Strengthening of Surface Urban Heat Island Effect Driven Primarily by Urban Size Under Rapid Urbanization: Empirical Evidence From China

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Abstract

Context

Surface urban heat islands (SUHIs) have received worldwide attention owing to their significant adverse impacts on socio-economic and environmental conditions. Although SUHI patterns have been studied previously, how the SUHIs change across cities with different sizes and whether there is a threshold of city size for affecting SUHIs remains poorly understood.

Objectives

The primary objective is to facilitate more appropriate and effective planning of SUHI mitigation in urbanized areas of different sizes.

Methods

The SUHI effects were deployed to surface urban heat island intensity (SUHII). we systematically analyzed the spatio-temporal patterns of SUHIs at the national scale under the conditions of China's rapid urbanization, and explored the impact of natural and anthropogenic factors on SUHI by spatial error model.

Results

Intense urbanization occurred in China between 2000 and 2015, primarily dominated by the expansion of petty and mega urbanized areas. The SUHII gradually increased at the national scale from 2000–2015, and SUHIs also appeared in petty urbanized areas. We also found that the size of urbanized areas contributed the most to the increase in SUHII. In addition, the size of the urbanized areas had a positive non-linear relationship with SUHIs, and when the size was larger than 400 km², the growth of SUHIs maintained an equilibrium state.

Conclusions

Urban expansion is occurring rapidly. This study highlights the importance of impervious surface expansion for increasing heat island intensity. To confront SUHI effects, it is necessary to reduce the fragmented distribution of small towns and increasing green infrastructures.

1 Introduction

Urbanization is occurring at a remarkable rate worldwide. By 2050, the global urban population is expected to increase by approximately 2.5 billion and reach 60% (Ramaswami et al. 2016). Rapid urbanization can alter the surface radiation, humidity, and thermal environment in urban areas (Tran et al. 2017; Zhou et al. 2014b) and cause the urban heat island (UHI) effects (Zhou et al. 2017). UHIs adversely affect the net primary production of ecosystems (Li et al. 2019a) and can aggravate respiratory diseases and even cause death (Ren et al. 2018). For example, a study indicated that for every degree of temperature increase, the mortality rate of urban residents increased by 4% (Peng et al. 2012). To combat this, it is crucial to quantify spatiotemporal variations of UHIs and to identify their influencing factors, which can be used by city managers to develop programs to avoid thermal risks (Shang and Wu 2022).

Howard's monitoring of the phenomenon of urban areas being warmer than the surrounding countryside is arguably the earliest finding of the UHI effect. In contrast to air temperature data recorded at weather stations, land surface temperature (LST) data from remote sensing imagery can describe surface urban heat islands (SUHIs) in greater detail (Sekertekin and Zadbagher 2021). Previous studies related to LST data from moderate resolution imaging spectroradiometer (MODIS) have been conducted in different cities revealing, that the daytime SUHI intensity (SUHII) in major cities generally reaches 1.5 °C (Li et al. 2020a). Previous studies on SUHIs have primarily focused on specific regions, such as mega cities or major cities that have well-developed economies and rapid urbanization (Imhoff et al. 2010); however, small and medium cities have been neglected (Fei and Zhao 2019; Li et al. 2017). As these studies only selected large cities and did not examine the full coverage of city size, they concluded that city size had no significant effect (Schwarz et al. 2011; Tan and Li 2015). However, it has been suggested that SUHIs expands with the growth of urban size, and it is not clear whether there is a threshold range for this relationship between SUHIs and urban area size (Zhou et al. 2014a). Thus, some conclusions about large and mega cities may mislead decision-makers to the sustainable development of medium and small cities (Gao et al. 2016). SUHIs already exist and have expanded in urbanized areas (Li et al. 2021). However, previous studies have been limited to a few cities, primarily large cities; therefore, the relationship between city size and SUHIs remains largely unknown. As urbanization continues, the distances between cities have shrunk or even disappeared, and thus, SUHIs are no longer restricted to single cities (Du et al. 2016). Therefore, using urbanized areas with full sample coverage as the research object can decrease the inaccuracy of the results owing to sampling surveys in the study area and can more accurately estimate the SUHIs of cities of different sizes (Chakraborty et al. 2020).

