Reconciling the Spatial Distribution of the Surface Temperature Trends in the Southeastern United States

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ABSTRACT

This study attempts to explain the considerable spatial heterogeneity in the observed linear trends of monthly mean maximum and minimum temperatures (T_{max} and T_{min}) from station observations in the southeastern (SE) United States (specifically Florida, Alabama, Georgia, South Carolina, and North Carolina). In a majority of these station sites, the warming trends in T_{min} are stronger in urban areas relative to rural areas. The linear trends of T_{min} in urban areas of the SE United States are approximately 7°F century^{-1} compared to about 5.5°F century^{-1} in rural areas. The trends in T_{max} show weaker warming (or stronger cooling) trends with irrigation, while trends in T_{min} show stronger warming trends. This functionality of the temperature trends with land features also shows seasonality, with the boreal summer season showing the most consistent relationship in the trends of both T_{max} and T_{min}. This study reveals that linear trends in T_{max} in the boreal summer season show a cooling trend of about 0.5°F century^{-1} with irrigation, while the same observing stations on an average display warming trends in T_{min} of about 3.5°F century^{-1}. The seasonality and the physical consistency of these relationships with existing theories may suggest that urbanization and irrigation have a nonnegligible influence on the spatial heterogeneity of the surface temperature trends over the SE United States. The study also delineates the caveats and limitations of the conclusions reached herein due to the potential influence of perceived nonclimatic discontinuities (which incidentally could also have a seasonal cycle) that have not been taken into account.

1. Introduction

The increasing global mean surface temperature trend is regarded as strong evidence of global warming due to increasing greenhouse gases. However, regional surface

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temperature trends may have different warming rates or even cooling trends relating to land cover/land-use changes (Kalnay and Cai 2003; Pielke et al. 2007; Findell et al. 2009; McCarthy et al. 2010), such as urbanization and irrigation (Kueppers et al. 2007; Puma and Cook 2010).

A few studies in the past have examined the observed temperature trends in the second half of the twentieth century over the southeastern (SE) United States (Portmann et al. 2009; Trenberth et al. 2007; DeGaetano and Alen 2002). It is shown that the SE United States is one of a few regions on this planet that shows a cooling trend over the twentieth century (Trenberth et al. 2007). Portmann et al. (2009) find that this cooling trend is strongest in the late spring–early summer period. The cooling trends in the SE United States have been related to changes in sea surface temperatures (SSTs; Robinson et al. 2002), land–atmosphere feedback (Pan et al. 2004), and internal dynamics (Kunkel et al. 2006). Portmann et al. (2009) identify this ''warming hole'' as coincident with a region of relative abundance of rainfall in the continental United States in the May–June period, which conforms to the well-known relationship of trends in temperature and diurnal temperature ranges to precipitation amounts (Trenberth and Shea 2005; Zhou et al. 2008; Dai et al. 1999; Madden and Williams 1978). However, Portmann et al. (2009) suggest that the presence of negative temperature trends in the SE United States warrants more than the precipitation influence through increased evaporation and cloudiness. They conjecture that the additional influences of an increasing strength in the direct and indirect impact of aerosols, as well as changes in vegetation, could also be causing these temperatures to cool in the region. DeGaetano and Allen (2002) examined the temperature extremes of the twentieth century and found a strong influence of urbanization. They found that, consistent with the spatial distribution of urban stations, the rate of extreme temperature warming is greatest in the eastern United States and least in the central region of the country.

While mean surface temperature is a frequent metric for measuring climate variability and change, several studies have argued that this method is probably inaccurate (Christy 2002; Pielke et al. 2007; Pielke 2008; Christy et al. 2009). The mean surface temperature T_{mean} is generally obtained by averaging the maximum and minimum surface temperatures (T_{max}, T_{min}; although this definition of T_{mean} can vary in other parts of the world), but because trends and variations in T_{max} and T_{min} represent different physical processes (Christy et al. 2009), T_{mean} trends may not be true representations of these physical processes. For example, linear trends in T_{max} generally represent a thicker layer of atmospheric behavior because T_{max} is usually measured in the daytime, when the surface is relatively well coupled to the overlying atmosphere through dry-adiabatic and turbulent mixing (Pielke et al. 2007; Christy et al. 2009). However, T_{min}, which usually occurs at night, is measured when the boundary layer is shallow and decoupled from the rest of the atmosphere and, thereby, represents surface characteristics more than the overlying atmosphere.

In addition, evidence suggests that surface temperature observation methods have not been consistent for many stations. In particular, changes in instrument, measurement height, and location can affect the accuracy and continuity of temperature measurements (Pielke et al. 2007). For example, there are substantial biases associated with the widespread transition from liquid in glass thermometers housed in cotton region shelters to the electronic thermistors known as the Maximum/Minimum Temperature System (MMTS) or, later, Nimbus. The MMTS instrument has been shown to have a negative (cool) bias in T_{max} with respect to the liquid-in-glass instrument and a warm bias in T_{min} both in side-by-side comparisons (Wendland and Armstrong 1993; Doesken 2005) and network wide (Quayle et al. 1991; Hubbard and Lin 2006; Menne et al. 2009). Surface temperature measurements are also sensitive to changes in the immediate environment of the instrument, including the addition or removal of vegetation, concrete pavement, and buildings.

