



A New Method for Correcting Urbanization-Induced Bias in Surface Air Temperature Observations: Insights From Comparative Site-Relocation Data

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Specialty section:

This article was submitted to
Interdisciplinary Climate Studies,
a section of the journal
Frontiers in Environmental Science

Received: 03 November 2020

Accepted: 09 February 2021

Published: 30 April 2021

Citation:

Shi T, Huang Y, Sun D, Lu G and
Yang Y (2021) A New Method for
Correcting Urbanization-Induced Bias
in Surface Air Temperature
Observations: Insights From
Comparative Site-Relocation Data.
Front. Environ. Sci. 9:625418.
doi: 10.3389/fenvs.2021.625418

The effect of urbanization on surface air temperature (SAT) is one of the most important systematic biases in SAT series of urban stations. Correcting this so-called urbanization bias has the potential to provide accurate basic data for long-term climate change monitoring and research. In the western region of the Yangtze River Delta, 42 meteorological stations with site-relocation history from 2009 to 2018 were selected to analyze the statistical characteristics of the differences in comparative site-relocation daily average SAT. The annual average differences in comparative site-relocation SAT series between the old and the new stations (SAT_{DON}) were used to characterize the impact of urbanization bias on the air temperature observation series. Using remote sensing technology, spatial datasets of land-use, landscape, and geometric parameters of the underlying surface in the 5-km buffer zone around the station were established as the observed environmental factors of the site, and the differences in these observed environmental factors (DOEFs) between the old and the new stations were calculated to indicate the change induced by urbanization. Next, multiple linear regression models of SAT_{DON} and DOEFs were constructed, showing that the error range of the model for simulated SAT_{DON} was 3.66–18.21%, and the average error was 10.09%. Finally, this new correction method (NCM) and conventional correction method (CCM) were applied to the correction of the urbanization bias of SAT series at Hefei station. After comparison, it is found that the NCM could reveal clear contributions of the rapid and slow stages of the urbanization process and resultant environmental changes around the stations to the observed SAT. In summary, the NCM based on remote sensing technology can more reasonably and effectively correct the urbanization bias caused by local human activities,

Abbreviations: AR, area ratio; CCM, conventional correction method of urbanization bias correction; DIS, distance between the station and the gravity center of various lands; DOEFs, differences in these observed environmental factors; FRAC_MN, mean fractal dimension; LPI, largest patch index; LUCC, land use/cover change; NCM, new correction method of urbanization bias correction; NDVI, normalized difference vegetation index; SAT, surface air temperature; SAT_{DON} , differences in comparative site-relocation SAT series between the old and the new stations; YRD, Yangtze River Delta.

as well as reduce the error caused by the selection of reference stations *via* the conventional correction method.

Keywords: surface air temperature series, urbanization bias, remote sensing technology, relocation, correction method

INTRODUCTION

Urbanization directly affects the types of land use/cover and anthropogenic heat emissions around meteorological stations, leading to major changes in the observation environment (Gallo et al., 1996; Peterson, 2006; Trusilova et al., 2008; Chen et al., 2020), which in turn has an important impact on the accuracy, representativeness, and homogeneity of meteorological observation data (Davey and Sr, 2005; Vose, 2005). The contribution of the so-called urbanization bias (the effect of urbanization on surface air temperature (SAT), the list of abbreviations used in this article and their expanded names can be found in Appendix A) to meteorological observation data usually stems from changes in the observation environment against the background of urbanized areas (Ren et al., 2017). The urbanization bias is the largest systematic bias in SAT observation records in China and correcting this bias has the potential to provide accurate basic data for large-scale climate change monitoring and research (Wen et al., 2019b).

Urbanization bias has received a great deal of attention in the literature (Hansen et al., 2001; Fujibe, 2009; Zhang, 2009; Zhang, 2014; Wen et al., 2019a). Zhang (2009) used the method of subtracting the warming trend of rural stations from the warming trend of urban stations to correct the regional average SAT series after removing the urbanization bias. Fujibe (2009) divided the meteorological stations in Japan into six categories in terms of the population density within a certain radius around the city station and corrected the urbanization bias in the third–sixth-category sites using the first and second types of stations as reference stations. Hansen et al. (2001) corrected the urbanization bias of one typical station by utilizing the two-stage linear trend based on the assumption that the SAT increased linearly in two periods. Zhou et al. (2019) pointed occurrence probability of the heatwave events in summer over the Yangtze River Delta is closely related to the contribution of urbanization effect. These imply that the correction method of urbanization bias is very crucial to explore accurately the regional climate change.

However, the conventional correction method (CCM) of urbanization bias still has some shortcomings as follows: 1) many studies have utilized the population density or city size as the criteria for classifying meteorological stations. For example, Bai and Ren (2006) chose meteorological stations with a population of more than 100,000 as urban stations, but Liu (2006) divided the stations with a population of more than 40,000 and the stations that were not described as “rural” into urban stations. However, there have also been some studies that have utilized satellite remote sensing data to select reference stations, such as Zhang. (2014), who visually selected the stations outside the closed contour as reference stations in the temperature field retrieved from remote sensing data. Thus, it can

be seen that there is no unified standard for the selection of reference stations, and it is difficult to find a pure reference station near the urban station as reference stations are inevitably affected by urbanization, so the urbanization bias in the SAT series is the minimum estimate (Zhang, 2014). 2) Previous studies corrected the SAT series based on the assumption that the urbanization bias presents a linear increase trend (Hansen et al., 2001; Zhang, 2009). However, in reality, the urbanization processes at different times and in different regions are variable, so it is impossible to subdivide the specific degree of contribution of the urbanization bias to the SAT series on temporal and spatial scales. In addition, there are considerable differences in the mechanisms and magnitudes of the impact of urbanization on different temperature elements (Li et al., 2014), despite the possibly limited contribution to regional warming (Chao et al., 2020), while its impact on extreme temperatures are huge (Li and Huang, 2013; Li et al., 2014; Zhou et al., 2019).

