Research Article

Spatiotemporal Changes in the Urban Heat Island Intensity of Distinct Local Climate Zones: Case Study of Zhongshan District, Dalian, China

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Intensified due to rapid urbanization and global warming-induced high temperature extremes, the urban heat island effect has become a major environmental concern for urban residents. Scientific methods used to calculate the urban heat island intensity (UHII) and its alleviation have become urgent requirements for urban development. This study is carried out in Zhongshan District, Dalian City, which has a total area of 43.85 km² and a 27.5 km-long coastline. The mono-window algorithm was used to retrieve the land surface temperatures (LSTs), employing Landsat remote sensing images, meteorological data, and building data from 2003, 2008, 2013, and 2019. In addition, the district was divided into local climate zones (LCZs) based on the estimated intensities and spatiotemporal variations of the heat island effect. The results show that, from 2003 to 2019, LCZs A and D shrank by 3.225 km² and 0.395 km², respectively, whereas LCZs B, C, and 1–6 expanded by 0.932 km², 0.632 km², and 2.056 km², respectively. During this period, the maximum and minimum LSTs in Zhongshan increased by 1.365 °C and 1.104 °C, respectively. The LST and UHII levels of all LCZs peaked in 2019. The average LSTs of LCZs A–C increased by 1.610 °C, 0.880 °C, and 3.830 °C, respectively, and those of LCZs 1–6 increased by 2°C–4°C. The UHIIIs of LCZs A, C, and D increased by 0.730, 2.950, and 0.344, respectively, and those of LCZs 1–6 increased from 1.370–2.977 to 3.744–5.379. Overall, the regions with high LSTs are spatiotemporally correlated with high building densities. In this study, the land cover was then classified into four types (LCZs A–D) using visual interpretation and object-oriented classification, including forested land, low vegetation, bare ground, and water. Besides, the buildings were categorized as LCZs 1–6, which, respectively, represented low-density low-rises buildings, low-density high-rises buildings, low-density super high-rises buildings, high-density low-rises buildings, high-density high-rises buildings, and high-density super high-rises buildings.

1. Introduction

The urban population of China has grown significantly since the Chinese Economic Reform, with the permanent population urbanization rate of China reaching 60.60% in 2019 [1]. Although the rapid urbanization of China has promoted economic growth, it has also led to negative environmental consequences. According to the Fifth Assessment Report of the IPCC [1], the global average land surface temperature (LST) increased by 0.85°C from 1880 to 2012, with global warming [2] as the defining climatic trait of this period [3, 4].
areas) as the urban heat island (UHI) effect. The difference between urban and rural LSTs is defined as the urban heat island intensity (UHII), which is an important metric for identifying UHIs [17]. In recent years, UHII levels have increased due to the combined actions of global warming and extreme heat waves. In addition to reducing the comfort of urban living [18], this phenomenon also poses a significant threat to the health of urban residents [19, 20].

At present, two methods are commonly used to measure the LST. The first is based on on-site observations of air temperatures at ground monitoring stations, and the second uses the inversion of thermal-infrared (TIR) remote sensing data to retrieve the LST product. Compared to the conventional observation-based method, which is limited by the number of weather monitoring stations and the nonuniformity of their distribution [21], TIR remote sensing is more time-effective [22] and robust against topographic effects [23, 24]. Therefore, TIR remote sensing is an effective tool for studying the spatial distribution of the UHI effect [25]. Urban climate researchers worldwide have used TIR remote sensing to study the relationship between the UHI effect and land-use types [26, 27] or blue-and-green spaces [28] and to establish metrics for assessing the UHII [29, 30]. Although the UHI effect has been extensively studied, a standardized definition of UHII has yet to be agreed upon by the scientific community [17]. To this end, Auer [31] proposed a zonal approach to urban climatology, which was built upon by Stewart and Oke [32] to suggest urban climate zones (UCZs), where urban and rural landscapes are incorporated into the analysis to enable the description of temperature differences between different landforms. With this background, Mills and Alexander incorporated GIS technology with a standardized local climate zone (LCZ) classification framework to create the World Urban Database and Access Portal Tools (WUDAPT, http://www.wudapt.org) [33], which helped to standardize the definitions and characterizations of UCZs.

Studies of LCZs have generally been performed at large scales, e.g., at a city, provincial, or city cluster level [34–38]. In contrast, the spatiotemporal dynamics of street-level localities have rarely been studied. In this study, using the mono-window algorithm, high-resolution Landsat images from 2003, 2008, 2013, and 2019 were utilized in conjunction with contemporary building and meteorological data to determine the spatiotemporal variations in UHII for a number of LCZs. The findings of this study can serve as a scientific reference for urban planning researchers and guide efforts to improve the quality of urban residential environments.

