Quantifying the influences of various ecological factors on land surface temperature of urban forests

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ABSTRACT

Identifying factors that influence the land surface temperature (LST) of urban forests can help improve simulations and predictions of spatial patterns of urban cool islands. This requires a quantitative analytical method that combines spatial statistical analysis with multi-source observational data. The purpose of this study was to reveal how human activities and ecological factors jointly influence LST in clustering regions (hot or cool spots) of urban forests. Using Xiamen City, China from 1996 to 2006 as a case study, we explored the interactions between human activities and ecological factors, as well as their influences on urban forest LST. Population density was selected as a proxy for human activity. We integrated multi-source data (forest inventory, digital elevation models (DEM), population, and remote sensing imagery) to develop a database on a unified urban scale. The driving mechanism of urban forest LST was revealed through a combination of multi-source spatial data and spatial statistical analysis of clustering regions. The results showed that the main factors contributing to urban forest LST were dominant tree species and elevation. The interactions between human activity and specific ecological factors linearly or nonlinearly increased LST in urban forests. Strong interactions between elevation and dominant species were generally observed and were prevalent in either hot or cold spots areas in different years. In conclusion, quantitative studies based on spatial statistics and GeogDetector models should be conducted in urban areas to reveal interactions between human activities, ecological factors, and LST.

Keywords: urban forest; land surface temperature (LST); spatial statistical analysis; GeogDetector model; multiple ecological factors; driving mechanism; integrated quantitative analysis

Capsule: Interactions between human activity and specific ecological factors linearly or nonlinearly increase LST in urban forests.

1. Introduction

The urban heat island effect caused by rapid urbanization leads to a multitude of eco-environmental problems such as increased energy consumption, photochemicals, smog, slow-diffusing pollutants, and human respiratory disease (Buyantuyev and Wu, 2010). Urban forests are the main source of natural productivity in urban areas (Salvati et al., 2014; Cetin, 2015). The cooling effect (cold island effect) caused by dense shade from branches and leaves limits direct radiant heat from the sun and reflected heat from pavement, walls, and adjacent objects; water transpiration through leaves further consumes radiant heat. The cooling effect plays an extremely important role in mitigating the urban heat island effect, adjusting urban climate, and addressing future climate change (Kong et al., 2014).

Many studies have confirmed an obvious cooling effect in the land surface temperature (LST) of urban forests compared with surrounding areas, and this effect is closely related to the type (e.g., tree species, forest age, forest canopy) and spatial characteristics (e.g., shape, area) of urban forests. Many scholars have applied field survey data or remote sensing images of various resolutions (Kuang et al., 2014; Ren et al., 2014; Zhao et al., 2016) and adopted multivariate statistical analyses to study the relationship between urban forest LST and ecological factors such as forest area, canopy density, vegetation richness, and vegetation index (Chen et al., 2006).

However, most of these previous studies analyzed the relationship between urban forest LST and a single ecological factor without comprehensively considering the quantitative relationships between LST and multiple ecological factors (Heffeman et al., 2014; Zhao et al., 2015). During the interactions between human and natural factors, the diversity, complexity, nonlinearity, and heterogeneity of various ecological factors jointly influence the entire process of urban forest growth.

Variations in the intensity of ecological factors, including biotic (e.g., area, dominant tree species, forest age, canopy density) and abiotic factors (e.g., topography, soil), result in a high degree of spatial and temporal heterogeneity in urban forest LST (Shoshany et al., 2005). The effects of human activities further enhance spatial and temporal heterogeneity (Bump et al., 2009). However, few reports have clarified the effects (including strengths and directions) of interactions between human activities, multiple ecological factors, and urban forest LST or quantified the spatial heterogeneity of urban forest LST. The influence of the above-mentioned factors on urban forest LST at the macro-scale (e.g., regional, national, or global) and the strength of interactions between these factors remain unclear (Buyantuyev and Wu, 2010).

Quantifying the spatial heterogeneity of LST requires the integration of remote sensing images, field surveys, and spatial statistical analyses to differentiate clustering regions (hot or cool spots) and identify influential factors (Barrell et al., 2013). Such clustering regions refer to areas with highly concentrated high or low LST over a period of time and have strong effects on the surrounding ecology and environment. The formation of these areas is closely related to ecological factors and human activities (Cañadas et al., 2014). The classification of clustering regions (hot-spot analysis) relies on the integration of geographical location and spatial relationships and requires spatial statistical analyses and models (Peeters et al., 2015). The degree of spatial clustering and spatial heterogeneity should be evaluated to reveal the spatial relationship between urban forest LST and multiple ecological factors. In contrast to classical statistical analyses, which typically omit spatial information, spatial statistical methods are suitable for analyzing the formation mechanisms of clustering regions by emphasizing the geographic variation in urban forest LST at temporal and

spatial scales. Although this method has widely been used in other fields (e.g., geography, humanities, social sciences, and medicine), it has not been widely employed in environmental ecology (Ahmad et al., 2015).

The purpose of this study was to reveal how human activities and multiple ecological factors jointly influence urban forest LST through the analysis of clustering regions (hot and cool spots). Two main questions were addressed: 1) In addition to human activity, what are the main ecological factors influencing urban forest LST? 2) How do interactions between human activity and multiple ecological factors influence urban forest LST? We proposed a new quantitative method that integrates remote sensing, field surveys, and spatial statistical analyses, and chose the urban forest of Xiamen City, a representative Chinese city undergoing rapid urbanization, for a case study (Appendix D, Fig.1). This work provides a scientific basis for the simulation and prediction of the spatial patterns of urban cold islands (Zhao et al., 2015).

2. Materials and methods

2.1. Overview

The methodology consisted of the following three steps (Fig. 1). 1) A spatial database was created by integrating multi-source data, including forest management planning inventory (FMPI), digital elevation models (DEM), population, and remote sensing images. 2) LST spatial distribution data were calculated using thermal remote sensing images. Forest patch and LST data were integrated spatially. Hot and cool spots were identified on an appropriate threshold distance scale using spatial statistical analysis. 3) The results from clustering regions, multi-source spatial data, and the GeogDetector model were combined to reveal the driving mechanism of

urban forest LST. For an overview of the study area, data sources, and other research methods, please see the overview in Appendix A.

2.2. Multi-source spatial database development

The multi-source data in 1996 and 2006 mainly included three types. The first type was FMPI data obtained by field observations, including graphical data and the corresponding attribute database. The attribute database provided data on stands, soil, topography, and other ecological factors, and the sampling accuracy was within 90%. The second type was raster data of the population density distribution of Xiamen City, which characterized human activity. The third type was Landsat-5 TM images. LST data from the summer were derived from the thermal infrared (TIR) band (10.40–12.50 μm) of two Landsat 5 TM images (Row 119/Path 43) acquired on July 20, 1996 and August 17, 2006. The two images were acquired at approximately 10:00 am local time under clear atmospheric conditions. Our study focused on the summer period (i.e., from July to September) because the forest canopy is fully developed during this time and the contrast between the LST of the forest and surrounding urban construction land is typically highest. Thus, summer is the optimal time to study the forest cooling effect. Moreover, from the perspective of urban forest planning, the focus of cooling is most relevant during summer. In contrast, during winter, the heat island effect on human health is relatively small and some trees are bare. It is ideal to select images from close dates to discern the LST variation during different periods and determine the contributions of various environmental factors. However, due to limited remote sensing image archives and the cloud-prone climate in southern China, only two qualified scenes (i.e., July 20, 1996 and August 17, 2006) under relatively clear and stable atmospheric conditions were selected (Appendix A, Data source).

With FMPI patches defined as the basic unit, the temporal and spatial distribution of population density was mapped using the kernel density tool and the zonal statistics function in the ArcGIS 10.0 spatial analysis module. Urban LST raster data were obtained by inversion using a single channel algorithm. The average values of population density and urban LST in each forest patch were calculated. The matched spatial data (temperature, population, and multiple ecological factors) were converted to the WGS 1984 UTM (50N) coordinate system. The readers are referred to Appendix A for details on the attribute database.

2.3. Urban forest LST calculation

Data preprocessing

First, the digital number (DN) values of the thermal band of the Landsat TM 5 were converted to radiance. Second, we used atmospheric correction methods to eliminate the influence of view angle and atmosphere on surface reflectance. Third, LST was estimated using the single-channel retrieval algorithm. Fourth, we used the cubic convolution interpolation method to resample the resolution from 120 to 30 m because the resolution of the Landsat TM 5 thermal infrared band was relatively coarse compared with the average area of the urban forest patches. Finally, the LST was normalized in order to evaluate the interactions among the multiple factors influencing urban forest temperature. Nondimensionalization can eliminate the influence of the viewing angle and different image acquisition times. A relative LST index T_R , proposed by Zhao et al (2010), was used to normalize LST values as follows:

$$T_R = (LST - T_b) / T_b$$

where LST is the surface temperature (K) of each pixel and T_b (K) is the background surface temperature defined as the average temperature of the study area images. See

the supporting information for the detailed processes (Appendix A).

Accuracy assessment

Many studies have confirmed that the temperature difference between LST generated from remote sensing images and air temperature obtained from meteorological stations decreases with increasing NDVI (normalized difference vegetation index) (Weng et al. 2004; Yuan et al. 2007). Thus, data measured at meteorological stations with known spatial locations were used for the urban forest LST test and a Pearson correlation analysis was conducted. We used the measured daily average air temperature data of 10 meteorological stations in Xiamen City to evaluate the accuracy of LST inversion (Appendix D, Fig 2). The Pearson correlation coefficient was used to evaluate the linear relationship between the estimated LST and observed air temperature (Li et al. 2011). The results showed that the estimated LST was correlated with observed air temperature (Pearson correlation coefficient: 0.848; $p < 0.01$).

2.4. Spatial statistical analysis

Determination of optimal threshold distance

The optimal threshold distance was determined considering 1) the peak value of a variable (e.g., area and z-score) and 2) the number of significant patches (in hot or cool spots) in a neighboring area (mean and minimum numbers) based on the local Getis-Ord G_i^* statistical results (Ord and Getis 1995; Barrell et al., 2013). We calculated the compartment area and the neighboring number of significant patches by continuously increasing the threshold distance of each compartment (i.e., 500-m step increases in the 500–5,000 m range) to find the maximum clustering distance (i.e., the optimal threshold). By increasing the threshold distance, the area of hot and cool spots

first increased and then decreased (Table 1). When the threshold was in the range of 500–3,500 m, the area of hot and cool spots in 1996 and 2006 both increased and reached a maximum value at 3,500 m. Meanwhile, the mean neighboring values were always greater than 8, which met the normal distribution assumption of autocorrelation. However, the minimum number did not exceed 8 until the distance reached the 2,500-m threshold in 1996 (Ord and Getis 1995). Therefore, we used 3,500 m, which met both the normal distribution assumption and the maximum area of hot and cold spots, as the optimal threshold (Table 1).

Global Moran's I and local Getis-Ord Gi statistical analysis*

The purpose of using global Moran's I and local Getis-Ord Gi* statistics was to test the statistical significance at a given level and detect the spatial position of hot- and cool-spot clustering regions of urban forest LST on an optimal threshold-distance scale.

Global Moran's I is the most commonly used index for spatial autocorrelation analysis, and it is calculated with the following formula:

$$I = \frac{N \sum_{i=1}^n \sum_{j=1}^n (X_i - \bar{X})(X_j - \bar{X})}{(\sum_{i=1}^n \sum_{j=1}^n W_{ij}) \sum_{i=1}^n (X_i - \bar{X})^2}$$

where N is the number of observed space units (polygonal region or point); $\bar{X}$ is the statistical mean; X_i and X_j are the observed value in the i-th and j-th region, respectively; and W_{ij} is the weight of the i-th region relative to the j-th region.

Local Getis-Ord Gi* is a local spatial statistical method that estimates the ratio of local values with different weights to the overall value based on distance

measurement standards only, without considering the condition of boundary adjacency. Its formula is as follows:

$$Gi^*(d) = \frac{\sum_{j=1}^n W_{ij}(d) X_j}{\sum_{j=1}^n X_j}$$

where d is the region size; W_{ij} is the weight matrix of sample points and region j ; and x is an indicator quantifying importance.

Definition of regions with various LST features

By setting the optimal threshold distance as 3,500 m, a clustering graph was generated using the local Getis-Ord Gi^* index. According to the z-score, regions with an absolute value greater than 1.96 were considered clustering regions (hot or cool spots). Areas with an absolute value less than 1.96 were considered non-significant (Mahboubi et al., 2015).

Three types of spatial patterns were identified and defined as follows:

- (1) Hot spot: locations of statistically significant clustering of high LST values ($z \geq 1.96$ refers to the upper limit of the 95% confidence interval).
- (2) Cool spots: locations of statistically significant clustering of low LST values ($z \leq -1.96$ refers to the lower limit of the 95% confidence interval).
- (3) Non-significant spots: locations showing no significant spatial correlation ($-1.96 < z < 1.96$).

A high z-score and low p-value indicate spatial clustering of high values. A low, negative z value and a low p-value indicate spatial clustering of low values. For significant positive z-scores, a higher z-score corresponds to a more sensitive degree of clustering of high values (Ivajnsiĉ et al., 2014) (Appendix A).

GeogDetector model description

The GeogDetector model was used to detect various factors that may influence urban forest LST, the degree of influence of each factor, and the interactions between factors based on spatial analysis of variance (Wang and Hu, 2012). The GeogDetector model quantitatively expresses various types of interactions strengths among different ecological factors. The model follows a spatial heterogeneity hypothesis-based approach and is suitable for ecological study areas with strong spatial heterogeneity. The GeogDetector model includes factor, ecological, and interaction detectors. The factor detector is used to explore the impact of different factors on the research target; the ecological detector is used to explore the impacts of different levels of significance on those factors; and the interaction detector is used to explore the strengths of combinations of different impact factors on the research target. The GeogDetector model is freely available from www.sssampling.org/geogdetector.

