On the Estimation of Daily Climatological Temperature Variance

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ABSTRACT

The climatological daily variance of temperature is sometimes estimated from observed temperatures within a centered window of dates. This method overestimates the true variance of daily temperature when the rate of seasonal temperature change is large, because the seasonal change within the date window introduces additional variance. The contribution of the seasonal change may be removed by performing the variance calculation using daily temperature anomalies, leading to a bias-free estimate of variance.

The difference between the variance estimation methods is illustrated using both idealized simulations of temperature variability and observed historical temperature data. The simulation results confirm that removing the climatological temperature cycle eliminates bias in the variance estimates. For several U.S. midlatitude locations, the difference in estimated standard deviation of daily mean temperature is on the order of a few percent near the seasonal peaks in climatological temperature change, but the maximum difference is larger in highly continental climates. These differences are shown to be significant when estimating the probability of temperature extremes under the assumption of a Gaussian distribution.

1. Introduction

Climatological normals, which describe observed properties of atmospheric behavior and variability over years or decades, are widely used and highly valued by science and industry (Arguez et al. 2012). Two of the primary uses of climatological normals are the interpretation of past, current, or expected conditions in reference to the benchmark that the normal provides, and the assessment of likely or possible future outcomes. In the latter role, climatological normals provide a basis for prediction, under the assumption that the future behavior of the atmospheric system will remain similar to that described by the normal (WMO 2007; Arguez and Vose 2011).

The most basic feature of climatological normals is the characterization of the mean or median aspects of atmospheric variables, such as temperature or precipitation. However, measures of variability are also useful to describe the observed or likely future fluctuations of climate. The NOAA 1981–2010 U.S. climate normals include standard deviations of monthly and daily temperature variables, percentiles of monthly and daily precipitation quantities, and percentiles of some hourly variables (Arguez et al. 2012).

Information about the variability of atmospheric behavior is valuable for describing departures from the long-term average in terms of position within the observed distribution or within a parametric distribution used to model the climate. In this way, departures from average can be easily interpreted in a probabilistic sense and can be compared between locations with widely varying climate. Moreover, if the probability distribution of a climatic variable is known or assumed, then probabilistic statements about future variability can be made, such as "The probability of July monthly mean temperature exceeding 25°C is 18%," or "The central 90% probability range for daily minimum temperature on October 15 is 2°–8°C" (e.g., Holder et al. 2006). Temperature variability is particularly well suited to this kind of analysis because the probability distribution is

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often close to Gaussian and is thus often adequately characterized by the mean and standard deviation.

The ability to create probabilistic statements about future climate behavior is perhaps the most valuable aspect of climatological normals that include measures of variability. However, such statements will be statistically reliable only to the extent that the measures of variability adequately describe the probability distribution in the time frame of interest. Here we describe two alternative methods of estimating daily climatological temperature variance; we show that one common method overestimates the variance, and we discuss the implications of the differences between the methods. Section 2 describes the two methods, reviews previous recommendations in the literature, and evaluates the differences between the methods, and section 3 illustrates the potential significance of these differences using an assumed Gaussian framework.

2. Comparison of alternative estimation methods

a. Description of methods

A simple and intuitive method for estimating the daily variance of temperature is to compute the sample standard deviation from the observed temperature values within a window of several days centered on the Julian day in question; this method will be referred to as the "simple method."

The daily variance estimated by the simple method is

$$V_{\text{simple}} = \frac{1}{n-1}\sum_{i=1}^{n}(T_i - \overline{T})^2, \tag{1}$$

where n is the size of the observation sample within the computation window (e.g., $n = 450$ for 30 annual sets of 15 observations), T_i is the ith observation, and $\overline{T}$ is the sample mean of the T_i. In practice the daily values of V_{simple} are smoothed to help eliminate the day-to-day fluctuations arising from sampling variability.

An alternative method for calculating the daily variance substitutes the daily climatological normal temperature for the sample mean temperature,

$$V_{\text{anom}} = \frac{1}{n-1}\sum_{i=1}^{n}(T_i - T_{ci})^2, \tag{2}$$

where T_{ci} is the estimated climatological normal temperature on the Julian day of the ith observation. The alternative method [(2)] reflects the idea that the variance of temperature arises fundamentally from the daily deviations of temperature away from the climatological normal. When the climatological normal varies significantly during the computation window—for example, during spring and autumn—then the daily temperatures will be closer on average to T_{ci} than to $\overline{T}$, and therefore V_{anom} will be smaller than V_{simple}.