Land-use/land-cover changes can also affect climate through variations in the partitioning of the available energy between sensible and latent heat and the breakup of precipitation between runoff, canopy storage, and evapotranspiration, which can alter the consequent atmospheric feedback (Zhao et al. 2001; Feddema et al. 2005; Kalnay and Cai 2003). Irrigation—a land management practice—is conjectured to have one of the largest impacts on local climate (Sacks et al. 2009). The addition of water to land increases the latent heat of evaporation and reduces the sensible heat flux, thereby cooling the local land surface (Bonfils and Lobell 2007, Puma and Cook 2010). Under some conditions irrigation may also influence cloud cover and downstream precipitation patterns (Kueppers et al. 2007).

The urban heat island effect can also have a significant impact on warming trends (Oke 1973; Karl et al. 1988a; Karl and Jones 1989). The heat capacity and conductivity of building and paving materials allow for more heat to be absorbed during the day in urban areas than in rural areas. The heat then becomes available at night to partially compensate for the radiational cooling from the outgoing longwave radiation loss. Another cause of increased heating comes from the trapping of the reflected solar radiation by the narrow arrangement of buildings (often referred as the reduced sky-view factor), which is ultimately absorbed by the walls of the buildings in the urban areas. Additional factors such as increased atmospheric pollutants; production of waste heat from air conditioning, refrigeration systems, and industrial processes; and obstruction of rural airflows by the windward face of the built-up surfaces can also contribute to the urban heat island effect. As a result of these factors of the urban heat island effect, a higher T_{min} is usually observed in the urban areas relative to the rural areas (Karl et al. 1988b).

In this study, we examine the spatial distribution of the T_{max} and T_{min} surface trends of five states in the SE United States (Florida, Alabama, Georgia, South Carolina, and North Carolina) and their relationship to land-cover heterogeneity from urbanization and irrigation.

2. Data

For the present study, we used monthly mean data from the U.S. Historical Climatology Network version 2, which are corrected for time of observation bias [TOB; Baker (1975); Karl et al. (1986); Menne et al. (2009); 9641C_YYYYMM_tob.max.gz and 9641C_YYYYMM_tob.min.gz available online at ftp://ftp.ncdc.noaa.gov/pub/data/ushcn/v2/monthly/; hereafter USHCN2]. These data as reported in Menne et al. (2009) were derived from the following U.S. Daily Surface Data datasets: DSI-3200, DSI-3206, and DSI-3210. There are 119 stations with temperature records from January 1948 to December 2010. The TOB adjustments account for the gradual shift in the observation time to morning over the past 50 yr, which otherwise artificially reduces the true temperature trends in the U.S. climate record (Karl et al. 1986). As a consequence of the TOB adjustments, the trends of T_{max} and T_{min} have increased by about 0.015° and 0.022°C decade^{-1}, respectively (Menne et al. 2009). In obtaining the USHCN2, the raw data were also quality controlled for several inconsistencies as outlined in Tables 1 and 2 of Menne et al. (2009).

Menne et al. (2009) also correct for discontinuities caused by changes in station location and/or instrumentation. They correct for these documented and undocumented discontinuities by using the homogenization algorithm following Menne and Williams (2009). We deliberately avoided using the dataset with this correction as it does not distinguish between the nonclimatic discontinuities from undocumented instrument changes, station shifts, changes in the environment surrounding the instrument site, and discontinuities associated with land-cover and -use changes. In fact, Menne et al. (2009) indicate that the homogenization algorithm accounts for much of the urban heat island effect addressed in Karl et al. (1988b).

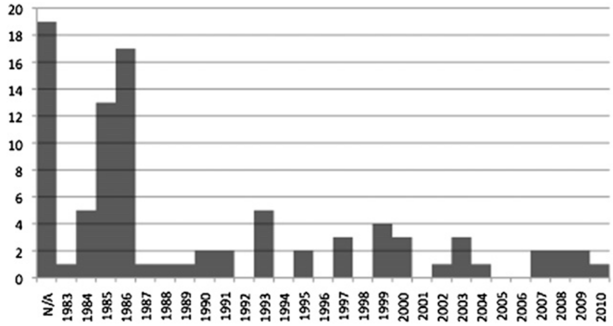

FIG. 1. The distribution of the year of instrument change from LiG thermometers to the MMTS across the observing stations in the SE United States (i.e., FL, AL, GA, SC, and NC).

We however have corrected for the systematic bias introduced by the change from liquid-in-glass thermometers (LiGs) to the MMTS. Quayle et al. (1991) showed that this transition led to an average drop of 0.4°C in T_{max} and an average rise of 0.3°C for T_{min} measurements. Incidentally, this change in instrumentation is rather well documented by the National Weather Service in its B44 document (available online at www.nws.noaa.gov/om/forms/resources/b44.doclinked). Figure 1 shows that only about 19 of the 119 stations used in this study have no mention of an instrument change. Furthermore, the stations in the SE United States have undergone this instrument change at various times since 1983, with a significant number of them changing to MMTS in the mid-1980s.

