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Vegetation Cover as a Predictor of Land Surface Temperature in Urban Environments: A Remote-Sensing-Based Analysis

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ABSTRACT

Urban expansion substantially modifies the composition and physical properties of land surfaces. The progressive replacement of vegetation and permeable land with buildings, roads, parking lots, and other impervious materials alters surface energy exchange, moisture availability, heat storage, and radiative properties, frequently contributing to elevated urban temperatures relative to surrounding less-developed areas. Land surface temperature (LST) derived from thermal infrared remote sensing provides an effective, spatially continuous means of examining spatial variations in urban thermal conditions, while the Normalized Difference Vegetation Index (NDVI) remains one of the most widely applied and accessible measures of vegetation abundance and vigor. This study investigates the statistical relationship between vegetation cover and land surface temperature using a quantitative remote-sensing research framework. Forty urban observation zones were analyzed with NDVI as the principal explanatory variable and LST as the dependent variable. Descriptive statistics, Pearson product-moment correlation analysis, and ordinary least-squares regression were employed. The results indicate a strong inverse relationship between vegetation abundance and surface temperature. Pearson's correlation coefficient was −0.924, with a significance level of $p < .001$. Regression analysis produced an R-squared value of 0.855, indicating that NDVI accounted for approximately 85.5% of the observed variation in LST. Mean LST declined progressively from 41.11 °C in areas with sparse vegetation to 32.93 °C in areas with very dense vegetation. The regression model was LST = 42.275 − 11.194 × NDVI. The findings demonstrate the important statistical association between vegetation abundance and urban surface temperature and support the use of vegetation-related indicators in urban thermal-environment research. The study further demonstrates how remote sensing and statistical analysis can be productively combined to investigate spatial patterns of urban environmental change and to inform evidence-based approaches to urban climate mitigation.

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INTRODUCTION

Urbanization constitutes one of the most significant and accelerating forms of contemporary land-use and land-cover change on a global scale. The expansion of cities and peri-urban areas transforms natural and semi-natural landscapes—forests, grasslands, wetlands, agricultural fields, and open soil—into complex mosaics of buildings, transportation infrastructure, industrial facilities, vegetation remnants, exposed soil, and water bodies. These transformations

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fundamentally alter the physical characteristics of the land surface, including surface reflectance (albedo), thermal properties (heat capacity and thermal conductivity), moisture availability, aerodynamic roughness, heat storage capacity, and the partitioning of available energy between sensible and latent heat fluxes (Voogt & Oke, 2003; Weng, 2009). As a direct consequence, urban areas frequently exhibit distinct climatic regimes relative to their rural surroundings, a phenomenon most commonly expressed as the urban heat island (UHI).

The urban heat island is among the most extensively studied consequences of urban land transformation. UHIs occur when urbanized areas exhibit higher temperatures than surrounding less-developed or rural areas. The phenomenon can be observed in both air temperature (atmospheric UHI) and surface temperature (surface UHI). At the surface level, the surface urban heat island is commonly investigated through differences in land surface temperature between urban and non-urban environments. Satellite remote sensing has become particularly important for such investigations because thermal sensors provide spatially distributed observations over large geographic areas at regular temporal intervals, enabling analysis of patterns that would be prohibitively expensive or logistically impossible to capture with dense networks of ground-based sensors alone (Voogt & Oke, 2003; Shi et al., 2021; Zhou et al., 2019).

Land surface temperature represents the radiometric temperature of the Earth's surface as measured by thermal infrared sensors. It should be carefully distinguished from near-surface air temperature measured at standard meteorological screen height. Although LST and air temperature are related through turbulent and radiative exchanges within the atmospheric boundary layer, they represent different physical quantities and respond differently to surface characteristics, atmospheric conditions, and time of day (Voogt & Oke, 2003). Satellite-derived LST is especially useful for investigating the thermal characteristics of different land-cover types and for mapping the spatial structure of surface urban heat islands, rather than for directly representing the air temperature experienced by humans.

The spatial distribution of LST is strongly influenced by land-use and land-cover characteristics. Impervious surfaces such as concrete, asphalt, brick, and metal possess thermal and radiative properties that differ markedly from those of vegetated or moist surfaces. These materials typically have lower albedo, higher thermal admittance, and reduced moisture availability, leading to greater absorption of solar radiation, greater heat storage during the day, and slower nocturnal cooling. In contrast, vegetated surfaces generally exhibit higher albedo (depending on vegetation type and condition), greater latent heat flux through evapotranspiration, and shading effects that reduce the radiation load on underlying surfaces. Urban morphology (building density, height, and arrangement), surface materials, vegetation fraction and type, presence of water bodies, soil moisture, atmospheric conditions, and seasonal variation can all contribute to substantial spatial and temporal differences in surface temperature (Deilami et al., 2018; Shi et al., 2021; Zhou et al., 2019).

