



Article

Sensitivity of Local Climate Zones and Urban Functional Zones to Multi-Scenario Surface Urban Heat Islands

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Abstract: Local climate zones (LCZs) and urban functional zones (UFZs) can intricately depict the multidimensional spatial elements of cities, offering a comprehensive perspective for understanding the surface urban heat island (SUHI) effect. In this study, we retrieved two types of land surface temperature (LST) data and constructed 12 SUHI scenarios over the Guangdong–Hong Kong–Macao Greater Bay Area Central region using six SUHI identification methods. It compared the SUHI sensitivity differences among different types of LCZ and UFZ to analyze the global and local sensitivity differences of influencing factors in the 12 SUHI scenarios by utilizing the spatial gradient boosting trees, geographically weighted regression, and the coefficient of variation model. Results showed the following: (1) The sensitivity of different LCZ and UFZ types to multi-scenario SUHI was significantly affected by differences in SUHI identification methods and non-urban references. (2) In the morning, the shading effect of building clusters reduced the surface urban heat island intensity (SUHII) of some built environment types (such as LCZ 1 (compact high-rise zone) to LCZ 5 (open midrise zone)). The SUHIIs of LCZ E (bare rock or paved zone) and LCZ 10 (industry zone) were 4.22 °C and 3.87 °C, respectively, and both are classified as highly sensitive to SUHI. (3) The sensitivity of SUHI influencing factors exhibited regional variability, with importance differences in the sensitivity of importance for factors such as the impervious surface ratio, elevation, average building height, vegetation coverage, and average building volume between LCZs and UFZs. Amongst the 12 SUHI scenarios, an average of 87.43% and 89.97% of areas in LCZs and UFZs, respectively, were found to have low spatial sensitivity types. Overall, this study helps urban planners and managers gain a more comprehensive understanding of the complexity of the SUHI effect in high-density cities, providing a scientific basis for future urban climate adaptability planning.

Keywords: local climate zone (LCZ); urban functional zone (UFZ); multi-scenario; surface urban heat island (SUHI); sensitivity



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1. Introduction

According to United Nations statistics, the global urban population ratio reached 56% in 2021, and it is projected that 68% of the population will live in urban areas by 2050 [1]. The rapid increase in urban population will inevitably lead to increased demand for urban land, converting many natural areas into construction land and potentially resulting in ecological problems related to human activities. The urban heat island (UHI) effect is one

of the most apparent ecological issues caused by urbanization and becomes a crucial factor affecting sustainable urban development. UHI refers to the phenomenon where the temperature in urban areas is higher compared to their neighboring non-urbanized areas [2,3]. The UHI is directly related to health issues such as cardiovascular and cerebrovascular diseases and respiratory infections, highlighting the importance of public health (Sustainable Development Goal (SDG) 3). Therefore, the mitigation of the UHI effect can not only improve the quality of life and urban climate resilience of residents (SDG 11) but also reduce the negative impact of climate change on cities (SDG 13) [4].

The surface urban heat island (SUHI) derived from satellite observations is an essential field of study in urban climatology, with significant implications for urban planning, environmental management, and human health. Many scholars focus on several aspects of SUHI, including its spatiotemporal characteristics and evolution patterns, driving factors and mechanisms, mitigation and adaptation strategies, and scale transformation [5]. There are four popular methods for identifying the extent of SUHIs, including the urban–rural temperature thresholds, temperature grade thresholds, Gaussian fitting parameters, and temperature decay mutation [6,7]. However, many studies neglect the information on non-urban references (i.e., rural areas) used in calculating SUHI [8]. There are also significant differences in the definitions of rural areas in previous studies; for example, areas located 5–10 km [9], 20–25 km [10,11], and 40–45 km [12] away from urban areas were classified as rural regions. Moreover, the selection of the non-urban references failed to consider the rural water bodies and areas of extreme elevation [9,13–15]. These can introduce many uncertainties to SUHI assessments [16,17].

The SUHI effect is closely associated with urban morphology (such as 2D and 3D urban forms), including the urban surface characteristics (such as vegetation cover and urban surface materials), climatic background (such as precipitation and climatic zones), and socioeconomic factors (such as population density, intensity of human activities, and energy consumption patterns) [6,18–22]. Current global models considering UHI influencing factors might overlook an urban area's spatial heterogeneity and spatial autocorrelation. Due to the intricate spatial configurations and inherent spatial heterogeneity in urban environments, the spatial-temporal patterns of the SUHI are complex. By considering finer spatial resolutions and integrating local observational models, researchers can capture the subtle variations in urban temperature's temporal and spatial patterns [15,17]. Local climate zones (LCZs) [23], urban functional zones (UFZs), transportation analysis zones, and grids all belong to fine spatial scales. Compared with transportation analysis zones and grid scales, LCZs and UFZs can more comprehensively reflect local zones' climatic characteristics and urban planning purposes, aligning more closely with the needs of urban managers and planners.

LCZs, based on the physical and environmental characteristics of the surface, offer a scientific insight to understand the spatial patterns of the UHI better, facilitating inter-city comparisons and climate adaptability planning [23]. UFZs, which directly link human activities and land use types, are more suited for policy making and assessing the impact of the UHI on different socioeconomic groups, promoting targeted urban planning and management [24]. However, some SUHI studies, considering LCZs and UFZs, mainly adopt single SUHI scenario analyses [25–27]. For a single SUHI scenario analysis, it is hard to provide a comprehensive perspective on addressing the SUHI effect due to the lack of consideration of multidimensional urban planning and design needs. Some scholars had realized this issue and attempted to predict the SUHI under different future land use/cover scenarios by establishing correlations between land use/cover types and landscape indices [28].

However, there were still some issues needed further exploration. One of the crucial issues is the impact of different LST retrieval methods on evaluating SUHI [29]. For instance, the radiative transfer equation (RTE) method uses atmospheric parameter information of the study area to reduce errors in LST retrieval caused by atmospheric absorption effects and water vapor [30,31]. The RTE method can accurately capture the minute variations in

LST between urban and rural areas, as well as within different land use/cover types, due to changes in atmospheric conditions. The nonlinear split-window (NSW) method has the advantages of being simple in algorithm and fast in computation. It adapts well to various land use/cover types and atmospheric conditions without requiring precise atmospheric parameter input [32]. The NSW method effectively handles different surface types and complex atmospheric conditions, making it more practical, reliable, and consistent for LST retrieval over large spatial scales, including urban agglomerations. SUHI is influenced by various factors such as urban climate conditions, land use/cover, and anthropogenic heat emissions [33]. In SUHI assessments, the local climate conditions, land use types, and surface complexity of urban and rural areas differ. Using different LST retrieval methods can better capture the LST differences of various surface types in urban and rural areas, thus improving the accuracy of SUHI assessment. We need to investigate whether different LST retrieval methods, SUHI identification methods, and non-urban reference selections will lead to significant differences in SUHI research or not. In different SUHI scenarios, do various LCZ types and UFZ types exhibit significant variations in SUHI sensitivity? Additionally, do the factors influencing SUHI show significant differences in sensitivity across these scenarios?

The Guangdong–Hong Kong–Macao Greater Bay Area Central (GBAC) region is one of the regions with the highest population density in China, with an urbanization rate far exceeding that of most other regions in the world, and the SUHI phenomenon over this region has received widespread attention [34,35]. Our study considers two types of LST datasets and six SUHI identification methods to generate twelve SUHI scenarios over the GBAC region and analyzes the sensitivity of LCZs and UFZs to SUHI in these twelve scenarios. There are three main objectives of this study: (1) to analyze the uncertainties brought to the assessments of multiple SUHI scenarios due to differences in LST data, SUHI identification methods, and non-urban references; (2) to compare the differences of SUHI sensitivity between LCZ types and UFZ types in 12 SUHI scenarios; and (3) to evaluate the global and local sensitivity differences of factor importance in different SUHI scenarios, analyzing the spatial sensitivity of the SUHI regarding different crucial factors at a fine scale of amongst different LCZs and UFZs. Based on the fine-scale analyses of LCZs and UFZs, our study can provide scientific decision support for future urban planning and the construction of climate-resilient cities.

2. Study Area and Data

2.1. Study Area

The Guangdong–Hong Kong–Macao Greater Bay Area (GBA) is China's most economically vibrant and urbanized urban agglomeration [36]. The Guangdong–Hong Kong–Macao Greater Bay Area Central (GBAC) region encompasses the most densely populated and built-up areas within the GBA region, including Guangzhou, Dongguan, Zhuhai, Zhongshan, Macao, Hong Kong, Shenzhen (excluding Dapeng), Foshan (excluding Gaoming), and Jiangmen (excluding Heshan, Kaiping, Enping, and Taishan), covering a total area of 20,264.80 km²; (Figure 1). This region is primarily characterized by plains, with an average elevation of 67.75 m. In 2019, the population density of the GBAC region was 7465 persons/km², with the urbanization rates of Hong Kong, Macao, Shenzhen, Zhuhai, and Foshan exceeding 90% [37]. We used land use/cover data from 2000 to 2019 [38] and found that the area of built-up land within the GBAC region increased by 3180.97 km², while farmland and water bodies decreased by 1131.34 km² and 484.06 km², respectively. As one of China's most densely populated regions, the GBAC region has garnered significant attention due to its dense urban infrastructure, substantial heat emissions from industrial operations, and transportation activities, all contributing to the UHI phenomenon.

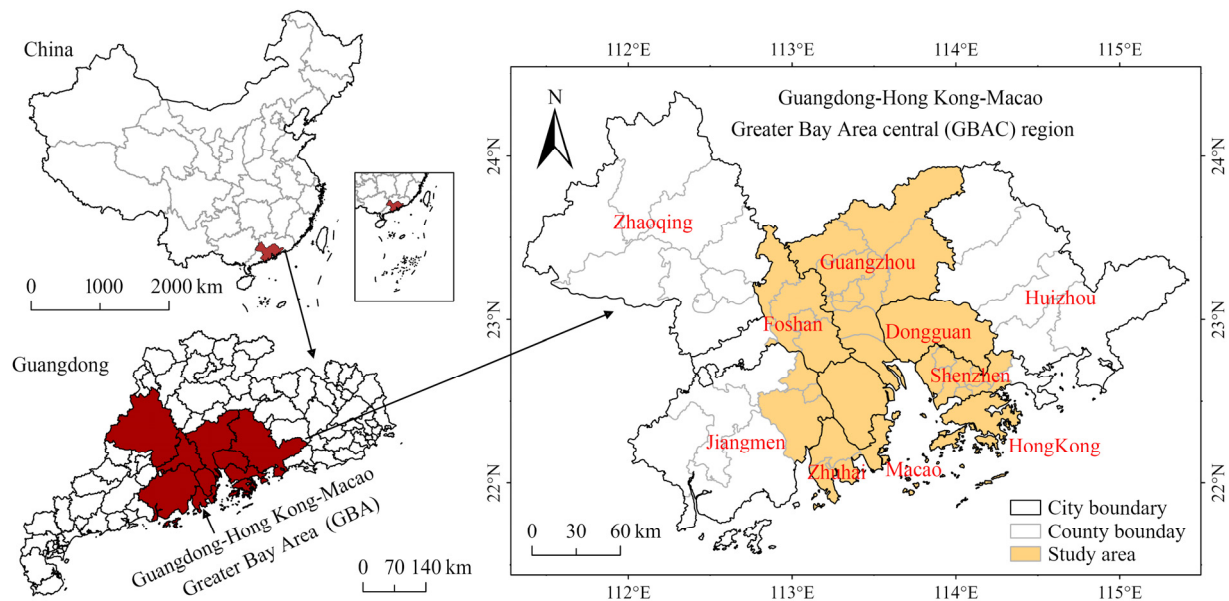


Figure 1. Geographic location of the Guangdong–Hong Kong–Macao Greater Bay Area Central (GBAC) region.

