Ecosystem Services 23 (2017) 38–46

Contents lists available at ScienceDirect

Ecosystem Services

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

Effects of green space dynamics on urban heat islands: Mitigation and diversification

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ARTICLE INFO

Keywords:
Land surface temperature
Temperature mitigation
Landscape pattern
Landscape design
Urbanization

ABSTRACT

Understanding how green spaces affect urban temperature is crucial for assessing thermal benefits of landscape planning. This study investigated green space dynamics and land surface temperature (LST) in the Beijing metropolis. Landscape types were classified from QuickBird (2002) and IKONOS (2012) images and LST values were extracted from Landsat TM images. Five landscape types were obtained in this region including impervious land (IL), forest land (FL), grass land (GL), water body (WB), and bare land (BL). Green expansion indicated landscape change from IL and BL to FL and GL. Green loss indicated landscape change from FL and GL to IL. Green exchange indicated landscape change between FL and GL. Results show that (1) the area of green space dynamics accounted for 38.24% of the total research area, including green space losses (108.86 km^2), expansion (92.49 km^2), and exchange (53.83 km^2). (2) LST change was not significant in the unchanged (0–0.19 °C) and exchanged green space (in the range of −0.02–0.25 °C). However, there were minor decreases of LST in areas of green expansion (in the range of −1.11 °C to −0.67 °C) and major increases in LST in the areas of green losses (1.64–2.21 °C). The results indicated that the number of green spaces is not the only criteria that should be assessed for temperature mitigation. Ecosystem services of temperature mitigation are not equal between the loss and expansion of green spaces even within same area. Greater focus on protecting natural forests in cities might provide greater benefits for climate mitigation.

1. Introduction

Rapid urbanization leads to a significant transformation of green spaces to impervious surfaces and urban infrastructures (Holt et al., 2015; Liu and Yang, 2013). A large number of cities throughout the world have experienced "urban heat island" (UHI) effects. UHI are characterized by a temperature difference between urban and rural regions. In highly urbanized regions, urban sprawl is spatially heterogeneous due to land availability and management requirements. This heterogeneous urbanization creates a complex energy balance and microclimate system inside large cities (Oke, 1982). Thermal comfort decreases and energy consumption for cooling increases with the degradation of the thermal environment of cities. Thus, the urban resilience to heat waves is negatively affected (McPhearson et al., 2015). Urban green spaces can contribute to a broad range of ecosystem services, among which temperature mitigation is regarded as an important ecosystem regulating service (Braat and Groot, 2012; Riechers et al., 2016). Understanding the influences of green space dynamics on the temperature variability is therefore of great interest for mitigating the UHI effect in metropolitan regions (Buyantuyev and Wu, 2012).

The UHI effect can be assessed by measuring surface air temperature (SAT) (Schwarz et al., 2012; Wang et al., 2014) and land surface temperature (LST) (Buyantuyev and Wu, 2012; Cao et al., 2010; Rotem-Mindali et al., 2015). Studies have shown that LST was significantly correlated with SAT in the daytime (Nichol and Wong, 2008; Weng, 2009). Urban green infrastructure has been commonly used to address climate-related impacts and other environmental ills (Gaffin et al., 2012; Haase et al., 2014; Shashua-Bar and Hoffman, 2000; Yuan and Bauer, 2007). Green spaces can generate a cooling effect on LST via higher levels of evapotranspiration compared with impervious surfaces (Zhou et al., 2014; Zhao et al., 2014). Some research has shown that the mean LST was 6–12 °C higher for impervious surfaces compared to green spaces (Kuang et al., 2015). Other studies suggest that a 10% increase in green spaces could result in a 0.86 °C decrease in LST (Li et al., 2012). The spatial variation of

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http://dx.doi.org/10.1016/j.ecoser.2016.11.011
Received 14 July 2016; Received in revised form 28 October 2016; Accepted 22 November 2016
Available online 01 December 2016
2212-0416/

UHI from city center to outskirts is particularly significant in large metropolitan areas (Kuang et al., 2015; Zhang et al., 2013). Given the complex thermal background, green spaces could produce a different latent heat of evapotranspiration and thus result in diverse cooling effects during summer (Spronken-smith et al., 2000; Sun and Chen, 2012).

Landscape structure, such as the size, shape, and configuration, is another contributor to the surface heat flux and therefore affects temperature mitigation (Li et al., 2011; Lindberg and Grimmond, 2011; Peng et al., 2016; Zhou et al., 2011). Recent studies have shown that the spatial complexity of landscapes was important in maintaining the stability of LST throughout different seasons (Liu and Weng, 2008; Sun et al., 2013). The relationship between landscape structure and LST may vary among different landscape types (Connors et al., 2013). In some cities, the spatial structure of green spaces contributed more to the LST variation than the total area of green spaces (Asgarian et al., 2015; Chen et al., 2014).

Urban greening is often implemented to offset the negative impact of impervious surfaces on urban temperature. Although the areas of green spaces can be compensated quickly, the underlying mechanism of their cooling effect (e.g., vegetation activities and albedo) may be different among various types of green spaces. Different types of green space may exhibit different capabilities for temperature mitigation. To our knowledge, no studies have compared the change of LST based on different types of green spaces. Apparently, a more detailed assessment on the LST change and underlying mechanism is required for a better understanding of the climate mitigation. This study aims to determine whether two landscape types that are converted into the same landscape type will exhibit the same temperature and to identify what factors affect the benefits of urban greening in rapidly urbanized regions.

