Impact of Urban Agglomeration and Physical and Socioeconomic Factors on Surface Urban Heat Islands in the Pearl River Delta Region, China

Zhifeng Wu, Yong Xu, Zheng Cao, Jinxin Yang, and Hong Zhu

Abstract—**An understanding of the driving factors of urban heat islands could improve the urban thermal environment and provide planning strategies for sustainable urban/regional development. We selected Guangdong province in China as a case area, which covers 21 cities and more than 110 million people. We used multitemporal remote sensing data from multiple sources and socioeconomic statistical data to analyze the effects of various drivers of surface urban heat islands (SUHIs). The tested drivers include urban agglomeration, physical indicators (e.g., vegetation and built-up indices), and socioeconomic indicators (e.g., population, gross domestic production, and nightlight intensity). The results show that physical indicators are determinants of daytime SUHIs whereas socioeconomic indicators are determinants of nighttime SUHIs, which indicates that daytime and nighttime SUHIs have different causal mechanisms in this region. Moreover, the results reveal that the influence of urban agglomeration on urban surface temperature is more significant at nighttime than in daytime, which implies that the warming effect of urban agglomeration is stronger at night. Together, the results indicate that joint control of urban size, urbanization level, and socioeconomic activities is crucial to alleviate SUHIs and safeguard sustainable development in this region.**

Index Terms—**Driving factors, nightlight data, socioeconomic, surface urban heat islands (SUHIs).**

I. Introduction

URBAN heat islands (UHIs) are features in which the air or surface temperature in a town or city is higher than those in its surrounding rural or suburban areas, which is likely related to the alteration of urban physical space (e.g., increased impervious surface area and less vegetation) and increased human activities that increase heat emissions in a city. The negative effects of UHIs include high-energy consumption, thermal discomfort, health-related illness, and air pollution. High energy consumption due to UHIs may further exacerbate UHIs and increase the frequency of heat waves. This is an urgent issue for some large cities in China, such as Guangzhou in the Pearl river delta (PRD) region, where heat-related deaths account for 10% of total deaths [1], [2]. An understanding of urban thermal dynamics and its driving factors is thus crucial for urban climatic planning and for the formation of appropriate strategies to mitigate its associated environmental impacts for sustainable development.

UHI research has a long history. Howard (1833) proposed the concept of a UHI effect according to temperature differences between the urban areas (UAs) and suburbs of London in the nineteenth century [3]. Later studies have been mostly devoted to understanding the causes and mechanism of UHIs [4], [5]. The pioneering works of Oke *et al.* [4], [5] showed a relationship between heat island intensity and urban size and population based on observation data from multiple cities in Europe and North America. This was also an earlier investigation into the key drivers of UHIs at the city scale. Previous studies based on meteorological observation data played an important role in understanding the distribution and temporal characteristics (e.g., diurnal variation) of UHIs [6].

The driving factors of UHIs at different spatial scales were rarely discussed before the 2010s because there were too few meteorological stations [7]. Satellite data now provide a method to understand large-scale land surface attributes and urban thermal environments in a fast and efficient way, even though satellite data only provide the land surface temperature (LST) instead of air temperature [8]. Recent studies have thus preferred the use of both dataset types to explore the main influencing factors on UHIs and analyze the key drivers of urban thermal environments at various spatial scales (e.g., district and city levels) [9], [10]. The classification scheme of local climate zones (LCZ) proposed by Stewart and Oke is representative at the district level [11]. Based on the LCZ classification system, a city area can be classified into 17 standard classes according to land surface conditions, and the thermal conditions within different urban structures can be standardized and quantified in a standard way [12]. At the city scale, several studies have confirmed that

Manuscript received February 26, 2021; revised June 25, 2021 and August 19, 2021; accepted August 20, 2021. Date of publication August 30, 2021; date of current version September 15, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 42071394, Grant 41901283, and Grant 41671430, in part by the Open Fund of Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources under Grant 201904028, and in part by the Natural Science Foundation of Guangdong Province under Grant 2018B030312004. (*Corresponding author: Yong Xu.*)

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Digital Object Identifier 10.1109/JSTARS.2021.3108456

urbanization has a strong effect on daytime UHIs and that the impact of urban size is more significant for some humid-hot and well-developed cities [13], [14]. Aside from urban size, vegetation configuration and composition have been observed to have a strong impact on the seasonal variability of surface UHIs [15], although the UHIs can vary across background climates and social and economic conditions [7].

