

Article

Urban Heat Island Effect in Different Sizes from a 3D Perspective: A Case Study in the Beijing–Tianjin–Hebei Region

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Abstract: In the Beijing–Tianjin–Hebei urban agglomeration—one of China’s three largest city clusters, the GDP reached CNY 950 billion with a population of approximately 110 million in 2021. While megacity expansion has slowed, rapid growth in small and medium-sized cities is expected to increase their vulnerability to urban heat island (UHI) effects. This necessitates urgent, size-differentiated studies of the UHI to inform sustainable urban planning. This study examines the Beijing–Tianjin–Hebei urban agglomeration using Landsat 8 data to explore the UHI between different-sized cities and analyze the driving mechanisms of UHI intensity attributed to urban buildings. The results indicate the following: (1) Beijing displays the smallest temperature change (1.39 °C) and lower heating effect intensity (484.44 km² °C) compared to Shijiazhuang (919.11 km² °C); (2) a logarithmic relationship ($R^2 = 0.4261$) exists between the building volume and heating effect intensity, and the specificity of megacities significantly influences the regional analysis results of the heat island effect; and (3) the total energy consumption power of the heating effect in 10 cities within the Beijing–Tianjin–Hebei region is 326.23×10^{12} KJ/h, which is equivalent to 11.14×10^9 kg/h of standard coal.

Keywords: urban heat island; Beijing–Tianjin–Hebei; heat island intensity; remote sensing; urban agglomeration



Academic Editor: Rui Alexandre Castanho

Received: 26 January 2025

Revised: 18 February 2025

Accepted: 20 February 2025

Published: 23 February 2025

Citation: Li, B.; Zhang, Y.; Zhao, S.; Zhao, L.; Wang, M.; Pei, H. Urban Heat Island Effect in Different Sizes from a 3D Perspective: A Case Study in the Beijing–Tianjin–Hebei Region. *Land* **2025**, *14*, 463. <https://doi.org/10.3390/land14030463>

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1. Introduction

The urban heat island (UHI), an urban microclimate phenomenon caused by urbanization where temperatures are higher in urban areas compared to surrounding rural environments, restricts the sustainable development of cities and has become a significant ecological and environment issue worldwide [1]. Due to urban expansion, where vegetation is replaced by impervious surfaces, the extreme urban thermal environment is exacerbated [2]. Extreme high temperatures, increasingly reported in cities globally, raise morbidity and mortality from heat-related diseases among urban residents and drive up urban energy demands and costs upward worldwide [3,4]. Urban agglomerations, as the main feature of China’s current urban development, are the regions with the most intense human activities and the hotspots for climate change research [5]. As urban areas expand, urban populations grow, and extreme heat events increase, it is critical to clarify the drivers of the UHI effect and improve the resilience of urban agglomerations to future climate conditions [6].

As an important characteristic of the UHI, land surface temperature (LST) has been reported by previous studies to be affected by climate type and change [7], geographical location [8], and land-use change and spatial patterns [9,10]. Numerous studies have shown that 2D urban metrics significantly correlate with the urban heat island effect by influencing land surface temperature. Areas with high-density impervious surfaces intensify the urban heat island effect [11], whereas the configuration and planning of blue-green landscapes, such as urban green spaces and water bodies, can considerably mitigate it [12–14]. Furthermore, with continuous advancements in remote sensing technology, 2D urban landscape metrics, such as the landscape patch index in street patterns, have also been found to affect the urban heat island effect [15]. Combining the heating and cooling effects of landscapes can help better understand the urban heat island effect and develop more effective mitigation strategies.

Additionally, both 3D urban landscape patterns and 2D land-use organizations modulate the urban thermal environment by affecting the absorption and reflection of thermal radiation [16,17]. Increasing studies have quantified the relationship between the UHI and urban 3D elements [18]. Using LiDAR remote sensing technology, researchers have investigated the vertical characteristics of urban landscapes by creating 3D metrics such as the height and volume of the buildings [19]. The 3D urban metrics have a greater impact on LST than 2D urban landscape indicators, with building height emerging as the most critical metric at the block scale [20]. The urban 3D metric essentially builds upon the city's 2D pattern by incorporating height information. However, its representation is not confined solely to height but also encompasses additional features derived from it. Factors such as the sky view coefficient (SFC), block height-to-width ratio (H/W), outdoor space ratio (OSR), and floor area ratio (FAR) have all been shown to exert a significant influence on the urban heat island effect [21,22]. It should be noted that existing research has produced inconsistent findings regarding the relative importance of 2D urban patterns versus 3D morphological characteristics in influencing thermal environments. For instance, some studies demonstrate that certain 2D parameters, such as vegetation coverage and the impervious surface ratio, exhibit stronger correlations with temperature variations compared to numerous 3D urban form metrics [23]. Given that different researchers have selected various study areas and methodologies, and considering the high heterogeneity of urban environments, the results can vary. Consequently, it remains challenging to determine which three-dimensional morphological indicator most significantly impacts air temperature in a specific urban climate. The relative contributions of 3D urban morphology characteristics to LST need to be fully explored.

Previous studies have shown that the UHI phenomenon is highly influenced by building form, roads, streets, and canopies at grid scales and block scales [24]. Additionally, there is a linear relationship between the UHI and urban area, with larger urban areas corresponding to smaller heat island intensities in some situations [25]. As major urban landscape elements, buildings affect the thermal storage of the city, absorbing solar radiation and releasing more heat than the natural landscape [26]. From a 3D perspective, the building volume can be the most dominant feature of the city and the main contributor to the “heating effect”. Additionally, the average building height can serve as an indicator of the vertical extent of the heat island effect. This raises several important questions that this study seeks to answer: (1) How do buildings contribute to the “heating” of cities? (2) How do these effects vary with the size of the city? (3) How much energy corresponds to the temperature change induced by the heating effect?

Based on satellite remote sensing data, this paper reveals the evolving dynamics of the heat island effect in built-up areas. This study adopts an approach that first determines the influence range of the heat island and then calculates its intensity. By focusing on buildings

within the built-up area, this study integrates the heat island impact range and intensity, clarifies the driving influence of buildings on heat island intensity, calculates the energy corresponding to temperature shifts, and explores the differences in heat island effects among cities of varying scales. The findings of this study are scientifically significant for assessing regional climate change and developing strategies to mitigate the heat island effect.

2. Materials and Methods

2.1. Study Area

This study was conducted in Beijing–Tianjin–Hebei (BTH) urban agglomeration, located in the northeastern part of the North China Plain between $36^{\circ}05' \sim 42^{\circ}37' \text{ N}$ and $113^{\circ}27' \sim 119^{\circ}50' \text{ E}$ (Figure 1). Covering a total area of $2.16 \times 10^5 \text{ km}^2$, BTH is one of the three largest city clusters in China. In 2021, BTH's GDP exceeded CNY 950 million, with a resident population of about 110 million people, making it one of the fastest-growing and most economically advanced regions in China [27]. The region features a variety of landforms, with highland mountainous landscapes dominating in the northwest and plain landscapes in the southeast, and a temperate, semi-humid, semi-arid continental climate. With the implementation of the Beijing–Tianjin–Hebei coordinated development strategy, urbanization in the region has increased, exacerbating ecological and environmental problems such as the urban heat island effect. The ecological and environmental situation in the region is becoming increasingly severe, posing significant challenges to the sustainable development of BTH [28].

