Exploring Adaptive UHI Mitigation Solutions by Spatial Heterogeneity of Land Surface Temperature and Its Relationship to Urban Morphology in Historical Downtown Blocks, Beijing

Liukuan Zhang, Xiaoxiao Shi and Qing Chang *

Abstract: Heat stress brought on by the intensification of urban heat island (UHI) has caused many negative effects on human beings, which were found to be more severe in highly urbanized old towns. With the inconsistent findings on how urban spatial morphological characteristics influence land surface temperature (LST) and gaps between design practices being found, we chose Beijing Old Town (BOT) as the study area and took the basic planning implementation module “block” as a study to reveal the spatial heterogeneity of LST and its relationship to multiple urban morphological characteristics with higher spatial resolution calculated via WorldView3. Our results have shown that (1) UHI effect was significant and spatially homogeneous in BOT, and significant hot areas with high LST value and small LST differences were found, as cold areas were the exact opposite. (2) The proportion of vegetated area, water, impervious surface, and urban spatial structure indicators i.e., building coverage ratio, mean height, highest building index, height fluctuation degree, space crowd degree and sky view factor were identified as significantly affecting the LST of blocks in BOT. (3) The effects of GBI components and configuration on LST varied within different block types; generally, blocks with GBI with larger patches that were more complex in shape, more aggregated, and less fragmented were associated with lower LST. Finally, in the context of integrating our study results with relevant planning and design guidelines, a strategy sample of adaptive GBI planning and vegetation design for blocks with different morphological features was provided for urban planners and managers to make a decision on UHI mitigation in the renewal process of BOT.

Keywords: Beijing Old Town; land surface temperature; urban morphology; green and blue infrastructure; composition & configuration

1. Introduction

It has long been recognized that urbanization changes spatial morphology and brings about population aggregation of cities, thus resulting in various urban problems [1]. One of the most reported examples is that urban areas are warmer than the surrounding countryside, a phenomenon known as the urban heat island (UHI) [2]. The UHI effect has been observed worldwide, contributing to a suite of negative impacts such as increasing energy consumption [3,4] and urban smog formation [5], reducing thermal comfort of urban dwellers, and increasing health problems [6–8] and mortality rates [9,10]. Consequently, the UHI effect of urban spatial morphology and how to mitigate it via Nature-based Solution (NbS) has attracted increasing attention from scientists and urban managers [11–14]. Lately, the UHI effect has been generally studied by remote-sensed land surface temperature (LST) or station-based air temperature [12,13,15]. Due to convenience and effectiveness in acquiring spatial variations of temperature, LST is widely applied to analyze the spatial pattern of UHI and its relationship to urban morphology [16–18].
1.1. Studies on the Impact of Urban Spatial Morphology on LST

The morphological characteristics of urban elements significantly affect the aggregation of heat, which in turn leads to the spatial and temporal differentiation of LST, thus identifying the relationship between urban spatial morphology and LST as an effective way to improve thermal environment [19–21]. Spatial morphology is usually demonstrated by two-dimensional variables (generally characterized by land cover characteristics) and three-dimensional variables (generally characterized by spatial structure of built-up) [17,22,23].

The impact of land cover characteristics on LST was proposed earlier and attracted the attention of many researchers. Many studies have pointed out that LST varies significantly across different land cover classes [24], most of which have shown that vegetation and water areas have a cooling effect, an increase of vegetation, and water proportion which helps to improve the urban thermal environment. On the other hand, impervious surface area (ISA) is the most significant factor contributing to higher LST and thereby the UHI effect [25]. Dark ISA (e.g., asphalt) decreases the amount of albedo of land surface and thus increases the LST [26]. Imhoff et al. reported that ISA explains around 70% of the total LST variance in 38 of the most populated cities in the US [27]. Therefore, in those downtown areas with higher impervious surface, mitigating the UHI effect by optimizing land use and land cover is a considerable challenge for urban planners.

At present, there are more and more studies that have focused on the impact of urban spatial structure on LST. It has been accepted that the expansion of urban buildings and traffic in vertical spaces affects land surface energy balance processes and air flow on a local scale, which may aggravate the UHI effect [28]. Indicators of building density, height, and volume, as well as the floor area ratio (FAR), sky view factor (SVF), and height/width ratio (H/W), etc. are inarguably some of the most important factors influencing the LST [28,29]. Nevertheless, urban structure factors are shown to have a non-stationary relationship with the LST according to existing conclusions [30–32]. For example, building density was one of the top 2 features intensifying the UHI effect in one case study [33], while SVF is the significant index indicating the UHI effect in other studies [34,35]. One study argued that LST tends to be lower in low building density areas [30], whereas another showed opposing results [36]. Inconsistent results indicate the relationship between urban spatial structure and LST remains under debate, which suggests that more study is needed to analyze the influence of urban morphology on a thermal environment.

In addition, the relationship between LST and morphological indicators varies by analysis unit [37,38] and spatial resolution [11,39]. In recent years, the main study units selected by researchers were land use classes, grids, local climate zones, census blocks, urban clusters, and climate zone types [39]. Most of these studies focused on a whole city by taking administrative districts or general blocks as the analysis unit [13,22,24,40], ignoring the difference of urban morphology among blocks. It was revealed that remote-sensing images with higher spatial resolution can more accurately quantify urban characteristics. This might be a green light to study the effect of spatial configuration on LST at a finer level of spatial resolution, as well as to find some informative indicators that affect the thermal environment significantly, such as patch size, edge density, and interspersion juxtaposition index [40,41].

1.2. Studies on the Impact of Green and Blue Infrastructure’s Spatial Pattern on LST

Cooling is reported to be the strongest when a city’s green and blue infrastructure (GBI) coverage lies between 70% and 80% [42]. However, land use for GBI is usually limited for social-economic development. Consequently, quantitative evaluation of the impact of GBI’s spatial pattern on LST is a prerequisite for proposing urban thermal mitigation measures [17,36]. There are two fundamental aspects of landscape pattern: composition and configuration, both of which influence the LST [24]. Previous studies showed that land cover composition has a clear and significant influence on LST, the relationship between the proportion of GBI compositions (i.e., trees, grassland, and water bodies), and LST varies widely depending on the characteristics of urban sites [43].
Numerous studies have concerned the relationship between GBI configuration and their cooling effect. The configuration of GBI can be broadly divided into four categories: area-related, shape complexity, connectivity, fragmentation, and aggregation [13]. The results from these studies are, however, inconclusive and contradictory, and rarely were the same methods replicated [13,44–46]. For example, some studies showed that fragmented GBI may have a higher cooling effect [47], while some researchers have come to the opposite conclusion [11,48]. In some studies, GBI with regular form tend to be more effective at cooling [49,50], other studies, on the other hand, were supporting the opposite conclusion [47,51]. Contradictory findings also exist in the analysis of the impact of the GBI aggregation on the thermal environment [11,52], indicating that there is no consensus on whether GBI patches should be of regular or irregular form, nor should they be more aggregated, fragmented or connected from the perspective of enhancing their cooling effect. This may be due to scale-dependency and contextual difference between cities [13]. In addition, fewer studies have examined whether the thermal environmental impacts of GBI are consistent across different urban forms under the premise that significant spatial morphological differences are identified in the same study area. Therefore, it is necessary to explore how GBI should be composed and spatially arranged in order to achieve better cooling benefits in blocks with different urban morphology.

