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Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas

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ABSTRACT

Urban heat island (UHI) has become an urban eco-environmental problem globally. Land surface temperature (LST) is widely used to quantify UHI. This study used Shenzhen, a southern coastal city in China, as an example to explore the relationship between spatial variation of LST in different seasons and the influencing factors in five dimensions, integrating the methods of ordinary least-squares regression, stepwise regression, all-subsets regression, and hierarchical partitioning analysis. The results showed that the most important factor affecting spatial heterogeneity of LST in summer was the normalized difference build-up index (53.62%, for contributing rate), whereas in the transition season the most important factor was the normalized difference vegetation index (NDVI) (47.84%). In winter the construction land percentage and NDVI (26.84% and 25.56%, respectively) were the most influential. Artificial surface and green space had a dominant effect on LST spatial differentiation. Landscape configuration and diversity were not the dominant influencing factors in summer or in the transition season. Furthermore, the independent contribution rate of the Shannon diversity index (SHDI) reached 8.79% in the transition season, while in winter, the independent contribution rates of SHDI and the landscape shape index were 8.52% and 3.45%, respectively. The influence of landscape diversity and configuration factors tended to increase as LST reduced, while the contribution rate of the important factors such as artificial surface and green space decreased significantly. These relationships indicate that the influence of landscape configuration and diversity factors on LST is relatively weak, and can be easily concealed by the influence of landscape components, especially when the spatial variation of LST is not strong. These findings can help to develop UHI adaptation strategies based on local conditions.

1. Introduction

More than 54% of the world's population lives in urban areas, and according to the World Health Organization's World Urbanization Prospectus this proportion will increase (Ayansina, 2016). Over the past few decades, China has experienced rapid urbanization process, with China's urban area expanding by > 20% since 1985 (Liu and Tian, 2010). Along with the dramatic urbanization, natural vegetation and farmland have been rapidly replaced by artificial surface (Li et al., 2015; Rhee et al., 2014), resulting in temperatures in urban areas are higher than that in suburbs, which is commonly known as urban heat island (UHI) effect (Oke, 1982). UHI not only deteriorates a city's water quality and air quality (Grimm et al., 2008), thus affecting the livability of the urban areas (Zhang et al., 2013), but also accelerates urban energy consumption (Konopacki and Akbari, 2002) and increases human risk of violence and mortality (Jenerette et al., 2016; Patz et al., 2005). As a result, a better understanding and monitoring of the UHI effect is critically important to improve the quality of life and the environment of urban residential areas, and to develop strategies related to sustainable development (Zhou et al., 2017).

The basic premise of UHI study is to quantitatively measure the heat island, and widely used methods can be divided into two categories. The first method uses atmospheric temperature data acquired from traditional ground meteorological sites (Eludoyin et al., 2013; Hamdi and Schayes, 2008), and compares the difference between urban and suburban meteorological sites to identify the UHI. However, low density of monitoring sites and the uncertainty in weather limit the precision of the traditional method. The second method uses remote sensing data to retrieve the land surface temperature (LST) (Imhoff et al., 2010; Li et al., 2013; Peng et al., 2012). Although the data from ground meteorological sites have a higher temporal resolution than remotely sensed data, they are difficult to be applied to large-scale research. Easy access, better spatial resolution and greater spatial coverage prompt more researchers to use remote sensing data to measure UHI (Ayansina,

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2016; Clinton and Gong, 2013; Lu et al., 2014; Weng, 2009). A variety of remotely sensed data have been used to assess LSTs and UHIs, such as the Landsat Thematic Map-per/Enhanced Thematic Mapper+ (TM/ETM+), Moderate-resolution Imaging Spectroradiometer (MODIS), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Advanced Very-High-Resolution Radiometer (AVHRR) satellite data (Cheval and Dumitrescu, 2009; Yuan and Bauer, 2007).

