Urban Forestry & Urban Greening 29 (2018) 113–121

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

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

Original article

Variations in land surface temperature and cooling efficiency of green space in rapid urbanization: The case of Fuzhou city, China☆

Zhaowu Yu[a,*], Xieying Guo[a], Yuxi Zeng[b], Motoya Koga[c], Henrik Vejre[a]

[a] Department of Geosciences and Natural Resource Management, Faculty of Science, University of Copenhagen, Copenhagen 1958, Denmark
[b] Geography Science and Resource Institute, Chinese Academy of Sciences, Beijing, 100101, China
[c] Department of Architecture Faculty of Engineering, Sojo University, Kumamoto 860-0082, Japan

ARTICLE INFO

Keywords:
Cooling efficiency
Land cover change
Land surface temperature
Land use transfer matrix
Urbanization

ABSTRACT

Rapid urbanization has caused significant land cover change (LCC) as well as changes in the land surface temperature (LST). However, the crucial land dynamic process, which could significantly contribute to the increase in LST and aggravation of the urban heat island (UHI) effect, remains poorly understood. Additionally, a strategy to optimize the most significant decreased land cover type in order to maximize the cooling effect is still lacking. Therefore, in this study, we selected the rapidly urbanizing and 'hottest' city in China, Fuzhou, as a case study. Two algorithms were selected to compare and obtain reliable LST data. A land use transfer matrix was used to detect critical contributions leading to the LST variations. The concept of cooling efficiency (CE) and the threshold value of efficiency (TVoE) are also proposed, defined, and calculated. The results show that LST values increased with increasing proportion of built-up land and sharply decreasing proportion of green space. Areas where LST differences exceed 4 °C cover 93% of the areas where green spaces decreased. Additionally, the LST variation is not only associated with the dominant land cover types but is also affected by the land cover transfer pattern and dynamics. Finally, we have calculated the TVoE of green space in Fuzhou city to be 4.55 ± 0.5 ha. This finding implies that when Fuzhou municipality implements urban/landscape planning, a green space area of 4.55 ± 0.5 ha is the most efficient to reduce the heat effect. This study extends the current understanding of LCC dynamics and LST variation. The concepts of the CE and TVoE are meaningful for landscape planning practice and can be used in other cases.

1. Introduction

Urbanization is the population shift from rural to urban areas, and is often characterized by an intense concentration of the urban population, influx of human activities, extensively built-up land development, and a sharp decrease of blue-green space (Foley et al., 2005; Forman, 2016; Grimm et al., 2008). Urbanization around the world is continuing. The United Nations projected that nearly all-global population growth from 2016 to 2030 will be absorbed by cities. By 2050, about 64% of the developing world and 86% of the developed world will be urbanized, much of which will occur in Africa and Asia. In China, the 2015 urbanization rate was 56.10% such that the urban population is expected to increase by 70% in 2030 (Sun et al., 2016). The urbanization process also induces the replacement of natural and semi-natural land cover types into sealed impervious surfaces, modifications of the biophysical environment, and alterations of land surface energy processes (Fu and Weng, 2016; Voogt and Oke, 2003). The variation of thermal inertia and albedo depends on the types of land cover. As a consequence, rapid urbanization has caused the significant urban microclimate phenomenon—urban heat island (UHI)—which is one of the major concerns related to the urban thermal environment (Akbari and Kolokotsa, 2016; Oke, 2002).

