# Study on Spatial Pattern and Driving Mechanism of Cooling Effect in Chongqing Based on the "Quantity-Shape-People" Framework

Qihui Xu

Southwest Jiaotong University, Chengdu, 610097, China

**Abstract:** Affected by rapid urbanization and extreme high temperatures, urban thermal environment imbalance is worsening. Academically, there's a notable gap in integrated research on the full chain of "unit green quantity cooling efficiency—overall cooling capacity—actual resident benefits" in mountainous cities. This study uses the "Quantity-Shape-People" framework to build a 3D indicator system (Cooling Efficiency/CE, Cooling Capacity/CC, Cooling Benefit/CB). It integrates 1km-resolution multi-source remote sensing data, statistical data, and Local Climate Zone (LCZ) classification to analyze Chongqing's urban cooling effect spatial features.

Results show Chongqing's main urban cooling effect distribution aligns with LCZ types, with clear hierarchy: high-rise built-up areas have the lowest CE/CC; waterfront green spaces and mountain parks form stable high-CE zones; high-CB zones cluster in dense mixed residential areas. Policy-wise, to cut population-weighted thermal vulnerability, prioritize "cooling measures × reducing exposure" in "high built-up ratio × high population density" areas. To boost CE/CC, focus on urban form optimization, surface material improvement, and ventilation design. The study offers scientific support for mountainous cities to tackle warming and advance climate-adaptive governance.

## 1. Introduction

Against the dual background of the continuous acceleration of global urbanization and the intensification of climate change, the frequency and intensity of extreme high-temperature events in large and medium-sized cities have increased significantly, gradually becoming a normalized climatic phenomenon. The resulting issues, such as spatial differentiation of heat exposure levels and uneven distribution of heat risks, have increasingly become important bottlenecks restricting the improvement of public health, energy sustainability, and urban governance capabilities (Oke, 1982[1]; Santamouris, 2014[2]).

Existing empirical studies have pointed out that green infrastructure can effectively reduce surface and canopy air temperatures by enhancing evapotranspiration and regulating the surface energy balance, thereby improving the urban thermal environment to a certain extent. However, its actual cooling efficiency is often significantly affected by factors such as regional climatic conditions, built environment structure, and land use patterns (Bowler et al., 2010[3]; Zhao et al., 2014[4]). Against this practical and theoretical background, how to systematically reveal the formation mechanism of the urban thermal environment and, on this basis, fairly evaluate the benefit distribution of cooling measures—namely, clarifying "the causes of high-temperature areas, heat-generating mechanisms, and the social beneficiaries of mitigation measures"—has become a core issue to be solved urgently in current urban climate adaptation research.

Current studies on evaluating the cooling effect of green infrastructure often rely on quantitative indicators such as green space area or vegetation coverage. Although these indicators are easy to obtain, they cannot reflect the marginal regulatory effect of unit vegetation on air temperature, its actual cooling efficiency, or accurately measure the actual heat relief benefits obtained by different populations (Bowler et al., 2010[3]). On the other hand, the formation of the urban local thermal environment is jointly affected by multiple factors, including geometric structure (e.g., building density and height), surface physical properties (e.g., albedo and thermal inertia), distance to cold sources (e.g., water bodies), and intensity of human activities. These factors determine the cooling capacity of cold sources and their actual benefits after being covered by the population. Relying solely on a single area indicator or conducting simple linear comparisons across cities makes it difficult to reveal this complex coupling mechanism (Stewart and Oke, 2012[5]; Grimmond and Oke, 1999[6]). In addition, due to the high sensitivity of the Surface Urban Heat Island (SUHI) effect to the regional climate background, statistical models or linear coefficients between different eco-climatic zones often lack transferability, which makes the "one-size-fits-all" evaluation method face significant limitations in practical applications (Peng et al., 2012[7]; Zhao et al., 2014[4]).

