RESEARCH ARTICLE

Assessment of urban blue-green space cooling effect linking maximum and accumulative perspectives in the Yangtze River Delta, China

Yingxue Cui[1] · Beibei Guo[1] · Wei Li[1] · Xuemin Kong[1]

Abstract

The development of urban blue-green spaces is highly recommended as a nature-based solution for mitigating the urban heat island phenomenon, improving urban sustainability, and enhancing resident well-being. However, limited attention has been given to the accumulative impact of the cooling effect and the comparison of different types of landscapes. Based on the maximum and accumulative perspectives, this study selected 375 green spaces, water bodies, and urban parks in 25 cities of the Yangtze River Delta (YRD) region in China to quantify their cooling effect. Correlation and regression analyses were employed to identify the dominant factors influencing the cooling performance. The results indicated that (1) compared to other landscape patches, water areas, and parks exhibited a reduction in daily average air temperature by 3.04 and 0.57 °C, respectively. Urban parks provided the largest cooling area (CA) of 56.44 ha in the YRD region, while water bodies demonstrated the highest cooling effect (CE) of 6.88, cooling intensity (CI) of 0.02, and cooling gradient (CG) of 0.99. (2) From the maximum perspective, the perimeter of the patches played a dominant role in CA and CE for all landscape patch types, contributing more than 40% in CA variation. (3) The dominant factors varied among different landscape types from accumulative perspectives. Green spaces were influenced by road density, shape index, and the proportion of water bodies within the CA, whereas water bodies were primarily affected by the coverage of blue spaces. Vegetation growth and densely populated surroundings contributed the most to the cooling of parks. These findings enhanced the comprehension of the cooling effect in comparable urban contexts and provided valuable insights for sustainable urban management.

Keywords Cooling effect · Urban heat island effect · Land surface temperature · Urban blue-green space · Accumulative effect · Yangtze River Delta

Introduction

By 2065, more than 68% of the global population is projected to reside in urban areas (United Nations Department of Economic and Social Affairs 2018). Rapid population growth and economic improvement have resulted in intensified urbanization and expansion, leading to profound impacts on landscape patterns and processes (Kaza 2013; He and Zhu 2018; Yu et al. 2019). The replacement of natural landscapes with impervious surfaces has affected the balance of urban climate regulation, causing numerous adverse effects, including deforestation, the energy crisis, and air pollution, which negatively affects human health and well-being (Silva et al. 2017; Peng et al. 2016). The urban heat island (UHI) phenomenon has emerged as a prominent feature of urban climate change in the context of global warming and urbanization (Rasul et al. 2016). High land surface temperatures (LST) in cities caused by the UHI effect have adverse effects on the physical and psychological health of residents and may even decrease their lifespan (Ebi et al. 2021). Therefore, there is an urgent need for sustainable and effective measures to mitigate the UHI effect. Through proper urban planning and management, urban spaces can be resilient to escalating thermal risk while fostering sustainability. A blue-green landscape is renowned for promoting a healthy thermal environment that can enhance the equity of urban life (Zhou et al. 2017). Consequently, identifying strategies to manage blue-green spaces reasonably and obtain the maximum

✉ Beibei Guo
guobb@ahu.edu.cn

[1] School of Business, Anhui University, Hefei 230046, China

ecological benefit has become an essential topic in urban ecology (Gao et al. 2022; Wang et al. 2022a).

The urban heat island effect commonly refers to the climatic phenomenon observed in urban areas where surface temperatures are higher compared to the surrounding rural regions (Oke et al. 2017; Yu et al. 2019). Given the frequent occurrence and negative impacts of extreme heat events, research on UHIs has not only focused on the spatiotemporal heterogeneity and dynamics monitoring of land surface temperatures but also identified methods for adapting to UHIs and mitigating their effects (Sun et al. 2014). Numerous research has presented various solutions to alleviate the UHI effect, such as modifying building materials and colors, implementing green roofs, and utilizing other ecological infrastructures (Buyantuyev and Wu 2010; Byrne and Jinjun 2013; Yang et al. 2020). Nonetheless, scholars argue that adopting blue-green landscape cooling may be a more suitable solution due to their cost-effectiveness, ecological friendliness, and political acceptability (Yu et al. 2020). Thus, achieving a systematic and comprehensive understanding of the landscape cooling effect is critical for effectively mitigating UHI and creating livable urban environments (Hamada and Ohta 2010; Santamouris et al. 2018).

Previous research has explored the cooling impact of urban blue-green landscapes. The urban areas' water bodies, parks, residual farmland, grassland, shrubberies, and other ecological land cover types have been confirmed to exert substantial cooling effects, termed urban blue-green spaces in this study (Gunawardena et al. 2017; Kong et al. 2014). Specifically, green spaces refer to the landscape that comprises vegetation (i.e., forests, grasslands, croplands, and other areas dominated by vegetation cover), while blue spaces refer to the land covered by water (i.e., lakes, reservoirs, rivers, and other areas dominated by waterbodies or watercourses) (Gunawardena et al. 2017; Guo et al. 2021; Zhou et al. 2022). Most of the relevant literature suggests that blue infrastructures exhibit a better cooling performance than other categories of landscape, while controversies persist regarding whether blue spaces or green spaces demonstrate a greater cooling influence (Gunawardena et al. 2017; Tan et al. 2021). Additionally, the cooling effect of blue-green spaces depends not only on external factors such as local climate context, vegetation selection, and the surrounding areas but also on the landscape metrics (Du et al. 2022; Zhou et al. 2017). Urban parks are classified as a separate urban landscape category in this study due to their common composition of both blue and green space patches together (Völker and Kistemann 2015; Yu et al. 2020). As the most common ecological spaces in cities, urban parks could modify localized heat retention via increasing evapotranspiration with urban greening and porous surfaces (Jay et al. 2021; Wu and Chen 2017; Yu et al. 2020). However, available studies primarily concentrate on examining the relationship between individual types of urban spaces and the thermal environment, neglecting a comprehensive assessment of landscape composition and configuration across diverse landscape categories (Liu et al. 2022a). Consequently, there is an urgent need to determine how to maximize the cooling capacity of various blue-green spaces.

Various indexes have been proposed to quantify the cooling effect of blue-green landscapes. For instance, cooling intensity refers to the difference in LST between the selected patch and its cooling boundary (Li et al. 2022; Wu et al. 2022), while cooling distance represents the maximum distance over which a patch's cooling effect can extend (Jiang et al. 2021; Zhang et al. 2017). Unlike early calculation methods that focused solely on the maximum cooling effect (Feyisa et al. 2014; Peng et al. 2020), recent research tends to integrate both maximum and accumulative indicators to quantify the cooling effect (Du et al. 2022; Peng et al. 2021). However, studies that have integrated both perspectives are mainly conducted on park patches, disregarding the spatial continuity of the cooling effect generated by blue and green landscapes (Du et al. 2022; Yao et al. 2022). Therefore, further research linking the maximum and accumulative perspectives is required to provide insights into the cooling characteristics across various landscapes, offering targeted and practical strategies for urban spatial planning.

As one of the fastest urbanizing areas in the world, the Yangtze River Delta (YRD) region has witnessed substantial socioeconomic growth and dramatic climate change in recent decades (Cheng et al. 2020; Zhan and Xie 2022). The corresponding rapid landscape change has led to severe air pollution and aggravated heat stress at the regional scale, which has been observed in many metropolitans (Shen et al. 2020; Zhang et al. 2021). Consequently, 375 blue-green spaces in the YRD have been selected as cases to quantify and compare their cooling performance comprehensively. This study aims to (1) investigate the spatial patterns of the cooling effect and potential influencing factors from both maximum and accumulation perspectives, (2) compare the cooling effect among different types of urban blue-green spaces, and (3) explore optimal cooling solutions for urban space planning and management.

