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On "observation minus reanalysis" method: A view from multidecadal variability

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[1] The observation minus reanalysis (OMR) method is widely used to investigate the impact of urbanization and land use change on climate. Here we present the OMR trends for the periods of 1979–1998 and 1989–2008 in eastern China, which appear inconsistent for the regions experiencing rapid urbanization during recent decades. Using Ensemble Empirical Mode Decomposition, we extract the secular trend and multidecadal variability (MDV) from the temperature observations at stations and the corresponding reanalysis data for the last century and find that, in general, MDV in the reanalysis data is weaker than that in the station observations. This systematic difference considerably modulates the magnitude of the OMR trends during different periods, leading to inconsistent estimates of the impact of urbanization. After MDV adjustment, the OMR trends for Beijing and Shanghai are consistent for the different periods, about 0.04°C–0.1°C/decade, much smaller than some previous estimates. We caution those using OMR methods to estimate the effect of urbanization and also for those using reanalysis data for a limited period in studies of this kind.

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1. Introduction

[2] It is unquestionable that urbanization may induce biases in local temperature observation series across the world [*Böhm*, 1998; *Ren et al.*, 2007; *Gaffin et al.*, 2008; *Yan et al.*, 2010]. However, it remains controversial how to quantify the effect of urbanization for large-scale temperature averages. One problem arises from the inhomogeneity of meteorological observation time series, which is very common due to changes in local observing systems (e.g., relocation of station and changes of observing protocols in the history). The contribution of urbanization to the recorded warming trend at Beijing, a station well influenced by the rapid expansion of the city during recent decades, was estimated to be as large as 80% of the total trend based on an analysis of the original observations [*Ren et al.*, 2007] but was only about 40% based on a homogenized series [*Yan et al.*, 2010] or even smaller if all reference observation series are strictly chosen and homogenized [*Wang et al.*, 2013]. For estimating regional mean warming trends, previous studies for China suggested an urbanization-induced warming bias of about 0.1°C/decade in association with a rapid process of urbanization in the region since the late 1970s [*Jones et al.*, 2008; *Hua et al.*, 2008; *Ren et al.*, 2008]. However, a recent study based on homogenized observations suggests that the average urbanization-related warming bias for China for the last half century was only 0.012°C/decade [*Li et al.*, 2004]. Using the U.S. as another example, there was no significant difference in the country-wide mean warming trend between urban and rural records after homogenization of the data [*Peterson*, 2003]. Another issue causing much discussion in this field is the use of two contrasting approaches. While most of the works discussed above are based on analyses of surface observations, there are a number of studies involving reanalysis data by using the "observation minus reanalysis (OMR)" method [*Kalnay and Cai*, 2003]. A recent study using OMR estimated that the effect of urbanization on winter temperature in eastern China could be as large as 0.466°C/decade [*Yang et al.*, 2011]. The basic idea of OMR is that the National Centers for Environmental Prediction/National Centers for Atmospheric Research reanalysis (NNR) data represent large-scale climate change but do not assimilate surface observations of temperature, moisture, and wind over land. As a result, the NNR should not be sensitive to land use changes [*Kalnay and Cai*, 2003]. *Trenberth* [2004] argued that the NNR did not include effects of the changing atmospheric composition on radiation either. However, *Cai and Kalnay* [2005] replied that even if a model used in reanalysis does not include the forcing due to the increase in greenhouse gases, the trend from this forcing should be present in the reanalysis. Despite these arguments, many studies [*Zhou et al.*, 2004; *Lim et al.*, 2005; *Kalnay et al.*,

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2006; *Pielke et al*., 2007; *Nunez et al*., 2008; *Fall et al*., 2010] have applied OMR to estimate the effect of land use changes on climate. By using the National Centers for Environmental Prediction/Department of Energy (NCEP/DOE) reanalysis, *Zhou et al*. [2004] indicated that urbanization in southeastern China enhanced the winter temperature warming at a rate of 0.05°C/decade for the years 1979–1998. However, according to Figure 3 in *Zhou et al*. [2004], urbanization has almost no contribution to the warming of mean winter surface temperature for the same period in east China around the Yangtze River Delta, where strong OMR trends for 1981–2007 were found, with rates up to 0.466°C/decade [*Yang et al*., 2011]. Although the recent study involved updated observations from 1999 to 2007, it is unlikely that the rapid process of urbanization in east China since the end of the 1970s did not influence the local temperature records until the end of last century. Moreover, *Zhou et al*. [2004] showed that the OMR trends in winter minimum temperature in the Pearl River Delta in south China were significant while those in the Yangtze River Delta were negligible. This difference is difficult to reconcile, as both the regions have experienced rapid urbanization over the same period. *Vose et al*. [2004] found that the OMR trend in the study of *Kalnay and Cai* [2003] decreased with time. According to their calculations, the discrepancy between the observation trend using homogenized data and the NNR trend during the first two decades is more than twice as large as during the last two decades. Having considered the various results and arguments in previous studies, we infer that there might be systematic differences in some multidecadal variability between the surface observations and the reanalysis data.

