Do industrial parks generate intra-heat island effects in cities? New evidence, quantitative methods, and contributing factors from a spatiotemporal analysis of top steel plants in China

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ABSTRACT

Industrial parks emit large amounts of anthropogenic heat and aggravate the urban heat island effect, which has become a severe environmental problem worldwide. Few studies explored if the warming effect generated by concentrated industrial facilities (i.e., steel plants in this study) produces an intra-heat island effect in urban built-up areas. Sufficient evidence of an industrial heat island (IHI) effect is lacking, and new quantitative methods are urgently needed to address these issues. Therefore, we proposed a new scheme to quantify the warming effect of large, heat-emitting urban objects versus complex surroundings, and the IHI effect was accordingly defined at a finer scale. This study separated the industrial park from other artificial lands and comprehensively estimated the IHI effects’ spatiotemporal variation. The IHI intensities were measured based on varied natural and urbanized references, which provided new evidence for the existence of the IHI effect over space and seasons. The land surface temperature (LST) profiles delineated the downward trend in LST variation from inside to surroundings in the IHI cases on both spatial and temporal scales. The time-series analysis revealed that the IHI effects demonstrated more significant disparities regarding the LSTs between the industrial parks and their surrounding backgrounds during warm seasons than in cold seasons. And a more severe IHI effect was observed in spring and summer, and the weakest IHI intensity occurred in winter. Moreover, the IHI intensity is positively associated to the anthropogenic heat, indicating that the industrial activities contribute to the increased LSTs of the industrial park to a great extent. The rationale of the IHI effect can broaden insight for understanding how urban industrial heat sources influence the regional thermal environment, especially at a finer scale.

1. Introduction

Worldwide, human activities are transforming agriculture-dominated societies into industry-dominated ones at an unprecedented rate of urbanization (Seto et al., 2011; Huang et al., 2019), which is driving significant changes in urban climates and ecological processes (Buyantuyev and Wu, 2010; Zeng et al., 2015; Koralegedara et al., 2016; Wei et al., 2016; Meng et al., 2017). The urban heat island (UHI) effect refers to the air temperature of urban areas exceeding those of their surrounding rural areas (Oke, 1982; Voogt and Oke, 2003). Rising urban (air and surface) temperatures have affected the quality of life of urban residents, aggravated air pollution, increased the energy consumed for cooling, and negatively impacted human health (Patz et al., 2005; Kolokotroni et al., 2006; Sarrat et al., 2006; Zhang et al., 2013; Massetti et al., 2014; Chen et al., 2016; Renard et al., 2019; Abbassi et al., 2020). For these reasons, urban researchers are eager to develop strategies that could mitigate the further warming of urban areas.

Generally speaking, anthropogenic heat emission is one of the most significant factors that intensify UHI effects (Chandler, 1961). In past studies, the anthropogenic waste heat emissions generated by industrial, transportation, and building energy have been found to be significant contributors to UHIs (Papadopoulos and Moussiopoulos, 2004; Kato and...
It is also well known that industrial lands play a dominant role in generating high land surface temperature (Li et al., 2011), and hot urban regions are generally highly concentrated in industrial lands (Pearsall, 2017; Tran et al., 2017). To sum up, the environmental pollution induced by industrial activities has inevitably affected the ecosystems (C. Yuan et al., 2020).

The exploitation and use of resources to produce the essential materials and energy for industrial development have caused many environmental problems (Rao et al., 2018; Zhang et al., 2019; Liu et al., 2020; Pena-Paras et al., 2020). In this context, the local climate zone (LCZ) system and empirical evidence show that industrial activities contribute to intra-urban surface temperature differences (Bechtel et al., 2019). Nevertheless, regarding the differences in land surface temperature (LST) between industrial parks and their complex surrounding backgrounds, few studies have examined industrial lands as a separate object to clarify this warming effect. Besides, it is unknown whether there is a correlation between the industrial activities and these LST differences and how much the industrial processes contribute to the (surface) industrial heat island (IHI) effect. Thus, scholars should pay more attention to the quantitative investigation of industrial lands.