A further refinement may be undertaken by recognizing that (2) still overestimates the variance, because the estimated climatological normal T_{ci} is typically derived using some smoothing or spline fitting, and therefore the sample mean $\overline{T}$ may differ considerably from the sample mean of the T_{ci}. As a consequence the random variability in the sample mean $\overline{T}$ relative to the true (unknown) climatological normal will add a positive contribution to V_{anom} that would not be present if a very large sample were available. If the climatological normals could be adequately computed from the mean of temperatures within the observation window, then this subtlety would not arise. However, this is not possible in practice, and therefore the appropriate method for estimating the variance is

$$V_{\text{anom}} = \text{Var}(T_i') = \frac{1}{n-1}\sum_{i=1}^{n}(T_i' - \overline{T'})^2, \tag{3}$$

where T_i' is the departure from normal of the ith observation,

$$T_i' = T_i - T_{ci} \tag{4}$$

and $\overline{T'}$ is the (generally nonzero) sample mean of the T_i'. An additional justification for using (3) rather than (2) is that the presence of missing data does not bias the results of (3), whereas (2) may suffer from a discrepancy between the daily temperature normals T_{ci} and the daily data that are available for this calculation.

The difference between the alternative method [(3)] and the simple method [(1)] may be rewritten as follows:

$$\begin{aligned}
&V_{\text{anom}} - V_{\text{simple}}\\
&= \frac{1}{n-1}\sum_{i=1}^{n}[(T_i - T_{ci} - \overline{T} + \overline{T_c})^2 - (T_i - \overline{T})^2],\\
&= \frac{1}{n-1}\sum_{i=1}^{n}[2(T_i - \overline{T})(\overline{T_c} - T_{ci}) + (\overline{T_c} - T_{ci})^2],\\
&= -\frac{1}{n-1}\sum_{i=1}^{n}(T_{ci} - \overline{T_c})(2T_i - 2\overline{T} + \overline{T_c} - T_{ci}),\\
&= -\frac{1}{n-1}\sum_{i=1}^{n}(T_{ci} - \overline{T_c})(2T_i - 2\overline{T} + \overline{T} - \overline{T'} - T_i + T_i'),\\
&= -\frac{1}{n-1}\sum_{i=1}^{n}\overbrace{(T_{ci} - \overline{T_c})}^{\text{A}}\overbrace{(T_i - \overline{T}}^{\text{B}} + \overbrace{T_i' - \overline{T'})}^{\text{C}},
\end{aligned} \tag{5}$$

where $\overline{T_c}$ is the sample mean of the T_{ci}. Examining (5), we see that during seasons of significant climatological temperature change, terms A and B will tend to be of the same sign, and therefore their product will contribute to the reduction in variance relative to V_{simple}. However, term C will vary randomly within the computation window and therefore may contribute either positively or negatively to V_{anom}.

The principal message of (5) is that the simple method [(1)] tends to produce a larger estimate of variance, and the difference between the methods grows with the rate of change of the climatological normal within the computation window. In locations and seasons where the climatological normal shows little change in comparison to the amplitude of daily temperature variations, then the two methods [(1) and (3)] will give similar results. However, when the computation window includes significant change in the climatological normal in comparison to the magnitude of daily temperature variations, then the methods will differ substantially.

b. Literature review

The significance of the climatological temperature cycle with respect to estimates of daily temperature variance has been recognized in previously published studies, but the magnitude and significance of errors related to this issue have not been explored to the authors' knowledge. For example, in a detailed study of changes in daily temperature variability from long-term European instrumental records, Moberg et al. (2000, p. 22 851) stated, ''it is important that day-to-day variability [analyses] are not confounded by changes from day to day caused by the average annual cycle, which can lead to considerable changes from one day to the next in the spring and autumn when the slope of the annual temperature cycle is steep.'' Moberg et al. (2000) compared several measures of temperature variability, and the calculations were based on daily anomalies of temperature rather than full temperature values. Similarly, according to Brinkmann (1983, p. 173), ''the time series of daily temperatures exhibit a strong seasonal cycle which tends to increase interdiurnal variability about the monthly means. For this reason, the seasonal cycle was removed before calculating means and variances.'' More recently, Walsh et al. (2005, p. 215) stated that ''mean temperatures undergo strong seasonal cycles. . . . The quasi-continuous change of the daily mean temperatures must be considered in a quantitative evaluation of variance.''

In some studies, the need to calculate temperature variance with daily anomalies rather than full values was recognized but not explicitly discussed (e.g., Collins et al. 2000; Vincent and Mekis 2006). However, many other studies calculated the standard deviation of daily temperature based on the full temperature values (e.g., Michaels et al. 1998; Robeson 2002; Mearns et al. 1984; Rebetez 2001; Gough 2008; Rusticucci and Barrucand 2004; Holder et al. 2006). In most of these studies the standard deviation was calculated separately for each month of the year, and the focus was on long-term changes in variance, so there would have been little change in the results if temperature anomaly values had been used. Nevertheless, the diversity of approaches suggests that the significance of the climatological temperature cycle may not always be recognized.