We compared station location with an index of land use called the Population-Interaction Zones for Agriculture (PIZA), developed by the U.S. Department of Agriculture's Economic Research Service (USDA-ERS 2011). The PIZA is a population interaction index (PII) that is designed to represent residential, commercial, and industrial urban activities affecting the economic and social environments of agriculture. The PIIs are primary measures of the potential interaction between nearby urban-related population and agricultural production activities in each (5 km) grid cell. USDA-ERS developed PIZA from PII in the 20 USDA Land Resource Regions (LRRs) over the continental United States. PIZA uses a five-category classification system, which is based on the interaction of the urban population with agriculture. The classifications of 1, 2, 3, 4, and 5 represent negligible, low, medium, medium-to-high, and high interaction, respectively. PIZA is available at 5-km grid resolution and is based on the data for the year 2000. The thresholds for individual LRRs were established at the 95th percentile of the distribution of PII for 5-km grid cells in the set of totally rural tracts in the LRR.

We also compared the surface temperature trends with irrigation data. We obtained global maps of the area equipped for irrigation at 5-min resolution (Siebert et al. 2006). These digital global maps for irrigation were developed by combining irrigation statistics with geospatial information on the position and extent of the irrigation schemes to compute the fraction of 5-arc-minute cells equipped for irrigation, which is called irrigation density. These data were obtained from national census surveys and from reports available from the United Nations Food and Agricultural Organization (FAO) through its AQUASTAT global water and agriculture information system, from the World Bank, and from other international organizations.

3. Methodology

We used the ensemble empirical mode decomposition (EEMD; Wu and Huang 2009) to identify the trend. The use of a simple linear regression for diagnosing temperature trends is an inappropriate method (Wu et al. 2007, 2011) because trends defined by simple linear regression are prescribed by parameters or functions that are extrinsic and subjective. This approach is incorrect when the time series is nonstationary and has nonlinear (aperiodic) oscillations. As a consequence, estimates of linear trends obtained from simple least squares fit or maximum likelihood fit are sensitive to the choice of start and end dates of the time series. Wu et al. (2011) state that the short-term linear trends are an amalgamation of the secular trend and fluctuations with time scales too long to be resolved by conventional time series analysis tools. EEMD is a data-adaptive time series analysis tool that does not require any predetermined basis functions. EEMD seeks to determine the intrinsic modes of oscillations in the data on the principle of local-scale separation.

EEMD is an extension on the empirical mode decomposition (EMD; Huang et al. 1998; Huang and Wu 2008). EMD is capable of decomposing the local characteristic of the temporal variations into complete sets of near-orthogonal components called intrinsic mode functions (IMFs). The IMFs can be thought of as basis functions, which are determined by the time series itself rather than predetermined kernels. Thus, it is a self-adaptive signal processing method, which is most suited for nonlinear and nonstationary time series. The IMFs are obtained through a sifting process that involves identifying local extrema (both maxima and minima) and connecting the extrema with a cubic spline to obtain the upper and lower envelopes. A "component" is obtained from the difference of the data between the local mean of the upper and lower bound envelopes. This two-step procedure is repeated till the two envelopes are symmetric about zero or within a certain tolerance to obtain the "component" as the first IMF. The sifting process is deemed complete when the residue as the difference of the IMFs and the original data yields a monotonic function containing one internal extremum from which no more IMFs can be extracted. This last isolated IMF is therefore the trend. Mathematically, following Wu et al. (2011), this is

$$y(t) = \sum_{i=1}^{m} c_i(t) + R_m(t) \quad \text{and} \tag{1}$$

$$c_i(t) \equiv \mathrm{IMF} = b_i(t)\cos\left[\int \omega_i(t)\,dt\right], \tag{2}$$

where $y(t)$ is the raw time series and R_m is the residue after m IMFs have been extracted from the raw time series. The instantaneous amplitude is obtained directly from the IMF as the difference between the extrema and the equilibrium value, and thereafter the frequency is obtained from Eq. (2).

However, EMD is plagued by mode mixing, meaning a single IMF can consist of components of widely disparate scales, or a component of similar scale can reside in different IMFs. EEMD, a noise-assisted data analysis method, alleviates this problem. EEMD defines its IMFs through an ensemble of trials, wherein each trial involves adding Gaussian white noise to the time series. This process enables the components of the signal in the time series to automatically project onto proper scales of reference established by the background white noise. The IMFs in the EEMD are obtained exactly as in EMD, with the difference that a white noise time series is added to the original data series. The IMFs obtained consist of the signal and the white noise, which are rather noisy, but the noise in each trial (or ensemble) is different. This noise component in the IMF can be substantially decreased or eliminated by taking the mean of several trials (or ensembles), thereby retaining the true estimate of the signal in the time series.

