International Journal of Applied Earth Observation and Geoinformation 54 (2017) 65–71

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Impacts of urban landscape patterns on urban thermal variations in Guangzhou, China

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ARTICLE INFO

Article history:
Received 28 April 2016
Received in revised form 7 September 2016
Accepted 10 September 2016

Keywords:
Surface urban thermal variations
Urban landscape patterns
Remote sensing
Land surface temperature

ABSTRACT

One of the key impacts of rapid urbanization on the environment is the effect of surface urban thermal variations (SUTV). Understanding the effects of urban landscape features on SUTV is crucial for improving the ecology and sustainability of cities. In this study, an investigation was conducted to detect urban landscape patterns and assess their impact on surface temperature. Landsat images: Thematic Mapper was used to calculate land surface temperature (LST) in Guangzhou, the capital city of Guangdong Province in southern China. SUTV zones, including surface urban heat islands (SUHI) and surface urban heat sinks (SUHS), were then empirically identified. The composition and configuration of landscape patterns were measured by a series of spatial metrics at the class and landscape levels in the SUHI and SUHS zones. How both landscape composition and configuration influence urban thermal characteristics was then analysed. It was found that landscape composition has the strongest effect on SUTV, but that urban landscape configuration also influences SUTV. These findings are helpful for achieving a comprehensive understanding of how urban landscape patterns impact SUTV and can help in the design of effective urban landscape patterns to minimize the effects of SUHI.

1. Introduction

Land surface modifications are a direct environmental consequence of urbanization (Deng and Wu, 2013b; Zhou et al., 2014b). Urbanized and urbanizing areas exert significant impacts on local and global climate, driving changes in the local and global environment (Buyantuyev and Wu, 2010; Grimm et al., 2008; Lazzarini et al., 2013; Li et al., 2009). One of the most significant impacts is surface urban thermal variations (SUTV), including surface urban heat islands (SUHI) and surface urban heat sinks (SUHS) (Clinton and Gong, 2013). SUTV are a local phenomenon that significantly affects not only the urban internal and surrounding microclimatology, surface energy changes, biodiversity, ecosystem functioning, and human thermal comfort, but also regional and global climate and environment (Deng and Wu, 2013b; Grimm et al., 2008; Liu and Zhang, 2011; Lu et al., 2014; Xie et al., 2013). Assessing SUTV and investigating the factors that contribute to their development is essential to achieving a better understanding and mitigating the ecological and environmental consequences of urbanization.

SUTV properties are a result of surface-atmosphere interactions and energy budget (Grimm et al., 2008; Hu and Brunsell, 2013). Several features of urban environments contribute to the development of SUTV (Grimm et al., 2008; Hu and Brunsell, 2013). They are closely related to urban surface conditions (such as land cover and structure, urban geometry, and materials) and urban subsurface properties (such as conductivity) (Deng and Wu, 2013a; Hu and Brunsell, 2013; Weng, 2009). Because the composition and structure of the urban surface is an important factor in determining the reception and loss of radiation (Foley et al., 2003; Oke, 1982; Weng et al., 2007), many documented studies have extensively analysed and estimated the relationship between SUTV and land use/land cover (LULC) characteristics (Weng, 2009), especially between SUTV and the abundance of vegetation or prevalence of impervious surfaces (Li et al., 2011; Lu and Weng, 2006; Weng et al., 2007, 2004; Xiong et al., 2012). Such SUTV are well known as the SUHI phenomenon, and SUHI and the effects of spatial LULC patterns on SUHI have been extensively documented in many studies (Buyantuyev and Wu, 2010; Cao et al., 2010; Deng and Wu, 2013b; Hu and Brunsell, 2013). However, although SUHS are an important SUTV characteristic, this phenomenon has been ignored by most existing studies, and few attempts have been made to relate SUHS to urban surface characteristics (e.g., the spatial patterns of

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http://dx.doi.org/10.1016/j.jag.2016.09.007
0303-2434/

LULC inside SUHS zones). The relationship between SUHS and urban landscape patterns is not yet fully understood, which limits the development of optimal urban designs for significant SUHI mitigation. Therefore, analysis of SUHS and understanding the link between urban landscape patterns and SUHS can provide valuable information and advice for designing effective mechanisms to mitigate SUHI (Song et al., 2014; Zhou et al., 2011) and can result in specific recommendations for optimizing urban landscape patterns (Sun and Chen, 2012) and protecting the environment. A synthetic understanding is needed of how urban landscape patterns affect SUTV (including SUHI and SUHS) (Yue et al., 2012). Studies of the interactions between SUTV and urban landscape patterns will provide valuable insights into the urban environment as well as assistance in decision-making for urban planning and sustainable development of urban areas.

As an important environmental factor, land surface temperature (LST) is a crucial parameter in SUTV studies (Deng and Wu, 2013a; Heldens et al., 2013; Lazzarini et al., 2013; Weng, 2009), mainly for assessing SUTV and for analysing the relationship between SUTV and urban landscape patterns (Weng, 2009). Remotely sensed data are a unique source of information because they provide a continuous and simultaneous view of large areas to measure LST and to study SUTV and its relationships with urban landscape patterns (Hu and Brunsell, 2013; Myint et al., 2013; Weng, 2009; Weng et al., 2007).