In order to improve the representativeness of the observation environment of meteorological stations, many stations with severely damaged observation environments have been relocated. Taking 2015 as an example, 92 meteorological observation stations across the country were relocated in this year alone (Meteorological Observation Centre of CMA, 2013; Comprehensive Observation Department of China Meteorological Administration, 2015). According to the requirements of “the criterion of surface meteorological observation,” “protection methods for meteorological exploration environment and facilities,” and other documents formulated and issued by China Meteorological Administration, site selection has a series of strict restrictions on factors such as altitude, distance, and obstacles. The area around the relocated station should be dominated by open vegetation, and the representativeness of the meteorological observation environment must have been greatly improved. Meteorological observation series can represent the climate background of the region (Yang et al., 2013; Yang et al., 2017), so relocated stations can be used as relatively pure reference stations. In addition, “the criterion of surface meteorological observation” stipulates that the relocation of meteorological stations must involve the carrying out of at least one year of comparative observations between the new site and the old site, and the difference in comparative site-relocation annual average SAT between the old and the new stations (SAT_{DON}) provides high-quality data for us to study the impact of urbanization bias on the SAT series. Therefore, SAT_{DON} can reduce the error caused by the selection of reference stations *via* the traditional urban–rural comparison method.

The meteorological observation environment refers to the environmental space constituted by the minimum distance necessary to avoid various interferences and ensures that the

facilities of the meteorological observation station accurately obtain the meteorological observation information. With the rapid development of remote sensing technology, the use of satellite data to study changes in the meteorological environment has become an emerging method (Yang et al., 2013; Li et al., 2015; Shi et al., 2015). Yang et al. (2013) evaluated the observation environment by using land use/cover and normalized difference vegetation index (NDVI) in the buffer zone around the meteorological station. Li et al. (2015) quantitatively studied the relationship between land use/cover change (LUCC) and the thermal environment in the buffer zone and subdivided the stations into three types by the contribution index of the thermal environment. The above researches show that it is feasible to utilize satellite data to investigate and study the observation environment, and it has the advantages of visualization and remodeling. However, existing remote sensing research on the observation environment only uses indicators such as LUCC and NDVI and does not fully consider the impact of the spatial pattern and configuration of different land-use types on the observation environment. Consequently, this study uses remote sensing technology to establish land-use parameters, landscape parameters, geometric parameters, and other spatial datasets around meteorological stations to characterize the differences in observation environment factors (DOEFs) between the old and the new stations and analyzes and discusses the physical mechanisms by which urbanization bias influences the SAT series.

The Yangtze River Delta (YRD) urban agglomeration is one of the most highly urbanized areas in China for the past 30 years (National Bureau of Statistics, 2019). However, the development of Anhui in the western region of the YRD has been relatively slow, having not developed rapidly until the past 10 years. Therefore, the observation environments of national meteorological stations in Anhui Province have been seriously damaged in the past 10 years, and a large number of stations have been forced to relocate on a frequent basis (Meteorological Observation Centre of CMA, 2013; Comprehensive Observation Department of China Meteorological Administration, 2015), and this provides us with an opportunity to study the process of urbanization and station relocation. In summary, taking Anhui Province as the research area, meteorological stations with site-relocation history were selected in this study, and the SAT_{DON} results between the old and the new stations were used to characterize the impact of urbanization bias on the SAT series. Landscape parameters, geometric parameters, and other spatial datasets in the 5 km buffer zone around the stations were established to characterize the DOEFs between the old and the new stations, and statistical models of the SAT_{DON} and DOEFs were constructed. This paper corrected the urbanization bias of the SAT series at a typical station by the new method and the conventional method, respectively, and the advantages of the new method were discussed finally.

DATA AND METHODS

Data

- 1) Ground observation data. The SAT data mainly include national reference climatological stations, which observe

8 times a day (once every 3 h); national basic meteorological station, which observes four times a day [02:00, 08:00, 14:00, and 20:00 BT (Beijing time)]; national general meteorological stations, which observe three times a day (08:00, 14:00, and 20:00 BT) and obtain the daily-averaged SAT by calculating the arithmetic mean of the temperature values observed for each time per day.

- 2) Satellite remote sensing data. The remote sensing data used in this study were Landsat data from the United States' EOS (Earth Observation System) for the detection of earth resources and the environment. Specifically, this study uses the remote sensing images of the Landsat-7/ETM+ (Yao et al., 2010) and Landsat-8/OLI (Saputra et al., 2017) sensors to study the changes in the observation environment of the stations relocated before 2013 and after 2013, respectively. A comparison of the band information of the above two remote sensing images is given in **Table 1**.

Methods

Selecting Samples for Relocated Stations

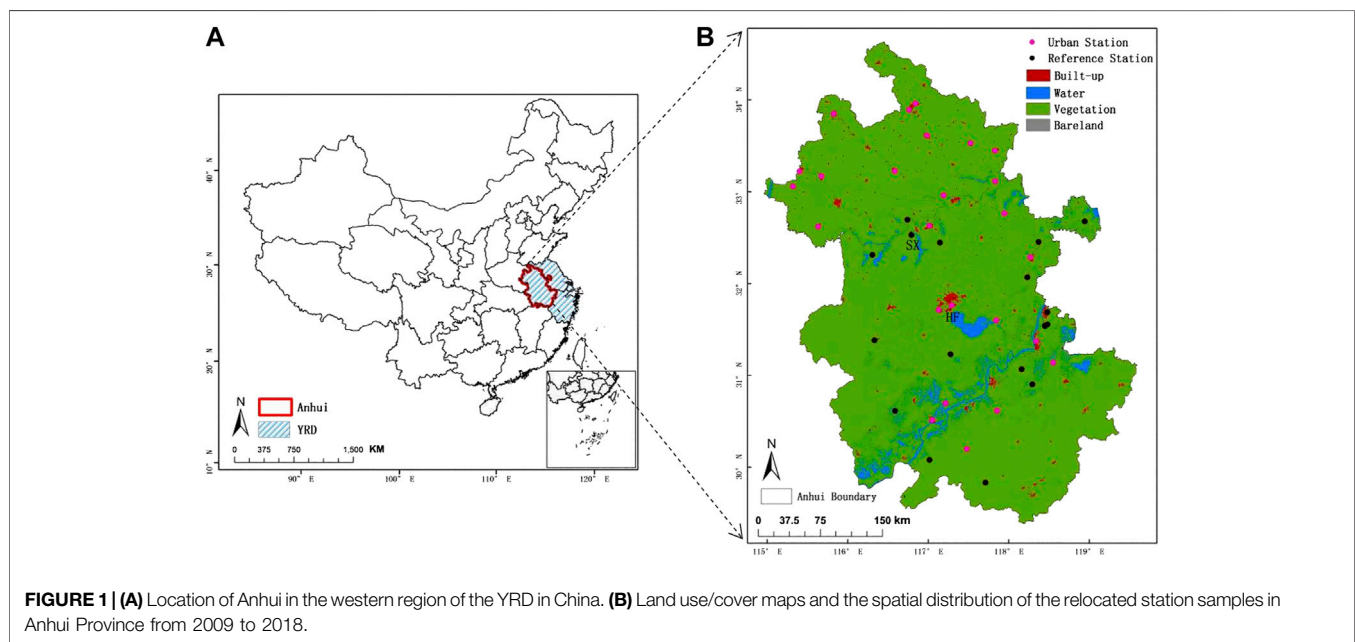
For this study, we selected meteorological stations with site-relocation history as the research samples from 2009 to 2018, according to the historical evolution data and comparative observation data of the relocated stations, surveys and evaluation reports of the observation environment of the national ground meteorological stations, and high-resolution satellite remote sensing images. The selection criteria were as follows: 1) the main reason for the relocation was that the observation environment of the station had been seriously damaged; 2) in order to minimize the influence of the difference of regional and local climate background, the difference in altitude between the sites (before and after relocation) was less than 50 m, and a horizontal distance between the sites of 20 km was selected according to previous studies (Wen et al., 2019; Shi et al., 2011); 3) there was no significant difference in topography; and 4) the type of observation instrument, the frequency of daily observations, and daily mean methods of temperature series did not change before and after station relocation. Based on the above criteria, 42 samples of relocated stations were selected, as shown in **Figure 1**. The relocated station samples include 25 urban stations and 17 reference stations, according to the meteorological station classification method of Ren et al. (Ren et al., 2010), and the samples were evenly distributed throughout northern Anhui, the Yangtze–Huaihe region, Yangtze River area, southern Anhui, and other regions. Therefore, the samples in this study can represent the impact of the urbanization development level of different regions in Anhui Province on different types of stations.

