Spatial quantitative analysis of the potential driving factors of land surface temperature in different “Centers” of polycentric cities: A case study in Tianjin, China

Die Hu a,b,c, Qingyan Meng a,c,⇑, Linlin Zhang a,b,c, Ying Zhang a,b,c

a Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
b University of Chinese Academy of Sciences, Beijing 100049, China
c Sanya Institute of Remote Sensing, Sanya 572029, China

HIGHLIGHTS
• Potential LST driving factors are explored in a multidirectional perspective.
• Polycentrism is introduced from the perspective of spatial configuration.
• Three types of city centers pose varied UHI characteristics.
• LST driving laws in different city centers of polycentric city is identified.
• Multiple driving factors have bilinear or nonlinear interactions among them.

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ABSTRACT
Revealing the dominant driving factors of land surface temperature (LST) plays an important role in mitigating the urban heat island (UHI) effect. Numerous international metropolises are developing polycentric forms under the process of suburbanization in conjunction with rapid urbanization, generating new UHI spatial patterns in internal urban areas. To comprehensively understand the effects of multi-factors on the thermal environment, our study examined a typical polycentric city, Tianjin. According to the concept of polycentrism, this study focused on three types of city “centers”: major city core, new district core and industrial park. Eleven potential driving factors of LST were explored from four layers, and the geo-detector model was applied to rank the explanatory degree of these factors on LST. Three different city centers of the polycentric city showed varied UHI spatial pattern characteristics, and their response to the effect of natural factors and social factors on LST were quite diverse. Heat island areas were distributed homogeneously in the major city core; the UHI pattern on the east-west axis was unbalanced in the new district core due to the unsaturated urban space and dynamic planning policies; in industrial park, production areas were segregated by green belts with clear boundaries. For the whole city and the major city core, the imperviousness factor had the highest explanatory rate for LST, followed by the greenness factor. In contrast to the results of previous studies, the wetness factors had a greater impact on LST in the new district core and industrial park, second only to the greenness factor. Furthermore, selected factors exhibited bilinear or nonlinear enhanced relationships in their interactions. The driving laws of LST in different city centers were summarized with an explorative case study, aimed at providing...
1. Introduction

The world has experienced rapid urbanization in recent decades, leading to the replacement of natural landscapes with impervious surfaces, corresponding with the increased thermal energy emissions from human activities (Lu et al. 2013, Xu, Ding and Wen 2009, Yusuf, Pradhan and Idrees 2014). This transformation of surface physical properties has considerably altered the energy balance and microclimate characteristics, resulting in a series of environmental problems (Wang et al. 2018). One of the most common problems is the urban heat island (UHI) effect (Oke, 1982, Arnfield 2003, Zhang et al. 2014, Doick, Peace and Hutchings 2014), that is, the phenomenon in which atmospheric or surface temperature of urban areas is higher than that of the surrounding suburbs. The temperature increase leads to increased energy consumption for air conditioning, aggravating air pollution and greenhouse gas emissions (Sarrat et al. 2006), thus; the livability of the city is severely affected by the UHI effect (Zhang et al. 2013). Therefore, the thermal behavior and characteristics of urban areas are important information for both researchers and policymakers, aiming to design an eco-friendly city and improve the residents’ environmental quality.

The UHI effect can be quantitively described based on atmospheric temperature or land surface temperature (LST) (Eludoyin et al. 2014, Melaas et al. 2016, Ogashawara and Bastos 2012). With the gradual development of satellites, remote sensing technology has become the main tool for the acquisition of LST (Voogt and Oke 2003). Thermal infrared remote sensing data have been widely used to assess the UHI effects (Yusuf et al. 2014, Liu and Zhang 2011). Consequently, LST derived from thermal infrared remote sensors has become a low-cost and convenient means for UHI analysis, providing easy access and fine spatial resolution. The differences between urban and suburban LST have been widely used to measure the UHI intensity (Heaviside, Vardoulakis and Cai 2016, Tomlinson et al. 2012, Zhou et al., 2018), which is regarded as a major indicator of the UHI effect (Zhou, Rybski and Kropf 2013a). With the launch of updated sensors, it is believed that high-resolution remote sensing images enable researchers to obtain detailed surface radiation information, and contribute to comprehensive studies of the relationship between urban morphology and thermal performance at fine scales.

An adequate understanding of the LST driving laws at a fine scale lays the foundation for the development of strategies to mitigate the UHI effect. The spatial variation of LSTs results from the varied characteristics of landcover features and their interactions; thus, comprehensively selecting the potential driving factors is necessary to clarify how LSTs are affected by these factors. Generally, according to previous studies, the potential driving factors of LST can be divided into four layers: (1) Greenness layer. Green or natural vegetation-dominated areas in the metropolitan area show characteristics of UHI mitigation (Dos Santos et al. 2017). The correlations between the normalized difference vegetation index (NDVI) and temperature have been found to be negative (Chen et al. 2006, Liu and Zhang 2011). (2) Imperviousness layer. Regression statistics reveal that built-up land has a positive exponential relationship with LST (Xu et al. 2009). The normalized difference built-up index (NDBI) has significantly positive effects on LST (Dai, Guldmann and Hu 2018), which means that the built-up land can strengthen the UHI effect (Liu and Zhang 2011). (3) Wetness layer. The normalized difference water index (NDWI) (Jiang, Fu and Weng 2015, Chen et al. 2006) and modified normalized difference water index (MNDWI) (Xu 2006) are frequently used to substitute for surface moisture availability. In addition, the MNDWI has a significant effect on the LST in the transition season (Peng et al. 2018). (4) Social-economy layer. In the process of urbanization, the increasing population due to urban expansion can decrease the vegetation; increase roads, buildings and energy consumption; and thereby increase the UHI intensity indirectly (Yao et al. 2018). Population density, nighttime light density and road density (RD) are all highly correlated with LST (Peng et al. 2018). However, existing studies lacked of integrated ranking of the overall influencing factors of LST from both natural and social economic aspects. It is difficult to determine the dominant influencing factor of LST without a comprehensive catalog of the potential driving factors, and uncertainties has remained in relevant studies. With widespread suburbanization, the urban spatial structure has begun to evolve to a polycentric form; not only in China but also in Europe and the United States. The drawbacks of the monocentric layout in traditional large cities are increasingly apparent. Thus, numerous cities have devised the development strategies establishing a polycentric spatial structure (Liu, Derudder and Wu 2015), and the concept of the polycentric city has been widely disseminated (Catalán, Saurí and Serra 2008). The polycentric development strategy has received wide attention, mainly from the European Union’s European Space Planning Observation Network (ESPN), which proposed the European Space Development Perspective (ESDP) in Europe, and the concept of polycentric city development was developed (Davoudi 2003). The European Multi-center Mega-City Regional Sustainable Development Project (POLYNET, Sustainable Management of European Polycentric Mega-City Region) has moved the discussion of multi-center cities from the academic field to practical application (Hoyer, Kloosterman and Sokol 2008). Reasonably, along with the globally polycentric development trend of urban spatial structure, the UHI patterns have transformed simultaneously. However, polycentric cities have typically been studied as a whole in the applied research on UHI pattern monitoring at a relatively coarse scale (Peng et al. 2018, Ren et al. 2016). Even if part of the research is directed toward the built-up area (or metropolitan region) (Sun et al. 2018, Peng et al. 2016) from a microscale perspective, no study has sufficiently investigated the spatial heterogeneity of LST and the ranking of the potential drivers of LST within different city centers of a polycentric city.