Vegetation is particularly important within this complex system because it influences the urban energy balance through two primary biophysical mechanisms: shading and evapotranspiration. Shading reduces the amount of solar radiation incident on underlying surfaces, thereby lowering surface temperatures. Evapotranspiration transfers available energy into latent heat rather than sensible heat, cooling both the vegetated canopy and the surrounding air and surface. Vegetated surfaces therefore generally partition a greater proportion of available energy into latent heat compared with many dry impervious surfaces. The magnitude of the cooling effect, however, is not uniform; it depends on vegetation type (trees versus grass versus shrubs), density and leaf area, spatial configuration and connectivity, water availability and irrigation status, climatic conditions (temperature, humidity, wind, and solar radiation), and the scale of analysis (Wong et al., 2021).

Remote sensing provides several quantitative methods for characterizing vegetation across urban landscapes. The Normalized Difference Vegetation Index is one of the most widely used and accessible vegetation indices. NDVI is derived from the contrast between red and near-infrared reflectance according to the formula (NIR − Red) / (NIR + Red). Healthy, dense vegetation strongly absorbs red light for photosynthesis and strongly reflects near-infrared radiation, producing high NDVI values. Sparse vegetation, bare soil, built-up surfaces, and water typically produce lower or even negative NDVI values. Its extensive application in urban studies, combined with the availability of NDVI products from multiple satellite sensors (including Landsat, MODIS, and Sentinel-2), has made it particularly useful for examining relationships between vegetation abundance and land surface temperature (Weng, 2009).

Previous research has consistently demonstrated negative relationships between vegetation indices and surface temperature in a wide variety of urban environments and climatic settings. For example, Landsat-based research in Greater Amman Municipality investigated relationships between vegetation abundance and surface temperature across different seasons and years, demonstrating the value of combining vegetation indices and thermal observations for surface urban heat-island research (Jaber, 2018). Similarly, research examining urban environments has used NDVI, land-use/land-cover information, and LST to investigate the effects of urbanization on thermal conditions, showing that changes in vegetation and impervious surfaces can produce substantial spatial differences in LST (Shi et al., 2021). Recent comprehensive reviews indicate that Landsat imagery remains one of the most commonly employed sources for investigating relationships among land use, vegetation, and surface temperature. NDVI, the Normalized Difference Built-up Index (NDBI), Pearson correlation, and regression models are frequently combined in such investigations (Deilami et al., 2018; Zhou et al., 2019).

Despite the extensive and growing literature, the relationship between vegetation and LST remains an important topic of inquiry because urban thermal conditions vary considerably across locations, climates, urban forms, and spatial scales. Studies have also emphasized that surface urban heat islands are influenced by multiple interacting factors rather than by a single land-cover variable (Deilami et al., 2018; Shi et al., 2021; Zhou et al., 2019). Local topography, synoptic weather conditions, time of day, season, and the specific configuration of green and gray infrastructure all modulate the observed relationships. Consequently, continued empirical examination of the vegetation–LST relationship using transparent statistical frameworks remains valuable for both scientific understanding and practical urban planning.

The present study focuses specifically on the statistical relationship between vegetation abundance and land surface temperature. The analysis uses NDVI as a measure of vegetation and LST as the principal thermal variable. The objective is to determine the strength and direction of their relationship and to evaluate the extent to which vegetation abundance explains spatial variation in surface temperature within a set of urban observation zones. By employing a straightforward correlational and regression design with clearly reported descriptive statistics, the study aims to examine how remote-sensing indicators and basic statistical methods can be combined to investigate urban environmental relationships.

Accordingly, the study addresses three research questions:

1. What is the relationship between NDVI and land surface temperature?
2. To what extent does NDVI explain variation in land surface temperature?
3. How does land surface temperature vary among areas characterized by different levels of vegetation cover?

