

Article

Wetland Loss, Impervious Surface Expansion, and Urban Thermal Stress: A Spatiotemporal Analysis of Land Use Change and Urban Thermal Patterns in Colombo District, Sri Lanka

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Abstract

Rapid urbanization in tropical Asia has fundamentally transformed land use–land cover while intensifying urban thermal stress, yet the relationship between land cover change and thermal conditions is frequently assumed to be spatially uniform. This study challenges that assumption by demonstrating that land cover–thermal relationships in Colombo District, Sri Lanka, are highly spatially and temporally heterogeneous, with statistically significant associations detected in only 17–47% of the study area in any given year, underscoring that context, not land cover type alone, governs thermal outcomes. Using multi-temporal Landsat satellite imagery, LULC maps were derived, and the urban heat island effect (UHIE) and urban thermal field variance index (UTFVI) were calculated for seven time periods (1989, 1996, 2002, 2009, 2014, 2019, 2024). Geographically weighted regression (GWR) was applied to model local relationships between LULC classes, namely wetland vegetation, water bodies, impervious surfaces, and other pervious surfaces, and thermal indices across a 500 m spatial grid, revealing a 74% loss in wetland vegetation and a 326% increase in impervious surfaces over the study period. Water bodies exhibited spatially variable cooling effects relative to wetland vegetation, most pronounced in eastern regions during earlier periods, while impervious surfaces showed consistent, spatially persistent warming effects concentrated in western and southern urban cores. By coupling GWR with a 35-year multi-sensor time series, this study provides a spatially explicit, longitudinal account of how land cover–thermal relationships evolve as tropical urbanization intensifies, offering an evidence base for spatially targeted rather than uniform climate adaptation planning in rapidly urbanizing tropical cities.

Keywords: land use–land cover change; urban heat island effect; urban thermal field variance index; wetland vegetation



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1. Introduction

1.1. Background

Urbanization has rapidly transformed the global population distribution, with cities now accommodating around 45% of the world's 8.2 billion people, compared to about 20% in 1950. By 2050, roughly two-thirds of the global population is projected to live in urban areas, with most additional growth in low- and middle-income countries [1]. Urbanization has emerged as one of the most transformative processes of the 21st century, fundamentally

altering land use–land cover (LULC) patterns through the conversion of natural and semi-natural land covers such as croplands, forests and wetlands into built-up surfaces, leading to substantial loss of ecosystem functions and associated thermal environments. Urban areas across Asia and Africa have experienced the most rapid expansion since 1975, with cities like Shenzhen and Guangzhou, China, growing at 11% and 9% annually, respectively [2], while many cities in Eastern Europe and parts of East Asia are experiencing slower or stabilizing urban growth [1]. This unprecedented urban growth has triggered environmental consequences, particularly through modifications to surface energy balance, wetland degradation, and intensification of urban heat island effects [3]. Case studies from rapidly growing secondary cities in Africa show marked declines in vegetated and agricultural land as urban footprints expand [4].

Built-up areas, characterized by materials such as concrete and asphalt with low albedo and high heat capacity, absorb and retain significantly more solar radiation than vegetated surfaces. This transformation decreases latent heat through reduced evapotranspiration, reduced infiltration, and increased runoff and elevates sensible heat, resulting in elevated land surface temperatures (LSTs) and atmospheric warming [5]. The urban heat island effect (UHIE) is defined as the phenomenon by which temperatures in urban areas are higher than those in surrounding rural areas, impacting microclimate, atmospheric environment, and the wellbeing and health of urban residents [6]. Rising urban temperatures and more frequent extreme heat events are already imposing significant health burdens, with recent global assessments warning that climate inaction is costing millions of lives each year through heat stress, air pollution and related pathways [7].

Wetlands, which provide critical ecosystem services, including flood mitigation, biodiversity conservation, and climate regulation, face threats from urban encroachment. Global assessments indicate that natural wetland extent declined by approximately 35% between 1970 and 2015 [5]. In rapidly urbanizing regions, wetland degradation has reached alarming rates, with some areas experiencing losses exceeding 60% since the 1980s [8]. The Colombo Wetland Complex lost nearly 60% of its extent over the 35-year period from 1980 to 2016 [9]. The thermal properties of wetlands offer cooling benefits in urban landscapes. Research demonstrates that wetlands can reduce daytime surface temperatures by up to 5.1 °C compared to non-wetland land uses through enhanced evapotranspiration, increased albedo, and modified aerodynamic properties [10].

1.2. Quantifying Urban Thermal Dynamics

The quantitative measurement of UHIE has evolved substantially, progressing from simple direct LST comparisons to sophisticated multidimensional thermal indices. Early approaches in the Colombo region employed basic LST mapping derived from Landsat ETM+ imagery [11]. More recent studies have adopted refined UHIE calculations that directly quantify the deviation of local surface temperature from area-wide mean values, facilitating spatially explicit comparison of thermal anomalies [12].

A critical methodological advancement came with the introduction of the urban thermal field variance index (UTFVI) [13], which not only quantifies individual pixel thermal anomalies but also enables categorical classification of thermal environments into ecological assessment levels ranging from “excellent” to “worst” conditions [14]. The UHIE and UTFVI combination enables examination of both absolute thermal patterns and relative ecological conditions, which are essential for identifying neighborhoods requiring targeted heat mitigation [15].

Geographically weighted regression (GWR) approaches have emerged as essential tools for examining spatial non-stationarity in land cover–thermal relationships, addressing limitations of global regression models by capturing local-scale variations in how LULC

categories influence thermal indices [16]. Combining UHIE and UTFVI with geographically weighted regression therefore enables neighborhood-scale mapping of thermal anomalies and their ecological implications, revealing how specific land cover transitions amplify or mitigate heat. Because these analyses draw primarily on freely available satellite imagery and open-source spatial tools, they are readily transferable to data-limited tropical cities that lack dense meteorological monitoring networks.

1.3. Research Question and Study Context

Although the macro-scale impacts of land use and land cover (LULC) changes on urban thermal environments are well-established globally, the recent literature emphasizes that these interactions exhibit significant spatial non-stationarity, with the strength and direction of land cover–thermal relationships varying drastically across micro-scale distances [17]. Addressing this critical conceptual gap requires moving beyond static, global regression assumptions to apply localized models like geographically weighted regression (GWR) longitudinally [18], thereby tracking how the spatial heterogeneity of thermal outcomes actively evolves over multi-decadal urbanization trajectories.

The Colombo District, Sri Lanka, provides an optimal context for investigating these dynamic shifts, as it encompasses a diverse landscape of urban centers, peri-urban zones, and ecologically significant wetlands. As Sri Lanka's commercial capital, Colombo has undergone rapid urbanization over recent decades, resulting in transformations in LULC. Colombo was accredited as a 'Wetland City' in 2018 and is home to the Thalangama Lake, and Kolonnawa and Kotte marshes, which are critical for urban flood mitigation, urban food production, biodiversity conservation, and climate regulation. These wetlands face increasing threats from urban sprawl, illegal encroachments, and infrastructure development, exacerbating the urban heat island effect [19].

Previous studies in Colombo have examined UHI patterns using LST and LULC change [11,20] but have not quantified UHIE or UTFVI comprehensively across extended temporal scales and have not covered the entire Colombo District. A significant knowledge gap exists on how changes in land use classes, including wetland vegetation, water bodies, impervious surfaces, and other pervious surfaces (land cover types that are neither wetlands nor water bodies but still allow infiltration of water into the soil), affect thermal indices (UHIE and UTFVI) in Colombo District over time. Identifying where and when land cover change most strongly influences urban thermal conditions is essential for designing spatially targeted adaptation strategies, including prioritizing wetland conservation, regulating impervious expansion and integrating cooling corridors into urban design. In a rapidly urbanizing district such as Colombo, spatially explicit evidence of land cover–heat interactions can inform zoning, infrastructure siting and ecosystem-based adaptation measures aimed at avoiding the worst thermal consequences of future population growth and urban expansion. Therefore, the objective of this paper is to analyze the spatially and temporally heterogeneous relationships between LULC changes (considering land use classes: wetland vegetation, water bodies, impervious surfaces, and other pervious surfaces) and thermal indices (UHIE and UTFVI) in Colombo District from 1989 to 2024 using GWR to track how these spatial interactions evolve over a 35-year urbanization trajectory.