The IMF with the linear trend in this study was isolated from a 100-member EEMD. That is, the final linear trend is the outcome of averaging the corresponding IMF from each of the 100 trials obtained from adding Gaussian white noise to the original time series. To compute the significance of these trends, the EEMD was repeated 20 times for each of the time series to obtain 20 independent (ensemble averaged) estimates of the trends. The mean trend of these twenty 100-member EEMDs was considered significant (or physically valid) and included in the analysis only if the standard deviation of the ensemble spread of the 20 estimates was 1.1°F century^{-1} or less; this value was found to be at the upper limit of the Gaussian distribution for the observed station temperature trends. All others were assumed to be outliers. The basis for this discretion stems from the Gaussian white noise applied to the temperature time series in EEMD. This results in the ensemble spread of the trends from the EEMD being part of a Gaussian distribution unless the input series to EEMD is physically unable to realize trends that fail this test. In this case the unphysical nature of the temperature series would arise from relatively long temporal data gaps. Of the available 119 USHCN2 stations, 28 displayed trends in T_{max} and/or T_{min} that failed this test. Therefore, the results are shown over the remaining 91 stations distributed over the SE United States.

To compute the fitness of the linear regressions made between the surface temperature trends against both the PIZA grid and the irrigation data, we applied the bootstrapping technique (McClave and Dietrich 1994; Efron and Tibshirani 1993) to resample the slope of the least squares fit line one million times (with replacement). In other words, the temperature trends were shuffled with respect to the functionality sought after (PIZA and the irrigation index) a million times. For each of the million scatters, a slope is obtained from which a distribution of the slope is computed. The 5% significance level of the slope was determined on the basis of the distribution of this resampling.

4. Results

a. *Surface T_{max} and T_{min} trends over the SE United States in relation to urbanization*

The linear trends of annual mean T_{min} are overlaid on the PIZA grid (Fig. 2a). In many regions the higher warming trends are coincident with urbanized areas. Furthermore, very few stations display cooling trends. The annual mean T_{max} trends (Fig. 2b), on the other hand, do not show such apparent dependence on the urbanization. This spatial heterogeneity of the trends is objectively displayed as a scatterplot between the T_{min} and T_{max} trends with the PIZA index in Figs. 3a,b, respectively. A majority of the measurement sites in the SE United States show that the slope of the warming trends in T_{min} is stronger in urban areas relative to rural areas (Fig. 3a). Contrary to the trends in T_{min}, the T_{max} trends (Fig. 3b) display a negative slope with the PIZA index. However, the relationship is rather weak and statistically insignificant. The fact that T_{min} trends show a dependence on the PIZA index while T_{max} trends do not reaffirms the effect of the urban heat island (Karl et al. 1988b). In fact, we also examine the relationship between the trends in T_{min} and T_{max} with the PIZA index by seasons (Table 1). It is found that the linear relationship of the T_{min} trends with the PIZA index