### 1.3. Planning Orientation of Urban Thermal Environment Improvement Studies

As the basic unit of urban construction in China, block is the main unit used to manage land use, control development intensity, allocate public facilities, etc. [53]. It is also the basic scale for shaping urban morphology [54]. Therefore, it is very meaningful to study the relationship between LST and urban morphology at this scale, and to explore the applicable thermal mitigation strategies for urban planning (UP). Some researchers have conducted studies on block level in Chinese cities such as Wuhan and Xi’an [22,24]. They revealed the significant impact of urban characteristics on LST and proposed some directions for optimizing urban 2D or 3D characteristics; however, these findings can be further refined to form a research strategy and integrate the results with local planning documents to enhance the value of practical application.

In order to offer practical, operational guidelines for urban managers, the selection of morphological indicators and the research process should be more comprehensively considered. Some researchers mentioned that the indicators selected for the study should be those that can be directly used or provide specific directions for urban planning; e.g., building height, floor area ratio, building coverage ratio, and so on [28,29]. As for indicators that are not used in UP practices but characterize the urban form in a comprehensive way, their significance for guiding UP should be explored [24]. In addition, urban planning and design has a comprehensive process and a clear sequence, in which after the spatial layout of the city is clearly defined and a regional infrastructure planning framework is formed, various important urban construction projects can be drawn up; i.e., the construction at the three-dimensional level is restricted by the planning at the two-dimensional level [54]. Most of the current studies have analyzed different levels of indicators simultaneously during the analysis [30,55], which may lead to interference in the analysis results.

Therefore, this study aims to explore the adaptive UHI mitigation solutions based on the correlations between fine-texture morphological indicators and LST in old downtown areas by using imagery with high spatial resolution. We conducted this research in the historical downtown blocks in Beijing City, China. Specifically, it addresses three questions as follows: (1) what are the LST characteristics of blocks and how do these LST characteristics differ among different blocks in Beijing Old Town? (2) Which urban morphological indicators influence the LST significantly in these blocks? (3) What are the differences in relationships between the LST and GBI pattern among blocks with different morphological features?
Important insight of adaptive GBI planning and vegetation design can be provided for urban planners and managers to make decisions about mitigating the UHI effect in the old city renewal process.

2. Materials and Methods

2.1. Study Area and Block Units

Beijing Old Town (BOT), located in the center of Beijing City (39°28′~41°50′ N, 115°25′~117°30′ E), with a total area of about 62.5 km², was defined as the area within the Second-Ring Road by the Urban Master Plan of Beijing (2016–2035) [56] (Figure 1). BOT has been developed for 3000 years, and has been the capital city for 800 years, where not only cultural relics and historic sites are richer, but where a greater variety of buildings exist and a larger population aggregates. BOT acts as the most key area for the preservation of urban historical and cultural heritage in Beijing. Nevertheless, there are both significant hot and cool spots of UHI observed in this area [57]. Consequently, efforts to mitigate the UHI effect should strictly implement the requirements of “the old town can no longer be demolished”.

![Figure 1](image-url)

**Figure 1.** (a) Location & blocks division of the study area and location of famous hutongs, here (b) Dashilar commercial street and its photo; (c) Nanluoguxiang Alley and its photo; (d) Dongjiaominxiang alley and its photo. (photos taken by the authors).

According to the Detail Regulatory Plan in the Functional Core Area of Beijing (Block Level) [58], BOT involves 25 districts that are composed of 123 blocks (including 47 historical and cultural blocks, HCB) (Figure 1a). HCB refers to blocks with historical value that need to be protected, in which they are dotted with many traditional housing quadrangles (siheyuan) and alleyways (called as hutongs). Some of the most famous hutongs such as Dashilar Commercial Street (Figure 1b), Nanluoguxiang Alley (Figure 1c) and Dongjiaominxiang Alley (Figure 1d) were distributed in this region.

2.2. Data Source and Processing

We obtained the LST and urban morphological indicators by remote sensing image data and building vector data. The former, including Landsat-8 OLI Imagery (September, 2017) from the Geographical Spatial Data Cloud (http://www.gscloud.cn (accessed on 9 September 2020)) and WorldView-3 Imagery (October 2018) with a high resolution of 0.30 m, are used to extract the LST value and landscape characteristic indicators [46].
They are high-quality images in which cloud cover in the study area is less than 3%, and the weather on these days was mainly sunny with light wind; that is, the thermal environment was not affected by rainfall or wind [59]. Based on the ENVI5.3, the remote sensing data was pre-processed through radiometric calibration, atmospheric correction, and orthorectification, as well as image fusion, cropping, and enhancement [60]; the latter are the Amap building vector data (2016). After spatial correction, we applied it to calculate the spatial structure indicators of built-up.

2.3. Characteristic Indicators of UHI Based on LST

The radiative transfer equation (RTE) method was applied to retrieve the LST in the thermal infrared (TIR) band (10.60–11.90 μm) of pre-processed Landsat-8 OLI using ENVI5.3, the specific calculation steps of which are described below [60]:

\[
B(T_S) = \frac{[L_A - L \uparrow - \tau(1 - \varepsilon)L \downarrow]}{\tau \varepsilon}
\]

where \(B(T_S)\) is the blackbody radiance, \(L_A\) is the thermal infrared radiance brightness value; \(\varepsilon\) is the surface emissivity. The atmospheric profile parameters include \(\tau\), \(L \uparrow\), and \(L \downarrow\), where \(\tau\) is the atmospheric transmittance in the thermal infrared band, \(L \uparrow\) is the atmospheric upward radiance, and \(L \downarrow\) is the atmospheric downward radiance; parameters were obtained from media files of USGS ([https://www.usgs.gov](https://www.usgs.gov) (accessed on 3 March 2021)).

\(\varepsilon\) was calculated differently for different regions with following formulas [61]:

\[
\varepsilon_{wt} = 0.995
\]

\[
\varepsilon_{ua} = 0.9589 + 0.086P_v - 0.0671P_v^2
\]

\[
\varepsilon_{ns} = 0.9625 + 0.0641P_v - 0.0461P_v^2
\]

where \(\varepsilon_{wt}\), \(\varepsilon_{ua}\), \(\varepsilon_{ns}\) are surface emissivity of water body, urban area and natural surface, respectively. The equation for \(P_v\) (vegetation coverage) is [62]:

\[
P_v = \frac{(NDVI - N_{Soil})}{(N_{Vegetation} - N_{Soil})}
\]

where \(NDVI\) is the normalized vegetation index of the whole BOT; \(N_{Soil}\) is the NDVI of the completely bare, soil-covered area; \(N_{Vegetation}\) is the NDVI value of areas with complete vegetation covered. Based on empirical values, \(N_{Soil}\) equals 0.05 and \(N_{Vegetation}\) equals 0.70 [59]. Planck’s formula was further applied to calculate the land surface temperature \(T_s\) [63]:

\[
T_s = \frac{K_2}{\ln \left(\frac{K_1}{B(T_s)} + 1\right)}
\]

where \(T_s\) is the surface brightness temperature; constants \(K_1 = 774.89\) W/(m\(^2\) μm sr), \(K_2 = 1321.08\) K [22]).