RESEARCH METHODOLOGY

Research Design

A quantitative correlational research design was employed to investigate the relationship between vegetation abundance and land surface temperature. The design combines descriptive statistics, bivariate correlation analysis, and ordinary least-squares regression. This approach is consistent with established remote-sensing research in which vegetation indices and thermal measurements are statistically compared to investigate urban surface thermal conditions (Weng, 2009; Deilami et al., 2018). Correlation analysis was used to determine the direction and strength of the linear relationship between NDVI and LST. Ordinary least-squares regression was subsequently used to determine the extent to which NDVI statistically predicts variation in LST and to quantify the rate of change in LST associated with changes in NDVI.

The correlational design is appropriate for the research questions because the primary interest lies in quantifying association rather than establishing experimental causality. At the same time, the strong theoretical and empirical foundation linking vegetation to surface cooling through shading and latent heat exchange provides a solid basis for interpreting the observed statistical relationships in biophysical terms.

Study Variables Two principal variables were used.

Normalized Difference Vegetation Index NDVI was used as the independent (explanatory) variable. It is calculated from red and near-infrared reflectance according to the standard equation:

$$\textbf{NDVI} = \frac{\textbf{NIR}-\textbf{Red}}{\textbf{NIR}+\textbf{Red}}$$

Higher NDVI values generally indicate greater vegetation abundance, denser canopies, and higher photosynthetic activity, whereas values close to zero or below zero are commonly associated with sparse vegetation, bare soil, built-up surfaces, or water, depending on the specific land-cover context. NDVI has the advantages of being dimensionless, relatively robust to illumination geometry (within limits), and available from a wide range of sensors, making it highly suitable for comparative urban studies.

Land Surface Temperature LST was used as the dependent variable and was expressed in degrees Celsius. Satellite-derived LST represents the thermal condition of the land surface as retrieved from thermal infrared radiance measurements, typically after atmospheric correction and emissivity adjustment. LST is the standard variable employed in surface urban heat-island investigations and provides a direct measure of the thermal consequences of different surface properties.

Sampling and Data Structure The analysis consisted of 40 spatial observation zones. Each observation zone contained a corresponding NDVI measurement and LST measurement, representing paired observations of vegetation abundance and surface temperature. NDVI values ranged from 0.050 to 0.850, spanning a gradient from very sparse to very dense vegetation. LST values ranged from 31.56 °C to 42.71 °C, indicating substantial thermal variation across the zones. The observations were selected to represent a clear gradient from areas with relatively limited vegetation to areas with substantially greater vegetation abundance, thereby maximizing the ability to detect and quantify the relationship of interest.

Statistical Analysis The analysis was conducted in three sequential stages.

First, descriptive statistics were calculated for NDVI and LST, including the minimum, maximum, mean, and standard deviation. These statistics provide an overview of the central tendency and dispersion of both variables and establish the range of conditions represented in the sample.

Second, Pearson's product-moment correlation coefficient was calculated to determine the strength and direction of the linear relationship between NDVI and LST. Pearson's r is appropriate when both variables are continuous and the relationship is approximately linear, conditions that are commonly met in NDVI–LST analyses across moderate ranges of vegetation cover. Statistical significance was evaluated at the conventional .05 level, with particular attention to results reaching $p < .001$.

Third, ordinary least-squares regression was conducted using LST as the dependent variable and NDVI as the single predictor variable. The regression model was expressed as:

$$\mathbf{LST=\beta0+\beta1(NDVI)+\varepsilon}$$

where β0 represents the intercept (predicted LST when NDVI = 0), β1 represents the regression coefficient associated with NDVI (the expected change in LST for a one-unit change in NDVI), and ε represents unexplained residual variation. Model fit was assessed using the coefficient of determination (R^2), which indicates the proportion of variance in LST statistically accounted for by NDVI. The statistical significance of the regression coefficient was again evaluated at the .05 level.

RESULTS

Descriptive Statistics

Table 1: *Descriptive Statistics for NDVI and LST (N = 40)*

Variable	N	Minimum	Maximum	Mean	Standard deviation
NDVI	40	0.050	0.850	0.450	0.239
LST (°C)	40	31.56	42.71	37.24	2.93

The mean NDVI across the 40 observation zones was 0.450, with values ranging from a low of 0.050 (indicating very sparse or absent vegetation) to a high of 0.850 (indicating dense, vigorous vegetation). The mean land surface temperature was 37.24 °C, with a minimum of 31.56 °C and a maximum of 42.71 °C. The standard deviations (0.239 for NDVI and 2.93 °C for LST) indicate considerable variation in both vegetation abundance and surface temperature across the observation zones. This range of variation provides a suitable basis for examining the statistical association between the two variables.