2.2. Data Source and Processing

Datasets used in our study are shown in Table 1: (1) two Landsat 8 imagery datasets (on 14 November 2019, at 10:52 and 10:54 Beijing time) with cloud coverage less than 2%, used for the inversion of land surface temperature (LST); (2) the moderate resolution imaging spectroradiometer (MODIS) LST data were calculated based on the MOD11A1 dataset on the Google Earth Engine (GEE) platform, which was used to verify the accuracy of the Landsat 8 LST retrieval; (3) data from 117 meteorological observation stations provided by the Guangdong–Hong Kong–Macao Greater Bay Area Weather Research Center for Monitoring Warning and Forecasting (GBAMWF). The air temperature data from 117 meteorological observation stations, recorded between 10:35 and 10:58 Beijing time on 14 November 2019, are used to validate the accuracy of the LST data retrieved from Landsat 8; and (4) the LCZ data for the GBAC region were secondarily processed based on the LCZ data provided by Liu and Shi [39], with misclassified LCZ types reclassified, resulting in a total of 17 LCZ types from LCZ 1 to LCZ G (Appendix A Figure A1). This paper added samples to the LCZ validation data provided by the Word Urban Database and used them to validate the accuracy of the LCZ classification. The accuracy of the LCZ classification data processed in this paper was validated using two sets of LCZ validation data, resulting in accuracies of 74.87% (Kappa: 0.72, with a validation sample size of 435) and 93.18% (Kappa: 0.82, with a validation sample size of 453), respectively.

UFZ data were provided by Gong et al., with a classification accuracy of 61.30% [40]. Due to the low classification accuracy of UFZ data and the absence of a “mixed-use functional zoning” category, this study combined POI data and Google Earth imagery data. Using the Shannon information entropy model [41] and visual interpretation methods, some inaccurately classified UFZ data were corrected, and 1724 plots were reclassified into the newly added mixed-use functional zoning (06) category. The revised urban functional land use is divided into six primary categories: residential (01), commercial (02), industrial (03), transportation (04), public management and service (05), and mixed-use (06), and twelve secondary categories (Appendix A Table A2). Urban boundary data were at a spatial resolution of 0.25 km, with an accuracy of 86.00% [42].

Table 1. Data used in this study.

Type	Spatial Resolution	Date	Sources
Landsat 8 image	0.03 km	14 November 2019	Chinese Academy of Sciences Geospatial Data Cloud
MODIS image	1 km	11 November 2019 to 17 November 2019	GEE (https://doi.org/10.5067/MODIS/MOD11A1.061 , accessed on 26 January 2024)
Meteorological observation data	-	14 November 2019	GBAMWF
LCZ data	0.1 km	2019	[39]
UFZ data	-	2018	[40]
POI data	-	2018	AutoNavi map
Road data	-	2019	Open Street Map
Building data	-	2018	Baidu Map
Population density data	0.1 km	2019	WorldPop (https://hub.worldpop.org/ , accessed on 22 January 2024)
Luoja01 nighttime light data	0.13 km	2019	Wuhan University (http://59.175.109.173:8888/app/login.html , accessed on 21 January 2024)
Land use/cover data	0.03 km	2019	[38]
ASTER GDEM V3 dataset	0.03 km	2019	https://srtm.csi.cgiar.org/ , accessed on 13 January 2024
Urban area boundary data	0.25 km	2018	[42]
China coastline data	-	2021	https://www.webmap.cn/commres.do?method=result100W , accessed on 11 January 2024

We select 15 SUHI influencing factors, as shown in Table 2, considering urban residents' work and life, buildings, population, land use/cover, transportation, and geographical conditions. The densities of companies and enterprises (COM), public organizations (PUBs), and life and entertainment facilities (LIE) were analyzed using the kernel density analysis method [43] for three major categories of points of interest (POI). The factors of average building volume (BUV), average building height (BUH), and average building density (BUD) are calculated based on the building vector data from Baidu Maps. Among them, BUD was processed using the kernel density analysis method. Population density (POP) and population activity intensity (POC) indicators were based on WorldPop population density data and Luoja-01 nighttime light data, respectively.

Table 2. Details of SUHI influencing factors.

Category	Factors	Unit	Variable
Work and living	The density of companies and enterprises	unit/km ²	COM
	The density of public organizations	unit/km ²	PUB
	The density of life and entertainment	unit/km ²	LIE
Buildings	The average building volume	m ³ /km ²	BUV
	The average building height	m/km ²	BUH
	The average building density	-	BUD
Population	Population density	-	POP
	Population activity intensity	DN/km ²	POC
	Impervious land ratio	%	IMP
Land use/cover	Water area ratio	%	WAT
	Vegetation area ratio	%	VEG
	Road density	-	ROD
Traffic	Road intersection density	-	ROI
	Distance from coastline	km	DIC
Geography	Elevation	m	DEM

The ratio of impervious surface area (IMP), water area (WAT), and vegetation area (VEG) were obtained using the Pixel Information Expert (PIE) engine to process land use/cover data [38]. Road density (ROD) and road intersection density (ROI) indicators were analyzed using the kernel density analysis method for OSM road and OSM road intersection data, respectively, and then the density value of each analysis unit was calculated. The distance to the coastline (DIC) indicator measures the distance from each LCZ and

UFZ to the coastline, calculated by combining coastline data with the nearest neighbor method [38]. The DEM reflects the elevation of each analysis unit.

3. Methodology

The workflow in this study is illustrated in Figure 2. We used the radiative transfer equation and nonlinear split-window methods to retrieve two types of LST data. Six SUHI identification methods were considered to construct 12 SUHI scenarios over the GBAC region using the two LST data types. The study compared the differences in SUHI sensitivity between different LCZ types and UFZ types by utilizing the spatial gradient boosting trees, geographically weighted regression, and the coefficient of variation model to unravel the global and local sensitivity differences of influencing factors in the 12 SUHI scenarios.

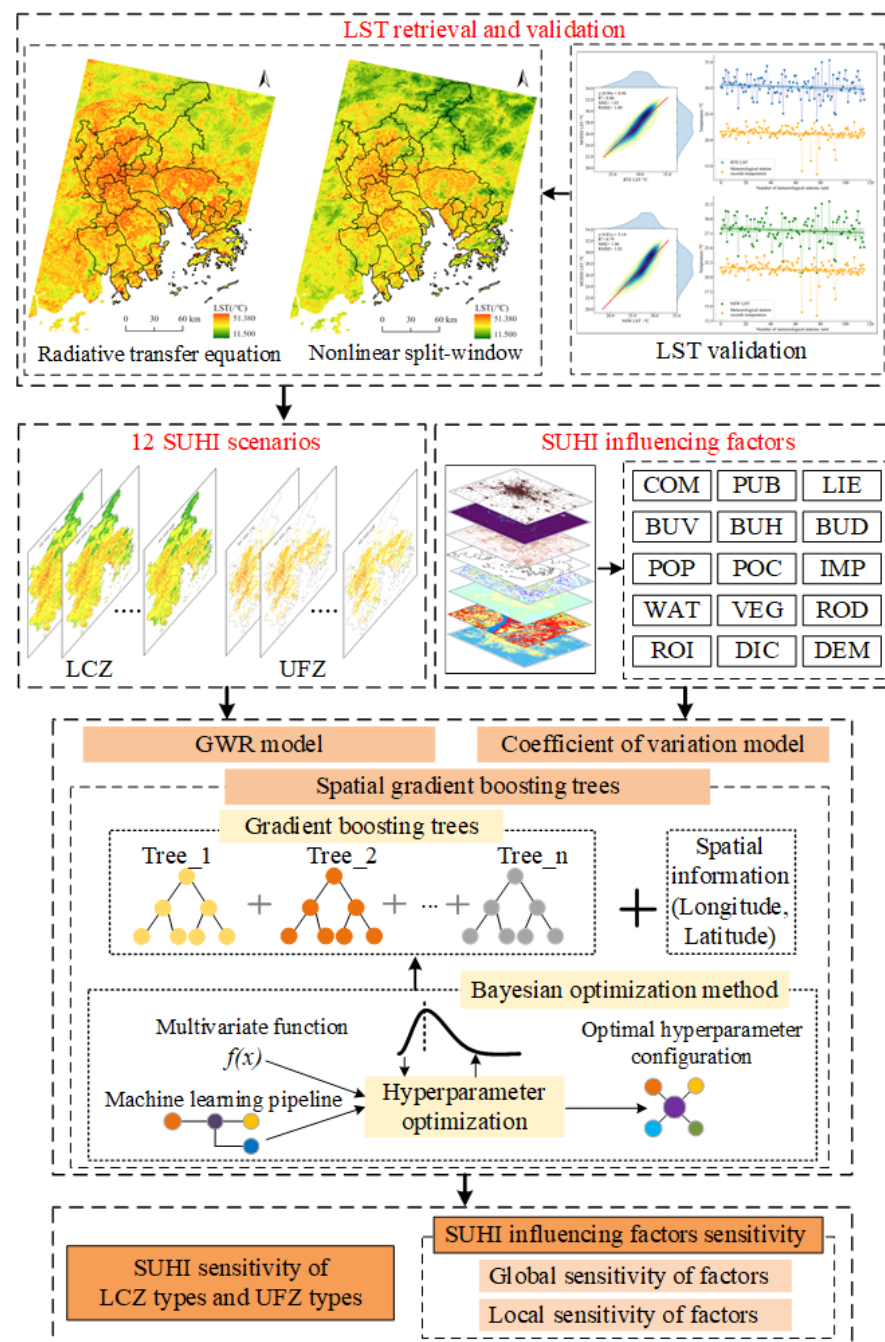


Figure 2. Workflow in this study.

3.1. LST Retrieval

This study used two methods for retrieving the LST in the GBAC region on 14 November 2019: the radiative transfer equation method and the nonlinear split-window method.

(1) Radiative transfer equation (RTE) method

The RTE method is a technique for retrieving LST using the thermal infrared bands of satellites. The RTE considers various factors, including atmospheric absorption, emission, scattering, and surface reflection. It estimates and reduces errors caused by atmospheric factors, thereby obtaining the surface radiant quantity [32]. The RTE method considers the atmospheric effects between the land and the satellite. The RTE is defined as follows:

$$L_{\lambda} = [\varepsilon \cdot B(T_S) + (1 - \varepsilon)L_{\downarrow}] \cdot \tau + L_{\uparrow} \quad (1)$$

where L_{λ} represents the brightness of thermal infrared radiation received by the sensor. ε represents the surface emissivity. The parameter ε is calculated according to the reference literature [44], based on the threshold set by the normalized difference vegetation index (NDVI), and then different land cover types are classified, and the ε values are calculated accordingly. T_S is the true LST. BT_S is the blackbody radiance brightness at the true LST T_S . τ represents the atmospheric transmittance. $L_{\uparrow}$ and $L_{\downarrow}$, respectively, represent the brightness of the atmospheric upward and downward radiation, with a unit of $W \cdot m^{-2} \cdot sr^{-1}$. τ , $L_{\uparrow}$, and $L_{\downarrow}$ can be queried on the Atmospheric Correction Parameter website of the National Aeronautics and Space Administration. Solving Equation (1) yields BT_S , and the LST can then be calculated using the inverse function of Planck's law [32].

