# NOTES AND CORRESPONDENCE

## An Update of U.S. Temperature Trends

QIQI LU

*Department of Mathematics and Statistics, Mississippi State University, Mississippi State, Mississippi*

ROBERT LUND

*Department of Mathematical Sciences, Clemson University, Clemson, South Carolina*

LYNNE SEYMOUR

*Department of Statistics, University of Georgia, Athens, Georgia*

(Manuscript received 8 December 2004, in final form 8 March 2005)

ABSTRACT

This note updates the temperature trend study of the contiguous 48 United States by Lund et al. for data observed during the 4-yr period 1997–2000. A parsimonious changepoint parameterization is now used, and the methods for handling missing data are improved. The number of stations with useable data has now increased from 359 to 969, thereby improving the accuracy of the reported spatial patterns in the trends. The average record length of the 969 stations is now 103 yr, with the longest record starting in 1812 and the shortest in 1926. The methodological improvements and additional 4 yr of data produce slightly smaller trend estimate standard errors. Warming is found in the Northeast, West, and northern Midwest, with slight cooling in the Southeast; overall, the trends here suggest more warming than those of the Lund et al. study.

### 1. Introduction

This note updates the U.S. temperature trend study in Lund et al. (2001) for recent data and for improvements in the methods of analysis. U.S. temperature changes have been previously studied in Diaz and Quayle (1980) and Karl et al. (1995) (among many others). Global temperature change studies (cf. Ellsaesser et al. 1986; Hansen et al. 1999, 2001; and the references therein) also provide insight into U.S. temperature trends.

The Lund et al. (2001) study was a statistically detailed examination of temperature changes in the United States. It made three fundamental analysis contributions. First, the reported standard errors of the trend estimates accounted for temporal correlations in the data. Second, seasonal aspects were considered in that monthly (rather than yearly) series were examined. Third, the analysis allowed for the crucial effect of changepoints at times where changepoints were known to occur. Many (unfortunately, not all) changepoint times are explicitly noted in the station history logs; such records permit for adjustment of this factor (cf. Karl and Williams 1987; Karl et al. 1990).

However, there were some drawbacks in the Lund et al. (2001) study. One is that the spatial coverage there was worse—only 359 of 1221 stations in the network were deemed usable, because of data quality (missing data in particular). For instance, only 2 stations in Oklahoma, 4 stations in Mississippi, and 10 stations in Texas were included in this study. This update contains data from 34 Oklahoma stations, 29 Mississippi stations, and 39 Texas stations. The primary reason driving the improved spatial coverage lies with the revised methods for handling missing data. As the number of stations with useable data has now increased from 359 to 969, the spatial coverage of climate change in the United States is now significantly more complete and reliable.

The other statistical improvement in this update involves parsimony techniques for handling change-

*Corresponding author address:* Dr. Lynne Seymour, Department of Statistics, University of Georgia, Athens, GA 30602-1952.
E-mail: Seymour@stat.uga.edu

© 2005 American Meteorological Society

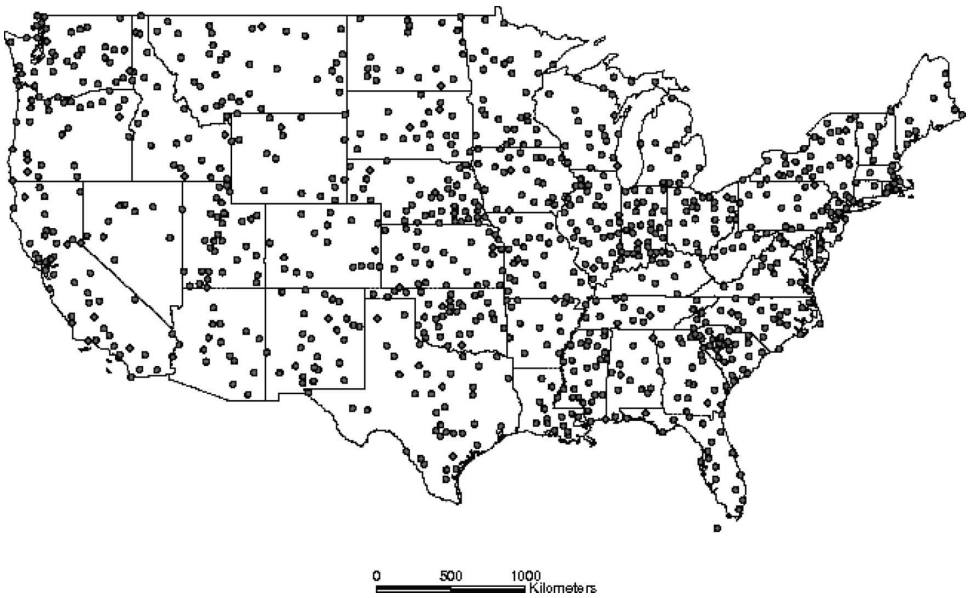


FIG. 1. Station locations.

points. The Lund et al. (2001) study expended a large number of changepoint parameters in its mathematical regression model: one for each different changepoint and season (month). For example, in a monthly series (period 12) with six changepoints per century, which is the average number of documented changepoints experienced by the stations in this study, the regression model employed there expended $96 = 24 + (12 \times 6)$ parameters. In contrast, the periodic simple linear regression model used here assumes the same changepoint mean shift response over all seasons, thereby reducing the number of parameters to a more parsimonious number of $30 = 24 + 6$. An overparameterized statistical model typically has less power in estimating significant parameters (the trends in this case).

