A Satellite Image-based Analysis of Factors Contributing to the Green-Space Cool Island Intensity on a City Scale

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Abstract: Urban green spaces provide cooler microclimates and create localized urban cool islands and, as part of an adaption 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, based on the satellite image, the land surface temperature (LST) was retrieved and the UCI was first identified, then the UCI intensity, one of the UCI characteristics, is defined and at last multiple linear regression models used to explore and quantify the combined effects of factors related to UCI intensity. The results show that the intensity differed between UCIs, and that it was correlated significantly with the extent of and mean temperature reduction associated with a UCI. Multiple linear regression analysis shows 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 mitigate the effects of the urban heat environment and help cities adapt to the climate change.

1. Introduction

In most cities around the world the impact of urbanization on local climate is alarming (Oke, 1982; Rosenfeld et al., 1995; Shobhakarand 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; Changnon et al., 1996; Rosenfeld et al., 1998; McMicha el et al., 2003; Fouill et et al., 2006; Lafortezza et al., 2009; Bowler et al., 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). 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 & Oke, 1998; Upmanis et al., 1998; Potcher et al., 2006; Chang et al., 2007; Jusuf et al., 2007; 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 & Hoffman, 2000; Svensson & 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: increased paved area has been shown to correlate positively with air temperature difference (Barradas, 1991; Cao et al., 2010). Further, the cooling effect may decay with increasing distance from the boundary of a green space (Spronken-Smith & Oke, 1998; Upmanis et al., 1998; Chen & Wong, 2006; Hamada & 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 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 & 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 (Cao et al., 2010, 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 (Gedzelman et al., 2003; Lee and Baik, 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 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 to quantify its characteristics through its intensity; 3) to explore any factors contributing to the UCI intensity, especially with consideration of the UCI composition, spatial pattern, and the neighboring environment.

2. 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 4,723 km^2 (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 1951–2009, 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 km^2.

Fig. 1. Location of Nanjing and the land use map of the study area.

3. Data and defining explanatory variables

3.1 Image pre-processing and retrieval of LST

The data used in this research comprise a rectified and georeferenced (Universal Transverse Mercator (UTM) coordinate system) IKONOS image (18 June 2009, 4 bands, 3.2m spatial resolution) and a LANDSAT TM 5 image (13 June 2009, 30m 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, 120m 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 pixels.

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℃ respectively. The mean temperature and wind velocity of the study time 10:00-11:00 were 29.5℃ and 3m/s, 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 & 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. 2a).

3.2 Identification of UCI and its intensity

In this research, the mean LST ($\bar{T}$) 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 ΔT, is less than 0 °C, i.e. $\mathrm{UCI} = \Delta T = T - \bar{T}$ ($\Delta T \leq 0$). Once identified, the UCIs, were extracted.

Previous research using stationary measurements of diurnal changes of urban microclimate in four types of ground cover of Nanjing found that grassland has a weak cooling effect at daytime (Huang, et al., 2008). Other recent research analyzing LST (Kong et al., 2014) found that when at least 99.69% of the fixed scale 240 m×240 m is covered by grassland, then a cool island is created. Hence the effects of grassland has been documented but the effects of forest vegetation (trees mixed with shrubs and grass) have not been studied and hence the focus of the research reported here is on UCIs caused by forest vegetation 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, Memon et al., 2009, Lee and Baik, 2010). Following this definition, Cao et al. (2010) defined UCI intensity as the difference between the mean LST in a greenspace and the mean temperature in a specific buffer area. However, Chang et al. (2007) defined UCI intensity as the difference in air temperature between a greenspace's interior and reference points in its surroundings. Conversely, Sugawara et al. (2006) and Shigeta et al. (2009) defined UCI intensity as the mean air temperature difference between the greenspace and the urban center. However, the actual air or surface temperature may vary significantly within the UCI due either to the boundary effect of the surrounding land use and land cover (LULC) and its impact on the UCI. Furthermore, the representativeness of observation points is questionable, since selection of the reference points and the size of the surrounding buffer will introduce bias. Thus, if UCI intensity is quantified in this way, the analysis may be unable to determine the features of the UCI. For example, if two UCIs of different sizes have the same mean temperature and the same local temperature as the reference locations, then based on the definitions of most previous studies, they will have the same UCI intensity. Thus, as a result of the ambiguous and equivocal definitions currently used in cool island studies, irrespective of the air or surface temperature, it may not be possible to indicate the characteristics of the UCI. Consequently, they cannot be related to the cooling effect of greenspace and other factors contributing to the cool island.