The daily standard deviation estimates that were included in the initial release of NOAA's 1981–2010 climate normals were calculated without removing the climatological cycle from the temperature values. The NOAA calculations used a variant of the simple method [(1)] in which the sample mean $\overline{T}$ was set equal to a ''raw daily normal'' for each individual day within the 15-day window (Arguez et al. 2011). NOAA's 1981–2010 daily temperature standard deviation normals have since been updated to reflect the anomaly method [(3)].

c. Evaluation of differences

It is straightforward to evaluate Eqs. (1) and (3) using daily temperature data from any observing station that has a sufficiently long period of record. However, historical temperature data are often affected by inhomogeneities arising from various causes, including changes in instrumentation, observing location or environment, or observing practice (Menne and Williams 2009; Menne et al. 2009). To mitigate these problems, NOAA applied a homogenization procedure to the historical monthly mean temperatures prior to calculating the 1981–2010 monthly temperature normals, and the daily normals were then constrained by the 12 monthly normals (Arguez and Applequist 2013). The issue of historical inhomogeneities is an important consideration here, because large inhomogeneities could affect the results of Eqs. (1) and (3) and the subsequent interpretation of the differences. Consequently, we restrict our evaluation (with one exception discussed below) to observing stations at which no homogenization adjustments or ''time of observation'' adjustments were made in any month from 1981 to 2010 for either maximum or minimum temperature. Only seven U.S. stations met these criteria and had nearly complete data from 1981 to 2010; these stations are listed in Table 1.

Figures 1–4 show a comparison of the 1981–2010 standard deviation of daily mean temperature obtained from the two methods [(1) and (3)] at three stations from Table 1 and for Fairbanks International Airport, Alaska [GHCN identification (ID) USW00026411]. The stations have widely differing climates, and Fairbanks is included as an example of extreme seasonal temperature change.

TABLE 1. List of U.S. stations at which no homogenization adjustments or time of observation adjustments were performed by NOAA and at which fewer than 10 observations were missing or flagged during the period 1981–2010. ICAO denotes International Civil Aviation Organization.

Station name	State	GHCN-Daily ID	ICAO ID	No. of missing days
Hartford Bradley International Airport	CT	USW00014740	KBDL	0
Concord Municipal Airport	NH	USW00014745	KCON	2
Portland International Jetport	ME	USW00014764	KPWM	0
Columbus Metropolitan Airport	GA	USW00093842	KCSG	6
Midland International Airport	TX	USW00023023	KMAF	7
Billings Logan International Airport	MT	USW00024033	KBIL	4
Glasgow International Airport	MT	USW00094008	KGGW	0

The simple method following (1) uses a 15-day calculation window and a 29-day equal-weight smoothing, as described by Arguez et al. (2011). For the alternative method following (3), referred to here as the ''anomaly method,'' the daily mean temperature anomalies were first calculated relative to the NOAA 1981–2010 normal values for the daily mean temperature, and then the standard deviation was computed with the same 15-day calculation window and subsequent 29-day smoothing. Daily temperature data were taken from the Global Historical Climatology Network (GHCN)-Daily database (Menne et al. 2012), and days with missing data were excluded from the calculation.

The results show that the anomaly method variance is nearly always smaller than the simple method variance, as expected based on (5), and that the maximum difference in standard deviation is on the order of a few percent for the three midlatitude locations. Similar differences were observed for the four additional midlatitude locations (not shown). However, at Fairbanks, where the seasonal climate shift is very rapid in spring and autumn, the difference in standard deviation exceeds 5% in both transition seasons. Each of the locations shows a greater difference between the two methods in autumn than in spring, because the peak rate of seasonal temperature change is greater in autumn. At all locations the two methods produce very similar results near the midsummer and midwinter extremes in the annual temperature cycle.

It is useful to compare the differences between the two methods to the sampling uncertainty associated with estimating the standard deviation from a finite set of data. According to Cochran's theorem, for a sample of independent observations from a Gaussian distribution, the ratio of the sample variance to the population variance follows a scaled chi-squared distribution, so that the sample variance approaches the population variance as the sample size increases. For a 15-day sampling window with 29-day smoothing, taken from 30 years of data, the sample size is 1290, and the 90% confidence interval for the standard deviation ranges from $0.9687\hat{s}$ to $1.0336\hat{s}$, where $\hat{s}$ is the sample standard deviation. Therefore, the sampling uncertainty for the estimation of the standard deviation is on the order of 3% and is comparable to the difference between the two calculation methods in seasons of rapid temperature change. However, in spring and autumn in Fairbanks, the difference between the methods is greater than the uncertainty due to finite sampling.