[3] *Wu et al*. [2011] suggested that short-term temperature trends are an amalgamation of the secular trend (ST) and multidecadal variability (MDV). In *Wu et al*. [2007], they indicated that the rapid warming in the late twentieth century was a result of concurrence of a secular warming trend and the warming phase of a multidecadal oscillatory variation and they estimated the contribution of the former to be about 0.08°C/decade since the 1980s. They consider that MDV essentially arises from internal variability of the climate system. If the reanalysis data cannot fully reproduce MDV, which is well recorded in surface observations, the OMR trends calculated based on time series of a few decades should be partly affected by the difference in MDV between the observations and reanalysis. If so, previous conclusions based on the OMR method would be questionable, since these OMR trends are not only caused by the so-called "impact of urbanization and land use change" but also by the discrepancy of MDV between the data sets.

[4] In the present paper, we first show some contradictory results obtained by the OMR method. Second, we demonstrate some inherent differences of MDV between the different data sets. Finally, we present a possible means of adjusting MDV in the reanalysis data before applying OMR.

2. Data and Methods

[5] The data used in this study include three gridded reanalysis data sets (NCEP/DOE [*Kanamitsu et al*., 2002], ERA-Interim [*Dee et al*., 2011], and twentieth century [*Compo et al*., 2011]); a homogenized daily surface air temperature data set [*Li and Yan*, 2009] of observations at 549 meteorological stations in China for the period 1960–2008 and centennial-scale series of daily temperature observations for Beijing, Shanghai [*Yan et al*., 2001], and a few other sites across the world for comparison; and global gridded land surface air temperature records CRUTEM4 [*Jones et al*., 2012].

[6] To facilitate the discussion, we performed an analysis identical to that of *Zhou et al*. [2004], except that we used homogenized observations with most of the nonclimate biases in the time series due to changes in the local observing system (e.g., relocation) having been accounted for. Specifically, we compare the monthly mean temperature recorded at the stations located below 500 m in eastern China, with those from the NCEP/DOE reanalysis interpolated to the station locations, for the periods 1979–1998 and 1989–2008, respectively. Temperature anomalies are calculated with respect to the climatological mean annual cycle for each series. Linear trends are calculated by using the ordinary least squares method, with Student's t test for testing statistical significance. Note that the mean annual cycle for 1979–1998 is slightly different from that for 1989–2008, but the OMR trend for the given time window is not affected.

[7] For further illustration that the decadal change of OMR trends not only occurs in China but also in other regions, we compare the reanalysis data with the gridded data of CRUTEM4, which are based on surface station observations [*Jones et al*., 2012]. To facilitate calculation of the OMR trends based on CRUTEM4, we interpolate the reanalysis data to 5 × 5 latitude × longitude grids. The OMR trends are estimated by the ordinary least squares method, with statistical significance assessed by Student's t test.

[8] To demonstrate MDV in the time series, we employ the long-term temperature series at Beijing and Shanghai and interpolate the twentieth-century reanalysis (20CR) to the corresponding locations. 20CR is the only reanalysis data set which covers a sufficiently long period for analyzing MDV in the time series. An adaptive and temporal local analysis method, namely, Ensemble Empirical Model Decomposition (EEMD) [*Huang and Wu*, 2008; *Wu et al*., 2008], is applied to partition the time series into variations of different time scales (including MDV and ST). Compared with other traditional decomposition methods (e.g., Fourier Transform and wavelet analysis), EEMD emphasizes the adaptability and temporal locality of the data decomposition [*Wu et al*., 2011]. EEMD is a major refinement of the original empirical mode decomposition (EMD) method. EMD is an adaptive (without using any a priori basis) and uses a temporally local analysis algorithm aimed at providing a more accurate expression of a time series in the time-frequency-energy domain [*Huang and Wu*, 2008]. By applying EMD, we can decompose any complicated data series into a small number of amplitude-frequency modulated oscillatory components called intrinsic mode functions (IMFs) of different time scales [*Huang and Wu*, 2008]. In this study, the major steps of the EEMD method are as follows [*Qian et al*., 2009]: (1) add a white noise series, with an amplitude 0.2 times the standard deviation of data, to the annual average temperature series to provide a relatively uniform, high-frequency extrema distribution to facilitate EMD to avoid the effect of the possible intermittent noise in the original data; (2) decompose the data with the added white noise into

