

Does the Morphological Evolution of Green Spaces Directly Influence Their Thermal Regulatory Capacity? Evidence from the Guangdong-Hong Kong-Macao Greater Bay Area

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Does the Morphological Evolution of Green Spaces Directly Influence Their Thermal Regulatory Capacity? Evidence from the Guangdong-Hong Kong-Macao Greater Bay Area

Abstract

Green space is a pivotal factor influencing the urban thermal environment. Focusing on the Guangdong-Hong Kong-Macao Greater Bay Area (GBA), this study first employs Morphological Spatial Pattern Analysis (MSPA) to identify the morphological components and evolutionary trends of urban green spaces. Second, integrated with regional geospatial characteristics, a Space-Time Cube model is applied to investigate the annual spatio-temporal thermal trends since 2000, alongside diurnal and seasonal patterns. Finally, the XGBoost model coupled with SHAP interpretation was leveraged to decipher both the linear and non-linear relationships between MSPA elements and the seasonal thermal environment, providing a scientific basis for urban heat resilience planning. The results indicate that: (1) The total area of green space followed a "decrease-then-increase" trajectory, characterized by the coexistence of regional divergence and convergence; while Core areas remain the largest in extent, they exhibit a shrinking trend and are transitioning to other landscape types. Furthermore, green spaces show signs of fragmentation, with marked differences between urban and rural shifts. (2) The thermal environment exhibits an overall warming trend, with significant seasonal variations in spatial distribution and spatio-temporal evolution. Specifically, the changes in core thermal elements during summer differ distinctly from the other three seasons. (3) A strong correlation exists between green space and the thermal environment, with Core, Perforation, and Edge elements showing the most significant associations across all seasons. The regulatory effects of these spaces vary seasonally, and there is a notable synergistic interaction between the "Core" and other morphological elements.

Keywords: Morphological spatial pattern; Green space; Thermal environment; Machine learning; Influencing factors

1. Introduction

Climate change exerts a profound influence on human health and well-being, with the Urban Heat Island (UHI) effect standing out as a hallmark of urban environmental shift. Arising from the interplay of meteorology, urban surface properties, and human activity, the UHI effect drives urban temperatures substantially above those of surrounding rural areas, thereby intensifying extreme heat waves and precipitating challenges such as energy spikes and air quality degradation^{[1][2]}. While green spaces serve as a primary buffer against urban heat, their efficacy hinges on meticulous planning and layout^{[3][4][5]}. Nevertheless, rapid urbanization has reshaped these green assets, altering not just their total area but also their spatial morphology^{[6][7]}. Does this morphological evolution directly alter the capacity of green spaces to regulate the thermal environment? Addressing this question is pivotal for decyphering urban ecological dynamics and formulating precision-based cooling interventions.

The urban thermal environment constitutes a complex physical system integrating temperature, humidity, surface characteristics, and anthropogenic activities—all of which profoundly impact human comfort and public health—as an extension of the UHI effect^[8]. Beyond exploring the spatio-temporal evolutionary patterns of the thermal environment itself, existing research has increasingly focused on deciphering its underlying drivers^[9], including urban land cover dynamics, spatial configurations, and the built environment^[10]. Furthermore, substantial evidence suggests that urban green and blue spaces—including forests, grasslands, water bodies, and wetlands—play a pivotal role in modulating urban heat and shaping responses to future climate change^{[11][12][13]}. Consequently, as ecological functional units centered on vegetation cover, the morphological evolution of green spaces and its regulatory influence on the urban thermal environment has emerged as a critical research frontier^{[14][15]}.

Conventional research has firmly established a significant negative correlation between green space area and land surface temperature (LST), forming the fundamental premise of "quantity-based cooling"^[16]. The academic focus, however, has pivoted from mere quantitative assessments toward in-depth explorations of quality and spatial morphology in recent years^[17]. In terms of research scale, studies now span from macro-

level urban patterns to micro-simulations of street blocks and specific green space types^{[18][19]}, such as leveraging microclimate models to quantify the localized cooling effects of diverse greening layouts^[20]. Regarding research scope, social, institutional, and management factors are increasingly integrated to decipher the driving mechanisms behind morphological evolution^[21]. Notably, an increasing body of literature examines how urban green space (UGS) patterns regulate the thermal environment, specifically the contribution of landscape metrics to LST and the varying influences of green space size, shape, composition, and spatial configuration^{[22][23][24][25]}. Methodologically, while early linear models were effective in identifying the direction of influence, they struggled to capture complex non-linearities. Consequently, machine learning techniques, particularly XGBoost, have gained prominence for their ability to handle high-dimensional, non-linear data, offering a more authentic representation of the intricate relationship between urban morphology and thermal dynamics^{[26][27][28]}.

Notwithstanding these advancements, few studies have explored the nexus between diverse UGS morphologies and thermal environments across multi-temporal and seasonal scales. Existing literature remains largely preoccupied with mono-seasonal impacts—typically during the summer—thereby overlooking thermal dynamics in other seasons^{[29][30]}, despite the pronounced seasonal variability inherent in green space morphology. Consequently, adopting a seasonal perspective is essential for a broader understanding of how the morphological evolution of green spaces regulates the urban thermal environment^[31]. Furthermore, effectively embedding the correlation between UGS patterns and thermal environments into advanced predictive models, such as machine learning frameworks, continues to represent both a research frontier and a significant challenge.

Given the limited research on the long-term coupling between green space morphology and the thermal environment in the GBA, this study investigates whether the morphological evolution of green spaces directly influences their thermal regulatory capacity. Defining green spaces as spatial units encompassing cropland, forest, shrubland, and grassland, we utilized the Google Earth Engine (GEE) platform and Landsat imagery to retrieve seasonal LST. These were integrated with land-use data

from 2000 to 2022 to characterize the evolutionary features of both urban green spaces and the thermal environment. By employing MSPA for fine-grained structural identification, and integrating Multiple Linear Regression (MLR) with machine learning models like XGBoost, this research addresses three pivotal questions:

- (1) What are the morphological elements and evolutionary trends of urban green spaces in the GBA from 2000 to 2022?
- (2) What are the annual spatio-temporal thermal trends, as well as the diurnal and seasonal patterns, during this period?
- (3) How do the non-linear relationships and seasonal variations manifest in the impact of green space evolution on thermal environment dynamics?

This research bridges the gap at a regional scale by transcending the limitations of previous studies that focused on isolated core urban areas. Its innovation lies in the systematic seasonal analysis of thermal evolution over two decades and the deployment of advanced non-linear models to enhance the accuracy of relationship identification. This work provides a quantitative foundation and decision-making reference for regional climate-resilient planning and the optimization of green space structures.

2. Materials and methods

2.1 Study area

The study area encompasses the GBA, located between 111°21'E—114°53'E and 21°27'N—24°24'N. This region comprises the Pearl River Delta (PRD) cluster—consisting of nine cities: Guangzhou, Foshan, Zhaoqing, Shenzhen, Dongguan, Huizhou, Zhuhai, Zhongshan, and Jiangmen—alongside the Special Administrative Regions (SARs) of Hong Kong and Macao (Fig. 1). The GBA is characterized by a subtropical climate, defined by warm and humid conditions year-round. Rapid economic development has catalyzed an intensive urbanization process, leading to significant population growth and large-scale land cover transitions. Driven by the dual pressures of climate change and rapid urbanization, the region is highly susceptible to heatwaves, making it an ideal laboratory for investigating the thermal environments of urban agglomerations.

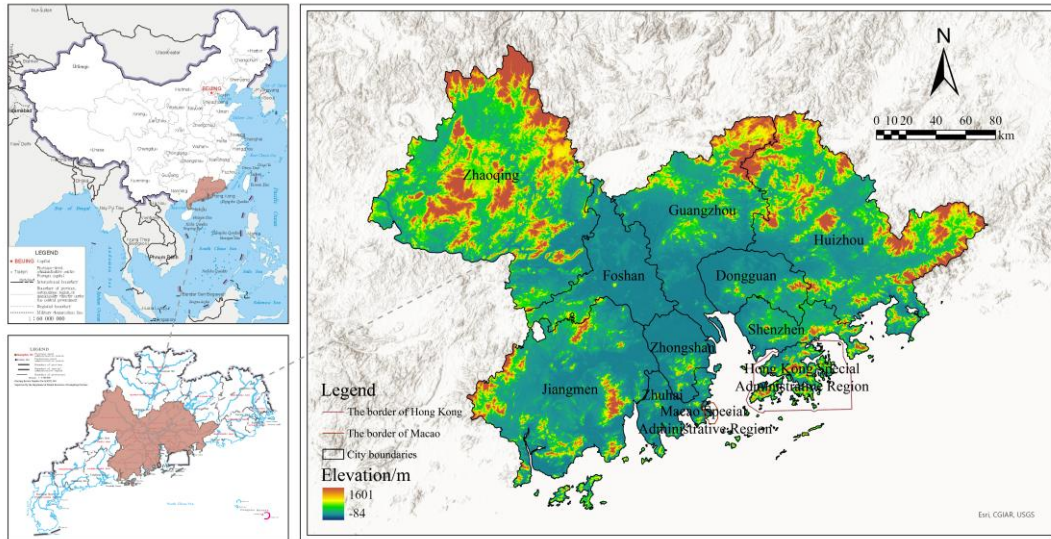


Fig. 1 Location map of Guangdong-Hong Kong-Macao Greater Bay Area(GBA)

[Image Source: Map drawn by the author based on Survey Numbers GS(2019)1652 and Yue S(2022)340]

2.2 Data source

The dataset for this study integrates administrative boundaries, LST remote sensing products, land cover data, and digital elevation models (DEM) (Tab. 1). LST data were derived from the MOD11A2 product provided by NASA. This product is collected by the Terra and Aqua satellites, which together observe the Earth's surface four times daily. Using the MODIS split-window algorithm, the retrieval accuracy reaches 1K (better than 1°C), meeting the requirements for multi-scale thermal environment safety pattern research^[32].

