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The influences of data precision on the calculation of temperature percentile indices

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ABSTRACT: Percentile-based temperature indices are part of the suite of indices developed by the WMO CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices. They have been used to analyse changes in temperature extremes for various parts of the world. We identify a bias in percentile-based indices which consist of annual counts of threshold exceedance. This bias occurs when there is insufficient precision in temperature data, and affects the estimation of the means and trends of percentile-based indices. Such imprecision occurs when temperature observations are truncated or rounded prior to being recorded and archived. The impacts on the indices depend upon the type of relation (i.e. temperature *greater than* or *greater than or equal to*) used to determine the exceedance rate. This problem can be solved when the loss of precision is not overly severe by adding a small random number to artificially restore data precision. While these adjustments do not improve the accuracy of individual observations, the exceedance rates that are computed from data adjusted in this way have properties, such as long-term mean and trend, which are similar to those directly estimated from data that are originally of the same precision as the adjusted data.

KEY WORDS climate indices; climate extreme; climate change detection

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1. Introduction

There is consensus within the climate community, that change in the frequency or severity of extreme climate events will have profound impacts on nature and society. It is thus very important to monitor and analyse change in extreme events. The monitoring, detection and attribution of changes in weather extremes usually requires daily data. However, the compilation, provision, and update of globally complete daily datasets are difficult tasks. This comes about, in part, because not all National Meteorological and Hydrometeorological Services have the capacity or mandate to freely distribute the daily data that they collect. Consequently, the WMO joint CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) and its predecessors have coordinated an international effort to develop the capacity to calculate and analyse a suite of indices to study some types of climate change. As this capacity continues to develop, individuals, countries, and regions should be able to calculate the indices in exactly the same way such that their analyses will fit seamlessly into the global picture (Karl *et al*., 1999; Peterson *et al*., 2001). This effort has already made an important contribution to the monitoring of weather extremes (Alexander *et al*., 2006; Trenberth *et al*., 2007).

The percentile-based temperature indices developed by the ETCCDI have been used to analyse changes in temperature extremes for various parts of the world (e.g. Peterson *et al*., 2002, 2007; Klein Tank and Können, 2003; Aguilar *et al*., 2005; Klein Tank *et al*., 2005; Vincent *et al*., 2005; Zhang *et al*., 2005a; Alexander *et al*., 2006; New *et al*., 2006; Vincent and Mekis, 2006). These indices are calculated by counting the number of days in a year or a season for which daily values exceed (or lie below) a time-of-year-dependent threshold. Such a threshold is typically defined as a percentile of daily observations in a fixed base period (e.g. 1961–1990) that fall within a few Julian days of the day of interest.

The use of a fixed base period, rather than the entire record, for computing thresholds has many advantages, including making it easy to compare indices among stations of different record lengths and to update records. However, it also causes problems such as those described here and in Zhang *et al*. (2005b) which found that sampling error in the threshold estimate results in overestimated exceedance rates outside the base period used to determine the thresholds. This occurs because even an unbiased quantile estimator will result in a biased estimate of the exceedance rate (Buishand, 1991; Zhang *et al*., 2005b). Zhang *et al*. (2005b) proposed a bootstrap re-sampling procedure to estimate exceedance

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frequencies within the base period in order to ensure that the exceedance rate time series is homogeneous throughout the period of record. This procedure results in an exceedance rate that is consistent throughout the period of record but slightly higher than the nominal level.

The main objective of this note is to describe another type of bias in the estimation of percentile exceedance rates that results from low recording precision in temperature observations, and to propose a method to eliminate such bias. We describe the problem in the following section, and the method in Section 3. Results are given in Section 4, followed by Conclusions and Discussion in Section 5.

2. The problem

It is possible to design an unbiased quantile estimator if the underlying probability distribution is known, and if observations are collected with infinite precision. However, in practice, observations are recorded with finite precision on a discrete scale, such as in increments of 1/10th of a degree Celsius or coarser in the case of surface temperature. In these cases, the measurement resolution may affect the numerical realization of the quantile estimator, a known problem in the statistical literature and as shown in the following example.