2. Materials and Methods

2.1. Study Area

The study area (Figure 1) comprises Colombo District, Sri Lanka, encompassing 13 Divisional Secretariat Divisions (DSDs) with a total area of 699.0 km². The district supports a population of 2,374,461 (2024 census), representing 10.9% of Sri Lanka's national population, with a population density of 3397 persons/km². Colombo District is characterized by a

heterogeneous landscape including dense urban cores, peri-urban residential zones, and ecologically significant wetland systems.

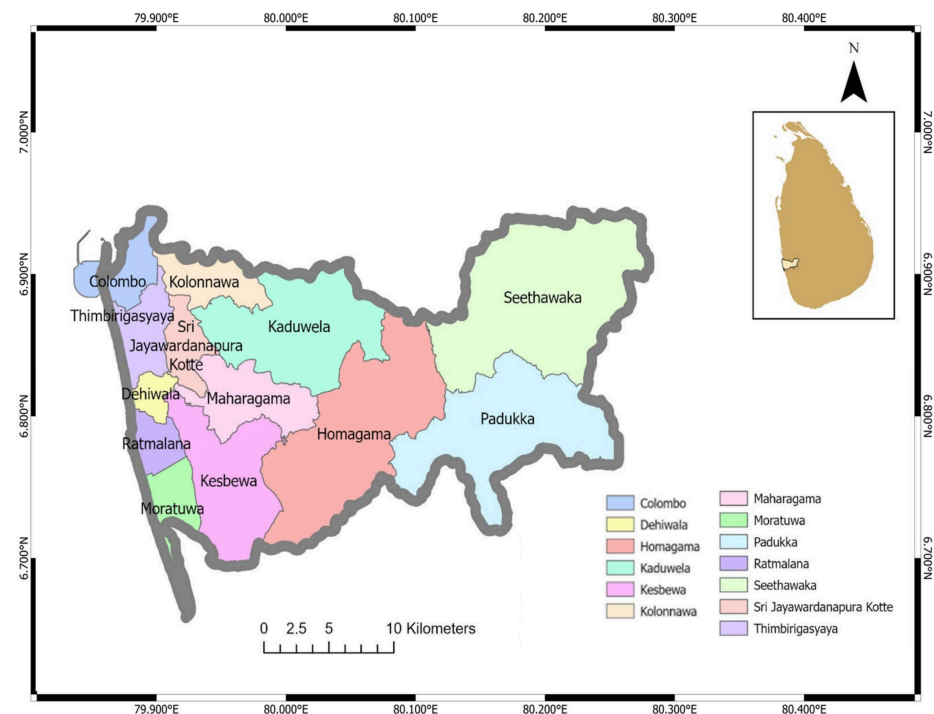


Figure 1. Administrative boundaries of the thirteen Divisional Secretariat Divisions (DSDs) of the study area—Colombo District, Sri Lanka.

2.2. Data Sources and Satellite Imagery

Multi-temporal Landsat satellite imagery was sourced from the Landsat series, Level 2, Collection 2, Tier 1 datasets, accessed via the Google Earth Engine (GEE) platform, providing surface reflectance and thermal infrared data at 30 m spatial resolution suitable for urban-scale analysis [5]. Seven acquisition years were selected: 1989, 1996, 2002, 2009, 2014, 2019, and 2024, each representing the warmest year within successive five-year intervals as determined from long-term temperature records obtained from NASA's POWER Data Access Viewer (DAV), ensuring that peak thermal conditions were captured for each period. Imagery was sourced from four Landsat sensors depending on availability and data quality for each target year: Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 Operational Land Imager (OLI) Thermal Infrared Sensor (TIRS), and Landsat 9 OLI/TIRS. Landsat 7 ETM+ data acquired after 2003 were excluded due to scan-line corrector failure, which introduces systematic data gaps that compromise spatial and thermal analysis [5].

For the LULC classification, the ten clearest Landsat images from each target year (lowest cloud cover) were selected. A median composite was generated by calculating the median value for each pixel location across these images, resulting in a single representative image for the year. For thermal indices, temporal filters were applied to select imagery from the warmest month within each 5-year interval (1989–2024), determined using long-term temperature records from NASA's POWER Data Access Viewer (DAV) (2025) database. Landsat 7 ETM+ data post-2003 was excluded due to scan-line errors, ensuring data quality [5].

2.3. LULC Classification

Satellite images were classified into four categories: wetland vegetation, water bodies, impervious surfaces, and other pervious surfaces. Other pervious surfaces encompassed

land uses such as home gardens, landscaped areas, abandoned land and forested patches. A comprehensive set of spectral indices was calculated using a hierarchical approach to enhance class separability.

Wetland vegetation was identified by combining thresholds of the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and Modified Normalized Difference Water Index for SWIR2 (MNDWIS2) [21,22]. Water bodies were identified using the Modified Normalized Difference Water Index (MNDWI) with a threshold value of 0.2000 [23]. Impervious surfaces were classified using the Modified Normalized Difference Impervious Surface Index (MNDISI) with sensor-specific threshold values, while other pervious surfaces were identified by complementary MNDISI thresholds [24].

Training samples were generated via stratified random sampling, selecting 300 points per LULC class (total 1200 points) within index-defined regions. Samples were split into 80% for training and 20% for accuracy assessment. The Random Forest (RF) classifier was employed for classification due to its robustness, scalability, and superior accuracy [25]. Classifier performance was evaluated using confusion matrices, computing overall accuracy, Kappa coefficient, producer accuracy, and user accuracy.

This approach was used because, for historical years (1989–2019), independent ground-truth data suitable for pixel-level validation were unavailable, and classification accuracy metrics therefore represent internal consistency between the Random Forest classifier and the spectral index-based threshold masks rather than fully independent validation. This approach is analogous to ‘back-classification’ and cross-validation strategies recommended for time series Landsat analysis when reference data are limited, where later-year or partial ground truth is used to validate the classification protocol rather than every historical map individually [26]. In our study, independently collected 2024 ground-truth data provide an external benchmark demonstrating that the index-threshold/RF protocol can achieve high accuracy under contemporary conditions; this supports confidence in the reconstructed time series but does not retrospectively verify each historical pixel label.

2.4. Thermal Indices Derivation

Land surface temperature (LST) was retrieved using the Jiménez-Muñoz and Sobrino (JM&S) Single-Channel algorithm, which incorporates atmospheric correction and surface emissivity [27]. Land surface temperature retrieval used the following thermal infrared bands: Landsat 5 TM Band 6 (10.40–12.50 μm , natively 120 m, resampled to 30 m by USGS via cubic convolution during Level-1 processing); Landsat 7 ETM+ Band 6 (10.40–12.50 μm , natively 60 m, resampled to 30 m via cubic convolution); and Landsat 8/9 TIRS Band 10 (10.60–11.19 μm , natively 100 m, resampled to 30 m via cubic convolution). All thermal bands were delivered pre-resampled to 30 m in the Collection 2, Level 2 products used in this study. Emissivity was estimated based on NDVI-derived fractional vegetation cover (FVC). NDVI thresholds of 0.2 (bare soil) and 0.5 (dense vegetation) were used to classify pixels guided by [6].

The urban heat island effect (UHIE) was quantified using:

$$\text{UHIE} = \frac{T_s - T_{\text{mean}}}{\text{SD}}$$

where T_s is the pixel’s surface temperature, T_{mean} is the regional mean, and SD is the standard deviation. This method highlights thermal hotspots relative to the regional average [16].

The urban thermal field variance index (UTFVI) was calculated as:

$$\text{UTFVI} = \frac{T_s - T_{\text{mean}}}{T_{\text{mean}}}$$

UTFVI quantifies thermal deviations and was classified into six levels as tabulated in Table 1 (None, Weak, Middle, Strong, Stronger, Strongest) to reflect ecological impacts [13].

Table 1. Classification of urban thermal field variance index (UTFVI) values into six ecological evaluation categories [2].

Urban Thermal Field Variance Index (UTFVI)	Urban Heat Island Phenomenon	Ecological Evaluation Index
<0	None	Excellent
0.000–0.005	Weak	Good
0.005–0.010	Middle	Normal
0.010–0.015	Strong	Bad
0.015–0.020	Stronger	Worse
>0.020	Strongest	Worst

2.5. Spatial Grid Framework

The study area was divided into a 500 m × 500 m regular spatial grid to facilitate spatially explicit statistical analysis. This grid framework enabled computational efficiency in examining relationships between LULC changes and thermal indices while capturing local-scale spatial heterogeneity.

