What are hot and what are not in an urban landscape: quantifying and explaining the land surface temperature pattern in Beijing, China

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Abstract

Context Understanding how landscape components affect the urban heat islands is crucial for urban ecological planning and sustainable development.

Objective The purpose of this study was to quantify the spatial pattern of land surface temperatures (LSTs) and associated heat fluxes in relation to land-cover types in Beijing, China, using portable infrared thermometers, thermal infrared imagers, and the moderate resolution imaging spectroradiometer.

Methods The spatial differences and the relationships between LSTs and the hierarchical landscape structure were analyzed with in situ observations of surface radiation and heat fluxes.

Results Large LST differences were found among various land-use/land-cover types, urban structures, and building materials. Within the urban area, the mean LST of urban impervious surfaces was about 6–12 °C higher than that of the urban green space.

LSTs of built-up areas were on average 3–6 °C higher than LSTs of rural areas. The observations for surface radiation and heat fluxes indicated that the differences were caused by different fractions of sensible heat or latent heat flux in net radiation. LSTs decreased with increasing elevation and normalized difference vegetation index.

Conclusions Variations in building materials and urban structure significantly influenced the spatial pattern of LSTs in urban areas. By contrast, elevation and vegetation cover are the major determinants of the LST pattern in rural areas. To alleviate urban heat island intensity, urban planners and policy makers should pay special attention to the selection of appropriate building materials, the reasonable arrangement of urban structures, and the rational design of landscape components.

Keywords Urban heat island · Land surface temperature · Urban landscape · Land-use/land-cover · MODIS · Portable infrared thermometer

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Introduction

Urban microclimate alteration is often characterized by urban heat islands (UHIs), which are defined as the phenomenon where atmospheric and land surface temperatures (LSTs) are higher in urban areas than in surrounding rural areas (Oke 1995; Voogt and Oke 2003). UHIs are thought to be one of the most prominent environmental issues related to urban climate and the sustainable development of cities (Oke 1984; Grimm et al. 2008; Alberti 2009; Wu 2010; Pickett et al. 2011; Wu 2013). The UHI effect is mainly caused by the difference in surface physical properties, urban structure, land cover, land use, anthropogenic heat sources and air pollution (Oke 1982; Streutker 2003; Buyantuyev and Wu 2010). The land surface physical properties (e.g., albedo, emissivity, thermal capacity, thermal conductivity, and thermal inertia) of various land-cover types (e.g., impervious surface, vegetation, and water) are significantly different, which could result in LST heterogeneity. Indeed, the LST difference among various intra-urban land surfaces may be as large as, or even larger than, the urban–rural difference (Buyantuyev and Wu 2010). Accordingly, the intra-urban LST variations result largely from the different physical properties, including urban structure, which refers to the spatial dimensions of buildings and street canyons; urban land-cover, including impervious surfaces, green space, bare soil, and water; urban fabric, which refers to building materials; and urban metabolism, including anthropogenic sources of water, heat, and pollutants (Oke 2004). It is important to understand and quantify UHIs associated with a hierarchical landscape structure so that the residential environment of urban dwellers might be improved (Wu 2010).

Urban landscape patterns, including landscape composition (i.e., the fraction or abundance of physical properties) and configuration (i.e., the spatial arrangement of physical properties), are closely related to LST (O'Neill et al. 1988; Li et al. 2011; Connors et al. 2013; Wu 2014). Landscape composition identifies the abundance and variety of land-cover types without considering their spatial characteristics, for example, the impacts of vegetation fraction and impervious surface area on LST (Zhang et al. 2008; Zhou et al. 2011a, b; Zhang et al. 2013). Cities are characterized by large fractions of impervious surfaces composed of concrete, asphalt, brick, pebbles or

aggregates which absorb and store radiation during the daytime and slowly release heat during the night (Buyantuyev and Wu 2010; Kuang et al. 2014). Furthermore, landscape composition directly affects UHI through the modification of surface physical properties. The selection of building materials will greatly influence the land surface physical properties, such as albedo (Oke 1984). For example, lighter-colored building materials generally have higher albedo and absorb less heat, while darker materials generally absorb more heat than lighter materials and result in higher LSTs. Landscape configuration represents the spatial arrangement or distribution of land-cover features within landscape heterogeneity, and plays an important role in UHI due to the effect of surface fluxes. Therefore, it is crucial to consider both landscape composition and configuration in urban design to mitigate potentially harmful LST changes across urban areas (Wu 2010).

Currently, there are three major approaches for studying UHI including air temperature measurement from meteorological stations, LST retrieved from satellite remotely sensed images, and in situ observations of surface radiative temperature using portable infrared thermometers or thermal infrared imagers. The LST obtained from meteorological stations can reflect differences in atmospheric temperature over long periods; however, the extrapolation of the station data to region level is often biased by the distribution of the meteorological stations (Oke 1982; Chen and Pan 1997; Ouyang et al. 2007; Yang et al. 2011). LST retrieved from remotely sensed products can be used to quantitatively represent spatial characteristics of LST at various urban surfaces, but is limited by low temporal resolution and shorter data records (Dale and Jeffrey 1999; Ouyang et al. 2007) and by difficulty in validating the retrieved results using ground-based measurements at different spatial scales (Mao et al. 2005; Ji et al. 2006; Wang and Hu 2006; Li et al. 2013). Ground-based measurements using thermal infrared instruments at a specific time and location can provide timely and accurate LST for specific land-use and land-cover types (Wang et al. 2011).