Determining the Research Range of the Station Buffer Zone

Studies (Cai, 2008; Yang et al., 2013; Shi et al., 2015; Yang et al., 2020a) have shown that since the observation height of the thermometer shelter in the observation field is 1.5 m, the maximum impact of urbanization on the observation data usually does not exceed 5 km under advection and turbulence

TABLE 1 | Comparison of band information between the Landsat-7/ETM+ and Landsat-8/OLI sensors.

Band no	Landsat-7/ETM+ sensor		Landsat-8/OLI sensor	
	Wavelength (μm)	Spatial resolution (m)	Wavelength (μm)	Spatial resolution (m)
1	0.45–0.515	30	0.433–0.453	30
2	0.525–0.605	30	0.450–0.515	30
3	0.63–0.690	30	0.525–0.600	30
4	0.75–0.90	30	0.630–0.680	30
5	1.55–1.75	30	0.845–0.885	30
6	10.40–12.50	60	1.560–1.660	30
7	2.09–2.35	30	2.100–2.300	30
8	0.52–0.90	15	0.500–0.680	15
9			1.360–1.390	30
10			10.60–11.19	100
11			11.50–12.51	100



transport conditions. Therefore, for this study, we selected a station buffer zone with a center radius of 5 km to quantitatively study the impact of environmental changes on the SAT series.

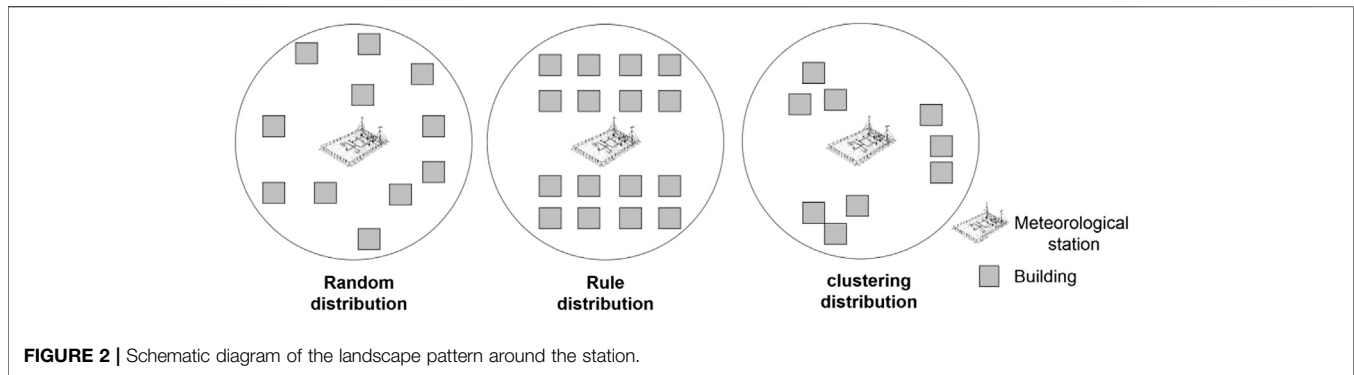
Establishing a Dataset of Characterization Parameters of the Observation Environment in the Buffer Zone

Land-use parameters (Carolina et al., 2013) reflect the results of various land resource utilization activities produced by human beings, which are an important part of urban environmental change research. This study uses the supervised classification method to classify land use in ENVI software and establishes four parameter indicators: built-up area ratio (AR_{BT}), water area ratio (AR_W), vegetation area ratio (AR_V), and bare land area ratio (AR_B).

The landscape parameters mainly include the largest patch index (LPI) (Wu, 2000) and the mean fractal dimension (FRAC_MN) (Wu, 2000) of the land type. The LPI represents the dominant land

type in the study area. The larger the LPI value, the more obvious the advantage of this type of patch in the overall landscape. The FRAC_MN represents the index of the patch shape. The larger the FRAC_MN, the more complex the shape of the patch and the more discrete the patch distribution. For this study, eight parameter indicators were calculated in the landscape index software Fragstats, including the built-up largest patch index (LPI_{BT}), water largest patch index (LPI_W), vegetation largest patch index (LPI_V), bare land largest patch index (LPI_B), built-up mean fractal dimension ($FRAC_{MN_{BT}}$), water mean fractal dimension ($FRAC_{MN_W}$), vegetation mean fractal dimension ($FRAC_{MN_V}$), and bare land mean fractal dimension ($FRAC_{MN_B}$).

The geometric parameters mainly include the distance between the stations and the gravity centers of different land types in the buffer zone, and the distance between the station and the city center (Liu et al., 2014). For this study, we used ArcGIS software to extract the land types of “built-up,”



“water,” “vegetation,” and “bare land” in the station buffer zone, then used the “Calculate Geometry” function to obtain the gravity centers of the different land types, and finally, the “Point Distance” function could then be used to calculate four parameter indicators, including the distance between the station and the gravity center of built-up land (DIS_{BT}), water (DIS_W), vegetation (DIS_V), and bare land (DIS_B). In the same way, the parameter indicator of the distance between the station and the city center (DIS_C) could be obtained in the ArcGIS software.

