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Effects of green space spatial pattern on land surface temperature: Implications for sustainable urban planning and climate change adaptation

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ABSTRACT

The urban heat island (UHI) refers to the phenomenon of higher atmospheric and surface temperatures occurring in urban areas than in the surrounding rural areas. Mitigation of the UHI effects via the configuration of green spaces and sustainable design of urban environments has become an issue of increasing concern under changing climate. In this paper, the effects of the composition and configuration of green space on land surface temperatures (LST) were explored using landscape metrics including percentage of landscape (PLAND), edge density (ED) and patch density (PD). An oasis city of Aksu in Northwestern China was used as a case study. The metrics were calculated by moving window method based on a green space map derived from Landsat Thematic Mapper (TM) imagery, and LST data were retrieved from Landsat TM thermal band. A normalized mutual information measure was employed to investigate the relationship between LST and the spatial pattern of green space. The results showed that while the PLAND is the most important variable that elicits LST dynamics, spatial configuration of green space also has significant effect on LST. Though, the highest normalized mutual information measure was with the PLAND (0.71), it was found that the ED and PD combination is the most deterministic factors of LST than the unique effects of a single variable or the joint effects of PLAND and PD or PLAND and ED. Normalized mutual information measure estimations between LST and PLAND and ED, PLAND and PD and ED and PD were 0.7679, 0.7650 and 0.7832, respectively. A combination of the three factors PLAND, PD and ED explained much of the variance of LST with a normalized mutual information measure of 0.8694. Results from this study can expand our understanding of the relationship between LST and street trees and vegetation, and provide insights for sustainable urban planning and management under changing climate.

1. Introduction

The urban heat island (UHI) refers to the phenomenon of higher atmospheric and surface temperatures occurring in urban areas than in the surrounding rural areas. This phenomenon is widely observed in cities regardless of their sizes and locations (Connors et al., 2013; Cui and de Foy, 2012; Imhoff et al., 2010; Li et al., 2012; Tran et al., 2006). The UHI is mainly caused by the modification of land surfaces by urban development, which uses materials that effectively store short-wave radiation (Solecki et al., 2005). As a result, land surface temperature (LST) increases due to the UHI, which may disrupt species composition and distribution (Niemelä, 1999) by increasing the length of growing seasons, decrease air quality (Feizizadeh and Blaschke, 2013; Lai and Cheng, 2009; Sarrat et al., 2006; Weng and Yang, 2006), leading to greater health risks (Patz et al., 2005). The UHI may also decrease water quality as warmer waters flow into streams putting additional stress on aquatic ecosystems (James, 2002). Therefore, it has become a major research focus in urban climatology and urban ecology since first reported in 1818 (Howard, 1818).

The intensity and spatial pattern of UHI are largely exacerbated from population dynamics and development of build-up areas (Arnfield, 2003; Wu et al., 2013). Specifically, urban structure

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(e.g., height-to-width ratio of buildings and streets), proportion of built-up versus green spaces per unit area, weather conditions (e.g., wind and humidity), and socioeconomic activities determine the development of the UHI (Hamdi and Schayes, 2007; Rizwan et al., 2008b; Taha, 1997; Unger, 2004; Voogt and Oke, 1998). For example, Huang et al. (2011) found statistically significant relationship between the UHI and socioeconomic factors indicating that higher UHI effects were linked to block groups characterized by low income, high poverty, less education, more ethnic minorities, more elderly people and greater risk of crime. As many of these factors, especially land surface characteristics are primarily represented by land-cover and land-use (LCLU), the relationship between the LST and LCLU has been the focus of numerous studies on the UHI (Buyantuyev and Wu, 2010; Dousset and Gourmelon, 2003; Pu et al., 2006; Voogt and Oke, 2003;Weng et al., 2004). This is due to the fact that vegetation usually has higher evapotranspiration and lower emissivity than built-up areas, and thus has lower surface temperatures (Hamada and Ohta, 2010; Weng et al., 2004).

Composition and configuration of green spaces are the two major elements of LCLU. The former refers to the abundance and variety of land cover types and the latter is related to the spatial arrangements and layout of land cover types (Connors et al., 2013; Turner, 2005). Remarkable proliferations of studies focusing on the relationship between LST and green space composition has been reported over the last two decades (Chen et al., 2006; Tran et al., 2006; Voogt and Oke, 2003; Weng, 2009; Weng et al., 2004). Though the magnitude of correlations varied among these reports, a negative relationship between the vegetation amount/fraction and LST was consistently observed. However, the spatial characteristics and configurations of vegetation patches within the urban environment have significant impacts on the distribution of the UHI (Bowler et al., 2010; Cao et al., 2010; Honjo and Takakura, 1991; Yokohari et al., 1997; Zhao et al., 2011), and that the size and shape of a vegetation patch creates cool island effects, a phenomenon that the temperature of green space is lower than its surrounding areas (Cao et al., 2010; Zhang et al., 2009). Based on a case study of a heavily urbanized Beijing metropolitan area in China, Li et al. (2012) also indicated that increasing patch density results in significantly higher LST when the size of urban green space unaffected, and that spatial configuration has a significant influence in the variability of derived LST.