The United States (US) National Climatic Data Center stores US temperature data in whole degrees Fahrenheit, which is equivalent to a resolution of about 0.56 °C when converted to Celsius. As a result, the daily minimum temperatures at the Marshall Island station (171.38 °E, 7.08 °N), which were converted from data originally stored in whole degrees Fahrenheit, for the days January 1–5 during 1961–1990 that are used to estimate the 90th percentile for January 3 (Zhang *et al.*, 2005b), have only eight distinct values ranging from 22.8 to 26.7 °C with either 0.5 or 0.6 °C intervals between values. Figure 1 shows the frequency with which individual values occur. The true value for the 90th percentile should lie between 26.1 and 26.7 °C, but such a value never occurs in the recorded observations due to the limited data precision. The 90th percentile estimate obtained by means of a plotting position such as that used in RClimDex (Zhang *et al.*, 2005b) is 26.1 °C. This is a negatively biased estimate that will result in the average exceedance rate for the base period being very different from its nominal value (10%) for the station. If occurrence of a daily temperature *greater than* (GT) the estimated 90th percentile is counted as an extreme event, then only the days with a temperature reading of 26.7 °C are counted as exceeding the 90th percentile, effectively raising the threshold to a higher percentile. Consequently, the exceedance rate will be substantially smaller than 10%. However, if daily temperatures *greater than or equal to* (GE) the estimated 90th percentile are counted as extreme events, then the days with temperature readings of either 26.1 or 26.7 °C are counted as exceeding the 90th percentile, effectively reducing the threshold to a lower percentile. The resulting exceedance rate will therefore be much larger than the 10%. The annual mean exceedance rates for the base period are 5.9 and 15.9% for the GT and GE methods, respectively. When there is a trend in the temperature, this bias will also have an important impact on the trend estimate for the indices series as the trend will not correspond to the trend in the 90th percentile exceedance rate. Rather it will correspond to the trend in a lower or a higher percentile exceedance rate depending upon whether the GE or GT criterion is used in estimating the exceedance rate. Thus, while the use of GE *versus* GT should make an infinitesimally small difference in theory, it can make a large difference for data of finite resolution. Other means of estimating the 90th quantile, such as by estimating quantiles from probability distributions fitted to the data, do not resolve this difficulty because of the coarse resolution of the recorded observations.

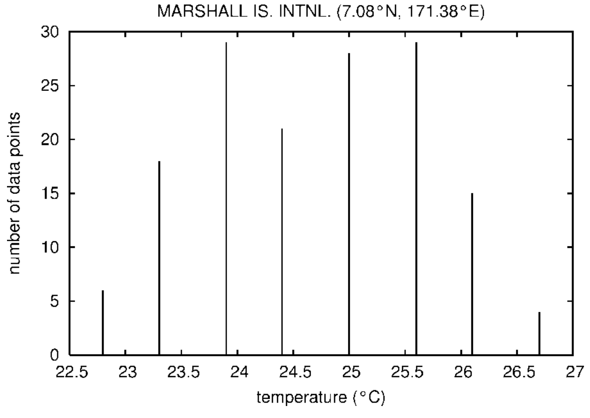

Figure 1. Frequency of daily minimum temperatures recorded on January 1–5 at Marshall Island for 1961–1990.

This problem is not unique to the USA or to the Marshall Island station; in North America, the precision of temperature data for Canada and Mexico is also not very high. Mexican stations report temperatures at resolutions of either 0.5 or 1.0 °C. Canadian stations have mixed resolutions as well, with some reporting at 0.1 °C resolution and other non-principal stations reporting at 0.5 °C resolution. These resolutions are much poorer than the observation accuracy and reporting resolution of 0.1 °C recommended by the World Meteorological Organization (WMO, 1996).