Based on the literature review, three types of driving factors can be identified as highly relevant for urban thermal environments. These include physical factors, socioeconomic factors, and climatic factors [16], [17]. Based on urban physical indicators, Zhou *et al.* [18] found that a single urban size can well explain UHIs. Similarly, *Li et al.* [19] showed that larger urban sizes can exacerbate UHIs based on a set of simulations. The reason that large urban sizes have high UHIs can be well explained by the altered thermal properties (e.g., reflection, capacity) of urban materials, which thus influences the local climate and thermal environment of the entire city. Socioeconomic factors have also been widely used to explain UHIs because they describe the heat emissions from various sectors (e.g., manufacturing, transportation) by trapping, storing, and emitting heat. This category of indicators should thus show positive correlations with UHIs [20]. The effects of climatic factors (e.g., precipitation, temperature, wind speed, and solar irradiance) are highly variable; nevertheless, some recent studies have indicated that climatic background might be an ultimate determinant for the variability of UHIs over large areas [21]–[23].

Although numerous studies have investigated the causes and drivers of UHIs, large discrepancies and uncertainties remain for different cities. For example, some studies have shown that anthropogenic heat emissions might be the dominant factor of UHIs [24], [25], whereas others showed that urban size might be the dominant factor [13]. In addition to heating drivers, additional inconsistencies exist when using cooling factors such as vegetation. Peng *et al.* [15] indicated that the normalized difference vegetation index (NDVI) exerts a strong effect in reducing UHIs during transition seasons, such as autumn in Shenzhen, China. However, others studies reported that the influence of vegetation is stronger in winter instead of autumn. Even the conventional understanding of the cause of UHIs due to urban-rural differences was challenged by Zhao *et al*. [21], who proposed a new explanation for the existence of UHIs owing to background climate instead of urban-rural differences because the former affects heat convection efficiency to the lower atmosphere.

In addition to the discrepancies and uncertainties regarding UHI drivers, few studies have systematically investigated the influence of various factors on surface UHIs (SUHIs) in different periods (e.g., diurnal, seasonal cycles) [26]. Moreover, the impact of polycentric agglomerations on UHIs might be different from that of a single city, as the interaction between heat islands in urban agglomerations may increase the UHI intensity or produce additive effects [27], [28]. The main factors that induce heat flows in individual cities are the horizontal pressure gradients between urban and rural areas and inhomogeneous plumes impinging on the inversion layer, which is characterized by a "dome-shaped" heat flow over the city. The horizontal extent of the urban heat dome is usually around 1.5 to 3.5 times the UAs diameter according to a number of previous studies [27], [29]. When multiple cities begin to merge and form a city cluster, each city may generate its own heat dome, and the additive effect of multiple heat domes might cause more serious regional thermal environment problems.

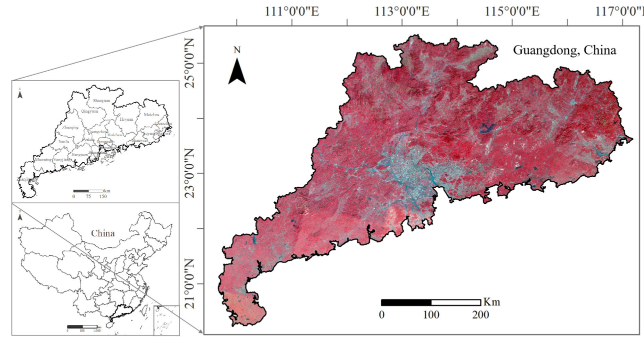


Fig. 1. Study area location (Guangdong province, China).

