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Quantifying cumulative cooling threshold of greenspaces using a newly developed 3D model across global cities

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ABSTRACT

Urban greenspaces are widely recognized as an effective nature-based strategy to mitigate urban heat. However, previous studies have often oversimplified the cooling process of greenspaces, leaving their cumulative cooling effect insufficiently quantified. To address this gap, we developed a novel three-dimensional (3D) quantitative model to evaluate spatially accumulated cooling benefits. A total of 668 greenspace patches across 37 cities globally, representing varying climatic conditions, were selected. We then tested the relative importance of intrinsic drivers (landscape composition and spatial configuration) versus built environment drivers (landscape patterns of surrounding areas) in explaining the cooling effect. The results indicate that greenspaces provide an average cumulative cooling effect of 4.92 °C on the surrounding land surface temperature (LST), with a maximum reduction of up to 25.3 °C, far exceeding expectations. The cooling effect is primarily and positively influenced by patch area, the intrinsic green-blue proportion, and surrounding socioeconomic characteristics. More importantly, we emphasize the necessity of an accumulated perspective in the threshold value of efficiency (TVoE) assessments, as existing quantitative frameworks tend to largely underestimate the cooling benefits of large greenspaces. Our analysis reveals a U-shaped relationship between the aridity index and TVoE. To maximize cumulative cooling efficiency, optimal greenspace areas were identified as 2.25 ha for arid cities, 1.48 ha for semi-arid cities, 1.64 ha for dry sub-humid cities, and 1.8 ha for humid cities. This work opens new avenues for quantifying cumulative cooling effect from a 3D perspective, which may also scientifically inform urban greenspace planning and climate adaptation strategies.

1. Introduction

The urban population share is projected to reach 68 % by 2050, with over six billion people expected to reside in urban areas (UNDESA, 2019). As the cradle of constructive development activities, urban areas are particularly vulnerable to the synergetic effects of both climate warming and urban heat island (UHI) effect (Manoli et al., 2019; Tuholske and Chapman, 2024). The resulting urban overheating are anticipated to have significantly adverse social, economic, and ecological impacts, and pose a major threat to human mortality and morbidity (Ebi et al., 2021; Maggiotto et al., 2021). Hence, developing effective solution to climate adaptation through targeted modifications to the urban environment is of utmost importance.

Increasing urban vegetation can buffer heat stress through shading and evapotranspiration cooling (Lachapelle et al., 2023; Yu et al., 2024, 2025). Studies have generally reported average land surface temperature (LST) differences of 4.2 °C between greenspaces and their adjacent areas (Wong et al., 2021). The cooling effect of urban greenspaces is further found to be influenced by their size, composition, and configuration (Peng et al., 2021; Yao et al., 2022; Yu et al., 2017). In this context, active management is required to maximize their thermal benefits, which has led to a substantial amount of research (Chen et al., 2022; Schwaab et al., 2021). General procedures of the studies include evaluating the cooling effect, identifying the driving factors, and providing suggestions for the management of greenspaces based on the aforementioned results (Amani-Beni et al., 2018; Spronken-Smith and

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Oke, 1998). Among the procedures above, the most fundamental and crucial aspect is to quantify the cooling effect.

Existing 2D models for assessing urban greenspace cooling effects can be broadly categorized into two perspectives: maximum perspective and accumulation perspective. Under the maximum perspective, scholars have introduced metrics such as cooling intensity, cooling distance, cooling area, cooling efficiency, and cooling rate (Cao et al., 2010; Chang et al., 2007; Du et al., 2016; Lin et al., 2015). These indices provide valuable insights into the extreme values of cooling benefits, such as the maximum temperature difference between the greenspace and its surroundings (cooling intensity) or the farthest spatial extent of the cooling effect (cooling distance). Some subsequent studies likewise adopted this methodology and further investigated the threshold size of greenspaces to obtain the maximum cooling efficiencies. Yu et al. (2017) proposed the concept of the threshold value of efficiency (TVoE) based on the law of diminishing marginal utility. The TVoE in Temperate Monsoon climate and Mediterranean climate cities are found to be generally around 0.5 ha. Similarly, Fan et al. (2019) explored seven hot-humid Asian cities and reported that the threshold size of 0.60 ha – 0.96 ha is optimal.

However, greenspaces with identical maximum cooling intensity may exhibit vastly different cooling curves (i.e., the relationship between distance and temperature), reflecting differences in cooling benefits accordingly (Yu et al., 2017). Consequently, the maximum perspective primarily focuses on discrete, peak-value metrics, rather than the spatial continuity and nonlinear gradients of cooling effects. To address this limitation, Peng et al. (2021) introduced an accumulation perspective, modeling cooling effects using a cubic polynomial function to integrate temperature reductions across incremental distances, thereby capturing spatial continuity. However, increasing areas and total edges may enhance energy flow between greenspaces and the surrounding environment, intensifying the cooling effect (Li et al., 2012; Zhou et al., 2011). Therefore, with similar cooling curve, larger greenspaces have a greater influence extent, leading to an increase in the corresponding cooling benefits overall. It can be anticipated that existing studies have overlooked the synergistic effect yielded by both area and the cooling process, underestimating the cooling potential of large greenspaces. Furthermore, given that large greenspaces might have a greater cooling effect than expected, the prior estimates of TVoE may be lower than the actual value, because they would experience a shortfall in additional cooling benefits.

Inspired by the concept of Accumulated Temperature (AT), which traditionally sums temperature values over a specific period, we adapted this idea to sum temperature reductions over a spatial range. Introducing the vertical axis to represent temperature data of each pixel, the cooling process can be reconstructed accurately from a 3D perspective, reflecting the spatial patterns of thermal environment. Specifically, the integrated cooling impact can be captured by quantifying the total reduction in land surface temperature (LST) across the region affected. This method advances traditional 2D approaches by accounting for both the intensity and spatial extent of cooling, thereby offering practical utility in urban greenspace planning and management contexts. In this instance, to what extent greenspace exerts an overall cooling effect in a region, as well as the optimal size of greenspaces, warrants further discussion.

Understanding relationships between landscape characteristics and cooling indexes can reveal the determinants of the cooling effect (Fan et al., 2019; Geng et al., 2022). However, researches based on specific cases could lead to controversial results. For example, Yao et al. (2022) found a positive relationship between the cooling intensity and complexity of greenspaces in Fuzhou, China. In contrast, Jaganmohan et al. (2016) investigated that the increasing complexity of smaller greenspaces harms the cooling intensity in the city of Leipzig, Germany. These contradictory conclusions can be explained by the inconsistency in methodologies and the background extents of selected city cases. Given these conflicting results, it is imperative to comprehensively quantify the cooling effect of greenspaces in diverse cities globally based on a standardized and accurate quantification system, while also examine the underlying factors on that basis (Wang et al., 2020; Yu et al., 2020).

The overall goal of this study is to assess the cooling effect of urban greenspaces using a newly-developed 3D Model. Supported by quantitative methods, our study aims to further investigate the spatial distribution of the cooling effect and potential factors globally, focusing on comparisons across differing climate conditions. Thus, we selected 37 cities from 4 climate classes across the world and investigated the potential underlying factors of the cooling effect. Specifically, the objectives of this study are: (1) to propose a quantitative cooling index system that comprehensively measures the cooling effect of urban greenspaces from a 3D perspective; (2) to identify the greenspace cooling effect in cities from differing local background climates based on the cumulative cooling index system; (3) to assess the relative importance of the landscape characteristics (landscape patterns of greenspace patches compared with surrounding areas) on the cooling effect.

