Research Article

Associated Determinants of Surface Urban Heat Islands across 1449 Cities in China

Yuanzheng Li ^{1,2,3}, Lan Wang ⁴, Min Liu ^{1,3}, Guosong Zhao ⁵, Tian He ⁶,
and Qizheng Mao ¹

¹School of Resources and Environment, Henan University of Economics and Law, Zhengzhou 450046, China

²Academician Laboratory for Urban and Rural Spatial Data Mining of Henan Province,
Henan University of Economics and Law, Zhengzhou 450046, China

³State Key Laboratory of Urban and Regional Ecology, Research Center for Eco-Environmental Sciences,
Chinese Academy of Sciences, Beijing 100085, China

⁴Key Laboratory of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences,
Xiamen 361021, China

⁵Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research,
Chinese Academy of Sciences, Beijing 100101, China

⁶School of Water Conservancy and Environment, Zhengzhou University, Zhengzhou 450001, China

Correspondence should be addressed to Lan Wang; wlsunshinelz@163.com and Guosong Zhao; zhaogs86@126.com

Received 18 April 2019; Revised 25 May 2019; Accepted 12 June 2019; Published 21 July 2019

Academic Editor: Stefania Bonafoni

Copyright © 2019 Yuanzheng Li et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The thermal environment is closely related to human well-being. Determinants of surface urban heat islands (SUHIs) have been extensively studied. Nevertheless, some research fields remain blank or have conflicting findings, which need to be further addressed. Particularly, few studies focus on drivers of SUHIs in massive cities with different sizes under various contexts at large scales. Using multisource data, we explored 11 determinants of surface urban heat island intensity (SUHII) for 1449 cities in different ecological contexts throughout China in 2010, adopting the Spearman and partial correlation analysis and machine learning method. The main results were as follows: (1) Significant positive partial correlations existed between daytime SUHII and the differences in nighttime light intensity and built-up intensity between cities and their corresponding villages except in arid or semiarid western China. The differences in the enhanced vegetation index were generally partially negatively correlated with daytime and nighttime SUHII. The differences in white sky albedo were usually partially negatively correlated with nighttime SUHII. The mean air temperature was partially positively correlated with nighttime SUHII in 40% of cases. Only a few significant partial relationships existed between SUHII and urban area, total population, and differences in aerosol optical depth. The explanation rates during daytime were larger than during nighttime in 72% of cases. The largest and smallest rates occurred during summer days in humid cold northeastern China (63.84%) and in southern China (10.44%), respectively. (2) Both the daytime and nighttime SUHII could be well determined by drivers using the machine learning method. The RMSE ranged from 0.49°C to 1.54°C at a national scale. The simulation SUHII values were always significantly correlated with the actual SUHII values. The simulation accuracies were always higher during nighttime than daytime. The highest accuracies occurred in central-northern China and were lowest in western China during both daytime and nighttime.

1. Introduction

In 2018, 55% of the world's population lived in urban areas and this proportion is expected to reach 68% in 2050 [1]. Rapid, high-intensity urbanization has obviously changed the ecosystems and environment at urban, regional, and

even global scales [2]. One of the most obvious urban climate features is the urban heat island effect [3]. This effect can directly and indirectly affect regional climate [4], energy use [5], air quality [6], urban hydrology [7], soil physicochemical properties [8], creature distribution and activities [9], and human health, comfort, and quality of life [10].

The approaches used for studying urban heat island (UHI) include weather station observations [11], fixed-point field measurements [12], mobile belt transect surveys [13], numerical modelling [14], and remote sensing monitoring, which have been widely accepted and adopted [15, 16]. Although land surface temperatures (LSTs) derived by remote sensing are not identical to above-ground air temperatures, they are closely related [17, 18]. Nonetheless, UHIs are called “surface urban heat islands (SUHIs)” when derived from remote sensing data in order to distinguish them from traditional UHIs analyzed using air temperatures [15, 19–21]. Many determinants of SUHIs have been extensively studied and can be divided into seven categories [22]: land use and land cover types, surface biophysical conditions, landscape components and configurations, manners and intensities of human activity, meteorological conditions and geographical location, policy factors, and synthetic analyses of the abovementioned factors. The analytical methods applied to assess the relationship between drivers and SUHI intensity (SUHII) have mainly included Pearson’s correlation analysis, Spearman correlation analysis, comparative analysis, ordinary least squares regression, geographically weighted regression, regression tree model [16], and machine learning models [23, 24].

Nevertheless, certain issues remain unresolved. First, most previous studies only used simple correlation analysis [21, 25–28] or linear [27–30] or nonlinear regression [30] methods to analyze the relationships between the drivers and SUHIs. More effective and innovative methods should be considered, particularly when synthetically analyzing multiple factors. Additionally, several influencing factors should be considered together rather than simply analyzing the relationships between SUHI and a single influencing factor, such as vegetation index [20, 25, 30, 31], albedo [20, 25], built-up intensity [30, 32], total population [31, 32], and urban area [33, 34]. Second, the research has concentrated on large and mega cities [25–28, 34, 35], while few studies focus on medium-sized and small cities. Third, certain disadvantages are associated with the use of previously proposed monitoring indices of SUHII [36]. For instance, certain studies defined SUHIs as the differences in LSTs between a city or central city and its adjacent regions within a certain radius [27, 28, 37–39]. Nonetheless, rapid urbanization usually occurs in areas surrounding cities, particularly large or mega cities in certain developing countries [40, 41]. Thus, biases can be introduced when monitoring SUHIs. In addition, certain previous studies utilized differences in LSTs between cities or central cities and rural regions. In addition, rural regions were defined as zones within a certain distance from a city. However, the distance values in previous studies were too large for monitoring cities of different sizes [29, 30, 42], specifically because only regions that were sufficiently far away could be defined as reference villages. Therefore, few regions remained due to the dense distribution of cities in certain well-developed regions with dense populations. Moreover, certain studies have used the Gaussian fitting method [32, 43, 44], but this approach is only effective when the left field of the LST fits the Gaussian distribution after extraction of the background

LST. However, this condition does not always exist [41]. For example, the method will fail when cold heat islands occur [28, 37] or when the outskirts or village regions have not been limited by the terrain [27–29, 37], water bodies [29], or satellite towns. In addition, the impervious surface percentage should be considered when defining rural regions [29]. Fourth, although the ecological context has an obvious impact on SUHII, including water and heat combinations, vegetation characteristics, landforms, and human activities, most previous studies at large scale have not considered this factor [25, 28, 34, 35, 37, 45] but simply use administrative boundary data to determine regions of different contexts [27, 42] or identify these regions too coarsely [20, 26], with the exception of a few studies [29, 30, 46, 47]. Finally, certain research areas remain unstudied or have conflicting findings [22]. For instance, to our knowledge, unlike during the daytime, the impacts of vegetation on SUHIs during the nighttime are still in debate [21, 28, 42, 48–51]. The relationships between albedo and daytime SUHIs are complex [27, 28, 52, 53]. Very few previous studies have analyzed impacts of aerosol optical depth (AOD) on SUHIs combined with other factors [38]. The effects of city size and total population on SUHIs have always been controversial [31, 33, 38, 54]. Different findings have been reported on the correlation between air temperature and SUHIs [26–28, 34, 38, 42, 55]. Therefore, the objective of this study is to accurately study 11 associated determinants of SUHII for 1449 cities of different sizes in different ecological contexts throughout China in 2010.

2. Materials and Methods

2.1. Data. Monthly LST data at a 1 km resolution and enhanced vegetation index (EVI) data at 250 m resolution from Dec. 2009 to Nov. 2010 from MODIS/Aqua were downloaded from the Geospatial Cloud of Computer Network Information Center, Chinese Academy of Sciences website. Each pixel value of LST or EVI is a simple average of all the corresponding MYD11A1 LST pixels or maximum of all MYD09GQ EVI pixels collected within that month. The MYD11A1 product uses the split-window technique to derive LSTs. From the official MODIS website, we downloaded 8-day albedo data (MCD43B3) and quality data (MCD43B2) at 1 km resolution and daily aerosol data and quality data (MCD04_3K) at 3 km resolution from Dec. 2009 to Nov. 2010.

