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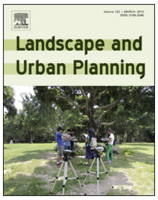

The relationships between landscape compositions and land surface temperature: Quantifying their resolution sensitivity with spatial regression models

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HIGHLIGHTS

- The LST and landscape compositions were extracted from ETM+ and Quickbird images.
- LST-landscape relationships were analyzed with spatial regression model at 18 resolutions.
- The variation of the relationships over resolutions was analyzed.
- Two resolutions 660 m and 720 m are the best spatial resolutions to measure LST-landscape relationships.

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ABSTRACT

Understanding the relationships between landscape compositions and land surface temperature (LST) is important for mitigating urban heat island effect. Existing studies have investigated the impacts of land-cover types on LST, while the effects of LST autocorrelation are overlooked. This study used spatial regression model to distinguish the contributions of land-cover types on LST from that of LST autocorrelation. Its objectives are as follows: (1) to build quantitative relationships between LST and land-cover types at multiple resolutions and (2) to find suitable resolutions for measuring the relationships. LST is retrieved from a Landsat ETM+ image, and land-cover information is extracted from a Quickbird image. Two spatial regression models, spatial lag and spatial error models, are used to quantify the relationships at 18 resolutions ranging from 60 m to 1080 m, at 60 m intervals. Results of this study indicate that the resolutions of 660 m and 720 m are most suitable for measuring the relationships between landscape compositions and LST. At these resolutions, all the five coefficients of dependent variables characterizing landscape compositions attain the maximum value, while the coefficient of the autocorrelation of LST is reduced to minimum. At resolutions finer than 660 m, the autocorrelation of LST affects LST more significantly than land-cover types. At resolutions coarser than 720 m, most coefficients are insignificant. This study also measures the impacts of major land-cover types on LST. These findings provided valuable insights into how thermal environmental impacts of urbanization can be mitigated through local-level planning and zoning approaches.

1. Introduction

The past few decades have witnessed a rapid and unprecedented growth in urbanization across the globe (Seto, Sánchez-Rodríguez, & Fragkias, 2010). From the perspective of landscape ecology, urbanization is a process of transforming natural landscapes such as vegetation cover, water bodies, and agrarian lands into man-made impervious surfaces containing cement, asphalt, metal, and other chemical materials. The transformation abates land surface evaporation and moisture availability, elevates sensible heat fluxes (Carlson, Dodd, Benjamin, & Cooper, 1981; Owen, Carlson, & Gillies, 1998), reduces precipitation (Kaufmann et al., 2007), eliminates farmland reserves (Seto, Kaufmann, & Woodcock, 2000), modifies urban thermal environment, and leads to the urban heat island effect (Seto et al., 2010).

The urban heat island effect is often captured by land surface temperature (LST) patterns derived from thermal infrared remote sensing imagery (Weng, 2009). Numerous studies have been conducted in landscape ecology to identify the relationships between a range of indicators of landscape patterns and LST in

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various geographical contexts. The three key factors involved in this field are as follows: datasets for deriving the LST and landscape patterns, indicators for characterizing landscape patterns, and models for exploring the relationships between the retrieved LST and the chosen indicators.

Regarding the datasets, in most studies, LST values were retrieved from Landsat TM/ETM+ images (resolutions ranging from 120 m to 60 m, Chen, Zhao, & Li, 2006; Li, Song, Cao, Zhu, & Meng, 2011; Liang & Weng, 2008; Weng, Lu, & Schubring, 2004; Yuan & Bauer, 2007); in some cases, NOAA-AVHRR (1.1 km, Dousset & Gourmelon, 2003), MODIS data (1 km, Cheval & Dumitrescu, 2009; Rajasekar & Weng, 2009; Tran, Uchihama, Ochi, & Yasuoka, 2006), and ASTER data (90 m, Buyantuyev & Wu, 2010; Liu & Weng, 2008) were used. Most landscape patterns were obtained by classifying Landsat TM/ETM+ images (Chen et al., 2006; Li et al., 2011; Liang & Weng, 2008; Weng et al., 2004), ASTER images (Liu & Weng, 2008), SPOT images (Dousset & Gourmelon, 2003), and aerial photos (Li et al., 2011). In a few cases, image data were combined with land-use maps to improve accuracy (Li et al., 2011). Low-resolution images are useful only for coarse-scale urban landscape mapping. The availability of TM/ETM+ data as well as Quickbird/IKONOS images has made it possible for researchers to study local-scale LST, and establish more accurate relationships between LST and surface biophysical parameters (Nichol, 1994; Nichol, 2009; Weng, 2001).