Assuming that human activities and certain ecological factors jointly influence urban forest LST, the temporal and spatial distribution pattern of LST could then be determined. We first loaded map layers of all human and ecological factors and urban forest LST values into ArcGIS. We extracted the average values of the ELE (elevation), SDe (slope degree), and PD (population density) factors based on forest patches. The data was classified according to the classification criteria of the FMPI instruction manual (e.g., SDe); the factors not classified in the manual were classified using the Natural Breaks (Jenks) method (e.g., PA or patch area). The average LST of each forest patch was set as the dependent variable in the statistical analysis. Multiple ecological and human activity factors deemed as independent variables were introduced into GeogDetector model. All the different impact factor values were input

into the GeogDetector model for simulations. For additional details, please see Appendix A, Spatial statistical analysis.

3. Results

3.1. Urban forest LST and stand structure

Landsat 5 images from 1996 and 2006 were combined with the corresponding FMPI data ($n = 14,901$ in 1996 and $n = 14,944$ in 2006). A multi-source dataset, in which the LST of each forest patch corresponds to various ecological factors, was generated on the same urban scale. In 1996 and 2006, the relative average urban forest LST was -0.014 and -0.042 , respectively (Fig. 2).

The stand structure varied greatly from 1996 and 2006. Specifically, the clustering degree increased by 0.118 (Moran's index was 0.155 in 1996 and 0.273 in 2006) (Table 2), the total area of forest patches increased by 12.227% ($68,559.733$ ha in 1996; $89,279.067$ ha in 2006; total area of $165,036.300$ ha) (Appendix C, Table 1), the average forest age increased by 1.877 yr (16.066 ± 11.758 yr in 1996; 17.943 ± 10.271 yr in 2006), and the average canopy density increased by 0.046 (0.229 ± 0.276 in 1996; 0.275 ± 0.297 in 2006). The dominant tree species in 1996 were *Dimocarpus longan*, *Pinus massoniana*, *Acacia confuse*, *Pinus elliottii*, *Cunninghamia lanceolata*, *Camellia sinensis*, *Casuarina equisetifolia*, and *Schima superba*. The same species were dominant in 2006, in addition to *Eucalyptus* spp. The planting area of dominant tree species changed. For example, the area of *Acacia confuse* increased by 1.764% (5.148% in 1996; 6.912% in 2006), the area of *P. massoniana* decreased by 9.821% (34.475% in 1996; 24.654% in 2006), and the area of *D. longan* decreased by 8.165% (28.096% in 1996; 19.931% in 2006) (Fig. 3, Appendix C, Table 2).

3.2. Population density

The population density in Xiamen City increased from 565.0 ± 12.6 persons/ha in 1996 to 755.5 ± 11.9 persons/ha in 2006 (t-test, $p < 0.01$). Regions with different degrees of urbanization all showed an increasing trend. However, the degree of population aggregation tended to decrease, as seen in Fig. 4 (Moran's index = 0.348, z score = 650.417 in 1996; Moran's index = 0.331, z score = 532.505 in 2006). The results based on classification through local Getis-Ord G_i^* statistics show that hot and cool spots of population and LST showed similar temporal and spatial distribution patterns. For example, 92.831% of population hot spots and 64.115% of population cool spots overlapped with corresponding areas of urban forest LST in 2006.

3.3. Influence of human activities and multiple ecological factors on urban forest LST

After classification through local Getis-Ord G_i^* statistics, the GeogDetector model was used to compare hot and cool spots of urban forest LST. Stand and topography groups were dominant ecological factors that influenced forest LST in 1996 and 2006. In particular, dominant tree species (stand factor) and elevation (topography factor) had greater impacts in different clustering regions and time periods compared with population density (Fig. 5, Table 3). In addition, during different time periods and in different clustering regions, linear or nonlinear interactions were observed for all relationships between population density and the 11 selected factors: $(\text{population density} \cap \text{ecological factor}) > (\text{population density} + \text{ecological factor})$ or $(\text{population density} \cap \text{ecological factor}) > (\text{population density}, \text{ecological factor})$ (Table 4, Appendix C, Table 3). There were strong interaction effects between the dominant factor and other ecological factors. In particular, strong

interactions between two ecological factors were generally observed in the elevation (ELE) and dominant species (DS) (Fig. 6).

Ecological factors had varying impacts on forest LST in different clustering regions and during different time periods. For example, in 2006, the main influential factors in hot spots were elevation ($q = 0.139$), slope ($q = 0.129$), dominant tree species ($q = 0.099$), and forest patch area ($q = 0.085$); the main influential factors in cool spots were dominant tree species ($q = 0.07$), elevation ($q = 0.069$), population density ($q = 0.069$), and canopy density ($q = 0.036$) (Table 3). Moreover, significantly interacting ecological factors varied among hot and cool spots. For example, population density significantly interacted with forest patch area, forest age, and elevation in hot spots. In cool spots, population density significantly interacted with canopy density, soil quality, soil thickness, humus depth, slope, slope direction, and slope position (Table 4). In addition, the factors with strong interaction effects changed from hot to cold spot areas during different years. Specifically, in 1996, elevation and the dominant species were dominant interaction effect factors in hot and cold spots of urban forests, respectively. In contrast, dominant species and elevation became the dominant interaction factors in hot and cool spots, respectively, in 2006. (Fig. 6, Appendix C, Table 4).

4. Discussion

4.1. Interaction effects on urban forest LST

In this study, remote sensing imagery, FMPI, spatial statistical analysis, and GIS technology were integrated to reveal the complicated interactions (direct and indirect) between various ecological factors and their effects on urban forest LST. Two key properties of these interactions were addressed: strength and direction. We identified the strength of interactions between two ecological factors and their impact on spatial heterogeneity of urban forest LST. Furthermore, the interaction strengths showed that elevation and dominant species had a greater influence on urban forest LST in comparison to other factors (e.g., patch area). In addition, elevation and dominant species displayed strong interactions with other ecological factors and linearly or non-linearly enhanced the urban forest cooling effect.

Our results confirm that elevation had a direct and dominant impact on urban forest LST and displayed strong interactions with multiple ecological factors (e.g., dominant species, population density). This indicates that elevation, which controls urban vegetation growth by changing light, moisture, and soil nutrients, and thus influences urban forest LST, is the major cause of spatial heterogeneity of urban LST. Recently, many studies have revealed interactions between elevation and vegetation cover, soil depth, and vegetation type using multiple linear regression models and plot-scale transplanting experiments in natural ecosystems (Grassein et al., 2014). Tayyebi et al. (2016) proposed that further research on the interactions of urban forest LST and elevation at the city scale can alleviate regional and global warming and provide a scientific basis for addressing climate change adaptation policies. However, due to the lack of a database of multi-source data, routine experimentation and empirical equations cannot adequately quantify the complex non-linear interactions

between elevation and multiple factors on an urban scale. This leads to difficulty in elucidating the quantitative interactions between elevation and urban forest structure (e.g., dominant species). Therefore, under scarce urban land resources, urban forest conservation and landscape planning should take into account elevation factors to enhance the urban forest cold island effect. Our results also show that interactions among dominant tree species and topographical factors (e.g., ELE, SDe, SPo) linearly or non-linearly enhanced the urban forest cooling effect. The results based on the GeogDetector model support the study by Long et al. (2015), which used an elevation gradient experiment in arctic tundra of Sweden to show that dominant tree species had more significant direct and interaction effects on temperature variation than other factors. This study indicated that the dominant tree species depends on a variety of factors including shape, breadth, crown length, clear length, tree morphology, density, leaf size, and leaf opacity, as well as interactions with topographical factors (e.g., ELE, SDe, SPo) and their effects on urban forest LST. Compared with elevation, few quantitative studies have focused on the interactions between species composition and multiple ecological factors on urban forest LST. Moreover, previous studies on the biological characteristics of the cooling effect due to different tree species have mainly been carried out on smaller scales such as in parks and sample plots (Lin et al. 2015). Our interaction study compares patches with different dominant trees species on an urban scale. For example, patches with *D. longan* as the dominant tree species mainly exist in hot spots, whereas those dominated by *S. superba* are mainly distributed in cool spots. This may be related to the above-mentioned biological factors. *S. superba* has thicker leaves and a higher and larger crown compared with *D. longan* trees of the same age. Norton et al. (2015) also demonstrated that dominant

tree species are the main determinants of the cold island effect on a regional scale, and this is feasible in cities with limited land.

Although the interactions of elevation and dominant species with other ecological factors significantly affected urban forest LST in different clustering areas (hot and cold spots) and years, the strongest interaction factors varied. Specifically, in 1996, elevation and dominant species were the dominant factors showing interaction effects in hot and cold spots of urban forests, respectively. In contrast, dominant species and elevation became major interaction factors in hot and cool spots, respectively, in 2006. This change may be related to human willingness to reform urban forests, which varied among different spatial clustering regions. Human impacts in higher elevation regions varied among different years according to transportation accessibility. These changes resulted in variation in the interactions between elevation and other factors in the hot and cold spots. Moreover, large-scale afforestation changed the dominant species composition. Significantly different urban forest LST in hot and cold spots among different years may have been caused by interactions between tree species and other factors. The results of the study by Connors et al. (2013) confirm our point; they concluded that human activities caused positive and negative double impacts on urban forest LST, and LST was affected to various degrees by elevation and other topographical factors because of changes in urban forest structure among different locations and years. Interactions between these factors were complex, non-linear, and diverse. In our study, interactions between human activities and multiple ecological factors in hot and cool spots linearly or nonlinearly increased urban forest LST. Previous studies on urban LST mechanisms have quantified the relationships between human activities, mainly including landscape composition (e.g., vegetation coverage, impermeability, water proportion),

spatial configuration (e.g., shape index, Shannon diversity index), and LST, whereas they only slightly consider human activities and the aforementioned factors. Nowadays, more and more urban forests are located in high population density regions. Human activities and other ecological factors modify urban forest spatial structure and composition and have inevitable large impacts on urban forest LST. The intervention is perennial and continuous (Josefsson et al., 2009). Kuang et al. (2014) proposed that using ecological process models for precise predictions of urban forest LST spatial distributions and variation trends under different human activity intensities can provide a scientific basis for urban forest landscape planning considering long-term cold island effects. Our research demonstrates that indirect effects generated by human activities elevate urban forest LST in highly heterogeneous urban forest ecosystems. Furthermore, the interaction between two factors can have a greater influence than the direct effect of a single ecological factor, and the interaction effect may even be greater than the combination of two factors' direct actions. As urban ecological processes advance, interactions will continue to grow and impede the cold island effect of urban forests. Therefore, the relationship between population distribution variations and urban forest construction management should be considered, in addition to interactions of elevation and dominant tree species with other factors.

In addition, although the influence of stand area on urban forest LST was relatively lower in 1996, we cannot simply infer that stand area is not important to urban forests' cooling effect. The influence of patch area on urban forest LST is closely related to the degree of forest fragmentation at a specific time and site and the connectivity between patches. More importantly, the indirect effect between patch area and multiple ecological factors has a stronger influence on urban forest LST than

direct effects. In fact, when a strong interaction exists between ecological factors, statistical significance does not have true ecological significance when only considering the impact of dominant factors (Levy et al., 2014).

In recent years, numerous studies have emphasized that in order to clarify the driving mechanism of urban cool islands, the direction of interactions between ecological factors must be determined. The results of such studies are important for sustainable urban forest landscape planning (Kuang et al., 2014; Long et al., 2015). In our study, Pearson's correlation analysis was used to determine directions, where the direction of the Pearson's correlation coefficient represents the direction of a single-factor direct effect for urban forest LST (Appendix Table 5). For example, canopy density was significantly negatively related to the relative LST index in 1996 and 2006 ($P < 0.01$), indicating that the relative LST index moved in the negative direction with a changing canopy density. However, the relationship between two ecological factors is non-linear in urban ecosystems; thus, the direction of a single factor could not be used to infer the direction of a two-factor interaction. In addition, the statistical software (e.g., SPSS) was inadequate for analyzing the types of variables investigated in our study (e.g., dominant tree species composition; the order of numbers assigned had no real meaning). As seen from current literature, the issue of interaction direction has become a difficult and hot topic in ecology. To our knowledge, the development of models can hardly solve the issue. Similarly, the GeogDetector model does not have a function to deal with the direction of two-factor interactions. However, GeogDetector has obvious advantages over traditional software that are only able to use a certain type of variable, which constrains data input. In contrast, the GeogDetector model processes both type and numeric variables, in parallel to solving all types of quantitative calculation problems. In addition, the

GeogDetector model quantitatively expresses various types of interaction strengths among different variables. Most importantly, the GeogDetector model is a spatial heterogeneity hypothesis-based approach, as ecological study areas have strong spatial heterogeneity. Some studies have shown that the solution to interaction direction can be achieved by combining statistical analyses and spatial heterogeneity of environmental conditions (Heffernan et al., 2014; Tayyebi et al., 2016). For instance, Grassein et al. (2014) integrated R software and spatial heterogeneity of environmental conditions, to demonstrate that biotic interactions can affect plant performance but their direction depends on local environmental conditions. In our results, the spatial interactions between any two ecological factors, as well as their linearly enhanced or nonlinearly enhanced urban forest LST, were revealed. Therefore, the interaction direction may be determined based on the spatial heterogeneity results in the future. The GeogDetector model may be applied to study the effects of multiple ecological factors when analyzing interaction directions in spatially heterogeneous systems.

In summary, because of limited land resources and frequent human activities in urban areas, urban forest planning should be used to create urban cool islands. A multi-source spatial database should be constructed and be used for urban forest planning. In addition, spatial statistical analyses should be used to differentiate clustering regions. In particular, the strengths and directions of interactions between any two ecological factors in urban forest patches should be quantitatively analyzed. Policies that protect landscape based on urbanization stage, clustering regions, and driving mechanisms of urban forest LST should take into account direct and indirect effects of various ecological factors. For instance, according to the results of interaction strengths, urban forest planning should consider the change due to elevation in hot

spot areas in 1996. In contrast, changes in species composition should focus on urban forest planning in hot spot areas in 2006.

4.2. Recommendations and future studies

We put forward the following three suggestions according to our research results.