d. Simulation results

The difference between the simple and anomaly methods was also investigated in an idealized setting by performing repeated simulations of 30-yr station histories. The advantage of this approach is twofold: first, the climatological variance is known and thus the errors in the estimation methods are precisely calculable; and second, a large ensemble of simulations produces stable statistics that alleviate uncertainty associated with sampling variations. For each simulation, a 30-yr series

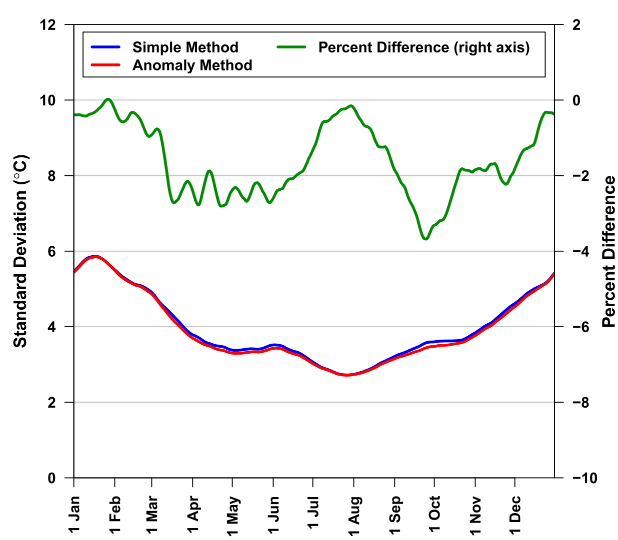

FIG. 1. Estimated standard deviation of daily mean temperature at Portland, OR (GHCN ID USW00014764), using two alternative methods as described in the text; the green line shows the percent difference between the methods.

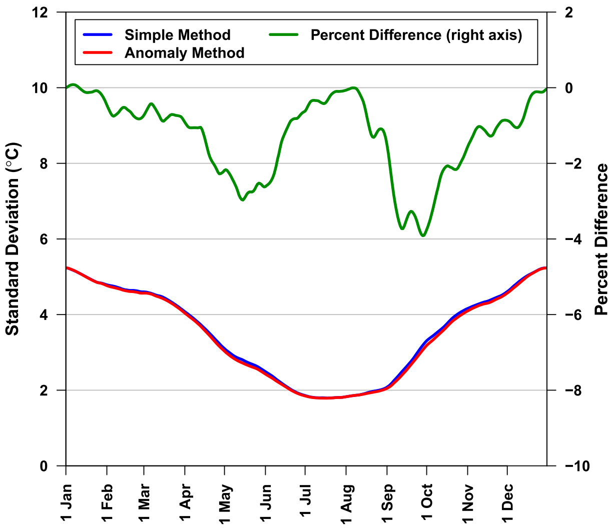

FIG. 2. As in Fig. 1, but for Columbus, GA (GHCN ID USW00093842).

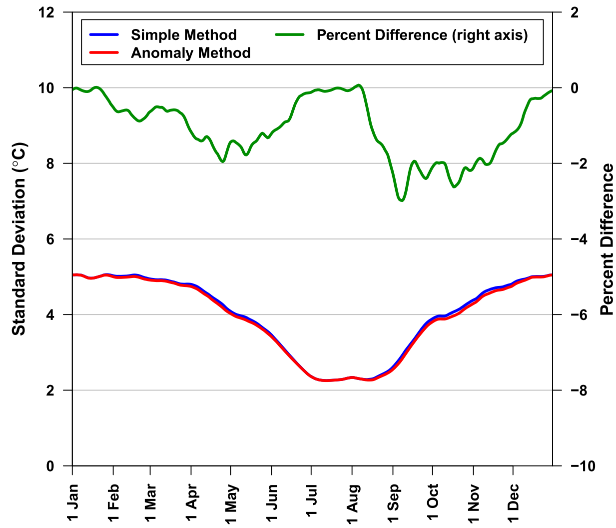

FIG. 3. As in Fig. 1, but for Midland, TX (GHCN ID USW00023023).

of synthetic daily temperatures (°C) was created by random sampling from a Gaussian distribution with the mean and standard deviation specified based on the day of the year j as follows:

$$\mu = 10 - 10\cos\left[\frac{2\pi(j-15)}{365}\right] \quad \text{and} \tag{6}$$

$$\sigma = 4 + 2\cos\left[\frac{2\pi(j-15)}{365}\right]. \tag{7}$$

Owing to the random sampling procedure, consecutive daily temperature departures from normal were independent of each other; the absence of autocorrelation here leads to slightly larger variance estimates than in real-world temperature data, but for a 30-yr series the difference is negligible. After obtaining each 30-yr daily temperature series, the climatological daily normals T_{ci} were estimated for each simulation separately by fitting six harmonics, as in the NOAA method for calculating daily temperature normals (Arguez and Applequist 2013); however, monthly mean constraints were not imposed. Note that estimated daily normals were used instead of the known climatological mean μ in order to more closely mimic the real-world procedure for estimating daily temperature variance. Finally, the simple and anomaly methods [(1) and (3), respectively] were applied to each 30-yr time series, and the estimated standard deviation was then compared to the known climatological standard deviation σ for an ensemble of 1000 simulations.