The rest of the note is organized as follows. We first describe the sources of data and quality restrictions imposed upon series entering this study. The methods used to obtain the trends and their uncertainty margins are then narrated. A case study of 1 of the 969 stations is then presented for illustration. Spatial contour maps of the smoothed trend estimates are then presented and discussed.

## 2. The data

The dataset used in this study is taken from the U.S. Historical Climatology Network (USHCN). The USHCN consists of 1221 stations in the 48 contiguous United States; these data are raw but adjusted for biases due to the time of observation. Karl et al. (1990) describes the USHCN in more detail.

Data quality is an issue because of site changes (changepoints) and missing observations. We take a changepoint as a change of station location, station instrument, or station shelter. The dates of the changepoints that are known were noted and rounded to the nearest month. Stations having two changepoints within 4 months were discarded; in comparison, Lund et al. (2001) discarded series with two or more changepoints occurring within 3 yr. The driving improvement here is that the regression model introduced in sections 3a and 3b below is more parsimonious and can accommodate a smaller number of observations sampled from one "regime." As before, a minimum of 75 yr of record is required to enter the study and stations missing 5% or more of their observations during their period of record were discarded, or the starting date of the series was advanced if possible so as to make the series meet the above constraints.

After these data quality restrictions were imposed, 969 stations remained for study. Figure 1 graphically depicts the location of these stations; the spatial coverage is excellent. The duration of record at each station is variable, with the average series containing 103 yr of data. The starting month of every series is rounded to the "nearest viable January"; the last observation is taken during December of 2000. The earliest starting year is 1812 (New Bedford, Massachusetts); the latest starting year is 1926 (eight stations).

Any missing observations that remain were infilled

with a model-based expectation maximization (EM) algorithm (cf. Dempster et al. 1977). In the first step, missing values are replaced with regression-based interpolations; then an autoregressive moving-average (ARMA) model was chosen for the residuals of the regression fit via Akaike's corrected information criterion (AICC) statistic (cf. Brockwell and Davis 1991). Predictions for the missing values were computed as one-step-ahead predictions based on the chosen ARMA model. The process was iterated until the ARMA parameters and predictions converged. Such an EM procedure can be used to infill series with many consecutive missing observations; in comparison, stations with six or more consecutive points missing were discarded in Lund et al. (2001). Infilling is needed for automation of computation; specifically, it would be a daunting task to individually infill the series for all missing data configurations arising in the 969 stations.

## 3. Statistical methods

### a. Periodic regression model

Consider a fixed temperature station. As the data are monthly in structure, our methods center on the periodic simple linear regression model under multiple changepoints with period $T = 12$:

$$X_{mT+\nu} = \mu_\nu + \alpha_\nu(mT + \nu) + \delta_{mT+\nu} + \varepsilon_{mT+\nu}, \quad (3.1)$$

where the series $\{\varepsilon_{mT+\nu}\}$ is zero mean random error with periodic temporal autocovariances as elaborated upon below. The notation here uses $X_{mT+\nu}$ as the observed monthly mean temperature during the $\nu$th month of year $m$, where $\nu$ is a monthly index satisfying $1 \le \nu \le T$ and $m$ is a yearly index satisfying $0 \le m \le d - 1$. Time is scaled at each station so as to make $m = 0$ the first year in the data record. The data record length is $n = dT$, where $d$ is the total number of years of data; to avoid trite work, we take $d$ as an integer.

For parameter interpretations, $\mu_\nu$ is the average temperature during month $\nu$ in the absence of trend ($\alpha_\nu \equiv 0$) and changepoints ($\delta_{mT+\nu} \equiv 0$); $\alpha_\nu$ is the month $\nu$ linear trend, which will be our focus later, or the average temperature change rate during month $\nu$ in the absence of changepoints; and $\{\delta_{mT+\nu}\}$ is a changepoint mean shift factor. In particular, the changepoints are parameterized as the step effects

$$\delta_{mT+\nu} = \begin{cases} \Delta_1, & 1 \le mT + \nu < \tau_1 \\ \Delta_2, & \tau_1 \le mT + \nu < \tau_2 \\ \vdots & \vdots \\ \Delta_k, & \tau_{k-1} \le mT + \nu \le n \end{cases}, \quad (3.2)$$

where $\tau_1 < \tau_2 < \ldots < \tau_{k-1}$ are the months of the known changepoint times and $k - 1$ is the total number of changepoints in the record (hence there are $k$ different regimes). One can regard the $k - 1$ changepoints as inducing a $k$-phase simple linear regression, extending the two-phase setup in Lund and Reeves (2002). Until the first changepoint time, the mean effect in the regression is $\Delta_1$; between the first and second changepoint times, the mean effect becomes $\Delta_2$, and so forth. For parameter identifiability, we take $\Delta_1 = 0$ (or else the $\Delta_i$s and the $\mu_\nu$s become confounded).