Many studies have identified that physical processes, such as radiative fluxes, and land surface material characteristics (e.g., albedo, emissivity, thermal capacity, and conductivity) can explain the correlations between land cover types and temperature (Forman, 2014; Oke, 2002). For example, blue-green spaces and impervious surfaces are the most important elements in urban landscape for explaining the variation in heat distribution (Hamada and Ohta, 2010; Huang and Cadenasso, 2016; Ren et al., 2016). Land surface temperature (LST) values retrieved from airborne or satellite-borne remotely sensed thermal infrared imagery are regarded as a measurable indicator to simulate the air temperature (Foley et al., 2005; Ren et al., 2016; Schwarz et al., 2012; Voogt and Oke, 2003). The variation of LST and

☆ The JSPS KAKENHI (Grant Number JP15KK0142) financed this study. The Chinese Scholarship Council (CSC) also supported this study.
* Corresponding author.
E-mail addresses: zhyu@ign.ku.dk (Z. Yu), vls817@alumni.ku.dk (X. Guo), 171797240@qq.com (Y. Zeng), koga@arch.sojo-u.ac.jp (M. Koga), hv@ign.ku.dk (H. Vejre).

https://doi.org/10.1016/j.ufug.2017.11.008
Received 19 March 2017; Received in revised form 9 September 2017; Accepted 10 November 2017
Available online 15 November 2017
1618-8667/

urban thermal patterns are interlinked with land cover types in different ways. For example, the spatial pattern of LST in an urban area is heterogeneous and is affected both directly and indirectly by the landscape composition and configuration. (Fu and Weng, 2016; Kuang et al., 2015; Monteiro et al., 2016; Sun and Chen, 2012).

The LST variation also depends on the spatial and temporal scale. Ma et al. (2016) pointed out that urban impervious surfaces and LST were positively correlated in summer daytime/nighttime and winter nighttime but negatively in winter daytime. Chen et al. (2017) found that LST diurnal variations increase with the urbanization index and that adverse effects are more substantial in the earlier stages of urbanization. The LST distribution is not only influenced by the physical elements of cities, but a relation between the social conditions of the population (e.g., income and education level) and the LST pattern has also been reported (Huang and Cadenasso, 2016). Some studies indicated that neighborhoods with low levels of income and education, as well as an aging population, often related to higher LST than other neighborhoods which can be explained by different backgrounds in the citizens' ability to mitigate and adapt to the heat effect, such as the usage of air conditioners (Buyantuyev and Wu, 2010; Huang and Cadenasso, 2016; Klinenberg, 2015).

The benefits of urban green spaces have been assessed by many studies as an approach to mitigate the UHI effect. The studies proposed that urban green space has a positive effect on the adaptation of the thermal environment in cities by evapotranspiration and shading mechanisms provided by green vegetation (Jaganmohan et al., 2016; Santamouris, 2014; Žuvela-Aloise et al., 2016). The landscape composition, structure (e.g., size, shape, configuration), and vertical structure of green spaces also influence the urban cooling island (UCI) effect (Akbari and Kolokotsa, 2016; Bowler et al., 2010; Monteiro et al., 2016). Previous studies have investigated the relationships between green spaces and UHI/LST (Asgarian et al., 2015; Ren et al., 2016). In addition, some indexes such as the normalized difference vegetarian index (NDVI), leaf area index (LAI) and the sky view factor (SVF) were identified to have correlations with the green space (Kuang et al., 2015; Yan et al., 2014; Yu and Hien, 2006). However, with further understanding of the cooling effect of green spaces, some researchers noticed that the relationships between green space and LST are hard to support within urban planning and management practicality (Sun and Chen, 2012; Yu et al., 2015). Therefore, quantification of the cooling extent and intensity of green spaces has been addressed by many researchers. For example, Bowler et al. (2010) concluded from a *meta*-analysis that the mean reductions of urban temperature by green spaces are 0.94 °C during the day and 1.15 °C at night and that the cooling extents of green spaces are 500 m. However, in the case of Japan, a separate study showed that the cooling effect can exceed 300m, but that there is no cooling extent beyond 500 m (Hamada and Ohta, 2010). In a high-latitude city, Gothenburg, the maximum summer temperature difference between a park and a built-up area is 5.9 °C, and the cooling extents reached over 1.1 km from the park border (Upmanis et al., 1998), while in low latitude, the cooling extents of Mexico City reached over 2 km (Jauregui, 1991). A study by Oliveira et al. (2011) acknowledged that while the temperature reduction in Lisbon can reach 6.9 °C on a hot summer day, the cooling effect of green spaces also has a relationship with the different climate zones, which was also proven by other studies (Zhao et al., 2014).

