

Article

Analysis and Optimization of Thermal Environment in Old Urban Areas from the Perspective of “Function–Form” Differentiation

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Abstract: High-density urban areas have spatial characteristics, such as complex functions, population gathering, and complex forms, that lead to more severe urban heat island effects. Systematically evaluating the thermal environmental benefits of urban spatial forms to optimize the urban physical environment is important. In this study, Tianjin’s central urban area, which is a typical representative of high-density urban areas, was selected to invert the multi-period land surface temperature by relying on the existing two- and three-dimensional morphological data set of communities. The multi-scale geographically weighted regression model was used to fit the regression relationship between the urban land surface temperature and spatial morphological parameters. From this, the influencing factors of different types of existing community spaces and their spatial stabilities were explored. The results show the following: (1) The summer surface temperature varies greatly in the central urban area, and the high-temperature areas are mainly distributed in the industrial, residential, and commercial districts. (2) The MGWR model has the better model-fitting ability. The positive influence coefficients of temperature include ISP and BD, while the negative influence coefficients are BSD, BH, NDVI, and SVF. (3) There is significant spatial heterogeneity in the impact coefficients among the blocks that can be targeted to mitigate the heat island effect. This study provides ideas for optimizing the spatial morphological parameters of surface temperature in urban centers. Future challenges include increasing the spatial morphological parameter selection range, dissecting the interactive relationships between spatial morphological parameters and their effectiveness on the surface temperature, and refining the study’s spatial and temporal granularity.

Keywords: old urban areas; spatial morphology; geographically weighted regression model; surface temperature



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1. Introduction

With global climate change intensifying, the urban heat island phenomenon has become an unavoidable environmental problem in urban development [1]. High-density urban areas are characterized by “complex function–population–complex morphology”, and these characteristic factors have complex multi-directional parallel effects on the urban surface temperature, which can promote local surface temperature increases and cause the urban heat island effect.

In recent years, research on the impact of high-density urban areas’ spatial morphologies on the thermal environment has gradually progressed, primarily focusing on the effects of two-dimensional land cover and three-dimensional spatial morphology on spatial and temporal land surface temperature changes and proposing corresponding optimization strategies [2]. Researchers obtained the general picture of surface temperature distribution from the scale of urban built-up areas and urban residential areas. Their studies mainly include the following three aspects: (1) exploring surface temperature’s spatial distribution characteristics in established high-density communities [3], (2) analyzing the influence of

spatial morphological parameters on the land surface temperature [4], and (3) proposing planning measures to mitigate the urban heat island effect. Based on determining the mechanism of urban spatial morphological parameters' influence on thermal environments, this study explores feasible solutions for optimizing the thermal environment regarding planning and implementation [5].

At present, researching urban morphological parameters' thermal environment effect has achieved certain results, but there is still room for improvement in terms of research contents, research methods, and statistical caliber, which can be summarized in the following three aspects. (1) The differences in spatial morphology's effects on the thermal environment in urban plots with different functions are considered less. On the one hand, the spatial form of urban neighborhoods and the dominant function of urban neighborhoods should be used as the basis to comprehensively explore the multiple influence paths of urban thermal environments. On the other hand, the spatial form parameters should be selected from the "temperature increase + temperature decrease" perspective to explore their environmental performance. (2) The existing studies are less likely to fit the correlation function between spatial parameters and the thermal environment from multiple scales and to pay attention to the spatial heterogeneity distribution of morphological parameters and the difference in thermal environment performance caused by morphological parameters. (3) Existing studies mostly use standardized grids as statistical units, which cannot fully characterize the effects of scale differences on the surface temperature in old urban areas. Urban blocks can be used as the basic statistical unit to avoid statistical loss of spatial parameters caused by single dimensional pixels and to explore the thermal environmental performance of morphological parameters in combination with classifying dominant functions to improve the study's practical guidance.

Responding to the above problems, this paper constructs a research method to classify and analyze the relationship between urban spatial morphological factors and the urban thermal environment and explores the influence of spatial morphological scales on thermal environments with existing high-density communities in Tianjin from the plot function perspective, which includes the following three steps. Firstly, using Landsat 8 satellite remote sensing images to invert Tianjin city's surface temperature, multiple time series were used to characterize the surface temperature's spatial and temporal distribution and the heat island footprint's spatial and temporal variation. Secondly, a "subtype-subscale" spatial morphology database was constructed using the identified functional types of land parcels as statistical units. Again, the regression models of the spatial morphological parameters and surface temperature were fitted, and the seasonal differences in the OLS, GWR, and MGWR models' fitting performances were compared. Finally, the dominant regions of the summer heat island drivers were classified, the morphological parameters' influence was determined, and corresponding optimization strategies are proposed. This study can help urban planners to evaluate the thermal environment's influencing factors in central urban areas and provide references for the targeted regulation of neighborhood spatial morphological parameters.

2. Literature Review

2.1. Links between Morphological Parameters and the Surface Temperature

The function of urban parcels and buildings' spatial morphologies can significantly affect urban surface temperatures, thus causing the heat island effect in cities, which is a phenomenon that has attracted urban researchers' attention [6,7]. Currently, two- and three-dimensional perspectives have been constructed to observe the effect of urban spatial morphological parameters on the surface temperature. The two-dimensional morphological indicators include the urban density (BD), NDVI index, and percentage of impervious surface (ISP), while the three-dimensional morphological indicators mainly include the building height (BH), floor area ratio (FAR), and sky openness (SVF) [8]. These urban morphological parameters can change the ecological service system and physical property changes in the ground surface in urban areas, as well as cause microclimatic changes, thus

synthetically affecting the difficulty of heat exchange between the area and the surrounding environment; this phenomenon is more prominent in cities' old urban areas. Simultaneously, due to old urban areas' high population densities, intensive human activities can also increase local heat emissions. Furthermore, the aggregation degree of urban spatial morphological parameters is often significantly correlated with crowd activities, so the study of spatial morphological parameters also implies considering the impact of crowd activities. For this reason, researchers have investigated the impact of urban spatial morphological parameters on the surface temperature at multiple scales; for example, Li Z used an intelligent algorithm to quantify the multi-scale marginal contribution of 3D spatial morphological parameters on surface temperature [9]. On this basis, Berger [10] coupled the use of 2D and 3D data to construct a relationship function between spatial morphological parameters and surface temperature around meteorological stations in the Berlin area, and their results demonstrated that 2D and 3D spatial morphological parameters had the highest model superiority when they simultaneously participated in model fitting, with parameters such as vegetation cover and building volume ratio exhibiting diverse surface temperature influence coefficients in different neighborhoods. Gardes [11] conducted a similar study on 42 cities in France and found that, for cities located less than 10 km from the coastline, meteorological factors' influence on the surface temperature exceeded the urban spatial morphological parameters' contributions, which implies that the city type and the specifics of urban parcels should be considered when constructing urban surface temperature correlation coefficients based on spatial morphological parameters.

2.2. *Links between Urban Functional Zone (UFZ) and Urban Surface Temperature Studies*

Traditional urban surface temperature studies are often carried out on a two-dimensional "urban–rural" scale, with less research on specific parcels within cities, while urban planning activities for surface temperature improvement need to be guided more directly [12]. Neglecting the spatial heterogeneity of the effectiveness of parcel function and spatial morphological parameters on surface temperature may lead to incorrectly assessing surface temperature and its effects. Therefore, some scholars have introduced urban zoning to explore these diverse influences and have adopted the local climate zone (LCZ) to discuss the surface temperature problem, which divides urban areas according to different ground covers and building morphologies to form several homogeneous parcel units with similar spatial morphological parameters and then classifies and discusses the surface temperature of the same parcel units [13,14]. In recent years, the traditional LCZ model has been accordingly extended, among which the urban functional zone (UFZ) is widely used, being a classification aid in developing differentiated urban planning control measures that can directly guide micro-detailed planning efforts [15]. UFZ divides the study area according to differences in socio-economic and population activities, reflecting the differences in the dominant functions of urban parcels; moreover, the spatial boundaries of UFZs are usually enclosed by urban streets and natural landscapes [16]. In this paper, we construct a UFZ model for the old urban area of Tianjin, China, and explore the relationship between the spatial morphological parameters of different types of UFZs on the surface temperature from two levels: (1) Different types of UFZs have different surface temperature thresholds, so the coefficients of the same spatial morphological parameters' influence on different UFZs' surface temperatures need to be quantified. (2) The spatial scale differences in different spatial morphological parameters' effects on surface temperatures in the same UFZ need to be measured.