2.6. Geographically Weighted Regression Analysis

The analysis was implemented in R (version 4.5.1) using a multi-step workflow. Spatial data were extracted within 500 m grid cells. To capture temporal dynamics, land-cover proportions and thermal indices were first differenced between consecutive periods. The GWR models therefore quantify how changes in land cover composition are associated with changes in UHIE and UTFVI over each interval. For readability, the resulting coefficient maps are labeled by the later year of each change interval. Prior to GWR fitting, grid cells experiencing more than 50% land cover change between consecutive intervals were excluded to reduce instability caused by extreme transitions. Pearson correlation matrices were examined among differenced predictors to assess collinearity, and the bandwidth minimizing AICc was retained after testing adaptive and fixed kernel options. Adaptive kernels were selected for 1996–2014 (297–656 neighbors), whereas fixed kernels of 8485.28 m were selected for 2019 and 2024. This 500 m spatial grid was explicitly selected to balance computational efficiency with the necessity of capturing neighborhood-scale urban thermal dynamics; it optimally aggregates excessive pixel-level noise inherent at the 30 m resolution while preserving critical microclimate heterogeneity [17]. Proportional area coverage of each land cover class (water bodies, wetland vegetation, impervious surfaces, other pervious surfaces) was calculated using extraction of pixel coverage fractions, yielding continuous proportions bounded between 0 and 1 that summed to unity within each cell. Because these four class proportions are compositional and therefore perfectly collinear (any one class's value is fully determined by the other three), wetland vegetation proportion was omitted from the predictor set and treated as the implicit baseline reference category, consistent with standard practice for handling compositional predictors in regression frameworks. To capture temporal dynamics and reduce the influence of time-invariant grid-cell characteristics, first-differences in land cover proportions between consecutive

time periods (ΔWater , $\Delta\text{Impervious}$, $\Delta\text{Pervious}$) were calculated and used as predictors and related to first-differences in mean thermal indices (ΔUHIE , ΔUTFVI) aggregated per grid cell within a change-based regression framework. [28].

Geographically weighted regression (GWR) analysis was conducted for each year with sufficient data using adaptive bandwidth selected by either AICc (Akaike Information Criterion corrected) or cross-validation. Both adaptive and fixed kernel types were considered, and the configuration yielding the lowest AICc was retained for each model. Other pervious surfaces were excluded as predictors in instances where their variance approached zero, specifically, $< 1 \times 10^{-10}$ in each grid cell per year, providing insufficient contrast for reliable coefficient estimation; in such cases, the model was re-specified using the remaining predictors with adequate variance. The models predicted spatially variable relationships between first-differenced LULC proportion variables (ΔWater , $\Delta\text{Impervious}$, with wetland vegetation proportion omitted as the reference category) and first-differenced dependent variables (ΔUHIE , ΔUTFVI), calculating local model diagnostics that included coefficient estimates, local R^2 , and statistical significance ($\alpha = 0.05$, $p < 0.05$) [13,14,29].

Coefficient maps, significance maps, and quality indicators were generated to visualize the spatial heterogeneity in LULC–thermal relationships. The maps were overlaid with Divisional Secretariat Division (DSD) boundaries to support spatial interpretation.

3. Results

3.1. LULC Changes Relevant to Thermal Response

Temporal analysis of LULC changes from 1989 to 2024 (Figure 2) revealed distinct trajectories across the four major land cover classes. Wetland vegetation exhibited a marked declining trend, decreasing from approximately 200 km² in 1989 to 52 km² in 2024, representing a loss of nearly 74% over the study period. The steepest decline occurred between 1989 and 2002.

Impervious surfaces displayed a dramatic increase from 42 km² in 1989 to 179 km² in 2024, representing more than a four-fold expansion (326% increase). The most significant growth occurred between 1989 and 1996, when the area increased to 172 km².

Water bodies remained the most stable land cover class throughout the study period, maintaining relatively consistent coverage between 7–12 km². The area showed minor variations, with a slight decline from 11.6 km² in 1989 to 7.0 km² in 2024, representing less than 2% of the total study area.

Other pervious surfaces demonstrated the most variable pattern, initially declining from 429 km² in 1989 to 352 km² in 1996, then showing considerable fluctuation. The category peaked at 477 km² in 2002 before stabilizing around 445–475 km² in the latter half of the study period, ending at 445 km² in 2024.

LULC classification achieved consistently high accuracy across all seven study years, with overall accuracy ranging from 0.984 to 0.999 and Kappa coefficients above 0.979 (Table 2). Class-level producer and user accuracies remained strong throughout the time series, generally exceeding 0.96, with only marginally lower values observed for the spectrally similar wetland vegetation and other pervious surfaces classes in earlier years (Table 2). For 1989–2019, these metrics reflect the internal consistency between the Random Forest classifier and the spectral index-based threshold masks used to define the four land cover classes rather than fully independent validation against ground truth, as detailed in Sections 2.3 and 4.7. For 2024, independently collected ground-truth reference data were available and used for accuracy assessment (overall accuracy: 0.995; Kappa: 0.993), providing a genuine external benchmark for the classification protocol under contemporary conditions. The close correspondence between this ground-truth-validated result and the threshold-derived accuracies for earlier years increases confidence in the robustness of the

classification approach, while we explicitly acknowledge that it does not retrospectively verify individual pixel labels for 1989–2019.

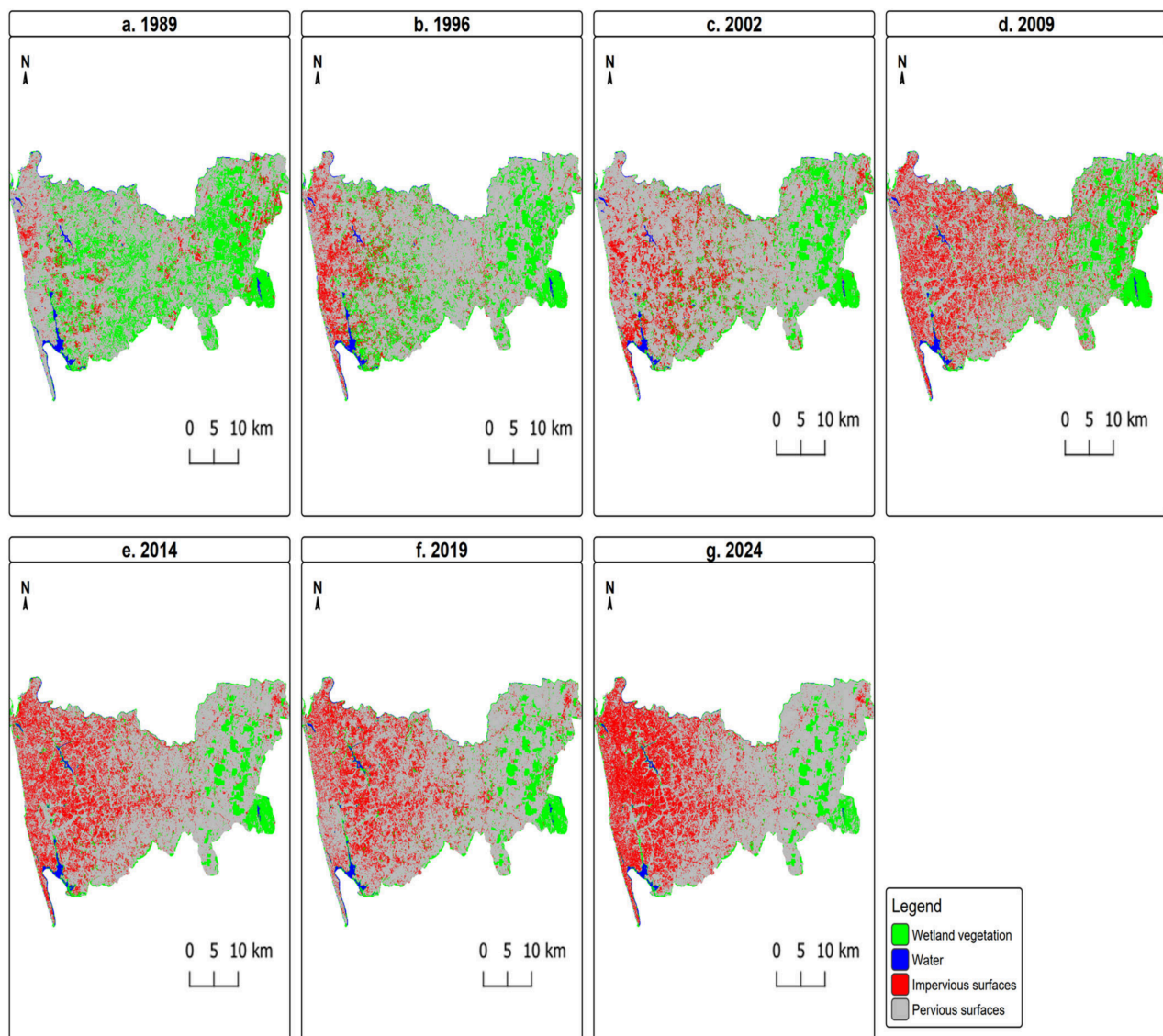


Figure 2. Land use–land cover (LULC) maps for Colombo District for the years (a) 1989, (b) 1996, (c) 2002, (d) 2009, (e) 2014, (f) 2019, and (g) 2024, showing the spatial distribution of wetland vegetation, water bodies, impervious surfaces, and other pervious surfaces.

