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(Manuscript received 29 July 2011, in final form 23 April 2012)

ABSTRACT

Long-term (1901–2002) diurnal temperature range (DTR) data are evaluated to examine their spatial and temporal variability across the United States; the early century origin of the DTR declines; and the relative regional contributions to DTR variability among cloud cover, precipitation, soil moisture, and atmosphere/ocean teleconnections. Rotated principal component analysis (RPCA) of the Climatic Research Unit (CRU) Time Series (TS) 2.1 dataset identifies five regions of unique spatial U.S. DTR variability. RPCA creates regional orthogonal indices of cloud cover, soil moisture, precipitation, and the teleconnections used subsequently in stepwise multiple linear regression to examine their regional impact on DTR, maximum temperature (Tmax), and minimum temperature (Tmin).

The southwestern United States has the smallest DTR and cloud cover trends as both Tmax and Tmin increase over the century. The Tmin increases are the primary influence on DTR trend in other regions, except in the south-central United States, where downward Tmax trend largely affects its DTR decline. The Tmax and DTR tend to both exhibit simultaneous decadal variations during unusually wet and dry periods in response to cloud cover, soil moisture, and precipitation variability. The widely reported post-1950 DTR decline began regionally at various times ranging from around 1910 to the 1950s. Cloud cover alone accounts for up to 63.2% of regional annual DTR variability, with cloud cover trends driving DTR in northern states. Cloud cover, soil moisture, precipitation, and atmospheric/oceanic teleconnection indices account for up to 80.0% of regional variance over 1901–2002 (75.4% in detrended data), although the latter only account for small portions of this variability.

1. Introduction

The increase in surface average air temperatures over most of the planet in recent decades (e.g., Jones et al. 1999; Trenberth et al. 2007, 235–336) has occurred asymmetrically with warming taking place more at night than during the daylight hours (e.g., Karl et al. 1993; Easterling et al. 1997). This leads to upward trends in daily minimum air temperatures (Tmin) that are larger than those of maximum temperatures (Tmax) and a significant reduction in diurnal temperature range (DTR; DTR = Tmax – Tmin). Temporal and spatial variability of the DTR decline continues to be a focus in recent studies. Vose et al. (2005) used data for 71% of the world’s landmasses and showed the spatial variability in the downward DTR trends since 1950 (their Fig. 3). They find, however, that a worldwide flattening of the DTR trend (Vose et al. 2005) occurs over the period 1979–2004 produced as Tmax trends have increased and matched those of Tmin. Makowski et al. (2008) show the pan-European DTR variability since 1950 over 24 regions, finding that 17 of the areas have had increasing DTR trends since the 1970s and 1980s. Zhou et al. (2008) evaluate the worldwide temporal DTR changes over the same period across climatic regions based on their climatological precipitation as well as land cover types and find that the global desert areas experience the greatest DTR declines.

Many environmental variables potentially affect Tmax, Tmin, and DTR (Easterling et al. 1997). Physical mechanisms for the DTR decline in the last half century may include changes in land cover (Gallo et al. 1996; Collatz et al. 2000; Zhang et al. 2009), aerosol concentrations (Makowski et al. 2008), and atmospheric circulation patterns (Durre and Wallace 2001; Wu 2010).
Collatz et al. (2000) argue that increasing vegetation cover in recent decades is associated with DTR decreases, and Gallo et al. (1996) show that weather stations in rural land use/land cover areas have larger DTR compared to those in urban land use areas. Wu (2010) shows that atmospheric circulation teleconnections explain some Northern Hemisphere winter DTR variability, 1951–2000, but leave much unexplained variance even after removing trends from their data. Many studies have presented evidence regarding the role of cloud cover, precipitation, soil moisture, and humidity on DTR variability (Karl et al. 1991; Knappenberger et al. 1996; Dai et al. 1997; Dai 2006; Zhou et al. 2008). An all-encompassing study by Dai et al. (1999) evaluated the relation between these variables and Tmmax, Tmin, and DTR using 30-min-averaged data from a field site in Kansas as well as longer-term seasonal and annual data averages from around the world. They found that clouds, combined with secondary effects from soil moisture and precipitation, reduce DTR by up to 50% compared to clear-sky days over most land area while water vapor has little impact on DTR. Cloud cover largely determines the geographic patterns of DTR variability and on decadal scales averaged over the entire United States there is a strong inverse link between cloud cover and DTR. Numerical models have underestimated the global DTR decrease that has been observed, and Braganza et al. (2004) suggest this is due to inadequate representation of model cloud cover increases that lead to unrepresentative Tmmax increases when compared to climate observations.

This study uses data extending to 1901 to evaluate longer-term twentieth-century spatial and temporal DTR changes occurring regionally over the United States and small adjacent parts of Canada and Mexico. Unique regions of U.S. DTR variability are identified and the causes of the temporal DTR variability within these regions are analyzed in terms of variations in cloud cover, precipitation, and soil moisture as well as the impact of atmospheric circulation and ocean temperature teleconnection indices. The analysis helps evaluate the origins of twentieth-century DTR declines, how the temperature and DTR trends vary regionally across the country, and the regional variations occurring in the relation between moisture parameters and DTR. The purpose of the paper is to examine long-term regional DTR variability and to estimate the regional variability in the causal mechanisms of DTR variations linked to moisture variables and atmospheric teleconnections. It is an outgrowth of the studies by Dai et al. (1999) and Wu (2010) emphasizing some of the regional decadal U.S. DTR variability and broadly evaluates the regional variations in the impact of cloud cover, precipitation, soil moisture, and atmospheric teleconnections on regional DTR changes over the twentieth century.