* Corresponding author: 179956819@qq.com

To address this, this study draws on the "Quantity-Shape-People" comprehensive analytical framework and decomposes the cooling effect into three dimensions: CE (reflecting the sensitivity of unit vegetation to temperature, i.e., the efficiency of "quantity"), CC (reflecting the composite capacity of cooling efficiency and vegetation scale, i.e., the role of "shape"), and CB (reflecting the welfare effect weighted by population exposure, i.e., the benefits for "people"). By integrating multi-source data and combining LCZ classification, it systematically analyzes the spatial pattern of the cooling effect in Chongqing. Compared with existing studies, the innovations of this study are mainly reflected in three aspects: first, it incorporates the impacts of mountainous terrain and water body distribution on the cooling effect into the analytical framework, which is more in line with Chongqing's geographical characteristics; second, based on the actual distribution characteristics of LCZ types, it proposes differentiated cooling effect optimization strategies, providing a reference analytical framework for heat risk governance in similar mountainous cities.

## 2. Data and Methods

### 2.1. Study Area

Chongqing is located in the mountainous and hilly areas of southwest China, with a subtropical monsoon climate. The average summer temperature ranges from 28°C to 32°C. Its main urban area is distributed along the banks of the Yangtze River and Jialing River, where built-up areas are interspersed with mountains and water bodies, with obvious topographic relief and an altitude range of 168–1421m. As a megacity in western China, the permanent population of Chongqing's main urban area has exceeded 9 million, with a high development density of built-up areas. Urban green spaces are mainly concentrated in mountainous parks and along river banks, resulting in significant spatial differences in the thermal environment.

The spatial scope of this study focuses on the main urban area of Chongqing (geographic coordinates: 29°33′–29°41′N, 106°29′–106°52′E). This area is not only the core area with the most prominent urban heat island effect but also a key area with urgent needs for green infrastructure optimization and high population heat exposure risks (Stewart & Oke, 2012[5]).

### 2.2. Data Sources and Processing

This study comprehensively uses multi-source spatiotemporal data. All data are uniformly converted to the WGS84 UTM Zone 48N projection coordinate system, and their spatial resolution is unified to 1km through resampling. The specific data sources and processing methods are as follows:

Land Surface Temperature (LST) data are obtained from the LANDSAT_LC08_T2_L1[13] dataset on the Google Earth Engine platform (corresponding to the MODIS satellite MOD11A2[14] product).Normalized Difference Vegetation Index (NDVI) data come from the same source as LST data (corresponding to the MODIS satellite MOD13A2[14] product).Digital Elevation Model (DEM) data can be accessed at https://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_DEM/[11] (the Global 30 Arc-Second Elevation (GTOPO30) product is selected).

Temperature and precipitation data are from the Multi-year Average Precipitation Spatial Distribution Dataset (website: www.gisrs.cn)[12].Built-up area ratio (Built) data are based on the SinoLC-1 national land cover map (DOI: 10.5281/zenodo.7707461)[9]. Distance to water body data are obtained from the COPERNICUS_Landcover_ 100m_Proba-V-C3_Global dataset[15] on the Google Earth Engine platform. Building height data can be referenced at https://data.jrc.ec.europa.eu/dataset/JRC-GHSL-P2023 - STATS[10] (the building height product of the Global Human Settlement Layers (GHSL) is adopted).Local Climate Zone (LCZ) data can be downloaded from https://zenodo.org/records/8419340[19] (the global LCZ classification data published in Earth System Science Data in 2022 is selected, Demuzere et al., 2022, DOI: 10.5194/essd-14-3835-2022[8]).Land use data adopt the land cover data of the Copernicus Global Land Service (CGLS)[16].Population data use the LandScan global population dataset[17].

In the data preprocessing stage, based on the building boundary data from OpenStreetMap (OSM)[18], the kernel density estimation method is used to determine the actual scope of Chongqing's main urban area. Outliers and missing values in the dataset are removed, and spatial overlay analysis is conducted to ensure the spatial consistency of all multi-source data, laying a data foundation for subsequent analysis.