Table 2. Land use–land cover (LULC) classification accuracy assessment for Colombo District, Sri Lanka (1989–2024).

Year	Classification	Overall Accuracy	Kappa Coefficient	Producer Accuracy	User Accuracy
1989	Wetland Vegetation	0.984	0.979	0.974	0.966
	Water			1.000	0.996
	Impervious Surfaces			0.996	1.000
	Other Pervious Surfaces			0.966	0.975
1996	Wetland Vegetation	0.989	0.987	0.987	0.976
	Water			1.000	1.000

Table 2. Cont.

Year	Classification	Overall Accuracy	Kappa Coefficient	Producer Accuracy	User Accuracy
2002	Impervious Surfaces	0.996	0.988	0.996	1.000
	Other Pervious Surfaces			0.979	0.984
	Wetland Vegetation			0.999	0.988
	Water			1.000	0.991
	Impervious Surfaces			0.996	1.000
2009	Other Pervious Surfaces	0.997	0.997	0.979	0.987
	Wetland Vegetation			0.991	0.995
	Water			1.000	1.000
	Impervious Surfaces			1.000	1.000
	Other Pervious Surfaces			0.996	0.991
2014	Wetland Vegetation	0.999	0.996	0.996	1.000
	Water			1.000	1.000
	Impervious Surfaces			1.000	1.000
	Other Pervious Surfaces			1.000	0.996
	Wetland Vegetation			0.996	0.991
2019	Water	0.997	0.996	0.996	1.000
	Impervious Surfaces			1.000	1.000
	Other Pervious Surfaces			0.996	0.996
	Wetland Vegetation			0.987	0.996
	Water			1.000	1.000
2024	Impervious Surfaces	0.995	0.993	0.991	1.000
	Other Pervious Surfaces			1.000	0.983
	Wetland Vegetation				
	Water				

3.2. Relationships Between LULC and UHIE

Geographically weighted regression (GWR) analysis revealed spatially heterogeneous relationships between land cover types and UHIE.

Model diagnostics indicated moderate explanatory power across intervals. Global R² ranged from 0.214 (2009) to 0.404 (2019) for UHIE and from 0.241 (2014) to 0.386 (2024) for UTFVI, while mean local R² ranged from 0.213 to 0.396 for UHIE and from 0.226 to 0.375 for UTFVI (Table 3).

Here, the map labeled 1996 represents the model for change from 1989 to 1996, 2002 represents 1996 to 2002, and so on.

Water bodies (Figure 3) exhibited coefficient ranges from −100 to +60 relative to wetland vegetation (mean ± SD: −0.27 ± 1.84). Negative coefficient values (shown as blue zones in spatial maps) indicated that, relative to wetland vegetation, water bodies were associated with lower UHIE, representing localized cooling effects. Positive coefficients (red zones) suggested that water bodies corresponded to higher UHIE values in those locations and years.

In early periods (1996, 2002), blue zones were more prominent and widespread, particularly in eastern regions (Padukka and Seethawaka DSDs). However, in subsequent years (2009, 2014, 2019, 2024), these blue zones became increasingly sparse and confined. By 2024, the cooling effect of water bodies relative to wetland vegetation showed some

expansion in Homagama DSD, presenting patterns similar to 2002, though overall water body cooling effects remained reduced compared to the early study period.

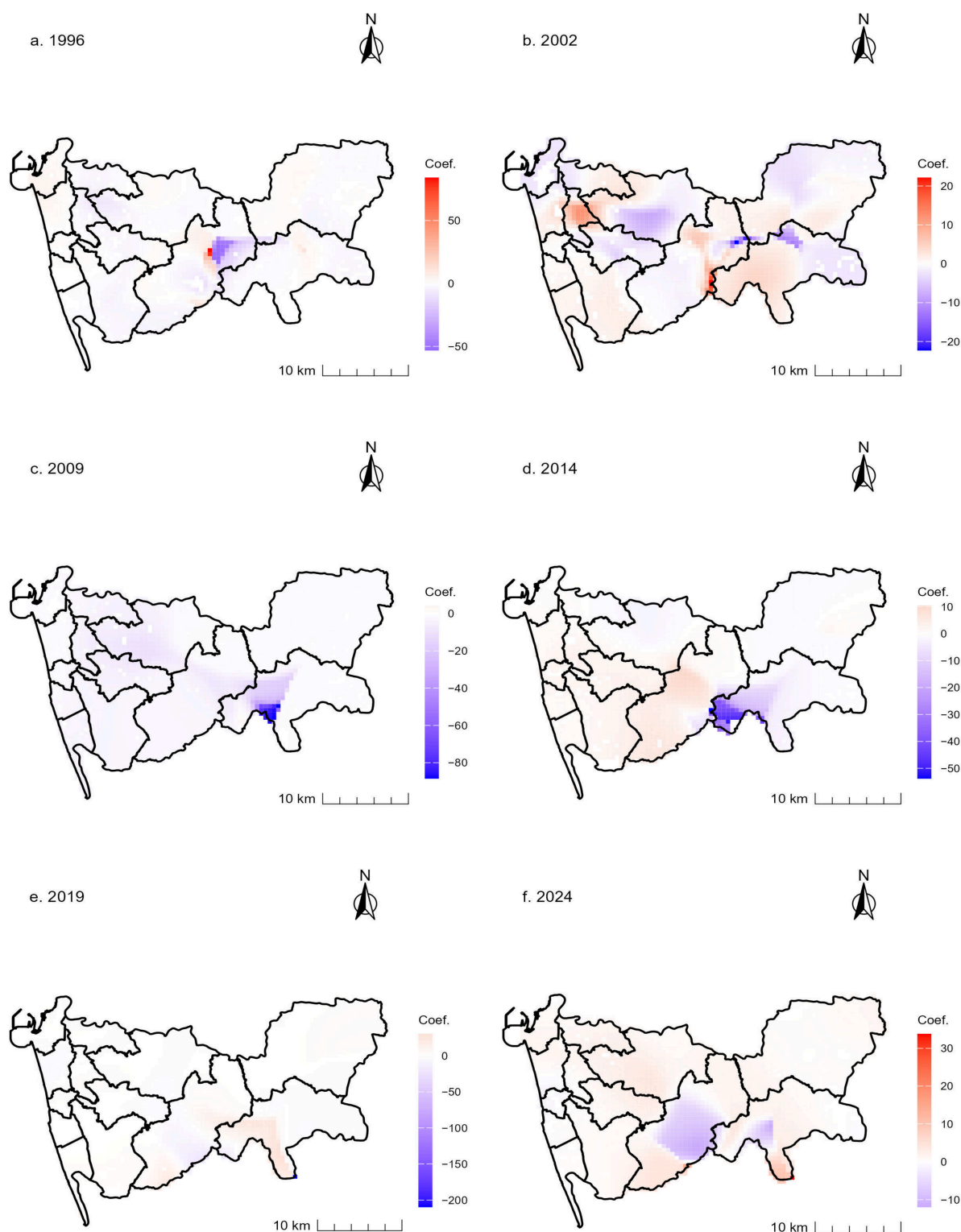


Figure 3. Spatial relationships between water bodies and UHIE and UTFVI relative to wetland vegetation for the years (coefficient maps) (a) 1996, (b) 2002, (c) 2009, (d) 2014, (e) 2019, and (f) 2024. Black boundaries delineate Divisional Secretariat Divisions (DSDs). Individual legends for each year indicate coefficient scales, which are adapted to optimize visualization of spatial heterogeneity in each time period.

Table 3. Geographically weighted regression (GWR) model diagnostics for UHIE and UTFVI across change intervals in Colombo District, Sri Lanka.