During the past two decades, a few studies addressed the phenomena of UHI or the relationship between landscape patterns and LST in Beijing. Based on landsat thematic mapper (TM) images and a regression tree model, Xiao et al. (2007, 2008) estimated the spatial distribution of LST in Beijing

and explored its relationship with the proportion of impervious surface. Li et al. (2012) revealed the relationship between the proportion of green space and LST based on Landsat TM images, and indicated that 10 % increase in green space could result in 0.86 °C decrease in LST. Based on air temperature data from 20 weather stations during a 41 year period (1960–2000), Lin and Yu (2005) indicated that UHI intensity in Beijing had increased significantly with the accelerated urbanization, with a trend of +0.31 °C/decade. Ji et al. (2006) estimated the impact of urban growth on UHI in Beijing based on MODIS LST products. The frequency of extreme high-temperature events in Beijing increased significantly over the last decade (Chen and Pan 1997). Impervious surface area is positively correlated with UHI, as LST has increased by approximately 9.18 °C due to replacement of natural surfaces with impervious surfaces (Xiao et al. 2007). These studies suggest that LSTs in Beijing have significantly changed as the process of urbanization replaces natural vegetation with impervious surfaces.

Although several studies referenced above address the spatial and temporal patterns of LST in Beijing, no studies investigate the LST and surface energy fluxes for various landscape components. Through implementation of synchronized LST observations using portable infrared thermometers, thermal infrared imagers, and improved MODIS data, our specific objectives were to (1) quantify the LST and energy fluxes over various land-use/land-cover types, as well as building materials based on ground-based observations, (2) improve MODIS retrieval parameters to retrieve and estimate regional LST along an urban–rural gradient, and finally (3) assess the impacts of different land surface physical properties and urban structures on the magnitude and spatial distributions of LST.

Methods

In this study, we adopted a synchronized approach to explore LST of different land surfaces by integrating remotely-sensed data with ground-based observations at local and regional scales. We measured LST of various land surfaces using thermal infrared imager and portable infrared thermometer at multiple observation sites. Using the ground-based observations, we calibrated the parameters of a MODIS LST algorithm

and analyzed regional differences of LST for various land-use/land-cover types, urban building materials, and urban structures.

Ground-based measurements of LST

We used the portable infrared thermometer and thermal infrared imagers to measure LST. The portable infrared thermometer used in this study is the MAX4TM produced by Raytek Inc. (Germany). For this instrument, the range of temperature measurement is −30–900 °C, the measurement precision is ±0.75 % or 1 °C, the response time is 250 ms, the spectral response is 8–14 μm, the optical resolution is 60:1, and the environmental temperature of operation is 0–50 °C (Wang et al. 2011). The thermal infrared imager used in this study is a Forward Looking Infrared Radiometer (FLIR) T425 model manufactured by FLIR Systems Inc. (USA). The field of view (FOV) of the device is 25° × 19°/0.4 m, the thermal sensitivity is less than 0.05 °C, the wavelength range is 7.5–13 μm, the infrared image resolution is 320 × 240 pixels, the temperature range is −20–1,200 °C, and the measurement precision is ±2 %.

The portable infrared thermometer and thermal infrared imager were calibrated with a standard calibration blackbody (BDB15, with a temperature precision of ±0.1 °C and a resolution of 0.1 °C) prior to the observations in order to eliminate the systematic error generated by the use of different instruments (Wang et al. 2011). To observe LST, the portable infrared thermometer MAX4TM was placed far away from the observers. This device was placed at a height of 0.5 m above the object surface to measure the surface radiative temperature. We began to record temperatures after the devices became stable for 1–3 s. Continuous observations were made at all sites in the morning (11:00–11:30 a.m.) and at noon (12:30–13:00 p.m.). Ten observations were collected at each site during the study period, and the average values were calculated as the final temperature for this object. The thermal infrared imager FLIR T425 was installed 100 m above the ground. At this height, it can effectively observe the spatial characteristics of surrounding land surfaces. To preserve the measurement precision, the tilting angle of the imagers was less than 40° and the maximum FOV distance was 2 km. Prior to measurement, the thermal infrared imager was calibrated using the LST measured by the portable

infrared thermometers for the same objects. During the measurement, the daily mean air temperature was 18–24 °C, with 3 °C higher at noon than that in the morning. The air humidity was close to the long-term mean (30 %) for Beijing, and the wind speed was lower than 2 m/s.

We selected four representative land-use/land-cover types to implement the LST measurement experiments for urban–rural landscape components including urban impervious surface, urban green space, cropland, and water body (Fig. 1). The first

selected zone (Z1) represented the urban impervious surface and green space in the city. On the roof of a 100-m tall building in the Breezy Woods Oasis residential area in Chaoyang District of Beijing, we installed a thermal infrared imager and a high-resolution camera to acquire infrared images for the surrounding buildings, the impervious surface area of a plaza, and green space in Olympic Park. Meanwhile, we also used the portable infrared thermometer to measure temperature at the ground surfaces of buildings, plaza, green space, and water bodies around this

Fig. 1 The study area and the selected observation sites for ground-based observations of land surface temperature (LST) as well as radiation and energy fluxes. Z1, LST observation site for urban impervious surface (UIS) and urban green space (UGS); Z2, LST observation site for concrete surface; Z3, LST observation site for cropland; Z4, LST observation

site for water body. S1 radiation and energy flux observation site for UIS; S2 radiation and energy flux observation site for UGS; S3 radiation and energy flux observation site for cropland. The aerial photos at the right column showed the landscape structure in the LST observation sites (Z1, Z2, Z3 and Z4, respectively)

observation site. The second zone (Z2), which is located at the Beijing International Airport, was selected to represent a concrete land surface. Portable infrared thermometers were used to measure surface temperature of the airport tarmac. We selected the third zone (Z3) to represent cropland located in Xiaotangshan and the fourth zone (Z4) to represent the Miyun Reservoir water body.