Digital elevation data with a 1 km resolution were taken from the Cold and Arid Regions Sciences Data Center at Lanzhou. Land use (Supplementary material Text S1) and population data from 2010, which had 1 km resolutions, were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences. Population data are produced using the spatial interpolation method on statistical population data from each county. The 500 m resolution impervious percentage data for 2010 were provided by the Beijing City Lab (Supplementary material Text S2). The calibrated 1 km nighttime light data for 2010 were downloaded from the National Centers for Environmental Information website. Monthly $0.5^\circ \times 0.5^\circ$ resolution

temperature and precipitation data for Dec. 2009 to Nov. 2010 were downloaded from the Meteorological Data Website of China (Supplementary material Text S3).

Ecological function recognition data were provided by the Data Sharing Infrastructure of Urban and Regional Ecological Science. China is divided into three first-level, 50 second-level, 206 third-level, and 1434 fourth-level ecological function regions based on their landforms, water and heat combinations, and vegetation characteristics.

2.2. Methods

2.2.1. Regionalization of the Background Environment in China for SUHII Analysis. China was divided into four regions based on the ecological function recognition results for the first, second, and third levels (Figure 1) to analyze the potential different influencing factors of SUHII in each region. Region I mainly corresponded to the vast majority of northeastern China, which has climatic zones that range from cold temperate to midtemperate. The region is affected by monsoons and has four distinct seasons—warm and rainy summers and cold and dry winters—with long periods of melting ice and snow. The climate of region II is similar to that of region I. However, winters there are warmer and shorter than those in region I. Region III is the only zone that is not affected by monsoons in China. It is a typical arid temperate climate, with a mean annual precipitation (MAP) below 400 mm. Region III is subjected to cold winters and hot or warm summers. The vast majority of region IV belongs to the subtropical zone, and the rest is in the tropical zone. This region has a typical rainy and hot temperate climate, with MAP exceeding 800 mm and evergreen vegetation.

2.2.2. Definitions of Urban and Rural Regions. The urban land polygons were first aggregated at a distance of 1.1 km, which is sufficient to include most adjacent and scattered urban land polygons into the urban class and is able to separate the main city zones and satellite cities or two closely adjacent cities that should be considered separately according to normal human perceptions. Subsequently, only the urban land regions in these separate aggregated polygons remain. These polygons with remaining areas of larger than 6 km² were considered, which included the vast majority of cities in the eastern regions in China, those with the densest populations and most well-developed economies. The corresponding rural zones were defined as the buffer zones of cities, with buffer distances between 5 and 10 km [37] and impervious percentages below 5% [29, 30]; however, the rural zones did not include waterbodies, regions with slopes exceeding 7.5°, or elevations that are 50 m greater than or less than the maximum or minimum elevations of the urban zones, respectively [30, 33, 42]. We found that 99.70% of the cities in China were located in plains regions with slopes less than 7.5° in 2010.

2.2.3. Calculation of SUHII and Its Drivers. The study timeframes were defined based on the definitions of

meteorological seasons [56]. Winter ranges from December of the previous year to February of the current year, spring from March to May, summer from June to August, and autumn from September to November. The annual and seasonal mean values of daytime and nighttime LST, EVI, white sky albedo (WSA), and aerosol optical depth (AOD) in China were first calculated, and the differences in the abovementioned indices, population density (PD), nighttime light intensity (NL), and built-up intensity (BI)—defined as the percentage of the landscape taken by built-up land—in between the urban and rural regions were further calculated. Moreover, the urban area size (UAS) and total population (TP) values for these cities as well as the mean air temperature (MAT), total precipitation (P), and humidity index (HI) values at the centroids of the cities were calculated.

2.2.4. Exploration of the Relationships between SUHII and Its Drivers. The Spearman and partial correlation coefficients between SUHII and its drivers in China, as well as within its four regions, were calculated during daytime and nighttime for all four seasons and the entire year. Moreover, the explanation rates for the daytime and nighttime SUHII in each region and timeframe were derived using the stepwise regression method.

To simulate the SUHII based on drivers using the machine learning method, the cities were first randomly divided into training and testing sample sets at ratios of 4:1 for China and its four regions. Then, several simulation models were built, adopting four intelligence algorithms (Supplementary material Text S4), including the general regression neural network (GRNN), support vector machine based on genetic algorithm (SVM_GA), particle swarm optimization (SVM_PSO), and grid search method (SVM_GS), using three types of indices (Supplementary material Text S5), including all drivers, the drivers that were found to be significantly partially correlated, and those that were simply correlated with SUHII. Finally, the model was used to estimate the SUHII of the test samples, and the root-mean-square errors (RMSEs), correlation coefficients, and significance levels were calculated to indicate the simulation accuracy. The parameter optimization and simulation processes were repeated 49 times in order to avoid uncertainties during the process and to obtain stable results.

3. Results

3.1. Effects of Single Associated Determinants of SUHII. The differences in NL and BI between cities and villages (ΔNL and ΔBI) were both partially and positively correlated with SUHII in many cases ($p < 0.01$) (Table 1). Nonetheless, they were almost insignificantly partially correlated with daytime SUHII in region III. Moreover, they were almost insignificantly partially correlated with daytime and nighttime SUHII in region I and daytime SUHII in region IV. UAS was only significantly positively partially correlated with daytime SUHII in region II in summer ($p < 0.01$) and autumn ($p < 0.05$) and with nighttime SUHII in region I in

FIGURE 1: Locations of the 1449 cities selected for this study in the four environmental subareas.

winter and spring. However, significant positive correlation coefficients generally existed, except in winter in northern China. Similarly, significant partial correlation did not exist or rarely existed between TP and SUHII during daytime and nighttime, respectively. In addition, positive correlations generally existed during daytime, except in winter in each region and in spring in region III. During nighttime, the differences in PD between cities and villages (ΔPD) exhibited significant positive partial correlations with nighttime SUHII in most cases in region IV and at the national scale although a significant positive Spearman correlation always existed, except in region III during winter, spring, and autumn and in region IV in summer. During daytime, significant partial correlations were minimal.

The differences in the EVIs between cities and villages (ΔEVI) were generally partially or negatively correlated with daytime and nighttime SUHII in many cases ($p < 0.01$). ΔEVI had a predominant cooling effect on daytime SUHII in region III. This was the only determinant that was significantly partially correlated with SUHII in summer ($r = -0.79$, $p < 0.01$), autumn ($r = -0.69$, $p < 0.01$), and the entire year ($r = -0.66$, $p < 0.01$). However, during nighttime, ΔEVI and SUHII were not significantly partially correlated in region III, with the exception of summer ($r = -0.50$, $p < 0.01$), in region I, with the exception of winter ($r = -0.44$, $p < 0.01$), and the entire year ($r = -0.48$, $p < 0.01$). ΔWSA was generally partially and negatively correlated with nighttime SUHII ($p < 0.01$). Both the partial and Spearman correlation coefficients were larger in northern China than in southern China. Nevertheless, the relationships were complex during daytime. For the most part, significant partial or Spearman

correlations did not exist in southern China. ΔWSA was significantly partially negatively correlated with SUHII in winter in northern China ($p < 0.01$). ΔWSA was the only driver that was significantly partially correlated with daytime SUHII in winter in region I ($r = -0.39$, $p < 0.01$). During nighttime, the differences in AOD between cities and villages (ΔAOD) were only negatively significant relative to SUHII at the national scale in spring ($p < 0.01$) and autumn ($p < 0.05$) and in region II in spring ($p < 0.01$). During daytime, significant positive partial relationships existed in spring in region I ($p < 0.01$) and in autumn in region IV ($p < 0.05$). Nevertheless, significant negative partial relationships existed in summer at the national scale ($p < 0.05$) and in autumn in region II ($p < 0.01$).

During nighttime, HI was significantly partially negatively correlated with SUHII in all four seasons at a national scale and in region II ($p < 0.01$), but this correlation was not observed or was seldom observed in other regions. In addition, significant negative correlations existed in all four seasons at a national scale and in region I and during certain seasons in other regions ($p < 0.01$). During daytime, significant positive partial correlations existed in region IV, with the exception of spring, which seldom existed in other regions. In addition, significant negative correlations did not exist in region III but did occur in all four seasons at a national scale ($p < 0.01$) and during certain timeframes in other regions, especially II and IV. The patterns for P were similar to those for HI. However, the timeframes in which significant relationships existed in those regions may have differed. MAT was insignificantly partially correlated with nighttime SUHII in region I but was positively correlated at

TABLE 1: Partial and Spearman correlation coefficients between SUHII and its drivers (multiplied by a scale factor of 0.01).