The complex interaction between LST and various driving factors leads to the spatial heterogeneity of UHI pattern. How can the dominant driving factor determine among diverse potential factors with an appropriate and effective method? Statistical analyses combining both the Pearson correlation matrix and multiple linear regressions were used to examine the strength of correlations between LST and variables related to the composition and configuration of land cover features. Furthermore, principal component analysis (Zhou, Huang and Cadenasso 2011, Qihaol et al. 2008), linear regression analyses (Chen et al. 2014, Morabito et al. 2016, Sun, Wu and Tan 2011), stepwise multiple-linear regression (Asgarian, Amiri and Sakieh 2014, Huang and Wang 2019) and ordinary least-squares regression (OLS) (Peng et al. 2018) have been widely applied to the multivariate analysis of
driving factors. Current statistical methods have proved to be effective in LST driving force analysis; however, three limitations remain. First, most of the abovementioned statistical methods are based on linear assumptions. However, the factors contributing to the spatial heterogeneity of LST are diverse and their interaction are quite complicated. Therefore, the internal mechanism is difficult to adequately measured with a linear-based hypothesis. Second, certain methods require that there be no collinearity between the driving factors or the statistical results will be affected. This constraint on the selection of potential driving factors greatly limits the applicability of these methods, and scholars must determine the independent and significant factors before correlation analysis. Third, the combined effects of multiple influencing factors are difficult to measure with the above methods simultaneously whereas the spatial pattern of LST is not usually affected by a single influencing factor. A statistical model based on spatial hierarchical heterogeneity, called the geo-detector model, is able to address these limitations since it involves no linear assumption and its results will not be affected by collinearities of multiple variables. Furthermore, the combined contribution of two individual driving factors to geographical phenomena can be detected based on the geo-detector model. This method has been widely used in driving force analyses in various fields, such as public health (Liao et al. 2017, Liao et al. 2016, Huang et al. 2014), regional economic (Tan et al. 2016, Xu, Zheng and Zhang 2018), meteorology (Ren et al. 2016, Wu et al. 2016), and land use (Ju et al. 2016, Ren et al. 2014) fields. Therefore, to avoid the influence of collinearity among multiple factors and other above-mentioned limitations, this study explores the application of the geo-detector model in research on the driving mechanisms of the thermal environment.

To address the above problems, this study takes a typical polycentric city, Tianjin, as a study case. The relationship between urban morphology and the spatial pattern of the UHI is comprehensively examined; specifically, the influence of natural and socio-economic factors on LST in different city “centers” is investigated using the geo-detector model. The main objectives of this study were (1) to characterize the UHI spatial patterns of three types of city centers based on LST retrieval at a microscale; (2) to perceive the heterogeneity of LST responses to natural and socio-economic characteristics in subdivided centers based on the polycentric form of the urban space; and (3) to interpret the driving factors of LST and their interactions in different city centers from an innovative perspective of urban development and regional functional characteristics. This study aimed to provide referential theoretical and practical guidance for optimizing thermal environmental management, especially for highly urbanized polycentric cities.

2. Study area and dataset

2.1. Study area

In this study, we choose Tianjin, the largest comprehensive port and most important foreign trade port in North China, as a case study. Tianjin (38.57°N-40.25°N, 116.72°E-118.07°E) is one of the four municipalities in China and is located northeast of the North China Plain and west of the Bohai Sea. As the core city of the Bohai port city group and one of the important channels for foreign communications, Tianjin is an important economic center in northern China, with a population of 15.5687 million in 2017, and an urbanization rate of 82.93% (Tianjin Municipal Bureau of Statistics 2018). The city has 15 districts, including six in the major city core (Heping, Hedong, Hexi, Hebei, Nankai and Hongqiao), and three in the Binhai New District (BHD): Hangu, Tanggu, and Dagang.

The BHD is the first national comprehensive reform and innovation zone approved by the State Council and is a national comprehensive reform pilot area of Tianjin, which is known as “the third growth pole of China’s economy”. The Nangang Industrial Park (NIP), is located southeast of the BHD 45 km away from the Tianjin major city core and 20 km from the Tianjin port and includes petrochemical, metallurgical equipment manufacturing and port logistics as the leading industries. The major city core, new district core and industrial park were selected as typical “centers” of the polycentric city, represented by the Tianjin major city core and the BHD and NIP centers, respectively, in this study. The boundary of the major city core was clearly defined in the administrative division of Tianjin (http://www.tj.gov.cn), and the boundaries of new district core (BHD) and industrial park (NIP) were derived from the “Urban Master Plan of Tianjin (2005–2020)” and the zoning plan of the Tianjin NIP (2009–2020) (Li and Zhu, 2009).

2.2. Multisource data

LST data were derived from Landsat 8 thermal infrared sensor (TIRS) images, which were collected on August 9, 2013; July 27, 2014; August 15, 2015; August 4, 2017; and August 22, 2018, from the United States Geological Survey (USGS, https://glovis.usgs.gov/). The average amplitude of the UHI is remarkably asymmetric, with a larger temperature difference in summer than in winter (Imhoff et al. 2010). Furthermore, recent studies have largely concluded that the UHI intensity always reaches its maximum in summer, during which it is clearly higher than in other seasons (Kourtidis et al. 2015, Meng et al. 2018). Therefore, numerous related studies have chosen summer as the study (Tomlinson et al. 2012, Li et al. 2018). Consequently, the selected thermal infrared images in this study came from summer (July and August) (Chen et al. 2016). Five years of data were used to study the UHI patterns and driving laws of LST in the three city centers. Radiometric distortion of the TIRS and Operational Land Imager (OLI) data was corrected before the LST retrieval and other processing steps of the factor calculation. On this basis, the intensity of the UHI effect in the three study areas was calculated and graded quantitatively.