The model in (3.1) is a parsimonious version of that used by Lund et al. (2001); here, changepoint mean shifts in (3.1) are constrained as equal over varying seasons for statistical parsimony. Such parsimony renders more accurate estimation of the remaining parameters in the regression (specifically, the trends $\alpha_\nu$). Trial fits with some of the series with regression-model-fitting criteria [e.g., AICC and Bayesian information criterion (BIC)] show seasonally constant changepoint effects to be generally preferable. Of course, exceptions exist where the season of the changepoint time is important (e.g., changes related to solar radiation in summer or cold-air drainage in winter), but stations with such structure are comparatively scarce.

The changepoint effects for a fixed station are also now easy to interpret: $\Delta_k$ is the mean shift, as measured against the first regime, of series values from the $k$th regime. Second, the regression parameter numbers are reduced from $2 \times T + (k - 1) \times T$ in the Lund et al. (2001) study to $2T + k - 1$ here. This is a very large reduction in settings with a large $k$.

The seasonal parameterization in (3.1) has advantages over annual formulations. For instance, it allows one to address uniformity of temperature change over different seasons. Indeed, some authors suspect that temperature warming is most rapid during winter due to decreased nightly radiational cooling, the later attributed to increasing carbon dioxide [see Callendar (1961), Madden and Ramanathan (1980), and Jones et al. (1982) for early references].

For brevity's sake (12 maps is excessive), we partition the monthly trends into the four seasons: winter, spring, summer, and fall. Winter is taken as December–January–February (DJF), spring as March–April–May (MAM), summer as June–July–August (JJA), and fall as September–October–November (SON). A trend for spring, for example, is obtained by adding the trends during MAM: $\hat{\alpha}_{\mathrm{MAM}} = \hat{\alpha}_3 + \hat{\alpha}_4 + \hat{\alpha}_5$. Trends for the other three seasons, denoted by $\hat{\alpha}_{\mathrm{DJF}}$, $\hat{\alpha}_{\mathrm{JJA}}$, and $\hat{\alpha}_{\mathrm{SON}}$ for winter, summer, and fall, respectively, are obtained analogously. An annual or yearly trend estimate,

denoted by $\hat{\alpha}_{\mathrm{YR}}$, is obtained by adding all monthly trends:

$$\hat{\alpha}_{\mathrm{YR}} = \sum_{\nu=1}^{T} \hat{\alpha}_{\nu} = \hat{\alpha}_{\mathrm{DJF}} + \hat{\alpha}_{\mathrm{MAM}} + \hat{\alpha}_{\mathrm{JJA}} + \hat{\alpha}_{\mathrm{SON}}.$$

For ease of interpretation and a standard basis of comparison, all trend estimates are converted into degrees Celsius per century. This entails multiplying seasonal trends by 400 and annual trends by 100.

### b. Inference for the trend parameters

To estimate $\alpha_\nu$ for each month $\nu$, we use the method of ordinary least squares (OLS). The OLS estimates of the $\alpha_\nu$s cannot be explicitly derived in closed form akin to (5) in Lund et al. (2001). The regression in (3.1), however, does have the general linear model's representation

$$\mathbf{X} = \mathbf{D}\boldsymbol{\beta} + \boldsymbol{\varepsilon},$$

where $\mathbf{X} = (X_1, \ldots, X_n)'$ is the observed series ($'$ indicates matrix transpose), $\mathbf{D}$ is the $n \times (2T + k - 1)$ dimensional design matrix

$$\mathbf{D} = (\mathbf{D}_1|\mathbf{D}_2|\mathbf{D}_3), \tag{3.3}$$

$\boldsymbol{\beta} = (\mu_1, \ldots, \mu_{12}, \alpha_1, \ldots, \alpha_{12}, \Delta_2, \ldots, \Delta_k)'$ is the $2T + k - 1$ dimensional parameter vector, and $\boldsymbol{\varepsilon} = (\varepsilon_1, \ldots, \varepsilon_n)'$ contains all regression errors. The component matrices $\mathbf{D}_1$ and $\mathbf{D}_2$ in (3.3) are $n \times T$ dimensional with $(i, j)$th entry of zero except that $(D_1)_{mT+\nu,\nu} = 1$ and $(D_2)_{mT+\nu,\nu} = mT + \nu$ for $0 \le m \le d - 1$ and $1 \le \nu \le T$. The components in $\mathbf{D}_3$ are zero except for $(D_3)_{\ell,j} = 1$ when $\ell \in [\tau_i, \tau_{i+1})$ and $j = i$ as $1 \le i \le k-1$ (take $\tau_k = n + 1$ here).

An estimator of $\boldsymbol{\beta}$ is computed from the classical OLS formula,

$$\hat{\boldsymbol{\beta}} = (\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'\mathbf{X}. \tag{3.4}$$

The estimator $\hat{\alpha}_\nu$ is merely the $(T + \nu)$th component of $\hat{\boldsymbol{\beta}}$.