Variables	D/N	P/C	China						Region I						Region II						Region III						Region IV																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																									
			Ann	Win	Spr	Sum	Aut	Ann	Win	Spr	Sum	Aut	Ann	Win	Spr	Sum	Aut	Ann	Win	Spr	Sum	Aut	Ann	Win	Spr	Sum	Aut																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																									
ΔNL	D	P	16 ^a		28 ^a	11 ^a	14 ^a	49 ^a		42 ^a	48 ^a	31 ^a	16 ^a		27 ^a	12 ^a	16 ^a																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																			</

Note: ^asignificant at the 0.01 level; ^bsignificant at the 0.05 level; Δ AOD stand for the differences between cities and villages for the nighttime light intensity, built-up intensity, population density, enhanced vegetation index, while-sky albedo, and aerosol optical depth, respectively; UAS, TP, HI, P, and MAT stand for urban area size, total precipitation, total population, humidity index, total precipitation, and mean temperature, respectively; Ann, Win, Spr, Sum, and Aut stand for during the whole year, winter, spring, summer, autumn, respectively; D and N stand for during daytime and nighttime, respectively; P and C stand for the partial and Spearman correlation coefficients, respectively.

certain times at a national scale and in other regions, especially in region II. Only one partial negative correlation existed during summer nights in region IV ($r = -0.16$, $p < 0.01$). In addition, significant negative and positive Spearman correlations existed in many cases at the national scale and in region IV, respectively. Few or complex significant Spearman correlations were identified for the other regions. During daytime, no significant partial correlation coefficients existed at the national scale, but positive Spearman correlation coefficients existed, except during summer. At the regional scale, significant partial or Spearman correlations seldom existed or were complex.

3.2. Combined Effects of Associated Determinants of SUHII. The explanation rates during daytime were larger than those during nighttime in 72% of the cases (Table 2). During daytime, they were larger in summer than in winter in northern China and smaller in southern China. The largest and smallest rates were found for summer days in regions I (63.84%) and IV (10.44%), respectively.

The SUHII values was considered to be best simulated by adopting the SVM-GA algorithm using the drivers that were found to be significantly partially correlated with SUHII values, after comparing four intelligence algorithms (Supplementary material Text S4 and Table S1) and three types of indices (Supplementary material Text S5 and Table S1). Both daytime and nighttime SUHII values were estimated at the national scale (Table 3). The simulation accuracy was always higher during nighttime than during daytime. The most accurate results were obtained for annual nighttime measurements (RMSE = 0.49°C , $r = 0.71$), while the least accurate results were obtained during daytime in summer (RMSE = 1.54°C , $r = 0.55$). Significant correlations always existed between the estimated and actual SUHII ($p < 0.01$).

At the regional scale, SUHII could also be simulated in each region for each timeframe. The simulation accuracy was always higher during nighttime than during daytime. The most accurate results were obtained for annual nighttime measurements in region I (RMSE = 0.38°C , $r = 0.80$, and $p < 0.01$), while the least accurate measurements were recorded in region IV during summer days (RMSE = 2.18°C , $r = 0.53$, and $p < 0.01$). Significant correlations existed between the estimated and actual SUHII ($p < 0.05$) in 87.50% of cases. In northern China, the daytime SUHII results for autumn and summer were most accurate, while the results for spring and winter were less accurate. In southern China, the most accurate results also occurred in autumn, but the least accurate results were measured in summer. Seasonal variability was complex for nighttime SUHII in different regions. Spatially, the most accurate results for daytime SUHII usually occurred in region II although the results for winter in region IV also exhibited high accuracy. However, the least accurate results usually occurred in region III, with poor results also evident during summer in region IV and autumn in region I. Similarly, the most accurate nighttime SUHII values were associated with region II, except in winter and autumn, during which the most accurate results were associated with regions IV and I, respectively. The least

TABLE 2: Explanation rates of daytime and nighttime SUHII in China and in the four regions annually for four seasons (%).

Time slot		China	Region I	Region II	Region III	Region IV
Ann	D	31.55	45.89	26.22	43.53	22.64
	N	49.68	59.72	59.75	41.61	40.75
Win	D	25.87	15.23	17.34	43.53	27.69
	N	37.45	52.98	46.03	32.42	20.72
Spr	D	31.96	39.04	45.28	20.54	35.50
	N	47.98	62.81	54.19	33.37	30.18
Sum	D	28.52	63.84	36.28	62.40	10.44
	N	35.77	46.27	49.49	62.92	19.84
Aut	D	44.12	31.41	33.29	47.19	28.20
	N	43.34	51.31	53.53	38.07	39.08

Note: D and N stand for day and night, respectively.

accurate results also usually occurred in region III, except in summer, when they occurred in region IV.

4. Discussion

4.1. Associated Determinants for SUHII

4.1.1. Anthropogenic Heat Emissions. ΔNL is considered to be an indicator of anthropogenic heat flux. This factor can be converted into sensible heat flux or other energy components [57], thereby indirectly enhancing SUHII during daytime [28, 58] or nighttime [27, 28]. These findings are supported by the results of the current study. ΔNL exhibited a positive partial correlation with SUHII in most cases, except during daytime in regions I and III and nighttime in region I. These exceptions were due to the influence of ΔNL , which was much smaller than the influences of the other factors. For example, the key determinants were the cooling effects caused by vegetation in arid and semiarid western China and the low ΔALB in cold, humid northeastern China due to the presence of ice and snow over long periods in the villages there (Table 1). In addition, ΔNL was collinearly correlated with other factors in the regression, such as ΔBI [59–61]. Previous studies also found that ΔNL was not significantly partially correlated with daytime SUHII in 419 large cities globally [28] and 32 large cities in China [27].

4.1.2. Built-Up Intensity. Increases in BI can cause reductions in latent heat flux and increases in sensible heat [30, 62]; decreases in sky views that reduce outgoing long-wave radiation [63]; the emergence of urban topographies, including the “canyon effect,” which increases the absorption of short-wave radiation [63]; and increases in surface roughness, which reduces boundary layer winds and hinders sensible loss [63], among other impacts. In addition, BI can cause the shade effect [64, 65]. Together, these factors generally enhance SUHII, except during daytime in cities in desert or xeric shrubland biomes [27, 30, 32, 65, 66], especially after stored heat is released at night [27]. The rules are complex for desert cities during daytime. Different conclusions have been drawn. In five cities in desert environments across the continental USA, uncharacteristic

TABLE 3: Accuracy statistics for the daytime and nighttime SUHII simulation for all of China and its four regions annually and for four seasons.

Time slot		China		Region I		Region II		Region III		Region IV	
		RMSE	R	RMSE	R	RMSE	R	RMSE	R	RMSE	R
Ann	D	1.10	0.59 ^a	0.99	0.54 ^a	0.69	0.59 ^a	1.24	0.79 ^a	0.99	0.45 ^a
	N	0.49	0.71 ^a	0.61	0.65 ^b	0.38	0.80 ^a	0.91	0.13	0.61	0.59 ^a
Win	D	1.30	0.56 ^a	1.77	0.25	1.23	0.48 ^a	1.99	0.42	1.20	0.52 ^a
	N	0.84	0.62 ^a	1.40	0.14	0.66	0.65 ^a	0.88	0.50 ^a	0.71	0.56 ^a
Spr	D	1.41	0.64 ^a	1.84	0.37 ^b	1.23	0.74 ^a	1.99	0.43 ^b	1.25	0.70 ^a
	N	0.58	0.66 ^a	0.52	0.78 ^a	0.43	0.70 ^a	0.90	0.38	0.56	0.69 ^a
Sum	D	1.54	0.55 ^a	1.22	0.77 ^a	0.99	0.62 ^a	1.87	0.80 ^a	2.18	0.19
	N	0.62	0.63 ^a	0.56	0.71 ^a	0.45	0.71 ^a	0.76	0.79 ^a	0.61	0.43 ^a
Aut	D	0.95	0.69 ^a	1.61	0.32 ^b	0.70	0.61 ^a	1.24	0.58 ^a	0.98	0.59 ^a
	N	0.63	0.63 ^a	0.51	0.74 ^a	0.55	0.76 ^a	0.93	0.42 ^b	0.53	0.67 ^a

Note: ^asignificant at the 0.01 level; ^bsignificant at the 0.05 level; Ann, Win, Spr, Sum, and Aut stand for during the whole year, winter, spring, summer, autumn, respectively; D and N stand for during daytime and nighttime, respectively.