Year	Thermal Index	Bandwidth Type	Bandwidth Size	Selection Approach	Valid N (Grid Cells)	Residual Sum of Squares (RSS)	AICc	Global R ²	Mean Local R ²
1996	UHIE	Adaptive	297	AICc	2561	624.581	3780.550	0.330	0.296
1996	UTFVI	Adaptive	297	AICc	2561	10.621	−6653.649	0.312	0.320
2002	UHIE	Adaptive	321	AICc	2776	518.244	3350.216	0.275	0.279
2002	UTFVI	Adaptive	321	AICc	2776	4.823	−9633.338	0.284	0.291
2009	UHIE	Adaptive	582	AICc	2789	453.889	2924.312	0.214	0.213
2009	UTFVI	Adaptive	582	AICc	2789	4.089	−10,210.888	0.247	0.237
2014	UHIE	Adaptive	656	AICc	2716	641.354	3848.248	0.257	0.256
2014	UTFVI	Adaptive	656	AICc	2716	6.945	−8443.335	0.241	0.226
2019	UHIE	Fixed	8485.28 m	AICc	2778	557.019	3492.271	0.404	0.396
2019	UTFVI	Fixed	8485.28 m	AICc	2778	6.761	−8762.841	0.379	0.375
2024	UHIE	Fixed	8485.28 m	AICc	2845	324.580	1972.525	0.368	0.356
2024	UTFVI	Fixed	8485.28 m	AICc	2845	3.533	−10,888.305	0.386	0.371

Impervious surfaces showed coefficient ranges from -0.2 to $+0.1$ (Figure 4) relative to wetland vegetation (mean $\pm$ SD: -0.11 ± 0.13). Positive coefficients (red zones) indicated that impervious surface areas tend to have higher UHIE values than wetland vegetation, while negative coefficients (blue) represented lower relative UHIE. Across the district, widespread and persistent positive coefficients were evident, particularly in the western and southern zones (Colombo, Kolonnawa, Thimbirigasyaya, Dehiwala, Ratmalana, Moratuwa DSDs), demonstrating that impervious land cover was frequently associated with elevated contribution to urban heat compared to wetland vegetation.

Certain portions of the study area, especially impervious surfaces in Padukka and Seethawaka DSDs, showed reduced warming effects or even cooling effects. In these DSDs, the extent of impervious surfaces remained low throughout the study period, with comparatively higher extent of wetland vegetation and pervious surfaces, preventing thermal intensification.

Across the seven study periods, GWR coefficients for water bodies and impervious surfaces exhibited consistent directional patterns but a declining spatial extent of significant cooling/warming effects over time. Water bodies showed a mean cooling coefficient of -0.27 ± 1.84 for UHIE across all years, with the proportion of the district exhibiting statistically significant cooling declining from a peak in the early 1990s–2000s to progressively more localized effects by 2024. Impervious surfaces showed a consistent, narrower-magnitude warming coefficient (mean: -0.11 ± 0.13 for UHIE) that expanded in spatial coverage over the same period, tracking the 326% areal expansion of impervious surfaces documented in Section 3.1. This inverse temporal trend contracting water body cooling extent alongside expanding impervious warming extent constitutes the central spatiotemporal finding of this study and is detailed below by index and land cover type.

3.3. Relationships Between LULC and UTFVI

Water bodies exhibited UTFVI coefficient ranges from -1.0 to $+1.0$ (mean $\pm$ SD: 0.01 ± 0.20), with spatial patterns closely mirroring those observed for UHIE (Figure 2). This similarity is expected given that both indices are mathematically derived from the deviation of pixel-level land surface temperature from the regional mean. UHIE, which normalizes this deviation by the standard deviation of LST, while UTFVI normalizes by the mean LST itself. Consequently, although the two indices produce numerically different coefficient magnitudes, the spatial arrangement of the two indices remains analogous.

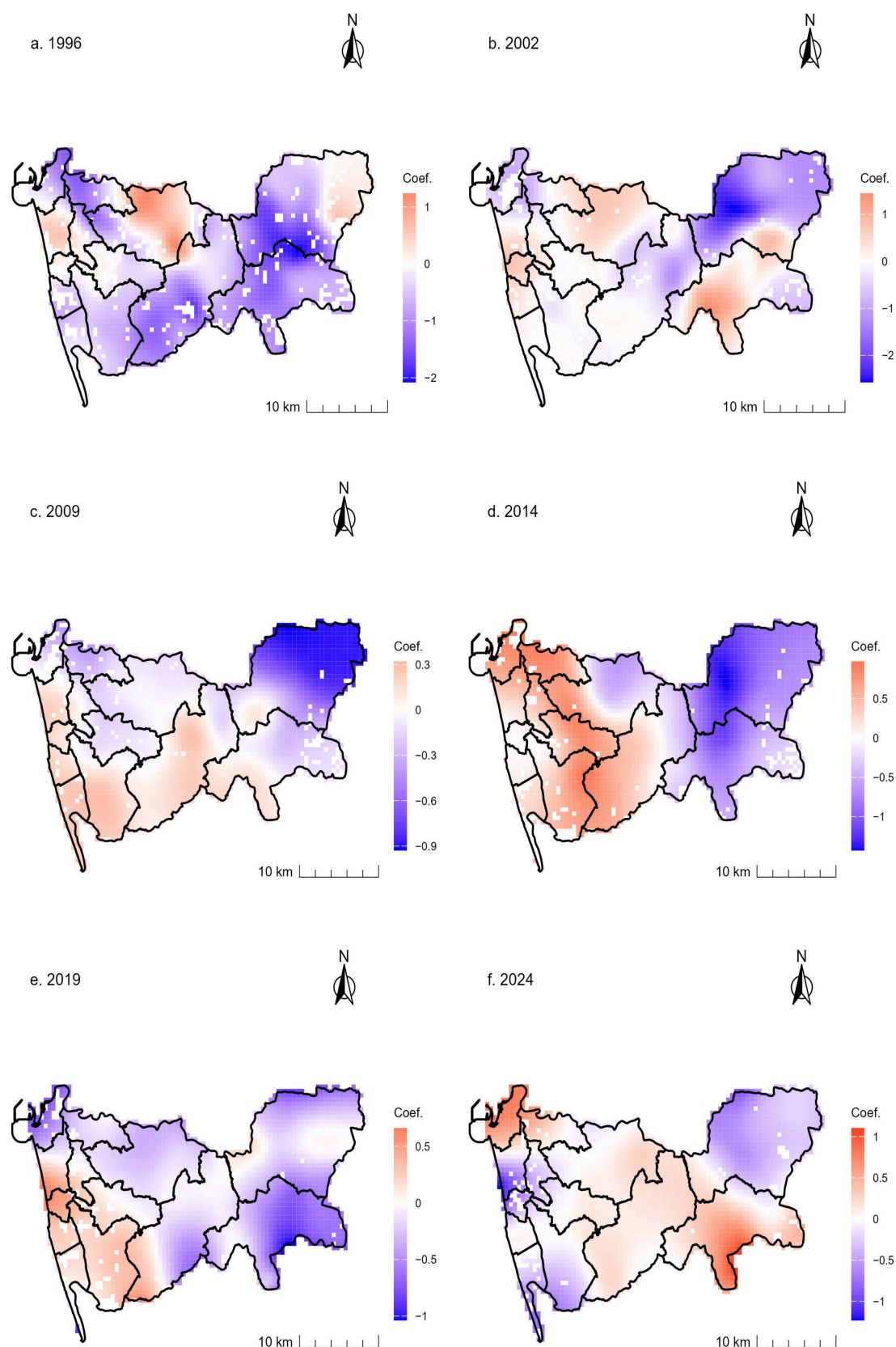


Figure 4. Spatial relationships between impervious surfaces and UHIE and UTFVI, compared to wetland vegetation (coefficient maps): (a) 1996, (b) 2002, (c) 2009, (d) 2014, (e) 2019, and (f) 2024. Individual legends for each year indicate coefficient scales, which are adapted to optimize visualization of spatial heterogeneity in each time period.

Impervious surfaces showed UTFVI coefficient ranges from -0.2 to $+0.1$ (mean $\pm$ SD: -0.008 ± 0.009), again paralleling the narrower coefficient range observed for UHIE, for the same mathematical reasons described above.

3.4. Spatial Patterns of Statistical Significance

The spatial distribution of statistically significant relationships ($\alpha = 0.05$, $p < 0.05$) varied considerably across years and space. As illustrated in Figure 5, water bodies showed statistically significant relationships with UHIE and UTFVI in 17–47% of the study area in any given year. Significant areas showed clustering patterns, with higher concentrations in eastern DSDs (Padukka, Seethawaka) during early periods and more dispersed patterns in later years.