## 3. Research Methods

### 3.1. Calculation of Cooling Effect Indicators

The calculation of Cooling Efficiency (CE) is realized through Ordinary Least Squares (OLS) regression of LST on NDVI, terrain (DEM), building height, and distance to water bodies. The specific steps are as follows: first, create raster data; then, extract LST, NDVI, terrain, building height, and distance to water body data; finally, perform OLS regression. The coefficient of NDVI obtained from the regression is the cooling efficiency. A larger absolute value of the slope indicates a stronger vegetation cooling effect.

To further capture the spatial autocorrelation and complex non-linear relationships between LST and predictor variables (e.g., NDVI, DEM), supplementary analyses using spatial regression models (e.g., Spatial Lag Model, Spatial Error Model) and machine learning techniques (e.g., Random Forest) are recommended for subsequent model optimization. These methods may help address the low $R^2$ value (0.06) of the current OLS-based CE model and improve the explanatory power of the model.

$$CE = \frac{\Delta LST}{\Delta NDVI} \quad (1)$$

The calculation of Cooling Capacity (CC) combines CE and the average NDVI value, reflecting the composite effect of cooling efficiency and green quantity. The formula is:

$$\mathrm{CC} = \frac{\sum(NDVI_i - NDVI_{min}) \times CE_{lcz}}{n} \quad (2)$$

Where $NDVI_i$ is the $NDVI$ value of the raster, $NDVI_{MIN}$ is the minimum $NDVI$ value of the city, $CE_{lcz}$ is the CEwithin the LCZ zone, and n is the number of rasters within the LCZ zone.The average cooling capacity of the city is calculated as:

$$\mathrm{CC} = \frac{\sum CC_{lcz} \times n_{lcz}}{m} \quad (3)$$

Where m represents the total number of rasters in the city. The calculation of Cooling Benefit (CB) introduces population weighting to quantify the actual benefits for residents. The formula is:

$$CB_{lcz} = \frac{\sum(NDVI_i - NDVI_{min}) \times CE_{lcz} \times pop_i}{pop_{avg} \times n} \quad (4)$$

Where $pop_i$ is the population within raster i, and $pop_{avg}$ is the average population of the city. The cooling benefit of the city is calculated as:

$$\mathrm{CB} = \frac{\sum CB_{lcz} \times n_{lcz}}{m} \quad (5)$$

### 3.2. Spatial Pattern Analysis

Based on the LCZ zoning results and 1km grid units, combined with the spatial distribution maps of CE, CC, and CB, this study identifies the spatial distribution laws of high-value and low-value zones of the cooling effect and analyzes the internal connections of cooling effect differences in different regions.

To capture the micro-scale effects of green infrastructure (e.g., small parks, street trees) and building morphology, a supplementary analysis at a finer spatial resolution (e.g., 30m using Landsat data) is suggested for a representative subset of the study area. This high-resolution analysis can validate and enrich the findings from the 1km grid-based analysis, especially for understanding the cooling effect of small-scale green spaces in dense built-up areas.

## 4. Results

In terms of spatial distribution characteristics, the cooling effect in the main urban area of Chongqing presents a hierarchical feature highly associated with LCZ types, with significant differences between different regions.

### 4.1. Spatial Pattern of Cooling Efficiency (CE)

From Figure1. the concentrated areas of mountain forests and parks in the northeastern, eastern, and western parts of the city, as well as the waterfront green spaces along the rivers, form significant high-CE zones. Analyzing the causes in detail: the concentrated mountain forest park areas in the northeastern and eastern parts have high vegetation coverage, mainly with closed tree canopies, and the dense vegetation continuously cools the environment through evapotranspiration. The waterfront areas along the rivers in the northeastern and southwestern parts have large heat capacity and strong evapotranspiration of water bodies, which form a synergistic cooling effect with the surrounding green spaces, jointly increasing the CE value.