Remote sensing (RS) technologies provide a means of conducting quantitative urban surface temperature studies, and RS data/products can be quickly collected in large amounts relative to test-point data measured in field experiments (Peng et al., 2012). Numerous studies have demonstrated that the satellite-derived LST could effectively indicate the urban thermal environmental variations with reasonable precision (Weng, 2009; Xu et al., 2013; Zhan et al., 2014; Tran et al., 2017). Thereby, thermal remote sensors could observe the urban surface heat island (SUHI) effect (Estoque and Murayama, 2017; Meng et al., 2018). Besides, thermal infrared RS images also enable researchers to detect industrial heat sources (Xia et al., 2018). They show great potential for use in most industrial case studies (Huang and Wang, 2019). However, most industrial case studies have been conducted only for a single time or in only one city. Thus, more multi-temporal and multi-regional experiments are needed to understand the existence and intensity of the IHI effect.

An urban thermal environment’s spatial pattern and temporal variation can be quickly and efficiently characterized by classifying the LST (Meng et al., 2018; Rao et al., 2018). However, no method exists to measure the geometric morphology of thermal patches (i.e., clusters of different LST classes) for evaluating the SUHI effects from the morphological perspective. Since the literature shows that landscape qualities significantly impact LSTs and SUHIs (Shaker et al., 2019; Sun et al., 2020), we designed new metrics for characterizing thermal landscapes to quantitatively indicate thermal configurations based on LST classification maps, especially for the large, heat-emitting urban targets (e.g., industrial parks). Uncertainties have persisted in recent studies. To fill these gaps, we aimed to: (1) present new evidence of the IHI effect generated by industrial parks over space and seasons using RS data; (2) propose a quantitative method, including applicable indicators, to evaluate spatial patterns and temporal variations in IHI effects comprehensively; (3) establish thermal landscape metrics for characterizing the configuration of thermal patches inside IHIs; (4) explore the potential of RHIs to impact the spatial patterns of LSTs in the IHI areas.

2. Materials and methods

2.1. Study sites

Since 1978, China has experienced rapid industrialization (J.-J. Yuan et al., 2020). As a leading industrial power in the world, the industrial status of China is somewhat globally representative. Therefore, ten industrial parks (where the large steel plants are located, more detailed information are listed in Table S1) from different cities in China were taken as the study sites (Fig. 1). Representative sites were selected regarding the “Evaluation of development quality and comprehensive competitiveness of iron and steel enterprises (2020)” issued by the China Metallurgical Industry Planning and Research Institute (http://www.mpi1972.com)/.

2.2. Multisource data

In this study, we employed cloudless Landsat 8 thermal infrared sensor (TIRS) images (spatial resolution: 100 m) from 2013 to 2020, which were downloaded from the United States Geological Survey (USGS, https://glovis.usgs.gov/). A total of 54 images were used for LST retrieval. The daily nighttime light satellite imagery product of Suomi-NPP/VIIRS (national polar-orbiting partnership visible infrared imaging radiometer suite, https://ngdc.noaa.gov/eog/viirs/download_utmos.html) was collected to detect the anthropogenic heat emission at the same days corresponding to the LST datasets. The original RS images preprocessing was calibrated in ENVI v.5.3 (L3Harris Geospatial, USA). Multi-source classification data products were collected to obtain the spatial distribution of different reference areas: (1) the map of LCZ (Bechtel and Daneke, 2012; Bechtel et al., 2015) produced by World Urban Database and Access Portal Tools (WUDAPT) (Ching et al., 2018), (2) the land cover map, (3) annual map of artificial impervious areas (Gong et al., 2020) and impervious surface data products from the National Earth System Science Data Center of the National Science & Technology Infrastructure of China (http://www.geodata.cn). The vector data for the industrial parks were artificially framed based on visual interpretation and empirical knowledge.

2.3. Retrieval of land surface temperature

The land surface temperature data were acquired from a practical split-window algorithm (Du et al., 2015), widely applied in temperature studies, and demonstrated good thermal detection performance (Bahi et al., 2016; Alavipanah et al., 2018; Xue et al., 2019; Zawadzka et al., 2021). The required atmospheric parameters and the emissivity were estimated based on atmospheric water vapor retrieval (Ren et al., 2015) and vegetation coverage (Du et al., 2015), respectively. The formula for
### Anthropogenic heat flux evaluation

Anthropogenic heat flux (AHF) indicates the heat release from human activities to the environment, i.e., anthropogenic heat emissions (AHEs) per unit time and unit area (Taha, 1997). Therefore, the measurement of AHF is essential for meteorological heat-related investigations (Sailor, 2011), which is the basis for examining the impacts of anthropogenic heat on the urban thermal environment (Chen et al., 2019). This study utilized the nighttime lights (i.e., NL) as a proxy to estimate the AHES (Zhou et al., 2014). At present, numerous NL-based gridded AHF estimation schemes have been constructed and more generally applied to characterize the spatial patterns of anthropogenic heats on the city scale (Chen et al., 2019; Wang et al., 2019). Given that the application of these approaches at the local scale remains to be investigated, we introduced an exploratory case to discuss the relationship between NL and LST in the industrial park. To facilitate multi-temporal comparison, the original NL time-series datasets were normalized by the linear membership function, transforming the pixel values to a scale of 0–1 (Huang and Wang, 2019).

