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Citation for published version:
Wang, J, Tett, SFB & Yan, Z 2017, 'Correcting Urban Bias in Large-scale Temperature Records in China, 1980-2009' Geophysical Research Letters. DOI: 10.1002/2016GL071524

Digital Object Identifier (DOI):
10.1002/2016GL071524

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Geophysical Research Letters

Correcting Urban Bias in Large-scale Temperature Records in China, 1980–2009

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Abstract

Trends in urban fraction around meteorological station are used to quantify the relationship between urban growth and local urban warming rate in records from Chinese temperature stations. Urban warming rates are estimated by comparing observed temperature trends with those derived from ERA-Interim reanalysis data. With urban expansion surrounding observing stations, daily minimum temperatures are enhanced, and daily maximum temperatures slightly reduced. On average, a change in urban fraction from 0% to 100% induces additional warming in daily minimum temperature of +1.7±0.3 ℃; daily maximum temperature changes due to urbanization are -0.4±0.2 ℃. Based on this, the regional area-weighted average trend of urban-related warming in daily minimum (mean) temperature in eastern China is estimated to be +0.042±0.007 (+0.017±0.003) ℃/decade, representing about 9% (4%) of overall warming trend and reducing the diurnal temperature range by -0.05 ℃/decade. No significant (at a 95% confidence level) relationship between background temperature anomalies and the strength of urban warming were found.

Key words:

Urban bias, Land surface air temperature, China, Atmospheric reanalysis

Key points:

Relationship between urban growth and local urban warming rate in Chinese temperature records is quantified;

A change in urban fraction from 0% to 100% induces additional warming in daily minimum temperature of +1.7±0.3 ℃;

No significant relationship was found between background temperature anomalies and the strength of urban warming;

1. Introduction

Apart from data inhomogeneity, the effect of urbanization is probably the most common source of systematic bias in land station temperature records. While many studies have documented that urbanization processes imposed negligible influence on the global temperature series [*Jones et al.*, 1990; *Hansen et al.*, 1999, 2001; *Peterson et al.*, 1999; *Folland et al.*, 2001; *Parker*, 2004, 2006, 2010], the urbanization-induced effect in local and even regional temperature observations, especially in some developing countries or regions, could be considerable [*Wang et al.*, 1990; *Portman et al.*, 1993; *Ren et al.*, 2007; *Jones et al.*, 2008; *Yan et al.*, 2010]. Many authors have estimated the urban-related warming in large-scale temperature series (for example [*Ren et al.*, 2008; *Hua et al.*, 2008; *Yang et al.*, 2011]), mostly based on comparison of urban and rural temperature series. *Wang and Yan* [2016] presents a concise review of urban warming, noting that there is considerable uncertainty in the magnitude of the urban warming bias [*Peterson and Owen*, 2005].

The most straightforward way to obtain regionally averaged temperature series that are free of urbanization effect is to use nonurban stations [*Hansen et al.*, 1999; *Ren and Zhou*, 2014; *Sun et al.*, 2014, 2016]. This is a useful approach for the regions with numerous uniformly distributed nonurban stations. But, in most cases, long-term temperature series observed at purely rural stations are rare. Faced by this challenge, *Karl et al*. [1988] developed a series of equations that related the effect of increasing population to the annual/seasonal averaged temperatures using the station observations across the United States (US). Based on the equations in *Karl et al*. [1988], *Jones et al*. [1989] assessed the significance of the urban warming effect on hemispheric mean temperature series to be less than 0.1 ℃ over the first eight decades of 20th century. However, population information is spatially generalized and outdated, and the urban-related changes in the observing environment surrounding the stations could not be reflected objectively and precisely [*Peterson and Owen*, 2005]. Satellite remote-sensing data provide a basis to identify the extent to which the effect of urbanization has been imposed on the temperature records [*Gallo et al*., 1999; *Hansen et al*., 1999, 2001; *Yang et al*., 2011]. Since urbanization is a dynamic process, changes in urban land use around observing stations, rather than current urban status, can be used to better understand the urban warming effects [*Jones et al*., 2008].