Ground-based measurements of surface radiation and heat fluxes

We also observed surface radiation and heat flux components for urban impervious surface, urban green space, and cropland. We established stations S1 and S2 to observe radiation components and heat fluxes at urban impervious surface and urban green space, respectively, which are located at the same zone (Z1) for LST observation (Fig. 1). The observation instruments at S1 and S2 were installed at 2.5 and 1.6 m above the ground, respectively. Within the 1-km buffer zones of the two observation sites, the major land-cover types are impervious surface and vegetation. The urban impervious surface area at the station S1 accounts for 71 % of the buffer zone, and the vegetated area at station S2 accounts for 78 % of the buffer zone. In addition, we also collected the flux data at station S3 for cropland in Daxing District (Fig. 1) (Liu et al. 2013). The observation instrument was installed at 3.0 m above the ground. The instruments for measuring radiation and surface heat fluxes include a three-dimensional ultrasonic anemometer (CSAT3), a humidity and temperature sensor (HMP155), a 4-component net radiation sensor (HFP01), and a soil heat flux sensor. The observation variables include upwelling and downwelling short-wave/long-wave radiation, albedo, land surface net radiation, sensible heat flux, latent heat flux, soil heat flux, and radiation temperature. For analysis, we first selected all the observation data during daytime (i.e., the hours with net radiation flux > 0) and removed the hard spikes and soft spikes. The data were further corrected using time-lagging, ultrasonic virtual temperature and air density (WPL correction) methods (Webb et al. 1980). Finally, the sensible and latent fluxes were corrected using the Bowen ratio energy balance closure method (Twine et al. 2000). We obtained the land surface radiation and energy fluxes for impervious surface, urban green space, and cropland during the time when

the MODIS satellite passed over the observation sites between 11:00 and 11:30 a.m..

MODIS-based observations and parameterization

On September 20th, 2011, the Terra MODIS satellite passed the observation sites at 11:10 a.m. local civil time (LCT) with a solar angle of 40.37°–41.84°. Two datasets from MODIS products were used to retrieve LST: (1) the 250-m spatial resolution MODIS 1B products and the 1-km resolution brightness data from the thermal infrared bands 31 (10.78–11.28 μm) and 32 (11.77–12.27 μm). The brightness can be calculated as:

$$T_i = \frac{C_2}{\lambda \ln(1 + C_1/\lambda_i^5 R_i)}, \quad (1)$$

where T_i is the brightness of bands 31 and 32, i is the band number (31 or 32), R_i is the radiance at the top atmosphere of band i , λ is the effective wavelength, C_1 and C_2 are constants $C_1 = 1.19104 \times 10^8 \text{ W } \mu\text{m}^4/\text{m}^2/\text{srand}$ $C_2 = 1.43887 \times 10^4 \text{ } \mu\text{m K}$ (Zhou et al. 2009).

The parameters (e.g., C_1 and C_2) are derived from either empirical knowledge or regression analysis in terms of the natural land surfaces. Split-window algorithms were first introduced by Becker and Li (1995), and then Mao et al. (2005) and Wan et al. (2002) further developed two generalized split-window algorithms for LST retrieval based on MODIS data. Subsequent studies indicated that the Mao et al. (2005) retrieval algorithm was better than other algorithms for retrieving LST based on MODIS data (Zhou et al. 2009); therefore, we applied the Mao et al. (2005) algorithm to retrieve LST in this study. We calculated the specific emissivity based on the 30 m $\times$ 30 m Landsat TM land-use/land-cover information and 1-km resolution data for the fractions of impervious surface area and green space (Liu et al. 2010; Kuang 2012a; Kuang et al. 2013, 2014).

The Mao et al. (2005) retrieval algorithm after calibration is listed as follows:

$$T_S = \alpha(C_{32}(B_{31} + D_{31}) - C_{31}(D_{32} + B_{32}))/ (C_{32}A_{31} - C_{31}A_{32}) + \beta, \quad (2)$$

where T_S is the LST and α and β are the fitted regression parameters for surface temperature

between the sampled ground-based and remote-sensing observations of four zones in Fig. 1, which were set as 0.7554 and 7.5146. The coefficient of A_{31} , A_{32} , B_{31} , B_{32} , C_{31} , C_{32} , D_{31} , and D_{32} are the intermediate parameters determined by the atmospheric transmittance and surface emissivity from the following formula.