2. Study Area

Zhongshan District is the financial and economic center of Dalian City, China. It is located in the eastern part (38°51′–38°55′30″N, 121°37′30″–121°42′30″E) of Dalian City, which includes 9 subdistricts (Figure 1) and has a total area of 43.85 km² and a 27.5 km-long coastline. Over the last decade, the Donggang subdistrict has undergone significant landscape changes as a result of land reclamation work, which has artificially altered the length and shape of its coastline. Such alterations are typical of Dalian City and other coastal cities. Hence, changes in the UHII of this region are likely representative of other coastal areas of China.

3. Data Sources

Dalian City is located in the northern warm temperate zone and has an oceanic, warm temperate monsoon climate. From 2003 to 2019, hot days, during which the UHI effect is most significant, occurred most frequently in August. The average August temperature has increased by 2.3°C over the past 20 years, albeit with fluctuations. In 2003 and 2019, the average August temperatures were 23.6°C and 25.9°C, respectively, reflecting intensified discomfort of urban environments in Dalian City. Therefore, we selected remote sensing images of Zhongshan in August to calculate its UHII.

Table 1 lists the remote sensing data, meteorological data, and building data used in this study, along with their sources. The remote sensing data are used for classifying the land use types, while the open source building data are employed for the detailed descriptions of building types. Building height and building density are indicative of building aggregation in the vertical and horizontal directions. To a certain extent, the two have the largest impacts on the urban form [39] and also correlate most strongly with the formation and development of UHIs [26]. Buildings were divided by height into three categories, per the 2019 Uniform standard for design of civil building (GB 50352–2019): low-rise residential buildings (≤27 m), high-rise residential buildings (27–100 m), and super high rises (>100 m). Based on the findings of previous studies [40] and the current state of the study area, the buildings were also divided into low-density buildings (≤40%) and high-density buildings (>40%).

4. Methods

4.1. Local Climate Zones. The Landsat data were first geometrically calibrated and then masked and cropped. A polygon grid in the Albers projection of the study area was then generated using the Fishnet tool in the ArcGIS software (ESRI), and its intersections with the vector building data were tabulated. The land cover was then classified into four types (LCZs A–D) using visual interpretation and object-oriented classification, and the buildings were categorized as LCZs 1–6. The technical framework of this process is presented in Figure 2. Finally, the UHII of each LCZ was calculated from the LSTs inverted using the mono-window algorithm.

The procedure for dividing an area into LCZs is as follows. First, the climate of an area is divided into a number of smaller LCZs according to variations in the underlying surface. The LCZs that represent urban and rural climates are then selected and the UHII is determined by calculating the differences in temperature between these zones. The LCZ classification framework comprises 17 subclassifications of
buildings (LCZs 1–10) and land cover (LCZ A–G) [32]. In this manner, we enhanced the LCZ classification system to suit the needs of this study. High-resolution contemporary Google Earth images of the 10 subclasses were also used to validate the land cover types in the study area. A total of 1,000 samples were selected for this study, 600 of which were used for classification. The remaining samples were used to verify the accuracy. A high level of classification accuracy was achieved, with Kappa coefficients of 0.934, 0.952, 0.914, and 0.963 for the 2003, 2008, 2013, and 2019 data, respectively.

4.2. LST Inversion. LST is an important parameter for studying surface energy balance, as well as characterizing the UHI effect. Methods for obtaining LSTs from inverted remote sensing data include the radiation transfer equation, mono-window algorithm, single-channel algorithm, and split-window algorithm. In an analysis of atmospheric water vapor contents estimated using the mono-window algorithm, Qin Zhi-hao and Ruieli [41, 42] found a significant negative correlation between atmospheric transmittance and LST estimation error. As Dalian City is located in the southernmost Liaodong Peninsula and experiences a hot and humid summer, its atmospheric transmittance is relatively low. Therefore, we selected the mono-window algorithm to retrieve the LSTs from the Landsat 5 TM and Landsat 8 TIRS 10 data. The equations for the mono-window algorithm are as follows (please note that all temperatures in this study are expressed in units of °C):

![Figure 1: Location of the study area.](image-url)
Ts = \frac{(a(1 - C - D) + T_a(b(1 - C - D) + C + D) - DT_a)}{C}.