In contrast, the commercial core areas with dense medium and high-rise buildings are concentrated low-CE zones. This is because these areas have high building density and large areas of hardened surfaces, which easily accumulate heat and make it difficult to dissipate. In addition, the relatively scarce vegetation coverage further weakens the cooling capacity.

It is also found that the CE values in the mountainous areas with large topographic relief around the city are generally higher than those in the flat built-up areas. This is because the mountainous areas have more concentrated vegetation coverage, and the complex terrain can form local microclimates, which are conducive to the evapotranspiration of vegetation and thus enhance the cooling effect.

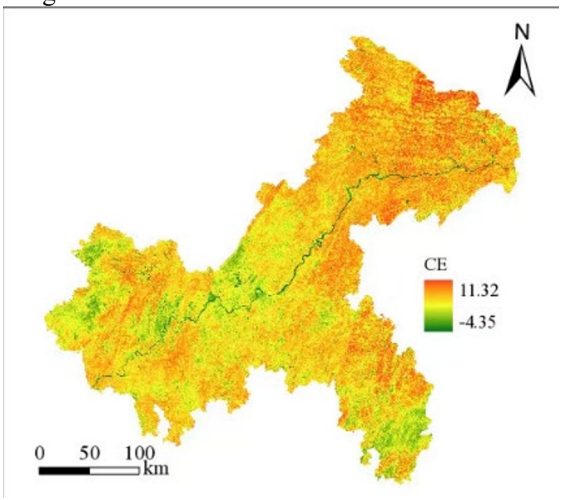


**Figure 1.** Spatial Distribution Characteristics of Cooling Efficiency in Chongqing Municipality.(Note: The value range of CE is -4.35 to 11.32; the map scale is 0–100 km)

### 4.2. Spatial Pattern of Cooling Capacity (CC)

According to Figure 2, the open tree canopy areas and non-arbor vegetation areas in the southern and northeastern parts of the city are concentrated high-CC zones, with values mostly ranging from 1.50 to 1.81. The core mechanism for the formation of high values lies in the fact that these areas have a wide and uniform distribution of vegetation. Although the cooling efficiency (CE) is not the best in the whole city, the cooling capacity is significantly enhanced through the composite effect of cooling efficiency and green quantity. The urban core areas with dense buildings (typically high-rise built-up areas) are concentrated low-CC zones, with values only ranging from 0.29 to 0.9. This is due to the high building density and low green space ratio in these areas, which limits the cooling capacity.

From the perspective of directional characteristics, the concentrated green space areas in the southern and northeastern parts of the city show more prominent CC performance. This is directly related to the balanced layout of green spaces and the extensive vegetation coverage in these areas. In contrast, other areas of the city have relatively low cooling capacity due to scarce or unevenly distributed green space resources.

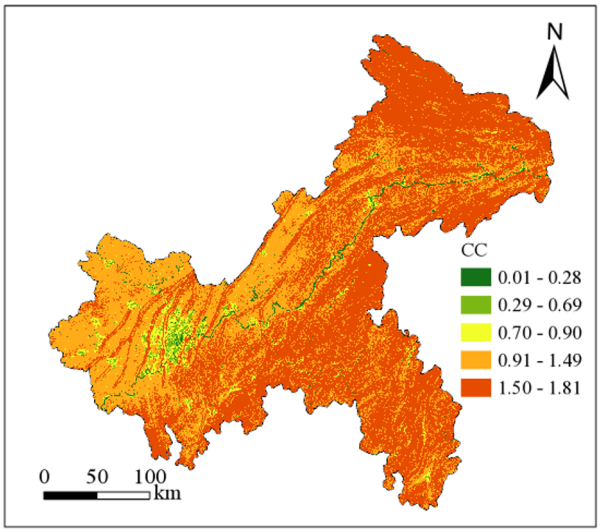


**Figure 2**.Spatial Distribution Characteristics of Cooling Effect in Chongqing Municipality. (Note: The value range of CC is 0.01–1.81; the map scale is 0–100 km)