In fact, because of poor recording precision, temperature percentile exceedance rates estimated from most North American stations are biased. Because resolutions are mixed at different stations, there are differences in bias amongst different stations, making it difficult to uniformly assess changes in percentile indices across the continent. Furthermore, changes in the precision in time would introduce an artificial jump in the indices time series. Figure 2 shows the percentage of the time within the 1961–1990 base period when daily minimum temperature exceeds its corresponding 90th percentile as estimated using the RClimDex plotting position. It is clear that the base period exceedance rate is below the nominal level at almost all Mexican and US stations, at some

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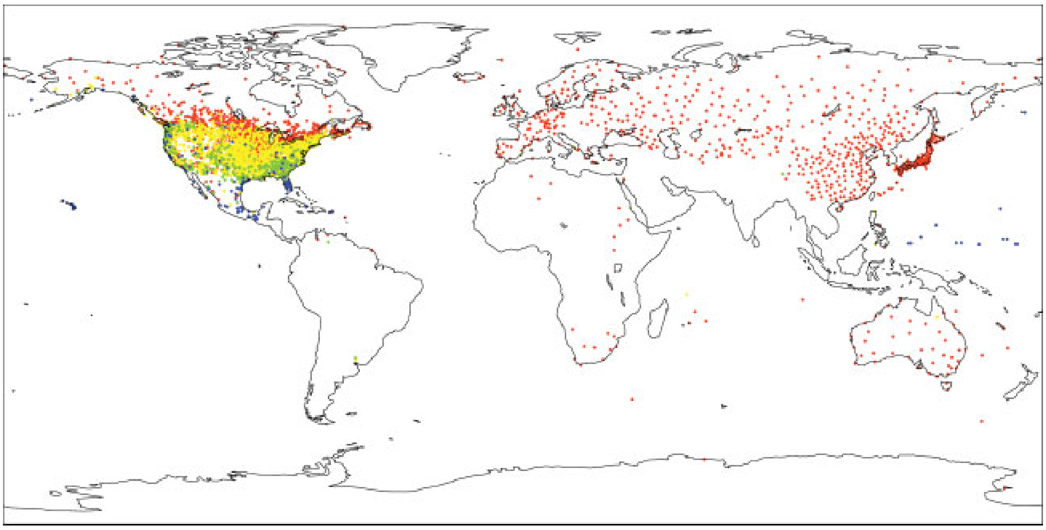

Figure 2. Percentage of time daily minimum temperatures are greater than their corresponding 90th percentiles averaged over the base period 1961–1990. Red, yellow, green, blue dots indicate stations with exceedance rate greater than 10%, between 10 and 9.5%, between 9.5 and 9%, and less than 9%, respectively.

Canadian stations, and also at some ocean island stations. Detailed inspection indicates that the lowest base period exceedance rates tend to occur at Mexican stations where temperature is accurate at 1.0 °C and where day-to-day temperature variability is the smallest. Some tropical island stations also showed very low base period exceedance rates owing to very low temperature variability in those regions, exacerbating the effect of the graininess of the data.

3. Method

The bias in the exceedance rate is caused by the discrete nature and low precision of the temperature records and cannot be corrected by using different quantile estimators. One way to solve this problem is to artificially restore the resolution of low precision data by adding a small random number to each datum such that the 'improved' temperature data have a resolution of 0.1 °C, as recommended by the WMO on required observation accuracy and reporting resolution for surface air temperature (WMO, 1996) and as used in other parts of the world. Although this does not increase the accuracy of the recorded observations, we will show that it does improve the characteristics of the derived index time series. Because, when small random numbers are added, the addition should not substantially change estimates of long-term variation such as the trend in the exceedance rate. In the following, we describe a suite of Monte-Carlo simulations for investigating the influence of data precision on the estimation of the exceedance rate and its trend, and the effect of data resolution enhancement by adding small random values to data of poor resolution.

We use the AR(1) process described in Zhang *et al.* (2005b) to simulate 60-year daily temperature time series. This process simulates daily temperature as the sum of a lag-1 auto-regressive process and an annual cycle. The lag-1 auto-correlation of daily temperature is set to 0.6, which is appropriate for mid-latitude land areas (Zhang *et al.*, 2005b). We consider seven cases:

1. A, the simulated original series, which has the highest resolution.
2. AI, the A series truncated so that it has a resolution of 0.1 °C.
3. AV, which is as AI except with a truncation of 0.5 °C.
4. AX, with resolution of 1.0 °C.
5. AVCV, the AV series adjusted so that it has a resolution of 0.1 °C. This is achieved by adding a uniform random number from the interval (−0.25, 0.25), and then rounding to the nearest 0.1 °C.
6. AXCX, the AX series adjusted to have a resolution of 0.1 °C by adding a uniform random number from the interval (−0.5, 0.5) and then rounding to the nearest 0.1 °C.

