while correlation strength weakened modestly over time in Islamabad (from -0.778 in 2011 to -0.674 in 2024).

4.3.2 Regression slope and explained variance

The OLS regression slope (β_1), which can be read as the change in LST, in $^{\circ}\text{C}$, per unit increase in NDVI, showed the sharpest contrast between the two urban forms. In every reference year, the cooling slope in unplanned Rawalpindi was roughly twice as steep as in planned Islamabad: -23.58 versus -12.40 $^{\circ}\text{C}$ per NDVI unit in 2011, -18.50 versus -10.34 in 2016, -21.12 versus -9.64 in 2021, and -16.80 versus -7.60 in 2024. The regression models explained 45–61% of the variance in Islamabad ($R^2 = 0.455\text{--}0.606$) and 51–72% in Rawalpindi ($R^2 = 0.507\text{--}0.718$), and all were highly significant.

One caveat on spatial dependence is worth flagging here: because Moran’s I for the LST surface is as high as ≈ 0.95 (Section 4.5), OLS residuals are not fully spatially independent, so it is the slope magnitudes and their relative ordering, rather than their exact confidence intervals, that should be treated as the primary result.

4.3.3 Interpretation

The much steeper slope in Rawalpindi means that, per unit of vegetation, the marginal cooling effect on the surface is considerably larger there than in the planned city. This follows directly from the greater thermal contrast within Rawalpindi documented in Section 4.1: against a hot, largely impervious baseline interrupted by only limited green patches, each added increment of vegetation produces a large temperature difference. Islamabad’s planned, already well-vegetated, and thermally uniform fabric leaves much less room for such a gradient, which is why its marginal cooling slope is shallower. Section 4.4 compares the two cities formally on this basis.

Table 5. Per-city OLS regression of LST on NDVI by year.

Year	City	n	Pearson r	β_1 (slope)	Intercept	R^2	R^2 adj	p
2011	Islamabad	1119	-0.778	-12.399	31.14	0.606	0.605	<0.001
2011	Rawalpindi	6251	-0.847	-23.585	34.38	0.718	0.718	<0.001
2016	Islamabad	1119	-0.719	-10.339	31.53	0.517	0.517	<0.001
2016	Rawalpindi	6251	-0.712	-18.503	34.58	0.507	0.507	<0.001
2021	Islamabad	1119	-0.714	-9.640	30.48	0.510	0.510	<0.001

2021	Rawalpindi	6251	-0.727	-21.122	34.86	0.528	0.528	<0.001
2024	Islamabad	1119	-0.674	-7.605	28.91	0.455	0.454	<0.001
2024	Rawalpindi	6251	-0.724	-16.797	32.38	0.524	0.524	<0.001

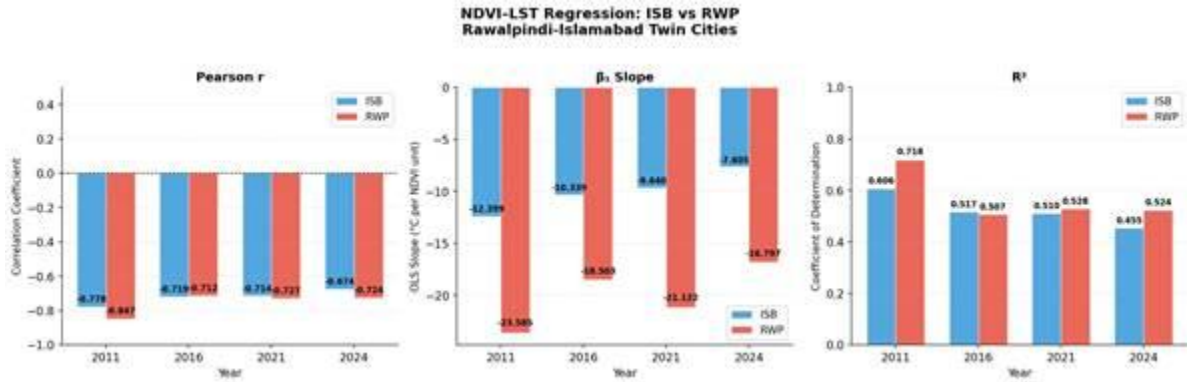


Fig. 6 Per-city comparison of NDVI–LST regression parameters (Pearson r , OLS slope β_1 , and R^2) for Islamabad (ISB) and Rawalpindi (RWP) across the four reference years.

4.4 Planned vs. Unplanned Cooling Efficiency: Statistical Comparison

difference in cooling slope (β_1) was tested with a z-test on the two cities' independent regression coefficients, summarised in Table 6. The two tests told a complementary story. On correlation strength, the NDVI–LST relationship was significantly stronger in Rawalpindi in 2011 (Fisher $Z = 6.33$, $p < 0.001$) and 2024 ($Z = 2.97$, $p = 0.003$), but the two cities were statistically indistinguishable in 2016 ($Z = -0.45$, $p = 0.65$) and 2021 ($Z = 0.80$, $p = 0.42$), so the underlying strength of association was broadly similar across both urban forms.

