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RESEARCH ARTICLE

Spatial pattern of greenspace affects land surface temperature: evidence from the heavily urbanized Beijing metropolitan area, China

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Abstract The urban heat island describes the phenomenon that air/surface temperatures are higher in urban areas compared to their surrounding rural areas. Numerous studies have shown that increased percent cover of greenspace (PLAND) can significantly decrease land surface temperatures (LST). Fewer studies, however, have investigated the effects of configuration of greenspace on LST. This paper aims to fill this gap using Beijing, China as a case study. PLAND along with six configuration metrics were used to measure the composition and configuration of greenspace. The metrics were calculated based on a greenspace map derived from SPOT imagery, and LST data were retrieved from Landsat TM thermal band. Ordinary least squares regression and spatial autoregression were employed to investigate the relationship between LST and spatial pattern of greenspace using the census tract as the analytical unit. The results showed that PLAND was the most important predictor of LST. A 10 % increase in PLAND resulted in approximately a 0.86 °C decrease in LST. Configuration of greenspace also significantly affected LST. Given a fixed amount of greenspace, LST increased significantly with increased patch density. In addition, the variance of LST was largely explained by both composition and configuration of greenspace. The unique variation explained by the composition was relatively small, and was close to that of the configuration. Results from this study can expand our understanding of the relationship between LST and vegetation, and provide insights for improving urban greenspace planning and management.

Keywords Urban heat island · Urban greenspace · Landscape metrics · Configuration · Spatial autocorrelation · Spatial autoregression · Greenspace planning · Thermal infrared remote sensing

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Introduction

The urban heat island (UHI) describes the phenomenon that air/surface temperatures are higher in urban areas compared to their surrounding rural areas. The UHI phenomena are widely observed in cities despite their sizes and locations (Tran et al. 2006; Imhoff et al. 2010). Increased temperatures due to UHI may alter species composition and distribution (Niemelä 1999), increase air pollution (Sarrat et al. 2006; Weng and Yang 2006; Lai and Cheng 2009), and affect the comfort of urban dwellers and even lead to greater health risks (Patz et al. 2005). Therefore, since first reported in 1818, UHI has become a major research focus in urban climatology and urban ecology (Arnfield 2003; Weng 2009).

The intensity and spatial pattern of UHI is a function of land surface characteristics (e.g. albedo, emissivity, and thermal inertia), urban layout/street geometry (e.g. canyon height-to-width ratio and sky view factor), weather conditions (e.g. wind and humidity), and human activities (Taha 1997; Voogt and Oke 1998; Unger 2004; Hamdi and Schayes 2008; Rizwan et al. 2008). Many of these factors, especially land surface characteristics, are primarily determined by land use/land cover (LULC). For example, vegetation usually has higher evapotranspiration and emissivity than built-up areas, and thus has lower surface temperatures (Weng et al. 2004; Hamada and Ohta 2010). This suggests that increases in the amount of greenspace can be an effective means to improving the urban thermal environment.

The rapid development of thermal infrared remote sensing greatly advanced the exploration of the relationship between land surface temperature (LST) and LULC (Voogt and Oke 2003; Weng et al. 2004; Pu et al. 2006; Buyantuyev and Wu 2010). LULC pattern has two components: composition (the abundance and variety of land cover classes) and configuration (the spatial arrangements of land cover classes) (Turner 2005). The past two decades witnessed proliferations of studies focusing on the relationship between LST and greenspace composition. In particular, the significant negative relationship between LST and vegetation abundance was well documented (Voogt and Oke 2003; Weng et al. 2004; Chen et al. 2006; Tran et al. 2006; Weng 2009). However, less studied is the relationship between LST and configuration of greenspace (Weng et al. 2007; Liu and Weng 2008; Zhao et al. 2011; Zhou et al. 2011). Some preliminary studies have demonstrated that both air and surface temperatures may be related to the configuration of greenspace (Honjo and Takakura 1991; Yokohari et al. 1997; Zhang et al. 2009; Bowler et al. 2010; Cao et al. 2010). For example, two recent studies showed that the size and shape of a vegetation patch affected its cool island effects, the phenomenon that the temperature of greenspace is lower than its surrounding areas (Zhang et al. 2009; Cao et al. 2010). These studies were conducted at the patch level, only focusing on the size and shape of greenspace, however few have examined the effects of configuration of greenspace on LST at the landscape level (Yokohari et al. 1997; Zhang et al. 2009; Zhou et al. 2011), at which urban greenspace planning and management are usually implemented. Exploring the relationship between LST and spatial pattern, especially configuration of greenspace at the landscape level, can help us better understand the LST–vegetation relationship, and provide insights for urban greenspace planning and management.

