Influence of Changes in Meteorological Observational Environment on Urbanization Bias in Surface Air Temperature: A Review

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It is important to quantify changes in the local meteorological observational environment (MOE) around weather stations if we are to obtain accurate assessments of the regional warming of the surface air temperature (SAT) in relation to urbanization bias. Current studies often use two-dimensional parameters (e.g., the land surface temperature, land use/land cover and the normalized difference vegetation index) to characterize the local MOE. Most of the existing models of the relationship between urbanization bias in SAT series and MOE parameters are linear regression models, which ignore the non-linear driving effect of MOE changes on SAT series. By contrast, there is a lack of three-dimensional parameters in the characterization of the morphological features of the MOE. Changes in the MOE related to urbanization lead to uncertainties in the contribution of SAT series on different scales and we need to introduce vertical structure indexes to enrich the three-dimensional spatial morphology of MOE parameters. The non-linear response of urbanization bias in SAT series to three-dimensional changes in the MOE and its scale dependence should be explored by coupling computational fluid dynamics model simulations with machine learning.

Keywords: meteorological observational environment, urbanization bias, regional warming, scale dependency, spatial morphology

INTRODUCTION

The meteorological observational environment (MOE) around weather stations is fundamental to the accurate and continuous recording of the meteorological elements used for disaster prevention and mitigation, economic development, public health decision-making and climate change adaptation (Ren et al., 2007, 2015; Luo and Lau, 2018, 2019; Zheng et al., 2021). The MOE of stations changes with rapid urbanization, which leads to inhomogeneities in the surface air temperature (SAT) series (Li, 2011; Yan et al., 2014; Cao et al., 2016; Du et al., 2020). For example, local changes in the microclimate immediately surrounding the thermometer shelter mean that the temperature records of poorly exposed stations are likely to contain non-climate biases that are not representative of the climate in the surrounding area (Davey and Pielke, 2005; Yilmaz et al., 2008). We refer to these non-climate biases as urbanization bias

(Zhang, 2009; Connolly and Connolly, 2014). Urbanization bias has become an important cause of systematic bias in the SAT in China, leading to uncertainties in regional and even global climate change predictions (Mahmood et al., 2006; Ren et al., 2017; Tysa et al., 2019; Wen et al., 2019). Quantitative analysis of the effects of environmental change on urbanization bias in the SAT is fundamental work at the forefront of climate change research.
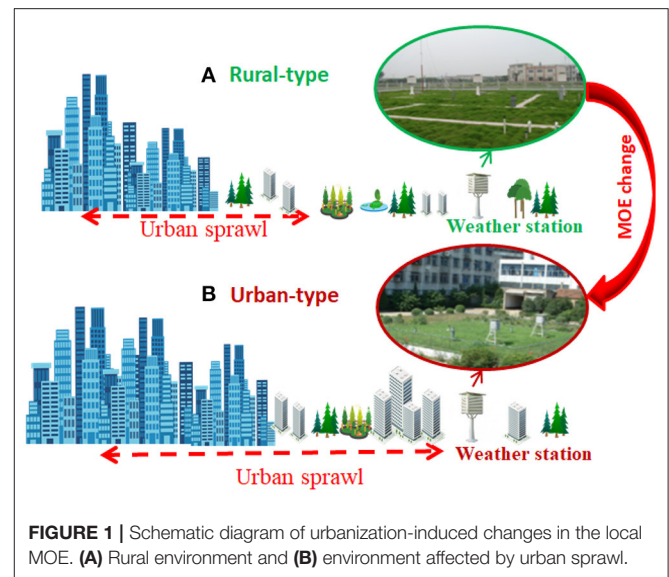
According to the World Meteorological Organization, the observational biases caused by changes and disruptions in the MOE are usually greater than instrumental errors and may even completely drown out signals of climate change (Watts, 2009). The impact of changes in the local MOE related to urbanization bias on the SAT should therefore be quantified in large-scale studies of climate change (Brohan et al., 2006; Zhang, 2009; Soon et al., 2018). The spatial morphological characteristics of the MOE around a weather station are important in driving urbanization bias in the SAT (Erell et al., 2011; Shi et al., 2021). Previous studies have attempted to quantify the contribution of this urbanization bias to regional warming by using the results from surface stations (Jones et al., 2007; Menne et al., 2010; Ren et al., 2010a; Fall et al., 2011; Stewart and Oke, 2012; Estoque et al., 2017; Scarano and Mancini, 2017), although this is still controversial as a result of uncertainties in quantifying the impact of the MOE on urbanization bias.

This paper summarizes and reviews recent progress in the characterization of the spatial morphology of the MOE, the relationship between changes in the MOE and the urbanization bias in SAT series, and considers future research directions.

RESEARCH PROGRESS ON THE CHARACTERIZATION OF THE SPATIAL MORPHOLOGY OF THE MOE

An undisturbed MOE with long-term stability is required to obtain valuable, continuous, uniform and accurate observational data. Quantitative representation of the spatial morphology of the local MOE around weather stations is an important prerequisite in studies of urbanization bias. **Figure 1** shows that weather stations are usually sited far away from cities in the early stages of station construction and therefore their observed temperature series represents the local climate background (**Figure 1A**). The representation of the MOE continues to be damaged as urban sprawl encroaches the weather station (**Figure 1B**). The thermal properties of the underlying surface are changed by the addition of impervious surfaces and buildings around the station (**Figure 1B**) and the built-up area warms faster than the natural underlying surface under the same amount of solar radiation (Ren, 2015; Yang and Bou-Zeid, 2019).

