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The influence of local background climate on the dominant factors and threshold-size of the cooling effect of urban parks

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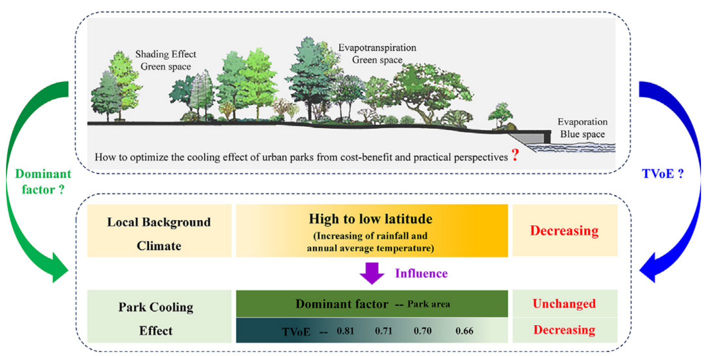
HIGHLIGHTS

- Urban parks at low latitudes have a greater cooling effect.
- Park area is the dominant factor of PCE under different local background climates.
- Water bodies play a more significant role in PCE in high latitudes, dry areas.
- The TVoE of urban parks decreased with decreasing latitude.

GRAPHICAL ABSTRACT



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ABSTRACT

Urban parks can mitigate the urban heat island (UHI) by creating microclimates that lower in temperature than their surroundings, which are known as park cooling effect (PCE). The local background climate has a significant impact on the PCE, however the dominant factors and threshold value of efficiency (TVoE) of the PCE under different local background climates are still uncertain. Here, we selected 207 urban parks in 27 cities in East China with four different local background climates, warm temperate sub-humid monsoon (WTC), northern subtropical sub-humid monsoon (NSC), northern subtropical humid monsoon (NHC), and middle subtropical humid monsoon climate (MSC), for comparative studies. The relative contributions of multi-influencing factors to the PCE and TVoE of urban parks were quantified through a multivariate stepwise regression model and curve fitting. The results show that: (1) PCE increases from WTC, NSC, NHC to MSC, and urban parks at low latitudes have a greater cooling effect in general than those at high latitudes; (2) the area of the park is the dominant factor of PCE under four different local background climates (the explanation rate exceeds 50%) and water bodies within urban parks play a more significant role in the cooling effect in high latitudes, dry areas; (3) the TVoE of park on WTC, NSC, NHC, and MSC are 0.81, 0.71, 0.70, and 0.66 ha, respectively, revealing that the background climate significantly affects the TVoE. These findings are essential to decision-makers and can provide actionable knowledge for climate adaptation planning on a regional (climate) scale.

1. Introduction

Climate change and rapid urbanization have exacerbated the urban heat island (UHI) effect (Oke, 1982; Stewart and Oke, 2012; Zhao et al., 2014) and have caused several undesirable environmental changes and adverse effects, such as impairing air quality, increasing the cooling energy consumption, and compromising the health of urban residents (Buchin et al., 2016; Li et al., 2019; Ulpiani, 2020; Voogt and Oke, 2003). Therefore, reducing the UHI effect and enhancing the resilience of urban areas has received a lot of attention (Estoque et al., 2016; Norton et al., 2015; Santamouris, 2014; Zhou et al., 2011). Measures such as replacing building materials and building green roofs and other urban green infrastructure have been studied to alleviate the UHI effect (Akbari and Kolokotsa, 2016;

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Santamouris, 2013; Zhang et al., 2017). In particular, urban parks are a promising measure to combat the UHI effect because they are cost-effective, environmentally friendly, and politically acceptable way (Aflaki et al., 2016; Gunawardena et al., 2017; Yu et al., 2020). Many studies have found that urban parks are 1–2 °C, or even 5–7 °C, cooler than their surroundings, forming a "park cool island" (Feyisa et al., 2014; Gunawardena et al., 2017; Jaganmohan et al., 2016; Oliveira et al., 2011; Peng et al., 2021). Hence, the park cooling effect (PCE) is considered essential for mitigating UHI on both local and global scales (Algretawee et al., 2019; Lee et al., 2016; Oke et al., 2017).

Previous studies have mainly focused on the definition and quantification of the cooling effect of blue-green space (Alexander and Wu, 2010; Jaffal et al., 2012; Leuzinger et al., 2010; Ng et al., 2012), and the relationship between PCE and influencing factors has been intensively investigated at multiple scales (Gillner et al., 2015; Hunter et al., 2015; Masoudi and Tan, 2019; Peng et al., 2018). PCE is mainly influenced by park characteristics (e.g., plant individual, community and landscape levels), park surrounding environment (e.g., biophysical characteristics and socio-economic characters), and local background climate (e.g., climate zone and latitudes) (Algretawee et al., 2019; Gunawardena et al., 2017; Rahman et al., 2018; Yu et al., 2018). It should be noted that these studies mainly concentrate on the correlation analysis between PCE and partial influencing factors (Amani et al., 2018; Du et al., 2017; Jaganmohan et al., 2016). For example, previous studies have shown that plant species composition and community structure differ significantly in their ability to affect the surrounding thermal environment (Feyisa et al., 2014; Gillner et al., 2015). Landscape composition and configuration metrics, such as landscape shape index (LSI) (Peng et al., 2020) and fractal dimension (FRAC) (Fan et al., 2019), account for great variability in PCE. The surrounding environment, such as impervious surface index, nighttime light index, and road density, have also been confirmed to be related to PCE (Algretawee et al., 2019; Farshid et al., 2019; Jérémy et al., 2018). These studies have provided a better understanding of PCE and have furthered the knowledge for optimizing the design of urban parks (Mohajerani et al., 2017; Yu et al., 2017). However, the identification of dominant factors and the independent contributions of multiple factors to PCE, which are critical in urban park design, are still less understood, especially when not all influencing factors can be considered simultaneously (Oliveira et al., 2011; Park et al., 2019).

Although the contribution of the local background climate to PCE has been studied, there is no consensus on the contributions of these factors (i.e., latitudes and climate zones) (Yu et al., 2020). First, previous studies demonstrated that local climate background conditions can significantly affect the PCE (Bowler, 2010; Gunawardena et al., 2017; Yang et al., 2020), and urban parks have different cooling intensities in various local background climates, such as the savanna climate (Mexico City, Mexico) (Jauregui, 1990) and temperate maritime climate (Goteborg, Sweden) (Konarska et al., 2016). The cooling effect of urban green vegetation is lower in cities with high relative humidity in both temperate monsoon and Mediterranean climates (Yu et al., 2018). Second, the local background climate can also affect the factors influencing PCE. For instance, in plateaus, the cooling effect is mainly determined by the species groups, canopy cover, size, and shape of parks (Addis Ababa, Ethiopia) (Feyisa et al., 2014). In addition, the patch size of water bodies in parks was found to have the largest contribution to the cooling intensity in subtropical monsoon climates (Peng et al., 2020). In the Mediterranean climate, green spaces with a higher density of trees were more efficient in delivering the cooling effect (Grilo et al., 2020).

