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Detection of spatial-temporal variations in forest canopy surface temperature in response to urbanization: a case study from Longyan, China

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Urban forests are fundamental components of localized surface energy budgets. Understanding the factors controlling urban forest surface temperatures (UFSTs) should be helpful in mitigating the negative effects of urbanization on urban energy budgets. This study aimed to identify the factors controlling the spatial-temporal pattern of UFSTs by utilizing a variety of data layers and spatial statistical analysis methods. Our results showed that UFST values become more spatially heterogeneous as urbanization progresses. Elevation and degree of slope were the main factors explaining the increase in spatial heterogeneity. Human activities were also significantly related to variations in UFST. Interactions between human activities and almost all environmental factors were related to higher UFST values. Therefore, human activity directly impacts on the spatial heterogeneity of UFST and indirectly affects variations in landscape patterns. Human activities compatible with ecologically sustainable development should be considered for mitigating the deterioration of urban thermal environments.

Keywords: urban forest; interactive influence; driving mechanism; human activity; GeoDetector model

1. Introduction

Urbanization has become a core concern worldwide due to its negative impacts on land use and eco-environmental changes. Rapid conversion from natural (especially forested) landscapes to urban areas with complex impervious surfaces has led to radical alterations in land surface characteristics in cities (Oke 1982). Variations in urban surface characteristics are known to alter local climates by modifying processes that influence the energy balance of urban surfaces (Coutts, Beringer, and Tapper 2007). Local climate modification may lead to changes in coupled human-ecological systems and declines in the well-being of people dependent on services provided by natural ecosystems (Jenerette *et al*. 2007).

China has undergone rapid urbanization over the past four decades, which has led to a rapid loss of forest cover and increases in impervious surfaces in many regions of China (Lin *et al*. 2019). Urban forests are an integral component of urban ecosystems in that they provide a wide variety of ecosystem services to urban inhabitants, such as

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reducing water and air pollution, providing recreational and aesthetic qualities, and regulation of urban thermal environments (Jim and Chen 2009; Zhang *et al*. 2018). An examination of the ramifications of forest loss during urbanization could be used by policymakers to decide how to best manage, protect, and preserve urban forests and ecosystem services.

Earth's ecosystems are becoming increasingly impacted by urbanization and so, to a great extent, human quality of life will depend on how we make urban environments more sustainable for humans (Alberti 2010). Establishing a healthy urban environment requires additional insights into how environmental elements converge and interact to form and influence urban ecosystem functions and dynamics (McPhearson *et al*. 2016). Although urban systems have, for decades, been conceptualized as being complex and dynamic, empirical examinations of relationships between various patterns of urbanization and agent interactions have only recently been a focus of study (Alberti 2016). Due to this complexity, scholars need to apply an interdisciplinary approach to address the complex interactions and the uncertainties surrounding such interactions. In addition, capturing the often non-linear interactions demands multiple types of data and new analysis techniques (Alberti 2017).

Previous studies have shown that many environmental factors are responsible for the growth rate of vegetation, such as elevation, topography, soil properties (e.g., texture and fertility), soil moisture, and human influences (Calfapietra, Peñuelas, and Niinemets 2015; Cantlon 1953; Fadrique, Homeier, and Woods 2016). Environmental factors not only affect plant growth rates, but they also impact vegetative growth form, reproduction, and the abundance and diversity of plant communities (Bauman *et al*. 2013). However, environmental factors do not act independently of one another; rather, they jointly influence vegetation structure and heterogeneity (Ren *et al*. 2016). Thus, spatial variations in the intensity of biotic or abiotic factors are responsible for the high degree of spatial and temporal heterogeneity of landscape composition and configurations (Rödig *et al*. 2017). Direct and indirect effects of human activities can further reinforce landscape heterogeneities and the resulting heterogeneities may negatively influence the cooling efficiencies of urban forests.

Although previous studies have applied field survey data and/or remote sensing images at a variety of resolutions to study the relationship between land surface temperature and ecological measurements, such as forest area, tree density, plant species richness, and vegetation index (Kuang *et al*. 2014; Li *et al*. 2011), research that directly focuses on canopy surface temperatures of urban forests are limited. In addition, although many studies have applied multivariate regression models to analyze the relationship between surface temperatures and environmental factors one at a time (Guo *et al*. 2015; Wang and Ouyang 2017), few studies have addressed the characteristics of interactions (e.g., strengths and types) between land surface temperatures and a suite of environmental factors. Complicated interactions among controlling factors limit our understanding of the underlying mechanisms for variations in urban forest surface temperatures (UFSTs), thus making it difficult to accurately estimate the cooling potential of urban forests.

In order to identify factors that potentially influence the heterogeneity of UFSTs, it is important to first identify and quantify the spatial variability of UFST. Generally, there are three different approaches for characterizing the spatial heterogeneity of UFSTs: landscape metrics, spatial statistics, and statistical modeling (Wagner and Fortin 2005). Landscape metrics have been widely used to quantify forest landscape structure, including characterizing the variety and abundance of forest patch types within a landscape and the spatial arrangement, position, and orientation of urban forest patches. Some studies have detected the effects of landscape patterns on urban thermal environments (Kong *et al*. 2014; Liu, Peng, and Wang 2018; Zhang *et al*. 2017), but they all suffered from problems related to the autocorrelation of landscape metrics (Wagner and Fortin 2005). After Chen *et al*. (2014) used 45 class-level metrics to investigate the spatial patterns of land surface temperature in Beijing, China, they suggested that future investigators should carefully select useful and representative metrics when modeling specific ecological processes.

In our study, we applied spatial statistics (hotspot analysis) and statistical modeling (GeoDetector modeling) to quantify spatial heterogeneity and explore the factors potentially controlling landscape patterns. We believe that the integration of spatial statistical analysis methods and data from multiple sources can be used to effectively identify and quantify the spatial variability of UFSTs.

The main purpose of our study was to identify the interactive influences of a suite of environmental factors that might affect variations in surface temperatures in urban forests. Two hypotheses have been proposed regarding the mechanism(s) involved in controlling UFST: (1) linear and non-linear relationships between variations of UFST and environmental factors coexist to affect temperature regimes and (2) human activities alter UFSTs via interactions with other environmental factors. We integrated remote sensing technology, field surveys, and used spatial statistical analyses to identify the factors most responsible for variations in UFSTs in a typical urban environment in China. We hope that our results can be used to optimize the spatial configuration of urban forests at a landscape scale and thus provide a tool for urban planners who wish to better manage urban thermal environments.

2. Materials and methods

2.1. Study area

We conducted this study in the city of Longyan, located in the southwest part of Fujian Province, China. We specifically focused on the Xinluo District of Longyan (24.78–25.59 ˚N, 116.67–117.19 ˚E) where the highest human population density occurs. Longyan, situated in a landscape dominated by mountains and hills, has a subtropical, maritime monsoon climate, with an annual average air temperature varying from 18.7 °C to 21 °C and an average annual precipitation varying from 1,031 to 1,369 mm. Approximately 81% of Longyan was covered by forest before experiencing rapid development from 2000 to 2010. According to Longyan's statistical yearbook, urban land-use cover increased from 35.98% in 2000 to 45.05% in 2010. Estimating the variation in biophysical attributes of forest stands in Longyan is important for sustainably developing the regional ecosystem and improving human quality of life (Figure 1).

