Quantifying urban cooling benefits with SDGSAT-1 nighttime light and thermal infrared datae

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Abstract: *With the acceleration of urbanization and the expansion of impervious surfaces, the urban heat island (UHI) effect has become one of the major challenges in urban environmental issues. This study focuses on the central urban areas of five representative cities in China. Using thermal infrared (TIR) and nighttime light (NTL) data from the SDGSAT-1 satellite, along with digital elevation model (DEM), normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), and normalized difference water index (NDWI), we constructed two random forest (RF) models for predicting land surface temperature (LST) for summer and winter in each city. Model 1 used nighttime light intensity and DEM as baseline predictors, while Model 2 incorporated all variables for comprehensive LST fitting. Based on Model 1,we innovatively proposed a Cooling Benefit Index (CBI = Predicted LST − Actual LST) to quantify urban cooling benefits. Using Model 2, we further analyzed the influence and regulatory roles of different variables on LST. The results indicate that the maximum CBI values in most cities exceeded 2.2 K, with spatial high-value clusters predominantly located at urban fringes and suburbs, while significant UHI effects were observed in central urban areas. Furthermore, a four-quadrant analysis of CBI and NTL revealed that in areas with extremely high human activity intensity, the CBI per unit NDVI was the highest, suggesting that even moderate vegetation coverage can yield significant cooling benefits. In addition, SHAP analysis based on Model 2 demonstrated that Light Intensity and NDVI consistently exhibited high explanatory power, respectively representing the driving effect of human activities on UHI and the mitigating role of vegetation. The proposed CBI index provides a scientific basis and decision-support tool for mitigating UHI effects, formulating urban cooling strategies, and advancing Sustainable Development Goal 11 (SDG11).*

Keywords: Night-time light, Land surface temperature, Cooling benefit index (CBI), Random forest(RF), Urban heat island

Introduction

Accelerated urbanization, characterized by the expansion of impervious surfaces, increased building density, and rising energy consumption, has made the Urban Heat Island (UHI) effect a prominent environmental issue. The UHI effect refers to the phenomenon where urban areas exhibit higher temperatures than their surrounding rural regions, primarily due to anthropogenic alterations to the natural environment(Rizwan et al., 2008) . This abnormal temperature rise poses multiple risks, including increased energy demand for cooling (Gabriel & Endlicher, 2011; Santamouris et al., 2015), deteriorated air quality(Hoag, 2015), adverse effects on human health(Mora et al., 2017), and further acceleration of climate change(Hoag, 2015). Consequently, quantifying and mitigating the UHI effect has become a critical task in urban planning and sustainable development strategies (Chakrabortty et al., 2025). This study focuses on the central urban areas of five major cities in China. Leveraging the unique capability of the SDGSAT-1 satellite to simultaneously acquire thermal infrared and nighttime light data, and incorporating additional datasets including NDVI, NDBI, NDWI, and DEM, we constructed two distinct Random Forest (RF)-based models for both summer and winter seasons in each city: a baseline LST prediction model (Model 1) using Light Intensity and DEM, and a comprehensive LST fitting model (Model 2) integrating all variables. Building on Model 1, this study innovatively proposes and develops an Urban Cooling Benefit Index (CBI = Predicted LST − Actual LST) to quantify urban cooling benefits. Meanwhile, Model 2 was employed to analyze the influence and regulatory effects of various variables on LST.

This research is closely linked to Sustainable Development Goal (SDG) 11. In alignment with Target 11.6, which aims to reduce per capita negative environmental impacts in cities with special attention to air quality and municipal waste management, the urban heat island effect represents a major environmental challenge. The proposed CBI metric serves as an effective monitoring tool to quantify and evaluate the effectiveness of UHI mitigation policies, thereby supporting the achievement of this target. In relation to Target 11.7, which emphasizes providing safe, inclusive, accessible, and green public spaces for all, the CBI-NTL four-quadrant analysis can accurately identify thermal risk zones, thereby offering a scientific basis for prioritizing the planning and construction of green infrastructure in areas most in need of improved thermal comfort. This approach aids in advancing the equitable development of urban environments. Ultimately, this research aims to provide a scientific basis for urban thermal environment management and to offer innovative tools and theoretical support for the formulation and optimization of urban cooling strategies.