Further, we take the Hefei station in eastern China as an example to discuss the changes of MOE from 1979 to 2018. **Figure 2** gives the distribution of land use within the 20-km buffer zone around the center of Hefei (Shi et al., 2021). In the last 40 years, the built-up area within 20 km of Hefei in 2018 is about 20 times larger than that in 1979, leading to the continuous deterioration of MOE. In 1979, the Hefei station was relocated

FIGURE 1 | Schematic diagram of urbanization-induced changes in the local MOE. **(A)** Rural environment and **(B)** environment affected by urban sprawl.
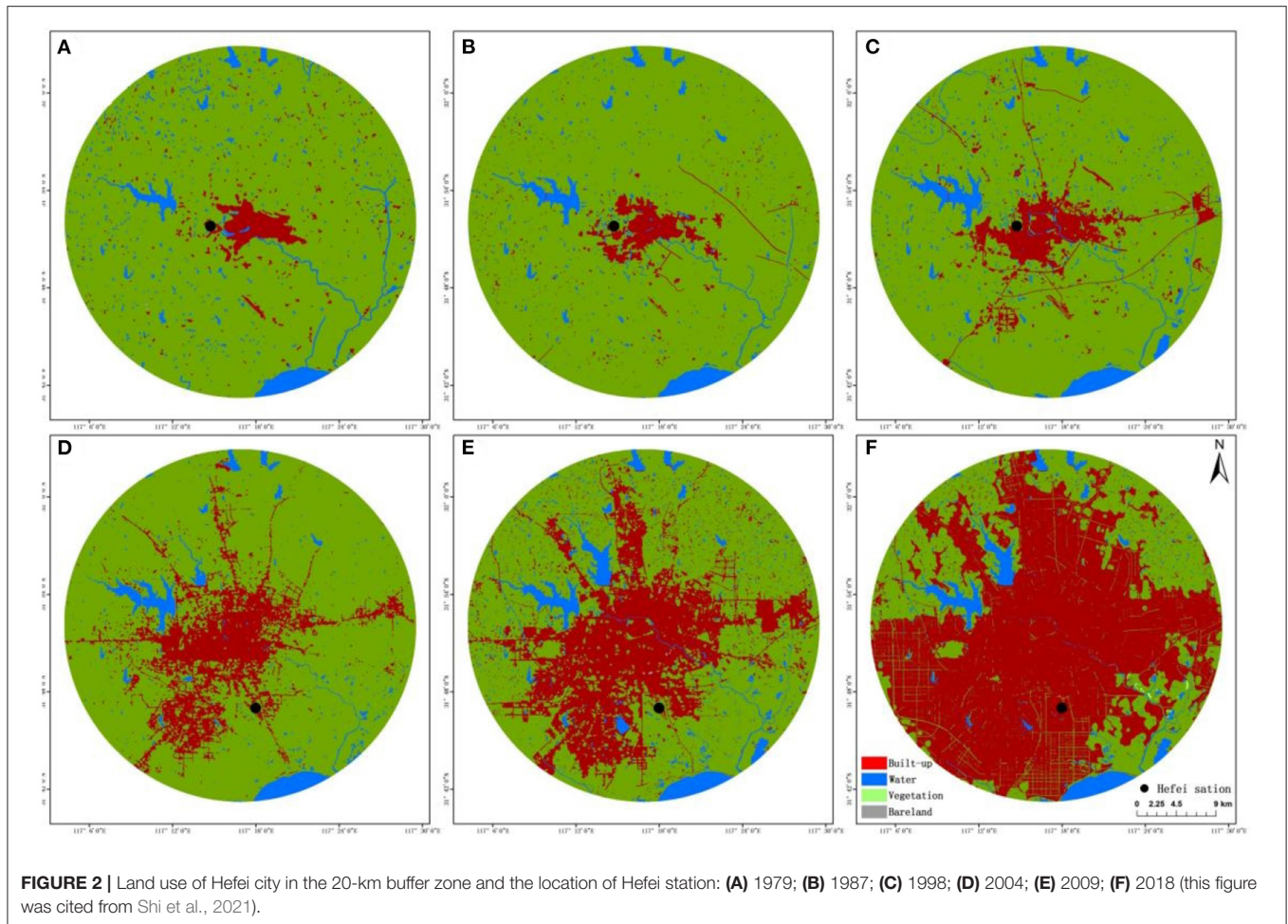
to the outskirts of the city (**Figure 2A**). As time went by, the residential and industrial land around the observation site was increasing, and by 1998 the urban sprawl had affected the MOE of Hefei station (**Figure 2C**). As a result, the site was relocated to the suburban area in 2004 (**Figure 2D**). 2018, when the MOE of the site was again destroyed (**Figure 2F**).

In addition, anthropogenic heat released from boilers, air conditioners and motor vehicles within the city is transferred via the urban boundary layer (Zhang et al., 2016, 2021; Yang et al., 2020a). The pollutants emitted exacerbate the urban heat island effect at night through the interaction of aerosols with solar radiation (Zheng et al., 2018). Greater air pollution can generate more intense nocturnal heat islands, for example, Yang et al. (2020b) suggested that the UHII at the time of daily maximum/minimum temperature (UHIImax/UHIImin) exhibits a decreasing/increasing tendency as $PM_{2.5}$ concentration increases, causing a continuous decrease in the diurnal temperature range (DTR), and these effects are mediated via aerosol-radiation interaction (aerosol-cloud interaction) under clear-sky (cloudy) condition.

Characterization Indexes of the Two-Dimensional Morphology of the MOE

Microclimate observation networks and high-density automated meteorological observation networks have been used to study the changing characteristics of meteorological observation sequences and to analyze the extent to which the MOE is affected by urbanization (Stewart and Oke, 2012; Liu et al., 2013). However, these methods are not suitable for large-scale use as a result of their high impact on natural conditions and social activities and the relatively high cost of construction and maintenance. The use of satellite data to study the representation of the MOE has become more common with the rapid development of remote sensing technology (Ren et al., 2010b; Ren and Ren, 2011; Yang et al., 2013; Li Y. et al., 2015; Shi et al., 2015, 2021). Satellite

FIGURE 2 | Land use of Hefei city in the 20-km buffer zone and the location of Hefei station: **(A)** 1979; **(B)** 1987; **(C)** 1998; **(D)** 2004; **(E)** 2009; **(F)** 2018 (this figure was cited from Shi et al., 2021).

remote sensing data cover a wide area and are periodic; they can therefore provide multi-temporal and large-scale information for the study of dynamic changes in the MOE. Computer image processing and pattern recognition technology can be used to effectively reproduce historical information about environmental changes, such as land use/cover types around a weather station (Yang et al., 2013; Zhang, 2014; Li Y. et al., 2015; Shi et al., 2021).