2. Data

The Climatic Research Unit (CRU) TS 2.1 dataset (Mitchell and Jones 2005) contains gridded high-resolution (0.5° longitude × 0.5° latitude) global land surface climate parameters extending from 1901 to 2002. CRU data used here cover land areas over the United States and parts of southern Canada and northern Mexico extending from 25° to 50°N and include monthly maximum air temperature (Tmmax), minimum air temperature (Tmin), DTR, and precipitation. Temperature data were converted from monthly to annual means, and annual precipitation totals were determined. Although CRU climate datasets are intended for use in ecological modeling, the availability of their high-quality U.S. temperature and precipitation data on a high-resolution grid is very useful for the DTR principal component and regression analyses performed here and described in sections 3 and 4.

CRU TS 2.1 air temperature and precipitation station data are originally based on Jones and Moberg (2003) and Eischeid et al. (1991) data. Temperature data from the Global Historical Climatology Network (GHCN; Peterson et al. 1998) were its primary DTR data source, updated at the CRU through 2002. Temperature and DTR inhomogeneities were identified by Peterson et al. (1998) using correlation techniques on annual time series between neighboring stations in an effort to identify abrupt discontinuities. Mitchell and Jones (2005) improve on other aspects of temperature and precipitation data quality control for CRU TS 2.1 by requiring that monthly (rather than annual) time series be used in the homogeneity testing. Their homogenization procedure builds on GHCN efforts (e.g., Peterson et al. 1998) through construction of reference time series, using an iterative process on data for a group of neighboring stations that are used in testing other time series for homogeneity. Although these methods are good at detecting abrupt discontinuities in data, they are less able to isolate widespread gradual time series changes due to large-scale urbanization or land use changes, and such gradual changes may remain in the data. The corrected and homogeneous station data are then placed on the high-resolution CRU grid such that every grid point has a station reporting DTR or precipitation with 750 or 450 km, respectively (Mitchell and Jones 2005). Monthly data from over 100 U.S. GHCN version 3 stations (GHCN3) are averaged annually and used to make comparisons to results obtained with the CRU data.
U.S. cloud cover data are available from weather stations starting in 1891 and extending through 1987 and available as the historical sunshine and cloud data in the United States (HSC) set (Steurer and Karl 1991). They are used because the CRU TS 2.1 only has DTR-derived cloud estimates before 1950 (Mitchell and Jones 2005). The HSC data are monthly percentages, turned to annual averages, of U.S. sky cover produced by Steurer and Karl (1991) and based on observer estimates of fractional cloud amount occurring at any level from sunrise to sunset. Missing HSC data were always replaced using the long-term period of record monthly-mean values. Observational methodology changes in cloud reporting have taken place (Karl and Steurer 1990) over the HSC period of record including the number of daily observations (in the 1930s), and the 1948 change to sky cover observations that added obstructions to visibility (e.g., fog, haze, smoke, dust) to the cloud amounts. The century-long upward trend in cloud cover data (described further in the results) observed through the HSC period of record may partly be due to these reporting changes. Some of the trend, however, is likely associated with concomitant upward trends in U.S. precipitation (Karl et al. 1996; Dai et al. 1997; 1999) and water vapor (e.g., Gaffen and Ross 1999) and are linked to long-term downward trends in sunshine duration reported at the same weather stations (Changnon 1981; Angell et al. 1984; Karl and Steurer 1990). U.S. commercial airplane traffic in the second half of the twentieth century has also led to increases in jet contrails that boost sky cover reports (Changnon 1981; Minnis et al. 2004). The analyses in this study retain the trends in cloud cover data, whether natural or anthropogenic, but it also provides a comparative evaluation in which all data are detrended.

Analyses in this study are based on five identified regions of unique DTR variability across the United States and parts of Canada and Mexico. HSC and airways (see below) cloud cover data are averaged over the stations lying within these regions: each of which has a minimum of 8 and up to 15 reporting sites. Cloud data can be very limited spatially because of land cover, topography, and other station siting considerations, but these station data provide the best available opportunity to evaluate cloud–DTR relationships back to 1901.

Annual station cloud cover values used after 1987 are from the National Climate Data Center (NCDC) hourly surface airways data (TD-3280) from 1988 to 1996. These hourly cloud observations were changed to fractional tenths (Steurer and Bodosky 2000) from octals and include nighttime values that are typically lower than sunrise to sunset values (Dai et al. 2006). Regionalized CRU TS 2.1 cloud data are used from 1997 to 2002 using all grid points lying within the five DTR regions. The use of CRU cloud cover estimates after 1996 is necessitated by a national change to automated cloud observations that result in underreported cloud cover above 12 000 ft (Dai et al. 2006). The CRU cloud data in this period are derived from sunshine reports that are adjusted and incorporated into the post-1950 CRU gridded cloud data (Mitchell and Jones 2005). Inclusion of these 6 yr of closely related (to cloud amount) sunshine-based data should provide a reasonable estimate of cloud cover interannual variations occurring regionally, and they allow the analyses to proceed through 2002, in keeping with the time frame of other recent DTR research studies. The airways and CRU cloud data were turned into departures from normal occurring over their brief time spans, and these annual values were added to the regional HSC cloud cover averages for the period 1971–87.

Soil moisture data are used here because they also have a significant impact on air temperature (Durre et al. 2000; Yang et al. 2004; Zhang et al. 2009), and the Palmer drought severity index (PDSI) has been used as its proxy (Huang et al. 1996; Alfaro et al. 2006). PDSI is a unitless parameter ranging in value from \( \leq -4.0 \) (extreme drought) to \( \geq +4.0 \) (extremely moist), with zero as midrange or normal, and the monthly data (converted to annual averages) used here (Dai et al. 2004) are available on a 2.5° longitude \( \times \) 2.5° latitude grid. The PDSI is a good measure of meteorological drought as it evaluates both moisture supply (precipitation) and demand (air temperature, which is linked to evapotranspiration). PDSI has shortcomings in representing winter and spring soil moisture content, especially when the ground is frozen, when it accumulates snow and when melt occurs (Dai et al. 2004). PDSI calculations involve simplifications related to the ability of soils to hold water and how rainfall and evaporation can change the soil moisture content. Dai et al. (2004) nonetheless show that PDSI has correlations between 0.5 and 0.7 to soil moisture content in warm season months. The three parameters (PDSI, cloud cover, and precipitation) are hereafter collectively referred to as the local moisture parameters.