The mean value (LST\(_\text{mean}\)) standard deviation (LST\(_\text{std}\)), and value range (LST\(_\text{range}\)) of LST were used to quantify the variation of thermal environment in BOT. Among them, LST\(_\text{mean}\) characterized the thermal intensity of urban blocks, the larger its value, the higher the LST, the stronger the UHI intensity. LST\(_\text{std}\) and LST\(_\text{range}\) characterized the degree of thermal variation of urban blocks, the smaller its value, the smaller the LST difference, the lower the thermal dispersion intensity [64]. Meanwhile, the Getis–Ord Gi* local statistics of LST\(_\text{mean}\) was also conducted to demonstrate the spatial heterogeneity of UHI (hot, warm,
and cold area) based on ArcGIS 10.6, as it was considered the most appropriate method to identify hot spots [65]. The equations for calculating the Getis–Ord Gi* are [66]:

\[ G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - X \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{1}{n} \sum_{j=1}^{n} w_{i,j}^2 - \left( \frac{\sum_{j=1}^{n} w_{i,j}}{n} \right)^2}} \]

\[ X = \frac{\sum_{j=1}^{n} x_j}{n} \]

\[ S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left( \frac{X}{n} \right)^2} \]

where \( i, j \) are designations of different raster cells/elements; \( w_{i,j} \) is the spatial weight between elements \( i \) and \( j \); \( n \) is the number of raster cells; \( x \) is the raster cell attribute; \( X \) is the average of attribute values [66]. The cohesion index and the aggregation index of hot, warm, and cold areas were calculated with the software of Fragstats 4.2 [67].

2.4. Spatial Morphological Indicators of Urban Blocks

Here, characteristic indicators of land cover and spatial structure indicators of built-ups (Table 1) were chosen to quantitatively describe urban morphology in BOT. The land cover characteristic indicators were calculated by the land cover map based on WorldView-3 Imagery. Based on the eCognition Developer 9.0, remote sensing interpretation was carried out using the pre-processed WorldView-3 images [68]. Basic units were divided using multi-scale segmentation, then the object-oriented classification method was applied to firstly distinguish the water body and non-water body areas based on values of NIR band, after which NDVI was defined in the software to distinguish the vegetated and non-vegetated areas [69]. Additionally, combining with the human-computer interaction method, grassland areas were distinguished from trees and shrubs. Final results were further corrected by visual interpretation. The accuracy was verified by the field accuracy check with sample points. Results showed that the overall interpretation accuracy was 93.7% with the kappa coefficient up to 0.92, which met the requirements of the experimental data analysis [70]. The Normalized Difference Vegetation Index (NDVI) and the Impervious Surface Area (ISA) were selected to represent the vegetation quality and the impervious status of the land surface. The urban spatial structure indicators were calculated based on modified Amap building vector data [71]. Formulas of these indicators are detailed in Table A1. Block-based zonal statistics were conducted by using images after interpretation in ArcGIS 10.6.

| Category                          | Indicators                          | Definition                                                                 | Unit  |
|----------------------------------|-------------------------------------|----------------------------------------------------------------------------|-------|
| Land cover characteristics       | Impervious land proportion (IP)     | The ratio of impervious area to block area.                               | %     |
|                                  | Vegetated land proportion (VP)      | The ratio of vegetated area to block area.                                | %     |
|                                  | Water proportion (WP)               | The ratio of water area to block area.                                    | %     |
|                                  | Bare soil proportion (SP)           | The ratio of bare soil area to block area.                                | %     |
|                                  | Normalized Difference Vegetation Index (NDVI) | The vegetation index calculated by the near-infrared band and red band value of Landsat-8 OLI [72] | -     |
|                                  | Impervious Surface Area (ISA)       | The impervious degree calculated by a linear spectral mixture decomposition model [73,74] | -     |
To find the mitigation measures of UHI in urban blocks, spatial pattern indicators of GBI were further selected in Table 2. The composition indicators of TP, GP and WP were calculated from interpretation results of WorldView3. By merging trees, shrubs, grass and water in ArcGIS10.6, we obtained the GBI raster map and calculated its spatial configuration within blocks by the software of Fragstats4.2. Formulas of the configuration indicators were detailed in Table A2.

Table 1. Cont.

| Category                                | Indicators                        | Definition                                                                 | Unit |
|-----------------------------------------|-----------------------------------|---------------------------------------------------------------------------|------|
| Urban spatial structure characteristics  | Building coverage ratio (BCR)     | The ratio of building coverage to block area.                              | %    |
|                                        | Mean height (MH)                  | The average height of buildings in the block.                              | m    |
|                                        | Highest building index (HBI)      | The ratio of the tallest building's height to the sum of all buildings' heights in the block. [71] | -    |
|                                        | Height fluctuation degree (HFD)   | The difference between the height of the tallest and shortest building in the block [71] | -    |
|                                        | Average Volume (AV)               | The average volume of buildings in the block.                              | m³   |
|                                        | Space crowd degree (SCD)          | The ratio of the sum of all buildings' volumes to the potential largest building volume in the block [71] | -    |
|                                        | Floor area ratio (FAR)            | The ratio of total above-ground floor area to block area.                  | -    |
|                                        | Building structural index (BSI)   | The average ratio of each building’s covered area to its height in the block [71] | -    |
|                                        | Building surface area (BSA)       | The surface area of buildings in the block.                               | m²   |
|                                        | Sky view factor (SVF)             | The average sky openness among buildings in the block [75,76]              | -    |

Table 2. Description of spatial pattern indicators of GBI.

| Category                          | Indicators                        | Definition                                                                 | Unit |
|-----------------------------------|-----------------------------------|---------------------------------------------------------------------------|------|
| Composition                       | Trees and shrubs proportion (TP)  | The ratio of tree and shrub covered area to block area.                    | %    |
|                                   | Grass proportion (GP)             | The ratio of grass covered area to block area.                             | %    |
|                                   | Water proportion (WP)             | The ratio of water area to block area.                                    | %    |
| Patch Size                        | Mean patch size (AREA_MN)         | Average area of all GBI patches within the block                          | Ha    |
|                                   | Largest patch index (LPI)         | Ratio of the area of the largest GBI patch to the total area of GBI within the block | %    |
| Patch shape                       | Area-weighted fractal dimension index (FRAC_AM) | The fractal dimension weighted by its area of individual GBI patches in the block | -    |
|                                   | Landscape shape index (LSI)       | Modified perimeter-area ratio of GBI patches in the block                  | -    |
| Fragmentation                     | Number of patches (NP)            | The number of GBI patches in the block                                     | -    |
| Connectivity                      | Area-weighted Euclidean nearest neighbor distance (ENN_AM) | The ENN-MN weighted by the area of GBI patches in the block                | %    |
| Aggregation                       | Aggregation index (AI)            | A measure of aggregation between GBI patches within blocks, obtained by dividing number of joins by the maximum possible number of joins among GBI patches in the block | m    |

Note: Definition of spatial pattern indicators are referring to McGarigal and Marks [67].

2.5. Relationship Analysis Methods

The Pearson correlation analysis was conducted between urban morphology and the LST with the help of SPSS25.0. Pearson correlation test was also conducted in order to avoid the effect of the multicollinearity of indicators. Variables with coefficients larger than 0.6 have a strong correlation to each other and one of them should be excluded from the following analysis [77]. By using the absolute values of correlation coefficients, we
explained the influence and dominance of the morphological indicators on the thermal environment. Indicators with significance coefficients less than 0.05 were considered being significantly correlated with the thermal environment [78].

Urban green space planning is dependent on block morphological characteristics. Thus, all above morphological indicators identified to be significant correlated with LST\textsubscript{mean} were selected to classify block types in BOT. The sum of the squared errors method (SEE) was applied in Python v3.8.5 to determine the optimal number of clustering “K” [79]. All indicators related were standardized in SPSS 25.0, and K-means clustering was performed afterwards. Partial correlation analysis was performed between the GBI pattern indicators and LST\textsubscript{mean} & LST\textsubscript{std} within different block types. Below, Figure 2 shows the flow chart of the methods and data pre-processing for the present study.

