

# SPATIAL EQUITY OPTIMIZATION FOR PARK COOLING SERVICES AND ECOLOGICAL BENEFIT EVALUATION: A CASE STUDY OF GANZHOU, CHINA

HE, X. W.<sup>1</sup> – WAN, Z. W.<sup>1\*</sup> – YUAN, B.<sup>1</sup> – LIAO, C. H.<sup>1</sup> – LI, X. J.<sup>1</sup> – WU, L. Q.<sup>1</sup> – ZHANG, A. H.<sup>1</sup>  
– YANG, X. F.<sup>1</sup> – LAI, W.<sup>2</sup>

<sup>1</sup>*School of Geography and Environmental Engineering, Gannan Normal University, Ganzhou, 341000; China*

<sup>2</sup>*Research Center for Geographic Process and Resource Utilization in Jiangnan Hilly Region, Gannan Normal University, Ganzhou 341000, China*

*\*Corresponding author*

*e-mail: wanzw.09b@ignrr.ac.cn; phone: +86-797-839-3756*

(Received 24<sup>th</sup> Mar 2025; accepted 13<sup>th</sup> May 2025)

**Abstract.** Urban parks, as critical green infrastructure for heat mitigation, necessitate equitable spatial accessibility to cooling services alongside thermal efficiency. This study develops a spatial equity-oriented framework integrating thermal regulation performance, accessibility justice, and urban development dynamics to evaluate and optimize park cooling services in Zhanggong District, Ganzhou City, China (33 parks were analyzed). Leveraging multisource geospatial data and Partial Least Squares Structural Equation Modeling (PLS-SEM), three equity-related findings revealed: (1) Spatially uneven cooling benefits: Among effective parks ( $n = 25$ ), cooling intensity ranges up to 2.95°C with service radii spanning 375.09 m, creating geographic disparities in heat relief accessibility; (2) Threshold-driven equity barriers: PLS-SEM identifies nonlinear landscape-cooling relationships, where green space coverage (+1.6065 path coefficient) and water body proportion exhibit critical thresholds beyond which marginalized communities gain diminishing accessibility benefits; (3) Systematic accessibility inequity: 43.48% of residential areas lack cooling access within a 15-min walk, while 52% of parks demonstrate supply-demand mismatches dominated by ‘low supply-high demand’ patterns. An equity-centric optimization matrix proposes: (a) high-demand urban cores require distributed pocket green spaces, and (b) peripheral areas need enhanced connectivity for existing park utilization. This framework advances spatial justice in urban heat resilience planning by synchronizing biophysical performance with human-centric accessibility needs.

**Keywords:** *urban parks, ecological benefit, cooling equity, spatial accessibility, supply-demand mismatch, thermal landscape thresholds*

**Abbreviations:** LST, Land surface temperature; FTP, First turning point; MPCD, Maximum Park Cooling Distance; MPCl, Maximum Park Cooling Intensity; PCG, Park Cooling Gradient; PCI, Park Cumulative Cooling Intensity; MPCA, Maximum Park Cooling Area; Area, Area of each park; Perimeter, Perimeter of each park; LSI, Landscape shape index of each park; Greenin, Area of green space in each park; Bluein, Area of blue space in each park; NDVIin, Normalized difference vegetation index of each park; GA, Area of grassland in each park; TA, Area of trees in each park; Greenout, Area of green space within MPCA of each park; Grey, Area of grey space within MPCA of each park; Blueout, Area of blue space within MPCA of each park; NDVIout, Normalized difference vegetation index within MPCA of each park; BV, Building volume within MPCA of each park; Light, Nighttime lighting index within MPCA of each park; RD, Road density within MPCA of each park; TVoE, Threshold Value of Efficiency; Population, Number of people within a 15-min walk to park cooling services; MPCA\_blue, Proportion of blue landscape in maximum cooling area; MPCA\_green, Proportion of green landscapes in the maximum cooling area; MPCA\_grey, Proportion of grey landscape within the maximum cooling area; MPCA\_BH, Total building height in the maximum cooling area; MPCA\_Light, Average nighttime light within the maximum cooling area; MPCA\_POI, Point of Interest within the maximum cooling area; MPCA\_RD, Average road density within the maximum cooling area; PCSI, Park Cooling Service Index

## Introduction

The rapid urbanization process and the progressive intensification of global climate change have synergistically exacerbated urban thermal environmental pressures (Foley, et al., 2005; Oke, 1973; Patz, et al., 2005). Urban heat island (UHI) effects and frequent heatwave events now present dual challenges to public health systems and sustainable urban development. Addressing urban thermal environment challenges through nature-based solutions has consequently become a critical focus in contemporary urban planning and ecological governance. Park cooling services are a hot topic today because of the role they can play in adaptation, mitigation and risk management decisions (Lan, et al., 2022). As vital components of urban green infrastructure, parks demonstrate irreplaceable advantages in microclimate regulation through three primary mechanisms: (1) vegetation evapotranspiration-driven cooling, (2) solar radiation interception via canopy shading, and (3) urban ventilation enhancement through airflow guidance. These biophysical processes collectively contribute to UHI mitigation at neighborhood scales (Cheung and Jim, 2019; Yang, et al., 2021; Yao, et al., 2022).

Current research advancements have systematically expanded the understanding of park cooling effects across three dimensions: fundamental mechanisms, determinant factors, and quantitative evaluation methods (Xiao, et al., 2023a; Xu, et al., 2017; Zhou, et al., 2024a; Zhu, et al., 2021). The establishment of multidimensional indicator systems has particularly strengthened the theoretical foundations for assessing cooling performance, enabling more scientifically informed decision-making in green space planning and management (Peng, et al., 2021; Xiao, et al., 2023a; Yu, et al., 2018; Zhang, et al., 2021).

Park landscape features and the surrounding environment are also key factors influencing the cooling effect (Irie, 2022; Jiang, et al., 2024; Zhang, et al., 2022). It was found that internal and external factors such as vegetation cover (NDVI), proportion of water bodies (NDWI), building density and road distribution has a significant effect on the cooling effect of parks (Liang, et al., 2023; Xu, et al., 2024; Zhang, et al., 2019; Zhou, et al., 2024b). It is worth noting that the relationship between park size and cooling effect is non-linear (Jaganmohan, et al., 2016; Monteiro, et al., 2016; Zhou, et al., 2022). Studies have shown that although the cooling effect and area covered by large parks are usually more significant, the cooling efficiency of parks decreases significantly when their size exceeds a certain threshold value of efficiency (TVoE) (Shi, et al., 2023). The concept of Thermal Value of Ecology (TVoE), introduced by Yu et al. (2017) through applying the law of diminishing marginal utility, provides a quantifiable framework to assess park size optimization for urban cooling. Their findings demonstrated significant spatial heterogeneity in TVoE values across climatic zones, with eastern Chinese cities exhibiting a relatively concentrated range (0.66-0.81 ha) (Geng, et al., 2022). This contrasted markedly with the divergent values recorded in Chengdu (30 ha) (Feng, et al., 2023), Fuzhou (1.08 ha) (Yu, et al., 2018), and Taipei (3 ha) (Chang, et al., 2007), suggesting regional climatic influences on ecological thermal efficiency. Despite extensive research quantifying park cooling effects, academic discourse remains disproportionately focused on biophysical mechanisms rather than service equity considerations (Lan, et al., 2022; Shi, et al., 2023; Shih, 2022; Tieskens, et al., 2022). As critical public goods, urban green spaces require equitable allocation strategies to ensure universal access to their cooling benefits. Accessibility serves as a critical metric for evaluating distributive justice, operationalized through multidimensional

assessments including per capita green space availability, proximity analysis, and mobility-based accessibility metrics (Tan and Samsudin, 2017). Current scholarship reveals three key research gaps: First, limited integration exists between microclimate regulation studies and socio-spatial accessibility models (Krekel, et al., 2016; Sister, et al., 2010). Second, insufficient attention has been given to differential cooling service accessibility among demographic subgroups. Third, the spatial mismatch between park cooling footprints and vulnerable populations remains under-investigated. These disparities stem from complex interactions between urban planning priorities, land use policies, and socioeconomic stratification, often resulting in thermal resource deprivation for marginalized communities (Kato-Huerta and Geneletti, 2023; Kong, et al., 2014; Wilson, 2020).

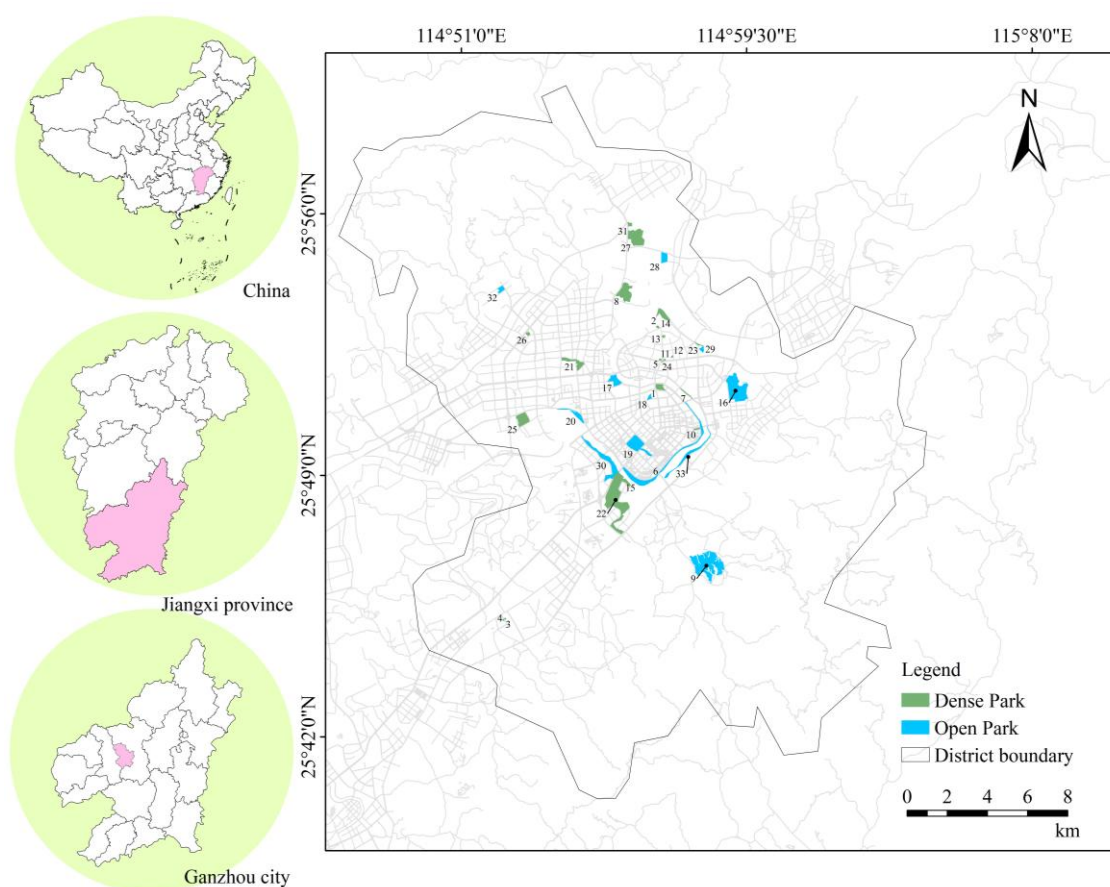
In the context of China's rapid urbanization, the conflict between supply and demand for urban parks within cities is particularly acute (Wolff, 2021). Due to urban biodiversity conservation, land development decisions and spatial planning constraints, urban park resources are not only scarce, but also significantly imbalanced in distribution. This status not only undermines the overall effectiveness of park cooling services, but also exacerbates social inequality (Chen, et al., 2020). Therefore, how to optimize the equity and accessibility of park cooling services has become an important issue in achieving urban environmental justice. On the other hand, most of the existing studies focus on analyzing the cooling effect of a single type or a specific area, and there is a relative lack of systematic exploration of the relationship between cooling efficiency and equity in multiple parks on a regional scale. In addition, there is a lack of in-depth analyses of the accessibility of park cooling services and their interactions with urban socio-economic development. Therefore, it is necessary to conduct a multifactorial and comprehensive study at the regional scale to comprehensively reveal the mechanisms of urban park cooling effects and explore the optimization paths to enhance the equity and efficiency of cooling services.

This study takes Zhanggong District, Ganzhou City, a major city in the hilly region of southern China, as an example. Based on remote sensing and geographic information technology, we quantify the cooling effect of urban parks, identify internal and external drivers and their relative contributions, and quantify the efficiency threshold TVoE of the factors affecting urban parks based on the cooling effect of the parks; we propose the following A comprehensive framework of 'cooling effect accessibility-urban development' is proposed to explore the fairness and optimization path of cooling services in parks. The main ideas of this study include: (1) constructing a cooling service efficiency threshold model based on multidimensional data to provide a new method for urban park layout planning; (2) evaluating the fairness of the cooling service of parks by combining the socio-economic and ecological characteristics of the city; and (3) proposing strategies and suggestions for optimizing the allocation of parks resources on a regional scale.

## Study area and data

Zhanggong District of Ganzhou City is located in the hilly area of southern China, belonging to the sub-center and major city of Jiangxi Province, with a total area of about 479 km<sup>2</sup>, located in the upstream area of the Gan River, a major tributary of the Yangtze River, with a subtropical monsoon climate, four distinct seasons, and a hot and concentrated rainfall in summer, which is characterized by a significant urban

heat island effect. Zhanggong District of Ganzhou City has a high level of urbanization, and rich ecological resources and urban infrastructure are distributed in the area, especially the green space represented by urban parks plays an important role in alleviating the urban heat island effect and improving the quality of life of residents. In this study, 33 major urban parks in Zhanggong District are selected (Fig. 1), which are distributed in different areas of the city, including both dense parks in the core urban area and open parks in the peripheral areas (Table 1). There are various types of parks, including traditional comprehensive parks and new urban green spaces aiming at ecological restoration. There are significant differences in the performance of these urban parks in terms of cooling effect, accessibility and urban development, providing an ideal case study for investigating the equity and efficiency of cooling services in urban parks.