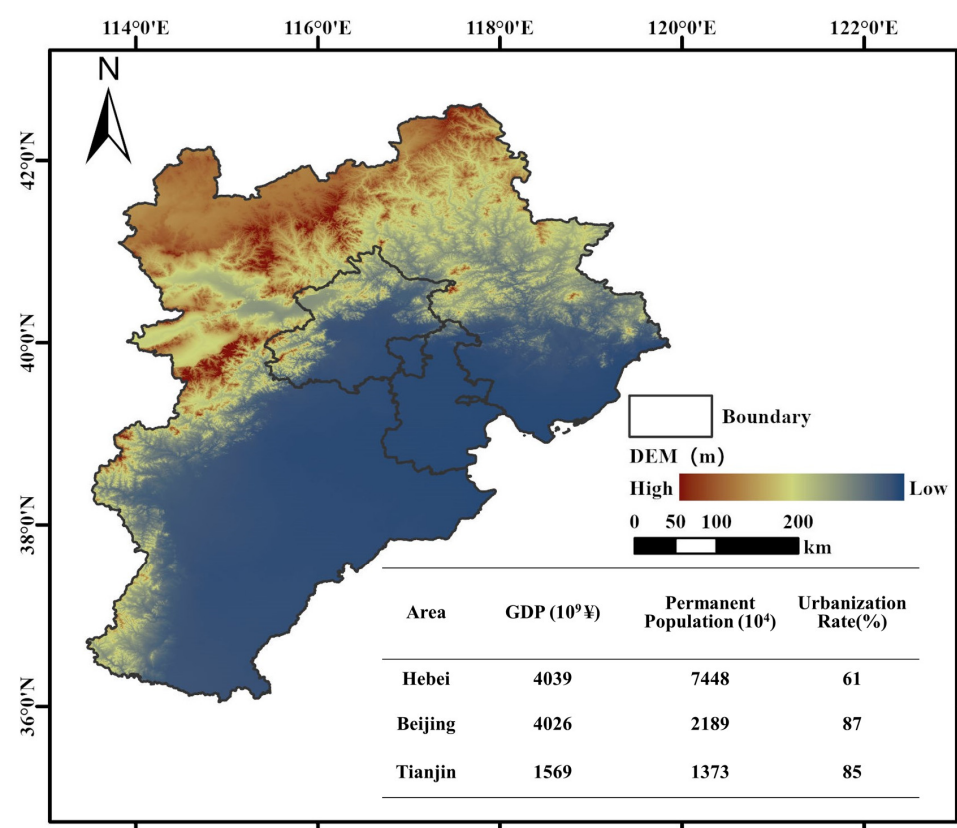


Figure 1. Overview of the Beijing–Tianjin–Hebei urban agglomeration. Note: DEM represents elevation values in terms of altitude.

2.2. Data Collection and Pre-Processing

Three datasets were used in this study (Table 1). The LST data source is Landsat 8 OLI/TIRS satellite imagery, which has a spatial resolution of 30 m. These data are freely

available through the EarthExplorer data sharing platform of the U. S. Geological Survey (<https://earthexplorer.usgs.gov/>, accessed on 15 August 2024). In order to ensure data quality and desirability, images were selected based on the criteria that all images in the study area have less than 5% whole scene cloud coverage and similar imaging time. The raw data acquired by thermal infrared sensors contain a series of systematic errors. To obtain the radiative signal at the sensor's aperture, radiometric correction is required. In this study, radiometric correction was performed on the selected Landsat 8 images using the radiometric calibration module in ENVI v5.3. Additionally, due to atmospheric absorption and scattering effects, the total radiance received by the remote sensing sensor from ground targets may contain certain inaccuracies. To eliminate these errors and obtain the true surface reflectance, the FLAASH module in ENVI v5.3 was employed to conduct atmospheric correction on the Landsat 8 data.

Table 1. Information of datasets that used in this study.

Data	Spatial Resolution	Final Data	Data Sources	Data Date (Year. Month)
Landsat 8	30 m	LST Data	https://earthexplorer.usgs.gov/ (accessed on 15 August 2024)	2020.April/May
A dataset of built-up areas of Chinese cities in 2020 *	Shape file	Built-up Area Data	https://www.scidb.cn/ (accessed on 30 August 2024)	2020
CNBH-10m	10 m	Building Height Data	https://zenodo.org/ (accessed on 10 September 2024)	2020

* "A dataset of built-up areas of Chinese cities in 2020" dataset does not contain resolution information.

The built-up area boundary data used in this study were sourced from a dataset of built-up areas of Chinese cities in 2020, available on the Science Data Bank data sharing platform [29]. This dataset is based on Sentinel data and provides standardized information on built-up areas for 433 cities in China. Due to the presence of numerous fine patches in the data, the main built-up areas were extracted using ArcGIS v10.7 to address the research needs of this study.

The building height data used in this study were sourced from the CNBH-10m dataset available on the Zenodo data sharing platform, with a spatial resolution of 10 m [30]. This dataset estimates the height of buildings in China in 2020 using Random Forest modeling.

2.3. LST Retrieval

Since the 1970s, researchers have utilized satellite remote sensing data to conduct research on LST inversion. This inversion technology has continuously developed and progressed, providing a time-efficient and low-cost method for obtaining large-scale and high-quality LST data [31,32]. Here, the atmospheric correction method was used to retrieve LST by the band math module in ENVI v5.3 [33], as shown in Equation (1).

$$L_b = [L_a - L_{\uparrow} - t \cdot (1 - \varepsilon) \cdot L_{\downarrow}] / (t \cdot \varepsilon) \quad (1)$$

where L_b is the surface radiance ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$); L_a is the cloud-top radiance ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$), obtained by radiatively calibrating the Landsat-8 TIRS band 10; $L_{\uparrow}$ is the atmospheric upward radiant brightness, $L_{\downarrow}$ is the atmospheric downward radiant brightness in ($\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$), t is the atmospheric transmissivity, and both of them can be obtained from the atmospheric correction parameter calculator provided by NASA (<https://atmcorr.gsfc.nasa.gov/>, accessed on 10 December 2024); and ε is the surface-specific emissivity.

Surface radiant intensity can be converted to radiant brightness temperature using the conversion equation [34], as shown in Equation (2).

$$T_s = K_2 / \ln(K_1 / L_b + 1) - 273 \quad (2)$$

where $K_1 = 774.89 \text{ (W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1})$, $K_2 = 1321.08 \text{ K}$ for band 10 of Landsat 8, and T_s is the surface inversion temperature ($^{\circ}\text{C}$).