Literature Review

In early research, the quantification of urban cooling benefits was primarily based on measurements from fixed meteorological stations or in-situ thermometers. While these direct measurement methods can yield accurate data, they are often constrained by the limited number of stations and their spatial coverage, making it difficult to capture the thermal environment characteristics over large areas or an entire city (Yan et al., 2021). With the advancement of remote sensing technology, it has gained widespread application in quantifying urban cooling benefits, owing to its advantages such as broad spatial coverage and convenient data acquisition(Du et al., 2017). Building on this, several quantitative metrics have been proposed and are extensively used in the assessment of urban cooling benefits, the most common of which include cooling intensity, cooling distance, and cooling area(Du et al., 2017; Shah et al., 2021). Cooling intensity generally refers to the temperature difference between an area with a cooling effect and its surrounding non-cooled areas. Cooling distance is typically defined as the distance from the boundary of a cooling body, generally vegetation or water, to the location where the cooling effect is no longer present; and cooling area refers to the spatial extent of the region with a discernible cooling effect (Guo et al., 2024). The calculation methods for these three metrics are not standardised in current research, with three main approaches being prevalent: the buffer averaging method, the visual interpretation method, and the basin analogy method. Among these, the buffer averaging method, also known as the turning point or equal radius method, is the most commonly used. Its fundamental principle involves creating a series of equidistant buffers around the outer boundary of an urban natural cooling body, such as a water body or vegetation, and calculating the average LST within each buffer. This process identifies the first turning point (FTP) on the temperature profile curve, which determines the cooling distance and area(Qureshi et al., 2023). The visual interpretation method involves drawing transect lines from the centre of the cooling body in multiple directions, manually reading the LST along these lines to identify the FTP in each direction, and delineating the cooling zone by connecting these points(Zhou et al., 2023; Zhou et al., 2025). The basin analogy method likens the cooling body to a basin or lake. It simulates water flow direction based on LST data and determines the cooling extent using a slope threshold, similar to watershed delineation. After excluding flat areas, the cooling zone is derived(Lin et al., 2015). Furthermore, a comparative study by some scholars indicated that the visual interpretation method offers the highest accuracy, whereas the buffer averaging method is the most efficient(Zhou et al., 2025).

Although these quantitative metrics and methods have been extensively studied and applied to quantify urban cooling benefits, most of the research has focused on quantifying the effects of large, discrete natural cooling bodies within cities, lacking a large-scale, continuous quantification across the urban landscape. For instance, Peng et al(Peng et al.,

2021) quantified the cooling benefits in Shenzhen by selecting only 24 urban parks. Concurrently, most studies are based on thermal infrared data from satellites such as Landsat, with few integrating this data with nighttime light data, which reflects the intensity of human activity(Small et al., 2011; Wu et al., 2023) and the level of urbanisation(L.Imhoff et al., 1997) and is closely correlated with the urban heat island effect. Therefore, this paper innovatively proposes the Cooling Benefit Index (CBI), which can provide a new assessment method and perspective for quantifying cooling benefits.

Methodology

a. Study area and datasets

This study selects the central urban areas of five major Chinese cities as research targets, namely Beijing, Shanghai, Hefei, Xi'an, and Guangzhou. These cities are representative of megacities and large urban centers in China, characterized by high population density and significant experiences of urban expansion, rapid industrialization, and urbanization. With the increase of impervious surfaces, these areas commonly exhibit pronounced urban heat island effects. Focusing on the central districts of these typical cities to investigate the urban heat island effect, quantify cooling benefits, and conduct spatial mapping analysis holds substantial practical significance. The study aims to provide valuable insights for mitigating urban heat island effects and is expected to contribute positively to the advancement of sustainable human development.

To analyze and quantify the cooling benefits of the UHI effect, as well as to compare the differences in UHI intensity and cooling benefits between the central urban areas in summer and winter, this study utilizes NIR and NTL from the SDGSAT-1 satellite, alongside multispectral data from Landsat 9 and SRTM (Shuttle Radar Topography Mission) data. This multi-source remote sensing approach ensures the accuracy and comprehensiveness of the analysis. The datasets used in this study and their attributes are summarized in Table 1. Preprocessing included radiometric calibration, atmospheric correction, spatial clipping, and reprojecting data into the WGS84/UTM coordinate system. The data were then divided into 500m*500m grids, and the average value for each grid was calculated to ensure spatial consistency and representativeness across the entire dataset.