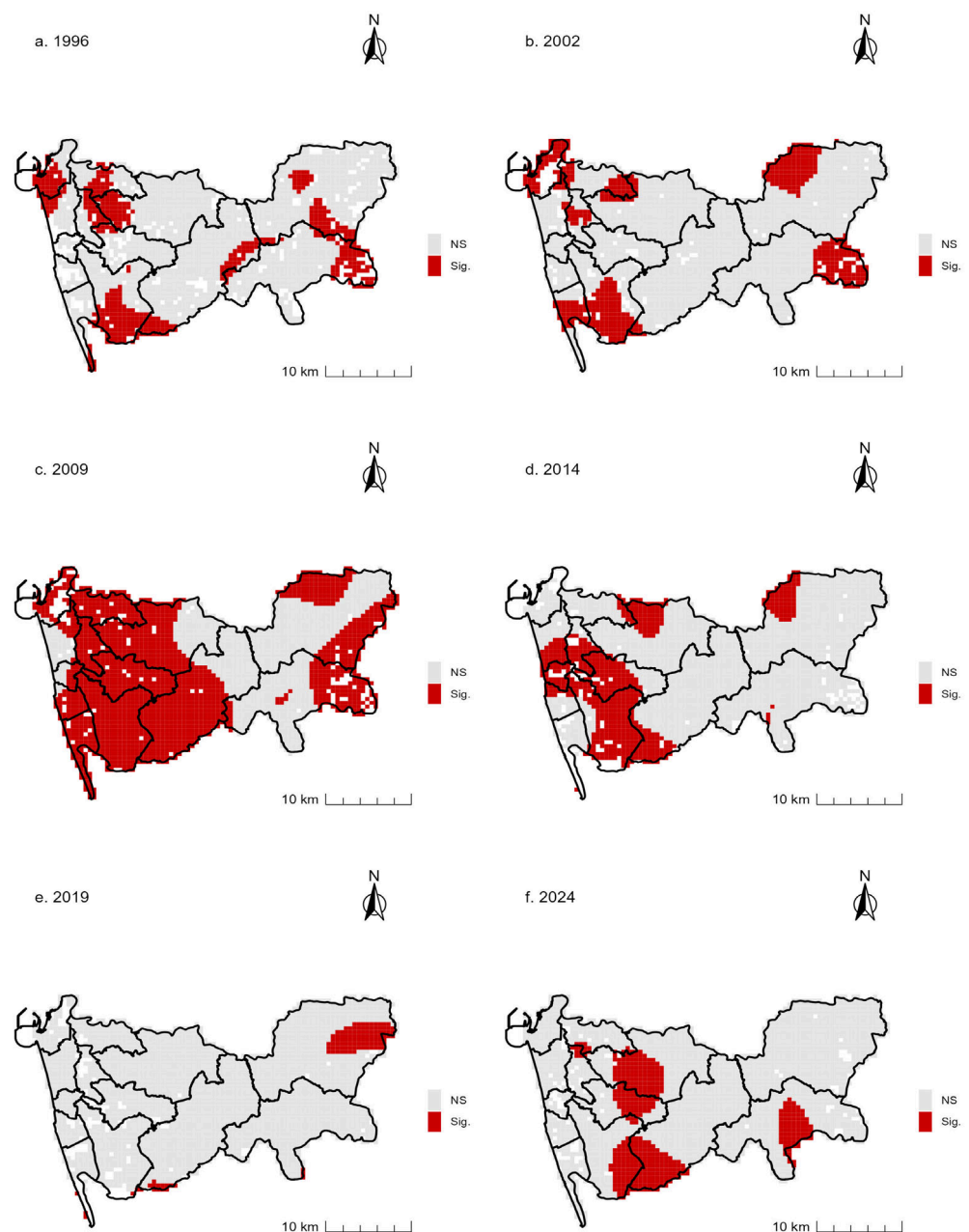


Figure 5. Spatial distribution of the area with a statistically significant relationship between thermal indices (UHIE and UTFVI) vs. water bodies compared to wetland vegetation from 1989 to 2024 ($\alpha = 0.05$, $p < 0.05$).

For impervious surfaces (Figure 6), statistically significant relationships with UHIE and UTFVI were similarly observed in 17–47% of the study area per year. Significant areas concentrated in western and southern urban cores (Colombo, Kolonnawa, Thimbirigasyaya, Dehiwala, Ratmalana, Moratuwa DSDs), corresponding spatially to areas experiencing early and complete wetland-to-impervious surface conversion.

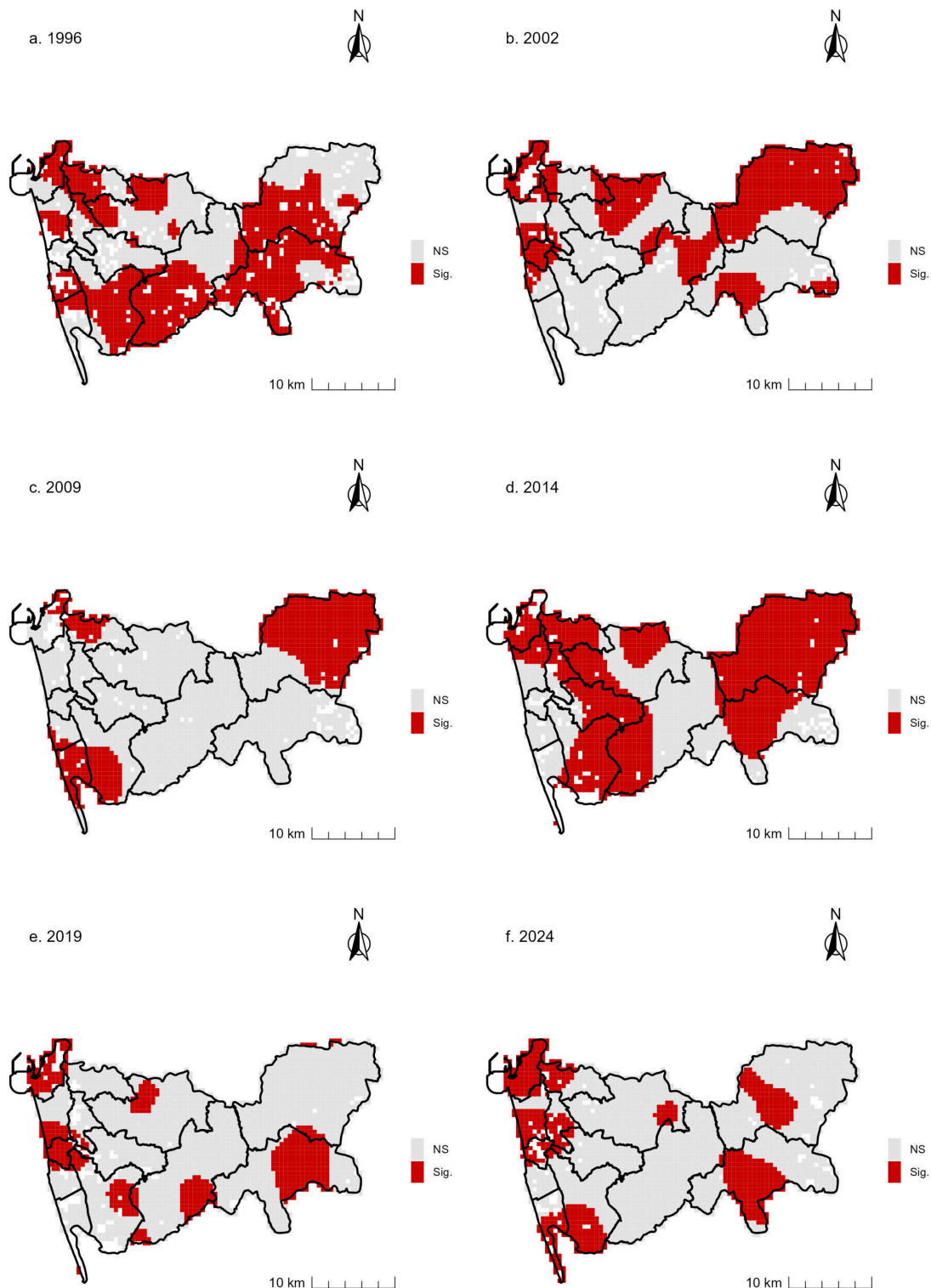


Figure 6. Spatial distribution of the area with a statistically significant relationship between thermal indices (UHIE and UTFVI) vs. impervious surfaces compared to wetland vegetation from 1989 to 2024 ($\alpha = 0.05$, $p < 0.05$).