2.3. *The Application of GWR and MGWR to Model the Surface Temperature*

When exploring the coefficients of spatial morphological parameters' influence on surface temperature, researchers often use global models to estimate the relationships between independent and dependent variables, including least squares (OLS) [17], stepwise regression [12], and machine learning models [9], to investigate the intervention effects and influence coefficients of urban spatial morphological parameters on surface temper-

atures from multiple scales. Such global models cannot consider spatial autocorrelation and spatial non-smoothness problems [18]. The urban surface temperature is typical of spatially autocorrelated data, where the value of the surface temperature at one location is influenced by the surface temperature at nearby locations. Therefore, the parameters obtained using the global regression model are averaged over the entire region rather than specific coefficients for specific locations within the region. These limitations weaken the model's ability to predict local variations in the surface temperature and thus weaken the results' generalization for specific types of regions. The GWR approach overcomes these limitations because the model accounts for spatial variables' non-stationarity, and GWR models' effectiveness in estimating spatially varying factors' effects has been extensively tested in various fields. For example, Zhao C et al. [19] used a GWR geographically weighted regression model at the urban scale and found that the model had a significant effect on the surface temperature's non-stationarity and could explain the influence factor's local variability on the surface temperature. Duncan [20] used the model to investigate the local relationship between land cover/use (LUC) patterns and the surface temperature. The study by Siomn [21] using the GWR model similarly demonstrated the existence of a non-smooth relationship between buildings and vegetation on the surface temperature. In addition, since the classical GWR model has a uniform bandwidth for each influencing factor, some scholars have improved it using the MGWR model [22], which allows for differences in each influencing factor's range of influence and allows for a more specific representation of spatial morphological parameters' ability to influence the surface temperature [23]. This can bridge the gap between urban climate research and urban planning applications and facilitate the application of surface temperature research results to actual urban planning practices [24,25]. Table 1 summarizes the reviewed studies on surface temperature and spatial morphological parameters using the above-mentioned models.

Table 1. The effects of spatial morphology parameters on thermal environment.

Author	Research	Cities	Methodology	Parameters
Simon [21]	Determine the relationship between biophysical variables and building spatial forms and surface temperatures.	Dar es Salaam Metropolitan, Tanzania	OLS, GWR	NDVI, NDBI, SAVI, building density
Shaker [26]	Use geographically weighted regression (GWR) to assess local patterns of correlated associations.	New York, US	OLS, GWR	SVF, land use cover, tree canopy class configuration, buildings class configuration, roads class configuration
Sihang Gao [27]	Explore the spatial heterogeneity in the relationship between landscape composition, urban morphology, urban functions, and land surface temperature (LST).	Wuhan, China	OLS, random forest model, SGWR, MGWR	BD, BH, BVD, SVF, NDVI, ISF
Duncan [20]	The effects of different vegetation configurations on land surface temperature were studied.	Perth, Australia	OLS, GWR, random forest model	Proportion of vegetation, land use cover

Table 1. Cont.

Author	Research	Cities	Methodology	Parameters
Soltanifard [28]	Discuss the spatial non-stationarity and spatial scale effect of land surface temperature in urban areas.	Mashhad, Iran	PCA OLS, GWR	Land use cover, population density, building density and height
J.R.Nelson [29]	The unequal community heat exposure caused by spatial differences in vegetation cover is studied.	Arizona metropolitan, US	OLS, GWR	Dwelling density, population density, tree density
Shahfahad [30]	The effects of land use/land cover (LU/LC) change on surface heat island intensity (SUHI) and urban thermal comfort were analyzed.	Delhi, India	OLS, GWR	Land use cover
Basu [22]	The patch-level correlation between green space and land surface temperature was discussed based on time and space.	Raiganj, India	OLS, GWR, MGWR	Landscape metrics
Budhiraja [31]	Four sub-cities in Delhi NCR, India, are classified using local climate zone (LCZ) and then analyzed for thermal performance and compactness.	Delhi, India	OLS	Area, population density, LCZ composition

3. Materials and Methods

3.1. Study Area

Tianjin is in the northeast of the North China Plain at the intersection of tributaries of the Haihe River. It has a temperate monsoon climate that is mainly affected by monsoon circulation, with a hot summer and cold winter and four distinct seasons. This paper's study area is the central urban area within Tianjin's outer ring road, covering an area of about 334 km². This region was developed earlier, has a large population, mixed land use, and has many historical buildings and various industrial sites. Complex urban spatial forms will greatly impact this region's surface temperature. To better calculate spatial form factors' influences on the land surface temperature in different types of blocks, they were classified into six types: industrial, residential, commercial, business office, public service, and green park (Figure 1).

3.2. Data Sources

The data used in this study mainly include satellite remote sensing images, urban land use functional zoning, and urban spatial form vector data. The former data are sourced from Landsat 8 satellite remote sensing images with a resolution of 30 m. The documents can be downloaded from the Geospatial Data Cloud (<http://www.gscloud.cn/> (accessed on 6 May 2022)) and the U.S. Geological Survey (<https://www.usgs.gov/> (accessed on 6 May 2022)). Among them, the collection time of the four summer images from 2017 to 2020 is 2 am, and the total collection interval is less than one year with significant seasonal characteristics. The data acquisition time, sensor, strip number, and image cloud cover are shown in Table 2. The land use functional zoning data are from the 2018 Chinese land-plot scale urban land use data set, which was opened by the Gong P team of Tsinghua University in 2019 [32]. This data set uses multi-source data and machine learning algorithms to classify land use with high credibility.

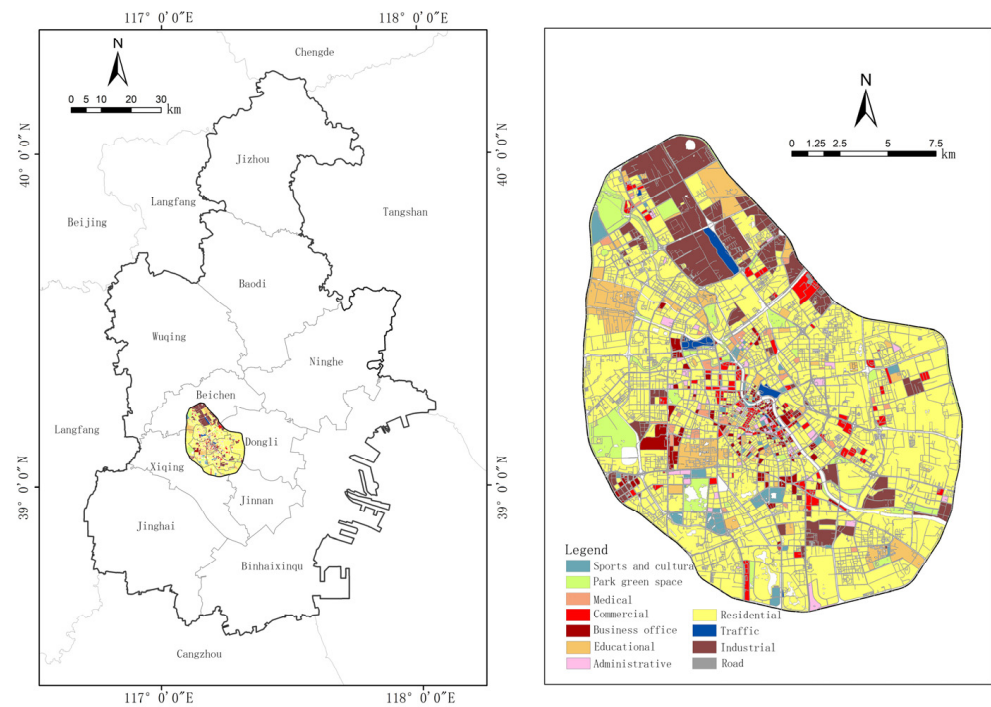


Figure 1. Research area.

Table 2. Data source statistics of remote sensing images.

Imaging Time	Satellites and Sensors	Strip Number		Cloud Cover/%
12 August 2017	Landsat 8 OLI_TIRS	122	33	3.91
23 August 2018	Landsat 8 OLI_TIRS	122	33	3.38
27 September 2019	Landsat 8 OLI_TIRS	122	33	2.95
5 March 2020	Landsat 8 OLI_TIRS	122	33	0.9
28 August 2020	Landsat 8 OLI_TIRS	122	33	1.74
16 November 2020	Landsat 8 OLI_TIRS	122	33	2.83
3 January 2021	Landsat 8 OLI_TIRS	122	33	5.28

3.3. Research Methods

3.3.1. Surface Temperature Inversion

In this study, the traditional algorithm based on the atmospheric radiation model, radiative transfer equity (RTE), is used to invert the surface temperature. The algorithm's main principle is to subtract the deviation value of the atmospheric influence from the total amount of thermal radiation observed by satellites. Then, the surface heat radiation intensity is converted into the corresponding surface temperature, and the specific calculation formula is as follows:

$$T_s = \frac{K_2}{\ln\left(\frac{K_1}{B(T_s)} + 1\right)}, \quad (1)$$

$$B(T_s) = \frac{[L_\lambda - L_\uparrow - \tau(1 - \varepsilon)L_\downarrow]}{\tau\varepsilon} \quad (2)$$

where T_s refers to the true surface temperature in degrees Celsius; $B(T_s)$ refers to black-body emissivity; ε refers to the specific surface emissivity; τ refers to the atmospheric thermal infrared band's transmittance; L_λ is the image radiation calibration; $L_\uparrow$ is the atmospheric upward radiation intensity; $L_\downarrow$ is the downward radiation intensity of the atmosphere; and K_1 and K_2 are the coefficients.