Hence, the main purpose of this study was to explore how urban landscape patterns affect SUTV, based on analysis of LST obtained from remotely sensed data. The study was implemented in Guangzhou, one of the most rapidly urbanizing metropolitan regions in China. As the economic locomotive and leading megacity in China, Guangzhou lends itself to a detailed study of SUTV. A comprehensive understanding of SUTV can help provide deeper insight into how complex urban landscapes influence local SUTV and how to optimize urban landscape patterns to mitigate SUHI effects. In addition, investigating the effects of landscape patterns on SUTV in Guangzhou has significant implications for other rapidly developing regions and other estuary cities around the world. The specific aims of this study were: (1) to profile LST spatial variations; (2) to identify SUTV zones (SUHI and SUHS); and (3) to explore how landscape patterns differ inside SUHI and SUHS zones and how these relationships compare inside SUHI and SUHS zones.

2. Study area and data used

Guangzhou is considered an appropriate place to study the development of SUTV because it is one of the most rapidly growing regions in China, with a huge economy and dense population, resulting in LULC changes and uncontrolled urbanization. Guangzhou is the capital of Guangdong Province, which is an important political, economic, cultural, and scientific centrein southern China, located in the centre of the Pearl River Delta between 112°57′1.1″ and 114°3′19.57″E and between 22°33′35.32″ and 23°56′1.99″N, and covering an area of approximately 7434.4 km^2. The terrain is high to the northeast and low to the southwest. The central portion is a hilly basin, the southern area is a coastal alluvial plain, and forest is concentrated in the northern mountains. Guangzhou is located in a southern subtropical area with a maritime subtropical monsoon climate, in which alternating winter and summer monsoons are a prominent climate feature.

Because Guangzhou is a typical maritime subtropical monsoon area with persistent clouds and rain in the wet season (spring and summer), clear views of the Earth's surface are limited, and hence good-quality images are often unavailable (Weng, 2012). For this reason, the dry season was chosen for analysis in this study. Two Landsat-5 Thematic Mapper (TM) images (Row 43/Path 122 and Row 44/Path 122) from global land survey (GLS) dataset (GLS2010) in the U.S. Geological Survey (USGS) web were processed for LST estimation and to generate LULC classes. Both images were acquired at approximately 10:15 A.M. local time on November 2, 2009, a day with cloud free-conditions. The multi-spectral bands of TM were utilized at a spatial resolution of 30 m, including three visible bands, one near-infrared band and two shortwave infrared bands; although the original resolution of TM thermal band is 120 m, the thermal band was obtained at a spatial resolution of 60 m from the USGS web. Therefore, the thermal bands were resampled using the nearest neighbour algorithm with a pixel size of 30 m to correspond to the resolution of multi-spectral bands (Li et al., 2012b).

Table 1
The accuracy assessment result of classification in year 2009.

	Water	IS	Soil	Forest	Farmland	Shrub-grass
Producer's accuracy	96.08%	93.88%	90.70%	92.45%	84.91%	82.35%
User's accuracy	98.00%	92.00%	78.00%	98.00%	90.00%	84.00%
Overall accuracy	90%					

Other ancillary data include the Guangzhou administrative map (2005), which was used to define the boundary of the study area, the high-resolution image (2009) from Google Earth, which was used for selecting classification samples and accuracy assessment.

3. Methods

The three key factors involved in the present study are as follows: datasets for deriving LST and landscape classification, indicators for characterizing landscape patterns, and analysis for exploring the characteristics of landscape patterns in SUHI and SUHS zones. Further details will be described below.

3.1. Urban landscape classification

Firstly, the Landsat Ecosystem Disturbance Adaptive Processing System (Masek et al., 2006) was employed to convert raw Landsat data to surface reflectance for the 2009 TM image. Normalization different vegetation index (NDVI) and modified normalization different water index (MNDWI) (Eqs. (1) and (2)) were calculated for the 2009 surface reflectance image. Then, NDVI and MNDWI images were layer-stacked into the surface reflectance image of 2009.

$$NDVI = \frac{Bn - Br}{Bn + Br} \tag{1}$$

$$MNDWI = \frac{Bg - Bs1}{Bg + Bs1} \tag{2}$$

Where Bg, Bn, Br, $Bs1$ represent green, near infrared, red, and the shortwave infrared band in the 2009 surface reflectance image.

A Support Vector Machines (SVM) technique was used to identify urban landscape categories. The urban landscape was divided into six classifications: water, impervious surfaces (IS), soil, forest, farmland, and shrub-grass. Then, more than 1500 random points were generated within the overlapped region between the high-resolution image (2009) from Google Earth and Landsat TM image. Points were visually classified as water, IS, soil, forest, farmland, and shrub-grass; of the >200 random points for each class, half of them were used for training and the other half were used for validation. The selected training samples were used to train the classifier for the SVM based on the layer-stacked image (2009). Then, the high-resolution image (2009) from Google Earth of the study area were used to validate the classification results of 2009 with an error matrix (Congalton, 1991). The results of an accuracy validation are listed in Table 1, showing an overall accuracy of 90%.