A new method to quantify surface urban heat island intensity

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HIGHLIGHTS

- Quantifying surface urban heat island intensity using the relationship between LST and Impervious Surface Areas.
- The impervious surface areas was regionalized within the footprint of remote sensing observation using a Kernel Density Estimation method.
- Linear functions of LST were well fitted using the regionalized impervious surface areas.
- Slope of the linear function of LST was defined as the surface urban heat island intensity.

GRAPHICAL ABSTRACT
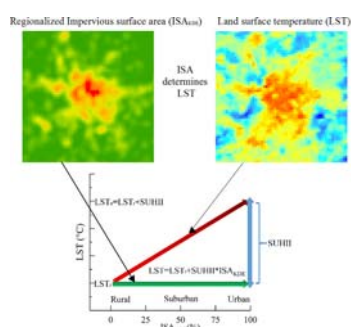
Linear functions of LST is well fitted using ISA that regionalized by a KDE method (ISA_{KDE}). Slope of the functions is defined as the surface urban heat island intensity.

ARTICLE INFO

ABSTRACT

Reliable quantification of urban heat island (UHI) can contribute to the effective evaluation of potential heat risk. Traditional methods for the quantification of UHI intensity (UHII) using pairs-measurements are sensitive to the choice of stations or grids. In order to get rid of the limitation of urban/rural divisions, this paper proposes a new approach to quantify surface UHII (SUHII) using the relationship between MODIS land surface temperature (LST) and impervious surface areas (ISA). Given the footprint of LST measurement, the ISA was regionalized to include the information of neighborhood pixels using a Kernel Density Estimation (KDE) method. Considering the footprint improves the LST-ISA relationship. The LST shows highly positive correlation with the KDE regionalized ISA (ISA_{KDE}). The linear functions of LST are well fitted by the ISA_{KDE} in both annual and daily scales for the city of Berlin. The slope of the linear function represents the increase in LST from the natural surface in rural regions to the impervious surface in urban regions, and is defined as SUHII in this study. The calculated SUHII show high values in summer and during the day than in winter and at night. The new method is also verified using finer resolution Landset data, and the results further prove its reliability.

1. Introduction

Urban areas show higher temperature than the surrounding rural areas, which is well known as Urban Heat Island (UHI) effect. Since its first observation by Howard in London (Mills, 2008), UHI phenomenon has been widely reported in different sized cities (e.g. Arnfield, 2003; Zhang et al., 2010; Zhou et al., 2017). Warmer air caused by UHI increases heat load stress of urban residents, potentially raising the threat of mortality (e.g. Tan et al., 2010; Constantinescu et al., 2016). Meanwhile, higher temperature increases energy consumption and associated greenhouse gas emissions due to the use of air conditioning (e.g. Zhou and Gurney, 2010; Zhou et al., 2012). Under the background of fast urbanization (e.g. Kuang et al., 2013, 2016b) and global change (e.g.

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Grimm et al., 2008), residential living in cities is suffering from higher risk of heat wave (e.g. Zhou et al., 2014, 2015; Yang et al., 2017). Concerning the increasing possible hazards cased by UHI, more and more attention has been paid to the studies of UHI (Inouye, 2015; McDonnell and MacGregor-Fors, 2016; Lee et al., 2015).

Accurate quantification of UHI can help to efficiently evaluate the potential heat risk and to guide the city management and development for government and city planners. Urban heat island intensity (UHII), the difference in temperature between urban and surrounding rural regions, is the classical indicator to quantitatively describe UHI effect (Rizwan et al., 2008; Stewart, 2011). Traditionally, the detection of UHII is conducted at two fixed in-situ stations, one in urban and the other in rural regions (e.g. Yang et al., 2013; Earl et al., 2016). Similarly, the study of the surface UHII (SUHII) using remote sensing data is conducted over selected pixels that are located in the urban and rural regions, separately (e.g. Stewart, 2011). The estimation of UHII (SUHII) relies on the definitions of urban and rural stations or pixels (e.g. Roth et al., 1989; Azevedo et al., 2016; Du et al., 2016). However, urban regions are strongly affected by human activities with high heterogeneity over the urban surface, and even the surrounding rural areas may have different ecosystems (Buyantuyev and Wu, 2010; Cadenasso et al., 2007). The urban-rural dichotomy alone cannot sufficiently guide the choice of the stations (Stewart and Oke, 2012). Schwarz et al. (2011) compared eleven approaches for quantifying SUHII with MODIS land surface temperatures for European cities, and found that the calculated SUHIIs using different rural pixels showed weak correlations. The different definitions of the urban/rural regions make the intercomparison study of UHII among different cities challenging. Stewart (2011) argued that previous UHI studies that used two stations measurements are often not comparable because of the different definitions of the measurement stations and the lack of the crucial description of these stations. On the other hand, fixed stations or pixels only represent the local micro-climate around these stations or pixels (Oke, 2006). Limited measurements only reflect parts of the characteristics of UHI (SUHI), and cannot identify the spatial variation and the structure of UHI within a whole city, especially for the cities which have multiple UHI centers (e.g. Li and Yin, 2013; Dou et al., 2015). The shape of cities could significantly influence the amplitude of UHI (Zhang et al., 2012; Zhou et al., 2017). To overcome the problems mentioned above, a promising way for the quantification of UHII (SUHII) should try to get rid of the limitation of urban/rural divisions, and consider the comprehensive conditions of cities by integrating the urban surface properties.