3.3.2. Selection of Fitting Model

(1) Ordinary least squares method (OLS)

This is a classical statistical analysis model, which is often used to fit the correlation model between the impact factors and land surface temperature from a global perspective.

(2) Geographically weighted regression model (GWR)

The geographically weighted regression model (GWR) is a location-dependent model. Based on the global model and non-parametric local weighted regression, the evaluation function is fitted, and the regression parameters are estimated in each region within the research scope to reflect the spatial non-stationarity of the spatial form parameters' influence on the land surface temperature [33]. The formula is as follows:

$$Y_i = \sum_{k=1}^p \alpha_k(u_i, v_i) X_{ik} + \varepsilon_i \quad (3)$$

where Y_i is the land surface temperature at point i , $\alpha_k(u_i, v_i)$ is the regression coefficient of each spatial form parameter at point i , X_{ik} is the value of each spatial form parameter index at point i , p is the number of spatial form indicators, and ε_i is a constant term.

(3) Multi-scale geographically weighted regression model (MGWR)

Compared with the classical GWR model, the MGWR model improves the unified bandwidth problem in the calculation process of the former, allowing the intervention range of the impact factors (bandwidth) to change on the whole parameter's surface, thus allowing the local correlation coefficients of different independent variables to be inconsistent in scale, so that all impact factors can establish a mathematical relationship model based on the optimal bandwidth and dependent variable [34]; the formula is as follows:

$$Y_i = \sum_{k=1}^p \alpha_{bwk}(u_i, v_i) X_{ik} + \varepsilon_i \quad (4)$$

where all parameters are the same as in Formula (3), and α_{bwk} is the optimal bandwidth for calibrating the regression relation.

4. Results

4.1. Spatial Morphological Characteristics of High-Density Old Urban Areas

The block building density (BD), impervious water ratio (ISP), and normalized vegetation index (NDVI) were used to characterize the physical environment's two-dimensional morphological characteristics in the central urban area. The average building height (BH), average floor area ratio (FAR), standard deviation of the building height (BSD), and sky openness (SVF) were used to characterize the physical environment's three-dimensional morphological characteristics in the central urban area. The spatial form parameters are shown in Table 3. The region's overall building density is relatively high, and the space form parameters of each functional area have a large interval gap. For example, due to the large building volume, the proportion of impervious water in traffic land is much higher than in other functional land. Commercial, residential, and industrial blocks have a large threshold space for the building density and NDVI index because of the rich building space combination. Public management and service land, commercial land, and residential land all have ultra-high plot ratio land, and the land's average height, the building height's standard difference, and other values vary within the same large range. The building space forms of these three land types are relatively complex, and the areas with high plot ratios and high densities may generate and gather many heat sources, reduce the airflow rate, and aggravate the heat island effect. Accordingly, the variation interval of the sky openness value of traffic land and park green space is small, indicating that the building space densities of these two types of land are low, which can cause urban cold islands with local cooling effects.

Table 3. Spatial form parameters of the central urban area.

		Traffic	Public Administration	Commercial	Residential	Industrial	Park
2D	BD	0–0.64	0–0.83	0–0.899	0–0.94	0–0.95	0–0.83
	ISP	0.801–1	0.01–1	0.293–1	0–1	0.017–1	0.01–1
	NDVI	0–0.484	0–0.699	0–0.564	0–0.72	0–0.66	0–0.72
	BH	0–86	0–177	0–360	0–199	0–141	0–72
3D	FAR	0–9.99	0–62	0–95	0–39.89	0–16.19	0–8.21
	BSD	0–77	0–86	0–174	0–123.66	0–136.99	0–64.93
	SVF	0.49–1	0.232–1	0.29–1	0–1	0–1	0.349–1

The spatial morphological parameters' spatial distribution is shown in Figure 2. The overall ISP index is relatively high in the two-dimensional morphological characteristic distribution. Most blocks in the six districts of the city are in the 0.91–1 range, and the coastal rivers decline to the northwest and southeast, respectively. The spatial distribution of NDVI and the SVF index were consistent, and the distribution trend was increasing from the center to the outer ring. Most of the blocks showed the development status of “more hardening-less vegetation-high density”. In the three-dimensional shape characteristic distribution, the average height of blocks (BH) and the standard deviation of blocks (BSD) are similar. The average height of blocks within the inner ring is greatly different, and the average height is higher in the north and lower in the south. Many blocks with large internal height differences have been distributed at the intersection of the Sanhe River and along Nanjing Road. It is in a block with a large height difference and an inner circle within the residential style difference. The block building density distribution and floor area ratio are similar, showing a “high center, low around” distribution. Many high floor area ratios and high-density blocks are distributed in the inner ring. There are more newly developed residential areas between the central and outer ring, and the average block height is higher, but the block building density and floor area ratio are lower than those in the inner ring. To summarize, problems such as a high development intensity, poor ventilation conditions, and the low ecological suitability of land cover exist in Tianjin's central urban area. Such an urban architectural form is bound to greatly impact the near-surface heat field dominated by the north–south wind in Tianjin.

4.2. Spatial and Temporal Distribution Characteristics of Heat Islands

4.2.1. Temporal and Spatial Distribution of Urban Surface Temperature

Landsat 8 remote sensing images were used to obtain the summer surface temperature from 2017 to 2020 (Figure 3) and the four seasons' surface temperature in 2020 (Figure 4) in Tianjin's central urban area. The natural discontinuous point method was used for classification. The summer high-temperature area in the central urban area decreased year by year, and the maximum surface temperature also decreased year by year, from 46.87 °C–56.75 °C in 2017 to 41.02 °C–48.96 °C in 2020. The minimum surface temperature increased slightly, from 23.59 °C–34.91 °C in 2017 to 28.52 °C–32.44 °C, and the temperature range decreased from 30 °C to 20 °C. The high-value area distribution shifted from contiguous agglomeration to point-like dispersion, and the high-value areas with summer surface temperatures were mainly concentrated in Hongqiao District, Nankai District, Heping District, western Hedong District, northern Hexi District, and other residential or industrial districts (Figure 3). The land surface temperature's seasonal variation was obvious, and the centripetal trend of the high-value area was obvious in the summer and winter. The high-temperature space in spring presented a chain distribution, and the high-temperature space in autumn was mainly located on the Haihe River's west bank and the Ziya River's south bank. The high-temperature patch of the Tianmu Town Industrial Park in the Beichen District significantly shrank (Figure 4).