### 4.3. Spatial Pattern of Cooling Benefit (CB)

According to Figure 3, the spatial distribution of CB is significantly driven by population density. Among them, the concentrated low-rise residential areas with high population density in the western part of the city are high-CB zones, with CB values ranging from 0.60 to 2.22. Although the cooling efficiency (CE) and cooling capacity (CC) in these areas are only at a medium level, the high population density leads to a significant performance of residents' welfare converted from the cooling effect after population weighting.

In sharp contrast, the waterfront green spaces along the rivers (such as the northeastern and southern parts of the city) have high cooling efficiency (CE), but due to the influence of urban functional layout, the population density in these areas is low. As a result, the CB values are mostly in the range of 0.01 to 0.22, and the actual number of residents benefiting from the cooling effect is relatively small.

The densely populated residential areas in the western part of the city have become the core distribution areas of high CB values due to their high residential density. In contrast, the waterfront areas in the eastern and southern parts of the city, despite their good ecological cooling potential, show significantly inferior performance in cooling benefits due to sparse population.

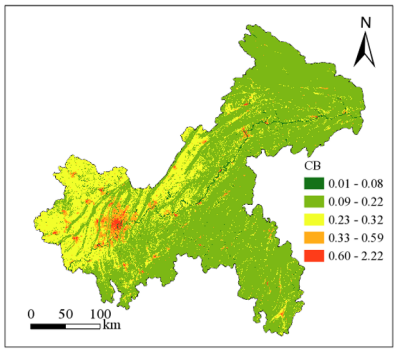


**Figure 3.** Spatial Distribution Characteristics of Cooling Benefit in Chongqing Municipality. (Note: The value range of CB is 0.01–2.22; the map scale is 0–100 km)

### 4.4. Driving Characteristics of the Cooling Effect

From the perspective of driving characteristics of the cooling effect, there are obvious differences in the dominant influencing factors of different indicators. In terms of natural factors, precipitation and distance to water bodies have a stable impact on CE and CC: more precipitation and shorter distance to water bodies are more conducive to improving CE and CC. In terms of human factors, the built-up area ratio has a significant impact on CB: areas with a higher built-up area ratio often have higher CB values. This is because areas with concentrated built-up areas also have relatively high population density, leading to more prominent cooling benefits after population weighting.

Building height has a certain impact on CE and CC: areas with taller buildings tend to have lower CE and CC. This is related to the obstruction of vegetation sunlight and local ventilation by high-rise buildings. However, the magnitude of the coefficient of this impact is small, indicating that changes in CE and CC are more affected by the interactive effects of nonlinear factors such as terrain, microclimate, and surface materials.

## 5. Discussion

The "spatial heterogeneity" of the cooling effect in the main urban area of Chongqing is closely related to the complex spatial pattern of "terrain—water body—built-up area" in mountainous cities. From the distribution of high-CE zones, the CE of waterfront green spaces and mountainous park areas is significantly higher than that of other regions. This phenomenon is closely related to the synergistic effect of water evaporation and heat dissipation, as well as vegetation evapotranspiration and cooling. It conforms to the basic law of the surface energy balance theory that "enhanced evapotranspiration can reduce sensible heat flux and alleviate surface temperature rise" (Oke, 1982[1]; Grimmond and Oke, 1999[6]).

In contrast, the low CE and CC values in areas with dense medium and high-rise buildings reflect the blocking effect of high-density built environments on cold air diffusion. High-rise buildings not only block sunlight,

leading to insufficient sunlight for vegetation in low-rise areas but also change local ventilation conditions, weakening the spatial transmission of the cooling effect (Stewart and Oke, 2012[5]).