Table 1. Data sources and attributes

Data Source	Sensor/Instrument	Data Type	Spatial Resolution
SDGSAT-1	Thermal Infrared Spectrometer (TIS)	Thermal Infrared (TIR)	30m
SDGSAT-1	Glimmer Imager (GIU)	Nighttime Light (NTL)	10m
Landsat 9	Operational Land Imager (OLI)	Multispectral (NDVI, NDBI, NDWI)	30m
SRTM	Digital Elevation Model (DEM)	Elevation & Terrain Data	30m

b. LST retrieval

The LST is retrieved using a practical single-channel algorithm applied to the thermal infrared (TIR) data from SDGSAT-1. This method, initially proposed by(Wang et al., 2019), was first used for LST retrieval from Landsat TIR data. The study employs this method to retrieve LST from the second thermal infrared band (TIR2) of the SDGSAT-1 satellite. The basic equation for LST retrieval is as follows:

$$T_s = \frac{c_2/\lambda}{Ln\left(\frac{c_1}{\lambda^5 B(T_s)} + 1\right)} \tag{1}$$

$$B(T_s) = a_0 + a_1\omega + (a_2 + a_3\omega + a_4\omega^2)\frac{1}{\varepsilon} + (a_5 + a_6\omega + a_7\omega^2)\frac{1}{\varepsilon}L_{sen} \tag{2}$$

Where:

Ts = Land Surface Temperature (LST) in Kelvin (K)

$B(Ts)$ = Radiance of a blackbody at temperature Ts

ln = Natural logarithm

ω = Atmospheric water vapor content

ε = Surface emissivity (calculated using Equations 3 and 4)

$Lsen$ = Sensor radiance (the result of radiometric calibration of the thermal infrared data)

c_1 =1.19104×108Wμm4m^{-2}sr^{-1}

c_2 =1.43877×10^4μmK

λ = Effective wavelength of the SDGSAT-1 TIR2 band (10.73 µm)

a_0 to a_7 are listed in Table 2.

The surface emissivity (ϵ) was calculated using the NDVI threshold method as follows:

$$\varepsilon = \begin{cases} \varepsilon_s & NDVI < NDVI_s \\ P_v\varepsilon_v + (1 - P_v)\varepsilon_s & NDVI_s \le NDVI \le NDVI_v \\ \varepsilon_v & NDVI > NDVI_v \end{cases} \tag{3}$$

$$P_v = \begin{cases} 0 & NDVI < NDVI_s \\ \left(\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s}\right)^2 & NDVI_s \leq NDVI \leq NDVI_v \\ 1 & NDVI > NDVI_v \end{cases} \quad (4)$$

Where:

ε = Surface emissivity

ε_s = Emissivity for bare soil (0.9668)

ε_v = Emissivity for pure vegetation (0.9863)

NDVIs = NDVI value for bare soil (0.2)

NDVIv = NDVI value for pure vegetation (0.55)

Pv = Vegetation proportion, based on the NDVI values

NDVI = Normalized Difference Vegetation Index value of the area

Table 2. Practical single-channel algorithm coefficients for SDGSAT-1 TIR2 data

a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
-0.03439	1.34063	-0.3163	-0.6831	-0.3976	1.0550	-0.0682	0.04673

c. Construction of the Random Forest model

The Random Forest (RF) model, proposed by Breiman(Breiman, 2001), is a nonlinear machine learning algorithm that operates by constructing multiple decision trees to perform regression or classification tasks. It aggregates predictions from these trees to enhance accuracy and generalization capability. The RF model is particularly effective in capturing complex relationships between various explanatory variables and Land Surface Temperature (LST), thereby highlighting the contribution and influence of different factors on LST. This makes it highly suitable for LST prediction and fitting.

In this study, two distinct RF models were independently constructed for summer and winter data in each city. Model 1 used Light Intensity and Digital Elevation Model (DEM) as independent variables, with LST as the dependent variable. This model aims to establish a theoretical prediction framework for LST by employing nighttime light intensity(NTL) as a proxy for human activity intensity, reflecting factors such as energy consumption and building density, and DEM data to represent macro-topographic conditions that remain largely independent of vegetation and water bodies. The resulting predicted LST can thus be interpreted as a theoretical temperature that would occur under the influence of urban development intensity and topography alone, without the moderating effects of vegetation or water bodies. This approach provides a foundational basis for the computation of the Cooling Benefit Index (CBI). Model 2 extended Model 1 by incorporating additional variables, including NDVI, NDBI, and NDWI, alongside Light Intensity and DEM, to fit LST. SHAP (Shapley Additive exPlanations) analysis was employed to interpret the influence and regulatory effects of each variable on LST.