### Modeling the industrial heat island effect versus complex surroundings

Previous urban climate studies have revealed that point sources of strong anthropogenic heat can influence the canopy layer heat island on small scales (Oke et al., 2017). However, there is no precise definition of the warming effect generated by industrial parks; moreover, a quantitative approach to delineate the LST change between industrial parks and their surroundings is still lacking. Given the complex urban context, we hypothesize that the LST difference/downward trend between the “core” area (i.e., industrial parks) and the surroundings are the criteria of a surface intra-heat “island” effect inside the cities, even if an inconsistent/heterogeneous background landscape can be expected. Taking the 5-km buffer as the background reference, this study defines the (surface) IHI effect as the condition under which the LST of an industrial park is higher than that of its surroundings. A quantitative modeling scheme of the IHI effect was developed in this Section.

### 2.5.1. Land surface temperature profile of the industrial park

The LST profile (Fig. 2) was proposed to quantitatively depict the ambient thermal conditions outside the industrial parks. Continuous buffers of 50 m in width within the 5-km ambient environment of the parks were produced, and the mean LSTs of each annulus were calculated; in one particular case, the continuous buffers were within 6 km ambient environment of the Baotou Industrial Park, and a width of 60 m was produced. This process was mainly accomplished using Python v. 2.7 (Python Software Foundation, USA) and ArcPy site package (Environmental Systems Research Institute, Inc., USA). The mean LST points derived from the continuous buffers consisted of the LST profiles. The horizontal axes represent the distance (m) of annuli from the edges of the industrial parks, and the vertical axes represent LSTs (°C).

According to the LST profiles, the IHI effect could be quantitatively estimated. Here, \(L_{\text{max}}\) (m) was identified by the first turning point of the curve. When the slopes of the LST curves changed sharply or plateaued, the turning points of the LST curves were determined manually. Meanwhile, \(L_{\text{base}}\) (°C) denoted the decline in LST between the industrial parks and their first turning point, and \(G\); \(G\) was the mean decline in LST (°C/km).

### 2.5.2. Indicators of industrial heat island intensities using different reference areas

The classical indicator of the SUHI effect is comparing the LST difference between urban and rural areas (Buyantuyev and Wu, 2010; Tomlinson et al., 2012). However, researchers developed varied methods to delineate the “urban” versus “rural” areas, and kinds of indicators using different reference areas (i.e., “rural” part) have been proposed in SUHII quantification. In this study, three types of SUHII intensities were applied to measure the warming effects generated by industrial parks inside the cities, which respectively emphasize microclimatic backgrounds, land cover types, and buffer-based surroundings: (1) A neighborhood-scale SUHII assessment approach (Betchel et al., 2019) according to the LCZs regime (Stewart and Oke, 2012). The LCZ D (low plants) is defined as the reference area: \(SUHII_{\text{LCZD}} = LST_{\text{LCZD}} - LST_{\text{core}}\). (2) The LST differences between urbanized land and other land cover types (Schwarz et al., 2011), described as \(SUHII_{\text{Landcover}} = LST_{\text{urban}} - LST_{\text{other}}\). (3) Taking a specific distance buffer around the city as background area (Peng et al., 2012), the SUHII can be expressed as \(SUHII_{\text{buffer}} = LST_{\text{core}} - LST_{\text{background}}\). Specifically, we defined the IHI intensity (IHI, °C) as the LST difference between industrial parks and their surroundings. The calculation of \(IHI\) is shown in formula (4), the \(T_{\text{Industrialpark}}\) is the mean LST of an industrial park and \(T_{\text{background}}\) represents the mean LST of their surroundings. Since the \(L_{\text{max}}\) of the ten IHIs in this study were all within 5 km, the 5 km buffers of the industrial parks were considered to be the background areas.