2.2. Methods

Our methods comprised three steps (Figure 2). First, we obtained UFST data from thermal remote-sensing images from Landsat-5 TM, classified UFST into hot/cool regions at an appropriate threshold distance by employing a spatial statistical analysis tool, and then normalized the data (methods detailed in next section). Second, we built a spatial database to integrate the normalized UFST data, Forest Management Planning

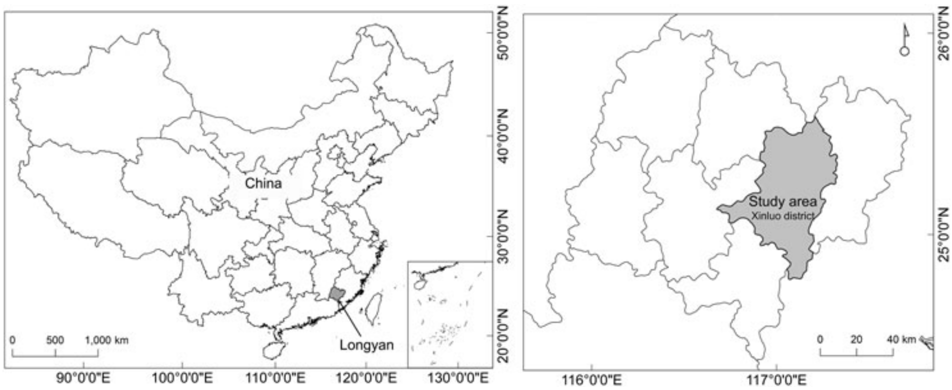

Figure 1. Location of the study area.

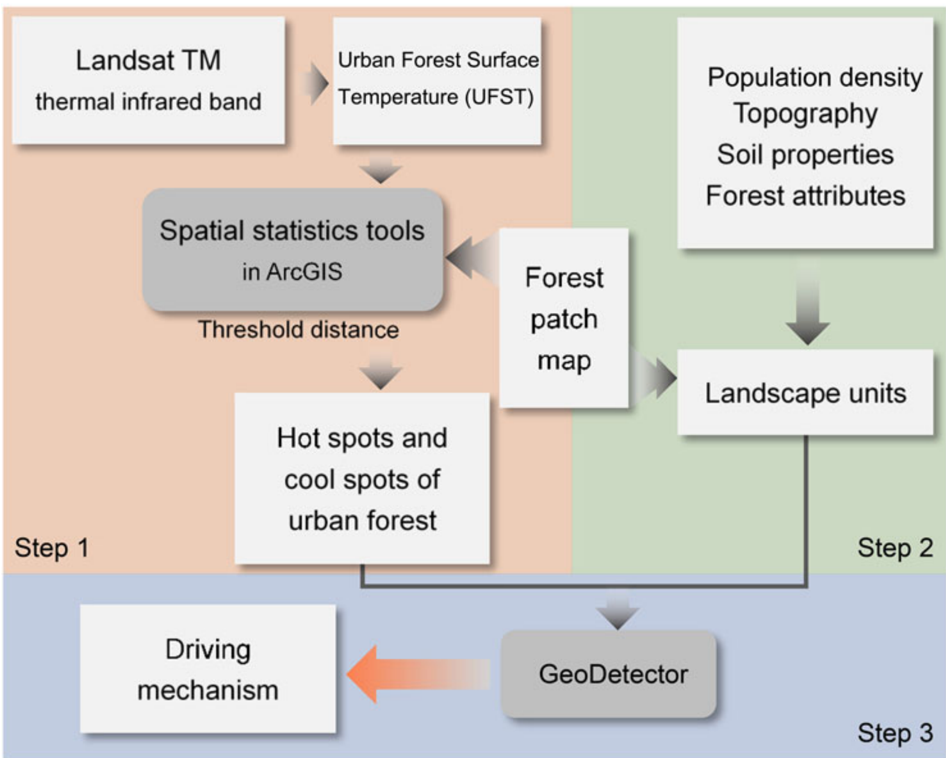

Figure 2. Flow chart of our methodological approach. Step 1: Retrieve surface temperatures and identify hot/cool spots in spatial data. Step 2: Screen and map factors believed to impact ground surface temperatures. Step 3: Determine primary factors controlling temperature distributions and driving mechanisms.

Inventory (FMPI) data, population density data, and digital elevation model (DEM) data (methods detailed below). Third, we applied the GeoDetector model to the spatial database to identify the main factors potentially controlling variations in UFST, using UFST data derived from step 1 as the dependent variable and other environmental factors as independent variables (methods detailed below).

2.2.1. Acquiring UFST data and identifying hot and cool spots

We obtained two cloud-free, Landsat-5 Thematic Mapper (TM) images (Row/Path: 120/43) from the United States Geological Survey (USGS) acquired on 1 September 2003 and 16 August 2009. We then rectified the images to the Universal Transverse Mercator coordinate system (50 N) and resampled the data by applying the cubic convolution algorithm with a pixel size of 30×30 m. We manipulated the thermal infrared bands of pre-processed Landsat-5 TM images to calculate UFST in three steps. First, we converted digital numbers (DNs) of the thermal bands to at-sensor radiance using the scaling parameter equations provided by Chander and Groeneveld (2009). Second, we converted at-sensor radiance values to at-sensor temperatures, according to Planck's Law. Third, we converted at-sensor temperatures to UFSTs using land surface emissivity data (Supplementary material, Appendix 1). To evaluate the interactions of environmental factors that could potentially influence UFST, we normalized UFST data using the following equation:

$$T_r = (\mathrm{UFST} - T_b)/T_b \tag{1}$$

where T_r is the normalized value of UFST and T_b is the background surface temperature, defined as the average value obtained for the study area. (To a certain extent, such non-dimensionalization can eliminate the influence of viewing angle and differences in image acquisition times.)

In order to characterize the driving mechanism(s) possibly responsible for the spatial heterogeneity of UFSTs, we used hot-spot analysis (*local Getis–Ord* G_i^*) to reclassify our UFST data into types of regions, referred to as areas with either significantly high temperatures (hot spots) or significantly low temperatures (cool spots). We applied an Increment Spatial Autocorrelation (ISA) tool to identify the optimal threshold distance for identifying boundaries of specific clustered regions. ISA measures spatial autocorrelations for a series of distances and creates a line graph of those distances and their corresponding z-scores. The z-scores reflect the intensity of spatial clustering. Statistically significant peak z-scores indicate distances where spatial processes promoting clustering are most pronounced. The z-scores are calculated by continuously increasing the threshold distance from 0 to 5,000 m. We found that at a distance of 3,487.65 m, the z-scores were greater than our threshold value of 1.96. Therefore, we used 3,500 m as our optimal distance threshold. We then set our optimal threshold distance of 3,500 m to generate a cluster map (Figure 3). Based on the generated z-scores, regions with an absolute value greater than 1.96 were used to define clustering regions. Positive values identified hot spots, whereas negative values identified cool spots. Areas with an absolute value of z smaller than 1.96 were assumed to be non-significant regions (neither hot nor cool).