The influence of atmospheric teleconnections on DTR variability is also examined. The atmospheric and oceanic teleconnections used here consist of nine numerical indices (Table 1). All teleconnection data were gathered as monthly means and then converted to annual averages. The North Atlantic Oscillation (NAO) represents the strength of the Atlantic westerlies (Rogers 1984). The Arctic Oscillation (AO) more broadly measures the strength of the midlatitude westerlies and is linked to U.S. air temperature variability (Thompson...
and Wallace 1998). The North Pacific index (NPI) is the area-weighted mean sea level pressure (SLP) over the North Pacific Ocean (30°–65°N, 160°E–140°W) and represents the strength of the Aleutian low (Trenberth and Hurrell 1994). It is used instead of the better-known 500-hPa Pacific–North American (PNA) index because the NPI extends back to 1901. The Southern Oscillation index (SOI) is an index associated with El Niño–Southern Oscillation (ENSO) that measures the SLP difference anomaly between Tahiti and Darwin, Australia (Chen 1982). Niño-3.4 is the mean SST in the eastern equatorial Pacific Ocean spanning 5°N–5°S and 170°–120°W, an area that best represents the SST variability of ENSO (Rasmusson and Carpenter 1982). The cold tongue index (CTI) measures the SSTs along the west coast of South America, which are characteristic of ENSO events (Deser and Wallace 1990). The tropical Pacific SST index (TrPac) is the averaged SST of the tropical Pacific Ocean between 20°N–20°S and 160°E–80°W (Zhang et al. 1997). The Atlantic multidecadal oscillation (AMO) is the mean SST between 0° and 60°N in the North Atlantic Ocean (Enfield et al. 2001). The Pacific decadal oscillation (PDO) is the leading principal component of North Pacific monthly SST poleward of 20°N (Mantua et al. 1997).

### Table 1. Names, abbreviations, periods of record, and data sources of the teleconnection indices used.

<table>
<thead>
<tr>
<th>Index name</th>
<th>Abbreviation</th>
<th>Period of record</th>
<th>Data source</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Pacific index</td>
<td>NPI</td>
<td>1899–2002</td>
<td><a href="http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#npmon">http://www.cgd.ucar.edu/cas/jhurrell/indices.data.html#npmon</a></td>
</tr>
<tr>
<td>Southern Oscillation index</td>
<td>SOI</td>
<td>1895–2002</td>
<td><a href="http://www.cgd.ucar.edu/cas/catalog/climind/SOIsignal.ascii">http://www.cgd.ucar.edu/cas/catalog/climind/SOIsignal.ascii</a></td>
</tr>
<tr>
<td>Atlantic multidecadal oscillation</td>
<td>AMO</td>
<td>1895–2002</td>
<td><a href="http://www.esrl.noaa.gov/psd/data/climateindices/list/#AMO">http://www.esrl.noaa.gov/psd/data/climateindices/list/#AMO</a></td>
</tr>
<tr>
<td>Cold tongue SST index</td>
<td>CTI</td>
<td>1895–2002</td>
<td><a href="http://jisao.washington.edu/data/cti/#data">http://jisao.washington.edu/data/cti/#data</a></td>
</tr>
<tr>
<td>Tropical Pacific SST index</td>
<td>TrPac</td>
<td>1895–2002</td>
<td>Obtained from oceanic SST data</td>
</tr>
</tbody>
</table>

3. Methodology

The major spatial and temporal patterns of U.S. DTR variability are identified using principal component analysis (PCA) on the dataset correlation matrix. The PCA eigenvectors maximize the variance explained in each component with the constraint that the second and subsequent eigenvectors are orthogonal to the first. This constraint prevents these second and higher eigenvectors from showing the simple, unique, robust patterns of spatial variability taking place in the dataset. To resolve this, the eigenvectors are subjected to a variance maximizing rotation procedure in which they are transformed into a nonorthogonal linear basis, leading to simple, compact patterns that regionalize the dataset variability (Richman 1986; Barnston and Livezey 1987). The five rotated principal components (RPCs) individually explain between 9% and 16% (63.3% total) of the variance retained from the original eigenvectors. Components beyond the fifth were excluded as they accounted for much less than 5% of the dataset variance. The spatial loadings have normalized values \( L \) between \(-1\) and \(+1\), and the regional cluster of largest positive loadings in each RPC spatially defines its DTR variability center. The RPC time series retain their temporal orthogonality (Richman 1986), and this is the basis for subsequent treatment of the data.

Mean annual values of \( T_{\text{max}} \), \( T_{\text{min}} \), DTR, and the three moisture parameters are averaged over the grid points defining each of the five regional RPC centers. Their 1901–2002 time series characteristics are discussed in section 4. The five regional sets of three local moisture parameters as well as nine atmospheric teleconnection indices are subsequently used as independent predictor variables in linear regression analyses below of \( T_{\text{max}} \), \( T_{\text{min}} \), and DTR. The predictor data are intercorrelated to some degree (e.g., precipitation and PDSI, the NAO and AMO, etc.), presenting a multicollinearity problem in the regression analyses that is removed by orthogonalizing the data time series using rotated principal component analysis (RPCA). RPCA is performed on the nine teleconnection indices and separately on the three moisture parameters in each of the five regions. The nine teleconnection indices were transformed to five new RPC-based orthogonal indices (Table 2, top), with each defined by the teleconnections having loading values \( L > 0.71 \) on a particular RPC. This arbitrarily chosen loading cutoff value is used as it indicates more than 50% of the indices’ variance \( L^2 \) is linked to the new RPC while less than 50% of its remaining variance is shared with other RPCs. For example, the SOI, Niño-3.4, CTI, and TrPac each had high loadings (Table 2, top) on RPC1 and this component was renamed the “equatorial Pacific” (“Equa Pac”) teleconnection. Another was a combination of the NAO and AO (“NAOAO”), but the AMO, PDO, and NPI were retained individually as
Table 2. (top) The RPC loadings matrix for the nine atmosphere/ocean teleconnection indices as they are reduced to five orthogonal teleconnection indices using an arbitrary loading cutoff value of absolute 0.71. (bottom) The highest RPC loading (only) on cloud cover, precipitation, and soil moisture in each of the five spatial regions of DTR variability (Fig. 1), yielding three regional orthogonal moisture indices of the same name.