In this study, we still follow the definition for UHI intensity. For the UCI intensity, however, we refer to the maximum temperature reduction within the cool island, which is the difference between the minimum LST of the UCI and the $\overline{T}$ (mean temperature of the study area). The UCI intensity information was captured using the zonal analysis of the spatial analysis tools in ArcMap. This tool calculates a statistic (e.g. minimum, mean, sum, and standard deviation) for each individual zonal spatial feature, such as a UCI polygon, based on values from another raster dataset (LST in this case) (Sommer & Wade, 2006; Ogneva-Himmelberger et al., 2009). There are 153 UCIs used for the following analysis (Fig. 2b). Before we obtained the UCI intensities, pre-processing of the retrieved LST data was conducted. Pixels with extremely high or low LSTs (non-valid pixels caused by image pixel information loss) were identified and substituted with the mean LST value of the adjacent pixels in a 5 × 5 pixel range. This procedure, based on a kernel convolution method (Rajasekar and Weng, 2009; Keramitsoglou et al., 2011) and a 5 × 5 pass supported by ERDAS (version 9.2), was selected as the critical step in the procedure to eliminate extreme values. The pre-processed LST map was then used to obtain the UCI intensity.

Fig. 2. (a) Retrieved LST (on 13 June 2009), and (b) UCIs of the study area

3.3 Selection of variables

In this study, UCI intensity was used as the dependent variable. In an attempt to capture the impact of the green-space pattern on UCI intensity, five landscape spatial indices – area of forest vegetation (CA_VT), mean patch size of forest vegetation (MPS_VT), patch density of forest vegetation (PD_VT), aggregation of forest vegetation (AI_VT), and mean patch radius of gyration of forest vegetation (GY_AM_VT) – were selected as the independent variables (Table1). In addition to the variables used to explain the impact of the characteristics of a green space on its cooling effect, it was assumed that the spatial pattern of land use in each UCI would also affect the UCI intensity. Therefore, the areas of impervious surface-CA_IS, water body-CA_WB, patch richness of land use-PRLA, and diversity of land use-SHDI were also calculated and included as independent variables.

Studies by Chen et al. (2012), Hamada et al. (2013) and Feyisa et al. (2014) found that the green spaces cooling distance was influenced by the surrounding environment. And some studies have confirmed that water bodies have a cooling effect in the urban environment (Buyantuyev & Wu, 2010; Sun et al., 2012). As the context temperature may cause an accumulative effect on the UCI intensity, the land-use pattern immediately surrounding a UCI, (such as the proximity to the hot spots or water bodies), may have an effect. This was, therefore, considered in the analysis of the UCI intensity. Previous studies have reported that the temperature of the heat island (hot spot) or the water body cooling effect vary in accordance with the general distance decay theory, even though it might fluctuate (Chen et al., 2012; Sun et al., 2012; Hamada et al., 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, b) as explanatory variables in the multiple regression analysis to explore their combined effects on UCI intensity.

A statistic analysis was conducted to calculate the mean LST of different land cover type. The results indicate that the $\bar{T}$ is 28.5 ℃ and the mean LST of impervious land is 31.5 ℃, which is 3.0 ℃ higher than $\bar{T}$. As previous research has also found that the LST which is 3℃ higher than mean LST could be defined as the high temperature area in the summer of Nanjing (Miao et al., 1991), 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 3km^2. 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, 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, *_IS, *_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.