**Figure 1.** Location and park distribution map of Zhanggong District, Ganzhou City. (1 is the Golden Square, 2 is the Eight Mirror Terrace, 3 is the New Century Square, 4 is the Cultural Square, 5 is the West Park, 6 is the Zhangjiang National Wetland Park, 7 is the Zhangjiang Park, 8 is the Baohulu. 9 is Fengshan National Forest Park, 10 is Longwu Park, 11 is Dongyuan, 12 is Ganzhou Children's Park, 13 is Ganzhou Park, 14 is Yugutai Park, 15 is Zhangjiang Football Park, 16 is Wulong Hakka Park, 17 is Yangmeidu Park, 18 is Zanxian Ecological Park, 19 is Ganzhou City Central Park, 20 is Outan Park, 21 is Golden Wind Plum Garden, 22 is New Century Park, 23 is Donghe Park, 24 is Nanmen Square, 25 is Panglong Park, 26 is Sule Park, 27 is Fangte Park, 28 is Harmony Bell Tower, 29 is Tianzhushan Park, 30 is Rongjiang New District Riverside Park, 31 is Polar Ocean World, 32 is Yongquan Wisdom Park, 33 is Zhangjiang Right Bank Riverside Park)

**Table 1.** Park attributes

Park code	Park name	Location	Type	Vegetation
1	Golden Square	South end of Nanhe Bridge, Zhangjiang New District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass
2	Eight Mirror Terrace	No. 22, Bajing Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
3	New Century Square	Tankou, Gold Development Zone, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass
4	Cultural Square	80 meters northeast of Tankou, Gold Development Zone, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass
5	West Park	Zhonglian Mall Pedestrian Street, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
6	Zhangjiang National Wetland Park	No. 6 Meiguan Avenue, Zhangjiang Street, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grasses, wetland plants and some trees
7	Zhangjiang Park	Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
8	Baohulu	Between Chizhu, Shuixi Town, Zhanggong District, Ganzhou City, Jiangxi Province and Shirenqian, Hubian Town	Dense Park	Shrubs, grass and some trees
9	Fengshan National Forest Park	Shashi Town, southern end of the urban area of Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Subtropical evergreen broad-leaved forest, coniferous and broad-leaved mixed forest, bamboo forest, secondary shrubs and grass
10	Longwu Park	No. 41, Ganjiangyuan Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
11	Dongyuan	No. 8 Wenqing Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
12	Ganzhou Children's Park	No. 32, Jiankang Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass
13	Ganzhou Park	No. 71, Wenqing Road, Jiefang Street, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
14	Yugutai Park	No. 2, Xijin Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
15	Zhangjiang Football Park	Meiguan Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grasses, wetland plants and some trees
16	Wulong Hakka Park	No. 18, Shahe Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
17	Yangmeidu Park	South of Yangmei Bridge, Yingbin Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
18	Zanxian Ecological Park	The intersection of Zanxian Road and Ganxian Road, Lingtou Community, Shuinan Town, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
19	Ganzhou City Central Park	No. 99, Xingguo Road, Zhangjiang New District, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
20	Outan Park	About 80 meters west of Furong Shangri-La, Binjiang Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
21	Golden Wind Plum Garden	Both sides of Jinfeng Road, Economic Development Zone, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
22	New Century Park	The intersection of New Gannan Avenue and Binjiang Road, Rongjiang New District, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
23	Donghe Park	No. 8 Dongfangshengjing, Ganjiang Street, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
24	Nanmen Square	South Gate, No. 8 Wenqing Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass
25	Panglong Park	Northeast of the intersection of Le'an Road and Baota Road, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees

26	Sule Park	Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
27	Fangte Park	No. 1 Fantawild Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
28	Harmony Bell Tower	Hugang Village, Shuidong Town, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
29	Tianzhushan Park	No. 89 Dongjiao Road, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
30	Rongjiang New District Riverside Park	The intersection of Binjiang East Road and Taohua Road, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grasses, wetland plants and some trees
31	Polar Ocean World	Huangsha'ao, Shuixi, Economic and Technological Development Zone, Zhanggong District, Ganzhou City, Jiangxi Province	Dense Park	Shrubs, grass and some trees
32	Yongquan Wisdom Park	Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grass and some trees
33	Zhangjiang Right Bank Riverside Park	Nanhe Bridge, Zhangjiang South Avenue, Zhanggong District, Ganzhou City, Jiangxi Province	Open Park	Shrubs, grasses, wetland plants and some trees

Geographically, the parks in Zhanggong District of Ganzhou City are closely related to the Gan River, and some of the parks are distributed along the river, reflecting the ecological characteristics of ‘blue-green intertwining’. The surface temperature in Zhanggong District has a decreasing distribution pattern from the center of the city outwards, with the heat island effect being most significant in the densely built-up core area of the city, while the parks and the surrounding areas show a certain cooling effect, making them an important place for urban residents to escape the heat during the hot season. The development plan of Zhanggong District emphasizes ecological priority and green development, providing policy support for the optimization and equitable distribution of park cooling services. However, the current distribution of park resources is still uneven, with some parks in the fringe areas being larger in size but serving fewer people, while parks in the central urban area have poor accessibility and scarce resources. Studying the cooling effect and equity of urban parks in Zhanggong District not only has significant local application value, but also provides a theoretical reference for the planning and design of parks in other similar cities. The dataset used in this study is shown in *Table 2*, and the workflow of this study is shown in *Figure 2*.

## Research methods

### *Land surface temperature retrieval*

In this study, land surface temperature retrieval is performed using the single window method based on Band 10 of Landsat 8 satellite image data (Guo, et al., 2020; Qin, et al., 2001). This method converts the bright temperature data received by the satellite to the actual temperature of the surface by means of atmospheric corrections and corrections to the surface specific emissivity. The Landsat 8 TIRS data record the thermal infrared radiation received by the satellite sensors, which consists of three components: the effective radiation from the surface as it passes through the atmosphere, the downward atmospheric radiation reflected from the surface, and the radiation emitted by the atmosphere itself. The single-window method corrects for the radiation absorbed and emitted by the atmosphere by means of an atmospheric radiative

transfer model, which is combined with the surface specific emissivity to convert the bright temperature to the surface temperature. The retrieval equation for the single-window method is given below:

$$LST = \frac{BT}{1 + \left(\frac{\lambda \cdot BT}{\rho}\right) \cdot \ln(\varepsilon)} \quad (\text{Eq.1})$$

where  $\lambda = 10.8 \times 10^{-6}$ ,  $\rho = 1.438 \times 10^{-2}$

$$BT = \frac{K2}{\ln\left(\frac{K1}{M \cdot Q_{cat} + A} + 1\right)} \quad (\text{Eq.2})$$

where  $K1 = 774.8853$ ,  $K2 = 1321.0789$

**Table 2.** Data sets used in this study

Data type	Source of data
Administrative division data	The administrative division data of Zhanggong District, Ganzhou City, Jiangxi Province comes from the National Geographic Information Public Service Platform ( <a href="https://www.tianditu.gov.cn/">https://www.tianditu.gov.cn/</a> ), the map review number is GS (2024) 0650, and the time point is May 2024
Park data	The 2024 park green space vector surface data from OSM was supplemented in GIS using high resolution images from Google Earth to compare the urban park boundaries between AOI and Open Street Map (OSM), and with reference to the Ganzhou City Centre Park System Plan (2022-2035)
Landsat8 data	Landsat8 data for July 2024 from the GEE platform at 30 m resolution
Land cover data	Land cover data and vegetation type data were taken from the 2021 ESA World Cover product at a resolution of 10 m
NDVI	Based on GEE, monthly mean NDVI in Zhanggong District, Ganzhou City from 1 May 2024 to 30 September 2024 was calculated using Landsat8 data
Data of built-up volume	Built-up volume data were obtained from the 2020 GHSL (Global Human Settlements Layer) product ( <a href="https://human-settlement.emergency.copernicus.eu/">https:// human-settlement.emergency.copernicus.eu/</a> ) at a resolution of 90 m
Population raster data	Population raster data at 100 m resolution from the 7th Census (2020) ( <a href="https://figshare.com">https://figshare.com</a> )
Night light data	Data from an extended time series (2000-2023) of similar NPP-VIIRS nighttime light data for the year 2023 globally ( <a href="https://doi.org/10.7910/DVN/YGIVCD">https://doi.org/10.7910/DVN/YGIVCD</a> , Harvard Dataverse, V5). The resolution is 500 m
Road data	2024 road data from OSM
Building height data	Building height data were obtained from the 2018 GHSL (Global Human Settlement Layer) product ( <a href="https://human-settlement.emergency.copernicus.eu/">https:// human-settlement.emergency.copernicus.eu/</a> ) at a resolution of 100 m
Neighborhood data	2024 settlement vector data from OSM
POI	POI data from OSM acquired in May 2024

In Equation 1, BT is the bright temperature in Kelvin,  $\lambda$  is the effective wavelength of the thermal infrared band,  $\rho$  is a constant,  $\varepsilon$  and is the surface specific emissivity,

which indicates the proportion of energy radiated outward from the surface to the radiant energy of the blackbody, and takes a value in the range of 0 to 1. In Equation 2, Qcal is the numerical value of thermal infrared band in the image, and M and A are the radiative corrected gain coefficients and the radiative corrected offsets, respectively, which can be obtained from the Landsat meta data file.

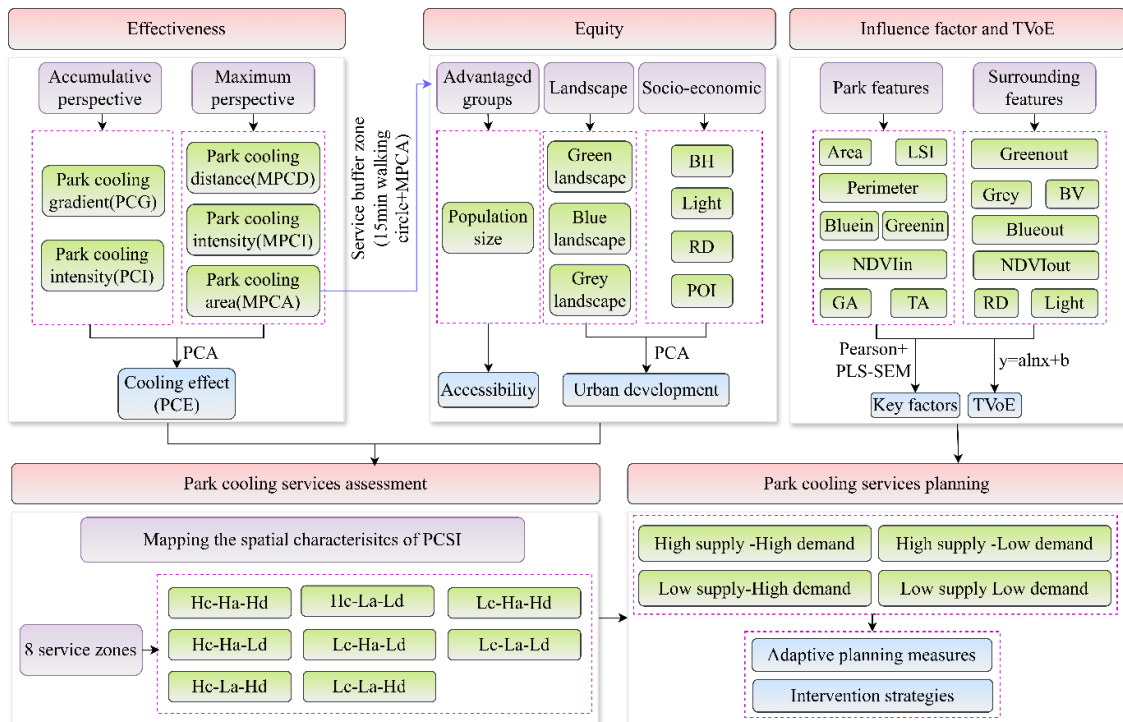


Figure 2. Assessment framework and workflow diagram for this study

Surface specific emissivity ( $\varepsilon$ ) is a parameter that characterizes the surface material and is usually estimated by the NDVI with the following formula:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (Eq.3)$$

$$\varepsilon = 0.004 \left( \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 + 0.986 \quad (Eq.4)$$

In Equation 3, NIR is the reflectance in the near-infrared band, i.e., Band 5 of Landsat 8, and RED is the reflectance in the red band, i.e., Band 4 of Landsat 8. In Equation 4, and are the maximum and minimum values of NDVI, respectively, which are usually taken to be 0.2 and 0.5. Based on the empirical model, when the  $NDVI < 0$ : assuming it is a body of water,  $\varepsilon = 0.99$ ; when it: assuming it is bare soil,  $\varepsilon = 0.97$ ; when  $NDVI > 0.2$ : calculated by Equation 4.

### Assessment of cooling effect

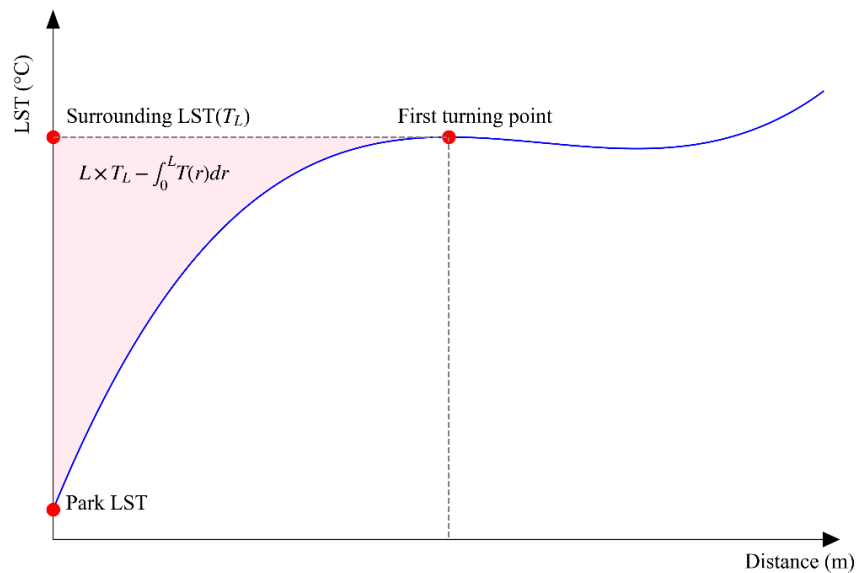
To rigorously quantify park cooling effects, we established a multi-ring buffering system extending 300 m outward from park boundaries. This analytical framework

comprised 10 concentric buffers (30-meter intervals) designed to capture thermal gradient patterns. For enhanced measurement accuracy, our temperature extraction protocol systematically excluded adjacent urban green spaces within overlapping buffer zones when calculating mean land surface temperature (LST), thereby controlling for inter-park thermal interference. A thermal-distance regression model was developed for individual urban parks using third-degree polynomial regression (Park, et al., 2019; Yao, et al., 2022). The mathematical representation of this relationship is expressed as:

$$T(r) = ar^3 + br^2 + cr + d \quad (\text{Eq.5})$$

where the independent variable  $r$  denotes the distance between the urban park boundary and the buffer zone, and the dependent variable  $T(r)$  is the average surface temperature at distance  $r$  from the urban park boundary.