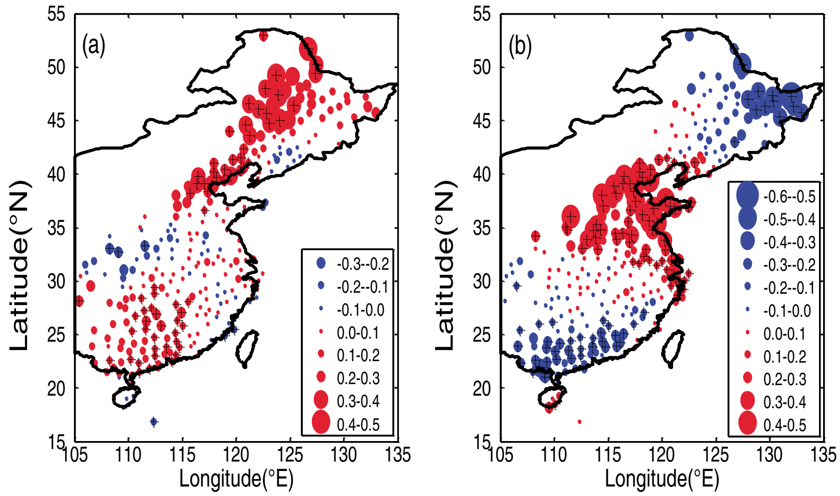

Figure 1. Observed minus reanalysis (NCEP/DOE) temperature trends in eastern China for the periods of (a) 1979–1998 and (b) 1989–2008. Plus signs indicate significant OMR trends ($p < 0.05$). The unit is °C/decade.

IMFs using EMD; (3) repeat steps 1 and 2 for 1000 times, but with different white noise series each time; and (4) obtain ensemble means of the respective IMFs of the decompositions as the final result.

3. Results

3.1. Inconsistent Results of OMR

[9] Figure 1a shows the observed minus reanalysis (NCEP/DOE) temperature trends in eastern China for the period of 1979–1998. It is notable that the geographical pattern and magnitude of OMR trends in southeast China (20°N–36°N, 102°E–123°E) are almost the same as the results of *Zhou et al.* [2004]. This is because we use almost identical data and methods. It is interesting to note that the OMR trends in the Yangtze River Delta (YRD) in east China are much smaller than those in the Pearl River Delta (PRD) in south China. This regional difference has not been explained, as both regions experienced a similarly rapid process of urbanization during the period 1979–1998. Figure 1b presents the OMR trends for the period 1989–2008. The magnitudes of OMR trends in YRD are much larger than those in PRD for 1989–2008. The OMR trends in most parts of southern China even become negative. These decreased OMR trends contradict the rapid urbanization and dramatic economic growth in PRD in the last couple of decades. Similarly, the OMR trends in northeast China for 1979–1998 are also quite large, but substantial decreases are evident for 1989–2008. This is also contradictory to the urbanization process in northeastern China. Note that the land use change in both YRD and PRD during the past few decades was mainly due to rapid urbanization; hence, the opposite OMR trends between the two subperiods and the two regions are contradictory, according to original OMR expectations [e.g., from *Zhou et al.*, 2004]. In short, the findings based on OMR so far are not consistent with regard to the impact of urbanization and land use change on climate. The expectation would be a more gradual change over the whole period from 1979 and not a relative warming in one period and a cooling in another.

3.2. Results Based on ERA-Interim and 20CR

[10] To demonstrate if the problem not only exists in NCEP/DOE reanalysis but also in other reanalyses, we repeat the analysis in section 3.1 but employ the ERA-Interim and 20CR reanalysis data. These two data sets were carried out with different forecasting and assimilating systems and different assimilation data sources. The 20CR has a long time span, from 1871 to 2010. This enables us to apply the EEMD method to properly extract the components of ST and MDV in the surface air temperature time series. As indicated by Figure 2a, the OMR (ERA-Interim) trends for the years of 1979–1998 in YRD and PRD are slightly negative. For the period of 1989–2008, the negative OMR trends in YRD are slightly more pronounced (Figure 2b). These indicate that the OMR (ERA-Interim) trends between the two periods are more consistent, although their negative values for the rapidly developing zones are not expected based on the earlier OMR results. The results based on 20CR show (Figure 2c) that the OMR trends for the years of 1979–1998 in central China, including the middle reaches of the Yangtze River, are all positive and more pronounced than those in the strong development zones in southeast coastal areas. For the period of 1989–2008, OMR trends in YRD are all positive and larger than those in PRD (Figure 2d). The inconsistency is even more apparent than that in section 3.1.

[11] To assess other regional cases across the world, we calculate the OMR trends derived from CRUTEM4 and three independent reanalyses (NCEP/DOE, ERA-Interim, and 20CR) for the periods 1979–1998 and 1989–2008, respectively. As shown in Figures 3a and 3b, the OMR trends based on NCEP/DOE reanalysis during the two periods change considerably in the U.S. Midwest, southern Europe, the Far East, and eastern Australia. In contrast, the OMR trends based on ERA-Interim show little change between the two periods (Figures 3c and 3d), similar to the cases in China. This indicates good agreement between near-surface temperature observations and ERA-Interim reanalysis data in terms of interdecadal climate variability.