AI represents the resolution of temperature observations available in many places in the world. AV has resolution that is similar to temperature data available in the USA, and at some stations in Mexico and Canada. AX corresponds to some other Mexican stations where temperatures are recorded at 1 °C resolution. AVCV and AXCX represent coarse resolution series adjusted to restore a resolution of 0.1 °C. We also consider another series, AVCX.

7. AVCX, an adjusted series obtained from AV by adding a uniform random number from the interval (−0.5, 0.5) and rounding to the nearest 0.1 °C.

We consider AVCX to determine whether it would be possible to apply the same correction to all stations, which would make adjustment easier when computing indices for many stations with mixed precisions.

We generate 1000 realizations of the A series and apply the various truncation and adjustments to each realization

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of the A series to obtain a corresponding realization of the AI, AV, AX, AVCV, AXCX, and AVCX series. The result is 1000 sets of related series. For each simulated time series, we compute the 60-year time series of annual exceedance rates using the bootstrap procedure of Zhang *et al.* (2005b), using the second 30-year period as the base period for the estimation of the 90th percentile. In order to examine the possible impacts on the exceedance rate bias caused by low data resolution, we also add a linear trend to the simulated temperature by adding the annual trend value to every individual day of the year. We consider trends of −1.0, 1.0, and 2.0 °C per 100 years. We assess trend in the exceedance rate using a non-parametric method (Wang and Swail, 2001). The average exceedance rate across the 1000 simulations in each year, the number of times a significant trend is detected, and the average of the trends in the exceedance rate time series are then computed and compared among different cases.

4. Results

Figure 3 shows the average 90th percentile exceedance rate in 1000 simulations obtained by counting instances when recorded values are GT or GE the estimated 90th percentile. It is clear that exceedance rate estimates are influenced by the resolution of the temperature series. In the GE case, daily values truncated to have a precision of 0.5 °C (AV) have a percentile exceedance rate that is only 9/10th of the rate for data recorded with a precision of 0.1 °C (AI), and the exceedance rate for temperatures with a precision of 1 °C (AX) is lower than that for data with a precision of 0.5 °C (AV). In the latter case, the exceedance rate is only 3/4th of that for data with a precision of 0.1 °C (AI). Opposite to the GT case, poorer data precision results in higher exceedance rates in the GE case; in fact, exceedance rates are approximately 3/20th and 2/5th GT in the AI case for the AV and AX cases respectively. This problem is caused by the fact that the data resolution is coarse when compared with the variability resulting in many ties in the data. However, raising the data resolution to 0.1 °C by adding uniform random numbers to the truncated daily values (AVCV, AVCX, and AXCX) results in exceedance rates that are not significantly different from those computed from the series originally recorded at the 0.1 °C resolution. Thus, readjusting the temperature record precision by adding uniform random numbers improves the exceedance rate estimate without detracting discernibly from their accuracy. Results for AVCV and AVCX cases are almost identical, suggesting that a universal adjustment in which a uniform random number in the interval (−0.5, 0.5) is first added to the recorded values and the sum subsequently rounded to a resolution of 0.1 °C will generally work for data with an original resolution of either 0.5 or 1.0 °C.

