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Original Articles

The influence of different data and method on estimating the surface urban heat island intensity

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ABSTRACT

Few studies have examined the influence of different data and method on estimating the SUHIs. This study aims at analyzing the impact of different method (to define rural area) and different data (MODIS Terra and Aqua satellite data) on estimating the SUHI intensity (SUHII, LST in urban minus rural reference) in 31 cities of China. The major findings include: (1) For SUHII, ignoring the influence of elevation and water body will overestimate the SUHII by 1.68 °C (averaged for 31 cities, hereafter) and 0.28 °C, respectively, in summer days (SDs). Using nearby suburban area as reference will underestimate the SUHII by 1.48 °C in SDs. Different data and method have smaller impact on estimating the SUHII in summer nights (SNs) than in SDs. (2) For spatial variation of SUHII, ignoring the influence of elevation will influence the spatial variation of SUHII in SDs ($r = 0.3$, $p > .05$), but other methods have little impact on estimating the spatial variation of SUHII. (3) For interannual variation of SUHII, using nearby suburban area will underestimate the increasing rate of SUHII (SD: 0.106 °C/year, SN: 0.012 °C/year), whereas ignoring the influence of elevation and water body have little influence on the changing rate of SUHII. The changing rates of SUHII in SDs monitored by Terra satellite were 0.025 °C/year lower than Aqua satellite. In all, the present study can enhance our understanding of the influence of different data and method on estimating the SUHII, and provide a useful reference to study the SUHII.

1. Introduction

Urbanization is accelerating around the world and brings a large amount of natural and social problems, for example, urbanization can lead to higher temperature in urban area than the nearby rural area. This phenomenon is called urban heat island (UHI), which can bring a series of negative effects to human beings (e.g. influencing the human health (Goggins et al., 2012; Mohan and Kandya, 2015) and increase energy consumption (Akbari et al., 2015)) and surface ecological environment (e.g. changing land surface phenology (Yao et al., 2017b; Zipper et al., 2016) and damaging water and air quality (Grimm et al., 2008)). Therefore, UHI studies contribute to many fields, including atmospheric environment, ecology, natural landscape, architecture and climatology, which has attracted more and more attentions from general public and scientific experts in recent decades (Li et al., 2017a; Luo and Lau. 2017; Sun et al., 2016; Wang et al., 2015a, 2016b; Zhou et al. (2017a,b).

Generally, there are two kinds of UHIs: The first one was air UHI, which was detected by *in situ* data (including within and above the canopy layer) (Chen and Frauenfeld, 2015; Ren et al., 2008; Wang et al., 2015a). However, the measured data from weather stations have many limitations for estimating the UHIs. Firstly, the stations are sparsely distributed and cannot completely reflect the UHIs for a whole city (Zhou et al., 2014b). Secondly, most stations are located in urban area and it is difficult to select rural stations that have not been affected by UHIs (Wang et al., 2015a). Thirdly, the high-quality data from weather stations are not available for all users (Wang et al., 2015b). The second one was called surface UHI (SUHI), which was observed by remote sensing products. Because of the full and wide coverage, open and easy access, more researchers began to study the UHIs using remote sensing technology. Due to the high temporal resolution (four times per day by two satellite), MODIS land surface temperature (LST) data has been used to study the SUHIs worldwide in recent years (Bounoua et al., 2015; Du et al., 2016; Imhoff et al., 2010; Peng et al., 2012; Tran et al., 2006; Wang et al., 2015b, 2016; Yao et al., 2017a; Zhou et al., 2014b).

An important parameter for studying SUHI was SUHI intensity (SUHII), which was calculated as the LST in urban minus rural (Du et al., 2016; Peng et al., 2012; Wang et al., 2015b; Zhou et al., 2014b), therefore, it is necessary to select reliable rural references. However, the methods to define the rural area varied greatly in different studies.

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Most studies calculated the SUHII between urban and nearby suburban area (Clinton and Gong., 2013; Du et al., 2016; Li et al., 2017b; Liao et al., 2017; Peng et al., 2012; Shastri et al., 2017; Wang et al., 2015b; Zhao et al., 2016; Zhou et al., 2014b), whereas some studies calculated the SUHII between urban and far rural areas (Imhoff et al., 2010; Yao et al., 2017a–c; Zhang et al., 2014; Zhou et al., 2016b). Actually, some studies showed that LST decreased gradually with rising distances from urban area and the spatial extent of SUHIs was much greater than the actual size of urban area (Han and Xu. 2013; Yao et al., 2017b; Zhang et al., 2004; Zhou et al., 2015) and using nearby suburban area as references may underestimate the SUHII (Zhou et al., 2016a, 2015). In addition, it was necessary to exclude the impact of water body and elevation on LST when calculating the SUHII (Haashemi et al., 2016; Imhoff et al., 2010; Zhou et al., 2016a), but many studies have ignored this point, for example, Zhang et al. (2014) and Wang et al. (2015b) did not exclude the influence of water body, and almost all studies ignored impact of elevation when using nearby suburban area (Clinton and Gong., 2013; Du et al., 2016; Li et al., 2017b; Liao et al., 2017; Peng et al., 2012; Wang et al., 2015b; Zhao et al., 2016, 2014b). Therefore, the SUHII results may vary substantially in different cases, for example, Peng et al., (2012) used nearby suburban areas as references to study the SUHII and the results indicated that the mean summer SUHII during 2003–2008 averaged for 419 global big cities were 1.9 °C and 1.0 °C for daytime and nighttime, respectively; Zhang et al. (2014) used 15–20 km buffer as rural area and the mean summer SUHII during 2003–2005 averaged for more than 3000 global cities were 2.6 °C and 1.6 °C for daytime and nighttime, respectively. There are large differences of SUHII for above studies, therefore, it was necessary to comprehensively analyze the impact of different methods in estimating SUHII at regional scale.

In addition, MODIS LST data can be obtained from two satellites: Terra and Aqua. Some studies used the Terra satellite to analyze the SUHIs (Bahi et al., 2016; Du et al., 2016; Gawuc and Struzewska., 2016; Morabito et al., 2016; Wang et al., 2016a; Yao et al., 2017a–c), whereas other studies used the Aqua satellite (Imhoff et al., 2010; Peng et al., 2012; Wang et al., 2015b; Zhao et al., 2016; Zhou et al., 2016a, 2014b, 2015). Previous study showed that the daytime SUHII monitored by Aqua satellite was higher than the Terra (Clinton and Gong. 2013), but the impact of different data on estimating the spatiotemporal variations of SUHII remain unclear.

Therefore, to solve the above mentioned problems and fill the current research gaps, a series of experiments were performed in this study. Different methods (to define rural area) used by previous studies were first analyzed and an appropriate method was selected. The influence of different data and method on estimating the SUHII and spatiotemporal variations of SUHII were also examined. The order of the rest paper is organized as follows. Section 2 describes the study area, data and method in this study. Section 3 shows the main results of the influence of different data and method on estimating the SUHII. The discussion and conclusions are presented in Section 4 and 5, respectively.