The trend estimators $\hat{\boldsymbol{\alpha}} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_T)'$ are unbiased for all zero mean errors $\{\varepsilon_t\}$. OLS estimators are asymptotically most efficient in time-homogeneous settings (cf. Grenander 1954); one does not expect drastic suboptimality in changepoint and/or periodic settings. The variance/covariance matrix of the trend estimators is obtained from (3.4):

$$\mathrm{var}(\hat{\boldsymbol{\beta}}) = (\mathbf{D}'\mathbf{D})^{-1}(\mathbf{D}'\boldsymbol{\Gamma}\mathbf{D})(\mathbf{D}'\mathbf{D})^{-1},$$

where $\boldsymbol{\Gamma} = \mathrm{var}(\boldsymbol{\varepsilon}) = E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}']$ is the covariance matrix of $\{\varepsilon_t\}$. Observe that $\mathrm{var}(\hat{\boldsymbol{\beta}})$ is a $(2T + k - 1) \times (2T + k - 1)$ matrix. The standard error of $\hat{\alpha}_\nu$ is the square root of the $(T + \nu)$th diagonal component of $\mathrm{var}(\hat{\boldsymbol{\beta}})$ (more precisely an estimate of this quantity).

Ignoring autocorrelations in $\{\varepsilon_t\}$ by taking $\boldsymbol{\Gamma}$ to be a multiple of the identity matrix typically underestimates true variabilities in $\hat{\alpha}_\nu$ (cf. Bloomfield and Nychka 1992; Lund et al. 1995 for discussion). To estimate $\boldsymbol{\Gamma}$, a periodic autoregressive moving-average (PARMA) model was fitted to the residuals of the regression fit. PARMA models are flexible short-memory periodic time series models. Their development in climatological settings is described in detail in Lund et al. (1995, 2001) and the references therein.

### c. Spatial smoothing

For each station in the study, the above methods provide a trend estimate and standard error for each of the four seasons and the entire year. To summarize these trends, we spatially smooth them by latitude and longitude with the weighted head-banging algorithm described in Hansen (1991) and Mungiole et al. (1999). Statistically, the weighted head-banging algorithm is a nonparametric local averaging smoother that is especially adept with rough (highly variable) spatial fields. The term head-banging was coined by the engineering community to describe the situation where nails protruding from a board at varying lengths are banged by an unlucky head, smoothing the nail lengths while leaving an impression of the face. Head-banging methods effectively preserve general features such as edges and ridges while simultaneously downweighting outliers. The algorithm variant we use weights the trends inversely to their standard errors before averaging; hence, more variable (questionable) trend estimates have less overall influence on the end result. This is but one reason to pursue accurate standard errors for the individual trends. The head-banging smoothing parameters used here were 15 triples with 30 nearest neighbors in each contour map. Selection of appropriate values of head-banging parameters is important, but not overly crucial in interpreting general spatial structure of the trends. (One will get a feel for smoothing aspects by comparing Figs. 3 and 4 below.)

Application of the head-banging algorithm yields a spatially smoothed trend estimate at each station latitude and longitude in the study; such smoothing accounts for spatial autocorrelations in the trend estimates in a nonparametric way. As an end step, the ESRI ARC geographic information system (GIS) soft-

TABLE 1. Chula Vista annual trend estimates in °C century$^{-1}$.

| Model | Annual trend | Standard error |
|---|---|---|
| Neglecting changepoints | 2.896 | 0.7184 |
| Lund et al. (2001) | 1.126 | 0.6581 |
| Model (3.1) | 0.932 | 0.6117 |

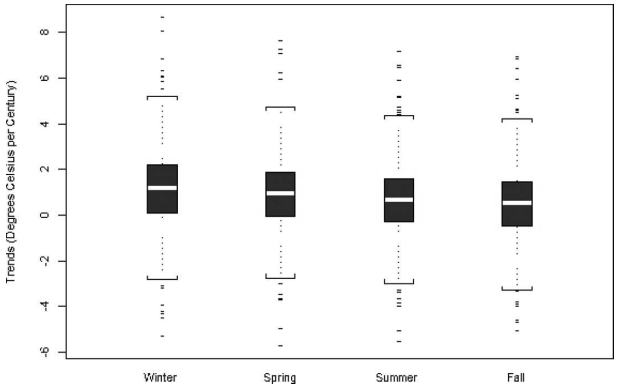


FIG. 2. Boxplot of trends by season.

ware was applied to the head-banging smoothed trends. Here, the inverse-distance-weighted interpolation method with 12 neighbors was applied to display the head-banging smoothed trends in the contour maps. The end product is reasonably attractive, while preserving general structure.

## 4. A comparison

To gain some feel for the methods, especially in regard to the different statistical models, we consider the station located at Chula Vista, California, in a case study. The data record at this station through 1996 is plotted in Fig. 1 of Lund et al. (2001). This series has seen three documented changepoint times since 1919; the effects of each changepoint are elaborated upon in Lund and Reeves (2002). Annual trend estimates and their standard errors are listed in Table 1.