Tab. 1 Data source and usage

Data Name	Data source	Resolution	Purpose	Time
Administrative boundary	https://mulu.tianditu.gov.cn/	/	Administrative boundary identification	2021
MOD11A2 v006	https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/61/MOD11A2/	1km	Thermal environment identification	2000-2022
CLCD	https://zenodo.org/records/5816591#.ZAWM3BVBBy5c	30m	Identification of green spaces	2000-2022
DEM	http://srtm.csi.cgiar.org/srtmdata/	30m	Topographic mapping	2024

Furthermore, green space identification was based on the land cover dataset developed by Professor Xin Huang's team at Wuhan University. This dataset, derived from Landsat imagery via the GEE platform, provides annual land cover information for China from 2000 to 2022 across nine distinct categories^[33]. The primary advantage of the CLCD dataset lies in its continuous 30-year record with an annual 30-meter resolution, offering superior temporal resolution compared to similar products.

2.3 Research methods

2.3.1 Green space extraction

Morphological Spatial Pattern Analysis (MSPA) utilizes image processing techniques, such as erosion and dilation, to characterize the geometric arrangement and connectivity of map elements. To date, most MSPA-based research has focused on green infrastructure identification^[34], ecological network and corridor construction^[35], and thermal environment characterization^[36]. Compared to traditional landscape pattern analysis, MSPA provides explicit metrics and a schematic visualization of diverse green space spatial configurations, thereby offering concrete spatial strategies for green space planning and management^[37]. Consequently, the MSPA method was selected for the morphological analysis of green spaces in this study.

Land-use data were reclassified in ArcGIS, where green spaces (cropland, forest, shrubland, and grassland) were designated as the "foreground" (assigned a value of 2) and all other types as the "background" (assigned a value of 1), resulting in 30m × 30m binary raster datasets. Using Guidos Toolbox 3.3, these binary images were segmented into seven mutually exclusive morphological elements: Core, Islet, Perforation, Edge, Loop, Bridge, and Branch.

2.3.2 Calculation based on the surface temperature

While regional LST retrieval typically relies on algorithms such as the mono-window, split-window, single-channel, or radiative transfer equation, the choice of method depends on specific research objectives. In view of the stable atmospheric conditions across the GBA and our primary focus on the seasonal dynamics and long-term spatio-temporal extent of regional heat, a 1 km spatial resolution is sufficient for the intended analysis. Therefore, leveraging the GEE platform, we utilized MODIS

imagery and implemented the mono-window algorithm to derive land surface temperatures.

Seasons were categorized into spring (March–May), summer (June–August), autumn (September–November), and winter (December–February of the following year). The local time of 13:30 was selected to represent daytime conditions. Annual and daily LST data from 2000 to 2022 were generated using mean value composition. These were then processed according to Equation (1) to obtain four seasonal LST datasets:

$$LST = LST_{MODIS} \times 0.02 - 273.15 \quad (1)$$

Where LST_{MODIS} denotes the land surface temperature at a 1 km resolution(°C); The values were derived from the original MODIS data products; 0.02 represents the scaling factor between the stored values and the physical temperature; and -273.15 is the constant used for the conversion from Kelvin to Celsius.

2.3.3 Space-time cube model and hotspot analysis

The Space-Time Cube (STC) model was initially proposed by Hägerstrand to represent the temporal evolution of geographic phenomena. By adding a vertical time dimension to the two-dimensional spatial plane, the STC effectively visualizes the temporal dynamics of geographic entities—a method now widely applied in medicine and geography^[38]. Integrating spatiotemporal thinking, this approach identifies clusters combined with temporal dynamics, categorizing hot or cold spots into diverse trends such as new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, or historical, as well as non-significant patterns.

LST raster files were first integrated into a mosaic dataset in this study. Subsequently, multidimensional information was built and multidimensional raster layers were generated to construct the STC. Using the Emerging Hot Spot Analysis tool with the STC as input, we explored spatiotemporal evolution patterns. For each cube column, the Getis-Ord method was employed, and the Mann-Kendall trend test was used to assess the hotspots and coldspots trends of UHI.

2.3.4 Correlation analysis method

Building on the grid-based approach widely used in studies of thermal environment drivers, this research established a 3KM×3KM fishnet to balance spatial

pattern representation with data integrity. We conducted a comparative correlation analysis using multiple methods, including Multiple Linear Regression (MLR), Partial Least Squares Regression (PLS), Principal Component Analysis combined with Random Forest Regression (PCA+RF), Gradient Boosting Decision Trees (GBDT), and eXtreme Gradient Boosting (XGBoost) integrated with SHapley Additive exPlanations (SHAP).

Machine learning algorithms, particularly XGBoost, have gained prominence for their ability to handle high-dimensional, non-linear data, offering a more authentic portrayal of the intricate relationships between the thermal environment and its influencing factors in recent years. This study further explores the specific correlation between green space morphology and thermal dynamics.

XGBoost is an ensemble learning algorithm based on gradient-boosted decision trees. Its core mechanism involves optimizing the model by minimizing the negative gradient of the loss function, thereby aggregating multiple weak learners into a single robust classifier. Unlike traditional methods that rely solely on first-order derivatives, XGBoost employs a second-order Taylor expansion of the loss function. To balance objective function minimization with model complexity and prevent overfitting, a regularization term is incorporated into the objective function, making the algorithm exceptionally well-suited for large-scale datasets^[39].

The XGBoost algorithm was selected to model the complex relationship between the urban thermal environment and green space morphological metrics in this study. The mathematical expression of the model is as follows:

$$\hat{y}_i = \sum_{k=1}^K f_k(X_i), f_k \in F \quad (2)$$

Where f_k denotes an individual regression tree, and F represents the functional space encompassing the ensemble of all regression trees. $\hat{y}_i$ signifies the predicted output of the model, while y_i refers to the ground truth or observed values recorded in the training dataset.

The objective function of the XGBoost model is defined as follows:

$$L_t = \sum_{i=1}^n I(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (3)$$

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (4)$$

In this formulation, $\sum_{i=1}^n I(y_i, \hat{y}_i)$ denotes the loss function, while $\sum_{k=1}^K \Omega(f_k)$ represents the regularization term. y_i and $\hat{y}_i$ signify the observed ground truth and the predicted model output, respectively. γ is the subtree penalty regularization term; T is the number of leaf nodes of the tree; λ is the sub-weight penalty regularization term; w_j is the output score of each leaf node of the tree^[40].

3. Results and Analysis

3.1 The morphological evolution characteristics of green spaces

3.1.1 The total area decreased first and then increased

Using GuidosToolbox 3.3, the MSPA results for green spaces in the GBA were calculated for the period from 2000 to 2022. An illustrative diagram of the 2022 results is presented (Fig. 2), where green spaces are segmented into seven distinct classes: Core, Islet, Perforation, Edge, Loop, Bridge, and Branch.

We calculated the total area of green space and its individual components across the Guangdong-Hong Kong-Macao Greater Bay Area (GBA), with the temporal trends from 2000 to 2022 illustrated (Fig. 3).