In addition, past studies have explored the relationships between the spatiotemporal variations of SUHIs and associated factors. These factors can be categorized into anthropogenic or natural factors (Kim and Brown 2021). Anthropogenic heat release and urban form are factors related to human activity that positively impact SUHII. However, vegetation activity, temperature, and precipitation are natural elements that negatively affect SUHII (Peng et al. 2019). Most past studies have analyzed the detailed effects of these factors on SUHII through statistical methods such as correlation analysis, stepwise regression analysis, and multivariate statistical analysis. These methods measure the interrelationship between variables, which are suitable for time series, without considering the spatial association between regions (Lichstein et al. 2002). However, previous studies have indicated that LST tends to correlate spatially with

LSTs observed nearby owing to atmospheric flows (Song et al. 2014). Statistical analysis ignores the spatial correlation of the SUHI distributions, leading to evident limitations. Therefore, some researchers have selected spatial autocorrelation models to eliminate the interactions that exist between geographic units.

Apparently, in the context of rapid urbanization, the spatiotemporal patterns and potential mechanisms of SUHI in different-sized cities need to be comprehensively evaluated. In this study, we examined urbanized areas in mainland China and analyzed the temporal change tendency and spatial patterns of SUHI, as well as the associated factors. The objectives of the study were to (1) illustrate the urbanization process with the characteristics of impervious surfaces in China over the period of 2000–2015; (2) characterize the SUHI evolution at diurnal, seasonal, and annual scales and analyze SUHI spatial patterns in urbanized areas of different sizes; (3) determine the non-linear relationships between SUHI and anthropogenic factors and natural factors, particularly for urbanized area size, using spatial autoregressive models.

2 Materials And Methods

2.1 Study area

China has a vast territory, covering an area of 9.6 million km² (Fig. 1). The terrain of China gradually decreased from west to east. Affected by the monsoons, the climate in China differs greatly between seasons and contains five climate zones, ranging from tropical to cold temperate zones. The average temperature in China decreases from south to north, while precipitation decreases from the southeast coast to the northwest inland. The socioeconomic development in China also presents significant diversity. China has urbanized rapidly owing to accelerated industrialization. By 2018, the proportion of urbanized population increased from 17.92–59.58%. According to the universal law of global urbanization (Kuang et al. 2016), China is still in a rapid development stage. However, the urbanization scale varies greatly within China because of different natural and economic conditions. The remarkable regional differences in urbanization and natural ecosystems make China an ideal study area for exploring urbanization and thermal environmental effects it generates. To investigate the geographical variations in SUHI, China was divided into seven regions according to its geographical location and urbanization: South China, Southwest China, Central China, East China, Northeast China, North China, and Northwest China. The South China, Southwest China, Central China, and East China have typical humid-hot climate. Northeast China, North China, and Northwest China have typical humid-cold, subhumid/semiarid-temperate, and arid climates, respectively.

2.2 Defining urbanization

The impervious surface data used in our study were derived from high-resolution the annual artificial impervious area dynamics at a 30 m resolution (<http://data.ess.tsinghua.edu.cn>). The data were interpreted from Landsat imagery (TM/ETM+/OLI) available on the Google Earth Engine with an overall accuracy of over 90% (Gong et al. 2019).

Urbanization has profoundly altered climate change. Urbanization has been widely simulated using indicators such as impervious surface area, population density, and building density. As SUHIs occur primarily because of the impervious surfaces absorbing radiation and emitting heat to the surroundings, our study selected the impervious surface area to quantify the urbanization (Dong et al. 2020).

The city is an abstract concept that exists in relation to the countryside, rather than just the concept of a city in administrative planning. Therefore, this study considered continuous impervious surface pixels as urbanized areas (Li et al. 2020b). We selected impervious surface data, performed the priority search algorithm, and defined urban areas as impervious surface patches around the county administrative centers of each city for the years 2000, 2005, 2010, and 2015. According to the impervious surface area, cities were classified into five categories: mega urbanized areas ($\text{area} > 1000 \text{ km}^2$), super urbanized areas ($400 < \text{area} \leq 1000 \text{ km}^2$), large urbanized areas ($200 < \text{area} \leq 400 \text{ km}^2$), medium urbanized areas ($50 < \text{area} \leq 200 \text{ km}^2$), petty urbanized areas ($\text{area} \leq 50 \text{ km}^2$) (Notice on Adjusting the Criteria for City Size Classification, Notice of the State Council, 2015).