C = \epsilon \tau,

D = (1 - \epsilon)[1 + (1 - \epsilon)\tau],

where Ts is the inverted surface temperature (K), a and b are empirical constants (a = -67.355351 and b = 0.458606), T_b is the brightness temperature (K), and T_a is the effective mean atmospheric temperature (K). C and D are intermediary variables, which are obtained from \epsilon (ground emissivity) and \tau (the atmospheric transmittance of the TIR band).

4.3. Calculation of UHII. Based on our augmented LCZ system and the definition of UHII given by Stewart and Oke [31], we defined the UHII of each LCZ as the difference between its mean LST (estimated using the mono-window algorithm) and that of rural areas, as shown in the following:

UHII_{LCZ} = \text{LST}_{LCZX} - \text{LST}_{LCZB},

where \text{LST}_{LCZ X} is the mean LST of all type-X LCZs and \text{LST}_{LCZ B} is the mean LST of LCZ B (low and short vegetation).

5. Results

5.1. Local Climate Zones. With the implementation of policies such as the Chinese Economic Reform, the urbanization of Dalian City has progressed at an accelerated rate. The accompanying changes in each LCZ are listed in Table 2. From 2003 to 2019, 0.759 km² and 0.040 km² of land were converted into LCZ A and LCZ D, respectively, but 3.983 km² and 0.435 km² of these zones were converted into other land use types. Overall, the coverages of LCZs A and D decreased by 3.225 km² and 0.395 km², respectively. During the same period, 1.129 km², 1.319 km², and 4.235 km² of land were converted into LCZ B, LCZ C, and LCZ 1–6, respectively, while 0.196 km², 0.687 km², and 2.179 km² of their lands were converted into other land use types. Overall, the coverages of LCZs B, C, and 1–6 increased by 0.932 km², 0.632 km², and 2.056 km², respectively. In Taoyuan, Laohutan, and Kuiying, large swaths of forested land were converted into construction land, roads, and areas with low vegetation cover. In Laohutan, Donggang, and Renmin Road, large amounts of riverine and marine areas were reclaimed and converted into residential areas, industrial and service areas, and roads.

From 2003 to 2019, the total area of construction land in Zhongshan increased substantially, and significant changes also occurred in terms of building heights and densities (Figure 3). The majority of low-density high-rises and super high-rises are located in the northern part of Guilin, the northeastern part of Navy Square, and along the border between Kuiying and Taoyuan, whereas high-density high rises and super high rises are mostly located in Qingniwajiao Road. Low-rise low-density and high-density buildings are mainly located in Laohutan, Taoyuan, and Renmin Road, and their lands were reclassified and converted into residential areas, industrial and service areas, and roads.

Figure 2: Technical framework of the method used in this study.
high rises, high-density low rises, and high-density super high rises.

5.2. Results of LST Inversion. The mono-window algorithm was used for LST inversion. The obtained data were validated against temperature data from ground-based weather stations and found to be highly accurate. The LST distribution in Zhongshan generally remained unchanged from 2003 to 2019 (Figure 4). High LST areas (red and orange-red zones) were mainly observed in the northwestern part of Zhongshan, which includes Renmin Road, Qingniwaqiao, Guilin, Kunming, and Navy Square, and low LST areas (blue and light blue zones) were mostly observed in Laohutan and Taoyuan. In 2003, the maximum LST in Zhongshan was 36.197°C (in the western part of Qingniwaqiao and at the border between Renmin Road and Donggang), and the minimum LST was 19.979°C (in the coastal areas of Taoyuan and Laohutan). The mean LST in Zhongshan in 2003 was 28.088°C. In 2008, the maximum LST was 33.382°C (mainly in Renmin Road, Qingniwaqiao, Guilin, Navy Square, and the center of Kuizing), and the minimum LST was 18.570°C (in the northern coastal areas of Donggang, southeastern coastal areas of Taoyuan, and coastal areas of Laohutan, which expanded due to land reclamation). The mean LST in Zhongshan in 2008 was 25.976°C. The coverage of high LST areas increased in 2008, compared to that of 2003, indicating a higher UHII. This may be attributed to significant landform changes and the large-scale conversion of forested lands and water bodies into construction land. In 2013, the maximum and minimum LSTs were 34.325°C and 21.128°C, respectively, and the mean LST was 27.726°C. The

| Land use types | Area in 2003 (km²) | Area in 2019 (km²) |
|----------------|-------------------|-------------------|
| LCZ A          | 15.769            | 19.752            |
| LCZ B          | 0.014             | 0.302             |
| LCZ C          | 0.079             | 0.560             |
| LCZ D          | 0.006             | 0.400             |
| LCZ 1-LCZ 6   | 0.660             | 20.428            |
| Sum            | 16.528            | 22.607            |

Table 2: 2003–2019 land use type transfer summary.
subdistricts with the highest LSTs were the same as those in 2008, but the coverage of the maximum LST area in Qingniwaqiao and Renmin Road was significantly larger in 2013. The high LST areas in Kunming, Guilin, Navy Square, and Kuying decreased to some extent, but the LSTs in Donggang increased in general. In 2019, the maximum, minimum, and mean LSTs in Zhongshan were 37.562°C, 22.083°C, and 29.823°C, respectively, and the distribution of LSTs in 2019 remained largely unchanged from that of 2013.