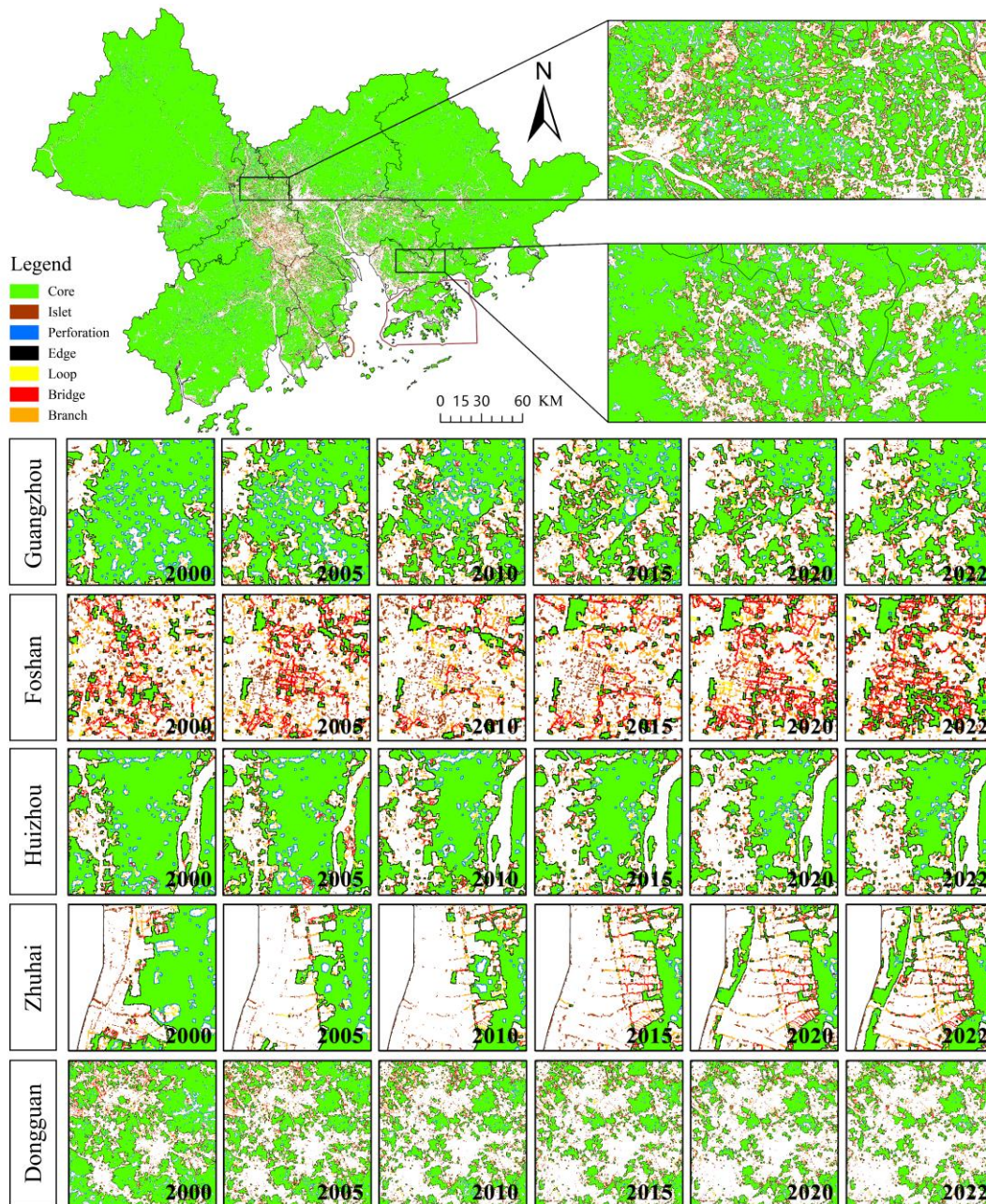


Fig. 2 MSPA and Partial City Map

Overall, the total green space area declined from 31871.06km² in 2000, reaching its lowest point in 2015 before rebounding, with a significant increase observed by 2020. The area stood at 30347.88 km² by 2022. The overarching trend reflects the fragmentation of large patches and the disappearance of smaller ones—a phenomenon closely tied to rapid urban expansion and land development. At the city level, green space areas generally followed a downward trajectory from 2000 to 2015, followed by a gradual recovery. The universal increase in green space across all cities after 2020 indicates that conservation and restoration efforts have yielded tangible progress.

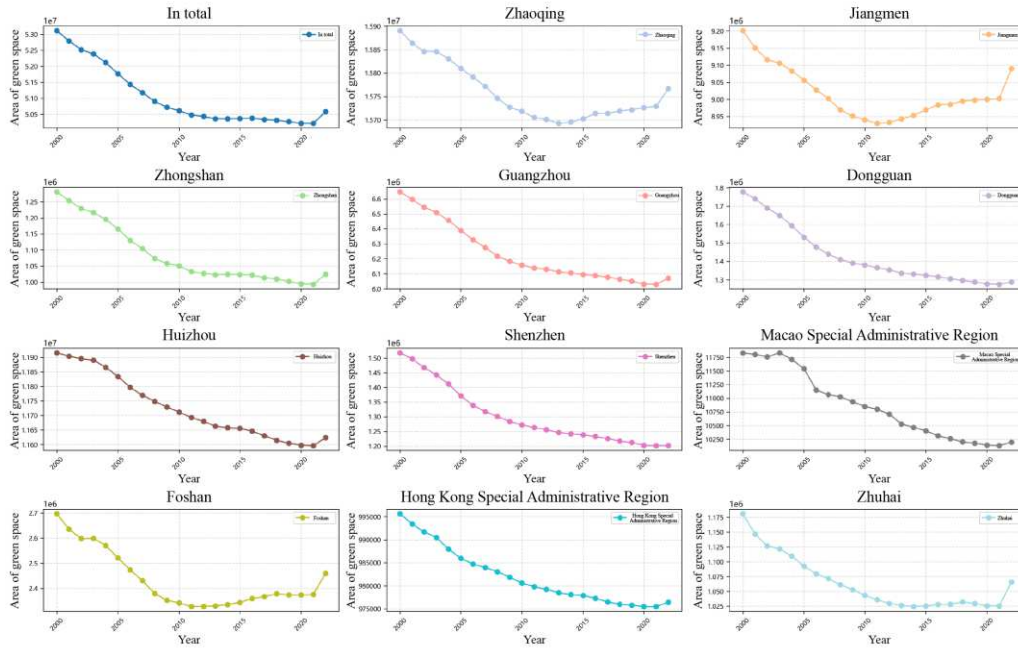


Fig. 3 Time evolution of green space area

3.1.2 The overall area, including the core and the isolated areas, is showing an increasing trend

Raster datasets of green spaces in the GBA for each year were exported and subsequently imported into ArcGIS based on the MSPA results. The area of each ecological morphological element was then calculated using the attribute tables. To effectively illustrate the disparities in these changes, the data underwent normalization, and a heatmap was generated (Fig. 4).

The green space elements in the GBA are broadly categorized into expansionary and contracting zones. The expansionary zones comprise Bridge, Edge, Branch, Loop, and Perforation elements, while the contracting zones consist of Core and Islet areas. Specifically, the Core area has exhibited a continuous decline, likely squeezed by rapid urbanization and the encroachment of construction land. The Islet area remained relatively stable, fluctuating between 10.85 and 11.66, suggesting no significant shifts in its spatial layout. The Bridge area underwent a trajectory of initial expansion followed by a slight contraction. Conversely, the Edge area showed an overall upward trend, potentially driven by regional green space protection policies and ecological initiatives. The Branch area displayed marked fluctuations and growth, while the Loop area expanded rapidly after 2013, reflecting green space development along major

transportation arteries. Perforation areas increased progressively throughout the study period, highlighting the trend toward small-scale distribution of green spaces.

Overall, the GBA maintains a robust landscape matrix. The top three morphological elements by mean proportion are Core, Edge, and Islet, which represent the dominant structural advantages within the GBA's green space network.

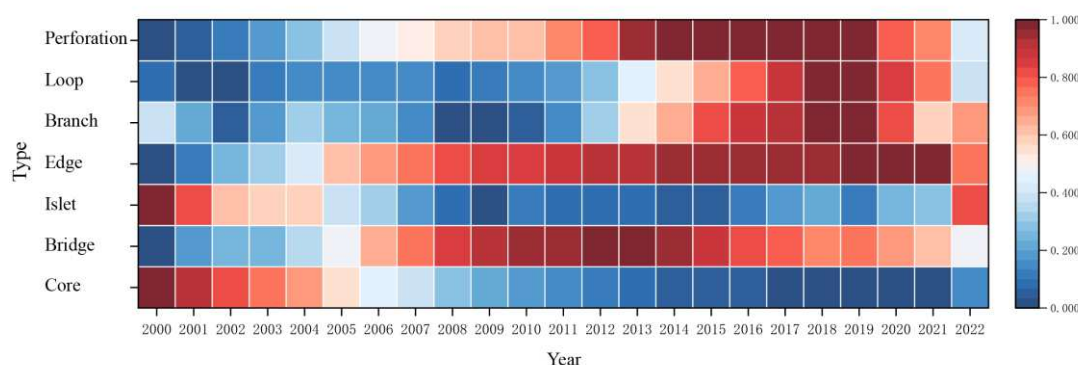


Fig. 4 Green space indicators year by year evolution area heat map

3.1.3 Evolutionary differences and convergence coexist in each city

Raster datasets of green spaces in the GBA for each year were exported based on the MSPA results. This study reveals significant inter-city variations in green space morphological elements. In most cities, the proportion of Core elements has followed a downward trajectory. Guangzhou and Zhongshan, in particular, experienced the most pronounced declines, indicating that contiguous green space resources have been significantly constrained by urban sprawl. Conversely, the Core proportions in Zhaoqing, Jiangmen, and Huizhou remained relatively stable. Most cities saw an increase in the Islet element, reflecting a gradual rise in the number of small-to-medium urban green patches. The Perforation element exhibited substantial spatial heterogeneity: while Jiangmen maintained a high and steadily increasing proportion, Zhongshan remained stable, and Shenzhen recorded a slight decline. With the exception of Dongguan and Macao, the Edge element generally trended upward across the region. Trends for Loop elements varied by city, while Bridge and Branch elements increased in the majority of municipalities.