**Figure 2.** Flowchart of this study. Note: Getis-Ord Gi*, a hotspot analysis tool, was applied to identify those spatially aggregated high and low LST points with statistically significance.

### 3. Results

#### 3.1. Spatial Heterogeneity of UHI in Historical Downtown Blocks

Beijing Old Town (BOT) was located in central Beijing, where high LST aggregated (Figure 3a). The LST\textsubscript{mean} of BOT was 33.06 °C higher than 27.09 °C of the whole city and 31.15 °C of the central urban area, while LST\textsubscript{std} was 2.09 °C and LST\textsubscript{range} was 25.25 °C, respectively, lower than those of the whole city and central urban area of Beijing (Table 3). The thermal characteristics of higher mean temperature value and lower temperature difference indicated that this historical downtown area was under more severe heat stress.
Table 3. Description of spatial pattern indicators of GBI.

| Region                        | The LST Indicator/$^\circ$C | The Spatial Characteristic Indicator |
|-------------------------------|-----------------------------|-------------------------------------|
|                               | $\text{LST}_{\text{mean}}$ | $\text{LST}_{\text{std}}$ | $\text{LST}_{\text{range}}$ | Area/km$^2$ | Proportion/% | Cohesion | Aggregation |
| Whole City of Beijing         | 27.09                       | 3.22                             | 32.07                         | /           | /           | /        | /          |
| Central urban area of Beijing | 31.15                       | 2.74                             | 27.66                         | /           | /           | /        | /          |
| Beijing Old Town (BOT)        | 33.06                       | 2.09                             | 25.25                         | 62.28       | 100         | 82.27    | 88.56      |
| Cold area                    | 29.92                       | 1.37                             | 17.47                         | 12.42       | 19.95       | 82.80    | 89.57      |
| Warm area                    | 33.19                       | 0.86                             | 3.88                          | 36.27       | 58.23       | 94.17    | 91.10      |
| Hot area                     | 35.61                       | 0.86                             | 4.95                          | 13.59       | 21.82       | 82.80    | 89.57      |

The thermal environment characteristics within BOT were spatially differentiated among blocks, while the hot and cold areas had conjugated each other (Figure 3a,b). Integrated with the LST value and spatial characteristics of hot, warm and cold areas, we found that the $\text{LST}_{\text{mean}}$ of hot areas reached as high as 35.61 $^\circ$C, while the $\text{LST}_{\text{std}}$ and $\text{LST}_{\text{range}}$ was 0.86 $^\circ$C and 4.95 $^\circ$C, respectively (Table 3). Those typical heat islands with higher cohesion and lower connectivity value (Table 3) were mainly aggregated in the Dashilar Block, Xinjiekou Block, Tiyuguanlu Block and Jianguomen Block (Figure 3c(i–iv)). Conversely, the $\text{LST}_{\text{mean}}$ of cold areas was lower than 30 $^\circ$C, with the $\text{LST}_{\text{std}}$ reaching 1.37 $^\circ$C and $\text{LST}_{\text{range}}$ up to 17.47 $^\circ$C. Those areas also had higher cohesion and lower connectivity value (Table 3) and mainly clumped in blocks of Shichahai, Tiantan and Longtan (Figure 3c(v–vii)).

Different from the above two types of areas, the warm area with highest cohesion and connectivity value (Table 3) consisted of the matrix of LST distribution pattern in BOT (Figure 3c). The $\text{LST}_{\text{mean}}$ of warm areas was 33.19 $^\circ$C that was lower than that of hot areas, while the $\text{LST}_{\text{std}}$ (0.86 $^\circ$C) was equal to that of the hot area and even the $\text{LST}_{\text{range}}$ (3.88 $^\circ$C) was lower than that of hot areas (Table 3). This indicated that the warm area also had a feature with high average temperature and smaller temperature differences but was not as significant as hot areas.

3.2. Relationship between UHI and Block Morphology

To avoid the multicollinearity of indicators in Table 1, the Pearson’s correlation coefficient among initial morphological features is calculated and shown in Figure 4. Here, the NDVI was highly correlated with the vegetation proportion (VP), ISA was highly correlated...
with the impervious surface proportion (ISP), the building surface area (BSA) was highly correlated with the mean height (MH), the average volume (AV) and the building structural index (BSI), BSI was highly correlated with MH and AV and AV was highly correlated with FAR, BSI and BSA, all of which had a correlation coefficient over 0.6. Because VP, ISP and MH are commonly used in urban planning and design, we excluded NDVI and ISA from land cover characteristic indicators, as well as BSI, BSA and AV from spatial structure indicators.

Table 4. Correlation between LST and land cover characteristic indicators.

| Indicator | LSTmean | LSTstd | LSTrange |
|-----------|---------|--------|----------|
| VP        | 0.451** | 0.294* |          |
| WP        | -0.303* | 0.114  | -0.042   |
| BP        | -0.252* | 0.114  | -0.042   |
| NDVI      | -0.551**| -0.015 | 0.229*   |
| ISA       | 0.695** | -0.513**| -0.175   |

Figure 4. Pearson’s correlation among urban morphological indicators. Note: ** means at the 0.01 level (two-tailed), the correlation is significant. * means at the 0.05 level (two-tailed), the correlation is significant.

Then, we further conducted the correlation analysis between screened block morphological indicators and the LST. As shown in Table 4, ISP reaching 67.86% of the total area of BOT is significantly positively correlated with LSTmean and negatively correlated with both LSTstd and LSTrange, while it is the opposite for GBI-related indicators such as VP and WP. Nevertheless, the presence of bare soil did not have a significant effect on either LSTmean or LSTstd, nor on LSTrange. Meanwhile, the absolute value of correlation coefficient between ISP and LSTmean was significantly higher than that of VP and WP, indicating that the positive influence of gray components (characterized by ISP) on LSTmean was higher than the negative influence of the blue-green components characterized by VP and WP. The absolute value of correlation coefficient between ISP and LSTstd (as well as LSTrange) was a bit lower than that of WP, but significantly higher than VP, showing that the influence of increasing the temperature difference from WP was greater than that from VP, as well as the influence of reducing the temperature difference from ISP.

Considering blocks with higher ISP tended to have higher LST, smaller temperature differences and more gathered hot areas, the relationship between spatial structure indicators of built-up and the LST was further analyzed by partial correlation analysis (Table 5). The building coverage ratio (BCR), the space crowd degree (SCD) and the sky view factor (SVF) were all positively significant with LSTmean, with the absolute value of correlation coefficient compared as BCR > SCD > SVF, while the building height related indicators including the mean height (MH), the highest building index (HBI) and the height fluctuation degree (HFD) were all negatively significant with LSTmean, with the absolute value of correlation coefficient compared as MH > HFD > HBI. Nevertheless, BCR was the only
indicator with significantly negative correlation with LST\textsubscript{std}. The above results indicate that the increase of buildings proportion in blocks will aggravate the increasing of LST value and the reducing of LST variation, while the increase of average building height, maximum building index and fluctuation can decrease the LST value but not affect the LST difference. Overall, the BCR and MH were the primary two indicators of built-up’s spatial structure affecting the LST in BOT blocks according to the absolute value comparison.

Table 4. Correlation between LST and land cover characteristic indicators.

| Indicators                      | Mean Value | LST\textsubscript{mean} | LST\textsubscript{std} | LST\textsubscript{range} |
|--------------------------------|------------|-------------------------|------------------------|--------------------------|
| Impervious surface proportion (ISP) | 67.86%     | 0.717 **                | 0.000                  | −0.529 **                | 0.000                  |
| Vegetation proportion (VP)     | 27.74%     | −0.675 **               | 0.000                  | 0.390 **                 | 0.000                  |
| Water proportion (WP)          | 3.20%      | −0.466 **               | 0.000                  | 0.583 **                 | 0.000                  |
| Bare soil proportion (BP)      | 1.19%      | −0.114                  | 0.208                  | 0.026                    | 0.778                  |

Note: C is the coefficient and S is the significance, and ** means at the 0.01 level (two-tailed), the correlation is significant.

