A satellite image-based analysis of factors contributing to the green-space cool island intensity on a city scale

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A R T I C L E    I N F O

Keywords:
Cool island intensity
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A B S T R A C T

Urban green spaces provide cooler microclimates and create localized urban cool islands and, as part of an adaptation strategy to cope with future urban climate change, have been proposed as a means to mitigate the urban heat island effect. Numerous previous research papers have discussed green-space size, type, and vegetation density, as well as many other factors that might influence green-space cooling effects. However, little has been done with regard to exploring and quantifying the characteristics of the green-space cool island (UCI). It is also largely unknown whether or how the patterns of green space and land use, as well as the adjacent urban thermal environment, affect UCIs. In this paper, the land surface temperature (LST) was retrieved from satellite imagery. The UCI was identified, and one of the UCI characteristics, the UCI intensity, was defined. Multiple linear regression models were then used to explore and quantify the combined effects of factors related to the UCI intensity. The results show that the intensity differed between UCIs, and correlated significantly with the extent of and mean temperature reduction associated with an UCI. Multiple linear regression analysis found that UCI intensity was affected by areas of forest vegetation and its spatial arrangements, as well as by the composition of the cool island and its neighboring thermal environment. The study validated the suitability of using intensity as an indicator of the UCI. Identifying the UCI as a result of the green-space cooling effect, will help in the management and planning of the spatial arrangement of green spaces in cities to reduce the effects of the urban thermal environment and help cities adapt to climate change.

C H A N G N O N   e t   a l., 1996;  R O S E N F E L D   e t   a l., 1998;  M C M I C H A E L   e t   a l., 2003;  F O U I L L E T   e t   a l., 2006;  L A F O R T E Z Z A   e t   a l., 2009;  B O W L E R   e t   a l., 2010). Urban greenspaces, mainly resulting from direct shading and cooling through evapotranspiration, can reduce air and surface temperature and may generate localized cooling (Taha et al., 1988; Oke et al., 1989; Tyrväinen et al., 2005; Onishi et al., 2010; Armson et al., 2012; Weber et al., 2014). Such a phenomenon is termed the “urban cool island” (UCI) (Shashua-Bar et al., 2009; Vidrih and Medved, 2013). Previous studies have found that an UCI is an effective means to mitigate the UHI effect, reduce the effects of heat stress, and provide a comfortable outdoor setting for citizens (Cao et al., 2010).

The effects of UCIs differ between greenspaces (Chang et al., 2007). Previous research, through onsite observations, has reported that vegetation type and density, green space size and shape, and tree shade area are all important factors in determining the cooling effect (Jauregui, 1990; Spronken-Smith and Oke, 1998; Upmanis

I n t r o d u c t i o n

In most cities around the world the impact of urbanization on local climate is alarming (Oke, 1982; Rosenfeld et al., 1995; Shobhakar and Hanaki, 2002; Giridharan et al., 2004; Hamdi and Schayes, 2007). The urban heat island (UHI) effect is one climate phenomenon associated with urbanization. A range of consequences for environmental pollution, energy demand, and human health are predicted from the intensification of the UHI (Kim, 1992; 1618-8667/© 2014 Elsevier GmbH. All rights reserved.
et al., 1998; Potchter et al., 2006; Chang et al., 2007; Jusuf et al., 2004; Giridharan et al., 2008). Research comparing the cooling effects produced by different types of vegetation has found that trees are more effective than bushes, which, in turn, are more effective than grass (Hemiddi, 1991; Narita et al., 2004; Jonsson, 2004; Wong et al., 2007; Cao et al., 2010). However, most of these studies are qualitative by design and do not establish quantifiable effects and statistical relationships. The partially shaded area under a tree canopy has also been found to have a strong relationship with cooling (Shashua-Bar and Hoffman, 2000; Svensson and Eliasson, 2002; Fahmy et al., 2010). Giridharan et al. (2008) confirmed that the sky view factor (a measure of the degree to which the sky is obscured by the surroundings for a given point) of a shrub or tree may influence the cooling effect. Green spaces may also vary in terms of the proportion of the total area without vegetation cover, and an increased paved area has been shown to correlate positively with differences in air temperature (Barradas, 1991; Cao et al., 2010). Further, the cooling effect may decay with increasing distance from the boundary of a green space (Spronken-Smith and Oke, 1998; Upmanis et al., 1998; Chen and Wong, 2006; Hamada and Ohta, 2010). Most previous studies only measured a small number of distinct green sites and confirmed that vegetation lowers air temperatures by shading, and by absorbing and converting ambient heat to latent heat through evapotranspiration at a local scale (Cao et al., 2010). Furthermore, there is a consensus that the relationship between the area of the green space and associated cooling effect may be non-linear (Jauregui, 1990; Chang et al., 2007). Therefore, conclusions drawn from an individual study cannot be easily verified (Bowler et al., 2010); and quantifiable cooling effects and statistical relationships at the urban scale cannot be established by such small-scale studies (Spronken-Smith and Oke, 1998; Chang et al., 2007). In addition, whether the effects are due to green spaces alone or to other factors, for example context-dependence factors, has yet to be demonstrated, and are more difficult to test within a single study. Consequently, the current evidence base does not allow recommendations to be made on how best to incorporate greening into an urban area (Bowler et al., 2010).