The cooling slope told a different, and far more consistent, story: in every single reference year, Rawalpindi's β_1 was significantly steeper than Islamabad's ($z = 27.1\text{--}39.1$, all $p < 0.0001$). This divergence is the study's central result. The marginal cooling efficiency of vegetation, the temperature reduction delivered per unit of greenness, is significantly and substantially higher in unplanned Rawalpindi than in planned Islamabad, even though Rawalpindi's overall surface UHI is far higher (Section 4.2). These two findings are not in conflict; they complement each other. Planned Islamabad has already achieved, through sustained green-infrastructure provision, a cool and thermally uniform urban environment, so there is little cooling gradient left to exploit, which yields both a low UHI and a shallow NDVI–LST slope.

Unplanned Rawalpindi, by contrast, still carries a steep latent cooling gradient: its hot, impervious fabric means that wherever vegetation does exist, it cools powerfully on a per-unit basis, but there

simply is not enough of it, nor is it arranged well enough, to suppress the city-wide heat island. The policy implication follows directly: targeted expansion of green infrastructure in Rawalpindi would deliver the largest marginal cooling returns anywhere in the conurbation.

Table 6. Statistical comparison of the NDVI–LST relationship between Islamabad and Rawalpindi.

Year	r (ISB)	r (RWP)	Fisher Z	p (r)	β_1 (ISB)	β_1 (RWP)	Slope z	p (slope)
2011	−0.778	−0.847	6.33	<0.001	−12.40	−23.58	39.1	<0.0001
2016	−0.719	−0.712	−0.45	0.654	−10.34	−18.50	27.1	<0.0001
2021	−0.714	−0.727	0.80	0.424	−9.64	−21.12	37.5	<0.0001
2024	−0.674	−0.724	2.97	0.003	−7.60	−16.80	36.8	<0.0001

4.5 Spatial Autocorrelation and Hotspot Analysis (Moran's I and Getis-Ord Gi*)

To characterise the spatial clustering structure of surface temperature across the conurbation, the Global Moran's I statistic (Moran 1950; Cliff and Ord 1981) and the local Getis-Ord Gi* statistic (Getis and Ord 1992; Ord and Getis 1995) were applied directly to the LST surface. Results for the four reference years are summarised in Table 4, while the full 2000–2024 temporal trends of Moran's I and of the hot- and cold-spot fractions are shown in Figures 8 and 9.

4.5.1 Global spatial autocorrelation

the spatially explicit regression framework adopted in this study. Moran's I for LST stayed consistently higher and more stable than for NDVI (≈ 0.53 – 0.77) or EVI (≈ 0.46 – 0.68) over the same period (Fig. 8), reflecting the strong, persistent thermal gradient set up by the forested Margalla Hills to the north and the dense urban core to the south.

4.5.2 Local hotspots and cool islands

The Getis-Ord Gi* analysis revealed a striking, and remarkably consistent, asymmetry between hot and cool clusters across all four reference years. Statistically significant cold spots, vegetation-sustained cool islands, covered 3.8–4.0% of the conurbation, while significant hot spots at the 99% confidence level were effectively absent, at 0.0% in every year (Table 4). At the 95% level, cold spots still dominated over hot spots ($\leq 0.03\%$). This dominance of cold spots held steady across the full 2004–2024 record (Fig. 9), in sharp contrast to the more variable, hot-spot-prone clustering seen in the NDVI and EVI surfaces.

That cold spots dominate, and significant hot spots are almost entirely absent, in the LST surface suggests that the conurbation's most thermally coherent vegetated zones, chiefly the Margalla Hills National Park, the Rawal Lake catchment, and Islamabad's well-planted sectors, act as concentrated cool cores. This is consistent with the strong vegetation-cooling signal documented elsewhere in this study and supports the interpretation in Sections 5.1–5.2 that protected green spaces exert a substantial moderating influence on the region's surface-temperature field.

Table 4. Global Moran's I and Getis-Ord Gi hot/cold-spot fractions of the LST surface, by year (conurbation level).*

Year	Mean LST (°C)	Moran's I	p	Hot spot 99 % (%)	Hot spot 95 % (%)	Cold spot 99 % (%)	Cold spot 95 % (%)
2011	27.90	0.957	0.0033	0.00	0.00	3.87	2.58
2016	27.92	0.951	0.0033	0.00	0.03	4.04	2.10
2021	27.42	0.955	0.0033	0.00	0.00	4.04	2.07
2024	26.17	0.952	0.0033	0.00	0.00	3.81	2.07