Previous studies have indicated that there is a non-linear relationship between park area and cooling intensity (Du et al., 2016; Jaganmohan et al., 2016; Monteiro et al., 2016; Ru et al., 2007). Thus, the concept of the threshold value of efficiency (TVoE) was proposed from the perspectives of "law of diminishing marginal utility" (Yu et al., 2017). This concept suggests that there is trade-off between blue-green space size and cooling effects in the cost-benefit principle (Peng et al., 2020; Yang et al., 2020). Specifically, in terms of the patch size, the blue-green space needs a minimum value to maintain the cooling effects; however, when it exceeds the marginal utility, the cooling efficiency decreases (Yu et al., 2017). The TVoE is critical in landscape planning and management in terms of the blue-green system, and has emerged as an urgent topic (Yu et al., 2021). The local background climate has been verified to be significantly correlated with the TVoE (Fan et al., 2019; Yu et al., 2018). For example, the TVoE of tree-covered green space is nearly 0.5 ha in both temperate monsoon and Mediterranean climates (Yu et al., 2018). Peng et al. (2020) showed that the TVoE of waterbody patches ranges from 0.49–0.70 ha in subtropical monsoon climates. Moreover, the seasonal changes could also affect the TVoE of blue-green space in temperate marine climates (Copenhagen) (Yang et al., 2020).

In the existing literature, attempts have been made on PCE measurement, various influencing factors analysis, and TVoE quantification, and most of these studies are specific-case-based (Yu et al., 2020). The dominant factors of PCE have not yet been identified, especially across different local background climates (Feyisa et al., 2014). Similarly, the effect of the local background climate on the TVoE of urban parks is still unclear and requires further research. Therefore, studies involving more sampled parks with different local background climates are vital for providing more generalizable conclusions. To address these insufficiencies, we selected 207 urban parks in 27 cities with four different local background climates in East China for a comparative studies. The specific objectives of this study are as follows: (1) to identify the dominant factors and their relative contribution to PCE in different local background climates; (2) to determine how the local background climate affect the TVoE of urban parks; (3) and to propose specific and actionable suggestions for urban park planning for UHI mitigation on a regional scale.

2. Materials and methods

2.1. Study area and data source

2.1.1. Study area

East China is a region with various climate zones, and rapid urbanization has led to serious UHI problems, especially in Shanghai, Anhui Province, Jiangsu Province and Zhejiang Province. Mitigation strategy of UHI is urgent in this region. Therefore, the region is suitable for us to explore how local background climate influence the dominant factors and threshold-size of the cooling effect of urban parks. Then several criterions are considered in selecting cities and urban parks to ensure our study more reasonable. For example, Zhoushan city in Zhejiang Province is an island city and has relatively unique climate characteristics, and therefore was removed from the study area. Moreover, to exclude the disturbance of the cooling effect from other urban green infrastructure (UGI), the selected urban parks should keep a certain distance from other landscapes, such as rivers, reservoirs, and mountains, etc. Finally, 207 urban parks in 27 cities were selected, including Shanghai, nine cities in Anhui Province, ten cities in Jiangsu Province, and seven cities in Zhejiang Province (Fig. 1). The local background climate of the 27 cities was an essential prerequisite for our study, however there were no distinct boundaries of climate zones among these cities. Therefore, based on the climatic regionalization of China (Xu, 2018), two values for climate regionalization (i.e., mean annual precipitation and average temperature) were considered to classify the 27 cities into four different local background climates by cluster analysis (Yu et al., 2017; Zheng et al., 2010) (Supplementary Tables 1, 2 and Supplementary Fig. 1). In general, the latitude of four climate zones decreased successively (Fig. 1). From north to south, the zones were: warm temperate sub-humid monsoon climate (WTC), northern subtropical sub-humid monsoon climate (NSC), northern subtropical humid monsoon climate (NHC) and middle subtropical humid monsoon climate (MSC) (Supplementary Table 3).

2.1.2. Data source

To obtain high-accuracy data, in this study, the boundary and land cover of urban parks were identified and digitized via artificial visual interpretation from high-spatial-resolution Google Earth images from 2017. To