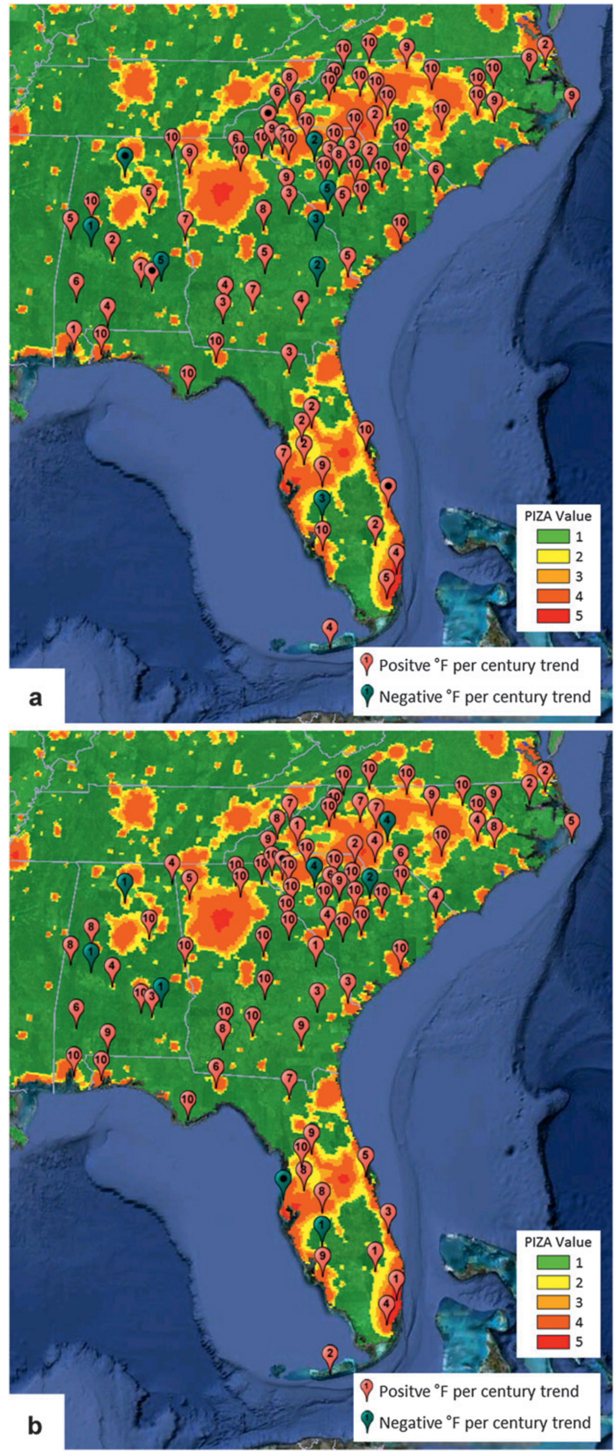

FIG. 2. The linear trends (°F century^{-1}) from station observations of annual mean (a) T_{min} and (b) T_{max} overlaid on the PIZA grid.

prevails in the boreal summer season, when the relationship is statistically insignificant. On the other hand, T_{max} trends consistently display an insignificant relationship with the PIZA index in all seasons.

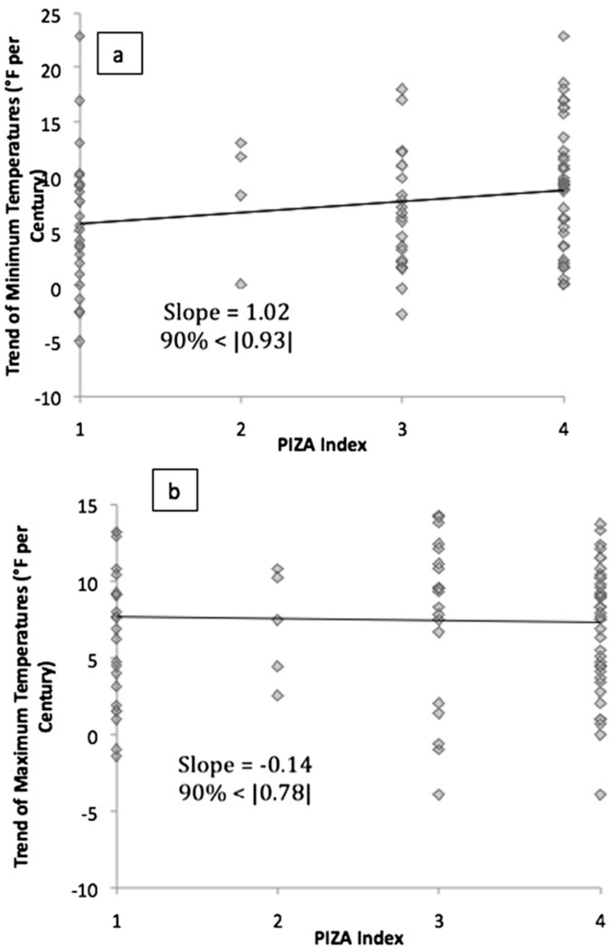

FIG. 3. Scatterplots of the linear trends (°F century^{-1}) over the SE United States (i.e., FL, AL, GA, SC, and NC) of (a) $T_{\min}$ and (b) $T_{\max}$ with the PIZA index. The slope and its 90% confidence level obtained from a Monte Carlo approach are shown in the bottom-left corner.

b. *Surface T_{max} and T_{min} trends over the SE United States in relation to irrigation*

Since $T_{\max}$ is measured during the day, the cooling trends in $T_{\max}$, especially in rural areas, suggest the potential influence of irrigation. Irrigation, by way of wetting the soil, raises evaporation during the day and changes the Bowen ratio, which leads to apparent cooling of the surface temperature (Kueppers et al. 2007; Sacks et al. 2009). On the other hand, irrigation raises the heat capacity and conductivity of the soil and, under weak wind conditions (typically at night, when the boundary layer decouples from the rest of the atmosphere), can lead to warming of surface $T_{\min}$ (Elsner et al. 1996).

Unlike the relationship with the PIZA index, the irrigation index shows a very weak, insignificant relationship with temperature trends without aggregation by seasons (not shown). Table 1 displays that the most robust and consistent linear relationship between $T_{\min}$ and $T_{\max}$ trends with the irrigation index occurs in the boreal summer season. In boreal spring, $T_{\min}$ has a robust relationship with irrigation while $T_{\max}$ does not. Figure 4 shows these trends in June–August (JJA) overlaid on the irrigation area map. With some exceptions (e.g., southern Georgia), there are cooling or weaker warming $T_{\max}$ trends in the irrigated areas of the SE United States (Fig. 4b). However, the relationship of $T_{\min}$ trends with the irrigation index is not so easily discernible (Fig. 4a). These relationships are more objectively displayed in the scatter between the temperature trends in JJA and the irrigation index in Fig. 5. Consistent with Table 1, the slope is positive for the linear regression between the $T_{\min}$ trends and the irrigation index (Fig. 5a). Similarly, the slope is negative for the linear regression of the $T_{\max}$ trends with the irrigation index (Fig. 5b). The seasonal functionality of these relationships attests to the known theories of these land features. However, it may be noted that some of the nonclimatic discontinuities prevalent in the data may also have a seasonal cycle.