<table>
<thead>
<tr>
<th>Teleconnection principal component loadings matrix</th>
<th>Highest moisture parameter loadings by region</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPC1 Equa Pac</td>
<td>RPC2 NAOAO</td>
</tr>
<tr>
<td>Nino-3.4</td>
<td>+0.96</td>
</tr>
<tr>
<td>SOI</td>
<td>-0.89</td>
</tr>
<tr>
<td>AMO</td>
<td>-0.05</td>
</tr>
<tr>
<td>PDO</td>
<td>+0.37</td>
</tr>
<tr>
<td>NPI</td>
<td>-0.16</td>
</tr>
<tr>
<td>NAO</td>
<td>-0.07</td>
</tr>
<tr>
<td>AO</td>
<td>+0.00</td>
</tr>
<tr>
<td>CTI</td>
<td>+0.92</td>
</tr>
<tr>
<td>TrPac</td>
<td>+0.76</td>
</tr>
</tbody>
</table>

separate RPCs and the five newly defined teleconnections have time series orthogonal to each other. The same was done for the three series of averaged moisture parameter data individually for the five regions. For each region, three rotated components were always formed each with high loadings on just one of the three moisture parameters. Table 2 (bottom) shows these highest loading values on the cloud cover, precipitation, and PDSI data for the five regions. It differs, for brevity, from Table 2 (top) in that none of the smaller loadings ($L \leq +0.71$) are shown. For example, in the northeastern region (described below in section 4a) cloud cover had a high loading ($L = +0.94$) on moisture RPC1 containing $L^2 = 88\%$ of its variance and only 12\% of cloud cover variance was shared between RPC2 (precipitation) and RPC3 (PDSI). In turn, RPC2 in the Northeast contained 77\% of the precipitation data variance ($L = +0.88$) and so forth. As Table 2 (bottom) shows, each of the three moisture parameters are, despite some shared variance, heavily weighted onto one individual RPC, and as such the five sets of three orthogonal moisture parameter time series will continue to be named cloud cover, precipitation, and soil moisture (PDSI), although they are now standardized indices, with values between $-3$ and $+3$, used in the regression analyses.

Ideally, the moisture parameters and the teleconnection indices should be evaluated together in the regression analyses in order to simultaneously determine their relative contributions to DTR variance. This could not be achieved in a meaningful way by performing RPCA on all 12 original raw data series together (nine teleconnections and three moisture parameters) because it produced difficult to characterize, complex mixtures of teleconnection indices and moisture variables that varied among the five regions. The blending of the two datasets was achieved instead by reapplying RPCA to the three orthogonal moisture time series and the five orthogonal teleconnections simultaneously, for each region, creating a set of eight distinctly separate orthogonal parameters that recurred in each region maintaining their identity as moisture variables or teleconnections. Essentially the five orthogonal teleconnection indices and the three orthogonal moisture indices were reorthogonalized as a group in each region. An equivalent to Table 2 is not shown for this analysis, but every highest loading value was always $L \geq 0.96$. The multiple linear regression analyses described below were performed using the eight orthogonal parameters simultaneously and separately using just the three orthogonal moisture parameters.

Stepwise multiple linear regression (SMLR) is used to identify the best combination of predictor (independent) orthogonal local moisture and teleconnection time series that explain the variance of the predictand (dependent) temperature variable (Tmax, Tmin, or DTR). For example, a multiple linear regression equation for modeling $n$ data points with $p$ independent variables is given as

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \epsilon_i, \quad i = 1, \ldots, n.$$  

The dependent variable $Y_i$ is modeled as a function of a constant term $\beta_0$, the independent variables $X_{ip}$, their
corresponding coefficients \( \beta_p \), and an error (or residual) term \( e_i \). The error term is a random variable, which represents variation in the dependent variable that is unexplained by the regression equation. The coefficients and constant are estimated using the least squares method and the coefficient sign determines if the independent variable affects the dependent variable positively or negatively.

The SMLR forward selection process starts by choosing the orthogonal predictor variable explaining the most predictand variance. Second and subsequent predictors retained in the prediction equation must explain the largest amount of remaining predictand temperature variance with 95% confidence, thereby increasing the multiple coefficient of determination \( r^2 \) with \( Y_i \) by the greatest amount. The SMLR stops the entry of variables when new independent variables no longer explain significant levels of residual variance. Regression coefficients are recalculated as each new predictor is entered and the number of degrees of freedom is reduced by one in each step, leading to a final \( r^2 \) value adjusted for the reduction in degrees of freedom. All orthogonal predictors identified by the SMLR analysis are reported here as long as their explained variance exceeds the overall \( r^2 \) reduction caused by the additional degree of freedom. Assessment of regression model statistical significance is facilitated by an F statistic while the significances of the predictors are tested with the \( t \) statistic. Adjusted \( r^2 \) values help quantify how each independent variable contributes to the variability of the dependent variable (Tmin, Tmax, or DTR).