2. Materials and methods

2.1. Study area and data sources

In the preliminary selection of cities, to focus on hotspot areas with more severe UHI effect, this study selected cities with a population exceeding 30,000 in 2020 and a built-up area of more than 100 km^2, based on the 2020 Global Urban Boundaries (GUBs) dataset (Li et al., 2020). The aridity index (AI) was derived from the Global Aridity Index and Potential Evapotranspiration (ET_0) Climate Database v326.26. Based on the aridity index (AI), the cities were categorized into four subtypes: Arid ($0.03 \leq AI < 0.2$), Semi-Arid ($0.2 \leq AI < 0.5$), Dry Sub-Humid ($0.5 \leq AI < 0.65$), and Humid ($AI \geq 0.65$), according to the climate classification scheme provided by United Nations Environment Program (https://wad.jrc.ec.europa.eu).

In this study, urban greenspaces were defined as delimited urban open spaces mainly covered with vegetation (Taylor and Hochuli, 2017). To ensure that these greenspaces were indeed green and in urbanized areas, we determined sample sites considering the following criteria: (1) the location would have to be categorized as 'park' on OpenStreetMap database (https://www.openstreetmap.org/); (2) due to the differing cooling benefits of tree-covered and grass-covered greenspaces (Yu et al., 2018), typical greenspaces composed primarily of trees and shrubs were selected, with their combined coverage exceeding 70 %; (3) only greenspaces located within the 2020 Global Urban Boundaries were selected. The green-blue space land-cover map was created based on European Space Agency's global baseline land cover product (World Cover) for 2020. This official global land cover map published by ESA with a resolution of 10 m, was assessed using the Google Earth Engine cloud computing platform (assessed on 23 July 2023). The accuracy of the data reaches 74.4 % overall. We calculated the proportion of vegetation and water bodies within greenspaces and corresponding buffer zones by defining the land cover type including 'Tree cover' and 'Shrubland' from the product as urban vegetation.

To ensure that the cooling effects of greenspaces do not interfere with each other and are not affected by the surrounding blue-green infrastructure, the following two steps were applied: (4) considering that the maximum cooling distance of greenspaces typically does not exceed 300 m (Peng et al., 2021), the distance between any two samples is ensured to be at least 300 m to minimize mutual interference; (5) if no large water bodies or greenspaces are present within the 1 km buffer zone of a prospective greenspace location, the greenspace was viewed as an ideal sample.

We extracted the boundaries of greenspace samples based on OpenStreetMap and selected 668 greenspaces for examination, with an average area of 4 ha (ranging from 0.011 ha to 88.72 ha). The greenspace boundaries were cross-verified using high-resolution Google Earth images (Figs. S1-S4). A total of 37 cities with a sufficient number of greenspace samples over 5 ha were selected (Table S1, Fig. 1), given that quantifying the cooling effects of large greenspaces can help us better determine the Threshold Value of Efficiency (TVoE).

The land surface temperature (LST) was calculated using the Statistical Mono-Window (SMW) algorithm developed by the Climate Monitoring Satellite Application Facility (CM-SAF). Given the stronger UHI effect and the more pronounced cooling effects of greenspaces in summer, we selected available cloud-free Landsat-8 Thermal Infrared Sensor (TIRS) images at a 30 m resolution taken during summer 2022 (June 1 to August 31, 2022) as input data for LST retrieval. When no available remote sensing imagery was found for 2022, we used images from 2021 or 2023 as substitutes (Table S2). Data acquisition and LST extraction were performed using the LST retrieval method implemented by Ermida et al. (2020) on the Google Earth Engine (GEE) platform (assessed on 18 August 2023). Ermida et al. (2020) reported an overall precision with RMSE below 1.0 K. Cities without available remote sensing images during the study period were excluded.

2.2. The measurement of the cooling effect and TVoE

2.2.1. Calculation of cooling indexes

Existing measures typically quantify cooling intensity of greenspaces as the maximum temperature reduction induced by the greenspace within its cooling footprint (Du et al., 2017; Yu et al., 2020). However, in this context, the cooling potential of large-scale greenspaces may be significantly underestimated, as their broader cooling extent is often overlooked. In this study, we instead calculate the total accumulated cooling effect, which can more objectively and accurately reflect cooling potential.

Given the 30 m resolution of Landsat images, we established 300 m-wide buffer zones from the boundary of each greenspace (comprising 10 buffer zones with a radius of 30 m). The mean LST of each buffer zone were retrieved on the GEE platform. Peng et al. (2021) demonstrated that this approach best simulates the cooling curve (LST-distance relationship) for greenspaces. The distance between the center of the greenspace and the buffer zone was set as the independent variable l, and the average LST of each buffer zone were set as the dependent variable T to establish the LST-distance relationship based on the cubic polynomial function as follows:

$$T(l) = al^3 + bl^2 + cl + d\# \tag{1}$$

As shown in Fig. 2, with increasing distance from the greenspace boundary, the averaged LST initially increases and subsequently decreases, reaching a local maximum point where the first derivative of the function is 0, and the second derivative is negative. Building on the above definition, we establish the following criteria for cooling indexes:

Cooling range (CR), is defined as the maximum range over which the cooling effect extends, measured from the boundary of the park. CR indicates the outermost place that the greenspace can cool significantly.

Cooling intensity (CI), is defined as the difference between the volume of the hollow cylinder, formed by rotating the line $y = T_L$ over the interval [r, r + CR] around the y-axis, and the volume of the solid of revolution, formed by rotating the integral of T(l) over the same interval around the y-axis, as shown in Eq. (2). T_L represents the LST value corresponding to the local maximum point of the cooling curve T(l). CI indicates the cumulative quantity of the reduced LST of the impacting region.

$$CI = \pi \bullet T_L \bullet \left[(r + CR)^2 - r^2 \right] - \pi \int_r^{r+CR} [T(l)]^2 dl \tag{2}$$

Cooling gradient (CG), is defined as the CI divided by CR, which represents the cumulative quantity of the reduced LST caused by the unit cooling distance of greenspaces, as shown in Eq. (3). CG indicates the magnitude of temperature reduction achieved by the greenspace, namely the pattern of cooling process. A higher CG indicates that the greenspace acts as a prominent heat sink in comparison to the surrounding environment.

$$CG = \frac{\pi \bullet T_L \bullet \left[(r + CR)^2 - r^2 \right] - \pi \int_r^{r+CR} [T(l)]^2 dl}{CR} \tag{3}$$

Cooling efficiency (CE), is defined as the CI divided by the area of the greenspace (A), which represents the cumulative quantity of the reduced LST within the cooling distance caused by the unit area of greenspaces, as shown in Eq. (4). Higher CE indicates enhanced economic benefits in terms of the cumulative cooling effect.

$$CE = \frac{\pi \bullet T_L \bullet \left[(r + CR)^2 - r^2 \right] - \pi \int_r^{r+CR} [T(l)]^2 dl}{A} \tag{4}$$

An R script was written to process data and cooling indexes of patches were automatically reported.