The normalized difference vegetation index (NDVI) and fractional vegetation cover (FVC) were used as conversion parameters for surface emissivity, as shown in Equations (3) and (4).

$$NDVI = (NIR - R) / (NIR + R) \quad (3)$$

$$FVC = [(NDVI - NDVI_s) / (NDVI_v - NDVI_s)]^2 \quad (4)$$

where NIR and R are the reflectance in the near-infrared and red light bands of Landsat 8; $NDVI_v$ and $NDVI_s$ are the NDVI values of vegetation and bare soil, respectively, both of which can be obtained by the empirical values ($NDVI_v = 0.7$, $NDVI_s = 0.05$) [35]. Surface-specific emissivity is calculated using the surface-specific emissivity estimation method [36], as shown in Equation (5).

$$\varepsilon = \begin{cases} 0.995, & NDVI \leq 0 \\ 0.9589 + 0.86 \cdot FVC - 0.0671 \cdot FVC^2, & 0 < NDVI < 0.7 \\ 0.9625 + 0.0614 \cdot FVC - 0.0461 \cdot FVC^2, & 0.7 \leq NDVI \end{cases} \quad (5)$$

2.4. UHI Effect Scope Measurement

The UHI effect is generally defined as the temperature difference between urban areas and rural areas [37,38]. Park studied the cooling effect of rivers by first establishing the LST–distance relationship and determining the UHI intensity based on the derived cooling distance of the river [39]. This method of determining the range of influence and then calculating the temperature change based on the range of influence to find the UHI intensity seems to be more reasonable.

Considering the 30 m resolution of Landsat images and the large size of built-up urban areas, different buffer widths were tested to analyze the temperature–distance relationship. Buffer widths that are either too large or too small may lead to poorer descriptions of the temperature–distance relationship. Finally, 800 m wide multi-ring buffer zones were established around the built-up areas. Due to the inability to achieve complete consistency in the selection of image times and the inevitable differences in geographic and climatic conditions between different cities, a simple comparison to analyze the UHI effect in each city does not have sufficient credibility. Here, setting the distance between the buffer zone and the boundary of the built-up area as the independent variable r , and the average LST of each buffer zone in the built-up area as the independent variable T , established the T - r relationship to analyze the heating effect of the built-up area. Linear regression fitting of the T - r relationship for each built-up area was performed using Origin v2020. Curve fitting analysis showed that the fifth-degree polynomial best described the relationship (average $R^2 = 0.9676$), and the fifth-degree polynomial function $T(r)$ was established, as shown in Equation (6).

$$T(r) = ar^5 + br^4 + cr^3 + dr^2 + er + d \quad (6)$$

As shown in Figure 2, as the distance r increases, T in the buffer zone decreases, but the decreasing rate gradually approaches 0. The initial turning point occurs when the first-order derivative of $T(r)$ is 0. Comparing this with the definition of the turning point of the maximum cold zone distance in the study of the greenfield cooling effect conducted by

Yu [40], the initial turning point here indicates that the heating effect of the built-up area decreases for the first time as the distance between the buffer zone and the built-up area increases. Beyond the distance, the built-up area will no longer have a significant heating effect. The distance from the boundary of the built-up area to the initial turning point is defined as L , representing the range of significant UHI effects in the built-up area.

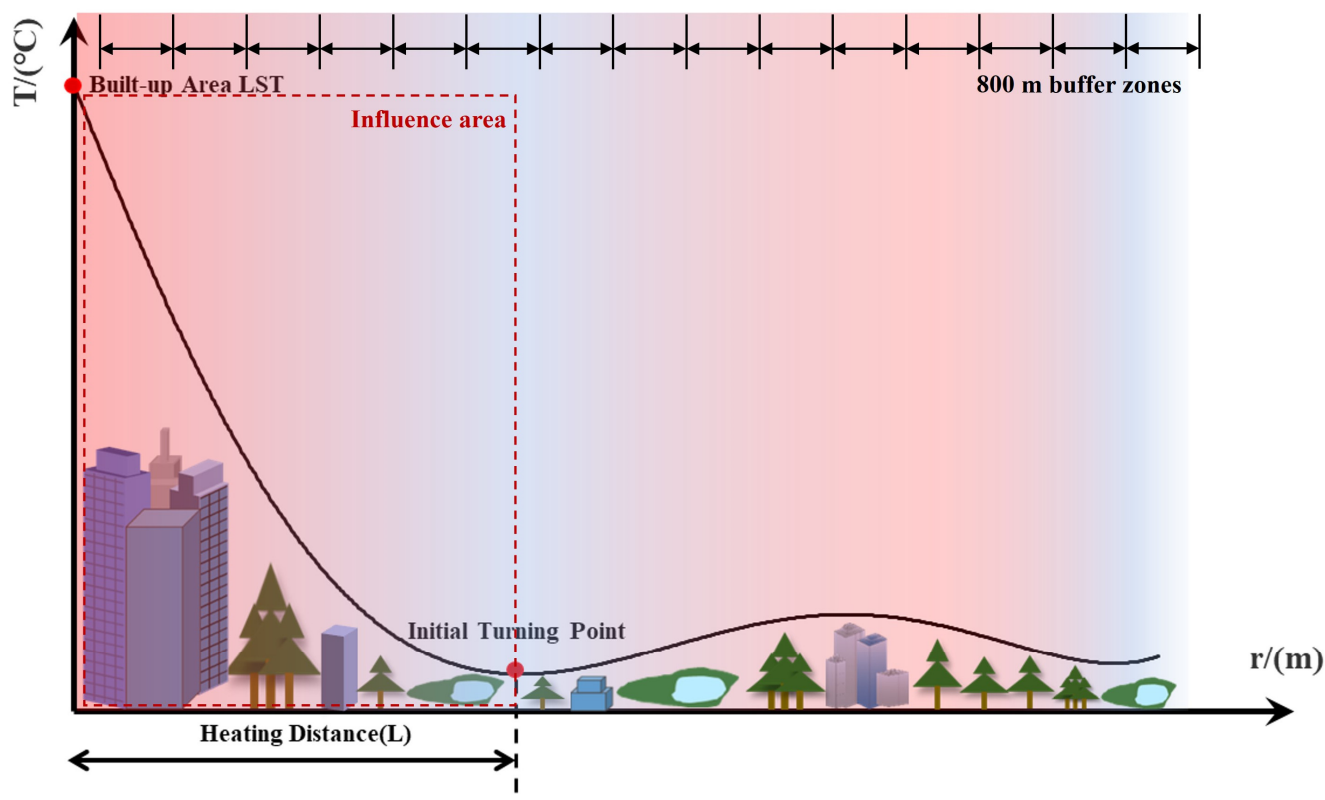


Figure 2. Illustration of land surface temperature change curve of urban built-up areas cooling process.

2.5. Heating Effect Intensity Measurement

Previous studies rarely describe the influence range of the heat island, and UHI intensity is often expressed simply by temperature change (ΔT) [7,41]. To more accurately describe the intensity of the UHI, the scope and intensity of the UHI were integrated, and the Heating Effect Intensity index (HEI) was defined. The HEI is obtained by multiplying the buffer area in the influence area with ΔT in the buffer, as shown in Equation (7).

$$HEI = \sum_{i=1}^n S_i \cdot \Delta T_i \quad (7)$$

where n is the number of buffers in the influence range, S_i is the area of the i th buffer (km^2), and ΔT_i is the average LST change in the i th buffer ($^{\circ}\text{C}$).