First, to solve regional-scale urban environmental problems, we need to combine the respective advantages of multi-source data and spatial statistical analysis, and explore the interaction effects of human activities, LST, and multiple ecological factors, rather than only focus on qualitative descriptions of urban forest spatial structure. Moreover, we need to integrate information on macro-spatial patterns and micro-urban patches and build a multi-source database with a unified spatial–temporal scale. Second, more emphasis should be given to studies on identifying influential factors in clustering regions of urban forests. The degree and location of changes in these areas should be determined to reveal variation due to urbanization. Finally, urban forest planning should pay close attention to the strength and direction of interactions between human activity, elevation, and dominant tree species on urban forest LST spatial heterogeneity and divide different functional clustering regions considering each ecological factors' direct and indirect (interacted) effects.

Our study quantitatively compares the interaction effects at two single time points. We propose the following future studies based on our results. 1) Future studies should take into account the temporal and spatial heterogeneity of LST. Quantitative studies on heterogeneity should be carried out on different temporal and spatial scales, in different cities and seasons, and with remote sensing images of various resolutions; 2) Accurate LST inversion methods should be used instead of the nondimensional relative temperature to overcome uncertainties due to field view, weather conditions,

etc. The integration of time series Landsat images on the same urban scale remains to be further studied; 3) The limited ecological factors selected in this study cannot fully express the driving mechanism of LST. Some of the selected ecological factors (e.g., species composition, and elevation) displayed dominant influences on urban forest LST, but the direct effects and degree of interaction of these factors in different regional environments and urbanization stages may vary; 4) The development of the GeogDetector model should focus determining the direction of interactions between ecological factors, and strength and direction of interactions should be applied to urban forest planning; and 5) The environmental impacts of combined pollution on urban forest health should be considered. Previous studies have shown that pollutants such as cement ash, fly ash, limestone dust, and other industrial particulate matter (dust pollution) settle onto plant leaf surfaces in different urban surface temperature (thermal pollution) environments. These pollutant have various impacts on plant growth indices, including leaf stomatal conductance, chlorophyll content, electron transfer rate, leaf temperature, photosynthesis rate, respiration rate, and transpiration rate (Naidoo et al., 2004; Van Heerden et al., 2007).

5. Conclusions

Our results show that during rapid urbanization, the degree of spatial aggregation of urban forest LST increased. Hot spots were mainly distributed in the urban core and suburbs, and cool spots were mainly located in suburbs and outer suburban districts. Compared with human activities, dominant tree species and elevation were the dominant factors influencing urban forest LST. The interactions between human activity and specific ecological factors linearly or nonlinearly

increased LST in urban forests. Strong interactions between elevation and dominant species were generally observed in both hot and cool spots, but varied during different years. Although our field survey and remote-sensing data are from Xiamen City, our research method and results can be used as a reference for the investigation of urban spatial patterns in other cities.

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Appendix A. Supplementary methods, results and discussions

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References

Ahmad, S. S., Aziz, N., Butt, A., et al. 2015. Spatio-temporal surveillance of water based infectious disease (malaria) in Rawalpindi, Pakistan using geostatistical modeling techniques. *Environmental Monitoring & Assessment* 187, 1-15.

- Barrell, J., Grant, J., 2013. Detecting hot and cold spots in a seagrass landscape using local indicators of spatial association. *Landscape Ecology* 28, 2005-2018.
- Bump, J. K., Peterson, R.O., Vucetich, J.A., 2009. Wolves modulate soil nutrient heterogeneity and foliar nitrogen by configuring the distribution of ungulate carcasses. *Ecology* 90, 3159-3167.
- Buyantuyev, A., Wu, J., 2010. Urban heat islands and landscape heterogeneity: linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. *Landscape Ecology* 25,17-33.
- Cañadas, E. M., Fenu, G., Peñas, J., et al. 2014. Hotspots within hotspots: Endemic plant richness, environmental drivers, and implications for conservation. *Biological Conservation* 170,282–291.
- Cetin, M., 2015. Using GIS analysis to assess urban green space in terms of accessibility: case study in Kutahya. *International Journal of Sustainable Development & World Ecology* 22,420-424.
- Chen, X. L., Zhao, H.M., Li PX., et al. 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. *Remote Sensing of Environment* 104,133–146.
- Connors, JP., Galletti, CS., Chow WTL., 2013. Landscape configuration and urban heat island effects: assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landscape Ecology* 28,271-283.
- Grassein, F., Lavorel, S., Till-Bottraud,I.,2014. The importance of biotic interactions and local adaptation for plant response to environmental changes: field evidence along an elevational gradient. *Global Change Biology*, 20:1452-1460.

- Heffernan, J.B., Soranno, P.A., Angilletta, M.J., et al. 2014. Macrosystems ecology: understanding ecological patterns and processes at continental scales. *Frontiers in Ecology and the Environment* 12, 5-14.
- Ivajnsič, D., Kaligarič, M., Žiberna, I., 2014. Geographically weighted regression of the urban heat island of a small city. *Applied Geography* 53, 341-353.
- Josefsson, T., Hornberg, G., Ostlund, L., 2009. Long-term human impact and vegetation changes in a boreal forest reserve: implications for the use of protected areas as ecological references. *Ecosystems*, 12: 1017–1036.
- Kong, F., Yin, H., James, P., et al. 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.
- Kuang, W., Liu, Y., Dou, Y., et al. 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, 1-17.
- Levy, O., Ball, B.A., Bond-Lamberty, B., et al. 2014. Approaches to advance scientific understanding of macrosystems ecology. *Frontiers in Ecology and the Environment* 12, 15-23.
- Li, J., Song, C., Cao, L., et al. 2011. Impacts of landscape structure on surface urban heat islands: A case study of Shanghai, China. *Remote Sensing of Environment* 115,3249–3261.
- Lin, W., Yu, T., Chang, X., Wu, W., Zhang, Y., 2015. Calculating cooling extents of green parks using remote sensing: Method and test. *Landscape and Urban Planning*, 134: 66–75.
- Long, J.R.D., Kardol, P., Sundqvist, M.K., et al. 2015. Plant growth response to direct and indirect temperature effects varies by vegetation type and elevation in

- subarctic tundra. *Oikos* 124, 772–783.
- Mahboubi, P., Parkes, M., Stephen, C., et al. 2015. Using expert informed GIS to locate important marine social-ecological hotspots. *Journal of Environmental Management* 160, 342-352.
- Naidoo, G., Chirkoot, D., 2004. The effects of coal dust on photosynthetic performance of the mangrove, *Avicennia marina* in Richards Bay, South Africa. *Environmental Pollution* 127, 359-366.
- Norton, B. A., Coutts, A. M., Livesley, S. J., et al. 2015. Planning for cooler cities: A framework to prioritise green infrastructure to mitigate high temperatures in urban landscapes. *Landscape and Urban Planning* 134, 127–138.
- Ord, J.L., Getis, A., Local spatial autocorrelation statistics: distributional issues and an application. *Geographical Analysis* 27, 286-306.
- Peeters, A., Zude, M., Käthner, J., et al. 2015. Getis–Ord’s hot- and cold-spot statistics as a basis for multivariate spatial clustering of orchard tree data. *Computers and Electronics in Agriculture* 111, 140-150.
- Ren, Y., Deng, L., Zuo, S., et al. 2014. Geographical modeling of spatial interaction between human activity and forest connectivity in an urban landscape of southeast China. *Landscape Ecology* 29, 1741-1758.
- Salvati, L., Ranalli, F., Gitas, I., 2014. Landscape fragmentation and the agro-forest ecosystem along a rural-to-urban gradient: an exploratory study. *International Journal of Sustainable Development & World Ecology* 21, 160-167.
- Shoshany, M., Goldshlager, N., Kutiel, P., Grossman, D., 2005. Chapter 9. Man-Landscape Relationships in Mediterranean Areas: A Study of Landscape Changes in the Mount Carmel. In: *Recent Dynamics of the Mediterranean Vegetation and*

- Landscape. Wiley Online Library, pp. 95-104.
- <http://onlinelibrary.wiley.com/doi/10.1002/0470093714.ch9/summary>
- Tayyebi, A., Jenerette, GD., 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.
- Van Heerden, P.D.R., Kruger, G.H.J., Louw, M.K., 2007. Dynamic responses of photosystem II in the Namib Desert shrub, *Zygophyllum prismatocarpum*, during and after foliar deposition of limestone dust. *Environmental Pollution* 146, 34-45.
- Wang, JF., Hu, Y., 2012. Environmental health risk detection with GeogDetector. *Environmental Modelling & Software* 33, 114-115.
- Wang, J., Zhang, T., Fu, B., 2016. A measure of spatial stratified heterogeneity. *Ecological Indicators* 67,250-256.
- Weng, J. H., Lu, D., Schubring, J., 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment* 89,467–483.
- Yuan, F., Bauer, M. E., 2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment* 106,375–386.
- Zhao, J., Liu, X., Dong, R., 2015. Landsenses ecology and ecological planning towards sustainable development. *International Journal of Sustainable Development & World Ecology* doi.org/10.1080/13504509.2015.1119215.
- Zhao, S., Zhou, D., Liu S., 2016. Data concurrency is required for estimating urban heat island intensity. *Environmental Pollution* 208, 118–124.

Zhao, XF., Huang JC., Ye, H., et al. 2010. Spatiotemporal changes of the urban heat island of a coastal city in the context of urbanization. *International Journal of Sustainable Development & World Ecology* 17, 311-316.

Table 1.

Results of local Getis-OrdG_i^{*} analysis at ten thresholds identified as the total area, mean and minimum neighbors of hot and cool spots in 1996 and 2006.

Thresholds (m)	Areas of hot spots (ha)		Areas of cool spots (ha)		Mean neighbors(SD)		Minimum(Maximum neighbors)	
	1996	2006	1996	2006	1996	2006	1996	2006
500	8,870.04	11,881.41	11,881.41	12,881.96	41.978(27.584)	47.193(36.351)	3(365)	3(235)
1,000	17,599.47	25,951.14	28,186.95	23,942.72	149.661(80.072)	204.524(99.217)	3(519)	7(523)
1,500	20,524.81	29,866.34	32,819.41	30,415.74	254.553(129.622)	356.025(157.762)	3(600)	20(774)
2,000	22,769.57	34,534.36	34,604.52	33,018.32	382.614(182.799)	547.685(224.356)	5(677)	34(1,112)
2,500	23,588.30	36,598.21	36,049.18	35,282.95	526.422(236.714)	775.431(299.343)	9(1,477)	54(1,585)
3,000	24,237.71	37,189.53	36,930.76	37,006.52	691.892(296.344)	1,035.21(381.458)	29(1,836)	87(1,963)
3,500	25,440.14	38,469.53	37,889.81	38,229.78	874.477(351.539)	1,324.292(466.504)	118(2,097)	124(2,312)
4,000	23,640.97	37,763.26	37,450.60	36,539.46	900.711(362.085)	1,721.579(606.407)	154(2,352)	154(2,636)
4,500	23,533.87	36,272.65	36,990.06	35,537.83	990.783(398.295)	1,854.009(653.056)	179(2,925)	183(2,985)
5,000	23,365.79	36,178.55	34,405.84	34,905.91	1,060.138(426.177)	2,118.867(746.347)	211(3,028)	225(3,377)

Table 2

Global spatial autocorrelation statistics (Moran's I) of urban forest LST in 1996 and 2006

Year	1996	2006
Moran's Index	0.155**	0.273**
z-score	244.504	432.03
Pattern	Clustered	Clustered

Note: $P < 0.001$ in all regions in 1996 and 2006; ** represent significant values.

Table 3.

Degree of the influence of forest attributes, soil, topography, and population on urban forest LST in the entire city and three temperature regions

		ALL		HS		CS		NS	
		1996	2006	1996	2006	1996	2006	1996	2006
Forest Attributes	PA	0.050	0.141	0.020	0.085	0.004	0.015	0.001	0.029
	DS	0.106	0.171	0.042	0.099	0.063	0.070	0.067	0.125
	CD	0.068	0.072	0.033	0.064	0.030	0.036	0.066	0.095
Soil	SA	0.066	0.051	0.032	0.061	0.026	0.017	0.047	0.082
	SI	0.005	0.007	0.001	0.009	0.004	0.004	0.006	0.011
	SD	0.003	0.017	0.003	0.035	0.002	0.008	0.002	0.011
	HD	0.002	0.005	0.002	0.009	0.004	0.000	0.002	0.002
Topography	ELE	0.033	0.257	0.045	0.139	0.033	0.069	0.006	0.079
	SDe	0.008	0.175	0.021	0.129	0.012	0.025	0.005	0.076
	SPo	0.018	0.102	0.011	0.061	0.067	0.027	0.007	0.072
	SDi	0.007	0.103	0.009	0.075	0.012	0.023	0.007	0.060
Population	PD	0.003	0.029	0.005	0.007	0.005	0.069	0.003	0.007

Note: Abbreviations: PA is patch area, DS is dominant species, CD is canopy density, SA is stand age, SI,site index, SD,soil depth, HD, humus depth, ELE is elevation, SDe is slope degree, SPo is slope position, SDi is slope direction, SI is site index, and PD is population density.

Table 4.

Influence of interactions between population density and other ecological factors in hot spots, cool spots, and non-significant spots in 1996 and 2006.