Nighttime light satellite imagery has been widely used to detect, estimate, and monitor socioeconomic dynamics (Bennett and Smith 2017). For instance, the Defense Meteorological Satellite Program Operational Line Scan System (DMSP-OLS) data (spatial resolution: approximately 1 km) may prove to be useful in informing a smart interoperation program to improve maps and data sets of human population distributions (Tripathy et al. 2017). With updated remote sensing data and the development of technology, nighttime light satellite data with higher resolution have become available. Suomi-National Polar-Orbiting Partnership (NPP)-Visible-Infrared Imaging Radiometer Suite (VIIRS) data (spatial resolution: 750 m) could be a powerful tool for modeling socioeconomic indicators, such as gross domestic product (GDP) and EPC (electric power consumption) (Shi et al. 2014). In this study, the nighttime lighting intensity (NLI) was established based on Suomi-NPP-VIIRS data (https://ngdc.noaa.gov/) to denote economic development in one region as one factor from the socioeconomic layer. The materials prepared for potential driving factors involved roads, railways and waterways, which were derived from Open Street Map (OSM, https://www.openstreetmap.org/). The influence of the data’s spatial resolution on LST should not be underestimated (Zhou et al. 2013b); therefore, all data for factor calculations were resampled to a 100 m × 100 m resolution. The impervious surface products (Gong et al., 2012) noted in the discussion section are derived from Beijing City Lab (BCL, https://www.beijingcitylab.com/).
3. Methods

3.1. Criteria for the selection of urban “centers”

Polycentrism refers to the existence of multiple centers in a conurbation. Although the descriptions of this concept in the previous literature are still vague (Musterd and van Zelm 2016), it is considered that a polycentric city is a group of discrete and similar areas, isolated by open space, with interaction beyond the average level (Parr 2004). A major difference among previous studies is the perspective of spatial analysis: Polycentricity can either refer to intraurban patterns of clustering of population and economic activity (for example, Los Angeles, London or Paris) or to interurban patterns such as the Dutch Randstad and the area of Padua–Treviso–Venice in northern Italy (Forstall and Greene 2013, Kloosterman and Musterd 2016). Outside the European Union, the southern Californian urban region in the US and the Kansai area in Japan can be seen as examples of this latter form of polycentricity (Batten, 1995). The research perspective taken in the present study reflects the former form.

The polycentric urban form is extremely common in Chinese mega-cities. Promoted by government policies, state-level new areas are gradually developing to become new metropolitan areas in China. Population, economic and industrial activities have gradually concentrated in state-level new areas following the opening and reform established in the early 1990s. Therefore, the new districts formed from these metropolitan areas conforms to the definition of center in polycentrism. However, industrial parks have seldom been studied as a separate type of area to isolate the driving factors of LST, despite the fact that hot spots are often highly concentrated in industrial parks (Tran et al. 2017); considering the special thermal environmental characteristics of industrial parks caused by production activities. Spatially, there are tens of thousands of industrial parks scattered throughout China, and industrial parks are regarded as a type of center in our study. As a functional area in which various types of industrial production activities are concentrated, the unique functions of industrial park conform to the concept of polycentrism. If the environmental problems of industrial parks are not given enough attention, they may cause added losses in human, material and financial resources.

Although there are other hot spots as shown in Fig. 1 (c), they have not been included in the selection of “centers” in this study because they do not completely satisfy the characteristics of intraurban areas in terms of polycentrism. These hot spots are mostly distributed along the highway between the major city core and the new district core and include the buildings around the highway. Their functional characteristics are inadequate, and they are not isolated by open space, precluding these areas from constituting a “center.” Moreover, some hot spots are distributed in county towns whose development is relatively independent, but the definition of polycentricity emphasizes the functional system of division of labor and cooperation among centers. The spatial configuration of county towns is similar to that of old urban core and county towns, and they are not typical representatives of a major city core; therefore, these areas are not taken into account in the research objectives.

Our study synthesized the definition of polycentrism and polycentricity, the development trends and policies of China, and the regional function characteristics. Accordingly, three types of city centers were selected as our study areas: a major city core, a new district core and an industrial park. The configuration of “major city core-new district core-industrial park” was regarded as a typical urban form of polycentric city to explore this case study of urban thermal environment. There are similar developing urban configurations in several metropolises in China, such as Shanghai, Guangzhou, Zuhai and so on.

3.2. Land surface temperature retrieval

In this study, a practical split-window algorithm based on Landsat 8 was used to retrieve the LSTs of the study areas. The estimation of the emissivity was based on vegetation coverage, as described by Du et al. (2015). The method is mainly based on the study of atmospheric water vapor inversion using Landsat 8 thermal infrared data to obtain the parameters of atmospheric water vapor (Ren et al. 2015).

The algorithm is based on the data superiority of the TIRS sensor with two thermal infrared channels, which have strong inversion accuracies. The formula of the dual-channel nonlinear split-window algorithm is as follows.

\[
T_i = b_0 + \left( b_2 \frac{1 - e}{e} + b_1 \frac{\Delta e}{e^2} \right) \frac{T_i + T_j}{2} + \left( b_2 \frac{1 - e}{e} + b_1 \frac{\Delta e}{e^2} \right) \frac{T_i + T_j}{2} + b_3 (T_i - T_j)^2
\]

In the formula, \(e\) and \(\Delta e\) represent the mean and difference in emissivity of the two channels, respectively, depending on the type of land cover and coverage density; \(T_i\) and \(T_j\) represent the observed radiation brightness of the two channels. \(b_i (i = 0,1,2,\ldots,7)\) is the coefficient, and its value can be obtained from experimental data, atmospheric parameter data or the simulated atmospheric radiative transfer equation, which depends on the water vapor content of the atmosphere to improve the accuracy. To reduce the coupling of atmospheric parameters, the algorithm estimates atmospheric water vapor content on thermal infrared data.