In order to more accurately assess the influence of buildings in the built area on the HEI, the volume of buildings in the built area (V_{Building}) is considered in this study. Based on the high-precision data of CNBH-10m, the building volume can be expressed as the pixel building height multiplied by the pixel area size, as shown in Equation (8).

$$V_{\text{Building}} = \sum H_i \cdot S_i \quad (8)$$

where H_i is the height of i th pixel building (m), and S_i is the area of i pixel (km^2). Since the resolution of CNBH-10m is 10 m, $S_i = 100 \text{ m}^2$ is a fixed value.

2.6. Energy Measurement Corresponding to Temperature Shifts

Previous investigations typically established correlations between UHI intensity and energy demand indicators (e.g., electricity consumption) to indirectly estimate UHI-induced energy impacts [42]. As noted, the UHI definition in this study integrates both impact extent and intensity, rather than relying on the conventional urban–suburban temperature difference. Based on this, we propose a hypothesis: if the vertical extent of UHI influence can be determined under our defined framework, it would be possible to estimate the energy associated with air temperature variations within the affected volume. The most critical aspect of this hypothesis is defining the vertical range of UHI influence. Shen et al. found that, during summer daytime, China’s surface UHI effect is approximately ten times stronger than the canopy UHI effect at a height of 2 m [43]. Additionally, Li et al. demonstrated that the near-surface air temperature lapse rate in China follows an overall linear trend below 100 m [44]. Building upon these findings, we attempted to quantify the UHI_{3D} (Figure 3), as shown in Equation (9).

$$UHI_{3D} = [(HEI + \alpha HEI) \cdot H] / 2 \quad (9)$$

where α is the canopy heat island effect multiplicity coefficient, $\alpha = 0.1$ is a fixed value according to Shen et al. [43], and H is the mean building height of each city (m).

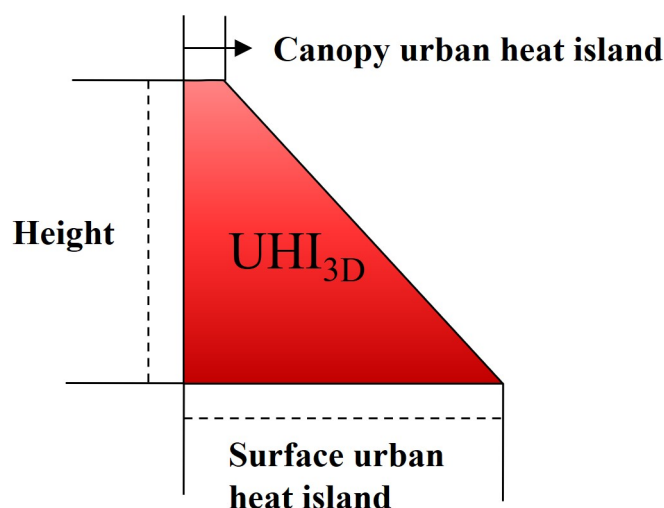


Figure 3. UHI_{3D} schematic.

Following the derivation of UHI_{3D} , the energy requirement for air temperature modification induced by UHI_{3D} effects can be quantified through thermodynamic calculations incorporating two critical atmospheric parameters: specific heat capacity (C_v) and air density (ρ_a). Building upon this foundation, we operationalize the thermal power metric (Power) to characterize UHI-induced energy consumption. The Power parameter quantifies the instantaneous energy flux required to maintain temperature elevation (ΔT) within the affected air volume per unit time, as shown in Equation (10).

The HEI measures the intensity of the heat gain effect in the horizontal plane, while the vertical extent of the heat gain effect is determined by the average height of the buildings in the built-up area. Building on this, this study establishes a three-dimensional heat gain effect energy field and defines the heat gain effect energy consumption power, denoted as Power. The physical meaning of Power is the amount of standard coal required to convert

the energy needed per unit hour of temperature change across the spatial extent of the heating effect, as shown in Equation (10).

$$Power = (UHI_{3D} \cdot C_v \cdot \rho_a \cdot \beta) / 3600 \cdot h \quad (10)$$

where C_v is the specific heat of air at constant volume ($\text{kJ}/(\text{kg} \cdot \text{K})$); ρ_a is air density (kg/m^3); air properties under static conditions at sea level on standard days according to NASA regulations ($C_v = 1.005 \text{ kJ}/(\text{kg} \cdot \text{K})$, $\rho_a = 1.229 \text{ kg}/\text{m}^3$); β is the standard coal conversion factor, $\beta = 1.229 \text{ kgce}/(\text{kW} \cdot \text{h})$ according to the General Rules for Calculating Comprehensive Energy Consumption (GB/T 2589-2020; General rules for calculation of the comprehensive energy consumption. China National Standardization Administration: Beijing, China, 2020.) issued by China in 2020; and h for unit hours.

3. Results

3.1. UHI Effect and HEI of Built-Up Area

A total of 18 urban areas were selected in the BTH urban agglomeration, of which 10 urban areas exhibited a significant heat island effect (Figure 4). As shown in Figure 4, the average LST of the built-up area of Beijing (BJ), which has the largest built-up area (2692.06 km^2 with 32.95°C), is 5.04°C lower than the average LST of the built-up area of Botou (BT), which has the smallest built-up area (45.14 km^2 with 37.99°C). As mentioned above, there are significant differences between cities due to variations in geographic location, climatic conditions, and construction, making a direct comparative analysis of the heat island effect across cities less credible.

In this study, the LST in each city's built-up area and its buffer zone was analyzed, the significant heating effect distance was determined according to the temperature–distance function $T(r)$, and the LST change ΔT (ΔT is the average LST of the built-up area minus the average LST of the buffer zone at the significant impact distance) was calculated. The HEI (Table 2) can be obtained by Equation (6). Tianjin (TJ) is a coastal city adjacent to the Bohai Sea, with an administrative coastline of 153.67 km , which results in a large area of water in its buffer zone, leading to the largest HEI in TJ ($2450.11 \text{ km}^2 \cdot ^\circ\text{C}$) and much higher than the next highest HEI in Shijiazhuang (SJZ) ($919.11 \text{ km}^2 \cdot ^\circ\text{C}$).

Table 2. UHI effect in urban built-up areas.

City	Heating Distance (m)	Impact Area (km^2)	ΔT ($^\circ\text{C}$)	HEI ($\text{km}^2 \cdot ^\circ\text{C}$)
TJ	2400	2861.28	3.62	2450.11
SJZ	3200	1181.44	3.70	919.11
BJ	13,600	8499.91	1.39	484.44
XT	6400	792.19	3.72	398.79
HD	1600	435.20	1.66	371.53
BD	2400	618.25	1.63	322.57
HS	5600	642.73	3.64	291.37
BT	2400	195.59	2.99	213.54
DZ	3200	165.85	1.97	80.45
ZZ	2400	213.63	1.14	52.35

Additionally, BJ, with the largest built-up area (2692.06 km^2) and the largest influence area (8499.91 km^2), has the smallest ΔT (1.39°C). The HEI of BJ ($484.44 \text{ km}^2 \cdot ^\circ\text{C}$) is much smaller than that of Shijiazhuang (SJZ) ($919.11 \text{ km}^2 \cdot ^\circ\text{C}$) and is closer to that of Xingtai (XT) ($398.79 \text{ km}^2 \cdot ^\circ\text{C}$), which has less than one-tenth of the built-up area of BJ. Megacities exhibit idiosyncrasies: larger cities do not necessarily have stronger heat island intensity, a point that will be elaborated on in the Discussion Section.