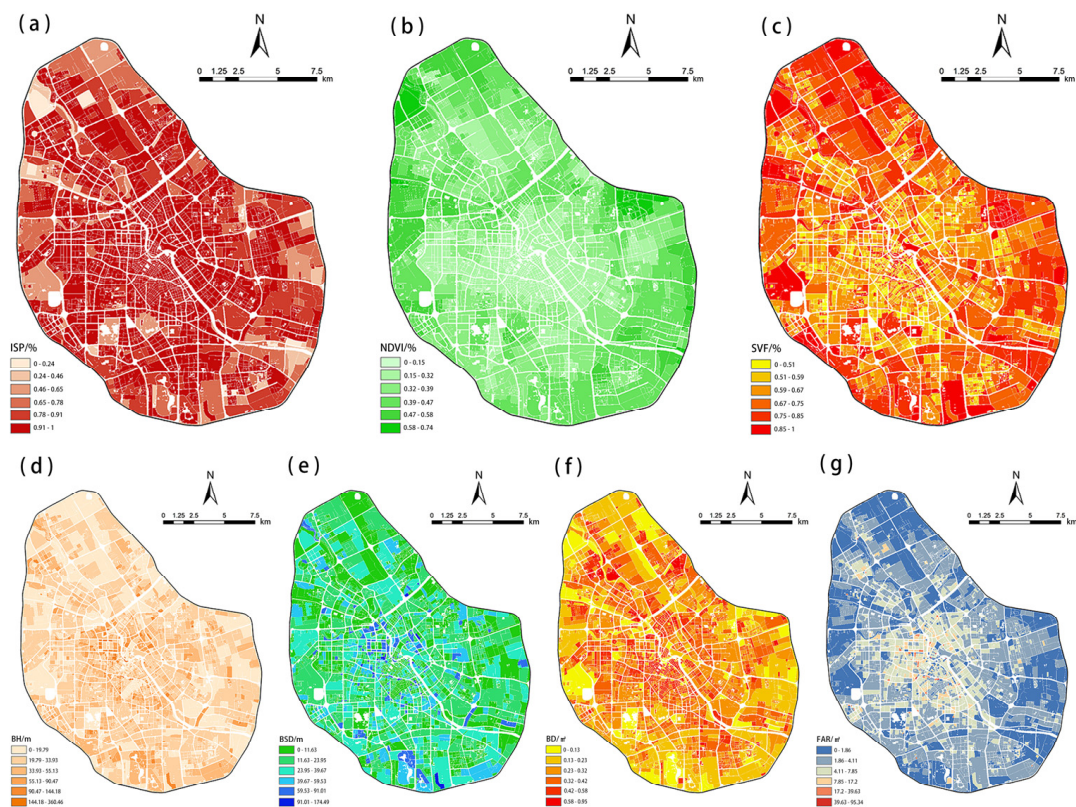


Figure 2. Distribution of urban form characteristic parameters. (a) The proportion of impervious water surface, (b) NDVI index, (c) sky openness, (d) the average height of block buildings, (e) standard deviation of block building height, (f) block building density, and (g) block floor area ratio.

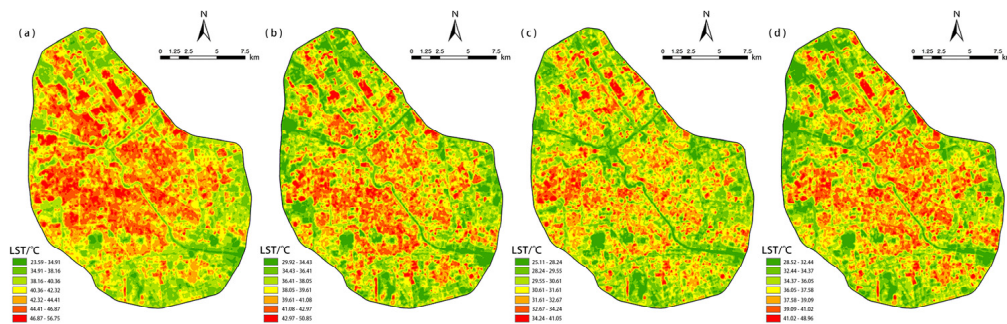


Figure 3. Inversion results of summer land surface temperature in Tianjin from 2017 to 2020. (a) Summer 2017, (b) summer 2018, (c) summer 2019, and (d) summer 2020.

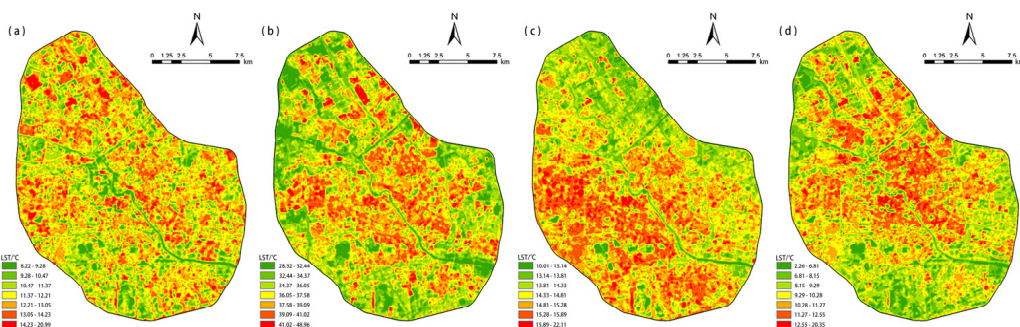


Figure 4. Surface temperature inversion results for four seasons in Tianjin in 2020. (a) Spring, (b) summer, (c) autumn, and (d) winter.

By comparing the temperature differences of various blocks (Figures 5 and 6), from the interannual summer surface temperature variation, we found (1) the temperature range of the blocks dominated by industrial, residential, and public management services is larger, and these blocks are prone to produce highly differentiated surface temperature intervals due to their diverse spatial forms; (2) high surface temperature occurs in industrial, residential, and commercial districts, which is consistent with the high intensity of human activities; (3) traffic blocks also have a higher surface temperature, mainly because they have the highest impervious water surface proportion (ISP), which will reflect a lot of solar radiation and cause the temperature to rise; and (4) the median surface temperature of parkland blocks was the lowest, and the temperature interval and outlier values were lower than those of the other five functional blocks, indicating that this block type had a stable cooling effect. According to the quarterly changes in the land surface temperature in 2020: (1) the median land surface temperature values in spring, autumn, and winter in 2020 were similar, and the temperature change range was smaller than that in summer; (2) the industrial blocks' surface temperature is the highest in spring and summer, but it decreases in autumn and winter, and the warming effect caused by human activities is more significant, with the industrial blocks' surface temperature being lower than that of the other blocks; and (3) the surface temperatures of green space and park blocks were higher than that of traffic blocks in spring and winter because the water area of the former was higher, meaning it could conserve more heat.

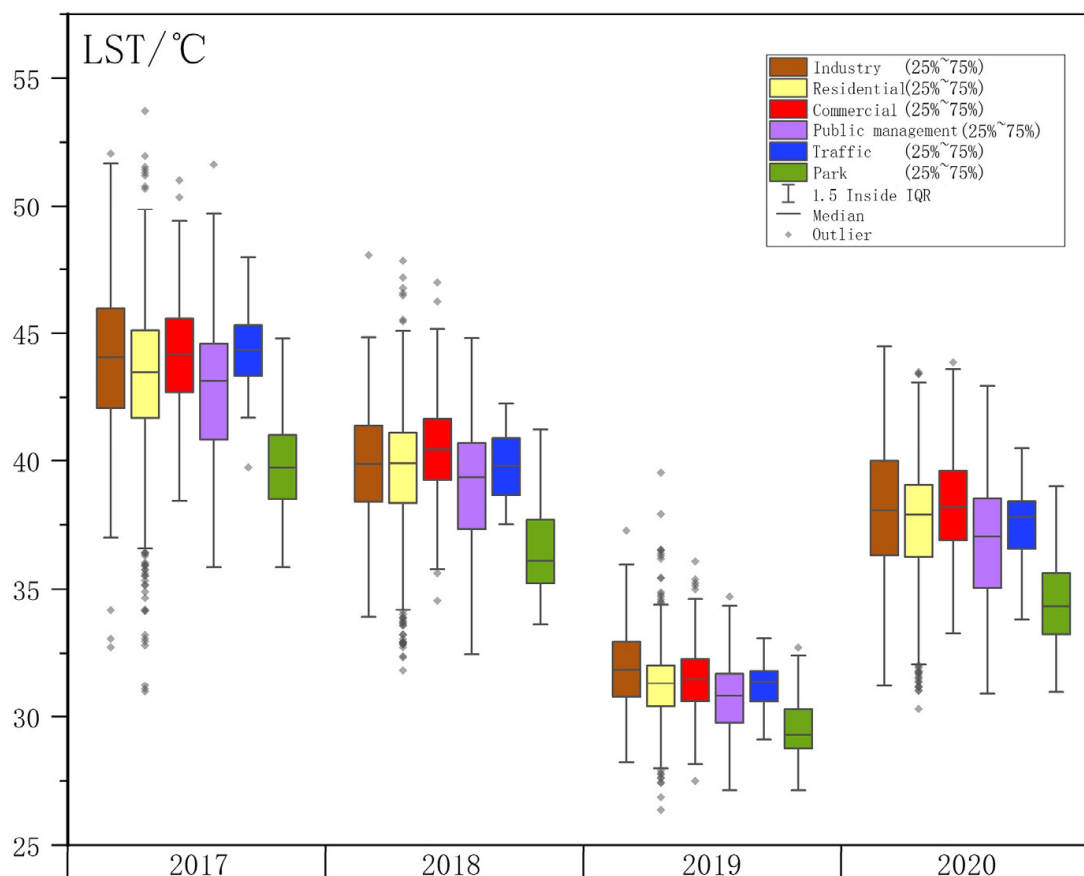


Figure 5. Summer temperature interval changes from 2017 to 2020.