Remote sensing provides detailed spatially explicit datasets on land cover and land use, as well as land surface temperatures (LSTs) (Cao et al., 2010; Schwarz et al., 2011). Recent developments in landscape ecology have made it possible to link the spatial heterogeneity of greenspaces quantitatively to their associated cooling effect. Numerous studies have shown that the percentage of greenspace cover has a positive relationship with cooling effects. More recently, by exploiting landscape ecological theory, some attempts have been made to identify those greenspace characteristics, especially the spatial arrangements, which might influence cooling effects (Xu, 2009; Li et al., 2011; Zhou et al., 2011; Li et al., 2012). However, little has been done to explore and quantify the characteristics of the UCI (Godzelnia et al., 2003; Lee and Balk, 2010). It is also largely unknown whether or how UCI might be affected by the landscape pattern of greenspace, the adjacent thermal environment, and the surrounding land use pattern (Chang et al., 2007; Li et al., 2011, 2012). Most observational studies are based on an individual greenspace site (e.g., Katayama et al., 1993; Shashua-Bar and Hoffman, 2000; Chang et al., 2007; Jusuf et al., 2007; Fahmy et al., 2010; Shashua-Bar et al., 2010). However, quantifiable cooling effects and statistical relationships between the green space cooling effect and its impact at the urban scale cannot be established based on an investigation of only one green space (Spronken-Smith and Oke, 1998). Consequently, the characteristics that determine cooling effects of green space are not fully understood, which limits the usefulness and applicability of data from previous studies for enhancing cooling through green infrastructure planning.

This study focuses on quantifying the UCI intensity using Nanjing, China as a case study. The main objectives of this study are: (1) to identify and delineate urban cool islands, especially the UCI, (2) to define the UCI intensity and quantify its characteristics through its intensity; (3) to explore any factors contributing to the UCI intensity, particularly relating to the UCI composition, spatial pattern, and the neighboring environment.

Study area

Nanjing (31°14′–32°37′N, 118°22′–119°14′E), the capital of Jiangsu Province in China, located in the west of the Yangtze Delta (Fig. 1), has a population of over 6.3 million within an area of 4723 km² (Nanjing Municipal Bureau Statistics, 2010). Nanjing has a subtropical monsoon climate with four seasons, and with Wuhan, Chongqing, and Jinan, is known as one of the “Four Furnace Cities” for its hot, humid weather conditions in summer. The mean daily maximum summer (June–August) temperature is 37.3 °C. Temperatures exceeding 40 °C have been recorded on three occasions since 1951 (Miao et al., 2008). Further, the number of hot days per year and the frequency of heat waves are increasing. For example, the number of days per year with a daily mean temperature exceeding 22 °C has increased by more than 20 during the past 60 years (Miao et al., 2008). From 1951 to 2009, there were 112 summer heat waves (defined as 3 consecutive days when the temperature is ≥35 °C) events in Nanjing (Xu et al., 2011). The area examined in this study includes the whole area of downtown Nanjing city, encompassing an area of 432 km².