2.3 Quantifying the surface urban heat island effect

MODIS LST data were selected for this study (Huang et al. 2013). Numerous SUHI studies have documented the spatial patterns of single intra-city SUHI that utilizes the resolution and long time series of Landsat TM/ETM+ (Li et al. 2009; Shen et al. 2016). The variability and characteristics of SUHI from the national to the global scale have also been studied using MODIS LST product (Clinton and Gong 2013). MODIS has stable transit moments, providing LST data of spatiotemporal continuity and integrity at typical moments. MODIS LST data are appropriate for large-scale SUHI studies.

LST was obtained from MODIS monthly composite products with a spatial resolution of 1 km (MODLT1M and MYDLT1M) from 2000–2015 (acquired at 01:30 and 13:30) (<http://www.gscloud.cn>). Specifically, the LST in 2000, 2005, 2010 and 2015 was further improved by correcting noise, mosaicking, clipping, and quality-checking, and the annual mean values were calculated for spring, summer, autumn, and winter respectively. In this study, we defined spring as March–May, summer as June–August, autumn as September–October, and winter as December–February.

The magnitude of the SUHI can be quantitatively expressed by the SUHI. In this study, we defined SUHI as the LST difference between the urban and surrounding rural areas. The two main methods for calculating SUHI are the reference pixel-based method and the buffer method. The buffer method can be divided into equal area and equidistance buffers. Correspondingly, we established a buffer zone with an area equal to its corresponding urban patch, which is defined as a rural area surrounding urban patches. The SUHI was calculated as the difference between the mean temperatures in urban and rural areas (Zhou et al. 2016). The seasonally averaged SUHIs for each city from 2000, 2005, 2010, and 2015 were obtained by subtracting the average LST over the urban areas from that over rural areas. By extracting impervious surface boundaries, urban patches with $\text{SUHI} > 0$ were selected for our study.

2.4 Driving factors of surface urban heat island effect particularly urban size

Influencing factors of multiple dimensions were selected, covering urban development, characteristics of the underlying surface, climatic backgrounds, geographic position, and community economy. Considering the magnitude of this study and availability of data, the following datasets were assembled to examine their relations with the SUHI: DEM (Digital Elevation Model), air temperature, precipitation, NDVI (Normalized Difference Vegetation Index), longitude and latitude, compactness index (CI), urban size, GDP (Gross Domestic Product), population density and night lights. DEM, air temperature, precipitation, NDVI, longitude, and latitude are natural factors. The compactness index, population density, urban size, GDP and night lights represent anthropogenic factors (Feng et al. 2021). The specific descriptions of the data are presented in Table S1.

Our study employs a spatial autoregressive model (SAR) to evaluate the relationship between SUHI and all independent variables. The spatial autoregressive model can be expressed by the following equation (1):

$$y = \rho W_1 y + \beta x + \mu + \alpha, \mu = \lambda W_2 \mu + \varepsilon \quad (1)$$

Where y is the dependent variable and represents SUHI, x is the independent variable and represents the relevant factors impacting the SUHI, β is the regression coefficient of the independent variables, α is the intercept, μ is a random error term, ε is a random error obeying a mean of 0 and a variance of δ^2 , W_1 is the spatial weight matrix of dependent variables, W_2 is the spatial weights matrix of random error, ρ regression coefficient of the spatial lag term, and λ is the regression coefficient of the spatial error term.

Spatial observations of the dependent and independent variables of the ordinary least squares (OLS) model were not affected by spatial variability. In the spatial error model (SEM), there was no spatial dependence of the spatially dependent variables. In the spatial lag model (SLM), the observations of the dependent variables are related to both the corresponding independent variables and the dependent variables in the neighboring regions.