The method establishes the empirical relationship between the atmospheric transmittance ratio \(\tau_i/\tau_j\) and the atmospheric water vapor content \(wv\) of the two channels by using Moderate resolution atmospheric Transmission (MODTRAN) and Thermodynamic Initial Guess Retrieval (TIGR) atmospheric profiles first and then using the covariance and covariance ratio between the brightness temperatures of the two channels in a moving window of a certain size to estimate the atmospheric transmittance ratio. The formula is as follows:

\[
wv = a + b \cdot (\tau_j/\tau_i) + c \cdot (\tau_j/\tau_i)^2
\]

Finally, the unitless temperature calculation results were divided by 100 to convert to degrees Kelvin (K). Then, the results were converted to Celsius (°C) as follows:

\[
LST = T_i - 273.15
\]

3.3. Intensity calculation and classification of the surface heat island effect

The intensity of the UHI is commonly defined as the difference between urban temperature and suburban temperature (Tomlinson et al. 2012); therefore, the UHI intensity has been built up according to the administrative boundary between the city and suburbs. The boundaries of the new district core and industrial park were designated in the zoning plan of the Tianjin NIP (2009–2020) (Li et al. 2009). The areas of the major city core, new district core and industrial park are 177 km², 673 km² and
117 km$^2$, respectively. The minimum influence area of the UHI effect is 150% of the urban area (Peng et al. 2012). Thus, 150% of the three “centers” was zoned as their boundaries (Fig. 2). The UHI intensity ($\text{UHI}_i$) in pixel scale is given by following.

$$\text{UHI}_i = \frac{T_i}{C_0} \sum_1^n T_{\text{suburb}}$$

3.4. Potential driving factor selection

The driving forces of the UHI effect are highly complex and diverse. Based on previous results on the driving forces of the UHI effect, the driving forces were divided into four layers: greenness, imperviousness, wetness and social economy. The greenness, imperviousness and wetness features are mainly composed of spectral factors that provide a robust explanatory power for LST change (Sun et al. 2018). Eleven potential driving factors were selected in the geo-detector model based on the literature review and available data (Table 1).

The normalized difference vegetation index (NDVI) (Tucker et al., 1985), normalized difference build-up index (NDBI) (Zha, Gao and Ni 2010) and modified normalized difference water body index (MNDWI) (Xu 2006), have been widely used to characterize vegetation coverage, to identify urban and built areas and to indicate water body features, respectively. These three factors have...
The potential driving factors selected in this study and their calculation formulas. Of the NPP-VIIRS nighttime light composite data has been used to establish a quantitative indicator, the NLI (Yu et al. 2018). Road density (RD) was calculated from urban road vector data, which are commonly used as indicators of the social economy (Sun et al. 2018, Peng et al. 2018).

Focusing on the polycentric structure, two factors were innovatively established in this study. Urban traffic is closely related to urban spatial structure, and the construction and development of rail transit stimulates the centrifugalizing of population, promoting the formation of polycentricty (Copus 2001). The urban form has a propulsive influence on the spatial distribution of UHI; therefore, railway density (RWD) was established and included in the social economy layer. In addition, the Haihe River crosses Tianjin, which is the largest river in North China, and there are 19 first-class rivers running through Tianjin, with a total length of 1095.1 km. Water-cooling islands are important to the mitigation of UHI effects (Du et al. 2016); therefore, waterway density (WD) has been built up as an indicator of wetness layer. When computing the RD, RWD and WD of each pixel, the search radius should be defined. The optimum radius was chosen by adjusting the radius parameters several times, with the minimum p value in the significance test. Factors from the same layer may be collinear, but they contain different spectral information with different adaptive applications. Therefore, the factors with the greatest degree of LST interpretation will be used as representative factors in the analysis.

According to the distribution density of waterways and railways and the significance test results of WD and RWD, WD was not included among the potential driving factors of LST in the new district core and industrial park, and RWD was not included among the potential driving factors of LST in the industrial park. Fig. 3 shows the spatial distribution of four potential driving factors from different layers.

3.5. Geo-detector model

Spatial variation is one of the basic characteristics of geographical phenomena. Geo-detector is a statistical method to detect spatial variation and reveal the driving forces behind this variation (Wang et al. 2010). The core ideology assumes that if an independent variable has an important impact on a dependent variable, then the spatial distributions of the independent variable and the dependent variable should be similar. Compared with other methods, the most prominent advantage of the geo-detector model is that the relationship between the driving factors and geographical phenomena can be detected without any assumption of linearity.

Table 1

The potential driving factors selected in this study and their calculation formulas.

<table>
<thead>
<tr>
<th>Layers</th>
<th>Potential Driving Factors</th>
<th>Acronym</th>
<th>Formula</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greenness</td>
<td>Normalized difference vegetation index</td>
<td>NDVI</td>
<td>NDVI = ((r_{SWIR} - r_{NIR}))/((r_{SWIR} + r_{NIR}))</td>
<td>(Tucker et al. 1985)</td>
</tr>
<tr>
<td></td>
<td>Tasseled cap transformation (greenness)</td>
<td>TCG</td>
<td>TCG = (-0.2941 * (r_{NIR}) + (-0.243 * (r_{Green}) + (-0.5424 * (r_{Red}) + (-0.2776 * (r_{NIR}) + (0.0713 * (r_{MNDWI}) + (-0.1608 * (r_{SAVI}) )))</td>
<td>(Bektas Balcik and Ergene 2016)</td>
</tr>
<tr>
<td>Imperviousness</td>
<td>Soil adjusted vegetation index</td>
<td>SAVI</td>
<td>SAVI = (1 + L)/((r_{NIR} - r_{NIR}))/((r_{NIR} + r_{NIR}) + L) = 0.5</td>
<td>(Huete 1996)</td>
</tr>
<tr>
<td></td>
<td>Normalized difference built-up index</td>
<td>NDBI</td>
<td>NDBI = ((r_{SWIR} - r_{NIR}))/((r_{SWIR} + r_{NIR})</td>
<td>(Zha et al. 2010)</td>
</tr>
<tr>
<td>Wetness</td>
<td>Modified normalized difference water body index</td>
<td>MNDWI</td>
<td>MNDWI = ((r_{Green} + r_{NIR}))/((r_{Green} + r_{NIR}) + (r_{SWIR}) )</td>
<td>(Xu 2006)</td>
</tr>
<tr>
<td></td>
<td>Tasseled cap transformation (wetness)</td>
<td>TCW</td>
<td>TCW = (0.1511 * (r_{NIR}) + (0.1973 * (r_{Green}) + (0.3283 * (r_{Red}) + (0.3407 * (r_{NIR}) + (-0.7117 * (r_{SAVI}) + (-0.4559 * (r_{MNDWI}) )))</td>
<td>(Bektas Balcik and Ergene 2016)</td>
</tr>
<tr>
<td>Social economy</td>
<td>Waterway density</td>
<td>WD</td>
<td>WD = (L_{Waterway}/Area_{water})</td>
<td>(Yu et al. 2018)</td>
</tr>
<tr>
<td></td>
<td>Nighttime lighting intensity</td>
<td>NLI</td>
<td>NLI = (NLI_{poly})</td>
<td>(Qihao et al. 2008)</td>
</tr>
<tr>
<td></td>
<td>Road density</td>
<td>RD</td>
<td>RD = (L_{Road}/Area_{circle})</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Railway density</td>
<td>RWD</td>
<td>RWD = (L_{Railway}/Area_{circle})</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Area\(_{water}\) represents the circular area centered over the pixel, with a radius of 1.5 km; Area\(_{poly}\) represents the circular area centered over the pixel, with a radius of 5 km; and Li represents the length of the target i inside the circle.
and its calculation processes and results will not be influenced by collinearities of multiple variables. Additionally, the interaction detector can compare the combined contribution of two individual driving factors to LSTs as well as their independent contribution. Accordingly, the factor detector and interaction detector are involved in the driving force analysis of LSTs in this study.