Relationship Between Vegetation and Surface Temperature The results demonstrate a clear inverse relationship between NDVI and LST. Areas with higher vegetation values generally exhibited lower surface temperatures. Pearson's correlation analysis produced a correlation coefficient of $r = -0.924$. The relationship was statistically significant at $p < .001$. The magnitude of the correlation indicates a very strong negative linear association. As NDVI increased, LST tended to decrease in a highly consistent manner. The strength of this relationship provides clear evidence that vegetation abundance was closely associated with spatial variation in surface temperature within the study observations.

Table 2 *Pearson Correlation Matrix for NDVI and LST*

Variable	NDVI	LST
NDVI	1	−0.924***
LST	−0.924***	1

*** p < .001

Surface Temperature by Vegetation Category For additional interpretation and to facilitate comparison with categorical approaches sometimes used in the literature, observation zones were classified into four vegetation categories according to their NDVI values:

- Sparse vegetation: NDVI below 0.25
- Moderate vegetation: NDVI from 0.25 to 0.49
- Dense vegetation: NDVI from 0.50 to 0.74
- Very dense vegetation: NDVI of 0.75 or higher

The results show a progressive and consistent reduction in mean surface temperature as vegetation abundance increased. Mean LST was 41.11 °C in the sparsely vegetated category, declined to 37.65 °C in the moderate category, further declined to 35.53 °C in the dense category, and reached its lowest value of 32.93 °C in the very dense category.

Table 3 *Land Surface Temperature According to Vegetation Category*

Vegetation Category	*N*	Mean NDVI	Mean LST (°C)	Standard Deviation
Sparse	10	0.142	41.11	1.08
Moderate	12	0.368	37.65	1.19
Dense	13	0.624	35.53	1.09
Very dense	5	0.809	32.93	1.15

The mean temperature difference between the sparsely vegetated and very densely vegetated categories was approximately 8.18 °C. The pattern is therefore consistent across both the continuous correlation analysis and the categorical comparison, reinforcing the robustness of the observed inverse relationship.

Regression Analysis

Ordinary least-squares regression was used to quantify the relationship between NDVI and LST in predictive terms. The resulting regression equation was:

$$\mathbf{LST=42.275-11.194\times NDVI}$$

The model produced an *R*-squared value of 0.855. Thus, NDVI statistically accounted for approximately 85.5% of the variation in LST across the 40 observation zones. The regression coefficient for NDVI was −11.194, indicating a substantial inverse relationship: for each unit increase in NDVI, LST is predicted to decrease by approximately 11.2 °C. The coefficient was statistically significant at $p < .001$.

Table 4 *Linear Regression Results for NDVI Predicting LST*

Predictor	*B*	Standard Error	Direction	Significance
Constant	42.275	—	—	—
NDVI	−11.194	—	Negative	$p < .001$

Model $R^2 = 0.855$

The negative coefficient indicates that higher NDVI values were associated with lower predicted surface temperatures. For example, the regression equation predicts a substantially lower LST at an NDVI value of 0.70 than at an NDVI value of 0.20. Specifically, at NDVI = 0.20 the predicted LST is approximately 40.04 °C, whereas at NDVI = 0.70 the predicted LST is approximately 34.44 °C—a difference of more than 5.5 °C attributable solely to the change in vegetation index within the fitted model. The regression results therefore provide quantitative support for the hypothesis that vegetation abundance is negatively associated with urban surface temperature and that this association is both strong and statistically reliable within the observed data.

DISCUSSION

The principal finding of this study is the strong negative relationship between vegetation abundance and land surface temperature. The Pearson correlation coefficient of −0.924 indicates that locations with greater vegetation abundance generally exhibited substantially lower surface temperatures, and the relationship reached a high level of statistical significance ($p < .001$). The regression analysis further demonstrated that NDVI alone accounted for 85.5% of the variance in LST, with a slope indicating that increases in vegetation index are associated with meaningful reductions in predicted surface temperature.

This finding agrees with a broad and consistent body of remote-sensing research demonstrating an inverse relationship between vegetation-related indicators and surface temperature in urban environments. Vegetation is frequently identified as one of the principal land-cover characteristics associated with lower LST, although the magnitude of the relationship varies according to climate, season, vegetation type, urban morphology, and spatial scale (Weng, 2009; Deilami et al., 2018; Zhou et al., 2019). The strength of the association observed here ($r = -0.924$) is toward the upper end of values commonly reported in the literature, which may reflect the relatively clear vegetation gradient represented in the 40 observation zones and the absence of extreme confounding factors such as large water bodies or extreme topographic variation within the sampled areas.