Many studies have used horizontal parameters [e.g., the land surface temperature (LST), land use/land cover (LULC), impervious surface area (ISA), the normalized difference vegetation index and the night-time light intensity] in the remote sensing monitoring and simulation of the MOE (Gallo et al., 1993; Imhoff et al., 1997, 2010; Schneider et al., 2009; Yang et al., 2011b,c, 2013; Yang X. et al., 2019; Li et al., 2021; Yu et al., 2021). For instance, Yang et al. (2011a) classified the urban and rural types of stations in different buffer areas by using night light intensity data in eastern China. Li Y. et al. (2015) found that stations can be regarded as rural type when the area ratio of the high-temperature in the 2-km buffer zone is <30%. Luo and Lau (2019) used land use/land cover to classify stations as urban and rural types to explore the urban dry island effect. In addition, a strong positive correlation between percentage of ISA and LST suggests that percentage of ISA can quantitatively describe

the spatial distribution and temporal variation of urban thermal patterns/and associated LULC and UHI intensity changes (Weng et al., 2011; Zhang et al., 2019).

The anthropogenic heat flux is closely related to changes in the built-up area around stations (Yang X. et al., 2019; Yang et al., 2020a; Chen G. et al., 2021; Zhang et al., 2021) and can reliably reflect the effects of both anthropogenic emissions and changes in land use related to the latent heat flux and the sensible heat flux. A characterization system of the MOE (the surface thermal environment class and the anthropogenic heat flux) centered on the thermal environment around a station has been developed based on remote sensing images and geographical information systems technology (Shi et al., 2015; Yang X. et al., 2019; Yang et al., 2020a,b; Zhang et al., 2021). This system solves the problem of the quantitative characterization of the influence of anthropogenic heat emissions on the SAT series under the effects of turbulent and horizontal advection.

However, the two-dimensional morphological indexes are limited to a single scientific discipline, which may not completely characterize the MOE and its impacts on observation. For example, in 2013, the national meteorological observational station in Anqing was surrounded by a high-density built-up area (**Figure 3A**), and the built-up area ratio within a of 5-km radius
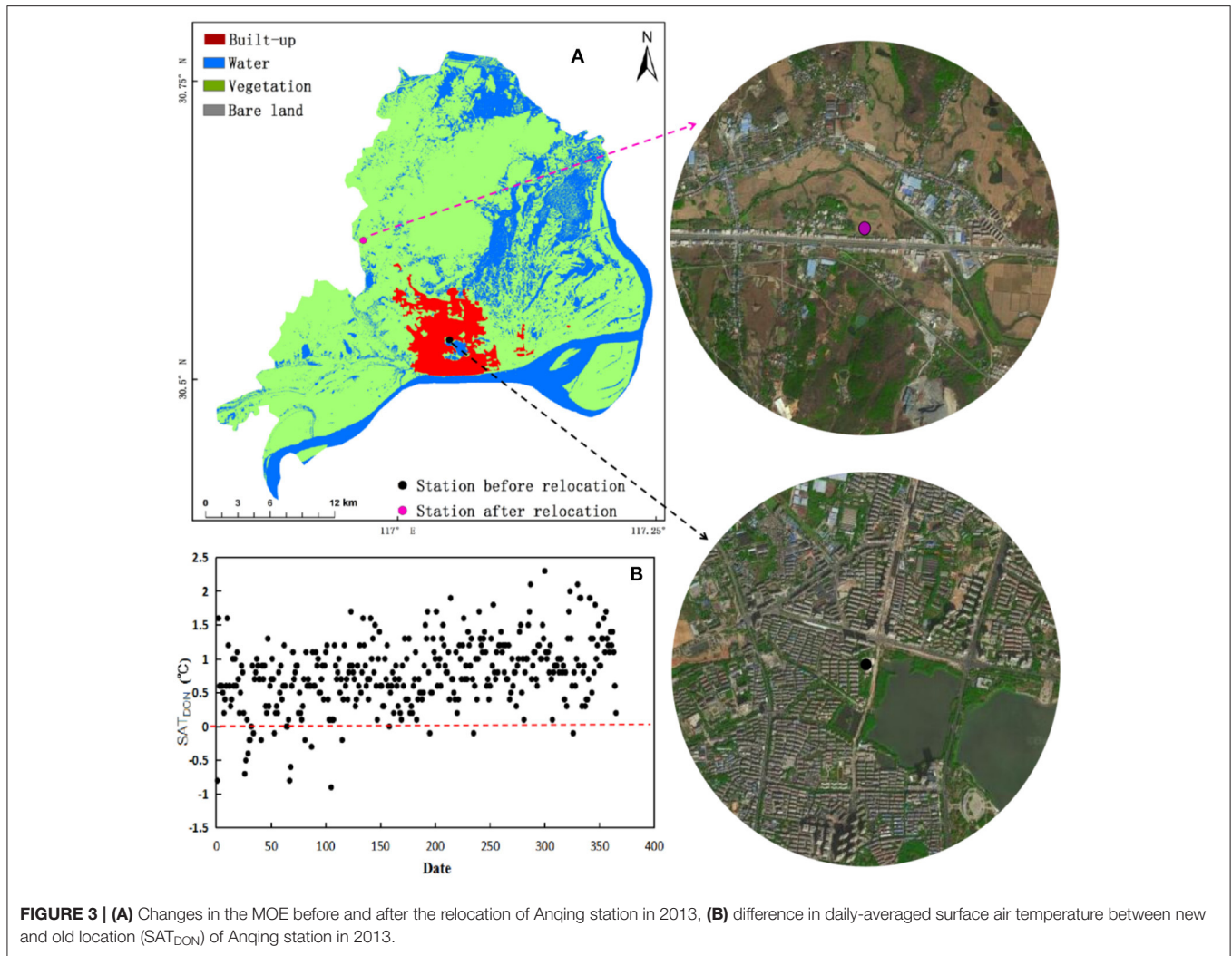
FIGURE 3 | (A) Changes in the MOE before and after the relocation of Anqing station in 2013, **(B)** difference in daily-averaged surface air temperature between new and old location (SAT$_{DON}$) of Anqing station in 2013.

buffer zone around station can reach 71.3%. Anqing station was therefore moved 12.5 km to the northwest of the old station, with an elevation difference of 6.0 m. Within a radius of 5 km, the proportion of buildings around the station decreased to 15.4%, and the MOE assessment score increased from 75 to 95 (MOE assessment conducted by the meteorological administration can be scored by 0–100, the high the score is, the better the MOE is). However, when comparing the synchronous observational data, we found that the daily average temperature of the new station was higher than that of the old station for 348 days after relocation and the annual average temperature was 0.76°C higher than that of the old station with a warming of 4.4% (**Figure 3B**). According to the current remote sensing assessment method, the MOE of the relocated Anqing station is greatly improved, but the SAT series is more significantly influenced by urbanization. Although the urban area within the MOE was significantly reduced after relocation, the new buildings to the east and northwest of the station were much taller than the old buildings. The structural layout of the planting, water bodies and buildings around the old station was well planned and effectively

mitigated the impact of urbanization on the thermal environment around the station.