(2) Nonlinear split-window (NSW) method

Under high atmospheric water content and cloud cover conditions, the NSW method exhibits lower atmospheric sensitivity compared to some linear LST retrieval methods [30]. In regions of South China affected by clouds and rain, the NSW method more effectively addresses the atmospheric impacts on LST retrieval, thereby enabling more accurate LST retrieval. The NSW method is described as follows:

$$LST = b_0 + (b_1 + b_2 \frac{1 - \varepsilon}{\varepsilon} + b_3 \frac{\Delta \varepsilon}{\varepsilon^2}) \frac{T_i + T_j}{2} + (b_4 + b_5 \frac{1 - \varepsilon}{\varepsilon} + b_6 \frac{\Delta \varepsilon}{\varepsilon^2}) \frac{T_i + T_j}{2} + b_7 (T_i - T_j)^2 \quad (2)$$

where ε and $\Delta \varepsilon$ represent the average emissivity and the difference in emissivity of two thermal infrared channels, depending on land use/cover. T_i and T_j are the observed brightness temperatures of the two channels, and b_i ($i = 1, 0, 2, \dots, 7$) are various coefficients, which can be obtained through laboratory data, atmospheric parameter data, and simulated atmospheric radiation transmission equations datasets. The coefficient b_i depends on the atmospheric water vapor content [30].

According to the reference [31], the atmospheric water vapor content is calculated by firstly establishing an empirical relationship between the atmospheric transmittance ratio of two split-window channels and the atmospheric water vapor content using the moderate-resolution atmospheric transmission model and thermodynamic initial guess retrieval atmospheric profiles. Secondly, the transmittance ratio is estimated using the covariance ratio to variance between the brightness of the two thermal infrared channels. This study used the vegetation coverage weighted method to estimate the surface emissivity.

3.2. Calculation of SUHI

SUHI refers to the phenomenon where urban areas exhibit higher temperatures than the surrounding rural regions, primarily caused by land use/cover changes, heat emission from buildings, and human activities [45,46]. We used RTE LST and NSW LST datasets to retrievably calculate 12 SUHI scenarios in the central area of the GBAC region based on the urban–rural temperature threshold method [45] and the LCZ temperature difference

method. The equation for calculating SUHI using the urban–rural temperature threshold method is as follows:

$$SUHI_i = T_i - \bar{T}_{Rural} \quad (3)$$

where $SUHI_i$ represents the surface urban heat island intensity (SUHI) for pixel i (unit: °C). T_i is the LST for each pixel point i (unit: °C). $\bar{T}_{Rural}$ is the average LST for rural areas (unit: °C). This study defines rural areas as those beyond 10 km and 20 km buffer zones around urban areas, with the identified SUHIs named SUHI_1 and SUHI_2, respectively. The GBA region encompasses super-large, large, and medium-small cities, so it has many towns/satellite cities [36,47]. In distinguishing between urban and rural areas, this study does not include towns with an impervious surface area of less than 5 km² within the urban area [16]. To minimize the errors in SUHI identification caused by elevation, this paper excludes rural areas exceeding the urban area's median elevation of ± 50 m [48,49]. The median elevation of the GBAC region is 19.12 m. Hence, rural areas between elevations of 0 and 69.12 m were selected.

The LCZ SUHI classification method uses the temperature difference between LCZ types to characterize the intensity of the SUHI, that is, the difference between the average temperature of LCZ_X and LCZ_Y [23,50]. LCZ types are classified mainly based on the type of buildings and land use/cover [7]. LCZ B represents a scattered tree zone, LCZ D represents a low plant zone, and LCZ 9 represents a sparsely built zone [23]. These three LCZ types conform to the natural environmental characteristics of rural areas [33]. This study calculates SUHI for three LCZ types: LCZ B [51], LCZ D [52,53], and LCZ 9 [33]. The LCZ SUHI classification method is as follows:

$$SUHI_3 = T_{LCZ_X} - \bar{T}_{LCZ_B} \quad (4)$$

$$SUHI_4 = T_{LCZ_X} - \bar{T}_{LCZ_D} \quad (5)$$

$$SUHI_5 = T_{LCZ_X} - \bar{T}_{LCZ_9} \quad (6)$$

where $SUHI_3$, $SUHI_4$, and $SUHI_5$ are the SUHI calculated by using LCZ B, LCZ D, and LCZ 9 as non-urban references, respectively. LCZ_X represents 17 types of LCZ categories. $\bar{T}_{LCZ_B}$, $\bar{T}_{LCZ_D}$, and $\bar{T}_{LCZ_9}$ are the average LSTs of LCZ B, LCZ D, and LCZ 9, respectively (unit: °C). To reduce the impact of elevation, we selected LCZ B, LCZ D, and LCZ 9 located at elevations between 0 and 69.12 m for analyzing the SUHI in the GBAC region.

This paper classifies the SUHI identification methods into five types, SUHI_1 to SUHI_5, based on the differences in non-urban references (Table 3). Figure 3 shows the non-urban references for this study's five SUHI identification methods.

Table 3. Six SUHI methods and their non-urban reference LST.

SUHI Method	General Definition and Location	Excluded Factors	NSW LST	RTE LST
SUHI_1	10 km outside administrative non-urban areas	Water bodies and elevations exceeding ± 50 m of urban areas median elevation	26.579 (SUHI_1N)	29.009 (SUHI_1R)
SUHI_2	20 km outside administrative non-urban areas	Water bodies and elevations exceeding ± 50 m of urban areas median elevation	26.593 (SUHI_2N)	29.040 (SUHI_2R)
SUHI_3	LCZ B	Elevations exceeding ± 50 m of urban areas median elevation	26.263 (SUHI_3N)	28.580 (SUHI_3R)
SUHI_4	LCZ D	Elevations exceeding ± 50 m of urban areas median elevation	27.078 (SUHI_4N)	29.263 (SUHI_4R)
SUHI_5	LCZ 9	Elevations exceeding ± 50 m of urban areas median elevation	27.488 (SUHI_5N)	29.552 (SUHI_5R)
SUHI_6	-	-	26.800 (SUHI_6N)	29.089 (SUHI_6R)

(Note: RTE LST refers to the LST retrieved by the RTE method (unit: °C). NSW LST refers to the LST retrieved by the NSW method (unit: °C). LST-Threshold represents the LST threshold of SHUI.)

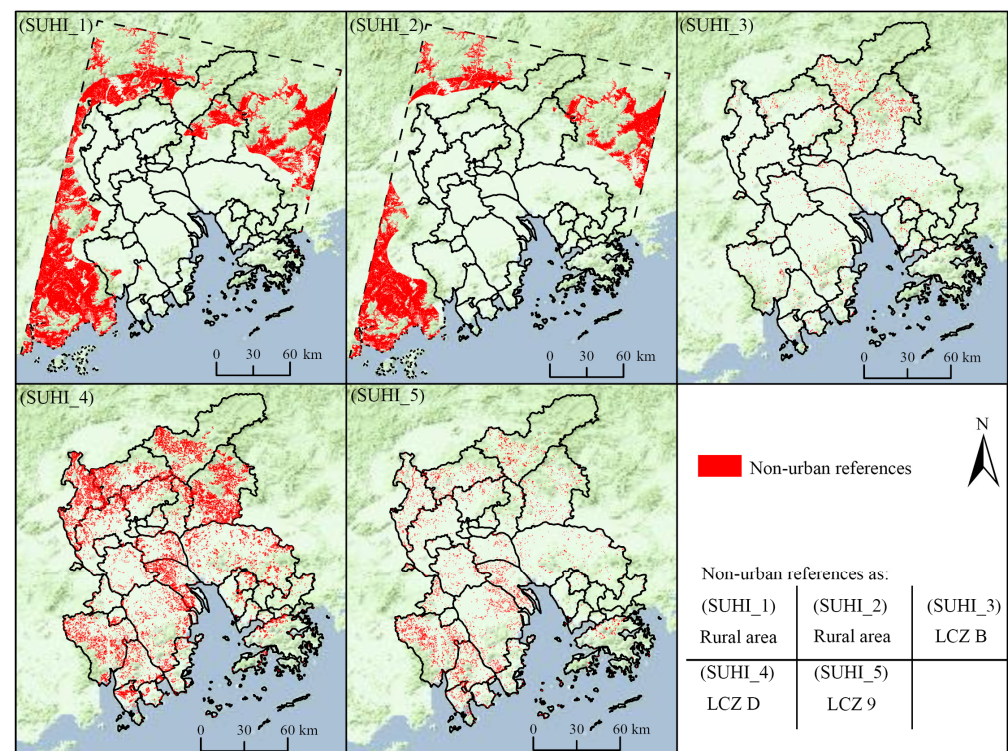


Figure 3. Non-urban references for five types of SUHIs.

The above five different SUHI identification methods independently reflect a particular scenario of SUHI. To obtain a more comprehensive and integrated representation of SUHI, we aggregated the results of these five methods and calculated their average value, thereby creating a sixth SUHI identification method, SUHI_6. SUHI_6 is defined as follows:

$$SUHI_6 = \frac{\sum_{i=1}^n (SUHI_i)}{n} \quad (7)$$

where $SUHI_6$ represents the SUHI identification method SUHI_6. SUHI_6 considers the results of the analysis using five SUHI methods, namely SUHI_1, SUHI_2, SUHI_3, SUHI_4, and SUHI_5. n represents the five methods to identify SUHI from SUHI_1 to SUHI_5. Based on these six SUHI identification methods and two types of LST data, we generated a total of 12 SUHI scenarios (Table 3).

3.3. Spatial Gradient Boosting Trees (SGBT)

The gradient boosting trees (GBT) model is an ensemble learning algorithm that improves prediction performance by combining multiple decision trees [54]. In general, the relationship between the UHI and influencing factors is nonlinear [22]. GBT is a nonlinear modeling algorithm capable of capturing the complex nonlinear relationships between UHIs and their influencing factors. However, traditional GBT models do not consider the spatial correlation between data, which may lead to the model's inability to capture the similarities and spatial dependencies between neighboring areas. This study considers the location information (longitude and latitude) of analysis units as additional features into the model training to expand the feature space of the GBT model named as the spatial gradient boosting trees (SGBT). The SGBT model can derive the complex relationships between the spatial features and variables during training, allowing for a more accurate quantification of the influencing factors on SUHI. In the SGBT model, the training and testing data account for 80% and 20% of the input data volume, respectively. This study

uses the SGBT model to analyze the importance of influencing factors across 12 SUHI scenarios. The input data for the SGBT model includes the following:

$$FImport = Input[(x_1, x_2 + \dots + x_{15}), SUHII], (lon, lat)] \quad (8)$$

where *FImport* represents the feature importance value of influencing factors on SUHII. The higher the *FImport* value, the more important the factor is to SUHII. *Input()* represents the data input for the SGBT model. $x_1, x_2, \dots, x_{15}$ are the 15 SUHI influencing factors in Table 2. *SUHII* refers to the intensity of the urban surface heat island. *lon* and *lat* are the longitude and latitude, respectively.

The Bayesian optimization method is applied to determine the optimal parameters of the SGBT model in each SUHI scenario [55,56]. These optimal parameters encompass the number of base learners, the learning rate, and the maximum depth of the trees. By constructing a probabilistic objective function model, Bayesian optimization efficiently identifies parameter combinations in high-performance regions. It comprehensively evaluates the SGBT model's performance with various hyperparameter settings within the same SUHI scenario, ensuring the model exhibits strong generalization capabilities to accurately quantify the impacts of the influencing factors on SUHI.