The morphological evolution of green spaces in the GBA is characterized by diverse and city-specific features in summary. It is imperative for each city to formulate

science-based ecological protection and urban planning strategies tailored to their unique conditions as urban development progresses. Strengthening the preservation and construction of green infrastructure will be essential for achieving sustainable development and collectively advancing the ecological integrity of the Guangdong-Hong Kong-Macao Greater Bay Area.

3.1.4 There are significant differences in the changes of green spaces between urban and rural areas

The evolution maps of green space for key years between 2000 and 2022 (Fig. 5) reveal a diverse array of transformation patterns across the GBA, including connection, expansion, contraction, and disappearance. Amidst rapid urbanization, green spaces at city margins and peri-urban interfaces have commonly undergone compression or structural modification. Vast tracts of rural greenery and agricultural land have been converted into residential, commercial, and industrial zones, a trend most pronounced in Guangzhou, Shenzhen, and Zhuhai.

Green spaces exhibit a trend toward dissolution and integration, specifically within the regional hub of Guangzhou; despite increasing fragmentation, the spatial network remains distinct, with concentrations primarily in the northeast.

Green spaces exhibit a trend toward dissolution and integration within the regional hub of Guangzhou. Furthermore, the spatial network remains distinct and primarily concentrated in the northeast regardless of increasing fragmentation. Shenzhen has experienced profound changes, showing a marked dissolution trend, with remaining green cover largely confined to the city periphery and nature reserves. Green space boundaries have merged more tightly with those of Guangzhou in Foshan, though a stark contrast remains between urban and suburban greening. Zhuhai leverages its rich silvicultural resources along the Pearl River Estuary, with green infrastructure concentrated in waterfront ecosystems and coastal belts. Meanwhile, in Dongguan, Huizhou, and Zhongshan, green spaces have faced persistent encroachment driven by industrial park expansion. Conversely, targeted initiatives like greenways and wetland restoration have improved local conditions. Zhaoqing, characterized by robust ecological preservation, has successfully maintained its mountainous green cover.

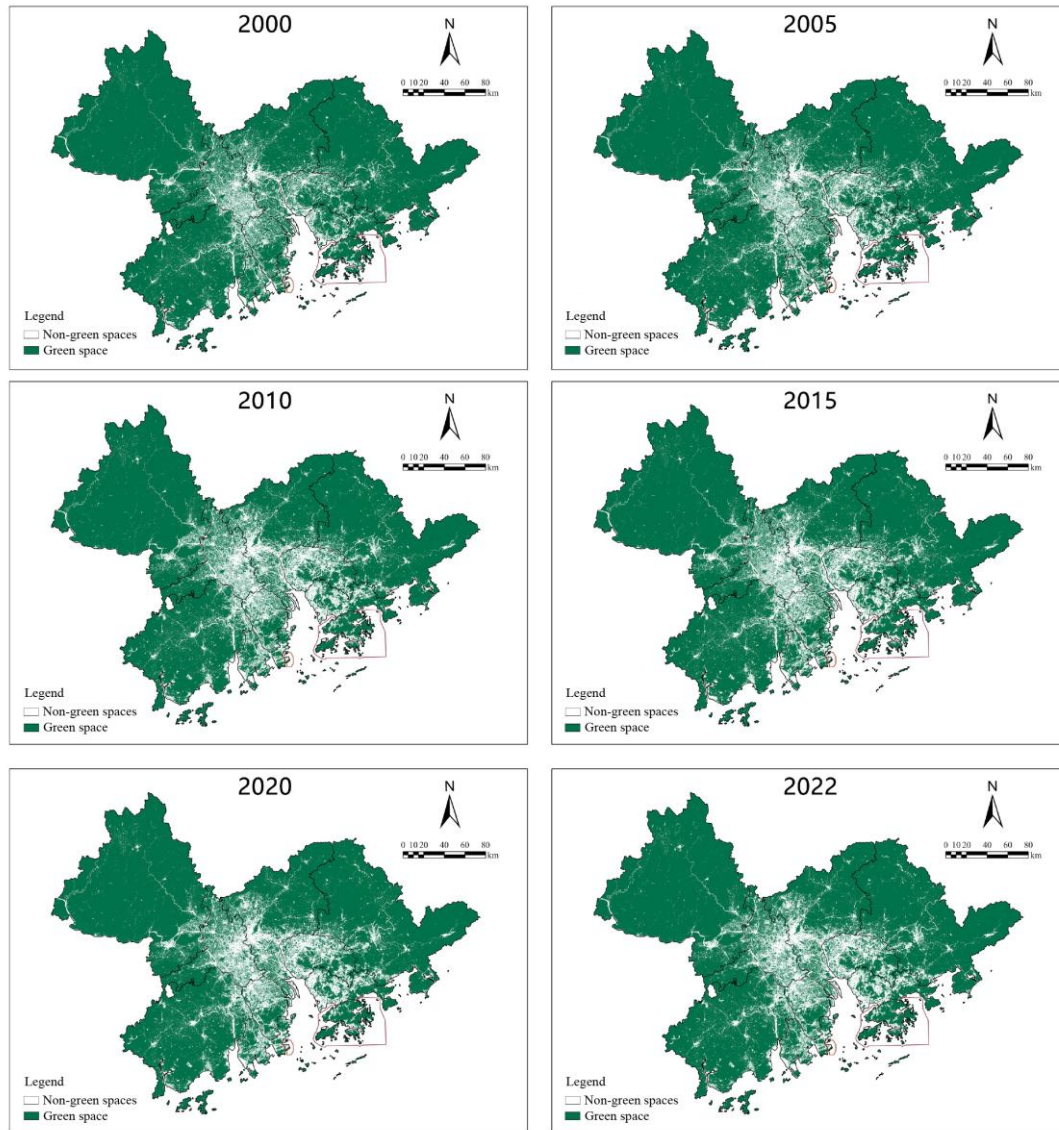


Fig. 5 Evolution of green space pattern

3.2 The spatiotemporal evolution characteristics of the thermal environment

3.2.1 Issues with extreme summer heat are prominent, while winter temperatures exhibit a broad range of fluctuations

Seasonal mean composites were generated for the LST raster data of the GBA throughout the study period, resulting in 92 raster images. Statistical analysis was then performed on the maximum values of each image (Fig. 6).

Overall, the seasonal peak LST in the study area was consistently highest in summer and lowest in winter; however, winter exhibited significantly higher thermal volatility. While summer temperatures were the highest and showed a progressive annual increase—highlighting a worsening heat stress problem—winter temperatures,

though lower, displayed the most dramatic fluctuations. Peak winter temperatures occasionally reached 30°C, driven largely by the interplay between cold air masses and regional climate change, which poses potential risks to agricultural productivity and ecological stability. Temperatures in spring and autumn remained relatively stable, though the frequency of extreme heat events has risen in recent years, notably in the spring of 2021 and the autumn of 2022.

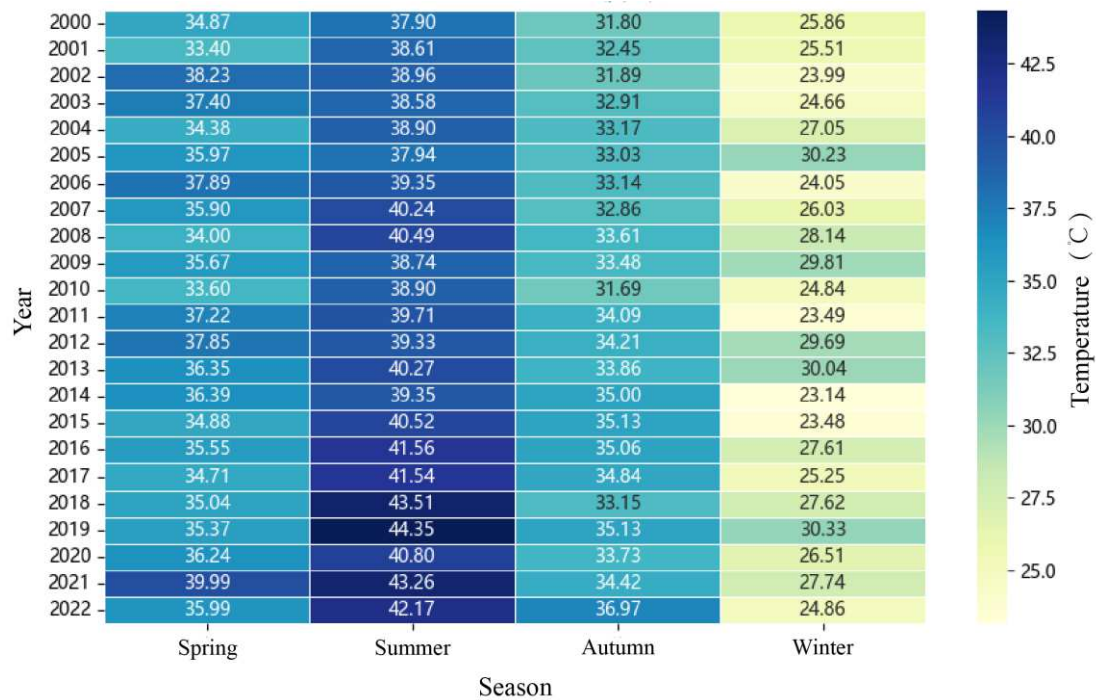


Fig. 6 The highest average LST value in each season from 2000 to 2022

3.2.2 The variations in the thermal environment patterns throughout the four seasons differ significantly in key years

Thermal environment maps for key years across the GBA were extracted and visualized based on the mean-standard deviation classification method (Fig. 7).