Three-Dimensional Morphological Index System for the MOE

The spatial morphology within the MOE can be divided into horizontal and vertical morphologies, where the vertical morphology is characterized using indexes related to the heights of buildings (Shi et al., 2021).

The vertical geometry of buildings has a much greater impact on the local microclimate than other factors (Oke, 2004). Changes in the three-dimensional MOE, which consists of the horizontal structure and vertical morphology of buildings, may have a pronounced effect on both the SAT series and high-temperature heat wave events (Luo and Lau, 2018; Ngarambe et al., 2020; Zong et al., 2021). Tian et al. (2019) showed that the ratio of vegetation to building volume showed a significant negative correlation with temperature. The sprawl of urban buildings within the vertical space around a station affects the surface energy balance and air flow on the local scale, leading

to changes in the thermal environment (Wang et al., 2016). Particularly, the multi-reflections of sunlight among high-rise buildings are important as well to capture more solar radiation, which significantly increase the absorptivity of heat in the urban canopy to warm the urban (Ren, 2015), especially in the heat wave periods (Zong et al., 2021). Stewart and Oke (2012) defined the concept of a local climate zone using characteristic parameters (e.g., the sky view coefficient, the aspect ratio and the average building height). This is mainly applicable to urban heat island studies at large scales (Yang Y. et al., 2019; Zhang et al., 2019), whereas the micro-scale MOE cannot be finely depicted by a separate local climate zone unit.

Existing methods for three-dimensional morphological assessment of MOE are at an early stage and can not be ignored (Voogt and Oke, 2004; Davis et al., 2016; Zong et al., 2021). For instance, Davis et al. (2016) investigated the effect of three-dimensional morphology on nighttime air temperature at five spatial scales and found that building volume had the strongest ability to explain air temperature change within a 100 m radius from the meteorological stations. With the development of remote sensing and LiDAR technology, it is no longer difficult to obtain quantitative information on the vertical structure or height of the urban canopy (Amfield, 2003; Berger et al., 2013; Freitas et al., 2015; Yan et al., 2015; Jamei et al., 2016), which provides an important technical support for us to enrich and improve the three-dimensional morphological characterization index system of the MOE.

INFLUENCE OF SPATIAL PATTERNS OF THE MOE ON URBANIZATION BIAS IN SAT SERIES

The rapid urbanization seen in recent years has meant that many meteorological stations previously located on the outskirts of cities with good observational environments have gradually moved into urban centers or are now surrounded by built-up areas. This has created biases in the SAT series, which cannot be ignored to regional warming in China (Ren et al., 2017). Other possible factors affecting the variation of SAT series mainly include station relocation, instrument height change, upgraded observation instrument, observation time and frequency changes, statistical method change, and so on (Xu et al., 2013; Yan et al., 2014; Li L. et al., 2015; Soon et al., 2018; Shi et al., 2021).

Station Relocation, Observational Environment Change and Inhomogeneity in Urbanization Context

Station relocation significantly influence on observational environment change. Taking Hefei station in eastern China as example (Shi et al., 2021), due to the process of urbanization in recent years, Hefei station had been completely surrounded by built-up land before relocation, and the observational environment score of Hefei Station was only 63.2. Hefei station was relocated in 2018, which moved 30.2 km to the northwest of the old site, with an altitude difference of 6.0 m. The observation environment of Hefei station greatly improved, and the score increased to 99.3. As a result, it is obvious different that MOE factors (including land-use parameters, landscape parameters and geometric parameters) between the old and the new stations in the 5-km buffer zone (Shi et al., 2021). For instance, after relocation, area ration of built-up decreased from 42.17 to 4.23%; the mean fractal dimension of built-up declined to a certain extent; and distance between the station and the gravity center of various land of built-up increased from 0.53 km to 3.13 km.

Previous studies have shown that the errors caused by MOE changes and destructions are usually greater than the instrumental observation errors, which can completely submerge the signal of climate change (Gallo et al., 1996; Peterson, 2003; Vose and Menne, 2004; Soon et al., 2018; Zhang et al., 2021). For example, Peterson (2003) proposed that the micro-scale and local-scale environments have greater influence on the observation data of stations than the meso-scale environments. Taking temperature observation as an example, the local environment within a few hundred meters of the observation station will form an unusual "microclimate," which cannot represent the environmental climate of the background area in which it is located. For another example, tall buildings and trees near the station will reduce sunlight, radiation and wind, and the temperature measured by the temperature station on the asphalt pavement will be higher than that on the soil and grass. Therefore, the temperature records of "hidden" sites with poor exposure include non-climatic biases caused by local "microclimate" changes, namely siting biases or inadequate station exposure biases (Connolly and Connolly, 2014). This kind of siting bias is a bit different from urbanization bias. That is, urbanization bias can impact the local climate in a wide range, while siting bias are strictly represented by the local microclimate in the area near the site. Similarly, both biases can be produced through regional modernization and urbanization. Therefore, these two biases can occur independently. For example, an urban site with a significant urbanization bias may have a good degree of environmental exposure, while a rural site that is not affected by the urbanization bias may have a siting bias due to insufficient environmental exposure (Davey and Pielke, 2005; Menne et al., 2010; Ren et al., 2015; Zhang et al., 2021). It can be seen that changes in meteorological elements are not only extremely sensitive to local MOE changes around the station but also to urbanization bias.