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IHI = T_{\text{Industrialpark}} - T_{\text{background}}
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the thermal patch density is the number of landscape patches in a target area (e.g., an industrial park) and indicates the degree of patch fragmentation. The thermal edge density and thermal landscape shape index were adopted to characterize the shape segmentation of patches, while the thermal Shannon’s diversity index reflects the heterogeneity of the thermal landscape. The LST classification maps based on these indices were taken as the input data to calculate the thermal landscape metrics, as performed using FRAGSTATS v. 4 (McGarigal et al., 2012) (https://www.umass.edu/landeco/research/fragstats/fragstats.html).

2.6. Statistical analysis

Pearson Correlation Coefficient was used to test the correlations between the anthropogenic heat and IHI intensities (IHIIs) in the time-series case. The correlation analysis and significance test were conducted in SPSS v. 20.0 (International Business Machines Corporation, USA). Further, the spatial statistical method based on the spatial heterogeneity characteristics of geo-phenomena, that is geographical detector model (GDM) (Wang et al., 2010) was adopted to assess the influence degree of local-scale landscapes (i.e., LCZs), land covers (LCs), and anthropogenic heat (i.e., quantified by NL) to the spatial patterns of LSTs within IHI areas over different seasons.

3. Results

3.1. Existence and quantitative evaluation of industrial heat island effects

3.1.1. Industrial heat island effects over space

The LST retrieval maps (Fig. S1) illustrate that the areas with heat anomalies concentrated highly within the industrial parks. Nevertheless, the LST differences between the industrial parks and other reference areas cannot be interpreted directly by visual inspection. Moreover, increases in the impervious surface percentage (ISP) dominate the growth of daytime SUHI intensity with regular urbanization (Li et al., 2021). Presumably, the existing relations between ISP and LST imply that industrial areas are likely to be warmer. So, whether the industrial areas are significantly above this relationship that applies more generally to urban areas remains to be demonstrated. In this context, we measured the ΔT_{max} from industrial parks to the surrounding areas using the LST profiles. 

Fig. 2. Map and LST profile based on continuous buffers in an industrial park.

Taking varied land surfaces into account, Fig. 4 illustrates the LST differences between the industrial parks and natural/urbanized areas. It can be observed that the mean LST of the industrial parks was not only higher than that of their ambient environments, with a 5.71 °C mean LST difference, but they were also warmer than the urban impervious surfaces and built-up areas. This result is consistent with the decline exhibited in the LST profiles; together, they confirm that IHI effects exist at a local scale. The LST difference between industrial parks and their 5-km background areas even reached a maximum of 9.08 °C in the Benxi Industrial Park (Fig. 4(4)). The industrial parks were significantly warmer relative to natural reference areas, with 8.40 °C, 7.90 °C, and 9.79 °C mean LST differences compared to non-urbanized areas, agricultural land, and water body, respectively. More seriously, it was observed that the mean LST of industrial lands was 2 °C higher than that of urban impervious surfaces, and their maximum LST difference reached up to 3.77 °C. A previous study demonstrated that the mean LSTs of impervious surfaces are the highest (Song et al., 2014). That is to say, the industrial parks generate extremely high LSTs inside the cities, even though considering the LSTs of urban artificial land (i.e., impervious surfaces) as the reference. The LST differences are mainly derived from different land uses and functional attributes (Li et al., 2014), implying that industrial lands release a large amount of anthropogenic heat during their activities, thus simultaneously affecting surrounding thermal environments (Zhang et al., 2017). These results indicate that the complex mechanisms drive the thermal characteristics of industrial lands at relatively fine spatial scales, which are determined not only from surface biophysical properties but also according to anthropogenic factors.
3.1.2. Industrial heat island effects over seasons

In order to present sufficient evidence of the existence of IHI effects over seasons, 45 Landsat 8 TIRS images were collected for time-series LST monitoring of the Wuhan Industrial Park. All LST profiles (Fig. S2) showed a downward trend within a 4-km surrounding area. Even though visible fluctuations exist in several LST profiles (e.g., 12/17/2017, 06/27/2018, July 12, 2019, etc.), the descents of the curves are still significant. The range of \( L_{\text{max}} \) was from 2.9 to 3.65 km, with a
The mean $\Delta T_{max}$ was 4.22 $^{\circ}$C, reaching its highest value (7.14 $^{\circ}$C) on April 29, 2020, and its lowest (1.01 $^{\circ}$C) on December 17, 2017. The mean $G_t$ was 1.24 $^{\circ}$C/km, indicating that the mean LST will decline by 1.24 $^{\circ}$C/km from the industrial park.