As discussed in section 2a, the estimated variance is expected to be too large on average when computed with the simple method; in other words, the simple method produces a positive bias. This characteristic of the simple method was clearly evident in the simulation results, as shown in Fig. 5; the median bias from 1000 simulations was about +0.035°C when using the simple method, but the median bias was very nearly zero when using the anomaly method. Therefore the simulations demonstrate that the anomaly method produces a bias-free estimate of variance, although sampling variability may still cause significant underestimates or overestimates of variance in some cases.

Figure 6 shows the joint distribution of the mean absolute percentage error (MAPE) for the simple and anomaly methods of variance estimation. Each point on

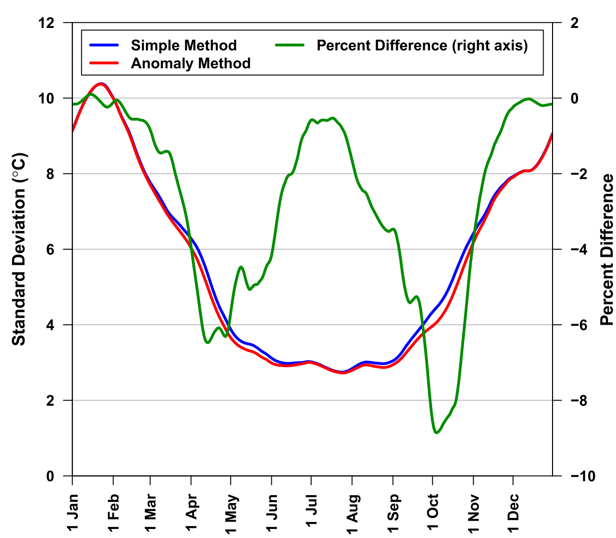

FIG. 4. As in Fig. 1, but for Fairbanks, AK (GHCN ID USW00026411).

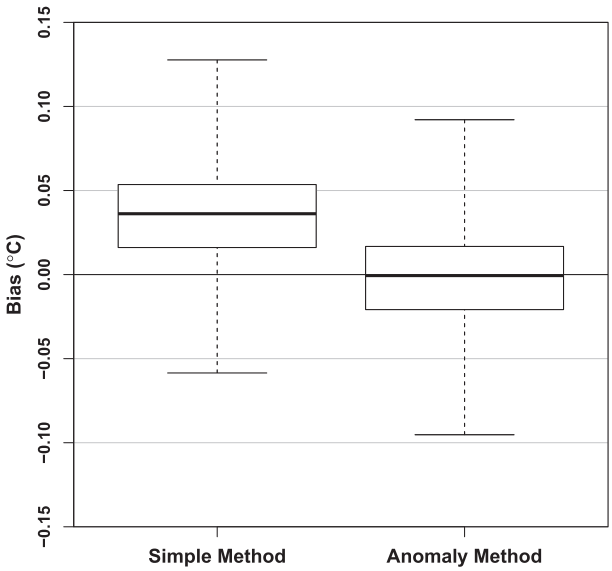

FIG. 5. Distribution of annual mean bias of estimated daily standard deviation from 1000 simulations of 30-yr temperature histories, using two alternative methods as described in the text.

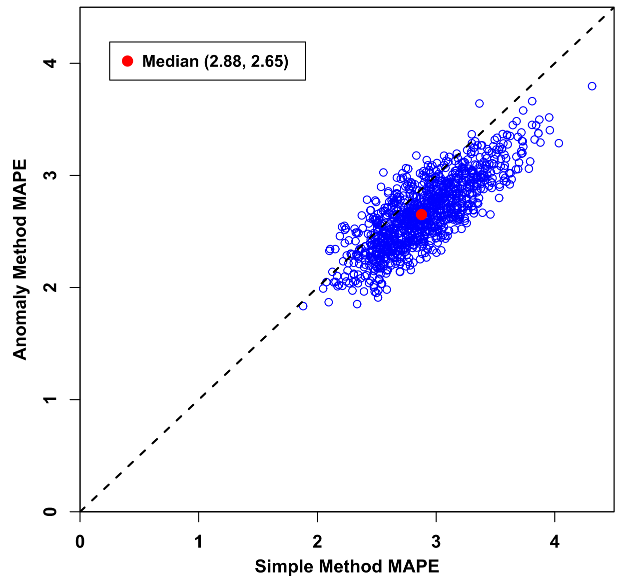

FIG. 6. Distribution of MAPE of estimated standard deviation from 1000 simulations of 30-yr temperature histories, using two alternative methods as described in the text.

the scatterplot indicates the MAPE for the two methods [(1) and (3)] over all 365 daily values of the estimated standard deviation. While there is considerable scatter in the accuracy of the estimates owing to sampling variations, approximately 85% of the simulations resulted in smaller MAPE when the anomaly method was used. Based on this error metric, then, the anomaly method could be expected to produce a superior estimate of standard deviation approximately 85% of the time for stations with climates similar to that represented by (6) and (7).

3. Discussion

The climatological variance of temperature is sometimes used to estimate the standardized anomaly associated with a temperature observation or the probability of a specific temperature threshold being exceeded within a given period of time. Such calculations assume that the underlying distribution of daily temperature anomalies is Gaussian, which is often approximately but not precisely true; alternative distributions may be superior in describing the climatological temperature variability (Barrow and Hulme 1996). Several of the stations in Table 1 exhibited considerable skewness and kurtosis in their daily temperature distributions; the stations in the northeastern United States exhibited slight positive skewness, but strong negative skewness was observed at the stations in Montana and Texas. The most non-Gaussian temperature distribution was found at Billings, Montana, with third and fourth standardized moments of −0.83 and +4.56, respectively (i.e., excess kurtosis of +1.56).

Despite the prevalence of departures from Gaussian behavior, however, it is useful to examine the results of calculations that are typically performed in tandem with the Gaussian assumption. For example, Fig. 7 shows the 1981–2010 frequency of daily temperature anomalies of two standard deviations or more, as computed using the two alternative methods, and compared to the expected frequency if the temperature distribution were indeed Gaussian. At every location except Billings, the frequency of large anomalies is too small when calculated using the simple method, but the anomaly method reduces the shortfall in frequency in each case. This result illustrates that the simple method tends to produce standardized anomalies that are too small as a result of the positive variance bias that is inherent in the method. The frequency of large anomalies is closer to the expected value when the anomaly method is used, even for some significantly non-Gaussian stations such as Glasgow, Montana.

While it is clear from the foregoing results that the anomaly method provides superior estimates of daily temperature variance, the differences in the estimates are generally only a few percent or less, and it is not yet clear that these differences are important. However, the significance of the differences becomes apparent when we consider the probability of relatively large deviations of temperature from the seasonal norm. The excess estimated variance produced by the simple method leads directly to an overestimate of the probability of temperature extremes, and for some locations and seasons

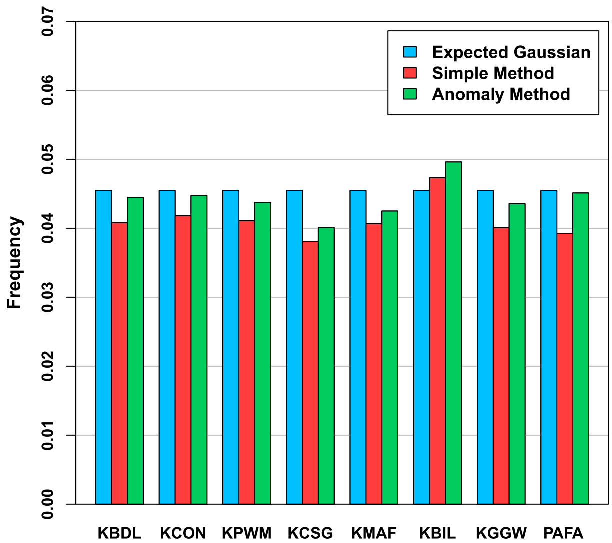

FIG. 7. Period 1981–2010 frequency of daily temperature departures from the climatological normal of two standard deviations or more, based on two alternative variance estimation methods and compared to the expected frequency in a Gaussian distribution.