The thermal pattern shifted from a uniform distribution of high-temperature values to a heterogeneous "south-high, north-low" configuration in spring; while cold islands dominated in 2005, UHI areas have since expanded, stabilizing in the central and southeastern regions after 2020. The thermal evolution was characterized by a progressive expansion of heat islands and a concurrent contraction of cold islands in summer,. High-value zones are concentrated in the urban core with low-value zones at the periphery; notably, high-temperature stress intensified within the core during the

2000–2005 and 2015–2020 periods. The evolution featured an accelerated proliferation of heat islands and a continuous shrinking of cold islands in autumn. High-value areas underwent alternating cycles of expansion and contraction, culminating in near-total coverage by autumn 2022, alongside pronounced regional differentiation. The overall trend showed a reduction in high-value areas and a fluctuating increase in low-value zones in winter. High-value areas diminished between 2000 and 2005 as low-value zones expanded significantly, reaching total coverage by 2015. However, high-value zones recaptured most regions except for Zhaoqing by 2020, indicating a persistent UHI effect with a clear trajectory for further development.

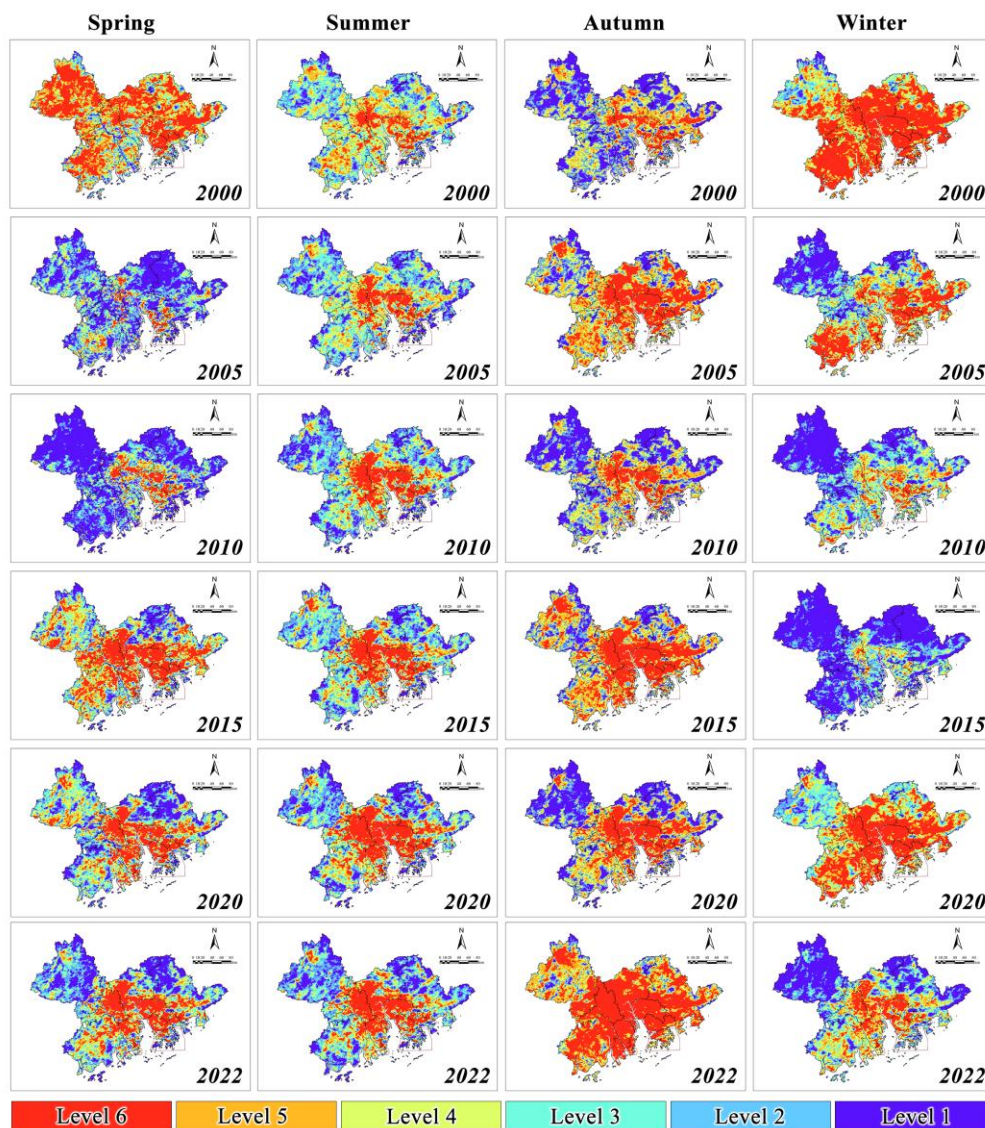


Fig. 7 LST seasonal variation diagram for some years

3.2.3 Spatiotemporal evolution patterns exhibit significant seasonal variations, with

distinct thermal environment characteristics observed across different cities

According to the results of the space-time cube cold and hot spot trend analysis (Fig. 8), the spatiotemporal evolution of the thermal environment in the GBA exhibits distinct seasonal disparities. While spring, autumn, and winter are characterized primarily by Oscillating Hot Spots, summer is dominated by Intensifying Hot Spots, showing a spatial distribution significantly different from the other three seasons.

The LST displays a north-low, south-high gradient in Spring. Oscillating Hot Spots are the most prevalent, distributed across all municipalities and indicating a fluctuating upward temperature trend. Persistent Hot Spots are concentrated in southern Huizhou and form a belt-like cluster spanning Guangzhou, Dongguan, Shenzhen, and Hong Kong. Intensifying Hot Spots are located in eastern Foshan, southern Guangzhou, Dongguan, Shenzhen, and central Zhongshan. Conversely, Persistent Cold Spots are primarily found in Zhaoqing and the northern borders of Guangzhou and Huizhou.

The thermal landscape is characterized by dense hot spots in the central region and cold spots at the periphery in Summer. Compared to spring, Persistent Hot Spots are more fragmented, appearing in clusters or linear patterns in northeastern Zhaoqing, northern Guangzhou, southern Shenzhen, and central Jiangmen, typically along the margins of intensifying zones. Intensifying Hot Spots are widespread in summer; Dongguan, Shenzhen, and Foshan are almost entirely covered by these zones, with significant presence in southern Guangzhou and northern Zhongshan. In contrast, Sporadic Hot Spots are limited, forming small clusters only near the Zhaoqing-Foshan border and central Jiangmen. Persistent and Intensifying Cold Spots are concentrated in Zhaoqing, Huizhou, and Jiangmen, forming a contiguous, stepped distribution pattern.

The thermal environment is defined by Stable Cold Spots and Oscillating Hot Spots in Autumn. Persistent Hot Spots are no longer scattered in clusters but are concentrated at the junction of Shenzhen and Hong Kong. The coverage of Intensifying Hot Spots has decreased, largely replaced by Oscillating Hot Spots. Similarly, the area of Persistent Cold Spots has expanded, while Intensifying Cold Spots have diminished, giving way to persistent ones. Oscillating Cold Spots are relatively sparse, primarily

situated at the interface between cold and hot spot regions.

The spatiotemporal LST results show a near-equal division between cold and hot spots in Winter, separated by a clearly identifiable boundary. Persistent Hot Spots are mainly anchored in the south, including Jiangmen, Shenzhen, Dongguan, and Hong Kong. Intensifying Hot Spots are distributed in northern Dongguan and central Guangzhou. Oscillating Hot Spots cover a broad area across the central and southern GBA, while Oscillating Cold Spots expand significantly compared to other seasons, primarily in Zhaoqing and Huizhou. Persistent Cold Spots remain concentrated in northern Zhaoqing and the northern border areas of Guangzhou and Huizhou.