3.4. Geographically Weighted Regression Model (GWR)

The Geographically Weighted Regression (GWR) model is an extension of traditional regression analysis that allows the model's parameters to vary across space in order to capture the local variations of variables at different geographical locations [57]. This paper uses the GWR model to calculate the explanatory coefficients of the influencing factors and introduces an improved coefficient of variation to calculate the spatial sensitivity change in explanatory coefficients of influencing factors across 12 SUHI scenarios. In the 12 SUHI scenarios, the variance inflation factor values (Appendix A Tables A3 and A4) of 15 SUHI influencing factors are all less than 10, passing the collinearity test.

When the average explanatory coefficient calculated by GWR is less than 0, the coefficient of variation (CV) can turn negative, making it ineffective for comparison with positive values. This paper replaces the average value with its absolute value to avoid negative CVs, allowing the fluctuations among values to be consistently and effectively compared. This study utilizes the improved CV to quantify the stability and sensitivity of the explanatory coefficients of influencing factors for SUHI spatial variation within the same spatial unit across 12 SUHI scenarios. The improved CV calculation equation is as follows:

$$CV = \frac{sd}{|\bar{x}|} \quad (9)$$

where CV represents the coefficient of variation (CV). *sd* represents the standard deviation of the explanatory coefficient of influencing factors within the same spatial unit across 12 different SUHI scenarios. $|\bar{x}|$ represents the absolute value of the average explanatory coefficient of influencing factors within the same spatial unit across 12 SUHI scenarios. A higher CV value indicates a higher spatial sensitivity of the SUHI influencing factors in that spatial unit.

4. Analysis and Results

4.1. LST Validation

This study used two scenes of Landsat 8 imagery data at 10:52 and 10:54 Beijing time, respectively, on 14 November 2019, to retrieve the LST as shown in Figure 4. Figure 4c presents the grid points of the average LST values at a spatial resolution of 2 km × 2 km by applying the two methods (i.e., RTE and NSW). The average LST obtained by using the RTE and NSW methods were 28.44 °C and 26.18 °C.

This study accurately validated Landsat 8 LST data using MODIS LST data from 11 to 17 November 2019, and air temperature data from a meteorological station between

10:35 and 10:58 on 14 November 2019. The R^2 fitting coefficients between the RTE LST and MODIS LST, and between NSW LST and MODIS LST, were 0.80 (Figure 5a) and 0.79 (Figure 5c), respectively. The trends of RTE LST and NSW LST data were consistent with the variations in air temperature recorded by meteorological stations.

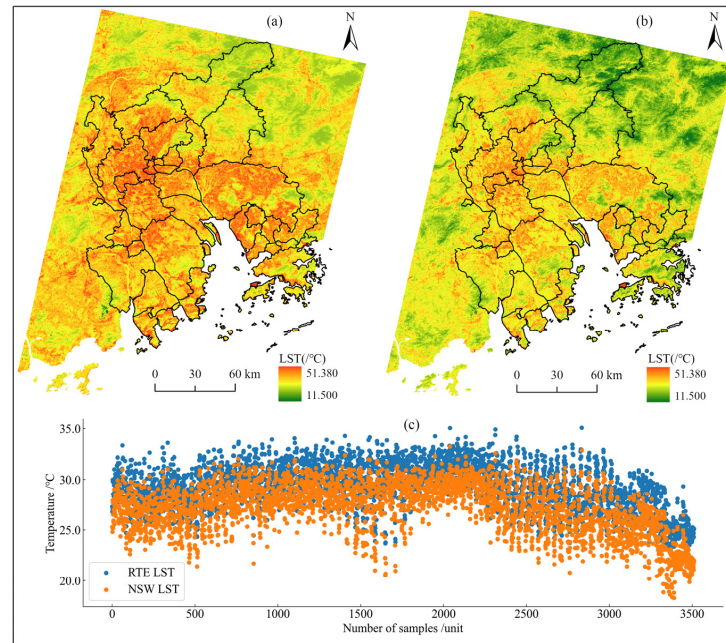


Figure 4. Comparison of LST derived from the radiative transfer equation (RTE) method and the nonlinear split window (NSW) method: (a) LST retrieved by the RTE, (b) LST retrieved by the NSW, (c) shows a comparison of RTE LST and NSW LST at the same spatial locations.

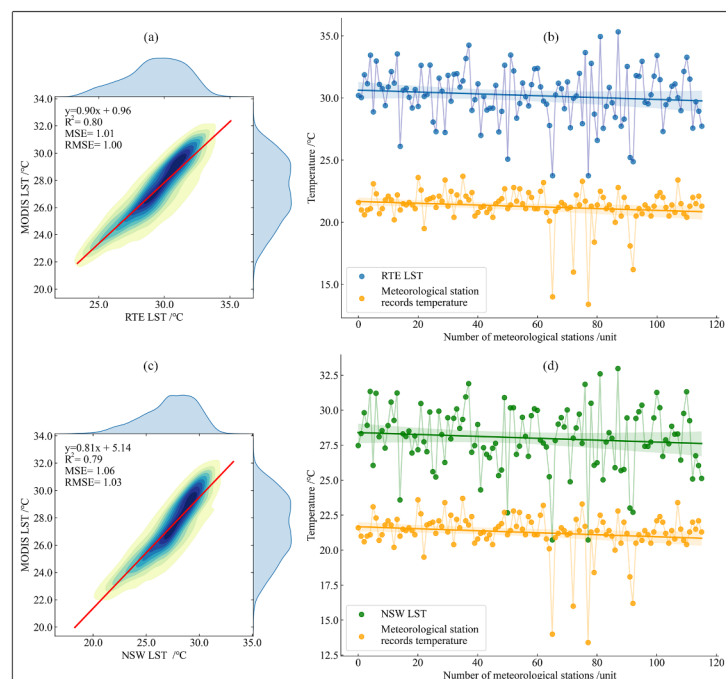


Figure 5. Comparison of Landsat 8 LST and MODIS LST data, and temperatures recorded by meteorological stations: (a) shows a comparison between RTE LST and MODIS LST, (b) shows a comparison between RTE LST and temperatures recorded by meteorological stations, (c) shows a comparison between NSW LST and MODIS LST, (d) shows a comparison between NSW LST and temperatures recorded by meteorological stations.

4.2. Sensitivity Analysis of LCZ Types and UFZ Types on SUHI

Six methods were applied to identify SUHI, among which the SUHI_3 method calculated the highest SUHII, and the SUHI_5 method calculated the lowest. The research discovered that the SUHI_1 and SUHI_2 methods, which use the urban–rural threshold approach to identify SUHI, produced similar SUHII results. Compared to the SUHI_1, SUHI_2, and SUHI_3 methods, the sensitivity of SUHI calculated by the SUHI_4 and SUHI_5 methods was significantly reduced (Figure 6). The sensitivity difference highlights the importance of choosing the SUHI assessment method and selecting non-urban references.

Due to the misclassification issues of LCZs and UFZs, this study eliminated the anomalous SUHII data within each type of LCZ and UFZ. According to the SUHII division standards for the GBAC region [58], the SUHI sensitivity of 17 LCZ types and 12 UFZ types was categorized into four levels: highly sensitive ($3.50\text{ }^{\circ}\text{C} < \text{SUHII}$), moderately sensitive ($2.50\text{ }^{\circ}\text{C} < \text{SUHII} \leq 3.50\text{ }^{\circ}\text{C}$), weakly sensitive ($1.50\text{ }^{\circ}\text{C} < \text{SUHII} \leq 2.50\text{ }^{\circ}\text{C}$), and insensitive ($\text{SUHII} \leq 1.50\text{ }^{\circ}\text{C}$). LCZ E (bare rock or paved zone, SUHII: $4.22\text{ }^{\circ}\text{C}$) and LCZ 10 (industrial zone, SUHII: $3.87\text{ }^{\circ}\text{C}$) were classified as highly sensitive to SUHI; the commercial and service zone (SUHII: $3.28\text{ }^{\circ}\text{C}$), industrial zone (SUHII: $3.28\text{ }^{\circ}\text{C}$), transportation station zone (SUHII: $3.24\text{ }^{\circ}\text{C}$), LCZ 8 (large low-rise building zone, SUHII: $2.90\text{ }^{\circ}\text{C}$), business zone (SUHII: $2.68\text{ }^{\circ}\text{C}$), LCZ 3 (compact low-rise building zone, SUHII: $2.61\text{ }^{\circ}\text{C}$), LCZ 2 (compact mid-rise building zone, SUHII: $2.54\text{ }^{\circ}\text{C}$), and medical zone (SUHII: $2.51\text{ }^{\circ}\text{C}$) were classified as moderately sensitive to SUHI (Table 4). It found that building clusters with different heights and densities can affect the amount of solar radiation received by the ground surface and the formation of ground-level wind circulation. These factors are the primary reasons for the differing sensitivities of various LCZ and UFZ types to SUHII.

Table 4. Sensitivity of SUHII in LCZ types and UFZ types.

Type	SUHII	TRank	Grade	Type	SUHII	TRank	Grade
LCZ E	4.219	1	H	LCZ 5	1.950	16	W
LCZ 10	3.872	2	H	LCZ 1	1.859	17	W
Commercial service	3.282	3	M	Educational	1.777	18	W
Industrial	3.275	4	M	Airport facilities	1.621	19	W
Transportation stations	3.243	5	M	Park and greenspace	1.440	20	I
LCZ 8	2.899	6	M	LCZ 4	1.106	21	I
Business	2.678	7	M	LCZ 6	0.725	22	I
LCZ 3	2.606	8	M	LCZ 9	0.203	23	I
LCZ 2	2.540	9	M	LCZ D	0.103	24	I
Medical	2.509	10	M	LCZ G	−0.076	25	I
Sport and cultural	2.401	11	W	LCZ 7	−0.224	26	I
Mixed-use	2.314	12	W	LCZ A	−0.617	27	I
Administrative	2.287	13	W	LCZ B	−1.147	28	I
LCZ F	2.237	14	W	LCZ C	−1.947	29	I
Residential	2.151	15	W				

Note: Type refers to LCZ or UFZ types. SUHII represents the average urban heat island intensity for 12 SUHI scenarios (unit: $^{\circ}\text{C}$). TRank is the sensitivity ranking for both LCZ and UFZ types to UHI effect. Grade classifies the SUHII into four categories: H for high sensitivity ($3.50\text{ }^{\circ}\text{C} < \text{SUHII}$), M for moderate sensitivity ($2.50\text{ }^{\circ}\text{C} < \text{SUHII} \leq 3.50\text{ }^{\circ}\text{C}$), W for weak sensitivity ($1.50\text{ }^{\circ}\text{C} < \text{SUHII} \leq 2.50\text{ }^{\circ}\text{C}$), and I for insensitivity ($\text{SUHII} \leq 1.50\text{ }^{\circ}\text{C}$).

The LCZ E (bare rock or paved zone) and LCZ 10 (industrial zone) are primarily characterized by their surface features, which have a high heat capacity, with a greater capacity to absorb and store more heat quickly (Figure 7). Furthermore, LCZ E (bare rock or paved zone) is distinguished by having few trees and buildings, resulting in a lack of shading and evaporative cooling effects. Airports and ports within the region are classified as the LCZ E (bare rock or paved zone), and the SUHII is significantly higher than other zones, such as the Guangzhou Port, Hong Kong International Airport, Guangzhou Baiyun International Airport, and Shenzhen Bao'an International Airport [59,60]. The higher SUHI sensitivity in LCZ 10 (industrial zone) is mainly due to dense building structures with large anthropogenic heat emissions from industrial activities. The cooling effect of green spaces and building shading is insufficient to offset the heat emitted during industrial production.