The current urbanization bias correction scheme still has deficiencies, mainly due to the limited assessment indicators for local observation environment around meteorological stations. Landscape ecological morphology (Figure 2) can be used to explore the relationship between the spatial pattern of urban land use and urban local microclimate (Zhou et al., 2011; Estoque et al., 2017). Landscape composition can distinguish land-use types, and landscape configuration can fully consider the respective geographic characteristics of different land-use types. In addition to the conventional land-use assessment indicators, therefore, our present work employs landscape ecological indicators and geometric indicators to assess observation environment around station. Finally, based on correlation analysis, six indicators, that is, AR_{BT} , AR_W , LPI_{BT} , LPI_W , DIS_{BT} , and DIS_W , were finally selected.

Simulation and Correction Method for the Urbanization Bias in the SAT Series

This article starts with the physical causes of the impact of urbanization bias on the observation environment and simulates the degree of impact of the urbanization bias on the SAT series by constructing statistical models of SAT_{DON} and DOEFs. Multiple linear regression is a statistical analysis method to determine the quantitative relationship between a dependent variable and multiple independent variables (Lynn, 2007; Li, 2020). Assuming there is a linear correlation between the dependent variable Y and the k independent variables X_1, X_2, \dots, X_k , then the functional relationship between Y and X can be expressed as:

$$Y = \beta + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon, \quad (1)$$

where β is the regression constant; $\beta_1, \beta_2, \dots, \beta_k$ are the regression coefficients; and ε is the regression residual.

After substituting the land-use, landscape, and geometric parameters in the buffer zone around the station into Eq. 1, the simulated values of the changes in the SAT series could be obtained, and then the urbanization bias could be corrected by the simulated values:

$$T'_i = T_i - \Delta T_i. \quad (2)$$

Here, i is the year number from the earliest year of recording to the latest year of correcting, T'_i is the annual average SAT after correction in the i th year ($^{\circ}C$), and ΔT_i is the change in the annual average SAT series caused by urbanization bias in the i th year compared with the earliest observation year ($^{\circ}C$).

RESULTS

Case Analysis of a Typical Station

Hefei National Meteorological Observation Station had been completely surrounded by built-up land before relocation because of the process of urbanization in recent years (Figure 3); the observational environment score of Hefei station was only 63.2. After relocation, Hefei station moved 30.2 km to the northwest of the old site, with an altitude difference of 6.0 m, and the observation environment of the station greatly improved, with the score increased to 99.3.

Table 2 shows the DOEFs between the old and the new stations in the 5-km buffer zone. AR_{BT} decreased from 42.17 to 4.23% after relocation, indicating that the area of built-up land around the station was greatly reduced; the $FRAC_{MN_{BT}}$ declined to a certain extent, indicating that the distribution of built-up patches around the station was more concentrated than before relocation; and DIS_{BT} increased from 0.53 to 3.13 km, indicating that the built-up land type had weakened the urbanization impact of the station after relocation. The parameters of water, vegetation, and bare land also improved to varying degrees. In addition, the SAT_{DON} in 2018 showed that the annual average SAT of the new station (Figure 3B) was $0.83^{\circ}C$ lower than the old station (Figure 3C) and the decline reached 4.8%. In summary, the representativeness of the observation environment at Hefei station improved after relocation, and the SAT_{DON} could represent the degree of the impact of the urbanization bias on the SAT series.

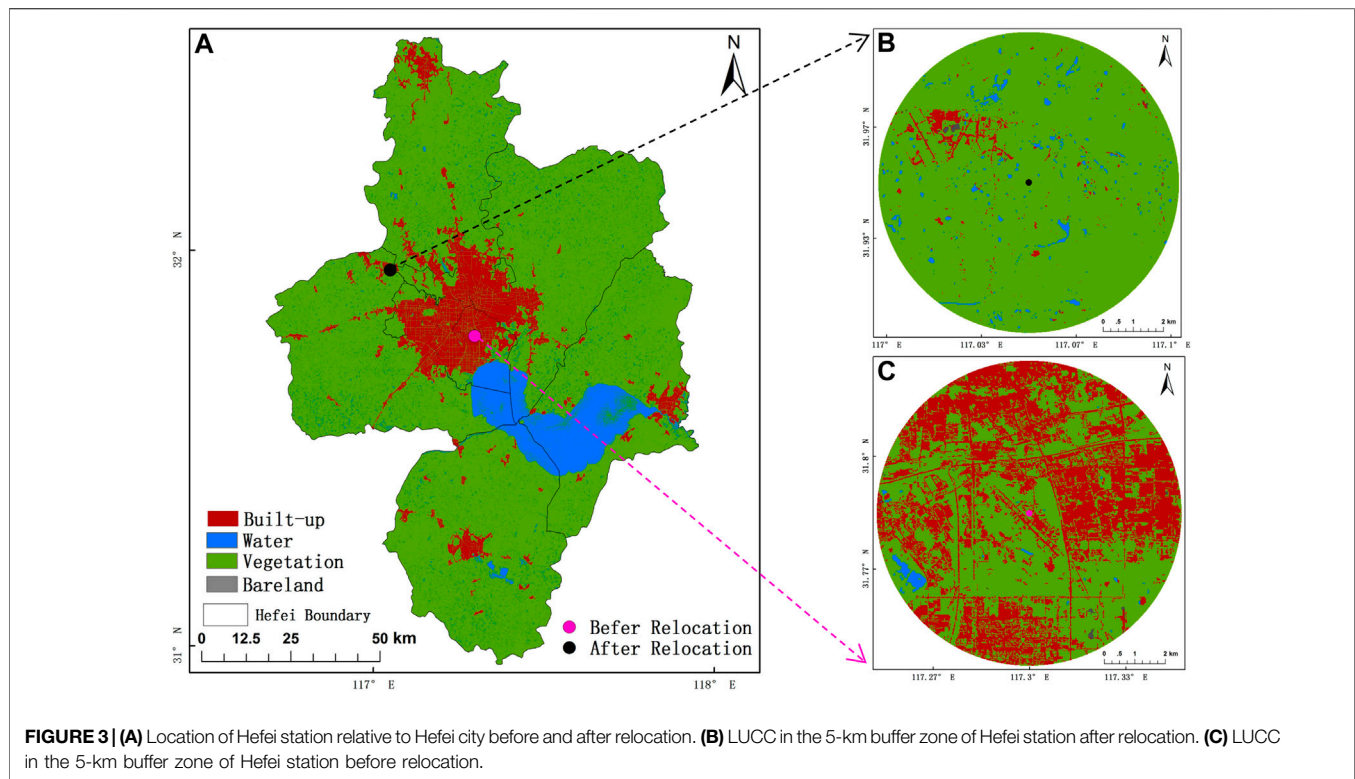


TABLE 2 | DOEFs in the 5-km buffer zone of Hefei station after and before relocation.