	1996				2006			
	All	Hot Spot	Cool Spot	Non-significant Spot	All	Hot Spot	Cool Spot	Non-significant Spot
PA	0.061 *↗↗	0.036↗↗	0.021↗↗	0.010↗↗	0.201 *↗↗	0.106 *↗↗	0.083↑	0.066↗↗
DS	0.129↗↗	0.063↗↗	0.087↗↗	0.105↗↗	0.244↗↗	0.143↗↗	0.141↗↗	0.169↗↗
CD	0.077↗↗	0.048↗↗	0.038↗↗	0.105↗↗	0.118↗↗	0.082↗↗	0.105 *↗↗	0.117↗↗
SA	0.072 *↗↗	0.048↗↗	0.034↗↗	0.059↗↗	0.115*↗↗	0.083 *↗↗	0.086↗↗	0.109 *↗↗
SI	0.007↑	0.006↗↗	0.007↑	0.016↗↗	0.040 *↗↗	0.022↗↗	0.074 *↗↗	0.023↗↗
SD	0.006↗↗	0.008↗↗	0.006↗↗	0.013↗↗	0.056↗↗	0.046↗↗	0.081 *↗↗	0.025↗↗
HD	0.004↗↗	0.006↑	0.005↗↗	0.026↗↗	0.039↗↗	0.016↗↗	0.070 *↗↗	0.010↗↗
ELE	0.0428↗↗	0.009↗↗	0.016↗↗	0.015↗↗	0.294 *↗↗	0.155*↗↗	0.137↑	0.103 *↗↗
SDe	0.012↗↗	0.010↗↗	0.014↗↗	0.012↗↗	0.218↗↗	0.166 ↗↗	0.095 *↗↗	0.113↗↗
SPo	0.025↗↗	0.008↗↗	0.018↗↗	0.020↗↗	0.139↗↗	0.090↗↗	0.096 *↗↗	0.101↗↗
SDi	0.013↗↗	0.010↗↗	0.013↗↗	0.016↗↗	0.141↗↗	0.092↗↗	0.092 *↑	0.085↗↗

Note: q indicates strength of two-factor interactions (Wang et al., 2016). Factor A or B indicates any two factors in various ecological factors. * indicates a significant interaction. $\uparrow$ indicates factor A enhances factor B, i.e., $q(A \cap B) > q(A)$ and $q(A \cap B) > q(B)$. $\nearrow \nearrow$ indicates non-linear enhancement of factor A and factor B, i.e., $q(A \cap B) > q(A) + q(B)$. PA is patch area, DS is dominant species, CD is canopy density, SA is stand age, SI, site index, SD, soil depth, HD, humus depth, ELE is elevation, SDe is slope degree, SPo is slope position, SDi is slope direction, SI is site index, and PD is population density.

Figure Captions

- Fig. 1.** Schematic of the proposed methodology. Data were processed using ArcGIS10.0 and the GeogDetector model.
- Fig. 2.** Spatial distribution maps and local distribution histograms of different temperature regions obtained through local Getis-Ord G_i^* statistics at a threshold value of 3,500 m in 1996 and 2006. Red ($G_i \text{ Zscore} \geq 1.96$) = area of hot spots; blue ($G_i \text{ Zscore} \leq -1.96$) = area of cool-spots; grey ($-1.96 < G_i \text{ Zscore} < 1.96$) = area of non-significant spots; white = non-forest land.
- Fig. 3.** Comparison of urban forest stand structure ((a) relative LST; (b) patch area; (c) canopy density; (d) forest age; (e) dominant tree species) for each forest patch from 1996 to 2006. Boxplots for different relative LST, forest age and canopy density are shown, including the mean (black dot), median (black line), inter-quartile range (25%-75% in the box) and 5%-95% range (whiskers).
- Fig. 4.** Population density in different clustering regions classified with local Getis-Ord G_i^* statistics during two periods (a: 1996, b: 2006) and overlapping population and LST hot-spot and cool-spot areas (c: overlapping hot-spot areas in 1996; d: overlapping cool-spot areas in 1996; e: overlapping hot-spot areas in 2006; f: overlapping cool-spot areas in 2006).
- Fig. 5.** Degree of the influence of forest attributes, soil, topography, and population on urban forest LST in Xiamen City (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 slope degree, SPo slope position, SDi slope direction, PD population).

Fig. 6. Comparison chart of the interactions of the elevation and dominant species with other factors. The black axles divide the circle into 4 sectors, representing the interactive quantitative relationships of the dominant factors (elevation (red) and dominant species (blue)) in hot and cool spots in 1996 and 2006. The central black circle demonstrates the quantification---q value, q indicates strength of two-factor interactions; the inner and outer ring show the top 4 factors with the highest interactive q value. Yellow indicates a significant interaction. Factor A or B indicates any two factors in various ecological factors. Brown indicates factor A enhances factor B, i.e., $q(A \cap B) > q(A)$ and $q(A \cap B) > q(B)$; Other colors indicate non-linear enhancement of factor A and factor B, i.e., $q(A \cap B) > q(A) + q(B)$; PA is patch area, DS is dominant species, CD is canopy density, SA is stand age, SI, site index, SD, soil depth, HD, humus depth, ELE is elevation, SDe is slope degree, SPo is slope position, SDi is slope direction, SI is site index, and PD is population density.

Fig.1.

(a) 1996

(b) 2006

Fig. 2.

Fig. 3.

(a)1996

Fig. 4.

Fig. 5.

Fig. 6.

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Appendix A

Overview

Study area

Xiamen City is located in the southeast of China (117°53'—118°25'E and 24°25'—24°54' N) (Appendix D, Fig. 1)). Lying in the subtropical zone, Xiamen City has a subtropical monsoon climate with maritime climatic characteristics. The average annual temperature is 21°C, and the relative humidity is 76%. The annual average precipitation is ~1,100 mm, concentrated between May and August. The topography is mainly characterized by hills and terraces, and the forest soil mainly consists of latosol and red soil. With a total area of 165,036.3 ha, the city has developed an urban forest system with suburban forests, city parks, botanical gardens, and greenbelts. In 2015, there were $8,690 \times 10^4$ trees in the study area, with an average planting density of 526.6 ha⁻¹ and forest coverage of 45.60%.

Xiamen City experienced rapid development from 1996 to 2006. The urbanization ratio was greater than 50% in 2000 and reached 68.11% in 2005. After 2006, the increase in urban population slowed (Appendix D, Fig. 1).

Methods

Factors influencing urban forest LST in hot and cool spots were investigated with a set of hierarchical spatial statistical analyses. The analyses integrate the advantages of multiple disciplines and take ecological processes into account using multi-source observational data, and thus are widely applicable. The process included three main features. (1) The integration and fusion of multi-source spatial data (including remote sensing and ground survey data) with GIS. (2) According to spatial autocorrelation, the basic assumption of data independence used in traditional statistical methods was invalid. Spatial statistical methods were applied to analyze the spatial distributions, patterns, processes, and relationships, and the spatial information combined with classic statistical analyses were used to reveal the spatial relationships between location-dependent urban forest LST and its relationship with multiple ecological factors. (3) Interactions between human activities, multiple ecological factors, and urban forest LST were quantified.

The study combined remote sensing, ground surveys, and spatial statistical analyses. LST information generated from remote sensing images reflects differences between macrostructural and microstructural land surface features. The ground surveys provided spatial information on multiple ecological factors and human activities, and the information was used to evaluate the accuracy of the inversed temperature from remote sensing data. The spatial statistical analyses mainly included clustering region analysis and the GeogDetector model. A multi-source observational

database was established based on remote sensing and ground surveys to reveal the causes of LST spatial heterogeneity in urban forests.

Data source

The urban forest ground survey data were obtained from the forest management planning inventory (FMPI) of Xiamen City conducted in 1996 and 2006. The data include a forest resource distribution map, forest patch archives over the past years, and a 1:10,000 topographic map of the study area. The forest patch archives record information on multiple ecological factors of each forest patch (e.g., patch area, dominant species composition, forest age, canopy density, site quality of soil, soil thickness, humus depth, elevation, slope, slope aspect, and slope position). These ecological factors characterize the different properties of forest stands, soil, and terrain. The terms "key field" or "ID" were added to the database, and the attribute database was connected with the graphic database to realize the mutual query function. The area of each forest patch was roughly equal. Systematic sampling and stratified sampling were combined to determine the differences in forest stand growth. For the total stand volume, the sampling accuracy was 90% and the reliability was 95% (Lei et al., 2009). Reexamination was conducted every 10 years, and the main forest resource data and various land types in each forest patch were determined. The FMPI data from forest patches have been applied previously to evaluate biomass and net primary productivity (NPP) of planted forests in China (Zhao et al., 2010). The urban population density and distribution data, accurate to the street level, were obtained from the government census database.

The data used in this study include two TM Landsat_5 images in 1996 and 2006. The two TM images were obtained from the US geological survey (USGS) as Level-1 products, and were radiometrically and geometrically corrected. The images were

acquired at approximately 10:00 am local time under clear atmospheric conditions. The remote sensing images were precisely corrected to the UTM zone (50N) using the WGS-84 ellipsoid as a spatial reference. The multi-spectral bands were atmospherically corrected using the MODTRAN Radiation Transfer Model to eliminate the influences of atmospheric factors (e.g., water vapor, oxygen, carbon dioxide, methane, and ozone) and viewing angle. Because Xiamen is situated at low latitude region, we used the tropical mode of the atmospheric model to represent the characteristics of water vapor and surface air temperature in Xiamen. As Xiamen is a high-density urban industrial area, the urban mode was chosen for aerosol characteristics. Aerosol retrieval was conducted with the 2-Band (k-T) method (similar to the blur reduction method). The calculation is based on the proper black value, otherwise, the visibility is in the range of 40–100 km. Because the thermal infrared wavelength range of Landsat TM 5 is 10.40–12.50 μm , within which two atmospheric windows (3–5 μm and 8–14 μm) exist, it was not necessary to correct the thermal infrared band for atmospheric effects and the standard error was less than a pixel size of 0.5(Li et al, 2004).

Calculation of land surface temperature

(1) Calculation of spectral radiance

The emission DN data of the thermal infrared band 6 of Landsat 5 was converted into spectral radiance. The specific formula for the conversion process is as follows:

$$L_{\lambda} = \frac{(LMAX_{\lambda} - LMIN_{\lambda})}{(Q_{calmax} - Q_{calmin})} \times (Q_{cal} - Q_{calmin}) + LMIN_{\lambda}$$

where L_{λ} is the spectral radiance at the sensor's aperture [$\text{W}/(\text{m}^2\text{sr}\mu\text{m})$]; Q_{cal} is the quantized and calibrated standard product pixel value (DN); Q_{calmin} , the minimum quantized calibrated pixel value corresponding to $LMIN_{\lambda}$ (DN); Q_{calmax} the maximum

quantized calibrated pixel value corresponding to $LMAX_{\lambda}$ (DN); $LMIN_{\lambda}$ is the spectrum of the sensor $[W/(m^2sr\mu m)]$ and its scale is the same as $Q_{cal\min}$; and $LMAX_{\lambda}$ is the spectral luminance whose scale is the same as $Q_{cal\max}$ $[W/(m^2sr\mu m)]$.

(2) Atmospheric correction

The purpose of atmospheric correction is to eliminate the influence of illumination conditions, atmosphere, light, and other factors on the reflectance of surface features. We used the radiative transfer model of MODTRAN 4, with the tropic atmospheric model (based on geographical location and time) and the urban aerosol model (Guanter et al., 2009; Schott et al., 2012). Aerosol retrieval was achieved with the 2-Band (k-T) method (similar to the blur reduction method) based on the proper black value (the shadows or water) or a visibility range from 40 to 100 km.

(3) Calculation of brightness temperature

Assuming the earth surface is a black body (spectral radiant power = 1), the obtained spectral luminance can be converted into brightness temperature with the following formula:

$$T_b = \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}} + 1\right)}$$

where T_b is the effective brightness temperature; L_{λ} is the spectral radiance at the sensor's aperture $[W/(m^2 sr \mu m)]$; and K_1 and K_2 are pre-launch calibration constants.

For the Landsat 5 TM image, $K_1 = 607.76$ and $K_2 = 1,260.56$.

(4) Calculation of land surface emissivity

The conversion of spectral radiance into brightness temperature is achieved through two formulas:

$$\varepsilon = \varepsilon_v F_v + \varepsilon_u (1 - F_v) + d\varepsilon$$

where ε_v is the vegetation emissivity; ε_u is the urban surface emissivity; and F_v is the vegetation proportion of the empirical NDVI model based on Sobrino et al (2004). The vegetation coverage F_v derived from spectral mixture analysis. $d\varepsilon$, where F is a shape factor, whose mean value is 0.55, considering different geometrical distributions (Sobrino et al 1990).

Finally, the obtained brightness temperature (T_B) and ε are used to calculate the LST formula:

$$T_s = \frac{T_B}{1 + (\lambda \times \frac{T_B}{\alpha}) \ln \varepsilon}$$

where λ is the radiation wavelength (according to Markham and Barker (1985), λ is 11.5 μm) and $\alpha = hc/b$, in which b is the Boltzmann constant, h is the Planck constant, c is the speed of light, and ε is land surface emissivity.

(5) Calculation of urban forest land surface temperature

To compare urban cold island effects during different times, the LST data were first normalized. The normalization was achieved through the following formula:

$$\Delta T$$

where ΔT is the relative land surface temperature (K); LST is the land surface temperature of each pixel (K); and T_b is the background value of land surface temperature (K), which can be determined as the mean value of the LST of urban

construction land at a specific time. It's worth noting that the relationship between thermodynamic and Celsius temperature is $T(K) = 273.15 + t(^{\circ}C)$.

(6) Accuracy assessment

Many studies have confirmed that the temperature difference between LST generated from remote sensing images and air temperature obtained from meteorological stations decreases with increasing NDVI (normalized difference vegetation index) (Weng et al. 2004; Yuan et al. 2007). Thus, data measured at meteorological stations with known spatial locations was used for the urban forest LST test and a Pearson correlation analysis was conducted. We used the measured daily average air temperature data of 10 meteorological stations in Xiamen City to evaluate the accuracy of LST inversion (Appendix D, Fig 2). The Pearson correlation coefficient was used to evaluate the linear relationship between estimated LST and observed air temperature (Li et al. 2011). The results show that the estimated LST was correlated with observed air temperature (Pearson correlation coefficient was 0.848; $p < 0.01$).

Fusion of remote sensing data and FMPI data

FMPI data and Landsat remote sensing images have been combined in studies of stand disturbance, biomass monitoring, and spatial mapping (Stephens et al., 2012; Williams et al. 2014). For example, Williams et al. (2014) used forest inventory data and Landsat images to comprehensively evaluate stand disturbance and carbon accumulation after regrowth. However, integrated studies on urban forest LST have not yet been reported. Such studies are faced with two main challenges with respect to the combination of remote sensing imagery and ground survey data: 1) a lack of comparable vegetation indices and 2) difficulties integrating data with different spatial

scales (Deng et al. 2013). In particular, vegetation indices obtained by remote sensing image interpretation (e.g., NDVI) lack verified ecological and environmental significance (Myint et al. 2013). Problems related to the establishment of statistical relationships between LST and vegetation indices still exist (Schroeder et al. 2014). However, the remote sensing method is based on pixels, and LST values obtained from images represent the average value of a plane rather than the sample value. Due to the complexity of urban LST, limited observational data cannot accurately represent all the forest space at large spatial scales (e.g., regional scales). This leads to a mismatch between ground survey data and interpreted information from remote sensing images. Therefore, although the spatial patterns of remote sensing imagery and ground survey data are similar, the concatenation of data from the two different sources is not straightforward (Li et al. 2013). Kennedy et al. (2014) argued that natural and human processes affecting urban ecosystems can be quantified through a series of mathematical response functions; however, the traditional analysis method, which solely relies on remote sensing imagery fails to reveal such ecological processes. FMPI data provide forest ground survey data on a regional scale. The main forest resource data and the area of various land types in each forest patch are included, and the forest resource distribution map is also provided. The combination of remote sensing technology, GIS, and FMPI data provides a theoretical framework for understanding how human activities impact urban forest LST.

