Varied Diagnosis of the Observed Surface Temperature Trends in the Southeast United States

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ABSTRACT

This paper diagnoses the temperature trends in maximum (T_{max}) and minimum temperatures (T_{min}) over a selection of 65 stations spread over the southeast United States (SEUS) from three observed datasets. They are the Cooperative Observer network program (COOP), the COOP data corrected for documented shifts in time of observation (COOP1), and the COOP data additionally corrected for documented changes in instrumentation (COOP2). These 65 stations have been isolated for having the three observed datasets for the same time period from 1948 to 2009. The authors' comparisons suggest that COOP2 displays stronger warming (cooling) trends in T_{max} (T_{min}) compared with COOP1 in all four seasons. This is consistent with the expectation from the bias correction applied for the instrument change. In comparison, the differences between COOP and COOP2 are relatively larger. In the spring, summer, and fall seasons, the median T_{max} trend is warming in COOP2 while it is cooling in COOP. In the winter season, the median trends of T_{max} in the two datasets are positive, but their magnitudes are substantially different. Similarly, in the winter, summer, and fall seasons, the warming trend in T_{min} in COOP is contrary to the cooling trend in COOP2. In the spring season, the median trend in T_{min} is comparable between the two datasets. COOP2 shows the relationship of trends in T_{min}, with the extent of urbanization in these 65 stations, to be statistically significant and to be consistent with expectations from theory in contrast to the COOP data.

1. Introduction

The ''warming hole'' in the southeast United States (SEUS) refers to the cooling trend in the surface temperature observed especially in the boreal spring and early summer seasons, which is unlike the rest of the United States (Pan et al. 2004; Kunkel et al. 2006; Portmann et al. 2009). In a more recent study, Misra et al. (2012) showed that some of the heterogeneity of the observed surface temperature trends in the SEUS can be explained by the spatial distribution of urbanity and irrigation in the rural regions. They find, consistent with theory, that urbanity raises the minimum temperature T_{min}; as a result, they find that warming trends of T_{min} are stronger in urban areas and weaker in rural regions. On the other hand, irrigation will tend to reduce the maximum temperature T_{max} measured during the day by way of evaporation (Bonfils and Lobell 2007; Puma and Cook 2010) and, in some cases, influence cloud cover and downstream precipitation patterns (Kueppers et al. 2007). Irrigation also raises the heat capacity and conductivity of the soil by way of wetting, which under weak wind conditions (which usually exist at night when the boundary layer tends to decouple from the rest of the atmosphere) lead to warming of the surface T_{min} (Elsner et al. 1996). Misra et al. (2012), consistent with these studies, find that the observed temperature trends of T_{max} (T_{min}) are relatively weaker (stronger) in highly irrigated regions than the less irrigated regions of the SEUS in the summer season.

In another related study, Meehl et al. (2009) show that in the last several decades the ratio of the daily record high temperatures to daily record low temperatures is

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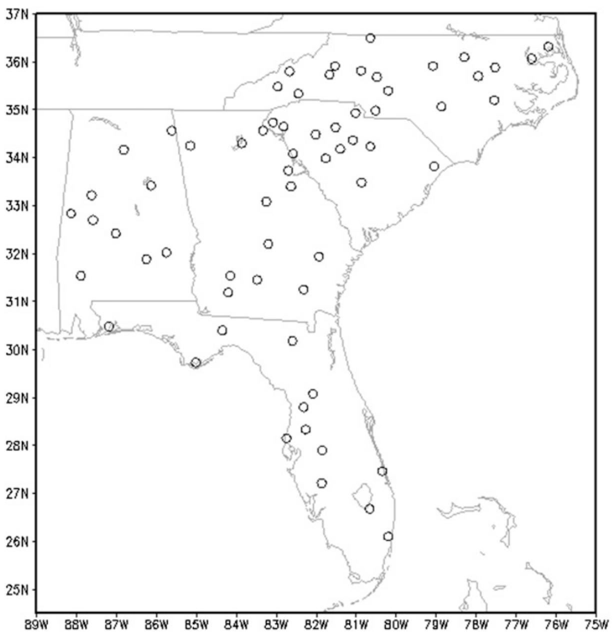

FIG. 1. Map showing the location of the 65 stations used in the analysis.

nearly twice as low in the eastern United States compared to the western United States, west of 100°W. This east–west differential of temperature extremes is observed to be consistent with the pattern of change of the mean temperature, with the western United States exhibiting stronger warming trends than the eastern half of the United States in the last several decades (Meehl et al. 2009; Anderson and Kostinski 2010).