Materials and methods

Study area and data source

The Yangtze River Delta (28° 90′N~33° 30′N, 118° 25′E~122° 42′E) is located along the southeastern coast of China, covering a total area of approximately 211,700 km^2 (Fig. 1a and b). In this study, the YRD refers to a region comprising 25 cities, excluding Zhoushan city in Zhejiang Province due to its relatively distinctive climate characteristics
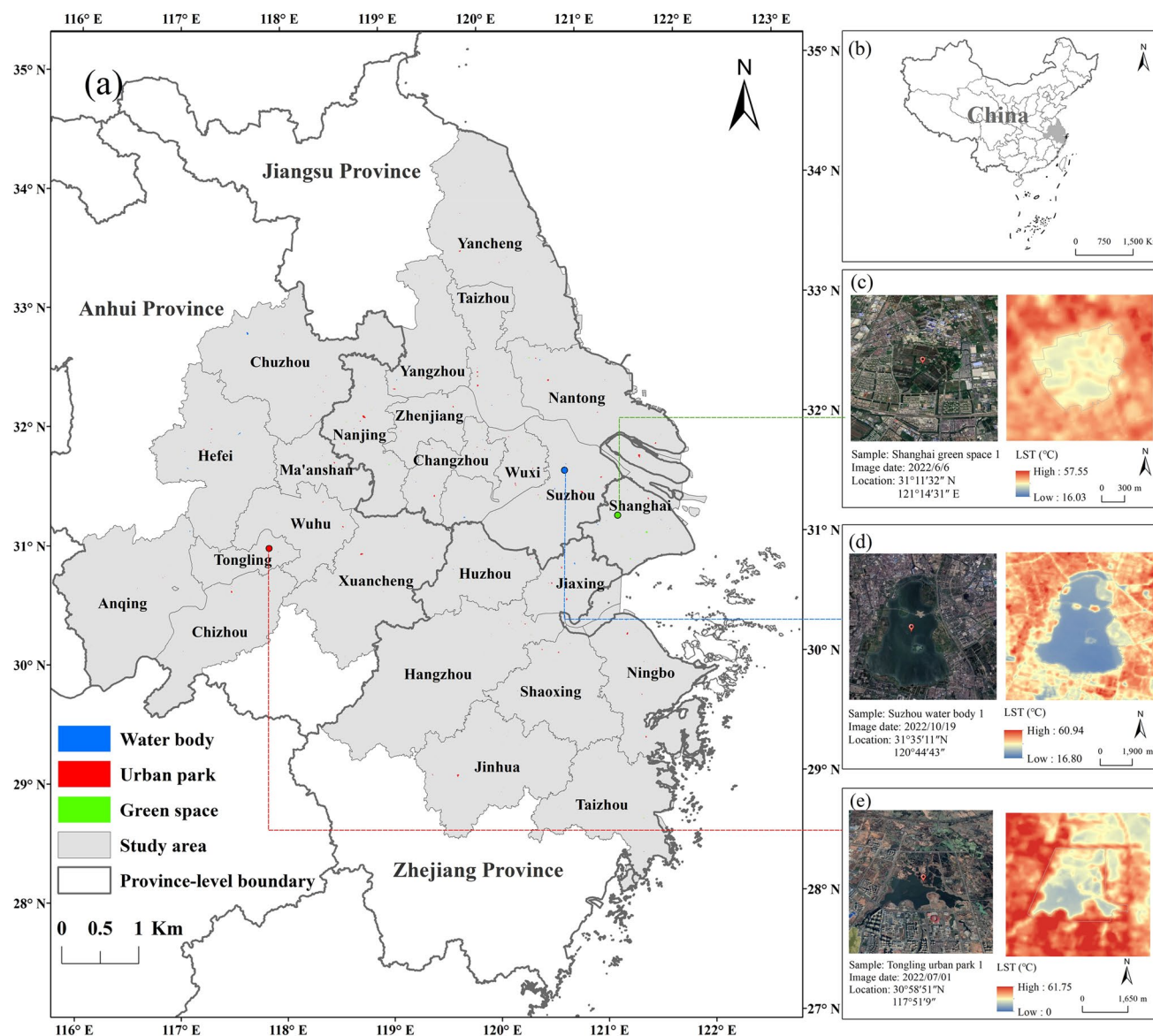
Fig. 1 The spatial distribution of different types of urban blue-green spaces in the YRD region

as an island city (Geng et al. 2022). This region falls within the subtropical monsoon climate zone, with an annual average temperature of 9.3 to 17.3 °C and precipitation of 804 to 2057 mm. Being one of the largest urban agglomerations in China, the YRD has experienced accelerated population growth and significant changes in its land surface, making it a highly representative region in terms of urbanization (Xiao et al. 2022). Further, municipalities in the YRD region have implemented ambitious policy measures to enhance urban greening and mitigate the thermal risks associated with urbanization.

Thirty-nine Landsat OLI 8/9 images were selected from the US Geological Survey (USGS) website (https://earth explorer.usgs.gov) to derive the LST pattern of each city,

quantify the cooling effect, and map the various land cover types (Supplementary Table 1). All selected images were cloud-free within the extent of the corresponding study city. Given the frequent occurrence of the UHI phenomenon during hot weather, image acquisition primarily focused on the period between June and September 2021. To mitigate the impacts of seasonal variation and ensure high image quality, images from adjacent years were also considered during data collection. Population counts sourced from WorldPop (https://www.worldpop.org/) and road network data from OpenStreetMap (https://www.openstreetmap. org) were also employed in this study. These datasets were utilized to obtain the population density and road network density in the YRD region, respectively.

The urban blue-green patch boundaries were delineated through artificial visual interpretation using a combination of land cover mapping and high-resolution remote sensing imagery. Four land cover types were mapped using the Support Vector Machine (SVM) method in ENVI 5.3: water bodies, green spaces, impervious surfaces, and other land cover types such as bare earth. The kappa coefficients of all classification results were consistently above 0.8. For accurate information retrieval, high-resolution Google Earth images captured closest to the Landsat image were used as a reference to identify sample patches for each city based on the results of land cover classification results. To ensure the applicability of the study results to urban regions, all blue-green patches were specifically selected within the urban extent that was dominated by impervious surfaces. Furthermore, the selected urban blue-green spaces adhered to the following criteria: (1) significant difference in patch area, (2) no adjacency to large blue-green landscapes, and (3) shared boundaries with impervious land cover (Peng et al. 2021; Zheng et al. 2022). Employing these criteria, five green spaces, water bodies, and urban parks were selected for each city in the YRD, resulting in a total of 375 samples in this study (Fig. 1c–e).

Land surface temperature retrieval

The YRD region is characterized by a humid and rainy climate with high atmospheric water vapor content during the summer season. Therefore, the radiative transfer equation (RTE), known for its highest accuracy in humid areas compared to other algorithms (Yu et al. 2017), was employed to derive the spatial pattern of LST. The RTE method can convert thermal radiance (L_λ) into the corresponding surface temperature (T_s). The values of downward radiance ($L\downarrow$), upward radiance ($L\uparrow$), and atmospheric transmittance (τ) are available on the NASA website (http://atmcorr.gsfc.nasa.gov/). By rearranging Eq. (1), the value of $B(T_s)$ can be calculated to retrieve the LST using Eq. (2) (Jimenez-Munoz et al. 2014). The thermal infrared radiation L_λ can be expressed as follows:

$$L_\lambda = \left[\varepsilon B\left(T_s\right) + (1 - \varepsilon)L\downarrow\right]\tau + L\uparrow \tag{1}$$

where ε represents the surface emissivity, $B(T_s)$ is the ground radiance, and the LST can be obtained by following Eq. (3):

$$B\left(T_s\right) = \left[L_\lambda - L\uparrow -\tau(1 - \varepsilon)L\downarrow\right]/\tau\varepsilon \tag{2}$$

$$T_s = K\_2/\ln\left[K\_1/B\left(T_s\right) + 1\right] \tag{3}$$

For the thermal infrared sensor of Landsat-8 OLI/TIRS, K_1 = 774.89 (mWm^{-2}sr^{-1}um^{-1}), K_2 = 1321.08 K.