2. Data and methods

2.1. Data

In this study, the 31 major cities in China were selected as study area because of the rapid urbanization and large variations in background climate and topography (Fig. 1). The 31 cities include 29 municipalities or provincial capitals, Pearl River Delta urban agglomeration (including Guangzhou, Shenzhen, Hongkong, Zhongshan, Dongguan, Foshan, Zhuhai and Jiangmen) and Yangtze River Delta urban agglomeration (including Shanghai, Wuxi, Suzhou and Changzhou). China has experienced rapid urbanization and socioeconomic development in recent decades (Liu et al., 2010, 2012), the total urban area in China increased from $4.85 \times 10^4\,km^2$ in 1990 to $9.08 \times 10^4\,km^2$ in 2010 according to Kuang et al. (2016), and the total urban population in China increased from 308 million in 1990 to 779 million in 2015 (United Nations, 2014). Deterioration of urban environment was observed in China in recent years (He et al., 2017; Yao et al., 2017c; Zhou et al., 2014a).

In this study, China's Land Use/Cover Datasets (CLUDs, derived from Landsat TM/ETM+ and HJ-1A/1B imagery, 5-year interval) for the year 2000, 2005, 2010 and 2015 were used to extract the urban and rural areas. The CLUDs were characterized by high spatial resolution (30 m), detailed classification (25 land cover types), high accuracy (overall accuracy was higher than 90% for the 25 land cover types) and wide coverage (for the whole China). Detailed information on the CLUDs can be found in Liu et al. (2010, 2014) and Kuang et al. (2016).

LST was obtained from MOD11A2 (Terra satellite, 8 day composite, 1 km spatial resolution, at 10:30 am and 10:30 pm local solar time, 2003–2016) and MYD11A2 data (Aqua satellite, 8 day composite, 1 km spatial resolution, at 1:30 am and 1:30 pm local solar time, 2003–2016) (Haashemi et al., 2016; Yao et al., 2017a). Both MOD11A2 and MYD11A2 have advantages: the MOD11A2 data have longer time series (available since 2000) than MYD11A2 (available since 2002); the monitoring time of MYD11A2 is closer to the time of occurrence of the highest and lowest temperature in the diurnal cycle than that of MOD11A2 (Clinton and Gong, 2013). In addition, the vegetation activity was quantified by the enhanced vegetation index (EVI) using MOD13A3 data (monthly composite, 1 km spatial resolution) (Liu et al., 2015; Wang et al., 2015b). The higher EVI represents higher vegetation coverage.

2.2. Methods

MODIS data (MOD11A2, MYD11A2 and MOD13A3) was first reprojected (to Albers Equal Area projection) and moisacked using MODIS Reprojection Tool (MRT). MOD11A2 data monitored at 10:30 am and 10:30 pm were used to represent the LSTs in daytime and nighttime, respectively. MYD11A2 data detected at 1:30 pm and 1:30 am were used to represent the LSTs in daytime and nighttime, respectively. We only studied the SUHII in summer since the SUHII was generally higher in summer than in other seasons (Peng et al., 2012; Wang et al., 2015b; Zhou et al., 2014b) and the UHIs in summer has the largest impact on human lives (Goggins et al., 2012). Therefore, this study mainly focused on two time periods: summer day (SD) and summer night (SN).

The CLUDs were first combined into three major types: built-up area (urban area, industrial land and rural settlement), water body and other types. Then we used a moving window method to calculate the urban development intensity (UDI, defined as the proportion of built-up area in each 1 km × 1 km pixel (Zhou et al., 2016a)) and proportion of water body (PWB, defined as the proportion of water body in each 1 km × 1 km pixel) maps. Finally, the areas with UDI more than 50% were aggregated with aggregation distance of 2 km to generate urban area (Liao et al., 2017; Zhao et al., 2016; Zhou et al., 2014b).

A total of 5 different methods were used in this study, including 4 different methods to define rural area according to previous studies (Table 1 and Fig. 2). Method 1 and Method 2 used the same method to define rural area but different data (Table 1). Rural areas in Method 1 and 2 were defined as Rural 1. Rural areas in Method 3, 4 and 5 were defined as Rural 2, 3 and 4, respectively (Table 1 and Fig. 2). The Rural 1 was generated in two steps. Firstly, we produced 20–25 km buffer based on the generated urban area previously. Secondly, the pixels meeting one of the following requirements were excluded from the 20–25 km buffer: a) UDI higher than 5%; b) classified as water body; and c) elevation outside the range of elevation of urban areas ± 50 m (Table 1). The resultant area was defined as Rural 1. The methods to define Rural 2, 3 and 4 can be found in Table 1. Note that the 20–25 km buffer was according to previous studies (Zhou et al., 2016c; Yao et al., 2017a,c), since the SUHI's footprint was much greater than the urban area size (Han and Xu. 2013; Yao et al., 2017b; Zhang et al., 2004; Zhou