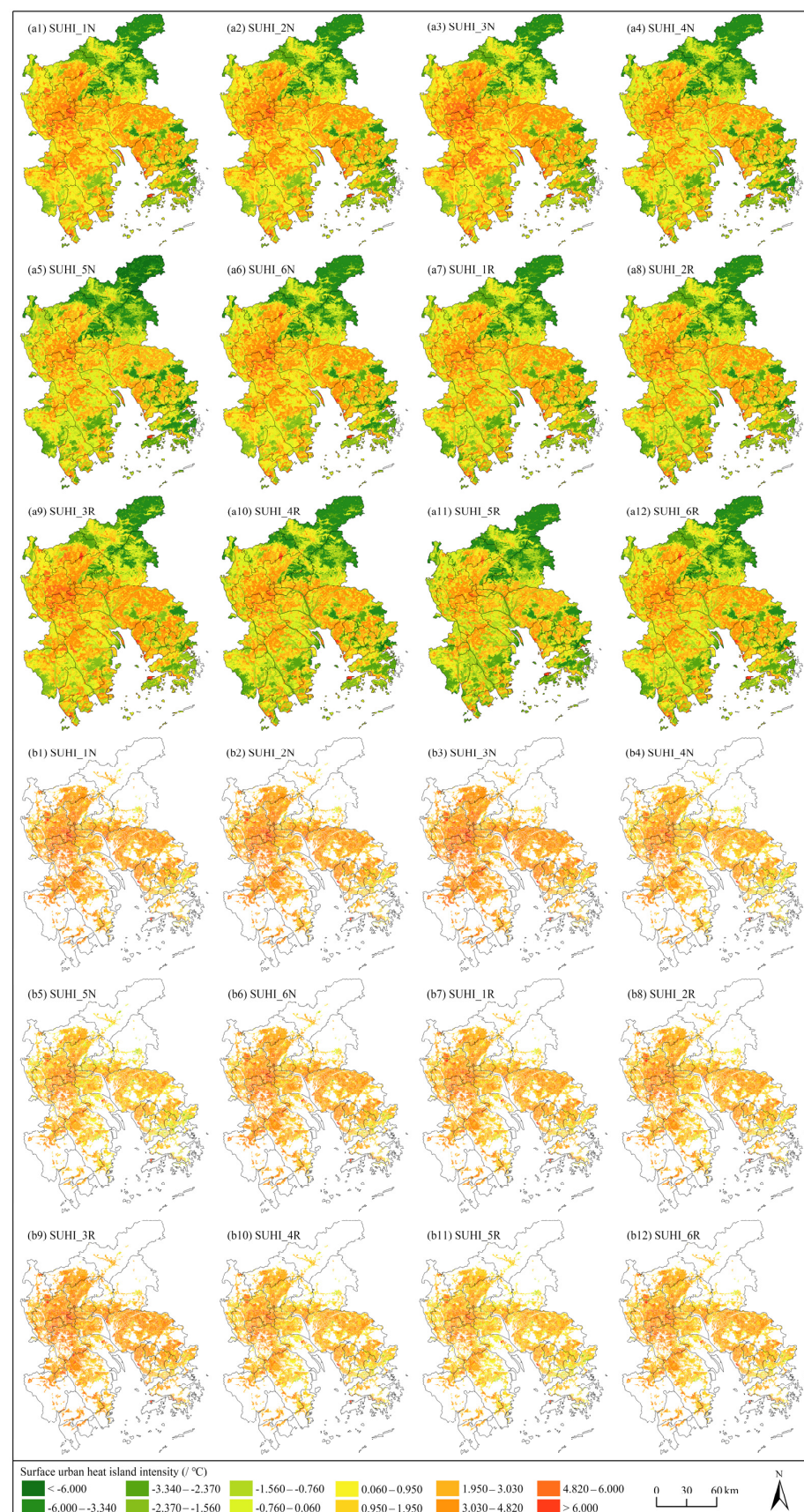


Figure 6. Spatial distribution of the SUHIs intensity in 12 scenarios within LCZs and UFZs: (a1–a12) show the spatial distribution of SUHI in LCZs, (b1–b12) show the spatial distribution of SUHI in UFZs.

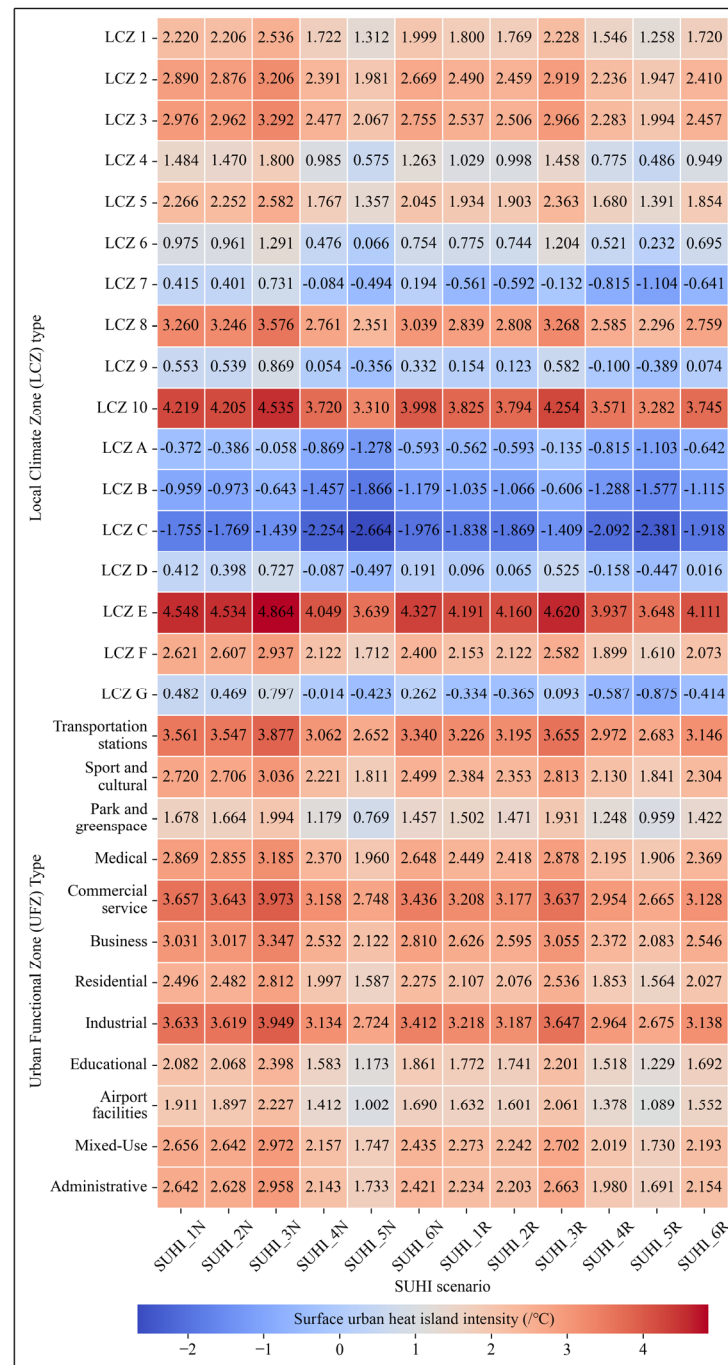


Figure 7. Sensitivity of different LCZ and UFZ types.

Impervious surfaces dominated LCZ 8 (large low-rise zone), LCZ 3 (compact low-rise zone), and LCZ 2 (compact midrise zone) (Figure 7). The reason why their SUHI sensitivities were lower than the ones from LCZ E (bare rock or paved zone) and LCZ 10 (industrial zone) can be mainly explained by the differences in building height and density, resulting in uneven reception of solar radiation and the effects of ground wind circulation, both of which reduce the efficiency of heat absorption by the surface. Meanwhile, the areas of moderate sensitivity in SUHI may have more effective mechanisms for heat dissipation. For example, commercial, industrial, transportation, and medical zones are divided by traffic analysis units and may include some urban green spaces and water bodies. Water bodies can effectively reduce the surrounding temperature through evaporation and cooling, mitigating the SUHI effect, while urban green spaces provide natural cooling through

shading and transpiration, helping to regulate the urban microclimate and further alleviate the SUHI phenomenon.

4.3. SUHI Influencing Factor Sensitivity

4.3.1. Global Sensitivity of SUHI Influencing Factors

The global importance of the SUHI influencing factors for LCZ and UFZ differ significantly, and the global importance of SHUI influencing factors also demonstrates different scenario sensitivity characteristics (Figure 8). During the daytime, the combined global importance value of the impervious surface ratio (IMP) and elevation (DEM) accounted for 77.69%, highlighting the crucial role of IMP and DEM in SUHI. IMP plays a crucial role in LCZ due to its direct relation to the absorption and re-radiation capability of solar radiation, exhibiting high stability across multiple SUHI scenarios with a coefficient of variation (CV) of only 0.86%, categorizing it as a factor of low sensitivity to SUHI scenarios. Compared to IMP, the influence of DEM fluctuates more significantly (with a CV of 13.69%), indicating that DEM is a sensitivity factor in different SUHI scenarios. In UFZ, average building height (BUH), vegetation cover ratio (VEG), DEM, and IMP were all crucial factors for SUHI and exhibited higher sensitivity to SUHI scenarios.

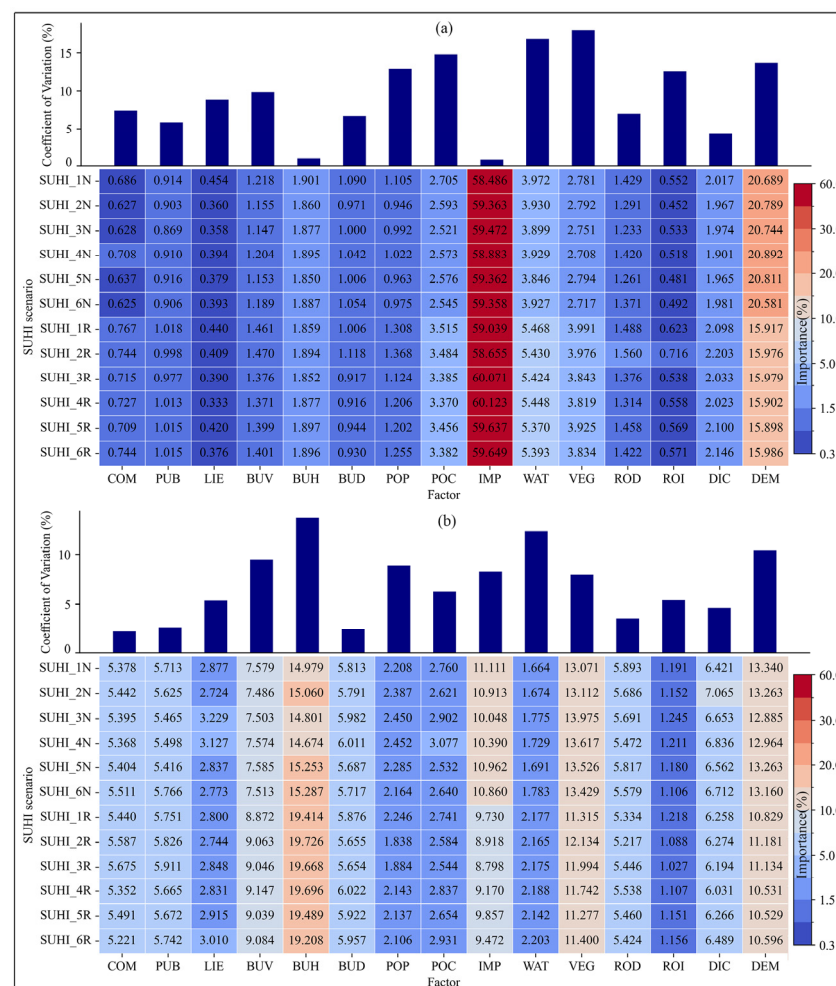


Figure 8. Importance of influencing factors in 12 SUHI scenarios: (a) for LCZ, (b) for UFZ, with heatmaps showing the importance values of influencing factors in the 12 SUHI scenarios, and bar graphs representing the coefficient of variation of importance values of influencing factors.