We constructed an OLS model using SUHI as the dependent variable. The observations and regression errors are independent of the OLS model. Therefore, in the second step, we identified whether the spatial dependence of the data affected the OLS model results using the global univariate Moran's I-statistic to test the presence of spatial autocorrelation of the residuals. Finally, if there was spatial dependence in the OLS model residuals, the Lagrange multiplier (LM), robust Lagrange multiplier (RLM), log likelihood (LogL), Akaike information criterion (AIC), and Schwartz criterion (SC) were used to determine whether an SEM or SLM should be selected; the higher the LogL, LM, and RLM values and the lower the AIC and SC values, the better the model. In our study, the CI of urban impervious surface, population density (POP), nighttime lighting (NL), DEM, urban size, GDP, longitude (Long.) and latitude (Lati.), NDVI, precipitation (PREC), and air temperature (TEMP) were selected as the influencing factors. Because each influence

factor has different dimensions and orders of magnitude with units, the Z-score standardization method was used to make the data dimensionless. Moran's *I* of SUHII for different seasons during day and night in 2015 is presented in Table 1. Moran's *I* values all > 0, with p-values < 0.01, indicating a strong positive spatial autocorrelation of SUHII.

Table 1
Moran's *I* of SUHII for periods in 2015

Periods	Spring Day	Summer Day	Autumn Day	Winter Day	Spring Night	Summer Night	Autumn Night	Winter Night
Moran's <i>I</i>	0.43**	0.40**	0.44**	0.44**	0.29**	0.29**	0.28**	0.40**
Moran's <i>I</i> (Errors)	0.26**	0.28**	0.19**	0.22**	0.14**	0.14**	0.18**	0.22**
Note: **p < 0.01								

The statistics of the SAR modeling result coefficients are summarized in Table S2. The goodness-of-fit of the SEM was better than that of the SLM. Thus, our study used SEM to explore the concurrent effects of the 11 independent variables on SUHI. The 11 independent variables were divided into two main categories. One is natural factors, including longitude, latitude, DEM, NDVI, precipitation and air temperature. The other is anthropogenic factors, including urban size, CI, population density, GDP, and night lights.

3 Results

3.1 Dynamics of impervious surface area in China from 2000–2015

Overall, the impervious surface area exhibited a rapidly increasing trend during 2000–2015, with a growth rate of 2.3 times (Fig. 2a). In 2000, the impervious surface area in China was dominated by petty and medium-sized urbanized areas; however, by 2015, the proportion of mega urbanized areas increased to 18.32% (Fig. 2c). Urban agglomerations in the mega urbanized areas are adjacent in space, and urbanization proceeded with a high degree of spatial symbiosis and consistency, particularly in Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta urban agglomerations. Meanwhile, petty urbanized areas decreased from 57.32% in 2000 to 40.14% in 2015 as they transformed to medium urbanized areas and others. Moreover, the major expansion pattern of mega urbanized areas, super urbanized areas, and large urbanized areas extended outward from the former center; however, the pattern of petty urbanized areas and medium urbanized areas was in-fill expansion.

Meanwhile, the dynamics of urban expansion across cities with different urbanized area sizes over time were delineated (Fig. 2b). The most drastic increase in the impervious surface area occurred from 2000–2010, particularly for the period 2005–2010, and the growth rate began to decline from 2010–2015. From 2000–2010, the expansion of petty urbanized areas was the absolute mainstay of urban expansion. Furthermore, the expansion of mega urbanized areas was the primary cause of urban expansion in China from 2010–2015, with a proportion of 28.68%.

The proportion of urbanized areas varied widely across different geographical regions (Fig. 3). In our study, petty urbanized areas had the largest proportion of area for all regions other than South China; the proportion of mega urbanized areas in South China was the highest owing to the rapid development of urban agglomeration in the Pearl River Delta. Second, we concluded that the proportion of petty and medium urbanized areas declined, whereas that of large urbanized areas remained invariant, and that of super and mega urbanized areas increased, particularly in East China. Petty urbanized areas in East China expanded and transformed into mega and super urbanized areas owing to the expansion of the Yangtze River Delta urban agglomeration.