Data resolution also has a significant impact on estimates of trends in exceedance rates, and on the detection of statistically significant trends. The magnitude of trends in the 90th percentile exceedance rate in the 1000 simulations for different temperature record resolutions, different schemes to readjust temperature resolution, and different annual mean temperature trends are shown in Figure 4. Trends estimated from index time series computed from data of poorer precision are different from those obtained from higher precision data. The difference also depends on the particular method with which the indices are computed. The magnitudes of trends in the AV and AX series are larger than those in the AI series in the case of GE, while they are smaller than those in the AI in the case of GT. Truncating observations on a continuous scale in effect replaces a continuous cumulative distribution function with a step-wise increasing cumulative distribution. The indices considered in this paper select a threshold to represent an extreme near the upper end of the discretized distribution. As the steps are wide, there is a substantial difference between threshold exceedance rates based on the GE and GT criteria. When a trend is present, the step represented by the threshold moves closer to the middle of the distribution, into the steeper part of the cumulative distribution. This increases

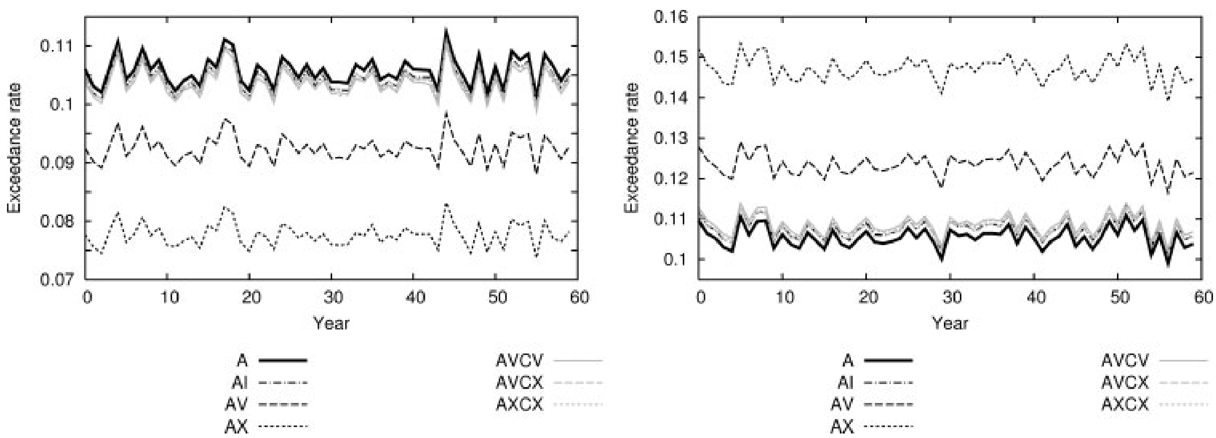

Figure 3. Average of exceedance rate of daily values GT (left) and GE (right) the 90th percentile in 1000 simulations in which the lag 1-day auto-correlation has been set to 0.6. Thresholds are estimated using data from a 5-consecutive-day moving window and the empirical quantile as defined in Zhang *et al.* (2005b). Daily values are truncated to represent temperature precisions at 0.1 °C (AI), 0.5 °C (AV), and 1.0 °C (AX). Results for artificially enhancing temperature precision to 0.1 °C (i.e. AVCV, AVCX, and AXCX) are also shown.