d. Construction of the CBI

To quantify urban cooling benefits, this study proposes and constructs a new metric termed the Cooling Benefit Index (CBI). The CBI is defined as follows:

$$CBI = x - y \tag{5}$$

where:

x = Predicted temperature(predicted by RF model)

y = Actual temperature(derived from TIR2 data)

If CBI > 0, indicating that the predicted temperature is higher than the actual surface temperature, it suggests that the area has a favorable cooling effect, often associated with better vegetation and water body coverage. A larger CBI value indicates better cooling benefits, which can enhance thermal comfort. Conversely, if CBI < 0, meaning the actual surface temperature is higher than the predicted temperature, it indicates the presence of an urban heat island effect. A smaller CBI value suggests a more severe heat island effect, and these areas should be prioritized in urban heat mitigation policies to promote sustainable urban development.

e. CBI evaluation

The evaluation of the Cooling Benefit Index (CBI) began with a statistical analysis of values where CBI > 0, including metrics such as range and mean, to characterize the overall distribution of CBI. Spatial mapping was further employed to visually reveal its spatial patterns. To comprehensively integrate cooling benefits and urban development intensity, a quadrant classification framework was established using CBI and nightttime light intensity(NTL) as the coordinate axes. Specifically, CBI values were divided into high and low groups using zero as the threshold. Since NTL values are typically concentrated in the lower range and exhibit a skewed distribution, logarithmic transformation was applied to reduce skewness, with the median of the transformed values used as the threshold for NTL. Based on these thresholds, the data were classified into four quadrants: Quadrant I represents High-Efficiency Cooling Zones (high NTL, high CBI), Quadrant II corresponds to Ecological Conservation Zones (low NTL, high CBI), Quadrant III denotes Potential Development Zones (low NTL, low CBI), and Quadrant IV indicates Thermal Risk Zones (high NTL, low CBI). Within each quadrant, sample points were color-coded according to their NDVI values to provide an intuitive representation of vegetation coverage levels.

Results and Discussion

a. Statistical and spatial distribution of CBI

The Cooling Benefit Index (CBI) was developed to quantify urban cooling benefits, where positive values indicate that the actual LST is lower than the predicted LST, reflecting a measurable cooling effect. Higher CBI values correspond to more significant cooling performance. Statistical analysis of CBI > 0 values for summer and winter across the studied cities (Figure 1) revealed that the maximum cooling benefit in all cities exceeded 2.2 K, while the minimum average cooling value remained above 0.4 K, confirming consistent cooling effects in both seasons. Variations among cities were observed: Hefei and Shanghai exhibited slightly higher maximum cooling values, whereas Xi'an showed relatively lower values. Beijing and Guangzhou demonstrated intermediate results. Differences in average cooling benefits, however, were modest, potentially influenced by climatic conditions, precipitation patterns, and vegetation coverage.

From the CBI distribution results in Figure 2, high CBI values were predominantly concentrated in suburban areas and urban peripheries, regions typically associated with higher vegetation coverage and elevated terrain, where cooling benefits were more pronounced. In contrast, central urban zones showed low or negative CBI values, aligning with areas of high Light Intensity, intensified human activities, elevated LST, and marked heat island effects.Notable seasonal variations were observed. During summer, high-CBI zones indicating significant cooling were relatively concentrated, while in winter, these zones appeared more dispersed. This difference may be attributed to reduced vegetation physiological activity and canopy coverage in winter, combined with increased anthropogenic heat release from heating systems, altering the spatial pattern of temperature regulation.

Overall, the integration of statistical and spatial analyses enhances the understanding of both the magnitude and distribution of urban cooling benefits, providing a scientific basis for targeted thermal environment management. It also should be noted that the use of grid cells as analytical units may introduce scale effects into the CBI results. The division into grids can smooth out localized CBI features, thereby reducing spatial heterogeneity in CBI values.

