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Research Paper

Efficiency of landscape metrics characterizing urban land surface temperature

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ABSTRACT

Identification of the relationship between landscape metrics and urban land surface temperature (LST) provides a basic understanding of the interaction of landscape pattern and ecological process. However, the evidenced relationships between landscape metrics and LST are still uncertain, and cannot provide fundamental support to landscape management. Other than a test of statistical significance, four judgments (median correlation value; temporal variation and statistical scale; threshold; and effects of key variables) are considered "efficient" criteria in this study. Partial correlation and piecewise linear regression are used to focus on the indicators of land cover proportion, biophysical proportion, and mainly area- or shape-related landscape configuration indicators. The results show: (1) land cover proportion can almost substitute for area-related landscape configuration indicators; (2) landscape composition is more efficient than configuration as an indicator because of its relatively stable temporal correlation values at different statistical scales; (3) the evident landscape composition threshold of vegetated land surfaces (50–70% for land cover proportion and 0.2–0.3 for biophysical proportion) is more indicative in application than the linear relationship for unvegetated land surfaces; and (4) landscape metrics are better correlated with LST in high temperature than in low temperature, and urban area weakly influences this correlation ($R^2 < 0.2$). Additionally, the configuration metrics at a landscape level are not recommended for characterizing LST. Depended on the efficient indicators, such as the application of thresholds, landscape planning can be linked to the quantitative observations and statistical evidence in landscape metrics.

1. Introduction

Climate warming and rapid urbanization have increased the heat stress in cities and especially in megacities (Dugord, Lauf, Schuster, & Kleinschmit, 2014; Harlan and Ruddell, 2011; Jenerette et al., 2016; Oke, 1973). Improving the ability of megacities to adapt to heat stress is an interdisciplinary issue that has aroused wide academic attention, particularly to reveal factors that influence urban heat island formation (Arnfield, 2003; Hu and Brunsell, 2015; Huang and Cadenasso, 2016; Imhoff, Zhang, Wolfe, & Bounoua, 2010). Observation of urban land surface temperature (LST) from remote sensing images is a common technique for studying the relationship between land cover and urban heat islands (Chen, Zhao, Li, & Yin, 2006; Huang, Zhou, & Cadenasso, 2011; Voogt and Oke, 2003; Weng, 2009; Weng, Lu, & Schubring, 2004). However, although relationships between landscape metrics and LST have been shown, the results are inconsistent and uncertain, and cannot yet provide explicit support for heat stress mitigation through landscape planning (Du, Xiong, Wang, & Guo, 2016; Estoque, Murayama, & Myint, 2017; Li et al., 2011; Zhou and Wang, 2011; Zhou, Wang, & Cadenasso, 2017).

In particular, although greenspace is commonly understood to have a cooling effect and impervious surface to have a warming effect, various landscape metrics, especially landscape configuration indicators, have an uncertain relationship with LST due to climatic conditions, statistical methods used, spatial resolution of data and the size of analytical units (Zhou et al., 2017). Furthermore, even when significant correlations between landscape composition and configuration and LST are found, their use in guiding landscape planning is obscure (Sun and Chen, 2017; Wu, Kong, Wang, Sun, & Chen, 2016; Xiao et al., 2007; Yuan and Bauer, 2007). This practical obstacle indicates that evidence from previous studies may not be powerful enough to adequately measure the relationship between landscape pattern and LST, and that more comprehensive consideration is required to identify this relationship.

To reduce the uncertainty and enhance the practicability of the relationship between landscape pattern and LST, we consider that the

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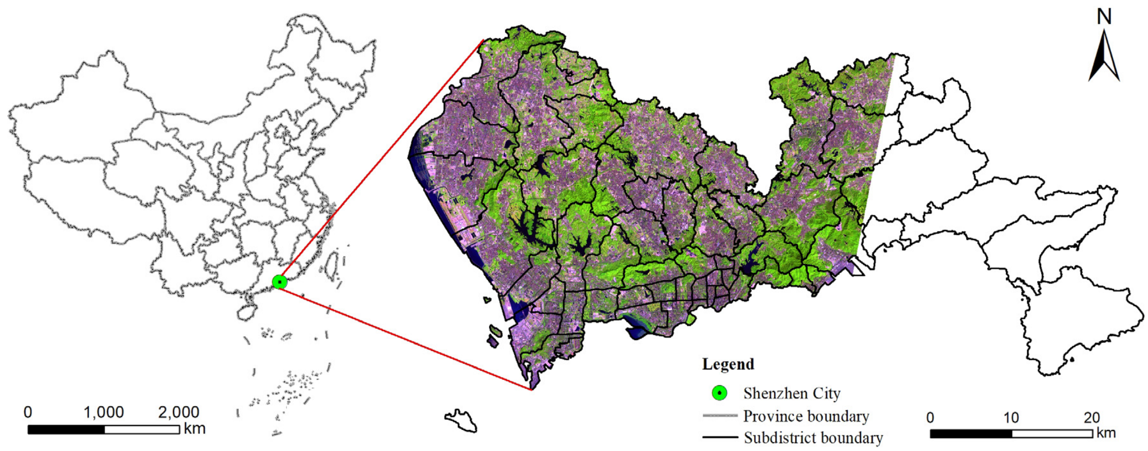