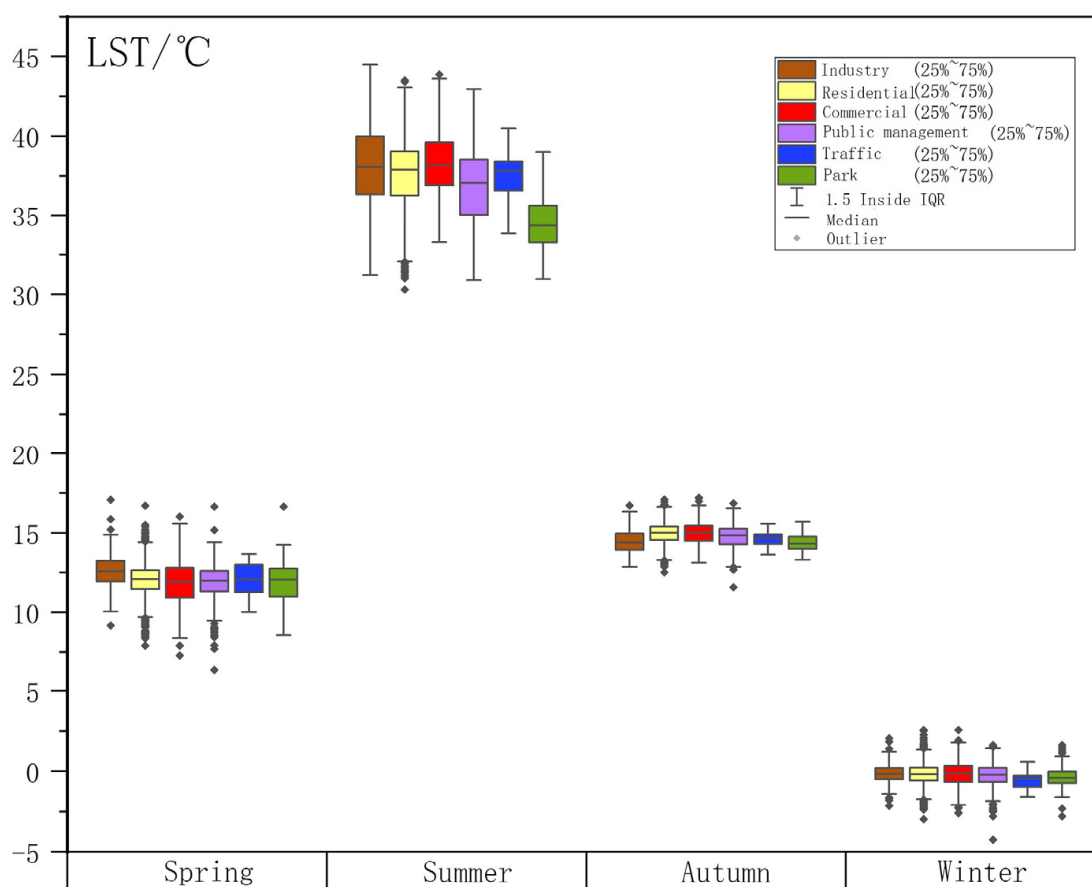


Figure 6. Seasonal land surface temperature interval changes in 2020.

Overall, the interannual summer land surface temperature variation range in Tianjin is small, and there are differences in temperature variation among the functional districts, but the median temperature order has no great change. The summer temperature variation interval is significantly larger than that of spring, autumn, and winter, and the temperature difference between the blocks has obvious seasonal variation. Therefore, local models should be used to fit the regression coefficients of various block morphological parameters to the land surface temperature, and corresponding strategies should be proposed.

4.2.2. Spatial and Temporal Distribution Characteristics of Urban Heat Island Footprint

The clustering analysis method was used to divide the urban surface temperature into four grades and identify the spatial–temporal distribution changes in the urban heat island footprint (Figure 7). The number of major urban heat island patches gradually decreased in summer and the major cold island patch distribution gradually became fragmented (Figure 7a–d). The main heat island patches' core areas are industrial and residential blocks, including the Tianmu Town Urban Industrial Park, Vanke Urban Garden, Tianpin Urban Industrial Park, and their surrounding areas. Their functional business forms will attract lots of traffic and people, thus raising the surface temperature in the inner and surrounding areas. With the overall urban functional structure adjustments and the continuous improvement of the urban greening system, these blocks' abilities to dissipate excessive surface temperatures will increase, thus resulting in smaller heat island patches. The main cold island patches' core blocks are mainly park green blocks outside the central urban area, including the Ziya Hebin River Park, Liulin Park, Meijiang Park, and Tianjin Water Park. In recent years, the blocks' spatial distribution shows their characteristics of infiltrating the center and fragmenting the original patches, which are consistent with the main heat island patch changes. Simultaneously, in summer, the minor temperature patches

mostly interlace with the major heat and cold island patches, and the minor temperature patches form a temperature transition zone outside the major temperature patches, thus promoting a local temperature balance. In summer, the minor heat island patches are mainly distributed around the open spaces of the city, including commercial blocks such as the Tianjin Railway Station and Bandung Grand Hutong. The surface temperature greatly contrasts the surrounding open spaces. In summer, the minor cold island patches are mainly distributed in residential and commercial blocks with a high standard deviation of the building height and greenbelt blocks with large NDVI values. The ventilation and heat storage capacities of these blocks can greatly reduce the surface temperature of the nearby main heat island core area.

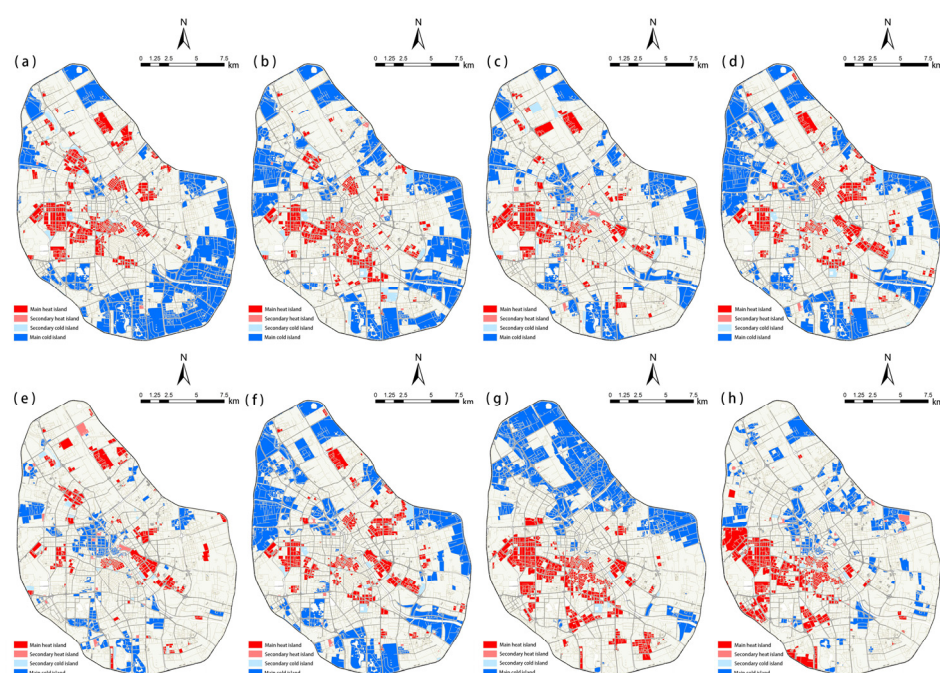


Figure 7. Temporal and spatial distribution of heat island footprint. (a) Summer 2017, (b) summer 2018, (c) summer 2019, (d) summer 2020, (e) spring 2020, (f) summer 2020, (g) autumn 2020, and (h) winter 2020.

In the heat island footprint's quarterly variation (Figure 7e–h), the major heat island patches in autumn and winter were more numerous and concentrated, while the major heat island patches in spring and summer were more dispersed, mostly distributed in residential and industrial blocks with a lower average height and smaller building height standard deviation. In summer and autumn, the major urban cold island patches' distribution area is large, mainly including suburban areas along rivers and urban greenbelts and other blocks with low development intensities, high vegetation indexes, and low impervious water surface proportions, so that these blocks' surface temperatures are significantly lower than for other blocks. As seen from the above, the summer heat island footprint's spatial and temporal distribution in Tianjin's central urban area has the characteristics of year-by-year stability and seasonal variation. There are great differences in surface temperature between different functional blocks, which are specifically shown as higher temperatures in industrial and residential blocks and blocks with higher impervious water contents. The architectural spatial form of these blocks is mostly "low sky openness–high building density–low standard deviation of building height–low average building height". The spatial form parameters of blocks' influence on the land surface temperature are flexible and restrictive to a certain extent, and the degree of the spatial form parameters' influence on the land surface temperature is also different between different functional blocks and within

the same functional blocks. It is necessary to analyze the effect regions and spatiotemporal constraints of these influences by combining them with the local regression model.