Urban blue and green spaces cooling effect quantification

Previous studies have indicated a non-linear relationship between LST and distance, which can be described using a cubic polynomial function (Bowler et al. 2010; Park et al. 2019). As shown in Fig. 2, the cooling effect gradually diminishes until it disappears within a certain range, coinciding with the LST peak (T_L) at the first turning point. The distance from the patch boundary to this turning defines the maximum distance (L), indicating the extent that urban blue-green spaces can provide cooling. To explore the LST–distance relationship, a buffer zone width of 30 meters was selected to account for the resolution of the Landsat images. Considering the cooling extent of urban blue-green space is typically less than 900 m, various buffer zones (300, 600, and 900 m) were created for polynomial fitting, determining the most accurate LST–distance relationship ($f(x)$) (Du et al. 2016).

In this study, the cooling area (CA) and cooling efficiency (CE) were used to quantify the cooling effect of urban blue-green spaces from the maximum perspective, while the cooling intensity (CI) and cooling gradient (CG) were used to measure from the accumulative perspective (Du et al. 2022; Peng et al. 2021). Specifically, CA represents the largest area that can be cooled by urban blue-green spaces, deriving from the buffer area within the maximum cooling distance. CE refers to the ratio of the cooling area to the patch area. The urban blue-green landscape with high CE generally has stronger cooling performance per unit area, which means a more efficient cooling process.

CI represents the cumulative impact of each patch on the cooling process of the blue-green landscape. It is defined as the reduction in LST compared to the scenario without any landscape elements (Eq. 4). CG is expressed in Eq. (5) and reflects the accumulated reduction in LST over the cooling distance. A higher CG indicates a greater capacity for heat absorption and a more pronounced cooling sensation for residents.

$$CI = \frac{L \times T_L - \int_0^L f(x)\mathrm{d}x}{L \times T_L} \tag{4}$$

$$CG = \frac{L \times T_L - \int_0^L f(x)\mathrm{d}x}{L} \tag{5}$$

Dominant influencing factors identification

The potential factors influencing the cooling effect of urban blue-green spaces are identified in terms of both
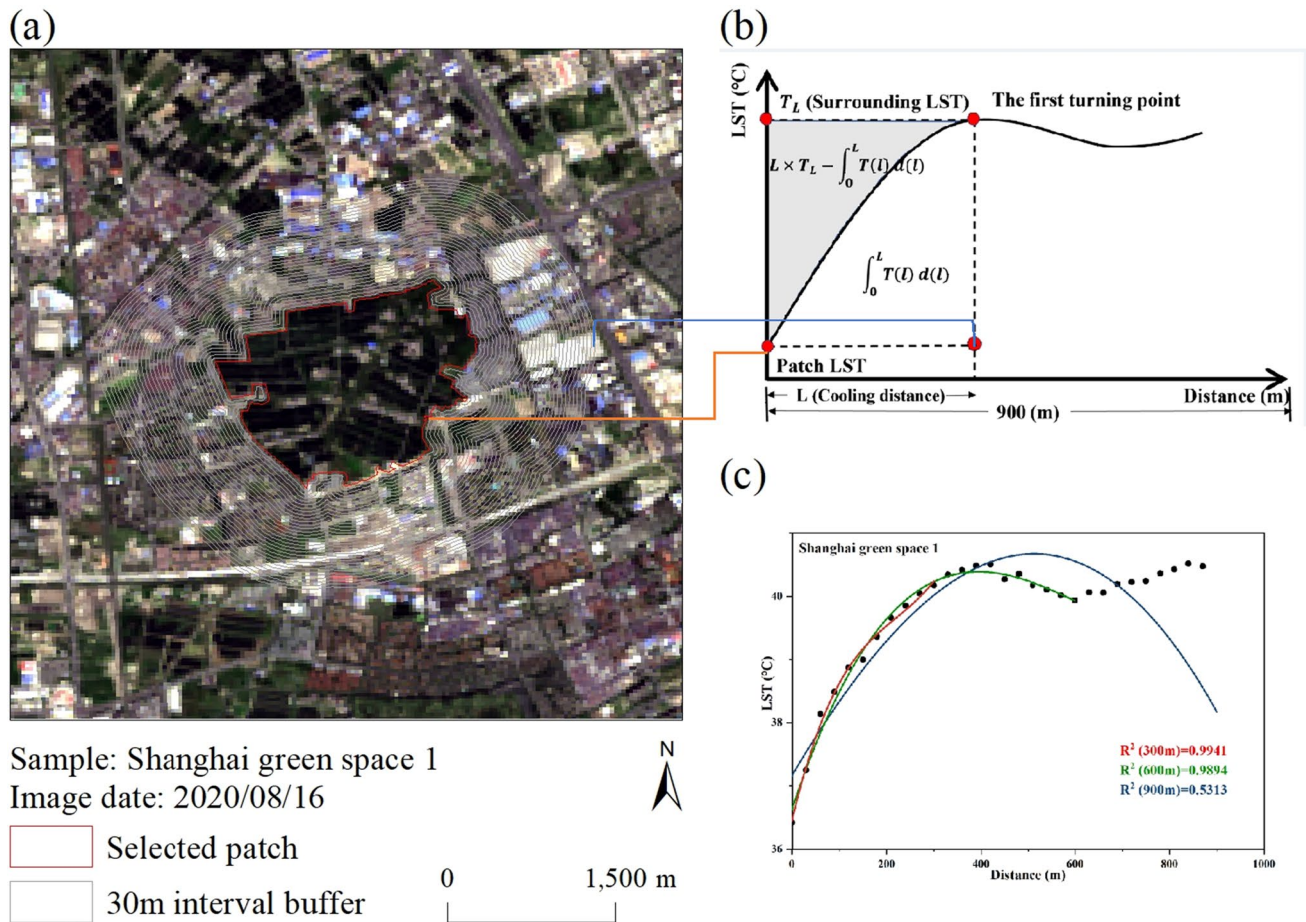
Fig. 2 Illustration of the LST change curve of the patch cooling process

internal and external factors in this study (Table 1). Internal factors refer to the landscape configuration and composition of each landscape patch, including patch area, perimeter, shape index (LSI), as well as the normalized

difference vegetation index (NDVI), modified normalized difference water index (MNDWI), and normalized difference impervious surface index (NDISI) (Xu 2010) within the selected patches. The first three metrics assess the

Table 1 Potential influencing factors on the cooling effect of urban blue-green spaces

Categories	Impact factors	Definition
Internal factors	LSTin	The average LST within a patch
	A	The area of a patch
	P	The perimeter of a patch
	LSI	The landscape shape index of a patch
	NDVIin	The proportion of vegetation in a patch
	MNDWIin	The proportion of water body in a patch
	NDISIin	The proportion of impervious surface in a patch
External factors	$T(L)$	The LST at the first turning point
	NDVIout	The proportion of vegetation in the buffer of a patch
	MNDWIout	The proportion of water body in the buffer of a patch
	NDISIout	The proportion of impervious surface in the buffer of a patch
	PD	The population density in the buffer of a patch
	RD	The road network density in the buffer of a patch

spatial configuration of analyzed patches, while the others describe their land surface coverage. External factors relate to the surrounding environment of sample patches, characterized by the NDVI, MNDWI, and NDISI within the CA of patches. Regarding the rapid urbanization process in the YRD region, people density (PD) and road density (RD) were developed as external factors to reflect the residential and traffic conditions of the surroundings (Xiao et al. 2023). In addition, the LSTin and T (L) were employed to quantify the temperature difference between the patches and their surrounding environment. Pearson's correlation analysis was used to determine the influencing factors among those potential factors, while multivariate stepwise regression analysis was employed to identify the dominant feature in the cooling process. Specifically, the dominant factors were determined as those with the highest contribution rate (Sun et al. 2018).