$$A_{31} = 0.13834 \times \varepsilon_{31} \times \tau_{31}, \quad (3)$$

$$B_{31} = 0.13834 \times T_{31} + 31.80148 \times \varepsilon_{31} \times \tau_{31} - 31.80148, \quad (4)$$

$$C_{31} = (1 - \tau_{31}) \times (1 + (1 - \varepsilon_{31}) \times \tau_{31}) \times 0.13834, \quad (5)$$

$$D_{31} = (1 - \tau_{31}) \times (1 + (1 - \varepsilon_{31}) \times \tau_{31}) \times 31.80148, \quad (6)$$

$$A_{32} = 0.11952 \times \varepsilon_{32} \times \tau_{32}, \quad (7)$$

$$B_{32} = 0.11952 \times T_{32} + 26.80148 \times \varepsilon_{32} \times \tau_{32} - 26.80148, \quad (8)$$

$$C_{32} = (1 - \tau_{32}) \times (1 + (1 - \varepsilon_{32}) \times \tau_{32}) \times 0.11952, \quad (9)$$

$$D_{32} = (1 - \tau_{32}) \times (1 + (1 - \varepsilon_{32}) \times \tau_{32}) \times 26.80148, \quad (10)$$

where ε_{31} , ε_{32} are the surface emissivity of bands 31 and 32; τ_{31} , τ_{32} are the atmospheric transmittance of bands 31 and 32; T_{31} , T_{32} are the brightness temperature (also see Eq. 1) (Mao et al. 2005).

We used the mean LST measured from ground-based observations during 10 min between 11:00 and 11:20 a.m. LCT when the MODIS satellite passed over the observation sites to recalibrate the α and β parameters in Eq. (2) for different land surfaces (both mixed and pure pixels). In the urban area, most of the land surfaces are impervious, green space, and water. By multiplying the LST with the fractions of each surface type within a MODIS pixel (i.e., 1 km $\times$ 1 km), we calculated the mean LST of this mixed pixel. The LST for each land-cover type in a pixel were derived from the thermal infrared imagers and portable infrared thermometers. We obtained 15 samples (or MODIS pixels) for calibration of the parameters for the Mao et al. (2005) algorithm. Finally, the parameters α and β in Eq. (2) were

determined as 0.7554 and 7.5146, respectively. The spatial patterns among the improved Mao algorithm (Fig. 2a), MODIS products (http://www.modis.gsfc.nasa.gov/data/dataproduct/dataproducts.php?MOD_NUMBER=11, Fig. 2b) and Mao algorithm (Fig. 2c) were compared and their accuracy were evaluated. Based on the calibrated parameters, the mean standard error was less than 2 °C and the root-mean-square error was 1.42 °C between the improved Mao et al. (2005) retrieval algorithm and observed LST.

Auxiliary data

Several auxiliary datasets were used to identify the causes of LST differences for various land surfaces at regional scale, including 2010 Landsat TM/ETM+ land-cover/land-use data (30-m spatial resolution) (Liu et al. 2010; Kuang 2012b; Kuang et al. 2013, 2014), 2010 aerial photos of Beijing (spatial resolution 0.5 m), SRTM elevation data (spatial resolution 90 m), and MODIS NDVI data (spatial resolution 1 km).

Data analysis methods

The analysis of the LST along an urban–rural gradient was organized at four levels (Fig. 3): observation objects (i.e., urban land, rural land), land-cover types, land-use types, and urban structures and materials (Wu and David 2002). The analysis of LST for various land surfaces was based on both ground-based observations and MODIS retrieval, whereas the regional LST was based on the MODIS retrieval LST derived from the calibrated Mao et al. (2005) algorithm.

The LST difference among various land surfaces is calculated as:

$$\Delta T_{i,j,n} = \frac{T_{i,n}\varepsilon_{i,n}}{0.95} - \frac{T_{j,n}\varepsilon_{j,n}}{0.95}, \quad (11)$$

where $\Delta T_{i,j}$ is the LST difference between i and j land surfaces, T_i and T_j are LSTs of i and j land surfaces, respectively, n is the observation time period, and ε_i and ε_j are the specific emissivity for i and j land surfaces at the wavelength between 8 and 14 μ m. For various observation periods and land surfaces, the specific emissivity is different (Table 1).

The statistical analyses were conducted using SPSS 16.0. We used one-way analysis of variance (ANOVA) to test the statistical significance of LST

Fig. 2 Spatial distribution of land surface temperature (LST) as retrieved from Mao et al. (2005) algorithm and MODIS products. **a** Improved Mao's algorithm; **b** MODIS products; **c** Mao's algorithm

among different land uses, land covers, and building materials. We considered statistical significance at a confidence level of 95 % ($p = 0.05$) unless specifically stated. LST is not only influenced by land-use/land-cover types, but also by elevation, vegetation coverage, local meteorological conditions, and landscape composition. Therefore, even for the same land-use type, the mean LST may be different in different locations along the urban–rural gradient. In this study, the simple linear regression was conducted to evaluate the relationships between LST and elevation (derived from digital elevation model, DEM) and polynomial

regression ($Y = aX^3 + bX^2 + cX + \delta$) was conducted to explore the relationship between LST and vegetation fraction (which is represented by the Normalized Difference Vegetation Index, NDVI).