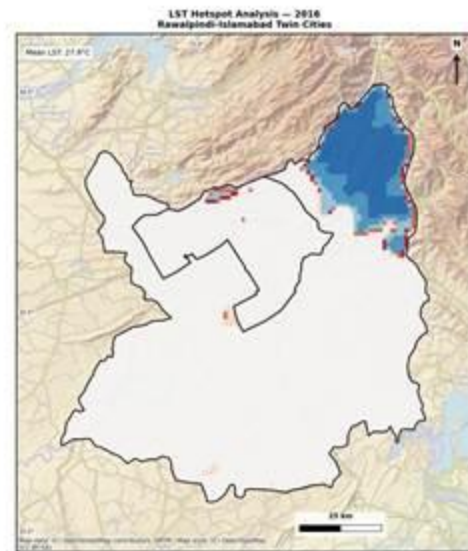
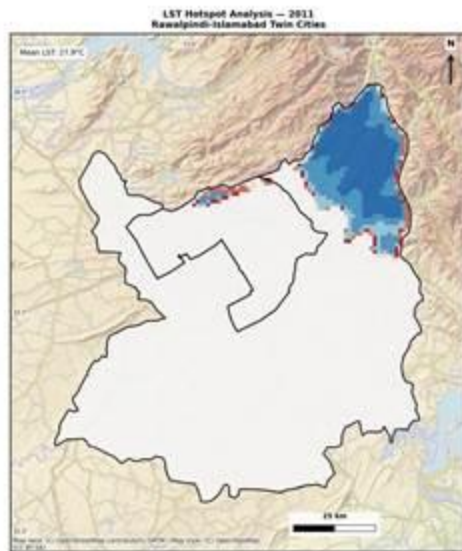


Fig. 7 Getis-Ord Gi hotspot maps of the LST surface for 2011, 2016, 2021, and 2024, showing statistically significant hot spots and cold spots at the 90/95/99 % confidence levels.

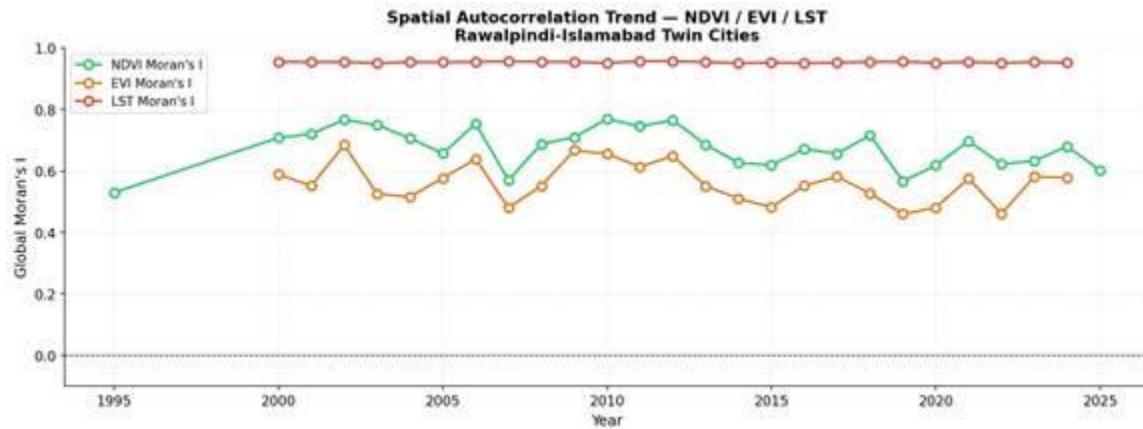


Fig. 8 Temporal trend (2000–2024) of Global Moran's I for the NDVI, EVI, and LST surfaces across the conurbation.

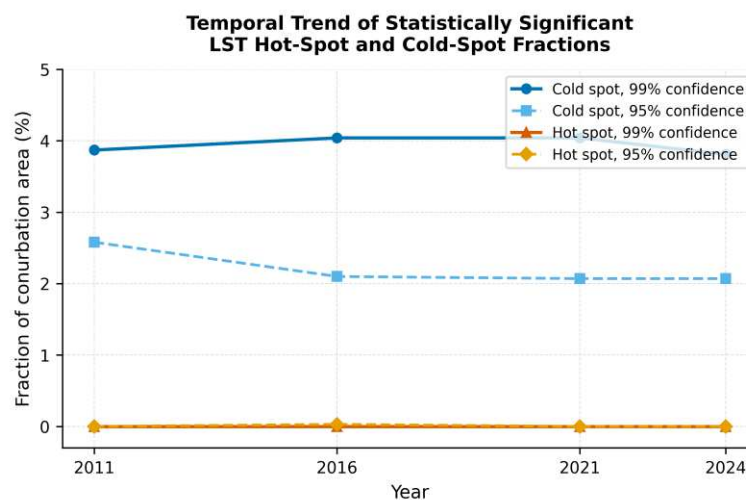


Fig. 9 Temporal trend (2011–2024) of statistically significant hot-spot and cold-spot fractions (Getis-Ord G_i^* , 99% and 95% confidence) for the LST surface across the conurbation.

