# Effects of the spatial configuration of trees on urban heat mitigation: A comparative study

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**ABSTRACT：**

Urban greenspace has significant cooling effects on urban heat. Recent studies investigating the effects of spatial configuration of greenspace show significant, but inconsistent results, including both positive and negative effects. To investigate the causes of this inconsistency, we compared Baltimore, MD and Sacramento, CA, USA, two cities with very different climatic conditions. We quantified and compared the relationships between the spatial configuration of trees and land surface temperature (LST) using different statistical approaches, and conducted the analyses using spatial units of different sizes, based on

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trees mapped from 1 m high resolution imagery. We found: (1) Trees' cooling efficiency was higher in Baltimore than in hotter and drier Sacramento. Additionally, percent cover of trees was more important than their spatial configuration in predicting LST in Baltimore, but the opposite was found in Sacramento. (2) Spatial configuration of trees affects LST more in Sacramento than in Baltimore, and the effects of spatial configuration of trees on LST varied greatly in terms of magnitude, significance, and even direction, between the two cities. Notably, mean patch size had significantly positive effects on LST in Baltimore, but negative effects in Sacramento. In contrast, edge density had negative effects on LST in Baltimore, but positive effects in Sacramento. (3) Different statistical approaches resulted in dramatic changes in the relationships between LST and configuration metrics. Our results underscore the necessity of controlling the effects of percent cover of trees, when quantifying the effects of spatial configuration of trees on LST. (4) Spatial autocorrelation may influence relationships between landscape metrics and LST, particularly when the unit of analysis is relatively small. (5) The relationships between spatial configuration metrics and LST are stronger with an increase of the size of the analytical unit. This study can enhance our understanding of the effects of spatial configuration of greenspace on urban heat island (UHI). It also provides important insights to urban planners and natural resource managers on how to mitigate the impact of urbanization on UHI through urban design and vegetation management.

**Keywords**: Urban tree canopy; Spatial configuration; Urban heat mitigation; Urban Ecology, Baltimore, Sacramento

## 1. Introduction

Urban heat island (UHI) describes the phenomenon by which urban areas are warmer than surrounding non-urban areas (Voogt and Oke 2003). Increased temperatures due to the UHI effect may increase water consumption and energy use in urban areas (Santamouris et al. 2015; Wan et al. 2012), alter species composition and distribution (Niemelä 1999; White et al. 2002), and lead to an increase in the production of ground level ozone which has direct consequences for human health (Akbari et al. 2001; Akbari et al. 1996). In addition, excess heat affects the comfort of urban dwellers and leads to greater health risks (Poumadere et al. 2005). In fact, extreme heat increases mortality and morbidity in cities worldwide (Fouillet et al. 2006; Harlan and Ruddell 2011). Consequently, how to mitigate and adapt to the UHI has become a major research focus in urban climatology and urban ecology (Arnfield 2003; Weng 2009; Zhou et al. 2011).

Considerable research has demonstrated the significant cooling effects of urban greenspace on urban heat (Fan et al. 2015; Jenerette et al. 2007; Kong et al. 2014; Li et al. 2016; Ma et al. 2010; Weng et al. 2004; Zhou et al. 2011). Increasing the percent cover of greenspace can greatly reduce ambient air temperatures and land surface temperatures (Bowler et al. 2010; Connors et al. 2013; Fan et al. 2015; Li et al. 2012; Weng et al. 2004; Zhou et al. 2011; Zhou et al. 2014). In addition, the spatial configuration (or arrangement) of greenspace, can also have significant effects on land surface temperature (LST) (Chen et al.

2014; Fan et al. 2015; Kong et al. 2014; Li et al. 2013b; Li et al. 2012; Maimaitiyiming et al. 2014; Myint et al. 2015; Zhou et al. 2011). Because cities have limited space for greening, managers and decision-makers would benefit from knowing how to optimize the spatial configuration of greenspace to further alleviate urban heat stress (Huang et al. 2011; Li et al. 2016; Myint et al. 2015; Zhou et al. 2011).

We know that simply increasing the percent cover of greenspace leads to a reduction of temperatures; this relationship is very consistent. What is less known, however, is the effects of the spatial configuration of that greenspace on urban temperatures. Research results are, in some cases, contradictory. For example, greater patch density of greenspace reduced LST in studies conducted in Shenzhen (Li et al. 2010) and Shanghai, China (Li et al. 2011), Baltimore, USA (Zhou et al. 2011), and Berlin, Germany (Dugord et al. 2014), but was associated with increased LST in Beijing, China (Li et al. 2013b; Li et al. 2012). Similarly, edge density of greenspace was found to be negatively correlated to LST in many cities (Dugord et al. 2014; Li et al. 2011; Li et al. 2014; Maimaitiyiming et al. 2014; Rhee et al. 2014; Zhang et al. 2009; Zhou et al. 2011), but positively correlated in others (Li et al. 2013b; Wu et al. 2014). This inconsistency prevents the application of results to urban greenspace planning and management (Li et al. 2013b).

The reasons for this inconsistency remain largely unaddressed. It may be because these studies have been conducted 1) in cities with contrasting climatic conditions; 2) using a variety of statistical analysis (Fan et al. 2015; Kong et al. 2014; Li et al. 2013b; Li et al. 2012;

Myint et al. 2015; Zhou et al. 2011); 3) based on maps from image data with spatial resolution ranging from sub-meter to1000 m (Li et al. 2013b; Rhee et al. 2014; Wu et al. 2014; Zhou et al. 2011); and 4) using a variety of analytical units with different sizes such as grids or pixels (Peng et al. 2016; Rhee et al. 2014), city blocks (Dugord et al. 2014), sub-districts (Li et al. 2013b), or self-defined polygons (Zhou et al. 2011). Does spatial configuration of greenspace affect temperatures differently in cities with different climatic conditions? Or, is this inconsistency due to the varied statistical approaches applied, or different units of analysis, or different resolutions of data to map greenspace?

Here, we address these questions by conducting a comparison study of Baltimore, MD and Sacramento, CA, USA, two cities with very different climatic conditions. We quantified and compared the relationships between spatial configuration of trees and LST using different statistical approaches, and conducted the analyses at sampling units of different sizes. We mapped tree canopies using 1 m resolution imagery. This decision was based on the work of Li et al. (2013b) and Zhou et al. (2014), which suggested that the spatial resolution of image data used to map greenspace influenced the statistical relationships between spatial configuration of greenspace and LST, and that high spatial resolution image data are more appropriate in such analysis. Results from the present study can enhance the understanding of the effects of spatial configuration of greenspace on UHI. In addition, important insights can be provided to urban planners and natural resource managers on how to mitigate the impact of urbanization on UHI through urban design and vegetation management.

## 2. Methods

### *2.1. Study area*

The research focuses on two cities with contrasting climatic conditions, Baltimore, Maryland, USA, and Sacramento, California, USA. Baltimore is a temperate coastal city characterized by hot and humid summers (Brazel et al. 2000), while Sacramento has a Mediterranean climate characterized by hot, but dry summers. Baltimore is built in a biome dominated by temperate broadleaf and mixed forest, whereas Sacramento belongs to a biome dominated by grassland, with riparian forests only along the streams and shrub and woodlands that do not occur until in the sierra foothills and higher elevation (Imhoff et al. 2010).

Baltimore is the largest city in Maryland, with a total area of 239 $km^2$ and total population of approximately 0.62 million in 2014. Close to the Chesapeake Bay, its annual average temperature is 12.6°C, and average precipitation is approximately 1070mm. Sacramento is the capital city of California. It has a total area of 259 $km^2$, and total population of about 0.48 million in 2014. Located at the confluence of the Sacramento and American rivers, its annual average temperature is 16.2°C and average precipitation is approximately 450mm. The similarity in the sizes of total population and area, but the contrast in climatic conditions and biomes, make the two cities ideal for the comparisons conducted in this research.