The annual trend estimate of 0.932°C century$^{-1}$ based on (3.1) is 17% smaller than the 1.126°C century$^{-1}$ reported in Lund et al. (2001). The standard error has decreased from 0.658° to 0.612°C century$^{-1}$, suggesting slightly improved accuracy. Comparisons at other stations also suggest some efficiency gains; specifically, an average standard error of 0.827°C century$^{-1}$ was obtained by Lund et al. (2001) whereas that here is 0.765°C century$^{-1}$. It should be stressed that the numbers quoted for the case where changepoints are neglected are invalid, but it is interesting to see how far off they indeed are.

## 5. Overall results

This section moves to the study of the estimated trends at all 969 stations. Figure 2 presents boxplots of the raw trend estimates during each season. Observe that the median line is positive in each plot, suggesting overall warming during every season. The variability of the estimated trends is greatest during winter and minimal during fall and summer. There are a few outlying trends in each season, of course in part attributed to the large number of stations (969). The average trend estimate over all stations is 1.167°C century$^{-1}$ for winter,

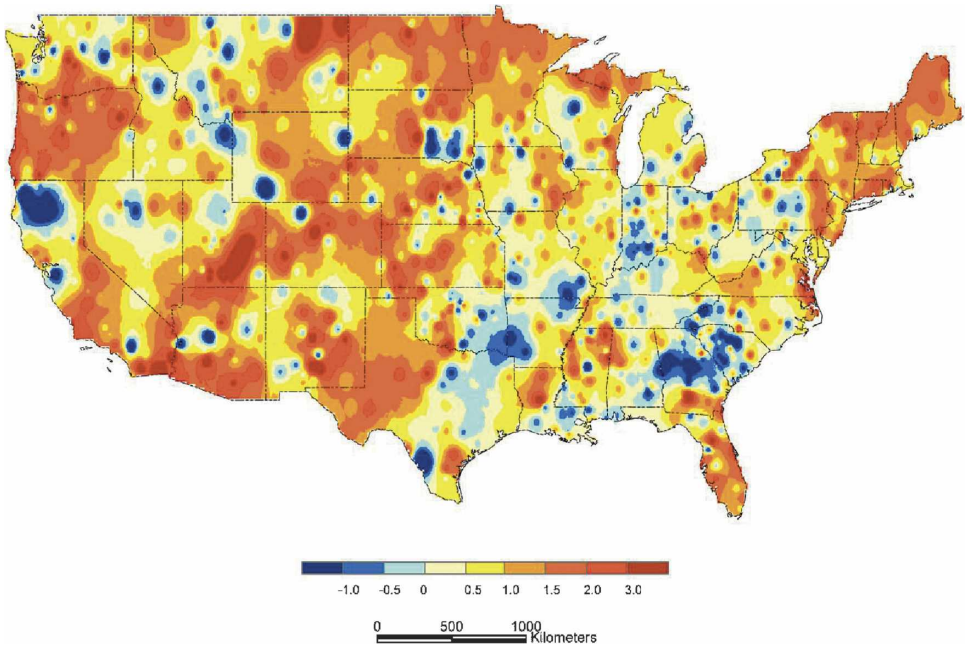


FIG. 3. Raw annual trends (red: warming; blue: cooling).

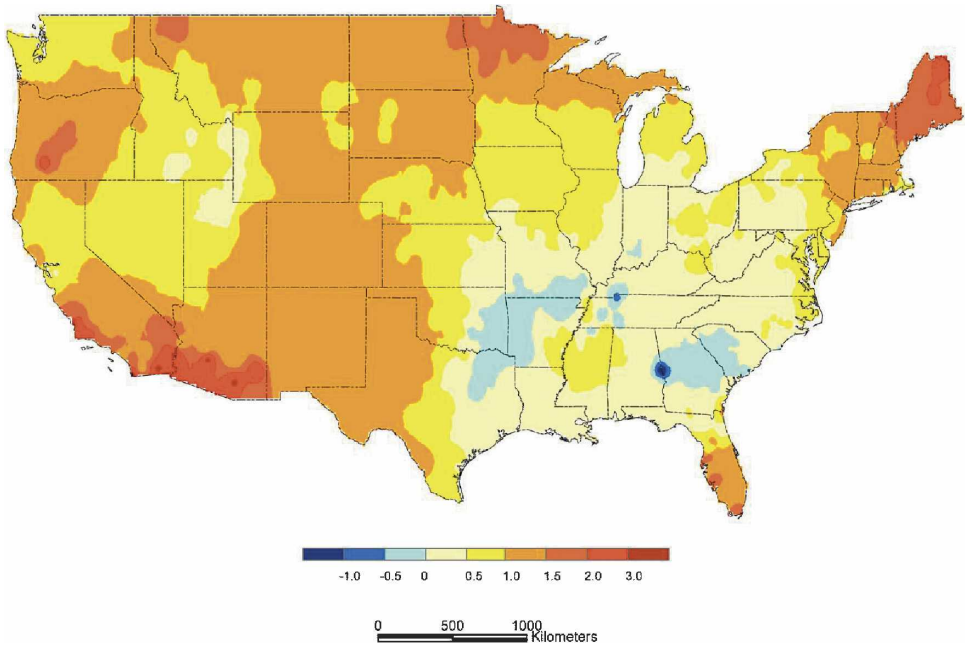


FIG. 4. Smoothed annual trends (red: warming; blue: cooling).