Although the spatial patterns of LST and UHI general characteristics of urban-to-rural temperature differences have been extensively studied, a comprehensive understanding of how the rapid urbanization dynamic process affects land cover change (LCC), as well as LST changes, has not received considerable attention. Explicitly, many studies focus on either LCC or LST change while very few studies combine LCC and LST change and interactions or quantify the land cover transfer process associated LST changes. We still lack understanding of the key LCC and transfer process, which could significantly contribute to LST variation and aggravate the UHI effect. Additionally, an approach to optimize the most significant decreased land cover type (urban blue-green space) in order to maximize the cooling effect is also lacking. Therefore, the city of Fuzhou, which is located in one of the most dynamic urbanization regions in China, was selected as a case study. The land use transfer matrix (LUTM) method was used and the concept of cooling efficiency (CE) has been proposed, defined and calculated. We use our results to (1) quantitatively investigate LST variations resulting from LCC dynamics, as well as differences and correlations in the rapid urbanization process, and (2) explore how to minimize the negative effect and maximize the cooling efficiency by studying the most dramatically decreased land cover type. Moreover, (3) provide operable implications for the urban planner and decision maker.

2. Methods

2.1. Study area

Fuzhou (118°08′E ~ 120°31′E, 25°15′N ~ 26°29′N), the capital city of Fujian Province, is located in southeast China. The Greater Fuzhou metropolitan region has an area of 12,251 km^2, including five urban districts (1026 km^2) and eight suburban and rural counties (Fig. 1). Fuzhou has a humid subtropical climate, influenced by the East Asian Monsoon, with long, hot and humid summers and short, mild and dry winters. The annual mean temperature is 19.7 °C and the annual precipitation ranges from 796.5 mm to 1913.6 mm. The average monthly temperature in July is 28.9 °C with extremely high temperatures usually occurring in July and August. Due to rapid urbanization, improper construction activities and climate change, Fuzhou has become the hottest city in China since the beginning of the 21 st century and is referred to as the so-called "Furnace City" (National Climate Center of China, 2013).

In 2000, the total population of Fuzhou metropolitan was 6.38 million and the urbanization rate was 51.1%. By the end of 2013, the permanent population of Fuzhou had increased to 7.34 million and the urbanization rate was 67.4%. Fuzhou is one of the most urbanized and dynamic cities in China. Meanwhile, in order to mitigate the increasingly serious UHI effect, the Fuzhou municipal government plans to implement more effective solutions to improve the urban resilience, particularly in the urbanized areas of the Greater Fuzhou metropolitan region. For these reasons, we selected the city of Fuzhou as a case study in the present work.

2.2. LCC matrix detection from 2000 to 2013

In order to assess LCC, we used 30 m × 30 m thematic maps obtained from the Landsat-7 ETM+ (July 23, 2000) Landsat-8 TIRS (August 4, 2013), and the SPOT-5 remote sensing (2.5 m) image collections. This process was also aided by the use of historic maps obtained from Google Earth software to improve the accuracy of land cover types. In light of the correlations between LST and LCC, four different land cover types were designated from the images using supervised classification and a decision tree tool: built-up land, green space, water body and other lands (bare land).

In this study, we used the LUTM method to detect LCC and dynamics from 2000 to 2013. The LUTM method is derived from the quantitative description of a system state and state transition in system analysis. Generally, in the LUTM method (Table 1), the row/column indicates the land cover type at times 1 and 2 (T1/T2). P_{ij} represents the area of land type i converted to land type j as a percentage of the total land area during T1-T2 while P_{ii} represents the area percentage of i-type land use that remained constant during T1-T2. P_{i+} and P_{j+} denote the total area percentage of the i-type and j-type land use at T1 and T2, respectively (Takada et al., 2010).