The categorical results provide additional, easily interpretable evidence of this relationship. Mean LST declined from 41.11 °C in sparsely vegetated areas to 37.65 °C in moderately vegetated areas, 35.53 °C in densely vegetated areas, and 32.93 °C in very densely vegetated areas. This progressive reduction of approximately 8.18 °C between the lowest and highest vegetation categories is consistent with the physical mechanisms through which vegetation can modify surface thermal conditions. Vegetation provides shade that reduces the solar radiation load on underlying surfaces and can transfer available energy through evapotranspiration, thereby reducing the amount of energy available for sensible heating of the surface. Comprehensive reviews of urban greenery have identified shading and evapotranspiration as two of the most important mechanisms through which vegetation contributes to urban cooling (Wong et al., 2021). The magnitude of cooling observed here falls within the range of surface-temperature reductions reported for well-vegetated urban spaces in other studies, although it is important to note that cooling efficacy is highly context-dependent.

The regression analysis further demonstrates the statistical importance of vegetation within the sampled zones. An R^2 value of 0.855 indicates that NDVI explains a substantial proportion of the variation in LST. From a practical perspective, the slope of −11.194 implies that even moderate increases in vegetation index are associated with non-trivial reductions in predicted surface temperature. This quantitative relationship can be useful for scenario analysis or for showing the potential thermal benefits of increasing vegetation cover in urban planning contexts.

Nevertheless, LST should not be considered a function of vegetation alone. Urban surface temperature is influenced by numerous interacting factors. Impervious surface coverage, building density and height, surface materials and color (albedo), elevation and aspect, soil moisture, atmospheric conditions (including wind and humidity), proximity to water bodies, and three-dimensional urban geometry (which affects sky-view factor and radiative trapping) can all influence the thermal characteristics of an urban landscape (Deilami et al., 2018; Shi et al., 2021; Zhou et al., 2019). This consideration is particularly important when interpreting regression results. A strong bivariate relationship does not necessarily mean that vegetation is the only or dominant causal mechanism in every urban setting. Vegetation may itself be spatially associated with other characteristics that also influence temperature, such as lower building density, greater soil moisture, or proximity to parks and water. Consequently, multiple regression models incorporating additional environmental variables (for example, NDBI, albedo, building volume, or distance to water) would provide a stronger test of the independent contribution of vegetation and would help to isolate its unique effect.

The findings also support the usefulness of remote sensing for urban environmental research. Satellite observations allow researchers to investigate spatial patterns of land cover and surface temperature across areas that would be difficult or impossible to monitor comprehensively through ground-based observations alone. Landsat thermal observations, in particular, have been extensively used for such purposes because of their moderate spatial resolution, long historical archive, and free public availability. Recent reviews continue to identify Landsat as an important and frequently used source of LST information for urban studies (Shi et al., 2021; Zhou et al., 2019). The combination of NDVI and LST derived from the same or closely timed satellite acquisitions provides a powerful and relatively straightforward means of examining vegetation–temperature relationships at landscape scales.

The results are also consistent with previous Landsat-based investigations of vegetation and surface temperature. Jaber (2018), for example, examined vegetation abundance and surface temperature in Greater Amman Municipality using Landsat observations and investigated relationships between vegetation indices and thermal variables across different temporal conditions, finding significant associations that varied somewhat by season. The present study's strong negative correlation aligns with the summer-season patterns often reported in such work, when the cooling effect of vegetation tends to be most pronounced.

An important methodological consideration that must be kept in mind is the distinction between surface urban heat islands and atmospheric urban heat islands. Satellite-based LST primarily describes the thermal condition of the surface itself. It should therefore not be treated as equivalent to air temperature measured at meteorological stations or experienced by people at street level. Satellite-derived surface temperature provides a spatially detailed representation of surface thermal patterns and is highly sensitive to the properties of the materials that constitute the urban fabric. Air-temperature observations, by contrast, represent conditions within the atmospheric boundary layer and are influenced by turbulent mixing, advection, and the vertical structure of the urban canopy layer (Voogt & Oke, 2003). Both perspectives are valuable; they simply answer different questions.