Climate models simulate large-scale average changes in temperature, which are not directly comparable with site observations in regions of rapid urbanization such as eastern China for the recent decades. From a different point of view, as human populations are concentrated in cities, if we want to quantify the changing risk of extreme temperatures to the human society based on projections of climate modeling, we need to apply a correction for the impact of urbanization to these results. One of the goals of this study is to produce such a correction. In this study, we employed the satellite-derived data of urban fraction surrounding meteorological station to estimate urban warming bias in surface temperature records in China, and compared the results with previous studies. Since most previous studies applied fixed values to adjust urban bias in annual or seasonal temperature averages [*Karl and Jones*, 1989; *Jones et al*., 1989; *Sun et al*., 2016], we also examine whether there is a significant relationship (at a 95% confidence level) between the intensities of urban warming and background temperature anomalies on monthly timescales.

In the rest of this paper, we next describe the data and analysis methodology we use, following this with our results before concluding. We find the urbanization has a significant (at a 95% confidence level) warming effect on daily minimum temperatures, but only a negligible cooling impact on daily maximum temperatures.

We also find no evidence of significant (at a 95% confidence level) relationship between large-scale temperature variability and urban warming intensity, meaning that a fixed urbanization correction is adequate.

2. Data and Method

We use a homogenized daily surface air temperature data set observed at 753 meteorological stations in China for 1980–2009 [*Li and Yan*, 2009; *Li and Yan*, 2010], ERA-Interim reanalysis data set [*Dee et al.*, 2011], and a long-term land cover data set in China for the years 1980 and 2009 [*Hu et al.*, 2015]. We focus our analysis on eastern China (east of 105 °E) as this is where large growth in urbanization has happened.

The station temperature observations we used have been corrected for most of the non-climatic biases due to the changes in the local observing system, such as station relocation. In most cases, meteorological stations had to be relocated to more rural sites due to the rapid urbanization [*Yan et al.*, 2010]. Large cooling biases could be introduced in by such relocations, which have been corrected for in the homogenized series. The Multiple Analysis of Series for Homogenization (MASH) method was used to homogenize station temperature series. MASH is an iterative procedure designed to detect break points by mutual comparison among all available series. MASH chose a candidate series from the available series and treated the remaining series as references. MASH algorithm changed the roles of candidate and reference series step by step. Homogenizations are made to the whole dataset based on statistical tests via Monte-Carlo method. More details about MASH can be found in *Szentimrey* [1999; 2008]. Homogenization was made for the local time series of daily maximum and minimum temperatures, respectively, in order to diminish any discontinuity due to non-climatic factors such as site-moves of a station [*Li and Yan*, 2009; *Li et al.*, 2016]. Since homogenization process considers only abrupt changes in surface temperature, the slowly varying urban warming trends are still retained in observations.

We used the fused land cover dataset of *Hu et al.* [2015] which classifies land by fractions of seventeen types of land cover (using the IGBP land cover classification scheme; *USGS* [2003]), for four representative years (1980, 1990, 2000 and 2009). *Hu et al.* [2015] made a detailed investigation of the accuracy of the land cover classification for data fusion, with multi-source best-quality datasets derived from satellite platforms including Landsat TM/ETM+, USGS, MODIS land cover and Chinese national land cover datasets. Based on multiple linear regressions, the fused urban land cover dataset used in this study was developed, combining the multi-source products. Based on previous studies [*Yang et al*., 2011 (7km); *Wang and Ge*, 2012 (16km); *Chrysanthou et al*., 2014 (10km)], we chose the land cover data set with spatial resolution of 10 km to represent the extent of environmental changes surrounding the observing stations due to urbanization. For each station we computed the linear trend in urban land fraction for the nearest 10x10 km pixel.

We treat the temperature trend observed at each urban station as a sum of large-scale trend, local urban trend, and noise representing unknown processes. Reanalysis data do not assimilate surface observations of daily 2-m maximum (T_{max}) and minimum (T_{min}) temperatures and so should be insensitive to the changes in urban land use. Thus, temperature trends derived reanalysis data can be used to represent the signal of large-scale climate change [*Dee et al*., 2011]. ERA-Interim reanalysis data perform better than other reanalysis datasets regarding the long-term trend and low-frequency variability in surface temperature series in China [*Wang et al*., 2013a]. We used it to separate the signal of local urban warming from overall warming trends. Specifically, T_{max} and T_{min} from ERA-Interim data set were linearly interpolated to stations located below 500m [*Kalnay and Cai*, 2003] in eastern China and converted to monthly-average anomalies relative to 1980–2009. Linear trends in both were estimated by ordinary least squares (OLS). Interpolated temperature trends in ERA-Interim reanalysis were subtracted from station observation trends, and the difference was treated as the local urban warming trends *plus* other local noise.