3.2 Spatiotemporal patterns of the SUHII from 2000 to 2015

The results showed the characteristics of the average daytime and nighttime SUHII across China (Fig. 4, Fig.S1 and Table S3). In this study, the annual SUHII was stronger in the daytime (0.40 ± 0.30 °C) than the in nighttime (0.30 ± 0.34 °C), particularly in spring, summer, and autumn. The maximum value of SUHII reached up to 7.71 °C in spring daytime. However, the SUHII at night was stronger than that during winter. Daytime and nighttime SUHII were also observed with significant spatiotemporal variations among the seven geographical regions (Fig. 5a, Fig. 5b). It demonstrated a larger spatial variation in the day (0.19 to 0.70 °C) than at night (0.21 to 0.58 °C). In the daytime, stronger SUHII occurred in South and Southwest China, where the climate is warmer and more humid. Stronger nighttime SUHII was primarily observed in the colder zones located in Northeast and Northwest China, where the background climates are characterized by lower temperatures and precipitation. In particular, the greatest SUHII was observed in Northeast China summer days (0.70 °C) and winter nights (0.58 °C).

SUHII also differed greatly by season, with the largest SUHII in summer and the lowest in winter (Fig. 6). Furthermore, the diurnal difference in SUHII was greater in spring and summer than in autumn and winter. From 2000–2015, SUHII exhibited a significant upward trend in all seasons, except during the spring daytime (Fig. 6b). In summary, the average daytime SUHII was stronger than that at night, and SUHII was stronger in summer than in other seasons from 2000–2015. Seasonal trends in large and asymmetric SUHIIs were observed during the day and night. In the daytime, SUHII was more prominent in summer than in other seasons; however, SUHII fluctuations were not conspicuous at night.

The SUHII for urbanized areas of different sizes from 2000 to 2015 is shown in Figure 6. We observed SUHIs in petty urbanized areas. However, the SUHII of the petty urbanized areas had the lowest magnitude (Fig. 7). During the day, the magnitude of SUHII differed considerably in urbanized areas of

different sizes. However, at night, the distinction between the different sizes of urbanized areas was minor, within 1°C. The average amplitude of SUHIs was remarkably asymmetric across urban sizes. Our analysis indicated that the strongest SUHIs occurred during the day in the largest urbanized areas, the mega urbanized areas. However, this was not the same at night.

3.3 Driving factors for the spatial autocorrelation of SUHII

The SUHII for urbanized areas of different sizes from 2000 to 2015 is shown in Figure 7. We observed SUHIs in petty urbanized areas. However, the SUHII of the petty urbanized areas had the lowest magnitude (Fig. 8). During the day, the magnitude of SUHII differed considerably in urbanized areas of different sizes. However, at night, the distinction between the different sizes of urbanized areas was minor, within 1°C. The average amplitude of SUHIs was remarkably asymmetric across urban sizes. Our analysis indicated that the strongest SUHIs occurred during the day in the largest urbanized areas, the mega urbanized areas. However, this was not the same at night.

Among the anthropogenic factors, urban size, night lights and population density had a strong positive correlation with SUHII, whereas CI had a negative correlation with SUHII at day and night. This indicates that the larger the impervious surface area and the higher the NL index, the more intense the SUHI; however, the more compact the impervious surface boundaries, the lower the heat island intensity in the urbanized areas. A weak negative correlation GDP was observed between SUHII and during the day, and a negative correlation was observed during the night. Meanwhile, GDP also had a stronger negative impact on SUHII during winter than during other seasons. Intra-annually, the regression coefficients indicated that anthropogenic factors contributed more to SUHII variations than land surface descriptors and background climate. Urban size had the most significant coefficient (5.13 during the daytime in spring) which was considerably stronger than other factors.

We propose that the size of the urbanized area is the most important driver for explaining the variations in SUHII. As the urbanized area size increased, the SUHII for both day and night increased. However, it is unclear whether there is a threshold range for this relationship between SUHIs and urban area size. To explore the potential impact of urbanized area size on SUHIs, we further analyzed the comprehensive relationships between urban size and SUHII. The relationships between SUHII and urban size were significantly and positively log-linear (Fig. 9). Consequently, the larger the urbanized area, the stronger the SUHI at day and night. However, the drastic increase in SUHIs due to the expansion of urban size was not infinite. As predicted, there was a gradient effect in the response of SUHIs to urbanization, and there was a certain threshold range. First, SUHII increased rapidly when the urban size grew from 0 to 200 km², which is from petty to medium urbanized areas. Afterward, the growth rate of SUHII started decelerating when the urban size increased from 200 to 400 km², which is from medium to the largest urbanized area. Ultimately, the heating effect of urban expansion flattened with increasing urban area when the size was larger than 400 km². Additionally, we found a stronger positive relationship between SUHII and urbanized area size at night than at day; however, it was also stronger in spring and summer than in autumn and winter.