4.6 Relative Explanatory Contribution of Vegetation, Built-up Density and Elevation

Objective 4 required an assessment of the relative explanatory power of vegetation cover and impervious-surface density in accounting for intra-urban variation in land surface temperature. The relationship was examined in three complementary steps (i) the standalone Pearson correlation of each index with LST; (ii) a full multiple-regression model in which LST was regressed jointly on NDVI, NDBI, and elevation (ELEV, derived from the SRTM DEM as a topographic control), with variance inflation factors (VIF) computed to verify that collinearity did not invalidate the

model; and (iii) an incremental-variance decomposition quantifying the unique contribution of NDVI and NDBI. The model is specified as:

$$LST_i = \beta_0 + \beta_1 \cdot NDVI_i + \beta_2 \cdot NDBI_i + \beta_3 \cdot ELEV_i + \varepsilon_i$$

All analyses were conducted separately per city and reference year on a common, harmonised pixel sample (n = 1140 for Islamabad, n = 6860 for Rawalpindi). Results are reported in Tables 7 and 8 and visualised in Figures 10 and 11.

4.6.1 Standalone index–LST correlations

Both indices were significantly correlated with LST in every city and reference year. The NDVI–LST correlation was negative throughout, indicating vegetation-driven cooling (−0.543 to −0.703 in Islamabad; −0.587 to −0.768 in Rawalpindi), whereas the NDBI–LST correlation was positive, indicating built-up-driven warming. Critically, the NDBI–LST association was stronger than the NDVI–LST association in absolute terms in every single city-year (NDBI: +0.627 to +0.777 in Islamabad and +0.773 to +0.854 in Rawalpindi). At the bivariate level, therefore, impervious-surface density tracked the surface-temperature field more closely than vegetation across the entire conurbation (Fig. 11a).

4.6.2 Full regression model with elevation control

In the joint model (Table 7), NDBI carried a strong, positive, and highly significant coefficient in every city-year (all $p < 0.001$), and elevation a consistently negative and highly significant coefficient (all $p < 0.001$), the latter confirming a distinct topographic cooling gradient associated with the elevated, forested Margalla terrain to the north. By contrast, the NDVI coefficient was weak and unstable, small in magnitude, non-significant in several years, and inconsistent in sign, a characteristic symptom of its strong collinearity with NDBI rather than evidence that vegetation warms the surface. The sign instability of the NDVI coefficient, alternating between negative and positive across years (e.g., Islamabad 2011: −0.198 vs. 2016: +0.269; Rawalpindi 2016: +0.658 vs. 2011: +0.001), is a direct manifestation of this collinearity. When two predictors are strongly correlated, as NDVI and NDBI are ($r \approx -0.85$ to -0.90 between them across all city-years), the allocation of shared variance between the two coefficients becomes unstable across samples, producing sign flips that have no physical interpretation. This collinearity is intrinsic: NDVI and NDBI jointly capture the vegetation-to-built-up gradient, so they share the same underlying

information. The incremental-variance analysis (Section 4.6.3) resolves this ambiguity by isolating each predictor's unique contribution. All variance inflation factors remained below 5 (range 1.09–4.63), confirming that, although NDVI and NDBI are correlated, multicollinearity was not severe enough to undermine the model. The full three-predictor model explained between 52 and 77 per cent of intra-urban LST variance ($R^2 = 0.523$ – 0.768).

4.6.3 Relative (unique) contribution of NDVI and NDBI

contributed substantial unique variance beyond NDVI alone ($\Delta R^2 = 0.068$ – 0.138). NDBI was consequently the dominant predictor in all eight city-years, in both the planned and the unplanned city. The vegetation-cooling signal, though strong when considered on its own, turns out to be largely shared with, rather than independent of, built-up density.

4.6.4 Interpretation

These results, which address Objective 4, point to built-up density rather than vegetation as the main proximate control on intra-urban land surface temperature across the conurbation, in both planning regimes. This does not contradict what Sections 4.3 and 4.4 established; it clarifies it. Because vegetated and built-up surfaces sit at opposite ends of the same land-cover continuum, NDVI and NDBI capture much of the same underlying information, so the strong NDVI–LST cooling slopes reported earlier largely reflect the fact that vegetation and impervious cover rarely coexist in the same place. Once built-up density is explicitly controlled for, vegetation adds little further explanatory power, while impervious density remains a significant secondary predictor of cooling.

The policy implication sharpens accordingly: in a conurbation where vegetated and built-up land occupy opposite ends of a single continuum, the strong NDVI–LST cooling relationship documented in Sections 4.3 and 4.4 largely reflects the absence of impervious cover rather than the presence of vegetation as such, so interventions that reduce impervious density are likely to deliver the largest cooling gains.