Taking the heavily urbanized Beijing metropolitan area as an example, this study tried to answer two questions: (1) does spatial pattern, especially configuration of greenspace affect LST? and (2) what is the relative importance of composition and configuration of greenspace on explaining the variance of LST? In this study, spatial pattern of greenspace refers to the composition (i.e., percent cover) of greenspace, and its spatial distribution or configuration. Spatial pattern of greenspace was measured by a series of selected landscape metrics that will be discussed in detail in the method section. We addressed the first question using ordinary least squares (OLS) regression and spatial autoregression (SAR), and the second question using variance partitioning.

Study area

Beijing, the capital of China, is located in the northern part of the North China Plain (longitude: 115°25′–117°30′E, latitude 39°28′–41°25′N; Fig. 1). It has a history of more than 3,000 years as a city and more than 800 years as a capital city. After the implementation of the Reform and Open Policy in 1978, Beijing witnessed an alarming urbanization rate (Mu et al. 2007). It is estimated that the size of the built-up area increased from 232.13 km^2 (1.5 % of the total area) in 1978 to 1209.97 km^2 (7.4 % of the total area) in 2005 (Mu et al. 2007). The typically concentric urban expansion pattern led to intensive UHI (Liu et al. 2007; Xiao et al. 2007, 2008).

This study focused on the areas within the fifth-ring road of Beijing (Fig. 1). The study area is flat, with an elevation range of 20–60 m. The climatic and the physiographic conditions are mostly constant across the study area. Therefore, it is an ideal area to explore the relationship between LST and spatial pattern of greenspace. The study area has a size of approximately 760 km^2, and it is the most highly developed area in Beijing where the population density for the four inner districts within the study area was greater than 20,000 people/km^2 in 2008 (Beijing Municipal Statistical Bureau 2009). Intensive UHI was observed in this area (Xiao et al. 2007, 2008).

Fig. 1 The location of the study area and the selected 109 census tracts

Methods

Analytical unit

We chose the census tract as the analytical unit. The census tract has been widely used as the analytical unit to examine the relationship between LST and LULC pattern, and the relationship between LST and socio-economic factors (Jenerette et al. 2007; Liang and Weng 2008; Buyantuyev and Wu 2010). In China, a census tract is the smallest territorial unit defined for the purpose of taking a population census. It is also the smallest administrative division, which is the township level division (also known as sub-district). Therefore, a census tract is the level at which most of the local urban planning and management decisions are designed and implemented. In this study, we selected census tracts that are entirely within or have a significant proportion (>30 %) within the fifth-ring road. Consequently, 109 census tracts were selected (Fig. 1). The size of the selected census tracts ranged from 0.55 to 51.98 km^2, with the mean and standard deviation of 7.07 and 8.64 km^2.

Land surface temperature

Data of LST was retrieved from Landsat-5 Thematic Mapper (TM) thermal band with a wavelength of 11.45–12.50 μm and a spatial resolution of 120 m (Xiao et al. 2007; Weng 2009). The TM imagery was taken on October 4, 2004. First the LST was retrieved following the procedure detailed in Xiao et al. (2007) then the mean value of LST was calculated for each census tract (see examples in Fig. 2), which was used as response variable in the statistical analyses.

Spatial patterns of greenspace

The multi-spectral SPOT data (taken on September 8, 2004), with a spatial resolution of 10 m, were used to map greenspace (i.e. vegetated areas). An object-based classification approach was applied to derive the vegetated area, using the Feature Extraction tool in ENVI 4.6. The four bands green, red, near-infrared, and shortwave infrared were all used for classification. An accuracy assessment was conducted based on 150 check points, using reference data that were visually interpreted from the QuickBird images (spatial resolution of 0.6 m) collected in 2002. The overall accuracy of the derived map was 89.33 %. Figure 2 shows a few examples of the greenspace maps at the census tract level.