As shown in *Figure 3*, the surface temperature in the buffer zone increases with increasing distance from the park boundary, but the rate of increase gradually slows down. The surface temperature reaches its maximum value when the first order derivative of the function  $T(r)$  (i.e.,  $T'(r)$ ) is equal to zero. The position at this point is defined as the first turning point (FTP) (Yu, et al., 2018). If there is no turning point for  $T(r)$ , the minimum value of its first-order derivative is used as the FTP. It is important to note that the surface temperature corresponding to the FTP is defined as the surrounding surface temperature ( $T_L$ ), and the distance from the boundary of the urban park to the FTP is referred to as the maximum park cooling distance (MPCD). In addition, the maximum buffer area affected by the cooling effect of the park is defined as the maximum park cooling area (MPCA) (Peng, et al., 2021; Yu, et al., 2018).



**Figure 3.** Schematic diagram of the park cooling curve (Park LST denotes the average surface temperature inside the park; TL denotes the surface temperature at the first turning point)

To systematically evaluate urban park cooling performance, our analysis employed a dual-metric framework comprising peak and cumulative indicators. The peak metrics quantify extreme cooling capacities through three parameters: Maximum Park Cooling

Intensity (MPCI), Maximum Cooling Distance (MPCD), and Maximum Cooling Area (MPCA). Conversely, cumulative metrics integrate thermal gradient effects via two indices: Park Cooling Gradient (PCG) and Cumulative Cooling Intensity (PCI). This dual-metric system was specifically designed to address the nonlinear cooling-distance relationship while maintaining comprehensive assessment capacity through complementary measurement approaches.

### Analysis of influencing factors

The drivers of park cooling effects can be systematically classified into two distinct categories: intrinsic landscape configurations and extrinsic environmental contexts (Cheng, et al., 2015; Guo, et al., 2023; Peng, et al., 2021). Our investigation incorporated fifteen determinant factors (Table 3) to comprehensively examine landscape composition and spatial characteristics. For the park itself, we selected eight factors: park area (Area), park perimeter (Perimeter), park status index (LSI), green space area in the park (Greenin), blue space area in the park (Bluein), NDVI in the park (NDVIin), grassland area in the park (GA), and forest area in the park (TA). The external landscape includes seven factors: green space area outside the park (Greenout), gray space area outside the park (Grey), blue space area outside the park (Blueout), NDVI outside the park (NDVIout), building volume (BV), night light index (Light), and road density (RD). GA and TA are derived from land cover data, and RD is derived from road data. Among them, GA and TA were calculated based on land cover classification, and RD was calculated using the ‘line density’ tool in ArcGIS. The calculation formula of LSI is as follows:

$$LSI = \frac{P}{\sqrt[2]{\pi \times S_{park}}} \quad (\text{Eq.6})$$

where P is the park perimeter and  $S_{park}$  is the park area.

**Table 3.** Selection of influencing factors

Classification	Influencing factors: abbreviations	Descriptions	Unit
Factors affecting the park itself	Area	Area of each park	ha
	Perimeter	Perimeter of each park	km
	LSI	Landscape shape index of each park	-
	Greenin	Area of green space in each park	ha
	Bluein	Area of blue space in each park	ha
	NDVIin	Normalized difference vegetation index of each park	-
	GA	Area of grassland in each park	ha
	TA	Area of trees in each park	ha
Influencing factors around the park	Greenout	Area of green space within MPCA of each park	ha
	Grey	Area of grey space within MPCA of each park	ha
	Blueout	Area of blue space within MPCA of each park	ha
	NDVIout	Normalized difference vegetation index within MPCA of each park	-
	BV	Building volume within MPCA of each park	-
	Light	Nighttime lighting index within MPCA of each park	-
	RD	Road density within MPCA of each park	-

To precisely quantify environmental impacts on thermal regulation, our analysis focused on the Maximum Park Cooling Area (MPCA) for each green space. The methodological framework employed dual analytical approaches: First, bivariate correlations through Pearson's coefficient were computed to identify preliminary associations between cooling metrics and determinants. Subsequently, Partial Least Squares Structural Equation Modeling (PLS-SEM) was implemented to elucidate complex pathway relationships influencing Park Cooling Efficiency (PCE). Notably, PLS-SEM offers distinct analytical advantages for this investigation: (1) flexibility in handling complex multivariate relationships without stringent distributional assumptions; (2) robustness in small-sample scenarios with multicollinear predictors; (3) predictive modeling capability particularly suited for exploratory environmental studies. This dual-method approach enables simultaneous examination of direct thermal regulation mechanisms and indirect mediation effects through pathway analysis.

### ***Threshold value of efficiency (TVoE) calculation***

Empirical investigations consistently demonstrate non-linear asymptotic relationships between environmental determinants and urban heat mitigation performance (Brown, et al., 2018; Chang, et al., 2007). Building upon established methodological frameworks, we employed logistic regression analysis ( $y = a \ln x + b$ ) to characterize the monotonic asymptotic relationship between thermal regulation capacity and predictor variables (Shi, et al., 2023; Yao, et al., 2022). TVoE represents a critical optimization parameter defined as the minimal spatial configuration required for green infrastructure (vegetated areas, aquatic systems, and park clusters) to achieve maximum cooling efficiency. This metric identifies the inflection point where additional spatial expansion yields diminishing returns in thermal regulation. Operationally, TVoE corresponds to the x-intercept at unity slope ( $dy/dx = 1$ ) of the logarithmic response curve when cooling efficiency demonstrates log-linear dependence on predictor variables (Fan, et al., 2019; Peng, et al., 2020). Notably, while parametric modifications of environmental variables influence thermal regulation magnitude, such effects exhibit bounded scalability constrained by TVoE thresholds. Beyond this critical value, the marginal cooling gain per unit change in determinant factors asymptotically approaches zero, establishing TVoE as the thermodynamic equilibrium point for cooling efficiency optimization.

### ***Accessibility and equity assessment***

The accessibility of park cooling services, quantified as a distance-based exposure metric, is operationalized through spatial pedestrian access to Maximum Park Cooling Area (MPCA) (Chen, et al., 2022). This parameter critically evaluates the realized cooling benefits urban populations derive from green infrastructure (Shi, et al., 2023). Leveraging Mapbox's high-resolution global road network datasets, we generated mobility catchment areas that account for real-world navigation constraints, including traffic regulations, velocity restrictions, and roadway hierarchies, thereby enhancing spatial modeling fidelity. Methodologically, park entrances were systematically positioned at 200-meter intervals along MPCA perimeters to simulate pedestrian ingress points. GIS-based isochrone analysis was subsequently performed to delineate walking ( $\leq 5$  km/h) and cycling ( $\leq 15$  km/h) accessibility zones. These mobility thresholds were stratified into four service tiers per China's Spatial Planning Guidelines for Community Residential Units (Ministry of Natural Resources, 2021):

<= 5 min (excellent), 5-10 min (good), 10-15 min (moderate), and > 15 min (deficient). A composite service buffer integrating MPCA with 15-min walking isochrones was developed to assess cooling service equity (Khavarian-Garmsir et al., 2023). Population-weighted accessibility metrics were calculated by aggregating residential demographics within these synergistic zones (Table 4). Crucially, households beyond 15-min walking thresholds to MPCA were designated as cooling service-deprived populations, enabling quantitative evaluation of thermal amenity distribution justice.

**Table 4.** Calculation and description of park cooling service indicators used in this study

Variable category	Variable	Formula and range of values	Meaning
Cooling effect	MPCD	$MPCD \geq 0$	Distance between FTP and park boundary (m)
	MPCI	$MPCI \geq 0$	Difference between average park surface temperature and surface temperature at the first turning point (°C)
	PCG	$PCG = \frac{L \times T_L - \int_0^L T(r) dr}{L}$	Ratio of cumulative cooling to maximum cooling distance (°C)
	PCI	$PCI = \frac{L \times T_L - \int_0^L T(r) dr}{L \times T_L}$	Ratio of the reduced surface temperature within the maximum cooling distance to the total surface temperature when the park was not built, reflecting the cooling perception of local residents
	MPCA	$MPCA \geq 0$	Buffer zone made at the park boundary with the maximum cooling distance as the radius (ha)
Accessibility	Population	$Population \geq 0$	Number of people within a 15-min walk to park cooling services; assessing accessibility levels
Urban development	MPCA_blue	$Blue = \frac{A_{blue}}{MPCA}; 0 \leq Blue \leq 1$	Proportion of blue landscape in maximum cooling area (%)
	MPCA_green	$Green = \frac{A_{green}}{MPCA}; 0 \leq Green \leq 1$	Proportion of green landscapes in the maximum cooling area (%)
	MPCA_grey	$Grey = \frac{A_{grey}}{MPCA}; 0 \leq Grey \leq 1$	Proportion of grey landscape within the maximum cooling area (%)
	MPCA_BH	$BH \geq 0$	Total building height in the maximum cooling area
	MPCA_Light	$Light \geq 0$	Average nighttime light within the maximum cooling area
	MPCA_POI	$POI \geq 0$	POI within the maximum cooling area
	MPCA_RD	$RD \geq 0$	Average road density within the maximum cooling area

### Assessment of the level of urban development

Urban development decisions have a direct and far-reaching impact on the allocation of urban park resources, especially in the context of frequent extreme heat events, where

the importance of the potential cooling effect of parks in improving the quality of life of residents becomes more and more apparent. In order to achieve equity and universality of park cooling services, it is necessary to combine landscape composition with socio-economic factors to comprehensively characterize the state and features of local urban development. Therefore, this paper combines indicators of different dimensions such as ecological (blue, green and grey landscape ratio), social (points of interest, road density) and economic (building height, night lighting) (*Table 4*) to form a comprehensive urban development evaluation system, and finally integrates the multi-dimensional indicators through the Principal Component Analysis (PCA) method to compute a comprehensive score of urban development.

### ***Integrated framework and index construction***

In order to measure the complexity of multidimensional concepts, a comprehensive index is needed to summarize and measure complex or multifaceted phenomena through an integrative approach (Kato-Huerta and Geneletti, 2023). These indices are able to represent different domains or dimensions, and therefore have an important supporting role in the study of park cooling services. In this paper, a hierarchical model of park cooling services is proposed, in which the indicators are divided into three sub-indicators (hereinafter referred to as the three dimensions). Based on this, a comprehensive framework containing cooling effect, accessibility and urban development is constructed (referring *Fig. 2* and *Table 2*). Among them, park cooling effectiveness serves as the core indicator for assessing the efficiency of cooling services, while urban development and accessibility together reflect the performance of park cooling services in terms of equity. The framework consists of a city Park Cooling Service Index (PCSI) and a reorganized system of categorized sub-indicators (8 service areas.) The PCSI is indispensable in reflecting the dynamics of the assessment object in a more comprehensive and quantitative way, while the categorization method of the sub-indicators helps to identify potential correlations, thus improving the depth and efficiency of the analysis. In addition, the study explores adaptive planning measures and intervention strategies based on both supply and demand to improve park cooling services for future urban park planning.

The city Park Cooling Services Index (PCSI) is derived from a comprehensive quantification of cooling effectiveness, accessibility, and urban development, allowing for a comprehensive assessment of the equity of cooling services. Since the cooling effect of parks and urban development are affected by several highly correlated indicators, we use principal component analysis (PCA) to assess and analyze their impacts (Dong, et al., 2020; Johnson, et al., 2012; Yu, et al., 2023).

In addition, the principle of addition or multiplication is often used when integrating target layers. Park cooling services are mainly influenced by cooling effectiveness, accessibility and urban development, and the relationship between these factors is not a simple linear addition. Studies have also shown that the multiplication principle better reflects the complex relationships between indicators than the addition principle (El-Zein and Tonmoy, 2015; Estoque, et al., 2020). Therefore, we calculate the composite score for park cooling services as follows:

$$PCSI = \sqrt[3]{C \times A \times U} \quad (\text{Eq.7})$$

The Park Cooling Service Index (PCSI) functions as a composite metric synthesizing three standardized parameters: cooling effect (C), accessibility (A), and urban development (U). To maintain analytical coherence, a directional normalization protocol was implemented, ensuring all parameters exhibit strictly positive scaling with the PCSI. This approach eliminates value-range conflicts by constraining normalized inputs to a [0,1] interval while preserving monotonic relationships between constituent variables and the composite index. The normalization procedure aligns with multivariate index construction best practices, mitigating distortion risks from heterogeneous value distributions.

$$F' = 0.1 + \frac{F - MIN}{MAX - MIN} \times (0.9 - 0.1) \quad (\text{Eq.8})$$

where F represents the standardized value, ranging from 0.1 to 0.9, denotes the original value, and MIN and MAX denote the minimum and maximum values of the original value, respectively.