3.5.1. Factor detector

The factor detector mainly quantitatively detects the effects of different factors on the LST; the larger the probability distribution (PD) value is, the stronger the effects of the influencing factors on the LST.

\[
PD = 1 - \frac{SSW}{SST} = 1 - \frac{1}{C0} \frac{\sum_{h=1}^{L} N_h \sigma^2_h}{N \sigma^2} = 1 - \frac{SSW}{SST}
\]

\[
SSW = \sum_{h=1}^{L} N_h \sigma^2_h, \quad SST = N \sigma^2
\]

In this study, the variable Y (or factor X) is composed of L grade \((h = 1, 2, \ldots, L)\); \(N\) and \(N_h\) denote the number of cells in the entire area and the \(h\) grade, respectively; \(\sigma^2\) and \(\sigma^2_h\) represent the variances in \(Y\) in the entire area and \(h\) grade, respectively. PD\(\in[0,1]\); in extreme cases, the PD value is equal to 1, indicating that factor \(X\) completely controls the spatial distribution of \(Y\), and a PD value of 0 illustrates that factor \(X\) has nothing to do with \(Y\); in other words, the PD value means that factor \(X\) explains \(100 \times \text{PD}\%\) of \(Y\). In this study, the dependent variable \(Y\) is LST, and the independent variable \(X\) is the potential driving factor. Although there may be collinearity between the selected variables, the results will not be affected because each factor is input separately when calculating the degree of LST interpretation.

3.5.2. Interaction detector

The purpose of interaction detectors is to identify the interactions between different factors (X), that is, whether factors \(X_1\) and \(X_2\) interact together to increase or decrease the explanatory

Fig. 3. Spatial distribution maps of four potential driving factors from different layers.
power of the dependent variable (Y) or whether the effects of these factors on Y are independent of each other. First, we calculate the PD values of two factors, X_1 and X_2; then, we overlay the two factors and calculate their PD value (PD(X_1 \cap X_2)). The relationship between the two factors can be divided into the following categories:

Enhance: PD(X_1 \cap X_2) > PD(X_1) or PD(X_2)

Bi-enhance: PD(X_1 \cap X_2) > PD(X_1) and PD(X_2)

Enhance, nonlinear: PD(X_1 \cap X_2) > PD(X_1) + PD(X_2)

Weaken: PD(X_1 \cap X_2) < PD(X_1) + PD(X_2)

Weaken, uni-enhance: PD(X_1 \cap X_2) < PD(X_1) or PD(X_2)

Weaken, nonlinear: PD(X_1 \cap X_2) < PD(X_1) and PD(X_2)

Independent: PD(X_1 \cap X_2) = PD(X_1) + PD(X_2)

3.5.3. Data discretization

The geo-detector model emphasizes the hierarchical heterogeneity of spatial attributes. Therefore, it is necessary to discretize the input data of the independent variables and dependent variables when using geo-detector for driving the analysis. However, it is difficult to control the number of classifications in the discretization process: excessive classifications are redundant, whereas too few classifications will fail to explain the spatial diversity; the selection of the discretization method also plays an important role (Cao et al., 2013). It is important to note that we generally choose a discretization scheme with the maximum PD value. To minimize the uncertainty to the greatest extent, several common discretization methods have been compared, such as the equal interval method, quantile classification method and natural breaks method. After comparison, finally, we choose the quantile classification method with the maximum PD value as the optimal scheme. Consequently, in this study, the quantile classification method is used to classify the potential driving factors into 8 grades, ensuring that each grade contains an equal number of elements, an approach that provided a suitable result in another similar study involving driving force analysis (Cao et al., 2013).

4. Results

4.1. Spatiotemporal pattern of the UHI in three city “centers”

Table 2 shows the average LSTs of three city centers and their boundaries in different periods, and the average UHI intensities of major city core, new district core and industrial park are 1.4, 1.29 and 2.23, respectively. In addition, the box plots (Fig. 4) illustrate the value distribution of LST in the whole city and three city centers. The LST medians of the three study areas were significantly higher than that of the whole city (Fig. 4), demonstrating that these three centers could be regarded as hot spots in Tianjin for thermal environment studies.

In the major city core, the spatial distribution pattern of the UHI is relatively uniform (Fig. 5) and the proportion of heat island areas increased by 10% from 2013 to 2018. Areas with higher heat island intensity are mainly distributed in commercial or high-density residential areas. No heat island areas were mainly concentrated in the Haihe River Basin, Ziya River Basin and the large park in the southeast. The large-scale green space and urban water have obvious cooling effects on the surrounding area, which is conducive to alleviating the UHI effect. The relatively homogeneous spatial pattern of UHI in the major city core is probably due to the early development of urbanization, the mature planning of the functional areas, and the coordinated spatial layout, avoiding the concentration of high temperature areas.