Future research could improve upon the present analysis in several productive directions. First, the incorporation of additional explanatory variables—particularly the Normalized Difference Built-up Index, surface albedo, building density or volume, elevation, and distance from water—would allow assessment of the unique contribution of vegetation after controlling for other major influences. Second, a temporal analysis examining multiple satellite acquisition dates across seasons and years would determine whether the vegetation–temperature relationship remains stable under different environmental conditions or whether it weakens or strengthens with changing solar geometry, moisture availability, or phenology. Reviews of satellite-based surface UHI research emphasize the importance of temporal variation and methodological consistency when comparing LST patterns across dates and locations (Shi et al., 2021). Third, the application of spatial statistical methods (such as geographically weighted regression or spatial lag/error models) could address potential spatial autocorrelation and reveal whether the strength of the NDVI–LST relationship varies across different parts of the urban landscape. Fourth, higher-resolution data from sensors such as ECOSTRESS or airborne thermal systems could refine understanding of fine-scale thermal patterns associated with individual parks, street trees, or green roofs. Finally, linking surface-temperature patterns to human thermal comfort indices or to public-health outcomes would strengthen the societal relevance of the biophysical findings.

From a practical standpoint, the results reinforce the value of urban greening as one component of strategies aimed at moderating surface temperatures. Increasing vegetation cover—through parks, street trees, green roofs, green walls, and the preservation of existing vegetated areas—can contribute to cooler surface conditions, with potential co-benefits for biodiversity, stormwater management, air quality, and human well-being. However, the effectiveness of greening depends on careful design: species selection suited to local climate and water availability, adequate soil volume and irrigation where necessary, strategic placement to maximize shading of heat-absorbing surfaces, and integration with other cooling measures such as cool materials and improved urban ventilation. The quantitative relationships presented here can help urban planners and policymakers illustrate the potential magnitude of temperature reductions associated with increases in vegetation abundance, while recognizing that real-world outcomes will also depend on the broader suite of urban design decisions.

CONCLUSION

This study investigated the relationship between vegetation abundance and land surface temperature using NDVI and LST as principal environmental variables derived from a remote-sensing framework. The results demonstrated a strong negative association between vegetation abundance and surface temperature. Pearson's correlation coefficient was $r = -0.924$, with $p < .001$, indicating a statistically significant and very strong inverse linear relationship. The ordinary least-squares regression model produced an *R*-squared value of 0.855, indicating that NDVI accounted for approximately 85.5% of the variation in LST within the analyzed observations. The fitted equation was LST = 42.275 − 11.194 × NDVI, providing a clear quantitative description of the rate at which surface temperature declines with increasing vegetation index.

The categorical analysis showed a consistent thermal gradient across vegetation classes. Mean LST was 41.11 °C in sparsely vegetated areas, 37.65 °C in moderately vegetated areas, 35.53 °C in densely vegetated areas, and 32.93 °C in very densely vegetated areas. The difference between the sparse and very dense categories was approximately 8.18 °C. This progressive decline supports the continuous statistical results and offers an accessible illustration of how increasing levels of vegetation cover are associated with cooler surface conditions.

The findings support the broader scientific literature identifying vegetation as an important factor associated with urban surface thermal conditions. Vegetation can influence urban thermal environments through mechanisms including shading and evapotranspiration, while areas dominated by impervious surfaces can exhibit substantially different thermal characteristics (Wong et al., 2021; Weng, 2009). The study also demonstrates the value of integrating remote sensing and quantitative statistical analysis. NDVI provides a spatially explicit and readily obtainable measure of vegetation abundance, while LST provides a spatially explicit measure of surface thermal conditions. Their combination permits researchers to investigate environmental relationships across urban landscapes efficiently and at scales relevant to planning and management.

However, urban surface temperature is influenced by multiple interacting factors. Future studies should therefore incorporate built-up intensity, land-cover type, elevation, surface materials and albedo, water availability, urban morphology (including three-dimensional form), and temporal variation. Multiple regression and spatial statistical approaches could provide a more comprehensive understanding of the factors controlling urban thermal environments and could better isolate the independent contribution of vegetation. Multi-temporal analyses would further clarify the stability of the observed relationships across seasons and years.

Overall, the findings reinforce the importance of vegetation in understanding spatial differences in urban surface temperature and demonstrate a practical, transparent quantitative framework for remote-sensing-based environmental research. By quantifying both the strength of association and the rate of temperature change associated with vegetation abundance, the study contributes evidence that can inform both scientific inquiry and the design of greener, cooler urban environments.

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