To investigate spatial heterogeneity in urban thermal regulation performance, we implemented a stratified classification scheme utilizing standardized evaluation metrics across target domains. All municipal parks underwent systematic categorization through geospatial analysis in ArcGIS, employing median thresholding to dichotomize cooling service parameters into high/low cohorts (Dong, et al., 2020; Yu, et al., 2023). This methodology generated eight distinct thermal service typologies: Hc-Ha-Hd, Hc-Ha-Ld, Hc-La-Hd, Lc-Ha-Hd, Hc-La-Ld, Lc-Ha-Ld, Lc-La-Hd, and Lc-La-Ld. The nomenclature convention contains dual semantic components:

(1) Performance Tier (Prefix):

H: High-performance cluster ( $\geq$  50th percentile)

L: Low-performance cluster ( $<$ 50th percentile)

(2) Evaluation Domain (Suffix):

c: Cooling effect

a: Accessibility

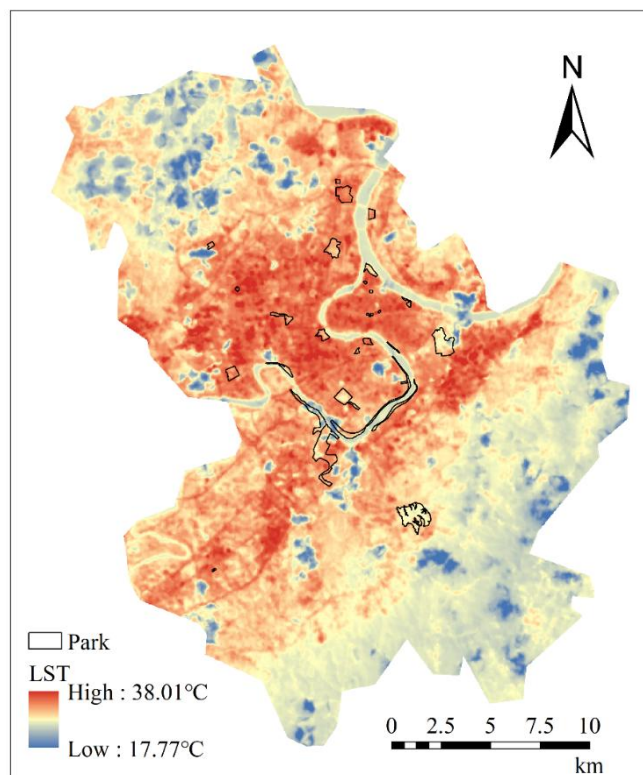
d: Urban development

This typological framework enables comparative analysis of multifactorial thermal service configurations while maintaining dimensional interpretability through standardized coding protocols.

## Results

### *Analysis of cooling effect*

The surface temperature LST in Zhanggong District, Ganzhou City in summer is inverted according to *Equations 1, 2, 3 and 4*. The results are shown in *Figure 4*. The LST range is 17.77~38.01°C, and the average LST is calculated to be 27.89°C. From the spatial pattern of surface temperature, Zhanggong District has different degrees of urban heat island effect, extending from the city center to the south-west and north-east, the surface temperature gradually decreases, and the core area of the city is most seriously affected by the heat island effect, while the surface temperature of the urban fringe and the natural area is relatively low. Most of the LST values located in the parks are significantly lower than those in the park surroundings, indicating that most of the parks have a significant cooling effect.

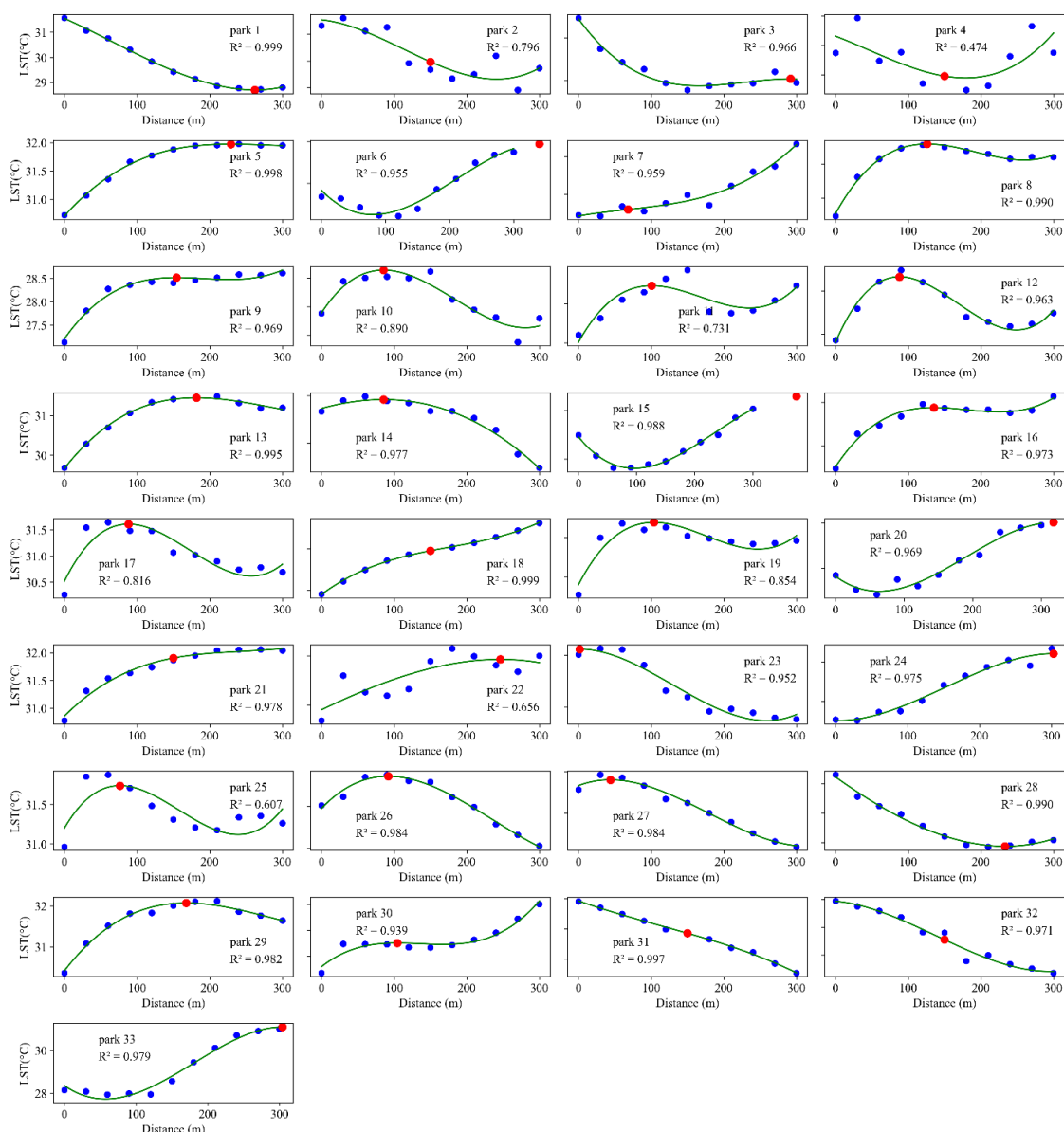


**Figure 4.** The average surface temperature in the study area in July

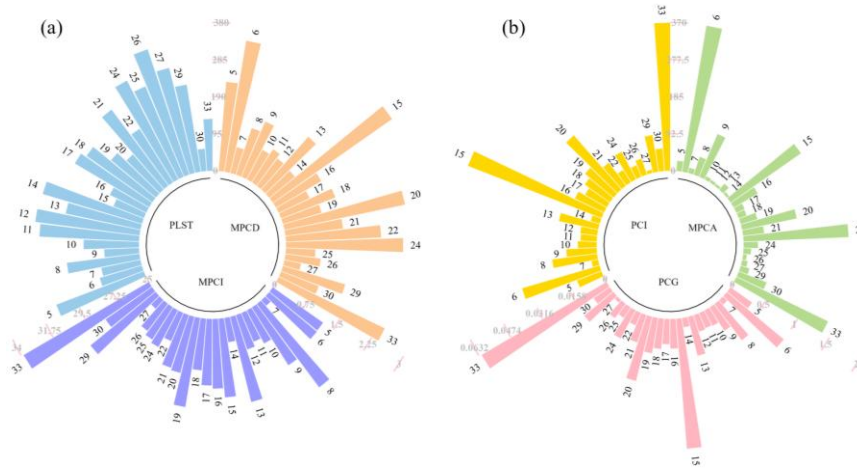
To further determine the specific cooling effect of each urban park, we fitted a multiple regression equation (Eq. 5) for each park (Fig. 5), which showed that 25 of the 33 urban parks were cooler than their neighborhoods, while 8 parks showed no cooling effect. Therefore, the 25 parks that showed a significant cooling effect will subsequently be analyzed and the corresponding calculations are shown in Figure 6. Park 26 has the highest internal PLST of 33.02°C and Park 30 has the lowest internal PLST of 26.36°C, a difference of 6.66°C. The average MPCA value of the urban parks with cooling effect was 75.38 ha, ranging from 6.31 to 369.50 ha, with Park 6 having the highest MPCA. The mean PCG value was 0.49°C with a range of 0.05 to 1.96°C with Park 33 having the highest PCG. The mean PCI value was 0.0162°C with a range of 0.0014 to 0.0631°C with Park 33 having the highest PCI. The mean MPCl value was 1.16°C with a range of 0.15 to 2.95°C, with Park 33 having the highest MPCl. The mean MPCD value was 164.66 m with a range of 43.82 to 375.09 m, with Park 15 having the highest MPCD.

Multifactorial indicators of park cooling effect were assessed using PCA (Principal Component Analysis). The KMO value of 0.727 exceeded the threshold of 0.6. Two principal components were extracted to determine the cooling effect, which explained a total of 91.05% of the variance. Figure 7 shows the spatial distribution of the cooling effect in urban parks in Zhanggong District. The cooling effect was averaged into five categories (Xiao, et al., 2023b): low (0.1-0.26), relatively low (0.26-0.42), medium (0.42-0.58), relatively high (0.58-0.74) and high (0.74-0.9). Overall, the cooling effect was extremely low, with the first two categories of low values accounting for 84% of the total number (25 parks with a cooling effect), and these parks were of different

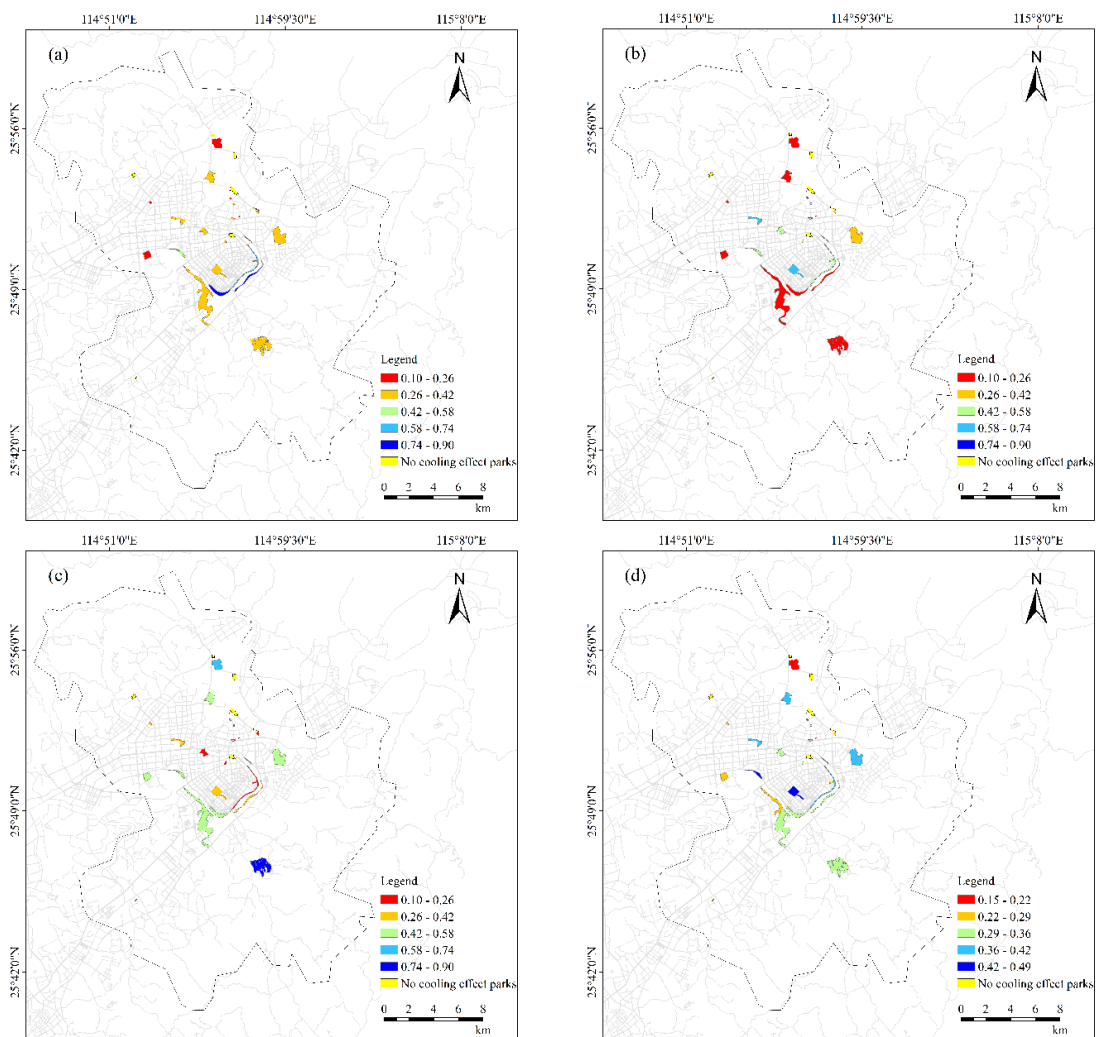
shapes, with a variety of park sizes, with an average size of 31.96 ha, which is slightly different from the average size of the 25 parks (31.35 ha), suggesting that the correlation between the cooling effect of the park and its size is weak, and may be more influenced by other factors (e.g. park landscape features). There is one park with a ‘medium’ cooling effect, one with a ‘relatively high’ cooling effect, and two with a ‘high’ cooling effect, and the latter two high values are distributed along the river in a band, indicating that the water bodies around the park have a significant influence on the cooling effect. The latter two categories of high values are all distributed in a band along the river, indicating that the water bodies around the parks have a significant impact on the cooling effect. Overall, the 25 urban parks have a high number of low values, and there are significant differences in the cooling effect.