We first geometrically adjusted the forest inventory sample plot data and TM images using topographic maps of the study area. We then performed a mask operation and clipped the forest area from the TM images according to forest inventory data, which was collected during field investigations. We believe that this data represents the actual forest status at the corresponding survey time. During this

process, we mainly relied on the topographic map and texture properties of TM images (we sometimes used Google Earth to help confirm the land use at certain areas). Because we relied on TM images to identify the land use properties not of a single image cell but rather a relative large area, the spatial resolution of TM images is not a major challenge to our application. Some forest patches (3,246 of the total number 14,901 in 1996; 3,798 of the total number 14,944 in 2006) belong to mixed forest in FMPI. In order to quantify the effect of different mixed proportions of tree species on LST, we counted and compared the LST of different mixed proportions of tree species in FMPI. Appendix C, Table 2 lists the assignment status of the main mixed forest patch LST in FMPI.

Spatial statistical analysis: spatial autocorrelation

Based on urban forest patch area, we first show that spatial correlation is agglomerated using global Moran's I index. On this premise, we adopted the local Getis-Ord G_i^* statistic to identify agglomerated areas of hot spots (high values adjacent to other high values) and cool spots (low values adjacent to other low values) on a specific threshold-distance scale (3,500 m) of LST in urban forest patches. We established statistical relationships through position data and applied traditional statistical methods to the spatial data. The exploration of spatial relationships and spatial variation laws with statistical methods improves the determination of landscape heterogeneity in key areas of urban ecosystems. Information on hot and cool spots generated by local Getis-Ord G_i^* statistics can be used to guide future space monitoring and mapping, as well as provide field verification and accuracy assessments for large-scale aerial remote sensing methods. It is also of great significance for revealing the formation mechanism of LST hot spots in urban forests

and can guide appropriate intervention measures to rationalize resource distribution in forests and reduce LST.

Spatial autocorrelation negates the basic assumption of mutual independence used in traditional statistical methods. A large number of studies have confirmed that the attribute values of short spatial distances are usually more similar than those of long spatial distances, and almost all spatial data have spatial dependence or spatial autocorrelation. Therefore, spatial autocorrelation statistical indices have been used to study spatial distribution patterns in the fields of epidemiology, tree health, seaweed landscape, and orchard distribution (Barrell et al. 2013; Ahmad et al. 2015). These indices can be classified as global indices (e.g., Moran's I, Geary's C, and Global G) and local indices (e.g., Moran's I (or LISA) and Getis-Ord G_i^*). At present, few studies have applied the concept of spatial autocorrelation to the study of urban forest LST, and most studies use traditional statistical analyses (e.g., correlation analysis, regression analysis, and principal component analysis) to explore the relationships between urban forest LST and environmental factors.

The application of spatial autocorrelation statistical indices is based on the hypothesis of spatial stability of urban forest LST. That is, it is assumed that in a given urban area, an ecological process exists that continuously changes with the space weight matrix, and this process can be quantified using spatial autocorrelation statistical indices. Moran's I is a global measure of spatial autocorrelation, covering the entire space of all forest area units. It is the most commonly used index for spatial correlation. Although Moran's I can indicate whether an agglomeration state exists, it cannot distinguish the agglomeration of hot or cool spots. Based on a local threshold-distance scale, G statistics can be calculated to identify hot and cool spots of urban forest LST and differentiate their agglomeration states. However, Global G indices

can only show that hot and cool spots of urban forest LST exist; it cannot identify their specific positions. Therefore, a local index (Moran's I (or LISA) or Getis-Ord G_i^*) is needed to identify the specific spatial position of agglomeration. At present, a few studies have used the local Moran's I index to explore the effect of biological composition of agglomerated areas of urban heat islands on LST. However, the local Moran's index has no rigorous statistical testing standards, so it can easily be affected by local boundary elements (e.g., different observation units). Therefore, the local Moran's I index can be used to explore spatial outliers of forest patch LST or differences between forest patch LST. However, the obtained results cannot provide the specific spatial position of hot and cool spots. The local Getis-Ord G_i^* does not take adjacent boundaries into consideration, but only adopts distance measurement standards to identify the specific position of the regional agglomeration of hot and cool spots of urban forest LST on a specific distance scale. Potter et al. (2015) studied the spatial structural pattern of plant invasion, plant deaths caused by pests, and forest fire frequency in the United States from 2002 to 2013. They confirmed that using both the global Moran's I index and Local $G_i^*(d)$ index for identifying the position of hot- and cool-spot agglomeration is a rigorous detection method, as it allows users to test the statistical significance at a specific level.

Spatial statistical analysis: GeogDetector model

The GeogDetector model was used to explore various factors influencing urban forest LST and its determinants and interactions with delta values (Hu et al. 2011; Wang & Hu 2012). The GeogDetector model detects various factors that influence urban forest LST, the degree of influence of each factor, and the interactions between factors based on spatial analysis of variance (Wang and Hu, 2012). The model integrates the power of the determinant indicator, logical inference, and existing

geostatistical techniques (Wang et al., 2010). The GeogDetector model has been used to comprehensively analyze the processes that influence ecological forecasting. The GeogDetector model has obvious benefits over traditional models that only rely on a certain type of variable, thereby limiting data input. In contrast, the GeogDetector model processes both categorical and numeric variables, in addition to quantitative calculations. Furthermore, the GeogDetector model quantitatively expresses various types of interactions and directions among different variables. The GeogDetector model is a spatial heterogeneity hypothesis-based approach suitable for ecological study areas with strong spatial heterogeneity. Thus, the model may be applied to study the effects of multiple ecological factors and analyze differences in spatial heterogeneity. Influential ecological factors may be identified, and the interactions among these factors can be quantified.

Assuming human activities and certain ecological factors jointly influence urban forest LST, the temporal and spatial distribution pattern of LST is similar to that of the ecological factors and can be determined. The GeogDetector model is freely available from www.sssampling.org/geogdetector. The model is based on the consistency of variable spatial patterns. GeogDetector models have been successfully used to explore determinants and their interaction with neural tube defects (Wang et al. 2010), mortality in children under 5 years old, and fluoroquinolone residues in soil (Li et al. 2013). GeogDetector models mainly include a factor detector, ecological detector, and interaction detector. The factor detector is used to explore the impact of different factors on the research target; the ecological detector is used to explore the impacts of different levels of significance on those factors; and the interaction detector is used to explore the impacts of combinations of different impact factors on the research target.

(1) Factor detector

This detector quantifies the impact of a factor D on the observed spatial pattern of dIIC residues using PD , the dispersion variance ($\sigma_{D,p}^2$) of pooled data of the entire region, and the summation of stratified dispersion variance ($\sigma_{D,z}^2$). Therefore, the PD value of factor D can be expressed using Equations (1–3):

$$PD = 1 - \frac{\sigma_{D,p}^2}{\sigma_{D,z}^2} \quad (1)$$

$$\sigma_{D,p}^2 = \frac{1}{n_{D,p}} \sum_{p=1}^{n_{D,p}} (y_{D,p} - \bar{y}_D)^2 \quad (2)$$

$$\sigma_{D,z}^2 = \sum_{z=1}^L \frac{\Re_z}{\Re} \frac{1}{n_{z,p}} \sum_{p=1}^{n_{z,p}} (y_{z,p} - \bar{y}_z)^2 \quad (3)$$

where $\bar{y}_D$ and $\bar{y}_z$ refer to the average FQ s residues within the entire region with area $\hat{A}$ and a specific subregion with area $\hat{A}_z$ stratified by D , respectively.

(2) Interaction detector

This detector quantifies the combined effect of two risk factors C and D (e.g., by overlaying geographical layers C and D in GIS to form a new layer E). The attribute of layer E is determined as the combination of the attributes of layers C and D . With the PD values for the layers C , D , and E , the interaction detector can deal with the issue of whether two factors acting together have a stronger or weaker effect on dIIC residues than when acting separately.

(3) Ecological detector

This detector uses the F -value test to compare C and D and explore whether C is more significant than D in controlling the spatial pattern of the dIIC residues by comparing the PD values of C and D . If C is more likely than D to cause dIIC residues over space, one would expect the dispersion variance of C ($\sigma_{C,z}^2$) to be larger than that of D ($\sigma_{D,z}^2$). The relevant test is calculated using Equation (4):

$$F = \frac{n_{C,p}(n_{C,p} - 1)\sigma_{C,z}^2}{n_{D,p}(n_{D,p} - 1)\sigma_{D,z}^2} \quad (4)$$

where $n_{C,p}$ and $n_{D,p}$ denote the number of sample units p within coverage of C and D , respectively. This statistic is asymptotically distributed as $F(n_{C,p} - 1, n_{D,p} - 1)$ with $df = (n_{C,p}, n_{D,p})$. The null hypothesis is $H_0 : \sigma_{C,z}^2 = \sigma_{D,z}^2$. If H_0 is rejected conditionally on a significant level α (usually 5%), the effect of risk factor C on dIIC residues is significantly different from that of D .

Statistical analysis

Differences between hot and cold spots were examined using a t -test for two groups or one-way analysis of variance followed by multiple comparison tests when more than two groups were compared. When variances were homogeneous (Levene's test), we used Tukey's test, otherwise, the Games-Howell test was used. Pearson's correlation analysis was performed to assess the associations between variables. Statistical analyses were conducted with SPSS version 20.0 (SPSS Inc., Chicago, IL, USA).

Results

Spatial pattern of urban forest LST

Temporal and spatial distribution pattern of LST by local Getis-Ord G_i^ statistics*

According to global Moran's I, urban forest LST showed strong spatial autocorrelation and its spatial clustering increased from 1996 to 2006 (Table 2 in main text). We used ArcGIS 10.0 to analyze the temporal and spatial variations in the LST of each forest patch. We combined global Moran's I and the local Getis-Ord G_i^* index to obtain information on local spatial heterogeneity. Hot spots ($n = 5,565$ in 1996 and $n = 5,679$ in 2006), cool spots ($n = 6,635$ in 1996 and $n = 6,975$ in 2006), and non-clustering areas ($n = 2,701$ in 1996; $n = 2,290$ in 2006) were classified based on neighbor distance (3,500 m). Statistically significant hot and cool spots accounted for 82.461% of the total forest area and represented the largest differences in spatial clustering degree (Fig. 2 in main text). The results are described with respect to variation in clustering degree and identification of clustering position.

The z-score results in main text Table 2 showed that clustering degree in the study area in 2006 was more significant than that in 1996 (global Moran's I = 0.155, z-score = 244.504 in 1996; global Moran's I = 0.273, z-score = 432.030 in 2006). In 1996, cool spots were dominant (hot spots: 37.107%; cool spots: 55.265%; and non-clustering areas: 7.628%). However, in 2006, the areas of hot and cool spots were similar (hot spots: 43.089%; cool spots: 42.821%; and non-clustering areas: 14.090%). The transfer matrix results show the most obvious conversion occurred in the urban core and southern suburbs (Appendix C, Table. 1; Appendix D, Fig. 4). Hot spots (i.e., areas with significantly higher G_i^* values; $t = 832.751$, $df = 5,564$, $P < 0.01$ in 1996; $t = 1,235.590$, $df = 5,678$, $P < 0.01$ in 2006) were mainly distributed in the urban core and suburbs. In 1996 and 2006, hot spots accounted for 34.122% and 67.492% of the total urban core area and 35.716% and 50.935% of suburban areas, respectively. Cool spots (i.e., areas with significantly lower G_i^* values; $t = 1,168.181$,

df = 6,634, $P < 0.01$ in 1996; $t = 1,023.991$, df = 6,974, $P < 0.01$ in 2006) were mainly distributed in the suburbs and exurbs. In 1996 and 2006, their proportion in the suburban region was 39.741% and 34.079%, and that in the exurban region was 46.189% and 60.886%, respectively.

Temporal and spatial distribution of LST using local Getis-Ord G_i^ statistics*

After classification using local Getis-Ord G_i^* statistics, the average LST in cool spots (-0.050 in 1996; -0.080 in 2006) was significantly lower than that in hot spots (0.026 in 1996; 0.036 in 2006) and non-clustering areas (-0.018 in 1996; -0.040 in 2006) (Appendix D, Fig. 3). According to the coefficient of variation of the three temperature regions, both hot spots (0.107 in 1996; 0.117 in 2006) and cool spots (0.103 in 1996; 0.129 in 2006) showed an increasing trend. In 1996 and 2006, the areas with the most significant clustering of temperature were cool spots and hot spots, respectively.

Stand structure dynamics based on local Getis-Ord G_i^ statistics*

As shown in Appendix D, Fig. 4, the stand structure indices (e.g., forest patch area, average canopy density, and average forest age) significantly increased in corresponding hot spots, cool spots, and non-clustering areas from 1996 to 2006 ($P < 0.01$, independent-sample t-test). The stand structure indices of cool spots were significantly higher than those of hot spots and non-clustering areas. It is worth noting that each temperature region had a distinctive composition of tree species. For example, the dominant tree species in hot spots was *D. longan* (59.687% in 1996; 34.346% in 2006) and that in cool spots areas was *P. massoniana* (37.434% in 1996; 33.676% in 2006).