In the new district core, the spatial distribution pattern of the UHI is unbalanced along the east–west axis (Fig. 5). No heat island areas are mainly concentrated over the southern agricultural fields and Beitang Reservoir in the north, and the high UHI intensity areas are aggregated in the central business district and southeastern harbor economic area. Heat island intensity was gradually alleviated after 2015 in the harbor economic zone. The establishment of artificial ecological wetlands has played an important role in optimizing the regional environment, and the ecological construction of the harbor economic zone has achieved preliminary results. The heterogeneous heat island spatial pattern has resulted primarily from complicated reforms since the establishment of BHD in 1994. After 2005, the internal spatial structure and industrial functional zoning of the BHD have been planned adequately. Several policy changes have brought about changes in the spatial structure of the region. As a type of pilot area in China, the spatial structure and development of the new district core are not sufficiently mature, which is one of the principal reasons for the change in internal sub-heat islands.

In industrial park, the distribution of high UHI intensity areas is stable and concentrated; industrial production areas are segregated by green belts with clear boundaries (Fig. 5). No heat island areas are mainly concentrated in the eastern coastal regions and the scattered green belts. The industrial park is mainly composed of petrochemical, metallurgical and other industrial land covers. Therefore, the artificial heat emissions generated by industrial activities become an important factor affecting the thermal environment. The thermal radiation caused by industrial activities is difficult to dissipate in a short time, and the aggregation of this high-temperature region can be easily captured by thermal infrared remote sensing images. However, in recent years, the UHI intensity has fluctuated greatly in industrial land (Fig. 5), which is probably related to the intensity of industrial production activities during the imaging time.

<table>
<thead>
<tr>
<th>Date</th>
<th>Major City Core</th>
<th>New District Core</th>
<th>Industrial Park</th>
</tr>
</thead>
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<tr>
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<tr>
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<td>40.10</td>
<td>36.71</td>
</tr>
</tbody>
</table>

Notes: LST_130089, LST_131233 and LST_131233 stand for the average LSTs of the major city core, new district core and industrial park, respectively. LST_131233 represents the average LSTs of the three city cores’ boundaries, respectively. UHIIc, UHIi and UHIi refers to the UHI intensities of the three city centers.
4.2. The dominant driving factors of LST in different city “centers”

Based on the factor detectors model, our study compared the driving factors of LST in the three study areas with those for the whole city of Tianjin, and each factor passed the significance test (p < 0.05). The results show that the driving factors for the whole city, major city core, new district core and the industrial park have distinct differences. The calculation of the PD value for each factor shows (Table 3) that the explanation rates of the greenness and imperviousness layers of LST are higher than those of other factors, in Tianjin and the major city core. More concretely, the imperviousness layer factor (IBI) exhibited significantly higher explanation rates (45.9% and 27.7%, respectively) than those of the other factors for LST in Tianjin and the major city core. However, the explanatory ratios of greenness factor and wetness factor to LST were higher in the new district and industrial park. The NDVI exhibited the highest explanation rate (42.5%) in the new district core, followed by MNDWI (39.6%). Similarly, the NDVI exhibited the highest explanation rate (54.2%) in the industrial park, followed by MNDWI (49.4%). This regional difference indicated that the explanatory ability of wetness factors and greenness factors to LST could be more prominent than that of imperviousness factors when the study area is located in the coastal condition. It is noteworthy that NDVI, NDBI and MNDWI were highly correlated with LST in every city “center”. Although WD passed the significance test (p < 0.05), its explanation rate of LST was negligible in Tianjin and in the major city core. Thus, the spectral factors (such as MNDWI) extracted by remote sensing data are still more suitable as a representative factor of the wetness layer than is WD, even if the waterway within the city are quite dense.

In the social economy layer, NLI was selected to represent the regional degree of economic development. There was a significant correlation between the NLI factor and LST in Tianjin (33.5%), the new district core (27.4%) and the industrial area (14.8%). In contrast, the explanatory ratio of NLI was quite small in the major city core (2.8%). Part of the reason is that, urban development in the major city core tends to be saturated, causing the night light intensity to exhibit almost no spatial differentiation. In this situation, it is difficult for night light data to show the spatial heterogeneity of regional economic development when the study area covers only urban areas without suburbs. A similar situation occurred in RW. From the perspective of urban spatial development form, to some extent, RWD represents the accessibility of a region. The explanatory degree of RWD to LST cannot be neglected in Tianjin (18.6%), the major city core (5.8%) or the new city core (12.7%).

The geo-detector model emphasizes the hierarchical heterogeneity of spatial attributes. If there is no similar spatial heterogeneity between dependent variables (potential drivers) and independent variables (LST) in the study area, then the PD value is low. As a result, the PD value of each factor in major city core is lower than that of other city “centers” because the urban development and planning are nearly optimal; the spatial layout is stable and coordinated, so that various attributes have little spatial heterogeneity within a given city center. As shown in Fig. 5, the rel-
The PD value calculation of Tianjin city represents a city-level result of LST driving factors. Relatively, the greenness factors and wetness factors in the new city core and industrial park exhibited a higher explanation for LST, which indicated that increasing green space coverage and regional humidity will effectively alleviate the UHI effects in these city “centers”. The ranking of the factors' layers is quite similar in the new city core and industrial park (greenness > wetness > imperviousness > social economy). As noted above, these two centers are both located in coastal areas and are spatially adjacent (Fig. 2), although they have large differences in terms of land cover types and regional functions. Tobler’s First Law (Tobler W R. 1970) that “Everything is related to everything else, but near things are more related to each other” can reasonably explain this result, which also partly explains the higher degree of interpretation of the wetness factor in the new district core and industrial park.

4.3. Average interaction between the driving factors of LST in different city “centers”

The interaction detector was used to evaluate and analyze the integrated effect of two driving factors on LST. Based on the interaction detector model, our study explored the interaction between factors and LST. The major purpose of this study is to capture the interaction between factors from different layers, rather than within the same layer. The following phenomena must be explained: (1) The interaction of the same factor (such as NDVI ∩ NDVI) has the same PD value as that of the factor detector because the interaction detector calculates the PD value after the two factors are overlaid, while the spatial distribution of the same factor has no change after the overlay process. (2) The interaction of factors from the same layer (such as NDVI ∩ TCG) has no profound implications for understanding the LST driving mechanisms since these factors come from the same layer and represent the spectral information of the same type of land cover. Therefore, no further discussion about the above contents will be made in this section. Eventually, bilinear or nonlinear interactions were observed for all relationships among the 11 potential driving factors, which shows that under the control of any two factors, the internal difference in LST changes will be reduced, significantly enhancing the influence of the factors after interaction.