Results

Spatial heterogeneity of LST and the cooling effect

As depicted in Fig. 3a, the average LST in the YRD region was recorded at 35.15 °C. According to the distribution of LST, cities in the central, southeast, and northwest regions exhibited a more pronounced UHI effect compared to the northern and south-central counterparts. The high-temperature zones were mainly distributed along the Yangtze River, Hangzhou Bay, and Qiantang River, the most densely populated and well-connected areas. Specifically, commercial locales and dense logistics networks were susceptible to forming heat islands in central urban areas. Conversely, the low-temperature zones corresponded to vegetated areas and water bodies, such as urban parks, rivers, lakes, and other ecological infrastructure (Fig. 3b). Furthermore, most of the
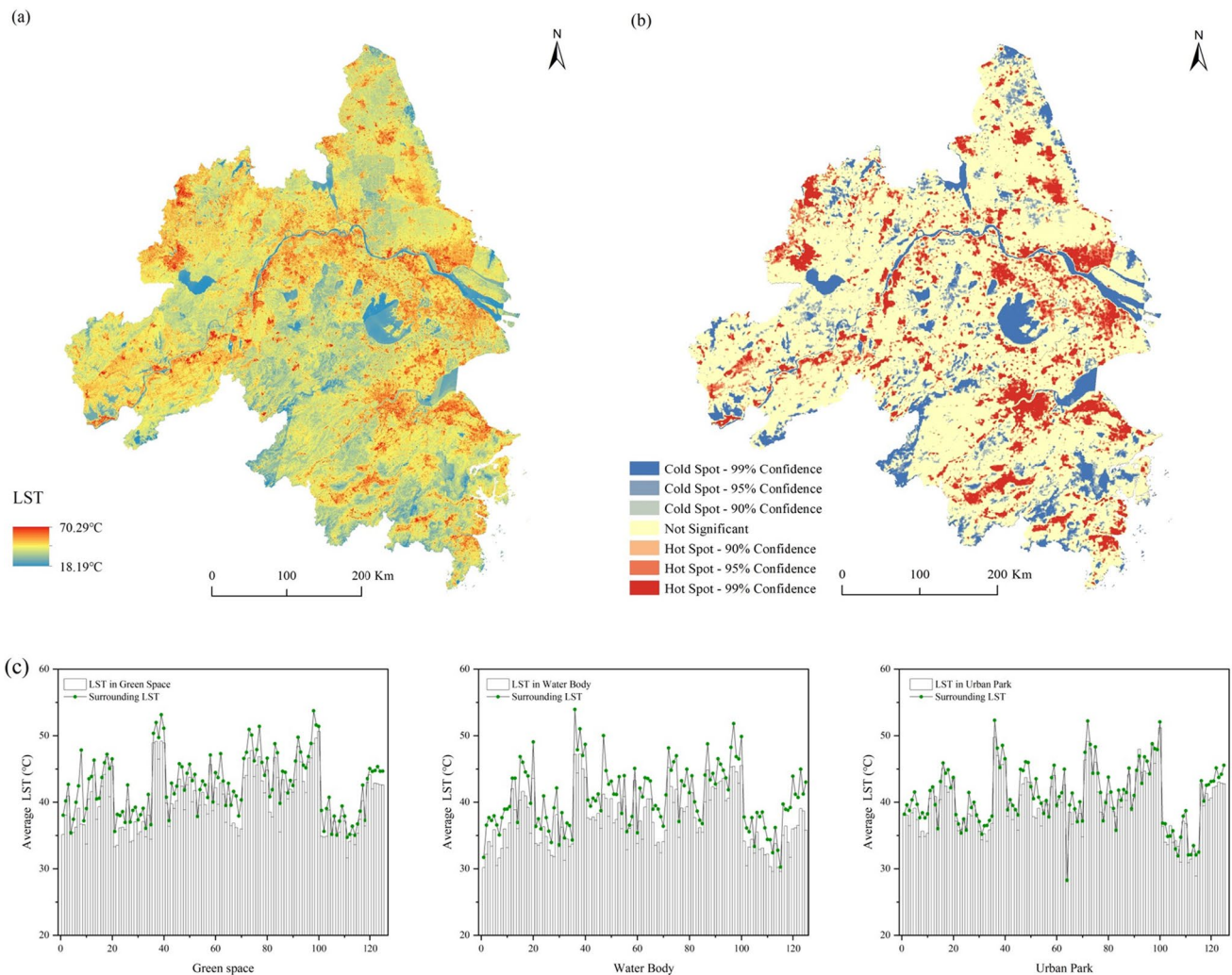

Fig. 3 Spatial pattern of **a** the LST and **b** the cold and hot spot areas in the YRD region; **c** average LST in patches and their surroundings

selected patches behaved at a lower temperature than their surrounding environments, suggesting an evident cooling effect provided by urban blue-green spaces (Fig. 3c).

Among all 375 analyzed blue-green spaces, the extracted samples ranged from 1.04 ha to 532.24 ha in area. The average CA, CE, CI, and CG values were 47.96 ha, 4.55, 0.02, and 0.99 °C, respectively. As depicted in Fig. 4, larger blue-green spaces tended to have higher CA, whereas smaller ones exhibited higher CE. It indicates that smaller blue-green spaces often have a more efficient cooling process in urban areas. Regarding spatial distribution, patches with high CI and CE were mainly located in the central and northern cities of the YRD region, concentrating in residential areas with high LST.

Cooling effect of urban blue-green spaces

There were 375 samples in the study region; the mean LST within the analyzed green spaces, water bodies, and urban parks was 40.24, 37.23, and 39.67 °C, respectively. The
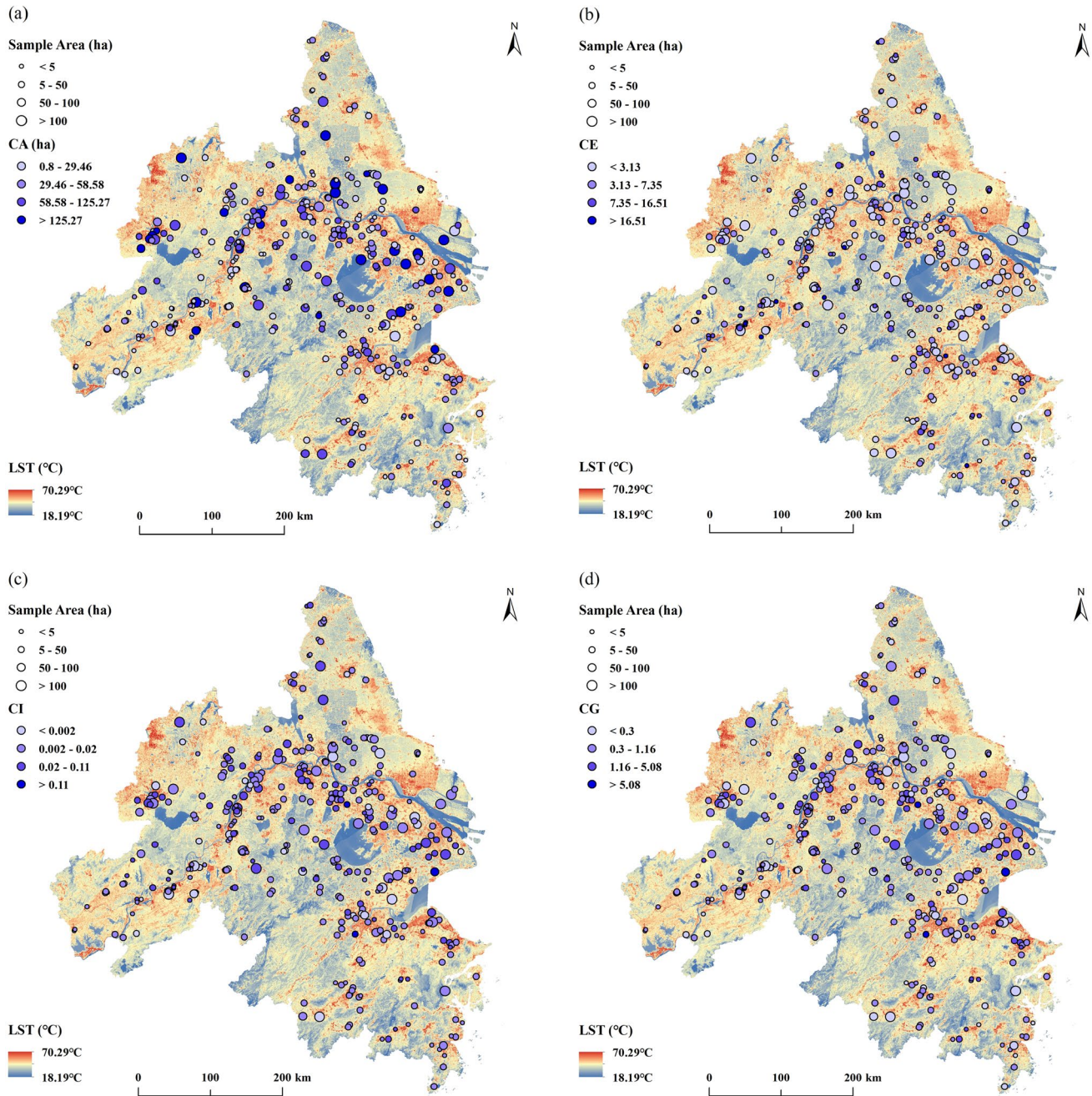

Fig. 4 The spatial pattern differences of the cooling effect in the YRD region

water bodies exhibited lower temperatures than other landscape types, indicating that blue landscapes had a stronger cooling effect in urban areas, creating prominent cold spots in the local thermal environment. Furthermore, comparing cooling indexes revealed significant variations in cooling performance among different landscape types.