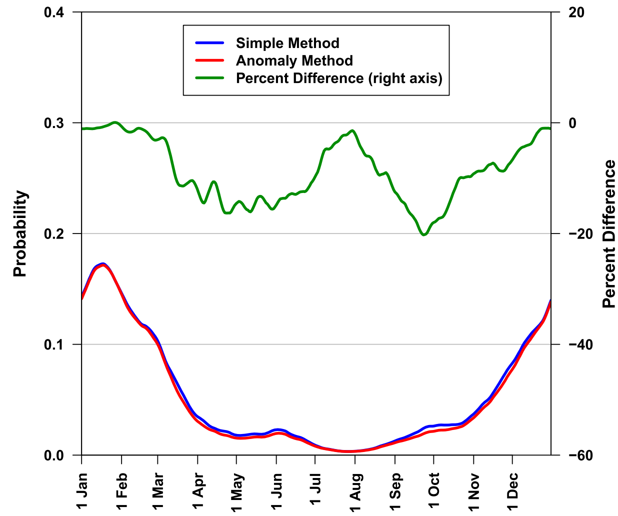

FIG. 8. Comparison between the estimated probabilities of an 8°C departure from normal of daily mean temperature at Portland using an assumed Gaussian distribution with the standard deviation estimated by two alternative methods.

the difference is considerable. For example, using an assumed Gaussian distribution, the estimated probability of an 8°C departure from the climatological mean at Portland, Maine, differs by more than 10% for nearly half of the year, depending on the method used to calculate the daily variance (Fig. 8). In Fairbanks, where temperature volatility is greater, we examine the estimated probability of a 12°C departure from the mean; the two methods [(1) and (3)] produce estimates that differ by considerably more than 20% for most of the spring and autumn (Fig. 9).

It should be emphasized that the exceedance probabilities portrayed here are estimates based on the Gaussian assumption, and it is likely that improved estimates of exceedance probability could be obtained either by using an alternative distribution that provides a superior fit or by examining historical frequencies of large anomalies. However, the Gaussian analysis provides a first-order estimate of the significance of the variance estimation differences within the tails of the climatological distribution. We therefore conclude that when the climatological variance is used to estimate the probability of extreme temperatures on any given day, or within a specified date range, significant errors may be obtained by using the simple method variance.

4. Conclusions

The climatological daily variance of temperature is an important metric for describing and predicting temperature variations about the mean, and probabilistic analysis of observed or expected temperature variability is sensitive to the estimated value of the true climatological variance. Both theoretical and observational considerations reveal that a common method of estimating the variance includes a contribution from seasonal climatological temperature change and therefore it overestimates the true daily variance in seasons of rapid temperature change. An alternative method is described in which the variance is estimated from the daily anomalies of temperature rather than from daily temperatures themselves.

Using data from eight U.S. locations, it is shown that the anomaly method produces estimates of temperature

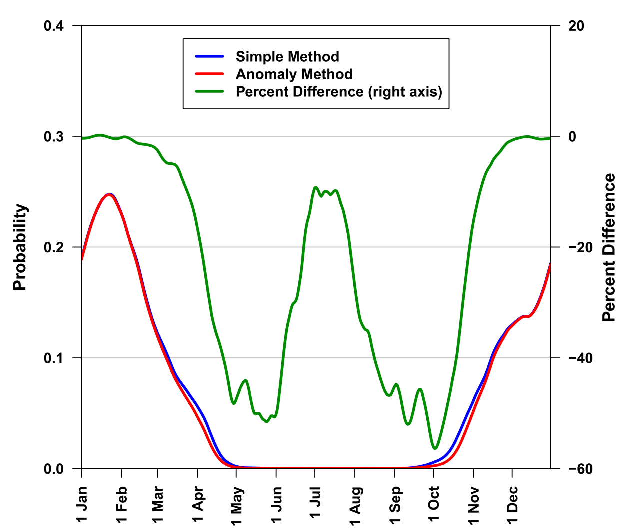

FIG. 9. As in Fig. 8, but for a 12°C daily anomaly at Fairbanks.

standard deviation that are up to several percent smaller than the simple method during seasons of rapid climatological temperature change. These differences may be comparable to or larger than the sampling uncertainty for estimating standard deviation from a 30-yr period. The superiority of the anomaly method is illustrated by examining a large ensemble of simulations of daily temperature histories, showing that the anomaly method is bias free. We also demonstrate that estimated probabilities of large daily temperature anomalies may differ by 10%–20% or more at certain times of year, depending on the variance estimation method.

It is recommended that weather and climate analyses that depend on measures of daily temperature variance employ the anomaly method described here to estimate the climatological variance. NOAA's 1981–2010 daily temperature standard deviation normals have been updated to reflect the anomaly method.

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REFERENCES

Arguez, A., and R. Vose, 2011: The definition of the standard WMO climate normal: The key to deriving alternative climate normals. *Bull. Amer. Meteor. Soc.*, **92**, 699–704, doi:10.1175/2010BAMS2955.1.

——, and S. Applequist, 2013: A harmonic approach for calculating daily temperature normals constrained by homogenized monthly temperature normals. *J. Atmos. Oceanic Technol.*, **30**, 1259–1265, doi:10.1175/JTECH-D-12-00195.1.