2.2.2. Calculation of the threshold value of efficiency (TVoE)

The TVoE was proposed to estimate the optimal patch size from a cost-benefit perspective (Yu et al., 2017). As shown in Fig. 3, the logarithmic regression was used to estimate the correlation between cooling intensity and patch area. The TVoE is defined as the point at which the slope of the associated logarithmic function is 1. Prior to this point, a modest increase in patch area leads to a substantial improvement in

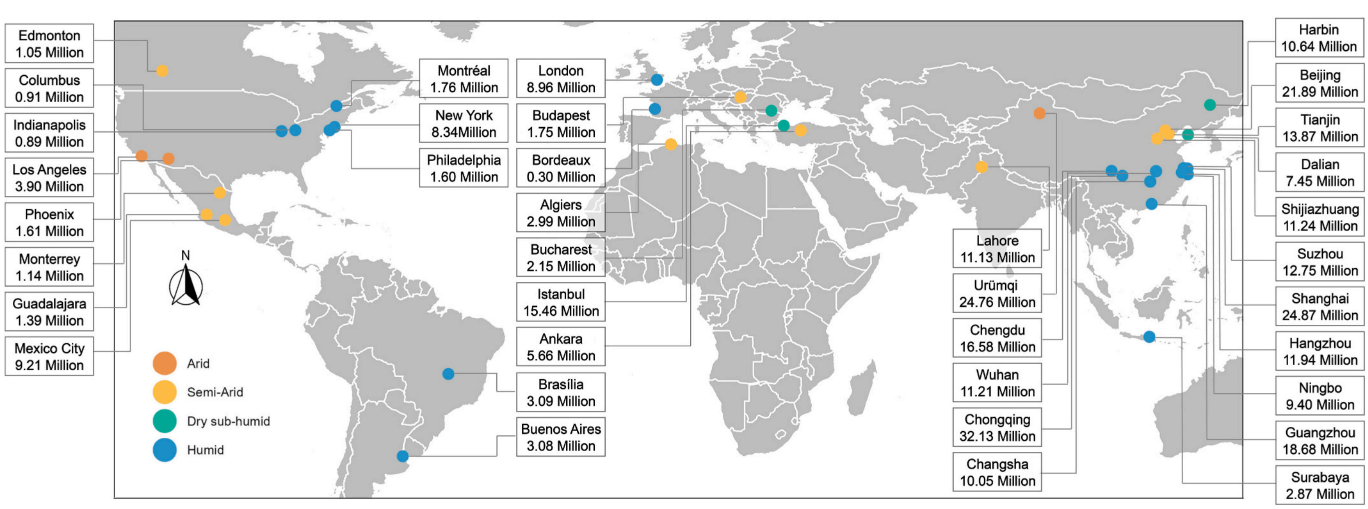

Fig. 1. The spatial distribution of cities grouped by climate classes (i.e., the same color represents the same climate class), with population size indicated.

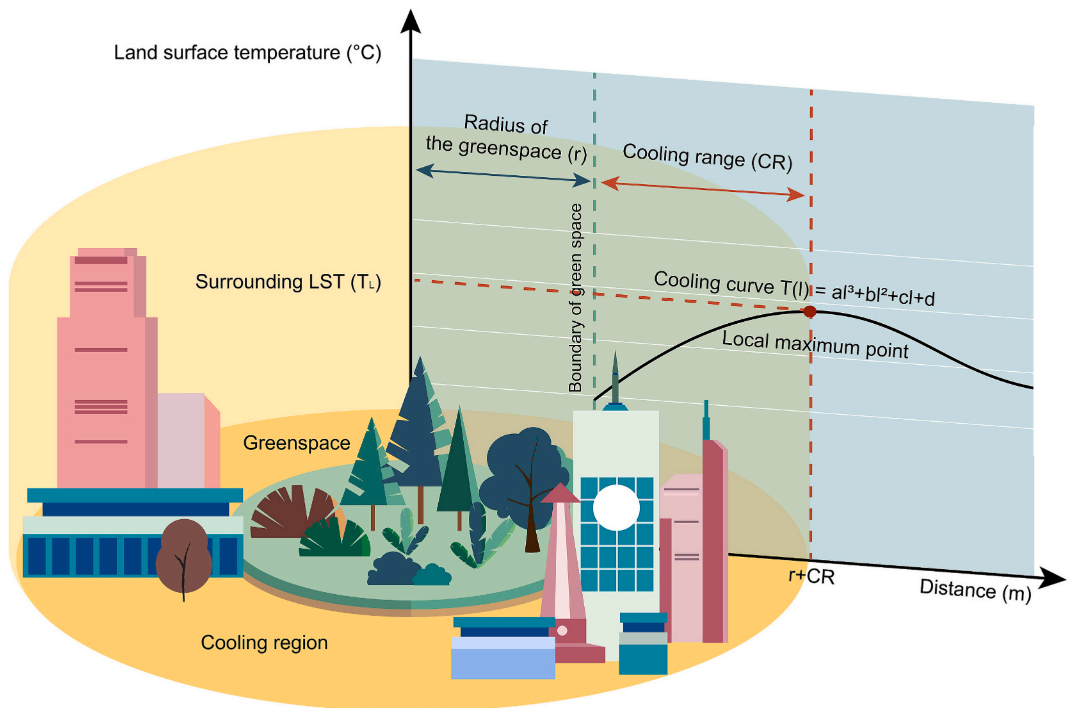

Fig. 2. The schematic diagram of the quantification for cooling indexes based on the cubic polynomial regression between distance and LST (land surface temperature). The volume of the hollow cylinder, formed by rotating the line $y = T_L$ over the interval [r, r + CR] around the y-axis, minus the volume of the solid of revolution, formed by rotating the integral of T(l) over the same interval around the y-axis, was cooling intensity conducted in this study.

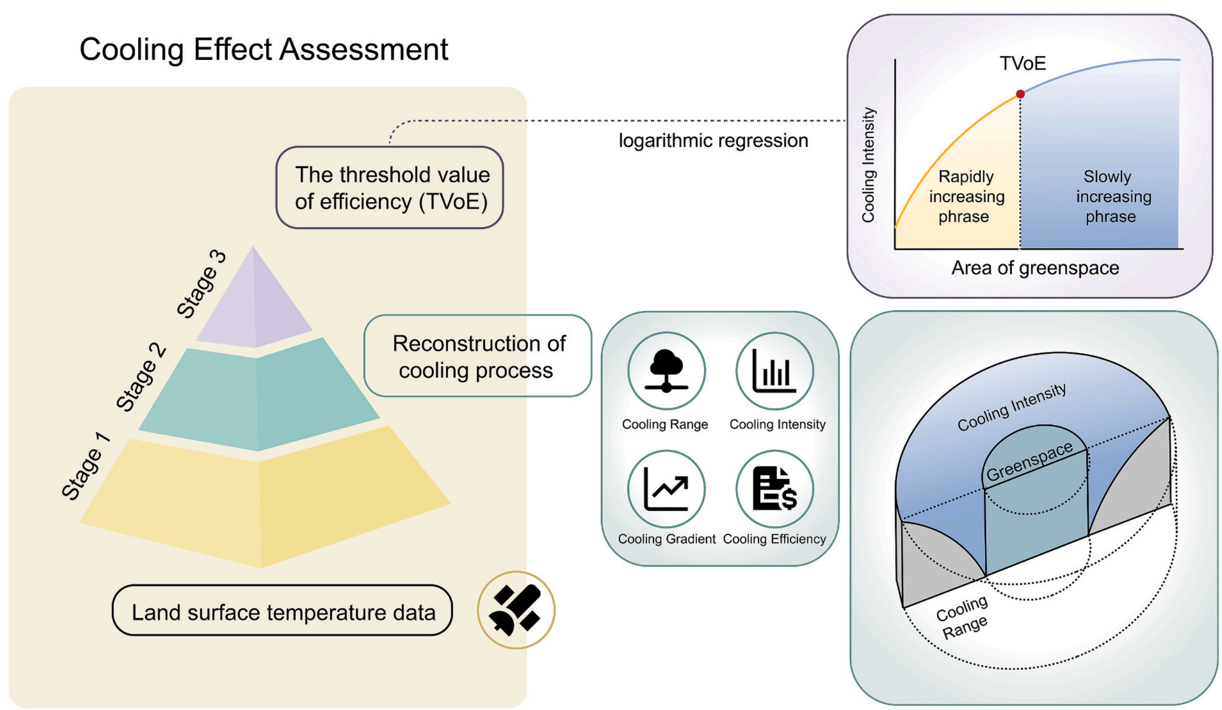

Fig. 3. The conceptual illustration of the cumulative cooling index system.

cooling intensity, making it economically efficient to expand the patch area. Once the patch area exceeds this threshold, each additional hectare contributes less than 1 °C to cumulative cooling, resulting in no significant improvement to the thermal environment. The TVoE indicates the ideal patch size for maximizing cooling efficiency, providing guidance for efficient and sustainable urban planning. We conducted the TVoE analysis using Excel software.