Data and defining explanatory variables

Image pre-processing and retrieval of LST

The data used in this research comprises a rectified and georeferenced (Universal Transverse Mercator (UTM) coordinate system) IKONOS image (18 June 2009, 4 bands, 3.2 m spatial resolution) and a LANDSAT TM 5 image (13 June 2009, 30 m spatial resolution). Based on the IKONOS image and supported by the ArcMap platform (Version 9.0, ESRI), urban land use categorical maps were created. Six land classes were identified: impervious surfaces, forest vegetation (trees mixed with shrubs and grass), other vegetation (shrubs and grass), water, agricultural land, and barren land. The Landsat 5 Thematic Mapper image was used to retrieve the LST. Thematic Mapper is composed of seven bands: six visible and near infrared, and one thermal infrared (TM6, 120 m spatial resolution) which was used for land surface temperature retrieval. The Landsat image taken at 10:29 local time on 13 June 2009 (Row/Path: 120/38) was projected to a common UTM coordinate system based on the IKONOS image, and was resampled using the nearest neighbor algorithm with a pixel size of 30 m × 30 m for all bands including the TM6 thermal band. The resultant RMSE was found to be less than 0.5 pixel.

According to the record of local Bureau of Meteorology, the highest, lowest and mean temperature on June 13, 2009 were 32.1, 20.4 and 26.1 °C, respectively. The mean temperature and wind velocity of the study time 10:00–11:00 were 29.5°C and 3 m/s respectively, the wind direction was westerly, and there was no cloud. Although the mid-morning timing of the Landsat overpass is not ideal for analysis of the cooling effect of green spaces (it is not the hottest time of day and according to previous research the higher the background air temperature, the stronger the cooling effect of green spaces (Shashua-Bar and Hoffman, 2000)) it is feasible without a major loss of information if the meteorological conditions are good, as they were. The selection of an image from the mid-morning of June 13 is therefore appropriate, although not optimal. The
methodology applied for retrieving LSTs and calculating the LST maps is based on the Mono-Window Algorithm from Qin et al. (2001) (Fig. 2).

Identification of UCI and its intensity

In this research, the mean LST ($T$) of the study area was treated as the reference land surface temperature, and we refer to a UCI as an area where the difference between the LST ($T$) and the $\bar{T}$, namely $\Delta T$, is less than $0 \, ^\circ C$, i.e. $UCI = \Delta T = T - \bar{T} (\Delta T \leq 0)$. Once identified, the UCIs were extracted.

Previous research on the stationary measurement of the diurnal changes of the urban microclimate within four types of ground cover of Nanjing found that grassland has a weak cooling effect at daytime (Huang et al., 2008). Further, recent analysis of LST by Kong et al. (2014) found that when at least 99.69% of the fixed scale $240 \times 240$ m is covered by grassland, a cool island will be created. Thus, in this research we focus upon the forest vegetation (trees mixed with shrubs and grass) only (Fig. 2b).

Most previous studies have defined UHI intensity as the temperature (air or land surface) difference between the heat center in a city (i.e., where it is warmest) and its suburbs or reference rural locations (Oke, 1973; Magee et al., 1999; Kim and Baik, 2005).
Fig. 3. (a) Extracted hot spots (areas $3\, ^\circ\mathrm{C}$ warmer than the average LST of the study area and areas greater than 3 km$^2$ ), and (b) water bodies.
2013; Feyisa et al., 2014). Therefore, a suitable transformation of the two variables was required prior to conducting regression analysis. In this research, an interaction term called the “size-distance index” was developed as \( \ln(S/D) \), where \( S \) is the size of the nearest hot spot (or water body) and \( D \) is the distance to the nearest hot spot (or water body). This index was incorporated into the regression model to estimate the effect of the proximity to a certain sized hot spot (or water body) on UCI intensity, allowing the effect of distance to vary with the size of the relevant hot spot (or water body). Therefore, the variables \( S_D WB \) and \( S_D HS \) were developed, to quantify the impacts of the nearby water bodies and hot spots respectively (shown in Fig. 3a and b) as explanatory variables in the multiple regression analysis to explore their combined effects on UCI intensity.