Generally speaking, in the past 30 years, with the rapid economy development and urbanization in China, MOE of national meteorological stations in mainland China has been seriously damaged, and a large number of stations have been forcedly and frequently relocated. Although the relocation of stations has improved the regional representation of meteorological observations, it has made the issue of non-uniformity of climate data in China increasingly prominent (Li et al., 2004, 2009; Yang et al., 2013; Yan et al., 2014). Therefore, the meteorological observation data adjusted by the homogenization should be employed to accurately reveal the facts of regional climate change in China (Li L. et al., 2015; Cao et al., 2016; Ren et al., 2017; Li et al., 2020).

TABLE 1 | Calculation results of urbanization bias of Hefei station based on the traditional linear trend method (cited from Shi et al., 2021).

Year	Observed temperature (°C)	Urban bias (°C)	Temperature after correction (°C)	Ratio of built-up area (%)	GDP (100 millions of USD)
1979	16.1236	0.1694	15.9542	18	–
1987	15.7956	0.2211	15.5745	20	–
1998	17.1285	0.2925	16.8360	25	42.30
2004	16.6333	0.3320	16.3013	28	92.23
2009	16.7197	0.3644	16.3553	53	328.77
2018	17.0615	0.4225	16.6390	92	1223.50

Detection and Revision of Urbanization Bias

Current research on urbanization bias has focused on the detection and revision of inhomogeneities in the SAT series (Hansen et al., 2001; Fujibe, 2009; Xu et al., 2013; Yan et al., 2014; Li Q. et al., 2015). The reference station comparison method is often used to calculate urbanization bias. This method is used to select target stations and their surrounding reference stations for comparative analysis and uses the difference between them to characterize the degree of homogeneity of the SAT series affected by urbanization (Stewart and Oke, 2012; Liu et al., 2013). Fujibe (2009) divided the meteorological stations in Japan into six categories in terms of the population density within a certain radius around city stations and corrected the urbanization bias at the sites in the third to sixth categories using the first and second types of station as reference stations. Hansen et al. (2001) assumed a linear increase in urbanization warming over two time periods and then used this linear trend to revise the urbanization bias in the SAT series. Wen et al. (2019) used the difference in the SAT series trends between urban and reference stations as the total revised value and then divided this by the number of years in the time series to obtain the multi-year average urbanization bias.

However, the technical solutions for studying urbanization bias are not yet complete as a result of a lack of in-depth analysis of the drivers (Shi et al., 2021). Many studies have utilized the population density or city size as the criteria for classifying meteorological stations to explore urbanization bias (Bai and Ren, 2006; Liu, 2006; Ren et al., 2017; Soon et al., 2018), for example, Bai and Ren (2006) chose meteorological stations in a city with a population of more than 100,000 as urban stations, but Liu (2006) divided the stations in city with a population of more than 40,000 and the stations that were not described as "rural" into urban stations. In fact, it is difficult to find a pure reference station near the urban station as reference stations are inevitably affected by urbanization, especially in high-density urban agglomeration areas (Chao et al., 2020; Yang et al., 2020a), so the urbanization bias in the SAT series exhibit minimum estimation (Wen et al., 2019). In addition, some studies corrected SAT series based on the assumption that the urbanization bias increases linearly year on year (Hansen et al., 2001; Shi et al., 2021). However, the urbanization process at different times and in different regions is 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 particular, there are considerable differences in the mechanisms and magnitudes of

the impact of urbanization on different temperature elements (Li et al., 2014) insofar as, despite the possibly limited contribution to regional warming (Chao et al., 2020), the impact of urbanization on extreme temperatures can usually be very large (Li and Huang, 2013; Li et al., 2014; Yang et al., 2017).

Table 1 shows that Hefei city developed relatively slowly before 2004, whereas the total GDP increased by $4.23 billion during the time period 2004–2018, with an average annual growth rate of 81.77%, ranking first in the economic growth rate of the Yangtze River Delta region. The proportion of built-up land around the station increased significantly after 2004, but the results obtained from traditional research methods show that the urbanization bias of Hefei station has remained consistent over the last three decades (multi-year average 0.0651°C/decade). The assumption that the urbanization bias increases linearly from year to year in the traditional approach is therefore questionable (Shi et al., 2021) and the contribution of the urbanization bias to the SAT series cannot be finely quantified in time and space. In addition, with urban sprawl, rural stations in suburban areas will also be gradually affected by urbanization and there is much uncertainty about whether rural reference stations can continuously represent the climate background of the area in which urban stations are located (Wang et al., 1990; Portman, 1993; Soon et al., 2018). This will require a lot of time and effort for the dynamic monitoring and evaluation of reference stations.

Drivers of the Spatial Morphology of the MOE on Urbanization Bias in SAT Series

Current research methods on the relationship between the three-dimensional morphology and surface air temperature series are divided into two main categories (i.e., statistical modeling and numerical modeling).

Statistical modeling method includes correlation analysis and regression equations, where the independent variable is the morphological parameter and the dependent variable is the temperature series obtained from station observations. For instance, by 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 MOE factors, and the differences in these MOE factors (DOEFs) between the old and the new stations were calculated to indicate the change induced by urbanization (Shi et al., 2021). Then, multiple linear regression models of differences in site-relocation SAT series between the old and the new stations and DOEFs can be constructed, which 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 (Shi et al., 2021). However, in reality, it is usually neglected that the complex non-linear driving effect of the influencing factors on the SAT series (Shashua and Hoffman, 2000). For instance, the shading effect of buildings within the micro-scale area of the station during the day may result in a lower SAT series than for stations with an open topography, whereas the longwave radiation from buildings at night may result in a higher SAT series (Liu et al., 2018). Wang et al. (2019) conducted a correlation analysis between information about obstacles within the MOE and the SAT series and showed that the spatial morphology of the MOE has a more complex and non-simple linear relationship with the SAT. These studies show that it is not possible to finely quantify the effects of the three-dimensional morphology of the MOE on urbanization bias through linear statistics.

Another approach is numerical modeling, in which numerical simulations are used to study the impact of changes in the MOE caused by urbanization on the meteorological observational elements (Zhang et al., 2002, 2016; Liu and Zhou, 2007; Yang et al., 2016; Chen, 2021; Chen G. et al., 2021; Yu et al., 2021). The simulations include physical equations and the laws of atmospheric radiation related to energy and mass and therefore explain the changes in terms of the mechanism of influence. These models are often used for scenario simulation—that is, different three-dimensional morphological scenarios are set and the climate parameters in each scenario are obtained by numerical model simulation. The impact of the three-dimensional morphology on the microclimate is then obtained by comparing the simulation results. Common numerical models include energy consumption models and regionalized models, such as the Weather Forecasting and Research, ENVI-met, computational fluid dynamics and EnergyPlus models (Liang et al., 2018). The simulation results often lack validation by fine-resolution observations.