2.2.2. Creating our spatial database

We obtained environmental spatial data for 2003 and 2009 from a variety of sources. These data were used to determine the independent or interactive influences of spatial variables on spatial distributions of UFSTs. The first type of data we used were FMPI data, which we obtained mostly from field surveys, with a sampling accuracy higher than 90%. These data comprised a large number of patches of similar size from which we obtained site-specific data on soil properties and forest attributes and into which

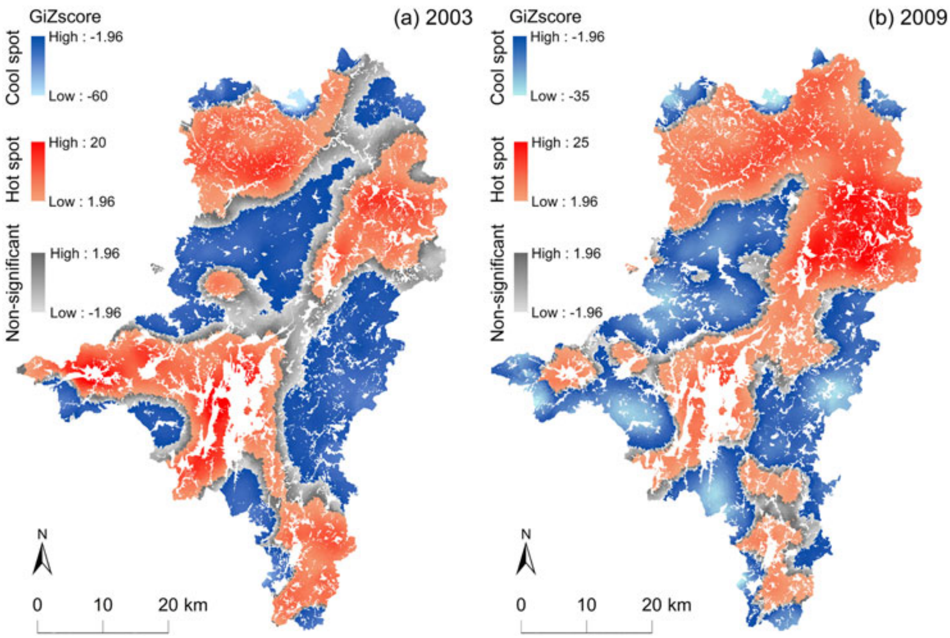

Figure 3. Spatial distribution maps of GiZ scores for two years of spatial data for Longyan, China. GiZ scores represent temperature at specific locations, based on local Getis–Ord G_i^* data set at optimal threshold distance of 3,500 m.

we incorporated data on spatial features, attributes, and metadata. We obtained human population density data from the spatial interpolation of demographic census data based on nighttime light images, which we used as a proxy for characterizing the intensity of human activities at any given location. We created a topographic dataset using DEM data in which we included geomorphic attributes, such as slope gradient and slope aspect.

We rectified all data, including the normalized UFST data, FMPI data, population density data, and topographic maps, to the Universal Transverse Mercator project system (datum WGS84, UTM Zone N50), thus allowing us to define an FMPI patch as the basic unit for our datasets. We then remapped our reclassified UFST, population density, and DEM data using the zonal statistics function in the ArcGIS 10.0 platform. We averaged values of all the pixels of normalized UFST, population density, and DEM data and added them as new attributes of the FMPI dataset. In this way, we unified all the environmental factors and normalized UFST data to a common spatial resolution.

2.2.3. Determining the main controlling factors and driving mechanisms

The third step in our methods focused on using the GeoDetector model to determine the environmental factors that most influence UFST. GeoDetector is a statistical model based on spatial-explicit, stratified heterogeneity of spatial phenomena. Its key underlying assumption is that if a spatial factor (Y) is controlled by another spatial factor (X), then factor X will present a spatial distribution similar to that of factor Y (Wang, Zhang and Fu 2016). GeoDetector has successfully identified factors controlling the spatial heterogeneity of a variety of phenomena (Shi *et al*. 2018; Xu *et al*. 2017). The GeoDetector model consists of three types of detectors, each designed for a specific purpose (Wang and Hu 2012): (1) a factor detector used to quantify the impact of an environmental factor on a given research target, (2) an ecological detector used to explore the relative importance of factors in shaping environmental heterogeneity, and (3) an interaction detector to reveal whether the various environmental factors show independent or interactive effects. In our study, we applied the interaction detector to determine the main factors controlling UFSTs. With this detector, we could assess the degree of interaction between two factors (X_1, X_2) by comparing $q(X_1 \cap X_2)$ with a logical or arithmetic operation between $q(X_1)$ and $q(X_2)$. For example, when $q(X_1 \cap X_2) > q(X_1)$ or $q(X_2)$, the two factors (X_1, X_2) enhance each other; when $q(X_1 \cap X_2) > q(X_1)$ and $q(X_2)$, the two factors bi-enhance each other; and, when $q(X_1 \cap X_2) > q(X_1) + q(X_2)$, the two factors non-linearly enhance each other. In contrast, when $q(X_1 \cap X_2) < q(X_1)$ [or/and/+] $q(X_2)$, the two factors weaken, bi-weaken, or non-linearly weaken each other (Table 1). In this present study, we imported various types of environmental data layers into the GeoDetector model as independent variables, and imported normalized UFST data (*Tr*) as dependent variables.

3. Results

*3.1. Variatio*ns in UFSTs and stand structure

When we combined Landsat-5 images from 2003 and 2009 with their corresponding FMPI data (30,342 patches in 2003 and 33,720 patches in 2009), we generated a multiple-source data layer that mapped UFST for each urban forest patch with its associated environmental factors, all at the same landscape spatial scale. In 2003 and 2009, Tr were all near zero (Figure 4(a)), but the UFSTs in 2009 showed less variation (0.11) than in 2003 (0.15).

From 2003 to 2009, the total area of all urban forest patches increased from 217,361 to 218,677 ha over a 6-year time frame. However, average patch size, declined from 105.84 to 97.37 ha over the 6-year period (Figure 4(d)). Tree canopy density also declined from 42% ± 29% (mean ± 1 standard deviation) to 39% ± 28% (Figure 4(b)). Forest canopy density expresses degree of tree stocking. The degree of forest canopy density is usually expressed in percentages and has been used to indicate the degree of forest degradation (Joshi *et al*. 2006). Average stand age declined from 23.7 to 21.8 years (Figure 4(c)). Variations in stand structure, including patch size, canopy density, and stand age, indicate that the structure of urban forests changed over the 6-year time frame.

Pinus massoniana, Acacia confusa, *Cunninghamia lanceolate*, *and Phyllostachys heterocycle* were the most common tree species in the study area. These four tree species comprised more than 90% of the total forest cover in both 2003 and 2009 (Figure 5). However, during the six years of our study, the relative cover of these four species changed. For example, the coverage of *Pinus massoniana* declined by 7.94% (from 37.03% in 2003 to 29.09% in 2009) and *Acacia confusa* increased by 6.20% (from 27.14% in 2003 to 33.34% in 2009).

Table 1. Interactive influences that can be detected by an interaction detector when two individual variable types are combined.