4.3. Regression Results Analysis

Using 2020 as an example, the three regression models' fitting accuracies and scale differences in fitting the spatial form parameters and land surface temperature were compared. The model precision comparison included the collinear parameters of the morphological factors and model performance indexes, which were used to avoid any interference caused by the interaction between the fitting effect of the model's factors and to also check the different models' fitting performance differences on the surface temperature in the four seasons. The comparison object of the model scale was the parameter bandwidth of the two geographically weighted regression models, and the seasonal differences of the facts' ranges were assessed.

4.3.1. Model Accuracy Comparison

The variance inflation factor (VIF), tolerance, and conditional index values were used to test the model's accuracy (Table 4). The VIF values of the seven types of spatial form parameters were all less than 7.5, tolerance less than 1, and most of the conditional index values were less than 15, indicating that there was no collinearity relationship between the spatial form parameters selected in this study. The goodness of fit index (R^2), Akaike information criterion (AICc), and residual sum of squares (RSSs) were used to evaluate the three models' overall performances and seasonal differences, respectively (Table 5). The goodness of fit R^2 of the three models showed an increasing trend in all seasons, and the R^2 of GWR and MGWR were similar to results from similar studies [22]. The Akaike information criteria (AICc) showed a decreasing trend in spring and summer, and the performance parameters of the OLS model were better than those of the two geographically weighted regression models in autumn and winter. The residual sum of squares (RSS) showed that the OLS was better than the model but showed a decreasing trend in the other three seasons.

Table 4. Results of the collinearity test of the model.

Variable	Spring			Summer			Autumn			Winter		
	VIF	Tolerance	Index	VIF	Tolerance	Index	VIF	Tolerance	Index	VIF	Tolerance	Index
SVF	1.302	0.768	2.9	1.309	0.763	29.356	1.311	0.763	2.87	1.314	0.761	4.214
ISP	1.378	0.726	4.417	1.391	0.719	13.649	1.384	0.722	4.286	1.393	0.718	6.278
NDVI	1.008	0.992	29.079	1.071	0.934	2.873	1.067	0.937	29.178	1.073	0.932	2.836
FAR	2.486	0.402	6.933	2.518	0.397	8.889	2.517	0.397	6.931	2.511	0.398	7.216
BSD	2.279	0.439	8.27	2.301	0.435	7.825	2.299	0.435	7.709	2.293	0.436	8.773
BH	3.414	0.293	8.757	3.414	0.293	6.984	3.414	0.293	8.851	3.414	0.293	13.601
BD	1.645	0.608	13.926	1.639	0.610	4.3	1.638	0.611	13.636	1.639	0.611	28.917

Table 5. Comparison of overall regression performance of models.

Index	Spring			Summer			Autumn			Winter		
	OLS	GWR	MGWR	OLS	GWR	MGWR	OLS	GWR	MGWR	OLS	GWR	MGWR
R^2	0.226	0.58	0.656	0.396	0.717	0.773	0.2	0.744	0.755	0.09	0.529	0.593
AICc	8912	7583	7350	12502	6490.7	6222	5727	6862	6554	6274	8098	7700
Rss	2972	1356	1111	9037	915.02	731.7	1108	826	790.1	1312	1520	1313

4.3.2. Model Scale Comparison

The GWR model's bandwidth is fixed, and the winter half-year's bandwidth is larger than the summer half-year's, which is speculated to be related to the large difference in the surface temperature threshold in summer and autumn (Table 6). Most regression

coefficients' bandwidth ranges in the MGWR model are large, and the spatial difference is significant. (1) The effect of the bandwidth of spring standard deviation (BSD) and the FAR is large. The spatial heterogeneity of the former is low, which is close to the global variable, while the bandwidth of the latter is close to the scale of a single administrative district, indicating that there is a large fitting gap between different administrative district floor area ratios. (2) In summer, the standard deviation bandwidth of buildings is 884, and its influence scale decreases from the global to the community scale, while the bandwidth of the sky openness (SVF) rises to the community scale, indicating that the spatial form parameters affecting the heat dissipation efficiency have a significant influence on the street surface temperature in summer. (3) In autumn and winter, the mean building height (BH)'s bandwidth shows an increasing trend, which is due to buildings' shadow surfaces increasing due to the direct sunlight angle increasing and the basic temperature decreasing. (4) Similar to spring, the building height standard deviation (BSD)'s bandwidth is larger in winter, and the influence of northwest wind in winter half-year causes the cooling effect of the wind environment of the block to be stronger. In general, the MGWR model has a better fitting performance than the traditional OLS model and GWR geographically weighted regression model and can explain the scale changes in the block spatial form factors' actions in different seasons. The spatial heterogeneities of blocks' wind environment-related form factors in spring, summer, and winter are low. The influence of highly correlated building form factors on the land surface temperature in autumn and winter is relatively consistent.

Table 6. GWR model and MGWR model bandwidth comparison results.

Variable	Spring		Summer		Autumn		Winter	
	MGWR	GWR	MGWR	GWR	MGWR	GWR	MGWR	GWR
SVF	174	106	343	92	152	64	184	94
ISP	44	106	44	92	44	64	44	94
NDVI	70	106	44	92	44	64	44	94
BD	44	106	44	92	52	64	44	94
BH	44	106	44	92	904	64	1380	94
BSD	3222	106	884	92	60	64	1440	94
FAR	962	106	68	92	44	64	130	94

4.4. Analysis of the Dominant Regional Division of Summer Heat Island Drivers

Summer 2020, the year with the best model fitting effect, was selected to explore the spatial distribution of the correlation between spatial form factors and the land surface temperature (Figure 8). The spatial form factors' significance was identified using a *t*-test (Figure 9), and the dominant regions of each driving factor were divided.

(1) Sky openness (SVF): The influence coefficient of the significant negative area is from -0.2448 to -0.1449 , and the influence area is mainly distributed in the densely populated residential areas with relatively new construction ages, such as the those along the Beitang Drainage River. These neighborhoods have the characteristics of "monotonous function—the low degree of the enclosed area-high building strength". Improving this area's sky openness is conducive to improving the block's wind environment configuration and reducing its surface temperature.

(2) Impervious water proportion (ISP): This coefficient's significant area is the block with positive parameter distribution, and the influence coefficient of the positive high value is from 1.7202 to 2.8372 , which is mainly distributed in the blocks with high-foundation opaque water levels, such as the Wangchuichang Sports Park, the surrounding blocks of Anshan Road and Duolun Road, Hexi Vientiane City, Hedong District Population Service Management Center, etc. Other significant positive parameters are distributed in an annular spillover pattern.



Figure 8. MGWR model regression coefficient distribution in Tianjin in the summer of 2020. (a) Sky openness, (b) proportion of impervious water, (c) NDVI index, (d) standard deviation of block building height, (e) block plot ratio, (f) average block building height, and (g) block building density.

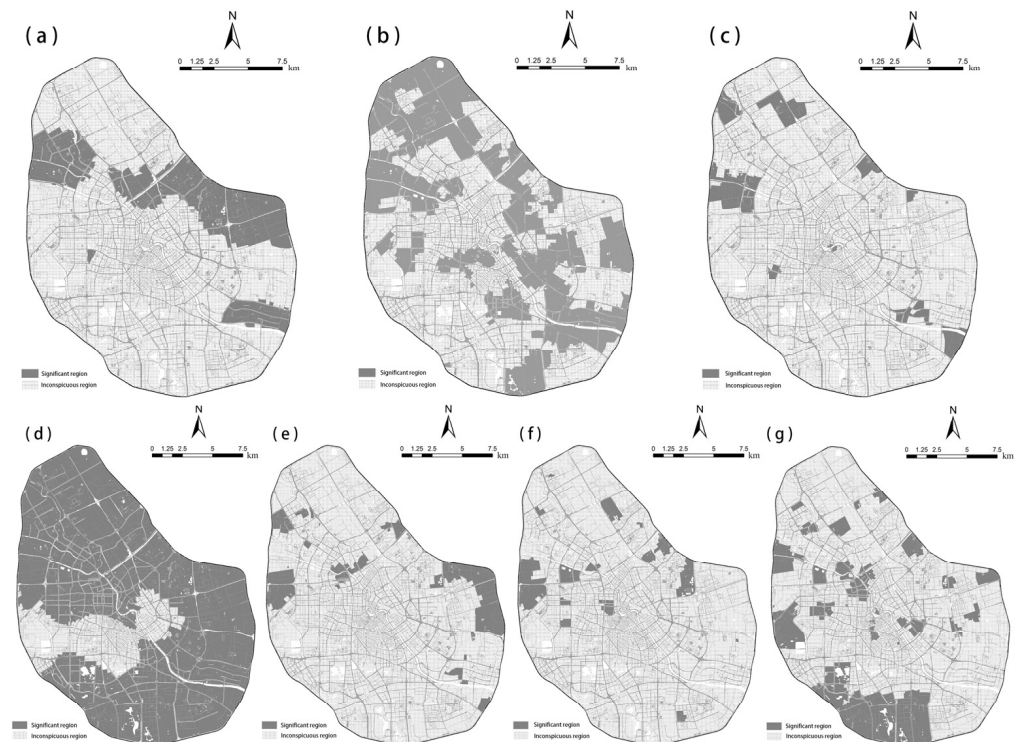


Figure 9. Significant regional distribution of MGWR model t -test in Tianjin in summer 2020. (a) Sky openness, (b) proportion of impervious water, (c) NDVI index, (d) standard deviation of block building height, (e) block plot ratio, (f) average block building height, and (g) block building density.