Discussion

Integrating research

Remote sensing imagery, FMPI, spatial statistical analysis, and GIS technology were integrated to reveal the influence of various ecological factors on urban forest LST. Numerous scholars have used remote sensing imagery, temperature and vegetation indices, energy balance models, and statistical analyses to characterize the spatial distribution of LST on a regional scale (Chen et al., 2006; Pelta et al., 2016). It is important to combine multiple methods for the quantitative evaluation of LST spatial heterogeneity. However, these studies characterized variations in forest area without reflecting changes in structure and function (Bagan et al., 2012). The lack of information on urban forest patches limits the quantification of LST spatial heterogeneity in urban forests and its causes (Kong et al., 2014). Some scholars have argued that analyses relying on remote sensing imagery alone suffer from a series of problems. For example, a study by Tooke et al. (2009) indicated that traditional remote sensing-based classification cannot explain mixed pixels. Specifically, the traditional method does not classify and quantify vegetation based on spectral reflectance characteristics. Moreover, it is difficult to characterize heterogeneity of urban forests on a local scale through single image pixels. Chen et al. (2006) confirmed that the field of view and illumination effects, in addition to geometric variability caused by intensification of high-resolution images, causes difficulty in extracting consistent vegetation information on different temporal and spatial scales. In addition, the accuracy of mapping and landscape patterns can also be impacted by resolution and classification errors. Myint et al. (2013) indicated that developing a multi-source database by coupling LST information from remote sensing images and corresponding urban forest information and unifying the scales of this information are the key steps to revealing the causes of LST heterogeneity.

FMPI can provide detailed information on forest patches (forest stand, soil, topography, etc.), which can be integrated with multiple ecological factors to measure the impacts of changes in forest patch structure on LST rather than just changes in forest area. The inventory can also help verify the accuracy of remote sensing interpretations and quantitative analyses (Ren et al., 2013). Using GIS technology, LST information from remote sensing images and attribute information from FMPI can be integrated to form urban forest spatial data on a unified scale. The spatial statistical analysis of hot and cool spots can reveal the joint influence of human activity and multiple ecological factors on urban forest LST, as well as the temporal and spatial heterogeneity of urban forest landscapes. Therefore, although the fusion of multi-source data may lead to uncertainty, it can be significantly reduced through calibrating the size and format of multi-source data and accuracy assessments (Li et al., 2011). The integration of remote sensing methods, FMPI data, and spatial statistical analysis can elucidate how the cold island effect is formed in specific urban forest areas, thereby providing a theoretical basis for the accurate prediction of the temporal and spatial evolution of urban forest LST through the integration of multiple ecological processes.

4.2. Spatial statistical analysis integrating global Moran's I and local $G_i^(d)$ index*

Urban forest LST showed strong spatial autocorrelation and an increasing spatial clustering trend. This corroborates the results of Zheng et al.'s study (2014) on the location of hot and cool spots of urban LST. This indicates that the degree of spatial heterogeneity of urban forest LST increases during urbanization. Increasing human activities, such as the acceleration of urbanization and large-scale population migration from rural to urban areas, change the composition and spatial patterns of

urban forests. Such disturbances are continuous and longstanding. The diverse, complex, and nonlinear interactions between ecological factors (e.g., soil and topography) and human activity also increase spatial heterogeneity of urban forests. A large number of studies have explained the relationships between urban forest LST and the spatial composition and configuration of forest patches, but few have used the spatial relationship between urban forest LST and forest patches to reveal spatial heterogeneity (Buyantuyev and Wu, 2010; Zhou et al., 2014). Although some scholars have used global Moran's I index to analyze the spatial distribution of urban forest LST over a single period, studies that discuss changes in this index over different periods based on ecological LST processes are scarce (Ahmad et al., 2015). Kennedy et al. (2014) found that the understanding of the driving forces of specific research objects in a number of studies based on remote sensing imagery is limited by incomplete knowledge of ecological processes.

In 1996 and 2006, urban forest LST hot spots were mainly distributed in the urban core and suburban areas, whereas cool spots were located in exurban areas. The hot and cool spots of population and urban forest LST showed similar spatial distribution patterns. This indicates that the spatial distribution of hot and cool spots is closely related to human activities. In densely populated areas of the urban core and suburban areas, anthropogenic heat emissions continue to increase with urbanization. Moreover, land-use/cover change caused by human activities destroys surface vegetation; the increase in developed land and decrease in cultivated land cause a higher degree of forest landscape fragmentation, constant reduction of forest areas, and degradation of forest structure (Josefsson et al., 2009). In sparsely populated exurban areas, abundant human effort and materials have been put towards afforestation to increase the quality of urban forest stands and forest coverage. In

addition, the influence of human activities on urban forests is related to geographic location. Forests with convenient traffic and flat topography in the urban core and suburban areas are significantly influenced by human activities. Deforestation and quarrying are also concentrated in these areas, causing the conversion of large areas of forest land into developed land. Comparatively, the influence of human activities on high-elevation exurban areas is slight due to inconvenient access (Kounatidis et al., 2008).

Under the neighbor distance threshold (3,500 m), the area of urban forest LST hot spots increased by 5.982% after 10 years of urbanization, whereas that of cool spots decreased by 12.444%. This indicates that spatial heterogeneity increased with increasing spatial clustering of urban forests. Moreover, the range in which high LST values were surrounded by high values expanded, whereas the range in which low values were surrounded by low values decreased. Not all types of urban forests can effectively alleviate the urban heat island effect. Studies have confirmed that there are many types of forest distribution patterns (e.g., hot spots, cool spots, non-significant spots, and random distribution) in urban forests with high spatial heterogeneity, and the distribution property varies with direction (Nelson et al., 2008; Ivajnsiĉ et al., 2014). However, previous studies on the spatial distribution pattern of forest hot spots based on the local $G_i^*(d)$ index have mostly focused on the competition, death, carbon accumulation, and disturbance of forest stands. No previous reports on urban forest LST hot spots exist (Ahmad et al., 2015). Thus, determining the specific position of hot and cool spots of urban forest LST with the local $G_i^*(d)$ spatial statistical analysis is a key step to understanding the occurrence of atypical spatial patterns. Based on the results and the GeogDetector model, we can clarify the spatial patterns of interactions

between human activities, urban forest LST, and multiple ecological factors in hot and cool spots.

Appendix B

References

- Bagan, H., Yamagata, Y., 2012. Landsat analysis of urban growth: How Tokyo became the world's largest megacity during the last 40 years. *Remote Sensing of Environment* 127, 210–222.
- Deng, C. B., Wu, C., 2013. Examining the impacts of urban biophysical compositions on surface urban heat island: A spectral unmixing and thermal mixing approach. *Remote Sensing of Environment* 131, 262–274.
- Guanter, L., Richter, R., Kaufmann, H., 2009. On the application of the MODTRAN4 atmospheric radiative transfer code to optical remote sensing. *International Journal of Remote Sensing* 30, 1407–1424.
- Hilker, T., Wulder, M. A., Coops, N.C., 2009. A new data fusion model for high spatial- and temporal-resolution mapping of forest disturbance based on Landsat and MODIS. *Remote Sensing of Environment* 113, 1613–1627.
- Kennedy, R.E., Andréfouët, S., Cohen, W.B., et al. 2014. Bringing an ecological view of change to Landsat-based remote sensing. *Frontiers in Ecology and the Environment* 12, 339–346.
- Kounatidis, I., Papadopoulos, N. T., Mavragani-Tsipidou, P., et al. 2008. Effect of elevation on spatio- temporal patterns of olive fly (*Bactrocera oleae*) populations in northern Greece. *Journal of Applied Entomology* 132, 722–733.

- Li, FQ., Jackson, TJ., Kustas, WP., et al. 2004. Deriving land surface temperature from Landsat 5 and 7 during SMEX02/SMACEX. *Remote Sensing of Environment* 92, 521–534.
- Li, X., Xie, Y., Wang, J., et al. 2013. Influence of planting pattern on fluoroquinolone residues in the soil of an intensive vegetable cultivation area in northern China. *Science of the Total Environment*, 458, 63-69.
- Markham, B. L., Barker, J. L., et al. 1985. Spectral characterization of the Landsat Thematic Mapper sensors. *International Journal of Remote Sensing* 6,697-716.
- Myint, S. W., Wentz, E. A., Brazel, A. J., et al. 2013. The impact of distinct anthropogenic and vegetation features on urban warming. *Landscape Ecology* 28, 959-978.
- Nelson, T. A., Barry, B., 2008. Detecting spatial hot spots in landscape ecology. *Ecography* 31,556-566.
- Pelta, R., Chudnovsky A. A., Schwartz J., 2016. Spatio-temporal behavior of brightness temperature in Tel-Aviv and its application to air temperature monitoring. *Environmental Pollution* 208, 153–160.
- Potter, K. M., Koch, F. H., Oswalt, C. M., et al. 2015. Data, data everywhere: detecting spatial patterns in fine-scale ecological information collected across a continent. *Landscape Ecology*,1-18.
- Ren, Y., Wei, X., Wang, D., et al. 2013. Linking landscape patterns with ecological functions: A case study examining the interaction between landscape heterogeneity and carbon stock of urban forests in Xiamen, China. *Forest Ecology & Management* 293, 122–131.

- Schott, J.R., Hook, S.J., Barsi, J.A., et al. 2012. Thermal infrared radiometric calibration of the entire Landsat 4, 5, and 7 archive (1982–2010). *Remote Sensing of Environment* 122, 41–49.
- Schroeder, T. A., Healey, S. P., Moisen, G. G., et al. 2014. Improving estimates of forest disturbance by combining observations from Landsat time series with U.S. Forest Service Forest Inventory and Analysis data. *Remote Sensing of Environment* 154, 61–73.
- Sobrino, J. A., Jiménez-Muñoz, J. C., Paolini, L. 2004. Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of Environment* 90, 434–440.
- Sobrino, J. A., Caselles, V., Becker, F. 1990. Significance of the remotely sensed thermal infrared measurements obtained over a citrus orchard. *ISPRS Journal of Photogrammetry and Remote Sensing*, 44, 343–354.
- Stephens, P.R., Kimberley, M.O., Beets, P.N., et al. 2012. Airborne scanning LiDAR in a double sampling forest carbon inventory. *Remote Sensing of Environment* 117, 348–357.
- Styers, D. M., Chappelka, A. H., Marzen, L. J., 2010. Scale matters: Indicators of ecological health along the urban–rural interface near Columbus, Georgia. *Ecological Indicators* 10, 224–233.
- Tooke, T. R., Coops, N. C., Goodwin, N. R., et al. 2009. Extracting urban vegetation characteristics using spectral mixture analysis and decision tree classifications. *Remote Sensing of Environment* 113, 389–407.
- Wang, J., Li, X., Christakos, G., et al. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. *International Journal of Geographical Information Science*, 24, 107–12.

- Weng, J. H., Lu, D., Schubring, J., 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment* 89,467–483.
- Williams, C.A., Collatz, G.J., Masek, J., et al. 2014. Impacts of disturbance history on forest carbon stocks and fluxes: Merging satellite disturbance mapping with forest inventory data in a carbon cycle model framework. *Remote Sensing of Environment* 151, 57-71.
- Wulder, M. A., White, J. C., Coops, N. C., 2008. Multi-Temporal Analysis of High Spatial Resolution Imagery for Disturbance Monitoring. *Remote Sensing of Environment* 112,2729-2740.
- Yuan, F., Bauer, M. E.,2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment* 106,375–386.
- Zhao, M. Kong, Z. H., Escobedo, F. J. ,2010.Impacts of urban forests on offsetting carbon emissions from industrial energy use in Hangzhou, China. *Journal of Environmental Management* 91, 807–813.
- Zheng, S., Myint, S. W., Fan,C.,2014. Spatial configuration of anthropogenic land cover impacts on urban warming *Landscape and Urban Planning* 130, 104-111.
- Zhou, W., Qian, Y., Li, X., et al. 2014.Relationships between land cover and the surface urban heat island: seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. *Landscape Ecology* 29, 153-167.

Appendix C

Table 1.

Areas of forest transfer (1996-2006) among clustering regions (hot spots, cool spots, non-significant spots) in the entire city and different urbanization gradients. A total of 71,130.310 ha (41.300% of the study area) of forest underwent conversion between hot-spot, cool-spot, and non-clustering areas.

Parts	Areas of total changed (1996-2006)								
	HS to CS(ha)	CS to HS(ha)	Ratio	HS to NS(ha)	NS to HS(ha)	Ratio	CS to NS(ha)	NS to CS(ha)	Ratio
Whole city	1,355.805	1,838.145	0.738	3,117.420	3,729.195	0.836	6,732.225	6,084.555	1.106
Urban core	N/A	362.655	N/A	N/A	578.235	N/A	1,373.415	N/A	N/A
Suburb	N/A	1,001.685	N/A	24.705	2,240.745	0.011	4,017.480	N/A	N/A
Exurb	1,355.805	473.805	2.862	3,092.715	910.215	3.398	1,341.315	6,084.555	0.220

Note: HS hot spot, CS cool spot, NS non-significant spots.

Table 2.

Comparison of relative LST between different mixed proportions within mature forest types.