Figures 3 and 4 show that high LSTs are spatiotemporally correlated with high-density buildings; high-density areas have a large number of buildings, forming a large impervious surface that increases the LST. With rapid urbanization, the building densities in Zhongshan have increased over time and the peak LSTs in this district have also increased accordingly.

5.3. Calculated UHII Values. From 2003 to 2019, all LCZs exhibited fluctuating growth patterns and significant increases in their average LSTs and UHIIs (Figure 5). The average LSTs of LCZs A–C increased by 1.610°C, 0.880°C, and 3.830°C, respectively, while the average LSTs of LCZs 1–6 increased by 3.225°C, 3.226°C, 4.111°C, 2.639°C, 3.768°C, and 4.052°C (~2°C–4°C), respectively. As LCZ C mostly corresponds to bare, reclaimed lands near Donggang and the previously forested areas of Laohutan that were converted into residential and production land (which are mostly unused construction land as of 2019), it exhibits a particularly high average LST and UHII.

In 2003, the average LSTs of LCZs A–C were 24.331°C, 26.526°C, and 27.187°C, respectively, whereas those of LCZs 1–6 ranged from 27°C to 29°C. From 2003 to 2008, the average LST of LCZ B changed significantly, decreasing by 2.403°C; the LSTs of LCZs A and C also decreased by 1.450°C and 0.888°C, respectively, and those of LCZs 1–6 ranged between 27°C and 28°C. Among LCZs 1–6, LCZ 4 had the largest decrease in average LST of 1.003°C, whereas LCZ 6 had the smallest decrease of 0.061°C. From 2008 to 2013, the average LST of LCZ C increased significantly by 2.437°C; the average LSTs of LCZs A and B also increased by 1.988°C and 1.954°C, respectively. The average LSTs of LCZs 1–6 in 2013 ranged between 28°C and 30°C; the average LST of LCZ 6 increased by more than 2°C (2.225°C), while LCZ 2 had the smallest increase of 1.344°C. The average LSTs of the other LCZs increased by 1.379°C–1.941°C. From 2013 to 2019, the average LST of LCZ C continued to increase significantly by 2.281°C, and the average LSTs of LCZs A and B each increased by approximately 1°C (1.072°C and 1.330°C, respectively). The average LSTs of LCZs 1–6 ranged between 31°C and 32°C, with LCZs 5 and 6 having the largest and smallest increases, respectively, in average LST (2.612°C and 1.889°C, respectively). The average LSTs of the other LCZs increased by 2.206°C–2.517°C.

In 2003, the UHIIs of LCZs A and C were −2.195 and 0.661, respectively. The UHIIs of LCZs 1–6 ranged from 1.370 to 2.977, following the order LCZ 4 > LCZ 5 > LCZ 2 > LCZ 3 > LCZ 6 > LCZ 1. Although the LSTs of all the LCZs decreased in 2008, their UHIIs continued to increase significantly. The UHIIs of LCZs A and C were −1.241 and 2.177, respectively, and the UHIIs of LCZs 1–6 ranged from 3.337 to 4.535, following the order LCZ 5 > LCZ 4 > LCZ 3 > LCZ 2 > LCZ 6 > LCZ 1. In 2013, although the UHIIs of the other LCZs increased significantly, their UHIIs did not increase. The UHIIs of LCZs A and C were −1.207 and 2.660, respectively, and the UHIIs of LCZs 1–6 ranged from 2.762 to 4.515, following the order LCZ 4 > LCZ 5 > LCZ 3 > LCZ 6 > LCZ 2 > LCZ 1. In 2019, all the LCZs reached their maximum LST and UHII values. The UHIIs of LCZs A and C were −1.465 and 3.611, respectively, and those of LCZs 1–6 ranged from 3.744 to 5.379, following the order LCZ 5 > LCZ 4 > LCZ 3 > LCZ 2 > LCZ 6 > LCZ 2 > LCZ 1.