Fig. 3 (a) Extracted hot spots (areas 3 °C warmer $\bar{T}$ of the study area and areas greater than 3km^2), and (b) water bodies

Table1 Description of variables and their expected effects on the UCI intensity

4. Results

4.1 Characteristics of UCIs

All the selected UCIs are found within areas where the percentage of forest vegetation >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 km^2, their mean temperature reduction is −0.6 °C, and the maximum temperature reduction is −6.9 °C.

4.2 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). The quadratic function relationship between UCI intensity and the

“LnUCI_extent” implies that with an increase of UCI size there will be an accelerated temperature reduction. The results 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 & Arthur 2000; Weng & Larson, 2005; Hung et al., 2006; Yuan & Bauer, 2007; Tiangco et al., 2008; Weng & 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.

Fig. 4 Correlation analysis between the maximum temperature reduction (°C) (UCI intensity) (a and b, y-axis) and the cool island area (LnUCI_extent) (a, x-axis) as well as mean temperature reduction of each UCI (°C) (b, x-axis).

4.3 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_DHS remained significantly associated with UCI intensity. These variables appear to be the main drivers of UCI intensity and all show significance at the $P < 0.1$ 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., 2014). 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 (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_DHS appears to have a weak significance indicating that the effects of hot spots on UCI intensity are not obvious, and the impact of S_DWB 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 needs to be explored further.

Table 2 Regression results of linear model (dependent variable: in °C)

Table3 Regression results after eliminating co-linear variables (dependent variable: in °C)

5. 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 a 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 surface temperature, based on the pixel scale, may need to be further explored. Scaling-up research beyond the pixel scale, such as to the landscape scale, is needed in order to inform urban planning and design of green space to maximize the cooling effect.

A multiple linear regression analysis was conducted to determine the main factors contributing to the UCI intensity. The results found that the area of forest vegetation (CA_VT) was negatively correlated with UCI intensity and that it was the strongest variable of all, which confirms the important role of the vegetation area in explaining UCI intensity. The variables: patch density of forest vegetation (PD_VT), diversity of land use (SHDI), mean patch size of forest vegetation (MPS_VT), and, mean patch radius of gyration of forest vegetation (GY_MN_VT), were statistically significant. 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 way we define the hot spot may also influence the results. Further research focusing on analysis of different size of hot spots and their thermal distance-effect would facilitate to select the hot spots in such research. Finally, meteorological factors (e.g. wind, relative humidity) or complex terrain are also likely to affect the cooling effect of greenspace (Hamada et al., 2010; 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 offer the possibility of improved 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 with regard to planning and managing urban greenspaces to mitigate the impacts of urban heat islands and to adapt cities to climate change.

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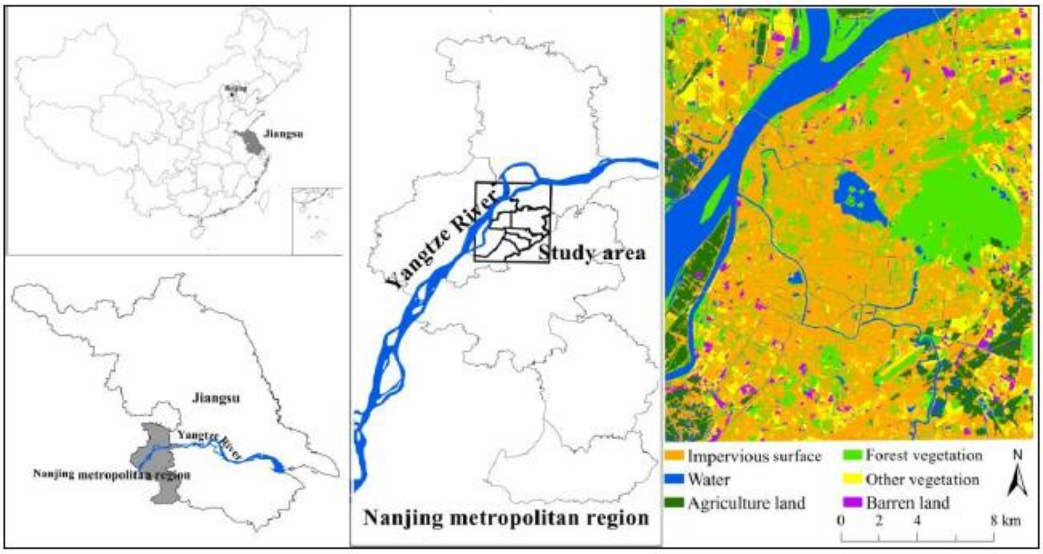