Thus, in this article, we take the largest urban agglomeration of the PRD region in China as an example to constrain the influence of different factors on SUHIs and evaluate the performance of different indicators in driving their spatio-temporal dynamics. We specifically address the following three issues.

1) We analyze the relative contribution of different factors on the urban thermal environment in the largest urban agglomeration area of China and test two physical factors (vegetation, impervious surface area) and three socioeconomic factors [i.e., population, gross domestic product (GDP), nightlight data].
2) We evaluate the performance of different driving factors on the thermal environment over different periods (diurnal, seasonal, multiple years).
3) We investigate the impact of urban agglomeration on the urban thermal environment. The findings and implications from this article provide beneficial guidance for decision makers to design appropriate heat mitigation strategies for sustainable development.

II. Study Area and Datasets

A. Study Area

Guangdong province in southern China near the South China Sea was selected as the study area (see Fig. 1). This area consists of 21 cities, including nine cities in the PRD region: Guangzhou (the provincial capital), Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing. The cities in the PRD region each have their own economic strengths: Guangzhou and Dongguan are well known for their manufacturing industries, Shenzhen has a booming innovation and startup culture, and Zhuhai is a center for leisure and tourism. These nine PRD cities, together with two Special Administrative Regions (Hong Kong and Macau), make up the largest urban agglomeration in China. Given the complementary advantages and the proximity of these cities, it can be predicted that further integration policies will usher in high-quality economic development in this area. As one of 34 provincial-level administrative units in China, Guangdong was among the earliest provinces in mainland China, benefit from its opening-up polices since 1978. Guangdong's economic aggregate has ranked first in China since 1989, and it accounts for largest share of China's economy. As its economy expanded, Guangdong attracted large numbers of immigrants from other provinces. Its total population ranked first in China with 115 million inhabitants in 2019.

Guangdong has a subtropical monsoon climate with hot and humid summers. Summer is also the most uncomfortable time for people in this region. Rapid urbanization and increasing population have exacerbated the effects of urban environmental degradation on the regional living environment. Previous studies in Guangzhou indicated that the average death rate during hot summers (>34°C) was 15.7% higher than in cooler summers. A similar study conducted in Hong Kong showed that the number of requests for health aid increased significantly when the maximum daily temperature exceeded 32°C, and approximately half of all requests were heat-related ailments [2]. Potential UHI drivers and the thermal environment mechanism in high-density cities form the basis upon which reasonable spatial planning strategies are designed for sustainable development, and are therefore the main aspects addressed in this article.

B. Datasets

We used multisourced satellite data including MODIS and VIIRS nightlight data, in which the former were used to obtain LST data and the biophysical parameters of vegetation and impervious surface indices, while the latter were used to reflect regional socioeconomic activity. Additional socioeconomic statistical data (e.g., GDP and population data) were collected for individual cities in Guangdong. Assuming that the effects of various indicators may change over time, the obtained GDP and population data from the local statistical departments includes figures from multiple years; namely, 2003, 2010, and 2017. There are two main motivations for choosing these three years to conduct this article. The first is data availability. In particular, MODIS observations are easily affected by the cloudy and rainy conditions in southern China. For example, in the summer, due to limitations in the availability of high-quality LST satellite products, data from three consecutive years were required to collate full seasonal data for a single year. Taking the example of 2003, the LST data from 2002, 2003, and 2004 were used, and likewise for 2017, the data from 2016, 2017, and 2018 were used. The second motivation is the need to ensure a representative result, given that the associations between LST and different driving factors might change over time. Thus, we chose three different periods from 2002 to 2018, including a starting point in 2003, an ending point in 2017, and a mid-point in 2010.

To ensure consistency between the raster-based satellite data and vector-based socioeconomic statistical data, we used a spatial analysis tool to generate the overall sum of each indicator into the administrative boundary of each city. These include the overall imperious surface area, overall vegetation coverage and overall nightlight intensity (NL) for each city. The obtained data were thus all in the same format and units for direct comparison.