4. Results

a. DTR Spatial regionalization

RPCA produces five spatial patterns (Fig. 1) of annual DTR variability having locations defined by the grid points with positive loadings \( L \geq +0.40 \). This low cutoff \( L \) value was necessitated as the large number of grid points produced a large number of unrotated eigenvectors across which variance was spread, resulting in few grid points in any RPC that could exceed the arbitrary \( L = 0.71 \) cutoff used elsewhere in the analyses. RPC1 (Fig. 1a) is comprised of a narrow region winding across the Midwest into parts of southern Canada and the northeastern United States. It is referred to here generically as the northeastern region for its relative location in the grid domain. The southwestern United States and northern Mexico forms RPC2 (Fig. 1b) while RPC3 (Fig. 1c) covers the south-central United States from eastern Texas to Louisiana and then northward to the Tennessee valley. RPC4 (Fig. 1d) has highest loadings across the northern Great Plains from Oklahoma to North Dakota, and RPC5 (Fig. 1e) lies broadly across the western United States. Areas with large negative loadings potentially have temporal DTR characteristics opposite those of the positive loading regions, but these areas (with loadings \( \leq -0.10 \)) are generally small and scattered about the data domain (Fig. 1).

The mean annual Tmax, Tmin, and DTR and the three local moisture parameters are averaged for each regional center and the statistical significance of their trend slopes appear in Table 3. Each region, except the
Table 3. Trends in CRU temperature and U.S. moisture variables for annual regional time series. Temperature trends are in degrees Celsius per century. Units of cloud cover are percentage of sky cover per century, precipitation is in centimeters per century, and PDSI is a unitless index, with each based on 1901–2002 data. GHCN3 regional station-based data are shown for comparison to 1901–2002 trends in the bottom three rows.

<table>
<thead>
<tr>
<th>Variable</th>
<th>RPC1 Northeast</th>
<th>RPC2 Southwest</th>
<th>RPC3 South central</th>
<th>RPC4 Northern plains</th>
<th>RPC5 West</th>
</tr>
</thead>
<tbody>
<tr>
<td>DTR (°C century^-1) 1901–2002</td>
<td>-1.88^a</td>
<td>-0.16</td>
<td>-1.29^a</td>
<td>-1.34^a</td>
<td>-1.53^a</td>
</tr>
<tr>
<td>DTR (°C century^-1) 1901–49</td>
<td>-0.95^b</td>
<td>-0.67</td>
<td>-0.22</td>
<td>-1.42^c</td>
<td>+1.05^e</td>
</tr>
<tr>
<td>DTR (°C century^-1) 1950–2002</td>
<td>-2.26^a</td>
<td>-1.33^c</td>
<td>-2.42^a</td>
<td>-1.42^b</td>
<td>-2.54^a</td>
</tr>
<tr>
<td>DTR (°C century^-1) 1979–2002</td>
<td>-0.71</td>
<td>+0.91</td>
<td>-1.26</td>
<td>-1.01</td>
<td>-3.10</td>
</tr>
<tr>
<td>Tmax (°C century^-1) 1901–2002</td>
<td>0.00</td>
<td>0.48^c</td>
<td>-0.80^a</td>
<td>0.12</td>
<td>-0.41</td>
</tr>
<tr>
<td>Tmin (°C century^-1) 1901–2002</td>
<td>1.88^a</td>
<td>0.65^a</td>
<td>0.50^b</td>
<td>1.46^a</td>
<td>1.13^a</td>
</tr>
<tr>
<td>Cloud cover (% century^-1)</td>
<td>8.19^a</td>
<td>1.94^c</td>
<td>4.43^a</td>
<td>3.46^a</td>
<td>4.12^a</td>
</tr>
<tr>
<td>Precipitation (cm century^-1)</td>
<td>5.55^a</td>
<td>0.69</td>
<td>8.55^c</td>
<td>2.88</td>
<td>3.00</td>
</tr>
<tr>
<td>PDSI (century^-1)</td>
<td>0.78^a</td>
<td>-1.05</td>
<td>1.00^a</td>
<td>-0.44</td>
<td>-0.11</td>
</tr>
<tr>
<td>DTR GHCN3 1901–2002</td>
<td>-0.99^a</td>
<td>+0.42</td>
<td>-0.56^b</td>
<td>-0.92^a</td>
<td>-0.66^b</td>
</tr>
<tr>
<td>Tmax GHCN3 1901–2002</td>
<td>+0.31</td>
<td>+1.09^a</td>
<td>-0.39</td>
<td>+0.42</td>
<td>+0.60^b</td>
</tr>
<tr>
<td>Tmin GHCN3 1901–2002</td>
<td>+1.29^a</td>
<td>+0.59^b</td>
<td>+0.12</td>
<td>+1.30^a</td>
<td>+1.28^a</td>
</tr>
</tbody>
</table>

^a Trend is statistically significant at 99.9% confidence.
^b Trend is statistically significant at 99% confidence.
^c Trend is statistically significant at 95% confidence.

The twentieth-century southwestern United States and northern Mexico, has highly significant century-long (1901–2002) downward DTR trends between -1.2° and -1.9°C century^-1. The 1950–2002 trends, covering a time frame similar to that used by Vose et al. (2005) and others are more sharply and significantly downward in every region by -1.3° to -2.6°C century^-1, albeit most weakly in the Southwest. From 1901 to 1949, a period not described in previous studies, DTR has significant downward trends in the northeastern region and the northern plains but not in the Southwest or south-central states. A significant upward 1901–49 trend occurs in the west. Following the suggestion by Vose et al. (2005) that worldwide DTR trends have flattened since 1979, the U.S. 1979–2002 trends (Table 3) reveal that all regions, except the Southwest, have downward trends while none are statistically different from zero.