**Figure 5.** The cubic polynomial relationship between land surface temperature (LST) and the distance to 33 urban parks. The x-axis ( $r$ ) represents the distance between the urban park boundary and the buffer zone, and the y-axis represents the average land surface temperature at  $r$  distance from the urban park boundary. The red dot in the figure is the first turning point



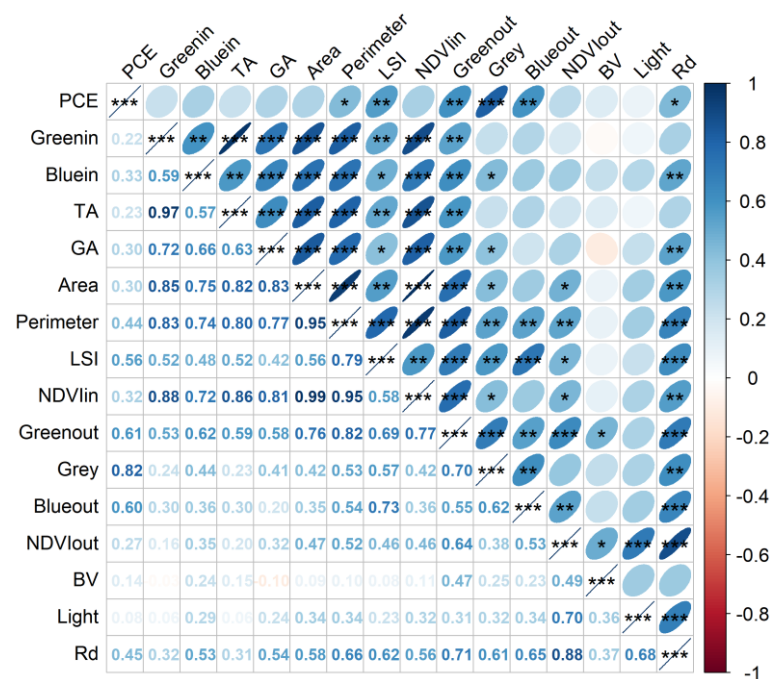
**Figure 6.** Six cooling indices for 25 urban parks (only parks with cooling effect). (a) MPCD, MPCl, and PLST indices for 25 urban parks, and (b) MPCA, PCG, and PCI indices for 25 urban parks



**Figure 7.** Spatial pattern and distribution of cooling effect (a), accessibility (b), urban development (c) and park cooling service index (PCSI) in urban parks (d)

### Identification of influencing factors

In order to systematically identify the key factors affecting the cooling effect of the park, this study first explored the relationship between the variables through Pearson correlation analysis (Fig. 8). The results showed that several factors were significantly and positively correlated with PCE: park perimeter ( $p = 0.029$ ,  $r = 0.44$ ), landscape shape index LSI ( $p = 0.004$ ,  $r = 0.56$ ), peripheral green space area Greenout ( $p < 0.001$ ,  $r = 0.61$ ), grey space area Grey ( $p < 0.000$ ,  $r = 0.82$ ), peripheral water body area Blueout ( $p < 0.002$ ,  $r = 0.60$ ) and road density RD ( $p < 0.025$ ,  $r = 0.45$ ). This suggests that the cooling effect of the park is jointly influenced by multi-dimensional factors, including not only the morphological characteristics of the park itself, but also the composition of the surrounding landscape. It is worth noting that, as with the findings of existing studies, no significant correlation was shown between park size and cooling effect in this study, suggesting that smaller parks can also achieve better cooling effect.

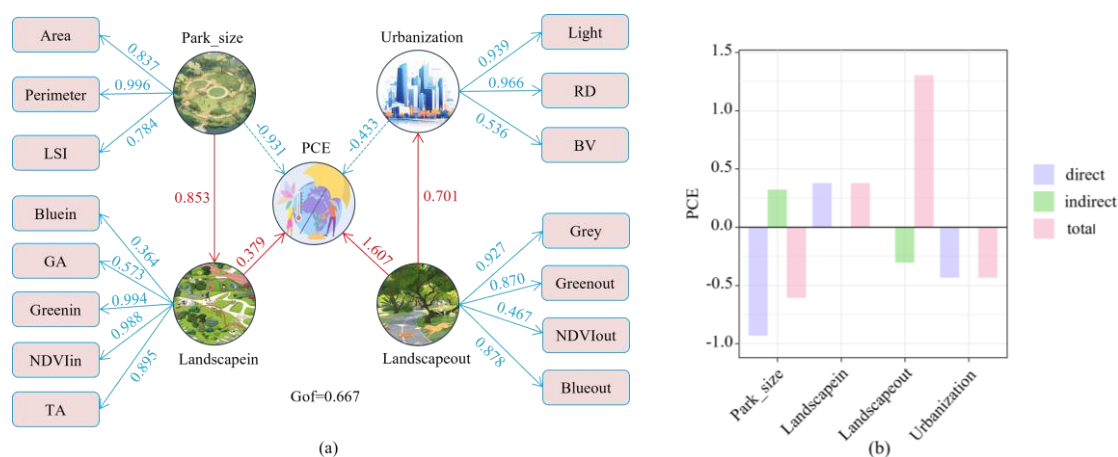


**Figure 8.** Pearson correlation coefficient matrix between variables. The lower triangle area shows the specific value, and the upper triangle area uses an ellipse to visualize the degree of correlation. The length of the ellipse represents the strength of the correlation, and the direction of the slope indicates the nature of the relationship (positive correlation from upper left to lower right, negative correlation from upper right to lower left). The statistical significance level is marked with an asterisk: \*\*\* indicates  $p < 0.001$  (highly significant), \*\* indicates  $p < 0.01$  (moderately significant), \* indicates  $p < 0.05$  (significant), and no mark indicates no statistical significance

Based on the results of the correlation analysis, the PLS-SEM model was constructed in this study to reveal the mechanism of action among the factors (Fig. 9). The overall fit of the model was 0.67 ( $>0.6$ ), indicating that the model has good explanatory power. The path analysis revealed that the most significant effect of surrounding landscape features (Landscapeout) on PCE (path coefficient + 1.6065) was much greater than that of internal landscape features. This finding highlights the importance of optimizing the

park surroundings to enhance the cooling effect, and echoes recent research on the importance of the ‘park-urban interface’. Park size indirectly affects the cooling effect mainly through its constraints on the internal landscape of the park (Landscapein). This negative effect (negative path coefficient) suggests that a simple increase in park size may reduce cooling efficiency due to the increased complexity of the internal landscape, which provides a new perspective to explain the unsatisfactory cooling effect of some large parks. Urbanization showed a significant negative correlation (path coefficient - 0.4326) on PCE, suggesting that the cooling effect of parks in highly urbanized areas may be inhibited. This is consistent with the discussion of existing studies on the trade-off between urbanization intensity and cooling effect.

The results of the PLS-SEM model analyses also reveal some important indirect effects: the synergistic effect of Landscapein and Landscapeout is a key contributor to PCE, while Park\_size further reinforces its negative effect on PCE by influencing Landscapein. In contrast, Landscapeout may indirectly mitigate the negative impact of socioeconomic development on the cooling effect by regulating urbanization. These findings have important implications for urban planning: the optimization of internal and external landscape features should be placed at the core of park design, rather than overly focusing on scale expansion; at the same time, the improvement of the surrounding environment may provide new ideas for mitigating the contradiction between urbanization and the cooling effect.



**Figure 9.** Relationship of each variable with PCE revealed by PLS-SEM. Circles and rectangles indicate latent and observed variables, respectively. latent variables are Park\_size, Landscapein, Landscapeout, and Urbanization. observed variables are Area, Perimeter, LSI, Bluein, GA, NDVIin, Greenin, TA, Grey, Greenout, NDVIout, Blueout, Light, RD, and BV. The blue dashed line and red solid line indicate negative and positive correlation, respectively

### Thresholds for cooling effect

The relationship between PCE and the influencing factors was further determined using classical parametric logistic regression ( $y = \ln x + b$ ) (Fig. 10). As shown in the logarithmic fitting plot, the PCE increased to a certain level and then levelled off as the influencing factors increased, among which, Greenin, TA, Area, Perimeter, LSI, NDVIin, Greenout, Grey, Blueout, and RD were fitted better, with the corresponding thresholds of 0.04 ha, 0.04 ha, 0.03 ha, 0.07 km, 0.24, 0.03 ha, 0.06 ha, 0.16 ha, 0.03 ha, 0.05, whereas Bluein, GA, NDVIout, BV, and Light did not show significant threshold

effects with PCE. This finding suggests that not all influencing factors have significant saturation points, and some of them may influence park cooling effects through other mechanisms. The logarithmic fitting curve further shows that when the influencing factors exceed the TVoE, increasing their values has limited effect on the cooling effect, e.g., when the green space area in the park exceeds 0.04 ha, it is difficult to significantly improve the cooling effect only by expanding the green space area. This finding has important implications for urban planning, i.e., under limited resources, priority should be given to ensuring that each influencing factor achieves its TVoE, rather than blindly pursuing the scale expansion of a single element. To verify the reliability of the fitting results, this study calculated the 95% confidence intervals and prediction intervals for each regression model (pink and grey areas in *Fig. 10*). The results show that most of the observations fall within the prediction intervals, indicating that the models have good explanatory power and predictive ability. These TVoE indicators provide specific quantitative references for park planning and design, and help to achieve the optimal configuration of cooling effect in practice.

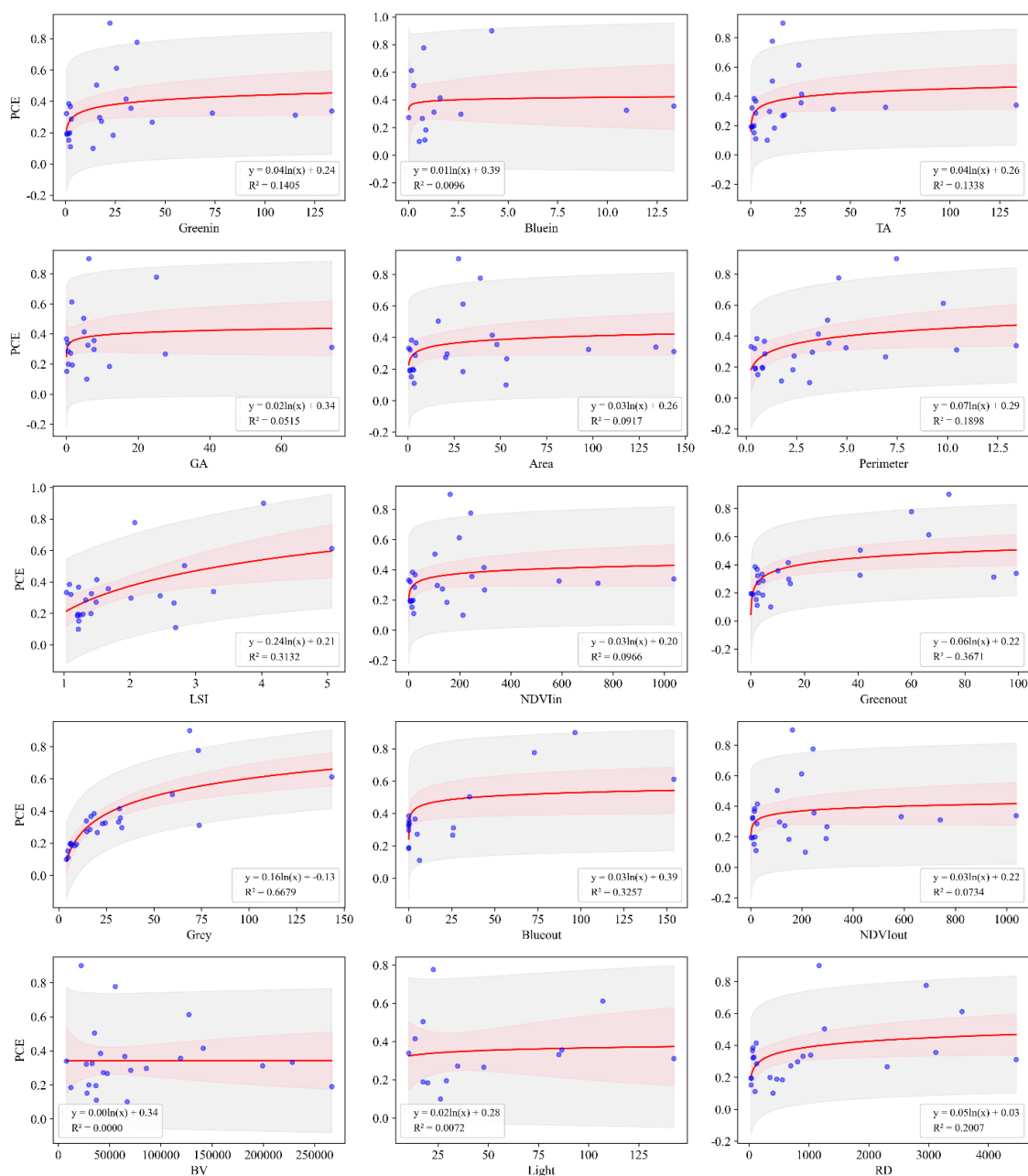
### ***Accessibility and equity analysis***

*Figure 11a, b* illustrate the spatial distribution characteristics of walking isochronous circles and cycling isochronous circles for different times of arrival of residents to the park cooling service area. It can be found that the accessibility of the walking mode of transport for residents is very poor compared to the cycling mode of transport. Under the walking mode, 7.61%, 15.51%, 18.68%, and 14.72% of the communities with travel times of less than MPCA, less than 5 min, 5 to 10 min, and 10 to 15 min, respectively, and 43.48% of the communities had residents who were unable to reach the park's cooling range within 15 min (*Table 5*). Under the cycling mode of transport, 7.61%, 47.92%, 17.79%, 4.55% and 22.13% of the communities had a travel time of less than MPCA, less than 5 min, 5 to 10 min, 10 to 15 min, and more than 15 min, respectively. The spatial pattern of accessibility shows that the urban parks we collated can serve 56.52% of the households in the study area within 15 min walking distance and 77.87% of the households in the study area within 15 min cycling distance, while only 7.61% of the households in the MPCA have direct access to urban parks to cool down during the hot summer months. Therefore, approximately half (43.48%) of the households do not have access to the cooling effects of these urban parks within a 15-min walk during the hot summer months.