2.3. Factors influencing cooling effect

Factors influencing the cooling effect of each urban greenspace patch can be categorized into two groups: landscape patterns of greenspace patches (including spatial configuration and landscape composition) as well as landscape patterns of surrounding areas (Peng et al., 2021; Qiu and Jia, 2020; Yu et al., 2020). Previous studies have shown that the cooling effect of greenspaces is closely related to their area and shape (Bowler et al., 2010; Cao et al., 2010). Therefore, we used two metrics to examine the importance of greenspace spatial configuration including (1) area and (2) shape index. Furthermore, the vegetation area ratio and water body area ratio inside the greenspace patch were used to indicate the area proportion of the green-blue landscape in the greenspace. Both vegetation and water bodies were mapped using the World Cover product for 2020, as detailed in section 2.1.

As for the urban landscape patterns of surroundings, the proportion of green-blue landscape was also examined. Apart from that, impervious surfaces will absorb and retain heat, impacting cooling processes (Zhang et al., 2022; Ziter et al., 2019). Therefore, we selected two major impervious surface types—buildings and roads—as influencing factors in our analysis. The global road and building vector data was obtained from OpenStreetMap. Road density is calculated by dividing the cumulative road length by the whole buffer area of the assessing unit. Moreover, building density, the ratio of area occupied by the planar projection of buildings in the buffer, was used to characterize the intensity of building development.

Also, the anthropogenic heat discharge elevates ambient temperatures, which may suppress evapotranspiration and further affect cooling effects (Kato and Yamaguchi, 2005). Therefore, Nighttime light, an effective indicator of socioeconomic activities such as industrial production (Miller et al., 2012), was selected as a proxy for anthropogenic activity. VIIRS nighttime light data with approximately 450 m spatial resolution of 2022 were obtained from the Payne Institute for Public Policy (Elvidge et al., 2021). The mean nighttime light within a 1 km buffer was calculated to characterize the intensity of human activities surrounding the greenspaces. These influencing factors including landscape patterns of greenspace patches and landscape patterns of the surroundings are shown in Table 1.

2.4. Statistical analysis

Spearman correlations between cooling indexes and landscape characteristics were performed to find primary relationships between cooling effect and influencing factors with the “psych” package in R (Spearman, 1961). Random forest, a non-parametric ensemble learning method, integrates numerous tree predictors. Each tree in the RF was constructed using a different bootstrap sample of the data, and at each node, the best predictor was selected from a randomly chosen subset of variables. This approach reduces the correlation among trees, enhancing model performance and robustness. Moreover, random forest can handle high-dimensional datasets without requiring complex feature selection while mitigating multicollinearity issues, which is particularly beneficial given the presence of multiple potential influencing factors on cooling effects. Additionally, the model investigates the relative importance of landscape characteristics’ changes on cooling indexes, identifying the most influential characteristics. Random forest model was performed with the ‘randomForest’ package in R. Each predictor’s importance was evaluated by increased Mean Squared Error (MSE). The random forest analysis and spearman analysis were used to evaluate the associations between cooling indexes and landscape characteristics.

Table 1
Potential influencing factors on cooling effect of urban greenspaces.

Categories of metrics	Metric	Definition
Landscape patterns of greenspace patches	Patch_area	The area of a greenspace patch.
	Patch_LSI	The landscape shape index of a greenspace patch.
	Patch_green_cover	The proportion of the vegetation in a greenspace patch.
	Patch_blue_cover	The proportion of the water body in a greenspace patch.
Landscape patterns of surrounding areas	Buffer_green_cover	The proportion of the vegetation in the 1 km buffer of a green pace patch.
	Buffer_blue_cover	The proportion of the water body in the 1 km buffer of a greenspace patch.
	Buffer_road_density	The road network density in the 1 km buffer of a greenspace patch.
	Buffer_building_density	The ratio of area occupied by the planar projection of buildings in the 1 km buffer of a greenspace patch.
	Buffer_NTL	The mean nighttime light in the 1 km buffer of a greenspace patch.

3. Results

3.1. Quantitative results of the cumulative cooling index system

3.1.1. Variability in cumulative cooling indexes by climate classes

The results show that urban greenspaces exert substantial cooling benefits on surrounding areas cumulatively, with an average cooling intensity of 4.92 °C across 668 analyzed greenspaces (Fig. 4a). Cooling intensity exhibited significant variability, ranging from 0.1 °C to 25.3 °C, with a standard deviation of 3.35 °C. The averaged cooling range was 136.6 m, which represents that the urban greenspaces averagely extended a cooling effect up to a distance of 136.6 m. The cooling gradient averaged 32.98 °C/km, while the cooling efficiency averages 4.65 °C/ha, demonstrating that each hectare of greenspace can, on average, cause a cumulative LST reduction of 4.65 °C in the surrounding area.

Greenspaces showed differing cooling intensities across various climate classes, as shown in Fig. 3(b-e). Specifically, 50 % of urban greenspaces in arid cities had cooling intensities in the range of 0–5 °C. In humid cities, 55 % of greenspaces had cooling intensities had cooling intensities of 0–5 °C. Whereas for semi-arid and dry sub-humid cities, 56.4 % and 68.7 % of greenspaces has cooling intensities of 0–5 °C, respectively. Cooling intensities increases from arid, humid, semi-arid to dry sub-humid cities, showing that greenspaces in arid and humid cities had a better cooling effect in general.

3.1.2. The spatial heterogeneity of TVoE

The average value of TVoE for the 37 cities was 1.72 ha, suggesting that the optimal area of urban greenspaces for the selected cities would be 1.72 ha averagely (Fig. 5). However, TVoE had a large variation, ranging from 0.62 ha to 3.03 ha, with a standard deviation of 0.43 ha, and varied greatly in space. It was generally higher in low-latitude regions including cities of Brazil and southwestern cities of China. For example, Brasília in Brazil and Choqing in China had relatively large value of TVoE, up to 2.53 ha and 2.95 ha respectively. Overall, TVoE value rises as latitude decreases, indicating that optimal area of greenspaces in higher-latitude cities is suited to be smaller, whereas lower-latitude cities benefit from larger ones.