TABLE 1. The slope of the linear regression of the scatter between the temperature trends and the indices of PIZA and irrigation by season. The boldface values indicate that the slope of the regression passes the 5% significance level of the Monte Carlo test.

	DJF	MAM	JJA	SON
$T_{\min}$–PIZA	0.48	0.19	**0.59**	0.32
$T_{\max}$–PIZA	0.58	−0.19	0.27	−0.13
$T_{\min}$–irrigation	0.01	**0.08**	**0.04**	0.01
$T_{\max}$–irrigation	−0.01	0.01	**−0.05**	−0.01

Some of the inconsistent results—like the robust relationship of $T_{\min}$ trends with irrigation in spring (Table 1)—can be surmised for any number of reasons, including changes in cultivated crops, the amount of fertilizers used, and irrigation practices, as well as (in more recent times) switches to year-round cultivation and the use of higher-N fertilizer.

5. Discussion and conclusions

Notwithstanding the outstanding issues with surface temperature observations, our results indicate that the observed spread of surface temperature trends over the SE United States has some significant relationship with urbanization and irrigation that fits our understanding of the underlying physical processes. In theory, irrigation would tend to reduce daytime $T_{\max}$ as it reduces the Bowen ratio. The theory further suggests that under light wind conditions, irrigation by way of wetting the soil raises its heat capacity and conductivity, which increases the potential for raising the nighttime $T_{\min}$. On the other hand, urbanization, in principle, will tend to

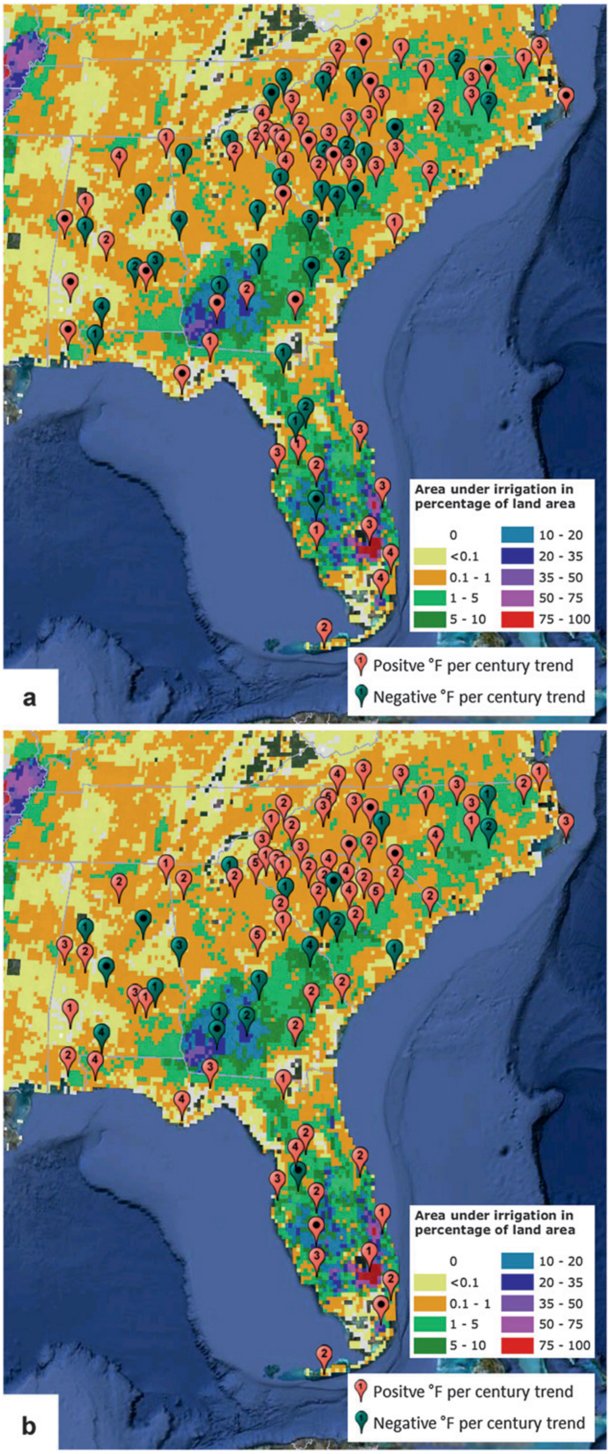

FIG. 4. The linear trends (°F century^{-1}) for JJA from station observations of (a) $T_{\min}$ and (b) $T_{\max}$ overlaid on an irrigated area map from the FAO.