The number of people living within the service area (encompassing the MPCA and the 15-min walking circle) was chosen to quantify accessibility. The accessibility of the various urban park service areas in the Chapter District varies greatly, indicating that the number of residents within each park service area is extremely heterogeneous. Park 11 had the highest accessibility value of 0.9 and Park 14 had the lowest accessibility value of 0.1 (*Fig. 7b*).

Accessibility was equally divided into five categories: low (0.1-0.26), relatively low (0.26-0.42), medium (0.42-0.58), relatively high (0.58-0.74) and high (0.74-0.9). Relatively high and high accessibility accounted for 12% and exceptionally high for only 4%, while relatively low and low accessibility covered 64% of urban parks, with accessibility to park cooling services becoming worse for residents as the central city extends outwards. In addition, the distribution of parks and neighborhoods and populations on the outskirts of the city shows that parks on the edges of the central city are larger, with lower population densities and more dispersed populations (*Fig. 11c, d*). This results in a small number of people enjoying most of the spatial resources, while others face

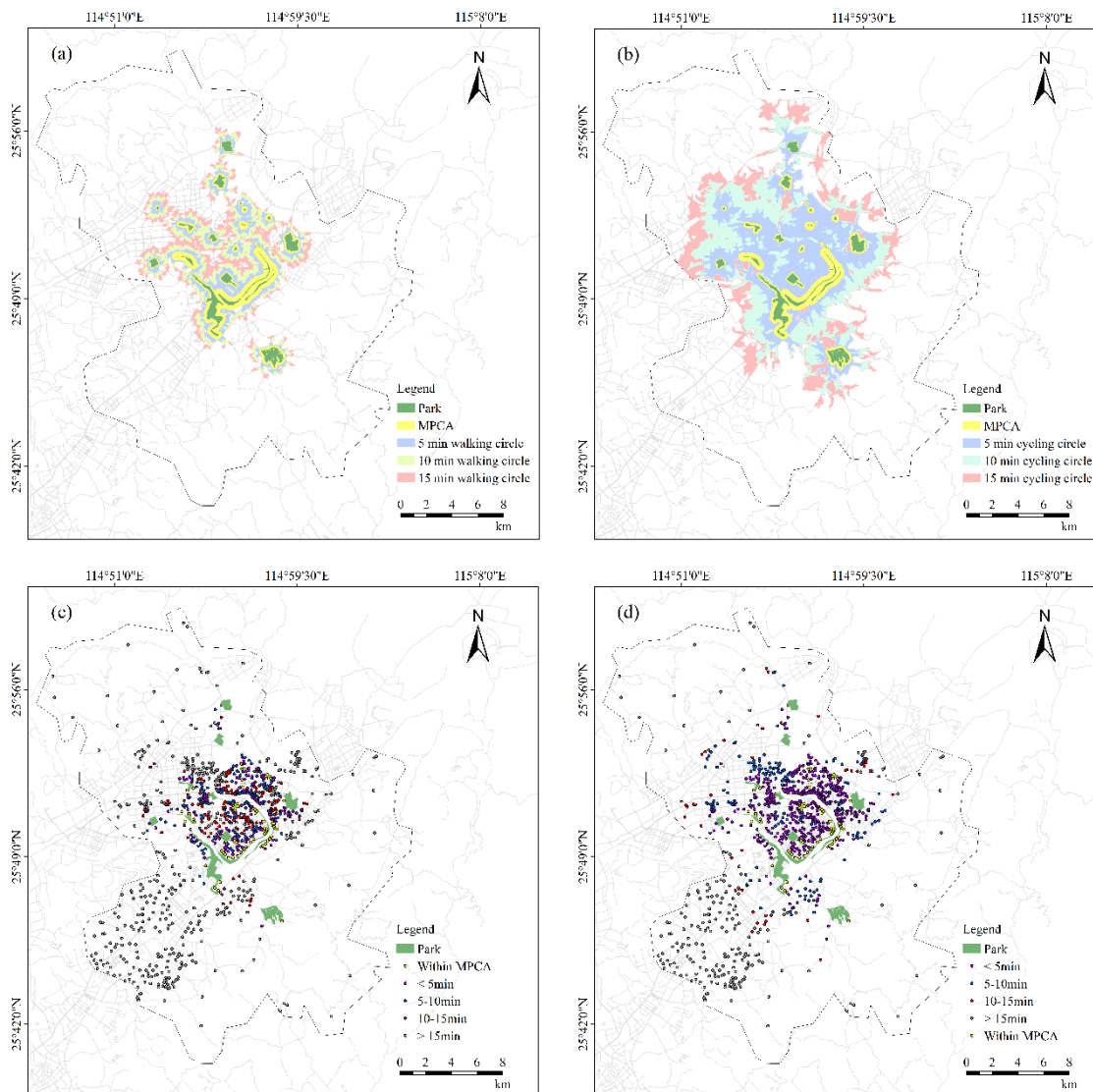
inconvenient access or even no access to cooling services. All these indicate the insufficient park supply and uneven distribution of parks in the central city of Ganzhou.



**Figure 10.** Logarithmic relationship between impact factors and PCE, pink areas are 95% confidence intervals and light grey areas are 95% prediction intervals

**Table 5.** Statistics on the proportion of communities with different time consumption by different modes of transport

Time consumption	Within MPCA	<5 min	5-10 min	10-15 min	>15 min
Walking mode	7.61%	15.51%	18.68%	14.72%	43.48%
Cycling mode	7.61%	47.92%	17.79%	4.55%	22.13%



**Figure 11.** (a) and (b) show the spatial distribution of walking isochronous circles and cycling isochronous circles for different times of the park's cooling service area, respectively, and (c) and (d) show the spatial distribution of settlements for two different isochronous circles, respectively (each point represents a residential location)

### Analysis of urban development level

The principal component analysis (PCA) method was used to integrate the multidimensional indicators of urban development, including the three dimensions of ecology (proportion of blue, green and grey landscapes), society (points of interest, road density), and economy (building heights, nighttime lighting). After KMO and Bartlett's test, three principal components were successfully extracted, which explained a total of 83.6% of the total variance. The results of the analyses showed that the level of urban development within the cooling service area of urban parks in Zhanggong District showed obvious spatial differentiation characteristics (Fig. 7c). The urban development values were classified into five levels: low (0.1-0.26), relatively low (0.26-0.42), medium (0.42-0.58), relatively high (0.58-0.74) and high (0.74-0.9).

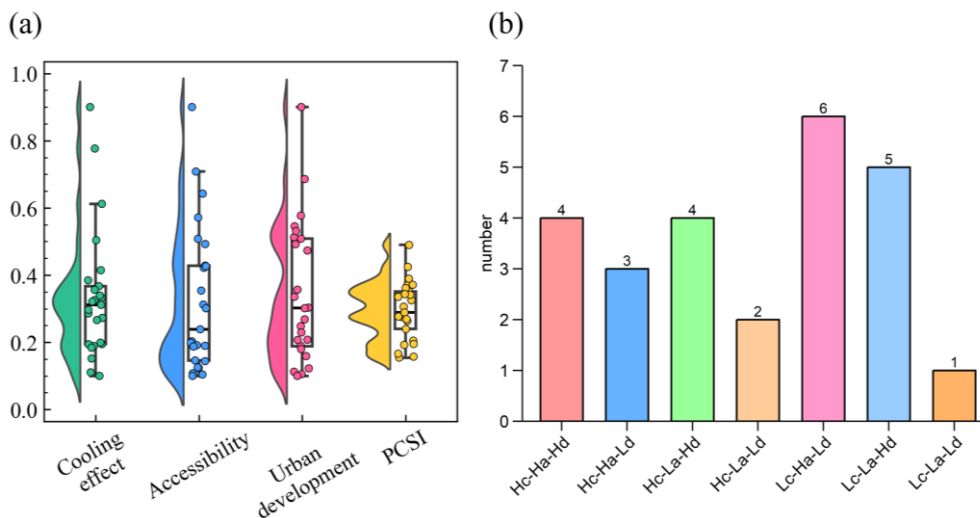
From the point of view of spatial distribution, the level of urban development generally shows the following characteristics: (1) the overall distribution is uneven. The 'low' and 'relatively low' categories account for more than half of the regions (64%), while the 'high' and 'relatively high' categories account for only 8% of the total, and the 'medium' category accounts for 28%, reflecting significant differences in regional development. (2) A clear core-periphery pattern. Areas with high levels of development are mainly concentrated in the city center and key functional areas, such as Park 12 and Park 27, which have well-developed infrastructure and vibrant socio-economic activities. In contrast, the development level of peripheral areas, such as the area where Park 15 is located, is generally lower, which is related to its poor infrastructure and low development intensity. (3) Diverse development drivers. Some areas (e.g., Park 12) are located at the edge of the central city, but have a high level of comprehensive development due to their excellent ecological conditions and comprehensive supporting facilities; while some areas (e.g., Park 27) rely mainly on high-intensity development and economic activities to drive their development.

The formation of this pattern of spatial differentiation is mainly influenced by three factors: firstly, the historical development path dependence has led to the central urban area receiving more construction resources and policy support; secondly, the natural environmental conditions (e.g. topography, water system) have influenced the functional layout and development intensity of the city; and thirdly, the urban renewal and functional area construction in recent years have further strengthened the unevenness of regional development. Such spatial differences in development levels directly affect the efficiency and equity of park cooling services and need to be focused on in future planning.

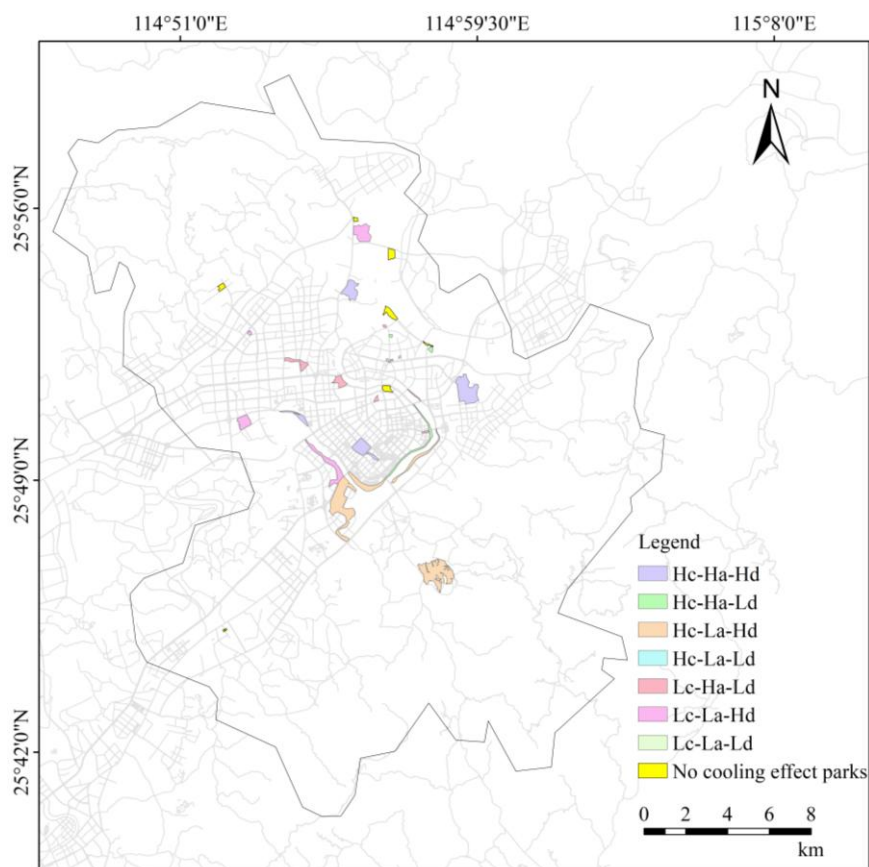
### ***Analysis of park cooling services***

The equity of park cooling services can be assessed by analyzing PCSI scores. The PCSI is assessed by combining findings on cooling effectiveness, accessibility, and urban development (*Fig. 12a*). Based on the combined PCSI scores, we averaged the PCSI scores into five categories: low (0.15-0.22), relatively low (0.22-0.29), medium (0.29-0.36), relatively high (0.36-0.42) and high (0.42-0.49). Park 20 had the highest PCSI value of 0.49, more than three times higher than the lowest, Park 12 (0.15), and urban parks had an overall low PCSI (*Fig. 7d*). The 'low' and 'relatively low' categories accounted for more than half of the total number of parks with 52% of the PCSI values, while the 'medium' category accounted for 24% of the PCSI values. The 'high' and 'relatively high' categories accounted for 24% of the cooling service value, which indicates that the overall level of cooling service in urban parks is relatively low. In addition, we analyzed the main characteristics of cooling services in each city park by dividing the 25 city parks into 8 different combinations and determining the number and spatial distribution of city parks within each combination (*Figs. 12b* and *13*). Among them, the number of urban parks in the combinations was relatively balanced, except for the combinations 'Hc-La-Ld' (2 parks, 8% of the total number of parks) and 'Lc-La-Ld' (1 park, 4% of the total number of parks), which had a relatively small number of parks (*Fig. 12b*). Specifically, 12% of the urban parks belonged to low accessibility and low urban development areas, with 66.7% of the parks having a high cooling effect and 33.3% of the parks having a low cooling effect. There are no urban parks that belong to the 'Lc-Ha-Hd' combination, and only 16% of the parks belong to high accessibility and high urban development areas, of which all of them have a

significant cooling effect. This suggests that there is a discrepancy between the supply of and demand for cooling services in urban parks, and therefore a high priority should be given to the equity of cooling services, in particular to optimize cooling services for a larger number of urban residents.



