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Characterizing spatial and temporal trends of surface urban heat island effect in an urban main built-up area: A 12-year case study in Beijing, China

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ABSTRACT

Accurately characterizing spatiotemporal changes in surface urban heat islands (SUHIs) is a prerequisite for sustainable urban development. Although urban administrative boundaries have typically been used for SUHI modeling, they are inaccurate, because urban main built-up areas (UMBAs) are not well characterized. In this study, we developed an UMBA extraction method based on impervious surface distribution density (ISDD), to better differentiate suburban boundaries and ensure the integrity of land cover types. Additionally, we propose a new intensity classification method to analyze SUHI spatial distribution and variation. The UMBA was extracted using LANDSAT-8 data, and the temporal dynamics of SUHI intensity (i.e., daily, monthly, seasonal, and yearly changes) were extracted from MODIS data. A case study for Beijing showed that the mean daytime and nocturnal SUHI intensities vary at multiple time scales. In the daytime, SUHI intensities in Beijing UMBA were mainly level-2 and level-3, with central-south Beijing, a high incidence area, at level-3 in spring and summer. At night, with the rise of SUHI intensity levels, the frequency of SUHI intensity levels increased from the periphery to the center within the same season. ISDD had a marked influence on the frequency of SUHI intensity levels during the daytime, and the frequencies of level-1 to level-4 intensities increased with ISDD. This influence tended to weaken when ISDD exceeded 50%.

1. Introduction

Temperature distribution depends mainly on latitude, height above sea level, topography, city size, and atmospheric stability (Stewart and Oke, 2009). With rapid urbanization, natural landscapes are replaced by impervious surfaces, which can alter surface radiation, thermal properties, and humidity over urban areas. Among these effects, the urban heat island (UHI) is a phenomenon in which urban areas tend to have higher atmospheric or surface temperatures than their surroundings. In the early 19th century, the UHI effect was discovered (Howard, 1833). Later, many researchers studied it by observing the air temperatures of urban and suburban areas in cities of different latitudes and types (Carlson et al., 1977; Carnahan and Larson, 1990; Matson et al., 1978; Oke and East, 1971; Rao, 1972; Weng et al., 2004; Zhao et al., 2014). With the development of remote sensing technology, UHI effects are typically estimated from thermal infrared remote sensing techniques (Hung et al., 2006; Imhoff et al., 2010; Melaas et al., 2016; Ogashawara and Bastos, 2012; Stathopoulou and Cartalis, 2009; Yusuf et al., 2014). Due to easy access and wall-to-wall continuous coverage of urban areas, the surface urban heat island (SUHI) has gained increasing attention in recent decades (Deng and Wu, 2013; Du et al., 2016; Haashemi et al., 2016; Schwarz et al., 2011; Takebayashi and Moriyama, 2007; Xu, 2009). Therefore, land surface temperatures (LSTs) derived from thermal infrared remote sensors are among the most commonly used indicators for SUHI analysis.

SUHI intensity is commonly measured by comparing the difference between urban and suburban temperatures (Heaviside et al., 2016; Mohan et al., 2013; Tomlinson et al., 2012). The difference in mean LST between urban areas and water surfaces (Chen et al., 2006), the Gaussian volume model (Quan et al., 2014; Streutker, 2002; Flores R et al., 2016), areas with LST higher than a mean-plus-one standard deviation (Zhang and Wang, 2008), and LST magnitude (Rajasekar and Weng, 2009) are also used in SUHI analysis. Although different types of indicators for heat island intensity have been proposed, the mean temperature difference between urban and suburban area is the most commonly used indicator (Zhou et al., 2013). However, differentiation

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between urban and suburban areas remains problematic in the literature (Schwarz et al., 2011; Stewart and Oke, 2009). Within the SUHI intensity-computing process, there are various methods to delineate boundaries between urban and suburban areas, such as urban administrative boundaries, pixels around urban and rural weather stations, city ring, roads, high-LST areas versus areas with rural land cover, or city land cover versus other types of land use (Roth et al., 1989; Tomlinson et al., 2012; Jin et al., 2011; Mathew et al., 2016; Shen et al., 2016; Walawender et al., 2014). However, urban boundaries extracted using these methods do not perfectly represent the urban main built-up area (UMBA), which refers to relatively centralized areas of constructed and intensive land use. Different definitions of the boundary between urban areas and suburbs yield different UHI intensity results (Wang et al., 2007). Thus, accurate determination of urban-suburban boundaries directly influences the results of SUHI intensity calculation.