Table 5. Correlation between LST and spatial structure indicators of built-up.

| Indicators                      | LST\textsubscript{mean} | LST\textsubscript{std} | LST\textsubscript{range} |
|--------------------------------|-------------------------|------------------------|--------------------------|
| Building coverage ratio (BCR)  | 0.543 **                | −0.203 *               | −0.145                   | 0.113                    |
| Mean height (MH)               | −0.785 **               | 0.100                  | 0.042                    | 0.653                    |
| Highest building index (HBI)   | −0.361 **               | −0.161                 | −0.236 **                | 0.009                    |
| Height fluctuation degree (HFD)| −0.411 **               | 0.144                  | 0.139                    | 0.129                    |
| Space crowd degree (SCD)       | 0.464 **                | 0.587                  | −0.129                   | 0.160                    |
| Floor area ratio (FAR)         | 0.020                   | 0.033                  | 0.028                    | 0.764                    |
| Sky view factor (SVF)          | 0.237 **                | 0.033                  | 0.028                    | 0.764                    |

Note: C is the coefficient and S is the significance, and ** means at the 0.01 level (two-tailed), the correlation is significant. * means at the 0.05 level (two-tailed), the correlation is significant.

3.3. Relationships between UHI and GBI in Different Spatial Morphological Blocks

Morphological indicators with significant correlation with LST\textsubscript{mean} obtained from the above were used to classify blocks with different urban form in BOT. After applying the sum of the squared errors method (SSE) to identify K-value (K = 3 in this study), we classified those blocks into three categories by K-means clustering, which were high GBI proportion and mid-rise blocks (HMB), mid GBI proportion and high-rise blocks (MHB), and low GBI proportion and low-rise blocks (LLB), with a quantity of 30, 45 and 48, respectively (Figure 5a). There existed significant differences of thermal environment and urban morphology among three categories of block types (Figure 5b,c). The LST\textsubscript{mean} of HMB was 31.57 °C, lower than 32.82 °C for MHB and 34.42 °C for LLB. HMB also had the highest LST\textsubscript{std} and LST\textsubscript{range} (1.61 °C, 7.02 °C), both higher than that for MHB (1.07 °C, 0.90 °C) and LLB (5.26 °C, 4.26 °C). As for block morphology, HMB had the highest GBI proportion (that is the sum of VP and WP) and the lowest ISP, while LLB was exactly opposite and MHB was in-between (Figure 5c). LLB has the highest proportion of buildings with the highest spatial congestion and lowest building height, which was significantly different from the other two block types (Figure 5c).
Then, we further conducted Pearson correlation statistics to analyze the relationship between the LST and GBI composition and configuration characteristic in three categories of blocks. Here, considering that $LST_{\text{std}}$ and $LST_{\text{range}}$ showed similar feature differences among three block types (Figure 5b), only $LST_{\text{std}}$ and $LST_{\text{mean}}$ was selected for the following correlation analysis. As shown in Table 6, the tree cover proportion (TP) in HMB and LLB while the grass cover proportion (GP) in MHB were presented significantly correlated with $LST_{\text{mean}}$, but no correlation with $LST_{\text{std}}$, and the water cover proportion (WP) in HMB had significant correlation both with $LST_{\text{mean}}$ and $LST_{\text{std}}$, and in MHB only had significant correlation with $LST_{\text{mean}}$, but no correlation with $LST_{\text{mean}}$ and $LST_{\text{std}}$ in LLB. The absolute values of correlation coefficients in HMB were obviously larger than those in MHB and LLB. The above showed that the relationship between GBI composition and LST varied depending on block types, and the mean LST value might be reduced by increasing the proportion of trees, shrubs, water bodies or grassland according to local conditions.

Figure 5. (a) Distribution of different types of blocks in BOT; (b) Statistical boxplots of LST characteristics of different block types; (c) Statistical boxplots of morphological characteristics of different block types, here, the numbers are the mean value of indicators, the sign “◦” are outliers for block water proportion statistics.
Table 6. Correlation coefficients of LST and GBI spatial pattern characteristics.

| Category       | Indicators | HMB | MHB | LLB |
|----------------|------------|-----|-----|-----|
| Composition    |            |     |     |     |
| TP             |            | 0.531 ** | 0.111 | -0.033 | -0.067 | -0.353 * | -0.109 |
| GP             |            | -0.050 | 0.021 | -0.313 * | 0.234 | -0.274 | -0.032 |
| WP             |            | -0.520 ** | 0.565 ** | -0.314 * | 0.112 | -0.145 | -0.031 |
| LPI            |            | -0.702 ** | 0.403 * | -0.182 | 0.110 | -0.401 ** | -0.047 |
| Patch Size     | AREA_MN    | -0.729 ** | 0.303 | -0.323 * | 0.312 | -0.600 ** | -0.117 |
|                | LSI        | 0.153 | 0.191 | 0.339 * | 0.060 | 0.060 | 0.037 |
|                | FRAC_AM    | -0.693 ** | 0.219 | -0.168 | 0.046 | -0.616 ** | -0.077 |
| Shape Complexity|            |     |     |     |
| LSI            |            | 0.153 | 0.191 | 0.339 * | 0.060 | 0.060 | 0.037 |
| Fragmentation  | NP         | -0.035 | 0.265 | 0.312 * | 0.061 | 0.131 | 0.047 |
| Connectivity   | ENN_AM     | 0.456 * | -0.295 | 0.011 | 0.285 | 0.483 ** | 0.082 |
| Aggregation    | AI         | -0.764 ** | 0.480 ** | -0.267 | 0.442 ** | -0.570 ** | 0.028 |

Note: TP-trees and shrubs proportion; GP-grass proportion; WP-water proportion; LPI-largest patch index; AREA_MN-mean patch size; LSI-landscape shape index; FRAC_AM-area-weighted fractal dimension index; NP-number of patches; ENN_AM-Mean Euclidean nearest neighbor distance; AI-aggregation index. ** means at the 0.01 level (two-tailed), the correlation is significant. * means at the 0.05 level (two-tailed), the correlation is significant.

As for the GBI configuration indicators, their correlations with the LST\textsubscript{mean} and LST\textsubscript{std} varied among different blocks, too. Overall, only the AREA_MN was negatively correlated with LST\textsubscript{mean} in all block types; the LPI, FRAC_AM, and AI were negatively correlated with LST\textsubscript{mean}, while the ENN_AM was positively correlated with LST\textsubscript{mean} significantly in HMB and LLB, and no significant correlation was found in MHB; the LSI and NP were positively correlated with LST\textsubscript{mean} in MHB. Fewer indicators were identified to be significantly correlated with LST\textsubscript{std}, which were the LPI and AI in HMB, and AREA_MN and AI in MHB.

By comparing the absolute values of correlation coefficients between LST\textsubscript{mean} and GBI configuration indicators, we further found that the absolute values of coefficients for indicators that characterized GBI patches’ area and their aggregation, including the LPI, AREA_MN and AI, were generally higher than those for other indicators, and the absolute values of coefficients in HMB were also larger than those in LLB (Table 5). As for the FRAC_AM, the indicator characterizing the shape complexity of GBI patches, the absolute value of coefficient in HMB was found to be higher than that in LLB. Nevertheless, for the indicator of ENN_AM representing the connectivity of GBI, the absolute value of coefficient in HMB were smaller than that in LLB.