It is evident from an exhaustive literature review hitherto that there is a lack of case studies within arid regions (Connors et al., 2013). As cities are growing fast in population, and urbanization is projected to be high (Baker et al., 2004), sustainable planning of urban environment to mitigate UHI effects highlights a pressing need for immediate attention. This is further emphasized by climate changes as arid regions are likely to become even drier in response to increasing temperature from global warming (Durack et al., 2012). Driven by fast economic growth and population increase, Northwestern China has experienced rapid urbanization in the past several decades, along with a drastic transformation of the urban environment and social equity (Aishan et al., 2013; Fan and Qi, 2010; Halik et al., 2013; Liu et al., 2013). In addition, the majority of the previous studies used ordinary least squares regression and/or spatial autoregression to analyze the relationship between the landscape metrics and LST. The statistical significance of the relationship between the landscape metrics and LST varied between the methods (Li et al., 2012). Comparative approaches with additional case studies are needed to generalize the methods and concepts demonstrated by these preliminary attempts. To that end, we investigate the effects of composition and configuration of urban green space on LST using a robust moving window algorithm of normalized mutual information measure in the arid city of Aksu, Xinjiang Uyghur Autonomous Region in Northwestern China. One of the advantages of using mutual information measures is that it can capture linear as well as strongly non-linear relationships among variables under the "umbrella" of just one concept ("mutual information"). The goal is to provide guiding suggestions for sustainable urban planning and development under future climate changes. We chose to use Landsat 30 m resolution data as previous studies (Liu and Weng, 2008; Li et al., 2013) have demonstrated that 30 m and 90 m are the optimal resolutions to study the relationship between LST and landscape patterns at patch level and landscape levels, respectively.

The paper is organized in the sections below. Following the description of the study area in Section 2, the methodology of calculating LST, landscape metrics, and a brief introduction to normalized mutual information measure are presented in Section 3. The results, discussions and conclusions are presented in Sections 4–6, respectively.

2. Study area

The study area, downtown Aksu City, Northwestern China, is a typical oasis city located in an arid region. Aksu City is the capital of Aksu Prefecture in Xinjiang Uyghur Autonomous Region, China. Geographically, the city is situated in south of the Tianshan Mountains and northwest edge of the Tarim Basin (39°30′N–41°27′N, 79°39′E–82°01′E; Fig. 1). Aksu City is known as "the Land of Melons and Fruits". It includes municipal total area of 14,300 km^2 and built-up area of 28.1 km^2.

Aksu City is rich in light and heat resources. It has a long frost-free period from 205 to 219 days. The climate is dry, and rainfall is extremely rare with less than 50 mm per year and average annual evaporation of 1950 mm. Topography of the study area is flat. The climatic and the physiographic conditions are mostly the same across the region. Therefore, it is an ideal area to explore the relationship between LST and spatial pattern of green space in arid and semi-arid land.

The proportion of green area in the metropolitan region has increased to 30.6% today from 12% in early 1980s. Urban green space coverage has reached 39.2% with the per capita public green area of 9 m^2. Meanwhile, city's ecological environment has been significantly improved. This rapid growth in green space emphasizes a need to develop most effective configuration of green space to reduce the urban heat island caused by expanding impervious surfaces and to adapt to the global climate change.

3. Methodology

3.1. Land surface temperature

Landsat-5 Thematic Mapper (TM) thermal infrared band 6 (11.45–12.50 μm) data with 120 × 120 m resolution were utilized to derive the LST (Fig. 2b). The satellite data were collected on August 19, 2011, which was a clear day with 0% cloud cover. Meteorological variables that influence the intensity of urban heat environment at the time of image capture were obtained from China standard meteorological station in the study site. These variables include daily precipitation (0 mm), daily average wind speed (1.6 m/s), wind direction (South-East) and humidity (46%). Due to the lack of detailed in situ atmospheric variables that allow physical inversion of brightness temperature to LST, a mono-window algorithm was applied for retrieval of LST (Qin et al., 2001)

$$T_S = [a(1 - C - D) + (b(1 - C - D) + C + D)T_{sensor} - DT_a]/C \quad (1)$$

with $C = \varepsilon\tau$, $D = (1 - \tau)\ [1 + (1 - \varepsilon)\ \tau]$, $\alpha = -67.355351$ and $b = 0.458606$, where ε land surface emissivity (LSE) is, τ is the total atmospheric transmissivity, T_{sensor} is the at-sensor brightness temperature, and T_a represents the mean atmospheric temperature given by: