Long-term analysis of the relationship between urban heat island and economic development over 34 major cities in China

Lu Niu$^{1,2}$, Ronglin Tang$^{1,2,*}$

$^1$State Key Laboratory of Resources and Environment Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
$^2$University of Chinese Academy of Sciences, Beijing 100049, China

* Authors to whom correspondence should be addressed: tangrl@lreis.ac.cn

Abstract. Exploring the relationship between surface urban heat island (SUHI) effect and urban economic development is a problem that people pay attention to for a long time. In this paper, we use MODIS surface temperature data to calculate the SUHI intensity of 34 major cities in mainland China from 2003 to 2017. Then we first analyze the relationship between annual average SUHI intensity and urban annual gross domestic product (GDP). A good linear relationship is found in most cities in north and northeast China with the coefficient of determination ($R^2$) reaching 0.63 at most. In addition, the relationship between SUHI intensity and GDP during the day is significantly better than that at night. These conclusions can provide a new insight for people to understand the impact of urban heat island effect on urban economic development in the future.

1. Introduction

Urban heat island refers to the phenomenon that the temperature in urban areas is higher than that in surrounding suburbs. As one of the most characteristic phenomena in the process of urbanization, it has attracted wide attention in the past few decades [1] [2] [3]. Voogt and Oke [4] have ever divided urban heat island into three types: canopy layer heat island (CLHI), boundary layer heat island (BLHI), and surface urban heat island (SUHI). Because satellite products have strong accessibility and high coverage, using remote sensing data to calculate SUHI has become the main method to understand UHI changes [5]. Previous studies have used various remote sensing data to study SUHI from different levels and different scales, and these studies usually use the SUHI intensity as the indicator to measure the strength of urban heat island in a region [3] [7] [8].

Scholars used to concern about the drivers of urban heat islands. Researches show that the difference in vegetation [6], albedo [2], impervious surface ratio [9], local background climate [10], between the urban and rural areas are main factors causing the UHI phenomenon. However, there are few studies focus on the relationship between SUHI and the long-term urban economic development, especially in mainland China. In this study, we aim to investigate the potential of SUHI-GDP data for estimating GDP in municipal units of mainland China, this work colour help people to further understand the causes and effects of urban heat island phenomenon.

2. Study Area and data
Located in East Asia and covering a vast territory, China’s urbanization level has improved rapidly over the past two decades. In this paper, 34 major cities in mainland China (Figure 1) were selected. Most of these cities are the capital of province-level administrative regions in China. The other three cities: Dalian, Chongqing, and Shenzhen are important port cities of China.

Figure 1. Study areas (adapted from [8]). BJ (Beijing); CC (Changchun); CS (Changsha); CD (Chengdu); CQ (Chongqing); DL (Dalian); FZ (Fuzhou); GZ (Guangzhou); GY (Guiyang); HK (Haikou); HZ (Hangzhou); HB (Harbin); HF (Hefei); HT (Hohhot); JN (Jinan); KM (Kunming); LZ (Lanzhou); LS (Lhasa); NC (Nanchang); NJ (Nanjing); NN (Nanning); QD (Qingdao); SH (Shanghai); SY (Shenyang); SZ (Shenzhen); SJZ (Shijiazhuang); TY (Taiyuan); TJ (Tianjin); UQ (Urumqi); WH (Wuhan); XA (Xi'an); XN (Xining); YC (Yinchuan); ZZ (Zhengzhou).

LST data was obtained from Aqua MODIS 8-days composite products ((MYD11A2) in version V006 with a spatial resolution of 1 km from 2003 to 2017. They include 33264 tiles of LST images in total (2 transits/8day × 22 tiles over China). The reason why we choose MYD11A2 products of Aqua satellite is that the overpass time (local time 1:30 and 13:30) of Aqua satellite is close to the moment when the temperature is the lowest and the highest throughout the day, respectively. The LST data were estimated using a generalized split-window algorithm [11]. The retrieval of LST was further improved by correcting noise resulting from cloud contamination, topographic differences, and zenith angle changes, with the absolute bias generally less than 1 K [12].

Urban and rural areas were extracted from China's Land Use/Cover Datasets (CLUDs, 1 km spatial resolution, in the year 2000, 2005, 2010 and 2015), which were generated from Landsat TM/ETM+ and HJ-1A/1B imagery. The dataset is provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The overall accuracy was over 90% for the 25 land cover types according to previous studies [13].

GDP statistics data for the 34 major cities across mainland China come from the National Bureau of Statistics of China. More information about the GDP data could be found on
The administrative borders data were obtained from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn).

3. Method

3.1. Delineation of urban and rural areas

The demarcation of urban and rural areas is based on China's administrative borders (The administrative borders were obtained from the National Geomatics Center of China) and CLUDs. First, we remove the pixels in LST data which classified as waters in the CLUDs. Due to the high specific heat capacity of the water, the temperature rises slowly during the daytime and drops slowly at night, it will eventually make us underestimate the SUHI during the day and overestimate the SUHI in the summer. Then we also exclude the pixels in LST data which classified as forests because forests in China are mostly distributed on undulating mountains. Mountain forests are not suitable for being considered as rural areas—their temperatures are significantly lower than ordinary rural areas. Finally, we define the pixels that are classified as building types within the administrative boundary as urban areas, and the remaining pixels are defined as rural areas.

The reason for choosing to use the administrative border rather than the buffer in the traditional method to define the scope of the suburbs is mainly due to the fact that (1) There is currently no universally accepted method for determining the size of the buffer range, especially in the context of the wide range of study areas in this study. (2) For Chinese cities, the rural areas within the administrative area usually have a well correspondence to the associated urban sizes [5]. (3) The GDP data in this study are strictly based on the survey of administrative regions.