Statistical analysis was conducted to obtain the mean LST of different land cover types. Results indicate that the average LST of the study area is 28.5 °C and the average LST of impervious land is 31.5 °C, which is 3.0 °C higher than the average LST of forest vegetation of the study area. Hence, the hot spots here were defined as being where the LST is 3 °C higher than \( \bar{T} \) of the study area and where the size of the area is more than 3 km². Altogether, six hot spots were identified in the study area, as shown in Fig. 3a.

All of the explanatory variables considered in establishing multiple regression models are listed in Table 1. A brief definition of each independent variable, as well as their expected effects, is also presented. Considering that there may be a complex relationship between SHDI and PRLA of land use, and temperature reduction, the effects of SHDI and PRLA on UCI intensity may change because of the different land use type as well as its composition. Thus, because it is difficult to make a decision prior to the analysis, the expected effects of SHDI and PRLA are not given. All the variables were captured at the scale decided by each UCI patch and supported by ArcGIS and batch file analysis in FRAGSTATS (version 3.3). The independent variables \( *_VT, *_JS, *_WB \) are the class-level metrics, which offer a fundamentally class-based perspective of each UCI. SHDI and PRLA are the landscape level metrics that characterize the overall structure and provide a landscape-based understanding of each UCI. All 153 UCIs were used in the analysis.