3.2. Determinants of cumulative cooling effect

3.2.1. The effects of landscape characteristics on cumulative cooling indexes

Spatial configuration of greenspaces had the highest importance for explaining variability in cumulative cooling indexes. The results from 37 cities worldwide, as presented in Fig. 6, indicate that the area of greenspaces is positively associated with the cooling range, cooling intensity, and cooling gradient, and it was identified as the dominant predictor of cooling effect. The area of greenspaces explained 35.16 % variations in the cooling range, 70.08 % variations in the cooling intensity, 80.22 % variations in the cooling gradient. That is, expanding the area can extend the cooling distance, increase the magnitude of temperature reduction, and result in a higher cumulative decrease in

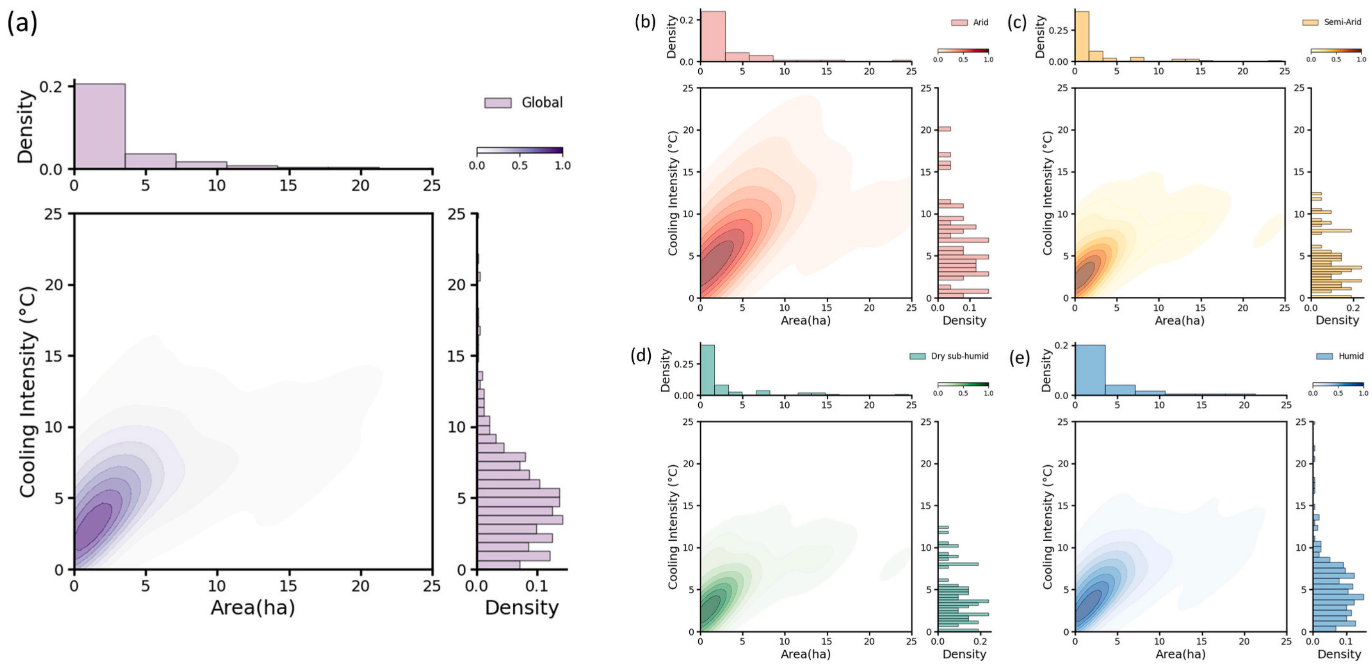

Fig. 4. Cooling intensity (y-axis) and the area of greenspaces (x-axis) distribution joint plot for different climate classes: (a) all the 37 cities; (b) arid; (c) semi-arid; (d) dry sub-humid; (e) humid.

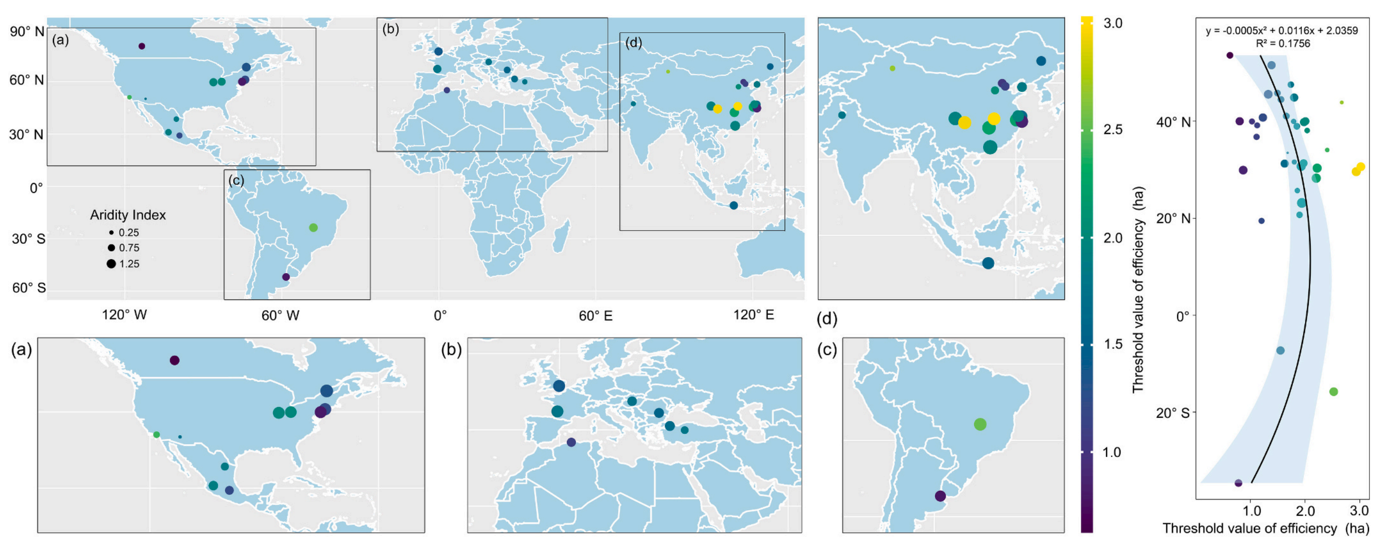

Fig. 5. The spatial distribution of the Threshold Value of Efficiency (TVoE) for 37 cities and the scatterplot of the relationship fitted by quadratic function between latitude and TVoE.

LST across the region. LSI was positively correlated with cooling range and cooling intensity, explaining 4.39 % and 5.05 % variations, respectively.

In contrast to spatial configuration, greenspace cooling effect was less constrained by landscape composition. The impact of green coverage of greenspaces on cooling range and cooling intensity was found to be positive, explaining 9.28 % variations in the cooling range and 6.96 % variations in the cooling intensity. Similarly, the blue coverage of the greenspaces acted as important drivers of both the cooling intensity and the cooling gradient, explaining 12.27 % variations in the cooling intensity and 11.06 % variations in the cooling gradient. This indicates that an increase in the proportion of vegetation and water bodies within greenspaces might promote cooling effect of greenspaces.

As for the landscape characteristics of surrounding areas, the green-blue coverage exerts negative influences on cooling range and cooling efficiency. In contrast, road density of adjacent regions positively impacts cooling intensity. Higher road density means increased vehicle volume and anthropogenic heat release, making nearby greenspaces relatively cooler and resulting in a stronger observed cooling effect. Similarly, the building coverage was positively correlated with cooling range and cooling efficiency. It shows that developing greenspaces in economically advanced areas leads to greater cooling efficiency. The road density and building coverage acted as generalists in predicting cooling range, cooling intensity and cooling efficiency. The road density explained 10.39 % variations in cooling intensity, while the building coverage explained 9.69 % and 9.22 % variations in cooling range and cooling efficiency, respectively.