### *2.2. Data*

#### *2.2.1. Land surface temperature*

The LST data were derived from the thermal infrared (TIR) band (10.40-12.50 μm) of two Landsat-5 Thematic Mapper (TM) images with a spatial resolution of 120 m (Fig. $1B_{LST}$, $S_{LST}$). The TM data for Baltimore and Sacramento were acquired on August 11, 2007 (row 33/path 15), and August 14, 2010 (row 33/path 44), respectively. LST was derived for different years in order to coincide with the years the land cover for the two cities was collected – Baltimore in 2007 and Sacramento in 2010.

We first calculated the top-of-atmospheric (TOA) radiance based on the digital number (DN) of the TM TIR band (Chander and Markham 2003; Landsat Project Science Office 2009). We then calculated the surface-leaving radiance from TOA radiance by removing the effects of the atmosphere in the thermal region (Asgarian et al. 2015; Barsi et al. 2005; Sobrino et al. 2004; Yuan and Bauer 2007; Zhou et al. 2014). Finally, LST was calculated from surface-leaving radiance using the Plank function (Chander and Markham 2003; Chander et al. 2009).

*2.2.2. Spatial pattern of tree canopy*

We mapped the urban tree canopy based on 1-m resolution imagery from the National Agriculture Imagery Program (NAIP), using an object-based classification approach (MacFaden et al. 2012; Zhou and Troy 2008). The imagery is 4-band color-infrared, with radiometric depth of 8 bits. Ancillary data, such as light detecting and ranging (Lidar) data and building footprint layers, were used to aid in classification. Six classes were included in the classification map: trees (i.e., tree canopy), grasses, pavement, buildings, water and bare soil (Fig. 1 $B_{TC}$, $S_{TC}$). The accuracies of the land cover classifications were assessed by visually referencing to sub-meter high-resolution imagery using protocol developed in Zhou and Troy (2008). The overall accuracies of the classifications were 95.7% for Baltimore and 93.6% for Sacramento. The user's and producer's accuracy of trees for Baltimore were 97.3% and 97.5%, and 98.2% and 96.7% for Sacramento.

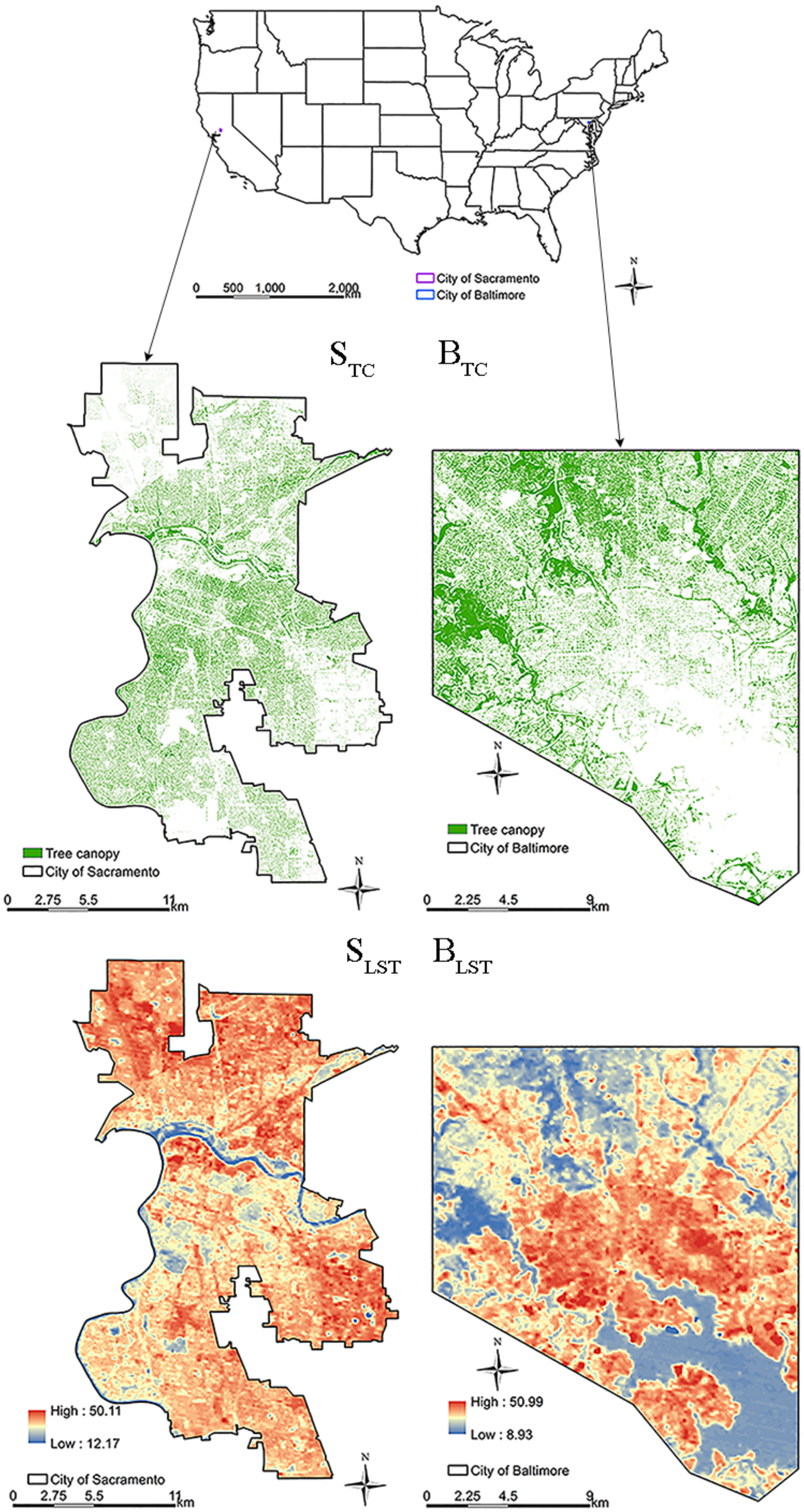

City of Sacramento
City of Baltimore
0 500 1,000 2,000 km
N
S_TC
B_TC
Tree canopy
City of Sacramento
0 2.75 5.5 11 km
Tree canopy
City of Baltimore
0 2.25 4.5 9 km
S_LST
B_LST
High : 50.11
Low : 12.17
City of Sacramento
0 2.75 5.5 11 km
High : 50.99
Low : 8.93
City of Baltimore
0 2.25 4.5 9 km

**Fig.1.** The spatial distribution of tree canopy and land surface temperatures in Baltimore (panels $B_{TC}$ and $B_{LST}$) and Sacramento (Panels $S_{TC}$ and $S_{LST}$).

There are numerous metrics that can be used to measure and describe spatial patterns of land cover features (Gustafson 1998; McGarigal 2002). Here, we chose 5 landscape metrics to measure the spatial pattern of urban trees, including one composition metric: percent cover of trees (PTree), and four configuration metrics: (1) mean patch size (AREA_MN), (2) edge density (ED), (3) mean patch shape index (SHAPE_MN), and (4) largest patch index (LPI) (Table 1). These metrics represent the primary characteristics describing the spatial pattern of trees, including the abundance of trees, size and shape of patches, edge density, and fragmentation. These metrics were chosen based on the following considerations: (1) importance in both theory and practice (Lee et al. 2009; Li and Wu 2004; Peng et al. 2010; Zhou et al. 2011), (2) easily calculated and interpretable (Li et al. 2012; Zhou et al. 2011), and (3) minimal redundancy (Riitters et al. 1995; Li and Wu 2004; Zhou et al. 2011). These metrics were calculated in ArcGIS™ 10.1.