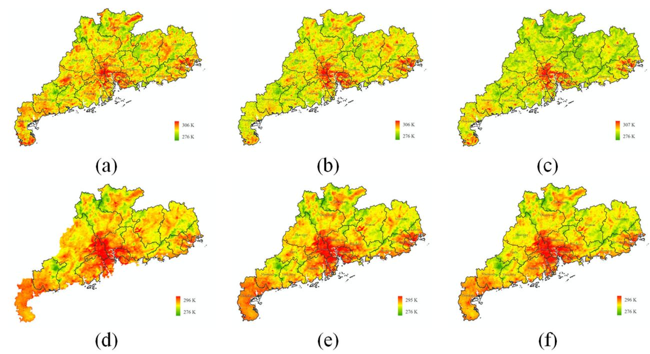


Fig. 2. Annual averaged LST in 2003, 2010, and 2017. (a) Daytime 2003. (b) Daytime 2010. (c) Daytime 2017. (d) Nighttime 2003. (e) Nighttime 2010. (f) Nighttime 2017.

III. Methods and Results

A. Surface Heat Islands

The MOD11A2 8-day composite LST product released by NASA was used and a split window algorithm was adopted to generate the surface temperature product [30]. The MOD11A2 LST product has been validated with a high accuracy of approximately 1 K for general areas [31]. Given that the eight-day composite LST observations are easily affected by weather conditions in southern China, the annual averaged and seasonal averaged LST data for 2003, 2010, and 2017 were synthesized using cloud-free 8-day LST time-series data. Specifically, the seasonal LST data were synthesized using the data for three consecutive years due to the limited availability of cloud-free data products in some seasons. Taking the summer-averaged LST data in 2003 as an example, we used the complete set of 8-day composite LST data from the summers in 2002, 2003, and 2004.

Fig. 2 shows the daytime and nighttime LST data products of Guangdong in 2003, 2010, and 2017, for which the SUHImax can be calculated as the surface temperature difference between the UA and its surrounding. The background area can be masked using the vegetation coverage data and nightlight data in this region. As indicated by Chakraborty *et al.*, the following formula was used to obtain the SUHIs for individual cities:

$$\mathrm{SUHImax} = \mathrm{Tmax}_{\mathrm{urban}} - \mathrm{Tmean}_{\mathrm{rural}} \tag{1}$$

where SUHImax is the intensity of the SUHI in the image, $\mathrm{Tmax}_{\mathrm{urban}}$ is the maximum surface temperature of the central UA, and $\mathrm{Tmean}_{\mathrm{rural}}$ is the averaged surface temperature of the rural area.

To reduce the impact of urban–rural differences on the calculation of UHIs in various cities, it was assumed that the rural areas around all cities in Guangdong were identical, and the average temperature of all vegetation areas was taken as the mean temperature of the rural areas for all cities. Based on this, the daytime and nighttime SUHIs for all cities in Guangdong can be further calculated using (1) (see Fig. 3). The average daytime

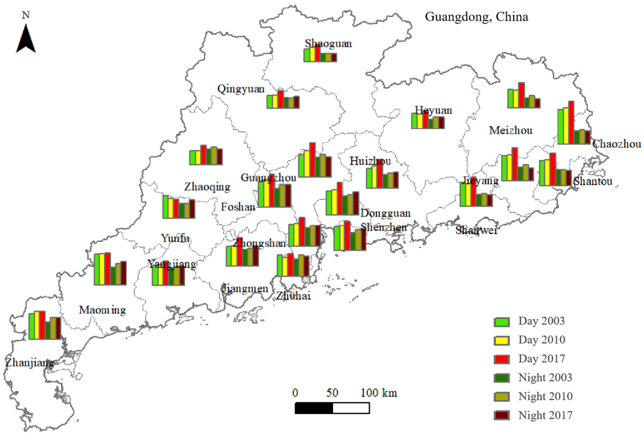
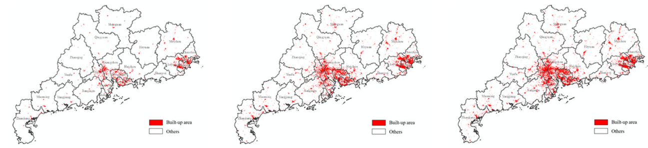
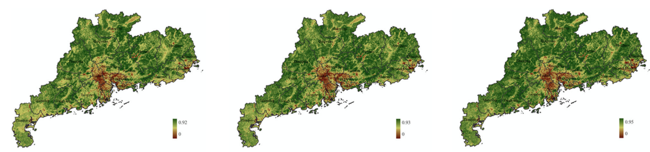


Fig. 3. Distribution of daytime and nighttime SUHIs of cities in Guangdong in 2003, 2010, and 2017.