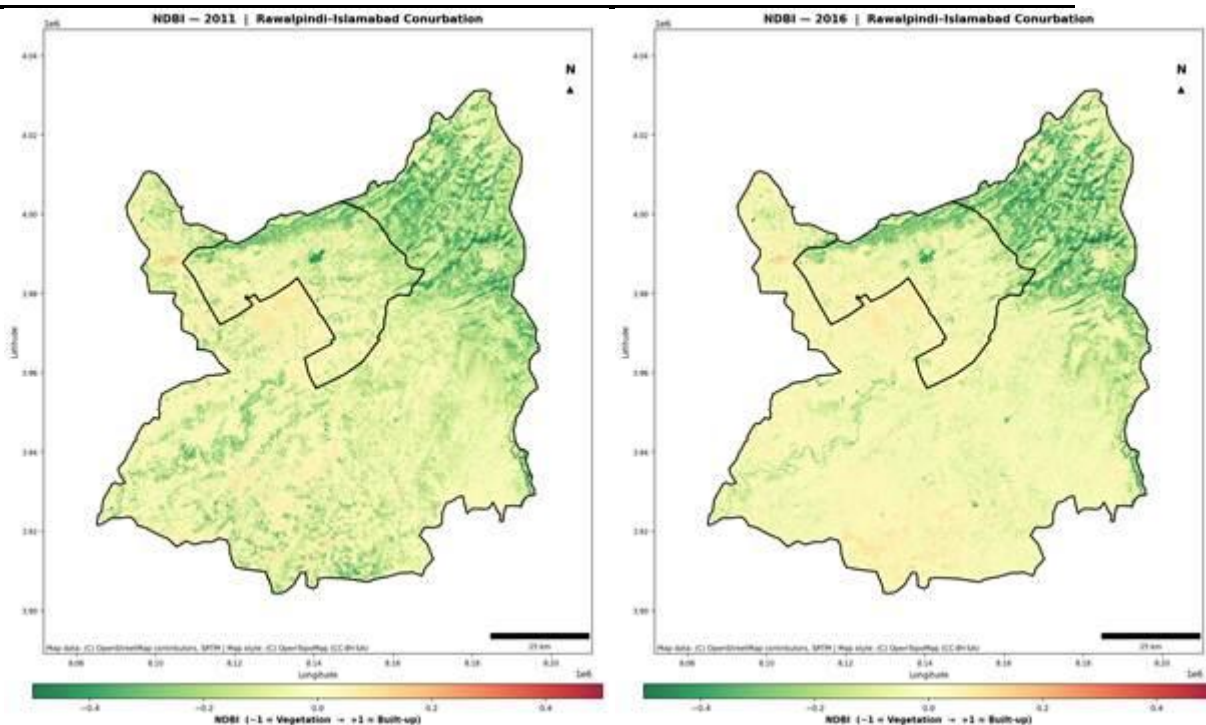
Table 7. Full regression of LST on NDVI, NDBI, and elevation (ELEV), by city and year. β = regression coefficient; VIF (V/B/E) = variance inflation factors for NDVI, NDBI, and ELEV. Significance: * $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns = not significant.**

Year	City	n	β NDVI	β NDBI	β ELEV	R^2	VIF (V/B/E)
2011	Islamabad	1140	–0.198 ns	+2.042***	–0.978***	0.674	3.6 / 3.3 / 1.4

2016	Islamabad	1140	+0.269**	+1.809***	-0.767***	0.639	4.0 / 4.0 / 1.2
2021	Islamabad	1140	-0.106 ns	+1.646***	-1.390***	0.658	4.0 / 4.0 / 1.2
2024	Islamabad	1140	+0.230*	+1.658***	-1.039***	0.523	4.1 / 4.0 / 1.1
2011	Rawalpindi	6860	+0.001 ns	+3.496***	-1.292***	0.766	4.5 / 4.5 / 1.8
2016	Rawalpindi	6860	+0.658***	+2.268***	-1.408***	0.740	3.2 / 3.6 / 1.4
2021	Rawalpindi	6860	+0.214***	+2.988***	-1.966***	0.768	4.1 / 4.6 / 1.7
2024	Rawalpindi	6860	+0.739***	+3.872***	-1.129***	0.682	4.0 / 4.6 / 1.6

1 **Table 8. Relative explanatory contribution of NDVI and NDBI. r = standalone Pearson correlation with LST;**
2 **R^2 single-index-only models; ΔR^2 = unique (incremental) variance added by each index over the other;**
3 **Dominant = index with the larger unique contribution.**

Year	City	r NDVI	r NDBI	R^2 NDVI-only	R^2 NDBI-only	ΔR^2 NDVI	ΔR^2 NDBI	Dominant
2011	Islamabad	-0.703	+0.777	0.494	0.604	0.001	0.107	NDBI
2016	Islamabad	-0.637	+0.749	0.406	0.560	0.003	0.132	NDBI
2021	Islamabad	-0.641	+0.697	0.410	0.486	0.000	0.068	NDBI
2024	Islamabad	-0.543	+0.627	0.295	0.393	0.002	0.090	NDBI
2011	Rawalpindi	-0.768	+0.854	0.589	0.729	0.000	0.105	NDBI
2016	Rawalpindi	-0.587	+0.773	0.345	0.597	0.013	0.138	NDBI
2021	Rawalpindi	-0.708	+0.820	0.501	0.673	0.000	0.080	NDBI
2024	Rawalpindi	-0.650	+0.800	0.422	0.641	0.006	0.136	NDBI