For this study, we selected the Beijing metropolis as a study case to investigate the mean LST of different landscape conversions. Beijing has experienced massive urban construction and greening since its successful bid for the 2008 Olympic Games in July 2001. Urban landscapes experienced more rapid changes in the 2000 s than any time in Beijing's history. Beijing should therefore be an ideal site to examine landscape conversion and associated thermal effects. We conducted this study to: (1) investigate the dominant combinations of landscape conversion in Beijing from 2002 to 2012 and (2) quantify the change of mean LST based on green space losses, expansion, and exchange.

2. Materials and methods

2.1. Study area

Beijing is the capital of China, covering an area of approximately 16,800 km^2, and has experienced rapid development in recent decades. Beijing is characterized by a warm temperature zone and has a typical continental monsoon climate with four distinct seasons. The resident population of Beijing reached 20.69 million in 2012 (Wang et al., 2014). Rapid urbanization and city expansion resulted in significant UHI effects, particularly during the summer (Ding and Shi, 2013; Kuang et al., 2015; Li et al., 2012; Sun and Chen, 2012; Peng et al., 2016). The UHI intensity in Beijing has increased at a rate of 0.031 °C per year (Yu et al., 2005). The mean daily temperature in urban areas is 4.6 °C higher than the mean daily temperature in the suburbs (Song and Zhang, 2003). Moreover, urban construction and greening was primarily due to the stimulus provided by the hosting of the Olympic Games. The investment in Beijing Olympics exceeded $42.9 billion and about $15.7 billion was used in environmental protection projects to achieve the goal of “Green Olympics” (Chen et al., 2013; Zhang and Qian, 2010). The green spaces increased by 100 km^2 from 2002 to 2008 and the green coverage reached 43.5% in the Beijing metropolis (Dong, 2009).

The pattern of Beijing's development was a typical concentric expansion, generating a ring-shaped pattern from the city center to outskirts. The urban construction and greening related to the Olympic Games was mostly located inside of the 5th ring-road (Kuang et al., 2015). Our study is targeted at the highly-urbanized region inside of the 5th ring-road of Beijing, which covers an area of 667.28 km^2. This region is relatively flat, with elevations ranging from 20 m to 60 m above sea level. The study area was divided into four sub-regions via the ring-roads, including the sub-region inside of the 2nd ring-road, the sub-region between the 2nd and 3rd ring-roads, the sub-region between the 3rd and 4th ring-roads, and the sub-region between the 4th and 5th ring-roads.

2.2. Landscape types

Remote sensing images with high spatial resolution were used to identify landscape types in the Beijing metropolis. (1) QuickBird images were acquired on July 5, 2002 with 4 multi-spectral bands (2.44 m spatial resolution) and 1 panchromatic band (0.61 m). Furthermore, (2) IKONOS images were collected on July 29, 2012 with 4 multi-spectral bands (4 m) and 1 panchromatic band (1 m). The image classification and change analysis were based on a 4 m spatial resolution. Geometric correction of QuickBird images was used to match the IKONOS images based on 40 control points. The spatial error between QuickBird and IKONOS images was less than 2 m (0.5 pixel). These images were geo-referenced to the Universal Transverse Mercator (UTM) coordinate system with a first-order polynomial transformation. The images in 2002 represent the original landscape before rapid urbanization, and the images in 2012 exhibit the changed landscape after rapid urbanization in the Beijing metropolis.

We combined the unsupervised classification and decision tree methods to extract the landscape type using the ENVI software (Exelis Visual Information Solutions, Inc., USA). First, several clusters of landscape types were obtained based on the unsupervised classification method. These clusters were classified by the image reflectance and were manually checked to determine their landscape type. The panchromatic band and municipal thematic maps were used to help select sample regions for classification and verification. Second, some mixed clusters with water and shadow were reclassified via two indices, i.e., the normalized difference vegetation index (NDVI) and water-shadow distinction index (WSDI). The NDVI was calculated from the near infrared and red bands, and the WSDI was developed via the near infrared, red, and green bands of multi-spectral images (Chen et al., 2014).

$$\mathrm{NDVI} = \frac{\rho(Band4) - \rho(Band3)}{\rho(Band4) + \rho(Band3)} \tag{1}$$

$$\mathrm{WSDI} = \frac{\rho(Band4) - \rho(Band3)}{\rho(Band2) - \rho(Band3)} \tag{2}$$

Where ρ (*Band* 4, 3, 2) represents top-of-atmosphere reflectance transformed from the digital value of remote sensing images. The thresholds of NDVI and WSDI was used to distinguish different landscape types. For example, the vegetation index (NDVI > 0) was used to identify the vegetation areas from non-vegetation areas. Water had a low WSDI (< 0.5) whereas shadow had a high WSDI (0.5 < WSDI < 1).

Five landscape types were obtained in this region based on the above classification procedures. They were impervious land (IL), forest land (FL), grass land (GL), water body (WB), and bare land (BL). Lastly, a standard procedure was applied to assess classification accuracy. Ground-truthing analysis was conducted by verifying 387 random points after classification. The correctness (producer's accuracy) of the QuickBird classification was 0.90, 1.00, 0.80, 0.83, and 0.81 for the impervious land, water, forest land, grass land, and bare land, respectively. The overall accuracy of the classification was 85.2%,