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Original Articles

Does subclassified industrial land have a characteristic impact on land surface temperatures? Evidence for and implications of coal and steel processing industries in a Chinese mining city

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A R T I C L E I N F O

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A B S T R A C T

The heat effects of industrialization pose challenges to national governments and scientists. Current studies largely conclude that the heat storage capacity of an urban surface creates hotter spots in man-made areas than in surrounding areas. Taking a Chinese mining city as a study case, our study further separates industrial land from these man-made areas and classifies it into two subtypes of coal and steel processing industrial land to reveal varying corresponding effects on land surface temperatures (LSTs). Three indicators (AREA, PERIM and SHAPE) that characterize the production scale of industrial enterprises are employed to simulate LST responses to internal and external characteristics of subclassified industrial patches. It is shown that industrial land plays a dominant role in generating high and extremely high LSTs, and that these two industries have different impacts on LSTs. Moreover, the responding areas of coal and steel processing industrial patches are 10 ha and 40 ha, respectively, and an increase of 1 ha in patch area generates a rise in the LST of 0.50 °C and 0.18 °C, respectively. Around the industrial patches, the AREA and SHAPE of an industrial patch significantly impact changes in LSTs in greenspaces surrounding coal and steel processing sites, respectively. For the coal processing industry, an increase in patch area expands the responding range (130 m/10 ha); for the other industry, an increase in the interacted patch area and perimeter expands the responding range (175 m/0.5 unit SHAPE). Our study furthers governmental and academic understanding of the impacts of industrial land on LSTs, and provides government officials, planners, conservationists, etc. with an explorative study case. Especially for industrial cities with coal and steel production activities serving as economic pillars, this study offers effective theoretical and practical guidance on rational industrial restructuring and land allocation.

1. Introduction

The exploitation and use of resources to produce essential materials and energy for industrial development creates a series of environmental issues. First, the universal phenomenon of the urban heat island (UHI) impacts both climatic and ecological processes (Buyantuyev and Wu, 2010). Urban land transformation greatly alter the structure and fluctuation of UHI (Chen et al., 2006; Hereher, 2016) and explains this phenomenon (Sheng et al., 2017). It is known that impervious surfaces generally generate the highest mean temperatures (Song et al., 2014) and reach temperatures of a few degrees Celsius higher than other areas (Estoque et al., 2016). Clearly, the mitigation of UHI must be based on a deep understanding of areas modified to build settlements and semi-natural habitats (Zhou et al., 2015).

The modification of urban surfaces and, especially during economic development, rapidly occurs through urbanization and industrialization. Consequently, the redistribution of urban heat fluctuates with surface energy processes (Chakraborty et al., 2015). Urban areas are covered by building materials to absorb visible and near-infrared light in the daytime, as a major source for heat generation (Service, 2017). In most, studies built-up land (man-made areas), including residential, commercial, industrial land, is usually studied as a whole to measure changes in surface energy levels (Chakraborty et al., 2015; Li et al., 2011; Shudo et al., 1997). Industrial land is seldom studied as a separated form of land to measure UHI effects. However, it is characterized by the highest land surface temperatures, though it must limited

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contributions to overall UHI values (Li et al., 2011). Rather, hot regions within a city are highly concentrated within industrial zones (Pearsall, 2017; Tran et al., 2017), marked by variations in distances to industrial sites (Coseo and Larsen, 2014). The emission of greenhouse gases in urban areas and pollutants generated through industrial activity can alter local environmental landscapes (Guo et al., 2017; Wogan, 2016). Environmentally speaking, governmental and academic concerns must extend to the separation of industrial land from impervious surfaces to simulate UHI effects.

Quantifying the relationship between LSTs and surface morphologies is central to UHI effects. As a widely used approach, the composition and configuration of a land use/landscape pattern is regarded as one way to link distinct behaviours of heat environments, including their sizes, shapes, spatial arrangements, etc. (Chen et al., 2014; Du et al., 2016; Wu et al., 2014; Zhang et al., 2015). Quantitatively speaking, a number of indicators are used to delineate dynamic interactions occurring between land uses/landscapes and UHI effects, including single indicators of edge density, patch density, fractal dimensions, etc. (Maimaitiyiming et al., 2014; Zhao et al., 2012) and an integrated indicator of the location-weighted landscape index (Chen et al., 2016). This process is recognized and expressed by characteristics of a heterogeneous mixture (Guo et al., 2015), and its structures and functions also change in urban areas due to the presence of diverse interacting social-ecological phenomena (Hamstead et al., 2016). Thus, means to simplify such combinations and to measure such relationships are worth discussing.