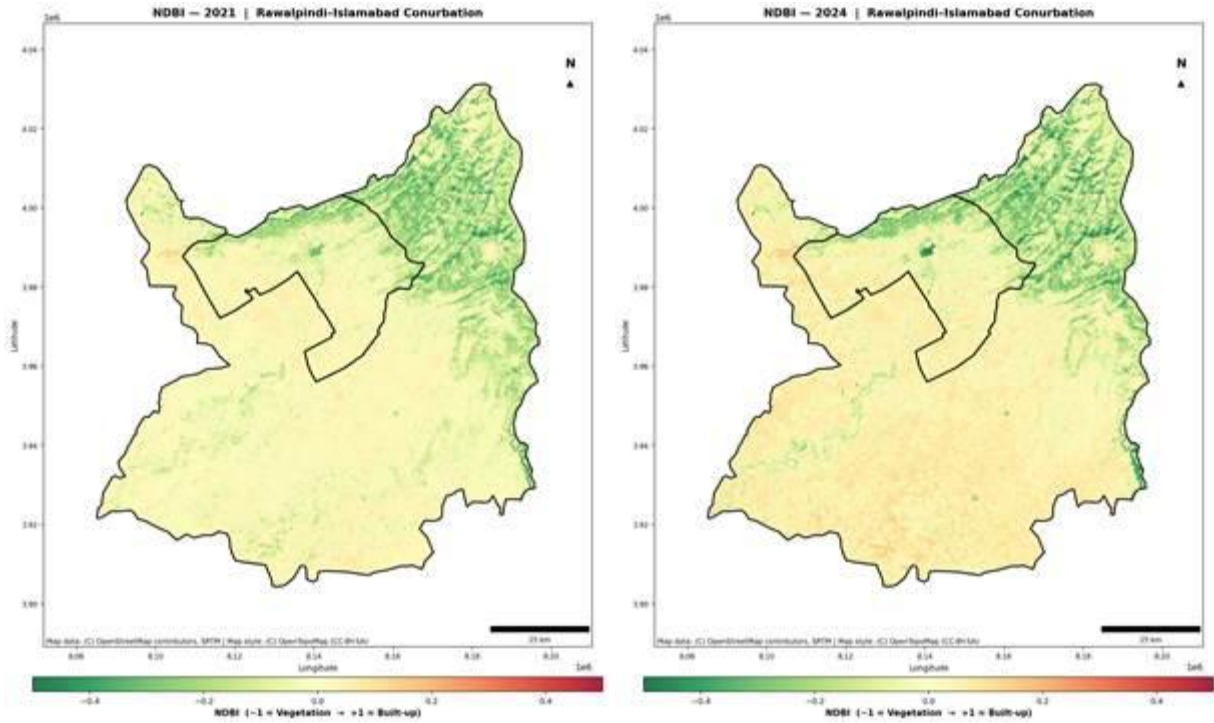


Fig. 10 Spatial distribution of NDBI across the Islamabad–Rawalpindi conurbation for 2011, 2016, 2021, and 2024 (−1 = vegetation → +1 = built-up).

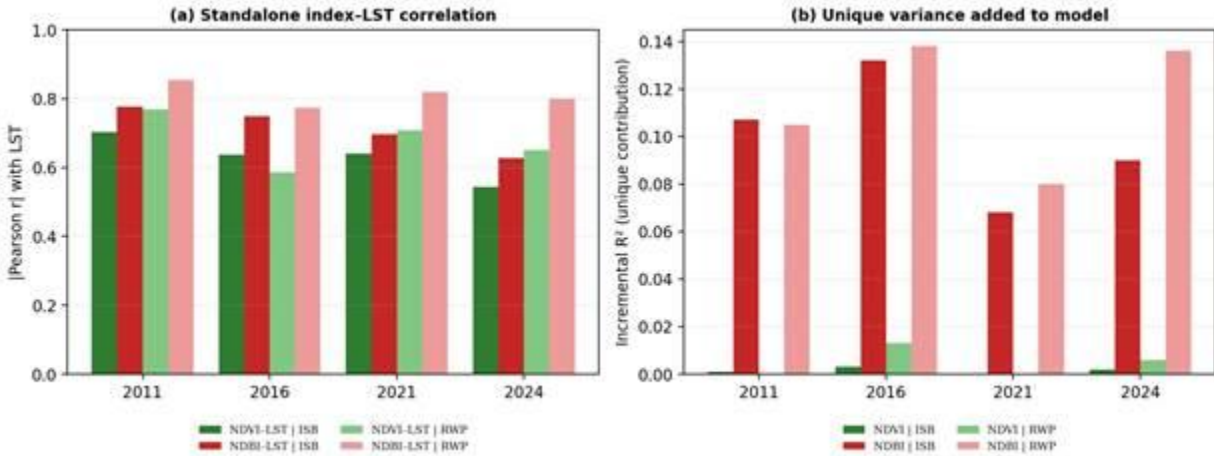


Fig. 11 Relative explanatory contribution of NDVI and NDBI to LST for Islamabad (ISB) and Rawalpindi (RWP), 2011–2024: (a) standalone |Pearson r| of each index with LST; (b) incremental R² (unique variance) added by each index to the model.

