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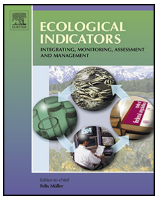

How many metrics are required to identify the effects of the landscape pattern on land surface temperature?

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ABSTRACT

Urban heat island (UHI) is a global issue as a result of urbanization. Land surface temperature (LST) is closely related to the thermal environment and energy budget of the earth surface, and is an important parameter in identifying UHI effects. Previous studies have proved the effects of landscape pattern on LST by using landscape metrics. However, the metrics used were inconsistent in number and type. Further, fewer studies tried to select representative metrics from the numerous metrics for LST indication. In this study we tried to explore the effects of landscape pattern on LST in Beijing by using the representative class level metrics selected through cluster analysis, factor analysis and regression. The results showed a composition metric such as PLAND (e.g. percentage of impervious surface in a landscape) alone explained about 56% of the landscape mean LST, whereas adding a configuration metric such as LSI (landscape shape index) or Gyrate_MN (mean gyration index) explained approximate another 6–12%. Adding more other configuration metrics does not improve the regression model performance more than 1%. The regression results also revealed that without targeted dependent variables, the factor analysis is of no use for choosing landscape metrics. These indicate that landscape composition and configuration both have effects on landscape mean LST, while composition is much more important than configuration, and that a combination of one composition metric with no more than four configuration metrics of impervious surface is sufficient for LST prediction. These results can help landscape ecologists in using landscape metrics and further help landscape planners to balance land cover in urban planning.

1. Introduction

The urban heat island (UHI) is a global phenomenon that affects air quality (Sarrat et al., 2006), water use, energy consumption, human health, and urban sustainability (Frumkin and McMichael, 2008; Gober et al., 2010; Grimm et al., 2008). It is important to realize that there are primarily two types of UHI: air UHI and surface UHI. Air UHI refers to the phenomenon whereby air temperature in urban areas is higher than in the surrounding suburban areas. Surface UHI refers to the difference in the land surface temperature (LST) between urban and less urbanized areas. The LST is the skin temperature of an area that is determined by air temperature and long-wave radiation between the surface and the atmosphere (Weng, 2009). Unlike air temperature, LST has higher spatially continuous coverage and has frequently been used to assess UHIs in recent decades (Voogt, 2002; Buyantuyev and Wu, 2010; Liu and Weng, 2008, 2009; Schwarz et al., 2011).

A large body of research has tried to identify surface UHI or the associated LST using landscape metrics (Connors et al., 2013; Li et al., 2011; Zhou et al., 2011). Landscape metrics as descriptions of landscape patterns are believed to have relationship with climate (Stone, 2009). Numerous indices have been proposed to measure landscape patterns (Baker and Cai, 1992; McGarigal et al., 2012; Riitters et al., 1995), including the composition and configuration characteristics of land use/cover. Of these indices, the landscape metrics advanced by McGarigal et al. (2012) are the most widely used measures (Kupfer, 2012; Uuemaa et al., 2013). The software FRAGSTATS developed by McGarigal et al. (2012) has became widely used for calculating landscape metrics in many fields, ranging from evaluating land use/cover changes to analyze the effects of landscape pattern on different kinds of ecosystem services (Uuemaa et al., 2013). However, the number of landscape metrics used in previous studies has ranged from 2 to more than 10 (Cao et al., 2010; Connors et al., 2013; Li et al., 2012, 2013; Sun et al., 2012; Weng et al., 2007). Frequently used metrics have

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included: percentage of landscape (PLAND), mean patch size (MPS), perimeter-area fractal dimension (PAFRAC), aggregation index (AI), cohesion index (COHESION), contagion index (CONTAG), and Shannon's diversity index (SHDI).

Yet less attention has been paid to the selection of landscape metrics either targeted to LST/UHI studies or to other environmental processes. In general, the metrics in common use have been selected on the basis of the results of Riitters et al. (1995). Riitters et al. (1995) carried out a factor analysis on landscape pattern indices to reduce the metrics dimension, but not to analyze urban heat islands. In some cases, all of the metrics have been used (Schindler et al., 2013). Uuemaa et al. (2013) reviewed the trend of using landscape metrics as indicators for ecological processes and found that climate/microclimate regulation had received limited attention. As landscape metrics provided a comprehensive description of the proportion, shape and spatial arrangements of different land cover, a selection based on targeted statistics would thus be necessary and helpful for metrics selection and urban planning. In addition, little is known about the role of configuration in affecting LST. Hence, it is necessary to conduct further test studies on the effects of landscape patterns on LST using landscape metrics.

This study focused on finding appropriate metrics that can effectively identify the effects of landscape patterns on urban heat islands. The objectives of this study were: (1) to explore the role of landscape composition and configuration in indicating UHI-associated LST for a metropolis; and (2) to select the most frugal and effective metrics for LST indication.