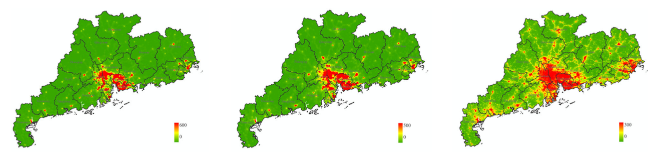
(a) (b) (c)

Fig. 4. Built-up UA in Guangdong in (a) 2003, (b) 2010, and (c) 2017.



(a) (b) (c)

Fig. 5. NDVI of Guangdong in (a) 2003, (b) 2010, and (c) 2017.



(a) (b) (c)

Fig. 6. Multitemporal nightlight images of the study area of Guangdong, China in (a) 2003, (b) 2010, and (c) 2017.

and nighttime SUHIs of Guangdong cities increased from 4.9 K and 3.4 K in 2003 to 6.2 K and 3.8 K in 2017, respectively. The results show that daytime SUHIs are usually higher than nighttime SUHIs in the tested cities, and the SUHIs of most cities increased over time for both daytime or nighttime. Cities in the central region of the study (particularly the big bay area) and in both eastern and western wings of Guangdong province had slightly higher SUHIs than the other cities, possibly due to their high urbanization rate.

B. *Potential Drivers of SUHIs*

Five variables representing both physical and socioeconomic factors in driving UHIs were selected in this article. Climatic factors (e.g., radiation, precipitation) were not included because the cities in Guangdong all belong to the same subtropical climate zone and thus have similar climatic conditions.

1) Physical Factors: Various urban surfaces have diverse physical attributes (e.g., absorption, scattering) and can be modulated to some extent based on the urban thermal environment. To simplify the analysis, two of the most widely used urban physical factors were used: urban size and vegetation coverage. Urban size was obtained by using the built-up class of the standardized global land use/cover product provided by the European Space Agency. Because the original land use/cover product covers the entire world, the boundary data of Guangdong province were used to crop its land cover map. The urban size of all cities in Guangdong was then obtained by summing up the built-up UA. show the built-up UA for individual cities in 2003, 2010, and 2017, from which it is apparent that the central and eastern parts of this region have higher urbanization rates than the other parts (e.g., the northern part).

The NDVI is another important parameter that controls the urban thermal environment because it determines the abundance and growth status of vegetation, such as forest and grass, which are highly related to the cooling rate in reducing the urban thermal environment via evaporation. Based on the multispectral satellite data, NDVI can be calculated from the red and near-infrared bands. Fig. 5 shows the NDVI results of Guangdong using MODIS satellite data for 2003, 2010, and 2017, in which green indicates the areas covered by vegetation and non-vegetation areas are masked in dark red.

2) Socioeconomic Factors: Socioeconomic development is vital for the urban thermal environment because intense human activities can cause large amounts of anthropogenic heat to be released into a city, which warm the urban surface and air temperature. Previous studies have identified some potential socialeconomic factors, including population, GDP, and nightlight satellite data. The population and GDP data can be obtained from the statistical departments of the local cities and nightlight data can be directly downloaded from a NASA website.[1]

Fig. 6 shows the nightlight satellite data after elimination of the cloud effects. Because the nightlight data products obtained in 2003 and 2010 are inconsistent with the 2017 data, we applied a standard calibration process to correct the digital number of nightlight images into compatible ones using a harmonized method given in Li *et al.* [32], where the calibration process of the nightlight satellite data is extensively discussed.