5. Discussion

5.1 Divergent thermal behaviour of planned and unplanned urban forms

Islamabad's near-neutral, and occasionally negative, surface UHI reflects its master-planned green infrastructure, regulated plot coverage, and integrated forested margins and sector parks, which together dampen the urban-rural thermal gradient. Rawalpindi's dense, fragmented, largely impervious fabric, by contrast, sustains a measurable heat island throughout the study period.

a positive surface UHI some six to seven times greater. This divergence fits the contrasting land-use trajectories Kamran et al. (2023) documented, and echoes Waleed and Sajjad's (2022) conclusion that planned areas achieve markedly better temperature control through green-space provision than their unplanned counterparts.

5.2 The cooling-efficiency paradox

One striking, and at first glance paradoxical, result is that vegetation's marginal cooling efficiency, the per-unit NDVI reduction in LST, was about twice as strong in unplanned Rawalpindi as in planned Islamabad in every reference year (slope $z = 27\text{--}39$), even though Islamabad carried the far lower city-wide heat island. These two findings are not in tension; they fit together. Islamabad has, through sustained investment in green infrastructure, already reached a cool, thermally uniform surface where little cooling gradient is left to exploit, which produces both a low UHI and a shallow NDVI–LST slope.

Rawalpindi, on the other hand, still holds a steep latent cooling gradient: its hot, impervious matrix means that wherever vegetation is present, it cools powerfully on a per-unit basis, yet there is neither enough of it nor is it arranged well enough to suppress the city-wide heat island. This reading is consistent with Huang et al. (2025), who show that the NDVI–LST relationship is spatially non-stationary across heterogeneous urban environments, and with Lu et al. (2025), who stress that cooling depends non-linearly on both the density and configuration of vegetation.

5.3 Built-up density as the dominant proximate driver

The multivariate decomposition refined the attribution of the thermal field. Once built-up density and elevation were controlled, the unique contribution of NDVI to explaining LST became

negligible, whereas NDBI contributed substantial unique variance and was the dominant predictor in both cities. Because vegetated and built-up surfaces lie at opposite ends of a single land-cover continuum, the robust NDVI–LST cooling relationship documented in Sections 4.3 and 4.4 largely reflects the co-located absence of impervious cover rather than an independent vegetation effect. This is consistent with the strong inverse NDVI–LST and positive NDBI–LST associations reported across the recent literature (Anand et al. 2025; Altınır and Bingöl, 2025), and it reframes the cooling question: in this conurbation, impervious-surface management is at least as central to heat mitigation as vegetation provision. Elevation emerged as a significant secondary control, consistent with the cooling influence of the forested Margalla Hills to the north.

5.4 Spatial structure of the surface-temperature field

The very strong and temporally stable Global Moran’s I (≈ 0.95) confirms that LST is highly spatially organised, forming coherent thermal clusters rather than a random field, and thereby justifies the spatially explicit analytical framework adopted here. The Getis-Ord G_i^* analysis revealed a striking and consistent asymmetry: statistically significant cold spots, vegetation-sustained cool islands centred on the Margalla Hills National Park, the Rawal Lake catchment, and well-vegetated planned sectors of Islamabad, dominated, while significant hot spots were virtually absent. This corroborates the inferential role of protected and planned green space in moderating the regional surface-temperature field, consistent with the hotspot-based local climate zone assessments of Getis and Ord (1992) and Ord and Getis (1995)

5.5 Wider regional and global context

The surface UHI magnitudes reported here (≈ 1 °C for Rawalpindi) are lower than the 2.9–5.0 °C range documented for major Pakistani cities by Khan and Shahid (2024) and the multi-decadal warming reported for Rawalpindi by Nawaz (2025); this difference is expected, since the present values derive from annual cloud-free median composites that smooth the diurnal and seasonal extremes captured by single-date or air-temperature-based estimates. The planned/unplanned cooling differential observed here echoes the global finding of Yuan et al. (2025) that unplanned urban expansion in lower-income countries drives greater SUHI increases than planned growth, and of Shen and Zhao (2024) that SUHI is tightly coupled to climate–vegetation interactions. The study thereby contributes a quantified, intra-conurbation case to a global evidence base that has called for greater representation of small and medium-sized cities (Duymuş, 2025).

5.6 Policy implications

The results translate into spatially specific guidance for the Capital Development Authority and the Rawalpindi Development Authority. Because built-up density is the principal proximate driver of surface heat, and because the steepest latent cooling gradient lies within the hot, impervious fabric of Rawalpindi, the largest marginal surface-cooling returns in the conurbation are available there. Interventions should therefore prioritise the greening and management of impervious surfaces in dense Rawalpindi, street trees, permeable surfaces, rooftop and pocket greening, and the protection of remaining green patches, rather than the addition of vegetation in already-open peri-urban land, while safeguarding the protected green cores that the Gi* analysis identifies as the conurbation's principal cool islands. Spatially, the highest-priority intervention zones within Rawalpindi include the dense commercial core of Saddar and Raja Bazaar, the Old City quarters, and heavily built-up residential areas of Chaklala and Westridge, where impervious cover exceeds 70% and no Gi* cold-spot clustering is detected. A quantified target of reducing Rawalpindi's surface UHI from $\approx 0.9^{\circ}\text{C}$ to $\leq 0.5^{\circ}\text{C}$ by 2030 is achievable through systematic greening of 15–20% of current impervious area, based on the NDVI–LST slopes documented here. Spatially, the highest-priority intervention zones within Rawalpindi include the dense commercial core of Saddar and Raja Bazaar, the Old City quarters, and heavily built-up residential areas of Chaklala and Westridge. A quantified target of reducing Rawalpindi's surface UHI from $\approx 0.9^{\circ}\text{C}$ to $\leq 0.5^{\circ}\text{C}$ by 2030 is achievable through systematic greening of 15–20% of current impervious area.