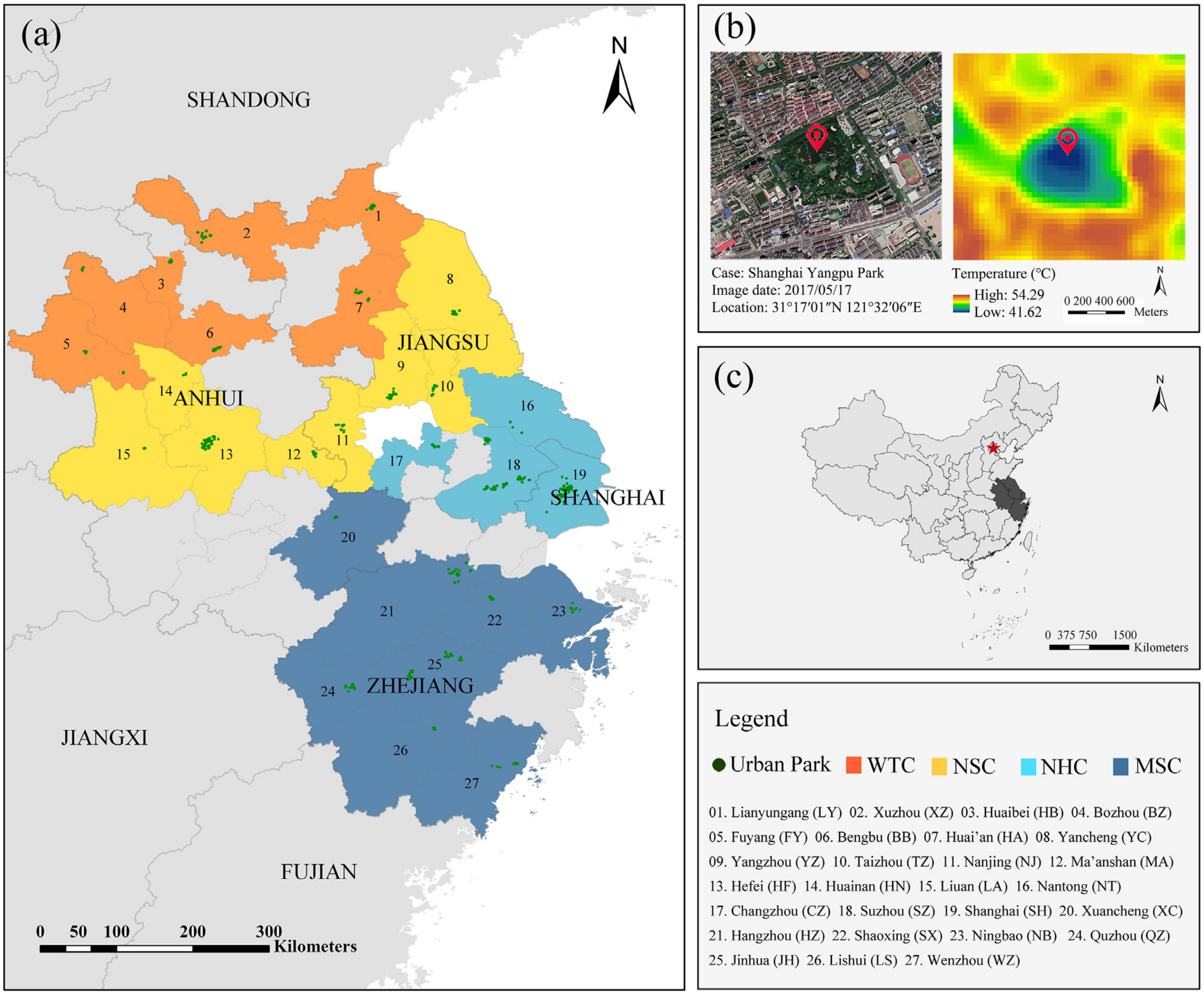

Fig. 1. The study area and its climatic regionalization. (a) 207 selected urban parks in 27 cities with four different local background climates in the East China, (b) one of the 207 selected urban parks (i.e. Yangpu Park in Shanghai) and (c) location of the study area in China.

avoid uncertainty or error, we ensured that the Landsat 8 OLI/TIRS images used for land surface temperature (LST) were taken close to the dates of the Google Earth images (Wu et al., 2019). Four types of land cover were mapped, that is, artificial surfaces, trees, grassland, and water body. Furthermore, the shape files were geo-referenced and projected with WGS_1984_UTM_Zone_51N and the topology rule was examined based on ArcGIS 10.2. The areas of the 207 urban parks ranged from 0.2–94.0 ha, mainly concentrated in the 1.0–5.0 ha range, however with an average value of 6.74 ha (Supplementary Fig. 2).

The Landsat-8 TIRS is the newest thermal infrared sensor used by the NASA Landsat project. It provides two adjacent thermal bands (10 μm and 12 μm) which is ideal for retrieving the LST (Jimenez et al., 2014). Fourteen Landsat 8 OLI/TIRS images from summer of 2016 and 2017 were obtained from the Geospatial Data Cloud (http://www.gscloud.cn/) (Supplementary Table 4). To minimize the impact of weather conditions on the PCE, the specific day of remote sensing image acquisition was sunny, with a wind velocity less than 4 m/s (Peng et al., 2021). Land cover, road density, and point of interest (POI) data (i.e., residential area and commercial buildings) within a 1 km buffer of park boundaries were also identified to explore the influence of park surrounding environment on PCE (Jérémy et al., 2018) (Supplementary Table 5; Supplementary Fig. 3).

2.2. Land surface temperature (LST) retrieval

Previous studies have proved that the radiative transfer equation (RTE) proposed by Jimenez et al. (2014) has the highest accuracy for LST retrieval (Yu et al., 2014). Therefore, the RTE was used to calculate the LST in this study.

First, radiometric calibration and atmospheric correction of remote sensing images were conducted based on the ENVI 5.3 platform to obtain the thermal radiance intensity (L_λ). Then, the atmospheric downward radiance ($L_{atm,\,i}\downarrow$), upward radiance ($L_{atm,\,i}\uparrow$), and transmissivity (τ) can be estimated (http://atmcorr.gsfc.nasa.gov/). With these four parameters, the surface radiance $B(T_s)$ in Eq. (1) can be calculated using Eq. (2), with a given land surface emissivity (ε). Finally, the LST can be directly calculated using Eq. (3).

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

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

In Eq. (1), L_λ is the surface thermal radiance intensity received by the satellite sensors, $B(T_s)$ is the ground radiance, T_s is the LST, and τ is the atmospheric transmittance.

$$T_s = K_2/\ \ln\left[K_1/B(T_s) + 1\right] \tag{3}$$

where $K_1 = 774.89$ ($\mathrm{mWm^{-2}sr^{-1}\,\mu m^{-1}}$), and $K_2 = 1321.08$ K for Landsat 8 OLI/TIRS data.

2.3. Definition and measurement of the park cooling effect (PCE) and TVoE

2.3.1. Calculation of park cooling effect (PCE)

There are several definitions and indicators that are used to express the cooling effect of blue-green space, such as cooling intensity, cooling gradient and cooling extent (Farshid et al., 2019; Jaganmohan et al., 2016; Norton et al., 2015). Among them, cooling intensity is one of the most widely used indicators in cooling effect studies, and is defined as the average difference in LST across the ring buffer where LST first drops with increasing distance from the urban park (Peng et al., 2020; Yang et al., 2020). In this study, the cooling intensity was quantified to determine the cooling effect of the urban park (Supplementary Fig. 4).

Considering the resolution of the Landsat OLI/TIRS images, 30 m was selected as the buffer. To calculate the cooling intensity, buffer analyses from 30 to 990 m (urban park area smaller than 15 ha) and 30 to 2100 m (urban park area larger than 15 ha) were carried out. The mean LST of each ring buffer and the associated urban parks were then calculated. Finally, the maximum ΔLST was regarded as the cooling intensity.

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

TVoE is the trade-off between cooling efficiency and park area from a cost-benefit perspective (Yu et al., 2017). The park cooling efficiency curve shows that ΔLST first increases significantly (u^2-u^1) with the increases in the size of the urban park (q^1 to q^2). Then, after at a certain point, when the size increases from q^3 to q^4, there is only a small increase in total utility (u^4-u^3) with additional park area. This point is the TVoE, which occurs at the point where the slope of the resulting logarithmic function equals one (Supplementary Fig. 4). The detailed derivation of TVoE is shown in Supplementary materials. This change-point is meaningful for actionable environmental planning so decision-makers can use the smallest blue-green space to obtain the optimal cooling effect (Fan et al., 2019; Yu et al., 2020).