The basic shapes of the seasonal LST profiles (Fig. 5(a)) are roughly the same over different seasons, and $L_{max}$ ranges from 3.35 to 3.4 km. This result implies that the fixed land configuration around the industrial park did not lead to dramatic variation in the primary LST trend among the seasons. Instead, seasonal variations of $\Delta T_{max}$ were observed, which were maximized in spring (5.17 $^{\circ}$C), followed by summer (5.11 $^{\circ}$C), and minimized in winter (1.82 $^{\circ}$C). The seasonal characteristics of the gradient of descent ($G_t$) were similar to those of $\Delta T_{max}$, being more significant in spring (1.52 $^{\circ}$C/km) and summer (1.5 $^{\circ}$C/km) and weakest in winter (0.54 $^{\circ}$C/km). The industrial park features the highest LST across seasons when looking at the LST magnitudes of varied reference areas (Fig. 5(b)). In spring, summer, and autumn, the mean LSTs of the industrial park were higher than the upper limits (i.e., the maximum value in the non-abnormal range) of natural reference areas, which approach the upper quartile value in winter. Not only that, the median LSTs of the industrial parks were significantly higher than those of their urbanized reference areas. When the land cover of the industrial park and its surroundings was fixed during

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**Fig. 4.** Box plots of LSTs ($^{\circ}$C) at the study sites (Nos. 1–10 in Table S1). The black asterisk and red line indicate the mean and median values, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
2013–2020, the IHI produced a mean LST difference of 5.05 °C from their 5 km background area, signifying the existence of IHI effects across seasons. The maximum LST difference between the industrial park and the 5 km background reached 6.73 °C in summer and gradually decreased in the cold seasons. In brief, the time-series case generally revealed a more severe IHI effect in spring and summer, which declined in autumn, and the weakest IHI occurred in winter.

On the other hand, thermal patches’ fragmentation/segmentation degree inside the IHI showed opposite seasonal variations with IHI intensities (Table S4). It can be seen that the IHI effects were aggravated in summer and spring, while the lower SUHI intensities were exhibited in winter and autumn (Table S4 and Fig. S3(b)). This seasonality was consistent with the temporal variation of the SUHI effects at the urban scale (Meng et al., 2018). In contrast, the fragmentation degree of thermal landscape induced by IHI was higher from September to December and lowered in spring. Correspondingly, Fig. S3(a) showed that the very-high-LST anomaly area (Level 3) was contiguously clustered within the park in winter, whereas thermal patches were more fragmented in summer. As expected, this result was similar to the previous finding that when the percent of the impervious surface area is controlled, the SUHI effect will be reduced if it is more spatially distributed (Li et al., 2011). Accordingly, we can reasonably infer that a fragmented thermal landscape tends to be accompanied by a more severe IHI effect at a finer scale. Likewise, the general conviction that an increase in the shape complexity and variability of impervious surfaces (i.e., buildings and paved surfaces) leads to increased LSTs was
showed that all the indicators of SUHI intensities (i.e., SUHI\text{\scriptsize{ref}}, and IHII/SUHI\text{\scriptsize{ref}}; Fig. S4) positively associated with NL (r = 0.322, P < 0.005 and r = 0.388, P < 0.005, respectively), implying that the anthropogenic heat emissions derived from industrial activities contribute to the increased LST inside the industrial park. Furthermore, Table S6 lists the mean and standard deviation of NL in different urbanized reference areas. The higher NL magnitudes of impervious surface and industrial park suggest that the heavy industries contribute to additional urban heat sources affecting air and surface temperatures. The previous studies consistently carried out a similar result, which demonstrated that, in industrial zones, the factors characterizing the anthropogenic heat might be more significant in influencing LSTs (Zhou et al., 2012; Huang and Wang, 2019; Hu et al., 2020). In summary, industrial production tends to aggravate the IHI effect to a certain extent.

3.2.2. Seasonal driving analysis of land surface temperature within industrial heat island

To further advance the understanding of the multifactorial driving force (Fig. S5) of the LSTs within IHI areas (i.e., the 5 km background of the industrial park), we applied the GDM to examine the impact of local-scale landscapes (i.e., LCZs), land cover types (i.e., LCs) and anthropogenic heat (i.e., NL) to the spatial heterogeneities of LSTs. According to the spatially stratified heterogeneities of the geo-variables, the GDM can effectively detect the explanatory rates of continuous (e.g., NL in this study) and discrete variables (e.g., classifications of LCZs and LCs). The contributions of the impact factors were assessed by the power of determinant (PD) values.