Local urban warming trends were assumed to be proportional to the changes in urbanization degree or extent. This assumption may be not precise enough for specific sites, but we believe reasonable for a large sample of stations. We estimated the relationship between urban warming and urbanization by linear regression between the urban fraction trend and T_{min}/T_{max} temperature trend.

To determine if using a fixed value to correct urban warming bias was appropriate, we further examined the relationship between urban bias and background temperature anomalies (derived from ERA-Interim) on monthly time-scale in three representative cities in China (Beijing, Shanghai, and Guangzhou) for 1980-2009.

3. Results

The trends in the fraction of urban land cover are notable over three large urban agglomerations in China (Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta) and in the North China Plain (Figure 1a). The trends in station observed T_{max} in central-eastern China are higher than other regions (Figure 1b). Some places, such as the North China Plain and Northeast China, have experienced slight changes in T_{max}. Station observed T_{min} shows a strong warming trend in North China Plain and central-eastern China (Figure 1c). This pattern is quite similar to the changes in the urban fraction, as shown in Figure 1a. Trends of T_{max} in ERA-Interim reanalysis are consistent with station observations on the whole (Figure 1d). In contrast, trends in T_{min} show some differences between observations and reanalysis, particularly in three large urban agglomerations and North China Plain (Figure 1e).

We removed reanalysis temperature trends from station observed ones (Figure S1) and see that the warming trends of T_{max} in southeastern China were enhanced by urbanization, consistent with *Zhou et al*. [2004]. However, in the North China Plain, the warming trends in T_{max} are decreased by urbanization process. For T_{min}, the urban-related trends are significant (at a 95% confidence level) and almost positive, especially for the three large urban agglomerations and North China Plain.

We find a weak and insignificant (at a 95% confidence level) relationship between urban fraction and urban warming trends in T_{max} (Figure 2a). This suggests that urbanization has had only a small effect on T_{max}. However, for T_{min}, the relationship between the changes in urban fraction and urban-related warming trends is significant (at a 95% confidence level) and almost linear: the larger the trend in urban fraction, the larger the urban-related warming rates (Figure 2b). The linear regression coefficient between them is +0.017±0.003 ℃/% (mean ± standard error), which implies that, on average, urban warming is about +1.7±0.3 ℃ for the stations with urban fraction increased from 0% to 100%. However, note that there is a large degree of scatter around the best-fit line suggesting other processes are influential for individual stations.

To test sensitivity of our results we repeated our analysis using robust regression. This gives less weight to values far from the best fit line than does OLS and we use it to deal with potential data quality problems. Its impact is to increase the magnitude of the urbanization effect on both T_{min} and T_{max} with the T_{max} effect now being significant (at a 95% confidence level; Table S1). We also replaced the interpolated ERA-Interim data with an alternative interpolated station dataset. Here, we applied multiple linear regression to estimate the patterns of large-scale climate change, using the station's latitude, longitude, and their high-order forms (Table S2). We find very similar results to those using ERA-Interim (Table S1 and Figure S1). Our results appear insensitive to those changes to our analysis procedure (Table S1) and so we conclude that urbanization, in low-altitude eastern China, causes significant (at a 95% confidence level) warming in T_{min} with only a small impact on T_{max}. In consequence, urbanization processes also increase the daily mean temperature (T_{mean}), but decrease the diurnal temperature ranges (DTR).

Therefore, there is no need to correct urban bias in large-scale T_{max} records in China. Urban bias in T_{min} could be corrected through the relationship between trends in urban fraction and urban warming rates. Result shows that the area-weighted (2°×2° grid box) average trend in the urban fraction around observing stations in eastern China (east of 105°E and with elevation less than 500m) is 2.45%/ decade for the period of 1980–2009. Therefore, the urban-related warming trend in area-weighted average time series of T_{min} (T_{mean}) in eastern China is estimated to be about +0.042±0.007 (+0.017±0.003) ℃/decade, representing an average of about 9% (4%) of overall warming in this region, and reducing the DTR by -0.052 ℃/decade.