6. Discussion

6.1. Improvements to Model Accuracy. In terms of scale, previous studies of the UHI effect have mainly focused on large-scale spatial analyses at a provincial or city cluster level using low-resolution remote sensing images. In contrast, this study used high-resolution Landsat TIR data to study the spatiotemporal variations of UHI over a small region. In terms of methodology, most studies have used the urban landscape index and land-use types to explain changes in LST or UHI based on the two-dimensional (2D) layout of cities. For example, Fabeku et al. used satellite-derived index maps and explained that the significant increase in the LST of Ibadan was caused by the large-scale conversion of vegetated land into construction land [43]. Based on MODIS and Landsat remote sensing images, Wang et al. used models to extract NMDI, IBI, and NDBI indexes to explore their relationship with LST [44]. However, this approach overlooks...
the constraints imposed by three-dimensional (3D) buildings on urban morphology, which can influence urban heat environments [45, 46]. In this study, we used an LCZ classification framework to account for 3D urban morphology attributes such as building height and building density. The LCZ classification framework was also modified according to the actual conditions in the study area and previous findings. By using a multiperspective method to compute the UHII of the study area, we effectively improved the practical implications and scientific rigor of our UHII calculations.

In summary, we conducted an empirical study of the UHI effect using the LCZ classification framework and fused 2D urban layouts with 3D morphological attributes to investigate spatiotemporal UHII variations from multiple perspectives. In addition, we analyzed spatiotemporal variations of LST and UHII in the study area over a comparatively long timescale. Whether and how the process of urbanization affects global climate change has consistently attracted significant attention over the last few decades. The results presented in this study clearly show how the 3D form of urban buildings (height and density) affect the quality of the urban thermal environment. It provides a scientific reference for government departments to aid in relevant decision-making in matters, such as urban planning and land use approval. Furthermore, the study enriches theoretical research on urban microclimate.

6.2. Limitations. This study had a few limiting factors and shortcomings. For example, the high-resolution Landsat TIR data used in this study are not sufficiently precise to provide detailed characteristics of the thermal-infrared features of the ground surfaces. Although the building data used in this study were calibrated in Google Earth Pro 2019, our data deviated slightly from real building data. Only building height and building density were used to represent building parameters, because they have the largest influences on urban morphologies and correspond most directly to the UHI effect. However, the effects of heat retention capacity and sky view factors on urban heat environments were not considered [45, 46]. Furthermore, we focused on investigating the effects of building morphology and land use type on UHII because, along with artificial heat sources, they are currently believed to be the main determining factors of UHII. However, we did not consider other factors such as artificial heat sources and building materials [47–49], which might result in localized UHII estimation errors.

Although the above limitations will affect the accuracy of the findings to some extent, they do not affect the objectivity or scientific rigor of this study. To resolve these issues, we plan to use long and accurate time series data from multiple sources to further investigate spatiotemporal variations in the UHI effect.

7. Conclusions

In this study, remote sensing, meteorological, and building data were used to investigate the spatiotemporal dynamics of the UHII of the LCZs in the Zhongshan District of Dalian City. The findings of this study are as follows:

1. Rapid urbanization has led to significant changes in urban land use and conversions of land types. From 2003 to 2019, the coverages of LCZs A and D decreased by 3.225 km² and 0.395 km², respectively, whereas the coverages of LCZs B, C, and 1–6 increased by 0.932 km², 0.632 km², and 2.056 km², respectively. The number of low-density high rises and super high rises increased in Laohutan and Taoyuan, and low-density low-rise buildings became increasingly dominant in Guilin. The number of buildings in Donggang also increased over time. On the whole, low-density high rises, high-density low
rises, and high-density high rises have become more common in Zhongshan.

(2) High LST regions usually contain large aggregations of high-density buildings and appear to be spatio-temporally correlated. High LST areas (red and orange-red areas) are concentrated around Renmin Road, Qingniwaqiao, Guilin, Kunming, and Navy Square, whereas low LST areas (blue and dark blue zones) are mostly located around Laohutan and Taoyuan. Over the past 20 years, the maximum and minimum LSTs of Zhongshan have increased by 1.365°C and 1.104°C, respectively.

(3) In 2019, all LCZs reached their maximum LST and UHII values. The average LSTs of LCZs A–C increased by 1.610°C, 0.880°C, and 3.830°C, respectively, and the average LSTs of LCZs 1–6 increased by approximately 2°C–4°C. The UHII of LCZs A and C increased by 0.730 and 2.950, respectively, and those of LCZs 1–6 increased from 1.370–2.977 to 3.744–5.379.

Data Availability
Data are available on request.

Conflicts of Interest
The authors declare that there are no conflicts of interest.

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