(3) Normalized vegetation index (NDVI): This coefficient's significant area is mainly negative parameter distribution blocks, including the boundary of the Ziya River outer ring West Road, Haihe River, and outer ring South Road junction; these blocks have higher NDVI base values. The influence coefficient of the blocks' negative high value is from -3.223 to -0.5734 , and the influence coefficient of the blocks' negative secondary high value is from -0.5734 to -0.2352 , that is, with every 0.01 increase in the block NDVI index, the land surface temperature in these regions will decrease by from 0.005 °C to 0.03 °C. However, the significant influence area of the normalized vegetation index is less. This is related to the index's sparse distribution in the study area.

(4) Standard deviation of the block building height (BSD): This coefficient is close to the global influence coefficient, all significant areas are negative parameter distribution blocks, and the regression coefficient shows an upward trend from the periphery to the core, which is consistent with BSD's spatial distribution trend. The areas with high BSD significance are mainly distributed in the periphery of the central urban core, but, for the core areas with complex spatial morphologies, BSD is not a significant parameter.

(5) FAR: This coefficient's significant area is mainly the blocks with positive parameter distributions. The coefficient value is between 0.6287 and 1.6583 , that is, the significant area content product rate increases by 0.1 , and the surface temperature increases between 0.06 °C and 0.16 °C.

(6) Average height of block buildings (BH): This coefficient's significant area includes both positive and negative parameter distribution blocks, among which the positive distribution areas are near the South Canal of the Jiuyuan West Road and the Lanjiang Xinyuan, Dingzigu, and Yucheng communities, with the coefficient interval from 0.6489 to 1.7951 . The negative distribution area is the Shuimu Tiancheng area, and the coefficient range is from -1.4484 to -0.5977 . The blocks' spatial form with significant positive parameter distribution is "high intensity and low density". The BH elevation of this type of block will drive the building strength of the block to further increase, but most of the impervious water surface cannot be blocked by the building shadow. The spatial form of the block with significant negative parameter distribution is "high intensity and high density". Due to the high building density, the BH elevation easily forms a large shadow area, which can shorten the sunshine duration of impervious surfaces and thus reduce the surface temperature.

(7) Block building density (BD): This coefficient's significant areas include positive and negative parameter distribution blocks, and the positive parameter distribution areas are the Nankai Kangtai Hospital, Huanxing Science Park, Hohai Garden, Chunhe Renju Community, Meijiang Convention, and Exhibition Center, with coefficient values ranging from 0.2956 to 0.9494 . These blocks' building strengths are high, and a further increase in the building densities will increase the blocks' heat emissions. The negative parameter distribution area includes blocks with complex functions and a large proportion of opaque water, such as the junction of the West Ring Road outside the Ziya River and Maoze Yayuan Community. The coefficient value is from -0.7843 to -0.2517 . The building density can reduce the temperature by increasing the building's shading area.

5. Discussion

5.1. Does MGWR Provide a New Perspective for Urban Thermal Environment Research?

In this study, the old urban area's surface temperature exhibited typical spatial heterogeneity, and the regression fit coefficients of the OLS regression model were not excellent. Meanwhile, previous studies have mainly investigated the model's fitting condition for the surface temperature in summer, meaning there is a lack of studies reported for other seasons [34,35]. This paper's results indicate that the surface temperature and spatial morphological parameters of Tianjin's old urban area have significant spatial non-smoothness, that the MGWR model's fit performance is better than the GWR model's in several seasons, and that these results are similar to those Basu [22] and Yang [36], where the summer fit superiority was higher than 0.75 . The study by Liu [37] on the central city of Wuhan's surface temperature also proved the MGWR model's excellent performance. In addition,

this study's MGWR model also reflects the surface spatial morphological factors' scale difference on the surface temperature intervention; for example, BSD's bandwidth in MGWR is larger than the fitting results of the GWR model in spring and summer, so urban planners can determine the spatial morphological factors' scale on the surface temperature intervention in different seasons based on this result and propose targeted improvement measures. In addition, the spatial morphological parameters' impact coefficients provided by the MGWR model based on plot function are effective for the local detailed differentiation of the surface temperature dominant impact coefficients. Based on the MGWR results, the study proposes urban planning policies to the reduce summer surface temperatures in terms of both the land allocation and spatial morphology, including considering the industrial-type parcel repositioning and urban green space allocation [38]. Overall, the traditional OLS model can fit the average values of all the variables across the study area, which is far from adequate for data sets with more pronounced spatial autocorrelation, which leads to its conclusions not being able to directly guide urban planning practice. MGWR, as a dynamic fitting model, is desirable in constructing the relationship between the surface temperature and spatial morphology parameters' influence; its results can also effectively guide micro-urban planning. The results can also effectively guide micro-urban planning practice and provide a reliable basis for urban surface temperature optimization.

5.2. What Are the Different Heat Island Impact Parameters within Different Functional Parcels?

The results show that the block impervious water ratio (ISP), block building density (BD), and block average floor area ratio (FAR) are significant positive factors. The standard deviation of block building (BSD) is a global negative factor. The significant negative factors were sky openness (SVF), average building height (BH), and normalized vegetation index (NDVI) (Table 7). Similar results were obtained by Sun [39] and He [40], where the positive tendency of impervious surface share (ISP) on surface temperature was generalized, and the inverse effect of building standard deviation (BSD) on surface temperature was interpreted as an important determinant of urban wind environment [41].

Table 7. Statistical information of fitting of spatial form factors of MGWR model.

	Minimum	Maximum	Average	Std	Positive	Negative	Minimum	Maximum	Average	Std	Positive	Negative
Industrial functional block						Residential functional block						
SVF	−0.188	0.104	−0.056	0.0834	28.218	71.782	−0.191	0.067	−0.081	0.0578	9.861	90.139
ISP	−0.317	1.676	0.483	0.3724	89.109	10.891	−0.462	2.8	0.638	0.5439	95.43	4.57
NDVI	−0.753	0.274	−0.128	0.2233	36.139	63.861	−3.223	0.897	−0.053	0.2041	41.655	58.345
BD	−0.499	0.866	0.222	0.2715	78.713	21.287	−0.784	0.949	0.21	0.2936	75.854	24.146
BH	−1.069	0.693	−0.224	0.3663	22.277	77.723	−1.448	1.795	−0.112	0.3821	26.936	73.064
BSD	−0.245	−0.057	−0.158	0.0553	0	100	−0.236	−0.05	−0.102	0.0347	0	100
FAR	0.62	1.418	0.218	0.3112	81.683	18.317	−0.795	1.619	0.107	0.3472	58.249	41.751
Commercial functional block						Public management service block						
SVF	−0.183	0.028	−0.063	0.0441	9.167	90.833	−0.183	0.099	−0.068	0.0588	13.567	86.433
ISP	−0.52	2.837	0.781	0.7026	91.389	8.611	0.483	2.818	0.565	0.5152	96.28	3.72
NDVI	−1.52	0.51	−0.03	0.2544	51.667	48.333	−1.384	0.838	−0.024	0.2344	52.516	47.484
BD	0.433	0.872	0.269	0.2098	90.278	9.722	−0.551	0.904	0.127	0.2812	38.95	61.05
BH	−1.131	0.734	−0.11	0.2402	29.167	70.833	−1.389	1.049	−0.05	0.3172	62.582	37.418
BSD	−0.195	−0.057	−0.084	0.0288	0	100	−0.23	−0.049	−0.094	0.0385	0	100
FAR	−0.601	0.774	0.05	0.2067	50	50	−0.801	0.943	0.096	0.2417	76.368	23.632
Traffic block						Green park functional block						
SVF	−0.103	0.06	−0.041	0.0501	23.81	76.19	−0.19	0.076	−0.084	0.0594	8.257	91.743
ISP	0.063	1.281	0.583	0.3341	100	0	−0.195	2.07	0.437	0.3852	95.413	4.587
NDVI	−0.296	0.246	0.011	0.1373	52.381	47.619	−0.81	0.411	−0.1	0.2103	35.78	64.22
BD	−0.378	0.68	0.021	0.3066	52.381	47.619	−0.382	0.845	0.162	0.3094	62.385	37.615
BH	−0.615	0.408	−0.079	0.2619	33.333	66.667	−1.126	0.649	−0.081	0.2634	38.532	61.468
BSD	−0.209	−0.065	−0.104	0.0401	0	100	−0.215	−0.052	−0.115	0.0371	0	100
FAR	−0.038	0.684	0.248	0.2573	76.19	23.81	−0.339	1.658	0.253	0.3178	79.817	20.183

The absolute average of the three positive influencing factors is ranked as $ISP > BD > FAR$. ISP is the most significant influence factor on the temperature increase in all block types. ISP not only reflects blocks' abilities to reflect solar radiation, but it is also closely related to urban crowd gathering and the human activity intensity. Especially, the positive influence coefficient of the land surface temperature is higher in the residential, commercial, and traffic blocks. The positive effects of BD and FAR are not significant in some blocks. For example, the positive rate of BD is low in public service functional blocks and traffic functional blocks. For FAR in the residential and commercial functional blocks, the influence trend of the land surface temperature is very fuzzy. This result is related to the two indicators' limitations and the complexity inside the block. On the one hand, BD only describes a block's construction from a two-dimensional perspective and does not generalize the building volume and height [42]. On the other hand, the complex parallel relationship between the FAR value and a variety of spatial form coefficients leads to its insensitive response to surface temperature, which usually occurs in residential and commercial blocks with more complex construction conditions [43].