As a whole, both the correlation significance between LST and GBI’s pattern indicators and the absolute value of their correlation coefficients were significantly different; thus, it is important to emphasize the spatial morphological dependence of the GBI pattern influence on the UHI effect in BOT blocks.

3.4. Potential Adaptive LIHI Mitigation Solutions for Historical Downtown Blocks with Different Spatial Morphology

As a typical historical downtown area, Beijing Old Town (BOT) has been strictly protected to preserve the original build style and cultural features; any planning and design acts must be initiated on the premise of protecting the historical and cultural heritage [56,58,80]. Thence, a comprehensive and feasible GBI planning design for thermal mitigation in BOT might consider at least the following three aspects: urban morphology characteristics, the composition and configuration of GBI, as well as the policy terms and control intensity. Integrated with a broad review of requirements and guidelines of urban planning and management in BOT, we extracted the GBI measures permitted in BOT, and provided a set of thermal mitigation measures by GBI, as Table 7 showed. Based on this measure set, we provided an adaptive thermal mitigation solution using GBI for each block (Figures 6–8).
Table 7. Summary of GBI measures to mitigate the UHI in Beijing Old Town.

| Direction 1: Improvement for Construction of Urban Green and Blue Space System | Key Points | Requirements | Sources |
|---|---|---|---|
| Promoting street shading | Improve the construction of boulevard system, promote the transformation of street shading facilities. | Optimize plant communities and improve the quality of street shade. | Regulatory plan, 2020. |
| Increasing the area and accessibility of green space | Promote greening coverage, green space per capita, etc. | Constructing both community parks and small pocket green spaces on marginal land, unused land and etc. | Regulatory plan, 2020; Design guideline, 2019. |
| Enhancing the quality of green space | Improve the level of green vision ratio in various urban spaces. | Improve the three-dimensional greening scenery by reasonably vertical and roof greening. | Regulatory plan, 2020; Design guideline, 2019. |
| Improve greening construction mechanism | Promote public participation in greening construction and education. | Carry out public participation in greening construction activities of hutongs and courtyard. | Regulatory plan, 2020; Design guideline, 2019. |
| Optimize plant species selection | Select native plants such as acacia, mulberry, willow, pomegranate, begonia, etc. | | Design guideline, 2019. |

| Direction 2: Preservation of urban spatial matrix and historical features | Key Points | Requirements | Sources |
|---|---|---|---|
| Promoting the tree protection | Integrate trees preservation with street greening or public space design programs, strictly implement the protection of famous trees, large trees, old and historic trees. | Carry out the “one tree for one courtyard” replanting program. | Regulatory plan, 2020; Design guideline, 2019. |
| Promoting shading transformation of checkerboard-shaped street network | Enhance the proportion of boulevards, improve greening rate of street network by increasing the green space on both sides of streets. | | Regulatory plan, 2020. |
| Strengthening preservation and maintenance of traditional buildings and alleys | Strictly implement the requirements of historical buildings or buildings with traditional features can no longer be demolished. | Promote housing decrement renewal, carry out retreatment and renovation of illegal or makeshift buildings. | Master plan, 2017; Regulatory plan, 2020. |
| Regulating population density | Control resident density integrated with economic and social planning. | | Regulatory plan, 2020. |
| Reinforce street characteristics and features | Select the materials (e.g., greenery, wall, and pavement and etc.) consistent with historical features in design and management works. | | Regulatory plan, 2020; Design guideline, 2019. |

Note: Regulatory plan—Detail Regulatory Plan in the Functional Core Area of Beijing (Block Level) [58]; Design Guideline—Design Guidelines for the Protection and Renewal of Beijing’s Historical and Cultural Districts [56]; Master plan—Urban Master Plan of Beijing (2016–2035) [56].

- High GBI proportion and mid-rise blocks (HMB)

These blocks are mainly located in the central and southern regions of Beijing Old Town; e.g., West Chang’an Block, Donghuamen Block, TianTan Block, Taoranting Block, etc. There are larger bodies of water, parks and historical gardens concentrated in some blocks, and the land surface temperature is relatively low. Spaces available for greening in such blocks are relatively limited and scattered due to historical and cultural heritage protection regulations. Hence, the priority in the GBI planning and design is the optimization of GBI composition such as increasing trees, shrubs and water bodies in HMB blocks.

As for the optimization of GBI configuration, priority is firstly given to greening the paved, vacant or unused lands in the residential clusters where heat islands exist (Figure 5a). New green spaces also might be integrated with the renovation of shanty towns, dangerous houses, economical houses and public spaces, which is helpful to increase the average area of GBI patches in HMB. Most of the existing parks, gardens and green patches in HMB should be further enlarged or connected by building greenbelts and shaded walkways if possible. Higher green view rate (GVR) often indicating abundant vegetation and better
plant communities is better for cooling. The boulevard with comfortable street shading might be considered by urban planners, which is a GBI type with complex shape and high connectivity. However, it is notable for areas around royal palaces and gardens, ancient government offices, altars and temple architecture clusters that the greening form, including plant selection and layout, should be consistent with their own spatial style.

Figure 6. Thermal mitigation measures for a typical block in HMB. (a) Distribution of current LST hotspots in the block; (b) Identification of vacancies and breakpoints should be connected spatially in green spaces; (c) Typical thermal mitigation measures in HMB, numbered in order of priority; (d) Schematic diagrams of typical UHI mitigation measures; (e) A short description of adaptive thermal mitigation solutions in Figure 6c.

Figure 7. Thermal mitigation measures for a typical block in MHB. (a) Distribution of current LST hotspots in the block; (b) Identification of vacancies and breakpoints should be connected spatially in green spaces; (c) Typical thermal mitigation measures in MHB, numbered in order of priority; (d) Schematic diagrams of typical UHI mitigation measures; (e) A short description of adaptive thermal mitigation solutions in Figure 7c.
Figure 8. Thermal mitigation measures for a typical block in LLB. (a) Distribution of current LST hotspots in the block; (b) Identification of vacancies and breakpoints should be connected spatially in green spaces; (c) Typical thermal mitigation measures in LLB, numbered in order of priority; (d) Schematic diagrams of typical UHI mitigation measures; (e) A short description of adaptive thermal mitigation solutions in Figure 8c.

- Mid GBI proportion and high-rise blocks (MHB)

These blocks are more concentrated in the east and west sides of Beijing Old Town, mainly dominated by residential and commercial buildings (e.g., Wangjing SOHO and Chaonai Block and Fenghuiyuan Block), with almost no historical and cultural blocks inside. There is a high proportion of tall buildings that provide both ground spaces for greening and shade, which contributes to the fact that the area and intensity of heat islands in MHB is not as high as in HMB. However, a certain proportion of bare lands exists in MHB. Thus, the planning and design of GBI to mitigate thermal stress gives priority to retrofitting these bare lands into community parks and small pocket parks, or part playgrounds into lawns. These renewal measures could be integrated with the Urban Master Plan of Beijing (2016–2035) that requires such neighborhoods (non-historical and cultural blocks, the main components of MHB) to achieve a 500 m service radius coverage of green spaces, and to achieve the goal of park area per capita >6.8 m² by 2035.

Considering that the shape complex and fragmentation of GBI has a significant impact on thermal environment in MHB, it is also encouraged to enlarge isolated green patches and to connect them with boulevards into a network. There are many feasible ways to enhance the GBI network such as building linear greenbelts along streets, enlarging small gardens around buildings and improving vertical greening of buildings. Here, green stormwater infrastructure and multilayer plantation could be integrated with greenbelt planning, as well as green roof or roof gardens with energy-saving building transformation. All of the above can make for great contributions to the formation of a green, cool, shared nature space system for all.