To characterize landscape patterns, two types of indicators have been used: landscape composition and landscape configuration. The former identifies each land-cover type and describes its relative abundance without referring to its spatial features, whereas the latter represents the physical distribution (i.e., placement and location) of patches within a landscape mosaic. Landscape composition factors reported in the current literature include the following: the impacts of vegetation abundance on LST (i.e., Normal Difference Vegetation Index—NDVI or vegetation fraction), amount (percentage) of impervious surface area, and amount of other land-cover types (Buyantuyev & Wu, 2010; Chen et al., 2006; Dousset & Gourmelon, 2003; Li et al., 2011; Weng et al., 2004; Zhou, Huang, & Cadenasso, 2011). While landscape composition influences LST directly by affecting the physical characteristics of the surface, such as moisture and albedo (Oke, 1982), landscape configuration also plays a role because it affects radiative fluxes and energy flows. Various landscape pattern metrics have been developed to measure these effects. Among these metrics, perimeter–area ratio, landscape shape index, and edge and patch density are frequently used (Li et al., 2011; Liu & Weng, 2008; Zhou et al., 2011).

Existing research on the relationships between LST and landscape patterns adopted both qualitative and quantitative models. Qualitative relationships such as the profiles of LST distribution across different land-cover types and the fractal dimension of LST surface have focused on the descriptive identification of land-cover types that elevate urban temperatures and biophysical forces (Jusuf, Wong, Hagen, & Anggoro, 2007). Quantitative analyses that measure the extent of impacts of different land-cover types on LST used Pearson correlations, scattergrams, and curve fittings. Conventional regression models such as single or multiple linear regression (Li et al., 2011; Weng et al., 2004; Yuan & Bauer, 2007), multiple stepwise regression, and principal component regression (Xiao, Weng, Ouyang, & Li, 2008) have widely been used.

A thorough examination of the literature reveals two significant deficiencies of these studies. First, previous studies have focused mainly on exploring the relationships at a single scale, which is often the spatial resolution of imagery data from which LST and landscape indices are derived. However, urban heat and landscape patterns as well as their spatial-temporal distributions and interactions are scale dependent. Landscape patterns and ecological processes may vary across scales, making it necessary to examine the scaling-up effects on the interrelationships between various landscape characteristics (Liu & Weng, 2009). To determine the appropriate scales at which the relationships can be observed and studied is fundamental for the validity of results and implications. Therefore, a multiscale analysis is required to reveal the extent to which the impacts of landscape patterns on urban heat patterns vary across different scales.

Second, LST is spatially auto-correlated or dependent because of land surface heat fluxes. The spatial autocorrelation of LST implies that the LST of a certain location is correlated with those of its neighboring locations. This leads to spatial autocorrelation problems in statistics that violate the assumption of conventional statistical techniques—independence among observations. Yet, few studies have taken spatial autocorrelation into account when performing a regression analysis of the relationships between LST and landscape indices. Most of the existing studies have used only conventional regression analysis or correlation analysis to model the relationships without considering the spatial dependency of LST (Chen et al., 2006; Li et al., 2011; Weng et al., 2004; Zhou et al., 2011). This may yield misleading parameter estimates and unreliable significance test results. Therefore, the impacts of landscape patterns on LST considering the effect of spatial autocorrelation need to be further explored.

The two aforementioned problems motivate our present research. This study examines the impacts of land-cover patterns on LST considering spatial autocorrelation of LST. The objectives of this study are as follows: (1) to analyze the spatial characteristics of LST and land-cover patterns in the area under study; (2) to explore and compare regression models used to investigate the association between LST and landscape compositions; (3) to examine resolution sensitivity of the relationships between LST and landscape compositions; (4) to establish quantitative relationships between LST and land-cover types, and compare the effects of underlying factors. The results in this study will contribute to our understanding of how urban landscape compositions may affect local LST across different scales. The study will enrich the existing literature as it takes into consideration autocorrelation of the values of LST. This will promote the effectiveness of land-use management and urban planning practices by improving landscape design and help alleviate the urban heat island effect.

2. Data and methodology

2.1. Study site

Beijing is the capital city of China and the country's political, cultural, and communication center (Fig. 1). It covers an area of around 17,000 km^2 with a population reaching 20 million. Since the past 20 years, Beijing has been undergoing an accelerated process of urbanization and population explosion along with rapid land-use/cover transformations. After five rearrangements of its administrative divisions, the metropolis currently consists of 16 districts and two counties. Our study region covers the northeast part of the Haidian district and the southwest part of the Changping district, occupying a total area of 70.056 km^2. Being a rural–urban fringe at the time when images for this study were acquired, the area consisted of both urban and rural landscapes, including cropland, greenhouses, residential and industrial buildings, water bodies, parks, and roads.

2.2. Image processing

A Landsat 7 ETM+ image was acquired on May 22, 2002, to measure LST quantitatively. The thermal infrared band (band 6) with a resolution of 60 m was used to retrieve LST. A Quickbird image acquired on March 22, 2002, was used to extract landscape