Global observed changes in daily climate extremes of temperature and precipitation

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[1] A suite of climate change indices derived from daily temperature and precipitation data, with a primary focus on extreme events, were computed and analyzed. By setting an exact formula for each index and using specially designed software, analyses done in different countries have been combined seamlessly. This has enabled the presentation of the most up-to-date and comprehensive global picture of trends in extreme temperature and precipitation indices using results from a number of workshops held in data-sparse regions and high-quality station data supplied by numerous scientists world wide. Seasonal and annual indices for the period 1951–2003 were gridded. Trends in the gridded fields were computed and tested for statistical significance. Results showed widespread significant changes in temperature extremes associated with warming, especially for those indices derived from daily minimum temperature. Over 70% of the global land area sampled showed a significant decrease in the annual occurrence of cold nights and a significant increase in the annual occurrence of warm nights. Some regions experienced a more than doubling of these indices. This implies a positive shift in the distribution of daily minimum temperature throughout the globe. Daily maximum temperature indices showed similar changes but with smaller magnitudes. Precipitation changes showed a widespread and significant increase, but the changes are much less spatially coherent compared with temperature change. Probability distributions of indices derived from approximately 200 temperature and 600 precipitation stations, with near-complete data for 1901–2003 and covering a very large region of the Northern Hemisphere midlatitudes (and parts of Australia for precipitation) were analyzed for the periods 1901–1950, 1951–1978 and 1979–2003. Results indicate a significant warming throughout the 20th century. Differences in temperature indices distributions are particularly pronounced between the most recent two periods and for those indices related to minimum temperature. An analysis of those indices for which seasonal time series are available shows that these changes occur for all seasons although they are generally least pronounced for September to November. Precipitation indices show a tendency toward wetter conditions throughout the 20th century.

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1. Introduction

[2] For decades, most analyses of long-term global climate change using observational temperature and precipitation data have focused on changes in mean values. Several well respected monthly data sets provide reasonable spatial coverage across the globe [e.g., *Jones and Moberg*, 2003; *Peterson and Vose*, 1997]. However, analyzing changes in extremes, such as changes in heat wave duration or in the number of days during which temperature exceeds its long-term 90th percentile, requires daily data in digital form. Unfortunately, these data are not readily available to the international research community for large portions of the world [*Folland et al.*, 2001]. In earlier "global" analysis of extreme indices by *Groisman et al.* [1999] and *Frich et al.* [2002], there were almost no data for most of Central and South America, Africa, and southern Asia. Subsequent studies such as *Kiktev et al.* [2003] provided gridded updates to some of the indices but the spatial coverage was still poor.

[3] The joint World Meteorological Organization Commission for Climatology (CCl)/World Climate Research Programme (WCRP) project on Climate Variability and Predictability (CLIVAR) Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) coordinated two complimentary efforts to enable global analysis of extremes. One effort was the international coordination of the development of a suite of climate change indices which primarily focus on extremes. These indices are derived from daily temperature and precipitation data. The development of the indices, including a user-friendly software package that is freely available to the international research community, involved not only ETCCDMI members but also numerous other scientists, including many of the authors. In all, 27 indices were defined and two software packages, one written in R (RClimDex) and the other written in FORTRAN (FClimDex), were developed. A website, http://ccma/seos.uvic.ca/ETCCDMI, dedicated to this effort provides comprehensive descriptions of all of the indices, details of quality control procedures and references to relevant literature. It also provides a free download of the software packages along with detailed user manuals. By setting an exact formula for each index and by using the same software package, analyses done in different countries or different regions can fit together seamlessly.