Results and analysis

Observed LST of various urban land surfaces

Using portable infrared thermometers and thermal infrared imagers to obtain ground-based observation

Fig. 3 The illustrations of four levels of analyses for comparing land surface temperatures of various land-cover types, land-use types, building materials and landscape components along the urban–rural gradient

Table 1 Specific emissivity (ϵ_i) of different land surfaces used in this study

Land surfaces	Specific emissivity	Reference(s)
Cropland	0.982	Qin et al. (2004)
Forest	0.988	Qin et al. (2004)
Shrubland	0.986	Humes et al. (1994), Liu et al. (2011)
Grassland	0.982	Labeled and Stoll (1991)
Water body	0.995	Zheng et al. (2010)
Bare soil	0.972	Qin et al. (2004)
Building	0.970	Qin et al. (2004)
Green space	0.985	Humes et al. (1994)
Asphalt and concrete	0.968	Wang et al. (2011)

points ($n = 2250$), we compared the LSTs for different land-use/land-cover types. In the morning (11:00–11:30 a.m. LCT), the highest value of mean LST was found on the building roof (36.80 °C), followed by the airport tarmac (30.65 °C), paved roads (30.03 °C), plaza (28.30 °C), and green space (24.14 °C). The lowest value of mean LST was recorded for the water body (11.87 °C, Fig. 4). The mean LSTs for various green-space types were ranked

as roadside green space (25.32 °C) > residential green space (24.76 °C) > park green space (22.34 °C). Buildings, plaza, and paved roads showed strong “hot fields,” while the green spaces acted as obvious “cold fields.” At noon (12:30–13:00 LCT), the mean LSTs of impervious surface areas (including building roof, airport tarmac, paved roads, and plaza) ranged 30–39 °C, while green spaces ranged 24–27 °C. The maximum LST difference was 24.93 °C between the building roof and water body. In addition, we also found large variations among the measurements for a specific land-use type. The variations among measurements for three green-space types ranged 6–14 °C, with lower variations in the park green space. The smallest variation (about 4 °C) occurred at the water body due to its high thermal inertia and thermal capacity, and relatively low thermal conductivity. We found large spatial heterogeneities of radiative temperatures based on the measurements from thermal infrared imagers (Fig. 5). In the urban area, green spaces had significantly lower ($p < 0.01$) radiative temperatures in contrast to the roads and the roofs of buildings, and the roofs were the hottest surface in the morning. The radiative temperatures were significantly different ($p < 0.05$) for the same types of buildings with various

Fig. 4 Mean, maximum, and minimum land surface temperatures for different land surfaces in two time periods (i.e., morning: 11:00–11:30 a.m. LCT; noon: 12:30–1:00 p.m. LCT)

materials and facades. For instance, the radiative temperatures of the roof and side facade of a building were 49 °C and 46 °C, respectively, although they were made of the same materials.

LST difference between urban and rural areas

Based on the MODIS-retrieved LST and land-use/land-cover maps, we analyzed the LST of various land-use/land-cover types in the urban and rural areas of Beijing. Various land-use components in the urban and rural areas exhibited significantly ($p < 0.05$) different LSTs, with a descending order of the built-up area > rural residential area > cropland > grassland > forest > water body (Table 2). The highest LSTs were primarily distributed in the urban and rural residential areas, where the major land-use component was built-up area, with a mean LST of 27.99 °C. The mean LST of the built-up area was about 2 °C higher ($p < 0.01$) than that of the cropland, which is primarily located around the residential areas in the eastern and northern Beijing, such as Shunyi District, Tongzhou District, and Daxing District (Fig. 1). LSTs of grassland were slightly ($p < 0.01$) higher than those of forest. The lower LSTs were primarily located in the northern and western mountainous regions, and were about 8 °C lower than those in the built-up areas (Fig. 2). The water bodies had the lowest LSTs. Thus, LSTs in the surrounding area of Miyun Reservoir were lower than those in the northern and western mountainous regions. The LST patterns of different land-use types retrieved from improved MODIS algorithms were consistent with that from the ground-based

observations using the portable infrared thermometer and thermal infrared imager (Fig. 4).

Overall, our results indicated that urban area LSTs were about 3–6 °C higher than those of rural areas. The LST generally descended with increasing distance from the urban center. The districts closer to the urban areas, such as Dongcheng, Xicheng, Haidian, Chaoyang, Shijingshan, and Fengtai districts, generally had ($p < 0.05$) higher LSTs than those in the suburban areas, such as Daxing, Tongzhou, Fangshan, Mentougou, Changping and Shunyi districts. The rural areas, such as Huairou District, Pinggu District, Yanqing County, and Miyun County, had even lower LSTs. For grassland and forest, the LSTs in the urban areas were about 3 °C and 2 °C respectively, higher than those in the suburban areas, and the difference between suburban areas and rural areas was smaller ($p < 0.01$). For water bodies, the urban LSTs were about 3 °C and 6 °C higher than those in the suburban and rural areas, respectively.

Land surface radiation and energy fluxes of different land-use types

Atmospheric conditions, radiation and energy fluxes, in addition to land surface physical properties, play a major role in the difference in LSTs for various land surfaces. Therefore, we specifically observed the net radiation, downwelling/upwelling shortwave and longwave radiation, and the energy fluxes during 11:00–11:30 a.m. LCT and daytime (i.e., the hours with downwelling short-wave radiation > 0 W/m²) on September 20th, 2011, at the selected sites S1, S2,

Fig. 5 The locations for observing land surface temperatures of various urban structures and landscape components (i.e., buildings, plaza, and park) in the Maple Oasis residential area (Z1 in Fig. 1) and the corresponding infrared images obtained from thermal infrared imagers. **a** The observation range of the thermal infrared imagers (yellow boxes) and observation position (yellow circle); **b1–b3** landscape pictures of buildings, plaza, and green space, respectively. **c1–c9** The images obtained from thermal infrared imagers; c1, c2, and c3 are the thermal infrared images of b1, b2, and b3, respectively; **c4–c6** represent impervious surfaces of buildings and plaza; **c7–c9** represent the green space

and S3 (Tables 3, 4). The downwelling short-wave radiation was higher than 700 W/m^2 for all three observation sites during 11:00–11:30 a.m. LCT (Table 3). The upwelling long-wave radiation was higher than 400 W/m^2 during 11:00–11:30 a.m. LCT, which was comparable with the daytime observations. Cropland had the highest net surface radiation on average, and the impervious surface had the lowest at 396.07 W/m^2 .