As shown in Fig. 5, urban parks had the largest cooling area, averaging 56.44 ha, indicating that their cooling effect extended to a larger surrounding area. However, the water bodies had the highest values for CE, CI, and CG, followed by green spaces and urban parks. Further, the mean values of CA and CE exceeded the median values for all patch types, showing fluctuating cooling performance among urban blue-green spaces. Specifically, the CA of green spaces was significantly lower, with an average value of 34.40 ha, while CE, CI, and CG were relatively low at 4.52, 0.02, and 0.77, respectively. The lower deviation suggested less variation in the cooling effect within green landscape patches, indicating relatively consistent cooling performance across different regions. Considering water bodies, the mean values of CA, CE, CI, and CG were 53.03 ha, 6.88, 0.02, and 0.99, respectively, suggesting a better cooling performance of blue spaces from an accumulative perspective. For urban park patches, the mean values of CA, CE, CI, and CG were 56.44 ha, 2.23, 0.01, and 0.36, respectively. Not all analyzed urban parks exhibited a cooling effect. Among the 108 park samples with lower temperatures than the surroundings, most parks had a cooling effect over short distances, with a mean distance of 155.56 m, compared to 161.32 m and 190.93 m for green space and water bodies, respectively.

Identification of dominant factors influencing the cooling effect

Correlation analysis

As illustrated in Fig. 6, the results of Pearson's correlation analysis revealed diverse correlations among different types
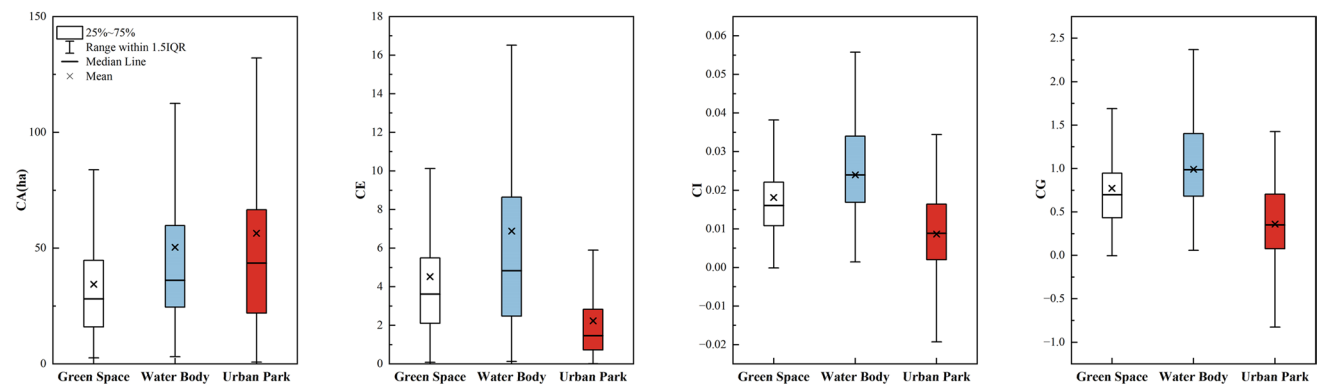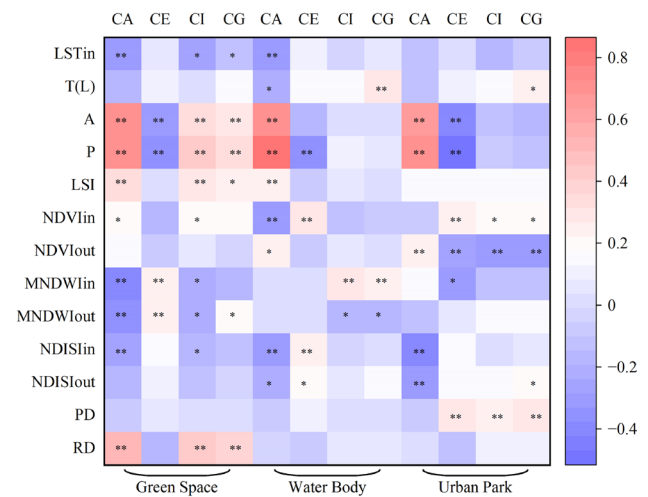

Fig. 6 Pearson's correlation between the cooling indexes and the influencing factors. Double (**) and single (*) asterisks indicate significant correlations at 0.01 and 0.05 level, respectively

of blue-green space patches. CA exhibited significant positive correlations with the patches' area and perimeter. However, CE (excluding water bodies) showed negative correlations with the patches' area and perimeter, indicating that patches with larger scales may enhance the cooling effect but result in fewer economic benefits. The landscape composition also demonstrated varying relationships with the cooling effect from a maximum perspective. In the case of green spaces, the proportion of blue landscape and impervious surfaces was significantly and negatively correlated with CA, while the ratio of blue landscape showed a positive correlation with CE. Regarding water bodies and urban parks, CA displayed diverse correlations with vegetation coverage within the patches and in the surroundings, suggesting that greater vegetation growth trends could improve the cooling effect in urban parks. Moreover, a significant negative correlation was observed between CA and the proportion of impervious surface, suggesting that an extensive artificial

Fig. 5 The differences in cooling effect among different types of urban blue-green spaces

surface was associated with weak cooling performance of blue-green spaces. Furthermore, it was noted that the overall correlation between CE and the influencing factors differed from the CA in the analyzed patches.

From an accumulative perspective, the CI of green space patches showed a positive correlation with landscape configuration but a weak negative correlation with landscape composition. Additionally, the results illustrated a significantly positive correlation between road density in the surrounding areas and both CI and CG in green landscapes, suggesting that an intensive traffic network was related to a stronger cooling effect. In the case of blue spaces, it was found that both CI and CG were related to the proportion of blue landscape. Furthermore, higher temperatures in the surrounding environment enhanced the CG of water bodies, implying that the water bodies could provide a stronger cooling effect during hot extremes. For urban parks, the NDVIout exhibited a significant negative correlation with CI and CG, indicating that the surrounding vegetation growth could weaken the cooling performance of urban parks. By contrast, population density displayed a positive correlation with the parks' cooling effect, suggesting that urban parks should be located in densely populated regions.

Regression analysis

Tables 2, 3, and 4 present the results of multiple stepwise regression analyses, highlighting the main influencing factors and their standardized beta coefficients for different types of landscapes. In green spaces, the patch perimeter emerged as the primary influencing factor from the maximum perspective, accounting for 53.6% and 11.9% of the variation in CA and CE (Table 2). This result suggests that larger green spaces exhibit a better cooling effect in their surrounding areas. While the descending temperature of patches contributes to the CA of green landscapes, it plays a minor role, explaining only 16.52% of the cooling effect. From an accumulative perspective, RD, LSI, MNDWIout, and LSTin were the main influencing factors, explaining 28.1% of the variation in CI. Similarly, RD, MNDWIout, and LSI were the main influencing factors for CG, indicating that the composition and spatial arrangement of surroundings significantly affect the cooling effect of green spaces. Furthermore, it was observed that the cooling effect of green spaces with complex shapes is better than those with simple shapes, which might be attributed to the enhanced connectivity with the surrounding areas.