C. *Analysis and Results*

To explore the influence and contributions of various factors on SUHIs, we first adopted a Pearson correlation coefficient analysis method to analyze the highly relevant indicators. The tested indicators were population (POP), UA, vegetation coverage (VEG), NL, and GDP. Based on the selected indicators, a step-wise regression method was further used to model the

[1][Online]. Available: https://ngdc.noaa.gov/eog/download.html

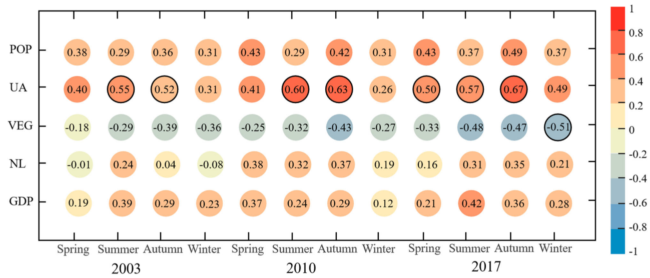


Fig. 7. Correlation coefficients between different factors and daytime SUHIs in different seasons of 2003, 2010, and 2017.

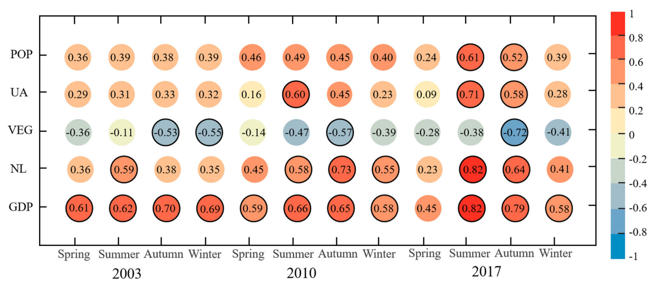


Fig. 8. Correlation coefficients between different factors and nighttime SUHIs in different seasons of 2003, 2010, and 2017.

TABLE I
ACCURACY AND REGRESSION RESULTS FOR BOTH DAYTIME AND NIGHTTIME SUHIS USING VARIOUS INDICATORS

	Regression result			Accuracy		
	LU	VEG	GDP	R2	RMSE	Percent (%)
Daytime SUHI	0.39**	-0.24 **	—	0.55	0.98	81%
Nighttime SUHI	—	-0.31 **	0.56 **	0.73	0.96	84%

**Significant level.

relationship between the different indicators and SUHIs and determine the relatively important factors over time.

The correlation coefficients between the driving factors and SUHI intensity are shown in Figs. 7 and 8. The dominant factors of daytime and nighttime SUHIs differ significantly, which indicates that the SUHI mechanism differs in this study area. Independent regression functions were thus designed to model the SUHIs in both day and nighttime.

Table I gives the linear regression results for daytime and nighttime SUHIs based on a stepwise regression model using the complete data from all cities of Guangdong in 2003 and 2010. The results show that the nighttime modeling results are substantially better than the daytime results when the dominant drivers are used, and both models achieve acceptable prediction accuracy. The daytime SUHIs showed a positive correlation with urban size, and the nighttime SUHIs showed a positive correlation with the GDP data. These results indicate that the daytime and nighttime SUHIs have different thermal driving mechanisms. The vegetation performance was stable in both day and night and had a consistently negative impact on the urban thermal environment. Accuracy assessment was conducted using the data from 2017, and the statistical results of the accuracy assessment are given in Table I.

IV. DISCUSSION

A. *Different Drivers of Daytime and Nighttime SUHIs*

The experimental results show that urban size has a significant positive impact on daytime UHIs in Guangdong, and continuing urbanization is expected have a sustained impact on the thermal environment. This finding is consistent with previous studies that showed that the urban metropolis size is the most important variable to predict heat differentials based on the results from global cities [13]. Our statistical analysis results also show that population size is highly correlated with urban size. The population performance should therefore be similar with the urban size and could also have a significant positive impact on daytime urban surface temperature. These findings are also consistent with previous studies that showed that UHIs can be determined by urban population instead of urban size [4].

Vegetation was found to have a significant negative impact on the urban thermal environment in both daytime and nighttime, which indicates that the greenery plan is the most efficient way to reduce SUHIs in this region. Nevertheless, the cooling effects of vegetation are weak compared to the warming effects of urban size. Most cities in Guangdong have therefore undergone a warming process over the past several decades, even though the greenery coverage has also increased in some cities. Figs. 7 and 8 show that the vegetation within a city has a seasonal impact of SUHIs because the cooling effects of vegetation become more notable in autumn and winter, especially at night. The reason might due to the deceasing temperature in the transition season that weakens the influence of the dominant warming factor and enhances the vegetation cooling effect more in the summer and wintertime.

Socioeconomic factors, including NL and GDP, were found to have a significant positive impact on the nighttime SUHIs instead of daytime SUHIs, which indicates that human activities might be a dominant driver of nighttime SUHIs in Guangdong cities. This finding also indicates that daytime and nighttime SUHIs have different mechanisms: daytime SUHIs are dominated by urban size, and nighttime SUHIs are likely dominated by the overall human activity. The GDP data exert a larger influence on the nighttime SUHIs than the NL, which means that GDP data better reflect real human activities than nightlight images.

Referring to Clinton and Gong, we evaluated the effects of these dominant factors on the daytime and nighttime SUHIs over time using raster-based datasets with a 5 km buffer for each sample. Fig. 9(a) and (b) shows the associations between various factors and SUHIs in 2003, 2010, and 2017, in which UA is the dominant factor with a positive relationship with the daytime SUHIs, and GDP is the dominant factor with a positive relationship with the nighttime SUHIs. The effects of both factors on either daytime or nighttime SUHIs increased over time, as demonstrated by the steeper slopes of the fitted curves for later years than those for earlier years. For example, the impact of UA on daytime SUHIs in 2017 [pink line, Fig. 9(a)] was higher than

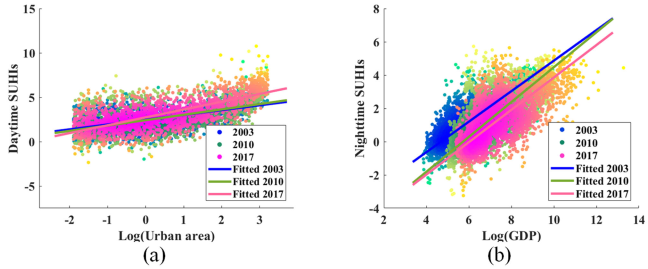


Fig. 9. Impact of dominant factors on SUHIs in different years. (a) Impact of urban size on daytime SUHIs. (b) Impact of GDP on nighttime SUHIs.

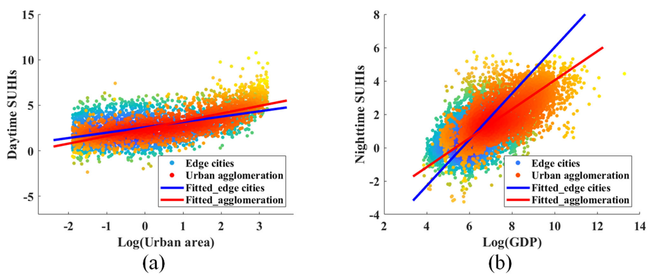


Fig. 10. Impact of dominant factors on SUHIs in different city types. (a) Impact of urban size on daytime SUHIs. (b) Impact of GDP on nighttime SUHIs.

in 2003 and 2010 (blue and green lines, respectively). The slopes of these fitted lines were 0.54, 0.60, and 0.88 for 2003, 2010, and 2017, respectively. This result also indicates that further urbanization development in the region will make the influence of the main factors (UA and GDP) more significant.

B. Urban Agglomeration and SUHIs

Understanding the impact of urban agglomeration on SUHIs is vital for sustainable urban development. Given that the world's largest urban agglomeration (the PRD region; population > 70 million) is located in Guangdong, it is therefore important to investigate the effects of this urban agglomeration instead of various drivers on the urban thermal environment. The target is to explore whether urban agglomeration has some negative/positive effects on the urban thermal environment of individual cities within this urban agglomeration.

