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Spatial regression models of park and land-use impacts on the urban heat island in central Beijing

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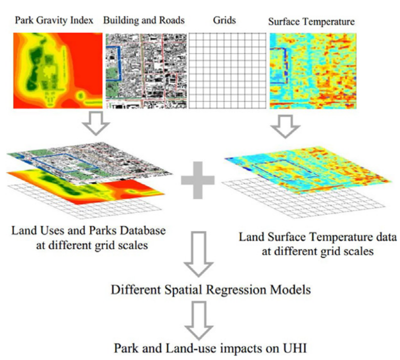
HIGHLIGHTS

- Land uses and parks simultaneously explain the urban heat island (UHI).
- A gravity index measures distance and size effect of parks on surface temperatures.
- Spatial regressions are used to account for spatial autocorrelation.
- The effects of the vegetation and building indices NDVI and NDBI are nonlinear.
- The results can be used in urban planning to mitigate the UHI at fine scales.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the relationship between urban land structure and land surface temperatures (LST) is important for mitigating the urban heat island (UHI). This paper explores this relationship within central Beijing, an area located within the 2nd Ring Road. The urban variables include the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Build-up Index (NDBI), the area of building footprints, the area of main roads, the area of water bodies and a gravity index for parks that account for both park size and distance. The data are captured over 8 grids of square cells (30 m, 60 m, 90 m, 120 m, 150 m, 180 m, 210 m, 240 m). The research involves: (1) estimating land surface temperatures using Landsat 8 satellite imagery, (2) building the database of urban variables, and (3) conducting regression analyses. The results show that (1) all the variables impact surface temperatures, (2) spatial regressions are necessary to capture neighboring effects, and (3) higher-order polynomial functions are more suitable for capturing the effects of NDVI and NDBI.

1. Introduction

Urbanization leads to the transformation of natural landscapes, such as vegetation cover, water bodies, and agrarian lands, into impervious surfaces and urban infrastructures. This transformation reduces vegetation evapotranspiration, increases solar radiation absorption, influences the local and regional climate, and gives rise to the urban heat island (UHI) (Yao et al., 2017; Morabito et al., 2016). The UHI refers to air and surface temperatures being higher in urban areas than in surrounding suburban/rural areas (Oke, 1982), and negatively impacts inhabitants' quality of life, physical health, and regional environment. Understanding the urban factors

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that influence temperature is therefore important for mitigating the UHI (Buyantuyev and Wu, 2012).

The objectives of this paper are to: (1) build a novel database of these factors and specify statistical regression models that account for both spatial neighborhood effects and the simultaneous effects of these factors; (2) assess how these effects vary across different grid scales; (3) determine which grid scale is best for UHI model estimation; and (4) apply the methodology to central Beijing, as included within the 2nd Ring Road. Six factors are used to represent the complex landscape of urban centers: (1) two remote-sensing-based indices measuring the building stock, NDBI, and vegetation, NDVI; (2) three areal measures: building footprints, water bodies and main roads; and (3) a gravity-based index accounting for the influence of park size and distance. Earlier UHI research on the cooling effect of parks has primarily focused on the size and shape of parks, and their cooling effects on surrounding areas, but without accounting for the simultaneous effects of other factors. Another distinctive feature of this research is the very detailed layer of building footprints, as such data are generally not available electronically in China. A hierarchy of grids, with cell sizes of 30 m, 60 m, 90 m, 120 m, 150 m, 180 m, 210 m, and 240 m, is used to integrated all the data, and spatial regression models are estimated to capture neighborhood effects on surface temperatures across the different grids. Further, polynomial expansions of these models are used to capture nonlinear temperature effects.

The paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 introduces the study area and the data sources and processing methods. The statistical modeling methodology is presented in Section 4. Section 5 presents and analyzes the estimated regression models. Section 6 concludes the paper.

2. Literature review

The UHI can be evaluated with both air and surface temperatures. Air temperature data are usually obtained from meteorological stations, but their sparse distribution makes a spatially-continuous analysis difficult (Shen et al., 2016). Therefore, the UHI has been mainly analyzed based on land surface temperatures (LST), which can be derived from thermal infrared remote-sensing imagery from Landsat, MODIS (Pandey et al., 2012) and ASTER (Duan et al., 2017). Zhu et al. (2013) show that daily maximum and minimum air temperature can be retrieved effectively from MODIS land surface products. Muster et al. (2015) report that MODIS LST provides a tool to detect changes in land surface energy exchanges, and that LST anomalies are strongly related to surface albedo and inundation. Using LST patterns retrieved from ASTER satellite images, Buyantuyev and Wu (2009) show that intra-urban temperature differences are as large as, or even larger than, urban-rural differences. Zhao et al. (2016) and Zhang et al. (2013) analyze the relationship between land-use/land-cover (LULC) changes and LST based on multi-temporal Landsat images. Shen et al. (2016) monitor long-term and fine-scale UHI effects by the fusion of multi-temporal and multi-sensor remotely-sensed data, such as Landsat images, MODIS images and AVHRR data.