The UHI effect is the result of regional greenness, imperviousness, wetness and socioeconomic factors. The results (Fig. 6) showed that the interactions of greenness and wetness were significantly greater in Tianjin. In details, the largest interactions between the factors were NDVI ∩ TCW (61.1%), SAVI ∩ TCW (61%), SAVI ∩ MNDWI (59.2%) and NDVI ∩ MNDWI (59.2%), which illustrated that natural factors have a greater impact on LST from a relatively macro perspective (in the whole city). When the research perspective was locked in the major city core, the interactions between imperviousness factors and greenness factors were the most prominent. In particular, the interactions between IBI and three greenness factors exceeded 36%. The dominant driving role

Fig. 5. Distribution maps of urban heat island intensity in three city “centers”. The first column is the main city core, the second column is the new district core, and the third column is the industrial park. Locations with blue rendering represents the area where the urban heat island intensity is less than 0°C, that is, the area without the heat island effect. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
of imperviousness factors is consistent with the results of the factor detector in the major city core. The interaction between TCG and TCW (58.23%) had the strongest effect on LST, followed by NDVI \( \cap \) IBI (58.16%) and MNDWI \( \cap \) TCG (57.87%) in the new district core. Although the differences between these interactions were quite low, it is undeniable that the interaction between the greenness factors and wetness factors are the most significant. At present, the interaction between greenness and wetness on LST is prominent, but with the development of the new district core, the interaction between greenness factors and the imperviousness factor is likely to increase gradually, approaching the results of the major city core. In the industrial park, the interactions between greenness factors (NDVI, SAVI) and social economic factors (NLI, RD) were stronger than in other city “centers.” Previous studies have shown that, the brightest areas in images of night-time lights are not necessarily the most populated areas as these well-lit areas may represent the industries or factories, and the night light data could be effectively used in electricity demand estimation (Tripathy et al. 2018). Accordingly, we could infer that the relatively high contribution of NLI to LST in the industrial park is related to its functional characteristics, partly because production activities are highly correlated with electricity demand. The spatially heterogeneous results of the three study areas will provide further insight into exploring the driving mechanism of LST and provide useful thermal environment governance guidance for planners requiring detailed information.

5. Discussion

5.1. Theoretical implications

This paper describes an exploratory study linking the polycentricism theory with the detection of the urban thermal environment through remote sensing. Suburbanization generates a polycentric urban form, which is a prevailing trend of metropolitan development in various countries, emphasizing the function and economic complementarity among the inner regions of cities. However, few studies take various “centers” as the basic units, adequately characterize heterogeneous UHI spatial patterns or identify the dominant LST driving factors. Scholars have paid considerable attention to the spatiotemporal patterns of UHI in built-up areas (Meng et al. 2018), and city-scale UHIs analysis (Schwarz, Lautenbach and Seppelt 2011). We believe that the new morphologic forms of polycentric cities should be taken into account, and it is worthwhile to study the surface change processes of the thermal environment at a microscale. A considerable contribution of this study is that the spatial diversity of UHI patterns under the polycentric urban mode and the dominant factors influencing LST in these areas have been examined thoroughly, to clarify the mechanisms driving LST with a typical study case.

Based on the geo-detector model, our study used the ranking of PD values as the criterion for determining the dominant driving factor of LST (Cao et al., 2013) and compared and analyzed the results of different city “centers.” The results showed that imperviousness factor was the foremost dominant driving factor of LST whether for the whole city or the major city core; similar results were also shown in relevant studies (Chen et al. 2006, Dai et al. 2018, Estoque, Murayama and Myint 2017, Chen et al. 2013). A previous study also found that the explanatory rate of the water body factor on LST was weak in each season (Peng et al. 2018). In contrast, a remarkable driving force of the wetness factor on the thermal environment in the new district core and industrial park was found in this study. One possible reason for this difference is that the proportions of different landcover types differ at varied research scales. To be more specific, the proportion of water body at the urban inner-center scale is smaller relative to that of city-scale, which probably lead to the underestimation of the effect of the wetness layer on LST. Urban water bodies form cooling effect on their surrounding areas (Du et al. 2016), correspondingly alleviating the UHI effect. Therefore, water bodies are an essential surface component affecting the spatial pattern of UHI and must be considered in ranking the various factors influencing LST.

The varied spatial pattern of UHI in the three city centers revealed the diverse driving mechanisms driving LST. The coverage ratio of artificial surface is lower in the new district than in the major city core, and the sensible heat flux of the artificial surface...
is relatively high, which partly explains why the UHI intensity in the major city core is higher than that in the new district core. Thermal emissions from industrial activities are likely to lead dramatic changes in roof surface temperature, which were difficult to reveal based on spectral factors indicating the type of impervious surface coverage (such as NDBI, IBI). When the LST of the same artificial surface varies widely, the imperviousness factors will no longer have strong explanatory power for LST because the values of spectral factors remain the same, whereas the thermal infrared radiation of the roof surface changes dramatically. Therefore, it is also reasonable that the standard deviation of the PD value of IBI was relatively larger than that of other “centers.” Moreover, twenty slices (Fig. 7) were randomly sampled in the heat island areas (UHI intensity greater than 0) to further examine the relationship between LSTs and the proportion of impervious surface in three city centers. The scatter plots (Fig. 8) showed the average LSTs in each sampling with different impervious surface proportions. The plots showed that in several samplings of the industrial park with a low proportion of impervious surface (10%-40%), the average LSTs could approach those of sampled areas with higher impervious surface proportion (60%-90%) in other city centers. A reasonable explanation for this phenomenon was related to the heat radiation source: the solar radiation from the same remote sensing image exhibited little differences among the three city centers; therefore, there was a strong possibility that the industrial activities generated extra heat sources. Given the above, it could be inferred that cutting down production maybe more effective in achieving a better balance of the thermal environment in industrial park than simply reducing the number of factories. Thus, the spatial variation of LST is influenced not only by landscape components or biophysical processes, but also by anthropogenic factors. This phenomenon further illustrates the complicated mechanism driving the urban thermal environment at a fine scale. This is only a tentative study, and whether the inferences could be generalized to other industrial parks requires further studies; additional explorations should be conducted to support our assumptions as well.

5.2 Management implications for polycentric cities

There is an increasing trend that numerous international metropolises are developing into a polycentric form under the process of suburbanization (Pain 2008, Liu et al. 2015, Lan et al. 2019). The results suggested that three typical types of city centers with diverse composition of land cover features in a landscape significantly influenced the magnitude of LST, and the socioeconomic development level is an indispensable factor in forming the UHI effect. These distinct responses within the inner-city centers are expected to provide novel and considerable insights into urban ecological design, and, therefore, may have irreplaceable merits for environmental quality improvement and the reorganization of regional resources. Thus, this study aimed to help decision-makers develop urban management policies with respect to natural resource allocation and industrial functional optimization, which is essential to mitigating the impact of urbanization on the UHI effect.