Considered together, Sections 3.1–3.4 establish a coherent pattern: as impervious surfaces expanded from 42 to 179 km² and wetland vegetation contracted from 200 to 52 km² (Section 3.1), the spatial footprint of statistically significant impervious-driven warming grew correspondingly, while the spatial footprint of water-body-driven cooling contracted despite water body area itself remaining nearly constant (Section 3.1). This indicates that the relative thermal influence of stable land cover features like water bodies is not fixed but is itself reshaped by surrounding land cover change, a finding with direct implications for how urban cooling infrastructure should be prioritized as urbanization proceeds (elaborated in Section 4).

4. Discussion

4.1. Spatial and Temporal Heterogeneity in Thermal–Land Cover Relationships

The GWR analysis reveals sophisticated spatial and temporal patterns in the relationships between land cover types and thermal indices that traditional global regression approaches would completely miss. The finding that only 17–47% of the study area exhibits this pattern indicates that the thermal influence of land cover is not spatially uniform but depends on local urban form, surrounding land cover composition, and the temporal stage of urban expansion. In other words, the same land cover type may cool one neighborhood while exerting a negligible or even opposite effect elsewhere, which is precisely why global regression models would obscure important localized relationships. This level of spatial heterogeneity is consistent with recent advances in urban climate research that emphasize the importance of local climate zones and micro-scale variability in determining thermal conditions [30].

Research using similar GWR approaches in other cities has demonstrated that the strength and direction of land cover–thermal relationships can vary significantly across distances as small as 500 m, highlighting the importance of neighborhood-scale analysis for understanding urban thermal dynamics [30]. The study by [18] found that spatial variation in relationships between environmental setting and surface temperature was significant, with only 17–23% of the study area showing statistically significant GWR coefficients for key predictors in different seasons and years, corroborating our findings.

The other pervious surfaces class exhibited near-constant proportion across all spatial samples, with variance below 0.5% of its mean value. Such extremely low variability provides insufficient contrast to reliably estimate spatially varying regression coefficients in GWR, effectively acting as a quasi-constant term rather than a meaningful predictor, thus justifying its exclusion from the analysis [31].

4.2. Water Bodies as Thermal Regulators

The predominantly negative coefficients for water bodies in relation to UHIE throughout the study period provide quantitative evidence for the cooling services provided by urban water features. The coefficient range of −100 to +60 indicates substantial cooling effects, with water bodies consistently exhibiting lower thermal stress compared to the wetland baseline in certain locations. In early periods (1989–2002), blue zones (negative coefficients) were more prominent and widespread, reflecting greater cooling capacity. In later years (2009–2024), these blue zones became increasingly sparse and confined to Padukka DSD, indicating that water’s cooling effect relative to wetland vegetation baseline was becoming reduced across the region.

Negative UTFVI coefficients indicated that water bodies were associated with better ecological thermal conditions relative to the wetland vegetation baseline, while positive coefficients reflected relatively poorer conditions. Most years were characterized by negative coefficients over substantial portions of the district, with the intensity and spatial extent

of these cooling associations shifting over time. Consistent with UHIE patterns, cooling effects were most pronounced in eastern regions (Padukka and Seethawaka DSDs) during earlier study periods, becoming progressively more spatially restricted in later years as surrounding urbanization intensified the broader thermal environment.

Since LULC change in terms of water bodies was minimal over the study period, the reduction in cooling effects cannot be attributed to water body loss alone, and the magnitude and persistence of this cooling effect should not be interpreted as fixed across the district. Instead, this pattern reflects intensifying thermal stress from surrounding urbanization. As surrounding impervious surfaces expand and fragment the landscape, the thermal buffering capacity of water bodies becomes more context-dependent, which helps explain why their apparent cooling influence is strongest in some eastern areas and weaker in more heavily urbanized western zones. This finding emphasizes that LULC impact on thermal conditions is dynamic and changes with the broader landscape context.

These findings align with extensive research demonstrating the cooling effects of urban water bodies through evaporative cooling and thermal mass effects. Studies from various urban contexts have documented cooling effects ranging from 1 °C to 8 °C, with the magnitude depending on water body size, surrounding urban morphology, and meteorological conditions. Previous research in Colombo documented temperature reductions of 1.13 °C over water bodies compared to 4.32 °C increases over built-up areas, providing regional validation for the cooling services quantified in this study [32].

4.3. Impervious Surfaces and Thermal Stress Amplification

The expansion of impervious surfaces shows strong positive thermal effects relative to the wetland vegetation baseline used in the GWR model. Red zones in the coefficient maps indicate areas where impervious materials are producing greater warming effects than the baseline wetland condition. In 1989 and 1996, impervious coverage was minimal, and the thermal indices showed only scattered areas of warming. From 1996 onwards, the LULC maps reveal rapid urbanization and expansion of impervious surfaces. This expansion accelerated through 2002, 2009, and 2014. From 2014 to 2019, there was a reduction in the rate of increase in impervious surfaces, which may explain the reduction in warming areas in 2019.

Impervious surfaces showed UTFVI coefficient ranges from -0.2 to $+0.1$ (mean $\pm$ SD: -0.008 ± 0.009). Positive coefficients (red zones) indicated areas where impervious surfaces were associated with higher UTFVI values reflecting poorer ecological thermal conditions relative to wetland vegetation while negative coefficients (blue zones) implied comparatively better ecological thermal quality. Most years exhibited broad, continuous zones of positive coefficients across the western and central urban core, consistent with the persistent association between high impervious cover and degraded ecological thermal environments documented in the UHIE analysis. Temporal progression revealed an expanding and intensifying pattern of positive coefficients as the built environment grew, with the spatial footprint of thermally degraded zones enlarging in correspondence with impervious surface expansion documented in Section 3.1

Impervious materials contribute to thermal intensification by reducing evapotranspiration and increasing heat storage, but the spatial effect observed here reflects not only the presence of impervious cover itself but also its interaction with surrounding wetland and pervious surfaces. By 2024, the extensive replacement of baseline wetland vegetation with impervious surfaces created positive thermal anomalies across much of the region. This spatial and temporal correspondence demonstrates that urbanization through impervious surface expansion is a main mechanism driving systematic warming relative to the natural baseline and that this warming effect compounds as development continues. This means

that impervious expansion should be understood as amplifying thermal stress within an already changing urban matrix rather than as acting in isolation.

Similar patterns have been identified in a 26-year analysis in Galle, Sri Lanka. Researchers found that impervious surfaces increased by 42.3% while green surfaces declined by 22.5%, resulting in a 2.74 °C increase in mean surface temperature and 9.5 °C increase in the urban heat island index [33]. A 2024 study using spatial regression methods found that areas with built-up and barren land revealed the highest LST values, with the observed rise in LST particularly emphasizing the exacerbation of the UHI effect in urban areas [34].

Certain portions of the study area, especially impervious surfaces in Padukka and Seethawaka DSDs, showed reduced warming effects or cooling effects. The extent of impervious surfaces is low in those DSDs, with a comparatively higher extent of wetland vegetation and pervious surfaces, preventing thermal intensification. This pattern aligns with research from the continental United States revealing a critical threshold phenomenon: when impervious surfaces represent less than 35% of an area, temperature increases remain relatively stable at approximately 1.3 °C. However, once impervious surface coverage exceeds 35% of the land area, temperature increases accelerate significantly, reaching 1.6 °C by 65% urbanization [35]. This finding helps explain the patterns observed in Colombo District, where lower-density peri-urban areas with limited impervious cover do not exhibit the same thermal intensification as dense urban cores.

4.4. Differential Coefficient Variability as a Function of Thermodynamic Properties and Spatial Heterogeneity

The GWR analysis revealed striking disparity in coefficient ranges between water bodies (range: −100 to +60) and impervious surfaces (range: −0.2 to +0.2), reflecting fundamental differences in their thermal behavior and spatial distribution patterns documented in the urban climate literature. Water bodies produce highly variable and intense localized cooling effects through evaporative processes and high heat capacity, creating sharp thermal contrasts where water meets surrounding land covers, particularly in neighborhoods adjacent to aquatic ecosystems. Their discrete spatial distribution results in edge effects and localized cooling, yielding high coefficient variability in GWR models.

In contrast, impervious surfaces exhibit a spatially continuous distribution across urban areas with gradual transitions, producing more uniform thermal responses captured by narrower GWR coefficient ranges. The absolute magnitude of impervious surface warming effects can be substantial when aggregated across large urban areas, but the local spatial variability is smaller due to pervasive distribution. This methodological outcome does not diminish the critical importance of impervious surface management for urban heat mitigation; rather, it reflects the different spatial scales at which these land cover types operate thermally.