Regarding water bodies, the patch perimeter, LSTin, and LSTout exhibited high correlations with CA, and the relative contribution of these factors accounted for 49.85, 27.71, and 22.44% of the overall impact on CA, respectively (Table 3). Compared to green spaces, blue spaces exhibited higher CA at higher surrounding temperatures. Patch perimeter and NDVIin were the main influencing factors for CE, suggesting that water bodies connected to green spaces have a greater cooling effect on the surroundings. From an accumulative perspective, MNDWIin was the primary influencing factor for CI and CG, although the explanation rate for CI was relatively low at 8%. This suggests that increased coverage of the blue landscape enhances the cooling effect

Table 2 Regression results with the influencing factors as the predictor variable and the cooling indexes as response variables in green spaces

Greenspace	Factors	Unstandardized coefficients		Standardized coefficients	T	P-value	R^2	Adjusted R^2	F ($p < 0.01$)	DW
		B	Std error	Beat						
CA	(Constant)	46.630	16.051	—	2.905	0.004	0.536	0.528	70.336	2.054
	P	12.436	1.152	0.687	10.797	0.000				
	LSTin	−0.815	0.383	−0.136	−2.130	0.035				
CE	(Constant)	6.022	0.493	—	12.216	0.000	0.119	0.112	16.611	1.797
	P	−0.906	0.222	−0.345	−4.076	0.000				
PCI	(Constant)	0.036	0.013	—	2.842	0.005	0.281	0.257	11.715	1.966
	RD	0.003	0.001	0.368	4.593	0.000				
	LSI	0.008	0.004	0.177	2.211	0.029				
	MNDWIout	0.035	0.013	0.209	2.663	0.009				
	LSTin	−0.001	0.000	−0.184	−2.285	0.024				
CG	(Constant)	0.599	0.280	—	2.142	0.034	0.201	0.181	10.156	1.996
	RD	0.138	0.034	0.340	4.086	0.000				
	MNDWIout	1.537	0.591	0.212	2.603	0.010				
	LSI	0.332	0.161	0.172	2.060	0.042				

When the DW value is close to 2, it indicates that there is no first-order autocorrelation in the model. *Std error* standard error *DW* Durbin–Watson test

Table 3 Regression results with the influencing factors as the predictor variable and the cooling indexes as response variables in water bodies

Waterbody	Factors	Unstandardized coefficients		Standardized coefficients	T	P-value	R^2	Adjusted R^2	F ($p < 0.01$)	DW
		B	Std error	Beat						
CA	(Constant)	535,046.571	209,383.900	—	2.555	0.012	0.778	0.772	141.076	2.238
	P	163,768.835	8654.986	0.833	18.922	0.000				
	LSTin	−56,312.730	14,309.183	−0.463	−3.935	0.000				
	$T(L)$	42,023.190	13,098.724	0.375	3.208	0.002				
CE	(Constant)	7.863	1.033	—	7.614	0.000	0.160	0.146	11.633	2.073
	P	−0.818	0.251	−0.288	−3.258	0.001				
	NDVIin	7.039	3.175	0.196	2.217	0.028				
CI	(Constant)	0.017	0.003	—	6.187	0.000	0.080	0.073	10.737	2.050
	MNDWIin	0.026	0.008	0.283	3.277	0.001				
CG	(Constant)	−1.781	0.653	—	−2.727	0.007	0.167	0.153	12.202	2.004
	$T(L)$	0.061	0.015	0.332	3.943	0.000				
	MNDWIin	1.139	0.310	0.309	3.670	0.000				

Table 4 Regression results with the influencing factors as the predictor variable and the cooling indexes as response variables in urban parks

Urban park	Factors	Unstandardized coefficients		Standardized coefficients	T	P-value	R^2	Adjusted R^2	F ($p < 0.01$)	DW
		B	Std error	Beat						
CA	(Constant)	25.291	10.639	—	2.377	0.019	0.487	0.478	57.876	2.082
	P	15.147	1.684	0.626	8.995	0.000				
	NDISIin	−48.823	21.708	−0.156	−2.249	0.026				
CE	(Constant)	2.988	0.419	—	7.127	0.000	0.322	0.305	19.148	1.868
	P	−0.433	0.087	−0.409	−4.982	0.000				
	PD	0.000277	0.000109	0.196	2.544	0.012				
	MNDWIin	−1.970	0.965	−0.163	−2.043	0.043				
CI	(Constant)	0.002	0.003	—	0.534	0.595	0.100	0.085	6.751	1.913
	PD	1.778 E-6	6.3184 E-7	0.244	2.814	0.006				
	NDVIin	0.012	0.006	0.172	1.991	0.049				
CG	(Constant)	−0.179	0.159	—	−1.124	0.263	0.145	0.124	6.840	1.970
	PD	7.337 E-5	0.000025	0.251	2.957	0.004				
	NDVIin	0.545	0.238	0.195	2.288	0.024				
	NDISIout	0.596	0.274	0.184	2.173	0.032				

in water bodies, but the dominant factor for CI remains relatively insignificant.

For urban parks, the perimeter and NDISIin were the main influencing factors for CA, explaining 48.7% of the variation (Table 4). Perimeter, PD, and MNDWIin were the dominant factors influencing CE, combined to explain 32.2% of the CE variation. This implies that the park land cover significantly impacts the cooling effect from a maximum perspective. From an accumulative perspective, PD and NDVIin were the main influencing factors for CI and CG, suggesting that increasing vegetation coverage within urban parks can lead to a more pronounced cooling experience for park visitors. Among the influencing factors, PD showed the highest standardized beta coefficient, indicating that urban parks located in densely populated areas exhibit a more intensive cooling process. NDISIout was only retained in CG, contributing 29.21%, implying that a higher coverage of impervious surfaces is associated with an enhanced heat absorption process.

Discussion

Quantify the cooling effect linking maximum and accumulative perspectives

Previous studies have investigated the cooling potential of different urban ecological spaces and identified their influencing factors (Geng et al. 2022; Tan et al. 2021; Yu et al. 2020; Zhou et al. 2022). Though recent studies have quantified the cooling effect from both maximum and accumulative perspectives, the analyzed objects were primarily restricted to urban parks (Du et al. 2022; Peng et al. 2021; Tian et al. 2023). This study adopted the maximum and accumulative perspectives to measure the cooling effect of urban blue-green spaces, directly affecting the cooling index values. From the maximum perspective, the water body exhibited the highest maximum cooling distance, averaging 190.93 m, followed by green spaces and urban parks at 161.32 m and 155.56 m, respectively. Consistent with existing studies (Qiu et al. 2023; Yang et al. 2020), water bodies showed greater cooling extent than other landscape types. The average CE values for green spaces, water bodies, and urban parks were 4.52, 6.88, and 2.23, respectively. Conversely, Pang et al. (2022) argued that green spaces containing water bodies are more efficient in mitigating the UHI in colder regions, potentially due to different urban climate contexts. Since urban parks typically integrate green and blue spaces, a park design encompassing a broader coverage of blue infrastructure may effectively enhance the cooling capacity of urban parks.

From the accumulative perspective, water bodies exhibited higher mean values of both the CI and CG, implying a stronger cooling effect in blue spaces. Several studies have supported that water bodies have a relatively more effective cooling process compared to green spaces, attributed to their better evaporation abilities (Gunawardena et al. 2017; Zhou et al. 2021a). Conversely, the research conducted by Yu et al. (2017) highlighted that connected blue-green spaces and tree-based green spaces have higher cooling effects in terms of intensity. In this study, the relatively weaker cooling effect observed in urban parks may be attributed to the combined effects of various land use types in both the patches and their surroundings, which could offset the heat absorption by blue-green spaces (Wu et al. 2020; Zhou et al. 2021b). In comparison to existing findings (Qiu et al. 2023; Yu et al. 2018a), the CI values excluding accumulative impacts in this study are generally lower, implying that quantification from the maximum perspective tends to overestimate cooling intensity (Du et al. 2022). These findings suggest that the cooling effect of urban ecological spaces is influenced by spatial continuity in practice, while the cooling capacity of water bodies is less affected by their spatial context.