We selected seven landscape metrics to measure spatial pattern of greenspace based on the following principles (Riitters et al. 1995; Li and Wu 2004; Lee et al. 2009; Riva-Murray et al. 2010): (1) important in both theory and practice, (2) easily calculated, (3) interpretable, and (4) minimal redundancy. The metrics selected reflect the major characteristics of spatial pattern of greenspace, including the abundance of greenspace, patch area, patch shape, edge density, patch isolation, fragmentation, and aggregation. The seven metrics were: (1) percent cover of greenspace (PLAND), (2) mean patch area (AREA_MN), (3)

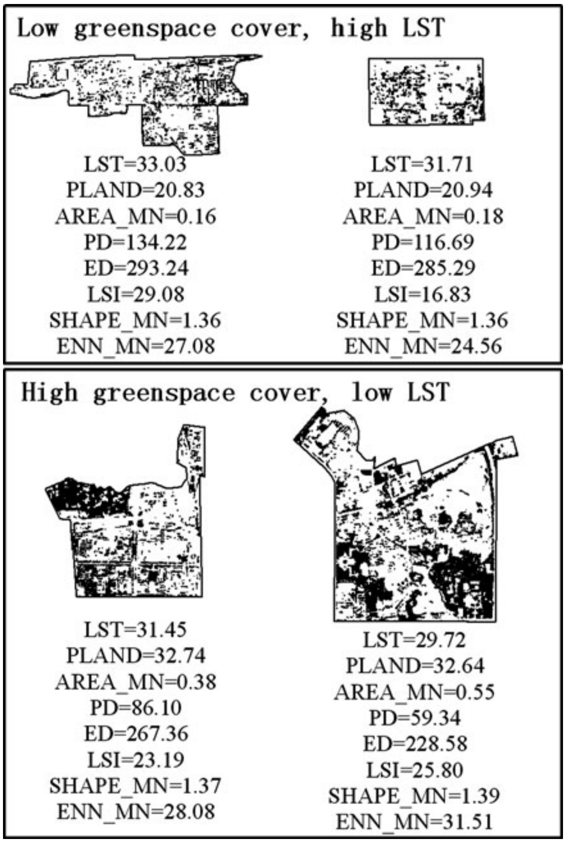


Fig. 2 Examples of the greenspace map, mean LST, and the value of the selected landscape metrics for four census tracts

patch density (PD), (4) landscape shape index (LSI), (5) edge density (ED), (6) mean patch shape index (SHAPE_MN), and (7) mean Euclidian nearest-neighbor distance (ENN_MN) (Table 1). Composition was measured using PLAND and configuration was measured using the remaining six metrics. These metrics were calculated for each census tract based on the greenspace map described above using Fragstats3.3 (McGarigal et al. 2002). The "8-cell rule" was used to define patch neighbors (McGarigal et al. 2002).

Statistical analyses

Ordinary least squares multiple linear regression and spatial autoregression

First a scatter plot was generated to explore the bivariate relationship between LST and each of the landscape metrics. An OLS multiple linear regression was then used to determine the effects of spatial pattern of greenspace on LST. Because there were a large number of predictor variables for configuration, with some being highly correlated to each other, we used a forward stepwise variable selection procedure to determine which configuration variables to add or drop from the model (Hosmer and Lemeshow 2000). We directly included PLAND in the model, as it was the only variable that measured composition of greenspace.

One of the important assumptions of OLS is that the error terms are independent. However, spatial autocorrelation is common for spatial data (Lichstein et al. 2002), which may bias the coefficient estimates of the variables from OLS regression, thus leading to increased type I errors (Lichstein et al. 2002; De Knegt et al. 2010). We tested the residuals of the OLS model, and found significant spatial autocorrelation ($P < 0.01$). Therefore, we conducted a SAR with variables included in the OLS model, and compared the results of the two regression methods.

SAR explicitly quantifies the neighborhood relationship of the response variable by a ($n \times n$) matrix of spatial weights with each element representing the interaction of two locations. SAR integrates this factor into the standard multiple linear regression to account for spatial autocorrelation (Anselin 2005a).

There are two approaches for SAR modeling: spatial lag model and spatial error model (Anselin 2005a). The spatial lag model assumes that the spatial autoregressive occurs only in the response variable and is expressed as:

$$y = \rho W y + \beta X + \varepsilon \quad (1)$$

where Wy is a ($n \times 1$) vector of the spatially lagged response variable, ρ is a spatial autoregressive coefficient, X is a ($n \times k$) vector of explanatory variables, β is a ($k \times 1$) vector of regression coefficients and ε is a ($n \times 1$) vector of independently distributed errors.