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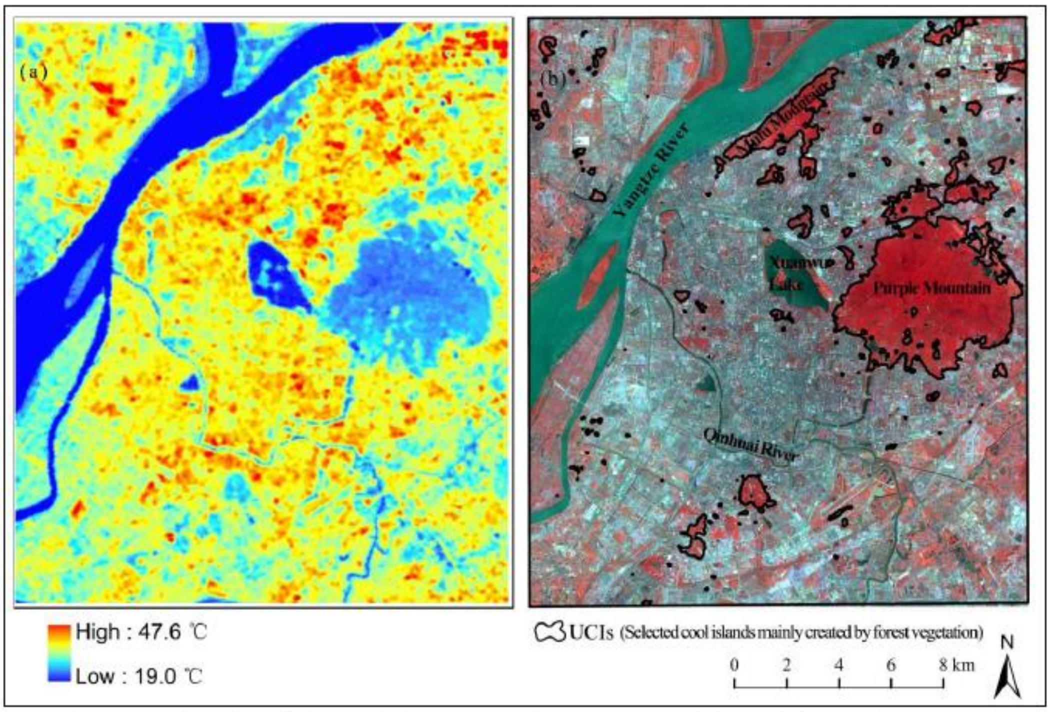