A. 1996

Tree species	Regions	Proportions (Percent)							
		Pure Stand	90%	80%	70%	60%	50%	40%	10%
DL	All	0.022	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	HS	0.037	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CS	-0.024	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	NS	0.003	N/A	N/A	N/A	N/A	N/A	N/A	N/A
PM	All	-0.030	0.004	-0.035	-0.034	-0.042	-0.046	-0.004	0.002
	HS	0.009	0.020	0.012	0.012	0.017	0.024	0.034	-0.031
	CS	-0.052	N/A	-0.042	-0.057	-0.052	-0.063	-0.076	N/A
	NS	-0.024	-0.012	-0.033	-0.032	-0.034	-0.034	-0.012	0.035
AC	All	-0.020	-0.018	-0.025	-0.038	-0.018	-0.022	-0.031	N/A
	HS	-0.008	-0.004	-0.022	0.003	-0.005	-0.028	-0.043	N/A
	CS	-0.055	-0.061	-0.074	-0.162	-0.105	-0.059	N/A	N/A
	NS	-0.024	-0.026	-0.013	-0.022	-0.017	-0.002	-0.01	N/A
PE	All	-0.035	-0.051	-0.044	-0.023	-0.025	-0.020	-0.053	N/A
	HS	0.037	0.018	0.013	0.014	0.082	0.045	N/A	N/A
	CS	-0.039	-0.056	-0.046	-0.028	-0.039	-0.028	-0.03	N/A
	NS	-0.027	0.017	-0.018	0.005	0.015	0.015	-0.072	N/A
CL	All	-0.052	-0.034	-0.030	-0.032	-0.018	-0.025	-0.060	0.009
	HS	-0.009	N/A	N/A	N/A	0.009	-0.046	-0.009	N/A
	CS	-0.056	-0.035	-0.034	-0.037	-0.025	-0.029	-0.047	N/A
	NS	-0.015	-0.024	-0.018	-0.013	0.003	-0.005	-0.067	0.009

B. 2006

Regions	Proportions (Percent)
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		Pure Stand	90%	80%	70%	60%	50%	40%	10%
DL	All	0.017	N/A	N/A	N/A	0.063	0.080	N/A	N/A
	HS	0.051	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CS	0.009	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	NS	0.017	N/A	N/A	N/A	0.063	0.080	N/A	N/A
PM	All	-0.061	-0.040	-0.061	-0.079	-0.050	-0.058	-0.041	-0.063
	HS	0.013	N/A	-0.026	N/A	N/A	N/A	N/A	N/A
	CS	-0.044	N/A	-0.175	N/A	N/A	N/A	N/A	N/A
	NS	-0.057	-0.040	-0.052	-0.079	-0.050	-0.058	-0.041	-0.063
AC	All	-0.025	-0.030	-0.016	-0.028	-0.015	-0.034	-0.010	-0.063
	HS	0.020	0.078	N/A	N/A	N/A	N/A	N/A	N/A
	CS	0.084	-0.018	N/A	N/A	N/A	N/A	N/A	N/A
	NS	-0.025	-0.031	-0.016	-0.028	-0.015	-0.034	-0.010	-0.063
PE	All	-0.087	-0.076	-0.104	-0.068	-0.076	-0.075	-0.061	-0.096
	HS	-0.076	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CS	-0.107	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	NS	-0.078	-0.076	-0.104	-0.068	-0.076	-0.075	-0.061	-0.096
CL	All	-0.092	-0.086	-0.088	-0.092	-0.222	-0.100	-0.100	N/A
	HS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	CS	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	NS	-0.092	-0.086	-0.086	-0.092	-0.222	-0.100	-0.100	N/A

Note DL, *D. longan*, PM *P. massoniana*, AC *A. confuse*, PE *P. elliotii*, CL *C. lanceolata*. HS hot spot, CS cool spot, NS non-significant spots.

Table 3.

Interactions between ecological factors in areas of hot spots, cool spots, and non-significant spots in 1996 and 2006.

Factors	Years	Regions	PA	DS	CD	SA	SI	SD	HD	ELE	SDe	SPo	SDi	PD
PA	1996	All		0.132*↑	0.103↑	0.096↑	0.055↗↗	0.054↗↗	0.055↗↗	0.094↗↗	0.077↗↗	0.079↗↗	0.070↗↗	0.061↗↗
		Hot Spots		0.071↗↗	0.054↗↗	0.051↑	0.025↗↗	0.025↗↗	0.024↗↗	0.076↗↗	0.055↗↗	0.045↗↗	0.040↗↗	0.022↑
		Cool Spots		0.084*↗↗	0.043↗↗	0.040↗↗	0.011↗↗	0.014↗↗	0.027↗↗	0.087↗↗	0.063↗↗	0.089*↗↗	0.051↗↗	0.012↗↗
		Non-significant Spots		0.087*↗↗	0.082*↗↗	0.060↗↗	0.012↗↗	0.007↗↗	0.004↗↗	0.012↗↗	0.013↗↗	0.012↗↗	0.016↗↗	0.007↗↗
	2006	All		0.254↑	0.200*↑	0.181*↗↗	0.150*↗↗	0.150*↑	0.143*↑	0.268*↑	0.207↑	0.190*↑	0.179*↑	0.201*↗↗
		Hot Spots		0.188↗↗	0.146↑	0.140↗↗	0.096*↗↗	0.108*↑	0.091*↑	0.158↑	0.157↑	0.130↑	0.140↑	0.106*↗↗
		Cool Spots		0.117↗↗	0.079↗↗	0.037↗↗	0.025↗↗	0.028↗↗	0.016↗↗	0.087↗↗	0.046↗↗	0.047↗↗	0.042↗↗	0.083↑
		Non-significant Spots		0.203↗↗	0.163↗↗	0.180↗↗	0.048↗↗	0.040↑	0.032↗↗	0.092↑	0.103↑	0.087↑	0.127↗↗	0.066↗↗
DS	1996	All	0.132'↗↗		0.140↑	0.125↑	0.118'↗↗	0.119↗↗	0.115↗↗	0.175↗↗	0.147↗↗	0.167↗↗	0.148↗↗	0.129↗↗
		Hot Spots	0.071↗↗		0.054↗↗	0.051↑	0.025↗↗	0.025↗↗	0.024↗↗	0.076↗↗	0.055↗↗	0.045↗↗	0.040↗↗	0.022↗↗
		Cool Spots	0.084'↗↗		0.111↗↗	0.092↗↗	0.083↗↗	0.111↗↗	0.099↗↗	0.209↗↗	0.145↗↗	0.258↗↗	0.183↗↗	0.082↗↗
		Non-significant Spots	0.087'↗↗		0.148↗↗	0.119↗↗	0.090↗↗	0.083↗↗	0.071↗↗	0.114↗↗	0.101↗↗	0.149↗↗	0.134↗↗	0.087↗↗
	2006	All	0.254↑		0.207↗↗	0.190↑	0.187↗↗	0.181↑	0.177↗↗	0.300*↑	0.245↗↗	0.238↑	0.260↑	0.244↑
		Hot Spots	0.188↗↗		0.196↗↗	0.129↑	0.128↗↗	0.128↑	0.109↗↗	0.185*↑	0.176↑	0.173↗↗	0.215↗↗	0.143↗↗
		Cool Spots	0.117↗↗		0.122↗↗	0.082↑	0.078↗↗	0.076↑	0.071↗↗	0.131↑	0.088↑	0.099↗↗	0.133↗↗	0.141↗↗
		Non-significant Spots	0.203↗↗		0.190↑	0.170↑	0.143↗↗	0.141↗↗	0.130↗↗	0.208↗↗	0.202↗↗	0.223↗↗	0.233↗↗	0.169↗↗
CD	1996	All	0.103↑	0.140↑		0.076↑	0.076*	0.074↗↗	0.071↗↗	0.110↗↗	0.086↗↗	0.101↗↗	0.086↗↗	0.077↗↗
		Hot Spots	0.054↗↗	0.088↗↗		0.049↑	0.040↗↗	0.043↗↗	0.040↗↗	0.100↗↗	0.074↗↗	0.057↗↗	0.065↗↗	0.042↗↗
		Cool Spots	0.043↗↗	0.111↗↗		0.040↗↗	0.034↗↗	0.050↗↗	0.050↗↗	0.096↗↗	0.065↗↗	0.137*↗↗	0.072↗↗	0.035↗↗
		Non-significant Spots	0.082*	0.148↗↗		0.088↑	0.077↗↗	0.073↗↗	0.068↗↗	0.075↗↗	0.092↗↗	0.084↗↗	0.104↗↗	0.086↗↗
	2006	All	0.200*↑	0.207↑		0.093↑	0.091↗↗	0.090↗↗	0.076↑	0.293*↑	0.210*↑	0.179*↗↗	0.170*↑	0.118↗↗

SA	1996	Hot Spots	0.146↑	0.196↗↗		0.141↗↗	0.084↗↗	0.087↑	0.073↑	0.170*↑	0.161*↑	0.130↗↗	0.157↗↗	0.082↗↗
		Cool Spots	0.079↗↗	0.122↗↗		0.059↗↗	0.047↗↗	0.054↗↗	0.036↗↗	0.142*	0.073↗↗	0.104↗↗	0.073↗↗	0.105*
		Non-significant Spots	0.163↗↗	0.190↑		0.117↑	0.113↗↗	0.102↑	0.097↗↗	0.200↗↗	0.212↗↗	0.237↗↗	0.191↗↗	0.117↗↗
		All	0.096↑	0.125↑	0.076↑		0.074*↗↗	0.071↗↗	0.071↗↗	0.108↗↗	0.085↗↗	0.095↗↗	0.083↗↗	0.074*↗↗
	2006	Hot Spots	0.051↑	0.058↑	0.049↑		0.038↗↗	0.057↗↗	0.055↗↗	0.110*↗↗	0.089↗↗	0.071↗↗	0.076↗↗	0.041↗↗
		Cool Spots	0.040↗↗	0.092↗↗	0.040↑		0.030↑	0.034↗↗	0.046↗↗	0.096↗↗	0.056↗↗	0.123*	0.063↗↗	0.032↗↗
		Non-significant Spots	0.060↗↗	0.119↗↗	0.088↑		0.059↗↗	0.052↗↗	0.049↗↗	0.057↗↗	0.059↗↗	0.057↗↗	0.066↗↗	0.057↗↗
		All	0.181↗↗	0.190↗↗	0.093↗↗		0.069↗↗	0.072↗↗	0.057↗↗	0.274↗↗	0.199↗↗	0.151↗↗	0.147↗↗	0.115↗↗
	1996	Hot Spots	0.14↑	0.129↑	0.141↗↗		0.077*	0.083↑	0.070*↑	0.167↑	0.158↑	0.120↑	0.142↗↗	0.083*
		Cool Spots	0.037↗↗	0.082↑	0.059↗↗		0.023↗↗	0.028↗↗	0.017↗↗	0.085↑	0.047↗↗	0.053↗↗	0.044↗↗	0.086↗↗
		Non-significant Spots	0.180↗↗	0.170↑	0.117↑		0.095*	0.089*↑	0.084*↑	0.211↗↗	0.200↗↗	0.258↗↗	0.166↗↗	0.109*
		All	0.055↑	0.118*	0.076*↗↗	0.074*↗↗		0.008↗↗	0.006↑	0.044*↗↗	0.085↗↗	0.025↗↗	0.013↗↗	0.007↗↗
	2006	Hot Spots	0.025↗↗	0.052↗↗	0.040↗↗	0.038↗↗		0.005↗↗	0.004↗↗	0.056*↗↗	0.089↗↗	0.015↗↗	0.016↗↗	0.007↗↗
		Cool Spots	0.011↗↗	0.083↗↗	0.034↗↗	0.030↑		0.007↗↗	0.009↗↗	0.040↗↗	0.056↗↗	0.085*	0.021↗↗	0.008↑
		Non-significant Spots	0.012↗↗	0.090↗↗	0.077↗↗	0.059↗↗		0.008↗↗	0.008↗↗	0.017↗↗	0.059↗↗	0.015↗↗	0.027↗↗	0.019
		All	0.150*↗↗	0.187↗↗	0.091↗↗	0.069*↗↗		0.020↑	0.013↗↗	0.261*↑	0.180↑	0.121↗↗	0.108↑	0.040*↗↗
1996	Hot Spots	0.096*↗↗	0.128↗↗	0.084↗↗	0.077*↗↗		0.042↑	0.016↑	0.152*	0.138↗↗	0.082↗↗	0.082↑	0.022↗↗	
	Cool Spots	0.025↗↗	0.078↗↗	0.047↗↗	0.023↗↗		0.011↑	0.005↗↗	0.071*↑	0.028↑	0.031↗↗	0.030↗↗	0.074*	
	Non-significant Spots	0.048↗↗	0.143↗↗	0.113↗↗	0.095*		0.017↑	0.012↑	0.092*↗↗	0.087↗↗	0.078↑	0.098↗↗	0.023↗↗	
	All	0.054↗↗	0.119↗↗	0.074↗↗	0.071↗↗	0.008↗↗		0.008↗↗	0.035*↗↗	0.012↗↗	0.020↑	0.011↗↗	0.006↗↗	
2006	Hot Spots	0.025↗↗	0.053↗↗	0.043↗↗	0.057↗↗	0.005↗↗		0.003↗↗	0.048*↗↗	0.024↗↗	0.014↗↗	0.013↗↗	0.009↗↗	
	Cool Spots	0.014↗↗	0.111↗↗	0.05↗↗	0.034↗↗	0.007↗↗		0.019↗↗	0.039↗↗	0.016↗↗	0.090*	0.021↗↗	0.008↗↗	
	Non-significant Spots	0.007↗↗	0.083↗↗	0.073↗↗	0.052↗↗	0.008↗↗		0.002↑	0.007↗↗	0.014↗↗	0.009↗↗	0.013↑	0.010↗↗	
	All	0.150*↑	0.181↑	0.09↗↗	0.072*↗↗	0.020↑		0.022↗↗	0.261↑	0.179↑	0.112↑	0.113↑	0.056*	