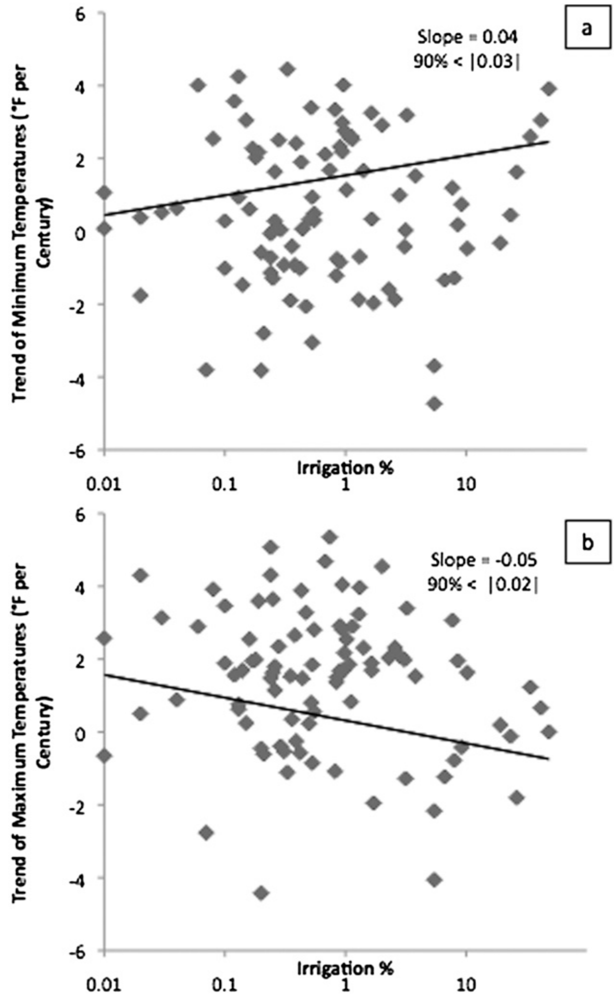

FIG. 5. Scatterplots of the linear trends (°F century^{-1}) in JJA over the SE United States (i.e., FL, AL, GA, SC, and NC) of (a) $T_{\min}$ and (b) $T_{\max}$ with the irrigation data. The slope and its 90% confidence level obtained from a Monte Carlo approach are shown in the top-right corner.

raise the nighttime $T_{\min}$ as a result of the heat island effect. These effects of urbanization and irrigation on the temperature trends are discernible over the SE United States in Florida, Alabama, Georgia, North Carolina, and South Carolina.

The datasets used in the paper do carry some artificial bias since they are not homogenized (Menne and Williams 2009). The surface temperature dataset used in this study addresses two relatively well-documented systematic biases, which relate to the changes in the time of observation and the instrument. However, this may be insufficient. As pointed out in Hubbard and Lin (2006), the transition from LiG to MMTS often accompanied significant micrometeorological changes in the immediate surroundings of the measurement site, which are poorly documented. We have deliberately avoided using the homogenized datasets that ameliorate some of these artificial discontinuities as they are unable to distinguish between undocumented artificial discontinuities and discontinuities from land-cover and land-use change. Furthermore, the seasonal dependence of the relationship between temperature trends and irrigation and the absence of a robust relationship in the trends of $T_{\max}$ with urbanization leads us to believe that the influence of irrigation and urbanization on the temperature trends in the SE United States is nonnegligible. However, the reader is cautioned to consider the potential prevalence of seasonal cycles in nonclimatic discontinuities too. It may also be noted that our study indicates that the land-use and management features are ‘‘second order’’ impacts on the already existent temperature trends.

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REFERENCES

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.

Christy, J. R., 2002: When was the hottest summer? *Bull. Amer. Meteor. Soc.,* **83,** 723–734.

——, W. B. Norris, and R. T. McNider, 2009: Surface temperature variations in East Africa and possible causes. *J. Climate,* **22,** 3342–3356.

Dai, A., K. E. Trenberth, and T. R. Karl, 1999: Effects of clouds, soil moisture, precipitation, and water vapor on diurnal temperature range. *J. Climate,* **12,** 2451–2473.

DeGaetano, A. T., and R. J. Allen, 2002: Trends in twentieth-century temperature extremes across the United States. *J. Climate,* **15,** 3188–3205.

Doesken, N. J., 2005: The National Weather Service MMTS (Maximum-Minimum Temperature System)—20 years after. Preprints, *15th Conf. on Applied Climatology/13th Symp. on Meteorological Observations and Instrumentation*, Savannah, GA, Amer. Meteor. Soc., JP1.26. [Available online at http://ams.confex.com/ams/pdfpapers/91613.pdf.]

Efron, B., and R. J. Tibshirani, 1993. *An Introduction to the Bootstrap*. Chapman and Hall, 436 pp.

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.

Feddema, J. J., K. Oleson, G. Bonan, L. O. Mearns, L. Buja, W. M. Washington, and G. Meehl, 2005: How important is land cover change for simulating future climates? *Science,* **310,** 1674–1678.

Findell, K. L., A. J. Pitman, M. H. England, and P. Pegion, 2009: Regional and global impacts of land cover change and sea surface temperature anomalies. *J. Climate,* **22,** 3248–3269.