The time-series case of Wuhan IHI showed that the anthropogenic heat estimated by NL obtained the highest PD values (Table S7) over different seasons, especially in spring and summer (PD = 0.951 and 0.874, respectively), indicated the dominant impact of anthropogenic heat emissions on LSTs in the IHI area. Namely, the anthropogenic heat flux induces the formation of the SUHI effect (Firozjafari et al., 2020), especially at a finer scale. Because industrial production processes (e.g., steel, petrochemicals, mechanical manufacturing, etc.) consume huge amounts of energy and are accompanied by a great deal of anthropogenic heat discharge (Li et al., 2014; Huang and Wang, 2019). The AHF could be transformed into sensible heat flux or other energy components (Christen and Vogt, 2004), indirectly affecting the SUHI intensities (Peng et al., 2012). Therefore, the high surface temperatures of the IHI area are probably a consequence of heavy energy consumption. Since most of the AHEs are transferred to the atmosphere in the form of sensible heat in both summer and winter, which was previously evidenced in a relevant study (Kato and Yamaguchi, 2007). In addition, the extensive roofs covering the steel plants form a relatively homogeneous surface where the long-wave radiation received by satellite sensors would not be interfered with by other surface materials, and therefore show a higher level than other areas consisting of rough architects (Roth et al., 2007). These effects potentially explain how AHF impacts the spatial variability of LST in the industrial park. As summarized in Section 3.1.2, the IHII gradually decreased from warm weather (spring/summer) to cold weather (autumn/winter); the AHE (i.e., NL magnitudes as shown in Table S6) and its dominant influence on LST also gradually declined in a similar pattern. This seasonality further suggests that the impact of anthropogenic factors on LSTs became more prominent under more severe IHI effects.

On the coarser scale (i.e., in the built-up area), the local-scale landscapes (i.e., LCZs) is the most potent driver to LST variations, followed by LCs. In contrast, compared to the result of the finer-scale investigation in the IHI area, the influence of anthropogenic heat was relatively weak (see the PD values in Table S8). In other words, the comprehensive effect of surface landscape and near-surface climate background (i.e., characterized by LCZs) determines more spatial patterns of urban LSTs at a coarser scale, and the factor of LCs was the moderate driving force. The possible reason is that the LCZs contain more specific surface structure/cover information (e.g., building forms, shape, density, or height of trees, etc.) (Yang et al., 2018); in contrast, the LCs only characterize the type/material of surface coverages (Grigoras and Uritescu, 2019). To sum up, the driving mechanism of the urban LST pattern demonstrated significant seasonal effects and scale effects. More attention should be paid to alleviate the local warming effect derived from the industrial park, especially in spring and summer, because the impact of anthropogenic heat on LSTs is more significant within the IHI area at a finer scale.

4. Discussion

4.1. Methodological and theoretical implications

A city is an extremely complex environmental system composed of varied components and landscapes. To present a general scheme to estimate the IHI effect, we used different natural and urbanized lands as the reference areas in modeling the indicator of IHI intensities. According to our spatiotemporal analysis, we suggest using the natural/unurbanized area as the reference to measure the IHI intensities for comparative studies on the spatial scale; while the IHII based on surrounding backgrounds (e.g., 5 km buffer in this study) was more suitable for time-series investigations of the IHI effect in the same sites. The correlation analysis (see Section 3.2) supports that the anthropogenic heat played a dominant role in shaping the spatial pattern of LST in the industrial parks, thus, under similar background conditions (e.g., in the same season), taking non-urbanized/natural surface as the reference could more accurately reveal the variabilities of artificial lands (e.g., industrial park) in different spatial cases. Regarding the time series analysis/seasonal contrast of the specific IHI case in Wuhan, this study recommended measuring the IHI effect by the LST difference with their surrounding background. Because impervious surfaces mainly cover industrial parks, while natural lands and artificial lands have different reflectivity and hydrothermal properties, impacting LST to varying degrees (Peng et al., 2018), these differences are more pronounced under varied meteorological backgrounds or in different seasons. Considering the land cover of a study site remains constant over a certain period, this study proposed a new approach to quantify the IHI effect, especially versus a complex surrounding background.