Comparing the spatial distribution of the cooling effect among three landscape categories, the maximum cooling indicators were primarily associated with specific space categories, while the accumulative cooling indicators exhibited distinct spatial characteristics (Fig. 7). Aligned with the findings of Dong et al. (2022) and Zhou et al. (2021b), patches with high CI were mainly observed along the Yangtze River and the East Sea coast. These are also home to economically developed cities such as Shanghai, Wuxi, Suzhou, and Nanjing, implying the presence of cooling inequities. Specifically, urban parks exhibited the lowest cooling effects from accumulative perspectives, clustering in the central areas of the YRD region, thereby confirming a positive correlation between the cooling effect and population density (Du et al. 2022). Green spaces, on the other hand, demonstrated a moderate cooling performance and were primarily distributed along the Yangtze River and near water resources.
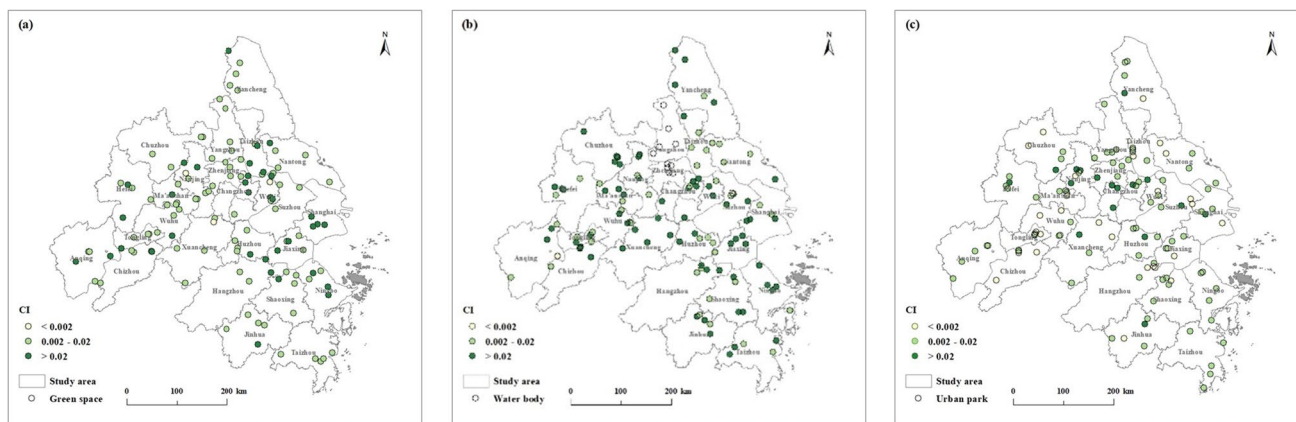

Fig. 7 Spatial distribution of CI of **a** green spaces, **b** water bodies, and **c** urban parks

Liu et al. (2022b) also noted that green spaces adjacent to a high proportion of water area exhibited higher CI, offering a strategy to mitigate the UHI effect by implementing green landscapes. While water bodies comprised more patches with a high CI, they were mainly distributed south of the Yangtze River, implying that the presence of the rich water system and a humid environment are related to the cooling effect of ecological spaces to some extent.

The dominant factors affecting the cooling effect

This study investigates the relationship between the cooling effect of urban blue-green spaces and their influencing factors in the YRD region, which varied significantly across different types of patches. While numerous factors influencing the cooling effect have been studied within specific landscapes, the impact of these factors on the cooling effect among different landscape categories remains to be determined. In accordance with previous research from the maximum perspective (Gilbert et al. 2016; Wang et al. 2022b; Xie and Li 2020), landscape configuration factors (patch area, perimeter, and shape) are widely acknowledged as essential factors influencing the cooling effect, regardless of the landscape category. Wang et al. (2022a) have found that larger areas contribute to a more effective cooling effect in green spaces across different climate zones globally. Similarly, Yang et al. (2020) have suggested that larger parks, typically characterized by longer circumferences, provide greater natural coverage and a larger shading area, thereby benefiting the cooling effect through transpiration. This study further confirms that patch perimeter is the dominant influencing factor for CA, and its importance remains consistent across all landscape categories. Moreover, patches with higher temperatures exhibit a smaller cooling extent for green spaces and water bodies than those with relatively lower temperatures, which may be due to increased solar radiation absorption (Ampatzidis and Kershaw 2020).

In the YRD region, CE is primarily regulated by patch perimeter, contributing more than 50% of all influencing factors. For water bodies, the vegetation coverage of patches is the second most crucial factor for CE after patch perimeter. Similarly, a case study conducted in Suzhou, China, found that an integrated blue and green space patch demonstrates a better cooling effect than a similarly sized patch with a single landscape, implying that the combined blue-green landscapes might be more efficient in the cooling process (Zhou et al. 2022). Compared to other landscape categories, the surrounding population strongly impacts the CE of urban parks. This finding aligns with the research conducted in Shenzhen, suggesting that smaller parks in densely populated areas tend to have the highest CE (Du et al. 2022). Additionally, the proportion of water bodies within parks

plays an essential role in CE, as supposed by previous research (Zheng et al. 2022).

From an accumulative perspective, both the area and perimeter did not pass the significance test within water bodies and urban parks, in contrast to the findings for the maximum cooling indexes (Gao et al. 2022; Geng et al. 2022; Li et al. 2022). This result implies that the impact of spatial continuity may be more pronounced for these two patch types. Specifically, the cooling performance of green spaces is significantly associated with landscape composition and the surrounding land use (Geng et al. 2022; Xiao et al. 2023). Among all factors, RD has the highest contribution rate in green spaces and is identified as the dominant factor for CI and CG in urban green landscapes. In contrast to the cooling performance of urban parks (Geng et al. 2022; Meng et al. 2018), this study reveals that green spaces located in areas with dense road networks exhibit a stronger cooling effect attributed to their distinct landscape category and geographical locations. Similarly, Wang et al. (2022b) reveal that anthropogenic factors reflecting urbanization have a positive impact on the cooling effect of green space in temperate and continual cities, indicating that highly urbanized regions experience a greater cooling effect from urban greening. Additionally, the patch shape of green space patches only plays a significant role in the cooling process, suggesting that optimal patch complexity in green landscapes should be considered in planning. However, a review by Yu et al. (2015) concluded that the effect of shape on cooling performance varies among scholars. One reason for this variation is the different methods used to determine shape index, and in this study, the LSI was positively correlated with the cooling effect, supporting the previous findings (Fan et al. 2019; Wang et al. 2022a).

Given the high heat capacity and evaporation rate of water, water bodies are generally accepted as vital landscape elements in alleviating high temperatures (Montazeri et al. 2017; Weng et al. 2011). The extent of blue landscape coverage and the surrounding temperature significantly impact the CI and CG of urban water bodies. Specifically, MNDWIin emerges as the sole driving factor for CI. Relevant studies, such as Yang et al. (2020), have highlighted the negative correlation between MNDWI and LST, whereas high temperatures may interact with high air humidity. Yu et al. (2015) have also suggested that increased humidity could diminish the thermal comfort experience for visitors around water bodies, thus corroborating the results of this study. The evaporation from water bodies lowers temperatures while increasing humidity in the surroundings, making it essential for urban managers to consider the number and placement of blue landscape patches to balance the cooling effects and the thermal comfort of residents. Additionally, the surrounding temperature is detected to be a driving factor for CG in water bodies, aligning with recent conclusions (Yang et al.

2020), indicating the significance of background temperature in influencing the cooling effect. For instance, Wang et al. (2022b) and Yang et al. (2020) have revealed that water bodies may exert a warming effect during nighttime and the end of summer, attributed to the absorption capacity of water bodies and the reduction of the LST gradient between the patch and its surrounding environment.