From the distribution of cooling benefits, densely populated low-rise residential areas have become high-CB zones. This phenomenon highlights the key role of the spatial matching degree between "population and green space" in the welfare conversion of the cooling effect. Even if the CE and CC in some areas are not the highest, the high concentration of population enables the cooling effect to benefit more residents. This also suggests that in urban planning, attention should be paid to the spatial coupling of green space layout and population distribution to improve the fairness and inclusiveness of the cooling effect.

At the same time, it should be noted that the overlapping areas of "high built-up area ratio × high population density" in Chongqing (such as emerging industrial and residential areas like Ranjiaba and Guangdianyuan) have significantly higher thermal vulnerability than other areas. These areas have high building density and concentrated population, but relatively insufficient green space resources. The supply of cooling effect is difficult to meet the demand, so they should be prioritized areas for cooling intervention in the future (Santamouris, 2014[2]).

This study has limitations in several aspects.

In terms of mechanism explanation, due to the complexity of the urban thermal environment system and the difficulty of linear models in capturing nonlinear relationships, the constructed models can only explain part of the variations in cooling efficiency (CE) and cooling benefit (CB). For example, the coefficient of determination ($R^2$) of the cooling efficiency model is only 0.06, which cannot fully reveal the role of nonlinear processes such as form—microclimate—materials. The low $R^2$ value of the CE model, though acknowledged, requires deeper investigation. As mentioned in the research methods section, adopting spatial regression models or machine learning techniques may help address this issue by accounting for spatial autocorrelation and non-linear interactions that the current OLS model fails to capture.

In terms of causal correlation, it fails to fully clarify the driving essence of the correlation between climate and urban green space scale, and cannot determine whether it is the direct impact of climate on vegetation growth or the indirect correlation with urban historical factors.

In terms of spatial and temporal scales, the 1km resolution grid data dilute the impact of micro-scale processes, and the study mainly relies on cross-sectional data, making it difficult to capture long-term climate change and intra-seasonal differences in the cooling effect. To address the limitation of coarse spatial resolution, a supplementary analysis using 30m-resolution Landsat data for a representative subset of the study area is recommended. This will allow for a more detailed assessment of micro-scale green infrastructure (e.g., small parks, street trees) and building morphology, which are critical for understanding localized cooling effects in urban areas.

In addition, the model does not include potential influencing factors such as social culture, governance, and ecology—for example, differences in evapotranspiration efficiency among different tree species, the "luxury effect", and the impact of governance capabilities on the cooling effect. Moreover, it does not fully consider practical constraints when estimating the potential for improving the cooling effect.

Future improvements can be made in several aspects. In terms of model methods, spatial econometric models and quantile regression can be adopted, and interaction terms can be added to capture nonlinear interaction effects, thereby improving the ability to explain mechanisms. Consistent with the supplementary model recommendations, integrating spatial regression models (e.g., Spatial Lag Model) and machine learning techniques (e.g., Random Forest) into future model frameworks will be a key focus to enhance the explanatory power of CE and CC models.

In terms of data scale, higher-resolution Landsat and Sentinel-2 data can be combined, the time series can be extended, and seasonal decomposition can be conducted to refine the description of green space form and building details, and reveal changes in the cooling effect across different time dimensions. The proposed 30m-resolution supplementary analysis (using Landsat data) will be a core part of future data scale optimization, complementing the 1km grid data to capture both macro-scale spatial patterns and micro-scale cooling processes.

In terms of mechanism identification, instrumental variables can be introduced or quasi-natural experiments can be used to strengthen the identification of the causal relationship between "green space and cooling effect". At the same time, socioeconomic and governance data can be integrated to analyze the correlation between social factors and ecological effects.

In terms of application, the spatial layout of green spaces can be optimized, and planning schemes that balance efficiency and accessibility can be proposed based on urban functional zoning. In addition, in response to future climate warming scenarios, climate-resilient green space systems can be designed.