“U-shaped” horizontal gradients were found for the response of LST to BI [30]. In other words, LST decreased from the urban core to the outskirts and then increased again in the suburban to rural zones. A quadratic polynomial fit was used in that study because LST was not significantly linearly correlated with BI. A nonlinear but positive relationship was found in the central region of the city of Phoenix in the USA [66]. LST increased more rapidly with BI when its values were less than 0.4 and increased more slowly thereafter. Our findings support those results. ΔBI generally exhibited a positive partial correlation with nighttime SUHII, except in southern China in winter and autumn. During daytime, positive partial correlations occurred much less frequently and the coefficients were smaller than during nighttime in most cases. No significant partial correlations were found for arid and semiarid western China.

4.1.3. City Size and Total Population. UAS and TP were generally significantly positively correlated with daytime SUHII and foot-print area [29, 30, 32, 42], with the strongest correlations found in summer [29, 30, 42]. Nevertheless, these partial correlations were quite weak [28]. The increases in amplitude slowed as UAS increased, especially when the area was larger than 100 km². Our work supports these findings. Significant positive correlations were generally found, with the exception of northern China, and the strongest relationships in each region occurred in summer. Nonetheless, in region I, significant partial correlations only existed in summer ($r = 0.25$, $p < 0.01$) and autumn ($r = 0.17$, $p < 0.05$). Nevertheless, different conclusions were also found in previous studies. Insignificant relationships have been found for 32 major cities in China [27]. The positive correlation coefficients associated with winter daytime SUHII in 419 large global cities were found to be quite similar to summer values [28]. These differences may have occurred because the correlation method only considers two variables, while their relationship may be influenced or masked by other factors that play more important roles [28, 54].

UAS and TP were generally significantly positively correlated with summer and winter nighttime SUHII and

foot-print area for 32 major cities in China [27, 33], pre-monsoon summer and winter nighttime SUHII for 84 major cities in India [31], summer nighttime SUHII for 38 major cities in the continental US [30], mean nighttime SUHII during cooling degree days for many global cities [37], and nighttime SUHII and foot-print area for 8 Asian mega cities [32]. Nevertheless, insignificant correlations were found relative to annual SUHII for 39 major cities in mainland China [38] and annual, winter, and summer SUHII for 419 global cities [28]. Moreover, UAS exhibited insignificant, 2% significant positive, and 5% significantly negative correlations with annual, winter, and summer SUHII for 419 global cities, respectively [28]. In our study, significant positive correlation coefficients generally existed, with weak positive partial correlations found in 16% of cases ($p < 0.05$).

4.1.4. Population Density. The effects of population density were found to be quite small relative to daytime and nighttime SUHII in 419 world cities [28]. In our study, ΔPD and nighttime SUHII were commonly significantly positively Spearman correlated ($p < 0.05$). In addition, they exhibited extremely significant positive partial correlations in 32% of cases, especially in southern China ($p < 0.01$). During daytime, ΔPD and SUHII commonly exhibited extremely significant positive Spearman correlations in humid cold region I ($p < 0.01$). Significant partial correlations were rarely found. The different findings may be due to different study objects or biases in the spatial distribution of the population. Furthermore, the gridded population data used in Peng et al. (2011) had a spatial resolution of 2.5', whereas the resolution for this study was 1 km.

4.1.5. Vegetation Activity. During daytime, the transpiration of vegetation can increase latent heat fluxes. Therefore, this factor can produce cooling effects on LST and mitigate SUHII [21, 26–28, 31, 32, 65], as verified here. ΔEVI exhibited a negative partial correlation with daytime SUHII in all cases except winter and spring in region I, winter in region II, and summer in southern China. This was mainly due to the minimal influence of low-activity vegetation in

these regions at these times [18, 27, 28], such as in winter in regions I and II; it may also have been due to the effects of ΔEVI , which was collinearly correlated with other factors in the regression [27]. For example, ΔEVI was correlated with ΔNT in southern China in summer and in region I for the entire year as well as with TP in spring in region I. Note that vegetation has a predominant cooling effect on daytime SUHII in arid and semiarid western China. ΔEVI was the only driver that was partially correlated with SUHII in summer ($r = -0.79$, $p < 0.01$), autumn ($r = -0.69$, $p < 0.01$), and annually ($r = -0.66$, $p < 0.01$).

The rules were more complex during nighttime than daytime. The LST of grass was generally found to be less than that for other vegetation, and short grasses are among the coolest urban elements [48, 49, 67]. Long-wave radiation from grass surfaces is released very quickly after sunset, and those surfaces continue to cool throughout the night due to their low heat capacity, soil canopy, high SVF values, and mixture of bare soil, gravel, and other inert materials [48]. Regarding forests, all-day changes in LST have been observed for various surface features using thermal video radiometers in the summer in Beijing and in the winter in Tel Aviv, Israel. Researchers have found that differences in LST between forests and other surface features are small at night and are less than those in daytime [48, 49]. Nevertheless, the mean forest LST was found to be lower than that of concrete pavement in the summer in Beijing [49] but higher than that of most other urban elements in the winter in Tel Aviv [48]. These differences may have been caused by vegetation types, density, coverage, and surface materials of man-made structures. Moreover, forest LST has been found to be higher than that for grasses or crops throughout the vast majority of China during nighttime [50]. Forests generally experience higher LSTs than most surface features for a number of reasons. First, penetrated solar energy can be stored within and beneath canopies because the water content and high foliage density of vegetation can decrease radiative heat loss from the ground [48]. Therefore, the observed surface temperatures of vegetation reflect a combination of re-emitted long-wave radiation from the vegetation canopy and the underlying ground [48]. Second, vegetation can decrease the sky view factor (SVF), reducing the amount of radiation emitted into the open sky [48]. However, the shading effects of vegetation, especially trees can reduce the amount of heat stored during the daytime and thereby reduce the nighttime SUHII [45, 53, 68]. In our work, ΔEVI generally exhibited a negative partial correlation with SUHII in China, except in arid and semiarid western China. These negative relationships likely exist because the corresponding rural regions of the vast majority of cities were mainly covered by croplands, after limiting the elevation. This conclusion needs to be confirmed using a thermal video radiometer to monitor the LSTs of urban man-made structures and croplands at the same time. The poorest vegetation conditions existed in western China and could not have efficiently produced an effect. Therefore, negative relationships disappeared there. Weak negative contributions were also found for nighttime SUHII in 419 world cities [28]. In addition, negative correlations existed between SUHII and EVI in certain global

cities during the growing season [21], and in certain cities in China during both summer and winter [26, 45], between LST and vegetation cover in the entire Phoenix metropolitan area in the USA during summer [69], and in the Yangon region of Myanmar regardless of seasonality [51]. However, insignificant correlations were found between EVI and nighttime SUHII of 32 major cities in China during summer, winter, and the whole year [27, 42].

EVI is commonly used to indicate vegetation activity. Nevertheless, it cannot represent differences in vegetation types. However, its values can correctly reflect the degree of vegetation density when only similar vegetation types are considered. If this is not accounted for, incorrect interpretations and decisions may result. For example, humans should plant trees more densely to mitigate nighttime SUHII , given the results of this study.

4.1.6. Albedo. Materials with lower albedos can absorb more energy. Stored heat can be emitted upward into the atmosphere during the night, contributing to higher surface and air temperatures in the vast majority of studies [27, 28, 38, 62, 70], which is supported by our results. ΔWSA exhibited a negative partial correlation with nighttime SUHII except in southern China in winter and summer. These exceptional cases occurred when the effects of ΔWSA were collinearly correlated with other factors in the regression. For example, ΔWSA was correlated with ΔEVI , P , and T in southern China during the winter ($p < 0.01$). Both the partial and Spearman correlation coefficients were larger in northern China than in the south. This weaker relationship for southern cities was primarily related to the presence of evergreen forests and continuous croplands surrounding them, which resulted in small positive ΔWSA values [27]. This was also consistent with previous findings that cities surrounded by croplands and deciduous trees exhibited larger contrasts in albedo relative to urban areas adjacent to suburban areas [70].

During daytime, the relationship was complex. Both significant positive and negative relationships have been identified in the literature [28, 52]; however, insignificant cases were also found [27]. WSA was found to weakly explain daytime SUHII for 419 world cities [28], while it was found to be the primary factor affecting seasonal amplitude in Beijing [53]. In our study, ΔWSA was found to exhibit both positive and negative partial correlations with daytime SUHII at the national scale and in the northern regions. The strongest correlation was negative and always occurred in winter. In particular, ΔWSA was the only factor that was partially correlated with daytime SUHII in winter in the humid, cold region I ($r = -0.39$, $p < 0.01$).