Scale Dependence of the Response of the SAT Series to Changes in the MOE

An appropriate buffer scale is essential for studying the relationship between the SAT series and the three-dimensional morphological characteristics of the MOE. The contribution of the observational bias caused by environmental damage in the surrounding area to the regional climate change signal has large uncertainties at different scales. For example, Gallo et al. (1996) studied the effect of nine land cover types within three scaled buffers (circles with radii of 100, 1,000 and 10,000 m) around stations on the diurnal temperature range and concluded that urban land use types have a large effect on the local temperature. Peterson (2003) suggested that the micro-scale and local-scale environments have a greater impact on observations of meteorological elements than meso-scale environments. In eastern China, rapidly increasing urban sprawl impacted on the MOE, showing that the maximum range of influence affecting observational data under advection and turbulence transport

conditions does not usually exceed 5 km (Ren and Ren, 2011; Tysa et al., 2019; Yang et al., 2020a; Zhang et al., 2021).

In the case of the SAT series, the local environment within a few hundred meters of stations can create an unusual microclimate that is not representative of the climate background of the region in which it is located. Other examples are nearby trees reducing the amount of sunlight and wind and stations located on asphalt roads observing a higher SAT than those located on soil and grass. It is therefore crucial to determine the sensitive area of the MOE around a station (Gallo et al., 1996; Peterson, 2003; Ren et al., 2010b; Stewart and Oke, 2012; Yang et al., 2013; Li Y. et al., 2015). Different response relationships are seen between the local microclimate and the urban spatial morphology at different scales (Chun and Guldmann, 2014; Chen et al., 2020), which may be related to the physical characteristics of the MOE (e.g., the block size, building density or infrastructure) and the background climate (Oke, 2004; Qian et al., 2018). While for regional-scale urbanization context, taking the Guangdong-Hong Kong-Macau region (GHMR) as case study, recent study show that the warming due to urbanization tends to be smaller as the spatial scale increases: the contribution to the local warming can reach as high as 50% in the metropolis, remains high (~25%) in GBA, and decreases to about 10% in GHMR (Chao et al., 2020). A lack of in-depth consideration of the dependence on spatial scale increases the uncertainty in the impact of changes in the MOE on the urbanization bias in SAT series.

DISCUSSION

Two important scientific questions need to be addressed in current researches on the effects of changes in the MOE on urbanization bias: (1) how can we improve the characterization indexes of three-dimensional spatial morphology of MOE; and (2) how can we analyze the non-linear response of urbanization bias to the three-dimensional spatial morphology of the MOE and its scale dependence?

Characterization Indexes of Three-Dimensional Morphology of the MOE

Most studies only use the horizontal parameters of the MOE in remote sensing assessments and lack in-depth research on the internal structural layout. Landscape patterns (**Figure 4**) can be used to explore the relationship between structural land use layout and the local microclimate (Zhang et al., 2009; Meng et al., 2010; Estoque et al., 2017). For example, Meng et al. (2010) explored the thermal environmental effects of park landscape patches and road landscape corridors through landscape patch characterization. Ren (2015) used landscape metrics to analyze the configurations of urban vegetation to obtain the relationship between urban landscape distribution and the SAT. Tysa et al. (2019) showed that the effect of urbanization on the SAT series is closely related to the distance of the stations from the center of urban buildings. In general, the landscape pattern index, mainly including the largest patch index (LPI) and the mean

FIGURE 4 | Schematic diagram of urban landscape patterns around weather stations (cited from Shi et al., 2021).
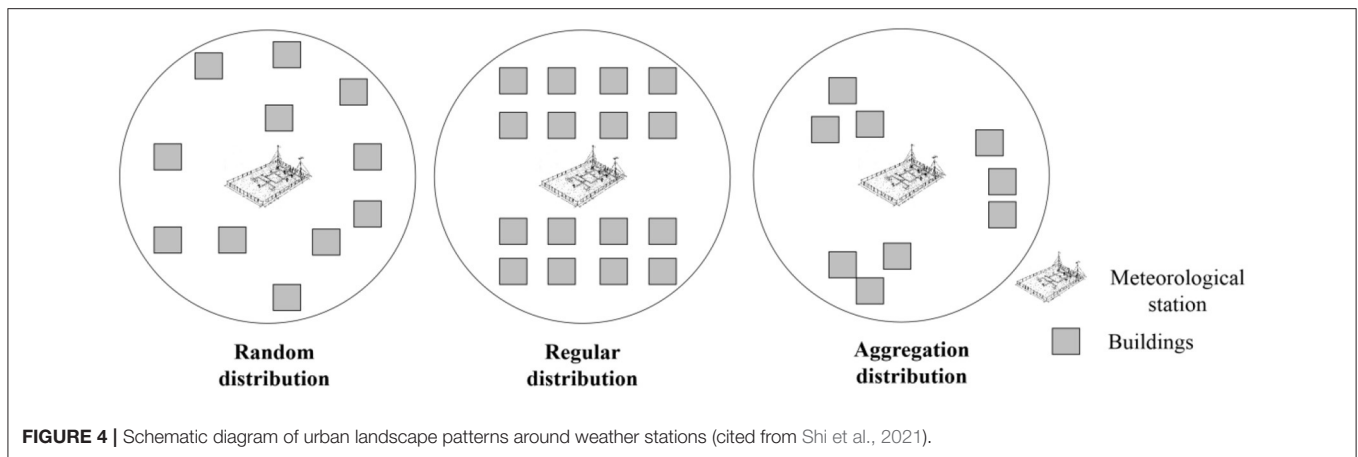
fractal dimension, can fully consider the respective types, shapes, sizes, quantities and spatial combinations of different land uses, such as the perimeter–area ratios, the landscape shape indices, edge and patch densities, fragmentation and fractal dimensions. The larger the LPI value, the more obvious the advantage of this type of patch in the overall landscape. For an example of case studies in Hefei, the correlations between the changed air temperatures and the LPIs of built-up and water were 0.66 and −0.503, respectively, passing the 0.05-level significance test (Shi et al., 2021). These two landscape pattern indexes are important input variables for multiple linear regression models of the urbanization bias simulations in case studies of Hefei, and the error range of the model for simulated temperature difference related to MOE change was 7.01–18.37% with an average of 12.28% (Shi et al., 2021). Therefore, the introduction of the landscape pattern index can enrich the indexes in remote sensing studies of the MOE and quantify the degree of response of each meteorological element to the configuration structure of different land use types.