## 6. Conclusions

Taking the main urban area of Chongqing as the research object, this study systematically analyzes the spatial pattern of the urban cooling effect based on the "Quantity-Shape-People" analytical framework and multi-source data. The main conclusions are as follows:

In terms of spatial distribution, the cooling effect is highly associated with LCZ types and presents obvious hierarchical characteristics: waterfront green spaces and mountainous parks are high-value zones for CE and CC; densely populated low-rise residential areas are high-value zones for CB; and commercial and industrial core areas with dense medium and high-rise buildings are low-value zones for all three indicators. This spatial pattern is essentially the result of the joint action of "topographic conditions—green space distribution—population agglomeration".

In terms of driving characteristics, there are differences in the dominant influencing factors of different cooling effect indicators: the core influencing factor of CB is the built-up area ratio, and built-up areas with dense populations are more likely to form high CB values; CE and CC are more regulated by the combined effects of natural factors (precipitation, distance to water bodies) and nonlinear factors such as form—microclimate—materials, while the linear impact of human factors is relatively limited.

From the perspective of policy application, differentiated strategies should be adopted for different governance goals: if the goal is to reduce population-weighted thermal vulnerability, priority should be given to implementing combined interventions in overlapping areas with "high built-up area ratio × high population density". Specific measures can include promoting cooling measures such as cool roofs and cool pavements, constructing waterfront greenways to enhance local cooling capacity, and reducing population heat exposure during heatwaves by adding shading facilities and optimizing public transportation. If the goal is to improve CE and CC, it is necessary to optimize the urban form from a refined perspective—for example, increasing the openness of street canyons to improve ventilation conditions, focusing on the layered arrangement of tree canopies and the combined configuration of water bodies and grasslands in green space construction, and selecting surface materials with high albedo and high water permeability.

## References

1. Oke, T. R., Boundary layer climates (Methuen, London, 1982)
2. Santamouris, M., Urban heat islands: Strategies for mitigation and adaptation (Earthscan, London, 2014)
3. Bowler, D. E., Buyung-Ali, L., Knight, T. M., Pullin, A. S., Ecol. Lett. 13, 1012-1020 (2010)
4. Zhao, L., Zhang, L., Liu, J., et al., Remote Sens. Environ. 145, 1-10 (2014)
5. Stewart, I. D., Oke, T. R., Int. J. Climatol. 32, 1849-1864 (2012)
6. Grimmond, C. S. B., Oke, T. R., J. Appl. Meteorol. 38, 1268-1281 (1999)
7. Peng, J., Piao, S., Ciais, P., et al., Proc. Natl. Acad. Sci. U.S.A. 109, 20016-20021 (2012)
8. Demuzere, M., Oke, T. R., Steeneveld, G. J., et al., Earth Syst. Sci. Data 14, 3835-3856 (2022)
9. SinoLC-1 national land cover map, DOI: 10.5281/zenodo.7707461 (2023)
10. Global Human Settlement Layers (GHSL) building height product, https://data.jrc.ec.europa.eu/dataset/JRC-GHSL-P2023-STATS (2023)
11. MERIT DEM dataset, https://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_DEM/ (2020)
12. Multi-year Average Precipitation Spatial Distribution Dataset, www.gisrs.cn (2022)
13. LANDSAT_LC08_T2_L1 dataset, Google Earth Engine platform (2023)
14. MODIS MOD11A2 product, MODIS MOD13A2 product, National Aeronautics and Space Administration (NASA) (2023)
15. COPERNICUS_Landcover_100m_Proba-V-C3_Global dataset, Google Earth Engine platform (2023)
16. Copernicus Global Land Service (CGLS) land cover data (2023)
17. LandScan global population dataset, Oak Ridge National Laboratory (ORNL) (2023)
18. OpenStreetMap (OSM) building boundary data (2023)
19. Global LCZ classification data, https://zenodo.org/records/8419340 (2022)