2.4. Factors influencing park cooling effect

Previous studies have revealed correlations between PCE and various influencing factors (Rahman et al., 2018; Steeneveld et al., 2014; Sun and Chen, 2012). In this study, 12 influencing factors that have been widely used in past studies (Feyisa et al., 2014; Gunawardena et al., 2017; Jaganmohan et al., 2016; Jérémy et al., 2018; Peng et al., 2020) were chosen to identify the dominant factors. These influencing factors include park landscape characteristics and park environment and are shown in Table 1.

2.5. Statistics analysis

To explore the correlation between potential influencing factors and PCE, multivariate stepwise regression analysis was used to identify the dominant factors and quantify the relative contributions of each independent variable to the total explanation of PCE variation (Sun et al., 2018). Specifically, the influencing factors with the highest standardized regression coefficient were identified as the dominant factors (Weng et al., 2008). Furthermore, the TVoE was examined based on curve fitting between the park area and cooling identity (Yang et al., 2020).

The method flowchart of this study is shown as Fig. 2.

3. Results

3.1. Quantification of urban park cooling effect (PCE)

As shown in Supplementary Fig. 5, urban parks were cooler than their surrounding areas. The mean cooling intensity of all 207 urban parks was 2.31 °C, with values ranging from 0.60–5.13 °C. The cooling intensity of urban parks in different local background climates varied to some extent.

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

Categories of variables	Impact factors	Definition
Landscape characteristics of urban parks	Park_shape_leng	The perimeter of an urban park
	Park_shape_area	The area of an urban park
	Park_water_ratio	The proportion of the water body in an urban park
	Park_tree_rate	The proportion of the forest land area in an urban park
	Park_green_rate	The proportion of the green area in an urban park
	LSI	The landscape shape index of an urban park
	FRAC	The fractal dimension of an urban park
Surrounding environment of urban parks	Buffer_imperious_rate	The proportion of the impermeable surface in the 1 km buffer of an urban park
	Buffer_water_rate	The proportion of the water body in the 1 km buffer of an urban park
	Buffer_green_rate	The proportion of the green area in the 1 km buffer of an urban park
	Road_density	The road network density in the 1 km buffer of an urban park
	Architecture_dendity	The building density in the 1 km buffer of an urban park (POI)

Specifically, 58% of urban parks in WTC had cooling intensities in the range of 0–2 °C. Whereas for NSC and NHC, 55.5% and 67.9% of urban parks had cooling intensities of 1–3 °C, respectively. In MSC, 56.6% of urban parks had cooling intensities of 2–4 °C (Fig. 3). PCE increases from WTC, NSC, NHC to MSC, showing that urban parks at lower latitudes had a better cooling effect in general (Fig. 4).

3.2. Influencing factors analysis of urban park cooling effect (PCE)

Multivariate stepwise regression analysis was conducted to identify the dominant factors of PCE. As shown in Table 2, all retention factors were significant at $P < 0.05$. The determination coefficients (R^2) represent the proportion of the variation in PCE explained by the regression model. The standardized coefficients of the predictive model represented the relative contributions of various factors influencing PCE.

Specifically, different influencing factors were retained, and 77.1%, 56.2%, 58.5%, and 50.7% of the variation was explained in the four final regression models. Park shape area had a significant positive relationship with PCE and was identified as the dominant factor. It explained over 50% of the PCE variation in four different local background climates. The fractal dimensions of the park (FRAC) were maintained in the WTC and NHC. FRAC was negatively correlated with the PCE, and its relative contribution to PCE was nearly 18% in two types of local background climates. This means that parks with higher geometric complexity may have a smaller the cooling effect on their surrounding area. The landscape shape index (LSI) was maintained in the NSC and NHC. LSI had a negative relationship with the PCE, with relative contributions to PCE of 29.90% and 19.59%, respectively. Urban parks with simple shapes has better cooling effects. The water body ration was only maintained in the WTC. It was positively correlated with PCE, and with relative contributions to PCE of 13.24%. Road density was found to be negatively correlated with PCE in MSC. Its relative contribution to the PCE was 20.37% (Table 2). Higher road density means heavier traffic and more anthropogenic heat release, which may limit the cooling effect of parks beyond their boundaries.

3.3. Threshold value of efficiency (TVoE) analysis

Fig. 5 shows the results of the TVoE with four different local background climates. The TVoE values of the park areas in WTC, NSC, NHC and MSC were 0.81 (R^2 = 0.64, $P < 0.05$), 0.71 (R^2 = 0.63, $P < 0.05$), 0.70 (R^2 =

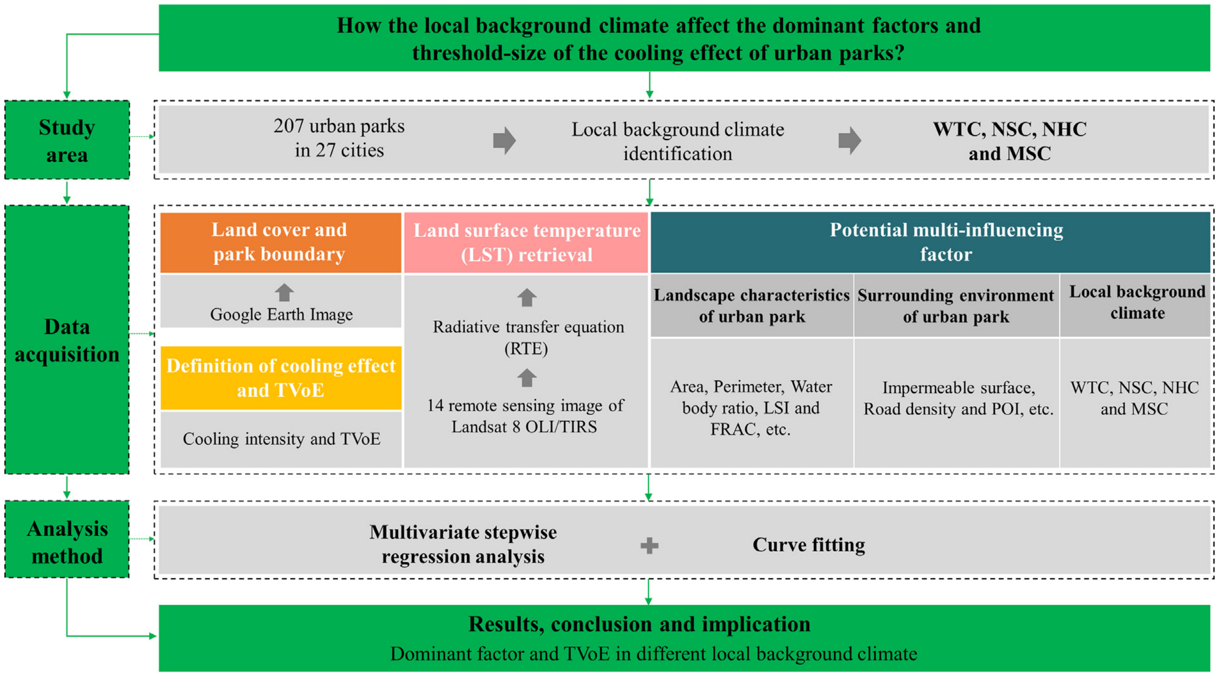

Fig. 2. Framework illustrating all the methodological steps taken in this study.