[4] The second ETCCDMI effort was to coordinate regional workshops with the aim of addressing gaps in data availability and analysis in previous global studies [e.g., *Frich et al.*, 2002]. In many parts of the world there are enough daily data available in digital form at the national level, although accessing digital daily data can still be problematic in some regions [*Page et al.*, 2004]. Also, some institutions are reluctant to part with data for various reasons. A solution to this problem proposed by the ETCCDMI was to hold regional climate change workshops modeled on the Asia Pacific Network (APN) workshops [*Manton et al.*, 2001; *Peterson et al.*, 2001; *Griffiths et al.*, 2005]. The APN approach was to bring together scientists from different countries within the Asia-Pacific region. These participants brought their own daily data to the workshops. Under guidance from international experts, during the workshop, they conducted data quality control and computed indices using a standard procedure and software. The APN approach made it possible to exchange indices data. Although some participants chose not to share their original daily data they made the derived indices series available for regional and global analyses. Two regional climate change workshops were held in 2001 in Jamaica, to cover the Caribbean region [*Peterson et al.*, 2002] and in Morocco, to cover Africa [*Easterling et al.*, 2003; *Mokssit*, 2003]. Recognizing the successes and problems of these workshops, the ETCCDMI held five additional workshops in 2004 and early 2005 in South Africa (M. New et al., Evidence of trends in daily climate extremes over southern and west Africa, submitted to *Journal of Geophysical Research*, 2005), Brazil [*Haylock et al.*, 2006; *Vincent et al.*, 2005], Turkey [*Sensoy et al.*, 2006; *Zhang et al.*, 2005a], Guatemala [*Aguilar et al.*, 2005] and India [*Peterson*, 2005; *Klein Tank et al.*, 2006] to provide additional coverage for Africa, South America, the Middle East, Central America and south-central Asia.

[5] The objective of this paper is to provide the most comprehensive analysis of observed global temperature and precipitation extremes. Toward this end, we use high-quality daily data from all possible sources. They include (1) data that are freely available to the international community, (2) data from all the ETCCDMI workshops that were not available previously and (3) data that only some of our coauthors have access to. The paper is organized as follows. We describe the data in section 2. This section includes detailed descriptions of the sources of daily data, data quality control and homogeneity testing procedures, and definitions and computation of the indices. In section 3 we provide a detailed account of the analysis of the indices data, including gridding and trend computation. Results are presented in section 4. We offer some discussion of the results in section 5 followed by conclusions in section 6.

2. Data

2.1. Daily Data

[6] There are three international daily data sets freely available to the research community. They are (1) the GCOS Surface Network (GSN) data set [*Peterson et al.*, 1997], (2) the European Climate Assessment (ECA) data set [*Klein Tank et al.*, 2002] and (3) the daily Global Historical Climatology Network (GHCN-Daily) data set [*Gleason et al.*, 2002]. The ECA data are used to cover Europe in this analysis, while GHCN-Daily data are used for the United States and Brazil. The GSN data are used to supplement these sources of data, primarily in Africa. Indices data from the workshops are used to cover the respective regions where data had not previously been available. Details of the workshop data are described in relevant workshop reports or papers. Data from the APN workshops are also included.

[7] Data were also provided by the authors' institutions for some parts of the world where the data for these regions from the above sources were not available or were of poorer quality. Though the level of development of high-quality daily station data sets differs from one country to another, we included the best available data sets. Canada supplied carefully homogenized daily temperatures up to 2003 for 210 stations [*Vincent et al.*, 2002] and a high-quality precipitation data set [*Mekis and Hogg*, 1999]. Australian temperature records have been adjusted for inhomogeneities at the daily timescale by taking account of the magnitude of discontinuities for different parts of the distribution [*Trewin*, 2001]. Stations that were likely to be affected by urbanization were excluded, although recent studies [e.g., *Peterson*, 2003; *Parker*, 2004; *Peterson and Owen*, 2005] show that urbanization effects have had little effect on large-scale temperature trends. Australian precipitation data also came from a high-quality precipitation data set [*Haylock and Nicholls*, 2000]. Temperature data for the United States were chosen from GHCN-Daily stations where statistical homogeneity tests on both maximum and minimum temperatures did not detect any inhomogeneities [*Menne and Williams*, 2005]. Precipitation data for the former USSR were homogeneity adjusted [*Groisman and Rankova*, 2001]. For some countries for which prescreened national data sets were not readily available, e.g., Argentina [*Rusticucci and Barrucand*, 2004], China [*Zhai et al.*, 2005], India, Iran [*Rahimzadeh and Asgari*, 2003] and Mexico, the authors chose stations on the basis of their knowledge of the best stations in their own country and/or recent analysis. The remaining data were supplied primarily from the GHCN-Daily data set, e.g., Brazil, and the Hadley Centre archives. In all cases at least one of the authors had access to the raw station records so that reference could always be made to the original data should quality issues arise during the analysis.