- Low GBI proportion and low-rise blocks (LLB)

These blocks with a high percentage of historic and cultural blocks, such as Dashilar Block and Andingmen Block, are mainly located in the core and north of Beijing Old Town. Dense bungalows and two-storied houses, narrow public spaces and stricter protection requirements are among the top three challenges posed to thermal mitigation by way of GBI in LLB. It is most urgent to increase the GBI proportion and improve the GBI connectivity as much as possible; it is more feasible to greening streets and courtyards in LLB.

Greening priority is given to hutongs with more serious heat islands. Greening corridors by planting street trees, bioswales or flower stands along wider hutongs is more advocated because of the better connectivity and shape complexity. Street trees in LLB are mainly tall species with larger canopies such as acacia and elm, mostly old or famous. So,
the protection of large trees should be firmly implemented to improve their maintenance, the plant community structure of trees and shrubs and grasses that can be enriched around large, old trees.

For the narrow streets and alleys, the potential spaces for greening should be various and the greening form should be flexible due to the constraint of spaces. The building setback spaces, unused paved frontiers, reserving micro-courtyards, paved spaces around public transport stations in LLB could be greened into corner gardens, “one-meter gardens” or hedgerows, etc. Integrated with pavilions and planters, the planting ponds, flower beds or flower stands could also be used to green streets, walls and courtyards. All plants should give priority to persimmon, acacia, magnolia, begonia and other native plants with traditional cultural characteristics and ease to grow natively. For example, traditional plants such as Parthenocissus tricuspidata can be used on the greening of walls or houses, which can promote cooling and humidification benefits at the pedestrian height. Here, it is worth emphasizing that public participation is very important to courtyard and hutong greening in LLB.

Moreover, asphalt pavements are most used in hutongs; these pavements with dark color and low albedo will lead to deterioration of the thermal environment. Those materials might be replaced by high albedo materials in an urban renewal solution, giving priority to the traditional pavement materials with light color and high reflectivity such as strips of stone, stone slabs and gray processed bricks.

4. Discussion

It is increasingly acknowledged that urban morphology has an important influence on the formation and distribution of UHI in cities [16,32,33,81]. Previous studies have paid more attention to the spatial heterogeneity of UHI and its relationship with spatial morphology in a city, although blocks are taken as the analysis units. Our study extends these studies by focusing on the finer spatial morphology and its influence on UHI in the highly urbanized downtown blocks, using Worldview3 remote sensing data with spatial resolution of 0.3 m.

We found there was a significant UHI effect in Beijing Old Town, a famous and typical historical downtown region of Beijing in China, as reflected by the higher average surface temperature (LST mean of 33.06 °C) and smaller temperature difference (LST std and LST range were 2.09 °C and 25.25 °C, respectively). It was demonstrated as the contiguous warm matrix and concentrated hot patches in Figure 3c. The combined application of LST mean, LST std, LST range and Hot Spot Analysis (Getis-Ord Gi*) can better reflect the spatial heterogenous characteristics of UHI in highly urbanized blocks.

The correlation analysis between the LST indicators and morphological characteristics revealed that the impervious surface, vegetation and water cover proportion were the main land cover indicators influencing the average surface temperature and temperature differences in the study area, which was consistent with the results of most related studies [7,47,82]. Unlike previous studies which rarely associated the correlation analysis with the process of urban planning, this study conducted partial correlation analysis between the LST indicators and spatial structure feature of built-up by controlling the impervious surface, vegetation and water cover proportion.

Results showed that the building coverage ratio (BCR) and sky view factor (SVF) were positively correlated within the LST mean, which were consistent with findings of most studies [24,34,35,83]. The space crowd degree (SCD)—a less used indicator—was also positively correlated with LST mean, which reflected the difference of outdoor space encroachment by buildings in blocks of Beijing Old Town; thus, this indicator was very applicable in this study area. Meanwhile, all height-related indicators, including MH, HBI and HFD, were negatively correlated with LST mean, which was consistent with the findings of most studies [30,84–87]. This probably resulted from increasing and differentiating building height in one area that can lead to shadows provision, wind corridors enhancement, building land saving and blue or green spaces reservation, thus contributing
to UHI mitigation. A comprehensive comparison of the absolute values of correlation coefficients showed that BCR and MH were the most important built-up factors influencing the LST\textsubscript{mean}. Since these two indicators are often used in urban planning, future consideration for buildings management should be mainly from these two aspects to make adaptive UHI mitigation measures.

This study tried to meet the needs of urban planning in terms of analysis process setting and indicators and research unit selection. It will be meaningful and suitable for urban planning, as it can offer practical, operational guidelines for urban managers. We therefore focused on the correlation between LST and the composition and configuration of GBI in blocks with different morphological characteristics, for GBI had been recognized as the nature-based solution (NbS) to mitigate the UHI effect in cities. It was reflected that both the GBI composition (trees/shrubs, water bodies, or grasslands) and the GBI patch size and aggregation (AREA\_MN and AI) all contributed to reducing the LST\textsubscript{mean}, but partly contributed to increasing the LST\textsubscript{std}, and the significance of the coefficients differed in three types of blocks. Greater cooling potential can be provided by changing the patch area and aggregation degree among three types of blocks in Beijing Old Town, which is similar to the findings with Masoudi [13]. Besides, in the configuration section, the relationships were more consistent in HMB and LLB, and significantly different in MHB. The relatively consistent in terms of architectural structure between HMB and LLB might be one possible reason, as they are both dominated by hutongs and bungalows. It is also found that the absolute value of the correlation coefficient between GBI configuration and LST\textsubscript{mean} was higher in HMB and LLB, where low or medium-rise buildings dominate, than in MHB, where there are more high-rise buildings, suggesting that the contribution of building shadows on heat reduction may make the benefits of GBI on cooling less remarkable. Consequently, cooling strategies should be differentiated by block types.

There are also some aspects that can be further improved in our study. We applied the Pearson correlation analysis method, which is a simpler and commonly used method (which was applied in 68% of the relevant studies [78]). However, some studies pointed to the fact that the UHI phenomenon should be modelled locally instead of having an aggregated model for an entire area, as thermal environment characteristics are context sensitive, i.e., it varies significantly over space [63,88]. Although the block types were divided and conducted the correlation analysis separately, which avoided the impact of spatial context differences to some extent, some methods can provide more precise results of morphological indicators and LST; e.g., curve fit linear regression. We will take these methods into account in future studies [89]. Additionally, improving the ventilation environment has an important role in enhancing urban thermal environment, and the element of wind is also closely related to some important indicators in UP. Therefore, conducting the air path studies at block level by assessing current ventilation environment and proposing potential and existing ventilation corridors should be taken into consideration in further studies. Finally, in the description of urban 3D morphology, we used spatial structure indicators of buildings. However, as vegetated areas are an important composition of urban landscape, different plant types also have differences in 3D characteristics, which may have an impact on thermal environment. In the future, we can combine high resolution remote sensing data with LiDAR data to describe urban 3D morphology characteristics more comprehensively.