Land use change caused by urbanization is the primary driving factor of UHI (e.g. Cheval and Dumitrescu, 2015; Du et al., 2016; Li et al., 2017). The lower albedo and higher sealing degree of urban areas significantly alter the surface energy budget and lead to higher temperature than rural areas (Oke, 1982, 1988; Kuang et al., 2015a, 2015b). Near surface temperatures are closely related to urban indicators, such as Impervious Surface Area (ISA). Yuan and Marvin (2007) found that there was a strong linear relationship between LST and ISA for all seasons in Minnesota. Rajasekar and Weng (2009) pointed out that the areas with high heat signatures had a strong correlation with impervious surfaces in central Indiana. Imhoff et al. (2010) concluded that ISA was the primary driver for the increase in temperature, explaining 70% of the total variance in LST for 38 the most populous cities combined in the continental United States. Zhang et al. (2010) pointed that >60% of the total LST variance was explained by ISA for urban settlements within forests at mid to high latitudes globally. Li et al. (2011) reported a strong positive relationship between LST and ISA in Shanghai. Schatz and Kucharik (2014) found that ISA within the footprint of measurement stations was the dominant driver of air temperature and accounted for 74% and 80% of the explained spatial variation of the air temperature at night and during the day, respectively, in Madison, Wisconsin. Kuang et al. (2017) found that the highly dense impervious surface areas significantly increased land surface temperature. Wang et al. (2017) found that ISA was responsible for 31%–38% and 49%–54% of air temperature variability during the day

and at night, respectively in Beijing. Compared with UHII, SUHII is usually more dependent on ISA. This is because that the land cover is the single-most dominant factor of LST, while the air temperature is affected by land cover, air advection and anthropogenic heat emission, together (Azevedo et al., 2016). To summer up, as a good indicator of urban land use, ISA could reflect the spatial pattern of UHI (SUHI). The relationship between temperature and ISA can be a potential powerful tool for the quantification of UHII (SUHII).

The temperature at each site is also affected by the surrounding environment (Rannik et al., 2000). There is a footprint for the temperature measurement (Oke, 2006). The measured temperature is related to the overall land use information within the footprint. Schatz and Kucharik (2014) and Wang et al. (2017) considered the footprint when examining the relationship between in-situ air temperature and ISA. As for the remote sensing, there is a mismatch between the observation results and its ground source, especially for the mixed pixels over heterogeneous areas, due to the variation of the view zenith angles and gridding processes. Campagnolo and Montano (2014) found that the width of the ground-projected instantaneous fields of view (IFOV) of MODIS products was larger than the nominal resolutions, and increased with the view zenith angles. The IFOV errors also exist in the Lansat data, especially in the thermal band (Lee et al., 2004). The satellite observation result in each pixel also contains information from neighboring pixels. Townshend et al. (2000) found that parts of the signal in MODIS pixels come from the surroundings. Peng et al. (2015) found that the size of the signal source of MODIS pixels is larger than the nominal resolution of the pixel. As thus, it is necessary to consider the influence of the footprint of remote sensing observation when study LST-ISA relationship.

This paper comes up with an approach to calculate SUHII based on the linear relationship between LST and ISA. Given the footprint of LST measurement, the ISA was regionalized to include the information of neighborhood pixels within the footprint using a Kernel Density Estimation (KDE) method. The linear regression function of LST was fitted using the KDE regionalized ISA (ISA_{KDE}). The regression slope of the fitted function was used as SUHII. The temporal variations of the calculated SUHII of Berlin in 2010 were investigated. In addition, the new developed ISA_{KDE} was compared with the raw ISA in terms of the fitted functions of LST and the calculated SUHII. The goal of this paper is to develop a promising approach for the quantification of SUHII.

2. Study area, data, and methodology

2.1. Study area

The study area is Berlin, the capital city of Germany. Berlin (52.34°–52.68° N, 13.10°–13.77° E) is located in Northeast Germany with a flat topography (34–122 m, altitude), and covers an area of about 900 km². According to a report in the year of 2015 of the Statistical Office of Berlin-Brandenburg (https://www.statistik-berlin-brandenburg.de), Berlin has >3.6 million inhabitants, with one third living in the inner city in an area of about 88 km². It is the second most populous city in the European Union. Fig. 1 shows the spatial pattern of CORINE land cover (Feranec et al., 2007) version 2012 in the study area. Berlin is an urbanized region with about 35% built-up areas. In addition, transportation and infrastructure areas cover about 20% of the city. Berlin's built-up areas create a microclimate with noticeable urban heat island effects, leading to a higher potential heat stress risk in the central inner-city areas (Dugord et al., 2014).

Berlin has a temperate maritime climate with a mean annual temperature of 9.5 °C and annual precipitation of 591 mm (data based on the German Meteorological Office Dahlem station measurements in the 30-years period of 1981–2010). Affected by the prevailing westerlies and abundant water vapor from Atlantic, Berlin has a windy and cloudy climate (Kottek et al., 2006). Fig. 2 exhibits the seasonal variations of the cloud fraction, wind speed, and precipitaion in 2010. Most of the winter days were cloudy with more than half of the sky covered by clouds,