	Parameter	After relocation	Before relocation
Land-use parameters	AR _{BT} (%)	4.23	42.17
	AR _W (%)	3.11	1.01
	AR _V (%)	91.09	56.04
	AR _V (%)	0.57	0.78
Landscape parameters	LPI _{BT}	5.97	24.73
	LPI _W	1.13	0.30
	LPI _V	60.18	38.88
	LPI _B	0.73	0.91
	FRAC_MN _{BT}	1.04	1.14
	FRAC_MN _W	1.18	1.09
	FRAC_MN _V	1.11	1.17
Geometric parameters	FRAC_MN _B	1.09	1.14
	DIS _{BT} (km)	3.13	0.53
	DIS _W (km)	1.73	3.69
	DIS _V (km)	0.02	0.87
	DIS _B (km)	1.28	1.01
	DIS _C (km)	2.1	8.3

Analyzing the Statistical Characteristics of the Samples' Daily Average Differences

For this section, daily-averaged SAT_{DON} series were close to a normal distribution and fluctuated in the range of -2.3 – 4.4°C (Figure 4). The sample size, mean, and standard deviation were 15,347, 0.572, and 0.568°C (Table 3), respectively. The above

statistics showed that the sample had a large variation range, but the data distribution was mainly concentrated near the mean value, and the overall sample volatility was relatively small. The kurtosis value of the sample was 2.057, the number of samples with a daily-averaged SAT_{DON} of 0.4°C was the largest, reaching 1,515, and the number of samples with a daily-averaged SAT_{DON} at 0.2 – 0.8°C reached 9,193, accounting for 59.6% of the total number of samples, indicating that the daily-averaged SAT_{DON} series was steeper than the normal distribution. The sample skewness value was 0.673, and the number of daily-averaged SAT_{DON} values greater than the mean was 8,226, accounting for 53.6% of the total sample and indicating that there were more points on the right-hand side of the data distribution, close to the mean.

In addition, there were 828 negative values in the sample, accounting for 5.39% of the total number of samples, which means that the SAT series of the old stations were lower than the new sites (Figure 4). The influence of the meteorological station observation environment on the SAT series was more complicated. Buildings cause the wind speed to decay downwind and reduce air circulation in the observatory, thereby enhancing the locality of temperature observation. However, under unstable stratification conditions during the daytime, the shadowing effect of solar radiation caused by buildings and aerosol cooling effects might make the SAT observed by the stations surrounded by buildings lower than the stations with open terrain (Li et al., 2011; Zheng et al., 2018; Zheng et al., 2020; Yang et al., 2020b).

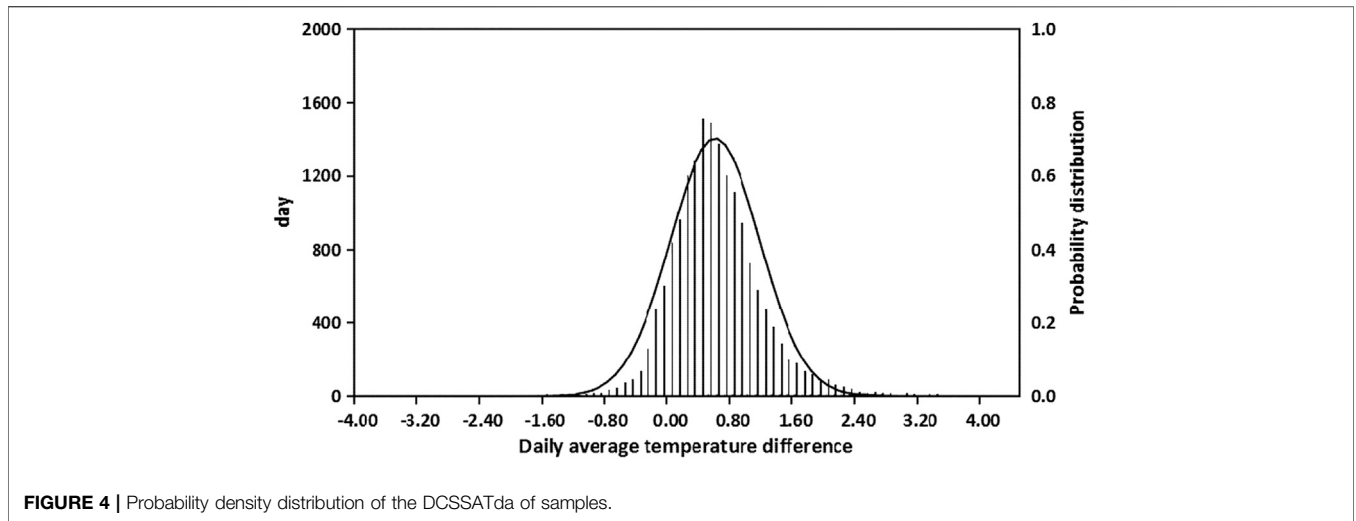


FIGURE 4 | Probability density distribution of the DCSSATda of samples.

TABLE 3 | Statistics of the DCSSATda of samples.

Data series	Sample size	Median (°C)	Mean (°C)	Standard deviation (°C)	Kurtosis	Skewness
ΔT_{avg}	15,347	0.500	0.572	0.568	2.057	0.673

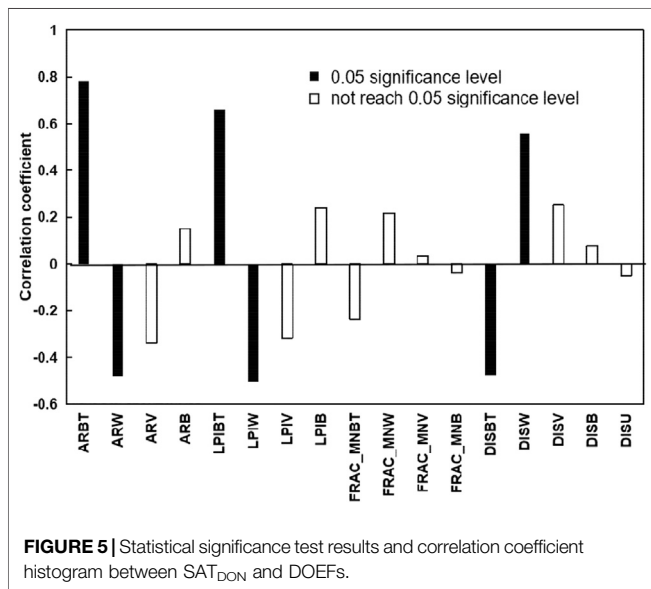


FIGURE 5 | Statistical significance test results and correlation coefficient histogram between SAT_{DON} and DOEFs.