0.56, $P < 0.05$) and 0.66 ha ($R^2 = 0.55$, $P < 0.05$), respectively. The TVoE of park area in NSC and NHC were close because of their relatively similar local background climates.

To explore how the local background climate affects the TVoE of urban parks, we analyzed the relationship between the TVoE and climate conditions. As shown in Fig. 5, the TVoE value increased with a decrease in the mean annual precipitation and average temperature. Pearson correlation analysis also proved this conclusion; specifically, the TVoE was significantly negatively correlated with mean annual precipitation and average temperature at the 0.05 confidence level, with related coefficients of −0.916 and −0.919, respectively (Supplementary Table 6). In general, latitude decreases from WTC, NSC, and NHC to MSC. Therefore, we determined that the TVoE decreased with decreasing latitude in the study area. This means that planners in low latitude regions in East China could design relatively smaller urban parks than high latitude regions while achieving the same cooling effect.

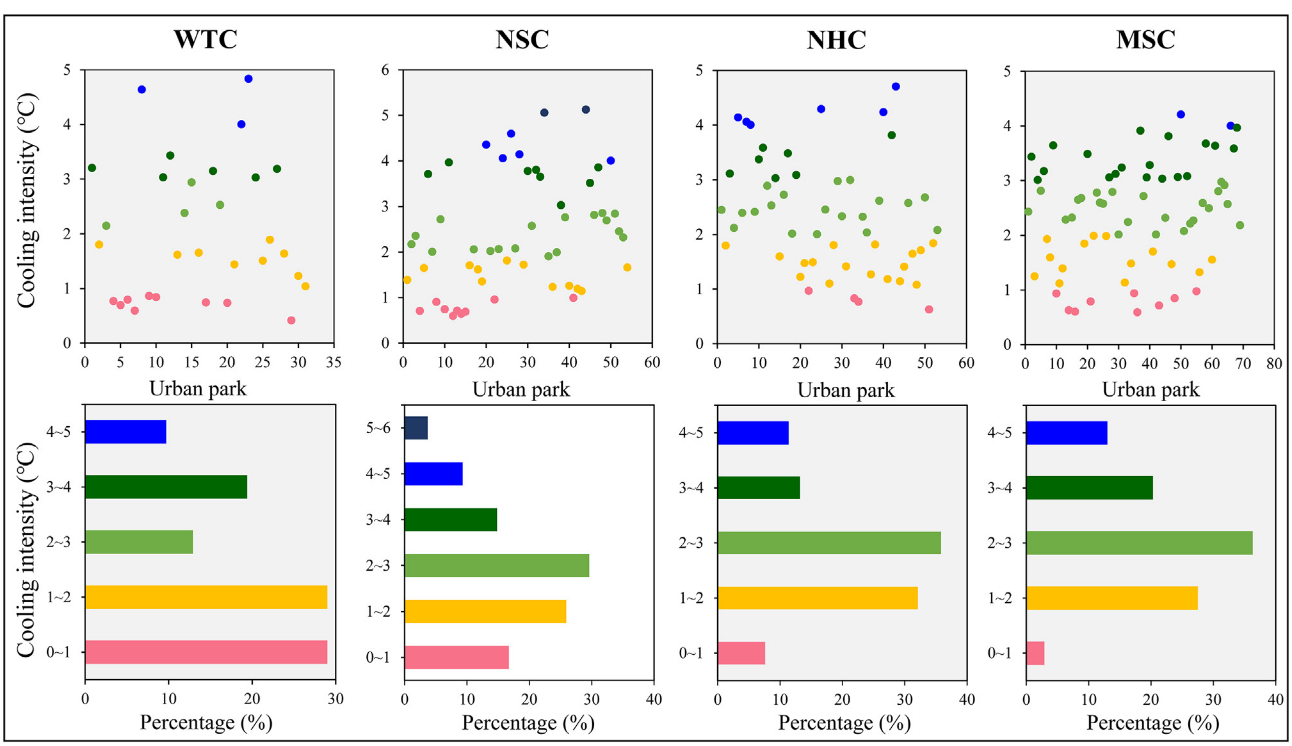

Fig. 3. Cooling intensity of 207 urban parks in four different local background climates. The "pink", "yellow", "light green", "green", "blue" and "dark blue" represent the cooling intensity of "0–1", "1–2", "2–3", "3–4", "4–5" and "5–6" °C.