b. Four-Quadrant results of CBI and NTL

Building upon the statistical and spatial analysis of CBI, a four-quadrant analytical framework was established using the cooling benefit (CBI) and urban development intensity (NTL) as axes, with NDVI values used for color-coding the sample points. This approach aimed to further elucidate the relationships among CBI, urban development intensity, and vegetation coverage. The results indicate that, despite variations in NDVI and NTL across cities and between summer and winter, common patterns emerged among the quadrants. The first quadrant (high NTL and high CBI, termed “High Cooling Efficiency Zones”) exhibited moderate average NDVI values, yet the highest CBI efficiency per unit NDVI (CBI/NDVI), indicating exceptionally efficient vegetation cooling in these areas. The second quadrant (low NTL and high CBI, termed “Ecological Conservation Zones”) showed the highest average NDVI accompanied by high CBI/NDVI ratios, reflecting significant cooling effects supported by high vegetation coverage under low urban development intensity. The third quadrant (low NTL and low CBI, termed “Potential Development Zones”) demonstrated moderate NDVI values but the lowest CBI/NDVI, suggesting limited cooling efficiency of vegetation in these regions. The fourth quadrant (high NTL and low CBI, termed “Thermal Risk Zones”) displayed the lowest average NDVI as well as low CBI/NDVI values, indicating insufficient capacity of sparse vegetation to mitigate urban heat islands under high urbanization intensity.

Using summer data from Beijing as an example (Figure 3), the first quadrant had an average NDVI of 0.431, intermediate among the four quadrants, while its CBI/NDVI ratio reached 0.876, the highest of all zones. In contrast, the fourth quadrant had both the lowest NDVI, with a mean value of 0.375, and one of the lowest CBI/NDVI values. This indicates that in areas with extremely high human activity and urban development intensity, the cooling benefit per unit vegetation (CBI/NDVI) is notably high. Thus, even moderate greening interventions can yield significant cooling effects, providing valuable insights for urban planning strategies. This finding offers strong practical guidance for urban planners in optimizing the allocation of limited green infrastructure resources to maximize cooling benefits, particularly under budgetary constraints.

The spatial distribution maps of the CBI and its four-quadrant classification framework can serve as decision-support tools for urban management. They facilitate the identification of areas severely affected by heat islands as well as ecologically sensitive zones, and provide guidance for urban green space system planning by directing limited resources toward the most critical thermal risk zones and the most efficient high cooling efficiency areas. Long-term application of the CBI methodology enables dynamic monitoring of the effectiveness of urban cooling strategies and supports the evaluation of progress in climate adaptation and sustainability enhancement. Mitigating the urban heat island effect constitutes a vital component of urban climate adaptation and resilience building, which aligns directly with the objectives outlined in SDG 11.b.

c. SHAP analysis results

To further elucidate the influence of various variables on land surface temperature (LST) beyond correlation analysis, this study compared the differences in feature importance across cities and seasons (Figure 4). The results reveal spatiotemporal heterogeneity in the mechanisms underlying thermal environment formation among different cities and seasons.

Across all cities and seasons, Light Intensity consistently emerged as one of the most important features, exhibiting higher feature importance in summer than in winter, with the most pronounced effect observed during summer in Beijing. This indicates a substantial positive contribution of human activities to elevated LST.NDVI also played a notable role in influencing LST. Its feature importance, reflecting its cooling contribution, was most prominent during summer in Hefei. However, its significance weakened markedly during winter in cities such as Beijing and Hefei, likely due to reduced thermal regulation capacity of vegetation caused by seasonal leaf fall. In contrast, the normalized difference built-up index (NDBI), normalized difference water index (NDWI), and digital elevation model (DEM) generally demonstrated higher feature importance in winter than in summer. This suggests enhanced regulatory effects of building coverage, water bodies, and topographic factors on LST during the cold season, a trend most evident in Beijing’s winter data.

In summary, the SHAP visualization method effectively reveals the mechanisms through which multiple features influence LST. The overall results indicate that, although the contribution of driving factors varies spatially across cities, Light Intensity and NDVI maintain high explanatory power in both seasons. This underscores the persistent driving role of human activities in the urban heat island effect and the significant mitigating effect of vegetation.

The Urban Heat Island (UHI) effect represents a critical challenge in urban development, necessitating professional and rational measures for mitigation. Traditional assessment of UHI has largely relied on direct temperature comparison methods, which often fail to adequately account for variations in urban development intensity across different regions. To address this gap, this study established a theoretical thermal environment model (Model 1) based on human activity intensity and innovatively proposed the Cooling Benefit Index (CBI). This index enables a more equitable and standardized evaluation of the actual cooling performance of urban green infrastructure by decoupling the inherent thermal effects of urban development.