Relationship	Type	Formula	Symbol
Enhance	Ordinary	$q(X_1 \cap X_2) > q(X_1)$ or $q(X_2)$	↑
	Bivariate	$q(X_1 \cap X_2) > q(X_1)$ and $q(X_2)$	⇑
	Nonlinear	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	⇑
Independent	Ordinary	$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	↔
Weaken	Ordinary	$q(X_1 \cap X_2) < q(X_1)$ or $q(X_2)$	↓
	Bivariate	$q(X_1 \cap X_2) < q(X_1)$ and $q(X_2)$	⇓
	Nonlinear	$q(X_1 \cap X_2) < q(X_1) + q(X_2)$	↓↓

Note: $q\epsilon[0 \sim 1]$ indicates the strength of the interaction between two individual factors, wherein a higher value of q indicates a stronger influence on the heterogeneity of UFST. X_1 (X_2) is a selected environmental factor that might explain the spatial patterns of UFSTs.

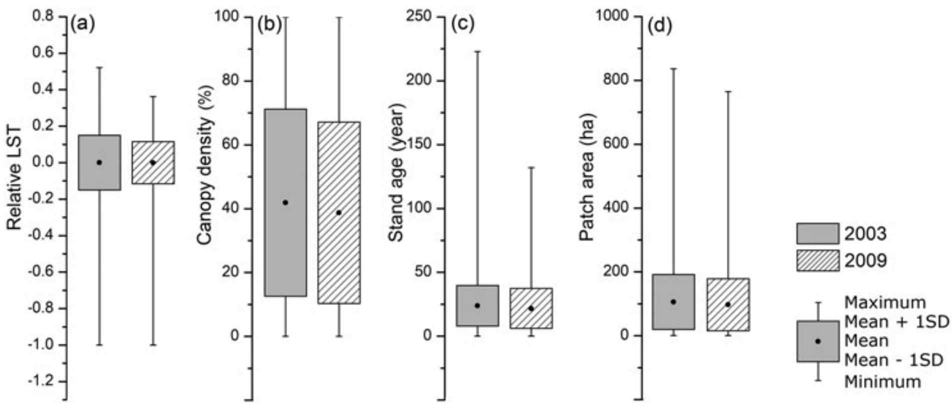

Figure 4. Mean stand structure of urban forests for 2003 and 2009 for all urban forest patches. Panels: (a) relative UFST, (b) canopy density, (c) stand age, and (d) patch size.

3.2. Changes in human population density

Human population density in the study area grew slowly (by 4.44%) from 2003 to 2009. Areas in the southwestern and southeastern parts of the study area showed an increase in human population density, whereas population density declined in the northeastern part of the study area. *Local Getis–Ord* G_i^* statistics indicated that hot and cool spots of population density and UFSTs were distributed similarly, both temporally and spatially (Figure 6). The hot spots located in southwestern and southeastern parts of the study area in 2003 clearly expanded by 2009 and the many fragmented hot spots of 2003 had fused together by 2009. The change in the pattern of population distribution followed the proposed economic development and land-use spatial layout of the city's master plan (1998–2020), which was based on government priorities for developing the southwestern and southeastern regions of the city.

3.3. Influences from multiple environmental factors on UFST

We used 11 environmental factors as independent variables in the GeoDetector model to identify the important factors controlling the spatial heterogeneity of UFST. These

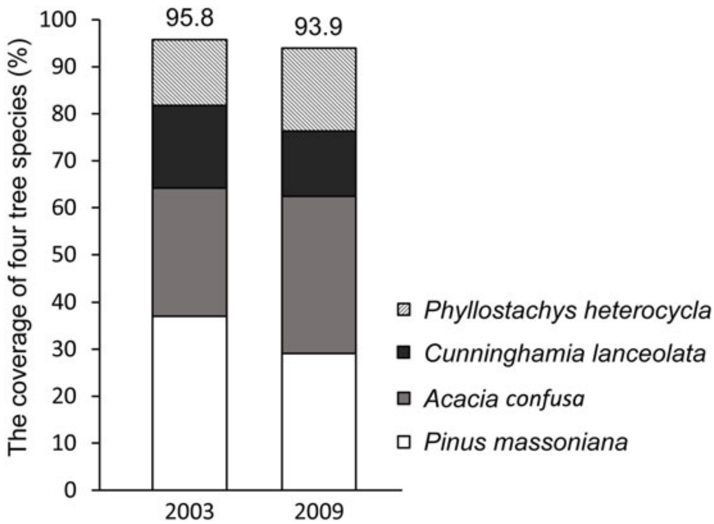

Figure 5. The coverage of four most common canopy tree species inhabiting the study area in Longyan, China.

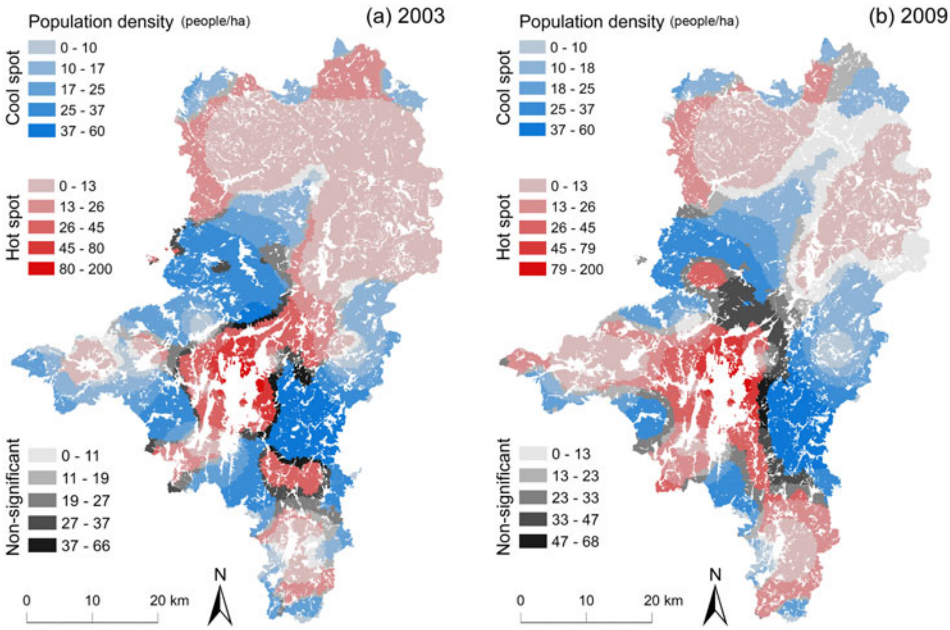

Figure 6. Population densities of the various clustering regions in Longyan, China, classified using local Getis–Ord G_i^*.

variables included soil properties, forest attributes, topography/geomorphology, and population density. The general directions of the associations (positive or negative relationships) between two specific variables were examined with Pearson correlation coefficients. Our model output showed that topographic characteristics were the primary environmental parameters related to the spatial patterns of UFST values in 2003 and 2009. Elevation and degree of slope were related more significantly to landscape patterns of UFSTs than were any of the other potential factors, not only for the study area as a whole, but also for the three types of spatial clusters on the landscape. Population density (PD) was also associated with the UFST patterns on the landscape. Specifically, population density (PD) was one of the top three highest determinants of UFST patterns for the entire study area (2003 and 2009) and for the locations of cool spots (2003 and 2009) (Figure 7).