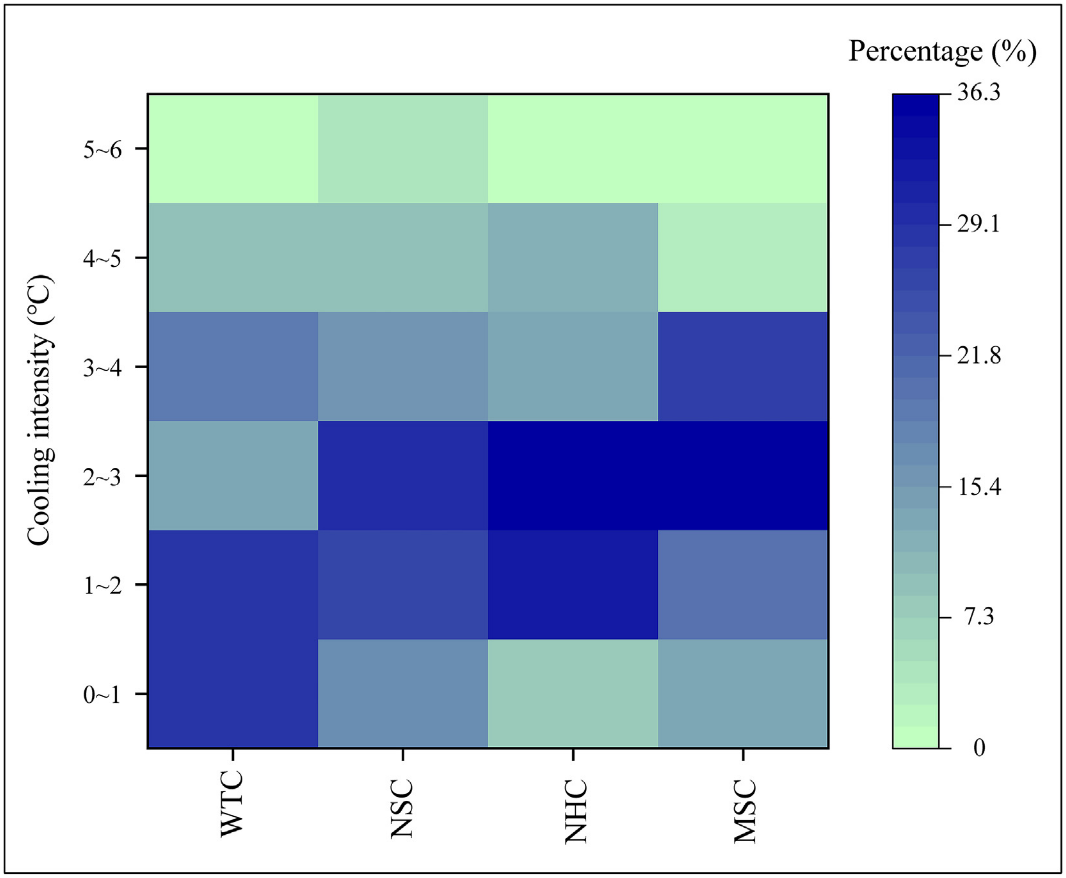

Fig. 4. Distribution of park cooling intensity in four different local background climates.

4. Discussion

4.1. Dominant influencing factors affecting PCE in different local background climates

Many potential influencing factors of PCE have been studied based on specific cases (Farshid et al., 2019; Grilo et al., 2020; Masoudi and Tan, 2019), but it is still unclear on how the local background climate affects these factors (Wong et al., 2021; Yu et al., 2020). Park size is widely acknowledged as an essential influencing factor of PCE, regardless of whether it is green space or blue space (Algretawee et al., 2019; Du et al., 2017; Ekwe et al., 2020; Jérémy et al., 2018; Peng et al., 2020). A study by (Cao et al., 2010) indicated that park size can explain 60% of PCE variation in a subtropical humid monsoon climate. In addition, for blue space, a study by (Sun and Chen, 2012) found that water body area had the highest relative contribution to the cooling intensity variation in a temperate continental monsoon climate. This study further verifies this conclusion: park area was the dominant influencing

Table 2
Regression results with the influencing factor as predictor variables and the UCI intensity as response variables in four different local background climates. "Std. error" represents standard error. "DW" represents Durbin Watson Test, when the "DW" value is close to 2, it indicates that there is no first-order autocorrelation in the model.

Climate zone	Factors	Unstandardized coefficients		Standardized coefficients	t	*p*-Value	Relative contribution (%)	Regression model	R^2	Adjusted R^2	F ($p < 0.01$)	DW
		B	Std. error	Beta								
WTC	(Constant)	9.810	3.751	/	2.615	0.015	/	PCI = 9.810 + 0.002 Shape_Area + 3.566 B_Green_Rate − 8.570 FRAC + 1.160 P_Water_Rate	0.771	0.736	21.904	1.677
	Shape_Area	0.002	0.000	0.765	8.019	0.000	52.47					
	B_Green_Rate	3.566	1.509	0.227	2.364	0.026	15.57					
	FRAC	−8.570	3.247	−0.273	−2.639	0.014	18.72					
	P_Water_Rate	1.160	0.605	0.193	1.916	0.046	13.24					
NSC	(Constant)	3.549	0.627	/	5.665	0.000	/	PCI = 3.549 + 0.001 Shape_Area − 1.653 LSI	0.562	0.5444	32.669	1.654
	Shape_Area	0.001	0.000	0.797	8.055	0.000	70.10					
	LSI	−1.653	0.480	−0.340	−3.441	0.001	29.90					
NHC	(Constant)	9.054	2.772	/	3.266	0.002	/	PCI = 9.054 + 0.001 Shape_Area − 1.528 LSI − 5.508 FRAC	0.585	0.560	23.066	1.600
	Shape_Area	0.001	0.000	0.659	7.132	0.000	62.05					
	LSI	−1.528	0.733	−0.208	−2.085	0.042	19.59					
	FRAC	−5.058	2.593	−0.195	−1.951	0.047	18.36					
MSC	(Constant)	1.832	0.332	/	5.512	0.000	/	PCI = 1.832 + 0.001 Shape_Area − 12.425 Road_Den	0.507	0.492	33.96	2.292
	Shape_Area	0.001	0.000	0.692	8.002	0.000	79.63					
	Road_Den	−12.425	6.063	−0.177	−2.049	0.044	20.37					