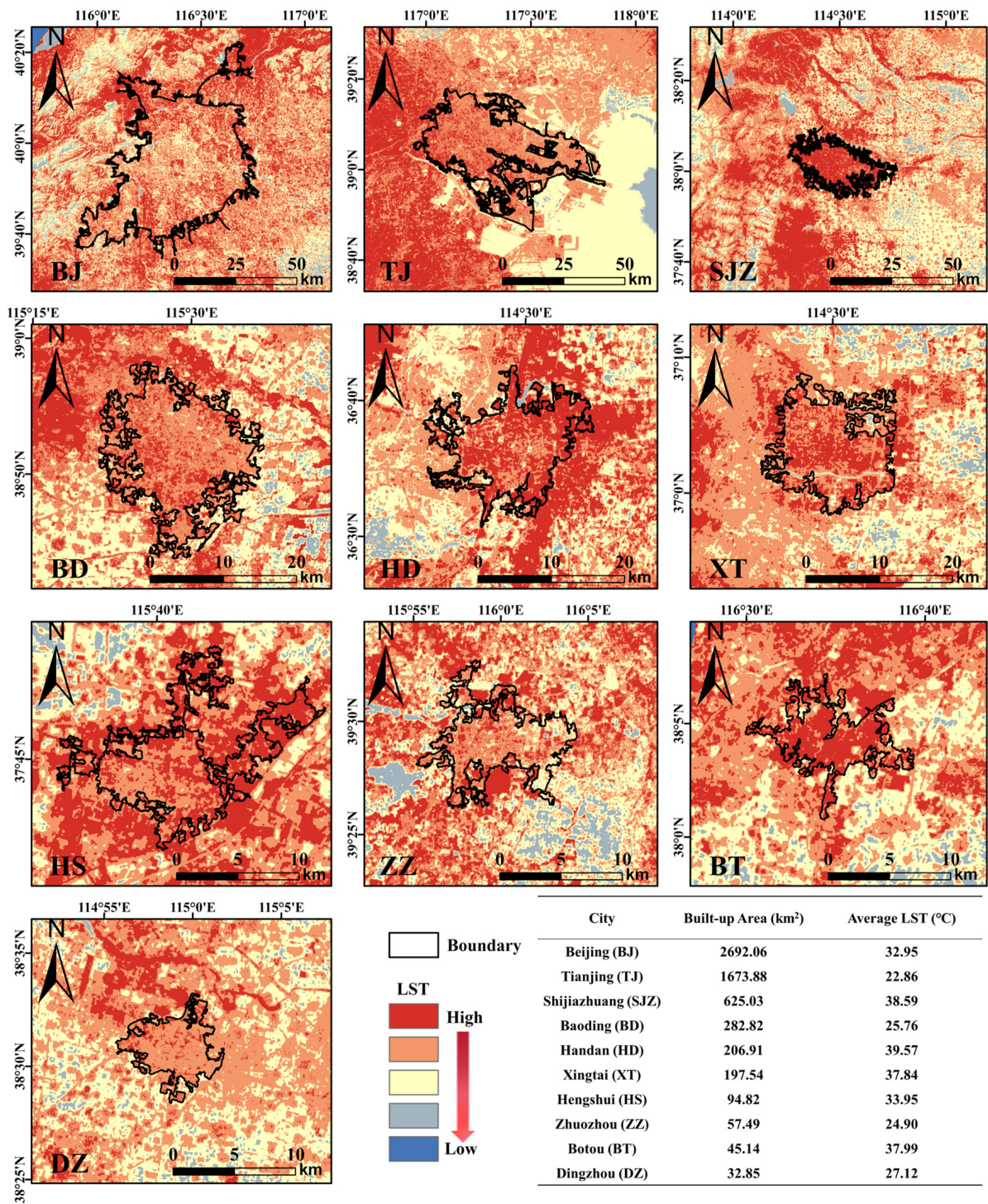


Figure 4. LST in cities with significant heat island effects. Note: The LST for each area is classified into five levels using the Arcmap natural discontinuity method. Due to differences in image timing across the areas, the data representation of the LST in the legend is arranged from high to low across the five levels.

3.2. Relationship Between Building Area and Significant Heating Range

The building areas of 10 cities (Figure 5) were obtained using the CNBH-10m data. The largest building area is BJ (1189. 66 km²), followed by TJ (652.91 km²). The smallest building area is Dingzhou (DZ) (19. 98 km²). Firstly, the HEI-building area driving law was determined from a 2D perspective to verify the feasibility of the driving law between building volume and HEI from a 3D perspective. In this study, the relationship between

the heat island impact area and building area was established (Figure 6), and the curve fitting results showed that the building area has a significant linear relationship with the heat island impact area ($R^2 = 0.9460$). The heat island impact area grows linearly with the expansion of the building area.

As mentioned earlier, megacities possess distinct characteristics, and the oversized built-up areas of BJ and TJ may potentially affect the results of the linear relationship. Meanwhile, when discussing the UHI within a specific region, the uneven distribution of data points caused by the significant differences between cities is unavoidable.