Additionally, property types can ameliorate LSTs (Middel and Li, 2016). Especially in a resource-dependent city, any feature related to industrial production, including industrial types, sizes, shapes, etc., may dominantly determine environmental performance. When the environmental impact of industrial activities is not addressed seriously, inputs of human, physical, financial resources for mitigating environmental deterioration can be doubled (Maryati et al., 2012; Wan et al., 2017). Furthermore, different industries are related to different environmental issues (Guo et al., 2017; Proto et al., 2017; Stern, 2004). Conceivably, characteristic impacts on LSTs may be closely related to subclassified industries (subclasses within industries), but a lack of related publications on this issue has left a gap to be filled in this field. Based on current studies on urban areas, we study Wu'an, a Chinese resource-dependent city mainly supported by coal and steel processing industries, as a study case, and we initially classify industrial land into two subtypes, to (1) retrieve LSTs by atmospheric correction and to link them to industrial plots of a mining city, to (2) present LST responses to internal characteristics of subdivided industries based on three indicators (AREA, PERIM and SHAPE), and to (3) determine LST responses to their external characteristics based on LST profiles for each industrial patch. Achieving these objectives will provide governmental officials, planners, conservationists, etc. with an explorative study case. Especially for cities relying on coal and steel industries as economic pillars, this study provides effective theoretical and practical guidance on rational industrial allocation and land use.

2. Materials and methods

2.1. Description of the study area

Wu'an lies in the hinterland of the Zhongyuan Economic Zone in China, covering a surface area of 1819 km^2, at 113°45′–114°22′E and 36°28′–37°01′N. Elevation levels are high to the west (the highest point reaches 1898.7 m) and low to the east (the lowest point reaches 87 m), with a small basin called the Wu'an Basin positioned in the central area. As an important energy supplier in Hebei Province, Wu'an is rich in coal, iron, cobalt, aluminium, and other resources. It also offers rich tourism resources, including a national geopark and the Xishimen Mine Park to the north (Fig. 1).

2.2. Methods

2.2.1. Research framework

Our study focuses on LST responses to industrial land so that our framework follows land classification → LST retrieval → heat response, as three main parts. Our first task involves extracting available industrial land based on the attributes of enterprises assigned through our field work and via our GIS database. We then retrieve LSTs via the atmospheric correction method to define brightness and distribution levels. Finally, we match industrial plots and LSTs, but subtypes of industrial land (for coal and steel processing) and corresponding areas, shapes and perimeters are jointly taken into account to compare heat responses and to further measure internal and neighbouring interactions between patches (Fig. 2).

2.2.2. Extraction of land use information

According to China's land classification system and local conditions (Chen and Zhou, 2007), the study area was classified into six types of land use, including cropland, forests, pastures, industrial land, build-up land and water bodies. For classification, unsupervised and supervised classification methods were employed. Prior to classification, remote sensing (RS) images were enhanced using the "K-L transform" method, which effectively differentiated various objects visually. The unsupervised classification was used as a pre-step to cluster a large number of objects of similar textures, colours, shapes, and other features, and a series of interpretation keys were defined. These keys were corrected or added via visual interpretation and field monitoring for primary land classification. However, we found that the spectrum feature of cropland, pastures and forests for Wu'an presents similar patterns of change, but slight differences between B and NIR bands. Thus, the normalized difference vegetation index (NDVI) was used to distinguish between them. Similarly, we adopted the normalized difference building index (NDBI) to separate industrial land from built-up land. Finally, region of interest (ROI) separability (1.8 as the threshold for judging the availability of classification results) and confusion matrixes were used to validate the classification accuracy level.

2.2.3. LST retrieval and grading

2.2.3.1. LST retrieval. One important way to effectively retrieve LSTs is still RS method (Peres et al., 2018; Rosas et al., 2017). The thermal band of Landsat 5 images was used to retrieve LSTs, using the following approach: estimate vegetation coverage → surface emissivity → radiation brightness values → LST acquisition.

In general, the estimate of vegetation coverage is defined from the proportion of mixed pixels. Water bodies, vegetation and built-up land are considered in this study. Due to low reflectance (generally less than 0.05) and high absorption levels, the digital number (DN) value for water bodies is much lower than that for other values. Thus, the coverage level is defined as "0". For a pixel including both vegetation and built-up land, its coverage is estimated from the NDVI value. The greater an NDVI value is, the higher its level of coverage is. However, most mixed pixels may include an uncertain proportion of vegetation. Such pixels can be estimated using Eq. (1).

$$C_{Vi} = \frac{NDVI_i - NDVI_B}{NDVI_V - NDVI_B} \tag{1}$$

where C_{Vi} is the coverage of vegetation within pixel i, $NDVI_i$ is the NDVI value of pixel i, and $NDVI_B$ and $NDVI_V$ are threshold values for vegetation and built-up land, respectively. After comparing land classifications and field monitoring results, we respectively assign $NDVI_B$ and $NDVI_V$ values of 0.70 and 0.05. When the $NDVI_i$ value is greater than 0.70, the C_{Vi} value is denoted as "1"; when it is less than 0.05, the C_{Vi} value is denoted as "0".

The surface emissivity value is calculated based on Planck's law (Liu, 2012) based, on surface roughness levels, dielectric constants, moisture content levels and wavelengths. The parameters used were