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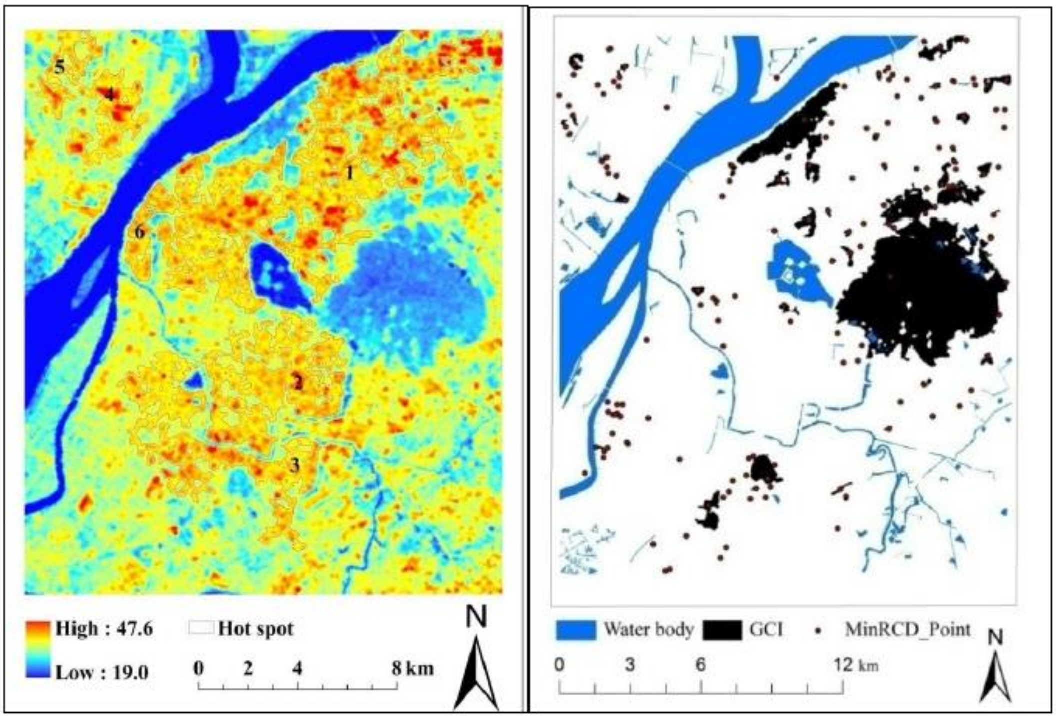

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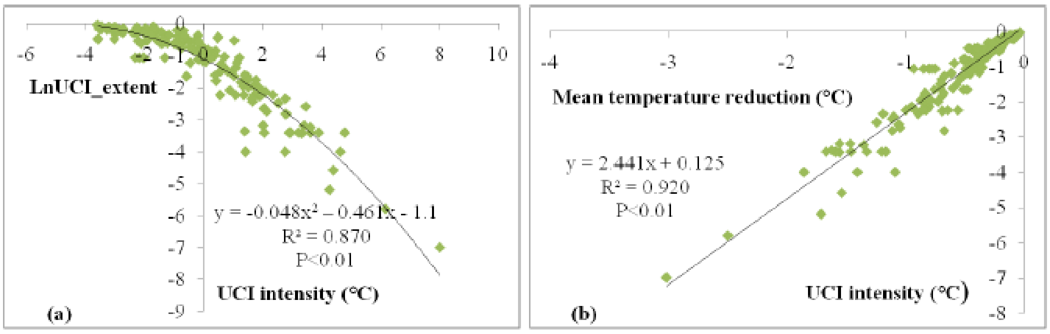

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Table 1 Description of variables and their expected effects on the UCI intensity

Independent variable		Description	Expected sign[a]
Background Characteristics	S_D WB (Size-distance index for water body)	A measure of the integrated impact of the nearest Water Body size (S_{Water}) and straight-line distance from the MinLST point to the boundary of the nearest Water body (D_{Water}), S_D WB = $\ln({}^{S_{Water}}/_{D_{Water}})$.	+
	S_D HS (Size-distance index for hot spots)	A measure of the integrated impact of the nearest Hot Spot size (S_{HP}) and straight-line distance from the Min LST point to the boundary of the nearest Hot Spot (D_{HS}), S_DSH =$\ln({}^{S_{HS}}/_{D_{HS}})$.	–
UCI Characteristics	CA_VT (Area of forest vegetation)	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); $CA\_VT = \frac{\sum_{j=1}^{n} v_{gj}}{10000}$, where v_{gj} is the forest vegetation covering area of patch gj in the corresponding patch UCI_g (unit: ha).	–
	CA_IS (Areas of impervious surfaces)	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); $CA\_VT = \frac{\sum_{j=1}^{n} b_{gj}}{10000}$,	+