In this study, we are comparing the temperature trends and their relationship with urbanity from three datasets obtained from the National Climatic Data Center (NCDC). The purpose of this comparison is to document and show the impact of nonclimatic discontinuities in our estimation of the surface temperature trends and its relationship with urbanization. This comparison is also relevant because two of the three datasets are archived at NCDC and are easily accessible on the web (NCDC 2009). The methodology to diagnose the trends and discern the statistical relationship of the temperature trends with urbanity follows Misra et al. (2012). Datasets are discussed in section 2, with results and conclusions discussed in sections 3 and 4, respectively.

2. Datasets and methodology

Following Misra et al. (2012), we selected 65 stations (Fig. 1) across the five states (Alabama, Florida, Georgia, South Carolina, and North Carolina) in the SEUS that had datasets from the National Weather Service's Cooperative Observer station network program (COOP), the COOP data corrected for documented shifts in time of observation (COOP1), and the COOP data additionally corrected for documented changes in instrument (COOP2) for an overlapping period of 62 years from 1948 to 2009. It should be mentioned that there are 327 stations across these five states, but only 65 of these had the temperature records for the same overlapping period in all three datasets with missing data that did not stretch more than 3 years in a row. The missing data were linearly interpolated. The trends were computed on the seasonal means, and therefore, the filling of the missing data for such short time periods with linear interpolation did not have a significant impact. The COOP data are available from the NCDC and are quality controlled, monthly mean T_{max} and T_{min} from 1948 to 2009. The COOP1 data are from the U.S. Historical Climatology Network, version 2 (USHCNv2), and are corrected for time of observation bias (TOB; Baker 1975; Karl et al. 1986; Menne et al. 2009) (see also 9641C_YYYYMM_tob.max.gz and 9641C_YYYYMM_tob.min.gz available from ftp://ftp.ncdc.noaa.gov/pub/data/ushcn/v2/monthly/). These data, as reported in Menne et al. (2009), were derived from the U.S. daily surface data DSI-3200, DSI-3206, and DSI-3210 (http://gcmd.nasa.gov/records/GCMD_gov.noaa.ncdc.C00314.html). The COOP2 is obtained from making corrections to the COOP1 data for the documented instrument change from liquid-in-glass thermometers to the Maximum–Minimum Temperature System (MMTS) by increasing T_{max} by 0.4°C (0.72°F) and reducing T_{min} by 0.3°C (0.54°F) from the time of the documented instrument change onward, following Quayle et al. (1991). We have deliberately avoided using the homogenized dataset (USHCNv2), as trends from it are well documented in Menne et al. (2009). Furthermore, Menne et al. (2009) notes that the homogenization algorithm used on USHCNv2 accounts for much of the urban heat island effect noted in Karl et al. (1988). Therefore, it makes the temperature trends from these data artificially appear insensitive to urbanization.

We also make use of the Population-Interaction Zone for Agriculture (PIZA) index dataset developed by the U.S. Department of Agriculture's Economic Research Service (USDA-ERS 2005), a proxy measure for urbanization. This dataset was generated at a 5-km grid resolution and is based on the data for the year 2000. The PIZA index ranges from 1 to 5, with 1 (5) representing negligible (highest) interaction of the urban population with agriculture.

The trends in this study are diagnosed using the ensemble empirical mode decomposition (EEMD; Wu and Huang 2009). The EEMD procedure results in multiple near-orthogonal components called intrinsic mode functions (IMFs). For further details on the methodology, the reader is referred to Misra et al. (2012).

3. Results

a. Comparison of COOP1 with COOP2

The scatter of the surface temperature trends for both T_{max} and T_{min} for all 65 stations and for each of the four seasons between COOP1 and COOP2 is shown in Fig. 2. At a glance, it seems that the temperature trends are comparable between the two datasets for both T_{max} and T_{min} in all seasons. However, the median temperature trends from the two datasets (m_{COOP2} and m_{COOP1} in Fig. 2) and the average trend (the large diamond in Fig. 2) show that the trends in COOP2 are stronger than in COOP1; COOP2 has stronger positive (negative) trends for T_{max} (T_{min}). This is consistent with the expectation from the correction applied to the measurements of T_{max} and T_{min} in COOP1 for the documented change in instrument in COOP2. The warming hole displayed by a cooling trend in the majority of the 65 stations (represented by both the mean and the median trend) is most strongly evident in both datasets in T_{min} in the boreal spring season (Fig. 2d), but this cooling trend in the median value is evident in all seasons in COOP2, with COOP1 displaying a weak positive median trend in the fall season (Fig. 2h).