The main reasons for the sensitivity differences of influencing factors across multiple SUHI scenarios are as follows: First, there are nonlinear effects between influencing factors and different SUHI scenarios [24,59]. For example, the combined effects of building height

and impervious surface ratio are more complex than the effects of individual factors, leading to different sensitivities and importance in various scenarios. The nonlinear effect causes the impact of influencing factors on SUHI to be either amplified or diminished in specific SUHI scenarios. Second, the sensitivity and variability of influencing factors in different SUHI scenarios indicated that these factors did not independently affect SUHI but might involve complex interactions. These results emphasized the significant differences in the contribution and mechanism of factors such as BUH, VEG, DEM, and IMP to SUHI effects under different SUHI scenarios. For instance, increasing vegetation might reduce SUHI, but if there was also high building density, natural wind flow could be obstructed, diminishing the cooling effect of the vegetation. Therefore, urban planners must consider these interactions when designing city layouts to manage and mitigate SUHI effects effectively.

In this study, UFZs were located within the built-up areas of the GBAC region, while LCZs covered the entire GBAC region, including urban, suburban, and rural areas. By comparing the importance of SUHI influencing factors between LCZ and UFZ, we found that the importance of these factors exhibited significant regional characteristics. In UFZ, the importance of IMP and DEM significantly decreased, whereas the importance of BUH, VEG, and BUH significantly increased (Figure 8). These results were mainly due to the enhanced influence of artificial structures and features, such as building height and vegetation cover, on the urban microclimate in highly urbanized environments, while the role of natural topography is relatively weakened. Within the built-up areas, the widespread presence of impervious surfaces and the artificial modification of topography reduced their marginal impact on SUHI, whereas the configuration of buildings and vegetation became crucial for regulating the urban thermal environment.

4.3.2. Local Spatial Sensitivity of SUHI Influencing Factors

This study utilizes the GWR model and the improved coefficient of variation model to calculate the CV for assessing the spatial sensitivity of influencing factors in 12 SUHI scenarios. After eliminating anomalous CV values, the CVs were categorized into five levels using a quintile approach: low sensitivity (CV: 0 to 20%), lower-medium sensitivity (CV: 20% to 40%), medium sensitivity (CV: 40% to 60%), higher-medium sensitivity (CV: 60 to 80%), and high sensitivity (CV: 80% to 100%). It has been found that the 15 influencing factors selected for this research mostly fall into the low sensitivity category for multiple SUHI scenarios, with an average of 87.43% and 89.97% being classified as low spatial sensitivity for LCZ and UFZ, respectively (Figures 9 and 10). We revealed that the 15 influencing factors selected in this study have low spatial sensitivity and high stability in multiple SUHI scenarios.

There are two primary explanations for the result described above. First, the high stability and minor differences in local SUHI across the 12 SUHI scenarios led to low spatial sensitivity of the influencing factors in LCZ and UFZ to multiple SUHI scenarios. Secondly, the classification accuracy of the LCZ and UFZ types is high, with a high degree of landscape homogenization within them. LCZs are classified based on physical and environmental characteristics of the surface, such as types, heights, and densities of buildings and land use/cover type [23]. UFZ, on the other hand, is differentiated based on the various functions within urban spaces. The environments and landscapes within different LCZs and UFZs have high consistency and homogeneity.

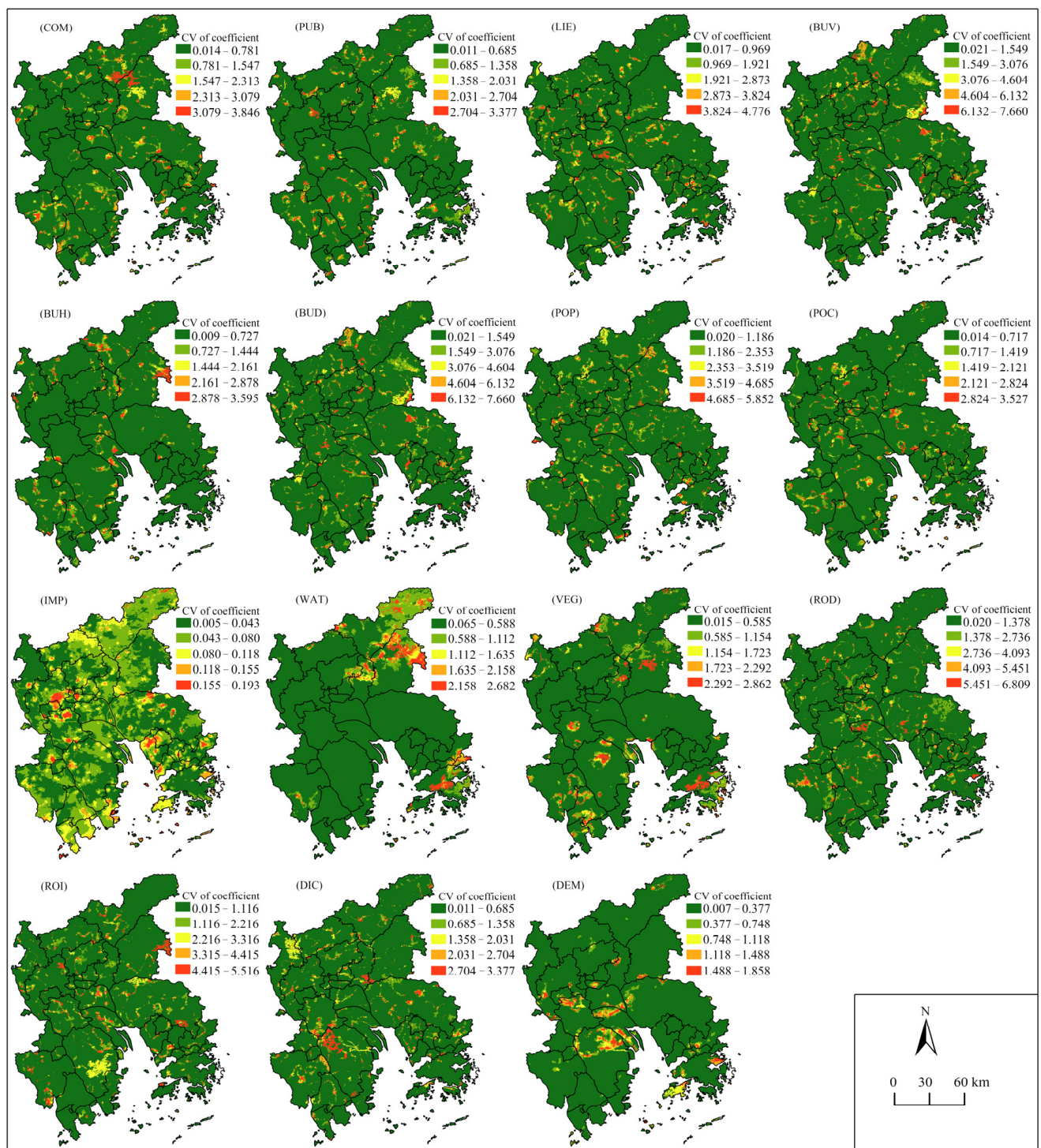


Figure 9. Coefficient of variation values for SUHI influencing factors in LCZs under 12 SUHI scenarios.

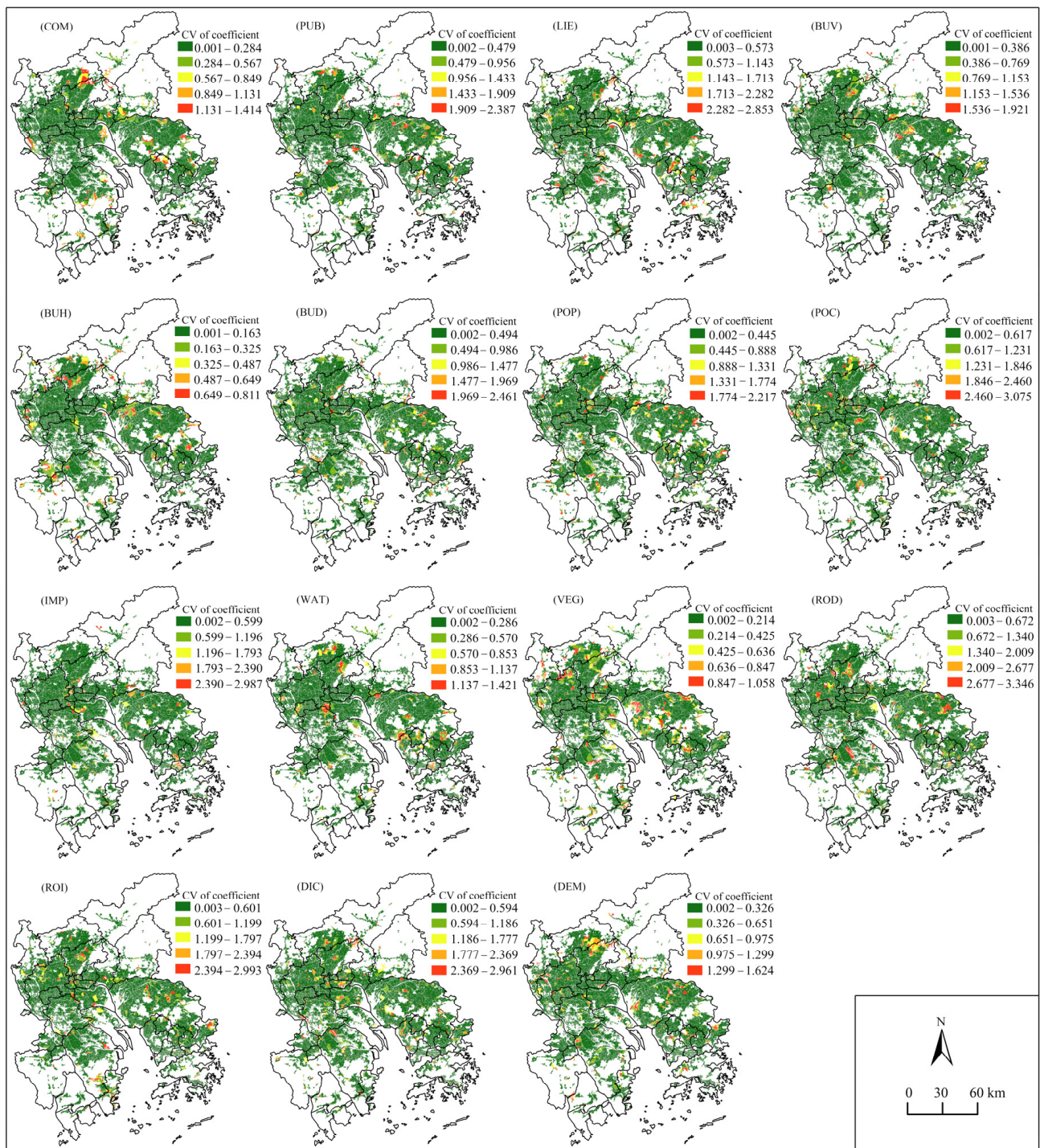


Figure 10. Coefficient of variation values for SUHI influencing factors in UFZs under 12 SUHI scenarios.

