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Thermal impacts of greenery, water, and impervious structures in Beijing's Olympic area: A spatial regression approach

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ABSTRACT

This paper explores the urban land-use determinants of the urban heat island (UHI) in Beijing's Olympic Area, using different statistical models, land surface temperatures (LST) derived from Landsat 8 remote sensing, and land-use data derived from 1-m high-resolution imagery. Data are captured over grids of different sizes. Spatial regressions are necessary to capture neighboring effects, particularly when the grid unit is small. Grass, trees, water bodies, and shades have all significant and negative effects on LST, whereas buildings, roads and other impervious surfaces have all significant and positive effects. The results also point to significant nonlinear and interaction effects of grass, trees and water, particularly when the grid cell size is small (60 m-90 m). Trees are found to be the most important predictor of LST. When the grids are smaller than 180 m, the indirect impacts are larger than the direct ones, whereas, the opposite takes place for larger grids. Because of their strong performance (R^2 ranging from 0.839 to 0.970), the models can be used for predicting the impacts of land-use changes on the UHI and as tools for urban planning. Finally, extensive uncertainty and sensitivity analyses show that the models are very reliable in terms of both input data accuracy and estimated coefficients precision.

1. Introduction

Rapid urbanization has led to the transformation of natural landscapes, such as vegetation cover, water bodies, and agrarian lands, into urban buildings and impervious surfaces. This transformation has reduced vegetation evapotranspiration and increased solar radiation absorption by impervious materials, leading to the urban heat island (UHI), with higher air and surface temperatures in urban areas as compared to suburban and rural areas. A precise understanding and modeling of the urban factors that influence temperature is therefore important for mitigating the UHI (Buyantuyev and Wu, 2012).

Making use of very precise land-use data derived from high-resolution satellite images for the Olympic Area of Beijing, this paper (1) investigates the spatial relationship between land surface temperature (LST) and the land-use pattern, (2) specifies statistical regression models accounting for spatial neighborhood effects, (3) assesses how these effects vary across different grid scales, and (4) explores nonlinear and interaction effects among water bodies, grass, trees, building shades, building footprints, impervious surfaces, roads, and bare lands. A hierarchy of grids, with cell sizes ranging from 30 m to 600 m, is used to integrated all the data.

The paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 introduces the study area and data sources. The regression methodology is described in Section 4. Section 5 presents and analyzes the regression results, with a focus on nonlinear effects and direct and indirect spatial impacts. Section 6 consists in uncertainty and sensitivity analyses of the estimated models. Section 7 further discusses the findings. Section 8 summarizes the results and outlines areas for further research.

2. Literature review

The UHI can be analyzed with both air and surface temperatures. However, due to the sparse and irregular distribution of weather stations, the UHI has been predominantly analyzed with land surface temperatures (LST) derived from thermal infrared remote-sensing satellite imagery (Sheng et al., 2017). The spatial pattern of LST provides a record of the radiation energy emitted from the ground surface.

The relationship between LST and land-use/land-cover (LULC) patterns has been the object of recent research (Tran et al., 2017; Wu

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et al., 2014). Several studies show that impervious construction increases the UHI (Peng et al., 2016). Estoque et al. (2017) find a strong correlation between LST and the density of impervious surface (positive), green space (negative), and the size, shape complexity, and aggregation of patches along the urban–rural gradient of several cities, using linear regression analysis. Zhao et al. (2016) find that the UHI spatiotemporal changes are consistent with urban land expansion. Berger et al. (2017) point to a high correlation between remotely-sensed urban site characteristics and LST. Chun and Guldmann (2014) report that larger building roof-top areas increase LST, and a larger NDVI decreases it. Song et al. (2014) find that spatial resolutions of 660 m and 720 m are best for measuring the relationships between landscape composition and LST.

Another important consideration is the relationship between the UHI and green land uses. Urban green spaces, such as trees and grass, can significantly reduce the UHI and modify the urban microclimate (Al-Gretawee, 2016). Armson et al. (2012) report that both trees and grass can reduce regional and local temperatures. Li et al. (2013) show that the spatial pattern of greenspace, both in composition and configuration, affects LST. Kong et al. (2014) find that the urban cool island is affected by the areas of forested vegetation and their spatial arrangement. Al-Gretawee (2016) reports that parks have a significant cooling effect up to a distance of 860 m from their boundaries. Zhou et al. (2017) show that the relationship between the spatial configuration of trees and LST varies across different cities with different climatic conditions. Feyisa et al. (2014) show that the cooling effects of green spaces are closely related to their species, canopy cover, and sizes.

The shortcomings of existing UHI research are as follows. First, it rarely focuses on the impacts of building shades. Middel et al. (2014) show that building shades may lead to a significant decrease in surface temperature, especially in the case of artificial surfaces. Second, investigations of greenspace cooling effects have mostly used NDVI or vegetation cover, thus combining all greenery, with little research distinguishing vegetation by type (Myint et al., 2015; Tayyebi and Jenerette, 2016; Zhou et al., 2011). Third, most studies have used conventional regression analysis, without considering spatial autocorrelation (Chun and Guldmann, 2014; Song et al., 2014; Zhou et al., 2017), leading to possible estimation biases. Finally, all impacts have been assumed linear, thus ignoring possible nonlinear and interaction effects (Tran et al., 2017). The present study addresses all these issues.