5.7 Limitations and future directions

Several limitations qualify for these findings. First, the use of annual cloud-free median composites, while maximising spatial coverage and comparability, smooths the diurnal and seasonal thermal extremes during which UHI intensity peaks, so the reported magnitudes are conservative. The seasonal composition of each annual composite is not explicitly controlled: if the proportion of summer versus winter imagery varies across the four reference years, inter-annual comparisons of mean LST may partly reflect differences in seasonal sampling rather than genuine land-cover change. Future studies should restrict composites to a fixed seasonal window (e.g., June–September) to ensure full temporal comparability. Second, NDVI and NDBI are intrinsically collinear; although the incremental-variance approach and acceptable VIF values mitigate this, the independent effect of vegetation cannot be fully isolated from built-up density. Third, the bivariate

analyses (Sections 4.3–4.4) and the multivariate analysis (Section 4.6) were computed on closely related but not identical harmonised samples, and full reconciliation on a single pixel set would further strengthen internal consistency. Finally, the analysis characterises surface rather than canopy-air temperature at 30 m resolution. Critically, the LST retrieval was not independently validated against in-situ meteorological station data. The mono-window and single-channel algorithms applied here carry a typical absolute uncertainty of 1–2 °C, which is comparable in magnitude to the reported UHI intensities for Islamabad (≈ 0.1 °C) and approaches that of Rawalpindi (≈ 0.9 °C). While the relative inter-city comparison and the NDVI–LST slopes are less sensitive to systematic retrieval biases, future work should cross-validate retrieved LST against Pakistan Meteorological Department station records or MODIS LST products to bound this uncertainty. Future work should incorporate multiscale geographically weighted regression to capture spatial non-stationarity (Huang et al. 2025), local-climate-zone stratification, finer-resolution and night-time thermal data, and explicit treatment of vegetation type and canopy structure.

6. Conclusion

This study delivered the first per-city comparative, formally-tested NDVI–LST regression analysis of the Islamabad–Rawalpindi conurbation, quantifying how planning context mediates the cooling efficiency of urban vegetation across the period 2011–2024. All four research objectives were met. The spatiotemporal analysis revealed a modest net cooling of mean LST and a progressive greening trend in both cities, but a sharp divergence in thermal structure, with unplanned Rawalpindi exhibiting roughly twice the thermal heterogeneity of planned Islamabad and a surface UHI six to seven times greater. Per-city regression established a strong vegetation-cooling relationship in both cities whose marginal efficiency was approximately twice as steep in Rawalpindi, while spatial-clustering analysis demonstrated a highly structured thermal field (Moran’s $I \approx 0.95$) dominated by vegetation-sustained cold spots. The multivariate decomposition identified built-up density, rather than vegetation, as the dominant proximate control on intra-urban surface temperature in both planning regimes, with elevation a significant secondary control. Taken together, these results show that it is the spatial configuration and planning context of land cover, not its mean greenness alone, that governs urban cooling efficiency. Planned Islamabad has converted sustained green-infrastructure provision into a cool, homogeneous thermal environment,

1 whereas unplanned Rawalpindi retains a large, unrealised cooling potential locked within its dense
2 impervious fabric. The conurbation's most effective heat-mitigation strategy is therefore the
3 targeted greening and management of built-up surfaces in Rawalpindi, coupled with the protection
4 of the green cores that already anchor the region's cool islands. The integrated Google Earth
5 Engine framework developed here, combining thermal retrieval, spatial autocorrelation, and
6 comparative regression, is directly transferable to other rapidly urbanising conurbations in which
7 planned and unplanned urban forms coexist.

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Statements and Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Mujtaba Ali: Conceptualization, data collection, formal analysis, and writing of the original draft. Qurat ul Ain: Methodology, data analysis, and critical review and editing of the manuscript. Muhammad Amin, Muhammad Farhan, Muhammad Naveed Tahir, Saqib Majeed, Hafiz Abdul Basit Zaid, and Mirza Umer Baig: Review and approval of the final manuscript. All authors have read and agreed to the published version of the manuscript.

Data Availability

The Landsat and Sentinel-2 imagery used in this study are publicly available through Google Earth Engine (<https://earthengine.google.com>). The SRTM DEM is available from the USGS

- 1 EarthExplorer (<https://earthexplorer.usgs.gov>). Processed datasets generated during this study are
- 2 available from the corresponding author on reasonable request.