In terms of dominant factors across different climate zones, aside from patch area, blue coverage within greenspaces served as an

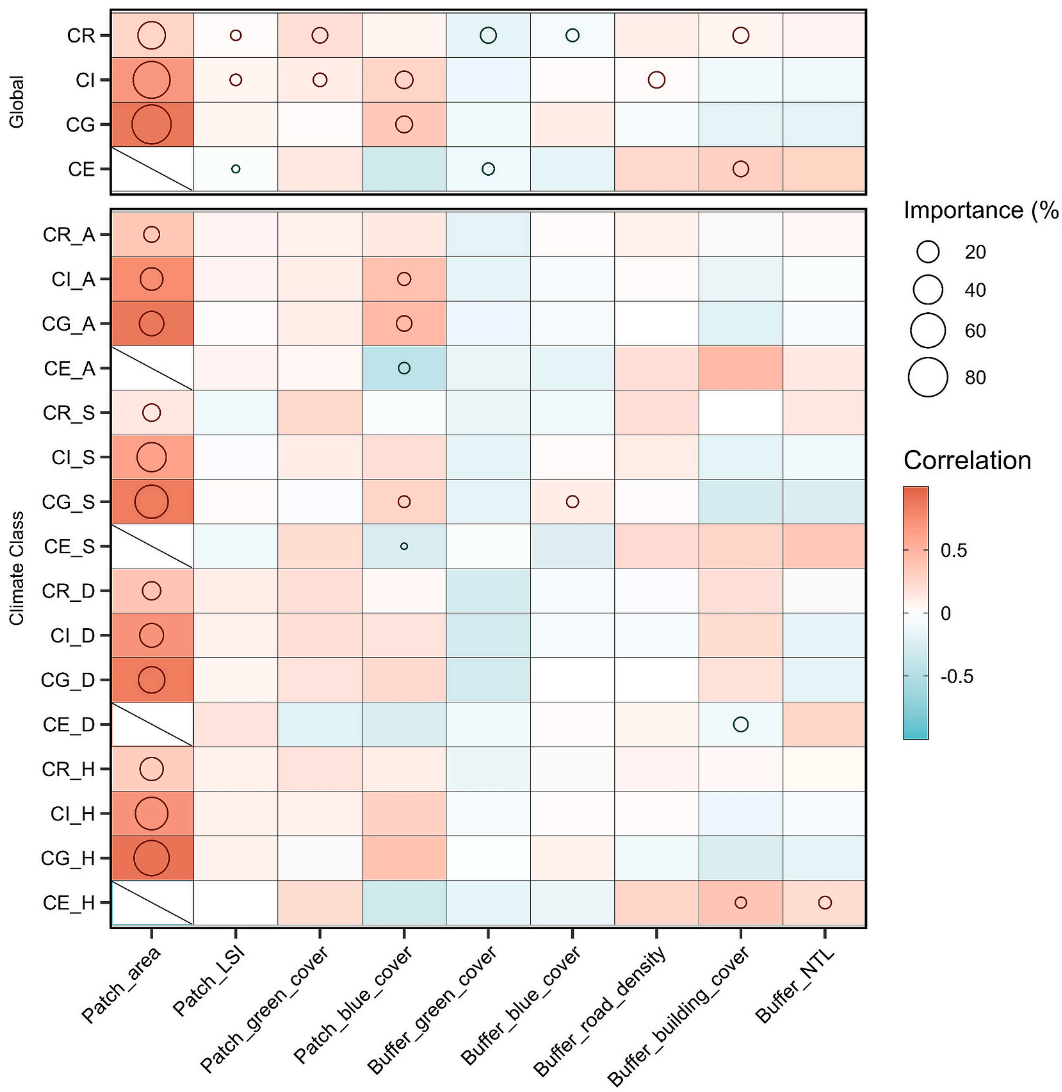

Fig. 6. Correlation and best random forest model for cooling effect in both global cities and various climate classes. For variable selection and estimating predictability, the random forest machine-learning algorithm was used. The circles over diamonds symbolize the importance of influencing factors (decrease in the prediction accuracy). The heatmap plots illustrate the spearman correlations. CR, CI, CG, CE denote the cooling range, cooling intensity, cooling gradient, and cooling efficiency, respectively. In CR_X, CI_X, CG_X, and CE_X, the variable X represents different climate classes, where A, S, D, and H correspond to arid, semi-arid, dry sub-humid, and humid, respectively.

important driver of cooling effect in arid and semi-arid cities. High blue proportion can lead to the increase in both cooling intensity and cooling gradient. On the other hand, in humid regions, the road density and building coverage of the surroundings acted as generalists in predicting cooling efficiency. Overall, in arid or semi-arid cities, the proportion of water bodies within greenspaces serves as the dominant factor, while in humid cities, the level of economic development surrounding greenspaces is the primary determinant of cooling effect.

3.2.2. *Potential drivers of TVoE spatial patterns*

The aridity affected TVoE strongly but not in a linear way. The scatter plot showed a U-shaped relationship between aridity index and TVoE when considering all the 37 cities (Fig. 7). This U-shaped curve exhibited a turning point (i.e., 0.62 from the first derivative of the quadratic model equaling zero, where the minimum TVoE value exists), indicating that the rising of aridity index leads to a decrease in TVoE first, but can higher it when the aridity index exceeds the threshold value. In general, it shows that TVoE has a large value when the aridity index value is either relatively low or high at continental scale.

Moreover, the values of TVoE varied across the 4 climate classes. The average TVoE values for the four climate zones—Arid, Semi-Arid, Dry Sub-Humid, and Humid—were 2.25 ha, 1.48 ha, 1.64 ha, and 1.8 ha. It should be noted that greater TVoE values mostly came from arid and humid climate classes. This suggests that cities in arid and humid climate classes are more suitable for the development of larger urban greenspaces.

4. Discussion

4.1. *Advancing cooling analysis: harnessing 3D perspective for cumulative effects*

Previous studies primarily quantify the cooling effect of urban greenspaces based on two perspectives: the maximum perspective and the accumulation perspective (Cao et al., 2010; Feyisa et al., 2014; Peng et al., 2021). For example, Chang et al. (2007) proposed cooling intensity, characterized by the difference between the greenspace interior and its nearby surroundings. Building on this, Cheng et al. (2015) further identified the maximum temperature within the outline of the influencing range as representative of adjacent thermal conditions.