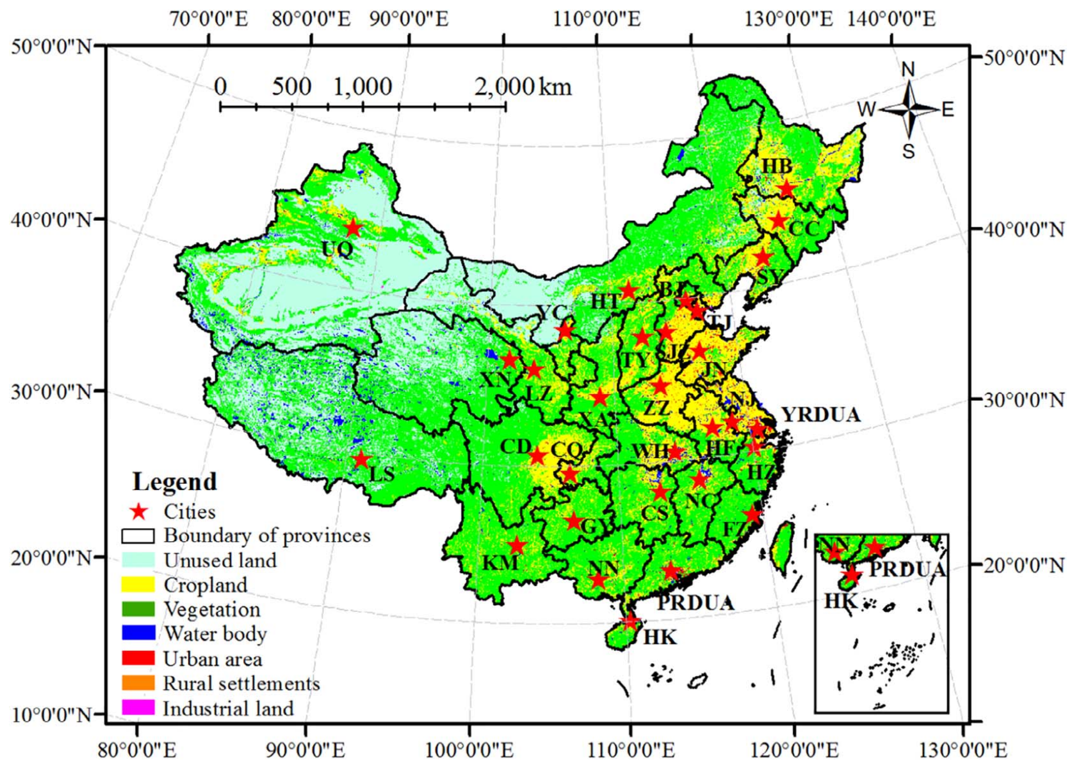

Fig. 1. The locations of 31 cities in China: Harbin (HB), Changchun (CC), Urumqi (UQ), Shenyang (SY), Hohhot (HT), Beijing (BJ), Tianjin (TJ), Yinchuan (YC), Shijiazhuang (SJZ), Taiyuan (TY), Jinan (JN), Xining (XN), Lanzhou (LZ), Zhengzhou (ZZ), Xi'an (XA), Nanjing (NJ), Yangtze River Delta Urban Agglomeration (YRDUA), Heifei (HF), Hangzhou (HZ), Wuhan (WH), Chengdu (CD), Chongqing (CQ), Nanchang (NC), Changsha (CS), Fuzhou (FZ), Guiyang (GY), Kunming (KM), Nanning (NN), Pearl River Delta Urban Agglomeration (PRDUA), Haikou (HK) and Lhasa (LS). The background land cover map was China's Land Use/Cover Datasets (in the year 2010).

et al., 2015). We did not select further buffer area for reducing the discrepancy of climate conditions between urban and rural areas (Yao et al., 2017a; Zhou et al., 2015). The references that used similar methods to define the rural area were listed in Table 1. The references that used similar methods to study the SUHII and the study areas that intersect with the 31 cities in this study were listed in Table 2. The characteristics of each method can be summed up:

Method 1: Excluding all influence in estimating the SUHII.
Method 2: Excluding all influence in estimating SUHII but using MOD11A2 data.
Method 3: Ignoring the influence of water body.
Method 4: Ignoring the influence of elevation.
Method 5: Using nearby suburban area as reference.

After urban and rural areas were generated, the SUHII was calculated using Eq. (1):

$$\Delta LST = LST_{urban} - LST_{rural} \tag{1}$$

where the LST_{urban} and LST_{rural} are the average LSTs for all the pixels in urban and rural areas, respectively. Therefore, ΔLST is the SUHII. In addition, the △EVI and △elevation was calculated using the same method as in Eq. (1).

To analyze the influence of different data and method on estimating the SUHII and the spatiotemporal variations of SUHII in China, we performed a series of experiments:

a) In the Section 3.1, we examined: (1) UDI in Rural 4; (2) △elevation between urban area and Rural 4; (3) △elevation between urban area and Rural 3; (4) PWB in Rural 2. Note that certain methods have excluded the influence of pixels with high UDI or elevation or water body. Thus we did not analyze the UDI, △elevation and PWB in these methods.
b) In the Section 3.2, CLUD in the year 2015, MODIS data for the period 2014–2016 and five methods mentioned above were used to analyze the influence of different data and method on estimating the SUHII.
c) In the Section 3.3, Pearson's correlation analysis was used to examine if different data and method influenced the spatial variations of SUHII. In addition, the spatial variations of SUHII and their relationships with △EVI were examined. Pearson's correlation analyses were performed across 31 cities in China.
d) In the Section 3.4, union area of urban areas in the year 2000, 2005, 2010 and 2015, above mentioned five methods and MODIS data for the period 2003–2016 were used to analyze the influence of different data and method on estimating the interannual variations in SUHII (Yao et al., 2017c). We studied the interannual variations of SUHII in the union urban areas for the purpose of comparing SUHII in the stationary areas across different years and examining the overall variation trends of urban areas (including urbanization and industrial relocation on SUHII (Yao et al., 2017c). Linear regression analyses were used to examine the interannual variations in SUHII. The interannual variations in SUHII and their relationships with △EVI were further examined. Pearson's correlation analyses were performed in each city during 2003–2016.

3. Results

3.1. Overview of different methods

3.1.1. The UDI in Rural 4

Most studies used the nearby suburban area around the urban area as reference and did not exclude the pixels with high UDI. We first calculated the UDI in the nearby suburban area (Rural 4) in each city in the year 2015 (Fig. 3a). The UDI in the Rural 4 averaged for 31 cities was 0.225. In addition, we calculated the UDI difference (UDID) in

Table 1
Detailed information about each method used in literature.

Method	Rural areas	Name	Data	Schematic diagram	References
Method 1	20–25 km, excluding UDI higher than 5%, water body, elevation outside the range of elevation of urban areas ± 50 m	Rural 1	MYD11A2	Fig. 2a	Imhoff et al. (2010), Zhou et al. (2016a), Zhou et al. (2016b) and Yao et al. (2017c)
Method 2	20–25 km, excluding UDI higher than 5%, water body, elevation outside the range of mean elevation of urban areas ± 50 m	Rural 1	MOD11A2	Fig. 2a	Imhoff et al. (2010), Zhou et al. (2016a), Zhou et al. (2016b) and Yao et al. (2017c)
Method 3	20–25 km, excluding UDI higher than 5%, elevation outside the range of mean elevation of urban areas ± 50 m	Rural 2	MYD11A2	Fig. 2b	Zhang et al. (2014)
Method 4	20–25 km, excluding UDI higher than 5%, water body	Rural 3	MYD11A2	Fig. 2c	Yao et al. (2017a), Yao et al. (2017b) and Kumar et al. (2017)
Method 5	3 km, excluding Water body	Rural 4	MYD11A2	Fig. 2d	Clinton and Gong. (2013), Du et al. (2016), Li et al. (2017b), Liao et al. (2017), Peng et al. (2012), Wang et al. (2015b), Zhao et al. (2016), Zhou et al. (2014b), Shastri et al. (2017), Zhou et al. (2017a,b), Huang et al. (2017), Miles and Esau (2017), Yang et al. (2017) and Mathew et al. (2016)

Rural 4 in each city between year 2000 and 2015 (Fig. 3b). The UDI in Rural 4 was higher in 2015 than that in 2000 for all cities. The UDID averaged for 31 cities was 0.103. It suggested that the Rural 4 may not be reliable rural references, and have errors in estimating SUHII and the interannual variations of SUHII. Therefore, for accurately calculating SUHII and the interannual variations of SUHII, it was necessary to use further rural area and exclude the pixels with high UDI.

3.1.2. The △elevation between urban area and Rural 3 or Rural 4

We examined the △elevation (elevation in urban minus rural) between urban area and Rural 3 (Fig. 4a) or Rural 4 (Fig. 4b). For all cities combined, the △elevation between urban area and Rural 3 was -195.34. There were more than half of the cities (18 out of 31) with △elevation lower than −50 m (Fig. 4a). In addition, the △elevation between urban and Rural 4 averaged for 31 cities was −37.68. Although the Rural 4 was close to the urban area, the △elevation were lower than −50 m in more than one quarter of the cities (8 out of 31) (Fig. 4b). Therefore, the influence of elevation cannot be ignored when calculating the SUHII.

3.1.3. The PWB in Rural 2

We examined the PWB in Rural 2 in each city (Fig. 5). The PWB in Rural 2 averaged for 31 cities was 0.11. There were more than one-third (12 of 31 cities) of the cities with PW higher than 0.1, thus the impact of water body (may be small) cannot be ignored when calculating the SUHII.