This contrast also reflects the differing spatial continuity of the two land cover types: water bodies are spatially clustered and function as localized cooling anchors, whereas impervious surfaces are more extensively distributed and thus produce broader but weaker, more uniform warming effects. The narrower coefficient range for impervious surfaces does not imply a weaker climatic role overall but rather a more spatially diffuse influence.

4.5. Comparison with Previous Studies

The findings from Colombo District align with and extend previous research on urban thermal dynamics in tropical cities. Research across approximately 270 tropical cities found that urban residents experience temperatures 1 °C higher than non-urban areas, with monsoonal tropical cities (similar to Colombo) experiencing the highest levels of urban warming over recent decades [36]. The spatial expansion of heat island effects beyond the traditional urban core documented in this study represents a concerning trend, as

it suggests that thermal stress is no longer confined to dense commercial districts but is becoming a district-wide phenomenon.

Compared with prior Colombo studies that primarily mapped LST or described land cover change separately [11,20], this study integrates both dimensions and demonstrates how their relationship varies across space and through time. The key contribution is not simply the confirmation that wetlands cool and impervious surfaces warm, but the demonstration that these effects are uneven, evolving, and highly context-dependent across a rapidly urbanizing tropical district.

The use of both UHIE and UTFVI provides complementary perspectives: UHIE measures standardized thermal anomalies, while UTFVI translates thermal conditions into ecological assessment categories directly applicable to urban planning.

4.6. Implications for Urban Planning and Climate Adaptation

The complex spatial and temporal patterns revealed by this research highlight the need for spatially explicit urban climate planning approaches that move beyond traditional zoning-based strategies. The finding that land cover–thermal relationships vary significantly across space and time suggests that standardized mitigation strategies may be less effective than context-specific interventions tailored to local conditions. Based on these findings, the following targeted recommendations are proposed for urban planners and policymakers:

- a. Wetland conservation: The dramatic 74% loss of wetland vegetation (200 km² to 52 km²) over the study period represents a critical threat to urban thermal regulation. Wetlands provide cooling services through evapotranspiration, water storage, and albedo modification. The findings demonstrate that preserving remaining wetland systems and restoring degraded wetlands should be prioritized in climate adaptation strategies. Development regulations should mandate minimum wetland retention thresholds and incorporate thermal impact assessments.
- b. Threshold-based planning: While the external literature highlights that rapid thermal deterioration often accelerates beyond specific impervious surface benchmarks, applying such generalized thresholds directly to Colombo's unique tropical and coastal microclimate presents limitations [33,35]. Therefore, rather than relying on rigid, imported benchmarks, future urban planning in the Colombo District must prioritize context-specific thresholds. Emphasizing localized ecosystem-based adaptation (EbA) strategies such as the strategic integration of green–blue infrastructure will provide a more robust and scientifically sound framework for mitigating thermal stress in rapidly developing zones.
- c. Context-sensitive interventions: The identification of areas where only 47% of grid cells show statistically significant LULC–thermal relationships indicates opportunities for strategic intervention during transitional periods. Because the strength of LULC–thermal relationships varies spatially, planning interventions should be prioritized in districts where land cover change is still active and thermal responses are most sensitive to additional impervious surface expansion or wetland loss.

4.7. Methodological Contributions and Limitations

The application of GWR to urban thermal analysis represents a significant advance over previous research that assumed uniform relationships across study areas. Integration of multiple thermal indices (UHIE and UTFVI) with advanced spatial statistical techniques (GWR) provides insights into the spatial heterogeneity of land cover–thermal relationships that traditional global regression approaches would obscure. Moran's I analysis of the GWR residuals revealed strong and statistically significant positive spatial autocorrelation

for both UHIE and UTFVI across all study years, with Moran's I values ranging from 0.3567 to 0.5203, Z-values ranging from 37.92 to 55.02, and all $p < 0.001$. The strongest residual clustering was observed in 2014, when the Moran's I values reached 0.5076 for UHIE and 0.5203 for UTFVI, with corresponding Z-values of 53.68 and 55.02, respectively. Several limitations should be acknowledged. The reliance on Landsat imagery, while providing consistent long-term coverage, limits the analysis to a 30 m spatial resolution, potentially masking fine-scale thermal variations important for understanding local climate dynamics. The 30 m resolution potentially prevents identifying two- and four-lane roads, which cover a larger part of the road network in Colombo District, masking their thermal impacts.

A further limitation concerns the classification accuracy assessment. For 1989–2019, validation samples were drawn from the same spectral index based threshold masks used to generate training data, a deliberate design choice made to preserve methodological consistency across the 35-year time series given that independent visual validation via high-resolution historical imagery was not a viable option for the Colombo District prior to approximately 2005–2006, and persistent wet zone cloud cover required a median-composite approach unsuited to single-date visual cross-referencing. As a consequence, accuracy metrics for these historical years quantify the internal consistency between the Random Forest classifier and the threshold-based reference masks rather than fully independent validation against error-free ground truth, and the 1989–2019 maps should be interpreted as best-estimate reconstructions with residual, unquantified classification uncertainty. Independent ground-truth validation was available only for 2024 (overall accuracy: 0.995; Kappa: 0.993), providing a genuine external benchmark for the classification protocol under contemporary conditions. While the close correspondence between this ground-truth-validated result and the threshold-derived accuracies reported for earlier years increases confidence in the robustness of the classification approach, it does not retrospectively verify individual pixel labels for 1989–2019, which is a standard constraint in long-term Landsat-based LULC reconstructions lacking contemporaneous historical reference data.

Resampling at a 500 m resolution for computational efficiency may ignore delicate patterns that occur at finer scales. If higher-resolution analysis were computationally feasible, the analysis would reflect finer spatial patterns. The use of the warmest month within 5-year intervals captures peak heat conditions relevant for mitigation planning, but annual time series would provide temporal continuity at the expense of potentially diluting peak thermal signals.

5. Conclusions

This study shows that urban land cover does not influence thermal conditions in a fixed or spatially uniform manner. By longitudinally tracking Colombo District over a 35-year trajectory, this research establishes that the cooling capacity of water bodies and the warming penalty of impervious surfaces are dynamically reshaped by the surrounding evolving urban matrix. The central scientific insight of this study is that local spatial context rather than land cover type alone governs urban thermal outcomes, fundamentally challenging the assumption of stationary land cover–thermal relationships prevalent in traditional, globally applied urban climate models.

While the district experienced a dramatic 74% loss in wetland vegetation alongside a 326% expansion in impervious surfaces between 1989 and 2024, the geographically weighted regression (GWR) framework revealed that these absolute shifts did not translate into uniform thermal penalties. Statistically significant land cover–thermal relationships were confined to 17–47% of the study area in any given year, illustrating profound spatial heterogeneity. Notably, the cooling footprint of structurally stable water bodies progres-

sively contracted as the impervious-driven warming of the surrounding landscape expanded. This inverse spatiotemporal trend proves that compounding urbanization actively erodes the relative cooling efficacy of remnant natural features over time.

Consequently, climate adaptation in tropical cities must transition from generalized, city-wide mandates to strategically targeted spatial interventions. Because the thermal severity of land cover transformation varies drastically by neighborhood, planning strategies should prioritize the preservation and restoration of wetlands specifically in transitional peri-urban zones, where thermal conditions remain highly sensitive to new development. Furthermore, rather than relying on rigid or imported impervious surface thresholds that exceed the evidence base of this localized study, future urban planning should utilize spatial thermal modeling to guide context-specific ecosystem-based adaptation (EbA) strategies.

To further advance the understanding of spatially heterogeneous thermal dynamics, future research must build upon these two-dimensional land cover findings by integrating three-dimensional urban morphology metrics such as building heights, street canyon geometry, and local climate zones (LCZs) into spatial regression frameworks. Additionally, employing higher-resolution multispectral imagery to capture fine-scale neighborhood dynamics and assessing seasonal thermodynamic variations represent the most critical next research steps. These advancements will be essential to untangle the micro-scale biophysical mechanisms driving the statistical non-stationarity observed in this study, ultimately refining the precision of climate resilience planning for rapidly expanding tropical cities.

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Abbreviations

The following abbreviations are used in this manuscript:

AICc	Akaike Information Criterion Corrected
DAV	Data Access Viewer
DSD	Divisional Secretariat Division
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
FVC	Fractional Vegetation Cover

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