The impact of urban sprawl on the MOE is not only reflected horizontally, but also vertically as an important part of the spatial structure (**Figure 5**). Indexes such as the sky visual factor (SVF), the block height to width ratio (BHWR), the floor area ratio (FAR), and Vegetation volume to building volume (VV2BV) are often used to depict vertical morphology within cities (**Figure 5**), which are expected to provide scientific assessments for the MOE changes and their effects on urban thermal environments (Chen G. et al., 2021; Chen X. et al., 2021). In detail, the SVF is the ratio of the area of sky visible at a fixed point on the surface to the total visible area (Oke et al., 1991) and the BHWR is defined as the ratio between the average building height within a street canyon and the width of the canyon (Oke, 1988). FAR and SVF are two important parameters for characterizing the geometry, density and heat balance of urban areas, in addition to generating and controlling the heat island effect (Svensson, 2004; Chen et al., 2020; Chen G. et al., 2021). The BHWR and VV2BV are two important indicators for characterizing the microscopic three-dimensional morphology and play key roles in radiation balance and outdoor thermal environment studies (Shashua and Hoffman, 2000; Chen, 2021).

The subsurface metadata of buildings, trees, roads and water bodies in the station buffer zone that affect the MOE can be established by field measurements and remote sensing, allowing us to retrieve parameters (e.g., the anthropogenic heat flux, land surface temperature and enhanced vegetation index) in the area around the station. Landscape pattern software (Fragstats) can be used to calculate the maximum number of patches, the average fractal dimension, the sprawl index and the distance from the station to the urban center for the land types around the station, reflecting the geographical characteristics and patterns of different land use types. For three-dimensional information about the MOE (**Figure 6**), the software can automatically read online map information and visual interpretations of high-resolution remote sensing images to obtain building height information. The software can then calculate the regional volume ratio around the station, the SVF, the BHWR and other urban vertical morphology parameters, extracting the characterization index system of the three-dimensional morphology of the MOE (**Figure 6**).

Non-linear Response of Urbanization Bias to the Three-Dimensional Morphology of the MOE and Its Scale Dependence

With the continuous development of high-performance computers and numerical simulation algorithms, researchers have increasingly used numerical modeling techniques to simulate the characteristics of urban climates (Zhang et al., 2002, 2016; Li L. et al., 2015; Li et al., 2016; Yu et al., 2021). This provides new ideas and methods to explore how the MOE is influenced by urbanization (You et al., 2014). An accurate description of the three-dimensional morphology of the MOE can provide effective subsurface information and boundary conditions for numerical simulations, which, in turn, can verify the accuracy of the remote sensing assessment of the MOE.