It is clear from above analysis that the influence of pixels with high UDI, elevation and water body on estimating the SUHII cannot be ignored. Rural 1 may be more appropriate to study the SUHII and the interannual variations of SUHII than other methods, since Rural 1 excluded all mentioned impact and may accurately reflect the actual urbanization effects on LST. In following sections, we will analyze the influence of different data and method on estimating SUHII, spatio-temporal variations of SUHII and relationships between SUHII and vegetation. Method 1 seemed as a best method, and other methods were compared with Method 1 separately in following sections.

3.2. The influence of different data and method on estimating the SUHII

3.2.1. The SUHII in SDs

Different data and method have great impact on estimating SUHII in SDs (Table 3 and Fig. 6). The SUHII in SDs averaged for 31 cities examined by Method 1 was 3.87 °C, which was much higher than the Method 2 (3.18 °C). The SUHII in SDs examined by Method 1 was higher than the Method 2 in 29 of 31 cities (Fig. 6a). These findings suggested that the SUHII in SDs monitored by Aqua satellite was generally higher than Terra satellite. Meanwhile, ignoring the impact of water body (Method 3) will overestimate the SUHII in SDs by only 0.28 °C averaged for 31 cities (Table 3), and nearly all points were close to the 1:1 line (Fig. 6b), which can be attributed to the less water body in Rural 2. Furthermore, ignoring the impact of elevation (Method 4) will overestimate the SUHII in SDs by 1.68 °C averaged for 31 cities (Table 3 and Fig. 6c). Finally, for all cities combined, using nearby suburban area (Rural 4) will underestimate the SUHII in SDs by 1.48 °C (Table 3)

3.2.2. The SUHII in SNs

Different data and method have smaller impact on estimating SUHII in SNs (Table 3 and Fig. 7). For all cities combined, the SUHII in SNs monitored by Aqua satellite was nearly equal to Terra satellite (1.55 °C vs. 1.62 °C; Table 3). Ignoring the impact of water body will underestimate the SUHII in SNs by 0.16 °C. Meanwhile, neglecting the impact of elevation (Method 4) will overestimate the SUHII in SDs by 0.87 °C averaged for 31 cities (Table 3). In addition, using nearby suburban area (Rural 4) will underestimate the SUHII in SNs by 0.43 °C averaged for 31 cities (Table 3).

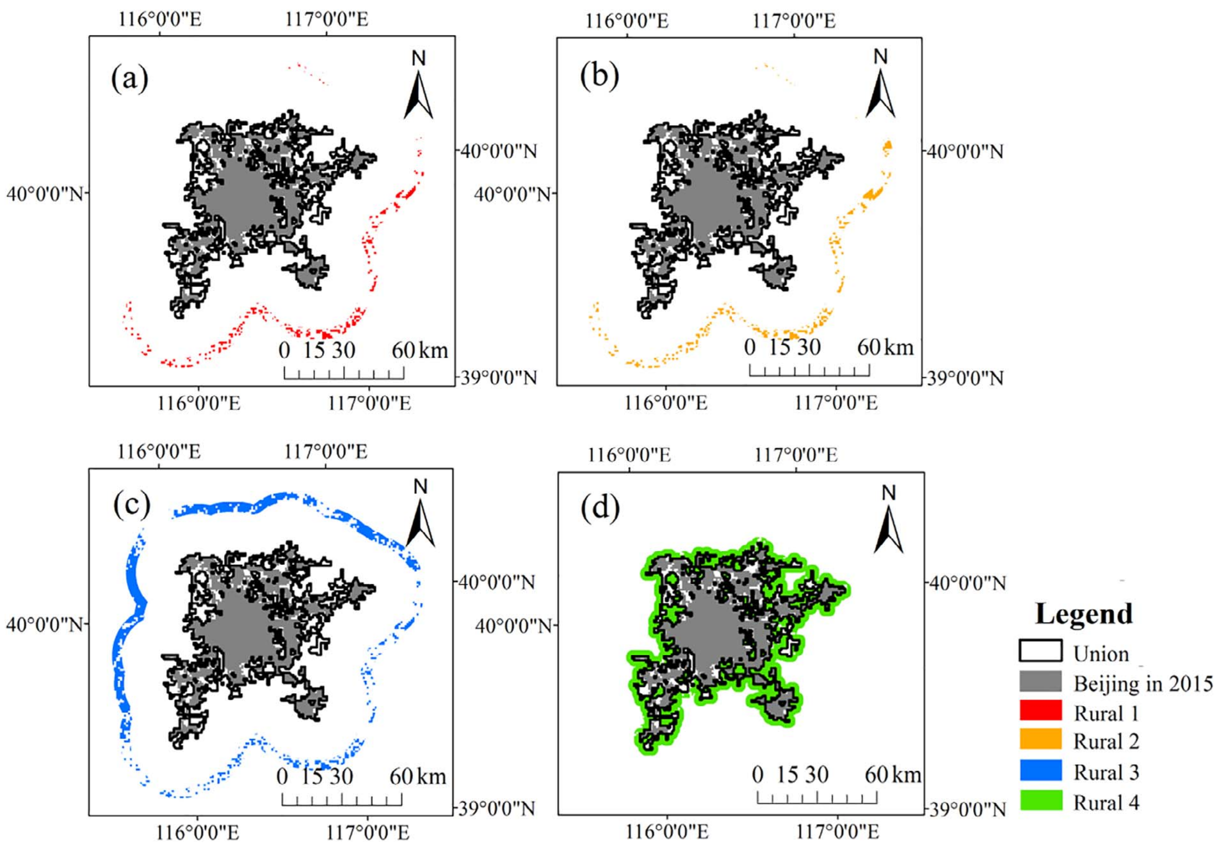

Fig. 2. The schematic diagrams of (a) Rural 1: rural areas in the Method 1 and Method 2, (b) Rural 2: rural areas in the Method 3, (c) Rural 3: rural areas in the Method 4, (d) Rural 4: rural areas in the Method 5.

Table 2
The references that used similar methods to define rural area and their study areas intersect with the 31 cities in this study.

References	Study area	Method
Zhou et al. (2016a)	32 cities in China	Method 1
Zhou et al. (2016b)	32 cities in China	Method 1
Yao et al. (2017c)	31 cities in China	Method 1
Zhang et al. (2014)	Over 3000 cities globally	Method 3
Yao et al. (2017a)	10 cities in China's Yangtze River Basin	Method 4
Yao et al. (2017b)	Northeast China	Method 4
Zhou et al. (2014b)	32 cities in China	Method 5
Du et al. (2016)	101 cities in China's Yangtze River Delta	Method 5
Liao et al. (2017)	32 cities in China	Method 5
Wang et al. (2015b)	67 cities in China	Method 5
Zhao et al. (2016)	32 cities in China	Method 5
Huang et al. (2017)	Shanghai	Method 5
Yang et al. (2017)	332 cities in China	Method 5
Peng et al. (2012)	419 cities globally	Method 5

3.3. The influence of different data and method on estimating the spatial variations in SUHII

Spatially, the Method 2, 3 and 5 have few effects on spatial variations of SUHII in SDs (Fig. 6). The Pearson's correlations were all significant at 0.01 level. However, Method 4 has large effects on spatial variations of SUHII in SDs, the correlation coefficient was only 0.3 ($p > .05$). This finding suggested that neglecting the influence of elevation will largely influence the spatial variations of SUHII in SDs.