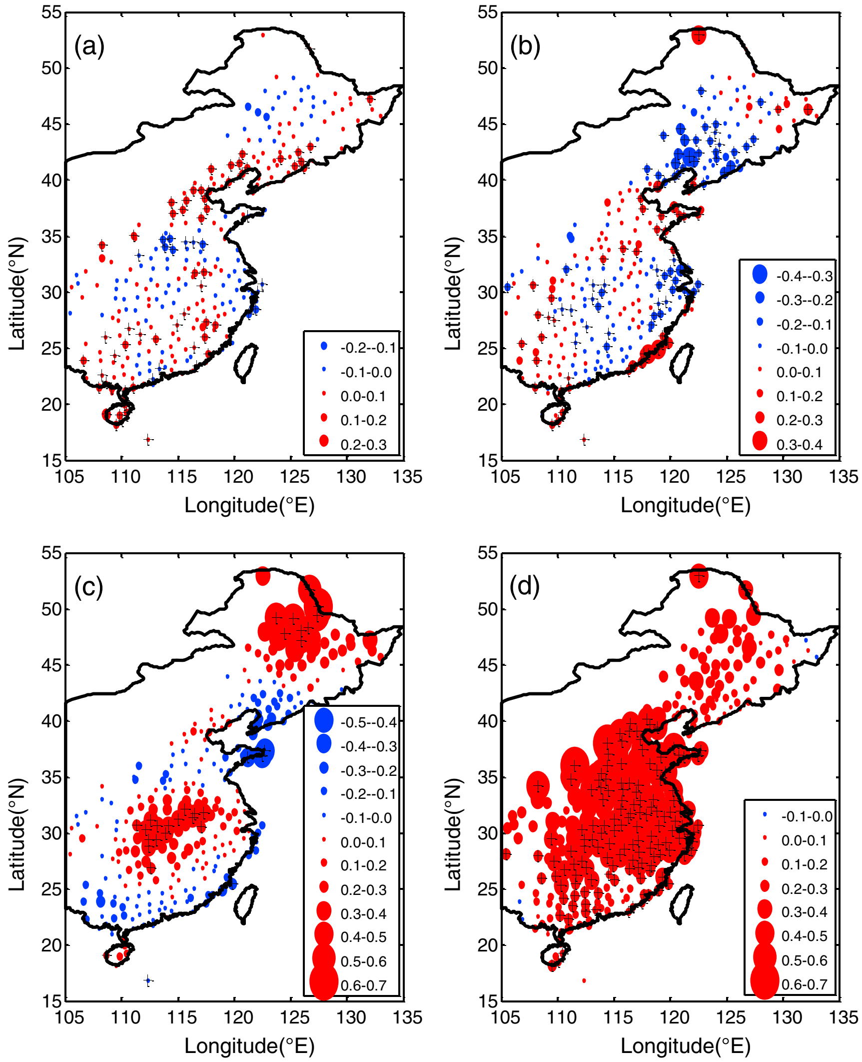

Figure 2. Observed minus reanalysis (ERA-Interim) temperature trends in eastern China for the periods of (a) 1979–1998 and (b) 1989–2008 and observed minus reanalysis (20CR) temperature trends in eastern China for the periods of (c) 1979–1998 and (d) 1989–2008. Plus signs indicate significant OMR trends ($p < 0.05$). The unit is °C/decade.

The OMR trends derived from 20CR are not consistent between the two periods in many places, e.g., southern United States, Siberia, northern China, and the Indian subcontinent (Figures 3e and 3f).

3.3. ST and MDV in Observation and Reanalysis

[12] Short-term OMR trends can be regarded as a combination of the differences of ST and MDV between observations and reanalysis. As shown in Figure 4, the STs of observed surface temperature for two stations in eastern China and those interpolated from reanalysis have changed little since the 1980s.