The spatial and temporal variation of the UHI is one of the most important themes in UHI studies (Quan et al., 2014). After the SUHI intensity is calculated from the difference between urban and suburban temperatures, the SUHI intensity of different periods must be compared using the same standard. Currently, two methods are used to accomplish this. One is equal interval classification, which classifies LST or its alternatives according to specific rules (Zhang et al., 2006; Xu and Chen, 2003; Wang and Sun, 2004; Zhang et al., 2005; Wu et al., 2006). Although this method can reflect the spatial distribution of LST in some degree, the determination of the best dividing point and number of classes is full of uncertainty. Different dividing points and numbers of classes can result in different SUHI structures, and these choices greatly affect SUHI quantitative studies (Chen and Wang, 2009). The second method involves combing the mean value and standard deviation (Zhang, 2006). Few in-depth analysis of this method have been conducted, and still fewer have compared different classification methods using various angles. These methods cannot be applied for long-term time series data. However, accurate comparisons of UHI intensity data are very important in monitoring SUHI growth (Streutker, 2003). Long-term time series data provide insights into the mechanism behind the evolution of the SUHI effect and its relationship with land use/land cover data and/or climate change (Li et al., 2012), and can aid decision-makers in developing and executing rational land-use policies (Zhang et al., 2013). Therefore, exploring scientific SUHI classification methods for long-term time series data is crucial.

The main objectives of this study were: 1) to extract UMBAs based on impervious surface distribution density (ISDD); 2) to explore the mechanism of SUHI evolution at diurnal, monthly, seasonal, and yearly scales, creating a new SUHI intensity classification method for long-term time series data to analyze SUHI spatial characteristics; and 3) to explore the relationship between UMBA and ISDD to provide references for SUHI mitigation. Based on long-term remote sensing time series data, a SUHI evolution analysis was performed for Beijing.

2. Study area and data set

2.1. Study area

This study was conducted in Beijing (Fig. 1), which is located within 39.4–41.6°N, 115.7–117.4°E, and belongs to the northern part of the northern China plain, which possesses sixteen districts and counties. The city's permanent population totaled 21,689,000 by the end of 2014. The climate in Beijing is a typical sub-humid north-temperate continental monsoon climate characterized by hot rainy summers, cold dry winters, and a short spring and autumn.

During the past 20 years, Beijing has experienced great changes in urban development. In 2008, the Olympic Games were held in Beijing, which necessitated the construction of many buildings. The UHI effect has become increasingly serious in Beijing during recent years. It is necessary to study the spatiotemporal changes in UHI intensity based on ISDD to solve ongoing problems related to Beijing's development.

2.2. Data set

UMBA were extracted from LANDSAT-8 data. Landsat 8 satellite carries two instruments: the Operational Land Imager (OLI) sensor and the Thermal Infrared Sensor (TIRS). These sensors provide improved signal-to-noise ratio (SNR) radiometric performance quantized over a 12-bit dynamic range. Improved SNR performance allows better characterization of land cover state and condition.

This study employed MOD11A2 and MYD11A2 Level-3 8-day 1-km LST products from March 2003 to February 2015, which were downloaded from LAADS Web (https://ladsweb.nascom.nasa.gov). These products adopt a universal split-window algorithm by optimizing the observation angle and range of water vapor column contents. The accuracy of the LST algorithm for terrestrial materials of known emissivity approaches 1 K (Wan et al., 2004).

During data processing, the process of joint, tailor, and projection transformation were completed using the MODIS Reprojection Tool (MRT). The results were then multiplied by a scale factor of 0.02 to obtain the real temperature of the land surface (Wan, 2006). Through this method, we acquired 2056 MODIS LST products for Beijing (UTM Zone 50N) from 2003 to 2015.

3. Methods

UMBA were extracted using Landsat 8 data, which included impervious surface extraction based on the biophysical composition index (BCI) and distance-weighted ISDD calculations, to obtain the Beijing UMBA boundary. Based on MODIS data, we examined the SUHI evolution process at diurnal, monthly, seasonal, and yearly scales. A new SUHI intensity classification method was then used to study SUHI spatial characteristics. The relationship between SUHI intensity and ISDD was explored to provide references for SUHI mitigation. The flow chart for the current study is as follows (Fig. 2):

3.1. Biophysical composition index

The BCI proposed by Deng and Wu (2012) was used to extract urban impervious surfaces. BCI is an urban environment index used to distinguish urban terrestrial materials, and is based on the vegetation–impervious surface–soil (V–I–S) model, a segmented model of the urban land surface (Ridd, 1995). BCI can be calculated as follows:

$$BCI = \frac{(H + L)/2 - V}{(H + L)/2 + V}, \tag{1}$$

where TC refers to the components of Tasseled Cap transformation (Kauth and Thomas, 1976), H is 'high albedo' or normalized $TC1$, L is 'low albedo' or normalized $TC3$, V is 'vegetation' or normalized $TC2$. H, V, and L can be described as follows:

$$H = \frac{TC1 - TC1_{min}}{TC1_{max} - TC1_{min}}, \tag{2}$$

$$V = \frac{TC2 - TC2_{min}}{TC2_{max} - TC2_{min}}, \tag{3}$$

$$L = \frac{TC3 - TC3_{min}}{TC3_{max} - TC3_{min}}, \tag{4}$$

where TCi (i = 1, 2, and 3) represents the first three TC components. TCi_{min} and TCi_{max} are the minimum and maximum values of the ith TC component, respectively.

Before the BCI index can be derived from Landsat 8 data (November 2014), three preprocessing steps were conducted: radiometric calibration, water masking, and Tasseled Cap transformation (Liu et al., 2014). Water masking was performed by adopting the normalized difference water index (NDWI) threshold value method. The Beijing BCI index was then calculated based on Eqs. (1)–(4), and the impervious surface was