According to the different characteristics of various city centers, this study recommends that greater attention to be given to the development of individual schemes with adaptive configurations of land cover at a fine scale. Specifically, the most prominent factor explaining LST in the major city core is the imperviousness factor,
followed by the greenness factor. Artificial surfaces determine the absorption of solar radiation, the formation of airflow and the generation of anthropogenic heat (Huang and Wang 2019); however, it is probably unrealistic to directly reduce the distribution of buildings in urban areas due to the scarcity of land resources. In contrast, increasing green coverage is an effective means to mitigate excess urban heat, such as by setting goals to increase tree canopy cover in selected locations in order to enhance ecosystem services (Zhou et al. 2011). Furthermore, the UHI intensity is much lower in the western edge of the new district core, indicating that there are still undeveloped lands within its boundaries; hence, we could control the amount of man-made areas by moving certain functional units to the new district core to spread out the pressure of the population and control the negative ecological impact derived
from high-density buildings in the major city core. In terms of the industrial park, the LST characteristics revealed by this study provide targeted suggestions to minimize the impacts of industrial production activities by reducing industrial production intensity. Furthermore, the wetness factor plays a significant role in the influence of LST in the new district core and industrial park; therefore, increasing waterbody proportions are preferable for UHI mitigation since waterbodies can absorb heat from ambient temperature (Du et al. 2016).

5.3. Limitations and uncertainties

In this study, we attempted to select the potential driving factors of LST comprehensively, but there are numerous factors affecting the LST, whose internal mechanisms is extremely complex. Therefore, certain potential factors have been neglected, which is worthy of further exploration and discovery in the future. For instance, the impacts of land use/land cover changes (Zhou and Chen 2018), meteorological conditions (Schatz and Kucharik 2014), spatial resolutions (Estoque et al. 2017) and other factors on LST have not been considered in this study. Furthermore, certain exploratory conclusions about the interaction of the LST factors have been summarized based on the interaction detector model, which not been reported in similar research. It is undeniable that the geo-detector model is hardly be used to complete the calculation of the interaction among three factors or more. Thus, further research must be developed to simulate the interactions in more complex situations.

This study focused on the polycentricity of the spatial development structure of metropolitan cities, compared the UHI spatial patterns of different city centers and the dominant driving factors of LST from a micro perspective, which required relatively high spatial resolution of thermal infrared bands. The open source thermal infrared remote sensing image provided by the TIRS sensor Landsat8 has the advantage of high spatial resolution, but its revisit period is 16 days. To ensure the quality of data, the scene cloud cover is<5% in this study. Additionally, to exclude the influence of seasonal factors, the data selected in this study are all from summer (July or August). Such strict data selection requirements limit the amount of employed remote sensing data, which also represents a considerable limitation of this study. Furthermore, in data preprocessing, night light intensity (NLI) data were resampled to 100 m despite their original resolution of only 750 m, which led to several inevitable effects on the final results. It is undeniable that such resampling of NLI is likely to lead to a lower PD value because the nighttime light satellite imagery with 750 m resolution are unable to capture the detailed spatial heterogeneity with 100 m spatial resolution. However, to a great extent, resampling all the potential driving factors at 100 m resolution could avoid the loss of detailed information on other factors since the spatial resolutions of their raw data are greater than 100 m. The basic research unit of this study is the “center” within a polycentric city, so the research spatial scale is relatively small. Although resampling all factors at 750 m resolution could avoid the influence of different spatial resolutions, such data could not satisfy a small-scale study. Another consideration is that there are other factors involved in the socio-economic layer; in case of probable error with NLI, the impact of socio-economic factors on LST could still be compared and ranked with other factors to a certain extent. With the development of remote sensing techniques, higher spatial resolution imageries can be expected to solve this problem.

6. Conclusions

In recent years, due to population agglomeration, traffic congestion, air pollution and other prominent problems of urbanization, the UHI effect has become increasingly serious. Based on current studies, our study took a typical polycentric city in northern China as a case study, Tianjin, and selected three types of city “centers”: a major city core, new district and industrial park. On this basis, eleven potential driving factors of LST were explored from four layers of greenness, imperviousness, wetness and social economy, and the geo-detector model was applied to measure the explanatory degree of the potential LST driving factors. Finally, we arrived at the following conclusions.

(1) Three different city “centers” (i.e., the major city core, new district and industrial park) of the polycentric city showed varied UHI spatial pattern characteristics, and the responses of the LST to natural factors and social factors was quite diverse among these centers.

(2) Heat island areas were distributed homogeneously in the major city core with a higher urbanization degree; the UHI spatial pattern on the east–west axis was unbalanced in the new district core because of the unsaturated urban space and dynamic planning policies; in the industrial park, production areas were segregated by green belts with clear boundaries.

(3) Whether for the whole city or the major city core, the imperviousness layer had significantly higher explanatory rates than the other factors for LST, followed by the greenness factor.

(4) In the new district core and industrial park, natural factors (greenness and wetness) played a dominant role in the influence of LST. It can be concluded that in the region with unbalanced development (such as the new district core) or vigorous production activities (such as the industrial park), increasing green space coverage and regional humidity can alleviate the UHI effect, more effectively than controlling the coverage of impervious surface.

(5) In the industrial park, the factors of each layer have relatively high explanation rates for LST. Strictly controlling the production intensity of industrial activities could be an effective measure to reduce the anthropogenic heat source, benefiting the thermal balance of the local ecological environment.

(6) The change in LST is the result of a combination of multiple factors that have bilinear or nonlinear interactions. Thus, the interpretation of LST by any two factors is enhanced after interaction. Certain factors with a lower explanatory degree may exceed that of the dominant factors after the interaction. The highest factor interaction probably does not arise from the dominant factors with the highest PD value.

Our results suggest the complex mechanism of LST within different kinds of city centers at a relatively fine scale; an individual scheme with adaptive configuration of land cover has been recommended accordingly. Although there are partial uncertainties and data limitations, further study on the selection of potential driving factors and technical frameworks remain. This study advances the LST driving laws in polycentric cities and provides a typical case for urban planners for urban management and UHI mitigation at a fine scale, especially for highly urbanized polycentric cities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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