b. Comparison of COOP with COOP2

Similar to Fig. 2, the scatter of the diagnosed temperature trends from COOP and COOP2 are shown in Fig. 3. Unlike Fig. 2, there is far more scatter in Fig. 3, suggesting larger and nonsystematic differences in the diagnosed temperature trends between the two datasets. It is to be noted that the median trend of T_{max} (T_{min}) diagnosed from the two datasets is of opposite sign in all seasons except in the December–February (DJF) [March–May (MAM)] season. The nonclimatic biases in COOP therefore have a profound impact on the diagnosed surface temperature trends. The ubiquitous cooling trend, as displayed by the negative values of median T_{min} trends in COOP2, is in fact a warming trend in the COOP dataset. Similarly, the negative median trends of T_{max} in the spring, summer, and fall seasons, as diagnosed from the COOP dataset, run contrary to the positive median trends diagnosed from the COOP2 dataset. Even in DJF (Fig. 3a), when the sign of the median T_{max} trends match in the two datasets, their magnitudes are significantly different.

c. Relationship with urbanization

To further highlight the differences in the diagnosed temperature trends from the three datasets, we computed the slope of the linear fit to the scatter of the observed temperature trends from COOP and COOP2 to the PIZA index (Table 1). The slopes from COOP1 were nearly similar to those in COOP2 and are therefore not shown. The relationship of the trends in T_{min} with PIZA is more robust in COOP2, which displays a statistically significant positive slope for the linear fit of the scatter between the trends of T_{min} with the PIZA index for all four seasons. In other words, this relationship in COOP2 suggests that T_{min} gets warmer with increased urbanity, which is not substantiated in the COOP dataset. This again points to the impact of the additional nonclimatic discontinuities prevalent in the COOP dataset on the diagnosed surface temperature trends.

4. Conclusions

A comparison of the diagnosed surface temperature trends over the 65 stations spread over Alabama, Florida, Georgia, North Carolina, and South Carolina in the SEUS show significant differences among the three datasets of COOP2 (which corrects for documented changes in time of observation and instrument change), COOP1 (which corrects for documented changes in instrument change), and COOP (with no corrections). The differences in the surface temperature trends between COOP2 and COOP1 are relatively small compared to COOP2 and COOP. The difference between COOP2 and COOP1 is consistent with the instrument bias adjustments applied in COOP2 to the temperature measurements, with diagnosed trends in COOP2 stronger than in COOP1.

The warming hole in the SEUS is reflected in the ubiquitous cooling trend in T_{min} that persists in all four seasons in the COOP2 dataset. In the COOP dataset, we diagnose a ubiquitous warming trend in all seasons except in the spring season. In contrast, the warming trends in T_{max} of the COOP2 dataset are matched by the cooling trends in T_{max} in the COOP dataset in all seasons (except in the winter season). Furthermore, the surface temperature trends of T_{min} display a robust relationship with urbanity in the COOP2 (and not in the COOP) dataset; increased urbanity is associated with stronger warming trends in T_{min} in all four seasons.

This study highlights the significant impact that the nonclimatic biases prevalent in the COOP and COOP1 datasets have on the diagnosed temperature trends in the SEUS. However, these 65 stations represent a much smaller subset of COOP stations distributed in these five states (327 stations). In a significant fraction of these COOP stations, which have different lengths of temporal coverage of observations, the nonclimatic shift of temperature caused by a shift in time of observation and instrument change is not properly documented.