Although remotely sensed data can help researchers depict the spatial pattern of LST, it is very difficult to put forward strategies to mitigate UHI effect only with the results of LST spatial pattern. Spatial heterogeneity of urban LST results from the correlation between LST and influencing factors and their interactions, and to clarify how LST was affected by these factors, the quantitative relationship between LST and each factor has been studied (Li et al., 2016). Generally speaking, widely focused factors can be roughly divided into the following three types: (1) Surface biophysical parameters. Because of the richness of land use and land cover information, surface biophysical parameters have been widely used in LST correlation analysis. The normalized difference vegetation index (NDVI) (Liu et al., 2016), normalized difference built-up index (NDBI) (Chen et al., 2006; Liu and Zhang, 2011), and normalized difference water index (NDWI) (Jiang et al., 2015) have shown good linear relationship with LST. (2) Landscape component, diversity and configuration factors. Urbanization makes dramatic changes in the structural components and diversity, and spatial configuration of urban landscapes. Landscape components characterize the different compositions and the richness of landscape types, and are usually quantified as proportions of land cover types (Du et al., 2016; Zhou et al., 2017). Different types of landscape components have different reflectivity and hydrothermal properties, and hence affect LST to varying degrees. Landscape diversity is an integrated characterization of combination relationship among all the landscape components, quantified through the number of landscape components and the evenness of their area proportions. The arrangement and spatial characteristics of landscape components are measured by landscape configuration, and different arrangements of landscape patches can affect the energy exchange patterns and the efficiency among the patches, thus affecting the land surface heat flow (Sun and Chen, 2012; Turner, 2005). Therefore, landscape metrics which characterize landscape configuration are usually used in LST study focusing on spatial variation (Zhou et al., 2011; Connors et al., 2013). (3) Socio-economic factors. The changes in natural landscapes are mostly the result of human activities (Lu et al., 2013), and population density has been proved to have a positive effect on the formation of UHI (Kotharkar and Surawar, 2016; Weng et al., 2008; Huang and Cadenasso, 2016). However, other socio-economic factors, such as road density (representing car ownership), gross domestic product (GDP, representing the strength of reshaping nature) and nighttime light data from the US Defense Meteorological Satellite Program (NTL, representing the intensity of human activities), are rarely used in LST study. A bunch of impact factors affect land surface temperature. However, considerable studies analyze only one or several of these factors. Previous studies have failed to integrate the overall influencing effects of green landscape, waterbody, high albedo, landscape configuration and socio-economic factors on LST. Consequently, it is difficult to determine the dominant influencing factor of LST, and existing studies contain results that are laden with uncertainty.

It is known that sunlight condition, hydrothermal condition, and spatial characteristics of vegetation coverage are variable across the seasons, which lead to uncertainty of the study on both LST spatial variation and its driving factors. Results are, in some cases, contradictory. For example, Neave et al. (2016) found five major cities in Australia had a strong UHI in winter. Schatz and Kucharik (2014) pointed out that UHI intensity in the Madison region of Wisconsin, USA was higher in the warm season and lower in the cold season. This inconsistency among different seasons also appeared in the study of LST driving forces. In Nigeria, Ayansina (2016) showed that NDVI explained the spatial differentiation of LST in the dry season much better than that in the wet season. Chen et al. (2013) indicated that NDVI had the best correlation with LST in summer, and Mukherjee et al. (2015) showed that compared with other seasons, NDVI had a better cooling effect in the spring. However, Sun and Menas (2007) found in North American NDVI could have a positive relationship with LST in winter. Zhang et al. (2009) showed that NDBI had a positive correlation with LST spatial variability during spring and summer, with significant warming effect. However, according to the study of Liu and Zhang (2011) in Hong Kong, the positive correlation and warming effect are more obvious in winter. This inconsistency had prevented the application of the results to urban planning and management.

As we all know that urban LST is affected by a number of driving factors, what is less known, however, which are the dominant factors? Many statistical methods are used to identify the dominant influencing factors of urban LST. Most common among these methods are the Pearson correlation analysis and ordinary least-squares regression analysis (OLS). To measure spatial correlations, some studies used geographically weighted regression (Zhou and Wang, 2011), and forward, backward and forward-backward stepwise regressions were often applied in multivariate analysis to find an optimal model (Asgarian et al., 2015). Factor analysis, such as principal component analysis, was also often used when a number of influencing factors were considered simultaneously (Chen et al., 2014; Weng et al., 2008). Currently used statistical methods are effective, however, two analytical problems remain. Firstly, many studies used only a single influencing factor to establish the regression model with LST, and compared the individual effects of different factors on LST based on the coefficient of regression (R^2) for each single-factor regression equation. However, LST spatial pattern is usually not affected by a single influencing factor, but rather is the result of the combined effects of multiple influencing factors. Thus, the strength of explanation (R^2) of a single-factor regression model does not accurately represent the independent contribution of the corresponding factor. The interpretation of LST should consider more than one influencing factor, and establish a multiple statistical regression model to quantify the independent effect of each factor on LST variability. Secondly, most of the studies used stepwise regression to determine the truly influencing factors and establish appropriate models. Although stepwise regression can identify a good model to explain LST variation, after the model is established, identifying the relative importance of all the factors is difficult. In summary, few studies are focused on identifying the dominant factor of LST and the importance ranking of all the influencing factors. This research gap prevents us from putting forward better strategies to mitigate the UHI.

Here, we address these problems by conducting a seasonal comparison study in Shenzhen City, Guangdong Province, China. This study aimed to explore the seasonal differentiation of urban LST influencing factors using the methods of all-subsets regression and hierarchical partitioning analysis. In particular, the main purposes of the study were: (1) to compare the spatial pattern of LST in different seasons; (2) to use OLS and stepwise regression to clarify the correlation between individual influencing factors and LST; and (3) to apply all-subset regression to select the best fitting model with multilevel influencing factors, to analyze the relative importance of the explanatory variables of the optimal model for different seasons using hierarchical partitioning analysis, and thus to identify the dominant influencing factor in different seasons.

2. Methodology

2.1. Study area and data source

Shenzhen City is located in the southern coastal area of Guangdong Province (113° 46′–114° 37′ E, 22° 27′–22° 52′ N), south of the cities of Huizhou and Dongguan, and north of the Hong Kong Special Administrative Region (Fig. 1). The topography in Shenzhen City has a