4.1.7. Aerosol Optical Depth. Aerosols can decrease LST by reducing the amount of short-wave radiation that reaches the ground surface [38]. They can also increase LST because they are more effective at absorbing and emitting radiation than are water vapour and greenhouse gases in the long-wave atmospheric spectrum under specific conditions [38, 71]. The combined effect depends on initial particle size

and growth due to ageing and absorption of water vapour [38, 72]. ΔAOD has been found to positively impact annual mean nighttime SUHII in 39 major cities in mainland China ($p < 0.01$) [38]. The impacts were stronger in semiarid cities than in cities in humid climates because coarser aerosols result in stronger long-wave radiative forcing [38]. Our work is consistent with these findings to some degree. ΔAOD was significantly positively correlated with SUHII in 56.00% of cases. In addition, the correlation coefficients were obviously greater in arid and semiarid western China than they were in other regions of the country. An exception was the negative relationship in winter at the national scale. Moreover, ΔAOD exhibited a positive partial correlation with SUHII in spring ($r = 0.11$, $p < 0.01$) and autumn ($r = 0.07$, $p < 0.05$) in China and in spring in region II ($r = 0.15$, $p < 0.01$). No significant contributions were found for the 39 major cities in mainland China for annual daytime SUHII. ΔAOD was poorly correlated with annual and summer SUHII. In this study, ΔAOD was found to be significantly positively correlated with SUHII in 48.00% of cases. In addition, the largest correlation coefficients ($r = 0.60$, $p < 0.05$) were also found for annual mean SUHII in arid and semiarid western China. Weak and negative partial correlations were only found in summer in China ($r = -0.07$, $p < 0.05$) and autumn in region II ($r = -0.14$, $p < 0.01$), while positive correlations were found in spring in region I ($r = 0.34$, $p < 0.01$) and autumn in southern China ($r = 0.12$, $p < 0.05$).

4.1.8. Climate. Large soil moisture differences between urban and rural regions can occur in areas with high HI or P. These drivers can mitigate nighttime SUHII and enhance daytime SUHII through increases in thermal inertia and soil moisture heat capacity, respectively [26, 27, 38, 42, 54, 73]. This conclusion was supported by our findings. In some cases, HI and P exhibited significant negative and positive partial correlations with nighttime and daytime SUHII, respectively. It is worth noting that farmlands are a highly prominent land cover type in rural regions. In China, 48% of farmland receives water from irrigation rather than from rain [38]. Irrigation causes domesticated plants to behave differently than vegetation in natural ecosystems [38]. This difference can impact the effects of HI and P on SUHII to a large extent [38].

Higher air temperatures can affect LST in both urban and rural regions [55]. This factor can also affect factors such as vegetation activity, evapotranspiration from soils and plants, and anthropogenic heat emissions [27, 42, 55], all of which can directly or indirectly affect SUHII. During nighttime, significant negative correlations have been found between MAT and SUHII in winter, summer, and annually in most studies [27, 28, 42]. Our study verified these findings to some degree. Negative relationships existed at the national scale in all seasons except in autumn. However, significant positive relationships existed in southern China during all seasons except summer, and both significant positive and negative relationships occurred in some regions of northern China during certain timeslots. Moreover, insignificant MAT contributions have been found relative to annual mean

SUHII for 39 cities in mainland China [38]. MAT exhibited a negative partial correlation with SUHII during winter and summer during the night in 419 world cities. Nonetheless, significant positive partial correlations existed in some cases, with one exception during summer in southern China.

MAT has been found to be significantly positively correlated with daytime SUHII in winter and annually, but this correlation was insignificant in summer for 32 major cities in China [27, 42]. The results of our study were consistent with these findings. Nevertheless, no significant MAT contributions were found to impact annual mean SUHII for 39 major cities in mainland China [38], and MAT was negatively correlated with SUHII during not only winter but also summer [26]. Moreover, we found significant positive correlations in spring and autumn at the national scale. Both significant positive and negative correlations existed in certain regions in China. In previous studies, MAT has also been found to be significantly negatively correlated with SUHII in summer and annually, while it was found to be quite weakly positively correlated in winter in 419 world cities [28]. SUHII was also found to be approximately 5°C higher during heat waves than on non-heat-wave days in Taipei [55]. The differences in SUHII for both large and medium cities can be as small as 1.0°C, suggesting that SUHII is enhanced in both large and medium-sized cities during heat waves [55]. During an extensive heat-wave event in Cyprus, SUHII was enhanced in two administrative districts but was less affected in two other districts [74]. Moreover, MAT was found to be insignificantly partially correlated with daytime SUHII for 419 world cities [28]. Similarly, no significant partial relationships were found at the national scale in our study. Nevertheless, both positive and negative significant partial relationships were found in certain regions during certain timeslots.

In addition, Yao and Wang [20] found that the LSTs in urban surface were less sensitive to climate variability than in rural areas in northern China. However, this phenomenon was less evident in hot and humid southern China.

4.1.9. Combined Effects. The factors studied here better explained daytime values than nighttime values in winter, summer, and the whole year for 419 global cities in a previous study [28] and 72% of the cases in our work. Nevertheless, opposite finding existed in winter and summer for 32 large cities in China [27]. The summer explanation rates were 4% and 18% smaller than the winter rates for daytime and nighttime SUHII in 32 cities in China, respectively [27]; however, they were 8% and 13% larger for 419 world cities, respectively [28]. Our study found that SUHII was found to be 2.65% greater and 1.68% smaller during summer than winter at the national scale, but this finding showed obvious spatial heterogeneity. During daytime, the explanation rates for summer were higher than for winter in northern China, especially in northeastern China. However, the patterns were reversed in northern China. During nighttime, the explanation rates for summer were slightly smaller than in winter. Nevertheless, different rules existed in the other two regions, especially in western China, where the explanation rates in

summer were 30.50% higher than in winter. The largest and smallest explanation rates were found for summer days in humid and cold northeastern China (63.84%) and in southern China (10.44%), respectively. The above results show that different background environmental conditions can have obvious and differing impacts on SUHII. The explanation rates in this study are generally lower than those reported in previous studies, mainly because our study objects are many cities of various sizes, whereas other studies only focused on large or mega cities [27, 28]. In addition, more years of data should be analyzed in order to obtain more reliable conclusions in future [27, 28].

To our knowledge, only one study has developed estimates of SUHII in several cities at large scale simply by using drivers and not adopting a climatologic model [39]. Daytime and nighttime summer and winter SUHII values were estimated for 67 major cities in northern and southern China [39]. In our work, we simulated the SUHII for the vast majority of cities in five ecological function zones and for the entirety of China for each season and annually (Table 3). The simulation accuracy was always higher during the night, which is consistent with previous findings [39]. Nevertheless, the variables analyzed better explained daytime values than nighttime values in 72% of cases. This conflict needs to be explored and discussed further in future. Multisubject knowledge and methods should be combined. To our knowledge, similar studies have not been reported. Nowadays, it is complex to clearly understand the mechanism of SUHIs and accurately estimate the distribution and intensity of SUHIs. The highest estimation accuracies were determined for central-northern China (region II) and were lowest in arid and semiarid western China for both nighttime and daytime SUHII. The RMSE for southern China in this work was 0.05°C and 0.76°C lower than in a previous study of nighttime and daytime summer SUHII in southern China, respectively. However, the present study simulated the nighttime SUHII for 517 cities and the daytime SUHII for 514 cities, rather than both for 27 major cities. Moreover, data on eleven variables related to SUHII were collected in a statistical yearbook in a previous study [39], whereas all indices employed in the present study used common remotely sensed or meteorological data, with the exception of TP and ΔPD , neither of which contributed significantly to daytime SUHII. Weak TP contributions were only found relative to 16% of nighttime SUHII ($p < 0.05$), whereas ΔPD impacted 32% of cases. In fact, population data were easier to obtain than most other social or economic indices. Therefore, in order to improve the generality of our method, neither can be excluded in practice.