### Table 1

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Description</th>
<th>Expected sign</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Background characteristics</td>
<td>( S_D WB ) (size-distance index for water body)</td>
<td>A measure of the integrated impact of the nearest Water Body size and straight-line distance from the Min LST point to the boundary of the nearest Water Body ( (D_{Water}, S_D WB) = \ln \left( \frac{S_{Water}}{D_{Water}} \right) )</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>( S_D HS ) (size-distance index for hot spots)</td>
<td>A measure of the integrated impact of the nearest Hot Spot size ( (S_{HS}) ) and straight-line distance from the Min LST point to the boundary of the nearest Hot Spot ( (D_{HS}, S_D HS) = \ln \left( \frac{S_{HS}}{D_{HS}} \right) )</td>
<td>-</td>
</tr>
<tr>
<td>UCI characteristics</td>
<td>CAVT (area of forest vegetation)</td>
<td>A measure of landscape composition, equaling the sum of the forest vegetation areas ( (m^2) ) of all patches in each UCI patch, divided by 10,000 (to convert to hectares); ( CAVT = \sum_{n=1}^{N} \frac{W_{gj}}{10},000 ), where ( W_{gj} ) is the forest vegetation covering area of patch ( g ) in the corresponding patch UCI ( (unit: ha) )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>CAJS (areas of impervious surfaces)</td>
<td>A measure of landscape composition, equaling the sum of the impervious surface areas ( (m^2) ) of all patches in each UCI patch, divided by 10,000 (to convert to hectares); ( CAJS = \sum_{n=1}^{N} b_{ij} / 10,000 ), where ( b_{ij} ) is the built-up land covering area of patch ( j ) in the corresponding patch UCI ( (unit: ha) )</td>
<td>+</td>
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<tr>
<td></td>
<td>CAWB (areas of water)</td>
<td>A measure of landscape composition, equaling the sum of the water body areas ( (m^2) ) of all patches in each UCI patch, divided by 10,000 (to convert to hectares); ( CAWB = \sum_{n=1}^{N} v_{ij} / 10,000 ), where ( v_{ij} ) is the water body covering area of patch ( j ) in the corresponding patch UCI ( (unit: ha) )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>MPSVT (mean patch size of forest vegetation)</td>
<td>A measure of landscape fragmentation, equaling the average area of all forest vegetation patches in each UCI ( (unit: ha) )</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>PDVT (patch density of forest vegetation)</td>
<td>A measure of the fragmentation of forest vegetation in each UCI ( UCLPDVT = \left( \frac{n_i}{A} \right) ) ( (10,000) ) ( (100) ), where ( n_i ) is the total number of forest vegetation patches in each UCI</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>ALVT (aggregation of forest vegetation)</td>
<td>A measure ( (in %) ) of aggregation of forest vegetation in each UCI, ( ALVT = \left( \frac{\sum_{i=1}^{N} g_{ij}}{\max - g_{ij}} \right) ) ( (100) ), where ( g_{ij} ) is the number of like adjacencies ( (joins) ) between pixels of forest vegetation ( (i) ); ( \max g_{ij} = \max ) number of like adjacencies ( (joins) ) between pixels of forest vegetation ( (i) ), based on the single-count method</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>GYAMVT (mean patch radius of gyration of forest vegetation)</td>
<td>A measure of the compactness of forest vegetation, which is the mean patch radius of gyration at the class level where each patch is weighted by its area. ( GYAMVT = \sum_{i,j} \left( \frac{h_{ij}}{z} \right) \frac{a_{ij}}{\sum_{a_{ij}}} ) where ( h_{ij} ) is the distance between cell ( ij ) (located within forest vegetation patch ( i ) and the centroid of patch ( j ); ( z ) is the number of cells in patch ( j ), where ( r = 1, \ldots, z; a_{ij} ) is the area of patch ( ij; n ) is the number of patches forest vegetation, where ( j = 1, \ldots, n; ) and ( h_{ij} ) is the distance from patch ( ij ) to nearest neighboring forest vegetation patch</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>SHDI (land use diversity)</td>
<td>A measure of patch diversity in a landscape that is determined by both the number of different patch types and the proportional distribution of area among patch types: ( H = \sum_{i=1}^{n} \left( P_i \ln(P_i) \right) ), where ( n ) is the total number of patch types and ( P_i ) is the proportion of the landscape area occupied by patch type ( i ) ( (unitless) ) in each UCI</td>
<td>?</td>
</tr>
<tr>
<td></td>
<td>PRLA (patch richness of land use)</td>
<td>A measure of the landscape composition, equaling the number of different land use types in each UCI</td>
<td>?</td>
</tr>
</tbody>
</table>
Results

Characteristics of UCIs

All the selected UCIs are found within areas where the percentage of forest vegetation is >60% and water area <20%. In total, 153 individual UCIs were identified (Fig. 2b). However, some UCIs were produced by the same greenspace. Thus, combining individual UCIs found within the same greenspace reduced the total number of UCIs to 116, which are used in further analysis. The total area of the UCIs is 43.94 km²; their mean temperature reduction is −0.6 °C, and the maximum temperature reduction is −6.9 °C.

Characteristics of UCI intensity

UCI intensity differed between the greenspaces and cool islands. UCI intensity has a strong significant relationship with the mean temperature reduction and the size of each UCI (Fig. 4) (Kong et al., 2014). The quadratic function relationship between UCI intensity and the “LnUCI extent” implies that with an increase of UCI size (VT), GY, VT, and SHDI, MPS contribute to the cooling effect (Chen et al., 2012). This result may be attributed to the definition of UCI used in this study. The result also indicate that a cool island is the aggregated result of the surrounding cooler areas, and the cumulative cooling effects of the surrounding greenspaces create the area of maximum temperature reduction in the cool island. However, the traditional method used to conduct the correlation analysis between the normalized difference vegetation index (NDVI) or vegetation fraction with LST is usually on the pixel scale (Carlson and Arthur, 2000; Weng and Larson, 2005; Hung et al., 2006; Yuan and Bauer, 2007; Tiangco et al., 2008; Weng and Lu, 2008; Amiri et al., 2009). Therefore, the results here suggest that it is important to consider such cumulative effects on a larger scale than a pixel-based scale.