4 Discussion

This research indicates that urbanized areas in China doubled during 2000–2015, which is consistent with other studies (Kuang et al. 2016). Our observations confirmed that the growth rate of impervious areas first increased and then decreased in China during 2000–2015. With rapid urbanization, the most drastic increase in the impervious surface area occurred during 2005–2010 and began to decline after 2010. In this study, the proportion of petty urbanized areas and medium urbanized areas decreased, whereas that of large urbanized areas remained constant, with a significant increase in super and mega urbanized areas. Furthermore, the inequality of different socioeconomic developments and policy orientations on urban expansion can be illustrated based on our comprehensive and comparative study between urbanized areas of different sizes. Super and mega urbanized areas were most vulnerable to policy preferences and resource concentration, as they were typically considered to be the “hubs” of national development (Huang et al. 2015). Thus, super and mega urbanized areas are the first rapidly developing regions in a country (Dou and Kuang 2020).

Our results showed that urban expansion was unequal across various regions in China. Similar to the overall trend, petty urbanized areas had the largest proportion of all regions except South China, which exhibited a downward trend. Notably, some regions are inherently well urbanized, particularly in South China, where the proportion of mega urbanized areas is over 50% and increases annually. We consider that as land urbanization proceeds, the petty urbanized areas were consolidated into large, super, or mega urbanized areas in various regions, implying less fragmented urbanization. We compared our results with those of other studies (Gao et al. 2016) and found that small cities experienced greater expansion than large cities in both China and the United States over the past ten years. In particular, petty and medium urbanized areas in western China should be further endeavored to develop compact and efficient urbanized patterns. Previous studies have also proved that conventional urban–rural boundaries are obsolete in modern densely populated regions (Yu et al. 2019). With the development of urbanization, the distance between urban areas tends to decrease and even disappear as urban land expansion accelerates. The expansion of the impervious surface area can explain the variations in SUHIs during rapid urbanization (Stewart and Oke 2012). Urbanization, as defined by impervious surface area, tends to be stronger within larger urban areas owing to the absorption and storage of solar radiation as well as anthropogenic heat release, thereby resulting in higher LSTs. Impervious surface expansion caused by SUHIs cannot be estimated by city boundaries of administrative districts but should be addressed in the patch scale of the impermeable surface.

In our study, the spatial patterns and temporal trends of the SUHII across urbanized areas were systematically analyzed at the national scale. Solar radiation is strongest in summer owing to direct sun irradiation on the Tropic of Cancer (Meng et al. 2018). With urbanization and the expansion of impervious areas, urban areas absorb more solar radiation in summer. This causes more sensible but less latent heat fluxes and causes summer to experience the strongest SUHII (Imhoff et al. 2010). The maximum values of SUHII in this study were similar to those reported in other studies (Li et al. 2019b). At the patch scale, the distribution of SUHII was not uniform because the standard deviation values were reasonably high.

Moreover, the diurnal characteristics of annual SUHII are similar to previous studies; however, the values were lower than them. The abovementioned studies focused on mega and large cities or major cities whereas our study calculated SUHII from impervious surfaces in all cities (Yu et al. 2019). We also observed significant differences in SUHII among geographical regions (Fig. 5a and b). The SUHII was stronger in higher latitude regions, such as Northeast and Northwest China. This phenomenon was due to the typical arid, semi-arid, and semi-humid temperate climate of Northeast and Northwest China (Si et al. 2022), where the seasonal variations in vegetation activity are the largest. This is consistent with previous findings that the UHI is stronger in cold-or high-latitude climates