The complex interactions between environmental factors made it difficult for us to understand the full role each factor plays in controlling UFSTs. Therefore, we explored the simultaneous interactions of many environmental factors using the interaction detector of the GeoDetector model. The model showed that all selected environmental factors interacted with one another in describing the spatial heterogeneity of UFST and that all the interactions either represented ordinary enhancement of the spatial heterogeneity of UFST (i.e., wherein the interacting influence of Factor X1 and Factor X2 is greater than the individual influence of Factor X1 or Factor X2 separately) or represented non-linear enhancement (wherein the interacting influence of Factor X1 and Factor X2 is greater than the sum of the contributions from both Factor X1 and Factor X2 together) (Table 1). Elevation and degree of slope were the most significant environmental factors (i.e., those with highest q values) in their degree of interaction with other factors, especially for 2003 data. Specifically, elevation and degree of slope interacted with other factors in areas of hot spots, mainly in an ordinarily enhanced manner, whereas in areas of cool spots, the two factors interacted with a different set of environmental factors, primarily in a non-linearly enhanced manner. Population density and slope aspect were also important in their interactive influences on variations in UFSTs. In 2009, degree of slope, elevation, and slope aspect also displayed either an ordinary or a non-linear enhanced interaction with other factors in hot spots. Furthermore, in 2009, population density was the most significant factor interacting with all other factors in a non-linear enhanced way (Figure 8).

When focusing only on interactive influences between population density and other environmental factors, all interactions in different regions and time periods exhibited enhancing influences, mainly non-linear enhancements (Figure 8), many of which were statistically significant. By partitioning the study area into three types of heat intensities, the data seemed to suggest quite different possible explanations for the contributions of various environmental factors for UFST values. Environmental factors (including forest patch area, dominant species, canopy density, stand age, soil depth, and humus depth) interacted significantly with population density in hot spots in the study area in 2003, whereas for cool spots, environmental factors (including patch area, dominant tree species, stand age, site index, and humus depth) interacted significantly with population density. In 2009, all environmental factors showed statistically significant interactive effects with population density relative to UFST for hot spots, but no factor represented a significant relationship.

4. Discussion

4.1. Spatial patterns of heterogeneity in UFST

Each land surface component in an urban landscape exhibits unique radiative and thermal properties, which is determined by specific conditions in its surrounding

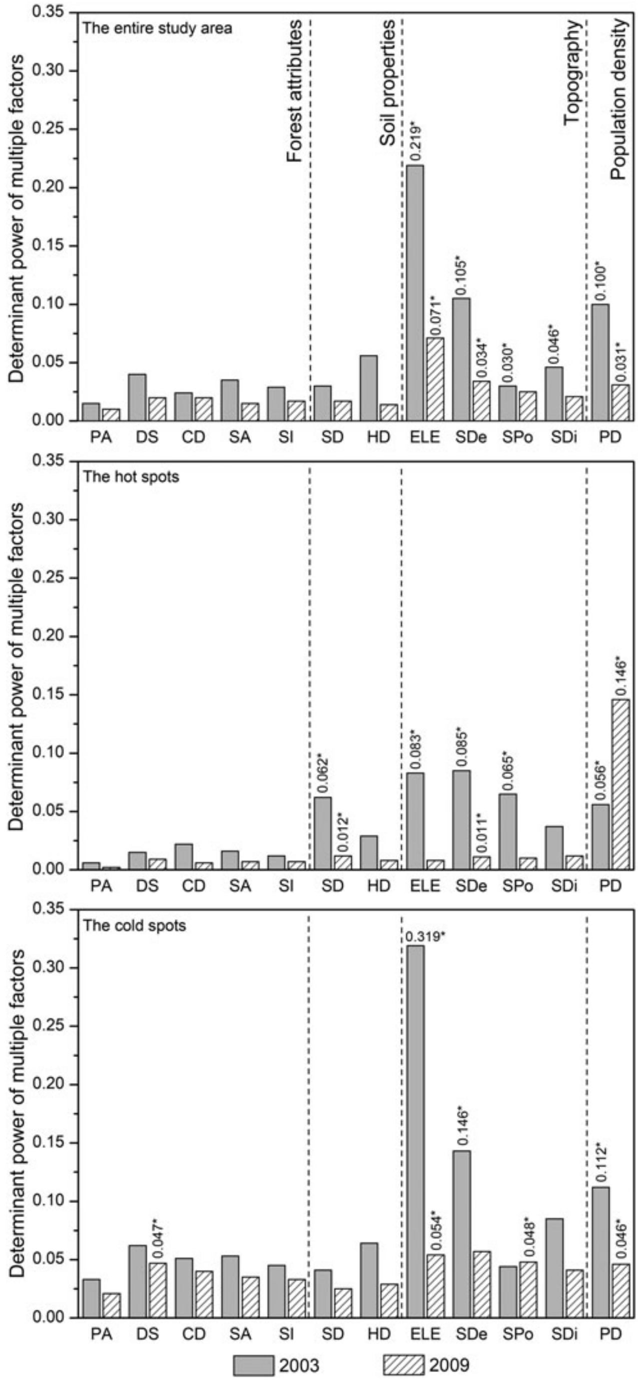

Figure 7. Contributions of environmental factors on UFSTs for the entire study area and for two types of spatial clusters. Abbreviations: PA (patch area), DS (dominant tree species), CD (canopy density), SA (stand age), SI (site index), SD (soil depth), HD (humus depth), ELE (elevation), SDe (degree of slope), SPo (slope position), SDi (slope aspect), and PD (population density). * Indicates a significant interaction effect.

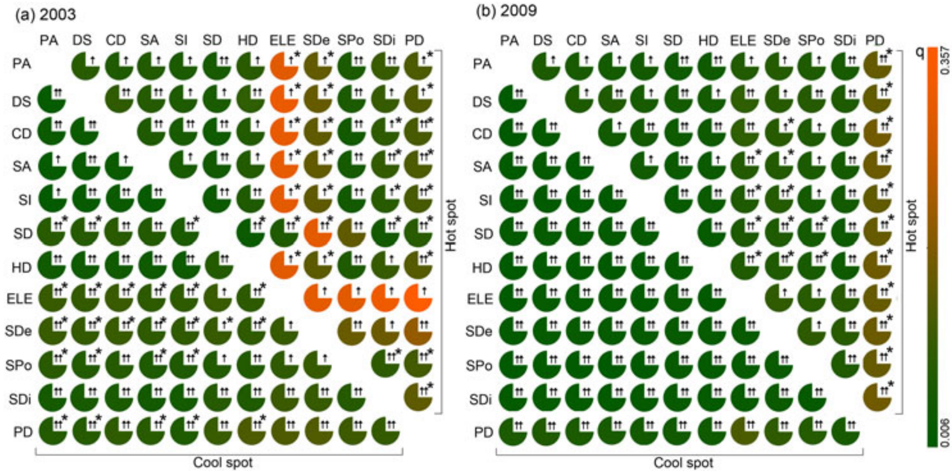

Figure 8. Interaction matrices between various environmental factors related to hot and cool spots for 2003 and 2009. *Indicates a significant interaction effect.

environment. Large numbers of surface types and high spatial complexity generate a limitless number of possible permutations in surface energy absorption and dissipation. Because these surface types are typically smaller than the spatial resolution of widely used remotely sensed imagery, such as the Advanced Spaceborne Thermal Emission Reflection Radiometer (90×90 m resolution for its thermal infrared band) and the Landsat Thematic Mapper (120×120 m resolution for its thermal infrared band), it is very likely that both vegetation and impervious surfaces are contained in one pixel in urban areas (Weng and Lu 2008). Therefore, pixels with various combinations of spectral characteristics complicate our understanding of the underlying mechanism(s) responsible for landscape heterogeneity.