3.2. Investigate the relationship between SUHI and GDP data

We use the general calculation method to calculate surface urban heat island intensity [3] [7]. The SUHI intensity is calculated as

\[ SUHI = U_{LST} - R_{LST} \]  

(1)

Where, SUHI is the urban heat island intensity value of the calculated city, \( U_{LST} \) is the average temperature of all pixels in the urban area, and \( R_{LST} \) is the average temperature of all pixels in the rural area.

Some researchers [8] [9] have pointed out that climate type is an important factor affecting urban heat island intensity. Meanwhile, china has a vast territory, and the 34 big Chinese cities in the study are spread across several climate regions. It is unreasonable to study the relationship between SUHI intensity and GDP in all cities [14]. Therefore, we divided mainland China into six parts: North, Northeast, Northwest, Center-south, Southwest, and East.

Three experiments were designed to investigate the relationship of SUHI-GDP in municipal units of mainland China. The first 10 cities in experiment 1 were selected from North and Northeast China. Then, we added five Center-south cities into experiment 2 and extra five Center-south or East China cities into experiment 3 (Table 1).

| Table 1. Cities list in three experiments. |
|-----------------------------------------|
| List of cities in Experiment 1          | Beijing, Dalian, Changchun, Haerbin, Huhehaote, Jinan, Lanzhou, Shenyang, Shijiazhuang, Zhengzhou |
| List of added cities in Experiment 2    | Nanning, Nanjing, Nanchang, Wuhan, Qingdao |
| List of added cities in Experiment 3    | Nanning, Nanjing, Nanchang, Wuhan, Qingdao, Guangzhou, Changsha, Shanghai, Hangzhou, Shenzhen |

4. Result

The regression results of the three experiments all showed linear relationships (Figure 2).
When the number of cities included in the linear regression model reached 10 (Experiment 1), the $R^2$ value of the relationship between the daytime SUHII (DSUHI) data and NSUHI data with GDP were 0.633 and 0.605 (Figure 2. (a), (b)), respectively. When the number of cities being calculated rose to 15 (Experiment 2), the $R^2$ value dropped to 0.445 and 0.340 (Figure 2. (c), (d)). When the number of cities being calculated rose to 20 (Experiment 3), the $R^2$ value of was as low as 0.366 and 0.163 (Figure 2. (e), (f)).

In addition, the DSUHI-GDP relationship and NSUHI-GDP relationship derived from the GDP data had all passed the F-test at the 0.01 level.
Figure 2. Linear regression results of three experiments. (a), (b) are the results of the analysis of DSUHI and NSUHI with GDP in experiment 1. Similarly, (c), (d) and (e), (f) are the results of the experiment 2 and experiment 3, respectively.

5. Conclusion
In this article, we use the MODIS LST data and the CLUDs to calculate the SUHI intensity of the 34 major cities in the mainland China from 2003 to 2017, with the administrative boundaries determined by the urban-rural demarcation method. We find that the relationship of SUHI and GDP in the cities of north China and northeast China is reasonably good. When more cities of mainland China incorporated, the linear relationship gradually deteriorates. Moreover, the relationship of DSUHI-GDP is better than that of NSUHI-GDP. These results can provide a new insight for people to understand the impact of urban heat island effect on urban economic development in the future.

Acknowledgments
This work was partly supported by the Youth Innovation Promotion Association CAS under 2015039, 2016333, and the Beijing Municipal Science and Technology Project (NO. Z181100005318003).

References
[1] Arnfield A 2003 Int. J. Climatol. vol 23 (Amsterdam: Wiley-Blackwell) p 1-26
[2] Du H, Wang D, Wang Y, Zhao X, Qin F, Jiang H and Cai Y 2016 Sci. Total Environ. vol 571 (Amsterdam: Elsevier) p 461-70
[3] Peng S and et al. 2012 Environ. Sci. Technol. vol 46 (American Chemical Society) p 696-703
[4] Voogt J and Oke T 2003 Remote Sens. Environ. vol 86 (Amsterdam: Elsevier) p 370-84
[5] Lai J and et al. 2018 Remote Sens. Environ. vol 217 (Amsterdam: Elsevier) p 203-20
[6] Zhou D, Zhang L, Hao L, Sun G, Liu Y and Zhu C 2016 Remote Sens. Environ. vol 544 (Amsterdam: Elsevier) p 617-26
[7] Peng J, Ma J, Liu Q, Liu Y, Hu Y, Li Y and Yue Y 2018 Remote Sens. Environ. vol 635 (Amsterdam: Elsevier) p 487-97
[8] Zhou D, Zhao S, Liu S, Zhang L and Zhu C 2012 Remote Sens. Environ. vol 46 (Amsterdam: Elsevier) p 696-703
[9] Zhao L, Lee X, Smith R and Oleson K 2014 Nature vol 511 (Amsterdam: Nature Publishing Group) p 216-219
[10] Deng C and Wu S 2012 *Remote Sens. Environ.* vol 131 (Amsterdam: Elsevier) p 262-74
[11] Wan Z and Dozier J 1996 *IEEE Trans. Geosci. Remote* vol 34 (Amsterdam: IEEE) p 892-905
[12] Wan Z 2008 *Remote Sens. Environ.* Vol 112 (Amsterdam: Elsevier) p 59-74
[13] Kuang W, Liu J, Dong J, Chi W and Zhang C 2016 *Landsc. Urban Plan.* Vol 145 (Amsterdam: Elsevier) p 21-33
[14] Shi K, Yu B, Huang Y, Hu Y, Yin B, Chen Z, Chen L and Wu J 2014 *Remote Sens.* Vol 6 (Amsterdam: MDPI AG) p 1705-24