**Figure 12.** Cloud and rain plots on different dimensions of the index of cooling services for parks in Zhanggong District (a) and the number of parks in different combinations (b)



**Figure 13.** Combined distribution of cooling service indices for parks in Zhanggong District

## Discussion

### *LST, PCE, influencing factors and TVoE of urban parks*

The results of the study show that urban parks in Zhanggong District have significant cooling effects in mitigating the urban heat island effect, but there is obvious heterogeneity in the intensity and spatial distribution of cooling effects. In terms of the spatial pattern of LST, although most of the parks showed a cooling effect, there were significant differences in the cooling effect among the 25 parks with a cooling effect, and the cooling capacity of some parks was relatively low. This phenomenon may be closely related to the landscape characteristics of the parks, the surrounding environment and the level of urbanization. In terms of the spatial distribution of PCE, the cooling effect of parks distributed along rivers is significantly higher than that of isolated green spaces in urban areas due to the moderating effect of the surrounding water bodies. The results further validate the positive role of water body landscape on urban cooling effect, which is consistent with the conclusions of existing studies (Liang, et al., 2023).

The analysis of the influencing factors showed that internal characteristics such as the perimeter of the park itself and the park landscape shape index (LSI) had a significant effect on the cooling effect, while the external environment such as the green space (Greenout), blue space (Blueout), grey space (Grey) and road density (RD) around the park further amplified the cooling effect of the park. The proportion of water body area within the park was weakly and positively correlated with the cooling intensity. The proportion of water bodies in the MPCA outside the park was strongly positively correlated with the cooling intensity, and there was no significant correlation between the park area and the cooling intensity, and some small parks could achieve the same cooling intensity as some large parks, which was consistent with the findings of the existing studies (Chen, et al., 2022). The PLS-SEM model found that the role of surrounding landscape features (Landscapeout) is particularly important, and its contribution to the cooling effect is much larger than that of the internal landscape features of the park. This is consistent with the results of the Pearson correlation analysis, further emphasizing the importance of optimizing the park's peripheral environment to enhance the overall cooling effect. In addition, the analysis of the threshold of cooling efficiency (TVoE) further reveals the non-linear relationship between the influencing factors of the park and PCE. The results show that when Greenin, TA, Area, Perimeter, LSI, NDVIin, Greenout, Grey, Blueout, and RD exceed a certain scale (TVoE), the PCE tends to saturate or even decrease, whereas changes in Bluein, GA, NDVIout, BV, and Light do not have a significant impact on the PCE. greatly. This finding is of great significance for urban planning: under the condition of limited resources, simply expanding the park area may not significantly enhance the cooling effect, and more attention should be paid to the coordination and optimization of the park design and the surrounding environment.

### *Equity status of urban park cooling services*

The accessibility and equity analyses show that the spatial distribution of cooling services in urban parks in Zhanggong District is characterized by significant inequality. In walking mode, only 56.52% of the community can reach the maximum cooling area (MPCA) of the park within 15 min, while 43.48% of the community residents are unable to enjoy the cooling service of the park in the middle of hot summer. In contrast,

accessibility by cycling mode is significantly higher, but 22.13% of community residents are still outside the coverage of cooling services. This spatial inequality mainly stems from the uneven distribution of park resources: parks in the central city are densely populated but generally small in size, making it difficult for them to meet the needs of the high-density population; while in the peripheral areas of the city, despite the large size of the parks, they have a limited radius of service, resulting in inefficient use of resources.

Further analysis reveals that inequity in cooling services is also closely related to the level of socio-economic development of the city. Parks in low-income neighborhoods and high-density neighborhoods are often under-resourced, making it more difficult for residents to access cooling services. This inequality not only undermines the overall effectiveness of park cooling services, but also exacerbates the problem of inequality in urban societies.

### ***Strategies for optimizing urban park planning***

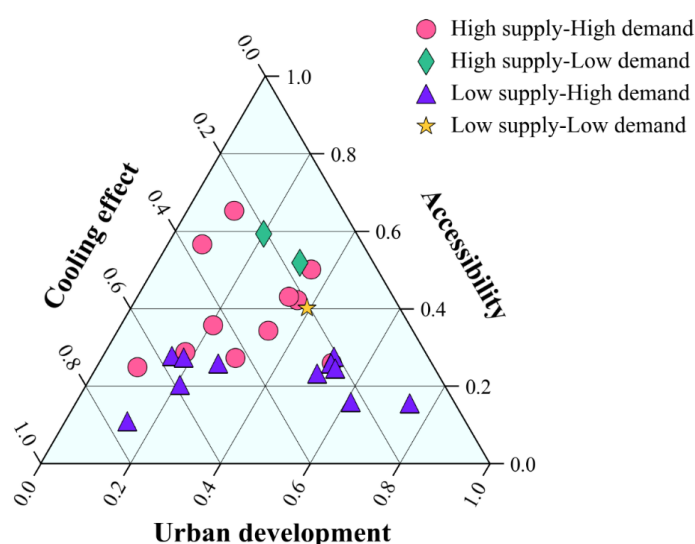
Urban parks, as nature-based solutions, have an important role to play in enhancing climate change adaptation. However, although this study reveals potential inequalities in park cooling services, the implications of these findings for practical landscape planning applications remain relatively limited (Chen, et al., 2019; Liu, et al., 2019). The main challenge lies in the fact that the current supply and demand for park cooling services has not yet been fully clarified. Therefore, there is an urgent need to prioritize the identification of those urban parks where supply and demand are out of balance, in order to provide local governments and urban planners with a basis for decision-making and help them to take more precise interventions to achieve a rational allocation of urban park resources (Geng, et al., 2022; Ma, 2020; Wang, et al., 2019).

To improve the equity of park cooling services, appropriate and targeted optimization strategies can be explored through scenario analysis. Based on the results of this study's park cooling service zoning, urban parks can be divided into four types: high supply-high demand (H-H-H, H-H-L, H-L-H), high supply-low demand (H-L-L), low supply-high demand (L-H-H, L-H-L, L-L-H), and low supply-low demand (L-L-L). The study shows that parks with supply-demand imbalances are mainly concentrated in the 'high supply-low demand' and 'low supply-high demand' categories. Of the 25 parks analyzed with a cooling effect, 10 parks were in the 'high supply-high demand' category, 2 parks were in the 'high supply-low demand' category, 11 parks were in the 'low supply-high demand' category and 11 parks were in the 'low supply-high demand' category. There are 11 parks in the 'high supply-high demand' category, 2 parks in the 'high supply-low demand' category, 11 parks in the 'low supply-high demand' category, and only 1 park in the 'low supply-low demand' category (Figs. 14 and 15). Overall, there were 13 parks with supply-demand imbalance, accounting for 52% of all parks. This result suggests that urban planning needs to pay more attention to the allocation of resources to this type of parks, so that the equity of cooling services can be improved through optimal design and reasonable intervention.

#### ***High supply-high demand parks (H-H)***

These parks are located in the central area of Zhanggong District and along the Gangan River, with a total of 10 parks, accounting for 40% of the analyzed sample. They generally have high cooling effect (mean MPC<sub>I</sub> > 1.5°C) and good accessibility

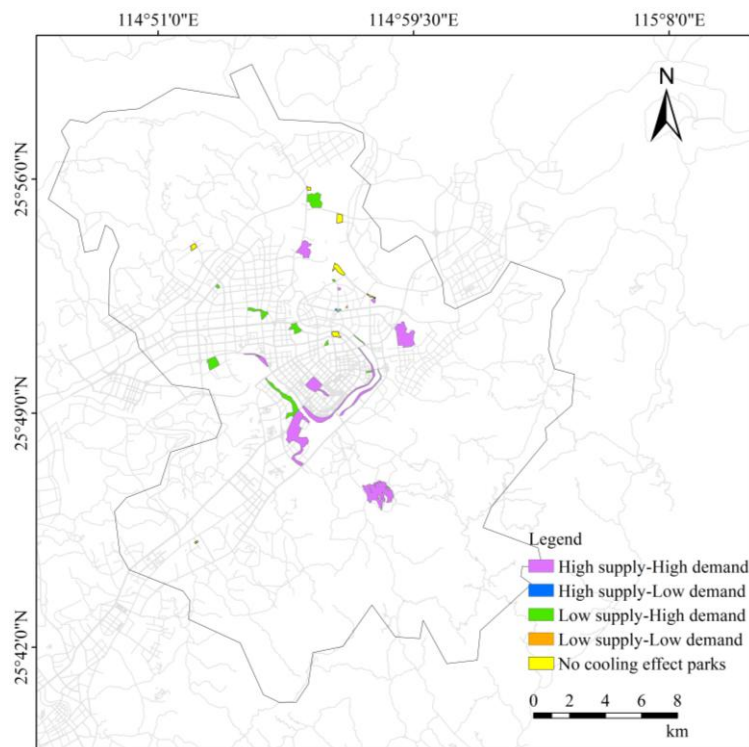
(15-min walk coverage > 65%). These parks are mostly located in densely populated areas with frequent commercial activities, with Zhangjiang National Wetland Park being the most typical, with a PCSI value of 0.42. For this type of parks with balanced supply and demand, the following optimization measures are recommended, i.e., to strengthen the existing cooling functions, to maintain and enhance the cooling effect by optimizing the vegetation structure and the layout of the water bodies, and to focus on the TVoE indicators (e.g., green space area 0.04 ha, water body area 0.03 ha, etc.) threshold control; enhance the service efficiency, add walking and cycling channels, improve the connection of the slow walking system between parks, and expand the effective service scope; and balance the pressure of use, reasonably disperse the intensity of use through functional zoning and facility configuration, and ensure the continuity of the cooling service.



**Figure 14.** Ternary phase diagram of Park Cooling Services: cooling effectiveness, accessibility and urban development. (The green diamonds and purple triangles are two groups of parks with a significant imbalance between supply and demand. Parks represented by green diamonds show higher cooling effectiveness, lower accessibility and lower urban development, while parks represented by purple triangles show lower cooling effectiveness, higher accessibility and higher urban development)

#### Low supply-low demand parks (L-L)

Only one park in the study area falls into this category, accounting for 4% of the total, and it is mainly located in the urban fringe areas. This type of park has a low cooling effect (MPCI < 0.8°C) and limited accessibility (15-min walk coverage < 30%). Considering its special characteristics, the following measures are recommended, namely, ecological function enhancement, by increasing the green area and optimizing the vegetation configuration to reach the basic threshold of the cooling effect (e.g. green area ≥ 0.04 ha); improving connectivity, perfecting the surrounding transportation network, especially the bicycle path system, and making 15-min cycling coverage as the target for improvement; integrating regional resources, and including the parks in the urban green space system planning, and strengthen its role as a node in the regional ecological network.



**Figure 15.** Spatial patterns of supply and demand for the four types of urban parks

#### *High supply-low demand parks (H-L)*

There are two parks of this type, accounting for 8 per cent of the total, which have a good cooling effect but are under-utilized. The MPCII values of these parks are generally over 1.2°C, but the 15-min walkability coverage is below 40%. In response to the status quo of oversupply, it is recommended to optimize transport links to enhance the accessibility of the parks, with a focus on improving walking and cycling conditions; to improve service efficiency, and enhance the optimization of the landscape around the parks based on the results of the PLS-SEM model (Path Coefficient + 1.6065) to enhance the radial range of the cooling effect; and to improve ancillary facilities, and combine with the needs of neighboring development to increase the number of necessary service facilities to improve the resource utilization efficiency.

#### *Low supply-high demand parks (L-H)*

This category has the largest number of parks, 11 or 44 per cent, and is mainly located in older urban areas and densely populated areas. These parks are generally characterized by insufficient cooling effect (MPCII < 1.0°C) but high demand for use. Based on the contradiction between supply and demand identified in the study, it is recommended to expand green space resources, use urban marginal land and roof space, and add small green spaces, taking care to control within the TVoE index (e.g., no less than 0.04 ha for a single green space); optimize the landscape structure, and based on the influencing factors identified in the study, focus on improving the landscape quality around the parks, in particular, increasing the proportion of water bodies and green coverage; and improve the efficiency of services. Maximize cooling benefits in limited space through refined management and facility configuration.

## Conclusions

This study focuses on the cooling services of urban parks that are relevant to residents, rather than simply analyzing the cooling effect. Therefore, we constructed a comprehensive framework that combines the three dimensions of cooling effect, accessibility and urban development to systematically assess 33 urban parks in Zhanggong District, Ganzhou City. By quantifying key indicators, including park cooling intensity, resident population size, building height and landscape type, we introduced the Park Cooling Service Index (PCSI) and the service zoning method to comprehensively analyze the cooling service level of the parks. Meanwhile, by quantifying the cooling effect of urban parks, the main drivers affecting the cooling effect and their relative contribution rates are clarified. Previous studies have mostly calculated the Threshold Value of Efficiency (TVoE) of parks from a single perspective, making it difficult to comprehensively reveal the influence mechanism. In this study, through principal component analysis (PCA), the park cooling-related indicators are downscaled and integrated to calculate the park comprehensive cooling score (PCE), and the TVoE of each influencing factor is quantified based on the PCE, thus providing a scientific basis for optimizing the scale and configuration of parks. Urban planning decision makers can select the corresponding threshold range according to the cooling needs of different regions and scenarios, and reasonably allocate park resources to improve the overall cooling service benefits. The main conclusions are as follows:

(1) Significant cooling effect but significant differences: urban parks in Zhanggong District have a significant cooling effect in general, but there are significant differences in cooling intensity and spatial distribution. The study shows that the cooling effect of parks distributed along the river is better than that of isolated green spaces in the urban area due to the moderating effect of the surrounding water bodies, while the cooling effect of some small parks is comparable to that of some large parks, which emphasizes the importance of the landscape features around the parks.

(2) Various influencing factors, and the influence of peripheral environment is particularly prominent: through multi-factor analysis, it is found that the cooling effect of parks is not only influenced by the internal landscape features (e.g., perimeter, green space ratio, etc.), but also by the peripheral landscape features (e.g., green space, blue space, and road density, etc.), which have a significant role in the cooling effect. The results of the PLS-SEM model further reveal that simply relying on the expansion of the park area cannot significantly enhance the cooling effect, while the expansion of the park area cannot significantly enhance the cooling effect. The results of the PLS-SEM model further revealed that simply relying on expanding the park area does not significantly enhance the cooling effect, while optimizing the environmental configuration of the park periphery can significantly enhance the comprehensive benefit of the cooling service.

(3) Application value of TVoE: This study clarifies the non-linear relationship between the influencing factors and the cooling effect of the park by quantifying the TVoE, which provides a theoretical basis for the scientific planning and design of the park.