Huang, N. E., and Z. Wu, 2008: A review on Hilbert–Huang transform: The method and its applications on geophysical studies. *Rev. Geophys.,* **46,** RG2006, doi:10.1029/2007RG000228.

——, Z. Shen, and S. R. Long, 1998: The empirical mode decomposition and the Hilbert spectrum for non-linear and nonstationary time series analysis. *Proc. Roy. Soc. London,* **454,** 712–723.

Hubbard, K. G., and X. Lin, 2006: Reexamination of instrument change effects in the U.S. Historical Climatology Network. *Geophys. Res. Lett.,* **33,** L15710, doi:10.1029/2006GL027069.

Kalnay, E., and M. Cai, 2003: Impact of urbanization and land-use change on climate. *Nature,* **423,** 528–531.

Karl, T. R., and P. D. Jones, 1989: Urban bias in area averaged surface air temperature trends. *Bull. Amer. Meteor. Soc.,* **70,** 265–270.

——, 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. Climate Appl. Meteor.,* **25,** 145–160.

——, and Coauthors, 1988a: *Time Series of Regional Averages of Maximum, Minimum, and Average Temperature and Diurnal Temperature Range across the United States: 1901–1984*. Historical Climatology Series, Vols. 4–5, National Climatic Data Center, 107 pp.

——, H. F. Diaz, and G. Kukla, 1988b: 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.

Madden, R. A., and J. Williams, 1978: The correlation between temperature and precipitation in the United States and Europe. *Mon. Wea. Rev.,* **106,** 142–147.

McCarthy, M. P., M. J. Best, and R. A. Betts, 2010: Climate change in cities due to global warming and urban effects. *Geophys. Res. Lett.,* **37,** L09705, doi:10.1029/2010GL042845.

McClave, J. T., and F. H. Dietrich II, 1994: *Statistics*. MacMillan, 967 pp.

Menne, M. J., and C. N. Williams Jr., 2009: Homogenization of temperature series via pairwise comparisons. *J. Climate,* **22,** 1700–1717.

——, ——, and R. S. Vose, 2009: The U.S. Historical Climatology Network monthly temperature data, version 2. *Bull. Amer. Meteor. Soc.,* **90,** 993–1007.

Oke, T. R., 1973: City size and the urban heat island. *Atmos. Environ.,* **7,** 769–779.

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., 2008: A broader view of the role of humans in the climate system. *Phys. Today,* **61,** 54–55.

——, and Coauthors, 2007: Unresolved issues with the assessment of multi-decadal 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.

Robinson, W. A., R. Reudy, and J. E. Hansen, 2002: General circulation model simulations of recent cooling in the east-central United States. *J. Geophys. Res.,* **107,** 4748, doi:10.1029/2001JD001577.

Sacks, W. J., B. I. Cook, N. Buenning, S. Levis, and J. H. Helkowski, 2009: Effects of global irrigation on the near surface climate. *Climate Dyn.,* **33,** 159–175, doi:10.1007/s00382-008-0445-z.

Siebert, S., J. Hoogeveen, and K. Frenken, 2006: Irrigation in Africa, Europe and Latin America: Update of the Digital Global Map of Irrigation Areas to version 4. Frankfurt Hydrology Paper 05, University of Frankfurt (Main), Frankfurt am Main, Germany, and FAO, Rome, Italy, 134 pp. [Available online at http://www.fao.org/nr/water/aquastat/irrigationmap/index60.stm.]

Trenberth, K. E., and D. J. Shea, 2005: Relationships between precipitation and surface temperature. *Geophys. Res. Lett.,* **32,** L14703, doi:10.1029/2005GL022760.

——, and Coauthors, 2007: Observations: Surface and atmospheric climate change. *Climate Change 2007: The Physical Science Basis,* S. Solomon et al., Eds., Cambridge University Press, 235–336.

USDA-ERS, cited 2011: ERS/USDA Data Population-Interaction Zones for Agriculture (PIZA): Overview. [Available online at http://www.ers.usda.gov/Data/PopulationInteractionZones/overview.htm.]

Wendland, W. M., and W. Armstrong, 1993: Comparison of maximum–minimum resistance and liquid-in-glass thermometer records. *J. Atmos. Oceanic Technol.,* **10,** 233–237.

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

——, ——, S. R. Long, and C.-K. Peng, 2007: On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proc. Natl. Acad. Sci. USA,* **104,** 14 889–14 894, doi: 10.1073/pnas.0701020104.

——, ——, J. M. Wallace, B. V. Smoliak, and X. Chen, 2011: On the time-varying trend in global mean surface temperature. *Climate Dyn.,* **37,** 759–773, doi: 10.1007/s00382-011-1128-8.

Zhao, M., A. J. Pitman, and T. N. Chase, 2001: The impact of land cover change on the atmospheric circulation. *Climate Dyn.,* **17,** 467–477.

Zhou, L., and Coauthors, 2008: Spatial dependence of diurnal temperature range trends on precipitation from 1950 to 2004. *Climate Dyn.,* **32,** 429–440, doi:10.1007/s00382-008-0387-5.