The relationship between remotely-sensed LST and landscape and LULC patterns has been a focus of recent research, providing a scientific basis for UHI mitigation and urban planning (Jenerette et al., 2015; Peng et al., 2016). Studies have shown that different landscape compositions and configurations can produce heterogeneous effects on the UHI (Wu et al., 2014; Lin and Lin, 2016; Zhou et al., 2011). These studies have mainly focused on the effects of land-use types, landscape proportions, and landscape metrics on the UHI. Numerous studies have shown that impervious construction increases the UHI (Li et al., 2013; Dos Santos et al., 2017), while urban green spaces, such as parks, decrease it (Feyisa et al., 2014; Susca et al., 2011). Estoque et al. (2017) find a significantly strong correlation between the mean LST and the density of impervious surface (positive), green space (negative), and the size, shape complexity, and aggregation of patches along the urban-rural gradients of several cities. Dos Santos et al. (2017) show that the positive correlation between LST and NDBI points to an increasing effect of developed areas on the UHI, while areas with a predominance of vegetation decrease the UHI. Berger et al. (2017) demonstrate the relationship between remotely-sensed urban site characteristics (USC) and LST, based on Spearman's rank correlation. Guo et al. (2015) report that both the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Build-up Index (NDBI) are strongly correlated with LST, whereas the Normalized Difference Bare Land Index (NDBaI) has a weaker correlation with LST in Guangzhou central urban districts. Peng et al. (2016) find that landscape composition affects the thermal environment more so than spatial configuration, using linear regression applied to the Beijing metropolitan region. Ivajnšič et al. (2014) estimate OLS and geographically-weighted regressions between mean air temperature and land cover diversity, distance to the urban center, and building volume density.

Urban green spaces can significantly reduce the UHI and modify the urban microclimate (Gunawardena et al., 2017; Li et al., 2013; Park et al., 2017). Several researchers have studied the cooling effects of park size, type and vegetation density. Lin et al. (2015) show that the cooling effect of a park can extent as much as 840 m away from the park, and this extent is influenced by the character of the area around each park. Feyisa et al. (2014) show that the cooling effect of green spaces depends mainly on vegetation species, canopy cover, and size and shape of parks. Kong et al. (2014) find that the urban green-space cool island (UCI) intensity is affected by areas of forest vegetation and their spatial arrangements. Doick et al. (2014) indicate that urban green space is an important component of UHI mitigation strategies, and its cooling extent display an exponential decay with increased distance from the greenspace.

The shortcomings of the existing UHI research are as follows. First, it focuses on landscape patterns or urban green space, but does not combine these two categories of factors. Also, parks have not only a cooling effect on themselves, but they also influence the areas around them, while the temperature within or around parks can be also influenced by landscape factors. Second, UHI research in China has made little use of building footprints data due to its lack of accessibility. While such data are open source in the US or other countries and are available electronically, only picture versions (e.g. Baidu Map) are available in China. Third, most past studies use conventional regression analysis, without considering spatial autocorrelation (Chun and Guldmann, 2014; Song et al., 2014; Wang et al., 2016; Zhou et al., 2017), hence with possible estimation bias. Finally, all impacts have been assumed linear, thus ignoring possible nonlinear effects (Tran et al., 2017).

3. Study area and data sources and processing

3.1. Study area

Beijing is located in northern China, with a total area of 164,100 km^2 across 16 districts. It is characterized by a warm-temperate, semi-humid continental-monsoon climate, with an annual mean temperature of 12.3 °C. Beijing has undergone an explosive urbanization and population growth after the 1978 reform and opening-up policy, reaching a population of 21.71 million by 2015, with an urbanization ratio of 86.5%. Beijing is structured by six ring roads (Fig. 1). The study area of this research is enclosed within the 2nd Ring Road, the central and oldest part of the city, with an area of 62.64 km^2.

3.2. Data sources and processing

3.2.1. Land surface temperatures

A Landsat 8 TIRS image for September 7, 2015, at approximately 10:53 am (Beijing time) was acquired from the United States Geological Survey (USGS). There are three reasons for this selection. First, the UHI and its negative effects are strongest in the summer. Understanding the