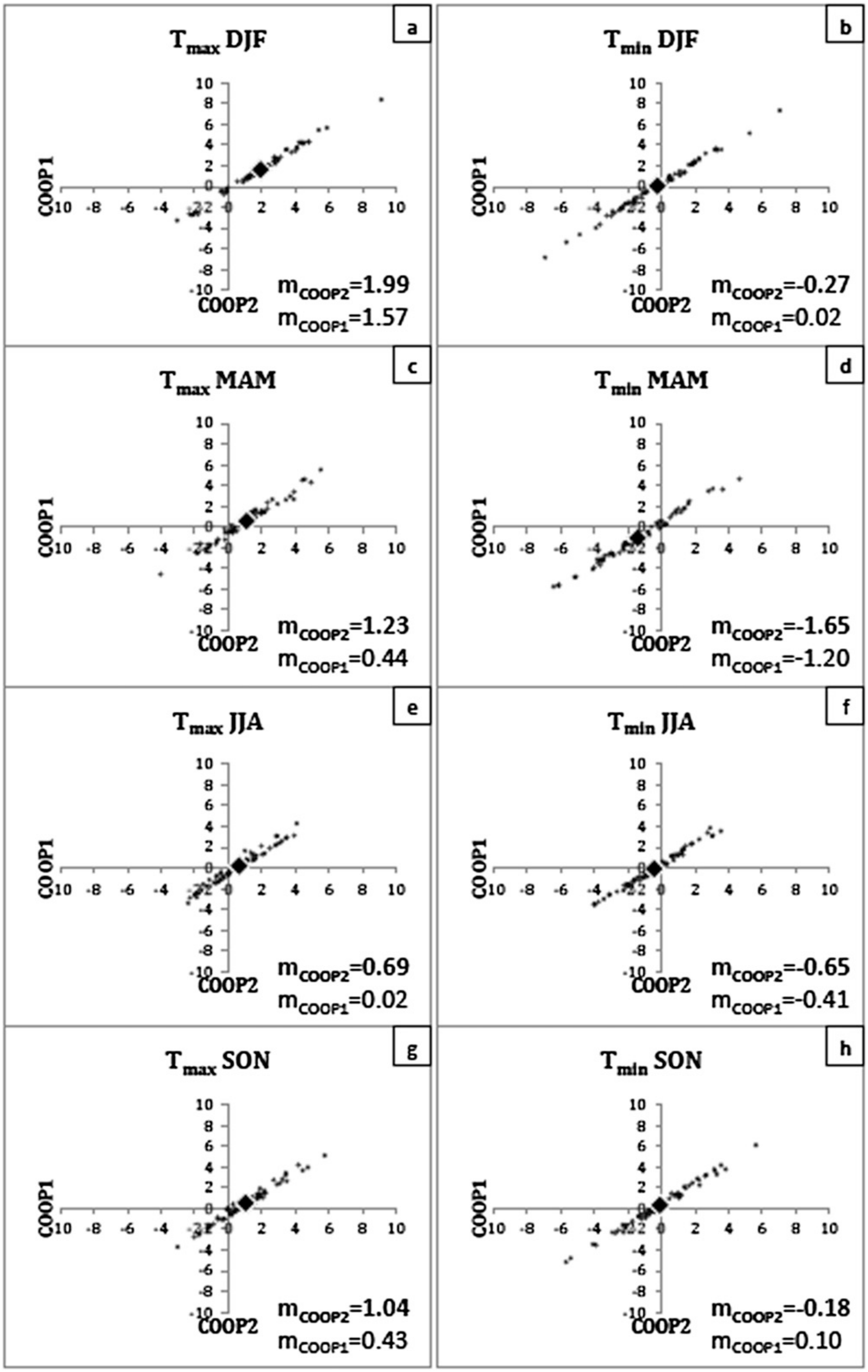

FIG. 2. The scatterplot linear trends (°F century^{-1}) from station observations of (left) T_{max} and (right) T_{min} between COOP2 data (on x axis) and COOP1 data (on y axis) for (a),(b) December–February (DJF); (c),(d) March–May (MAM); (e),(f) June–August (JJA); and (g),(h) September–November (SON) seasons. The large diamond in each panel is the mean trend over all stations from the two datasets. The COOP2 (in bold) and COOP1 median trends are also indicated in each panel.