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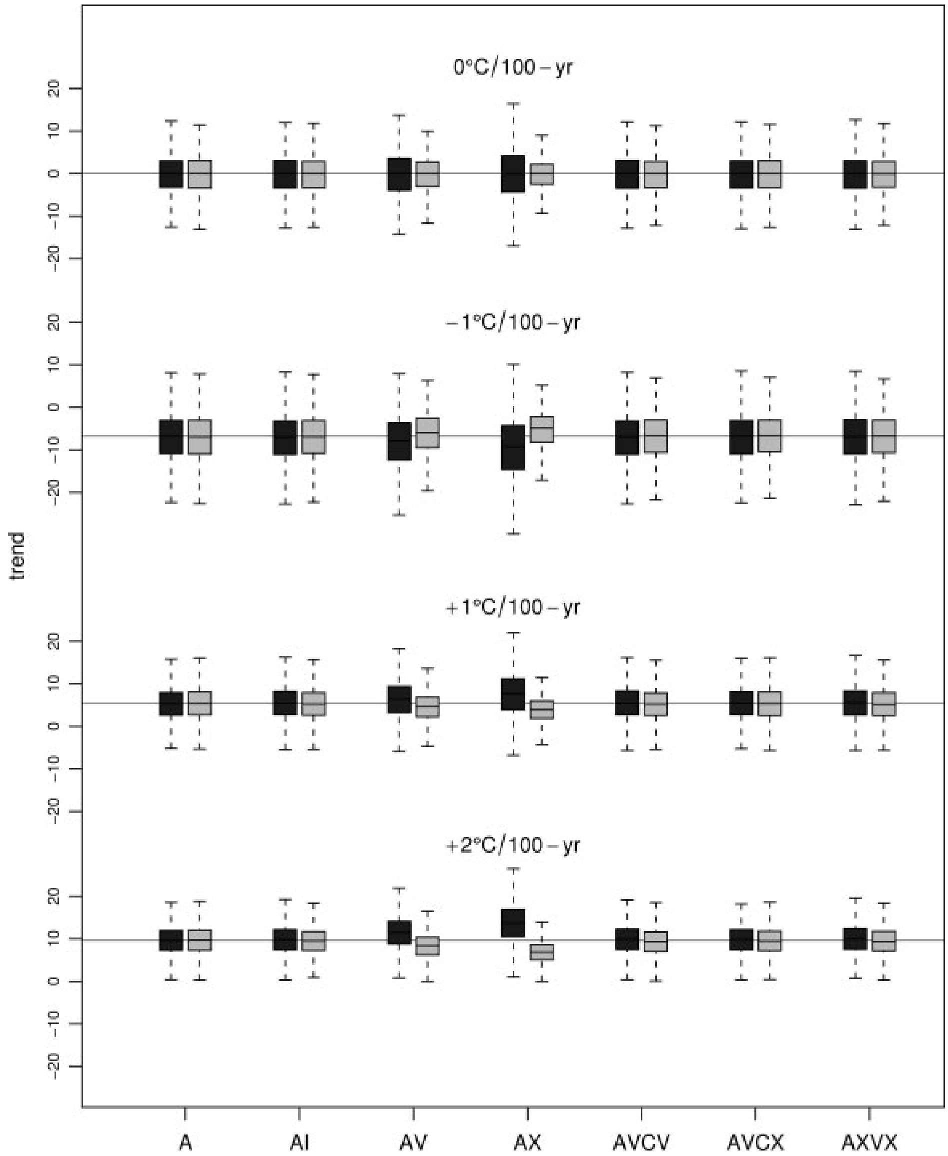

Figure 4. Trends in exceedance rate of daily values *greater than* (dark shade), or *greater than or equal to* (light shade) the 90th percentile in 1000 simulations in which the lag 1-day auto-correlation has been set to 0.6 and annual mean temperature trend is set to 0, −1, +1, +2 °C over 100 years. The upper and lower ends of each box are drawn at the 75th and 25th percentiles, and the bar through each box is drawn at the median. The upper and lower bars correspond to the 95th and 5th percentiles.

the difference between the GE and GT exceedance rates. Hence the trend in the GE exceedance rate that results from an underlying increasing trend is bigger than the trend that is induced in the GT exceedance rate. This effect, which produces differential trends in GE and GT exceedance rates, is more pronounced for coarser resolution, because the steps in the cumulative distribution of the truncated variable are larger.

Discrepancies increase with increasing mean temperature trend. When the annual mean temperature trend is 2 °C/100 year, the median trend in the 90th percentile exceedance rate in AI series lies outside the 25th to the 75th percentile range for trend estimates in the corresponding AX series; it lies above the 25th–75th percentile range of the GT series derived from the AX data series, and below the 25th–75th range of the GE series. Thus the different recording precisions used in North America could introduce artificial patterns in maps of exceedance rate trend estimates. This would distort the trend pattern and make it difficult to interpret. It may also hinder the detection of climate change signals from external forcing in the extreme indices since such artificial trend patterns would not exist in indices calculated from climate model simulated data. The differences between AI trends and those found in the adjusted AVCV, AVCX, AXCX series, and between GT and GE trends, are almost invisible indicating that adding a small random number to the original series to 'restore' the precision effectively resolves the problem.