The land surface reflectance of different land-use types were ranked as impervious surface area > urban

green space $\approx$ rural cropland (Table 4). The impervious surface area had significantly ($p < 0.001$) higher reflectance and lower net radiation than urban green space and rural cropland, while no significant difference ($p < 0.05$) between urban green space and rural cropland. The ratio of sensible heat to net radiation (H/R_n) was about 0.63 and the ratio of latent heat to net radiation (LE/R_n ratio) was 0.19 for urban impervious surface. The radiation energy at the impervious surface was primarily composed of sensible heat, with a Bowen ratio (H/LE) of 4.03. For urban green space,

latent heat fraction (0.58) was higher than sensible heat (0.32) because of vegetation transpiration. For rural cropland, the lowest reflectance (0.14) resulted in the highest net radiation. Similar to green space, the high plant transpiration in cropland caused higher latent heat fraction (0.63) than sensible heat fraction

(0.30). The impervious surface had a significantly higher H/R_n ratio as compared to urban green space and rural cropland, while LE/R_n showed an opposite pattern. The sensible heat flux dominated energy balance at the impervious surface, resulting in significantly ($p < 0.001$) higher LST; latent heat flux played the major role in the energy balance of green space and cropland, resulting in lower LST as compared to impervious surface. From these analyses, we concluded that the difference in LST between impervious surface and vegetated surface (i.e., urban green space and rural cropland) might be primarily determined by the significantly different energy balance pattern.

Table 2 Summary statistics for LSTs for different land use types along an urban–rural gradient

Land use types	Max (°C)	Min (°C)	Mean (°C)	SD
Built-up area	35.92	20.34	27.99	2.64
Rural residential area	34.51	18.47	26.59	2.55
Cropland	34.13	18.32	25.32	2.56
Forest	30.62	11.47	23.18	3.09
Grassland	34.19	12.81	24.81	2.94
Water body	23.63	10.97	21.24	3.67

The effects of topography and vegetation coverage on LST

We overlaid the retrieved MODIS LST with elevation and vegetation cover (represented by NDVI) to find

Table 3 Different components of solar radiation (W/m^2) during the observation periods (i.e., 11:00–11:30 a.m. and daytime) on September 20th, 2011

Site (land surface)	Time	Downwelling short-wave radiation	Upwelling short-wave radiation	Downwelling long-wave radiation	Upwelling long-wave radiation	Net radiation
S1 (UIS)	11:00–11:30 a.m.	759.29	219.47	310.79	454.54	396.07
	Daytime	409.55	119.29	303.96	443.96	262.47
S2 (UGS)	11:00–11:30 a.m.	777.37	142.85	330.42	472.02	492.92
	Daytime	451.85	83.12	325.79	428.73	351.87
S3 (Cropland)	11:00–11:30 a.m.	753.40	99.87	313.64	444.36	522.80
	Daytime	545.43	82.46	310.41	432.58	342.05

UIS urban impervious surface; UGS urban green space

Denotes the hours with downwelling short-wave radiation $> 0 W/m^2$

Table 4 Land surface reflectance, net solar radiation (W/m^2), Bowen ratio, and the ratios of different heat flux components to net radiation during the observations at selected sites on September 20th, 2011

Site (land surface)	Time	Reflectance	R_n (W/m^2)	LE/R_n	H/R_n	G/R_n	Bowen Ratio (H/LE)
S1 (UIS)	11:00–11:30 a.m.	0.29	396.07	0.17	0.63	0.20	3.64
	Daytime	0.30	262.47	0.19	0.63	0.18	4.03
S2 (UGS)	11:00–11:30 a.m.	0.18	492.92	0.55	0.40	0.05	0.74
	Daytime	0.18	351.87	0.58	0.32	0.10	0.57
S3 (Cropland)	11:00–11:30 a.m.	0.13	522.80	0.59	0.35	0.06	0.60
	Daytime	0.14	342.05	0.63	0.30	0.07	0.46

UIS urban impervious surface; UGS urban green space; R_n net radiation; LE latent heat flux; H sensible heat flux; G ground heat flux

the relationships between LST and elevation and vegetation cover (Fig. 6). A simple linear regression between LST and elevation indicated that LST decreased significantly with increasing elevation (Fig. 6; $R^2 = 0.80$; $p < 0.01$). Beijing is located in the North China Plain, with a mountainous terrain (between 1,000 m and 1,500 m elevation) in the northwest and a flat plain (between 0 and 100 m elevation) in the southeast. The mean LST in the northwestern Beijing (higher elevation) was 19.65 °C, ranging between 14.14 °C and 24.08 °C, while the mean LST in the southeast was 28.15 °C, ranging between 23.87 °C and 32.82 °C. The polynomial regression analysis between LST and NDVI indicated that LST first increased with NDVI when $NDVI \leq 0.2$, then slightly decreased with NDVI when $0.2 < NDVI < 0.4$, and greatly decreased when $NDVI \geq 0.4$ (Fig. 6). This pattern reflected an urban–rural gradient of NDVI: low NDVI values in the inner city (mostly built-up land), relatively high NDVI in the suburban area (mostly residential and cropland

area), and the highest NDVI in the rural area (mostly forest).