3. Study area and data sources

3.1. Study area

The focus of this research is the Olympic Area, located in the north of Beijing, across the fourth and fifth ring roads, with a surface of 67.40 km^2 (Fig. 1). It includes three zones: the Olympic core area, the Olympic central area, and the Olympic functional area. It is the world's largest comprehensive Olympic culture exhibition area, with the goal of integrating culture, residence, sports, exhibition, tourism, business and other functions. The reason for choosing this area is that it is different from most urban areas, including not only a variety of urban buildings and impervious areas, but also many urban greenspaces, such as the Olympic Green Park. This diversity and the availability of very detailed remote-sensing land-use imagery made this area a compelling choice for UHI analysis.

3.2. Data sources

3.2.1. Land surface temperatures

A Landsat 8 Thermal Infrared Sensor (TIRS) image was acquired from the United States Geological Survey (USGS) for May 18, 2015, at approximately 10:52 am (Beijing time). There are three reasons for this choice. First, the UHI and its negative effects are strongest in spring and summer. Understanding the UHI at such time is therefore very important. Second, vegetation is in bloom from May to September, when its effect on the UHI is very significant. Third, Landsat 8 images are not available every day, and clouds may render them unusable. Several clear images in the spring/summer of 2015 were compared, leading to the May 18 image.

The Image-Based Method (IBM) is used to compute land surface temperatures (Li et al., 2011). The IBM is relatively straightforward and highly accurate (Zhao et al., 2016). The band 11 of the TIRS image was used, and all the bands were resampled with a pixel size of 30 m. The digital numbers (DNs) of the thermal infrared band are first converted to radiation. The standard Landsat 8 products provided by the USGS EROS Center consist of quantized and calibrated DNs representing multispectral image data acquired by both the Operational Land Imager (OLI) and the TIRS. These products are delivered in 16-bit unsigned integer format, and TIRS band data are rescaled to the Top of Atmosphere (TOA) reflectance and/or radiance, using radiometric rescaling coefficients provided in the product metadata file (MTL), with:

$$L\lambda = ML * DN + AL \tag{1}$$

where $L\lambda$ is the TOA spectral radiance ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$), ML the rescaled gain (value = $3.342 * 10^{-4}$), and AL the rescaled bias (value = 0.1). OLI band data can also be converted to TOA planetary reflectance using reflectance rescaling coefficients provided in the MTL:

$$\rho\lambda = (M\rho * DN + A\rho)/\sin(\theta SE) \tag{2}$$

where $\rho\lambda$ is the TOA planetary reflectance, $M\rho$ the rescaled gain (value = $2.0 * 10^{-5}$), $A\rho$ the rescaled bias (value = -0.1), and θSE the scene center sun elevation angle.

After calculating the NDVI and vegetation fraction (Fv), the land surface emissivity ε is calculated using the method of decomposition of mixed pixels based on NDVI. Then, the radiation luminance is converted to at-satellite brightness temperature T:

$$T = \frac{K2}{\ln\left(\frac{K1}{L\lambda} + 1\right)} \tag{3}$$

where K1 = 480.89 ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$) and K2 = 1201.14 K.

Finally, T is corrected for the variable emissivity (ε) of different landscapes, and the resulting land surface temperature (LST) is computed (Artis and Carnahan, 1982):

$$LST = \frac{T}{1 + \left(\frac{\lambda T}{\rho}\right)\ln\varepsilon} \tag{4}$$

In Eq. (4), λ is the wavelength at the center of the thermal infrared band (12.0 μm for Landsat 8 TIRS band 11), $\rho = hc/\delta = 1.438 \times 10^{-2}$ mK, and ε is the land surface emissivity.

Based on the above steps, the LST map was retrieved (Fig. 2), showing that LST varies between 20 °C and 37 °C.

3.2.2. Land-use classification

Two Gaofen-2 (GF2) high-resolution remote-sensing images, acquired on August 27, 2016, at 11:30 am (Beijing time), have been used to extract land-use information. GF2 is the first civil optical satellite, with a resolution superior to 1 m, developed independently in China. GF2 was launched on August 19, 2014. GF2 imagery consists of four multispectral bands (4 m resolution) and a panchromatic band (1 m resolution). After ortho-rectification, the multispectral bands and panchromatic band are fused, producing a four-band pan-sharpened multispectral image with 1-m resolution. Through a series of mosaic and atmospheric corrections, computer-aided visual interpretation, error checking and field validation (Liu et al., 2003), a map with eight land-use classes, including water bodies, grass, trees, building shades, building footprints, impervious surfaces, roads, and bare land, is produced, as illustrated in Fig. 3.

In the Olympic Area, trees account for the largest land-use