[13] In contrast, the MDV components show differences between observations and reanalysis, which are critical in modulating the short-term linear OMR trends. Previous studies [*Huang and Wu*, 2008; *Wu et al.*, 2008; *Semenov et al.*, 2010; *DelSole et al.*, 2011] pointed out that MDV essentially arises from internal variability of the climate system. As shown in Figures 4a and 4b, the MDV curves of observations at Beijing and Shanghai have a similar shape, peaking in the 1940s and reducing by the end of the 1970s. However, the MDV components in the reanalysis series differ for the two sites. For Beijing and the period from 1960 to the present, the MDV component in the reanalysis data, when compared to the observations, has a nearly inverse phase. This discrepancy in MDV should modulate estimates of OMR trends for different periods. As inferred from Figure 5, after the year 1979, the MDV in observations goes up while that in the reanalysis declines markedly. Therefore, the OMR trend for Beijing for the period of 1979–2008 has been considerably enhanced due to the MDV discrepancy between observation and reanalysis. For the period 1960–1980, the MDV in observations goes down, but that in the reanalysis goes up slightly. Consequently, the OMR trend for Beijing is weakened during this period. For Shanghai, the MDV component extracted from observations is of the same phase as that from the reanalysis for the period of 1960–2000 but much larger in amplitude than that in the reanalysis. This leads to an enhanced OMR trend for the latter half of the period. It is inferred that

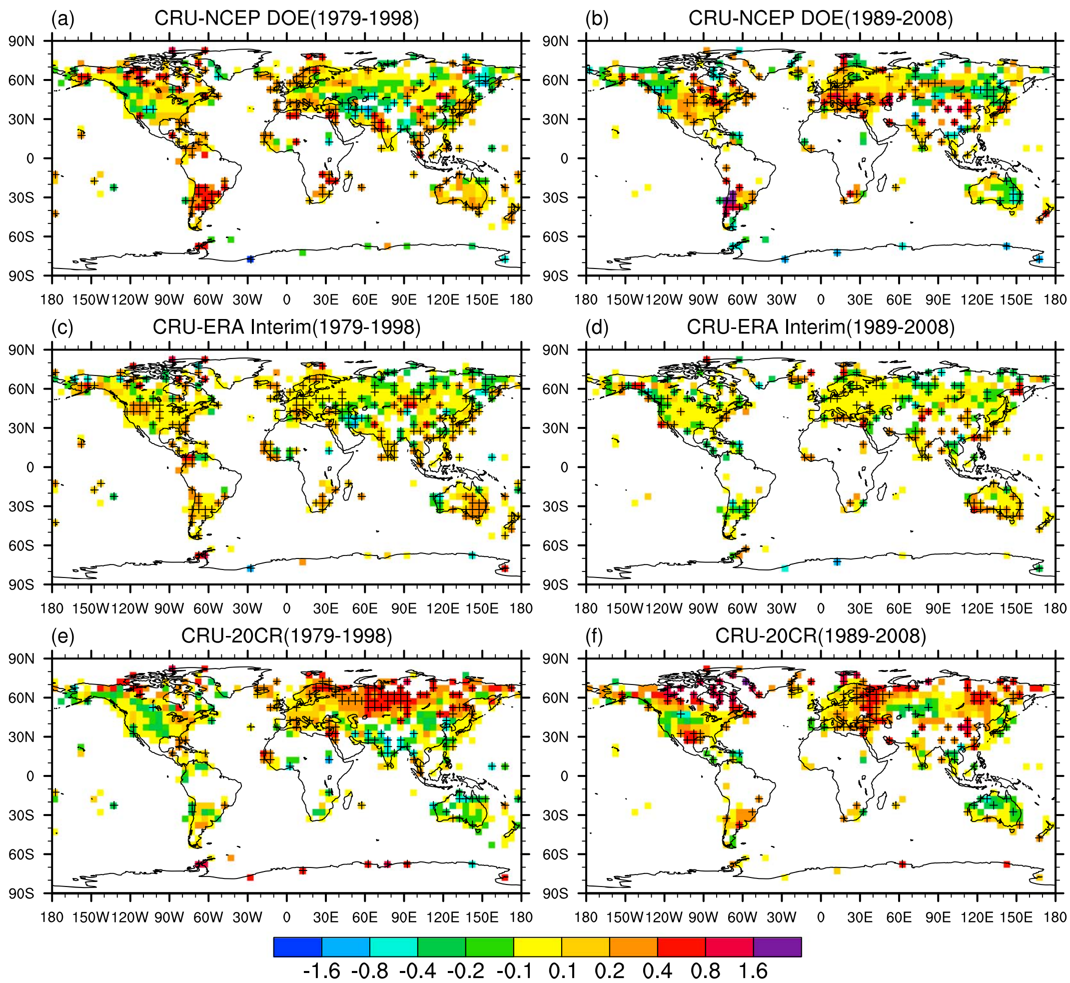

Figure 3. Linear trends of observation minus reanalysis over the period (left) 1979–1998 and (right) 1989–2008 using CRUTEM4 data with (top) NCEP/DOE, (middle) ERA-Interim, and (bottom) 20CR. In each grid box, where trend is significant, it is marked with a plus sign based on Student's *t* test ($p < 0.05$). Units are °C/decade.