Between 9 and 18 GHCN3 stations having relatively complete data extending back to 1901 in each of the five regions are also used to create long-term DTR, Tmax, and Tmin trends shown at the bottom of Table 3. GHCN3 downward DTR trends are substantially smaller than those of the CRU in every region but the Southwest, where the DTR trend is weakly positive. GHCN3 Tmax trends are also all more positive than those of CRU data are, while Tmin trends are smaller positive values than in CRU (i.e., more negative), except in the west, producing smaller DTR trends relative to the CRU. Differences between DTR and other temperature trends highlight the large range in values that can be obtained using different datasets. They might be attributable to differences in station sampling, particularly the small GHCN3 station sample size chosen here, or to methods of data error and inhomogeneity treatment, especially in early-twentieth-century data.

b. Regional regression analyses

The northeast region (RPC1; Fig. 1a) is characterized by a DTR decrease through the century (Fig. 2a) following a plateau of higher values in the 1910s. Figure 2c and its equivalent in similar subsequent figures illustrate the DTR trends of Table 3. The downward DTR trend is solely produced by the statistically significant upward Tmin trend (Fig. 2b; Table 3) as Tmax variability (Fig. 2a) has no century-long trend. DTR noticeably declines and remains below 12°C after 1965 associated with a concomitant increase in regional cloud cover, precipitation, and soil moisture (Figs. 2d–f). Significant century-long upward trends occur in these three moisture variables (Table 3), particularly in cloud cover.

The SMLR results in which eight northeastern orthogonalized moisture and teleconnection indices are regressed onto the temperature variables (Fig. 3a) shows that they explain 80.0% of DTR variance. Cloud cover alone explains 63.2% of northeastern DTR variance, which will be the highest of any region, while precipitation and the soil moisture explain the lowest DTR variance of any region. Cloud cover explains 21.8% of Tmin variability but under 5% of Tmax variability. The AMO explains relatively large amounts of and directly varies with northeastern Tmax and Tmin variance but has only a small inverse relation with DTR as its influence is subtracted Tmax minus Tmin.

The twentieth-century southwestern United States and northern Mexico DTR trend is nonsignificant (Fig. 4c),
produced by the small difference between significant upward trends in both Tmax and Tmin (Figs. 4a,b; Table 3). On decadal time scales, one feature (Fig. 4) is the 1945–56 dry period exhibiting low soil moisture and precipitation (Figs. 4d–f) associated with elevated Tmax and DTR values. Conversely, moist conditions from 1982 to 1986 produce low Tmax and DTR. Southwestern soil moisture and precipitation explain 39.1% of Tmax variance (Fig. 3b), the largest of any region when combined. In combination with the teleconnections, the AMO and equatorial Pacific add to the Tmax explained variance (55.0%). The AMO explains more Tmin variance than any individual local moisture parameter. The equatorial Pacific, PDO, and NPI explain a relatively large total 17.3% of DTR variance while the moisture variables account for the remaining 43.7%. Precipitation reduces Tmax (negative coefficient) but increases Tmin, leading to a large DTR impact, while soil moisture reduces both Tmax and Tmin, reducing its DTR impact.

The south-central United States is uniquely characterized by relatively high Tmax, Tmin, and DTR until a sharp drop occurs starting in 1957 (Figs. 5a–c). This decline occurs after the very apparent 1951–56 drought that had high Tmax and DTR (Figs. 5a,c) and low values of cloud, precipitation, and soil moisture (Figs. 5d–f). South-central U.S. annual Tmax and Tmin are in fact characterized by statistically significant upward trends (1.61°C and 1.20°C century⁻¹, respectively) from 1901 to 1956 and a nonsignificant 0.41°C DTR trend, which contrasts with the 1901–49 DTR trend (−0.22°C century⁻¹) in Table 3. The Tmax and DTR downturns starting in 1957 are coincident with a simultaneous increase to higher cloud cover (Fig. 5d) that is relatively persistent through the rest of the century. South-central U.S. moisture variables account for 66.5% of regional DTR variance (Fig. 3c) with the remainder accounted for by the equatorial Pacific and PDO. Cloud cover and soil moisture are important to Tmax variability but precipitation is more important to Tmin.

The northern plains have a significant decrease in annual DTR extending throughout the twentieth century produced by a sizeable increase in Tmin occurring with a small upward trend in Tmax (Figs. 6a–c; Table 3), tendencies similar to those of the northeastern region (Figs. 2a–c). Drought in the northern plains from 1930 to 1940, with low soil moisture and precipitation (Figs. 6e,f), is associated with relatively high Tmax and DTR and, in this region, also Tmin. Six moisture and teleconnection predictors account for 68.2% of the DTR variances, with 60.2% by moisture parameters alone (Fig. 3d). Teleconnections account for 30.4% of northern plains Tmin variance.

DTR peaks in the 1930s in the western United States (Fig. 7c) and then steadily decreases. In contrast, Tmin (Fig. 7b) steadily increases through the century. Relatively low precipitation and soil moisture from 1928 to 1939 are associated with the relatively high Tmax and DTR values of that period. The upward Tmax trend into the 1930s is associated with downward precipitation and soil moisture tendencies (Figs. 7e,f) occurring up to that decade. Soil moisture and precipitation show a relatively wet period in the early 1980s when Tmax and DTR achieve their lowest values up to that time. These variables are linked to Tmax variance (Fig. 3e), while cloud cover explains almost 20% of Tmin variance. Soil moisture, cloud cover, and precipitation account
for 57.0% of DTR variance (Fig. 3e) with a small (2.4%) contribution by the NAOAO.

c. Detrended analyses

The SMLR results of Fig. 3 are reevaluated after removing the century-long trends in the eight orthogonal local moisture and teleconnection indices as well as in Tmax, Tmin, and DTR. This reduces some of the low-frequency dataset variance brought about by the century-long trends listed in Table 3, although it will not remove the decadal-scale variance evident in dry and wet spells mentioned previously in conjunction with earlier figures. With detrended data (Fig. 8) the DTR variance explained by cloud cover decreases in every region but the Southwest, where the original cloud and DTR trends were the smallest. The largest decrease in
DTR explained variance is in the northeastern region, where the cloud cover trend was largest. The overall explained DTR variance by the eight orthogonal indices remains relatively unchanged in the detrended analyses, except in the Northeast, where a large decrease occurs. As cloud cover explained variance decreases, that explained by precipitation and soil moisture increases substantially indicating their importance to DTR was suppressed by trends in the data.