0.971°C century$^{-1}$ for spring, 0.658°C century$^{-1}$ for summer, and 0.515°C century$^{-1}$ for fall. The season with the largest temperature variability (winter) also shows the most warming. The average annual trend estimate at all 969 stations is 0.823°C century$^{-1}$. Toward decadal effects and the common period of record, we comment that the average trend for the 527 stations in the study that reported data during the subperiod 1898–2000 was 0.820°C century$^{-1}$; the trend for all 969 stations over the common period of record 1926–2000

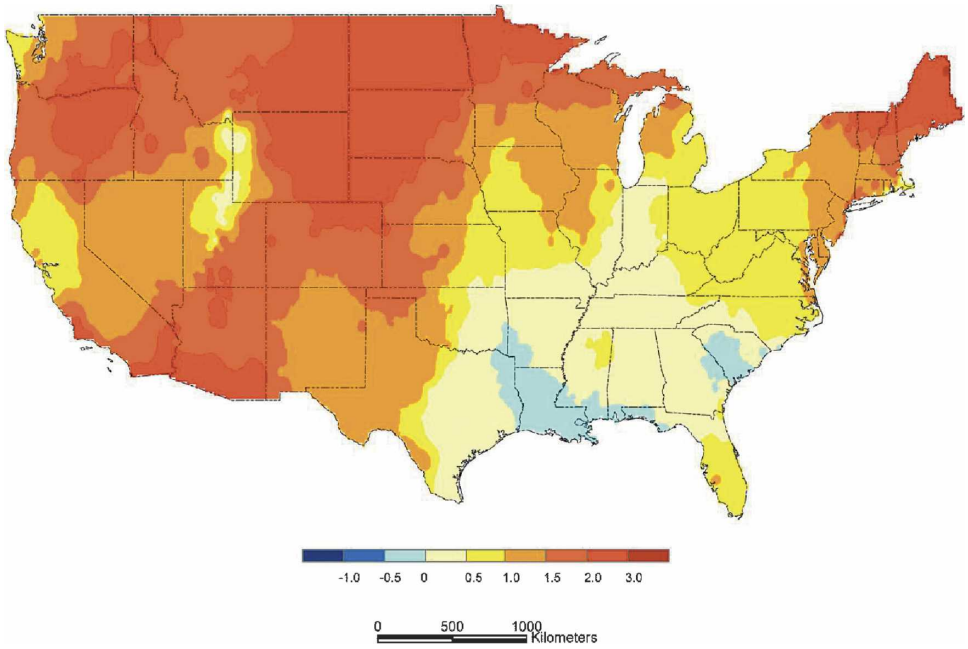


FIG. 5. Smoothed winter trends (red: warming; blue: cooling).

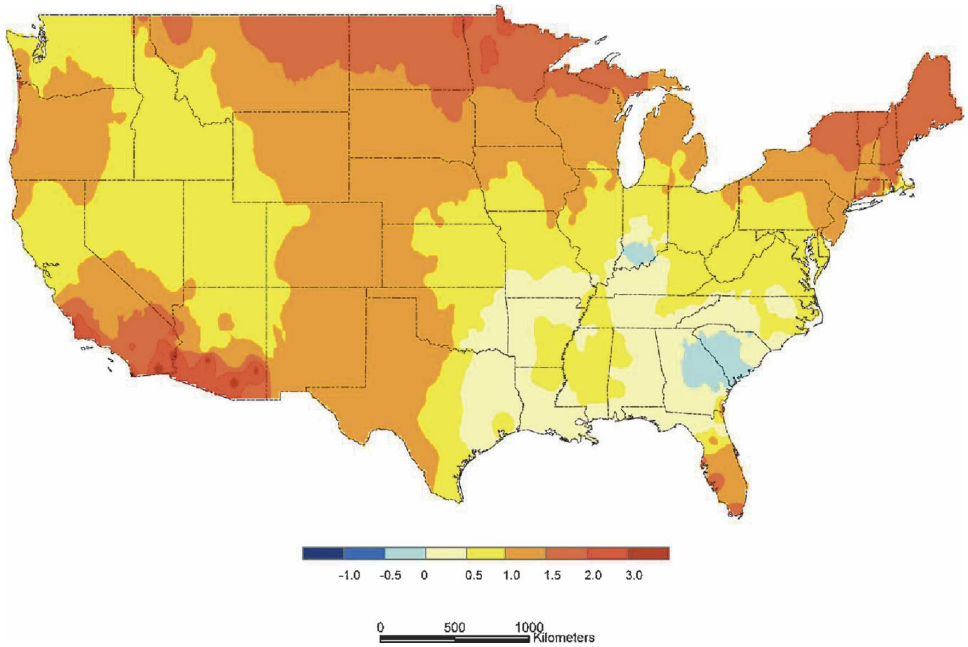


FIG. 6. Smoothed spring trends (red: warming; blue: cooling).

was 0.300°C century$^{-1}$. Overall, the results here suggest more warming than that reported in Lund et al. (2001), where the average annual trend was 0.725°C century$^{-1}$. The contribution of the last 4 yr to an overall trend of 0.823°C century$^{-1}$ is about 15% of the total, which represents warming at a rate of 3.327°C century$^{-1}$. The late 1990s was a very warm period for the continental United States.