The spatial error model assumes that the spatial autoregressive process occurs in the error terms when the spatial effects are not fully explained by the included explanatory variables. The form of the spatial error model is:

$$y = \beta X + \lambda W \mu + \varepsilon \quad (2)$$

where $W\mu$ is a ($n \times 1$) vector of spatially lagged errors, λ is a spatial autoregressive coefficient.

The selection of the modeling approach (e.g. spatial lag model or spatial error model) was based on the Lagrange Multiplier statistics (Anselin 2005a). In this

Table 1 Landscape metrics used in this study (McGarigal et al. 2002)

Metrics (abbreviation)	Description (unit)	Computing equation
Percent cover of greenspace (PLAND)	Proportional abundance of greenspace in the landscape (%)	$\frac{100}{A} \times \sum_{i=1}^{n} a_i$
Mean patch area (AREA_MN)	Total patch area divided by patch number (ha)	$\frac{1}{10{,}000 \times n} \times \sum_{i=1}^{n} a_i$
Patch density (PD)	Number of greenspace patches divided by total landscape area (n/km^2)	$\frac{n}{A} \times 10^6$
Edge density (ED)	Total length (border not included) of all edge segments of greenspace per hectare (m/ha)	$\frac{10{,}000}{A} \times \sum_{i=1}^{n} e_i$
Landscape shape index (LSI)	Total length of greenspace (or perimeter) divided by the minimum length of greenspace edge (or perimeter) possible for a maximally aggregated class	$\frac{E}{\min E}$
Mean patch shape index (SHAPE_MN)	Mean value of shape index	$\frac{1}{n} \times \sum_{i=1}^{n} \frac{e_i}{\min e_i}$
Mean Euclidian nearest-neighbor distance (ENN_MN)	Mean distance to the nearest neighboring patch of greenspace based on the edge-to-edge distance (m)	$\frac{1}{n} \times \sum_{i=1}^{n} h_i$

a_i area of patch i; e_i length of edge (or perimeter) of patch i; min e_i minimum length of edge (or perimeter) of patch i; h_i distance from patch i to its nearest neighboring patch; E total length of edge (or perimeter) of greenspace, includes all landscape boundary and background edge segments involving greenspace; *min E* minimum total length of edge (or perimeter) of greenspace; A landscape area; n number of patches

study, SAR used the first-order contiguity spatial weights based on the contiguity of census tracts (i.e., only adjacent census tracts were defined as neighbors) (Anselin 2005a).

The SAR model was performed with a maximum-likelihood method. We calculated the R^2 using the following equation (Lichstein et al. 2002):

$$R^2 = 1 - \exp[-2/n(l_A - l_0)] \quad (3)$$

where n is the sample size, l_A is the log-likelihood of the focused model, and l_0 is the log-likelihood of the null model with only the intercept as predictors. The R^2 calculated in this method is comparable to that obtained from OLS models (Lichstein et al. 2002; Tognelli and Kelt 2004) therefore we could compare the SAR to OLS based on the values of R^2.

We used SPSS 16.0 to run the OLS model, and GeoDa 0.9.5-i (Anselin 2005a) and spdep package (Anselin 2005b) of R (Version 2.12.1) (R Development Core Team. 2011) to run the SAR model. The spatial autocorrelation was tested by Moran's I with 999 permutations using GeoDa 0.9.5-i (Anselin 2005a).

Variance partitioning

The predictors in the SAR model were divided into three groups: composition of greenspace (COM), configuration of greenspace (CON), and spatial autocorrelation (SAU). Variance partitioning was conducted to examine the relative importance of each group in explaining the variation of LST (Anderson and Gribble 1998; Heikkinen et al. 2005). The variation of LST was decomposed into eight fractions: (1) unique effects of COM, (2) unique effects of CON, (3) unique effects of SAU, (4) joint effects of COM and CON, (5) joint effects of COM and SAU, (6) joint effects of CON and SAU, (7) joint effects of COM, CON, and SAU, and (8) unexplained. The calculation of each fraction followed the procedure detailed in Anderson and Gribble (1998) and Heikkinen et al. (2005). Variance partitioning was conducted using the spdep package (Anselin 2005b) of R (Version 2.12.1) (R Development Core Team 2011).

Results

Descriptive statistics

LST at the census tract level in the study area ranged from 27.59 to 35.43 °C, with a mean value of 31.56 °C and a standard deviation of 1.21 °C. A significant positive spatial autocorrelation was observed for LST (Moran's $I = 0.48$, $P < 0.01$). Greenspace area was 238.75 km^2, which covered 31.24 % of the study area.