All above methods have little effects on spatial variations of SUHII in SNs (Fig. 7), the Pearson's correlations between Method 1 and other methods were all significant at 0.01 levels. The lowest correlation coefficient was between the Method 1 and Method 4 (0.59, $p < .01$, Fig. 7).

All methods also have little effects on estimating the spatial variations of interannual changing rates of SUHII in SDs and SNs, the correlations were all highly significant ($p < .01$) (Figs. 8 and 9). The

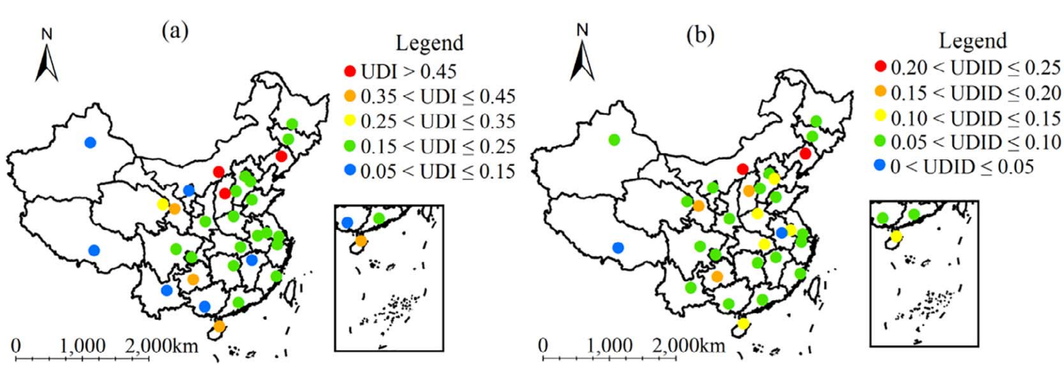

Fig. 3. (a) The UDI in Rural 4 in the year 2015 in each city. (b) The UDI difference (UDID) in Rural 4 from 2000 to 2015 in each city.

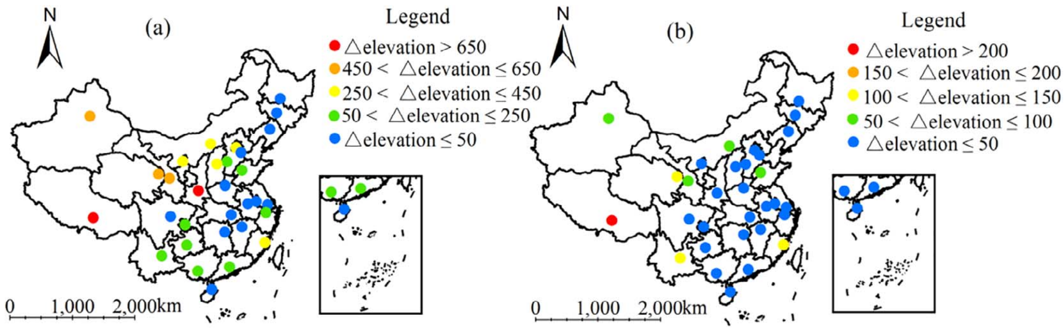

Fig. 4. (a) △elevation between urban area and Rural 3 in each city. (b) △elevation between urban area and Rural 4 in each city.

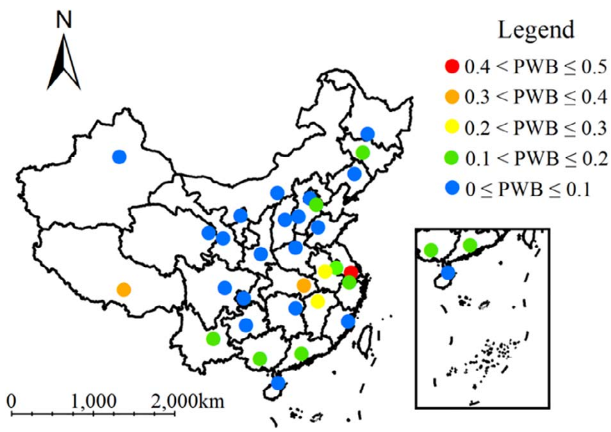

Fig. 5. The proportion of water body (PWB) in Rural 2 in each city.

Table 3
The comparisons of surface urban heat island intensity (SUHII) and temporal trends of the SUHII averaged for 31 cities between different methods. SDs: summer days, SNs: summer nights.

Results	Method 1	Method 2	Method 3	Method 4	Method 5
SUHII on SDs (°C)	3.87	3.18	4.15	5.55	2.39
SUHII on SNs (°C)	1.55	1.62	1.39	2.42	1.12
Temporal trends of SUHII on SDs (°C/year)	0.132	0.107	0.135	0.134	0.026
Temporal trends of SUHII on SNs (°C/year)	0.035	0.034	0.033	0.039	0.023

lowest correlation coefficient was between Method 1 and Method 5 (SDs: 0.73, $p < .01$, Fig. 8; SNs: 0.75, $p < .01$, Fig. 9).

Different methods can influence the correlation analyses between SUHII and △EVI across cities (Table S1). Method 3 and 4 have large impact on correlation analyses between SUHII and △EVI across cities (Table S1). In addition, the SUHII in SNs was generally invariant with △EVI across cities (Table S1).

3.4. *The influence of different data and method on estimating the interannual variations in SUHII*

The interannual increasing rate of SUHII in SDs averaged for 31 cities monitored by Aqua satellite was much higher than Terra satellite (1.32 °C/year vs. 1.07 °C/year; Table 3), nearly all cities were below the 1:1 line (Fig. 8a), but the result is opposite when it comes to the SUHII in SNs (0.35 °C/year vs. 0.34 °C/year; Table 3 and Fig. 9a). Meanwhile, ignoring the influence of elevation and water body have few effects on both changing rates of SUHII in SDs and the SNs. The increasing rates of SUHII estimated using methods 1, 3 and 4 were nearly equivalent (Table 3). Moreover, using Rural 4 has the largest effects on estimating the interannual variations of SUHII, which underestimate the increasing rates of SUHII in SDs and SNs by 0.106 °C/year and 0.012 °C/year, respectively (Table 3).

Additionally, different methods have little influence on correlation analyses between SUHII and △EVI across years (Table S1). The Pearson's correlation coefficients across years averaged for 31 cities estimated by different methods were nearly equivalent (Table S1).

4. Discussion

4.1. *The influence of different data and method on estimating the SUHII*

4.1.1. *The SUHII in SDs*

Different data and method have great impact on estimating the SUHII in SDs according to above mentioned results (Table 3 and Fig. 6). Ignoring the impact of elevation (Method 4) will overestimate the SUHII in SDs (Table 3). The increases in elevation can reduce the LST and ultimately influence the SUHII, which suggests that the influence of elevation must be removed when calculating the SUHII. In addition, ignoring the impact of water body (Method 3) will also overestimate the SUHII in SDs (Table 3), which can be attributed to the lower daytime LST of water pixels.