To further clarify the impact of urban agglomeration, the cities in Guangdong were separated into two categories: those within an urban agglomeration and those not. Urban agglomeration is unlikely to affect SUHIs if the associations between the dominant driving factors and SUHIs are similar between both categories. Otherwise, urban agglomeration should have an impact on SUHIs. Fig. 10(a) and (b) shows the associations between the dominant factors and SUHIs using samples belonging to core cities (orange) and edge cities (blue).

The results show a minor influence of urban agglomeration on the daytime surface temperature; the slopes of both fitted lines are quite similar within the two categories. However, samples from edge cities tend to have slightly larger SUHIs than those from core cities, which might indicate that the core cities might have had a lower surface temperature when the satellite data were acquired due to their large thermal load compared with edge cities. Urban agglomeration also has a great impact on nighttime surface temperatures, and the slopes of the fitted lines differ substantially within the two categories. In particular, the samples from cities that belong to an urban agglomeration have a shallower slope than those from edge cities, which might due to warming effects of the former. These results also indicate that SUHIs, especially by night, are determined by both regional (urban agglomeration) and local factors (e.g., physical, socioeconomic factors).

C. Limitations

One main limitation of this article is that the multi-temporal satellite-derived LST was used to reflect SUHIs, which does not well reflect the air temperature over streets that are more related to human beings with more practical implications. Thus, a future study might evaluate the findings with more mobile-based observation data over cities. The climatic background also alters the UHIs of individual cities, which is not addressed in this article because all sites within the big bay area lie within the same subtropical climate area and have similar climatic conditions over time. Future tests can thus include the use of climatic variations on UHIs for individual cities and analyze the driving factors of individual cities to obtain mitigation strategies at a prefecture level.

V. Conclusion

Based on multitemporal LST products, SUHIs have changed substantially over cities in Guangdong. Both daytime and nighttime SUHIs increased by approximately 1.3 and 0.4 K from 2003 to 2017, respectively, whereas the area with high surface temperature increased by about 25 km^2. Five potential driving factors of SUHIs were tested, including two physical indicators and three socioeconomic indicators. Correlation and regression analysis tools were used to investigate the effects and performance of driving factors and urban agglomeration on SUHIs. Some key findings are summarized as below.

First, physical indicators are the determinant factor of daytime SUHIs and socioeconomic indicators are the determinant factor of nighttime SUHIs. Among the tested factors, urban size, GDP, and NDVI are more important than population and nightlight images. All tested factors except for NDVI have a positive impact on SUHIs, whereas NDVI has a negative impact. Urban size can explain approximately 55% of the daytime SUHIs of the cities in the testing area, and GDP can explain approximately 70% of the nighttime SUHIs for the tested cities. This finding indicates that the heat island mechanism differs between day and night.

Second, the effects of various factors on UHIs vary over time. The effects of urban size and GDP data on the thermal environment increased from 2003 to 2017, in which urban size has an increased impact on daytime SUHIs and GDP data has an increased impact on nighttime SUHIs. The physical factors, including urban size and vegetation, were found to have some seasonal effects on the urban thermal environment. In particular, the impact of urban size increases in summer and decreases in winter, whereas the influence of vegetation on SUHIs increases in autumn and deceases in spring. This difference might indicate that SUHIs have some hysteresis effect over seasonal cycles because the large amount of heat obtained by and stored in urban surfaces in summer requires a longer time to emit, thus the cooling effect of vegetation becomes more significant in autumn.

Third, experiments indicate that the influence of urban agglomeration on urban surface temperature is more significant at nighttime than daytime because the cities that belong to an urban agglomeration have substantially smaller associations between SUHIs and GDP than the other cities. This might due to the warming effect of urban agglomeration, which suppresses the impact of driving factors on the thermal environment of individual cities. This result also indicates that SUHIs, especially nighttime SUHIs, are determined by both regional (e.g., urban agglomeration) and local factors, which implies that comprehensive urban planning at various spatial scales is necessary to ameliorate the warming process of the cities in this region.

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