PLAND varied greatly among census tracts, ranging from 7.91 to 61.83 %, with a mean value of 28.42 % and a standard deviation of 10.16 %. Patch density and edge density also had relatively large ranges and variances among census tracts (Table 2). Mean patch area and mean patch shape index, however, had a relatively small range and low variation. All the landscape metrics showed a significant positive spatial autocorrelation ($P < 0.01$) (Table 2).

Scatter plots showed significant relationships between LST and landscape metrics (Fig. 3). Census tracts with high PLAND, large mean patch size of greenspace or complex patch shape of greenspace tended to have low LST. While high LST was usually observed in census tracts with high patch density of greenspace. Landscape shape index, edge density, and mean Euclidian nearest-neighbor distance, however, were not significantly correlated with LST in the bivariate regression.

Results of the OLS model and SAR model

Four landscape metrics—PLAND, patch density, landscape shape index, and mean patch shape index—were included in the OLS model (Table 3). These metrics jointly explained 62 % of the total variance in LST. The results showed that LST had a negative relationship with PLAND and mean patch shape index, but a positive relationship with patch density and landscape shape index (Table 3). The residuals of the OLS model were spatially autocorrelated (Moran's $I = 0.34$, $P < 0.01$), indicating that the results of the OLS model might be biased (Table 4).

The Lagrange Multiplier statistics showed that both LM Lag and LM Error were highly significant, as well as the Robust LM Error (Table 4), indicating that the spatial error model was more suitable for our data (Anselin 2005a). The results showed that after

Fig. 3 Scatter plots of LST (°C) with each of the seven ▶ landscape metrics. The R^2s and the P-values were derived from bivariate regression

considering the effects of spatial autocorrelation, the spatial error model was greatly improved compared to the OLS model. The explained variance increased from 62 to 72 %, and the AIC value decreased from 252.36 to 219.45 (Table 5). The spatial autoregressive coefficient of 0.66 was highly significant ($P < 0.01$). However, only two of the four predictors—PLAND and patch density—remained significant when considering the effects of spatial autocorrelation (Table 5).