Most previous studies corrected urban bias in large-scale temperature series using fixed values [*Karl and Jones*, 1989; *Portman*, 1993]. A compelling question is whether urban warming biases are correlated with rural or background temperature anomalies. We examine for Beijing, Shanghai and Guangzhou the relationship between urban warming and background temperature anomalies (linearly interpolated from ERA-Interim) and find no significant (at a 95% confidence level) correlation between the background T_{max} or T_{min} anomalies and urban warming intensity on monthly timescales for most cases (Figure 3). This result holds regardless of for both warm and cold seasons. The detailed coefficients of linear regression between the anomalies of background monthly averaged temperature and monthly averaged urban heat island are listed in Table S3. Our results suggest that the background temperature anomalies have little impact on urban warming biases in monthly averaged temperature records.

4. Discussions and Conclusions

In this study, we examined the relationship between trends in urban fraction close to stations and local urban warming rate. We found that the urbanization impact on T_{max} in eastern China was small and statistically indistinguishable from zero. However, we found that urbanization has caused a significant (at a 95% confidence level) increase in T_{min}. Our results show that, on average, a change in urban fraction (around meteorological station within 10 km) from 0% to 100% will probably lead to an increase in urban warming by 1.7 ±0.3 ℃. Following this relationship, we estimated that the urban-related warming contributed about 9% (0.042 ℃/decade) to the trend in regional time series of T_{min} in eastern China during the years 1980–2009. Based on homogenized temperature observations, *Li et al*. [2004] found that the average urban warming trend in T_{mean} series (the mean of T_{max} and T_{min}) was 0.012 ℃/decade for the period 1954–2001. Our estimation results (urban warming rate in T_{mean}: +0.017 ±0.003 ℃/decade) are consistent with this. In developed regions, urban warming bias in temperature records would be much smaller as urban fractions have changed little in recent decades. By comparing European-averaged temperatures based on all meteorological stations with those based on three subsets of stations: from rural areas, from areas with low urbanization rate, and from areas with low temperature increase, *Chrysanthou et al*. [2014] found that urbanization explains

0.0026 ℃/decade of the annual-averaged European temperature trend of 0.179 ℃/decade. Using four different proxy measures of urbanity, *Hausfather et al.* [2013] suggested that urbanization accounts for 6-9% of the rise in unadjusted minimum temperatures in US and even less than 5% for homogenized observations.

Furthermore, we employed the relationship to estimate the urban warming rate for T_{min} (T_{mean}) at three representative urban stations, using the trends of urban fraction near them (Beijing: 17.3%/decade; Shanghai: 22.9%/decade; Guangzhou: 13.1%/decade). For these stations, the effects of urban warming biases in T_{min} (T_{mean}) for 1980-2009 are estimated to be about 0.29 ℃/decade (0.11 ℃/decade), 0.39 ℃/decade (0.15 ℃/decade) and 0.22 ℃/decade (0.09 ℃/decade), respectively. This estimation is consistent with previous studies on the urban warming bias in Beijing [*Wang et al*., 2013b] and East China [*Jones et al*., 2008].

It should be noted that urban fraction is an important factor determining the intensity of local urban warming, but not the only one. Other factors, such as urbanization degree, anthropogenic heat [*Feng et al*., 2014] and local background climate [*Zhao et al*., 2014], are also responsible for it. However, we believe it reasonable to assume, on average, that trends in urbanization degree and anthropogenic heat intensity are proportional to the trends in urban fraction. In this study, we focused on the correction of urban bias in large-scale temperature records in eastern China. Therefore, much of the influences due to background climate could cancel each other out. However, for some specific regions (e.g., southeastern China and North China Plain), local background climate should be considered in the urban bias correction.

Changes associated with urbanization may impose influences on surface-level temperature observation stations both at the mesoscale (0.1-10 km) and the microscale (0.001-0.1 km). For a specific observing station, small local environmental changes may overwhelm any background urban warming signal at the mesoscale. Due to the lack of a high-quality dataset of urban fraction at the macroscale, we can hardly quantify the microscale urban influence on the observed temperatures. Since data homogenization could adjust the abrupt temperature changes due to station relocations (e.g., from city center to a park-like setting or rural area) and local change such as construction developments [*Yan et al*., 2010], we consider that any microscale influence should have been reduced in the present analysis and should not substantially influence the result about the regional mean effect of urbanization.