**Table 1**

Landscape metrics used in this study, after McGarigal et al. (2002)

| Categories | Landscape Metrics (abbreviation) | Description | Equation (Unit) | Citations |
|---|---|---|---|---|
| Composition | Percent cover of tree canopy ( PTree ) | Proportion of tree canopy area within an analysis unit. | $\frac{\sum_{i=1}^{n} a_i}{A} * 100$ (%) | (Li et al. 2014; Zhou et al. 2011) |
| Configuration | Mean patch size ( AREA_MN ) | The average area of tree canopy patches within an analysis unit. | $\frac{\sum_{i=1}^{n} a_i}{N}$ ($m^2$) | (Kong et al. 2014; Zhang et al. 2009) |
| | Mean patch shape index ( SHAPE_MN ) | The average shape index of tree canopy patches within an analysis unit. | $\frac{\sum_{i=1}^{n} \frac{0.25 * p_i}{\sqrt{A}}}{N}$ | (Li et al. 2012; Peng et al. 2010) |
| | Edge density (ED) | The total perimeter of tree canopy patches per $km^2$ within an analysis unit. | $\frac{\sum_{i=1}^{n} p_i}{A} * 10000$ (m/ha) | (Connors et al. 2013; Maimaitiyiming et al. 2014) |
| | Largest patch index (LPI) | The proportion of the largest tree canopy patch within an analysis unit. | $\frac{\max a_i}{A} * 100$ (%) | (Rhee et al. 2014; Zhou et al. 2011) |

$a_i$ area of tree canopy patch *i*; $p_i$ perimeter of tree canopy patch *i*; *A* total area of analysis unit; *N* number of patches of tree canopy.

*2.3 Statistics analysis*

We investigated the relationships among spatial patterns of tree canopy and LST at multiple scales, that is, using different sizes of analytical units. Specifically, 5 sizes of analytical unit were used: 1) 1 x 1 pixel (or a grid cell of 120m x 120 m, the same as the pixel size of the Landsat TM thermal band), 2) 3 x 3 pixels (360m x 360 m), 3) 5 x 5 pixels (600m x 600 m), 4) 7 x 7 pixels (840m x 840 m), and 5) 9 x 9 pixels (1080m x 1080 m) (Liu and Weng 2009). For each analytical unit (i.e., a grid cell), we calculated the mean LST as the response variable for statistical analyses. The predictor variables were the percent cover of tree canopies, and the four landscape metrics (Table 1). Table A1 shows the mean and standard deviation of LST and landscape metrics.

A Pearson correlation matrix was first developed to examine the correlations between LST and the spatial pattern metrics of trees. We then conducted a partial correlation analysis to investigate the relationships between LST and the configuration metrics, by controlling for the effect of the percent cover of trees. Controlling for the effect tree canopy percent is necessary because the configuration metrics were highly correlated to percent cover of trees, and therefore the Pearson correlation analysis may obtain spurious relationships between LST and configuration metrics.

We then used ordinary least squares (OLS) multiple linear regression model and spatial autoregression (SAR) model to examine the effects of the spatial pattern of trees on LST. We used standardized coefficients (beta weights) to evaluate the relative importance of percent cover and configuration metrics on predicting LST (Weng et al. 2006; Yan et al. 2014; Zhou et al. 2011), and variance partitioning to quantify the explanatory power of the predictors

(Anderson and Gribble 1998; Li et al. 2013a; Li et al. 2012).

The OLS regression model is the most commonly used statistical analysis, with the assumption that the error terms are independent. The primary analyses showed that significant spatial autocorrelation ($P<0.01$) occurred in the residuals of the OLS model. Consequently, spatial autoregression models that integrate spatial autocorrelation into modeling were more appropriate to investigate the relationships between LST and spatial patterns of trees (Li et al. 2012). We also included the OLS regression model for comparison purposes, as many studies in the literature use such analyses. Below, we briefly describe the spatial autoregression models and variance partitioning. More details can be found in Li et al. (2012).

With SAR, the neighborhood relationship of the response variable is explicitly measured by a (n x n) matrix of spatial weights, which is integrated into the standard multiple linear regression to account for spatial autocorrelation (Anselin 2005a). The spatial autocorrelation can be modeled in two ways: a spatial lag model and a spatial error model (Anselin 2005a). The spatial lag model assumes that the spatial autoregressive occurs only in the response variable. The form of the spatial lag model is:

$$y = \rho Wy + \beta X + \varepsilon \qquad (1)$$

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

In contrast, the spatial error model assumes the spatial effects that are not fully explained by the explanatory variables occurs in the error terms, and therefore, is expressed as:

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

where Wμ is a (n x 1) vector of spatially lagged errors, and λ is a spatial autoregressive coefficient.

We used the Lagrange Multiplier statistics to compare the two modeling approaches, and found that the spatial error model better fit the data in this study. The regressions were then run using the spatial error model, and a maximum likelihood method. The $R^2$ values were calculated as detailed in Lichstein et al. (2002), which were comparable with those from the OLS regression model. The regressions were run in GeoDa 1.6.7 and spdep package of R (Version 2.12.1; R Development Core Team 2011)

Variance partitioning was used to quantify the relative variations in LST explained by: the percent cover of trees and the configuration metrics. The variation of LST was divided into four fractions: (1) unique effects of percent cover of trees, (2) unique effects of configuration metrics, (3) joint effects of percent cover of trees and configuration metrics, and (4) unexplained. Variance partitioning was conducted following the procedure detailed in Anderson and Gribble (1998) and in Heikkinen et al. (2005), using the spdep package (Anselin 2005b) of R (Version 2.12.1; R Development Core Team 2011).

## 3. Results

### *3.1. The spatial distribution of trees and LST in the two cities*

The percent cover of trees, as well as the spatial configuration, differed greatly between the two cities (Fig. $1B_{TC}$, $S_{TC}$). Approximately 27.1% of the land in Baltimore was covered by trees, but only 16.7% in Sacramento. Compared to Sacramento, trees in Baltimore are more clustered, especially in the northwest region of the city (Fig. $1B_{TC}$). For both cities, percent cover of trees varied greatly in space. Taking the analytical unit of 600 x 600 m as an example, percent cover of trees in grid cells varied from 0.50% to 92.62% across Baltimore, with a standard deviation of 18.73%. In Sacramento, percent cover ranged from 0 to 58.68%, with a standard deviation of 12.12% (Table A1). The mean patch size of trees in Baltimore was 599.6 $m^2$, much greater than that of 73.80 $m^2$ in Sacramento. In contrast, the patch density and edge density of trees in Sacramento were much higher than that of Baltimore (2227/$km^2$ versus 399/$km^2$ for patch density and 819.85 m/ha versus 422.31 m/ha for edge density), suggesting that tree cover was more fragmented in Sacramento. The mean shape index was similar in the two cities (1.32 in Baltimore and 1.39 in Sacramento), suggesting that the complexity of the tree patches is similar.

Land surface temperatures varied greatly in space for both cities (Fig. $1S_{LST}$, $S_{LST}$). LST in Baltimore ranged from 8.93°C to 50.99°C, with a mean of 33.37°C and standard deviation of 4.69°C, while it ranged from 12.17°C to 50.11°C, with a mean of 35.60°C and standard deviation of 3.25°C in Sacramento (Table A1). For both cities, LST was significantly autocorrelated in space, as indicated by Moran's I (Baltimore: Moran's I = 0.88, $p < 0.01$; Sacramento: Moran's I = 0.72, $p < 0.01$). LST tended to be higher in locations with less tree canopy coverage (Fig. 1$B_{TC}$, $B_{TC}$, $S_{LST}$, $S_{LST}$).

*3.2. Effect of spatial patterns of trees on LST: difference between cities and across analytical scales*

*3.2.1 Effects of percent cover of trees on LST*

The percent cover of trees was significantly negatively correlated with LST, across all analytical scales, for both cities, suggesting LST decreased with the increase of percent cover of trees (Table 2; Fig. A1). The Pearson correlation analysis showed that percent cover of tree canopy had the strongest correlation with LST among the 5 metrics. For both cities, the strength of the correlations between LST and percent cover of trees, as indicated by the correlation coefficients, increased with the increase of the size of the analytical unit. The correlations between LST and percent cover of trees, however, were generally stronger in Baltimore than in Sacramento across all 5 analytical scales, suggesting that percent cover of trees might explain more variations of LST in milder coastal regions compared to hotter and drier ones.