		2006												
		2006				2006				2006				
		Hot Spots	Cool Spots	Non-significant Spots	All	Hot Spots	Cool Spots	Non-significant Spots	All	Hot Spots	Cool Spots	Non-significant Spots	All	
SPo	1996	Hot Spots	0.157↑	0.176↑	0.161*↑	0.158↗↗	0.138↑	0.132↑	0.132↑	0.161*↑		0.141↑	0.159↑	0.166↗↗
		Cool Spots	0.046↗↗	0.088↑	0.073↗↗	0.047↗↗	0.028↑	0.025↑	0.025↑	0.081*↑		0.05↑	0.046↑	0.095*↗↗
		Non-significant Spots	0.103↑	0.202↗↗	0.212↗↗	0.200↗↗	0.087↗↗	0.077↑	0.077↑	0.101↑		0.102↑	0.154↗↗	0.113↗↗
		All	0.079↗↗	0.167↗↗	0.101↗↗	0.095↗↗	0.025↗↗	0.020↑	0.019↑	0.050↑	0.025↑		0.036↗↗	0.025↗↗
	2006	Hot Spots	0.045↗↗	0.093↗↗	0.057↗↗	0.071↗↗	0.015↗↗	0.014↗↗	0.011↑	0.065↗↗	0.030↗↗		0.037↗↗	0.028↗↗
		Cool Spots	0.089*↗↗	0.258↗↗	0.137*↗↗	0.123*↗↗	0.085*↗↗	0.090*↗↗	0.067*↑	0.086*↑	0.101*↗↗		0.092↗↗	0.089*
		Non-significant Spots	0.012↗↗	0.149↗↗	0.084↗↗	0.057↗↗	0.015↗↗	0.009↑	0.007↑	0.016↗↗	0.015↗↗		0.020↗↗	0.014↗↗
		All	0.190*↑	0.238↑	0.179*↗↗	0.151↑	0.121↗↗	0.105↑	0.105↑	0.263*↑	0.198↑		0.147↑	0.139↗↗
	1996	Hot Spots	0.130↑	0.173↗↗	0.130↗↗	0.120↑	0.082↗↗	0.066↑	0.066↑	0.152*↑	0.141↑		0.102↑	0.09↗↗
		Cool Spots	0.047↗↗	0.099↗↗	0.104↗↗	0.053↗↗	0.031*↗↗	0.028↑	0.028↗↗	0.080*↑	0.050↗↗		0.057↗↗	0.096↗↗
		Non-significant Spots	0.087↑	0.223↗↗	0.237↗↗	0.258↗↗	0.078↑	0.077↑	0.077↗↗	0.106↑	0.102↑		0.215↗↗	0.101↗↗
		All	0.070↗↗	0.148↗↗	0.086↗↗	0.083↗↗	0.013↗↗	0.011↗↗	0.012↑	0.057↗↗	0.030↗↗	0.036↗↗		0.013↗↗
SDi	1996	Hot Spots	0.040↗↗	0.107↗↗	0.065↗↗	0.076↗↗	0.016↗↗	0.013↗↗	0.010↗↗	0.096↗↗	0.065↗↗	0.037↗↗		0.016↗↗
		Cool Spots	0.051↗↗	0.183↗↗	0.072↗↗	0.063↗↗	0.021↗↗	0.021↗↗	0.026↑	0.071↗↗	0.065↗↗	0.092↗↗		0.018↗↗
		Non-significant Spots	0.016↗↗	0.134↗↗	0.104↗↗	0.066↗↗	0.027↗↗	0.013↗↗	0.007↗↗	0.023↗↗	0.024↗↗	0.020↗↗		0.015↗↗
		All	0.179*↑	0.260↑	0.170*↑	0.147↑	0.108↑	0.105↑	0.105↑	0.275*↑	0.193↑	0.147↑		0.141↗↗
	2006	Hot Spots	0.140↑	0.215↗↗	0.157↗↗	0.142↗↗	0.082↑	0.079↑	0.079↑	0.163*↑	0.159↑	0.102↑		0.092↗↗
		Cool Spots	0.042↗↗	0.133↗↗	0.073*	0.044↗↗	0.030*	0.024*↗↗	0.024*↗↗	0.093↗↗	0.046*↑	0.057*↗↗		0.092*↑
		Non-significant Spots	0.127↗↗	0.233↗↗	0.191↗↗	0.166↗↗	0.098↗↗	0.064↑	0.064↗↗	0.161↗↗	0.154↗↗	0.215↗↗		0.085↗↗
		All	0.061 *↗↗	0.129↗↗	0.077↗↗	0.072 *↗↗	0.007↑	0.006↗↗	0.004↗↗	0.0428↗↗	0.012↗↗	0.025↗↗	0.013↗↗	
	1996	Hot Spots	0.036↗↗	0.063↗↗	0.048↗↗	0.048↗↗	0.006↗↗	0.008↗↗	0.006↑	0.009↗↗	0.010↗↗	0.008↗↗	0.010↗↗	
		Cool Spots	0.021↗↗	0.087↗↗	0.038↗↗	0.034↗↗	0.007↑	0.006↗↗	0.005↗↗	0.016↗↗	0.014↗↗	0.018↗↗	0.013↗↗	
		Non-significant Spots	0.010↗↗	0.105↗↗	0.105↗↗	0.059↗↗	0.016↗↗	0.013↗↗	0.026↗↗	0.015↗↗	0.012↗↗	0.020↗↗	0.016↗↗	
		All	0.201 *↗↗	0.244↗↗	0.118↗↗	0.115*↗↗	0.040 *↗↗	0.056↗↗	0.039↗↗	0.294 *↗↗	0.218↗↗	0.139↗↗	0.141↗↗	
PD	2006	Hot Spots	0.106 *↗↗	0.143↗↗	0.082↗↗	0.083 *↗↗	0.022↗↗	0.046↗↗	0.016↗↗	0.155*↗↗	0.166 ↗↗	0.090↗↗	0.092↗↗	
		Cool Spots	0.021↗↗	0.087↗↗	0.038↗↗	0.034↗↗	0.007↑	0.006↗↗	0.005↗↗	0.016↗↗	0.014↗↗	0.018↗↗	0.013↗↗	
		Non-significant Spots	0.010↗↗	0.105↗↗	0.105↗↗	0.059↗↗	0.016↗↗	0.013↗↗	0.026↗↗	0.015↗↗	0.012↗↗	0.020↗↗	0.016↗↗	
		All	0.201 *↗↗	0.244↗↗	0.118↗↗	0.115*↗↗	0.040 *↗↗	0.056↗↗	0.039↗↗	0.294 *↗↗	0.218↗↗	0.139↗↗	0.141↗↗	
	1996	Hot Spots	0.040↗↗	0.107↗↗	0.065↗↗	0.076↗↗	0.016↗↗	0.013↗↗	0.010↗↗	0.096↗↗	0.065↗↗	0.037↗↗		0.016↗↗
		Cool Spots	0.051↗↗	0.183↗↗	0.072↗↗	0.063↗↗	0.021↗↗	0.021↗↗	0.026↑	0.071↗↗	0.065↗↗	0.092↗↗		0.018↗↗
		Non-significant Spots	0.016↗↗	0.134↗↗	0.104↗↗	0.066↗↗	0.027↗↗	0.013↗↗	0.007↗↗	0.023↗↗	0.024↗↗	0.020↗↗		0.015↗↗
		All	0.179*↑	0.260↑	0.170*↑	0.147↑	0.108↑	0.105↑	0.105↑	0.275*↑	0.193↑	0.147↑		0.141↗↗
	2006	Hot Spots	0.140↑	0.215↗↗	0.157↗↗	0.142↗↗	0.082↑	0.079↑	0.079↑	0.163*↑	0.159↑	0.102↑		0.092↗↗
		Cool Spots	0.042↗↗	0.133↗↗	0.073*	0.044↗↗	0.030*	0.024*↗↗	0.024*↗↗	0.093↗↗	0.046*↑	0.057*↗↗		0.092*↑
		Non-significant Spots	0.127↗↗	0.233↗↗	0.191↗↗	0.166↗↗	0.098↗↗	0.064↑	0.064↗↗	0.161↗↗	0.154↗↗	0.215↗↗		0.085↗↗
		All	0.061 *↗↗	0.129↗↗	0.077↗↗	0.072 *↗↗	0.007↑	0.006↗↗	0.004↗↗	0.0428↗↗	0.012↗↗	0.025↗↗	0.013↗↗	

Cool Spots	0.083↑	0.141↗↗	0.105*↗↗	0.086↗↗	0.074*↗↗	0.081*↗↗	0.070*↗↗	0.137↑	0.095*↗↗	0.096*↗↗	0.092*↑
Non-significant Spots	0.066↗↗	0.169↗↗	0.117↗↗	0.109*↗↗	0.023↗↗	0.025↗↗	0.010↗↗	0.103*↗↗	0.113↗↗	0.101↗↗	0.085↗↗

Notes: Symbol “↑↑”denotes factor A linearly increased factor B; i.e., $PD(A)+PD(B) > PD(A \cap B) > PD(A)$ and $PD(B)$. Symbol “↗↗”denotes a nonlinear increase in factors A and B; i.e., $PD(A \cap B) > PD(A)+PD(B)$. Symbol “*” denotes significant interactions ($P < 0.05$). For more details, see Wang et al. (2010).

Table 4.

Factor or factor interaction with top four q values

Cluster regions	1996				2006			
	Dominant factor	q	Dominant interaction	q	Dominant factor	q	Dominant interaction	q
All	DS	0.106	DS∩ELE	0.175↗↗	ELE	0.257	ELE∩DS	0.300*↑
	CD	0.068	DS∩SPo	0.167↗↗	SDe	0.175	ELE∩PD	0.294*↑
	SA	0.066	DS∩SDi	0.148↗↗	DS	0.171	ELE∩CD	0.293*↑
	PA	0.050	DS∩SDe	0.147↗↗	PA	0.141	ELE∩SDi	0.275*↑

HS	ELE	0.045	ELE $\cap$ DS	0.143 ↗ ↗	ELE	0.139	DS $\cap$ SDi	0.215 ↗ ↗
	DS	0.042	ELE $\cap$ SA	0.110 ↗ ↗	SDe	0.129	DS $\cap$ CD	0.196 ↗ ↗
	CD	0.033	ELE $\cap$ CD	0.100 ↗ ↗	DS	0.099	DS $\cap$ PA	0.188 ↗ ↗
	SA	0.032	DS $\cap$ SDe	0.109 ↗ ↗	PA	0.085	DS $\cap$ ELE	0.185↑
CS	SPo	0.067	DS $\cap$ SPo	0.258 ↗ ↗	DS	0.070	CD $\cap$ ELE	0.142*↑
	DS	0.063	DS $\cap$ ELE	0.209 ↗ ↗	PD	0.069	DS $\cap$ PD	0.141↑
	ELE	0.033	DS $\cap$ SDi	0.183 ↗ ↗	ELE	0.069	ELE $\cap$ PD	0.137↑
	CD	0.030	DS $\cap$ SDe	0.145 ↗ ↗	CD	0.036	DS $\cap$ SDi	0.133 ↗ ↗
NS	PA	0.125	SPo $\cap$ DS	0.149 ↗ ↗	DS	0.125	SPo $\cap$ SA	0.258 ↗ ↗
	DS	0.095	CD $\cap$ DS	0.148 ↗ ↗	CD	0.095	SPo $\cap$ PA	0.237 ↗ ↗
	CD	0.082	DS $\cap$ SDi	0.134 ↗ ↗	SA	0.082	SDi $\cap$ DS	0.233 ↗ ↗
	SA	0.079	SA $\cap$ DS	0.119 ↗ ↗	ELE	0.079	SPo $\cap$ DS	0.223 ↗ ↗

Note: PA is patch area, DS is dominant species, CD is canopy density, SA is stand age, SI is site index, SD is soil depth, HD is humus depth,

ELE is elevation, SDe is slope degree, SPo is slope position, SDi is slope direction, SI is site index, and PD is population density.

Table 5.

Pearson correlation coefficients between any two ecological factors in the whole city

Metrics	Year	PA	CD	SA	SI	SD	HD	ELE	SDe	PD	T _R
PA	1996	1	0.166**	0.279**	0.116**	0.134**	0.155**	0.307**	0.293**	0.026	-0.025
	2006	1	0.163**	0.127**	0.155**	-0.123**	0.109**	0.127**	0.247**	0.081**	-0.115**
CD	1996		1	0.411**	0.193**	-0.034	0.278**	0.249**	0.310**	0.124**	-0.237**

	2006	1	0.357**	0.163**	-0.304**	0.121**	0.156**	0.333**	0.117**	-0.258**
SA	1996	1	0.099**	0.304**	0.335**	0.379**	0.543**	0.027	-0.171**	
	2006	1	0.043**	-0.051**	0.102**	-0.058**	-0.044**	0.152**	0.006	
SI	1996		1	-0.142**	-0.012	0.034	0.064**	0.060**	-0.017	
	2006		1	-0.282**	0.008	0.060**	0.086**	0.072**	0.001	
SD	1996			1	-0.118**	0.331**	0.467**	-0.111**	0.032	
	2006			1	-0.129**	-0.282**	-0.322**	-0.070**	0.191**	
HD	1996				1	0.120**	0.077**	-0.02	-0.079**	
	2006				1	0.042**	0.077**	0.008	-0.054**	
ELE	1996					1	0.638**	-0.206**	-0.139**	
	2006					1	0.496**	-0.148**	-0.458**	
SDe	1996						1	0.060**	-0.100**	
	2006						1	0.121**	-0.414**	
PD	1996							1	-0.015	
	2006							1	0.080**	
T _R	1996								1	
	2006								1	

Note: **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed). Type variables (e.g. DS, SPo and SDi) can't be calculated. PA is patch area, DS is dominant species, CD is canopy density, SA is stand age, SI is site index, SD is soil depth,

HD is humus depth, ELE is elevation, SDe is slope degree, SPo is slope position, SDi is slope direction, SI is site index, PD is population density, and T_R is relative LST index.

Appendix D

Fig. 1 Map of the study area including three regions with different urbanization levels (urban core AB, suburb CD, and outer suburb EF) and inset locations in China.

Lansat_5 TM image 08/17/2006

Fig. 2. Comparison of LST between Landsat TM 5 and meteorological stations.

Fig. 3. Variations in urban forest LST in three temperature regions (hot-spots, cool-spots and non-significant spots) classified through local Getis-Ord G_i^* statistics in 1996 and 2006. Red points represent the average temperature of each region.

Fig. 4. Urban forest stand structure (A. Patch area B. Canopy density; C. Forest age; D. Dominant tree species) based on local Getis-Ord G_i^* statistics (red points represent the average value of each group). HS = hot-spots; CS = cool-spots; NS= non-significant spots. Fig. 4D only displays the 8 major dominant tree species.

Fig. 5. Urban forest change in Xiamen during 1996 and 2006. The map shows the location of nine transfer processes among clustering regions (i.e., hot spots, cool spots, and non-significant spots) from 1996 to 2006.

Forest Characteristics

Patch Area

Dominant Species

Canopy Density

Stand Age

Soil

Site Index

Soil Depth

Humus Depth

Population

Topography

Degree of Slope

Position of Slope

Direction of Slope

Elevation

Fig. 6 Locations of hot spot detectors of 12 attributes. Dominant species are the first five with the largest stand area. Site index: I-very fertile, II-fertile; II-moderately fertile, IV-barren; Slope aspect: 1-north, 2-northeast, 3-east, 4-southeast, 5-south, 6-

southwest, 7-west, 8-northwest, 9-no slope; Slope position: 1-ridge, 2-upper part, 3-lower part, 4-valley, 5-full slope, 6-flat ground.