In this study, we focused only on the urban, forested landscape and thus mostly avoided potential problems associated with mixed pixels. This focus was helpful in detecting changes in surface temperature and evaluating potential driving factors. However, we still found detectible spatial heterogeneity in UFST values even in relative homogeneous landscapes, although the variation was much less among urban forest patches than between vegetated and impervious-dominated patches. Spatial heterogeneity is a structural characteristic of landscapes that can be quantified by describing variability in the properties of its constituent components. Each heterogeneous landscape is composed of discrete, homogeneous patches that can be differentiated by biotic and abiotic structures or compositions (Pickett and Cadenasso 1995). Because similar controlling factors tend to develop in similar landscape patches, careful classification of a heterogeneous landscape into relatively homogeneous regions is helpful for uncovering complicated causes for relatively fine-scale mechanisms that may underlie the dynamics and structure of the entire landscape matrix. By classifying our study area into three relatively homogeneous types of area based on thermal reflection characteristics (hot spots, cool spots, and neither hot nor cool spots), we could gain insight into the principal factors contributing to the generation of spatial heterogeneity in an urban landscape.

4.2. Independent and interactive influences on UFST values

The provisioning of ecosystem services is strongly influenced by land-use configurations and the many environmental parameters that contribute directly or indirectly to the formation of specific landscape configurations. Maximizing the production of ecosystem services that natural forest cover provides requires an understanding of how alterations to environmental conditions in a landscape (at various spatial and temporal scales) affect ecosystem services. The fact that topographic characteristics (such as elevation and degree of slope) showed more influence on UFSTs than the other environmental factors we measured is probably due to the fact that growing conditions (e.g., light, moisture, and soil nutrients) are all strongly influenced by topography (Cantlon 1953). The effects of topography on species composition, productivity, and microsite environmental conditions have been well documented (Sariyildiz 2015; Scowcroft, Turner, and Vitousek 2000). Specifically, topography is an important factor influencing the heterogeneity of habitats, thus contributing to physiognomic differentiation of vegetation (Baldeck Claire *et al*. 2013), ultimately leading to differences in the composition and structure of plant communities (Rodrigues *et al*. 2018).

Based on a quantification of interactions among socio-economic status, elevation, vegetation characteristics, and land surface temperatures, some research has suggested that environmental conditions influence microclimates and climate adaptation strategies of vegetation at a local scale (Irmak *et al*. 2018; Tayyebi and Darrel Jenerette 2016). We found that interactions among dominant species and elevation enhanced the cooling effect of urban forests. Although human population density only appeared to have a dominating influence on hot spots in 2009, it showed linear or non-linear interactions with many other environmental factors.

A non-linear relationship between two factors can have a greater influence than the combination of direct actions of two factors. This type of influence was especially notable in areas of hot spots, where population density appeared to interact with all other factors in ways that suggest that human activities might appreciably influence many environmental characteristics, although independent influence of population density might not be as obvious.

Research on urban heat island (UHI) effects usually attribute the development of UHI to human activities that release anthropogenic heat or other pollutants into the atmosphere (Salamanca *et al*. 2014; Smith, Lindley, and Levermore 2009). However, this study shows that modifications to land surface properties and urban surface geometries by humans are probably the main causes of UHI effects. In fact, it is very likely that human activity also influences the thermal environment in other ways. For example, urban development reconfigures urban landscapes and changes the growing conditions of remnant vegetation by modifying topographic characteristics and soil properties (Zheng, Myint, and Fan, 2014). There is a significant and positive correlation between land surface temperature and the amount of impervious surfaces in a given area (Li *et al*. 2011). Urban sprawl contributes to the loss of natural vegetation cover and its forest fragmentation, which in turn leads to incremental increases in land surface temperatures. A number of studies have shown that even at small spatial scales, variations in geomorphologic conditions create a variety of environmental conditions that, in turn, affect recruitment and growth of vegetation (Sariyildiz 2015). In our study area, tree species composition and stand structure changed in measurable ways in just six years, which we believe is a response to an increased intensity of human alterations to the landscape and changes in land use. Human activities introduce ecological and biological changes to urban forests, which can lead to a deterioration of the urban thermal environment. This can occur even when sensible heat is not directly released into the atmosphere, or if the total cover of greenspace is not altered much.

Our results suggest that we should search for not-so-obvious implications of human activities in future studies, particularly those that may have great potential for changing heat dynamics in developed landscapes. Examining human activities and natural processes in a historical context could also help reveal how human activities have shaped ecosystem patterns and services in the urban landscape (Hessl and Graumlich 2002). In addition, with ongoing urbanization and ever-more intense human activities, interactions between humans and the environment will continue to intensify the UHI effect. Therefore, the regulation of human activities that deteriorate urban thermal environments should be considered to help ameliorate the effects of UHI effects.

4.3. Implications

In this study, we analyzed the independent and interactive influences of various environmental factors on variations in UFST. The methodological approach we applied in this study provides insight for future research. Rather than focusing on one data acquisition approach (such as remote sensing or field observation), we used a variety of environmental datasets to unearth the complex relationships between environmental factors and the provisioning of ecosystem services. More attention should be paid not only to urban planning or urban forest management options, but also to the most influential, underlying factors associated with human activities (i.e., human actions should be carefully implemented to minimize the potential side effects on urban vegetation).

Although there have already been many studies focusing on environmental stress, such as heat stress and high concentrations of pollutants in soil, and on vegetation function and growth in urban areas (Biasioli, Barberis, and Ajmone-Marsan 2006; Calfapietra, Peñuelas, and Niinemets 2015; Chahal, Toor, and Brown 2010), research on interactive influences between multiple environmental factors on urban vegetation (and the ecological services it provides) are limited and should be expanded in the future.

The influence of environmental stress to changing heat conditions on any single plant may be negligible, but if extrapolated over an entire city, the impacts could be significant and extensive on local ecosystems. Therefore, more work on heat impacts should be conducted at various temporal and spatial scales. The partitioning of heterogeneous landscapes of interest into homogeneous areas, by aggregating common characteristics of neighboring landscape components, is useful for revealing potential causes for specific landscape patterns. Therefore, due to the complex interactions among various environmental factors, better approaches are needed for classifying landscapes into homogeneous areas (clusters).

As a key strategy for improving environmental quality and sustainable development, the implementation of green infrastructure has attracted much concern in recent years. However, with rapid urbanization, urban sprawl invades existing greenspace and leads to highly fragmented urban forest patches. Because urbanization will likely continue in future decades, it is important to identify green infrastructure designs that can optimize ecosystem services of urban forests. Studies have shown that the urban forests located at various distances from urban centers differ in their cooling capacities (Marando *et al*. 2019). Therefore, specific management policies may be necessary to implement cost-effective improvements in the cooling capacity of urban forests that optimize cooling effects. Comprehensive consideration of ecosystem health and services should also be given in future studies.