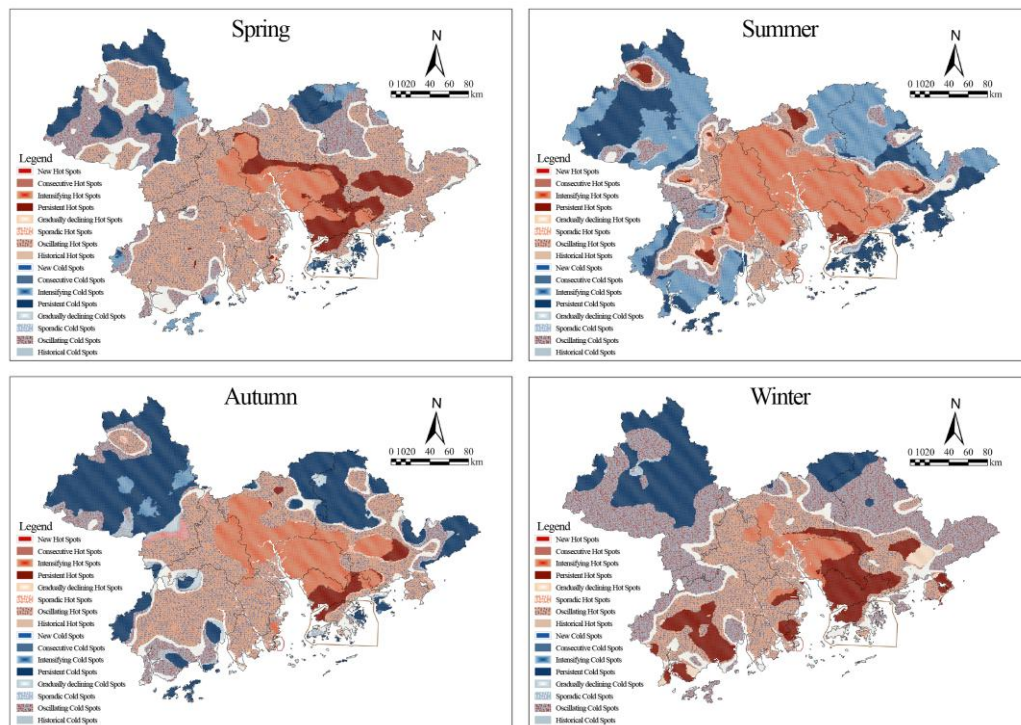


Fig. 8 Evolution trend chart of hot and cold spots in space-time cube of thermal environment in four seasons

Cold islands are primarily concentrated in the northern region, with Zhaoqing being the most prominent example, across the Guangdong-Hong Kong-Macao Greater Bay Area (GBA). Conversely, urban heat islands (UHIs) are largely clustered in the central GBA, notably within Guangzhou, Foshan, and Zhongshan. Based on the seasonal distribution of hot and cold spots, the 11 cities within the GBA can be categorized into three distinct thermal typologies: UHI-dominated, Cold-island-dominated, and Thermal-alternating. Specifically, the UHI-dominated group includes

Guangzhou, Shenzhen, Dongguan, Foshan, Zhongshan, Zhuhai, and the Macao SAR. Zhaoqing is the sole representative of the Cold-island-dominated type, while Jiangmen, Huizhou, and the Hong Kong SAR are classified as Thermal-alternating cities.

3.3 The correlation results between green spaces and the thermal environment

3.3.1 Comparison of performance parameters of multiple models

This study selected four widely used metrics to conduct a comprehensive assessment of model performance: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These indicators were employed to compare model outputs and identify the optimal configuration, with a comparative visualization of model performance presented (Fig. 9).

The XGB+SHAP model consistently outperformed other candidates across all seasons, demonstrating superior predictive accuracy, precision, and goodness-of-fit across all four performance metrics. The PCA + RF and GBDT models followed in performance, while the MLR and PLS models exhibited relatively lower efficacy. Consequently, the XGBoost + SHAP additive explanatory model was selected as the primary framework for this research.

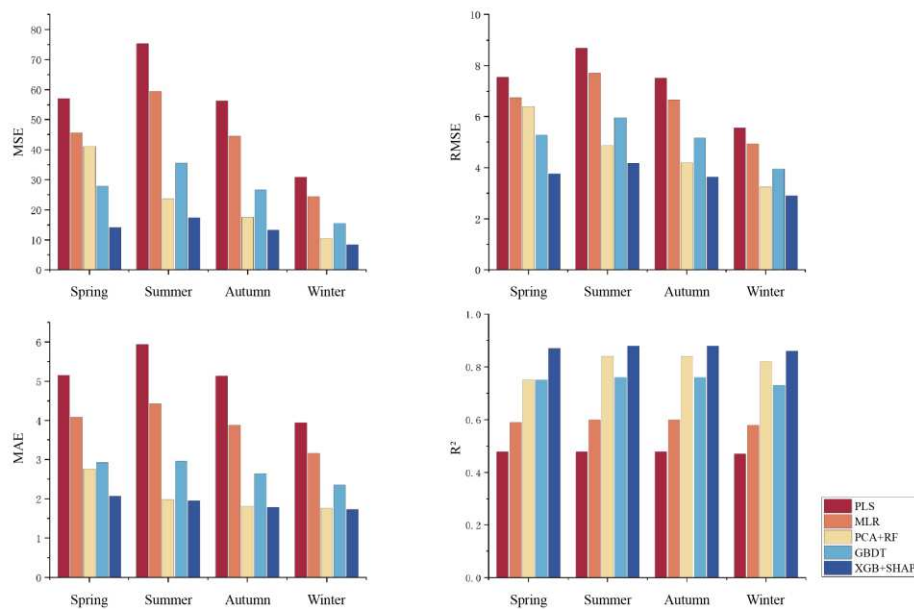


Fig. 9 Multi-model comparison performance parameter diagram

3.3.2 Core, Perforation, and Edge elements have a significant impact

The global feature importance bar chart (Fig. 10) was constructed by averaging the

absolute SHAP values across the entire dataset. This visualization ranks the MSPA characteristic indicators of green spaces by their overall importance across seasons, facilitating a summary of the seasonal disparities in their contributions.

Indicators are categorized into positive, negative, and seasonally variable contributors based on the directionality of influence. Core, Perforation, Edge, and Branch elements consistently exhibit negative SHAP values across all seasons, acting as negative contributors. In contrast, the Loop indicator shows a positive contribution only in spring while turning negative in the other three seasons, indicating seasonal variability. The Bridge element provides a marginal positive contribution throughout the year.

The Core, Perforation, and Edge elements consistently rank as the top three drivers across all seasons in terms of feature importance. Notably, the absolute SHAP values for the Core category remain high and negative year-round, underscoring its significant and consistent cooling role. Conversely, elements such as Islet, Loop, and Bridge yield lower absolute values, suggesting a relatively diminished impact on the thermal environment and a more volatile seasonal directionality.

The maximum absolute SHAP values for most indicators (except Islet) peak in summer, while the minimum values (except Branch) typically occur in winter in terms of seasonal disparities. This suggests that the summer thermal environment is more sensitive to regulation by green space morphology, whereas the regulatory potency of these structural indicators is generally lower during the winter months in the GBA.

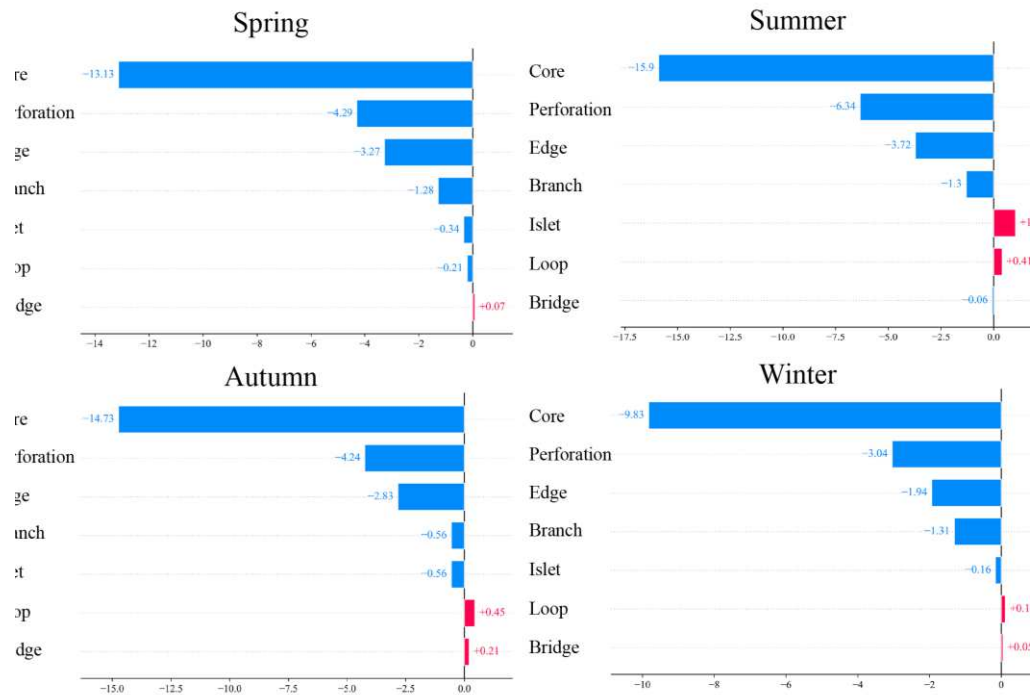


Fig. 10 Global feature importance bar chart

3.3.3 Except for the bridging indicator, all the other indicators contribute throughout the four seasons

Local explanation plots for green space indicators across different seasons were generated to illustrate their specific impact on predicted LST (Fig. 11).