5. Discussion

5.1. Uncertainty in SUHI Assessment

The instability of non-urban references and different LST datasets introduce considerable uncertainty to the assessment of the SUHI, such as errors in quantifying the SUHI or even statistical trends of SUHI that contradict each other [24]. Although there is a diversity in criteria for defining the non-urban reference in previous studies, some controversies exist [29,60]. We attempted to quantify the errors introduced by different non-urban references and set three scenarios for non-urban references: (1) NUR_Standard refers to the standard non-urban reference scenario, excluding water bodies and areas where the eleva-

tion exceeds the median urban elevation by more than ± 50 m; (2) NUR_Water excludes areas where the elevation exceeds the median urban elevation by more than ± 50 m but includes water bodies; and (3) NUR_DEM excludes water bodies but includes non-urban references where the elevation exceeds the median urban elevation by more than ± 50 m. Results found that NUR_Water and NUR_DEM are 0.07 °C and 0.48 °C lower, respectively, than NUR_Standard (Table 5), indicating that removing extreme elevations can significantly improve the accuracy of SUHI assessments. The difference in LSTs between non-urban references of NUR_3N_D and NUR_3N_W exceeds 1.00 °C.

Table 5. LST in non-urban reference in different scenarios.

SUHI Scenarios	NUR_Standard		NUR_Water		NUR_DEM	
	NUR Scenarios	ALST	NUR Scenarios	ALST	NUR Scenarios	ALST
SUHI_1N	NUR_1N_S	26.579	NUR_1N_W	26.536	NUR_1N_D	26.349
SUHI_2N	NUR_2N_S	26.593	NUR_2N_W	26.546	NUR_2N_D	26.023
SUHI_3N	NUR_3N_S	26.263	NUR_3N_W	26.277	NUR_3N_D	25.253
SUHI_4N	NUR_4N_S	27.078	NUR_4N_W	27.061	NUR_4N_D	26.892
SUHI_5N	NUR_5N_S	27.488	NUR_5N_W	27.393	NUR_5N_D	27.185
SUHI_6N	NUR_6N_S	26.800	NUR_6N_W	26.763	NUR_6N_D	26.341
SUHI_1R	NUR_1R_S	29.009	NUR_1R_W	28.876	NUR_1R_D	28.578
SUHI_2R	NUR_2R_S	29.040	NUR_2R_W	28.903	NUR_2R_D	28.296
SUHI_3R	NUR_3R_S	28.580	NUR_3R_W	28.578	NUR_3R_D	27.684
SUHI_4R	NUR_4R_S	29.263	NUR_4R_W	29.195	NUR_4R_D	29.111
SUHI_5R	NUR_5R_S	29.552	NUR_5R_W	29.358	NUR_5R_D	29.299
SUHI_6R	NUR_6R_S	29.089	NUR_6R_W	28.982	NUR_6R_D	28.594

Note: SUHI scenarios refer to the 12 SUHI scenarios constructed in this study. NUR stands for non-urban reference. NUR_1N to NUR_6N are six different non-urban reference scenarios based on the analysis of NSW LST data. NUR_1R to NUR_6R are six different non-urban reference scenarios based on the analysis of RTE LST data. ALST is the average LST of non-urban references (unit: °C).

Previous studies pointed out that considerable differences in topography elevations existing across different cities due to the complex and diverse geomorphology make the rule of removing extreme elevations debatable [16]. Some studies used the average elevation of urban districts [29] and the median elevation [49] as the benchmarks for quantifying extreme elevations. Whether it is more reasonable to use the average or median elevation of urban districts as the benchmark for quantifying extreme elevations remains a question. Our study only excludes areas exceeding the median urban elevation by ± 50 m and does not attempt other elevation thresholds. Future research exploring the impacts of different benchmarks for extreme elevations on the SUHI assessment is needed.

This study applied six SUHI identification methods to calculate the SUHII rankings from high to low: $SUHI_3 > SUHI_1 > SUHI_2 > SUHI_6 > SUHI_4 > SUHI_5$. Using RTE LST and NSW LST data, the maximum LST difference was 0.40 °C. The maximum SUHII difference among the 12 SUHI scenarios reached 1.23 °C (Table 6), with the highest and lowest SUHI scenarios being SUHI_3N (SUHII: 0.90 °C) and SUHI_5N (SUHII: -0.33 °C), respectively. It also indicated that unstable non-urban references and different LST data sources could lead to variations in the assessment of multiple SUHI scenarios, with unstable non-urban references causing more significant differences. Additionally, different non-urban references can modify the thermal island attribute and astonishing island patterns of LCZ types [16]. For instance, when using LCZ D (low plant zone) and LCZ 9 (sparsely built zone) as non-urban references, LCZ 7 (lightweight low-rise zone), LCZ D (low plant zone), and LCZ G (water zone) transitioned from heat island properties (in SUHI_1, SUHI_2, and SUHI_3) to cool islands (in SUHI_4 and SUHI_5) (Figure 7).

Table 6. The SUHII of the 12 SUHI scenarios.

SUHI Scenarios	SUHII		SUHI Scenarios	SUHII	
	LCZ	UFZ		LCZ	UFZ
SUHI_1N	0.581	2.818	SUHI_1R	0.224	2.440
SUHI_2N	0.567	2.804	SUHI_2R	0.193	2.409
SUHI_3N	0.897	3.134	SUHI_3R	0.653	2.869
SUHI_4N	0.082	2.319	SUHI_4R	−0.030	2.186
SUHI_5N	−0.328	1.909	SUHI_5R	−0.319	1.897
SUHI_6N	0.360	2.597	SUHI_6R	0.144	2.360

This study compares the RTE and the NSW methods under various SUHI scenarios, revealing local spatial differences in LST estimation for non-urban references. These differences are crucial for accurately calculating the local SUHII, as LST retrieval results can vary across different land cover types and meteorological conditions. Such variations can significantly influence the assessment of SUHI intensity. By comparing the results from these two methods, we can identify and correct potential errors, thereby enhancing the accuracy and reliability of the research.

5.2. The Impact of Zoning Schemes of Analysis Units on SUHI Sensitivity

The rules for dividing LCZs and UFZs may lead to different zoning effects [61–63]. Understanding the division rules for LCZs and UFZs is crucial for assessing SUHI. The LCZ data in this study are divided based on remote sensing imagery data according to rules such as land use/cover and buildings [9,33]. The focus of UFZs is on the organization of urban functional layouts. The UFZs used in this study are divided according to the road network, and the analysis units may include urban green spaces and lakes or water bodies.

The classification rules of LCZs, compared to traditional methods of UFZ, possess several advantages. These advantages are reflected in the detailed differentiation of surface characteristics and building features and the sensitive capture of urban microclimate variations, especially for the precise identification of types susceptible to SUHII, such as LCZ E (bare rock or paved zone, SUHII: 4.22 °C) and LCZ 10 (heavy industry zone, SUHII: 3.87 °C), which show higher SUHII values than any UFZ type in the GBAC region. This difference reveals the profound significance of LCZ classification in understanding and addressing urban heat environmental issues, indicating that different spatial unit division rules directly affect researchers' identification and understanding of SUHII sensitive areas. Therefore, when planning and designing measures to mitigate UHI effects, it is necessary to consider the zoning effects of spatial analysis units to ensure the effectiveness of these measures.

5.3. Insights and Recommendations for Urban Planning and Management

Previous studies have shown that building height would enhance the UHI [64] because the complex urban three-dimensional surface structure significantly affects airflow patterns, hindering effective air convection and leading to more accessible heat accumulation on the urban surface. This study argues that this conclusion should consider the timing of SUHI occurrence. Buildings absorb short-wave solar radiation during the day and block long-wave radiation from the urban surface to the sky at night, leading to the UHI effect [65]. This study found that the high density of tall buildings in the morning reduces the amount of solar radiation reaching the ground during the day and limits the exchange of heat between the surface and the surrounding environment, slowing down the surface warming speed and reducing the SUHII [66].

The findings of this study provide insights and suggestions for urban planning and management using the following strategies: (1) Promote the use of high-reflectivity roofing materials, which reflect rather than absorb solar heat, further reducing the temperature of both building surfaces and interiors, thereby mitigating the UHI effect. (2) Optimize the layout of urban green spaces and water bodies. Urban planners should prioritize increasing green spaces and water bodies in areas with severe UHI effects (such as LCZ

E and LCZ 10) to mitigate SUHI effects through natural cooling mechanisms. Urban planners should comprehensively consider the varying sensitivities of SUHI in different urban functional zones and develop differentiated building layouts and natural cooling strategies. For example, commercial and industrial areas should increase the proportion of greenery and water bodies, while transportation areas should optimize road layouts and traffic flow to reduce heat accumulation. (3) Adopt diverse SUHI identification methods and promote flexibility in urban planning. Different SUHI identification methods and non-urban references affect the accuracy of SUHI assessments. It is recommended that multiple SUHI identification methods be comprehensively used in urban planning and thermal environment management, and data such as extreme altitudes and water bodies should be removed to improve the accuracy of SUHI assessments [16]. The SUHI_6 method used in this study is a comprehensive quantification method of SUHI that considers five types of non-urban references, and it is recommended for use by urban managers and planners. Additionally, urban planners need to adopt a more comprehensive and integrated perspective to analyze the nonlinear responses of natural and anthropogenic factors to SUHI and the interaction effects of these influencing factors, thereby enhancing the city's climate adaptability. Specifically, factors such as urban form, vegetation cover, climate background, and anthropogenic heat emissions not only individually impact SUHI but also exhibit complex interactions among themselves. For instance, urban form can influence air flow and heat distribution, thereby interacting with vegetation cover and anthropogenic heat emissions to affect the urban thermal environment. Similarly, vegetation cover can directly lower surface temperature through evapotranspiration and indirectly influence heat accumulation in the city by altering surface albedo and surface roughness [59,67–70]. Additionally, urban planners can employ various methods to assess the nonlinear responses and interaction effects of SUHI factors, such as Shapley additive explanations [24] and geographical detectors [71].