**Table 2**

Correlation coefficients between LST and landscape metrics. The italic and bold rows are for partial correlation analysis, where for configuration metrics, the control variable was percent cover of tree, and for percent cover of tree, the control variables were the configuration metrics.

| City | Scale | PTree | AREA_MN | SHAPE_MN | ED | LPI |
|---|---|---|---|---|---|---|
| Baltimore | 120m | -0.830$^{**}$ | -0.561$^{**}$ | -0.418$^{**}$ | -0.559$^{**}$ | -0.782$^{**}$ |
| | | ***-0.260***$^{**}$ | ***0.054***$^{**}$ | ***0.003*** | ***-0.033***$^{**}$ | ***0.036***$^{**}$ |
| | 360m | -0.904$^{**}$ | -0.453$^{**}$ | -0.604$^{**}$ | -0.555$^{**}$ | -0.805$^{**}$ |
| | | ***-0.502***$^{**}$ | ***0.059***$^{*}$ | ***-0.143***$^{**}$ | ***-0.007*** | ***0.076***$^{**}$ |
| | 600m | -0.926$^{**}$ | -0.478$^{**}$ | -0.752$^{**}$ | -0.578$^{**}$ | -0.796$^{**}$ |
| | | ***-0.499***$^{**}$ | ***0.085*** | ***-0.308***$^{**}$ | ***-0.011*** | ***0.123***$^{**}$ |
| | 840m | -0.937$^{**}$ | -0.687$^{**}$ | -0.764$^{**}$ | -0.604$^{**}$ | -0.779$^{**}$ |
| | | ***-0.574***$^{**}$ | ***0.119*** | ***-0.363***$^{**}$ | ***-0.053*** | ***0.185***$^{**}$ |
| | 1080m | -0.948$^{**}$ | -0.535$^{**}$ | -0.767$^{**}$ | -0.618$^{**}$ | -0.778$^{**}$ |
| | | ***-0.562***$^{**}$ | ***0.149*** | ***-0.390***$^{**}$ | ***-0.116*** | ***0.224***$^{*}$ |
| Sacramento | 120m | -0.640$^{**}$ | -0.354$^{**}$ | -0.361$^{**}$ | -0.464$^{**}$ | -0.602$^{**}$ |
| | | ***-0.234***$^{**}$ | ***-0.147***$^{**}$ | ***-0.115***$^{**}$ | ***0.197***$^{**}$ | ***-0.157***$^{**}$ |
| | 360m | -0.723$^{**}$ | -0.704$^{**}$ | -0.332$^{**}$ | -0.525$^{**}$ | -0.611$^{**}$ |
| | | ***-0.134***$^{**}$ | ***-0.432***$^{**}$ | ***-0.051***$^{*}$ | ***0.309***$^{**}$ | ***-0.219***$^{**}$ |
| | 600m | -0.768$^{**}$ | -0.750$^{**}$ | -0.345$^{**}$ | -0.564$^{**}$ | -0.588$^{**}$ |
| | | ***-0.087***$^{*}$ | ***-0.475***$^{**}$ | ***0.041*** | ***0.341***$^{**}$ | ***-0.238***$^{**}$ |
| | 840m | -0.811$^{**}$ | -0.788$^{**}$ | -0.545$^{**}$ | -0.609$^{**}$ | -0.609$^{**}$ |
| | | ***-0.105*** | ***-0.529***$^{**}$ | ***0.025*** | ***0.375***$^{**}$ | ***-0.253***$^{**}$ |
| | 1080m | -0.819$^{**}$ | -0.822$^{**}$ | -0.578$^{**}$ | -0.610$^{**}$ | -0.589$^{**}$ |
| | | ***0.047*** | ***-0.565***$^{**}$ | ***-0.022*** | ***0.410***$^{**}$ | ***-0.259***$^{**}$ |

** P<0.01, * P<0.05 (2-tailed)

*3.2.2. Effects of spatial configuration of trees on LST*

The Pearson correlation analysis showed that all 4 metrics of tree configuration were significantly, negatively correlated with LST, across all analytical scales, for both cities (Table 2). Similar to percent cover of trees, the strength of the correlations between LST and the 4 configuration metrics also generally increased with the increase of the size of the analytical unit; the correlations between LST and the 4 configuration metrics were stronger in Baltimore than in Sacramento. Among the 4 configuration metrics, the largest patch index had relatively strong correlations with LST.

After controlling for the effects of percent cover of trees, the correlations (i.e., partial correlations) between configuration metrics and LST changed greatly, as indicated by the results from the partial correlation analysis (Table 2). These changes included the following: 1) the strength of partial correlations, measured by the partial correlation coefficients, greatly decreased, compared with their corresponding Pearson correlation coefficients; 2) some of the configuration metrics were no longer significantly correlated to LST; and 3) more notably, the relationships between some of the configuration metrics and LST changed from negative to positive.

These changes in the relationships between LST and configuration metrics, however, varied dramatically in the two cities, in terms of magnitude, significance, and direction.

Specifically, after controlling for the effects of percent cover of trees, the correlation between mean patch size (AREA_MN) and LST changed from negative to positive when the analytical unit was less than or equal to 360m, and then to no longer significant in Baltimore. Similarly, edge density (ED) was no longer significantly correlated to LST at the analytical unit greater than 120 m on a side. In Sacramento, however, AREA_MN still had a relatively strong negative relationship with LST across all scales, but the relationships between ED and LST changed from negative to positive. SHAPE_MN remained significantly correlated with LST in Baltimore, but not in Sacramento. LPI remained significantly correlated with LST for both cities. However, these correlations changed from negative to positive in Baltimore, when controlling for the effects of percent cover of trees (Table 2). For all 4 configuration metrics, the partial correlations were stronger in Sacramento than in Baltimore, in contrast to the Pearson correlations.

*3.2.3. Relative importance of amount and configuration of trees on LST*

Results from the OLS multiple linear regressions showed that in Baltimore, percent cover of trees (PTree) had significantly negative effects on LST, across the 5 analytical scales (Table 3). In addition, PTree was the most important predictor of LST, playing a much more important role in predicting LST than the other spatial configuration variables, as suggested by the standard coefficients (Table 3). None of the configuration variables were significant at any analytical scale. Among the 4 configuration metrics, shape index (SHAPE_MN) played a relatively important role in predicting LST, and had a negative effect (Table 3). Results from the variation partitioning also indicated that percent cover of trees played a more important role than that of configuration of trees (Fig. 2).

In Sacramento, however, the relative importance of percent cover of trees (PTree) and spatial configuration differed greatly from that of Baltimore. PTree became no longer significantly related to LST at the analytical units having length scales of 840 m and 1080 m. In contrast, mean patch size (AREA_MN) was significant at all 5 analytical units, and shape index (SHAPE_MN) and edge density (ED) were significant at all scales except for 360 m. In addition, configuration metrics became more important in predicting LST, with AREA_MN being the most important predictor of LST for analytical units larger than 120 m on a side (Table 3). Results from the variation partitioning also indicated that configuration of trees played a more important role than that of percent cover of trees (Fig. 2).