Synthetic analysis of the main factors contributing to UCI intensity

The results of the parameter estimates are presented in Table 2. All variables exhibit significant correlation to UCI intensity in the bivariate correlation analysis. The parameter estimates of the multiple regressions demonstrate that, in the multivariate framework, all variables are in line with the expected premises. In addition, the SHDI displays a negative sign in the regression model. This is largely as a result of the selected UCIs being mainly forest vegetation, and hence the increase SHDI will act to increase UCI intensity. The result also shows that PRLA has a positive impact on UCI intensity, which indicates that the addition of other land use types will act to decrease UCI intensity. After eliminating co-linear variables, CA, VT, PD, VT, SHDI, MPS, VT, GY, AM, VT, and S, D HS remained significantly associated with UCI intensity. These variables appear to be the main drivers of UCI intensity and all show significance at the P < 0.05 level (Table 3). The regression analyses confirmed the important role of CA, VT in explaining the UCI intensity. GY, AM, VT has a positive sign in the regression model, indicating that UCI intensity decreases with the increase of mean gyration radius of forest vegetation patches in the UCI.

A particularly noteworthy result is that the impact of water bodies (CA, WB) is not significant. This is not in agreement with findings from other studies, which have reported that ponds within greenspaces contribute to the cooling effect (Chen et al., 2012). This result may be attributed to the definition of UCI used in this study. Since the water cooling effect was influenced by the water body size, even though they are not linearly correlated (Sun et al., 2012), and the area of water within each of the UCIs in this study is less than 20%, it may be that the cooling effect of the water in the green space cannot be discerned.

S, D HS appears to have a weak significance indicating that the effects of hot spots on UCI intensity are not obvious, and the impact

Table 2

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Coefficients</th>
<th>t Ratio</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.585</td>
<td>6.988</td>
<td>0.000</td>
</tr>
<tr>
<td>PD, VT**</td>
<td>0.000</td>
<td>−4.607</td>
<td>0.000</td>
</tr>
<tr>
<td>MPS, VT**</td>
<td>−0.124</td>
<td>−4.280</td>
<td>0.000</td>
</tr>
<tr>
<td>AL, VT</td>
<td>−0.002</td>
<td>−0.360</td>
<td>0.719</td>
</tr>
<tr>
<td>CA, AM, VT**</td>
<td>0.008</td>
<td>3.826</td>
<td>0.000</td>
</tr>
<tr>
<td>SHDI**</td>
<td>−0.696</td>
<td>−2.744</td>
<td>0.007</td>
</tr>
<tr>
<td>PRLA</td>
<td>0.015</td>
<td>0.174</td>
<td>0.862</td>
</tr>
<tr>
<td>S, D WB</td>
<td>0.026</td>
<td>1.649</td>
<td>0.101</td>
</tr>
<tr>
<td>S, D HS**</td>
<td>−0.062</td>
<td>−2.599</td>
<td>0.010</td>
</tr>
<tr>
<td>CA, VT**</td>
<td>−0.541</td>
<td>−10.955</td>
<td>0.000</td>
</tr>
<tr>
<td>CA, JS**</td>
<td>0.010</td>
<td>0.536</td>
<td>0.593</td>
</tr>
<tr>
<td>CA, WB**</td>
<td>−0.004</td>
<td>−0.343</td>
<td>0.732</td>
</tr>
</tbody>
</table>

** Indicates statistical significance at the 1% level (two-tailed).
* Indicates statistical significance at the 5% level (two-tailed).

Table 3

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Coefficients</th>
<th>t Ratio</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.376</td>
<td>10.629</td>
<td>0.000</td>
</tr>
<tr>
<td>CA, VT**</td>
<td>−0.527</td>
<td>−13.985</td>
<td>0.000</td>
</tr>
<tr>
<td>PD, VT**</td>
<td>0.000</td>
<td>−4.672</td>
<td>0.000</td>
</tr>
<tr>
<td>SHDI**</td>
<td>−0.357</td>
<td>−4.194</td>
<td>0.000</td>
</tr>
<tr>
<td>MPS, VT**</td>
<td>−0.122</td>
<td>−4.414</td>
<td>0.000</td>
</tr>
<tr>
<td>GY, AM, VT**</td>
<td>0.007</td>
<td>3.824</td>
<td>0.000</td>
</tr>
<tr>
<td>S, D HS**</td>
<td>−0.056</td>
<td>−2.443</td>
<td>0.016</td>
</tr>
</tbody>
</table>