5.4. Limitations

This study had the following limitations: First, due to the lack of high-resolution nighttime LST data, the study only focused on daytime SUHI. Future research could include nighttime SUHI analysis to understand the sensitivity differences between LCZ and UFZ in various nighttime SUHI scenarios. Second, due to the GBAC region's location in tropical and subtropical climate zones, frequent cloudy and rainy weather, combined with the 16-day revisit cycle of the Landsat 8 satellite, made it challenging to obtain cloud-free seasonal LST data. Previous studies on urban SUHI across four seasons mainly analyzed the built-up areas of a single city [72,73] with smaller study areas. Given the GBAC region area of 20,264.80 km², acquiring cloud-free LST data was particularly challenging. On 14 November 2019, the cloud cover in the GBAC region images was less than 2%, so we chose the images from this date to reduce errors caused by cloud contamination. Third, the sensitivity of SUHIs across multiple scenarios depended on the classification accuracy of LCZ types and UFZ types. The accuracy of LST data retrieval and the classification precision of LCZ data both impacted the evaluation of SUHI. Notably, the methods we used to identify SUHI, namely SUHI_3, SUHI_4, and SUHI_5, relied on LCZ B, LCZ D, and LCZ 9 as non-urban references, respectively. If the classification accuracy of LCZ was low, the analytical results from these three methods would be of low credibility. Future research should investigate how the classification accuracy of different LCZ types and UFZ types, as well as inaccuracies in LST data retrieval impact research results.

6. Conclusions

The zoning schemes of LCZ and UFZ can reflect the spatial form, surface features, and human activities of specific urban parts, providing new insights for urban climate adaptability planning. We compared the sensitivity differences of LCZ types and UFZ types to 12 SUHI scenarios and revealed the global and local sensitivity differences of crucial influencing factors in multiple SUHI scenarios. The conclusions were as follows:

(1) Different SUHI identification methods and non-urban references influenced the sensitivity of LCZs and UFZs to multi-scenario SUHI, and the SUHI identification methods and non-urban references could alter the attributes of heat islands and cool islands in SUHI scenarios. Among the six SUHI identification methods, the SUHI_3 method, using LCZ B as the non-urban reference, calculated the highest SUHII, while the SUHI_5 method, using LCZ 9 as the non-urban reference, calculated the lowest SUHII. Removing extreme DEM in the non-urban references significantly improved the accuracy of SUHI assessments.

(2) Building clusters reduced the SUHI sensitivity of five types of built environment LCZs in the morning through their shading effect: LCZ 1, LCZ 2, LCZ 3, LCZ 4, and LCZ 5. The zoning schemes of traffic analysis zones often included urban green spaces and water bodies, which helped reduce the SUHI sensitivity of urban functional areas such as commercial, industrial, transportation, and healthcare zones.

(3) The nonlinear effects of SUHI influencing factors and factors' interaction effects were essential reasons for the differences in sensitivity of the global importance of SUHI influencing factors. In multiple SUHI scenarios, the differences in local SUHII and the consistency of the internal environment and landscape within zoning units (LCZs and UFZs) were crucial factors leading to differences in sensitivity of the local importance of SUHI influencing factors.

Our study can provide urban planners and decision makers with scientific data to support the enhancement of the city's adaptability and resilience to future climate change and improving the welfare of residents.

Author Contributions: H.D.: conceptualization, methodology, software, investigation, formal analysis, writing—original draft; S.Z.: conceptualization, writing—review and editing; M.C.: conceptualization, writing—review and editing; J.F.: conceptualization, data curation, funding acquisition, writing—review and editing; K.L.: conceptualization, project administration, data curation, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request. Some or all of the data, models, or code generated or used during this study are available from the corresponding author by request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

LST—land surface temperature; UHI—urban heat island; SUHI—surface urban heat island; SUHII—surface urban heat island intensity; LCZ—local climate zone; UFZ—urban function zone; GBA—Guangdong–Hong Kong–Macao Greater Bay Area; GBAC—Guangdong–Hong Kong–Macao Greater Bay Area central; COM—the density of company; PUB—the density of public organizations; LIE—the density of life and entertainment; BUV—the average building volume; BUH—the average building height; BUD—the average building density; POP—population density; POC—intensity of population activity; IMP—impervious land ratio; WAT—water area ratio; VEG—vegetation area ratio; ROD—road density; ROI—road intersection density; DIC—distance from coastline; DEM—elevation; NSW—nonlinear split-window; RTE—radiative transfer equation; SGBT—spatial gradient boosting trees; LCZ 1—compact high-rise zone; LCZ 2—compact midrise zone; LCZ 3—compact low-rise zone; LCZ 4—open high-rise zone; LCZ 5—open midrise zone; LCZ 6—open low-rise zone; LCZ 7—lightweight low-rise zone; LCZ 8—large low-rise zone; LCZ 9—sparsely built zone; LCZ 10—

heavy industry zone; LCZ A—dense tree zone; LCZ B—scattered tree zone; LCZ C—bush or scrub zone; LCZ D—low plant zone; LCZ E—bare rock or paved zone; LCZ F—bare soil or sand zone; LCZ G—water zone.

Appendix A



Figure A1. Examples of representative LCZs from Guangdong–Hong Kong–Macao Greater Bay Area Central (GBAC) region. This classification system is segmented into built types (LCZ 1 to LCZ 10) and natural types (LCZ A to LCZ G).

Table A1. Details of LCZ classification in the GBAC region.

Type	Count	TArea	Type	Count	TArea
LCZ 1	620	182.181	LCZ A	3224	4649.731
LCZ 2	2022	566.731	LCZ B	3289	948.687
LCZ 3	2863	1075.486	LCZ C	1336	242.570
LCZ 4	3313	1051.295	LCZ D	5394	3421.576
LCZ 5	1419	363.671	LCZ E	354	150.147
LCZ 6	1742	458.427	LCZ F	1831	713.175
LCZ 7	637	444.014	LCZ G	2637	1723.696
LCZ 8	2855	3044.345			
LCZ 9	4375	1082.230			
LCZ 10	400	87.114			

Note: TArea represents the total area (unit: km²).

Table A2. Details of UFZ classification in the GBAC region.

Level 1	Level 2	Descriptions	Count
01 Residential	0101 Residential	Houses and apartment buildings-places where people live.	8612
02 Commercial	0201 Business	Buildings where people work, including office buildings, and commercial office places for finance, internet technology, e-commerce, media, etc.	1364
	0202 Commercial service	Houses and buildings for commercial retails, restaurants, lodging, and entertainment.	2200
03 Industrial	0301 Industrial	Land and buildings used for manufacturing, warehouse, mining, etc.	8311
04 Transportation	0402 Transportation stations	Transportation facilities including motor, bus, and train stations and ancillary facilities.	303
	0403 Airport facilities	Airports for civil, military, and mixed uses.	113
05 Public management and service	0501 Administrative	Lands used for government, military, and public service agencies.	917
	0502 Educational	Lands used for education and research, including schools, universities, institutes, and their ancillary facilities.	1826
	0503 Medical	Lands used for hospitals, disease prevention, and emergency services.	808
	0504 Sport and cultural	Lands used for public sports, training, and cultural services, including gym center, libraries, museums, exhibition centers, etc.	844
06 Mixed-Use	0505 Park and greenspace	Parks and greenspace lands used for entertainment and environmental conservations.	3396
	0601 Mixed-use	Integration of diverse functionalities, such as the combination of residential and commercial, commercial and office, etc.	1724

Table A3. Variance inflation factor values of SUHI influencing factors in LCZ.

Factors	SUHI_1N	SUHI_2N	SUHI_3N	SUHI_4N	SUHI_5N	SUHI_6N	SUHI_1R	SUHI_2R	SUHI_3R	SUHI_4R	SUHI_5R	SUHI_6R
Intercept	26.842	26.812	27.598	25.928	25.433	26.395	25.773	25.732	26.495	25.471	25.241	25.668
COM	1.522	1.522	1.522	1.522	1.522	1.522	1.522	1.522	1.522	1.522	1.522	1.522
PUB	2.816	2.816	2.816	2.816	2.816	2.816	2.822	2.822	2.822	2.822	2.822	2.822
LIE	2.477	2.477	2.477	2.477	2.477	2.477	2.477	2.477	2.477	2.477	2.477	2.477
BUV	1.150	1.150	1.150	1.150	1.150	1.150	1.151	1.151	1.151	1.151	1.151	1.151
BUH	1.826	1.826	1.826	1.826	1.826	1.826	1.820	1.820	1.820	1.820	1.820	1.820
BUD	2.223	2.223	2.223	2.223	2.223	2.223	2.218	2.218	2.218	2.218	2.218	2.218
POP	1.649	1.649	1.649	1.649	1.649	1.649	1.649	1.649	1.649	1.649	1.649	1.649
POC	1.823	1.823	1.823	1.823	1.823	1.823	1.825	1.825	1.825	1.825	1.825	1.825
IMP	3.915	3.915	3.915	3.915	3.915	3.915	3.904	3.904	3.904	3.904	3.904	3.904
WAT	1.494	1.494	1.494	1.494	1.494	1.494	1.594	1.594	1.594	1.594	1.594	1.594
VEG	2.981	2.981	2.981	2.981	2.981	2.981	2.941	2.941	2.941	2.941	2.941	2.941
ROD	2.788	2.788	2.788	2.788	2.788	2.788	2.794	2.794	2.794	2.794	2.794	2.794
ROI	1.470	1.470	1.470	1.470	1.470	1.470	1.465	1.465	1.465	1.465	1.465	1.465
DIC	1.189	1.189	1.189	1.189	1.189	1.189	1.181	1.181	1.181	1.181	1.181	1.181
DEM	1.612	1.612	1.612	1.612	1.612	1.612	1.535	1.535	1.535	1.535	1.535	1.535

Table A4. Variance inflation factor values of SUHI influencing factors in UFZ.

Factors	SUHI_1N	SUHI_2N	SUHI_3N	SUHI_4N	SUHI_5N	SUHI_6N	SUHI_1R	SUHI_2R	SUHI_3R	SUHI_4R	SUHI_5R	SUHI_6R
Intercept	107.343	107.275	108.935	105.061	103.397	106.297	106.131	105.987	108.227	104.991	103.787	105.763
COM	1.509	1.509	1.509	1.509	1.509	1.509	1.510	1.510	1.510	1.510	1.510	1.510
PUB	2.088	2.088	2.088	2.088	2.088	2.088	2.089	2.089	2.089	2.089	2.089	2.089
LIE	1.751	1.751	1.751	1.751	1.751	1.751	1.751	1.751	1.751	1.751	1.751	1.751
BUV	1.153	1.153	1.153	1.153	1.153	1.153	1.158	1.158	1.158	1.158	1.158	1.158
BUH	1.826	1.826	1.826	1.826	1.826	1.826	1.846	1.846	1.846	1.846	1.846	1.846
BUD	1.679	1.679	1.679	1.679	1.679	1.679	1.679	1.679	1.679	1.679	1.679	1.679
POP	1.323	1.323	1.323	1.323	1.323	1.323	1.323	1.323	1.323	1.323	1.323	1.323
POC	1.406	1.406	1.406	1.406	1.406	1.406	1.406	1.406	1.406	1.406	1.406	1.406
IMP	8.391	8.391	8.391	8.391	8.391	8.391	8.380	8.380	8.380	8.380	8.380	8.380
WAT	1.093	1.093	1.093	1.093	1.093	1.093	1.099	1.099	1.099	1.099	1.099	1.099
VEG	8.654	8.654	8.654	8.654	8.654	8.654	8.674	8.674	8.674	8.674	8.674	8.674
ROD	2.228	2.228	2.228	2.228	2.228	2.228	2.222	2.222	2.222	2.222	2.222	2.222
ROI	1.165	1.165	1.165	1.165	1.165	1.165	1.163	1.163	1.163	1.163	1.163	1.163
DIC	1.207	1.207	1.207	1.207	1.207	1.207	1.209	1.209	1.209	1.209	1.209	1.209
DEM	1.162	1.162	1.162	1.162	1.162	1.162	1.130	1.130	1.130	1.130	1.130	1.130

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