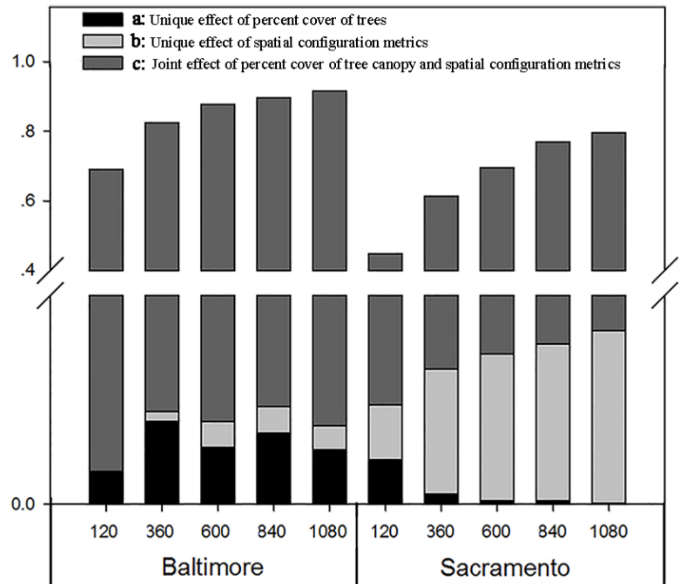
**Table 3**

Results from the OLS multiple linear regressions and the diagnostics for spatial dependence.

The bold and italic rows are standardized coefficients.

| City | Scale | PTree | AREA_MN | SHAPE_MN | ED | LPI | $R^2$ | Moran's I | AIC |
|---|---|---|---|---|---|---|---|---|---|
| Baltimore | 120m | -0.154** | 7.879E-05** | 0.024 | 1.772E-06 | 0.007 | 0.690 | 0.602 | 63539.400 |
| | | ***-0.911*** | ***0.043*** | ***0.002*** | ***0.014*** | ***0.042*** | | | |
| | 360m | -0.195** | 5.860E-05** | -2.071** | 1.359E-05** | 0.024** | 0.824 | 0.460 | 5478.030 |
| | | ***-1.046*** | ***0.060*** | ***-0.091*** | ***0.085*** | ***0.126*** | | | |
| | 600m | -0.168** | 1.291E-04** | -8.697** | 1.225E-05* | 0.001 | 0.877 | 0.427 | 1619.540 |
| | | ***-0.883*** | ***0.099*** | ***-0.203*** | ***0.073*** | ***0.005*** | | | |
| | 840m | -0.179** | 2.168E-04 | -10.290** | 1.692E-05* | 0.003 | 0.897 | 0.372 | 708.088 |
| | | ***-0.934*** | ***0.088*** | ***-0.202*** | ***0.097*** | ***0.017*** | | | |
| | 1080m | -0.168** | 1.080E-04 | -11.524** | 9.709E-06 | -0.003 | 0.915 | 0.424 | 365.764 |
| | | ***-0.865*** | ***0.064*** | ***-0.199*** | ***0.054*** | ***-0.014*** | | | |
| Sacramento | 120m | -0.160** | -0.001** | -0.993** | 1.435E-05** | -0.002 | 0.449 | 0.653 | 75885.800 |
| | | ***-0.817*** | ***-0.039*** | ***-0.138*** | ***0.304*** | ***-0.006*** | | | |
| | 360m | -0.083** | -0.014** | 0.309 | -1.991E-06 | 0.008 | 0.612 | 0.393 | 6578.530 |
| | | ***-0.419*** | ***-0.434*** | ***0.018*** | ***-0.041*** | ***0.019*** | | | |
| | 600m | -0.047* | -0.019** | 3.649** | -1.137E-05** | 0.016 | 0.696 | 0.323 | 1973.260 |
| | | ***-0.245*** | ***-0.596*** | ***0.142*** | ***-0.231*** | ***0.033*** | | | |
| | 840m | -0.051 | -0.023** | 7.498** | -1.450E-05* | 0.068* | 0.770 | 0.369 | 823.595 |
| | | ***-0.266*** | ***-0.700*** | ***0.203*** | ***-0.298*** | ***0.114*** | | | |
| | 1080m | 0.025 | -0.032** | 8.182** | -2.671E-05** | 0.028 | 0.796 | 0.318 | 413.287 |
| | | ***0.131*** | ***-0.876*** | ***0.212*** | ***-0.546*** | ***0.046*** | | | |

** P<0.01, * P<0.05 (2-tailed)




| | 120 | 360 | 600 | 840 | 1080 | 120 | 360 | 600 | 840 | 1080 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 0.023 | 0.059 | 0.041 | 0.051 | 0.039 | 0.032 | 0.007 | 0.002 | 0.003 | 0.000 |
| b | 0.001 | 0.007 | 0.019 | 0.019 | 0.018 | 0.040 | 0.090 | 0.106 | 0.113 | 0.124 |
| c | 0.667 | 0.758 | 0.817 | 0.827 | 0.859 | 0.377 | 0.515 | 0.588 | 0.655 | 0.671 |

**Fig. 2.** The results of variance partitioning for percent cover of tree canopy and spatial configuration across spatial scales.

Overall, results from the spatial error models were similar to those of the OLS regression models (Table 4). This was particularly true when the analytical units were relatively large. For example, when the analytical unit was greater than or equal to 600 m on a side, the coefficients of the predictors, and the $R^2$ values were similar between OLS models and spatial error models. However, it should be noted that at the analytical length scale of 120 m, the absolute values of coefficients from the spatial error models were much smaller than those from the OLS regression models, suggesting the importance of considering spatial autocorrelation at finer scales.

For both OLS and SAR, results from the standard coefficients and variance partitioning showed that among the five metrics, PTree was the most important predictor of LST in Baltimore. In Sacramento, however, configuration metrics, such as AREA_MN, were better predictors of LST than PTree, when the size of analytical unit was greater than 120m (for OLS) or 360m (for SAR).

**Table 4**

The results of spatial error models. The bold and italic rows are standardized coefficients.

| City | Scale | PTree | AREA_MN | SHAPE_MN | ED | LPI | R^2 | AIC |
|---|---|---|---|---|---|---|---|---|
| Baltimore | 120m | -0.059** | 9.370E-06 | -0.122** | -1.376E-06 | 0.004** | 0.932 | 42232.200 |
| | | ***-0.349*** | ***0.005*** | ***-0.012*** | ***-0.011*** | ***0.026*** | | |
| | 360m | -0.148** | 2.432E-05* | -0.997** | 1.072E-05** | 0.010 | 0.900 | 4663.350 |
| | | ***-0.790*** | ***0.025*** | ***-0.044*** | ***0.067*** | ***0.052*** | | |
| | 600m | -0.171** | 7.819E-05** | -5.565** | 2.306E-05** | 0.010 | 0.920 | 1405.970 |
| | | ***-0.900*** | ***0.060*** | ***-0.130*** | ***0.137*** | ***0.048*** | | |
| | 840m | -0.165** | 8.307E-05 | -10.560** | 2.135E-05** | 0.001 | 0.924 | 641.347 |
| | | ***-0.858*** | ***0.034*** | ***-0.207*** | ***0.123*** | ***0.004*** | | |
| | 1080m | -0.164** | 5.917E-05 | -11.100** | 1.735E-05* | -0.003 | 0.941 | 317.275 |
| | | ***-0.846*** | ***0.035*** | ***-0.191*** | ***0.097*** | ***-0.013*** | | |
| Sacramento | 120m | -0.063** | 0.000 | -0.251** | 5.363E-06** | 0.003 | 0.865 | 51781.6 |
| | | ***-0.319*** | ***0.001*** | ***-0.035*** | ***0.114*** | ***0.011*** | | |
| | 360m | -0.114** | -0.007** | -0.218 | 5.921E-06* | 0.015 | 0.741 | 5875.27 |
| | | ***-0.572*** | ***-0.211*** | ***-0.013*** | ***0.120*** | ***0.035*** | | |
| | 600m | -0.047* | -0.015** | 2.631** | -8.548E-06 | 0.001 | 0.763 | 1827.85 |
| | | ***-0.243*** | ***-0.480*** | ***0.102*** | ***-0.173*** | ***0.002*** | | |
| | 840m | -0.072* | -0.021** | 7.121** | -8.109E-06 | 0.061* | 0.827 | 744.035 |
| | | ***-0.379*** | ***-0.637*** | ***0.193*** | ***-0.167*** | ***0.102*** | | |
| | 1080m | 0.019 | -0.034** | 8.371** | -2.298E-05** | 0.029 | 0.838 | 379.032 |
| | | ***0.101*** | ***-0.932*** | ***0.217*** | ***-0.469*** | ***0.048*** | | |