Figure 3 is a GIS contour plot of the raw annual estimated trends without application of the head-banging smoother. The plot is included for smoothing feel and is color coded, with red representing warming

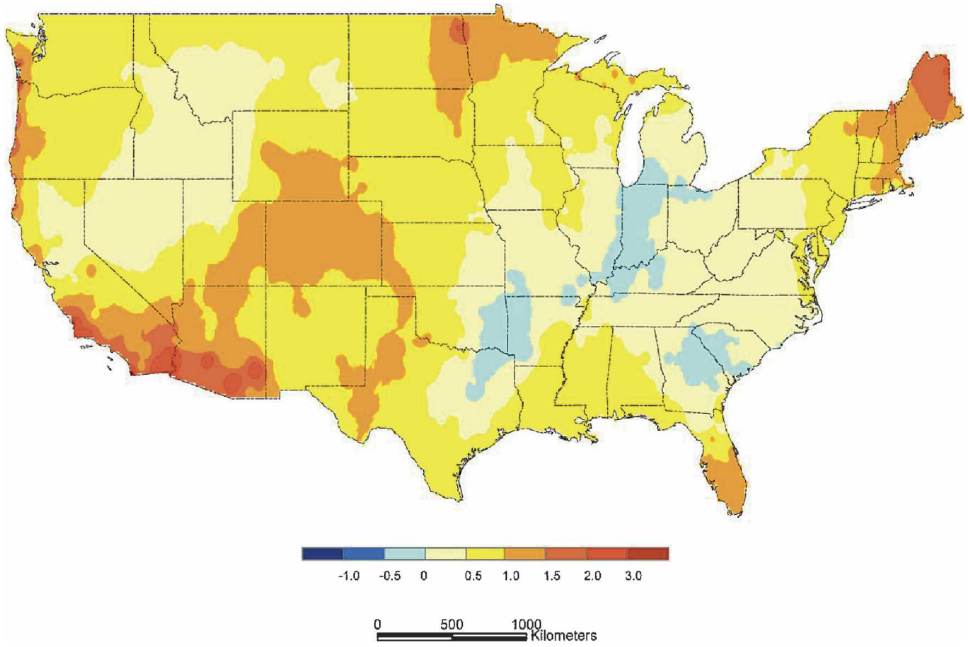


FIG. 7. Smoothed summer trends (red: warming; blue cooling).

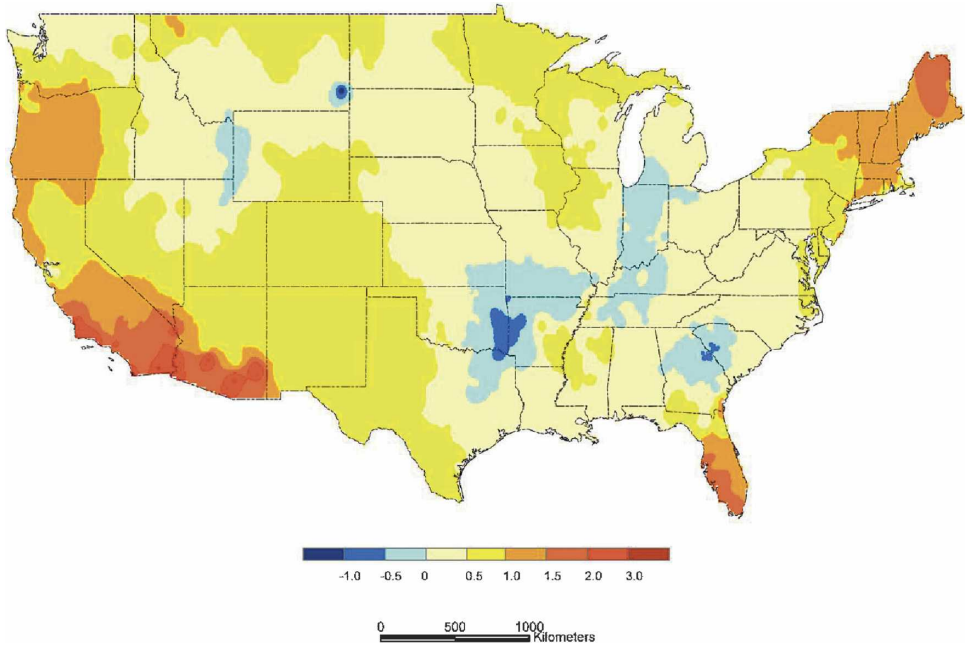


FIG. 8. Smoothed fall trends (red: warming; blue: cooling).

and blue cooling. One sees a speckled structure to the plot, indicating a rough spatial field, with cooling stations relatively more prevalent in the southeastern United States and warming stations relatively more frequent in the southern Rockies, northern Midwest, New England, and Oregon.