SUHII varied drastically in zones that depended on both natural and anthropogenic factors. SEM analysis revealed that among natural factors, daytime SUHII generally correlated positively with precipitation and negatively with NDVI and DEM. In addition, among natural factors, nighttime SUHII exhibited a significant positive correlation with air temperature and latitude but a negative correlation with precipitation. The correlation between natural factors and SUHII corresponded well with previous findings (Zhao et al. 2014). Zones with heavy precipitation typically have larger soil moisture content, which contributes to a reduction in the heating rate of the subsurface during the day, consequently leading to higher SUHII (Zawadzka et al. 2020). In contrast to impervious surface area, vegetation activities can increase the latent heat fluxes through transpiration and have a cooling effect on surface temperature, thereby mitigating daytime SUHII (Fang et al. 2021; Ning et al. 2016). In addition, vegetation activities can reduce nighttime SUHII owing to the shading effects of vegetation cover, which reduces the heat stored during the day, resulting in lower nighttime SUHII.

In this study, SUHII was positively correlated with urban size, night lights, and population density, whereas CI had a negative correlation with SUHII at day and night. Night light represents anthropogenic heat emissions. This direct anthropogenic heat flux also helps maintain SUHII (Peng et al. 2012). Areas with higher population densities normally have more indirect energy consumption, such as buildings and pavements; hence, more energy is released. In particular, we found that nighttime lights and population density had a stronger effect on SUHII during the daytime in summer, suggesting that heat release caused by air conditioning usage can increase SUHII. GDP had the most significant impact on SUHII in the winter. Studies have confirmed that increasingly developed cities pay more attention to the development of urban green spaces (Hsu et al. 2021; Huang et al. 2017). Briefly, underdeveloped cities with low incomes lose green space at a faster rate, making SUHII stronger (Dong et al. 2022). Overall, anthropogenic factors contributed more intensely to SUHII variability than natural factors.

The urbanized area can be considered as the fundamental basis for the creation of SUHIs; thus, the impacts of urban size on SUHII are complicated and involve population and building densities. It is well known that urbanization has significantly enhanced SUHIs; however, research on the thermal environmental impact of urban size is insufficient (Zhou et al. 2015). Our study identified that extreme spatial and temporal variations in SUHIs are extremely significant at different urban sizes from the patch scale. SEM analysis revealed that a correlation exists between urban area size and SUHI. Urban size had significantly more positive contributions to SUHII than other factors in both the daytime and nighttime,

and the correlation was statistically significant. Our results indicate that the relationship between SUHII and urban size is significantly and positively log-linear. Land urbanization increased LSTs on an annual mean scale, regardless of the urbanized area size. However, the increase in SUHII caused by urban expansion is not unlimited. Petty urbanized areas, which are smaller than 50 km², do present SUHIs, although they are considerably weaker than in other types of regions. Petty and medium urbanized areas, which are the smallest in size, had the lowest SUHII, which confirms the enhanced heating effect of urban expansion. A gradient effect exists in the response of SUHIs to urbanization. With the increasing size of urbanized areas, SUHII exhibits a logarithmic increase and reaches stability after a certain size. When the urbanized area is larger than 400 km², this heating effect may not be sufficiently significant or fade away, particularly at nighttime. Conversely, the logarithmic growth relationships of SUHI's response to urban size were more significant during the daytime (Figure 9). There are several explanations for this: first, the increase in the density of urban infrastructure and human activities with the increase in urban size is not infinite. Second, the cooling effect is reduced because small cities lose more urban green space than large cities during urban expansion (Rui et al. 2017). Third, the increased SUHIs due to urban expansion could alter the local wind system, thereby mitigating the heating effect of urban expansion (Yang et al. 2018). Hence, the extent of the urban impervious surface area should be greater than 400 km² when cities are developing, so that the increasing SUHIs may be mitigated.

Our study had some limitations that should be acknowledged. Although we processed the cloud cover of remote sensing images in the data pre-processing, the LST values of some areas were still disturbed by cloud cover. Our study only investigated change patterns in the urban impervious surface area and SUHIs for four-time points: 2000, 2005, 2010, and 2015. Therefore, the time scale portrayal was not sufficient, and in the future, longer LST time series should be combined to study the variations in SUHIs per year. However, it was difficult to explore the actual relationships for each variable, city, and period. In addition, while correlation analyses between SUHII and associated drivers can be conducted across space and time, we only analyzed the relationships across space. The temporal differences in the influencing factors should be investigated in future studies to develop policies to cope with SUHIs under different urbanization processes. Additionally, only macro factors were considered in this study, and future studies could select factors such as the shape, number, and structure of impervious surface patches at the landscape scale.