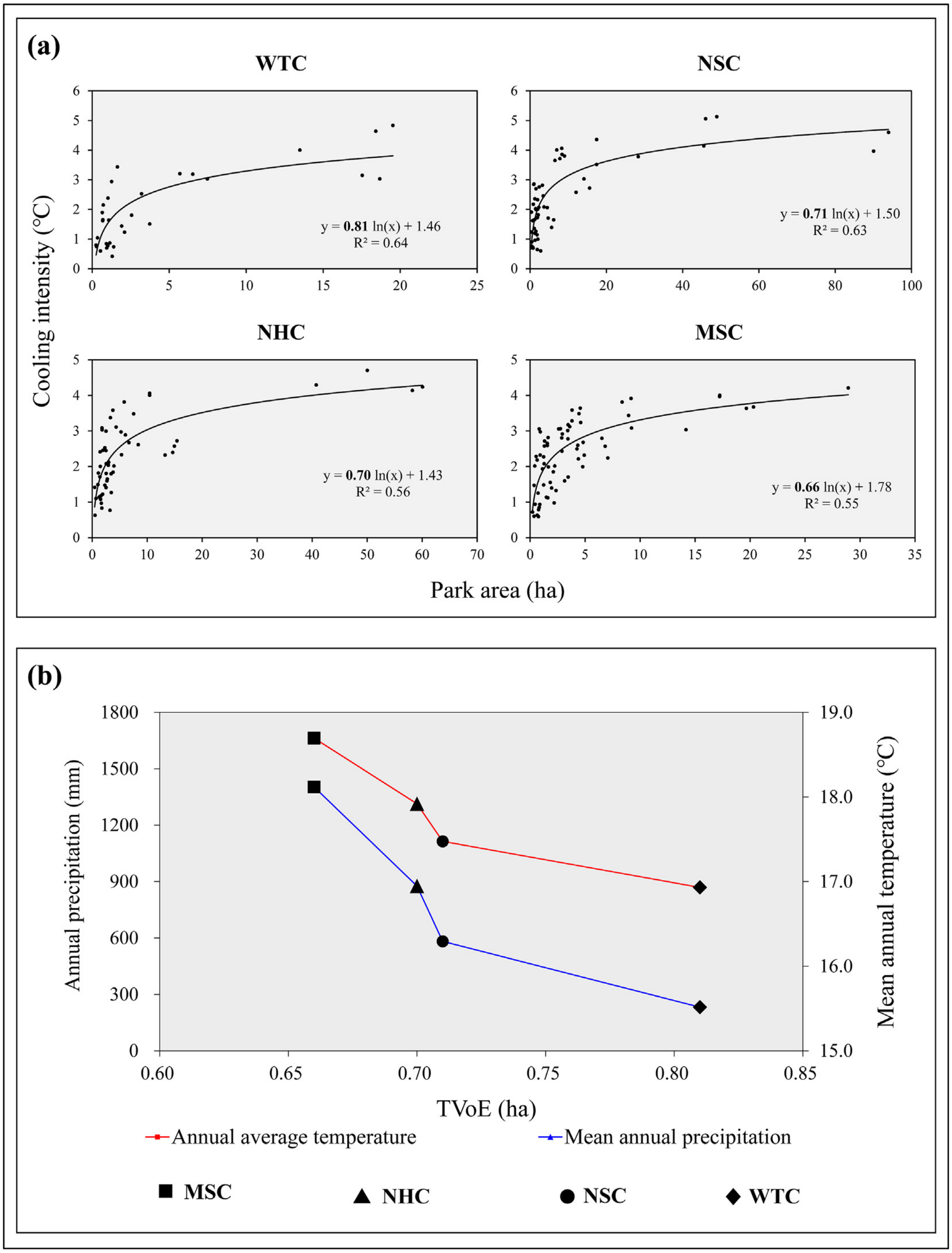

Fig. 5. The quantification of TVoE and its relationship with climate conditions. (a) TVoE of urban parks in four different local background, and (b) the relationship between TVoE and climate conditions.

factor of PCE, explaining more than 50% of the PCE variation in all four local background climates.

LSI is also an important influencing factor and has a negative correlation with PCE (Jaganmohan et al., 2016; Masoudi and Tan, 2019; Monteiro et al., 2016). Our studies showed that the relative contributions to PCE were from 20 to 30% in the NSC and NHC. In a temperate continental monsoon climate, LSI accounts for approximately 6–12% of the total variation (Chen et al., 2014). Specifically, for urban park design, parks with more complicated shapes have a smaller cooling intensity than park with circle or square shapes (Du et al., 2016; Yu et al., 2017). However, Yang et al. (2020) found that, in a temperate marine climate (Copenhagen), when the size of the blue-green space exceeds a threshold, a more complex shape will actually be more effective in decreasing the LST. In addition, the water body ratio of the urban park was the only influencing factor in the WTC. As the WTC was the highest latitude, with the lowest mean annual precipitation and average temperature, it may be concluded that the water bodies of urban parks in high latitude, dry areas play a more significant role in PCE. One possible reason is that plant transpiration is limited by low humidity, meaning that water evaporation is more critical in dry areas (Anderegg et al., 2018). This finding indicates that more or larger water bodies in parks could benefit PCE in these regions.

4.2. Impact of local climate background on TVoE

TVoE is essential for climate adaptation planning and has received considerable attention since it was first proposed in 2017 (Fan et al., 2019; Peng et al., 2020; Yang et al., 2020; Yu et al., 2017). TVoE research is still in its infancy and more research is urgently needed to draw more accurate and generalizable conclusions on a regional scale (Yu et al., 2020).

Existing studies on the TVoE of blue-green spaces are mainly based on single cities, with less attention paid to urban parks with different local background climates. However, the local background climate was found to be highly associated with the variance of the TVoE (Yang et al., 2020; Yu et al., 2018). For tree-cover green space, the TVoE in summer is 0.47 for Beijing and Tianjin (warm temperate continental monsoon climate) and 0.37 ha for Xi'an (warm temperate continental monsoon climate) (Yu et al., 2018). In subtropical monsoon climate, the TVoE of tree-cover green space is 0.58 ha for Fuzhou (subtropical marine monsoon climate) and 0.62 ha for Hong Kong (subtropical monsoon climate) (Fan et al., 2019; Yu et al., 2017). For tropical climate, the TVoE of tree-cover green space is 0.95 and 0.61 ha for Kuala Lumpur and Singapore, (tropical rainforest climate), respectively (Fan et al., 2019). Generally, the TVoE of tree-cover green space is larger in subtropical and tropical monsoon climates than in temperate climate zones. In other words, TVoE increases with a decrease in latitude (Fig. 6). However, the opposite conclusion has been determined for blue spaces (water body): as the latitude decreases, the TVoE of blue space has been shown to became smaller. Specifically, the TVoE of blue space is 1.12 ha in Copenhagen (temperate oceanic climate) (Yang et al., 2020), 0.9 ha in Wuhan (subtropical monsoon climate) (Yu et al., 2020) and 0.45–0.7 ha in the Pearl River Delta urban agglomeration (subtropical monsoon climate) (Peng et al., 2020). This means that, in low latitude regions, relatively smaller blue space is required to obtain the same cooling effect as larger blue space in high latitude areas. This is useful from a cost-benefit perspective (Fig. 6).

However, previous studies have not determined a generalizable conclusion for TVoE of blue-green space. In our study, 207 urban parks with four different local background climates were selected for a comparative studies. First, our results demonstrated that the local background climate can significantly affect the TVoE of urban parks. Also, the TVoE of urban parks generally decreased with an increase in mean annual precipitation and average temperature, in the order of WTC, NSC, NHC, MSC. Specifically, the TVoE were 0.81, 0.71, 0.70, and 0.66 ha, respectively. In other words, the TVoE decreased from the high latitude to low latitude in our study area. This conclusion is consistent with the TVoE change with latitude of blue space, whereas it is opposite to the green space. There are several possible explanations for this founding. First, for blue space, the cooling effect comes from water evaporation. Theoretically, in low latitude regions, higher atmospheric humidity will reduce evaporation and affect the cooling effect of the water body. However, existing studies indicate that the TVoE of blue space becomes smaller at lower latitudes. Second, for green space, plant transpiration and shading effect are mainly cooling mechanisms. Higher atmospheric temperature and humidity can change plant stomatal behavior, limit plant transpiration, and alter the cooling effect (Anderegg et al., 2018; Yu et al., 2018). Therefore, a large green space should be designed to obtain a better cooling effect in lower latitude regions. For urban parks that have both blue and green spaces, determining how the local background climate influences PCE is more complicated. Our study provides some preliminary conclusions, that is, the TVoE of urban parks decreases with decreasing latitude. Therefore, smaller urban parks in low latitude areas can have the same cooling effect as larger urban parks in high latitude areas. This is a useful insight from a cost-benefit perspective.