The SUHII in SDs monitored by Aqua satellite was higher than Terra satellite (Table 3), which was consistent with Clinton and Gong (2013). This is possibly due to the different monitoring time between Aqua satellite (1:30 pm) and Terra satellite (10:30 am) during the daytime. The monitoring time of Aqua satellite is closer to the maximum LST in a diurnal cycle than Terra satellite. It may be also closer to the maximum SUHII in a diurnal cycle since urban area warms faster than the rural area.

Using nearby suburban area will largely underestimate the SUHII in SDs (Table 3), which was consistent with Zhou et al. (2015, 2016a). This can be attributed to the high UDI in Rural 4. Generally, each pixel can be composed of multiple cover types (e.g. built-up area, water body, cropland and forest), especially for the coarse spatial resolution of MODIS LST data (1 km). Pixels in nearby suburban areas (Rural 4) may contain some built-up areas, therefore, using nearby suburban area may underestimate the SUHII in SDs.

4.1.2. *The SUHII in SNs*

In addition, different data and method have smaller impact on estimating the SUHII in SNs (Table 3 and Fig. 4). Ignoring the impact of elevation (Method 4) will overestimate the SUHII in SNs by 0.87 °C averaged for 31 cities (Table 3). In contrast to the SUHII in SDs, the SUHII in SNs estimated using Method 3 was 0.16 °C lower than the Method 1 (Table 3). This phenomenon can be explained by the properties of water body. Water body normally cool and heat more rapidly than other land cover types, therefore, water body generally has lower and higher LST than other land cover types (e.g. forest, cropland) during the daytime and nighttime, respectively. Next, SUHII in SNs

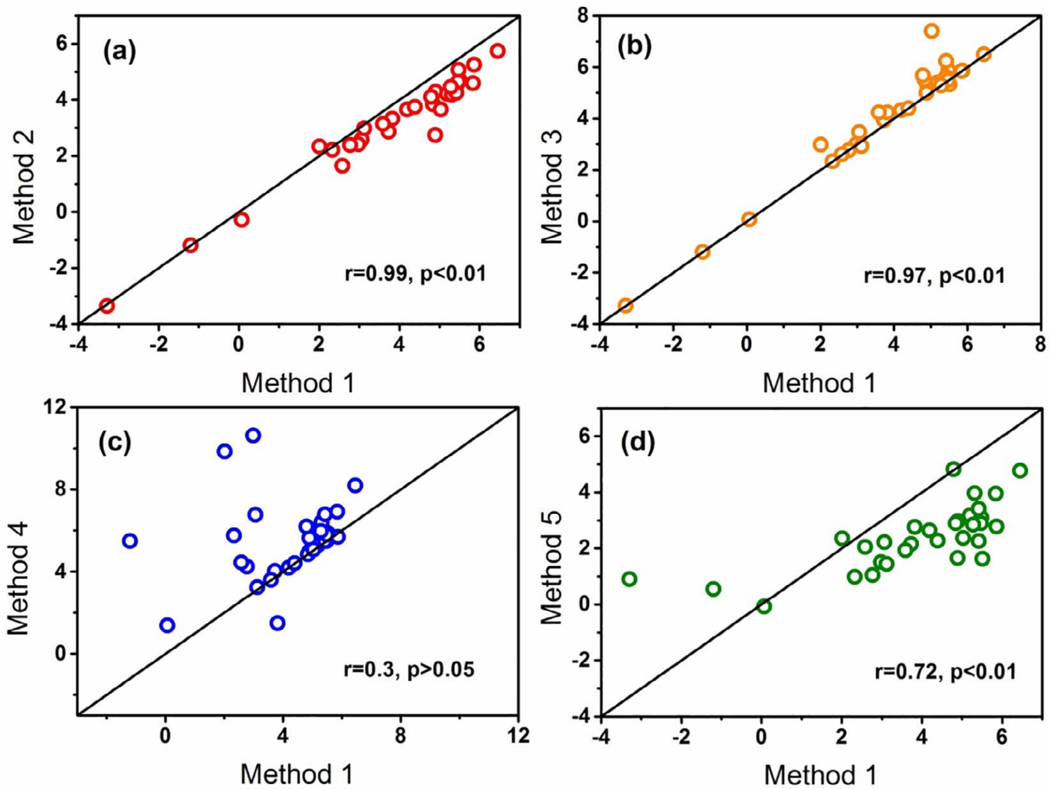

Fig. 6. Influence of different data and method on spatial variations of surface urban heat island intensity (SUHII) in summer days (SDs). A dot represented a city.

monitored by Aqua satellite was nearly equivalent with Terra satellite (Table 3), which suggested that the SUHII in SNs changed little over time. In addition, using nearby suburban area will largely underestimate the SUHII in SNs by 0.43 °C averaged for 31 cities (Table 3), which might also be related to the high UDI in Rural 4.

It was interesting that different data and method have smaller

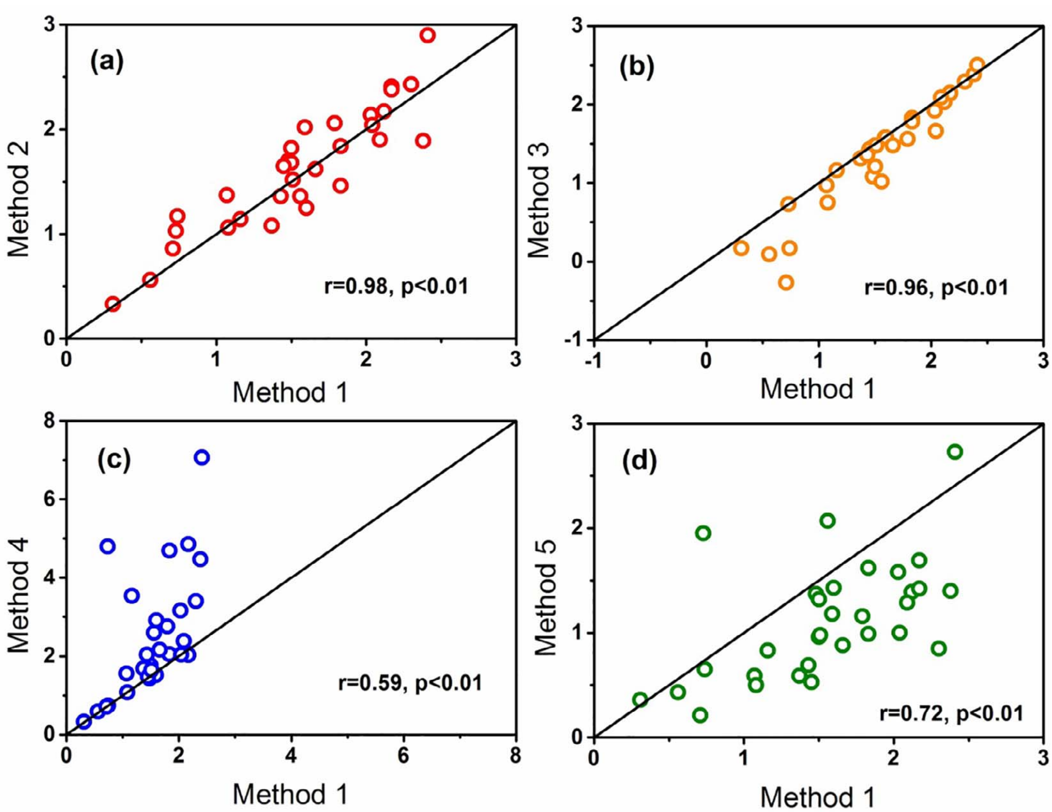

Fig. 7. The influence of different data and method on spatial variations of SUHII in summer nights (SNs).