Varied landscape configurations generally affect the patterns and the efficiency of energy exchange and consequently influences surface heat flow among the landscape patches (Turner, 2005). Concerned with urban spatial variation, the landscape metrics characterizing landscape configuration have been widely applied in LST-related studies (Zhou et al., 2011). Taking the classical landscape metrics as the reference, in an analogous manner, five thermal landscape metrics have been designed to characterize the configuration/morphology of thermal patches, which broadens a new insight for spatiotemporal SUHI evaluation concerning the thermal dimension. Moreover, the LST classification maps (Fig. S6(a)) revealed that there were several hotspots distributed within the high-temperature areas of the industrial parks, which spatially match well with the large mills inside the parks (Fig. S6(b)). Therefore, the heat anomaly extraction and LST classification method employed here show potential applicability for industrial heat source detection (Xia et al., 2018; Zbang et al., 2019).

The seasonal variation characteristics of IHI and thermal...
indicates the instantaneous condition at one point in the day, the time-series study case. Furthermore, as the satellite-derived LST only surrounding backgrounds (i.e., land cover ratios shown in Fig. S7) (Zhou and Chen, 2018; Tepanosyan et al., 2021), the inconsistent IHI

4.2. Limitations and uncertainties

Given that the SUHI is highly related to land use/land cover changes (Zhou and Chen, 2018; Tepanosyan et al., 2021), the inconsistent IHI surrounding backgrounds (i.e., land cover ratios shown in Fig. S7) constrain the spatial comparisons between the IHI cases. Although Landsat 8 has a high spatial resolution in thermal infrared channels, its revisit period is 16 days. To exclude the influence of clouds, the RS images (i.e., Landsat 8 and Suomi-NPP/VIIRS) selected in this study were from cloudless periods; such a strict data selection requirement limited the number of available RS images. We found only one site (i.e., Wuhan Industrial Park) with enough images to be employed as a time-series study case. Furthermore, as the satellite-derived LST only indicates the instantaneous condition at one point in the day, the temporal estimation of IHI effects is limited to satellite acquisition times. Regarding the NL-based AHF estimation, the nighttime light sensors tend to observe human habitation/activities (Xie et al., 2019) that links the energy consumptions to NL, and may limit its local-scale application in a specific region (i.e., industrial park), especially in the areas with intense anthropogenic heats but few human habitation. Thus, a more accurate AHF estimation for the industrial sites would reduce the uncertainties of our results.

On the other hand, since the factors contributing to the SUHI effects are extremely complex and diverse, some potential factors were not considered but warrant further exploration. For instance, the impacts of spatial resolutions (Estoque et al., 2017), diurnal temperature range (Hong et al., 2019), varied types of industrial activities (Rao et al., 2018), and local background climates (Zhao et al., 2014) should be examined. Existing studies have estimated the UHI effects based on temperatures measured from fixed points (Chang et al., 2007; Yan et al., 2018); however, our study lacks site-measured air temperatures to enhance the general microclimatic phenomenon of the IHI effect. Such meteorological data may help to support more reasonable arguments regarding IHI effects in future work.

5. Conclusions

In this study, we proposed an effective method to quantify the warming effect derived from the urban industrial park, and the spatiotemporal analysis presented new evidence for this surface intra-heat island effect, defined as the industrial heat island effect. The industrial parks were isolated from other artificial lands, which allowed for measuring quantifiable features related to IHIIs derived from the original LST maps. A system of thermal landscape metrics was designed to characterize the thermal morphology. Results showed that the IHI effects were more severe in warm seasons, which declined in autumn, and the weakest IHI intensities occurred in winter. In contrast, the fragmentation degree of thermal patches inside the IHIIs showed opposite seasonal variation. To enhance the understanding of the variation of the IHI effect, we examined the factors contributing to the IHI effect. The positive relationship between IHI intensities and NL indicated that the anthropogenic heat emissions (via industrial activities) were the dominant contributor to the increased LST. Further, the results of GDM revealed that the anthropogenic heat determined more spatial heterogeneities of LST than local-scale landscape/land surface factors in the IHI area over different seasons. According to our conclusions, we recommend limiting industrial production tasks in warm seasons may alleviate the IHI effect to a certain extent. This study has considerable implications for modeling and evaluating the SUHI effects, which is essential for environmental planning and urban micro-climatic research, especially at a finer scale.

Author statement


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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Appendix A. Supplementary data

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