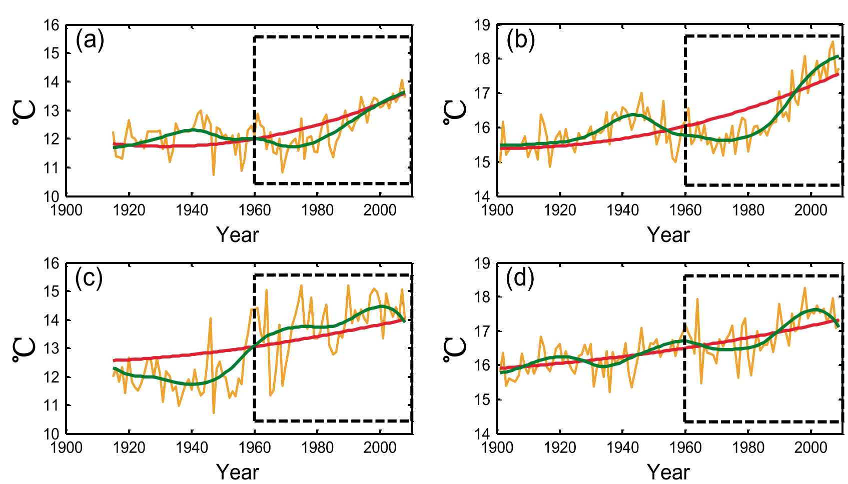

Figure 4. The raw surface air temperature time series (orange lines), ST, (red lines) and ST+MDV (green lines) that were derived from the observations at two stations and those interpolated to station locations using the 20CR. (a and c) Beijing and (b and d) Shanghai.

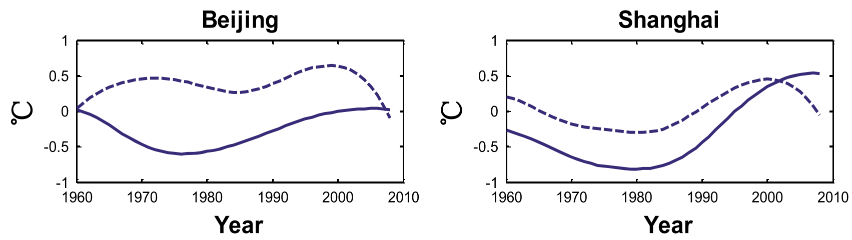

Figure 5. The MDVs derived from the observed temperature series (solid lines) and those interpolated to station locations using the 20CR (dashed lines) for Beijing and Shanghai.

the OMR trend contains not only the impact of urbanization and other land use influences but also discrepancies in MDV between the different data sets. Note that the MDV components in observations for Beijing are similar to those for Shanghai, while those in the reanalysis for Beijing, particularly before 1990, are quite different from those for Shanghai. The consistency in observations and the inconsistency in the reanalysis data imply issues in the reanalysis in terms of MDV.

[14] We also show the MDV differences between observed temperature series at a few other stations across the world and the reanalysis. Detailed information of these long-term temperature series can be found in Table 1 in *Xia et al.* [2012]. As shown in Figure 6, the MDV discrepancy between observations and reanalysis is quite common but varies significantly between the regions analyzed. In general, the reanalysis data tend to underestimate MDV compared with observations, in most cases. To help understand this general conclusion, Figure 7 shows the MDV components in the averaged temperature series over the land area of the Northern Hemisphere derived from different data sets. It is notable that, especially for the latter half of the last century, MDV in reanalysis (20CR) is considerably weaker than that in observations (CRUTEM4).

[15] To further understand how the OMR trends are modulated by the MDV inconsistency between observations and reanalysis for different regions, we calculate the changes of the biased-MDV-related OMR trends from 1950–1978 to 1979–2010 in Europe and North America, respectively. We subtract the MDV component in reanalysis from that in observations and then calculate the linear trend in the MDV difference series via the ordinary least squares method. As shown in Figure 8, the OMR trends in Europe and eastern United States are weakened for the early period and enhanced for the latter period by the MDV discrepancy. However, in some regions in central and western United States, the OMR trends are enhanced for the early period and weakened afterward by the MDV discrepancy.

[16] Due to limited length of the time series, we cannot properly extract MDV in the other reanalysis data currently available, but the fact that decadal changes in the OMR trends using ERA-Interim are less pronounced, particularly for the cases of YRD and PRD, suggests that ERA-Interim tends to perform better than the other reanalyses regarding MDV in surface temperature series. ERA-Interim performs better in capturing observed MDV, because this reanalysis incorporates more surface observations than the other reanalyses do.