** P<0.01, * P<0.05 (2-tailed)

## 4. Discussion

### *4.1. The effects of tree cover and its spatial configuration on LST: Relative importance varied greatly between cities in different climatic zones*

Percent cover of trees had similar effects on LST for both cities despite the different climatic conditions of these cities. These results are similar to findings from previous studies (Li et al. 2011; Li et al. 2013b; Weng et al. 2004; Zhou et al. 2011). Increasing the percent cover of trees can significantly decrease LST for both cities. However, the efficiency in cooling, defined as the decrease in degrees of LST with every 1% increase in tree cover (Buyantuyev and Wu 2010; Hamada and Ohta 2010; Li et al. 2013b; Peng et al. 2016; Xie et al. 2013), was higher in Baltimore than in Sacramento at all five scales of analytical unit (Table 5). The results remained the same even after considering the effects of spatial configuration, except for the analysis at the scale of 120m (Table 3&4). These results contrast with previous work conducted within southern California that showed more effective cooling by vegetation in hotter and drier desert regions compared to milder coastal ones (Tayyebi and Jenerette 2016). However, it should be noted that Tayyebi and Jenerette (2016) used the normalized difference vegetation index (NDVI) to measure the abundance of vegetation, which includes both trees and grass/lawns. But here we used the percent cover of trees. Previous findings have shown that grass is less effective than tree canopy for LST cooling (Myint et al. 2013), and its cooling effectiveness is likely to be more affected by different management practices such as irrigation.

The cooling efficiency of urban trees can be affected by many factors such as tree species, spatial configuration of trees, and management practices because, for example, transpiration rates of urban trees vary greatly by species (Pataki et al. 2011; Wang et al. 2011), and are affected by climatic factors such as air temperature, total radiation, vapor pressure deficit, and ambient pollutants such as ozone (Wang et al. 2011). These contrasting results warrant further research on the cooling effectiveness of vegetation/trees that requires field work on species identity, species transpiration rates, vegetation management such as irrigation, and more detailed climate records (McCarthy et al. 2011; Pataki et al. 2011; Polsky et al. 2014; Zhou et al. 2008).

**Table 5**

Results from OLS linear regression. The response variable, LST, was predicted by PTree

| | Baltimore | | Sacramento | |
|---|---|---|---|---|
| Scale | Coef. | $R^2$ | Coef. | $R^2$ |
| 120m | -0.144 | 0.689 | -0.129 | 0.409 |
| 360m | -0.173 | 0.817 | -0.147 | 0.523 |
| 600m | -0.18 | 0.858 | -0.152 | 0.59 |
| 840m | -0.184 | 0.877 | -0.158 | 0.657 |
| 1080m | -0.188 | 0.898 | -0.16 | 0.671 |

Effects of spatial configuration of tree cover on LST, however, varied greatly in the two cities, in terms of magnitude, significance, and even direction of effect. Some configuration metrics had contradictory effects on LST between the two cities. For example, after controlling for the effects of percent cover of trees, mean patch size was positively correlated to LST in Baltimore, but was negatively correlated in Sacramento. Because larger patches have lower edge densities (Table A2), it follows that edge density was negatively correlated to LST in Baltimore, but was positively correlated in Sacramento. Previous studies on different cities have also found contradictory results of spatial configuration of greenspace/tree canopy on LST. For example, edge density of vegetation cover was found to be negatively correlated with LST in Baltimore (Zhou et al. 2011), Shanghai (Li et al. 2011; Li et al. 2014), and Berlin (Dugord et al. 2014), but positive in Beijing (Li et al. 2013b). Our results from the comparison of the two cities indicated that the spatial configuration of trees may have different effects on LST in cities with different climatic conditions. These results enhance the understanding of the inconsistency of effects of spatial configuration of trees/greenspace on LST from previous studies.

Trees ameliorate temperatures primarily in two ways: providing shade and through evapotranspiration. The contradictory results of configuration metrics found in the two cities may be due to differences in the relative contributions of the two cooling processes and these differences may be related to different climatic conditions between the cities. Here, we again take edge density as an example. Increasing total edges and edge density may potentially lead to an increase of shade provided by trees to surrounding surfaces (Li et al.

2012; Zhou et al. 2011). In addition, greater total edges and edge density may also enhance energy flow and exchange between trees and their surrounding areas (Cadenasso et al. 2003; Zhou et al. 2011). Consequently, considering only the shading process, increasing edge density will lead to lower LST. However, increased edge density is frequently a result of more fragmented tree cover, given a fixed amount of total tree coverage. As large and continuous tree stands generally have lower temperature than that of fragmented and smaller patches (Cao et al. 2010; Yokohari et al. 1997; Zhang et al. 2009), suggesting stronger evapotranspiration efficiency of larger patches, increasing edge density is likely to reduce evapotranspiration efficiency. This is particularly predominant in cities such as Sacramento that have very dry and hot summers, during which vegetation is very likely to experience water and temperature stress (Connors et al. 2013; Maimaitiyiming et al. 2014). This is because the ambient temperature and humidity affect the transpiration rate of trees in a non-linear (an inverted U shape) way (Lambers et al. 2008; Schulze et al. 2005). That is, while increasing temperature and reducing humidity to some extent can induce the stomata open and thus enhance transpiration, excessive heat and increasing vapor pressure deficit between leaf and air will lead to dramatic reduction in transpiration (Lambers et al. 2008; Schulze et al. 2005). Therefore, whether the increase of edge density will lead to a decrease or increase in LST will largely depend on the net effects of increased shading effects and reduced evapotranspiration effects. In Mediterranean climate cities such as Sacramento, the reduction in evapotranspiration caused by increased edge density is likely to outweigh increased shading. Consequently, edge density has a positive relationship with LST, given a fixed amount of tree coverage. But this is the opposite in cities such as Baltimore that experience a relative humid summer.

Similar to edge density, whether the increase of mean patch size leads to a decrease or increase in LST largely depends on the joint effects of the two key cooling processes, shading and evapotranspiration of trees. In contrast to edge density, an increase in mean patch size will likely result in increased evapotranspiration efficiency (Cao et al. 2010; Yokohari et al. 1997; Zhang et al. 2009), but reduced shading effects. An increase in mean patch size will likely lead to reduced shading effects because given a fixed amount of tree cover, an increase in mean patch size leads to a decrease in edge density (Table A2), which results in reduced shading effects, as discussed above. In the hotter and drier Sacramento area, the increased evapotranspiration caused by increased mean patch size is likely to outweigh reduction in shading. Therefore, mean patch size has a negative relationship with LST, given a fixed amount of tree coverage. In Baltimore, however, reduction in shading outweighed increased evapotranspiration, and thus an increase in mean patch size led to higher LST.

Notably, the relative importance of mean patch size in predicting LST increased with the increased size of analytical unit in Sacramento, but the opposite was found in Baltimore, both suggesting clear scale effects. These scale effects may suggest that the two cooling processes, shading and evapotranspiration of trees, and their relative importance, change with scale, and differ by cities with different climatic conditions. This hypothesis, however, warrants further research.