Variance partitioning

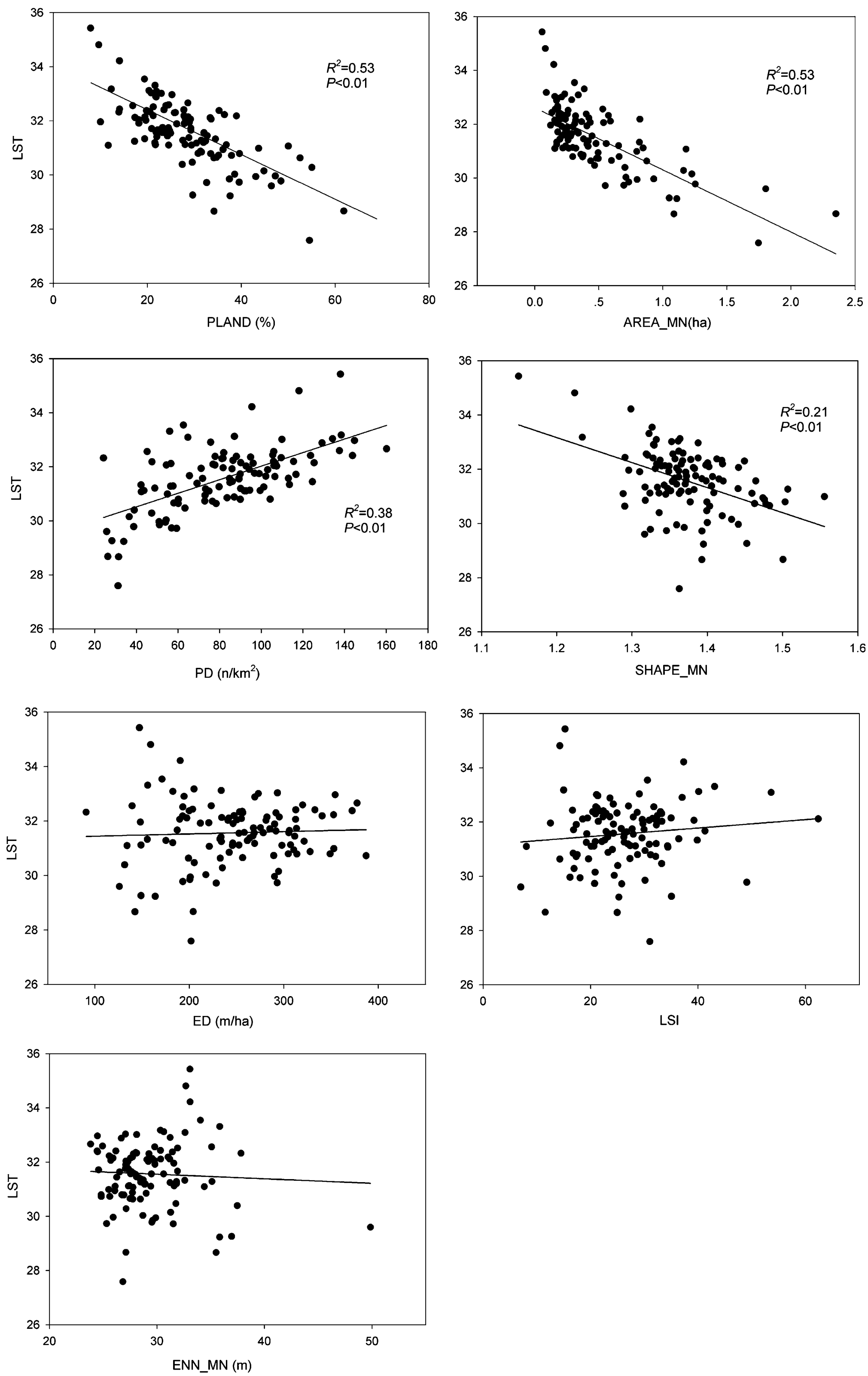
The three groups of variables jointly explained 72.25 % of the total variance in LST The composition alone explained 52.54 % of the total variance in LST, while configuration alone explained 51.52 %. However, 41.58 % of the total variance was jointly described by the composition and configuration of greenspace. Spatial autocorrelation alone explained 35.5 % of the total variance in LST, among which 19.29 % of the total variance was jointly explained by composition, configuration, and spatial autocorrelation (Fig. 4). The variances of LST uniquely described by composition, configuration, and spatial autocorrelation were 8.01, 6.45, and 9.01 %, respectively.

Discussion

Urban greenspace can potentially mitigate the UHI effects, and numerous studies have shown that increases in PLAND can significantly decrease LST (e.g. Weng et al. 2004; Buyantuyev and Wu 2010). Fewer studies, however, have investigated the effects

Table 2 Descriptive statistics of LST and landscape metrics; Moran's I indices of all variables were significant at the 99.9 % confidence level

	Min	Max	Mean	SD	Moran's I
PLAND (%)	7.91	61.83	28.42	10.16	0.37
AREA_MN (ha)	0.06	2.35	0.45	0.38	0.49
PD (n/km^2)	24.23	160.20	81.79	29.92	0.52
ED (m/ha)	90.74	387.13	245.67	62.75	0.36
LSI	7.01	62.37	26.30	8.65	0.24
SHAPE_MN	1.15	1.56	1.37	0.06	0.32
ENN_MN (m)	23.82	49.85	29.27	3.67	0.23
LST (°C)	27.59	35.43	31.56	1.21	0.48



LST
PLAND (%)
R^2=0.53
P<0.01
AREA_MN(ha)
R^2=0.53
P<0.01
PD (n/km^2)
R^2=0.38
P<0.01
SHAPE_MN
R^2=0.21
P<0.01
ED (m/ha)
LSI
ENN_MN (m)

Table 3 Results of the OLS model

Predictors	Coefficients	Std. error	*P*
Constant	35.25	1.87	0.00
PLAND (%)	−0.054	0.0098	0.00
Patch density (n/km^2)	0.014	0.0031	0.00
Landscape shape index	0.025	0.0085	0.00
Mean patch shape index	−2.56	1.38	0.04
R^2	0.62		
AIC	252.36		

Table 4 Diagnostics for spatial dependence of the OLS model

Test	Value	*P*
Moran's *I* of the residuals	0.34	0.00
LM lag	29.15	0.00
Robust LM lag	3.80	0.05
LM error	31.92	0.00
Robust LM error	6.58	0.01

Table 5 Results of the SAR model (spatial error model)