3.4. MDV Adjustment

[17] Supposing that MDV is a quite natural signal, then it should be well represented in the reanalysis data. We propose, therefore, an MDV adjustment to the reanalysis data before applying the OMR method in order to obtain more consistent estimates of the urbanization impact especially for Beijing and Shanghai. A simple way is to replace the MDV component in the reanalysis data with that from observations. After the MDV adjustment for the reanalysis data,

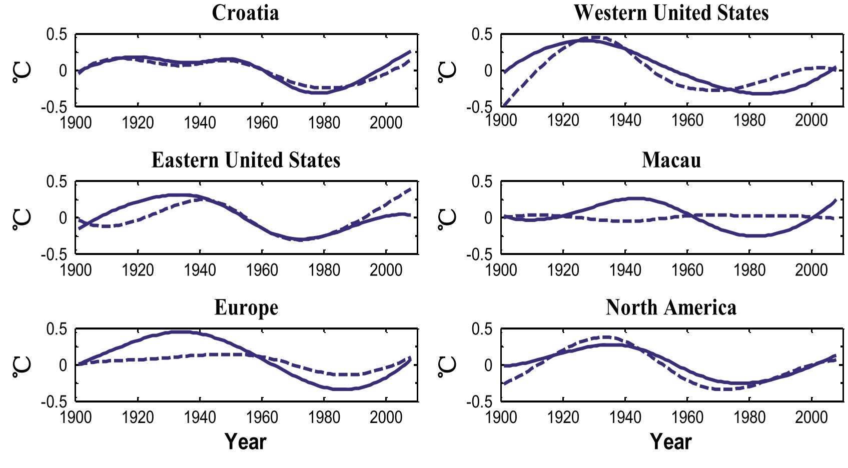

Figure 6. The MDVs derived from the observed temperature series (solid lines) and those interpolated to station locations using the 20CR (dashed lines) for other different sites and regions over the world.

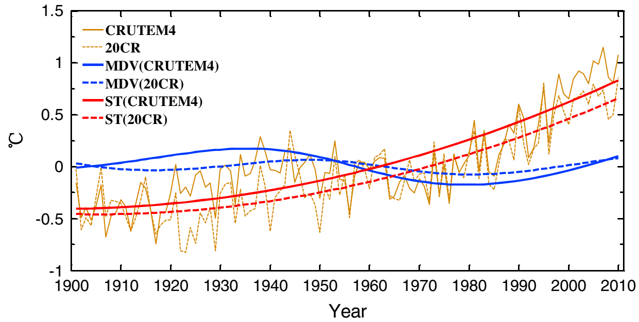

Figure 7. The averaged Northern Hemisphere land surface air temperature series (brown lines), ST, (red lines) and MDV (blue lines) based on CRUTEM4 (solid lines) and 20CR (dashed lines).

we recalculate the OMR trends. As shown in Figure 9, the conventional OMR trends for the years of 1979–2008 for Beijing and Shanghai are 0.260°C/decade and 0.445°C/decade, respectively, preceded by a strong negative trend. After MDV adjustment, the negative OMR trends for the early period tend to diminish, while the positive ones since the end of the 1970s are 0.039°C/decade and 0.103°C/decade, respectively, for Beijing and Shanghai. Note that China has experienced rapid urbanization since the late 1970s. For the years 1960–1980, other land use changes (e.g., vegetation recovery or agricultural development) might be more influential, which could induce a decreasing OMR trend. Nevertheless, after MDV adjustment, the negative OMR trend for the early period tends to diminish. Although there are more comprehensive schemes of MDV adjustment, the present results suggest that the effect of urbanization in China has been extensively overestimated in some recent publications based on the OMR method [e.g., *Yang et al.*, 2011].

4. Discussion and Summary

[18] The OMR approach is widely used to investigate the impact of urbanization and land use change on climate in recent years. The rationale of this method is that reanalysis represents the large-scale climate change caused by greenhouse gases and atmospheric circulation but is insensitive to regional surface processes associated with changes of land types because little surface information has been assimilated. Thus, comparing the temperature trends between observations and reanalysis allows an isolation of the impact of urbanization and land use changes from some global warming signal.

[19] In this study, we demonstrate the contradictory results of OMR applied to estimate the impact of urbanization on surface temperatures in China, where a rapid process of urbanization has occurred during the past few decades. Similar inconsistent OMR trends between different periods also exist elsewhere across the world, many of which cannot be explained by the effect of urbanization or other land use changes.