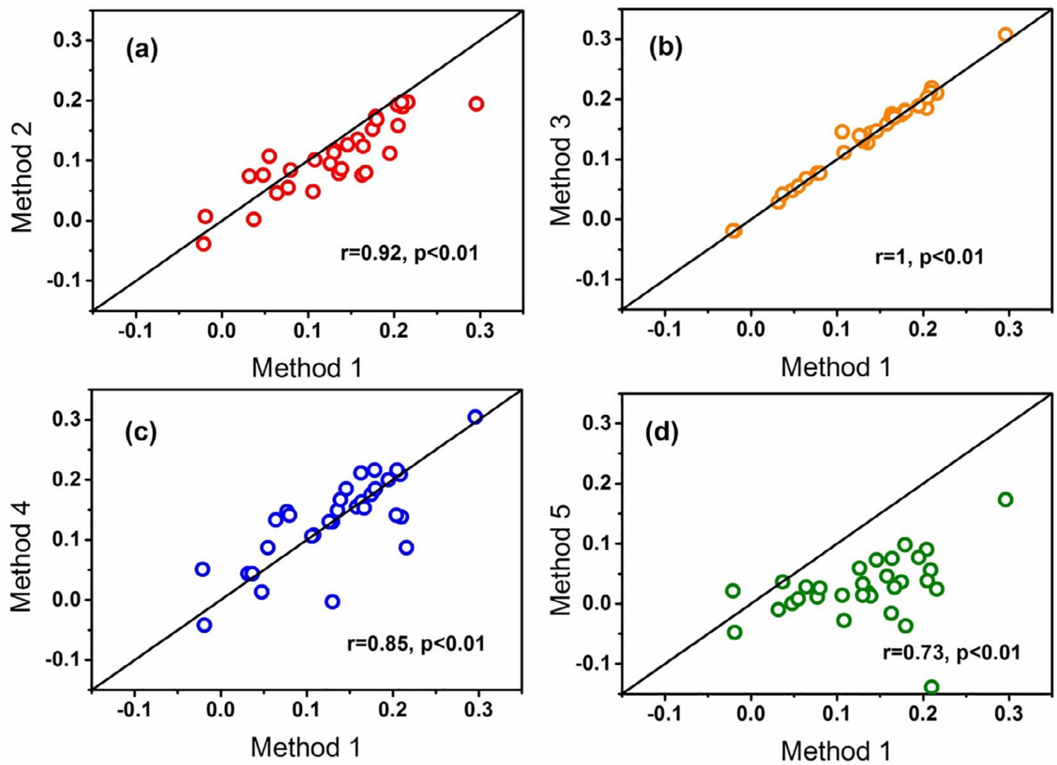

Fig. 8. Influence of different data and method on spatial variations in changing rates of SUHII in SDs.

impact on estimating the SUHII in SNs than SDs (Table 3). This can be explained by two reasons. Firstly, the SUHII in SDs was much higher than SNs and the LST gradient from urban to rural area in SDs was much larger than that in SNs. Secondly, the driving forces of SUHII between SDs and SNs were different (Zhao et al., 2016; Zhou et al., 2015). The dominant drivers of SUHII in SDs were built-up area and vegetation coverage, while in SNs were due to the anthropogenic heat release and albedo (Liao et al., 2017; Peng et al., 2012; Zhao et al., 2016; Zhou et al., 2014b). The UDI was closer related to the SUHII in SDs than SNs, thus the built-up areas in Rural 4 can lead to higher

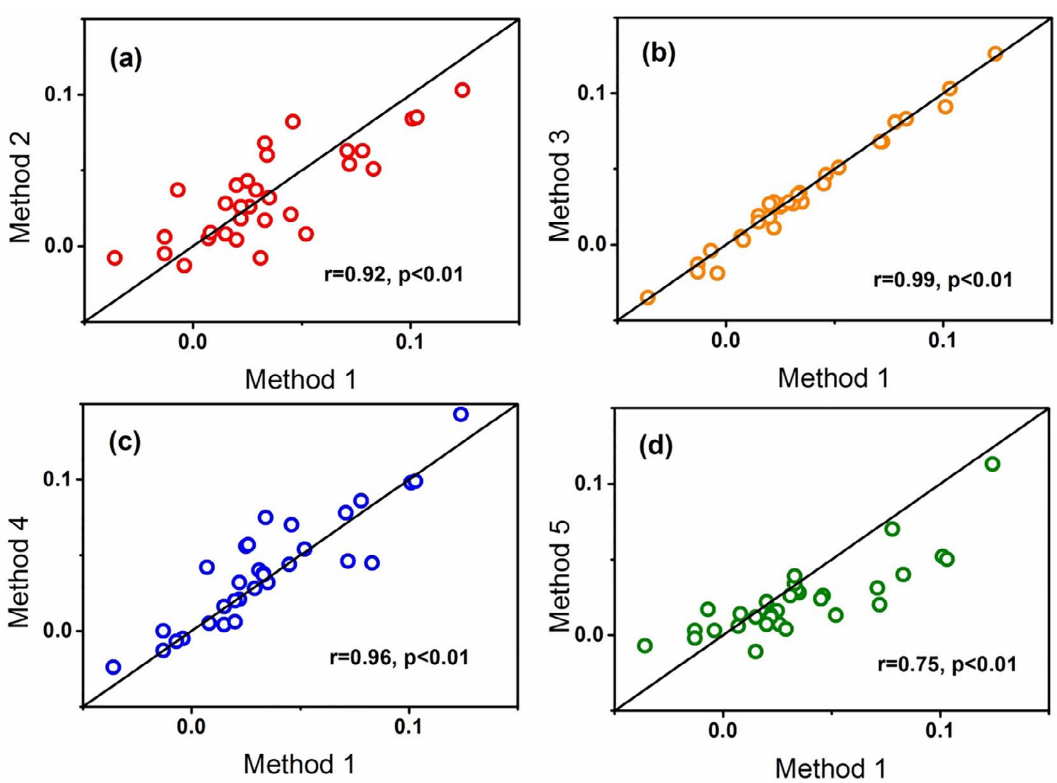

Fig. 9. Influence of different data and method on spatial variations in changing rates of SUHII in SNs.

discrepancy of SUHII in SDs than SNs (Zhao et al., 2016).