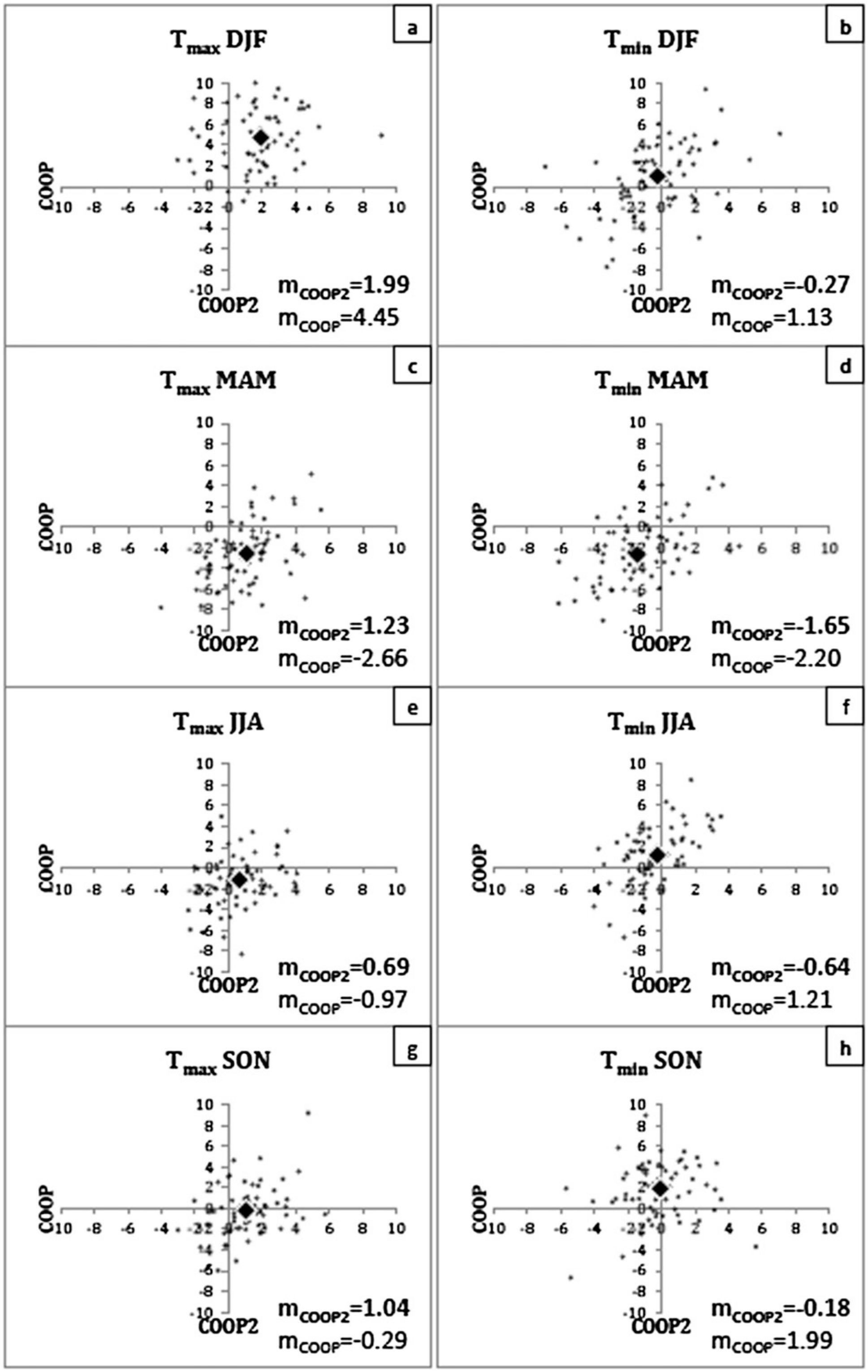

FIG. 3. As in Fig. 2, but for comparison between COOP2 and COOP datasets.

TABLE 1. The slope of the linear fit of the scatter between surface temperature trends and PIZA are shown from COOP and COOP2 datasets. The values in boldface are statistically significant at the 5% significance level by Monte Carlo approach; the values in italics are significant at 10%. The units are degrees Fahrenheit per century per index increase of PIZA.

	DJF		MAM		JJA		SON	
	$T_{\max}$	$T_{\min}$	$T_{\max}$	$T_{\min}$	$T_{\max}$	$T_{\min}$	$T_{\max}$	$T_{\min}$
COOP	0.120	0.661	−0.078	*0.789*	0.022	*0.538*	0.017	0.429
COOP2	0.040	*0.537*	0.091	**0.577**	0.186	**0.544**	0.035	**0.626**

Furthermore, discontinuities caused by other nonclimatic factors in the time series of the temperature measurements in the 65 stations of the COOP2 dataset used in this study also cannot be ruled out. Pielke et al. (2007) show evidence of several undocumented nonclimatic factors influencing temperature measurements, such as instrument site placement near a building, shift of the instrument site, or a shadow cast by a neighboring tree or building. However, in the absence of such information on nonclimatic factors influencing temperature measurements, it is indeed very difficult to unambiguously correct for them. This is especially true in regions where there is evidence for microclimatic influence from effects like urbanization on temperature, as robustly diagnosed in the COOP2 dataset.