The Weather Research and Forecasting model has a comprehensive physical scheme to describe various complex climate phenomena and can analyze the climate characteristics of cities at the local scale. This model can propose policy recommendations and improvement strategies for urban
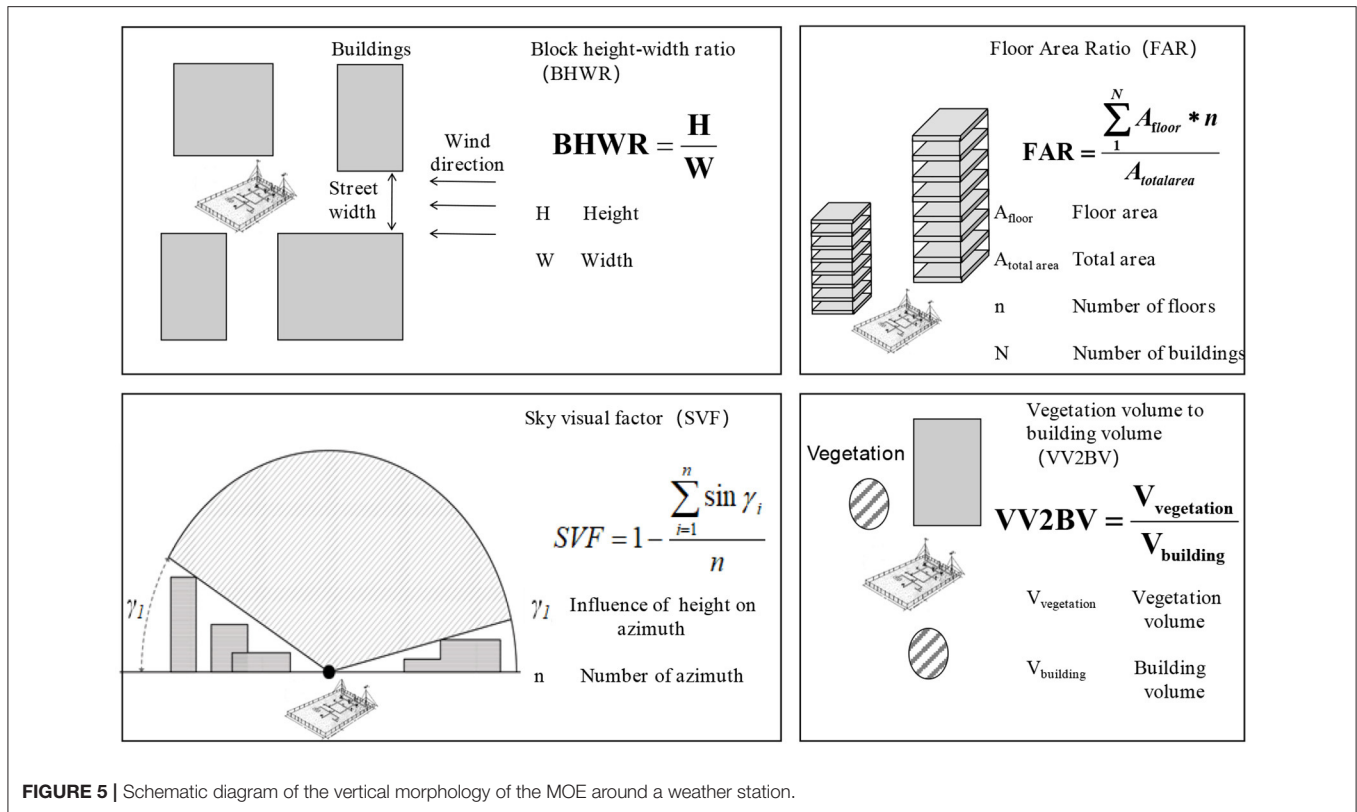
FIGURE 5 | Schematic diagram of the vertical morphology of the MOE around a weather station.
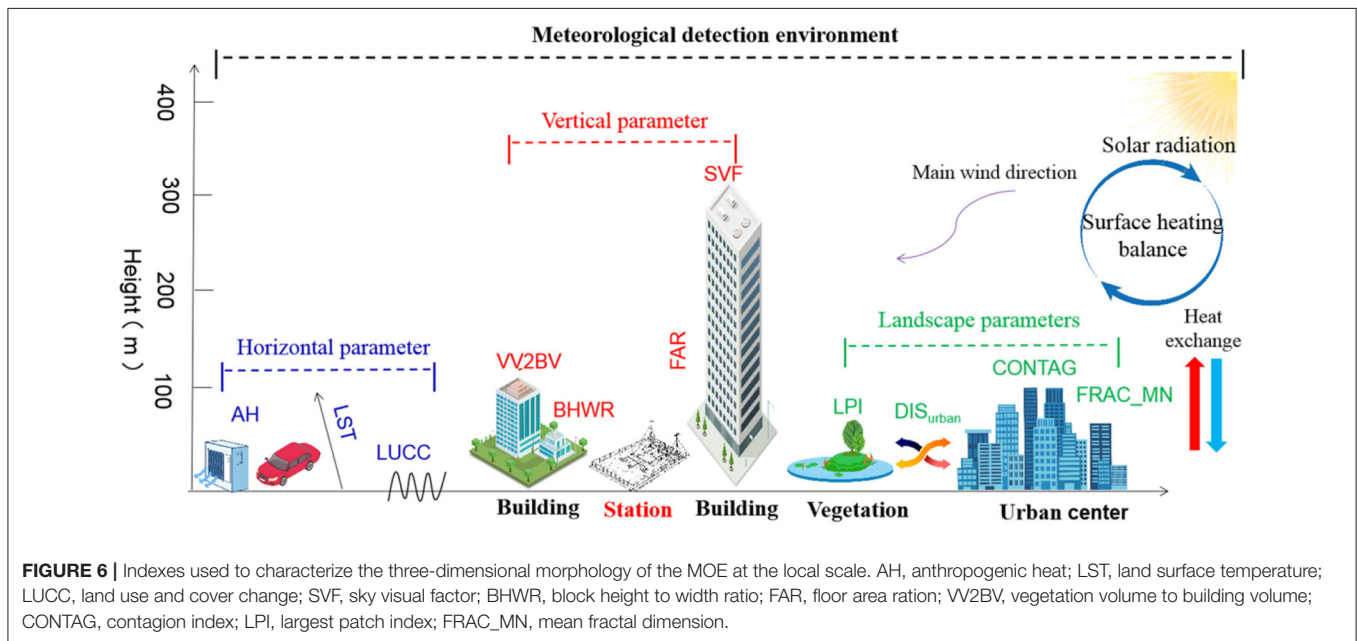

FIGURE 6 | Indexes used to characterize the three-dimensional morphology of the MOE at the local scale. AH, anthropogenic heat; LST, land surface temperature; LUCC, land use and cover change; SVF, sky visual factor; BHWR, block height to width ratio; FAR, floor area ration; VV2BV, vegetation volume to building volume; CONTAG, contagion index; LPI, largest patch index; FRAC_MN, mean fractal dimension.

construction, planning and management (Zhang et al., 2002; Fei et al., 2011). Computational fluid dynamics can quantitatively calculate the distribution of physical quantities (e.g., temperature and wind) at various points in space in a microscale open atmosphere and can describe in detail the characteristics of urban spatial patterns, building information and data on anthropogenic heat production, providing a powerful tool for understanding and evaluating microscale climate characteristics (Shao et al., 2012; You et al., 2014; Chen et al., 2020). In the future, the WRF model could be coupled with computational fluid dynamics models to obtain accurate information about meteorological elements from the large-scale circulation and the

energy balance on the mesoscale; computational fluid dynamics could be used to finely describe the influence of the complex underlying surface on the SAT series (Li L. et al., 2015; Nelson et al., 2016).

Statistical modeling is also an important method of studying the drivers of urbanization bias at different scales. The random forest algorithm is a natural non-linear modeling method suitable for analyzing complex datasets with a large number of unknown features. This method can be used to predict and analyze the intrinsic association of variables and to perform importance and local dependence analysis of independent variables (Genuer, 2010). The random forest algorithm is widely used in fitting complex problems and to factor importance measures, especially for simulations of changes in land use and urban morphological expansion (Ghosh et al., 2014; Feng et al., 2015). Machine learning methods could be used in the future to analyze the influence of three-dimensional morphological changes of the MOE on urbanization bias and its scale dependence.

SUMMARY

In the context of the current rapid increase in urbanization, studies of the impact of changes in the MOE on the urbanization bias in SAT series are of great scientific significance in monitoring regional and global climate change. These studies can also meet practical operational needs, such as the detection and revision of the asymptotic inhomogeneity of meteorological data, the standardized preparation of benchmark meteorological data, the environmental assessment of national meteorological stations, and the site selection and overall optimization of the layout of meteorological observational stations. Studies of the influence of changes in the MOE on urbanization bias in SAT series involve knowledge of urban meteorology, urban geography and the urban environment, as well as urban planning, architecture, landscape architecture and other disciplines. However, current research is mostly limited to a single discipline, resulting in relatively limited research findings. By effectively coupling multiple technical methods (e.g., machine learning, remote sensing and numerical models), we will be able to gain a greater understanding of the non-linear response of urbanization bias to the three-dimensional morphology of the MOE and its scale dependence.

AUTHOR CONTRIBUTIONS

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