(4) Imbalance between service supply and demand, and prominent equity issues: The accessibility analysis of park cooling services shows that there is a significant inequality in the distribution of resources in urban parks in Zhanggong District. Residents in the central city have difficulty in enjoying cooling services in parks within 15 min' walking distance in some communities due to the insufficient supply of park resources, while

parks in the fringe areas of the city are larger in size but serve a smaller population, and the efficiency of resource utilization is low.

(5) Clear direction for optimization of cooling services: Combining the spatial characteristics of the supply-demand imbalance, this study proposes optimization strategies for different types of parks. For parks in the central city, priority should be given to enhancing resource use efficiency by increasing small green spaces and pocket parks; for parks in the urban fringe, transport connections and integration of cultural and tourism resources should be strengthened to enhance their comprehensive use value.

**Funding.** This research was funded by National Natural Science Foundation of China (42267068) and Digital Intelligence and Humanities, Arts Integration and Innovation Interdisciplinary Research Cluster at Gannan Normal University.

**Conflict of interests.** The authors declare no conflict of interests.

## REFERENCES

- [1] Brown, G., Rhodes, J., Dade, M. (2018): An evaluation of participatory mapping methods to assess urban park benefits. – *Landscape and Urban Planning* 178: 18-31.
- [2] Chang, C., Li, M., Chang, S. (2007): A preliminary study on the local cool-island intensity of Taipei city parks. – *Landscape and Urban Planning* 80(4): 386-395.
- [3] Chen, J., Jiang, B., Bai, Y., Xu, X., Alatalo, J. M. (2019): Quantifying ecosystem services supply and demand shortfalls and mismatches for management optimisation. – *Science of the Total Environment* 650: 1426-1439.
- [4] Chen, M., Jia, W., Yan, L., Du, C., Wang, K. (2022): Quantification and mapping cooling effect and its accessibility of urban parks in an extreme heat event in a megacity. – *Journal of Cleaner Production* 334: 130252.
- [5] Chen, Y., Yue, W., La Rosa, D. (2020): Which communities have better accessibility to green space? An investigation into environmental inequality using big data. – *Landscape and Urban Planning* 204: 103919.
- [6] Cheng, X., Wei, B., Chen, G., Li, J., Song, C. (2015): Influence of park size and its surrounding urban landscape patterns on the park cooling effect. – *Journal of Urban Planning and Development* 141(3): A4014002.
- [7] Cheung, P. K., Jim, C. Y. (2019): Differential cooling effects of landscape parameters in humid-subtropical urban parks. – *Landscape and Urban Planning* 192: 103651.
- [8] Dong, J., Peng, J., He, X., Corcoran, J., Qiu, S., Wang, X. (2020): Heatwave-induced human health risk assessment in megacities based on heat stress-social vulnerability-human exposure framework. – *Landscape and Urban Planning* 203: 103907.
- [9] El-Zein, A., Tonmoy, F. N. (2015): Assessment of vulnerability to climate change using a multi-criteria outranking approach with application to heat stress in Sydney. – *Ecological Indicators* 48: 207-217.
- [10] Estoque, R. C., Ooba, M., Seposo, X. T., Togawa, T., Hijioka, Y., Takahashi, K., Nakamura, S. (2020): Heat health risk assessment in Philippine cities using remotely sensed data and social-ecological indicators. – *Nature Communications* 11(1): 1581.
- [11] Fan, H., Yu, Z., Yang, G., Liu, T. Y., Liu, T. Y., Hung, C. H., Vejre, H. (2019): How to cool hot-humid (Asian) cities with urban trees? An optimal landscape size perspective. – *Agricultural and Forest Meteorology* 265: 338-348.
- [12] Feng, X., Yu, J., Xin, C., Ye, T., Wang, T. A., Chen, H., Zhang, X., Zhang, L. (2023): Quantifying and comparing the cooling effects of three different morphologies of urban parks in Chengdu. – *Land* 12(2): 451.

- [13] Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K. (2005): Global consequences of land use. – *Science* 309(5734): 570-574.
- [14] Geng, X., Yu, Z., Zhang, D., Li, C., Yuan, Y., Wang, X. (2022): The influence of local background climate on the dominant factors and threshold-size of the cooling effect of urban parks. – *Science of the Total Environment* 823: 153806.
- [15] Guo, A., Yang, J., Sun, W., Xiao, X., Cecilia, J. X., Jin, C., Li, X. (2020): Impact of urban morphology and landscape characteristics on spatiotemporal heterogeneity of land surface temperature. – *Sustainable Cities and Society* 63: 102443.
- [16] Guo, A., Yue, W., Yang, J., Xue, B., Xiao, W., Li, M., He, T., Zhang, M., Jin, X., Zhou, Q. (2023): Cropland abandonment in China: patterns, drivers, and implications for food security. – *Journal of Cleaner Production* 418: 138154.
- [17] Irie, T. (2022): The cooling effect of green infrastructure in mitigating nocturnal urban heat islands: a case study of Yoyogi Park and Meiji Jingu Shrine in Tokyo. – *Landscape Research* 47(5): 559-583.
- [18] Jaganmohan, M., Knapp, S., Buchmann, C. M., Schwarz, N. (2016): The bigger, the better? The influence of urban green space design on cooling effects for residential areas. – *Journal of Environmental Quality* 45(1): 134-145.
- [19] Jiang, Y., Li, C., Li, X., Li, X., Song, T., Liu, Y. (2024): Exploring the adaptive spatial patterns and impact factors for the cooling effect of park green spaces in riverfront area. – *Urban Climate* 55: 101900.
- [20] Johnson, D. P., Stanforth, A., Lulla, V., Luber, G. (2012): Developing an applied extreme heat vulnerability index utilizing socioeconomic and environmental data. – *Applied Geography* 35(1-2): 23-31.
- [21] Kato-Huerta, J., Geneletti, D. (2023): A distributive environmental justice index to support green space planning in cities. – *Landscape and Urban Planning* 229: 104592.
- [22] Khavarian-Garmsir, A. R., Sharifi, A., Sadeghi, A. (2023): The 15-minute city: urban planning and design efforts toward creating sustainable neighborhoods. – *Cities* 132: 104101.
- [23] Kong, F., Yin, H., James, P., Hutyra, L. R., He, H. S. (2014): Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China. – *Landscape and Urban Planning* 128: 35-47.
- [24] Krekel, C., Kolbe, J., Wüstemann, H. (2016): The greener, the happier? The effect of urban land use on residential well-being. – *Ecological Economics* 121: 117-127.
- [25] Lan, T., Liu, Y., Huang, G., Corcoran, J., Peng, J. (2022): Urban green space and cooling services: opposing changes of integrated accessibility and social equity along with urbanization. – *Sustainable Cities and Society* 84: 104005.
- [26] Liang, Z., Li, Z., Fan, Z. (2023): Seasonal impacts of built environment and its interactions on urban park cooling effects in Nanjing, China. – *Building and Environment* 242: 110580.
- [27] Liu, H., Zhan, Q., Yang, C., Wang, J. (2019): The multi-timescale temporal patterns and dynamics of land surface temperature using Ensemble Empirical Mode Decomposition. – *Science of the Total Environment* 652: 243-255.
- [28] Ma, F. (2020): Spatial equity analysis of urban green space based on spatial design network analysis (sDNA): a case study of central Jinan, China. – *Sustainable Cities and Society* 60: 102256.
- [29] Monteiro, M. V., Doick, K. J., Handley, P., Peace, A. (2016): The impact of greenspace size on the extent of local nocturnal air temperature cooling in London. – *Urban Forestry & Urban Greening* 16: 160-169.
- [30] Oke, T. R. (1973): City size and the urban heat island. – *Atmospheric Environment* (1967) 7(8): 769-779.

- [31] Park, C. Y., Lee, D. K., Asawa, T., Murakami, A., Kim, H. G., Lee, M. K., Lee, H. S. (2019): Influence of urban form on the cooling effect of a small urban river. – *Landscape and Urban Planning* 183: 26-35.
- [32] Patz, J. A., Campbell-Lendrum, D., Holloway, T., Foley, J. A. (2005): Impact of regional climate change on human health. – *Nature* 438(7066): 310-317.
- [33] Peng, J., Liu, Q., Xu, Z., Lyu, D., Du, Y., Qiao, R., Wu, J. (2020): How to effectively mitigate urban heat island effect? A perspective of waterbody patch size threshold. – *Landscape and Urban Planning* 202: 103873.
- [34] Peng, J., Dan, Y., Qiao, R., Liu, Y., Dong, J., Wu, J. (2021): How to quantify the cooling effect of urban parks? Linking maximum and accumulation perspectives. – *Remote Sensing of Environment* 252: 112135.
- [35] Qin, Z., Karnieli, A., Berliner, P. (2001): A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region. – *International Journal of Remote Sensing* 22(18): 3719-3746.
- [36] Shi, M., Chen, M., Jia, W., Du, C., Wang, Y. (2023): Cooling effect and cooling accessibility of urban parks during hot summers in China's largest sustainability experiment. – *Sustainable Cities and Society* 93: 104519.
- [37] Shih, W. (2022): Socio-ecological inequality in heat: the role of green infrastructure in a subtropical city context. – *Landscape and Urban Planning* 226: 104506.
- [38] Sister, C., Wolch, J., Wilson, J. (2010): Got green? Addressing environmental justice in park provision. – *GeoJournal* 75: 229-248.
- [39] Tan, P. Y., Samsudin, R. (2017): Effects of spatial scale on assessment of spatial equity of urban park provision. – *Landscape and Urban Planning* 158: 139-154.
- [40] Tieskens, K. F., Smith, I. A., Jimenez, R. B., Hutyra, L. R., Fabian, M. P. (2022): Mapping the gaps between cooling benefits of urban greenspace and population heat vulnerability. – *Science of the Total Environment* 845: 157283.
- [41] Wang, C., Wang, Z., Wang, C., Myint, S. W. (2019): Environmental cooling provided by urban trees under extreme heat and cold waves in US cities. – *Remote Sensing of Environment* 227: 28-43.
- [42] Wilson, B. (2020): Urban heat management and the legacy of redlining. – *Journal of the American Planning Association* 86(4): 443-457.
- [43] Wolff, M. (2021): Taking one step further - Advancing the measurement of green and blue area accessibility using spatial network analysis. – *Ecological Indicators* 126(5): 107665.
- [44] Xiao, Y., Piao, Y., Pan, C., Lee, D., Zhao, B. (2023a): Using buffer analysis to determine urban park cooling intensity: five estimation methods for Nanjing, China. – *Science of the Total Environment* 868: 161463.
- [45] Xiao, Y., Piao, Y., Wei, W., Pan, C., Lee, D., Zhao, B. (2023b): A comprehensive framework of cooling effect-accessibility-urban development to assessing and planning park cooling services. – *Sustainable Cities and Society* 98: 104817.
- [46] Xu, C., Wang, W., Zhu, H. (2024): Spatial gradient differences in the cooling island effect and influencing factors of urban park green spaces in Beijing. – *Buildings* 14(5): 1206.
- [47] Xu, X., Sun, S., Liu, W., García, E. H., He, L., Cai, Q., Xu, S., Wang, J., Zhu, J. (2017): The cooling and energy saving effect of landscape design parameters of urban park in summer: a case of Beijing, China. – *Energy and Buildings* 149: 91-100.
- [48] Yang, Y., Wang, Z., Lin, G. (2021): Performance assessment indicators for comparing recreational services of urban parks. – *International Journal of Environmental Research and Public Health* 18(7): 3337.
- [49] Yao, X., Yu, K., Zeng, X., Lin, Y., Ye, B., Shen, X., Liu, J. (2022): How can urban parks be planned to mitigate urban heat island effect in "Furnace cities"? An accumulation perspective. – *Journal of Cleaner Production* 330: 129852.

- [50] Yu, S., Kong, X., Wang, Q., Yang, Z., Peng, J. (2023): A new approach of Robustness-Resistance-Recovery (3Rs) to assessing flood resilience: a case study in Dongting Lake Basin. – *Landscape and Urban Planning* 230: 104605.
- [51] Yu, Z., Guo, X., Jørgensen, G., Vejre, H. (2017): How can urban green spaces be planned for climate adaptation in subtropical cities? – *Ecological Indicators* 82: 152-162.
- [52] Yu, Z., Guo, X., Zeng, Y., Koga, M., Vejre, H. (2018): Variations in land surface temperature and cooling efficiency of green space in rapid urbanization: the case of Fuzhou city, China. – *Urban Forestry & Urban Greening* 29: 113-121.
- [53] Zhang, J., Gou, Z., Shutter, L. (2019): Effects of internal and external planning factors on park cooling intensity: field measurement of urban parks in Gold Coast, Australia. – *AIMS Environmental Science* 8(6).
- [54] Zhang, J., Gou, Z., Lu, Y. (2021): Outdoor thermal environments and related planning factors for subtropical urban parks. – *Indoor and Built Environment* 30(3): 363-374.
- [55] Zhang, J., Gou, Z., Cheng, B., Khoshbakht, M. (2022): A study of physical factors influencing park cooling intensities and their effects in different time of the day. – *Journal of Thermal Biology* 109: 103336.
- [56] Zhou, T., Jia, W., Yan, L., Hong, B., Wang, K. (2024a): Urban park's vertical canopy structure and its varied cooling effect under continuous warming climate. – *Urban Climate* 53: 101819.
- [57] Zhou, W., Yu, W., Wu, T. (2022): An alternative method of developing landscape strategies for urban cooling: a threshold-based perspective. – *Landscape and Urban Planning* 225: 104449.
- [58] Zhou, Y., Luo, Y., Yi, X., Lun, F., Hu, Q., Huang, N., Wen, G., Zhou, H., Hu, X. (2024b): Exploring the influence of local urban heat features on park cooling effects: insights from Chinese cities. – *Building and Environment* 262: 111782.
- [59] Zhu, W., Sun, J., Yang, C., Liu, M., Xu, X., Ji, C. (2021): How to measure the urban park cooling island? A perspective of absolute and relative indicators using remote sensing and buffer analysis. – *Remote Sensing* 13(16): 3154.