** Indicates statistical significance at the 1% level (two-tailed).
* Indicates statistical significance at the 5% level (two-tailed).
of $S_D$ WB is not significant on UCI intensity (Table 3). These results might arise because the magnitude of the effects of hot spots (or water bodies) is limited. As the UCIs were extracted, the neighboring temperature, which can be a contributory factor to UCI intensity, is only confirmed by the UCI extent. This has also been confirmed in the analysis of the relationship between mean temperature reduction and UCI intensity (Fig. 4b). However, whether these effects could be found at places where greenspaces cannot create UCIs because of the high thermal environment around the greenspace need to be explored further.

**Discussion and conclusion**

In the absence of standardized definitions for urban cool island (UCI) intensity, the characteristics as well as the functions of UCIs cannot be understood properly. In this study, UCI intensity was first defined and then its characteristics were analyzed at the patch-level scale. The analysis shows a strong relationship between the intensity and extent of an UCI, as well as the mean temperature reduction. This indicates that UCI intensity is good indicator of the UCI characteristics. The result also implies that the previously documented relationship between the NDVI or forest fraction with UCI intensity, as defined in this paper, is a good indicator of the UCI characteristics. The result also showed that the previously documented relationship between the NDVI or forest fraction with UCI intensity cannot be understood properly. In this study, UCI intensity was first defined and then its characteristics were analyzed at the patch-level scale. The analysis shows a strong relationship between the intensity and extent of an UCI, as well as the mean temperature reduction. This indicates that UCI intensity is good indicator of the UCI characteristics.

The results indicate that given a fixed amount of forest vegetation, the spatial pattern and patch shape of greenspaces in a UCI will have impact on their cooling intensity. The background characteristics indicated by the $S_D$ WB and $S_D$ HS variables show that the boundary effect of adjacent thermal environment have a weak influence on the UCI intensity, however the impact of water bodies was not found to be significant. The results further imply that UCI intensity, as defined in this paper, is a good indicator of the UCI characteristics.

Analysis of the relationship between the spatial pattern of greenspace and UCI intensity shows that the estimated coefficients of the 11 variables in this study are all in-line with the relationships expected. Although this may be conclusive, the current study does have some limitations that deserve further discussion. Firstly, one important consideration is the extent to which the chosen reference land surface temperature (RLST) influences the extent of the UCI. Taking the mean temperature of the study area ($\bar{T}$ as the RLST may mean that for some greenspaces (those surrounded by a higher heat environment, even though they have a local cooling effect) the LST of the greenspace site might be higher than the mean temperature of the study area and, thus, a UCI cannot be created. Secondly, the approach taken to define the hot spot may also influence the results. Further research is needed to analyze the effect of different statistical definitions and sizes of hot spots and their resulting impact upon thermal distance effects. Such guidance would also be helpful to aid comparison between studies. Finally, meteorological factors (e.g., wind, relative humidity) or complex terrain are also likely to affect the cooling effect of greenspace (Hamada and Ohta, 2010; Hamada et al., 2013). As a result of the limitation of available imagery, some relationships found here may become more enhanced during peak UHI times. We have not accounted for these effects.

This research offers a perspective on our scientific understanding of the cooling effects of urban greenspaces through an analysis of those factors that influence the UCI intensity. The results imply that UCI intensity is a good indicator of the characteristics of UCIs and can be used to evaluate the cooling effects of green spaces. The combined use of thermal infrared data, GIS, and landscape ecology theory offers the possibility to improve understanding of the characteristics of cooling effects of green space at the city scale. These results provide urban planners and natural resource managers with important guidance for planning and managing urban greenspaces in order to mitigate the impacts of urban heat islands and to adapt cities to climate change.

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