The findings reveal that Light Intensity, as an indicator of human activity intensity, exhibits a significant positive correlation with LST and serves as one of the most influential factors contributing to LST (Figure 4). This suggests that human activities play an important role in driving the formation of UHI, a result consistent with previous studies(Mpakairi & Muvengwi, 2019; Sun et al., 2020).Similarly, the negative correlation between NDVI and LST aligns with existing research(Beele et al., 2024; Dewan et al., 2021), supporting the positive contribution of vegetation in enhancing cooling benefits and mitigating the UHI effect.

d. Limitations of the study

This study focused on five Chinese cities, utilizing summertime and wintertime nighttime Light Intensity and LST data to investigate urban cooling benefits. However, certain limitations remain in terms of spatial and temporal scope. Spatially, the limited number of sample cities restricts the ability to fully reveal differences in cooling benefits across various climate zones and urban forms. Temporally, this research primarily addresses nighttime cooling effects in summer and winter, leaving daytime and seasonal variations throughout the year to be further explored. Future studies could leverage the advantages of SDGSAT-1 satellite data to expand the research scope to cities across China and globally, while also comparing differences between daytime and nighttime cooling effects. Such efforts would provide a more comprehensive scientific foundation for UHI mitigation strategies.

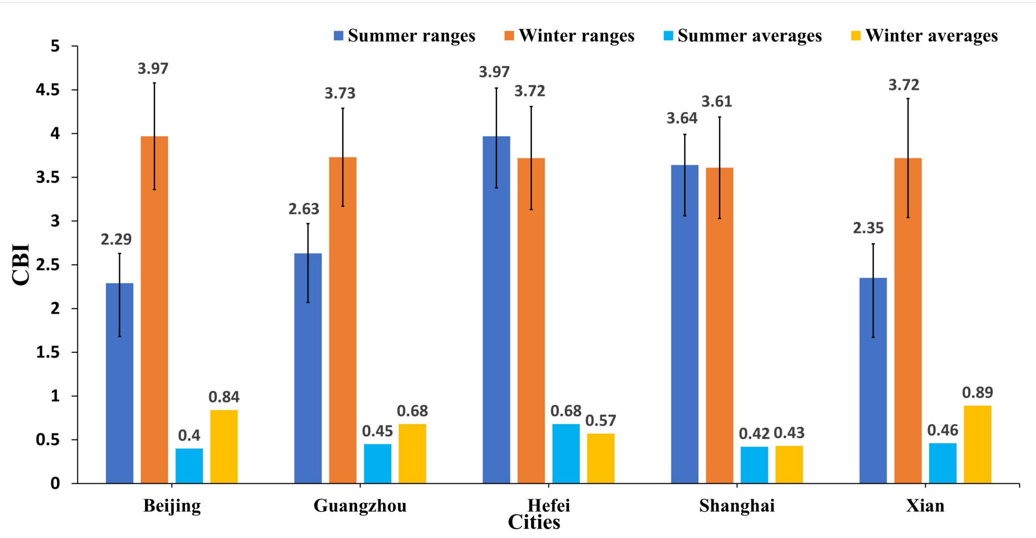

Figure 1: CBI ranges and averages for Winter and Summer across cities when CBI > 0