Urban parks typically exhibit a noticeable cool island effect due to the concentration of blue-green spaces in urban areas (Yu et al. 2018b). However, it should be noted that 17 parks showed a UHI effect with higher LST compared to their surroundings. The results confirm that these parks are mainly located in cities with higher water coverage and mountain terrain, such as Suzhou, Hangzhou, and Xuancheng. Therefore, the cooling capacity of parks is likely sensitive to landscape configuration. In line with related research (Gao et al. 2022; Tian et al. 2023; Vaz Monteiro et al. 2016), vegetation coverage plays a crucial role in both the CE and CG of urban parks, implying that increasing green landscapes to enhance the cooling effect of parks would be highly effective in the YRD region. Furthermore, PD shows the highest contribution rate among all factors and is identified as the dominant factor in the cooling process of parks. Research by Du et al. (2022) proposes prioritizing small-scale parks in densely populated areas to maximize the cooling effect without available urban spaces. Rapid land sprawl of built-up areas can also accommodate industries, infrastructures, and service facilities, attracting a more extensive working population and resulting in higher LST values (Rao et al. 2021; Xiao et al. 2022). Similarly, this study confirms that NDISIout is one of the driving factors affecting CG in urban parks. By clarifying the dominant factors influencing the cooling effect across various urban ecological spaces, these results offer valuable insights for ecological design and management in urban areas, assisting city planners in incorporating cooling services into the urban landscape design.

Improvement of the cooling effect in urban design and management

Blue-green spaces are considered crucial components that provide many ecosystem services within urban areas, including temperature regulation, air quality improvement, pollution reduction, and the essential cooling effect (Asgarian et al. 2015; Sun and Chen 2017). The findings regarding the influence on the cooling performance of urban blue-green spaces from multiple perspectives have significant implications for urban space planning and management in response to climate change. Consistent with the previous research, water bodies generally demonstrate superior cooling performance compared to green spaces and urban parks in urban areas (Li et al. 2022; Peng et al. 2020). However, it is

essential to exercise caution when considering simply adding blue space patches to enhance the cooling effect based solely on this statement. With sufficient land, resorting to water resources and integrating urban blue and green infrastructures can effectively enhance the accumulative cooling effect (Du et al. 2022). Meanwhile, due to the scarcity of space in cities, particularly in metropolitan areas, planning policies should be tailored to align with the unique characteristics of each location (Liu et al. 2022a).

Four cooling indices were utilized in this study to measure the cooling capacity of urban green spaces, water bodies, and urban parks. Investigating the influences of various factors on these cooling indices provides a pathway to optimize the cooling effect by adjusting the urban landscape pattern. For instance, in commercial office areas with high cooling demand and limited space, a small-sized water body can generate a cooling effect comparable to that of a larger landscape patch. However, a larger park is more suitable when the aim is to benefit a broader area and more residents ecologically. Considering the close relationship between NDVIin and the park cooling effect, increasing the proportion of vegetation within urban parks is highly effective in the YRD regions. In addition, urban parks are preferred when mitigating heat islands in densely populated areas with high human activities. Furthermore, urban parks contribute to environmental sustainability and enhance the well-being of visitors through recreational opportunities, psychological benefits, and improved quality of life (Brown et al. 2014). Therefore, landscape planning and management should consider not only the purpose of environmental sustainability but also the recreational and leisure needs of the local population. Studies have highlighted that urban green spaces are more prominent in highly urbanized areas, which aligns with the findings of this study (Wang et al. 2022a). Correspondingly, irregulated-shaped green spaces are recommended in urban areas with dense road networks. Moreover, strategies to improve heat exchange, such as connecting with small-sized water bodies and creating vegetation channels, have proven effective in green spaces.

Several studies have explored the area threshold interval of urban blue-green spaces, indicating that the cooling extent is not infinite (Fan et al. 2019; Peng et al. 2021; Yu et al. 2020). Figure 8 shows that CA gradually decreases as the area increases to a certain threshold. The results reveal that the threshold area for green spaces, water bodies, and urban parks is 108.65 ha, 269.03 ha, and 229.56 ha, respectively. This suggests that a smaller area is sufficient for optimal cooling in green spaces. Additionally, research has indicated that underdeveloped regions face a higher risk of extreme heat, while economically developed regions tend to experience a stronger cooling effect from green space, exacerbating thermal comfort disparities among global cities (Dong et al. 2022; Wang et al.
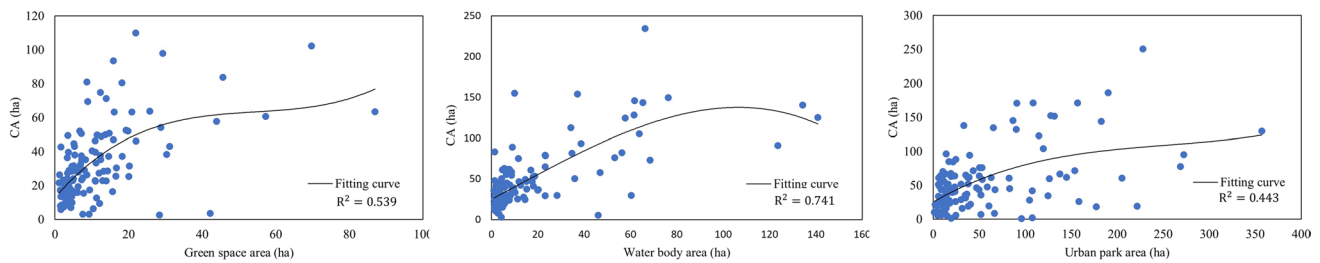
Fig. 8 The relationship between CA and the patch area in different types of blue-green spaces

2022b). Therefore, urban green spaces may be more suitable for economically underdeveloped areas with a high demand for cooling. In conclusion, landscape planning and management should consider the cooling demand of citizens and the geographical characteristics of different regions to achieve an appropriate match.

Limitations and prospects

Several limitations should be acknowledged. Firstly, the utilization of multi-temporal remote sensing images, constrained by the acquisition of Landsat images, may impact the consistency of LST across different patches and potentially affect the accuracy of the results (Geng et al. 2022). Additionally, the native resolution of the thermal infrared sensor in Landsat 8 is 100 m, whereas the buffer zones analysis was conducted using the 30-m Landsat standard product. Therefore, future research should prioritize improving the LST data's spatial and temporal resolution. Secondly, the findings have revealed that the dominant factors varied among different ecological patches in the YRD region. However, as a complex open system, the city shows a nonlinear and high uncertainty (Qian et al. 1993). In addition, the contribution of influencing factors to the cooling performance of water bodies is relatively limited in this study. This suggests the need for further investigation into potential influencing factors, particularly the anthropogenic impact on the cooling effect of blue spaces, to enhance the understanding of urban planning. Finally, this study was conducted only during specific seasons and contexts, which may restrict the generalizability of the cooling effect across multi-city combinations and different climatic backgrounds. Therefore, it is essential to explore diurnal dynamics and conduct seasonal comparisons to understand the cooling features of urban landscapes comprehensively. Additionally, investigating the cooling effect of various landscape categories in different climate zones and contexts is necessary to gain insights into the cooling effect from the city level to a global scale.

Conclusions

This research quantified the cooling effect of green spaces, water bodies, and urban parks in the YRD region from both maximum and accumulative perspectives. It was revealed that water bodies possess the most substantial overall cooling capacity among urban blue-green spaces, while urban parks of the same size can cool a larger surrounding area. The relationship between influencing factors and blue-green space cooling effects was assessed. From the maximum perspective, the patch perimeter had the most significant impact on the cooling effect in the YRD region. From the accumulative perspective, the dominant factor varied across different landscape types. Specifically, the cooling effect of green spaces exhibited significant correlations with road density and the proportion of water bodies. Similarly, the extent of blue spaces contributed most to the cooling capacity of water bodies. Urban parks with extensive vegetation cover and those situated in densely populated areas demonstrated better cooling performance, indicating the effectiveness of park construction in enhancing thermal comfort for residents. These results can expand knowledge on the cooling effects and provide valuable information for urban planning and management in comparable cities to a certain extent.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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