[20] Having applied the EEMD method to extract the secular trend and multidecadal variability components from observations and reanalysis, we find that the reanalysis cannot fully reproduce the MDV in general compared to that in observed temperature time series. The MDV discrepancy between observations and reanalysis seriously modulates the short-term linear OMR trends and leads to inconsistent estimates of the impact of urbanization and land use change on climate for different periods and places. After adjusting the MDV in the reanalysis data, the OMR trends for Beijing and Shanghai become more consistent throughout and an order of magnitude less than the original ones for the recent few decades. Our MDV-adjusted results are much less than previous estimates of urban-related warming in China based on conventional OMR analyses. Nevertheless, urbanization not only induces local warming due to the well-known Urban Heat Island effect, but this could also be accompanied by possible cooling effects due to increasing

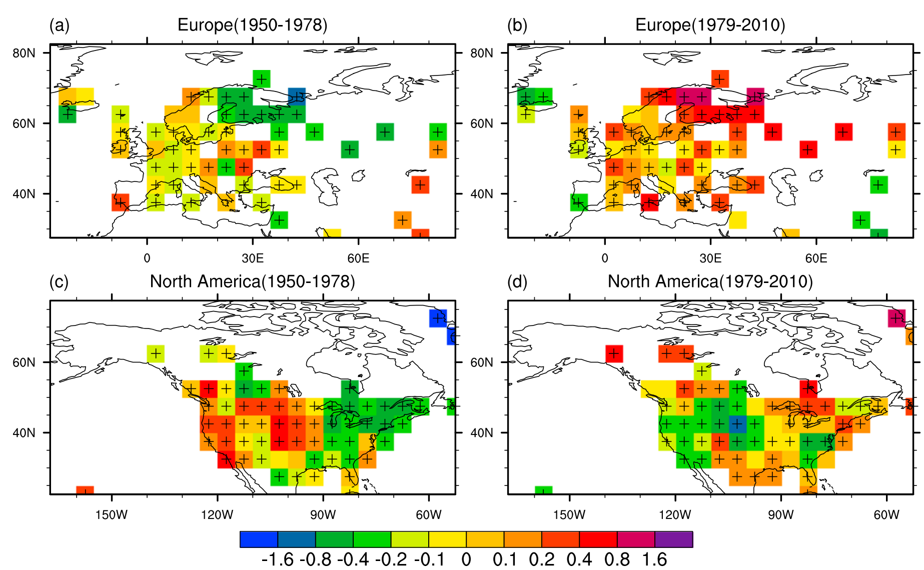

Figure 8. Change of the OMR trends in (a and b) Europe and (c and d) North America between two periods (1950–1978 and 1979–2010), caused by discrepancy of MDV between CRUTEM4 and the 20CR data. In each grid box where trend is significant, it is marked with a plus sign based on Student's *t* test ($p < 0.05$). Units are °C.

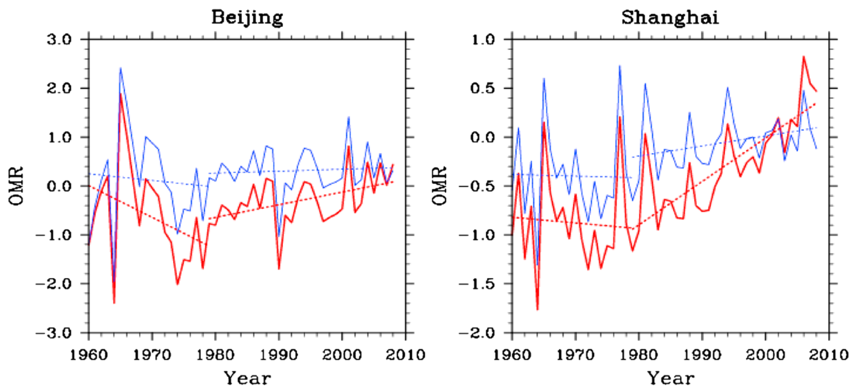

Figure 9. The original OMR (red lines) and MDV-adjusted OMR (blue lines) time series of temperature anomalies for Beijing and Shanghai.

aerosols especially in the case of China for the last few decades, which may not be fully captured by the reanalysis. Note that due to the complex nature of mechanisms of climate change, it is impossible to neatly isolate the signal of urbanization in surface climate observations. However, the present EEMD-based revision of the widely applied OMR method tends to clarify many of the issues apparent in previous results. For comparison, recent studies based on homogenized surface station temperature series [e.g., *Wang et al.*, 2013] also suggest that previous studies [e.g., *Ren et al.*, 2007; *Yan et al.*, 2010] have not taken sufficient consideration of the quality of station observations and have tended to overestimate the effect of urbanization in China.

[21] Because most reanalysis data sets are not long enough to extract the MDV, the conclusion of this study is partly based on the use of the 20CR reanalysis data set. Nevertheless, our results suggest that the MDV discrepancy tends to be a common problem in other reanalysis data sets, which needs consideration in further development. It is recommended that MDV adjustment for the reanalysis data should be carried out before applying the OMR method to estimate the impact of urbanization and land use change. We also advise caution in applying the reanalysis data to study climate change within a limited time period, especially with regard to multidecadal climate variability.

[22] **Acknowledgments.** This study was supported by Chinese Academy of Sciences SPRP grant XDA05090000 and CNNSF grant 41075063. Phil Jones has been supported by the USDoE (grant DE-SC0005689).

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