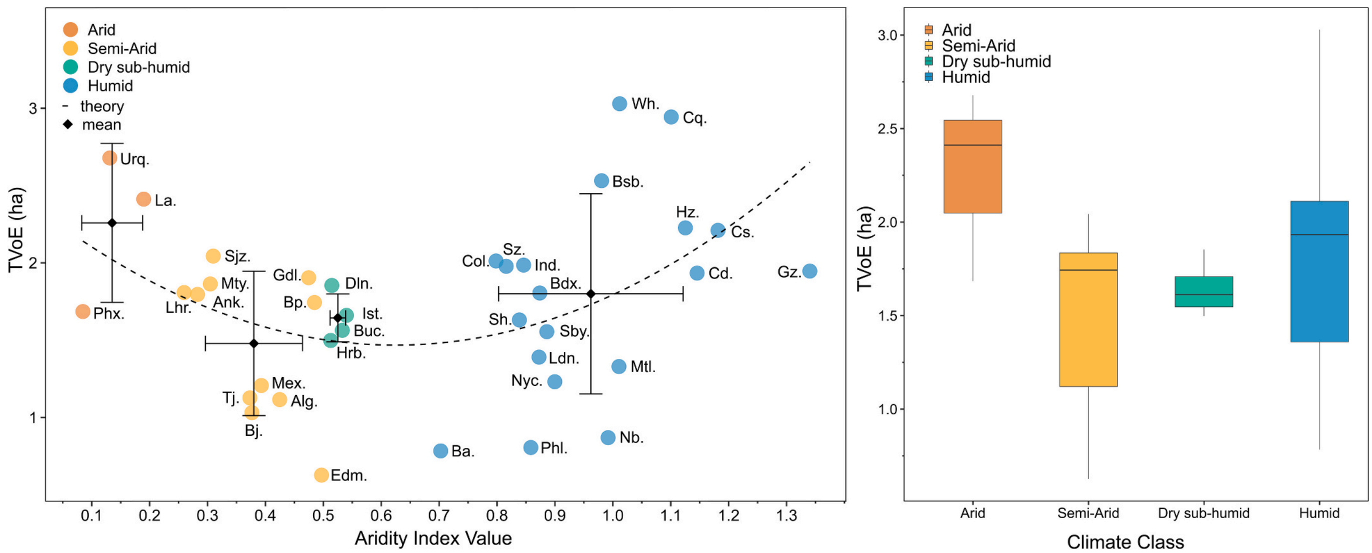

Fig. 7. The scatterplot of the relationship between the aridity index and the Threshold Value of Efficiency (TVoE) (Ank. = Ankara, Bj. = Beijing, Bp. = Budapest, Cd. = Chengdu, Cs. = Changsha, Cq. = Chongqing, Dln. = Dalian, Edm. = Edmonton, Gdl. = Guadalajara, Gz. = Guangzhou, Hrb. = Harbin, Hz. = Hangzhou, Ind. = Indianapolis, Ist. = Istanbul, La. = Los Angeles, Ldn. = London, Lhr. = Lahore, Mex. = Mexico City, Mtl. = Montréal, Mty. = Monterrey, Nb. = Ningbo, Nyc. = New York, Phl. = Philadelphia, Phx. = Phoenix, Sjz. = Shijiazhuang, Sh. = Shanghai, Sby. = Surabaya, Sz. = Suzhou, Tj. = Tianjin, Urq. = Urümqi, Wh. = Wuhan, Buc. = Bucharest, Bdx. = Bordeaux, Alg. = Algiers, Col. = Columbus, Bsb. = Brasília, Ba. = Buenos Aires).

However, they fail to provide a comprehensive understanding of the detailed process of temperature increase from the greenspace boundary to the outer limit of its cooling footprint. On the other hand, studies using the accumulation approach simplify this process into a cooling curve along a cross-section rather than realistic and accurate predictions (Peng et al., 2021). Unlike studies that focus on the cooling effect measured based on points (maximum temperature difference) or along a line (cooling curve). Our research examines the cumulative impact of greenspaces on an urban area, specifically the effects across the entire affected region (plane). The total cooling benefit of a greenspace can be assessed by summing the temperature reduction over the influencing region. By introducing the vertical axis to represent the temperature data of each pixel, and further modeling the thermal distribution around greenspaces within a three-dimensional spatial framework, the cumulative cooling effects can be quantified with greater accuracy.

Previous estimates of the cooling potential through large-scale greenspaces predicted much smaller impacts than our results. Du et al. (2017) estimated a cooling effect of 2.93 °C for a greenspace of 205.32 ha, which is nearly one-tenth of the maximum value found in this study (25.3 °C). Given that increasing patch areas and total edges may provide added shade for the surroundings and enhance energy flow between green patches and surrounding areas (Zhou et al., 2011), the discrepancy likely stems from the full-range temperature reduction captured by our approach. This enables a holistic representation of how greenspaces modify their surrounding thermal environment. The integration of temperature data enhances the precision of cumulative cooling calculations, addressing limitations inherent in traditional 2D models and providing a robust basis for optimizing urban greenspace design.

Earlier research comparing maximum temperature differentials or simplifying the cooling process into a one-dimensional cross-sectional analysis might also fail to accurately determine cooling parameters and corresponding influencing factors (Fan et al., 2019; Peng et al., 2021; Yu et al., 2017). Firstly, contradictory to earlier conclusions, we concluded that LSI has a positive correlation with both cooling range and cooling intensity (Geng et al., 2022; Jaganmohan et al., 2016; Masoudi and Tan, 2019). That is, although greenspaces with more complex shapes have been shown to reduce the temperature difference with their surrounding environments (Peng et al., 2021), they exert better cumulative cooling benefits overall. Secondly, the results showed that the road density, building coverage and nighttime light of the surroundings harbor positive correlations with cumulative cooling indexes, especially in humid regions. Although it is commonly believed that in economically advantaged areas, cooling effect of greenspaces may be limited (Cheng et al., 2015; Ren et al., 2016). With the increased urban heat, the enhanced temperature differential between greenspaces and their surroundings could allow greenspaces to provide more noticeable cumulative cooling capacity. These findings challenge the common notion that socioeconomically advantaged regions diminish the cooling effect of greenspaces.

From a research methodology perspective, our studies emphasized the necessity of shifting the standpoint from 2D to 3D when quantifying cooling quantity. In this model, the spatial dimensions are represented on the horizontal plane, with the temperature data being represented along the vertical axis. Our approach is one drawn from the objective realities of cooling process, enabling a more accurate quantification of cooling effect. This study could offer valuable methodological and strategic guidance for further researches at regional and global scale.

4.2. Implications for greenspaces planning and management

In an arid or a semi-arid climate, blue proportion had the highest relative importance for explaining variability in the quantity cooling metrics apart from the area. The importance of water bodies for cumulative cooling quantity aligns with findings of Geng et al. (2022), which showed that water bodies within urban parks play a significant role in the cooling effect in arid cities. Such cities will need to invest in more water bodies in greenspaces to alleviate urban heat. What's new in this study, however, is that when not being limited by low aridity, cumulative cooling effect was potentially more driven by socioeconomic characteristics of the surroundings including road density and building coverage. These results thus suggest that, in humid cities, strategically integrating greenspaces into urban hotspots could maximize their cooling potential.

The observed threshold in the effect of greenspaces patch area on the cooling intensity has important implications for landscape planning and design. Yu et al. (2017) proposed that once the area of the greenspace surpasses a specific threshold (TVoE), the cooling efficiency ceases to exhibit significant improvement. However, prior efforts have miscalculated and underestimated the cooling potential of greenspaces—particularly large-scale ones—leading to the inaccurate assessment of TVoE (Peng et al., 2021; Yu et al., 2018). This study identifies a higher optimum TVoE (1.72 ha) compared to prior estimates, likely due to the introduction of 3D perspective. Comparable cumulative cooling effects between greenspaces near the threshold and larger ones were demonstrated across multiple cities (Fig. 8), highlighting the robustness of the conclusion. The TVoE concept, refined based on cumulative cooling quantification, can contribute to the planning and design of urban greenspace to achieve optimal cooling benefits within limited urban space.

Interestingly, we further found that the value of TVoE is higher in regions with both the lowest and highest Aridity Index (AI). In areas with high AI, greenspaces have a more pronounced cooling effect due to the higher availability of water (Fig. 8d), which enhances evapotranspiration and productivity of vegetation. As a result, larger greenspaces are needed to reach a saturation point where further expansion does not yield proportionally higher cooling benefits. In contrast, in areas with low AI, the limited water availability restricts the transpiration cooling potential, as vegetation rooted in dry soils may close leaf stomata to conserve water (Sulman et al., 2016). Here, larger greenspaces are necessary to compensate for the reduced evapotranspiration capacity. Therefore, the interaction between vegetation cooling potential and water availability creates a nonlinear relationship between the TVoE threshold and aridity. Our findings suggest that aridity conditions may predetermine the optimal greenspace area to maximize cumulative cooling efficiency.