Correlation Analysis of SAT_{DON} and DOEFs

A total of 37 samples were selected from the relocation samples to analyze the correlation between SAT_{DON} and DOEFs, and existing buffer parameters were filtered in order to establish a revised model of urbanization deviation in the next step. Figure 5 presents the statistical significance test results and correlation coefficient histogram between the SAT_{DON} and DOEFs, in which the solid bars represent the significance level of the correlation reaching 0.05, while the hollow bars represent the opposite.

SAT_{DON} had a significant positive correlation with AR_{BT} after relocation, and the correlation coefficient reached 0.7843, which passed the significance level of 0.05. SAT_{DON} and AR_W showed a significant negative correlation, with a correlation coefficient of -0.4819 , which also passed the significance level of 0.05. This showed that with the continuous increase in built-up land around the meteorological station, the decrease in heat capacity of the underlying surface and the increase in anthropogenic heat in the buffer zone led to warming in the SAT series. The heat capacity of water bodies is relatively large, meaning heat in the buffer zone of a station could be taken away as water evaporates, which would lead to a drop in the SAT series (Zeng et al., 2010). In addition, the SAT_{DON} also had a high correlation with LPI_{BT} , LPI_W , DIS_{BT} , and DIS_W after relocation, which showed that the more obvious the advantages in the buffer landscape and the closer the distance of the station to the built-up center of gravity, the greater the SAT_{DON} , while for water this was opposite. Accordingly, this article uses six indicators (AR_{BT} , AR_W , LPI_{BT} , LPI_W , DIS_{BT} , and DIS_W) to study the response SAT_{DON} to the change in the DOEF in the buffer zone.

Simulation and Accuracy Evaluation of Urbanization Bias in the Annual Average SAT Series

The parameter indicators in the buffer zone have undergone great changes after relocation. As shown in Figure 6, the change values in the proportion of built-up area (ΔAR_{BT}) of all the relocation samples were positive, which shows that the area of built-up land around the relocated stations was reduced and 92.18% of the ΔAR_{BT} values were concentrated in the range of 0–50%. The

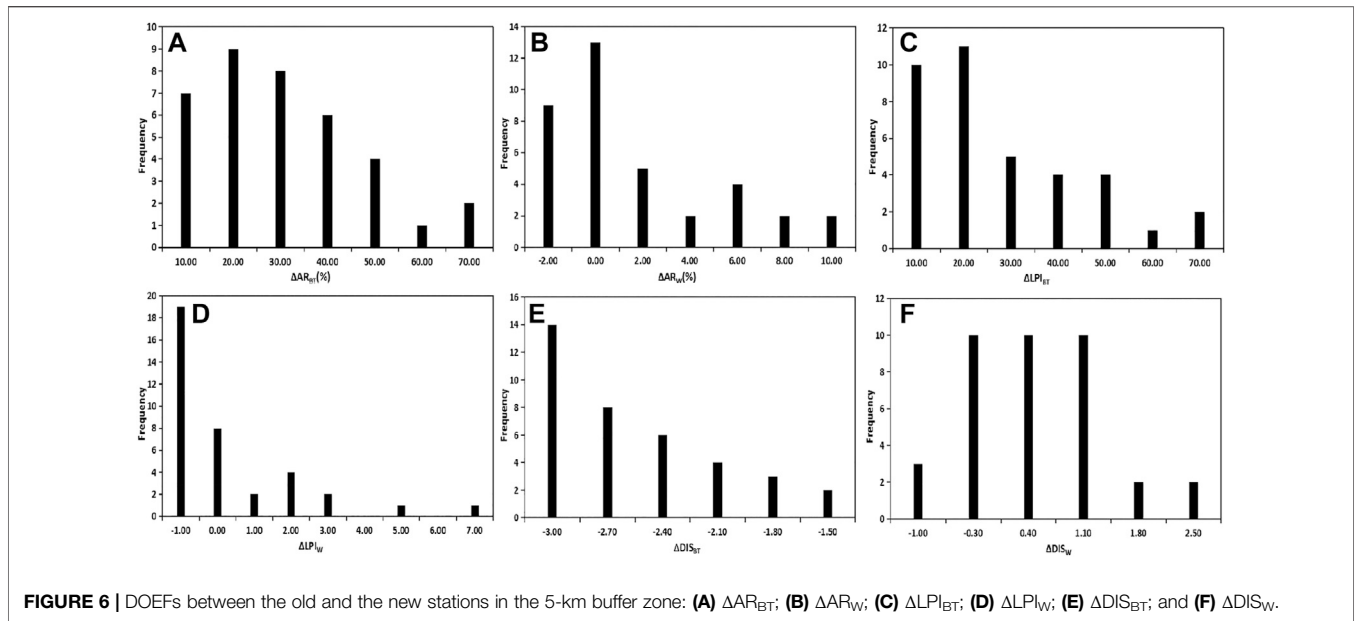


FIGURE 6 | DOEFs between the old and the new stations in the 5-km buffer zone: (A) ΔAR_{BT} ; (B) ΔAR_W ; (C) ΔLPI_{BT} ; (D) ΔLPI_W ; (E) ΔDIS_{BT} ; and (F) ΔDIS_W .

TABLE 4 | Coefficient of determination (R^2) for stepwise regression of the fitting model.