The absolute mean value of the four negative impact factors is slightly different among the different block types. In industrial, residential, and commercial blocks, the order of all negative impact factors is $BH > BSD > NDVI > SVF$. BH has the highest negative impact effect among these blocks, because the number of high-rise buildings in industrial, residential, and commercial blocks is larger than that in other block types. In summer, more building shadows can be generated to cover the surface to reduce the warming effect of solar radiation on the surface temperature [44]. Among the traffic and green park blocks, the order of various negative impact factors is $BSD > NDVI > BH > SVF$, with BSD having the most significant negative impact on these two blocks, which have a large difference in their building heights and have strong transmission capacities of their local wind structures [45]. In public service blocks, the absolute average values of the various negative impact factors are ranked as $BSD > SVF > BH > NDVI$, among which the absolute average values of the related parameters of the three building forms are greater than NDVI, which may be related to the limited proportion of green space planning indicators inside the four blocks and the influence of the blocks' external environments. Among all block types, the standard deviation of NDVI and BH is greater than that of SVF and BSD, which means that the latter two have a more stable cooling effect. When implementing space policy to optimize blocks' thermal environments, their influence on the blocks' surface temperatures and surrounding blocks' macro-influences should be simultaneously considered [46].

5.3. Optimization of Planning Strategies for Mitigating the Heat Island Effect in Old High-Density Urban Areas

From the perspective of the superimposed significant influence factors of various blocks, the optimal response strategies of the heat island effect in Tianjin's high-density urban areas include land use adjustment and spatial form optimization.

5.3.1. Land Use Adjustment

(1) Reduction in heat sources in industrial blocks of out-migration transformation

Industrial and residential blocks' mixed layouts in Tianjin's high-density urban areas intensify the impact of industrial heat emissions on residents' health. This study suggests that industrial blocks should be relocated to industrial parks far away from the city center, especially heavy industry that is more invasive. Replacing the land use of industrial blocks in the central city can effectively alleviate this impact [47]. In addition, as the blocks' impervious water surface proportion shows a strong correlation with the LST in this study, the proportion of soft and hard pavements in the industrial block can be moderately optimized, the building density can be controlled, and the heat emission's influence in the industrial block can be reduced by using light-colored building materials and coating [48].

(2) Mixed configuration of commercial and residential blocks to increase occlusion

In this study, the surface temperature of residential and commercial blocks has a significant negative correlation with the average building height, and the building shadow shows a significant cooling level for newly developed residential areas but not for old residential areas. To this end, it can be combined with urban renewal to increase the land use mixing degree of old residential areas, implant some commercial functional buildings into the inner blocks, and raise the building height in the southern part of the residential area to provide more shadow shielding area to achieve the cooling effect [49].

(3) Strengthen cold source of green space system in Darning Park

Park green space blocks are important urban cold source areas. According to heat island footprint analysis, water parks and existing park green space blocks are distributed in patches, showing a certain cooling effect on surrounding blocks. In the future, urban renewal means should be used to continuously “see the gap and insert green”, such as increasing community-level green space and belt green space along the road and weaving the multi-scale green space system of “city-district-community” parks [50]. At the same time, we can rely on the existing river network to improve the framework of the green space system, expand the cooling influence range of the Haihe River, Ziya River, and other important urban water systems, and release their cooling capacity.

5.3.2. Spatial Form Optimization

(1) Increase the proportion of blue and green facilities in public buildings

The minor heat island patch's core in summer is mostly the block where large public facilities are located. These blocks are accompanied by a large area of artificial surface; the high albedo level will promote the rapid rise of the surface temperature, resulting in continuous hot areas. The accumulation effect of heat sources around public buildings can be alleviated by adding a certain proportion of blue and green facilities in open spaces, building green roofs and vertical greening facilities, expanding the heat capacity, and blocking heat sources [51].

(2) Control the height difference to enhance the efficiency of the ventilation corridor

In this study, the standard deviation of the building height is a global negative morphological parameter, and the influence coefficient increases annularly from the outer ring to the core area (Figure 8). Collaborative control of the building height difference can significantly increase the surface temperature adjustment ability [52]. Specific measures should be implemented regionally, such as demolishing some old buildings in the open area near the intersection of the outer ring road and the water system to ensure the existing natural ventilation corridor's width. When developing secondary and tertiary air channels around various green parks and other air source spaces, reduce the building height of some tuiyere sections and introduce high-quality air sources to the plot's interior [53].

(3) Control building density optimization form

While optimizing the block's surface temperature, the economy should also be considered based on maintaining a certain building density [54]. In this paper, the areas with a significant positive correlation with the building density are mainly distributed around the outer ring road. Reducing the building density of industrial parks and residential areas using renewal means such as demolition, renovation, and relocation can effectively alleviate a block's heat island.

6. Conclusions

Based on urban spatial form parameters, this paper describes the spatial form inside Tianjin city's outer ring road. This study analyzed the interannual and seasonal variation in the land surface temperature in Tianjin's central urban area by using a remote sensing temperature inversion method and compared the performance and scale differences of three fitting models for representing the urban land surface temperature using spatial form. The main summer land surface temperature factors and their importance were studied and determined, and planning and control strategies to alleviate the heat island effect in the old urban area were proposed. The main conclusions are as follows:

(1) The summer land surface temperature's interannual variation range in the study area is small, and the high-value area is mainly distributed in industrial and residential blocks. The seasonal variation in the surface temperature fluctuates, and the temperature of the traffic block in the winter half-year is significantly lower than that of other blocks, mainly because of the high proportion of impervious water in this type of block and the fast heat dissipation in winter.

(2) From the regression analysis of the three models, the MGWR model's fitting effect is better than the OLS and GWR models in all periods. Regarding the impact factor bandwidths of MGWR and GWR, the MGWR model can more accurately show the spatial instability characteristics of various impact factors, among which is the spatial heterogeneity of building standard deviation and sky openness, and the spatial heterogeneity of the other impact factors is greater than the GWR fitting results.

(3) The MGWR model's fitting results show that the morphological factors with significant negative influences include BSD, BH, SVE, and NDVI, while the morphological factors with significant positive influences include FAR and BD. FAR has no clear alignment with the land surface temperature's influence due to its complex index composition. Integrating the above factors and ranking the factors' importance fully reflect the sensitivity and spatial differences of the spatial form factors in different block types with the land surface temperature change, so that planning and regulation can be conducted by type to guide collaboratively optimizing the spatial form and land surface temperature.

However, there are still some areas in the current study that can be optimized, such as expanding the range and dimensionality of the selection of spatial morphological parameters, incorporating machine learning models into the model-coupling process, and using more advanced methods to divide the study units. The future research prospects are as follows:

(1) Research based on morphological parameters focuses on characterizing static spatial environments. In the future, selecting morphological factors should be expanded from human behavioral activities and the natural environment, and comparing multi-regional, -type, and -level cities should be conducted to ensure the research conclusions are more general.

(2) The existing MGWR model only focuses on the unidirectional relationship between a single influence factor and the surface temperature, which ignores the complex mathematical correlation between the influence factors and means it has an alarming overfitting effect. Coupling the machine learning model and the MGWR model can effectively reduce this model interference. The relationship between the spatial morphological parameters and surface temperature can be explored in depth.

(3) This paper's results show that the block influence factors' significance in some of Tianjin's core areas is small, which is related to the area's block scale. In the future, remote sensing image data and street view data should be added to delineate the research units to improve the data abundance and accuracy for the region's blocks.

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