The relative importance of percent cover of trees, and spatial configuration on LST also varied greatly between the two cities. Percent cover of trees was the most important variable in predicting LST in Baltimore. This is consistent with many of the previous studies that have found that percent cover of trees (or greenspaces) plays a more important role than their spatial configuration (Li et al. 2012; Xie et al. 2013; Zhou et al. 2011). However, spatial configuration of tree cover, such as the mean patch size, played a more important role in predicting LST than the percent cover of trees in Sacramento. In fact, the importance of percent cover of trees in predicting LST decreased with the increase of the size of analytical unit, and even became insignificant at the size of 840m and greater (Table 3). This result is similar to the findings of Maimaitiyiming et al. (2014) in a study conducted in Aksu, Xinjiang, China, and of Li et al. (2016) in a study of Phoenix, Arizona, USA. Both cities are relatively dry and hot in summer, similar to Sacramento. These results indicated that the relative importance of percent cover of trees and their spatial configuration may vary by cities with different climatic conditions. It should be noted, however, that at the finest scale in this study -- analytical unit of 120m, -- percent cover of trees was a much better predictor of LST than any configuration metrics in Sacramento (Table 3). With the recent availability of very fine resolution LST data (7m resolution, e.g., Jenerette et al. 2016), research on how the relationship between spatial pattern of trees and LST varies by unit of analysis at a scale finer than 120m would be highly desirable to expand our understanding of the scale effects.

### *4.2. The methodological implications: It is crucially important to choose the appropriate statistical approaches*

Our results underscore the necessity of controlling for the effects of percent cover of trees when quantifying the effects of spatial configuration of tree cover on LST. For both cities, after controlling for the effects of percent cover of trees (either through partial correlation or linear regression modelling), the relationships between LST and configuration metrics dramatically changed, compared with results from the Pearson correlation analysis. For example, the relationship between LST and mean patch size (AREA_MN) changed from negative to positive in Baltimore. Similarly, the relationship between LST and edge density (ED) in Sacramento changed from negative to positive. This is because most of the configuration variables are inherently correlated to percent cover of trees (Table A3&A4; Li and Wu 2004; Peng et al. 2010; Riitters et al. 1995). For example, mean patch size had a significantly negative correlation with LST based on the Pearson correlation analysis ($r=-0.56$, $p<0.01$; Table 2) in Baltimore at the scale of 120m. This observed correlation, however, is due to the very strong positive correlation between mean patch size and percent cover of trees ($r=0.70$, $p<0.01$; Table A3). After controlling for the effect of percent cover of trees, mean patch size in fact had a significantly positive correlation with LST, due to the reasons we discussed in section 4.1. Therefore, it is crucially important to use statistical methods such as partial correlation and multiple regression models, instead of Pearson correlation, to assess the relative contributions of percent cover of trees and configuration to LST. Using Pearson correlation analysis may generate misleading results.

Other statistical approaches, such as path analysis and structural equation modeling have been increasingly used to identify the complex and nested relationships among social conditions, land cover and surface temperatures (Jenerette et al. 2007; Huang and Cadenasso 2016; Tayyebi and Jenerette 2016), which potentially allow the evaluation of direct and indirect effects of tree cover and configuration on LST.

Our results also showed that the spatial autocorrelation could influence the relationships between landscape metrics and LST. This is particularly true when the unit of analysis is relatively small. However, when the unit of analysis in this study is relatively large (i.e., equal to or greater than a linear dimension of 600 m), results from OLS modeling and SAR modeling were similar, in terms of both regression coefficient and $R^2$. This may suggest that the frequently used OLS is appropriate at such scales.

We found that with increasing size of the analytical unit, the relationships between LST and spatial pattern metrics, including both percent cover and configuration, became stronger. The spatial pattern of tree cover also explained more variation in LST. We did not find a “best” size of analytical unit, at which the correlations (or $R^2$) peaked, and a turning point occurred (Liu and Weng 2009; Peng et al. 2016; Weng et al. 2004). This may be due to the very different data used, as well as the approaches for scaling. Here, the spatial resolution of the image data used to map tree cover was 1 m, but most previous studies used the 30 m Landsat TM data.

## 5. Conclusions

Urban greenspace, particularly trees, has significant cooling effects on urban heat. It is widely recognized that increasing percent coverage of greenspace can greatly reduce ambient air temperatures and land surface temperatures in urban environments. However, recent studies investigating the effects of spatial configuration of greenspace show significant, but inconsistent results, including the direction of the effects. To investigate the causes of this inconsistency, we conducted a comparison study of Baltimore, MD and Sacramento, CA, USA, two cities with very different climatic conditions, using different statistical approaches and analytical units with varied sizes. We found: (1) Trees' cooling efficiency generally was higher in Baltimore than in the hotter and drier Sacramento. (2) The effects of spatial configuration of trees on LST varied greatly in terms of magnitude, significance, and even direction, between the two cities, suggesting spatial configuration of trees may play different roles in cities with different climatic conditions. Percent cover of trees was more important than their spatial configuration in predicting LST in Baltimore, but the opposite was found in Sacramento. Therefore, urban planners and managers should be cautious about directly applying results found in cities with different climatic conditions. (3)

When using different statistical approaches, the relationships between LST and configuration metrics could dramatically change. Our results underscore the necessity of controlling the effects of percent cover of trees, when quantifying the effects of spatial configuration of trees on LST. These results contribute to the understanding of the inconsistent results from previous studies, which may be caused by the different methods applied (e.g., Pearson correlation analysis versus partial correlation). (4) Spatial autocorrelation could influence the relationships between landscape metrics and LST, particularly when the unit of analysis is relatively small. (5) With the increase of the size of analytical unit, the relationships between spatial configuration metrics and LST became stronger. This study can enhance the understanding on the effects of spatial configuration of greenspace on UHI. It also provides important insights to urban planners and natural resource managers on how to mitigate the impact of urbanization on UHI through urban design and vegetation management.

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**Appendix**

**Table A1**

A Descriptive statistics of LST and landscape metrics of trees.

| City | scale | LST | | PTree | | AREA_MN | | SHAPE_MN | | ED | | LPI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | mean | SD | mean | SD | mean | SD | mea | SD | mean | SD | mean | SD |
| Baltimore | 120 | 31.87 | 4.14 | 27.51 | 24.45 | 950.02 | 2267.63 | 1.37 | 0.40 | 57518.11 | 33468.78 | 19.25 | 23.91 |
| | 360 | 31.87 | 3.83 | 28.11 | 20.52 | 1191.00 | 3949.92 | 1.37 | 0.17 | 52488.62 | 24066.84 | 14.66 | 19.97 |
| | 600 | 31.87 | 3.56 | 28.13 | 18.73 | 980.78 | 2740.28 | 1.35 | 0.08 | 51759.32 | 21151.46 | 12.34 | 17.99 |
| | 840 | 31.78 | 3.40 | 28.83 | 17.71 | 866.37 | 1379.75 | 1.35 | 0.07 | 52364.87 | 19491.47 | 11.50 | 17.04 |
| | 1080 | 31.68 | 3.28 | 29.73 | 16.89 | 901.85 | 1933.74 | 1.34 | 0.06 | 53401.59 | 18325.08 | 11.26 | 16.30 |
| | city | 31.87 | 4.14 | 27.10 | | 599.60 | 19526.35 | 1.32 | 0.54 | 478.26 | | 2.14 | |
| Sacramento | 120 | 33.27 | 2.97 | 16.93 | 15.10 | 81.65 | 243.84 | 1.25 | 0.41 | 90008.97 | 62935.26 | 6.82 | 9.99 |
| | 360 | 33.28 | 2.56 | 17.29 | 12.87 | 79.54 | 81.49 | 1.32 | 0.15 | 88252.77 | 51997.52 | 3.43 | 6.04 |
| | 600 | 33.31 | 2.35 | 17.42 | 12.12 | 80.66 | 73.43 | 1.33 | 0.09 | 87813.52 | 47579.94 | 2.39 | 4.94 |
| | 840 | 33.35 | 2.18 | 17.41 | 11.49 | 80.57 | 67.24 | 1.32 | 0.06 | 87552.63 | 44935.50 | 1.87 | 3.66 |
| | 1080 | 33.30 | 2.06 | 18.00 | 10.81 | 81.28 | 57.09 | 1.33 | 0.05 | 89677.74 | 42027.10 | 1.72 | 3.43 |
| | city | 33.27 | 2.97 | 16.66 | | 73.80 | 1098.00 | 1.39 | 3.33 | 819.85 | | 0.03 | |