d. GHCN3 station-based comparisons

A comparative SMLR analysis to that of Fig. 3 is made using GHCN3 data for 1950–2002 (Fig. 9), an analysis period used in many earlier DTR studies (see the introduction). This is performed using 18–25 GHCN3 stations per region, making use of more widely available data in recent decades. Cloud cover remains the lead DTR predictor (Fig. 9) in the Northeast, the northern plains, and the south-central states, although its explained variance is reduced in these regions between 1950 and 2002 relative to Fig. 3. The reduction in explained variance by cloud cover is sizably reduced in the western states and soil moisture and precipitation now have a larger DTR impact. These latter two predictors in fact explain more variance in 1950–2002 than between 1901 and 2002 (Fig. 3) in all five regions, especially so in the south-central states. The impact of precipitation and soil moisture on DTR in recent decades is underscored in several studies (e.g., Dai et al. 1999; Zhou et al. 2008; Zhang et al. 2009), and the result is in keeping with the fact that the second half of the twentieth century was wetter than the first half as precipitation and soil moisture trended upward in most regions of the country [panels (e) and (f) of Figs. 2, 4–7]. Teleconnections explain slightly more DTR variance since 1950 in every region, relative to
1901–2002, and they continue to dominate the explained variance of regional Tmin data among the parameters evaluated here. Tmax data since 1950 (Fig. 9) are widely influenced by soil moisture, just as in Fig. 3.

5. Discussion

Air temperature data from around the world indicate that decreases in DTR since 1950 are due to increases in Tmin that are larger than those in Tmax (Karl et al. 1993; Easterling et al. 1997; Vose et al. 2005). This occurs throughout the CRU data in Table 3, while a limited set of GHCN3 data suggests that Tmax trends are larger than Tmin in the Southwest, leading to a weak positive DTR trend. Tmin trends are almost solely the reason for century-long statistically significant DTR decreases in the northeastern region and northern plains (Table 3 and Figs. 2, 6), while Tmax increases are assisted by Tmin declines in the south-central United States (Fig. 5). The onset of the downward DTR trend, observed in other studies that used post-1950 data, occurs near the beginning of the twentieth century in the northeastern region and northern plains, while in other areas it begins after 1940 (western United States), as a sharp decline in the late 1950s (south-central United States), or without any significant long-term trend at all (southwestern region). Averaged together the regional onsets may cancel each other and Dai et al. (1999) present a time series of annual DTR (1900–90; their Fig. 11a) averaged over the contiguous United States that shows little trend in the first five decades until the 1950s, when a distinct DTR decline occurs that is similar to that in the south-central states in Fig. 5c. The cessation of the DTR decline since 1979 (Vose et al. 2005; Solomon et al. 2007) is observed.
Fig. 8. As in Fig. 3, but comparing the predictor explained variance (left) on raw DTR data (also given in Fig. 3) and (right) on predictors and DTR data that are detrended.
in the United States in the sense that 1979–2002 CRU trends are not statistically significant, although they continue to have negative values in four of the five RPC-based DTR regions (Table 3).

The SMLR analyses in Fig. 3 are designed to provide some estimates of the twentieth-century regional variability of Tmax, Tmin, and DTR that is due to orthogonal indices of cloud cover, soil moisture, precipitation, and five atmosphere/ocean teleconnections. Although the orthogonality constraint is necessitated for the SMLR, it must be recalled that all the local moisture predictors are all highly interrelated and even correlated to the teleconnections. The results can be compared to the comprehensive statistical analysis of Dai et al. (1999) that evaluated the same moisture parameters but also included specific humidity and wind parameters using 30-min-averaged data from one field site in Kansas and seasonal and annual data averages from around the

Fig. 9. As in Fig. 3, but based on regionally averaged GHCN3 station data for the period 1950–2002.
world. Dai et al. (1999) indicate (their Fig. 11a) that raw unfiltered DTR data averaged over the entire contiguous United States is correlated \( r = -0.58 \) \( (r^2 = 34\%) \) to U.S.-averaged cloud cover from 1900 to 1990. The annual data here indicate that cloud cover alone accounts for 9.9% (the Southwest) to 63.2% (the Northeast) of regional U.S. annual DTR variance (Fig. 3), while all eight indices used here explain between 59.4% and 80.0% of the regional DTR variance. The impact of increasing long-term cloud cover is especially noticeable after evaluating detrended data (Fig. 8) in which the cloud cover never accounts for more than 25.5% of DTR variance. Dai et al. (1999) described the modulating effects of soil moisture and precipitation on DTR variability. The U.S. regional contributions of these two parameters ranges from a low 10.1% of DTR variance in the Northeast (Fig. 3) to 33.8% in the Southwest over 1901–2002. Their impact appears to be even higher in data covering the wetter period, 1950–2002 (Fig. 9). The contribution to DTR variance by soil moisture and precipitation becomes even more pronounced (at cloud cover expense) when long-term 1901–2002 trends are removed from all data; between 30.7% and 48.3% of explained DTR variance is associated with these predictors among the five regions (Fig. 8). Precipitation explains more of the DTR variance than soil moisture across most U.S. regions. This is facilitated in all the annualized regionalized data (Fig. 3) by a negative (positive) precipitation relation with Tmax (Tmin) that creates relatively large negative regression coefficients with DTR. Soil moisture in contrast is inversely related to both Tmax (especially) and Tmin, producing weaker coefficients with DTR. The negative soil moisture link to Tmax and Tmin is also observed in field-site-averaged data from Dai et al. (1999) and in U.S. analyses by Alfaro et al. (2006) and Zhang et al. (2009).