Effects of landscape components and building materials on LST

Within the urban area, LSTs are closely related to the landscape components on the combination of multiple land-use/land-cover types and building materials. The urban land surface primarily consists of three major land-cover types: impervious surface, green space, and water. Based on the three observation approaches of direct measurements, thermal infrared imagers, and portable infrared thermometers, we found that the LSTs among these three land-cover types were significantly different, with a mean LST 6–12 °C higher at the impervious surface than at the green space. Therefore, the fractions of each land-cover component might finally determine the overall LST. In addition, we found that building materials, shapes, colors, and shadows significantly influenced the infrared images and thus LST. For example, the LST of a dark-gray roof was about 4.8 °C higher than that of a white-gray roof due to the higher energy absorption capacity of dark-gray materials. The LST of a concrete plaza in the shadow of tall buildings was about 10 °C lower than that of a concrete plaza without shadow. LST of an asphalt road was about 2 °C higher than that of a concrete road because the lighter color of the concrete has a higher reflectance and lower absorption to solar radiation. The building roof was directly exposed to solar radiation, so its LST was significantly higher than that of the lateral building walls. Therefore, the building materials with higher heat adsorption capacity should contribute more to the formation of UHIs. The different impacts of building materials were primarily reflected in their differences in thermal conductivity, reflectance, and thermal inertia. The buildings, roads, and plazas are generally made of bricks, tiles, concrete, and asphalt. Although these materials have high reflectance to solar radiation, they also have faster heat transfer and higher heat-trapping capacity. These characteristics lead to built-up land in the urban areas having the highest LSTs as compared to other land-cover types or locations along the urban–rural gradient. The green space with grass and trees has high vegetation evapotranspiration. Therefore, the thermal inertia and the resistance to rising surface temperature were very large, resulting in significantly lower LST than the impervious surface.

Fig. 6 The relationships between land surface temperatures and elevation (*top*) and normalized difference vegetation index (NDVI)

Discussion

Effects of urbanization on LST in Beijing

Urbanization, the process of converting natural vegetation or cropland to urban built-up land, is a major driver of land-use/land-cover change. The change in LST, an important parameter in studying UHI, is primarily related to the altered landscape structure due to rapid urbanization. For instance, urban areas covered with impervious surfaces such as buildings, asphalt, concrete, etc. generally have higher absorption of solar radiation and larger thermal conductivity and capacity, which may result in a relatively higher LST as compared to the surrounding areas. In this study, we found a significant descending trend in LST along the urban–rural gradient in terms of the distance from the city center. The land-cover types (such as vegetation or impervious materials) and spatial composition in the landscapes are also important in determining both internal and external urban LSTs (Rosenzweig et al. 2005; Zhou et al. 2011a, b). Furthermore, the spatial heterogeneity of landscapes may represent the largest intra-urban and rural differences in LST (Buyantuyev and Wu 2010). Using the ground-based observations and the MODIS remotely-sensed products, we found that the LSTs of various land surfaces followed an order of urban impervious surface > residential area > cropland > natural vegetation > water body. This implies that the higher fractions of urban impervious surface could result in higher LST in the urban area. Large magnitude of urban impervious surface is the dominant driver in the creation of a urban heat island. Beijing has experienced fast urban expansion in the past three decades, with more than a threefold increase in built-up area since 1984 (Kuang 2012b), which resulted in an increase of UHI by 0.31 °C/decade from 1960 to 2000 (Lin and Yu 2005). By the end of 2010, 19.62 million people lived in the city, and the population density was 1,195 persons/km². Its total area was 16,801 km², with 1,582.24 km² of impervious surface covering 72.6 % of the built-up area (Kuang 2011, 2012a; Kuang et al. 2013). Yu et al. (2005) indicated that the increasing urban impervious surface area in Beijing resulted in an increase of LST by 9.18 °C, although the increasing air temperature also partly contributed to increased temperatures. Our analysis for the relationship between NDVI and LST showed that LST significantly

decreased with increasing NDVI (Fig. 6). Increases of urban green space fraction in the urban area could reduce the increasing trend of LST (Weng et al. 2004; Buyantuyev and Wu 2010; Li et al. 2012). We found that the urban landscape cover components (e.g., impervious surface or green space) are the most important key factors related to LST. Therefore, the policy makers and city designers of Beijing should consider increasing the proportion of green space in urban and suburban areas to mitigate the UHI.