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REFERENCES

Anderson, A., and A. Kostinski, 2010: Reversible record breaking and variability: Temperature distributions across the globe. *J. Appl. Meteor. Climatol.,* **49,** 1681–1691.

Baker, D. G., 1975: Effect of observation time on mean temperature estimation. *J. Appl. Meteor.,* **14,** 471–476.

Bonfils, C., and D. Lobell, 2007: Empirical evidence for a recent slowdown in irrigation-induced cooling. *Proc. Natl. Acad. Sci. USA,* **104,** 13 582–13 587, doi:10.1073/pnas.0700144104.

Elsner, J. B., H. E. Fuelberg, R. L. Deal III, J. A. Orrock, G. S. Lehmiller, and P. H. Ruscher, 1996: Tallahassee, Florida, minimum temperature anomaly: Description and speculations. *Bull. Amer. Meteor. Soc.,* **77,** 721–728.

Karl, T. R., C. N. Williams Jr., P. J. Young, and W. M. Wendland, 1986: A model to estimate the time of observation bias associated with monthly mean maximum, minimum, and mean temperature for the United States. *J. Appl. Meteor.,* **25,** 145–160.

——, H. F. Diaz, and G. Kukla, 1988: Urbanization: Its detection and effect in the United States climate record. *J. Climate,* **1,** 1099–1123.

Kueppers, L. M., M. A. Snyder, and L. C. Sloan, 2007: Irrigation cooling effect: Regional climate forcing by land-use change. *Geophys. Res. Lett.,* **34,** L03703, doi:10.1029/2006GL028679.

Kunkel, K. E., X. Z. Liang, J. Zhu, and Y. Lin, 2006: Can CGCMs simulate the twentieth-century "warming hole" in the central United States? *J. Climate,* **19,** 4137–4153.

Meehl, G. A., C. Tebaldi, G. Walton, D. Easterling, and L. McDaniel, 2009: Relative increase of record high maximum temperatures compared to record low minimum temperatures in the U.S. *Geophys. Res. Lett.,* **36,** L23701, doi:10.1029/2009GL040736.

Menne, M. J., C. N. Williams Jr., and R. S. Vose, 2009: The U.S. Historical Climatology Network monthly temperature data, version 2. *Bull. Amer. Meteor. Soc.,* **90,** 993–1007.

Misra, V., J.-P. Michael, R. Boyles, E. P. Chassignet, M. Griffin, and J. J. O'Brien, 2012: Reconciling the spatial distribution of the surface temperature trends in the southeastern United States. *J. Climate,* **25,** 3610–3618.

NCDC, cited 2009: TD summary of the day. [Available online at http://ols.nndc.noaa.gov/plolstore/plsql/olstore.prodspecific?prodnum=C00314-TAP-S0001.]

Pan, Z., R. W. Arritt, E. S. Takle, W. J. Gutowski Jr., C. J. Anderson, and M. Segal, 2004: Altered hydrologic feedback in a warming climate introduces a "warming hole." *Geophys. Res. Lett.,* **31,** L17109, doi:10.1029/2004GL020528.

Pielke, R. A., Sr., and Coauthors, 2007: Unresolved issues with the assessment of multidecadal global land surface temperature trends. *J. Geophys. Res.,* **112,** D24S08, doi:10.1029/2006JD008229.

Portmann, R. W., S. Solomon, and G. C. Hegel, 2009: Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proc. Natl. Acad. Sci. USA,* **106,** 7324–7329.

Puma, M. J., and B. I. Cook, 2010: Effects of irrigation on global climate during the 20th century. *J. Geophys. Res.,* **115,** D16120, doi:10.1029/2010JD014122.

Quayle, R. G., D. R. Easterling, T. R. Karl, and P. Y. Hughes, 1991: Effects of recent thermometer changes in the Cooperative Network. *Bull. Amer. Meteor. Soc.,* **72,** 1718–1723.

USDA-ERS, cited 2005: Population–interaction zones for agriculture (PIZA). [Available online at http://www.ers.usda.gov/data-products/population-interaction-zones-for-agriculture-(piza).aspx.]

Wu, Z. H., and N. E. Huang, 2009: Ensemble empirical mode decomposition: A noise assisted data analysis method. *Adv. Adapt. Data Anal.,* **1,** 1–41.