——, ——, R. S. Vose, I. Durre, M. Squires, and X. Yin, 2011: NOAA's 1981-2010 climate normals: Methodology of temperature-related normals, June 30, 2011. NOAA, 7 pp. [Available online at http://www1.ncdc.noaa.gov/pub/data/normals/1981-2010/documentation/temperature-methodology.pdf.]

——, I. Durre, S. Applequist, R. S. Vose, M. F. Squires, X. Yin, R. R. Heim Jr., and T. W. Owen, 2012: NOAA's 1981–2010 U.S. climate normals: An overview. *Bull. Amer. Meteor. Soc.*, **93**, 1687–1697, doi:10.1175/BAMS-D-11-00197.1.

Barrow, E. M., and M. Hulme, 1996: Changing probabilities of daily temperature extremes in the UK related to future global warming and changes in climate variability. *Climate Res.*, **6**, 21–31, doi:10.3354/cr006021.

Brinkmann, W. A. R., 1983: Variability of temperature in Wisconsin. *Mon. Wea. Rev.*, **111**, 172–180, doi:10.1175/1520-0493(1983)111<0172:VOTIW>2.0.CO;2.

Collins, D. A., P. M. Della-Marta, N. Plummer, and B. C. Trewin, 2000: Trends in annual frequencies of extreme temperature events in Australia. *Aust. Meteor. Mag.*, **49**, 277–292.

Gough, W. A., 2008: Theoretical considerations of day-to-day temperature variability applied to Toronto and Calgary, Canada data. *Theor. Appl. Climatol.*, **94**, 97–105, doi:10.1007/s00704-007-0346-9.

Holder, C., R. Boyles, P. Robinson, S. Raman, and G. Fishel, 2006: Calculating a daily normal temperature range that reflects daily temperature variability. *Bull. Amer. Meteor. Soc.*, **87**, 769–774, doi:10.1175/BAMS-87-6-769.

Mearns, L. O., R. W. Katz, and S. H. Schneider, 1984: Extreme high-temperature events: Changes in their probabilities with changes in mean temperature. *J. Climate Appl. Meteor.*, **23**, 1601–1613, doi:10.1175/1520-0450(1984)023<1601:EHTECI>2.0.CO;2.

Menne, M. J., and C. N. Williams Jr., 2009: Homogenization of temperature series via pairwise comparisons. *J. Climate*, **22**, 1700–1717, doi:10.1175/2008JCLI2263.1.

——, ——, and R. S. Vose, 2009: The U.S. Historical Climatology Network monthly temperature data, version 2. *Bull. Amer. Meteor. Soc.*, **90**, 993–1007, doi:10.1175/2008BAMS2613.1.

——, I. Durre, R. S. Vose, B. E. Gleason, and T. G. Houston, 2012: An overview of the Global Historical Climatology Network-Daily database. *J. Atmos. Oceanic Technol.*, **29**, 897–910, doi:10.1175/JTECH-D-11-00103.1.

Michaels, P. J., R. C. Balling Jr., R. S. Vose, and P. C. Knappenberger, 1998: Analysis of trends in the variability of daily and monthly historical temperature measurements. *Climate Res.*, **10**, 27–33, doi:10.3354/cr010027.

Moberg, A., and Coauthors, 2000: Day-to-day temperature variability trends in 160- to 275-year-long European instrumental records. *J. Geophys. Res.*, **105**, 22 849–22 868, doi:10.1029/2000JD900300.

Rebetez, M., 2001: Changes in daily and nightly day-to-day temperature variability during the twentieth century for two stations in Switzerland. *Theor. Appl. Climatol.*, **69**, 13–21, doi:10.1007/s007040170032.

Robeson, S. M., 2002: Relationships between mean and standard deviation of air temperature: Implications for global warming. *Climate Res.*, **22**, 205–213, doi:10.3354/cr022205.

Rusticucci, M., and M. Barrucand, 2004: Observed trends and changes in temperature extremes over Argentina. *J. Climate*, **17**, 4099–4107, doi:10.1175/1520-0442(2004)017<4099:OTACIT>2.0.CO;2.

Vincent, L. A., and E. Mekis, 2006: Changes in daily and extreme temperature and precipitation indices for Canada over the twentieth century. *Atmos.–Ocean*, **44**, 177–193, doi:10.3137/ao.440205.

Walsh, J. E., I. Shapiro, and T. L. Shy, 2005: On the variability and predictability of daily temperatures in the Arctic. *Atmos.–Ocean*, **43**, 213–230, doi:10.3137/ao.430302.

WMO, 2007: The role of climatological normals in a changing climate. WCDMP-61, WMO/TD-1377, 46 pp.