He et al. [2013] used historical remote sensing data to examine the impact of urban expansion on the trends in near surface air temperature in Beijing and its surrounding local regions. They found that an increase of about 10% in urban growth around the meteorological stations could contribute to 0.13 ℃ rise in mean surface air temperature trend. It should be noted that *He et al.* [2013] focused on the impact of urbanization at specific local scale and didn’t remove the signal of large-scale climate change. Future studies could identify the contribution of local background climate (e.g., precipitation, solar radiation) to urban warming bias. There were other methods applicable for estimating the urban signal. For example, to analyze the diurnal cycle of urban heat island in the central Europe, *Zakšek and Oštir* [2012] used multiple regression analysis to downscale the low-spatial-resolution satellite-based land surface temperature data in a higher spatial resolution.

The reason for a more obvious urban warming trend in T_{min} than in T_{max} in this region could be that the radiative effect of increasing urban aerosol might cause decreasing solar radiation reaching the ground during the daytime. Meanwhile, any urban warming in T_{max} could be compensated by the effect of increasing hazes. A recent study attributed a part of the urban warming in the nighttime to haze pollution in China [*Cao et al*., 2016]. Enhanced longwave radiative forcing of coarser aerosols contributed to additional nighttime urban warming.

This study demonstrates an approach to estimate urban bias in large-scale surface temperature, particularly where there are few rural stations. This approach could be used in other regions. Compared with the equations that related urban bias to population growth in *Karl et al.* [1988], the regression functions developed in this study are more robust and objective with easily accessible and updated data since population data tend to be out-of-date for the cities in developing regions.

Acknowledgements

Data used for this study, our regression results and uncertainties are available from the corresponding authors (wangjun@tea.ac.cn). We sincerely appreciate the Earth Observation of Climate Change research group (http://green.tea.ac.cn) for supplying the high-quality land-use data for China; readers can contact corresponding author Jun Wang for these data. We thank ECMWF for providing the ERA-Interim reanalysis data (http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/). This study was carried out during Jun Wang's scientific visit to the University of Edinburgh funded by the UK-China Research & Innovation Partnership Fund through the Met Office Climate Science for Service Partnership (CSSP) China as part of the Newton Fund. Simon F B Tett was supported by CSSP China and NCAS-Climate (R8/H12/83/029). Zhongwei Yan acknowledges support from National Natural Science Foundation of China (41475078).