Figure 4 is a head-banging smoothed version of the annual trends in Fig. 3. Figure 4 conveys the general structure of Fig. 3 with much of the noise variability smoothed away. Overall, much of the West appears to be warming while a quasi-stationary climate, with perhaps slight cooling, is evident in the Southeast and Ohio River basin. This is less cooling than that reported in Lund et al. (2001). As before, rapid warming is apparent in Maine, southern Arizona, and northern Minnesota. Notice the scale in the plot is not symmetric: cooling rates are not less than $-1.5°C\ \text{century}^{-1}$ whereas some warming rates exceed $2.5°C\ \text{century}^{-1}$.

Figures 5–8 present spatially smoothed contours of trend estimates for winter, spring, summer, and fall, respectively. A consistent feature in these plots is the slight cooling in the Southeast and Ohio River basin and the warming in the Four Corners region and northern Midwest. The Dakotas show rapid winter warming as does southern Arizona and southern California. One can discern additional structure by examining the plots in detail. We do not encourage extrapolation and/or local inference in the plots beyond very general patterns; the usual disclaimer on interpreting local variations in a rough spatial field applies.

*Acknowledgments.* National Science Foundation support from Grants DMS 00071383 and DMS 0304407 is acknowledged. Comments from two referees substantially improved this manuscript.

## REFERENCES

Bloomfield, P., and D. Nychka, 1992: Climate spectra and detecting climate change. *Climate Change,* **21,** 275–287.

Brockwell, P. J., and R. A. Davis, 1991: *Time Series: Theory and Methods.* Springer-Verlag, 577 pp.

Callendar, G. S., 1961: Temperature fluctuations and trends over the earth. *Quart. J. Roy. Meteor. Soc.,* **87,** 1–12.

Dempster, A. P., N. M. Laird, and D. B. Rubin, 1977: Maximum likelihood from incomplete data via the EM algorithm. *J. Roy. Stat. Soc.,* **39B,** 1–38.

Diaz, H. F., and R. G. Quayle, 1980: The climate of the United States since 1895: Spatial and temporal changes. *Mon. Wea. Rev.,* **108,** 249–266.

Ellsaesser, H. W., M. C. MacCracken, J. J. Walton, and S. L. Grotch, 1986: Global climate trends as revealed by the recorded data. *Rev. Geophys.,* **24,** 745–792.

Grenander, U., 1954: On the estimation of regression coefficients in the case of autocorrelated disturbances. *Ann. Math. Stat.,* **25,** 252–272.

Hansen, J., R. Ruedy, J. Glascoe, and M. Sato, 1999: GISS analysis of surface temperature change. *J. Geophys. Res.,* **104,** 30 997–31 022.

——, ——, M. Sato, M. Imhoff, W. Lawrence, D. Easterling, T. Peterson, and T. Karl, 2001: A closer look at United States and global surface temperature change. *J. Geophys. Res.,* **106,** 23 947–23 963.

Hansen, K. M., 1991: Head-banging: Robust smoothing in the plane. *IEEE Trans. Geosci. Remote Sens.,* **29,** 369–378.

Jones, P. D., T. M. L. Wigley, and P. M. Kelly, 1982: Variations in

surface air temperature: Part 1. Northern Hemisphere, 1881–1980. *Mon. Wea. Rev.,* **110,** 59–70.

Karl, T. R., and C. N. Williams, 1987: An approach to adjusting climatological time series for discontinuous inhomogeneities. *J. Climate Appl. Meteor.,* **26,** 1744–1763.

——, ——, F. T. Quinlan, and T. A. Boden, 1990: United States Historical Climatology Network (USHCN) serial temperature and precipitation data. Environmental Sciences Division, Publication No. 3404, Carbon Dioxide Information and Analysis center, Oak Ridge National Laboratory, Oak Ridge, TN, 389 pp.

——, R. W. Knight, D. R. Easterling, and R. G. Quayle, 1995: Trends in U. S. Climate during the twentieth century. *Consequences Nature Implications Environ. Change,* **1,** 3–12.

Lund, R. B., and J. Reeves, 2002: Detection of undocumented changepoints: A revision of the two-phase regression model. *J. Climate,* **15,** 2547–2554.

——, H. L. Hurd, P. Bloomfield, and R. L. Smith, 1995: Climatological time series with periodic correlation. *J. Climate,* **8,** 2787–2809.

——, L. Seymour, and K. Kafadar, 2001: Temperature trends in the United States. *Environmetrics,* **12,** 673–690.

Madden, R. A., and V. Ramanathan, 1980: Detecting climate change due to increasing carbon dioxide. *Science,* **209,** 763–768.

Mungiole, M., L. W. Pickle, and K. Simonson, 1999: Application of a weighted headbanging algorithm to mortality data maps. *Stat. Med.,* **18,** 3201–3209.

Copyright of Journal of Climate is the property of American Meteorological Society and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.