Predictors	Coefficients	Std. error	*P*
Constant	32.30	1.67	0.00
PLAND (%)	−0.05	0.0089	0.00
Patch density (n/km^2)	0.016	0.0032	0.00
Landscape shape index	0.008	0.0072	0.28
Mean patch shape index	−0.56	1.22	0.64
R^2	0.72		
AIC	219.45		

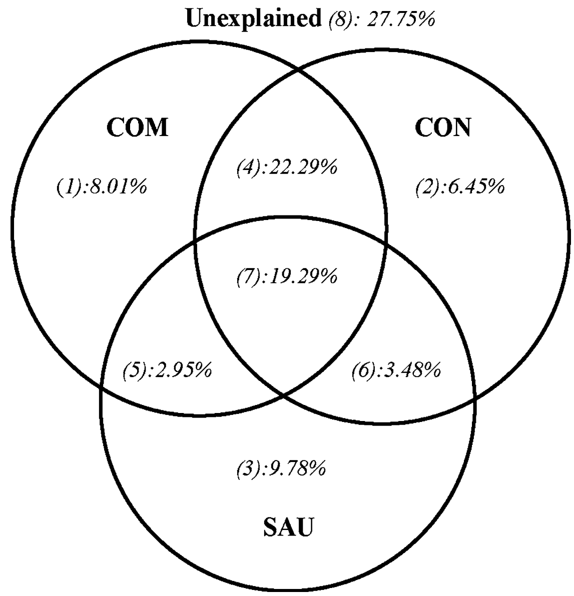


Fig. 4 Results of variation partitioning for composition of greenspace (*COM*), configuration of greenspace (*CON*), and spatial autocorrelation (*SAU*). (*1*)–(*3*) are unique effects; (*4*)–(*7*) are joint effects; (*8*) is the unexplained variance

of configuration of greenspace on LST (Yokohari et al. 1997; Zhang et al. 2009; Zhou et al. 2011). Taking the heavily urbanized Beijing metropolitan area as an example, we quantitatively demonstrated that the spatial pattern of greenspace, both the composition and configuration, significantly affected LST. These results have important theoretical, methodological and management implications.

Theoretical implications

Our results showed that PLAND was negatively correlated with LST. This is consistent with previous studies in which the abundance of greenspace was measured by vegetation index (e.g. Normalized Difference Vegetation Index) (Chen et al. 2006; Buyantuyev and Wu 2010), vegetation fraction (Weng et al. 2004), or percent cover of a certain type of vegetation (e.g., Forest, Grass, Cropland, etc.) (Weng et al. 2006; Zhou et al. 2011). The increase of greenspace mainly decreases LST because: (1) greenspace can generate cool island effects by evapotranspiration, combined with lower thermal inertia compared to impervious surfaces and bare soil (Lambin and Ehrlich 1996; Weng et al. 2004; Hamada and Ohta 2010); and (2) greenspace (i.e., trees) can produce shade that prevents land surfaces from direct heating by the sun (Zhou et al. 2011).

We also found that configuration of greenspace significantly affected LST, even after controlling for the effects of PLAND and spatial autocorrelation. Specifically, patch density of greenspace had a significant positive relationship with LST, meaning the increase of patch density will increase LST. These results are consistent with findings from previous studies that the more fragmented the greenspace the higher the air/surface temperatures (Yokohari et al. 1997; Zhang et al. 2009). Given the same amount of greenspace an increase in patch density leads to a decrease in mean patch size ($r = -0.77$, $P < 0.01$) resulting in a general increase in total patch edges ($r = 0.51$, $P < 0.01$). Therefore, the effects of the increase of patch density on LST were due to the joint effects of a decrease in mean patch size and increase in patch edges on LST. The decrease in mean patch size may increase LST because a larger, continuous greenspace produces stronger cool island effects than that of several small pieces of greenspace whose total area equals the continuous piece (Yokohari et al. 1997; Zhang et al. 2009; Cao et al. 2010). However, the increase of total patch edges may enhance energy flow and exchange between greenspace and its surrounding areas, and provide more shade for surrounding surfaces, which lead to the decrease of LST (Zhou et al. 2011).

In this study, we found a positive relationship between patch density and LST after controlling for the effects of PLAND, which suggests that the decrease in patch size played a more important role than the increase of edge density. This may be due to the fact that greenspace in Beijing is dominated by small patches, which are too small to produce significant cool island effects (Zhang et al. 2009; Cao et al. 2010). Further research is needed to see if these findings can be applied to other cities.