LST and land surface energy fluxes

LST plays a key role in controlling the land surface energy budget (Weng et al. 2013). In turn, the surface energy balance is an essential element of the climate system, and the land surface energy budget can be used to explain the changes of LST. Vegetated surfaces (e.g., green space and cropland) have a high evapotranspiration potential and can release a relatively large amount of absorbed energy as latent heat, resulting in a lower LST. In addition, vegetated surfaces have low thermal conductivity than impervious surfaces and tend to release slowly energy to the air, resulting in relatively low LSTs (Hafner and Kidder 1999; Hawkins et al. 2004). In contrast, urban impervious surfaces have higher thermal conductivity and capacity, and thus tend to absorb more incident solar energy and release their absorbed energy as sensible heat to the air, especially during night time, resulting in higher surrounding temperature. So the green space in an urban area is generally an “urban heat sink” (Carnahan and Larson 1990), whereas the impervious surfaces are “urban heat sources”. In this study, we found that the proportion of the components of net radiation (i.e., latent heat, sensible heat, and ground heat fluxes) between urban impervious surface, urban green space and cropland were significantly different. These differences might explain the higher LST in the urban impervious surface areas than in the green space and cropland areas. Based on ASTER remotely-sensed data, Weng et al. (2013) found that net radiation of various land-cover types followed an order of cropland > urban green space > urban impervious surface, which is consistent with our study (Tables 2, 3).

LST and building materials

Besides microclimatic conditions (e.g., air temperature, precipitation, and cloud cover), land use, urban

structure, and anthropogenic heat sources (Oke 1982), the thermal dynamics in an urban area are also significantly influenced by building materials (Meyn and Oke 2009). The influences of building materials on LST are reflected primarily in differences of the physical properties of materials (e.g., thermal conductivity, reflectance, albedo, and thermal capacity). For example, lighter-colored building materials generally have higher albedo and absorb less heat, while darker materials generally absorb more heat, resulting in higher LST associated with darker-material surfaces. A rough land surface often absorbs more heat as the surface area is larger than smooth land surfaces (Doulos et al. 2004). In addition, the LST of concrete pavements is generally lower than asphalt surfaces (Asaeda et al. 1996). An earlier report indicated that the building materials of old bricks and tiles within the second ring of Beijing had lower reflectance, resulting in an extremely high LST (Liu et al. 2011). Wang et al. (2003) found that the surface roughness of the inner city in Beijing is about an order of magnitude higher than that of the suburban area due to more tall buildings and complex landscape components, which resulted in significant changes in the thermal dynamics (Xu et al. 2009). In this study, we found that LSTs of dark-colored land surfaces and asphalt roads were and higher than white-colored surfaces and concrete roads, respectively. Building roofs had higher LSTs than lateral building walls, and LSTs in the areas of building shadows was lower than those areas without shadows. Therefore, we suggest that the city planners and designers should select building materials with higher albedo and low thermal capacity and rationally arrange land-use components in the urban area.

LST based on different retrieval algorithms

The measured LST from the portable infrared thermometers and thermal infrared imagers were compared with the retrieved LST based on Mao's algorithm and existing MODIS LST product (Fig. 2). The mean square of LST was 1.48 °C for improved Mao's algorithm, while it was 1.53 °C for the MODIS product, indicating a slightly higher accuracy for data retrieved from Mao's algorithm than that for MODIS products (Fig. 2a–c). For pure pixels in the rural areas, the LST from improved Mao's algorithm was generally lower than the observed LST. For cropland, improved Mao's

algorithm underestimated the LST, with 0.44 °C lower than that of the observed value; while MODIS product overestimated the LST, with 1.49 °C higher than that of the observed value. For forest, the LST from MODIS product was better than that from improved Mao's algorithm, with a difference of 0.73 °C and 2.27 °C for MODIS product and Mao's algorithm, respectively, as compared to the observed values. For the pure pixels of urban green space, improved Mao's algorithm was better than MODIS products, with a difference of 1.37 °C and 2.67 °C respectively from the observed values. For the pure pixels in the urban areas, such as the airport tarmac, improved Mao algorithm was close to the observations, with a small difference of 0.01 °C.

Conclusions

LST varied significantly along the urban–rural gradient, which is not only determined from the differences in solar radiation but also from the differences in atmospheric environment and land surface characteristics. The integration of ground-based observations with remotely-sensed data proved effective in exploring the spatial and temporal characteristics of LSTs along an urban–rural gradient from the perspectives of land-cover type, land-use types, urban structure, and building materials. The portable infrared thermometer and thermal infrared imagers can observe the LST differences at the local scale for different building materials and provide parameterization and validation data for MODIS retrieval at the medium scale. The improved MODIS retrieval algorithms reduced the mean error to 2 °C as compared to the observed LST.

The LST was significantly different between urban and rural land surfaces, with LSTs about 3–6 °C higher in the urban area than in the rural area. Large differences were also found among various intra-urban land-use types (i.e., impervious surface, green space, and water), with LSTs about 6–12 °C higher at the impervious surface than at the green space. Our results indicate that the different LSTs in the urban area were primarily caused by the differences in land surface radiation and energy fluxes. Sensible heat flux is the major component of net radiation for an impervious surface and thus resulted in increased LST, whereas latent heat flux is the major component of net radiation for green space.

LST is also significantly influenced by urban structure and building materials in built-up areas, and elevation and vegetation cover in rural area. We found that LSTs decreased with increasing elevation and NDVI. The concrete land surfaces had lower LST than that of asphalt surfaces, and dark-gray buildings had higher LST than white-gray buildings. To alleviate UHI intensity in Beijing, the city planners and designers should pay special attention to selecting appropriate building materials, reasonably arranging urban structures, increasing green space fractions, and designing rational landscape components.

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