Soil moisture explains a high amount of Tmax variance in the two southern regions (Figs. 4b,c). Durre et al. (2000) and Zhang et al. (2009) describe the summer impact of evapotranspiration and soil moisture in suppressing Tmax, while Huang et al. (1996) argue that soil moisture is a better predictor of Tmax than average daily temperatures because of the effect of evapotranspiration. Tmax exhibits a regional covariability with DTR on decadal time scales, associated with prolonged anomalous dry and wet periods, that is usually not apparent in Tmin data. Droughts in the western United States (1928–39), the northern plains (1930s), the south-central states (1951–56), and the Southwest (1945–56) are periods when DTR and Tmax simultaneously increase. Conversely, increases in cloud cover, precipitation and soil moisture are linked to Tmax and DTR declines in the western United States (from 1982 to 1985; Fig. 7) and on multidecadal scales in the Northeast after about 1970 (Fig. 2) and after 1956 in the south-central states (Fig. 5).

Over 50% of long-term annual Tmin variance remains unexplained by the eight SMLR predictor indices (Figs. 3, 9) used here. This leaves considerable uncertainty in the explanation for the significant century-long upward U.S. Tmin trends (Figs. 2b, 4b–7b) that play a key part in upward DTR trends. Tmin is furthermore not a participant in some of the aforementioned decadal shifts simultaneously appearing in Tmax and DTR that are linked to cloud cover, soil moisture, and precipitation. Teleconnections account for up to 35% of regional Tmin variance in the northern plains (Fig. 3d) and the Southwest in recent decades (Fig. 9b). It is likely however that a sizeable portion of unexplained Tmin variance might be accounted for by atmospheric humidity (i.e., dewpoint temperature) variability not evaluated in this study. Dai et al. (1999) show that specific humidity and Tmin are correlated \( r = +0.80 \) (summer) and \( r = +0.90 \) (autumn) in the Kansas field-site-averaged data, far larger correlations than they found between Tmin and soil moisture, cloud cover, or precipitation. Evidence indicates widespread increases in atmospheric humidity are occurring in the United States since the 1950s (Elliott and Angell 1997; Robinson 2000; Ross and Elliott 2001), including higher frequency of high dewpoint events (Gaffen and Ross 1999; Sandstrom et al. 2004). Increases in humidity or dewpoint with time may therefore lead to Tmin increases, especially given the strong correlational link in Dai et al. (1999). The CRU TS 2.1 dataset contains U.S. gridded vapor pressures that are estimated from Tmin data (Mitchell and Jones 2005) and are thereby unusable here.

Dai et al. (1999) show that specific humidity and Tmax have a smaller but still positive correlation. Specific humidity (or vapor pressure) would therefore be a parameter like soil moisture, or the AMO index, with regression coefficients of the same sign on both Tmax and Tmin and subsequently small negative DTR coefficients. Vapor pressure data might have shuffled some of the explained variance among the eight orthogonal indices used here or made a small additional contribution to explained variances, but Dai et al. (1999) in fact concluded that vapor pressure has only a small DTR influence.

Atmospheric circulation patterns and indices have been shown to be related to seasonal DTR changes (Durre and Wallace 2001; Easterling et al. 1997). Winter teleconnections such as ENSO, the AO, and PNA have been linked to global DTR variations (Wu 2010) occurring since 1950. Wu (2010) suggests that considerable unexplained variance remains after evaluating atmospheric teleconnection links to DTR. We show here that
local moisture variables sufficiently account for much of
the nonteleconnection-related DTR variance. SMLR
results in Fig. 3 indicate that the impact of atmospheric
teleconnections on DTR peaks in either time period in
the southwestern United States (Fig. 3b), whereas three
Pacific indices explain 17.3% of DTR variance. The
AMO contributes significantly and directly to Tmax and
Tmin variance in every region but only makes a small
DTR contribution in the northeastern region and
northern plains (Figs. 3, 9).

6. Conclusions

The goal of this study was to identify the twentieth-
century U.S. spatial and temporal DTR variability and
to obtain some estimates of the potential causes of that
variability. RPCA identified five regional areas of spa-
tial annual DTR variability exhibiting different charac-
teristic annual DTR variations. RPCA is also used to
create regional orthogonal cloud cover, soil moisture,
precipitation, and atmosphere/ocean teleconnection in-
dices that can be evaluated using SMLR in terms of their
(regional) impact on DTR, Tmax, and Tmin. Within
those regions mean annual values were obtained of
Tmax, Tmin, DTR, and three moisture variables cloud
cover, precipitation and soil moisture (PDSI). As
described (section 4) and discussed (section 5), the analysis
shows that the post-1950 DTR decline reported in ear-
lier studies (e.g., Easterling et al. 1997; Vose et al. 2005)
began at various times across the country ranging from
the 1910s to the 1950s. Every region exhibited century-
long Tmin increases while Tmax long-term trends vary
regionally and can either increase or decrease the
magnitude of the DTR downward trend. Tmax and
DTR decadal variability can be closely associated re-
gionally in the United States during unusually prolonged
wet and dry periods when changes in cloud cover, pre-
cipitation, and soil moisture simultaneously tend toward
extreme values. The southwestern United States and
northern Mexico are distinctly unique from other re-

gions in that DTR trends are insignificantly small while
significant increases have occurred in both Tmax and
Tmin (Fig. 4 and Table 3). The south-central United
States has a broad DTR decline, but it is composed
mostly of a sharp steplike downturn in both Tmax and
DTR around 1957 and the century-long Tmax down-
ward trend actually exceeds the Tmin rise (Fig. 5). The
SMLR suggests that cloud cover accounts for up to
63.2% of regional annual DTR variance from 1901 to
2002 while all the orthogonal moisture and tele-
connection data account for up to 80.0% of regional
variance. The twentieth-century upward trends in cloud
cover have a substantial impact on DTR trends over all
five regions of the study area and the impact of cloud
cover decreases noticeably when trends are removed
from the data. Analyses for 1950–2002 indicate that
explained variance by clouds is reduced at the expense
of soil moisture and precipitation relative to the 1901–
2002 analyses.

Acknowledgments. We thank Meng-Pai Hung for as-
sistance with the figures. We also thank Aiguo Dai and
the two anonymous reviewers for comments and sugges-
tions that greatly improved this paper.