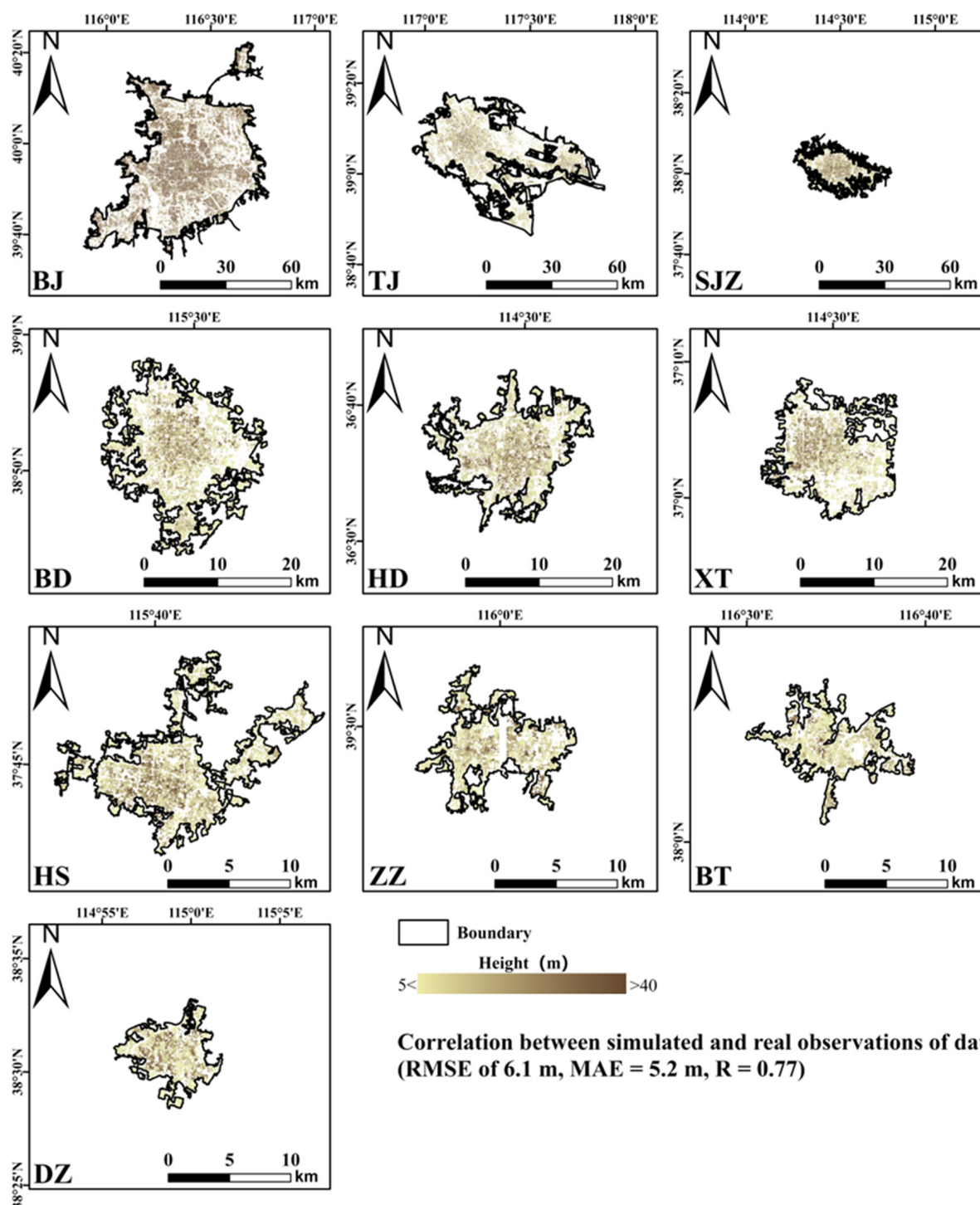


Figure 5. Building height profile in built-up areas.

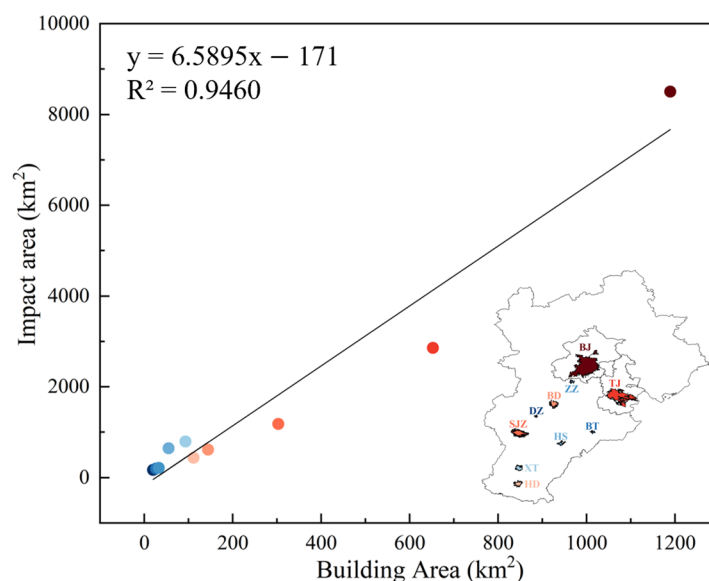


Figure 6. Relationship between building area and heat island impact area.

3.3. Power Corresponding to Temperature Shift by Heating Effects

The total energy consumption power of heat gain effect in the built-up area of Beijing–Tianjin–Hebei region is 11.14×10^9 kg/h (Figure 7), of which TJ is the highest at 5.52×10^9 kg/h, followed by SJZ (1.46×10^9 kg/h) and BJ (1.08×10^9 kg/h), and the smallest is ZZ (0.10×10^9 kg/h). Megacities are the most affected by urban heat island effects, as reflected by their higher power consumption for the heat island intensity, while smaller cities are still affected but to a lesser extent. As evident from Equations (9) and (10), Power is significantly correlated with the HEI of the built-up area and the average building height. Since there is no significant difference in the average height of each built-up area, the HEI emerges as the predominant predictor of Power. This suggests that the energy consumption related to the heat island effect is more strongly influenced by the size of the built-up area and its heat island intensity. Therefore, cities with larger built-up areas and higher heat island intensities tend to have higher energy consumption (Power) due to the heating effect.

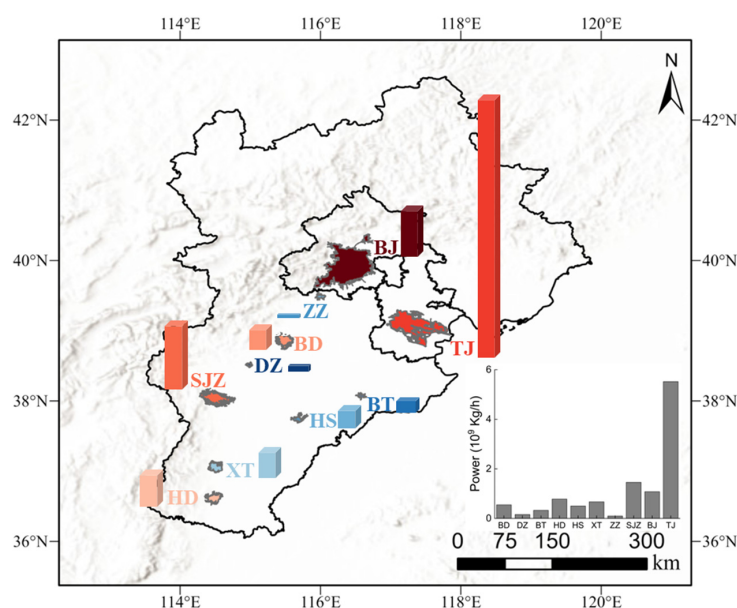


Figure 7. Power in Beijing–Tianjin–Hebei region.

3.4. Responses of HEI to Building Volume

The building heights of 10 cities (Figure 5) were obtained by the CNBH-10m data, and the volume of building $V_{Building}$ (Table 3) of the built-up areas were obtained by Equation (7). The largest building volume is BJ (17,521.89 km³), followed by TJ (9689.16 km³). The smallest building volume is BT (264.68 km³).

Table 3. Building volumes and areas in urban built-up areas.

City	$S_{Building}$ (km ²)	$V_{Building}$ (km ³)
BJ	1189.66	17,521.89
TJ	652.91	9689.16
SJZ	302.91	3169.11
BD	144.18	1609.57
HD	111.13	1532.93
XT	93.07	1029.66
HS	54.70	612.27
ZZ	32.92	397.04
DZ	19.98	268.72
BT	26.36	264.68

The HEI can be understood as the temperature change ΔT occurring on the effected area A (where the coordinates X·Y represent the effected area A, the coordinates Z represent the temperature change ΔT). After establishing the correlation between the building area and heat island impact area from a 2D perspective, the analysis was extended to a 3D level to establish the relationship between building volume and the HEI, exploring the patterns of the HEI driven by buildings. The results of curve fitting (Figure 8a) indicate that there is a logarithmic function relationship between building volume and the HEI ($R^2 = 0.4261$). The HEI increases with the increase in building volume, but the rate of increase gradually slows down.