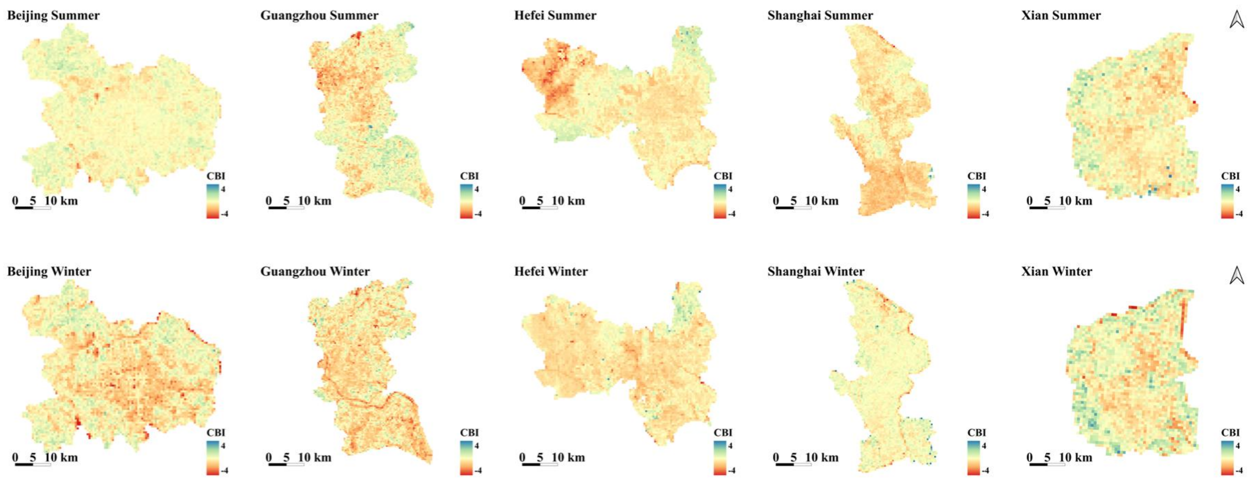

Figure 2: Spatial Distribution Map of the CBI

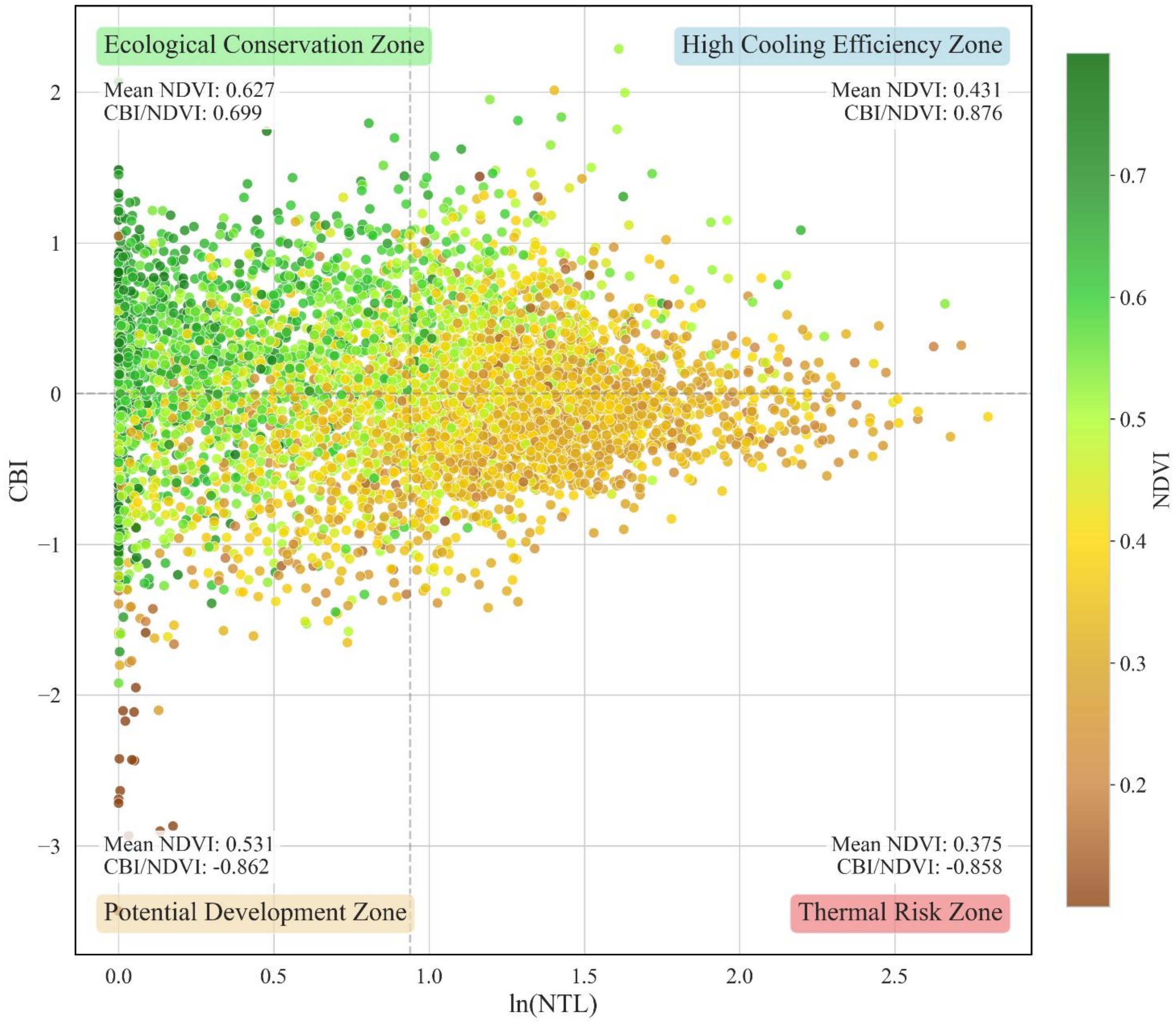

Figure 3: Four-Quadrant Analysis of CBI for Summer in Beijing

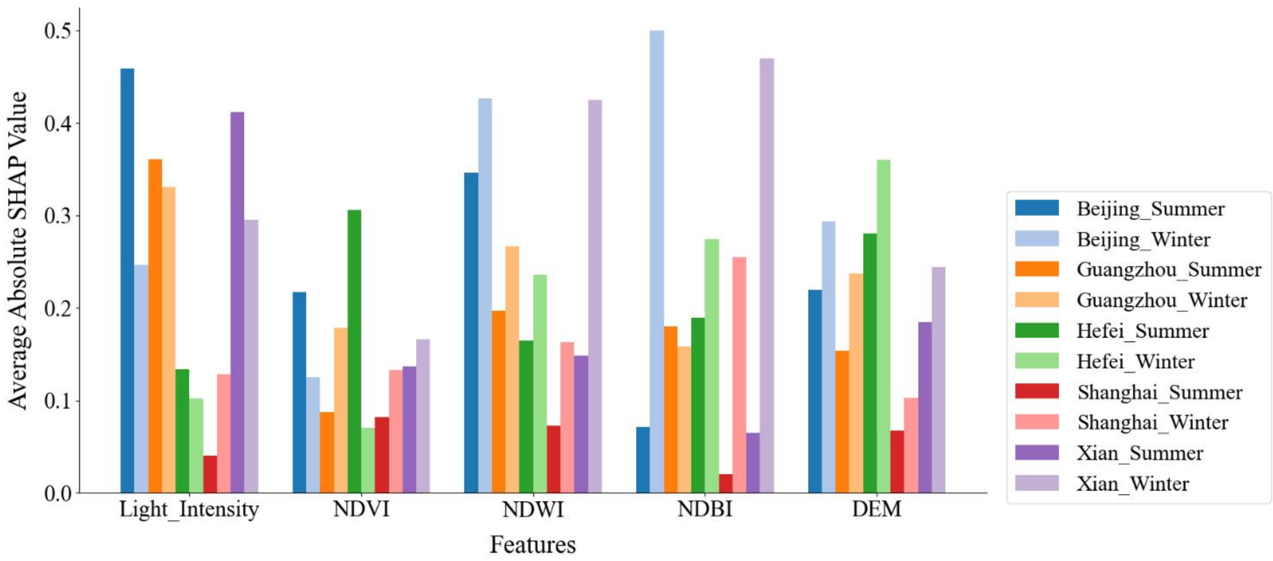

Figure 4: SHAP Feature Importance Plot

Conclusion

The results of this study indicate that the maximum Cooling Benefit Index (CBI) values in most cities exceeded 2.2 K. Spatial mapping revealed that areas with stronger cooling benefits were primarily concentrated in urban peripheries and suburbs, whereas central urban zones showed more significant heat island effects due to higher human activity intensity. The CBI and NTL four quadrant analysis demonstrated that in regions with extremely high human activity and urban development intensity, the CBI per unit NDVI, denoted as CBI/NDVI, reached the highest values. This suggests that even moderate vegetation coverage, represented by medium NDVI values, can produce considerable cooling benefits. SHAP visualization results derived from Model 2 indicated that although the influence and importance of variables varied across different cities and between seasons, both Light Intensity and NDVI consistently retained high explanatory power. These findings highlight the role of Light Intensity, an effective indicator of human activity intensity, in driving the urban heat island effect, as well as the significant mitigating contribution of vegetation cover.

In summary, the CBI proposed in this study, derived from SDGSAT-1 satellite data, offers a novel perspective and methodological tool for quantifying urban heat islands. The results provide a scientific basis for mitigating UHI effects, enhancing thermal comfort, and formulating urban cooling strategies. They also contribute to supporting the achievement of Sustainable Development Goal 11 (SDG11). Future studies could extend this approach to broader urban regions using increasingly available SDGSAT-1 data, and further investigate diurnal and nocturnal variations in cooling effects, thereby offering more comprehensive scientific support for global UHI mitigation strategies.

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