Table I shows the number of times when a statistically significant trend was detected (at the 5% level). It is clear from this table that significant trends are detected more frequently in lower precision data (AV, AX) than higher precision data (A, and AI) when the GE method is used

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Table I. Number of times when a significant trend is detected in the time series of the 90th percentile exceedance rate in 1000 simulations for different data resolutions and adjustment schemes, and, the annual mean temperature trends of 0.0, −1.0, 1.0, and 2.0 °C over 100 years. GE and GT represent the exceedance rate that is computed as daily temperature *greater than or equal to* and *greater than* its 90th percentile, respectively.

	0 °C		−1 °C		+1 °C		+2 °C	
	GE	GT	GE	GT	GE	GT	GE	GT
A	40	46	189	187	179	191	609	613
AI	41	43	194	194	181	193	612	601
AV	42	47	195	185	191	181	624	589
AX	41	42	206	183	193	177	647	570
AVCV	42	43	189	194	178	191	620	599
AVCX	38	44	189	193	179	179	608	606
AXCX	38	46	188	186	187	178	616	594

to compute the indices. The opposite occurs when the GT method is used to compute the indices. This occurs because the estimated 90th percentile exceedance rates computed by GE and GT methods actually correspond to percentiles that are respectively lower and higher than the nominal 90% level. The difference between the high precision and low precision data, and between GE and GT cases for the same data set, becomes larger as temperature trends increase. In contrast, the results for the precision adjusted data are very close to that of the originally high precision data.

5. Conclusions and discussion

We have identified a potential bias in estimates of percentile exceedance rates caused by inadequate recording resolution in temperature data by considering the 90th percentile index. This bias affects the estimation of means and trends in exceedance rates. The impacts are dependent upon the criteria used to count the exceedances (i.e. temperature GT or GE). In the GT case, poor data resolution results in under estimation of both the means and trends of the exceedances. In the GE case, poor data resolution is associated with overestimation in both the means and trends of the exceedances. If left uncorrected, these artifacts of poor data resolution could induce artificial, non-climatic, spatial patterns in index trends corresponding to differences in data recording practices in different regions. Such artifacts could subsequently compromise the use of index trends in formal detection and attribution studies. Indices for other percentiles (e.g. the 95th and 99th percentiles) and those from the opposite tail (e.g. 1st, 5th, and 10th percentiles) are similarly affected, and restoring data resolution similarly ameliorates the problem for those percentiles.

Adding a small random number to the data to artificially restore the data resolution to 0.1 °C corrects the problem, even when the data are over-adjusted such as in the AVCX case. We showed that the exceedance rates computed from resolution-adjusted data have properties such as long-term means and trends in percentile exceedance rates that are similar to those computed directly from the data of the same original resolution. We therefore recommend that resolution enhancement as proposed here be applied to coarse resolution data before the percentile indices are computed. Percentile-based precipitation indices would not be affected to the same extent as temperature data because the recording resolution of precipitation is 0.1 mm, which is far smaller than the range of daily precipitation amounts even in very dry regions.

Percentile-based indices for North America have been recomputed by adding a random number to the daily temperature data such that a resolution of 0.1 °C is restored to the data. This corrects the bias in the base period exceedance rate that results from coarse recording resolution. Trends in the resulting indices have also been computed and are reported in Peterson *et al.* (2007). In addition, we have updated RClimDex to eliminate the problem caused by poorer precision in the original daily temperature data.

We have considered the problem associated with low data precision when the same precision has been used throughout the data record. In some places, different reporting precisions have been used in different time periods. For example, daily temperatures for some Spanish stations in the 19th century (Aguilar, personal communication) have a reporting precision of 1 °C while the modern reporting precision for those stations is 0.1 °C. Our simulation results (not shown) indicate that a change in reporting precision in time has the potential to introduce a small inhomogeneity in the exceedance rate time series computed from precision adjusted data at the time when data precision is changed and if the original data precision is very low (e.g. 1 °C). However, such an inhomogeneity is usually small and does not significantly affect trend estimation and detection in the index series. If a large inhomogeneity in the index series is suspected, standard homogenization methods (e.g. Peterson *et al.*, 1998; Reeves *et al.*, 2007; Wang, 2007) are available to address data inhomogeneity problems.

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