4.2. The influence of different data and method on spatial variations of SUHII

Different data and method have little effects on spatial variation of SUHII, mostly owing to the large variation of background environment in China. The great elevation gradient decreasing from west to east and background climate gradient from hot-wet climate in southeast to cold-dry climate in northwest can lead to highly different background environment in China (Zhou et al., 2014b). Therefore, the spatial variation of SUHII may be less affected by different data and method.

The correlations between SUHII and △EVI across cities estimated using Method 3 and Method 4 were smaller than Method 1, 2 and 5 (Table S1). The correlations estimated using Method 4 was insignificant ($p < .05$), which was different from previous studies (Peng et al., 2012; Zhou et al., 2014b). The water body in rural areas and △elevation between urban and rural areas may also influence the SUHII, which further proved that it was necessary to exclude influence of water body and elevation when analyzing the SUHII. In addition, the SUHII in SNs was generally invariant with △EVI across cities, which was similar to previous studies (Peng et al., 2012; Zhou et al., 2014b). This can be attributed to the much lower evapotranspiration during nighttime than daytime (Peng et al., 2012; Zhou et al., 2014b).

4.3. The influence of different data and method on interannual variations of SUHII

It is interesting that neglecting the influence of elevation and water body has little effects on estimating the interannual variation of SUHII, although it has large effects on estimating the SUHII (Table 3). When using Method 3 and Method 4 to estimate the interannual variation of SUHII, the overestimation existed in each year, therefore, using Method 3 and Method 4 will not influence the interannual changing rate of SUHII in theory. In addition, we suggested not to exclude the influence of elevation when analyzing the interannual variation of SUHII, since: a) more pixels will be contained in rural area when not excluding the influence of elevation, the background LST change may be more accurately reflected, and b) the plains may be more affected by human activities than high mountains. Most cities in China are located in plains and surrounded by some mountains, the main vegetation types in mountains and plains are forest and cropland. The cropland may be affected by human activity (e.g. irrigation, planting and harvest) and cannot accurately reflect the background LST change (Yao et al., 2017b; Zhou et al., 2016c). Therefore, not excluding the influence of elevation can more accurately reflect the background LST change.

The SUHII in SDs monitored by Aqua satellite was higher than Terra satellite, this was consistent with Clinton and Gong. (2013). We further found that the increasing rate of SUHII in SDs monitored by Aqua satellite were usually higher than Terra satellite (Table 3). The newly built urban areas may have higher SUHII in SDs in early afternoon (Aqua satellite monitoring time) than morning (Terra satellite monitoring time). Thus the increasing rate of SUHII in SDs monitored by Aqua satellite may be higher than Terra satellite. We can infer from this study that the increasing rate of SUHII in SDs will be higher in previous studies (Yao et al., 2017a,c) if it was monitored at the same time using MYD11A2 data.

In this study, using nearby suburban area (Rural 4) will underestimate the SUHII, This was consistent with Zhou et al., (2015, 2016a). We further found that using nearby suburban area will underestimate the increasing rate of the SUHII. This can be attributed to the rapid urbanization in nearby suburban area. The UDI in Rural 4 increased from 0.108 to 0.210 averaged for 31 cities. Furthermore, the SUHII in SDs estimated using Method 1 increased at the rate of 0.132 °C/year, the SUHII in SDs estimated using Method 5 increased at the rate of 0.026 °C/year. These results suggested that the SUHII in SDs in nearby suburban areas increased at the rate of 0.106 °C/year.

In our previous studies, we analyzed the interannual variation in SUHII using MOD11A2 data since it has longer time series (Yao et al., 2017a–c). We can infer from this study that the increasing rate of SUHII on SDs will be higher in our previous studies if it was monitored at the same time using MYD11A2 data. In addition, the methods of our previous studies were mentioned in Table 1.

Interestingly, although using Method 3 and Method 4 will influence the correlation analyses between SUHII and △EVI across cities, it will not influence the correlation analyses across years (Table S1). The interannual variations in SUHII in a city may not be affected by elevation since the elevation may not change across years and the overestimation of SUHII existed in each year, thus vegetation may be dominant driver for interannual variation of SUHII in China. The strongest correlation was estimated by Method 4 (−0.594), which can also be attributed to vegetation type. The human activity may have more effects on cropland than forest. This further suggested that it was not necessary to exclude the influence of elevation and water body when analyzing the interannual variation of SUHII. In addition, not excluding the influence of elevation may be a better choice.

4.4. Suggestions and future works

From above analyses we can find that different data and method have large impact on estimating the SUHII. We suggest to use Method 1 (excluding all influence in estimating the SUHII) to study the spatial variation of SUHII. Previous studies that used unreliable methods to study SUHII may need to be reevaluated.

For studying the interannual variation in SUHII, it was not necessary to exclude the influence of elevation and water body, but it was necessary to use far rural area and exclude pixels with high UDI. Previous studies primarily investigated the diurnal, seasonal and spatial variation of SUHII, relatively few studies examined the interannual variation of SUHII at regional and global scales due to the short time series of MODIS LST products (Yao et al., 2017a,c; Zhou et al., 2016b). Thus, this study can provide valuable information for studying the interannual variation of SUHII in China or other country.

There were still some methods to define rural area that not mentioned in this study. For example, Ward et al., (2016) used the inner urban LST differences to calculate the SUHII. Cao et al., (2016) only selected several pixels outside the urban area as rural areas. Quan et al., (2016) only used the croplands as rural areas. Thus, to make the results comparable across different studies, a universal method to quantify the SUHII needs to be introduced in future.

5. Conclusions

In this study, we analyzed the impact of different method (to define rural area) and different MODIS data on estimating the SUHII, spatio-temporal variation of SUHII and the relationships between SUHII and △EVI.

The results showed that using nearby suburban area (Rural 4) will underestimate the SUHII in SDs, while ignoring the influence of elevation and water body will overestimate the SUHII in SDs. The SUHII in SDs monitored by Terra satellite was lower than Aqua satellite. Ignoring the influence of elevation will obtain insignificant correlations between SUHII and vegetation across cities in SDs. Different data and method have smaller influence on SUHII in SNs.

Meanwhile, ignoring the influence of elevation will influence the spatial variation of SUHII in SDs, while other methods and different data have little influence on estimating the spatial variations of SUHII.

Moreover, using nearby suburban area will underestimate the increasing rate of SUHII, but ignoring the influence of elevation and water body has little influence on estimating the interannual changing rate of SUHII. The interannual increasing rate of SUHII in SDs monitored by Terra satellite was lower than Aqua satellite. All data and method have little influence on correlation analyses between SUHII and vegetation across years.

Therefore, we suggested to exclude the influence of water body, elevation, and use far rural area from urban area for calculating the SUHII. For studying the interannual variation of SUHII, it was necessary to use far rural area from urban area, but it was not necessary to exclude the influence of elevation and water body.

Overall, this study comprehensively analyzed the influence of different data and method on estimating the SUHII for the first time. It can be concluded that different data and method have large impact on estimating SUHII in China. Attentions should be paid to the data and method for estimating SUHII. This study can provide a valuable reference to study the SUHII for future studies. Some previous methods to study SUHII need to be reevaluated. In addition, a universal method to quantitatively quantify the SUHII needs to be proposed in future studies.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2018.01.044.

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