5. Conclusions

As the UHI effect and its associated consequences are expected to be more severe, mitigation of UHI has attracted increasing attention in urban studies. We followed a common but practice-oriented framework of UHI research to guide thermal mitigation solutions in this study. The spatial heterogeneity of UHI in blocks of Beijing Old Town (BOT) are analyzed, with an emphasis on the relationship between thermal environment and urban morphological characteristics, including basic land cover proportions and spatial structure indicators of built-up, as well as landscape composition and configuration of green and blue infrastructure within different spatial formed blocks.
Results showed that an obvious UHI effect was found in BOT, thermal environment within was block heterogeneous and significant hot and cold areas with significant high or low land surface temperature, respectively, were all found, both of which were highly aggregated spatially. Proportions of vegetated area and water body were found to have a significant negative impact on block LST, while the proportion of impervious surface (ISP) was the opposite, with the highest absolute value of correlation coefficient among land cover characteristic indicators, reflecting its dominance in LST influencing. Bare soil area, on the other side, the only land cover type of which proportion was not significant with LST. By excluding the effect from land cover indicators, we revealed the significant correlation between LST and several spatial structure indicators, i.e., building coverage ratio, mean height, highest building index, height fluctuation degree, space crowd degree and sky view factor. It also showed that coverage ratio and the mean height of buildings were the two primary indicators having the greatest impact on LST in BOT through the comparison of absolute values; thus, more attention can be paid to those two aspects in further urban renewal as they are commonly used in urban planning.

The above laid a certain foundation for classifying block types in BOT by their morphological characteristics, after which we analyzed the impact of a comprehensive selection of indicators characterizing the composition and configuration of GBI in different block types. It showed that the effectiveness of different indicators for guiding the construction of GBI in each block varies, but generally by optimizing blue-green space composition, increasing patch size, aggregation, dominance and connectivity, all therefore have potential for promoting a block thermal environment. It is hoped that adaptive GBI planning and design for block thermal mitigation could be conducted based on this correlation study in the future renewal of old downtown.

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Appendix A

Table A1. Description of urban morphology indicators.

| Category       | Indicators                        | Formula                               | Note                                                                 |
|----------------|-----------------------------------|---------------------------------------|----------------------------------------------------------------------|
| Land cover     | Impervious surface proportion (ISP)| $ISP = \frac{A_{IS}}{A} \times 100\%$  | $A_{IS}$, $A_{V}$, $A_{W}$, $A_{S}$ represents the area of impervious surface, vegetated area, water bodies, bare soil, respectively, $A$ is block area. |
| characteristics| Vegetated area proportion (VP)    | $VP = \frac{A_{V}}{A} \times 100\%$   |                                                                      |
|                | Water proportion (WP)             | $WP = \frac{A_{W}}{A} \times 100\%$   |                                                                      |
|                | Soil proportion (SP)              | $SP = \frac{A_{S}}{A} \times 100\%$   |                                                                      |
|                | Normalized difference vegetation  | $NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$ | $\rho_{NIR}$ represents the reflection value in the NIR band, $\rho_{RED}$ represents the reflection value in the red band [72]. |
| index (NDVI)   |                                   |                                       |                                                                      |
Table A1. Cont.

| Category                        | Indicators                                      | Formula                                                                 | Note                                                                                                                                 |
|---------------------------------|-------------------------------------------------|-------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Impervious surface (ISA)        | In this paper, ISA of urban area was extracted by linear spectral hybrid image element decomposition model. It mainly includes the minimum noise separation, pure image element processing, end element collection, linear spectral separation, result checking and correction of the pre-processed images [73,74] |
| Building coverage ratio (BCR)   | $BCR = \frac{A_{GBI}}{A} \times 100\%$         |                                                                         |                                                                                                                                     |
| Mean height (MH)                | $MH = \frac{1}{n} \sum_{i=1}^{n} H_i$          |                                                                         |                                                                                                                                     |
| Highest building index (HBI)    | $HBI = \frac{H_{max}}{\sum_{i=1}^{n} H_i} \times 100\%$ |                                                                         |                                                                                                                                     |
| Height fluctuation degree (HFD) | $HFD = H_{max} - H_{min}$                       |                                                                         | Hi, Fi refer to the height, volume, footprint and perimeter of the building No.i respectively, $n$ is the number of buildings, $A$ is the area of the block, $C = 3.0 \text{ m}$ is a constant, $H_{max}$ is the maximum height of the buildings in the block, $H_{min}$ is the minimum height of the buildings in the block [71]. |
| Average Volume (AV)             | $AV = \frac{1}{n} \sum_{i=1}^{n} V_i$          |                                                                         |                                                                                                                                     |
| Space crowd degree (SCD)        | $SCD = \frac{1}{H_{max} \times \sum_{i=1}^{n} \left( \frac{V_i}{A} \right)} \times 100\%$ |                                                                         |                                                                                                                                     |
| Floor area ratio (FAR)          | $FAR = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{F_i}{H_i} \right)$ |                                                                         |                                                                                                                                     |
| Building structural index (BSI) | $BSI = \frac{1}{n} \sum_{i=1}^{n} \left( F_i + P_i \right)$ |                                                                         | $\Omega$ is the sky view stereo angle, $\gamma_i$ is the effect of terrain height angle on azimuth; $n$ is the number of calculated azimuths ($n = 36$), and the spatial resolution is 5 m [75,76]. |
| Building surface area (BSA)     | $BSA = \frac{1}{n} \sum_{i=1}^{n} \left( F_i + P_i \right)$ |                                                                         |                                                                                                                                     |
| Sky view factor (SVF)           | $\Omega = 2\pi \left[ 1 - \frac{\sum_{i=1}^{n} \sin \gamma_i}{n} \right]$ |                                                                         |                                                                                                                                     |
|                                 | $SVF = 1 - \frac{\sum_{i=1}^{n} \sin \gamma_i}{n}$ |                                                                         |                                                                                                                                     |

Appendix B

Table A2. Description of configuration indicators of GBI.

| Category                      | Indicators                                      | Formula                                      | Note                                                                                                                                 |
|-------------------------------|-------------------------------------------------|----------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Patch Size                    | Mean patch size (AREA_MN)                        | $AREA_{MN} = \frac{A_{GBI}}{n}$              | $A_{GBI}$ is the number of GBI patches in a block. $\sum_{i=1}^{n}$ is block area.                                               |
|                               | Largest index (LPI)                              | $LPI = \frac{a_{MAX}}{A} \times 100$        |                                                                                                                                       |
| Patch shape                   | Area-weighted fractal dimension index (FRAC_AM)  | $FRAC_{AM} = \frac{1}{n} \sum_{i=1}^{n} \frac{2 \ln(0.25 P_i)}{\ln a_i}$ | $a_i$ refers to the area of the GBI patch number $i$, $n$ is the number of GBI patches in a block, $P_i$ is boundary length of GBI patch No.i. $E$ is total length of the boundary of GBI patches in a block. $A_{GBI}$ is coverage area of GBI in a block. |
|                               | Landscape shape index (LSI)                      | $LSI = \frac{0.25F}{A_{GBI}}$                |                                                                                                                                       |
| Fragmentation                 | Number of patches (NP)                           | $NP = n$                                     | $n$ is the number of GBI patches in a block.                                                                                      |
|                               | Area-weighted Euclidean nearest neighbor distance (ENN_AM) | $ENN_{AM} = \frac{1}{n} \sum_{i=1}^{n} D_{ij}$ | $D_{ij}$ is the nearest distance between GBI patch No.i and No.j, $n$ is the number of GBI patches in a block.                    |
|                               | Aggregation index (AI)                           | $AI = \left[ \frac{g_{ii}}{\max_{ij} g_{ij}} \right]$ | $g_{ii}$ is the number of similar neighboring patches of GBI in a block.                                                        |

Note: Mathematical formulas of above indicators are referring to McGarigal and Marks [67].

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