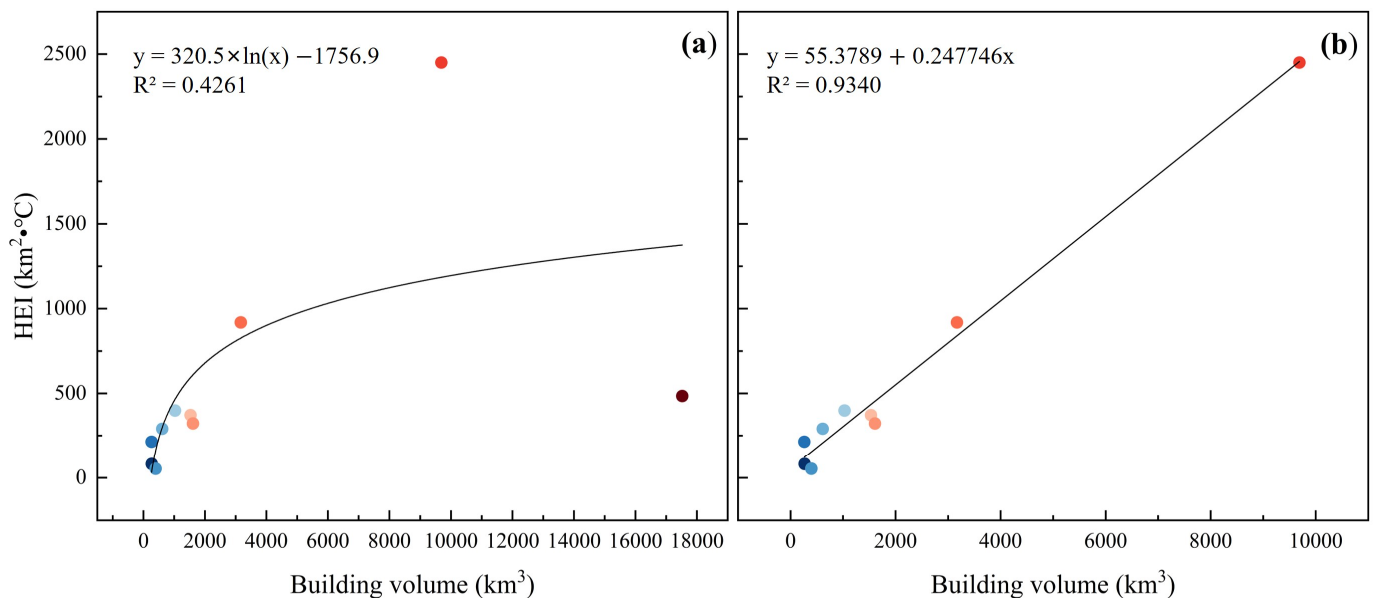


Figure 8. Relationship between building volume and HEI: (a) 10 urban built-up areas; and (b) 9 urban built-up areas except Beijing.

It is noticeable that the data points from BJ exhibit a significant offset from the trend line, similarly affecting the fitting results. To eliminate the influence of megacity specificity, the relationship between the building volume and the HEI was established after

removing BJ (Figure 8b). The results of curve fitting exhibit a significant linear relationship ($R^2 = 0.9340$), where the HEI linearly increases with the increase in building volume.

According to data from the National Bureau of Statistics of China, despite BJ having a significantly larger built-up area compared to other cities, the green coverage rate in BJ's built-up areas was 49.0% in 2020, which is higher than the green coverage rates of 37.6% in Tianjin and the overall level of 42.9% in Hebei Province. Due to significant differences in the construction situations of cities, data points from megacities may become outliers.

Here, it is suggested that the relationship between $V_{Building}$ and the HEI should be discussed based on different scenarios: under the condition of considering all cities, the relationship between $V_{Building}$ and the HEI exhibits a logarithmic function relationship; When excluding megacities, the relationship between $V_{Building}$ and the HEI shows a significant linear relationship.

4. Discussion

4.1. Differences Arising from Different Data and Method Selections

At the data scale level, studies on the urban heat island effect conducted in multiple cities using remote sensing techniques typically utilize temperature data with a spatial resolution of 1000 m. In this study, a multi-city analysis of the heat island effect was conducted using Landsat-8 imagery with a spatial resolution of 30 m, resulting in differences from previous studies. It was determined that significant heat island effects were observed in 10 cities. However, some studies have shown that other cities also exhibit significant heat island effects using data with a spatial resolution of 1000 m or meteorological data [45,46]. This discrepancy is believed to be due to differences in data and the limitations of the selected image acquisition time.

The width of the buffer zone can also be considered as the observation scale. The size of the buffer width can influence research outcomes and increase result uncertainty. Previous studies have utilized buffer widths based on the average radius length of the study subject [46,47], which is not applicable to this study due to the large area of urban built-up areas. Therefore, in the data preprocessing stage, buffer widths of 200 m, 500 m, 800 m, 1000 m, and 1200 m were tested to analyze the temperature–distance relationship. Different buffer widths result in varying inflection distances describing the temperature–distance relationship function. Buffer widths that are either too large or too small may lead to poorer descriptions of the temperature–distance relationship. It was found that, when the buffer width was set to 800 m, the statistical description of the temperature–distance relationship was optimal. Hence, 800 m was ultimately chosen as the buffer width for this study.

4.2. Uncertainty of Multiple Influencing Factors

The causes of the UHI effect are complex and are influenced by a combination of factors such as vegetation cover, water bodies, and climatic conditions [47]. This study focused on urban built-up areas and selected buildings within these areas as the primary research factor, which will inevitably be affected by other unconsidered factors. At the outset of defining the HEI, the initial HEI (the product of the impact area A and the temperature change ΔT) was roughly predefined, and the relationship between $V_{Building}$ and HEI was pre-analyzed (Figure 9). The pre-analysis curve fitting results of the HEI are satisfactory ($R^2 = 0.8921$), thus prompting this study to further consider the HEI in a layered manner, aiming to enhance the accuracy of the results.

However, compared to the layered consideration of the HEI, the rough pre-analysis results have higher accuracy from a mathematical analysis perspective, considering that the uncertainty associated with the single impact factor selected in this paper contributes to this result. The causes of urban heat islands and their internal driving mechanisms

are complex, with covariance between the influencing factors, and the uncertainty of the combined driving law of multiple factors is unavoidable.