4.2. Uncertainties and Limitations. Although MODIS LST data have been validated and have been found to be highly accurate in many cases and are widely accepted and used [25, 26, 37, 42, 43], uncertainties and issues remain, especially relative to urban environments and rural areas with complex terrain or vegetation caused by the highly complicated spatial heterogeneity of landscape components, greater air pollution in cities, and the known anisotropy

issue [37]. The ready-made composite monthly mean LSTs data of China were used rather than high-volume raw daily LST data stored in blocks. The processing of monthly data mainly included mosaicking, slicing, projection transformation, and mean value calculations. Whether quality control information was considered was not determined. Moreover, quality control was not performed on the albedo and aerosol data in order to retain a sufficient number of pixels for this variable. These issues for quality control of LST, EVI, and ALB may have introduced bias or uncertainty to our results [75], especially when cloudy conditions prevail. However, the impact of the MODIS quality on long-term SUHI intensity is weaker than that on the spatial pattern of LST [75]. Moreover, population data are generally collected based on administration cells at the county level. In fact, it is not difficult to accurately identify discrete spatial patterns in the data, especially for internal administrative units within which natural conditions change sharply.

In this study, the spatial extents of cities were derived from the aggregation results of urban land polygons rather than the raw data. Therefore, the raster cells within a certain distance can be treated together as a whole city. The extracted urban land patches are treated as independent cities, if they are far from other urban land patches. After the validation check, the distributions can be well extracted for overwhelming majority cities as the public understanding of humans. Nevertheless, very few exceptional cases existed, such as Panzhihua, whose western and eastern urban areas are more than 4 km apart.

Certain factors were not considered or needed to be modified for SUHII or LST. For example, BI cannot be used to derive detailed information on the two- and three-dimensional characteristics of man-made structures that have strong correlations with LST, including building materials, fraction of buildings or flat impervious surfaces, building volume, density, fraction index, building shadows, mean and maximum height, type, color, floor area ratio, sky view factor, road length, area, and number of nodes [22, 48, 65, 76, 77]. With the exception of EVI, LST is also correlated with the fraction of trees, grass, or vegetation combinations [22, 78], fractional coverage of tree canopy [23], vegetation height [79], canopy configuration (e.g., canopy area and edge) [23], etc. It has also been found to correlate with surface wetness or bareness [22]. Moreover, LST is commonly influenced not only by landscape components but also by landscape configuration and their interactions [22]. The NL data failed to support more detailed social or economic information, such as the proportions of different industries, races or consumption of various resources, and unemployment rates. Moreover, we did not consider certain cropland management activities that may affect SUHII, including irrigation [38] and crop harvest. Finally, more ecological process indices should be introduced using the combination of remotely sensed, observed, and numerical model methods. For example, researchers could attempt to calculate absorbed energy differences by considering AOD, albedo, and incoming solar energy outside the atmosphere in a closed experiment. Obviously, it is unrealistic to consider so many factors at a

large scale. A feasible method may be to choose typical cities in various climate zones based on observed spatiotemporal patterns and then study them thoroughly.

5. Conclusions

We studied the associated determinants of SUHII and estimated SUHII values across 1449 cities in China. Some important conclusions are summarized as follows:

- (1) In arid and semiarid western China, significant positive partial correlations were not found between daytime SUHII and the differences in NL and BI between cities and their corresponding villages. Although UAS and TP were generally positively correlated with daytime and nighttime SUHII, significant partial correlations only existed in 8% and 16% of cases. Δ PD was positively partially correlated with nighttime SUHII in 32% of cases, particularly in southern China. However, only two weak negative partial correlations were found.

Δ EVI was generally negatively partially correlated with daytime and nighttime SUHII, except under certain poor vegetation conditions or when disturbed by other collinear factors included in the regression. Δ WSA was usually negatively partially correlated with nighttime SUHII. During daytime, this relationship was complex. Δ AOD was significantly positively correlated with nighttime and daytime SUHII in 56% and 48% of cases, respectively. The correlation coefficients were obviously larger in arid and semiarid western China. Moreover, Δ AOD was weakly positively partially correlated with nighttime and daytime SUHII in three and two cases, respectively. Moreover, weak and negative partial correlations only existed in two cases.

In certain cases, HI and P were partially negatively correlated with nighttime SUHII and partially positively correlated with daytime SUHII, respectively. These relationships could be disturbed by common irrigation activities on farmlands. MAT was partially positively correlated with nighttime SUHII in 40% of cases. During daytime, no significant partial correlations existed at the national scale. Nevertheless, both positive and negative relationships were found in certain regions and during certain timeslots.

In total, the variables analyzed better explained daytime values than nighttime values in 72% of cases. The best and worst explanation rates occurred during summer days in humid, cold northeastern China (63.84%) and in southern China (10.44%), respectively.

- (2) Both daytime and nighttime SUHII can be accurately estimated based on drivers using machine learning. The simulation accuracy was always higher during nighttime than during daytime. The highest estimation accuracies for both daytime and nighttime SUHII occurred in central-northern China, while the lowest

occurred in arid and semiarid western China. At the national scale, RMSE ranged from 0.49°C to 1.54°C. Significant correlations always existed between the estimated and actual SUHII ($p < 0.01$). At the regional scale, RMSE ranged from 0.38°C to 2.18°C. Significant correlations existed in 87.50% of cases ($p < 0.05$).

Data Availability

Both LST and EVI data were downloaded from <http://www.gscloud.cn/>. Both albedo and aerosol data were provided by <https://ladsweb.modaps.eosdis.nasa.gov/search/>. The digital elevation data were taken from <http://westdc.westgis.ac.cn/data/92bb3089-cc0c-46d2-908d-aae810ef064e>. Both land use and population data were provided by <http://www.resdc.cn/>. The impervious percentage data were downloaded from <https://www.beijingscitylab.com/>. The nighttime light data were provided by the National Centers for Environmental Information website https://ngdc.noaa.gov/eog/dmisp/download_radcal.html. The temperature and precipitation data were taken from the Meteorological Data Website of China <http://data.cma.cn/>. The other data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The work was supported by the National Natural Science Foundation of China (41701501 and 31600375), Social Science Fund of China (General Projects) (grant no. 17BJL065), Key Scientific and Technological Project of Henan Province (192102310003), Key Scientific Research Projects of Henan Colleges and Universities (18A170014), and Philosophy and Social Science Planning Project of Henan Province (2017BJJ005).

Supplementary Materials

The following supporting information is available as part of the online article: Text S1: introduction of the land use data. Text S2: introduction of the impervious percentage data. Text S3: introduction of the temperature and precipitation data. Text S4: comparison of four intelligence algorithms for prediction of SUHII. Text S5: comparison of three types of indices for prediction of SUHII. Table S1: accuracy statistics derived from the adoption of different indices and intelligence algorithms for daytime and nighttime SUHII simulation in each region of China during the whole year and each season. (*Supplementary Materials*)

References

- [1] United Nations, *Department of Economic and Social Affairs, Population Division, World Urbanization Prospects: the 2018 Revision, Highlights*, New York, NY, USA, 2018.