Overall, within this sample, all green space types—with the exception of Bridge elements—contribute to the model’s predictions across all four seasons, though they vary significantly in direction and magnitude:

(1) Core, Perforation, and Edge elements consistently exhibit stable negative contributions year-round, identifying them as the primary drivers for LST reduction. The cooling effects of Core and Edge elements are particularly pronounced.

(2) Branch elements show identical behavior in spring and summer, characterized by a low-magnitude negative contribution, while exhibiting no discernible effect during autumn and winter.

(3) Islet elements yield no significant contribution in summer but provide minimal negative contributions in spring, autumn, and winter. Despite their low contribution level, they still play a supplementary role in cooling.

(4) Loop green spaces exhibit a positive contribution in summer, suggesting a

potential warming effect during the hot season. This contribution diminishes in autumn, a phenomenon likely related to the spatial configuration of green spaces and the localized impedance of cold air circulation.

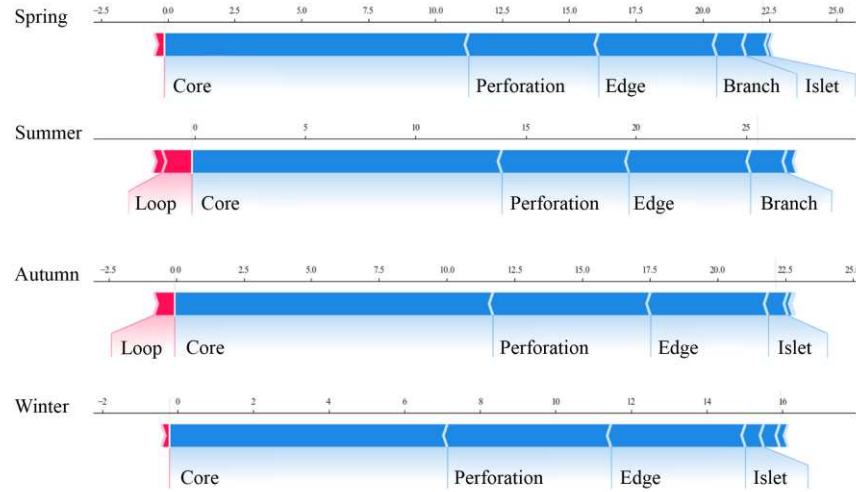


Fig. 11 Sample local explanation map

3.3.4 Core elements exhibit significant interactions with other landscape components

Given the significant impact of Core areas on the thermal environment, this study selected typical Core and other morphological elements for interaction analysis. Dependency plots (Fig. 12) were constructed using a 3KM×3KM grid. The x-axis represents the feature values, the left y-axis denotes the SHAP values (measuring the contribution to model predictions, representing cooling capacity in this study), and the right y-axis indicates the value range of the interacting feature, with a color gradient representing value magnitude.

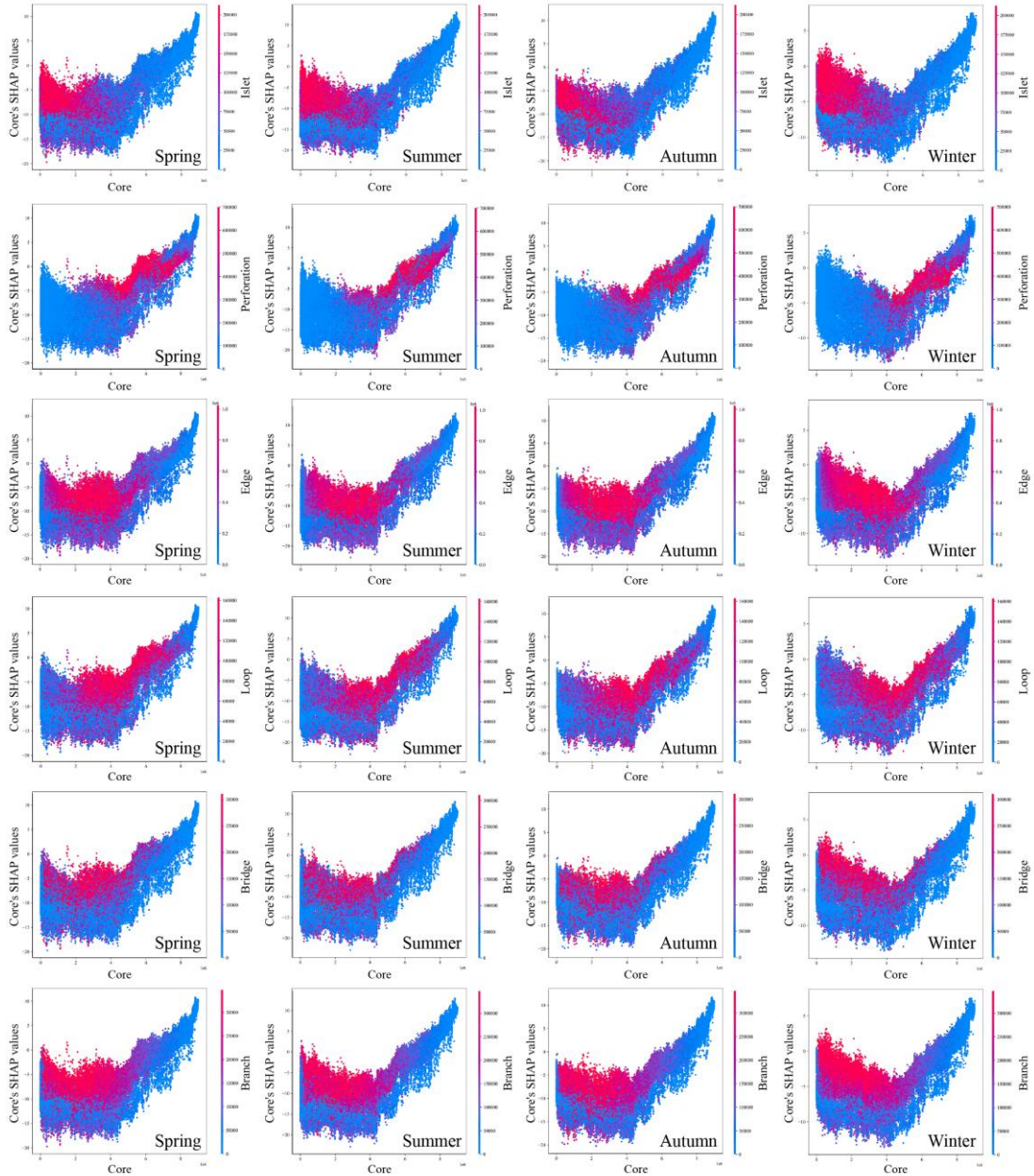


Fig. 12 Core and other metrics SHAP dependency graph

Overall, the scatter plots exhibit an upward trend, demonstrating that an increase in Core values leads to a progressive rise in their SHAP values. However, the influence of different landscape elements on this progression varies:

(1) Core and Islet: The interaction trends are consistent across all seasons. High Islet values can maintain stable SHAP values even when Core quantities are low, an effect particularly pronounced in winter.

(2) Core and Perforation: This interaction shows a complex, shifting trend. Extremely low Perforation values mostly inhibit the Core's SHAP values, though

promotion occurs in rare cases. Conversely, high Perforation values tend to decelerate the growth rate of the Core's SHAP values.

(3) Core and Edge: These elements exhibit a fundamental negative correlation; higher Edge values correspond to lower SHAP values for the Core, and vice versa.

(4) Core and Loop: Seasonal disparities are evident. In spring, when Core values are moderate, high Loop values enhance the Core's SHAP values. This likely reflects the gradual warming of the climate and increased ecosystem activity.

(5) Core and Bridge: A significant interaction is observed in winter, where Bridge values and SHAP values show a clear dependency. In the other three seasons, high Bridge values are primarily clustered within low-to-medium Core regions, most notably in spring.

(6) Core and Branch: The interaction mirrors that of the Bridge element but with greater magnitude. While both promote ecological connectivity between Core areas and other regions, the stronger influence of Branch areas may stem from their more extensive and deeper integration into diverse urban functional zones.