5 Conclusions

This study systematically quantified the dynamics of impervious surface areas and the spatiotemporal patterns of SUHIs in China from 2000–2015 using multi-source remote sensing data. It also evaluated the spatial effects of relevant factors on SUHII using spatial error models and further investigated the relationship between urban size and SUHIs.

Our results showed that impervious areas had an increasing trend over the period 2000–2015, with accelerated growth from 2000–2010, and the expansion of petty urbanized areas was the dominant contributor to urban expansion.

The SUHI magnitude was stronger at day than at night and in the summer than in other seasons. Furthermore, SUHIs existed in low-ranking urbanized areas (i.e., petty urbanized areas). The SEM results showed that city size was the most important variable in explaining SUHI variations. We observed a statistically significant and positive log-linear relationship between SUHIs and urbanized area size. The heating effect of urban expansion flattened out with increasing urban areas when the urbanized area was larger than 400 km². Hence, we consider that the impervious surface area of the city should exceed 400 km² during urban development. These results may have policy implications for city managers. To confront SUHI effects, it is necessary to reduce the fragmented distribution of small towns. Moreover, we found that anthropogenic factors contributed more intensely to SUHI variability than natural factors. There was a significant positive relationship between SUHI and anthropogenic factors, except for CI. This indicates that the more compact the shape of the urban area, the weaker the SUHI generated. NDVI has an evident cooling effect. To mitigate SUHIs, efforts should be made to increase urban vegetation activity and reduce anthropogenic heat emissions. Our results illustrate the spatial correlation between the surface temperature and urban development situation, as well as the cooling effects of the green space, which have important implications for urban planning to mitigate SUHI effects.

Declarations

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

All authors contributed to the study conception and design. **Yujie Guo**: Conceptualization, Methodology, Visualization, Writing - original draft preparation, Writing - review and editing. **Zhibin Ren**: Conceptualization, Writing - review and editing, Funding acquisition, Project administration. **Yulin Dong**: Validation, resources, Writing - review and editing. **Nanlin Hu**: Resources, Validation, Formal analysis. **Peng Zhang**: Validation, Formal analysis. **Chengcong Wang**: Validation, Formal analysis. **Guangling Jia**: Validation, Formal analysis. **Xingyuan He**: Supervision, Conceptualization.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request

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Figures

Figure 1

Urbanized area and rural buffers in China and the three enlarged examples for (a) Beijing-Tianjin-Hebei urban agglomeration (b) Yangtze River Delta urban agglomeration (c) Pearl River Delta urban agglomeration

Figure 2

Variations in impervious surface area in China from 2000–2015. (a) Variations in the total impervious surface area. (b) Expansion of urbanized areas of different sizes from 2000–2015. (c) Distribution of urbanized areas at different sizes in 2000, 2005, 2010, and 2015

Figure 3

Interannual dynamics of the proportion of impervious surface area in different sizes of urbanized areas from 2000–2015

Figure 4

Distribution of the SUHIIs during the daytime in (a) 2000 and (b) 2015, nighttime in (c) 2000 and (d) 2015 in China.

Figure 5

Mean and standard deviation of SUHII for the seven geographical regions from 2000–2015. The SUHII of geographical regions in China during the (a) day and (b) night. The median is identified by the horizontal line and the average value is identified by the triangle in the box.

Figure 6

SUHI variations in seasonal (a1) and diurnal (a2) during 2000–2015 and seasonal trends in SUHI (b1-4)

Figure 7

Temporal distribution of the SUHI from 2000 to 2015 in urbanized areas of different sizes

Figure 8

Relationships between the SUHII and 11 variables across cities as indicated by the spatial error model

Significance level $p \leq 0.01$

Figure 9

Relationship between seasonal and diurnal SUHII, with the urban area size for China in 2015

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