		where b_{gj} is the built_up land covering area of patch gj in the corresponding patch UCI_g (unit: ha).	
	CA_WB (Areas of water)	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); $CA\_VT = \frac{\sum_{j=1}^{n} w_{gj}}{10000}$, where w_{gj} is the water body covering area of patch gj in the corresponding patch UCI_g (unit: ha).	–
	MPS_VT (Mean patch size of forest vegetation)	A measure of landscape fragmentation, equaling the average area of all forest vegetation patches in each UCI (unit: ha).	–
	PD_VT (Patch density of forest vegetation)	A measure of the fragmentation of forest vegetation in each UCI. $PD\_VT = \left(\frac{n_i}{A}\right)(10000)(100)$, where N_i is the total number of forest vegetation patches in each UCI.	–
	AI_VT (Aggregation of forest vegetation)	A measure (in %) of aggregation of forest vegetation in each UCI, $AIVT = \left(\frac{g_{ii}}{\max g_{ii}}\right)(100)$, where g_{ii} = number of like adjacencies (joins) between pixels of forest vegetation (*i*); max-g_{ii} = maximum number of like adjacencies (joins) between pixels of forest vegetation (*i*), based on the *single-count* method.	–

	GY_AM_VT (Mean patch radius of gyration of forest vegetation)	A measure of the compact of vegetation trees, which is the mean patch radius of gyration at the class level where each patch is weighted by its area. $GYRATE\_AM_{VT} = \sum_{j=0}^{n}\left[\sum_{r=1}^{z}\left(\frac{h_{ijr}}{z}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$ where h_{ijr} is the distance between cell *ijr* (located within forest vegetation patch*ij*) and the centroid of patch*ij*; *z* the number of cells in patch *ij*, where $r = 1, \ldots, z$; a_{ij} the area of patch *ij*; *n* the number of patches forest vegetation, where $j = 1, \ldots, n$; and h_{ijr} the distance from patch *ij* to nearest neighboring forest vegetation patch.	+
	SHDI (Land use diversity)	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: $H = -\sum_{i=1}^{n} P_i \ln(P_i)$, 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.	?
	PRLA (Patch richness of land use)	A measure of the landscape composition, equaling the number of different land use types in each UCI.	?

Table 2 Regression results of linear model, dependent variable: in °C

Independent variable	Liner model(n= 153, R^2=0.881, adjusted R^2= 0.872)		
	Coefficients	t Ratio	Sig.
Constant	4.585	6.988	0.000
PD_VT**	0.000	-4.607	0.000
MPS_VT**	-0.124	-4.280	0.000
AI_VT	-0.002	-0.360	0.719
GY_AM_VT**	0.008	3.826	0.000
SHDI*	-0.696	-2.744	0.007
PRLA	0.015	0.174	0.862
S_D WB	0.026	1.649	0.101
S_D HS*	-0.062	-2.599	0.010
CA_VT**	-0.541	-10.955	0.000
CA_IS	0.010	0.536	0.593
CA _WB	-0.004	-0.343	0.732

* Indicates statistical significance at the 10% level (two-tailed).

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

Table 3 Regression results after eliminating co-linear variables, dependent variable: in °C

Independent variable	Linear model (n= 153, R^2= 0.879, adjusted R^2= 0.874)		
	Coefficients	t Ratio	Sig.
Constant	4.376	10.629	0.000
CA_VT**	-0.527	-13.985	0.000
PD_VT**	0.000	-4.672	0.000
SHDI**	-0.557	-4.194	0.000
MPS_VT**	-0.122	-4.414	0.000
GY_AM_VT**	0.007	3.824	0.000
S_D HPs*	-0.056	-2.443	0.016

* Indicates statistical significance at the 10% level (two-tailed).

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

Highlights

- Urban greenspace cool islands (UCIs) was identified and their intensity was quantified
- UCI intensity can indicate cool island characteristics quite well
- Factors contributing to UCI intensity, especially the UCI neighboring environment were evaluated