- [2] R. Sánchez-Rodríguez, K. C. Seto, D. Simon, W. D. Solecki, F. Kraas, and G. Laumann, *Science Plan: Urbanization and Global Environmental Change*, Bonn, Germany, 2014.
- [3] L. Howard, *Climate of London Deduced from Metrological Observations*, vol. 1, Harvey and Dorton Press, London, UK, 1833.
- [4] W. L. Filho, L. E. Icaza, V. O. Emanche et al., "An evidence-based review of impacts, strategies and tools to mitigate urban heat islands," *International Journal of Environmental Research & Public Health*, vol. 14, no. 12, p. 1600, 2017.
- [5] M. Zinzi, E. Carnielo, and B. Mattoni, "On the relation between urban climate and energy performance of buildings. A three-years experience in Rome, Italy," *Applied Energy*, vol. 221, pp. 148–160, 2018.
- [6] L. Chen, M. Zhang, J. Zhu, Y. Wang, and A. Skorokhod, "Modeling impacts of urbanization and urban heat island mitigation on boundary layer meteorology and air quality in Beijing under different weather conditions," *Journal of Geophysical Research: Atmospheres*, vol. 123, no. 8, pp. 4323–4344, 2018.
- [7] D. R. Richards and P. J. Edwards, "Using water management infrastructure to address both flood risk and the urban heat island," *International Journal of Water Resources Development*, vol. 34, no. 4, pp. 490–498, 2018.
- [8] B. Shi, C.-S. Tang, L. Gao, C. Liu, and B.-J. Wang, "Observation and analysis of the urban heat island effect on soil in Nanjing, China," *Environmental Earth Sciences*, vol. 67, no. 1, pp. 215–229, 2012.
- [9] L. Sfiică, P. Ichim, L. Apostol et al., "The extent and intensity of the urban heat island in Iași city, Romania," *Theoretical & Applied Climatology*, vol. 134, no. 3–4, pp. 1–15, 2017.
- [10] Y. Y. Lee, M. F. M. Din, M. Ponraj et al., "Overview of urban heat island (UHI) phenomenon towards human thermal comfort," *Environmental Engineering and Management Journal*, vol. 16, no. 9, pp. 2097–2111, 2017.
- [11] A. A. Scott, D. W. Waugh, and B. F. Zaitchik, "Reduced urban heat island intensity under warmer conditions," *Environmental Research Letters*, vol. 13, no. 6, article 064003, 2018.
- [12] D. X. Xiang, D. Li, H. Yan et al., "The influence of the spatial characteristics of urban green space on the urban heat island effect in Suzhou industrial park," *Sustainable Cities and Society*, vol. 40, pp. 428–439, 2018.
- [13] N. Yadav and C. Sharma, "Spatial variations of intra-city urban heat island in megacity Delhi," *Sustainable Cities and Society*, vol. 37, pp. 298–306, 2018.
- [14] H. Li, Y. Zhou, X. Wang, X. Zhou, H. Zhang, and S. Sodoudi, "Quantifying urban heat island intensity and its physical mechanism using WRF/UCM," *Science of the Total Environment*, vol. 650, pp. 3110–3119, 2019.
- [15] D. Zhou, J. Xiao, S. Bonafoni et al., "Satellite remote sensing of surface urban heat islands: progress, challenges, and perspectives," *Remote Sensing*, vol. 11, no. 1, p. 48, 2019.
- [16] K. Deilami, M. Kamruzzaman, and Y. Liu, "Urban heat island effect: a systematic review of spatio-temporal factors, data, methods, and mitigation measures," *International Journal of Applied Earth Observation and Geoinformation*, vol. 67, pp. 30–42, 2018.
- [17] W. Huang, J. Li, Q. Guo, L. Mansaray, X. Li, and J. Huang, "A satellite-derived climatological analysis of urban heat island over Shanghai during 2000–2013," *Remote Sensing*, vol. 9, no. 7, p. 641, 2017.
- [18] F. Marzban, S. Sodoudi, and R. Preusker, "The influence of land-cover type on the relationship between NDVI-LST and LST-Tair," *International Journal of Remote Sensing*, vol. 39, no. 5, pp. 1377–1398, 2018.
- [19] W. Zhan, W. Ju, S. Hai et al., "Satellite-derived subsurface urban heat island," *Environmental Science & Technology*, vol. 48, no. 20, pp. 12134–12140, 2014.
- [20] R. Yao, L. Wang, X. Huang, J. Chen, J. Li, and Z. Niu, "Less sensitive of urban surface to climate variability than rural in Northern China," *Science of the Total Environment*, vol. 628–629, pp. 650–660, 2018.
- [21] R. Yao, L. Wang, X. Huang, W. Gong, and X. Xia, "Greening in rural areas increases the surface urban heat island intensity," *Geophysical Research Letters*, vol. 46, no. 4, pp. 2204–2212, 2019.
- [22] Y. Li, K. Yin, Y. Wang et al., "Studies on influence factors of surface urban heat island: a review," *World Science Technology Research and Development*, vol. 36, no. 1, pp. 51–61, 2017.
- [23] J. M. A. Duncan, B. Boruff, A. Saunders, Q. Sun, J. Hurley, and M. Amati, "Turning down the heat: an enhanced understanding of the relationship between urban vegetation and surface temperature at the city scale," *Science of the Total Environment*, vol. 656, pp. 118–128, 2019.
- [24] N. Mostofi and M. Hasanlou, "Feature selection of various land cover indices for monitoring surface heat island in Tehran city using Landsat 8 imagery," *Journal of Environmental Engineering and Landscape Management*, vol. 25, no. 3, pp. 241–250, 2017.
- [25] Q. Yang, X. Huang, and Q. Tang, "The footprint of urban heat island effect in 302 Chinese cities: temporal trends and associated factors," *Science of the Total Environment*, vol. 655, pp. 652–662, 2019.
- [26] R. Yao, L. Wang, X. Huang, W. Zhang, J. Li, and Z. Niu, "Interannual variations in surface urban heat island intensity and associated drivers in China," *Journal of Environmental Management*, vol. 222, pp. 86–94, 2018.
- [27] D. Zhou, S. Zhao, S. Liu, L. Zhang, and C. Zhu, "Surface urban heat island in China's 32 major cities: spatial patterns and drivers," *Remote Sensing of Environment*, vol. 152, pp. 51–61, 2014.
- [28] S. Peng, S. Piao, P. Ciais et al., "Surface urban heat island across 419 global big cities," *Environmental Science & Technology*, vol. 46, no. 2, pp. 696–703, 2011.
- [29] P. Zhang, M. L. Imhoff, R. E. Wolfe, and L. Bounoua, "Characterizing urban heat islands of global settlements using MODIS and nighttime lights products," *Canadian Journal of Remote Sensing*, vol. 36, no. 3, pp. 185–196, 2010.
- [30] M. L. Imhoff, P. Zhang, R. E. Wolfe, and L. Bounoua, "Remote sensing of the urban heat island effect across biomes in the continental USA," *Remote Sensing of Environment*, vol. 114, no. 3, pp. 504–513, 2010.
- [31] H. Shastri, B. Barik, S. Ghosh et al., "Flip flop of day-night and summer-winter surface urban heat island intensity in India," *Scientific Reports*, vol. 7, article 40178, 2017.
- [32] H. Tran, D. Uchihama, S. Ochi, and Y. Yasuoka, "Assessment with satellite data of the urban heat island effects in Asian mega cities," *International Journal of Applied Earth Observation and Geoinformation*, vol. 8, no. 1, pp. 34–48, 2006.
- [33] D. Zhou, S. Zhao, L. Zhang et al., "The footprint of urban heat island effect in China," *Scientific Reports*, vol. 5, article 11160, 2015.
- [34] Y. Cui, X. Xu, J. Dong, and Y. Qin, "Influence of urbanization factors on surface urban heat island intensity: a comparison of countries at different developmental phases," *Sustainability*, vol. 8, no. 8, p. 706, 2016.