2. Methodology

2.1. Study area and materials

2.1.1. Study area

The city of Beijing, China was selected as the study area. The city spreads out in five concentric ring roads, from the Second to the Sixth Ring Road. The Second Ring Road follows the old city walls and the Sixth Ring Road connects satellite towns in the surrounding suburbs. The city has a monsoon-influenced humid continental climate characterized by hot-humid summers and cold-windy-dry winters. The average daytime high temperature in January (usually the coldest month) is around 1 °C, whereas that in July (usually the hottest month) is above 30 °C. Both air UHI and surface UHI of Beijing have been investigated and have shown a trend of incensement with enhancing urbanization (Miao et al., 2009; Ji et al., 2006). Though average summer daytime air UHI intensity (temperature difference) in the 1970s was only about 1 °C and had kept increasing by merely 0. 31 °C every 10 years since (Yu et al., 2005), surface UHI analysis have showed higher UHI intensity, ranging from 5 to more than 10 °C (Wang et al., 2007).

In this study, the region inside the Fifth Ring Road, as shown in Fig. 1, was used for study because this is the main metropolitan area. The study region ranges south to north from 39.75° N to 40.0° N and west to east from 116.25° E to 116.5° E, and takes up an area of 667 km^2. This region, which has an elevation of 40–60 m, occupies a relatively small but expanding proportion of the municipality's total area (about 16 800 km^2).

2.1.2. Materials

2.1.2.1. Land cover map. Six swaths of QuickBird (QB) images were used to obtain land cover data. The central parts of the study area (~75%) were covered by two QB images taken on July 5, 2002, and the other parts were covered by four QB images. The two eastern images were taken on April 24, 2002 and the two western images were taken on April 1, 2002.

Four types of land cover were firstly considered for land use classification: vegetation, water, bare soil and built up areas or impervious surface (IS). The vegetation in the metropolis was mainly a mix of grass, shrubs, and trees. IS included buildings and impervious roads. Bare soil was generally bare land that was intended to be built upon. "Water" refers to rivers and lakes.

Unsupervised classification and the Decision Tree method in the ENVI^{TM} (Version 5.0) software were combined to obtain the land cover data by the following three steps.

First, 12 classes, a maximum of 15 interactions and the K-means method were set to do the unsupervised classification based on the reflectance of four multi-spectral bands of QB images. The resulting 12 classes were checked manually to determine a class attribute, i.e. trees, shrubs, grass, crops, agricultural greenhouses, water, shadow, wet bare soil, dry bare soil, bright IS, medium bright IS, and dark IS. These classes were checked to ensure precise classification using sample regions, selected with the aid of the pan band images. Similar classes such as all the vegetations are combined. The mixed classes occurred between water, shadow and dark IS, and between wet bare soil and medium bright IS.

Second, the remaining mistaken classes were discriminated by the normalized difference vegetation index (NDVI) and an index that we constructed: the water-shadow distinction index (WSDI). The NDVI was used to discriminate wet bare soil from medium bright IS, and also to ensure the distinction between vegetation, water, and IS. The WSDI was used to discriminate water and shadow from dark IS. Wet bare soil mostly consisted of the croplands that had been irrigated, and had an NDVI value similar to vegetation but higher than IS.

The NDVI was calculated by Eq. (1):

$$\mathrm{NDVI} = \frac{\rho(\mathrm{Band\,4}) - \rho(\mathrm{Band\,3})}{\rho(\mathrm{Band\,4}) + \rho(\mathrm{Band\,3})}, \tag{1}$$

where ρ (Band 4) and ρ (Band 3) represent top-of-atmosphere (TOA) reflectance transformed from the digital value (DN) of QB Bands 4 and 3, respectively. TOA reflectance is the at-sensor reflectance with the cosine effect of the solar zenith and the exo-atmospheric solar irradiance due to variation in the sun–earth distance removed (Chander and Groeneveld, 2009; Li et al., 2011).

The WSDI was built according to the spectrum profiles of dark IS, shadow, and water. Their spectrum was similar to each other in the slope between Band 2 and Band 3, whereas the profiles of water were steeper between Band 3 and Band 4 than that of dark IS and shadow (See Appendix for detailed spectrum profiles).

Therefore, the WSDI was calculated with the following equation:

$$\mathrm{WSDI} = \frac{\rho(\mathrm{Band\,4}) - \rho(\mathrm{Band\,3})}{\rho(\mathrm{Band\,2}) - \rho(\mathrm{Band\,3})}, \tag{2}$$

similar as in Eq. (1), ρ (Band 2) represents TOA reflectance of QB Band 2. In our study, water often had a mean WSDI less than 0.5, whereas dark IS and shadow had mean WSDIs higher than 0.5 but less than 1. The areas of shadow were mainly built-up roads shaded by nearby buildings. Shadow and built-up roads were therefore also combined as a single type. Each image has a slightly different WSDI because of environmental effects such as the acquisition date and the atmosphere. Basic statistic analysis of NDVI and WSDI of each image was conducted to decide the thresholds for the building of the decision trees.

Finally a 3 by 3 window was used to clump the classification results. This eliminated very small pieces of pixels within a patch. The overall precision was 85.2% (31 674/37 174 pixels), and the Kappa coefficient was 0.79. The land cover mapping resulted in a pattern of land cover with 931.0 ha (1.4%) of water, 26 882.5 ha (40.3%) of vegetation, 38 915.3 ha of impervious surface (50.3%) and 5320.0 ha (8.0%) of bare soil, as shown in Fig. 1.