Model	R^2	Standard deviation of the estimation
1	0.927	0.265
2	0.931	0.237
3	0.939	0.222
4	0.943	0.214
5	0.953	0.209

number of stations with a negative change value in water area ratio (ΔAR_w) reached 22, which showed that the water area of most stations increased after relocation. The change values of the built-up LPI (ΔLPI_{BT}) of all the relocation samples were positive, and 92.18% of the ΔLPI_{BT} values were concentrated in the range of 0–20. The number of stations with a negative change value of water LPI (ΔLPI_w) also reached 22, which showed that the water advantage of most stations increased after relocation. All the change values of the distance between the station and the built-up center of gravity (ΔDIS_{BT}) were negative, which showed that all samples of relocated stations were far away from the center of gravity of built-up patches. The change value of the distance between the station and the built-up center of gravity (ΔDIS_{BT}) was negative, revealing that all samples of relocated stations were far away from the center of gravity of built-up patches. The number of stations with a positive change value of the distance between the station and the water center of gravity (ΔDIS_w) reached 24, which showed that most samples of relocated stations were close to the center of gravity of built-up patches.

For this part of the study, we used statistics to analyze the response relationship between the SAT_{DON} and DOEFs and simulate the impact of the urbanization bias on the SAT series. The sample was subjected to colinearity diagnosis in SPSS; the statistical models of SAT_{DON} and DOEFs were constructed finally:

TABLE 5 | Accuracy evaluation of urbanization bias in the average SAT series.

Station no	ΔT_{avg}	Simulation value	Simulation error (%)
58,122	0.941	0.993	5.52
58,214	0.593	0.701	18.21
58,338	0.602	0.692	14.95
58,109	0.852	0.921	8.10
58,220	0.383	0.397	3.66

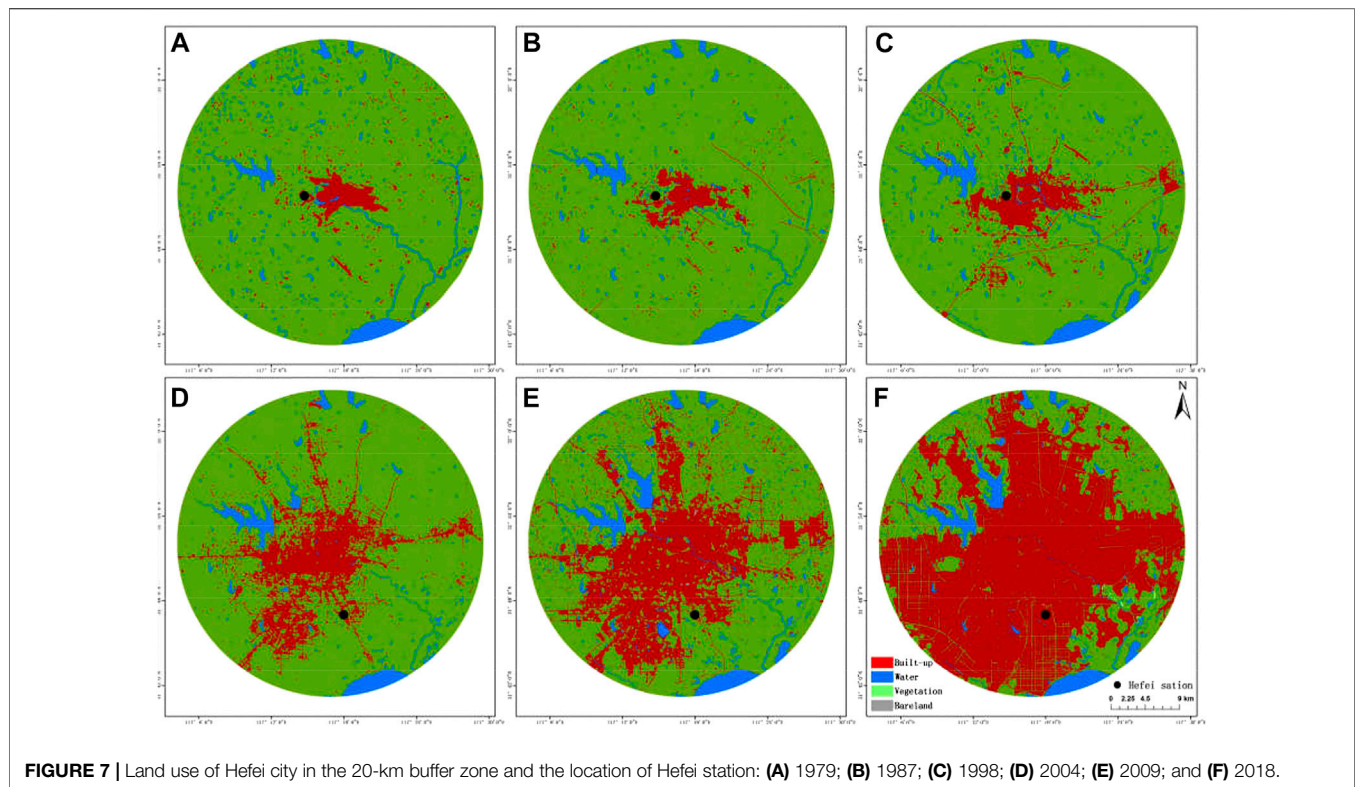
$$\Delta T_{avg} = 2.085 \times \Delta AR_{BT} - 1.515 \times \Delta AR_w - 0.017 \times \Delta LPI_w - 0.039 \times \Delta DIS_{BT} + 0.133 \times \Delta DIS_w. \quad (3)$$

Here, ΔT_{avg} is the annual averaged SAT_{DON} of meteorological stations. **Table 4** shows coefficient of determination (R^2) for stepwise regression of the fitted model. With the increase of independent variable, the R^2 of the model increases. The R^2 of the fitting model finally reached 0.953, which passed the 0.05 significance test, indicating that the above five influencing factors have a crucial impact on SAT_{DON} .

According to **Eq. 3**, the change values of the annual average SAT of the remaining five relocated stations in the sample were simulated to compare with the real change value of the sample. As shown in **Table 5**, the difference between the simulated and real value fluctuates in the range of 0.014–0.108°C. The simulation error range is 3.66–18.21%, and the average error is 10.09%.

DISCUSSION

The conventional correction method (Zhang, 2009; Zhang, 2014; Wen et al., 2019a) involves gradually decreasing the annual average urbanization impact from the earliest year of the target station series. The corrected series represents the



regional annual average SAT series in which the urbanization bias has been removed:

$$T'_i = T_i - (\Delta T_{u-r}/10) \times (i - 1). \quad (4)$$

Here, i is serial number from the earliest year of recording to the latest year of correcting, T'_i is the annual average SAT after correction in the i th year ($^{\circ}\text{C}$), T_i is the annual average SAT before correction in the i th year ($^{\circ}\text{C}$), and ΔT_{u-r} is the difference in the SAT warming rate between the urban and reference station ($^{\circ}\text{Cdecade}^{-1}$). It should be noted that **Eq. 4** has an assumption that the urbanization bias shows a linear growth trend.