**Table A2**

Partial correlation between mean patch size and dege density controlling for the effect of percent cover of trees.

| | Baltimore | Sacraemento |
|---|---|---|
| 120 | -0.655** | -0.438** |
| 360 | -0.475** | -0.746** |
| 600 | -0.454** | -0.789** |
| 840 | -0.643** | -0.807** |
| 1080 | -0.528** | -0.846** |

** P<0.01 (2-tailed)

**Table A3**

Correlation matrix between independent variables in Baltimore.

| scale | | PTree | AREA_MN | SHAPE_MN | ED | LPI |
|---|---|---|---|---|---|---|
| | PTree | 1 | | | | |
| | AREA_MN | 0.70** | 1 | | | |
| 120m | SHAPE_MN | 0.51** | 0.31** | 1 | | |
| | ED | 0.66** | 0.11** | 0.54** | 1 | |
| | LPI | 0.95** | 0.78** | 0.45** | 0.45** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.53** | 1 | | | |
| 360m | SHAPE_MN | 0.61** | 0.46** | 1 | | |
| | ED | 0.61** | 0.00 | 0.44** | 1 | |
| | LPI | 0.91** | 0.61** | 0.52** | 0.31** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.54** | 1 | | | |
| 600m | SHAPE_MN | 0.73** | 0.50** | 1 | | |
| | ED | 0.62** | 0.04* | 0.53** | 1 | |
| | LPI | 0.88** | 0.64** | 0.52** | 0.29** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.76** | 1 | | | |
| 840m | SHAPE_MN | 0.72** | 0.46** | 1 | | |
| | ED | 0.63** | 0.16 | 0.65** | 1 | |
| | LPI | 0.87** | 0.87** | 0.45** | 0.27** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.60** | 1 | | | |
| 1080m | SHAPE_MN | 0.72** | 0.34** | 1 | | |
| | ED | 0.62** | 0.05 | 0.67** | 1 | |
| | LPI | 0.86** | 0.71** | 0.40** | 0.25** | 1 |

** P<0.01, * P<0.05 (2-tailed)

**Table A4**

Correlation matrix between independent variables in Sacramento.

| scale | | PTree | AREA_MN | SHAPE_MN | ED | LPI |
|---|---|---|---|---|---|---|
| | Ptree | 1 | | | | |
| | AREA_MN | 0.40** | 1 | | | |
| 120m | SHAPE_MN | 0.44** | 0.20** | 1 | | |
| | ED | 0.85** | 0.12** | 0.48** | 1 | |
| | LPI | 0.84** | 0.52** | 0.31** | 0.50** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.67** | 1 | | | |
| 360m | SHAPE_MN | 0.41** | 0.38** | 1 | | |
| | ED | 0.87** | 0.31** | 0.40** | 1 | |
| | LPI | 0.70** | 0.76** | 0.19** | 0.36** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.69** | 1 | | | |
| 600m | SHAPE_MN | 0.48** | 0.46** | 1 | | |
| | ED | 0.87** | 0.32** | 0.44** | 1 | |
| | LPI | 0.61** | 0.72** | 0.14** | 0.28** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.70** | 1 | | | |
| 840m | SHAPE_MN | 0.69** | 0.57** | 1 | | |
| | ED | 0.88** | 0.34** | 0.65** | 1 | |
| | LPI | 0.61** | 0.75** | 0.22** | 0.28** | 1 |
| | PTree | 1 | | | | |
| | AREA_MN | 0.73** | 1 | | | |
| 1080m | SHAPE_MN | 0.69** | 0.62** | 1 | | |
| | ED | 0.88** | 0.38** | 0.64** | 1 | |
| | LPI | 0.57** | 0.69** | 0.21* | 0.27** | 1 |

** $P<0.01$, * $P<0.05$ (2-tailed)

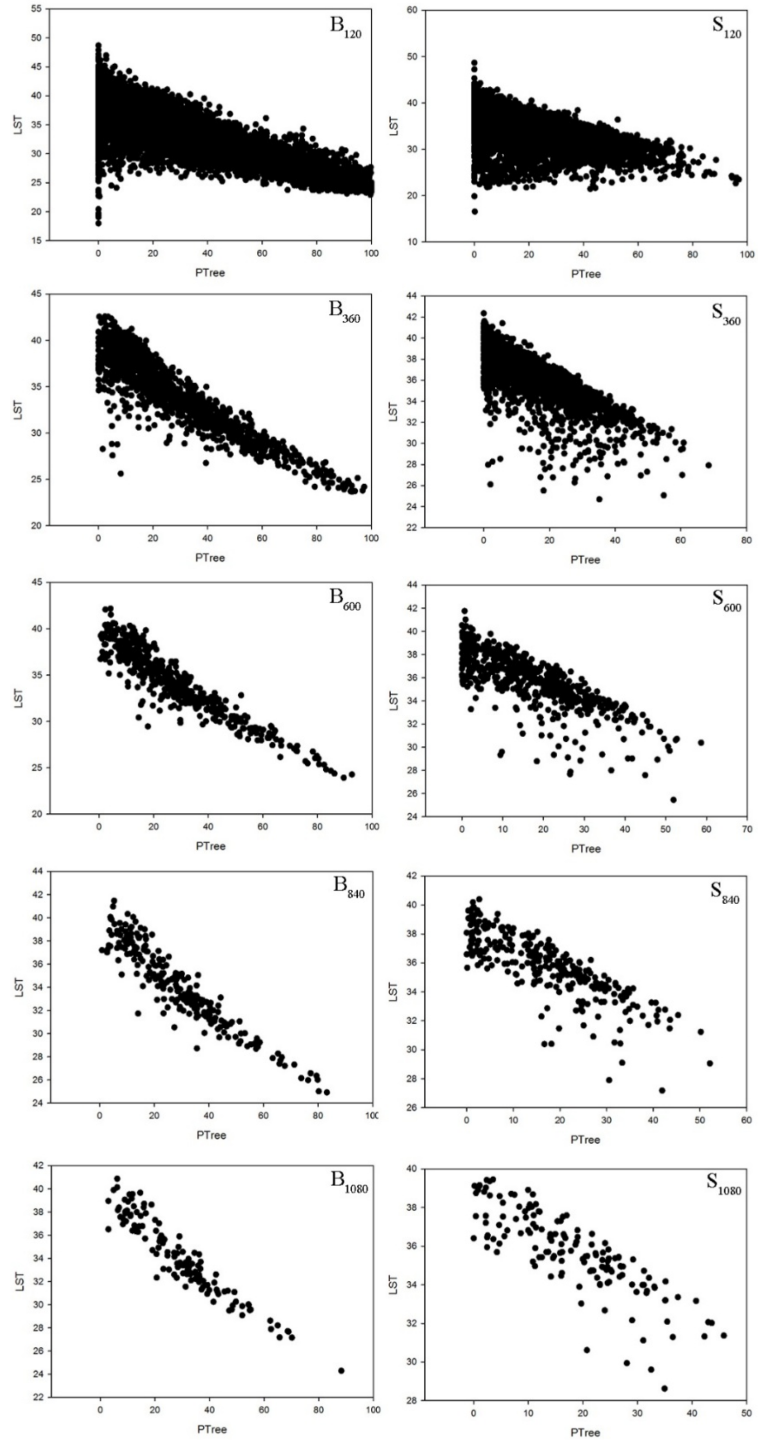


Fig. A1 Scattergrams of land surface temeprature (LST) VS.Percent cover of tree canopy across all scales at two cities: $B_{120}$, $B_{360}$, $B_{600}$, $B_{840}$ and $B_{1080}$: Baltimore; $S_{120}$, $S_{360}$, $S_{600}$, $S_{800}$ and $S_{1080}$: Scaramento.