4.3. Implication and limitation

With the development of urban agglomerations in China, the mitigation strategy of UHI effect need to be implemented on regional scale, and study on regional scale may also provide us some conclusions that beyond single-city research (Yu et al., 2020). To upscale the understanding of PCE from the city level to regional scale, a climate-zone-based upscaling study was conducted. Our study indicated that the TVoE of urban parks decreases with a decrease in latitude, therefore, relatively smaller urban parks can be designed to obtain optimal cooling effects. The optimal park areas in WTC, NSC, NHC and MSC to be 0.81, 0.71, 0.70 and 0.66 ha, respectively. Corresponding areas of urban park in cities of these climates are encouraged to design for obtaining better cooling effect from cost-benefit perspectives. For high latitude and dry areas, water body ratio plays a more important role in PCE, and large water body can be considered in park design. Both LSI and FRAC are negatively correlated with PCE, a simple shape and less landscape patch fragmentation will benefit the cooling effect of urban parks.

Some limitations of the study must be mentioned. Firstly, a total of 14 remote sensing images of Landsat 8 OLI/TIRS were used for LST retrieval, the application of multi-temporal remote sensing images might affect the consistency of the LST retrieval for different urban parks, and have impacts on the results to some extent. This is one of the challenging factors that

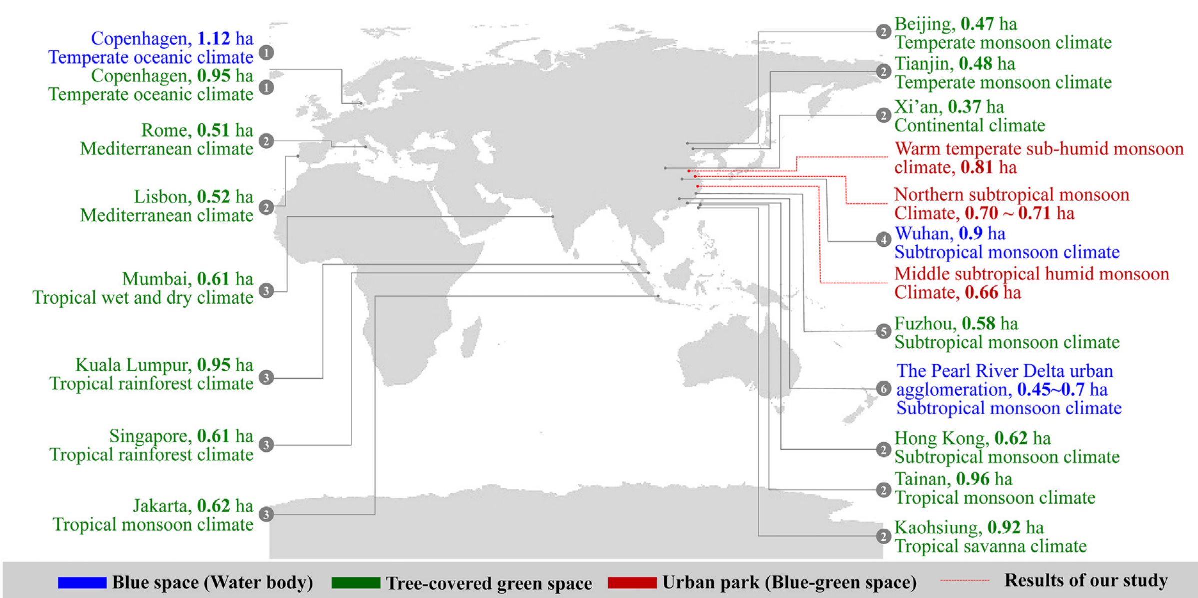

Fig. 6. The TVoE value of existing studies in different local background climates. Explanations: case 1, 2, 3, 4, 5 and 6 cited studies of Yang et al. (2020), Yu et al. (2018), Fan et al. (2019), Xie and Li (2021), Yu et al. (2017) and Peng et al. (2020), respectively.

cannot be avoided. Secondly, more potential influencing factors, such as leaf area index (LAI) (Gunawardena et al., 2017), plant species (Leuzinger et al., 2010; Rahman et al., 2018) and normalized difference vegetation index (NDVI) (Yu et al., 2020) should be considered for more comprehensive and further study. Thirdly, the exploration from the perspective of heat energy dynamics in urban parks was insufficient, including the latent and sensible heat flux changes of urban parks in different local background climates, which could tell us more accurate conclusions and should be encouraged in future research (Armson et al., 2012; Oke, 1982; Santamouris, 2014).

5. Conclusions

To explore how the local background climate influences the dominant factors of the cooling effect and threshold size of urban parks, 207 urban parks in 27 cities in East China with four different local background climates were selected for comparative study. Our findings suggest that PCE increases from WTC, NSC, NHC to MSC, and that urban parks at low latitudes have a better cooling effect in general than those at high latitudes. The park area is the dominant factor of PCE under the four different local background climates, with the explanation rate exceeding 50% in each region. In addition, the water bodies in urban parks can play a more significant role in cooling effect at high latitude and dry areas. The TVoE of parks in WTC, NSC, NHC and MSC were 0.81, 0.71, 0.70, and 0.66 ha, respectively, demonstrating that the background climate significantly affects the TVoE. These findings provide new insights into how the local background climate influences the dominant factors of the cooling effect and TVoE of urban parks at a regional scale, as well as provide actionable ecological knowledge for urban park design and climate-adaptive strategy referring to UHI mitigation.

CRediT authorship contribution statement

Dr. Xiaolei Geng collected, analyzed the data and wrote the manuscript. Associate Professor Zhaowu Yu proposed the study and wrote the manuscript. Professor Xiangrong Wang edited the manuscript and made constructive comments. Dr. Dou Zhang processed the data. Dr. Chengwei Li collected the data and did analysis. Dr. Yuan Yuan edited the manuscript.

Declaration of competing interest

The authors declaim that there is no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.153806.

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