For this part of the study, we take the annual average SAT series of Hefei station from 1953 to 2018 (homogenization correction was carried out to remove discontinuities or jumping points caused by the relocation) as an example to discuss the correction of the urbanization bias. The ΔT_{u-r} of Hefei station was $0.065^{\circ}\text{Cdecade}^{-1}$ with Shouxian station selected as the reference station (see **Figure 1**).

Because remote sensing images before the 1950s are not easy to obtain, and the observation environments of meteorological stations were basically unaffected by urbanization, we set the initial value of the various parameters in the station buffer zone in the earliest record year to be 0.

We used the new correction method based on remote sensing to correct the urbanization bias of Hefei station. According to the development process of Hefei's urbanization, the remote sensing image of six times (1979, 1987, 1998, 2004, 2009, and 2018) covering the Hefei area was selected (**Figure 7**). The five

parameters of AR_{BT} , AR_W , LPI_W , DIS_{BT} , and DIS_W were interpreted and substituted into **Eq. 3** to obtain the change values of the annual average SAT series, and then the urbanization bias was corrected using **Eq. 2**. In addition, we also used the CCM to correct the urbanization bias of Hefei station in the above the remote sensing image of six times, and the results obtained by the CCM and NCM methods were compared and analyzed.

The correction results obtained by the CCM were higher than those of the NCM (**Table 6**). The CCM did not take into account the impact of the urbanization bias on the reference station, and therefore, the urbanization bias obtained from the reference station was the minimum estimate.

The rate of urban development in Hefei was relatively slow before 2004. From 2004 to 2018, the total GDP of Hefei increased by ¥723.321 billion, with an annual average growth rate of 81.77%, and its economic growth rate ranked first in the YRD region (National Bureau of Statistics, 2019). The warming rate in the SAT series caused by the urbanization bias should change with economic development, but the warming rate at Hefei station obtained by the CCM was a fixed value ($0.065^{\circ}\text{Cdecade}^{-1}$), and this assumption that the impact of urbanization increases linearly year by year over time is questionable (Zhang, 2009). The results of the NCM show that the urbanization bias of Hefei station increased gradually from 0.233 to 0.457°C from 1979 to 1998. Due to the relocation of Hefei station in 2004, the observation environment improved significantly, and the NCM-based urbanization bias between 2004 and 2009 did not increase much, but the CCM-based

TABLE 6 | Comparison of results between the CCM and NCW at Hefei station.

Year	Observation (°C)	Urban bias (°C) (CCM)	After correction (°C) (CCM)	Urban bias (°C) (NCM)	After correction (°C) (NCM)	GDP
1979	16.124	0.169	15.954	0.233	15.891	-
1987	15.796	0.221	15.575	0.314	15.482	-
1998	17.129	0.293	16.836	0.457	16.672	270.47
2004	16.633	0.332	16.301	0.248	16.385	589.70
2009	16.720	0.364	16.356	0.436	16.284	2,102.12
2018	17.062	0.423	16.639	0.851	16.211	7,822.91

urbanization bias was increasing over time because station relocation was not taken into account. The urbanization bias of Hefei station increased quickly from 0.436 to 0.851°C as the city experienced rapid development from 2009 to 2018. The NCM constructed in this study produces results that are dynamically consistent with the observation environment of the station and the development of the city. In summary, the present work study mainly focused on the sample application exploration of our new urbanization bias correction method, which can make up for the shortcomings of the conventional linear method. We will find more relocation stations in the whole Yangtze River Delta region to extend our new method application in the future.

Based on the R^2 of the fitted results (Table 4), it is clear that all the selected parameters can explain more than 90% of the urbanization bias. In addition, urbanization is not only reflected by the two-dimensional horizontal urban expansion but also by the vertical morphology of the three-dimensional urban spatial structure. Previous studies suggested that the vertical geometry of urban canopy building also had an impact on local microclimate (Oke, 2004; Bonacquisti et al., 2006; Chen et al., 2020). In the future, we will expand three-dimensional indicators to supply the indicators of urbanization bias correction.

CONCLUSION

In this study, we selected 42 meteorological stations with site-relocation history in the western region of the YRD from 2009 to 2018 as research example samples and then utilized annual SAT_{DON} series between the old and the new stations to characterize the impact of the urbanization bias on SAT series. We proposed a new method for correcting urbanization-induced bias in surface air temperature observations based on comparative site-relocation data. The main conclusions are as follows.

Spatial land-use, landscape, and geometric parameters of the underlying surface in the 5-km buffer zone around the station were good to be as the DOEFs of the site. The comparative analysis revealed that parameters such as AR_{BT} , AR_W , LPI_{BT} , LPI_W , DIS_{BT} , and DIS_W in DOEFs had the highest correlation with SAT_{DON} , with absolute values of correlation coefficients exceeding 0.4, passing the 0.05 significance test. After colinearity diagnosis, a new linear regression model between five parameters (AR_{BT} , AR_W , LPI_W , DIS_{BT} , and DIS_W) and SAT_{DON} was finally

constructed to correct urbanization bias, which clearly reflected the effects of rapid and slow phases of urbanization and environmental changes around the site on the observed SAT. The CCM did not take into account that the reference station was affected by the urbanization, which may underestimate urbanization bias. In addition, CCM cannot consider the station relocation situation, which may overestimate urban bias when the station relocated. In contrast, the NCM constructed in this study can make up these shortcomings to correct the urbanization bias caused by local human activities more reasonably and effectively and can also reduce the error caused by the selection of reference stations in the traditional urban-rural comparison method.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, and further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

TS: methodology, formal analysis, results and discussion, and writing—original draft preparation; DS, discussion, and writing reviewing and editing; YH, discussion, and writing reviewing and editing; GL, discussion, and writing reviewing and editing; YY: conceptualization, data curation, methodology, results and discussion, and writing—reviewing and editing.

ACKNOWLEDGMENTS

This study was supported by the National Key R and D Program of China (Fund No: 2018YFC1506502), NSFC-DFG (42061134009) and the Beijing Natural Science Foundation (8202022 and 8171002). The data that support the findings of this study are openly available. The Meteorological Information Center of the China Meteorological Administration provided the meteorological data (<http://data.cma.cn/site/index.html>); and the remote sensing data used in this study were Landsat data from the United States' EOS (Earth Observation System) refined by Department of Earth System Science/Institute for Global Change Studies Tsinghua University (<http://data.ess.tsinghua.edu.cn/>).

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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