4. Discussion

4.1 The morphological evolution of green spaces exerts a direct and significant regulatory effect on the urban thermal environment

This study empirically demonstrates that the morphological evolution of green spaces in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) directly influences their thermal regulatory capacity, with significant variations observed across seasons and morphological elements, based on long-term data from 2000 to 2022. Our findings indicate that the cooling effect of green space is not solely a function of "total quantity." Instead, the Core, Perforation, and Edge elements play a more decisive role in thermal regulation. Specifically, the expansion of Core patches consistently correlates with lower land surface temperatures, emerging as the most robust cooling predictor across all seasons. Perforation and Edge elements further amplify this regulatory effect, exhibiting clear synergistic characteristics.

Moreover, the analysis reveals that the thermal regulation of green spaces is not a linear progression; rather, it is characterized by seasonal disparities and diminishing

marginal effects. As green space morphology becomes highly aggregated, the marginal cooling benefit tends to decline, suggesting a pronounced saturation effect. Furthermore, the regulatory influence of green space morphology is generally stronger in summer than in winter, with more distinct differences in cooling contributions among morphological types. In winter, however, the contribution of Core patches becomes relatively more prominent, reflecting how the broader climatic background constrains the thermal regulatory mechanisms of green spaces. Collectively, these results suggest that morphological evolution dictates not only the intensity of cooling but also its underlying mode and efficiency.

4.2 The Core, Perforation, and Edge elements collectively govern the spatial patterns of the urban thermal environment

The results of this study offer profound insights into the complex nexus between urban ecological processes and the physical environment. While previous research has primarily focused on cooling through "quantity"^[41], our fine-grained identification of seven morphological elements using the MSPA method underscores that the quality of spatial configuration is equally vital. We found that the Core, Perforation, and Edge elements contribute most significantly to reducing land surface temperatures across all seasons. This implies that large, contiguous green cores are indispensable for maintaining regional low-temperature zones^[42], while perforations and edges facilitate localized cooling by increasing the thermal exchange interface between vegetation and impervious surfaces.

We observed that this regulatory effect is not simply additive but is characterized by distinct threshold effects via the non-linear fitting of the XGBoost model. For instance, the influence of green space morphology on the thermal environment is far more pronounced in summer than in winter, as intense solar radiation amplifies the cooling efficiency of vegetative evapotranspiration. Furthermore, in the context of shrinking core areas, even if the total green space volume recovers later, the thermal mitigation efficiency rarely returns to its original levels because the new additions consist largely of fragmented Islets or Edges. This provides a plausible explanation for why regional heat island effects continue to intensify during rapid urbanization, despite

localized improvements in greening.

4.3 Generalizability, Seasonal Disparities, and Multi-factor Interactions of the Green Space Cooling Effect

This study situates the empirical evidence from the GBA within the global context of urban climate research, both corroborating classical theories and extending existing scholarship. First, our finding that Core elements are the most critical cooling factors aligns closely with previous studies, reaffirming the cornerstone status of large, contiguous green patches in providing urban ecosystem services^[43]. Furthermore, the observed negative correlation between green space area and LST validates traditional "cooling-by-quantity" theories. Specifically, the conclusion that green space fragmentation exacerbates heat islands supports long-standing tenets in landscape ecology regarding the relationship between landscape metrics and LST.

However, this research proposes a novel perspective, through multi-seasonal analysis: the cooling function of green space is not constant year-round and may even reverse under specific configurations. For instance, SHAP results reveal that Loop elements contribute positively to heat in summer—a finding that challenges the conventional wisdom that "all greenery cools." This anomaly likely stems from the fact that loops are often distributed along transportation corridors; their elongated morphology fails to aggregate cold air and instead acts as a heat conductor due to intense thermal radiation from adjacent impervious road surfaces. Such morphological nuances are frequently obscured in coarser studies based on linear regression.

This study extends the field by incorporating interaction effect analysis, compared to prior machine learning applications. While existing multi-factor research often assumes that morphological elements act independently, our results demonstrate that the cooling efficacy of Core elements is highly contingent upon the presence of Islets and Perforations. High islet density can maintain effective cooling even when the core area is limited. This extends the explanatory power of the "patch-corridor-matrix" model in thermal research, revealing the potential ecological role of small green spaces as "cooling relays" or buffers for larger patches. This provides theoretical backing for micro-renewal strategies in high-density built environments where large-scale greening

is unfeasible.

4.4 Construction of a Morphology-Constrained Non-linear Thermal Regulation Model and Differentiated Planning Strategies

Building on our findings, this study proposes a "Morphology-constrained Non-linear Thermal Regulation Model." This model posits that the thermal regulation of green spaces is not a simple function of area accumulation; rather, it is the result of a profound coupling between biophysical processes and spatial geometry.

Mechanistically, large contiguous green spaces—acting as Core elements—form the foundation of urban cool islands through shading effects from high-density canopies and intense physiological transpiration. However, their cooling capacity is governed by non-linear morphological thresholds; once a core patch reaches a certain scale, internal cool air accumulation and limited diffusion lead to a "diminishing marginal cooling effect"^[44]. Conversely, Edge and Perforation elements serve as energy exchange interfaces between green space and impervious surfaces. Their morphological complexity dictates the exchange efficiency of local micro-circulations; moderate porous structures can effectively disrupt the physical stability of heat islands and facilitate the infiltration of cool air into surrounding built-up areas. This mechanism exhibits pronounced seasonal variability between summer and winter. Theoretically, this research innovatively integrates MSPA-based morphological identification with the XGBoost-SHAP interpretable machine learning framework, establishing a dynamic non-linear attribution paradigm. This approach transcends the limitations of traditional linear regression in capturing complex inter-variable interactions and offers a new pathway for quantifying spatial thresholds in ecosystem services.

These mechanistic and theoretical insights offer differentiated governance strategies for climate change adaptation in the GBA. For ecologically rich regions such as Zhaoqing and Huizhou, planning should prioritize rigid protection to prevent the fragmentation of core patches caused by urban expansion, thereby maintaining regional cold-source stability. In contrast, for hyper-dense urban centers like Guangzhou and Shenzhen, the strategy should shift toward morphological efficiency. Given limited land resources, planners can activate the synergistic cooling potential of scattered

greenery by increasing the connectivity of "islet" pocket parks, optimizing edge complexity, and constructing porous green patterns. This approach facilitates a climate-resilient urban ecological network, providing sophisticated scientific support for the GBA's sustainable goals of habitability and low-carbon development^{[45][46]}.

4.5 Limitations and Prospects

This study has certain limitations, despite providing systematic, long-term evidence. First, we primarily relied on land-use remote sensing data, identifying vegetated areas within "non-construction land" as green spaces for the definition of green space. While effective for macro-pattern analysis, this approach may overlook disparities in transpiration efficiency and 3D structures across different vegetation types, leading to potential discrepancies with findings from other scholars. Future research should incorporate LiDAR data to explore the vertical regulatory mechanisms of 3D green space morphology on the thermal environment. Second, to facilitate the visualization of MSPA results, a 3KM*3KM grid was employed to analyze the correlation between green space and heat. However, the potential impact of "scale effects" on these results was not systematically explored; subsequent studies could utilize Modifiable Areal Unit Problem (MAUP) analysis to further verify the universality of these conclusions. Finally, as the thermal environment is influenced by multiple factors—including wind speed, humidity, and anthropogenic heat—future research should aim to construct more complex coupled models that integrate the physical morphology of green space with its social functional attributes, providing deeper decision support for precise climate mitigation and public health protection.

5. Conclusion

This study empirically validates that the morphological evolution of green spaces directly influences their thermal regulatory capacity, with pronounced seasonal variations. The primary findings are as follows: (1) Green space evolution exhibits a complex trend characterized by "recovering totals, shrinking cores, and structural fragmentation." While morphological changes are widespread, evolutionary patterns vary geographically across cities. (2) The spatiotemporal dynamics of the thermal environment show significant seasonal disparities, with an overall warming trend and

prominent high temperatures in summer. Based on thermal characteristics, cities can be categorized into three distinct types, each displaying unique spatial distribution patterns across seasons. (3) A robust correlation exists between green space morphology and the thermal environment, with Core, Perforation, and Edge elements exerting the most significant influence. Increasing the area of Core green space effectively reduces temperatures and remains key to mitigating heat islands. Furthermore, the cooling effect is seasonal, peaking in summer and weakening in winter—a disparity suggesting that optimized layouts must incorporate climate-adaptive strategies.

These findings enhance our understanding of the non-linear coupling between green space morphology and the thermal environment in the GBA. They also provide a differentiated basis for regional climate-resilient planning: core cities should prioritize optimizing green space connectivity and porous structures, while non-core cities should focus on preserving morphological integrity. In the future, integrating 3D features and multi-meteorological factors will further refine the precision of thermal regulation functions, supporting more sustainable urban ecological development in the GBA.

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