Overall, our cumulative cooling index system can accurately quantify the comprehensive cooling benefits and provide climate-adaptive planning strategies accordingly. Furthermore, it suggests a potential of improving cooling efficiency by optimizing urban greenspaces. The refinement of TVoE from the cumulative perspective, and the mapping of TVoE globally provide straightforward guidance for decision-makers to systematically enhance and maximize cumulative cooling efficiency.

4.3. Limitations and further studies

Some caveats to this study warrant attention. First, we chose LST over air temperature due to the need for continuous spatiotemporal data. However, previous studies have noted the differing responses of LST and air temperature to vegetation changes (Novick and Katul, 2020; Winckler et al., 2019; Zhou et al., 2011). Given that air temperature reflects atmospheric heat and is more closely related to human thermal sensation, future studies should incorporate field measurements to validate our findings (Oliveira et al., 2011). Second, due to the unavailability of remote sensing imagery, the temporal consistency of the LST data was not fully ensured. Subsequent studies should employ higher-resolution temporal and spatial data for long-term observations. Third, our model assumes an isotropic temperature decay pattern, implying uniform cooling in all directions. Future studies should refine the model by incorporating wind effects, urban geometry, and anisotropic temperature diffusion patterns. Moreover, the specific mechanisms through which background climatic conditions affect TVoE remain unclear. To capture the complex relationships and indirect effects, more advanced methods, such as Structural Equation Modeling, should be employed in future research. Finally, although we focus on the proposal of 3D quantitative model, additional consideration of spatial structural characteristics including canopy structure and building height is also warranted as influencing factors on the cooling effect. While we did not account for these factors in this analysis, estimating the dominant factors of the cooling effect will ultimately require much fuller accounting across all such factors.

5. Conclusion

Accurately measuring the cooling effect of greenspaces provides a scientific foundation for optimizing urban park planning to mitigate UHI effect. From a 3D perspective, our study introduces a novel quantitative model that enhances the reconstruction and precise quantification of the cooling process. We selected 668 greenspaces from 37 cities across

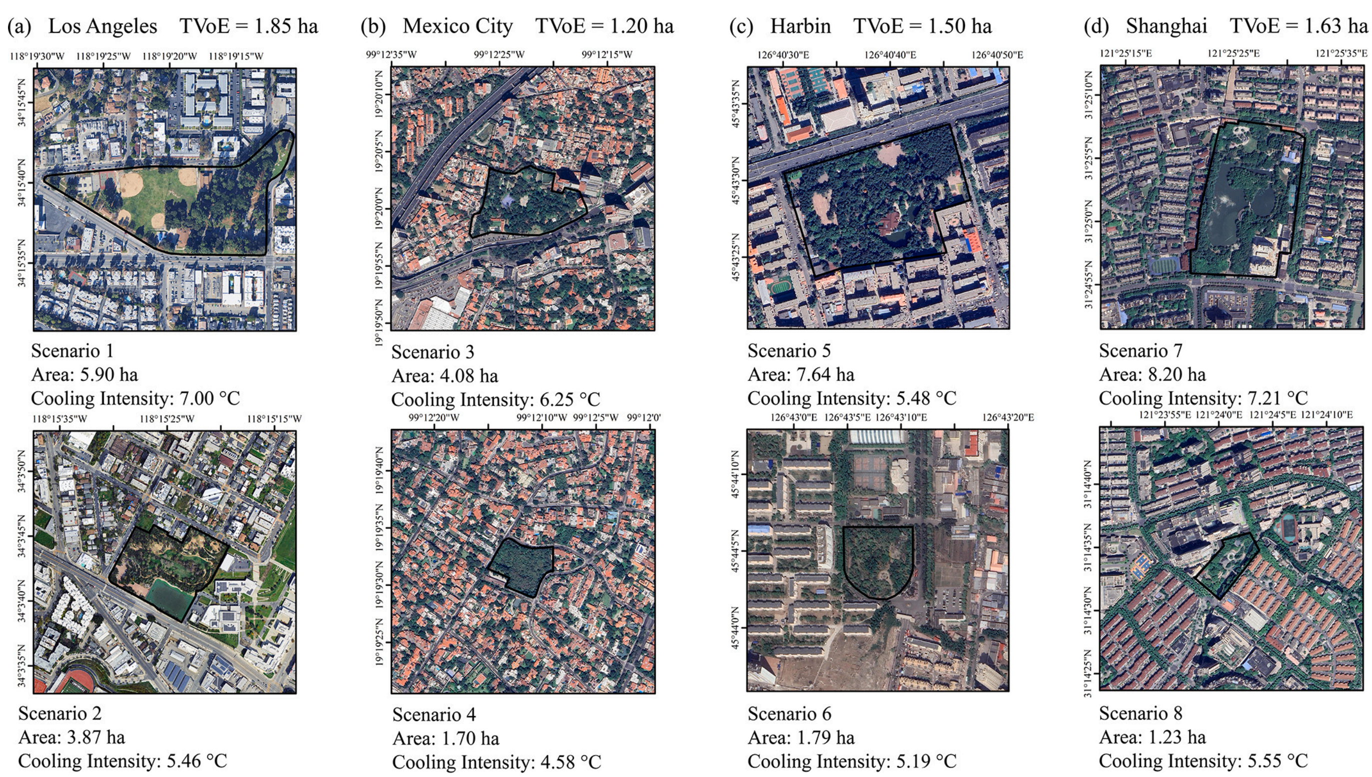

Fig. 8. Area and cooling intensity (CI) for representative greenspaces in (a) Los Angeles, (b) Mexico City, (c) Harbin, and (d) Shanghai.

different climate zones to explore the spatially accumulated cooling benefits and dominant influencing factors. Random forest models were used to assess the relationships between cooling indices and landscape characteristics. Our findings reveal that previous efforts to quantify the cooling benefit of urban greenspaces have considerably underestimated the cooling potential. We found that urban greenspaces exert a cumulative cooling effect of 4.92 °C on average, influenced positively by factors such as greenspace area, the intrinsic green-blue proportion, and surrounding socioeconomic characteristics. Furthermore, refined with the improved quantification of the cooling effect, we identified a cumulative-perspective global threshold value of efficiency ranging from 0.62 ha to 3.03 ha, with larger greenspaces recommended for cities at lower latitudes. Notably, cities in arid and humid climates are more conducive to the development of larger urban greenspaces. These results highlight the importance of introducing a 3D perspective for precise cooling effect assessment. This work deepens our understanding of greenspace cooling effect, and the proposed quantitative system offers practical recommendations for mitigating urban heat.

CRediT authorship contribution statement

Si-Qi Zhou: Writing – review & editing, Writing – original draft, Visualization, Software, Data curation. **Zhao-Wu Yu:** Writing – review & editing. **Wan-Ben Wu:** Methodology. **Wen-Jun Yang:** Data curation. **Yu-Jia Zhang:** Formal analysis. **Ying-Ying Hao:** Visualization. **Qi Yuan:** Software. **Dong-Fan Xu:** Conceptualization. **Jin-Yu Hu:** Resources. **Bin Zhao:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2025.114867.

Data availability

Data will be made available on request.

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