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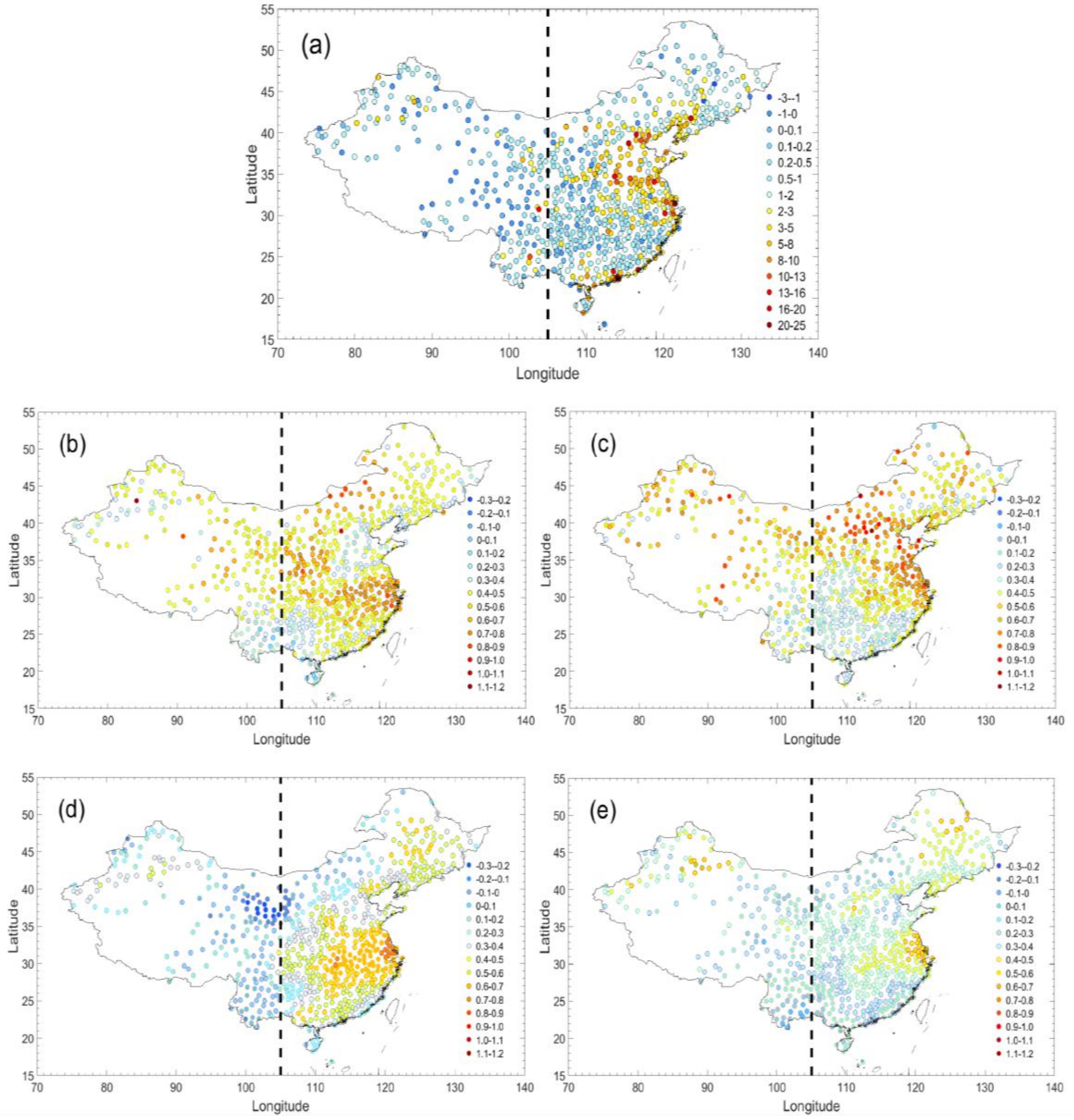

Figure 1 (a) Geographic locations of meteorological stations in China (circles) and the trends in the fraction of urban area at 10 km ×10 km resolution (%/decade: shaded colors) nearest the stations for 1980-2009; (b) Trends in annually-averaged daily maximum temperature recorded in station observations for 1980-2009 (c) Same as (b), but for daily minimum temperature; (d) Trends in annually-averaged daily maximum temperature linearly interpolated from ERA-Interim reanalysis data for 1980-2009; (e) Same as (d), but for daily minimum temperature. For b-d units are ℃/decade.