5. Conclusions

We analyzed the independent and interactive influences of environmental factors on UFST by thoroughly integrating remote sensing images, field surveys, and spatial statistical analyses. Our results showed that during rapid urbanization, the degree of spatial aggregation of UFSTs increased. Among the many potential influencing factors, topographic characteristics (elevation and degree of slope) were the one most significantly related to the spatial heterogeneity of UFST. Human activities were also significantly related to variations in UFST for both time periods we examined (2003 or 2009) and to almost all spatial clusters of hot and cool spots. Interactions between human activity and many environmental factors also showed a statistically significant relationship with variations in UFST across the landscape. For hot spot areas in particular, interactions between human activities and almost all environmental factors tended to result in more spatially heterogeneous landscapes. Although our study concentrated on the core (city center) of a major urban area in China, we believe that our research approach can also be applied to investigate spatial variations of UFSTs in other urban areas. Furthermore, our results can provide insight for future studies on urban greenspace management and the evaluation of ecological services provided by remnant urban forests.

Supplemental data

Supplemental data for this article can be accessed here.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Alberti, M. 2010. “Maintaining Ecological Integrity and Sustaining Ecosystem Function in Urban Areas.” *Current Opinion in Environmental Sustainability* 2 (3): 178–184. doi:10.1016/j.cosust.2010.07.002.

Alberti, M. 2016. *Cities That Think like Planets: Complexity, Resilience, and Innovation in Hybrid Ecosystems*. Seattle: University of Washington Press.

Alberti, M. 2017. “Grand Challenges in Urban Science.” *Frontiers in Built Environment* 3: 84–105. doi:10.3389/fbuil.2017.00006.

Baldeck Claire, A., E. Harms Kyle, B. Yavitt Joseph, R. John, L. Turner Benjamin, R. Valencia, H. Navarrete, et al. 2013. "Soil Resources and Topography Shape Local Tree Community Structure in Tropical Forests." *Proceedings of the Royal Society B: Biological Sciences* 280 (1753): 20122532. doi:10.1098/rspb.2012.2532.

Bauman, A. G., D. A. Feary, S. F. Heron, M. S. Pratchett, and J. A. Burt. 2013. "Multiple Environmental Factors Influence the Spatial Distribution and Structure of Reef Communities in the Northeastern Arabian Peninsula." *Marine Pollution Bulletin* 72 (2): 302–312. doi:10.1016/j.marpolbul.2012.10.013.

Biasioli, M., R. Barberis, and F. Ajmone-Marsan. 2006. "The Influence of a Large City on Some Soil Properties and Metals Content." *Science of the Total Environment* 356 (1-3): 154–164. doi:10.1016/j.scitotenv.2005.04.033.

Calfapietra, C.,. J. Peñuelas, and Ü. Niinemets. 2015. "Urban Plant Physiology: Adaptation-Mitigation Strategies under Permanent Stress." *Trends in Plant Science* 20 (2): 72–75. doi:10.1016/j.tplants.2014.11.001.

Cantlon, J. E. 1953. "Vegetation and Microclimates on North and South Slopes of Cushetunk Mountain, New Jersey." *Ecological Monographs* 23 (3): 241–270. doi:10.2307/1943593.

Chahal, M. K., G. S. Toor, and P. Brown. 2010. "Trace Metals and Polycyclic Aromatic Hydrocarbons in an Urbanized Area of Florida." *Soil and Sediment Contamination: An International Journal* 19: 419–435. doi:10.1080/15320383.2010.486048.

Chander, G., and D. P. Groeneveld. 2009. "Intra-Annual NDVI Validation of the Landsat 5 TM Radiometric Calibration." *International Journal of Remote Sensing* 30 (6): 1621–1628. doi:10.1080/01431160802524545.

Chen, A., L. Yao, R. Sun, and L. Chen. 2014. "How Many Metrics Are Required to Identify the Effects of the Landscape Pattern on Land Surface Temperature?" *Ecological Indicators* 45: 424–433. doi:10.1016/j.ecolind.2014.05.002.

Coutts, A. M., J. Beringer, and N. J. Tapper. 2007. "Impact of Increasing Urban Density on Local Climate: Spatial and Temporal Variations in the Surface Energy Balance in Melbourne, Australia." *Journal of Applied Meteorology and Climatology* 46 (4): 477–493. doi:10.1175/JAM2462.1.

Fadrique, B., J. Homeier, and K. Woods. 2016. "Elevation and Topography Influence Community Structure, Biomass and Host Tree Interactions of Lianas in Tropical Montane Forests of Southern Ecuador." *Journal of Vegetation Science* 27 (5): 958–968. doi:10.1111/jvs.12427.

Guo, G., Z. Wu, R. Xiao, Y. Chen, X. Liu, and X. Zhang. 2015. "Impacts of Urban Biophysical Composition on Land Surface Temperature in Urban Heat Island Clusters." *Landscape and Urban Planning* 135: 1–10. doi:10.1016/j.landurbplan.2014.11.007.

Hessl, A. E., and L. J. Graumlich. 2002. "Interactive Effects of Human Activities, Herbivory and Fire on Quaking Aspen (Populus tremuloides) Age Structures in Western Wyoming." *Journal of Biogeography* 29 (7): 889–902. doi:10.1046/j.1365-2699.2002.00703.x.

Irmak, M. A., S. Yilmaz, E. Mutlu, and H. Yilmaz. 2018. "Assessment of the Effects of Different Tree Species on Urban Microclimate." *Environmental Science and Pollution Research* 25 (16): 15802–15822. doi:10.1007/s11356-018-1697-8.

Jenerette, G. D., S. L. Harlan, A. Brazel, N. Jones, L. Larsen, and W. L. Stefanov. 2007. "Regional Relationships Between Surface Temperature, Vegetation, and Human Settlement in a Rapidly Urbanizing Ecosystem." *Landscape Ecology* 22 (3): 353–365. doi:10.1007/s10980-006-9032-z.

Jim, C. Y., and W. Y. Chen. 2009. "Ecosystem Services and Valuation of Urban Forests in China." *Cities* 26 (4): 187–194. doi:10.1016/j.cities.2009.03.003.

Joshi, C., J. D. Leeuw, A. K. Skidmore, I. C. v Duren, and H. van Oosten. 2006. "Remotely Sensed Estimation of Forest Canopy Density: A Comparison of the Performance of Four Methods." *International Journal of Applied Earth Observation and Geoinformation* 8 (2): 84–95. doi:10.1016/j.jag.2005.08.004.

Kong, F., H. Yin, P. James, L. R. Hutyra, and H. S. He. 2014. "Effects of Spatial Pattern of Greenspace on Urban Cooling in a Large Metropolitan Area of Eastern China." *Landscape and Urban Planning* 128: 35–47. doi:10.1016/j.landurbplan.2014.04.018.