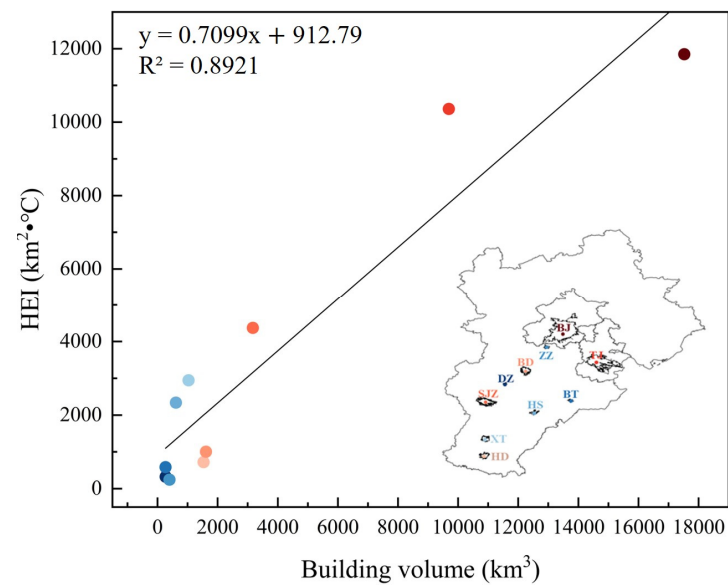


Figure 9. Building volume–HEI pre-analysis.

4.3. The Impact of City Specificity

Cities exhibit specificity due to differences in geoclimatic conditions and development, and the specificity exhibited by megacities are particularly significant, affecting the results of this study and increasing the uncertainty of the results. When analyzing the $V_{Building}$ –HEI relationship for the 10 urban built-up areas in this study from the perspective of mathematical statistics, the best describing function is the quadratic polynomial (Figure 10a), which is highly consistent with the greenfield–HEI relationship (Figure 10b). While Beijing has the largest built-up area and building volume, its built-up green area (123,900 km²) is also much larger than that of other cities combined (87,150 km²). Therefore, the area of green space, which is one of the manifestations of urban specificity, significantly influenced the results of this study. In addition, the number of cities selected for this study is limited, and a larger number of more evenly distributed city data points may yield different results.

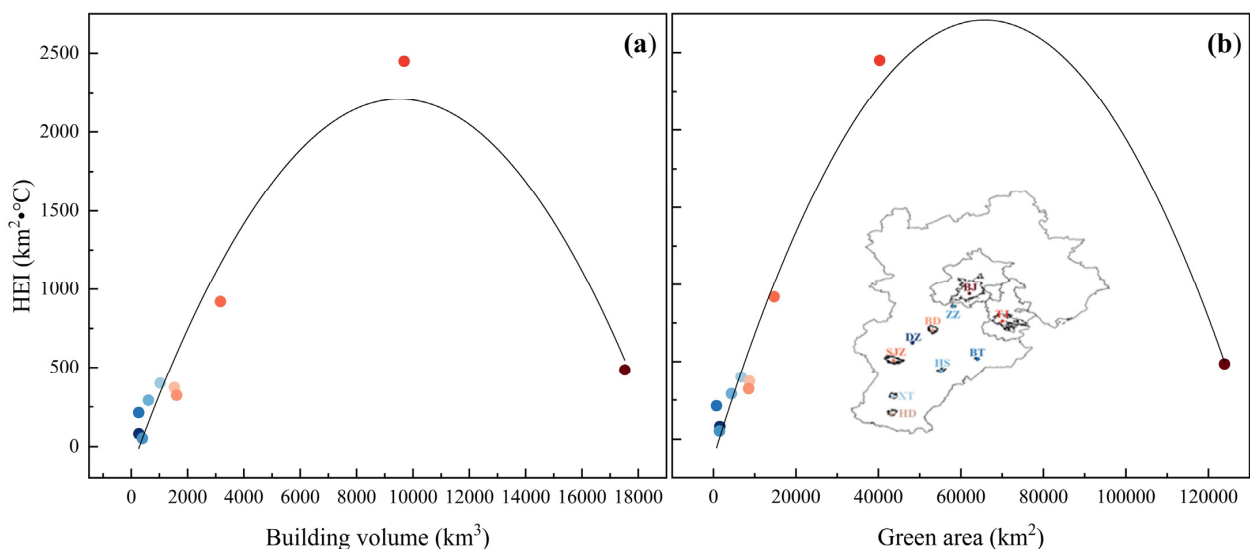


Figure 10. Impact of city specificity on HEI: (a) optimal mathematical statistical relationship for building volume–HEI; and (b) relationship between green area and HEI.

4.4. Limitations and Future Directions

This study has certain limitations. Firstly, by defining the basic research unit as the urban built-up areas within the Beijing–Tianjin–Hebei urban agglomeration, the limited number of cities in the region resulted in a relatively small final dataset, increasing the uncertainty of the results. Considering a broader range of urban built-up areas might yield different outcomes. Additionally, since this study treats the entire built-up area as a whole, it does not account for the internal heterogeneity of the urban heat island effect. The concept of heat island effect intensity, defined by the combined influence range and intensity, offers a framework for future research on internal heterogeneity. For example, classifying the internal areas of urban built-up regions based on architectural morphology into more detailed urban characteristic zones and combining influence range and intensity could facilitate an in-depth study of the differences in heat island effects between regions.

5. Conclusions

An accurate analysis of the heat effect of buildings can provide a scientific basis for effective urban building planning to mitigate the UHI effect. In this study, 10 cities from the Beijing–Tianjin–Hebei urban agglomeration were selected to analyze the heat island effect caused by buildings. A multi-ring buffer analysis method was utilized to comprehensively assess the extent and intensity of the urban heat island effect. The HEI was defined by integrating the scope and intensity, and the impact of buildings on the urban heat island was explored from a 3D perspective. It was found that the land surface temperature and the distance follow a fifth-degree polynomial functional relationship $T(r)$. Buildings in urban built-up areas exhibit a significant heating effect, with the heating range showing a significant linear correlation with building area. The HEI is influenced by the substantial differences in the construction of green area in cities. Specifically, the HEI is logarithmically correlated with building volume, and, after excluding Beijing, which has a vastly different construction situation compared to the other cities, the HEI shows a significant linear correlation with the building volume. The total energy consumption power of the heating effect in 10 cities within the Beijing–Tianjin–Hebei region is 326.23×10^{12} KJ/h, equivalent to 11.14×10^9 kg/h of standard coal. These results revealed the importance of considering both the extent and intensity of the urban heat island effect and the role of urban planning in mitigating these effects. Effective planning should account for the relationship between the building area and heating range, as well as the complex relationship between building volume and the HEI, to develop strategies that minimize the urban heat island effect while accommodating urban growth.

Author Contributions: Conceptualization, B.L.; methodology, B.L.; software, B.L.; validation, Y.Z. and L.Z.; formal analysis, B.L.; investigation, S.Z.; resources, H.P.; data curation, B.L.; writing—original draft preparation, B.L.; writing—review and editing, B.L. and H.P.; visualization, Y.Z.; supervision, M.W.; project administration, H.P.; funding acquisition, H.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Hebei Provincial Key R&D Program (No. 22377001D), the Natural Science Foundation of China (No. 41701017), the Central Government Guided Local Science and Technology Development Fund Project (No. 246Z3612G). and the Science Foundation of Hebei Education Department (No. ZD2022015).

Data Availability Statement: Data will be made available upon request due to privacy.

Acknowledgments: We would like to thank the Natural Science Foundation of China, the Science Foundation of Hebei Education Department, and the Hebei Province Department of Science and Technology for these fundings. Special thanks to Bin Su (Unitec Institute of Technology, New Zealand) for the valuable suggestions.

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

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