Fig. 1. Location of Shenzhen City in Guangdong Province, China (left) and the main city as defined by Landsat image width (right). The band combination was band-6, band-5, and band-4 coloured by red, green and blue, respectively.

significance test for variables correlation from only a few remote sensing images is not sufficient. Four additional aspects should be quantitatively examined, and we use the term "efficient" to comprehensively generalize the adequacy of these aspects. The first of these is the median correlation value of an indicator obtained from a large number of images (hereafter the "median correlation value" is shortened as "correlation value"). A high correlation is basic evidence that an indicator is efficient in individually characterizing LST (Asgarian, Amiri, & Sakieh, 2015; Chen, Yao, Sun, & Chen, 2014a; Connors, Galletti, & Chow, 2013; Estoque et al., 2017; Ma, Kuang, & Huang, 2010; Sun, Chen, Chen, & Lü, 2012). Second, the variation of a relationship in both temporal and spatial scales must be considered. A temporally stable and scale-dependent relationship is more efficient and widely applicable (Fan, Myint, & Zheng, 2015; Li, Zhou, & Ouyang, 2013; Song, Du, Feng, & Guo, 2014). The third aspect is the threshold in form of discontinuities in a mathematical sense. A clear threshold can effectively provide a planning target for constructing green infrastructure or limiting building land (Peng, Xie, Liu, & Ma, 2016). Last, the effects of key variable values on the relationship must be considered. Although the effect of LST in different seasons has been widely examined (Haashemi, Weng, Darvishi, & Alavipanah, 2016; Weng, Liu, Liang, & Lu, 2008; Zhou, Qian, Li, Li, & Han, 2014), the quantitative effect of LST difference remains to be detailed, and whether the relationship changes in the different amount of urban area is unknown. The identification of these effects can give evidence for when and where a landscape pattern-LST relationship will be efficient.

According to the above aspects, four scientific sub-questions can be formulated. Firstly, what kind of landscape configuration indicator is individually more highly correlated with LST than other configuration indicators? Secondly, which landscape metric is more stable in the time domain and dependent at various spatial scales? Thirdly, is there any practical threshold for a landscape metric that can guide landscape planning and management? Lastly, when or where can specific landscape metrics characterize LST best? Furthermore, the correlation value between landscape configuration and LST should be determined within a controlled landscape composition, in order to reduce the multicollinearity among the metrics (Peng et al., 2010; Uuemaa, Mander, & Marja, 2013).

Shenzhen City, one of China's 4 megacities, has experienced an obvious landscape change in the last 40 years. In this study, the main city of Shenzhen was used as the study area, and partial correlation and piecewise linear regression were used to examine the relationship between landscape metrics and LST. With the final goal of finding a way to mitigate heat stress through landscape adaption, four detailed objectives were defined using the "efficient" criteria: (1) identify which landscape indicator is valid or invalid in practice; (2) select an indicator that has a stable correlation with LST in the time domain and at various spatial scales; (3) quantify the practical threshold of landscape pattern nonlinearly influencing LST; and (4) detail the effects of mean LST and unvegetated land surfaces that influencing the relationships.

2. Methods

2.1. Study area

Shenzhen City (approximately 1997 km^2, 113°46′–114°37′E, 22°27′–22°52′N) has a subtropical oceanic climate. The average air temperature is 14.9 °C in January and 28.6 °C in July. The average annual air temperature is 22.4 °C, and is below 20 °C from December to March. The average annual precipitation is 1933.3 mm, and the wet season is from April to September. A long summer and short winter lead to a high thermal exposure for the city. Shenzhen City is one of the top four economic centers of China. During the last nearly 40 years, Shenzhen has urbanized from a small town in China's southern frontier to become a megacity. In 2016, the permanent resident population was almost 12 million, accompanied with the Gross Domestic Product of approximately 1950 billion Chinese Yuan. The economic success has been accompanied by rapid urban sprawl, and the increased impervious surface and energy emission aggravates the heat stress. As the administrative boundary of Shenzhen City cannot be completely covered by a unique Landsat images, we extracted the main city of Shenzhen defined by the width of Landsat images in this study (Fig. 1).

2.2. Data preprocessing

To ensure image quality, only clear-sky Landsat images were used (https://landsat.usgs.gov), and 49 images were selected from acquisitions made during 1987–2015 (Table 1); The atmospheric correction method was applied to retrieve LST from the images, and a decision tree method was used to interpret land cover type (Liu, Peng, & Wang, 2017). The algorithms were programmed in Matlab (Version 2014a, Mathworks, Inc., Natick, MA, USA). In order to avoid repetitive, we only introduce the data structure, and not detail the land cover classification and LST retrieval algorithm.