- [35] T. Sharmin, K. Steemers, and A. Matzarakis, "Microclimatic modelling in assessing the impact of urban geometry on urban thermal environment," *Sustainable Cities and Society*, vol. 34, pp. 293–308, 2017.
- [36] Y. Li, L. Wang, L. Zhang, and Q. Wang, "Monitoring the interannual spatiotemporal changes in the land surface thermal environment in both urban and rural regions from 2003 to 2013 in China based on remote sensing," *Advances in Meteorology*, vol. 2019, pp. 1–17, 2019.
- [37] N. Clinton and P. Gong, "MODIS detected surface urban heat islands and sinks: global locations and controls," *Remote Sensing of Environment*, vol. 134, pp. 294–304, 2013.
- [38] C. Cao, X. Lee, S. Liu et al., "Urban heat islands in China enhanced by haze pollution," *Nature Communications*, vol. 7, article 12509, 2016.
- [39] J. Wang, B. Huang, D. Fu, and P. Atkinson, "Spatiotemporal variation in surface urban heat island intensity and associated determinants across major Chinese cities," *Remote Sensing*, vol. 7, no. 4, pp. 3670–3689, 2015.
- [40] W. Kuang, J. Liu, J. Dong, W. Chi, and C. Zhang, "The rapid and massive urban and industrial land expansions in China between 1990 and 2010: a CLUD-based analysis of their trajectories, patterns, and drivers," *Landscape and Urban Planning*, vol. 145, pp. 21–33, 2016.
- [41] Y. Li, X. Gong, Z. Guo, K. Xu, D. Hu, and H. Zhou, "An index and approach for water extraction using Landsat-OLI data," *International Journal of Remote Sensing*, vol. 37, no. 16, pp. 3611–3635, 2016.
- [42] D. Zhou, L. Zhang, D. Li, D. Huang, and C. Zhu, "Climate-vegetation control on the diurnal and seasonal variations of surface urban heat islands in China," *Environmental Research Letters*, vol. 11, no. 7, article 074009, 2016.
- [43] N. Schwarz, S. Lautenbach, and R. Seppelt, "Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures," *Remote Sensing of Environment*, vol. 115, no. 12, pp. 3175–3186, 2011.
- [44] C. Keeratikasikorn and S. Bonafoni, "Satellite images and Gaussian parameterization for an extensive analysis of urban heat islands in Thailand," *Remote Sensing*, vol. 10, no. 5, p. 665, 2018.
- [45] R. Yao, L. Wang, X. Huang, Z. Niu, F. Liu, and Q. Wang, "Temporal trends of surface urban heat islands and associated determinants in major Chinese cities," *Science of the Total Environment*, vol. 609, pp. 742–754, 2017.
- [46] Q. Yang, X. Huang, and J. Li, "Assessing the relationship between surface urban heat islands and landscape patterns across climatic zones in China," *Scientific Reports*, vol. 7, no. 1, p. 9337, 2017.
- [47] J. Lai, W. Zhan, F. Huang et al., "Identification of typical diurnal patterns for clear-sky climatology of surface urban heat islands," *Remote Sensing of Environment*, vol. 217, pp. 203–220, 2018.
- [48] A. Chudnovsky, E. Ben-Dor, and H. Saaroni, "Diurnal thermal behavior of selected urban objects using remote sensing measurements," *Energy and Buildings*, vol. 36, no. 11, pp. 1063–1074, 2004.
- [49] T. Chen, *Studies on Spatiotemporal Dynamics of Thermal Radiation Temperatures of Different Landscapes in Beijing City*, University of Science and Technology of China, Hefei, China, 2017.
- [50] Y. Li, M. Zhao, S. Motesharrei et al., "Local cooling and warming effects of forests based on satellite observations," *Nature Communications*, vol. 6, p. 6603, 2015.
- [51] Y.-C. Wang, B. K. H. Hu, S. W. Myint, C.-C. Feng, W. T. L. Chow, and P. F. Passy, "Patterns of land change and their potential impacts on land surface temperature change in Yangon, Myanmar," *Science of the Total Environment*, vol. 643, pp. 738–750, 2018.
- [52] L. Klok, S. Zwart, H. Verhagen, and E. Mauri, "The surface heat island of Rotterdam and its relationship with urban surface characteristics," *Resources, Conservation and Recycling*, vol. 64, no. 7, pp. 23–29, 2012.
- [53] J. Quan, W. Zhan, Y. Chen, M. Wang, and J. Wang, "Time series decomposition of remotely sensed land surface temperature and investigation of trends and seasonal variations in surface urban heat islands," *Journal of Geophysical Research: Atmospheres*, vol. 121, no. 6, pp. 2638–2657, 2016.
- [54] S. Peng, S. Piao, P. Ciais et al., "Response to comment on 'surface urban heat island across 419 global big cities'," *Environmental Science & Technology*, vol. 46, no. 12, pp. 6889–6890, 2012.
- [55] C.-D. Wu, S.-C. C. Lung, and J.-F. Jan, "Development of a 3-D urbanization index using digital terrain models for surface urban heat island effects," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 81, no. 7, pp. 1–11, 2013.
- [56] G. Ren, J. Guo, M. Xu et al., "Climate changes of China's mainland over the past half century," *Acta Meteorologica Sinica*, vol. 63, no. 6, pp. 942–956, 2005.
- [57] A. Christen and R. Vogt, "Energy and radiation balance of a central European city," *International Journal of Climatology*, vol. 24, no. 11, pp. 1395–1421, 2004.
- [58] L. Chen, R. Jiang, and W.-N. Xiang, "Surface heat island in Shanghai and its relationship with urban development from 1989 to 2013," *Advances in Meteorology*, vol. 2016, no. 22, Article ID 9782686, 15 pages, 2016.
- [59] Z. Liu, C. He, Q. Zhang, Q. Huang, and Y. Yang, "Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008," *Landscape and Urban Planning*, vol. 106, no. 1, pp. 62–72, 2012.
- [60] C. D. Elvidge, "Mapping city lights with nighttime data from the DMSP operational linescan system, photogramm," *Photogrammetric Engineering & Remote Sensing*, vol. 63, no. 6, pp. 727–734, 1997.
- [61] M. L. Imhoff, W. T. Lawrence, D. C. Stutzer et al., "A technique for using composite DMSP/OLS 'City Lights' satellite data to map urban area," *Remote Sensing of Environment*, vol. 61, no. 3, pp. 361–370, 1997.
- [62] R. A. Memon, D. Y. C. Leung, and C.-H. Liu, "An investigation of urban heat island intensity (UHII) as an indicator of urban heating," *Atmospheric Research*, vol. 94, no. 3, pp. 491–500, 2009.
- [63] T. Oke, "The energetic basic of the urban heat island," *Quarterly Journal of the Royal Meteorological Society*, vol. 108, no. 455, pp. 1–24, 1982.
- [64] B. Zheng, S. W. Myint, and C. Fan, "Spatial configuration of anthropogenic land cover impacts on urban warming," *Landscape and Urban Planning*, vol. 130, no. 1, pp. 104–111, 2014.
- [65] Y. Zhang and L. Sun, "Spatial-temporal impacts of urban land use land cover on land surface temperature: case studies of two Canadian urban areas," *International Journal of Applied Earth Observation and Geoinformation*, vol. 75, pp. 171–181, 2019.
- [66] S. W. Myint, E. A. Wentz, A. J. Brazel, and D. A. Quattrochi, "The impact of distinct anthropogenic and vegetation features on urban warming," *Landscape Ecology*, vol. 28, no. 5, pp. 959–978, 2013.

- [67] H. H. Kim, "Urban heat island," *International Journal of Remote Sensing*, vol. 13, no. 12, pp. 2319–2336, 1992.
- [68] M. Tiangco, A. M. F. Lagmay, and J. Argete, "ASTER-based study of the night-time urban heat island effect in Metro Manila," *International Journal of Remote Sensing*, vol. 29, no. 10, pp. 2799–2818, 2008.
- [69] C. Wang, S. Myint, Z. Wang, and J. Song, "Spatio-Temporal modeling of the urban heat island in the Phoenix metropolitan area: land use change implications," *Remote Sensing*, vol. 8, no. 3, p. 185, 2016.
- [70] M. Jin, R. E. Dickinson, and D. Zhang, "The footprint of urban areas on global climate as characterized by MODIS," *Journal of Climate*, vol. 18, no. 10, pp. 1551–1565, 2005.
- [71] M. Z. Jacobson, "Studying the effects of aerosols on vertical photolysis rate coefficient and temperature profiles over an urban airshed," *Journal of Geophysical Research: Atmospheres*, vol. 103, no. D9, pp. 10593–10604, 1998.
- [72] Y. Rudich, N. M. Donahue, and T. F. Mentel, "Aging of organic aerosol: bridging the gap between laboratory and field studies," *Annual Review of Physical Chemistry*, vol. 58, no. 58, p. 321, 2007.
- [73] F. Xiao, Y.-z. Li, Y. Du et al., "Monitoring perennial sub-surface waterlogged croplands based on MODIS in Jiangnan plain, middle reaches of the Yangtze river," *Journal of Integrative Agriculture*, vol. 13, no. 8, pp. 1791–1801, 2014.
- [74] A. Retalis, D. Paronis, S. Michaelides et al., *Study of the August 2010 Heat Event in Cyprus*, Springer Berlin Heidelberg, Berlin, Germany, 2013.
- [75] L. Gawuc and J. Struzewska, "Impact of MODIS quality control on temporally aggregated urban surface temperature and long-term surface urban heat island intensity," *Remote Sensing*, vol. 8, no. 5, p. 374, 2016.
- [76] C. Yin, M. Yuan, Y. Lu, Y. Huang, and Y. Liu, "Effects of urban form on the urban heat island effect based on spatial regression model," *Science of the Total Environment*, vol. 634, pp. 696–704, 2018.
- [77] M. Ranagalage, R. Estoque, H. Handayani et al., "Relation between urban volume and land surface temperature: a comparative study of planned and traditional cities in Japan," *Sustainability*, vol. 10, no. 7, p. 2366, 2018.
- [78] C. S. Greene and P. J. Kedron, "Beyond fractional coverage: a multilevel approach to analyzing the impact of urban tree canopy structure on surface urban heat islands," *Applied Geography*, vol. 95, pp. 45–53, 2018.
- [79] Q. Yu, M. Acheampong, R. Pu, S. M. Landry, W. Ji, and T. Dahigamuwa, "Assessing effects of urban vegetation height on land surface temperature in the city of Tampa, Florida, USA," *International Journal of Applied Earth Observation and Geoinformation*, vol. 73, pp. 712–720, 2018.