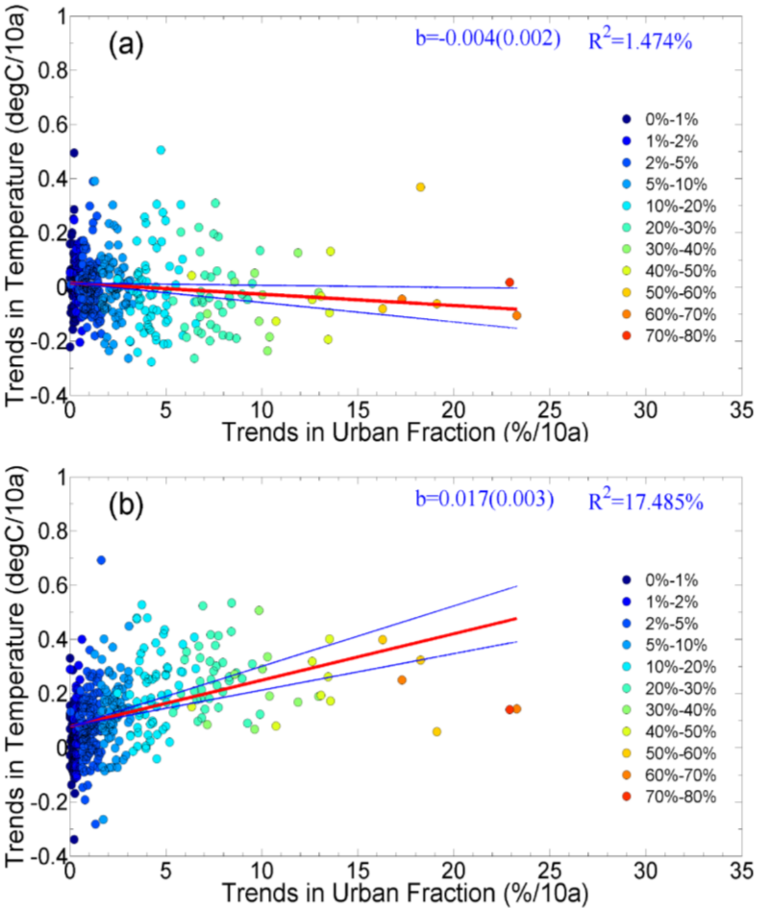

Figure 2 (a) Correlation between the trends in urban fraction and the trends in annually-averaged daily maximum temperature, but with the large-scale climate change pattern removed using ERA-Interim reanalysis data; (b) Same as (a), but for daily minimum temperature. ‘b’ indicates the linear regression slope between the changes in urban fraction and urban warming rate. ‘R^2’ represents the proportion of the variance of urban warming rates explained by the trends in urban fraction. The number in bracket is the bootstrap estimate of the standard error of the linear regression slope. Red line shows the linear regression line, and two blue lines show the 90% confidence interval of linear regression slope based on bootstrap estimates, with 5% below the bottom line and 5% above the top line. The color of each point represents the latest urban fraction in 2009 for each station.

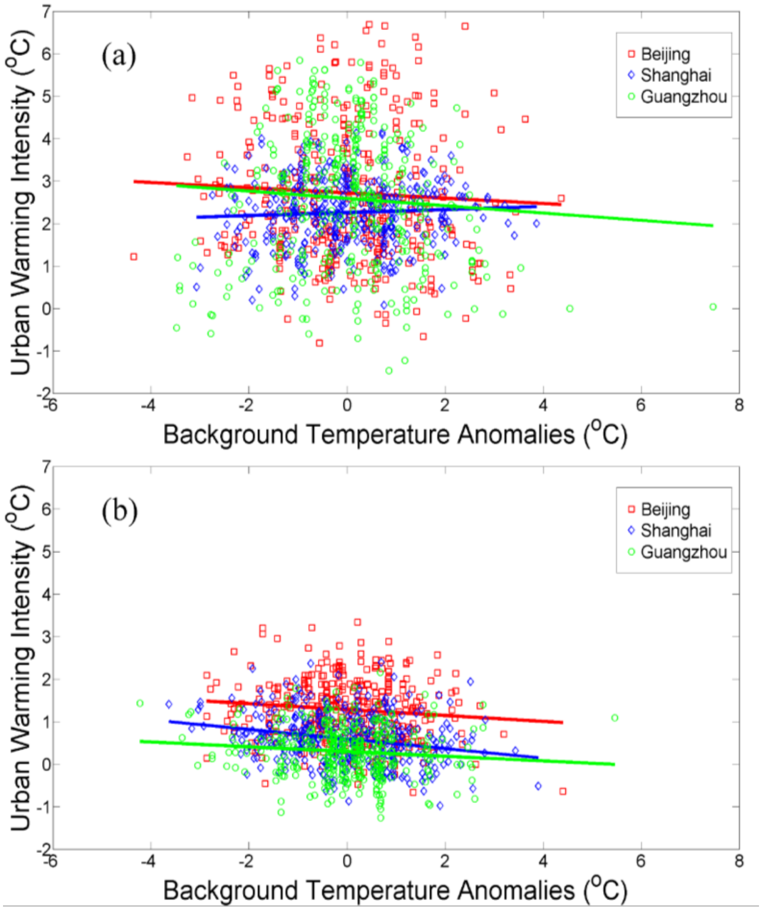

Figure 3 (a) Correlation between the anomalies of monthly averaged daily maximum temperature (reference period: 1980-2009) linearly interpolated from ERA-Interim reanalysis and the differences of monthly averaged daily maximum temperature between observation and reanalysis (urban warming intensity) in the cities of Beijing (red squares), Shanghai (blue diamonds), and Guangzhou (green circles) for the years 1980-2009; (b) Same as (a), but for daily minimum temperature. The detail regression coefficients are listed in Table S3.