Kuang, W., Y. Liu, Y. Dou, W. Chi, G. Chen, C. Gao, T. Yang, J. Liu, and R. Zhang. 2014. "What Are Hot and What Are Not in an Urban Landscape: Quantifying and Explaining the

Land Surface Temperature Pattern in Beijing, China." *Landscape Ecology* 30 (2): 357–373. doi:10.1007/s10980-014-0128-6.
Li, J., C. Song, L. Cao, F. Zhu, X. Meng, and J. Wu. 2011. "Impacts of Landscape Structure on Surface Urban Heat Islands: A Case Study of Shanghai, China." *Remote Sensing of Environment* 115 (12): 3249–3263. doi:10.1016/j.rse.2011.07.008.
Lin, Y., R. Qiu, J. Yao, X. Hu, and J. Lin. 2019. "The Effects of Urbanization on China's Forest Loss from 2000 to 2012: Evidence from a Panel Analysis." *Journal of Cleaner Production* 214: 270–278. doi:10.1016/j.jclepro.2018.12.317.
Liu, Y., J. Peng, and Y. Wang. 2018. "Application of Partial Least Squares Regression in Detecting the Important Landscape Indicators Determining Urban Land Surface Temperature Variation." *Landscape Ecology* 33 (7): 1133–1145. doi:10.1007/s10980-018-0663-7.
Marando, F., E. Salvatori, A. Sebastiani, L. Fusaro, and F. Manes. 2019. "Regulating Ecosystem Services and Green Infrastructure: Assessment of Urban Heat Island Effect Mitigation in the Municipality of Rome, Italy." *Ecological Modelling* 392: 92–102. doi:10.1016/j.ecolmodel.2018.11.011.
McPhearson, T., S. T. A. Pickett, N. B. Grimm, J. Niemelä, M. Alberti, T. Elmqvist, C. Weber, D. Haase, J. Breuste, and S. Qureshi. 2016. "Advancing Urban Ecology Toward a Science of Cities." *BioScience* 66 (3): 198–212. doi:10.1093/biosci/biw002.
Oke, T. R. 1982. "The Energetic Basis of the Urban Heat Island." *Quarterly Journal of the Royal Meteorological Society* 108: 1–24. doi:10.1256/smsqj.45501.
Pickett, S. T. A., and M. L. Cadenasso. 1995. "Landscape Ecology: Spatial Heterogeneity in Ecological Systems." *Science* 269 (5222): 331–334. doi:10.1126/science.269.5222.331.
Ren, Y., L.-Y. Deng, S.-D. Zuo, X.-D. Song, Y.-L. Liao, C.-D. Xu, Q. Chen, L.-Z. Hua, and Z.-W. Li. 2016. "Quantifying the Influences of Various Ecological Factors on Land Surface Temperature of Urban Forests." *Environmental Pollution* 216: 519–529. doi:10.1016/j.envpol.2016.06.004.
Rödig, E., M. Cuntz, J. Heinke, A. Rammig, and A. Huth. 2017. "Spatial Heterogeneity of Biomass and Forest Structure of the Amazon Rain Forest: Linking Remote Sensing, Forest Modelling and Field Inventory." *Global Ecology and Biogeography* 26 (11): 1292–1302. doi:10.1111/geb.12639.
Rodrigues, P. M. S., C. E. Gonçalves, R. Schaefer, J. d. O Silva, W. G. F. Júnior, R. M. D. Santos, and A. V. Neri. 2018. "The Influence of Soil on Vegetation Structure and Plant Diversity in Different Tropical Savannic and Forest Habitats." *Journal of Plant Ecology* 11: 226–236.
Salamanca, F., M. Georgescu, A. Mahalov, M. Moustaoui, and M. Wang. 2014. "Anthropogenic Heating of the Urban Environment Due to Air Conditioning." *Journal of Geophysical Research: Atmospheres* 119: 5949–5965. doi:10.1002/2013JD021225.
Sariyildiz, T. 2015. "Effects of Tree Species and Topography on Fine and Small Root Decomposition Rates of Three Common Tree Species (*Alnus glutinosa, Picea orientalis and Pinus sylvestris*) in Turkey." *Forest Ecology and Management* 335: 71–86. doi:10.1016/j.foreco.2014.09.030.
Scowcroft, P. G., D. R. Turner, and P. M. Vitousek. 2000. "Decomposition of Metrosideros Polymorpha Leaf Litter along Elevational Gradients in Hawaii." *Global Change Biology* 6 (1): 73–85. doi:10.1046/j.1365-2486.2000.00282.x.
Shi, T., Z. Hu, Z. Shi, L. Guo, Y. Chen, Q. Li, and G. Wu. 2018. "Geo-Detection of Factors Controlling Spatial Patterns of Heavy Metals in Urban Topsoil Using Multi-Source Data." *Science of the Total Environment* 643: 451–459. doi:10.1016/j.scitotenv.2018.06.224.
Smith, C., S. Lindley, and G. Levermore. 2009. "Estimating Spatial and Temporal Patterns of Urban Anthropogenic Heat Fluxes for UK Cities: The Case of Manchester." *Theoretical and Applied Climatology* 98 (1–2): 19–35. doi:10.1007/s00704-008-0086-5.
Tayyebi, A., and G. Darrel Jenerette. 2016. "Increases in the Climate Change Adaption Effectiveness and Availability of Vegetation across a Coastal to Desert Climate Gradient in Metropolitan Los Angeles, CA, USA." *Science of the Total Environment* 548–549: 60–71. doi:10.1016/j.scitotenv.2016.01.049.
Wagner, H. H., and M.-J. Fortin. 2005. "Spatial Analysis of Landscapes: Concepts and Statistics." *Ecology* 86 (8): 1975–1987. doi:10.1890/04-0914.
Wang, J.-F., and Y. Hu. 2012. "Environmental Health Risk Detection with GeogDetector." *Environmental Modelling and Software* 33: 114–115. doi:10.1016/j.envsoft.2012.01.015.

Wang, J.-F., T.-L. Zhang, and B.-J. Fu. 2016. “A Measure of Spatial Stratified Heterogeneity.” *Ecological Indicators* 67: 250–256. doi:10.1016/j.ecolind.2016.02.052.

Wang, J., and W. Ouyang. 2017. “Attenuating the Surface Urban Heat Island Within the Local Thermal Zones Through Land Surface Modification.” *Journal of Environmental Management* 187: 239–252. doi:10.1016/j.jenvman.2016.11.059.

Weng, Q., and D. Lu. 2008. “A Sub-Pixel Analysis of Urbanization Effect on Land Surface Temperature and Its Interplay with Impervious Surface and Vegetation Coverage in Indianapolis, United States.” *International Journal of Applied Earth Observation and Geoinformation* 10 (1): 68–83. doi:10.1016/j.jag.2007.05.002.

Xu, C., Y. Li, J. Wang, and G. Xiao. 2017. “Spatial-Temporal Detection of Risk Factors for Bacillary Dysentery in Beijing, Tianjin and Hebei, China.” *BMC Public Health* 17: 743. doi: 10.1186/s12889-017-4762-1.

Zhang, X., D. Wang, H. Hao, F. Zhang, and Y. Hu. 2017. “Effects of Land Use/Cover Changes and Urban Forest Configuration on Urban Heat Islands in a Loess Hilly Region: Case Study Based on Yan’an City, China.” *International Journal of Environmental Research and Public Health* 14 (8): 840. doi:10.3390/ijerph14080840.

Zhang, X., F. Zhang, D. Wang, J. Fan, Y. Hu, H. Kang, M. Chang, Y. Pang, Y. Yang, and Y. Feng. 2018. “Effects of Vegetation, Terrain and Soil Layer Depth on Eight Soil Chemical Properties and Soil Fertility Based on Hybrid Methods at Urban Forest Scale in a Typical Loess Hilly Region of China.” *PLoS One* 13 (10): e0205661. doi:10.1371/journal.pone.0205661.

Zheng, B., S. W. Myint, and C. Fan. 2014. “Spatial Configuration of Anthropogenic Land Cover Impacts on Urban Warming.” *Landscape and Urban Planning* 130: 104–111. doi:10.1016/j.landurbplan.2014.07.001.