Variance partitioning showed that the composition of greenspace was more important than the configuration of greenspace in predicting LST, which is consistent with previous findings (Zhou et al. 2011). However, our results also showed that the unique effects of the composition were slightly higher than that of the configuration, and much of the variance of LST was jointly explained (Fig. 4) because the composition and configuration of greenspace are highly interrelated.

Methodological implications

Our results indicated that SAR was more appropriate for quantifying the relationship between LST and spatial pattern of greenspace than OLS regression. Significant spatial autocorrelation existed in residuals of the OLS model, suggesting the violation of OLS assumption that the error terms are independent. This violation may lead to the underestimation of the standard errors of the OLS coefficient estimates, and thus inflate type I errors (Lichstein et al. 2002; De Knegt et al. 2010). For example, the OLS model rejected the null hypothesis that mean patch shape index and landscape shape index do not significantly affect LST.

In addition, methods that account for spatial autocorrelation can provide insights on the spatial pattern of LST and greenspace. The results indicated that there was a significant positive spatial autocorrelation of LST at the census tract level, suggesting that LST in a census tract may be affected by its neighbors. Landscape metrics of greenspace were also spatially autocorrelated, indicating adjacent census tracts tended to have similar values of landscape metrics. This may be due to the fact that adjacent census tracts are usually under similar patterns of urban development with similar urban greenspace management.

Management implications

It is widely accepted that greenspace can cool the urban environment (Weng et al. 2004; Hamada and Ohta 2010) therefore the focus of urban greenspace planning and management has been on increasing greenspace by planting more trees (Rizwan et al. 2008; Zhou et al. 2011). Results from this study showed that the increase in greenspace cover can significantly mitigate UHI effects. In addition, we found that not only composition (i.e., percent cover) but also configuration of greenspace affected LST. In other words, UHI effects can be mitigated by increasing greenspace cover and optimizing its configuration. These results have important implications for greenspace management, particularly in heavily urbanized areas, where available land area for increased greenspace cover is usually very limited (Zhou et al. 2011).

We found a positive relationship between LST and patch density in the Beijing metropolitan area. Given a fixed amount of greenspace a decrease in patch density is similar to an increase in the mean patch size of greenspace. Therefore, given a fixed amount of greenspace, an increase in the patch size can further mitigate the UHI effects (Yokohari et al. 1997). In highly urbanized areas, such as Beijing, urban planners should consider focusing more on optimizing the configuration of greenspace, such as increasing the size of greenspace patches through vegetation management. This can be done by planting trees in selected areas to increase the size of existing greenspace patches.

It should be noted that the relationship between LST and configuration of greenspace found in this study may differ from those in previous studies where different types of data and units of analysis were used

(Li et al. 2011; Zhou et al. 2011). We recognize that the individual characteristics of a city and the current spatial arrangement of the greenspace may affect the relationship between LST and spatial pattern of greenspace. Therefore, cautions should be taken when applying the results from this study to other cities or at a different scale (Hess et al. 2006; Feist et al. 2010). For future research we recommend multi-scale and multi-region comparison studies to advance our understanding of the relationship between LST and composition and configuration of greenspace.

Summary and conclusions

Taking the heavily urbanized Beijing metropolitan area as an example, this study quantitatively examined the effects of spatial pattern of greenspace on LST. We found that both composition and configuration of greenspace affected LST. The majority of the explained variance can be attributed to the joint effects of composition and configuration. The unique effects of configuration were only slightly lower than that of composition. Results from this study extend previous findings on the effects of greenspace on UHI and provide insights for effective urban greenspace planning and management.

Increasing greenspace cover is one of the most effective measures to mitigate UHI effects as PLAND has a significantly negative effect on LST. In addition, configuration of greenspace should never be ignored when making urban greenspace planning and management decisions because configuration of greenspace also affects LST, and the effects are comparable to composition (i.e. greenspace cover). Optimizing the configuration of greenspace may be a more practical means than increasing greenspace cover, particularly in heavily urbanized areas, where space is limited to increase greenspace cover. Our results suggest that by increasing patch area of the greenspace, the thermal environment in Beijing can be further improved in addition to increasing greenspace area. It should be noted that the relationship between LST and configuration of greenspace may be scale dependant, suggesting that cautions should be taken when applying findings across scales. Therefore, multi-scale comparison studies on the relationship between LST and configuration of greenspace are highly desirable.

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