2.2. Data Quality and Homogeneity

[8] In most cases, data supplied by the authors were quality controlled and the indices calculated using standard software before being collated for this study. The level of quality control differed from country to country (see above) but in all cases an attempt was made to use the best possible data sources. For data supplied from the workshops the quality control procedure in RClimDex was used. The main purpose of this quality control procedure was to identify errors in data processing, such as errors in manual keying. Negative daily precipitation amounts are removed and both daily maximum and minimum temperatures are set to a missing value if daily maximum temperature is less than daily minimum temperature. Outliers in daily maximum and minimum temperature are also identified. These are values outside a range defined by the user. In this study, the range is defined as lying within four standard deviations (std) of the climatological mean of the value for the day, that is, [mean $\pm$ 4 $\times$ std]. Daily temperature values outside this range are manually checked and edited on a case by case basis by workshop participants who are knowledgeable about their own daily data.

[9] Statistical tests were not generally applied to precipitation data analyzed at the workshops but any obvious outliers, identified by careful examination of graphs, were checked manually. Careful post workshop analysis was employed and data processed outside of the workshops were similarly tested for outliers but methods varied from source to source. Statistical tests, local knowledge, an investigation of station histories or comparison with neighboring stations can all be applied to determine whether an outlying precipitation value is erroneous. It is particularly important to identify multiday precipitation accumulations that can appear erroneously in records of daily precipitation [*Viney and Bates*, 2004]. These occur when accumulated rainfall values are reported as daily totals. For example, data extracted from GHCN-Daily for Brazil were rejected if a rainfall value greater than 1 mm fell after a missing observation [*Haylock et al.*, 2006]. Even after data were processed and collated for this study, annual time series of total precipitation and diurnal temperature range for each station were assessed again to identify outliers that may have been missed in the initial quality control procedure.

[10] Data quality is a relatively easy problem to address when compared with the problems associated with data inhomogeneity. Erroneous outliers and artificial step changes caused by changes in station location, observing procedures and practice, instrumentation changes etc. [*Aguilar et al.*, 2003] make trend analysis unreliable, and there is not always a consistent approach to deal with data inhomogeneity [*Peterson et al.*, 1998]. For this reason, RClimDex can be used in tandem with a software package called RHtest which identifies step changes in station temperature time series. RHtest is based on a two-phase regression model with a linear trend for the entire series [*Wang*, 2003]. Except for the data from the first few workshops, where a slightly different program based on a similar technique was used, RHtest has been used to test for inhomogeneities in the temperature data from most stations used in this study. Other exceptions include the use of the most homogeneous stations as defined by *Wijngaard et al.* [2003] for ECA temperature and precipitation data and the use of homogeneous stations identified by *Menne and Williams* [2005] for the United States.

[11] If station data were identified as being inhomogeneous then they were excluded from the analysis. Inhomogeneous data were not adjusted for two main reasons (although note that some data sources were already adjusted, e.g., *Groisman and Rankova* [2001] and *Vincent et al.* [2002] prior to inclusion in this study). First, there has been only limited success to date in adjusting daily temperatures [e.g., *Vincent et al.*, 2002]. Second, as the many stations we have cover many different climates, adjustment of temperatures would be an extremely complex task and difficult to do well [*Aguilar et al.*, 2003]. It is possible that some step changes could be real and not due to an inhomogeneity problem in the data. This highlights the importance of having access to station metadata which we generally lacked.

[12] Inhomogeneities other than step changes, such as gradual changes in temperature, are not accounted for. Such an inhomogeneity might occur through urbanization although *Peterson and Owen* [2005] suggest that the effects of urbanization on data averaged over an entire network of stations are minimal when compared to the magnitude of real climate variability and change. The problem of such inhomogeneities is also difficult to address though it could

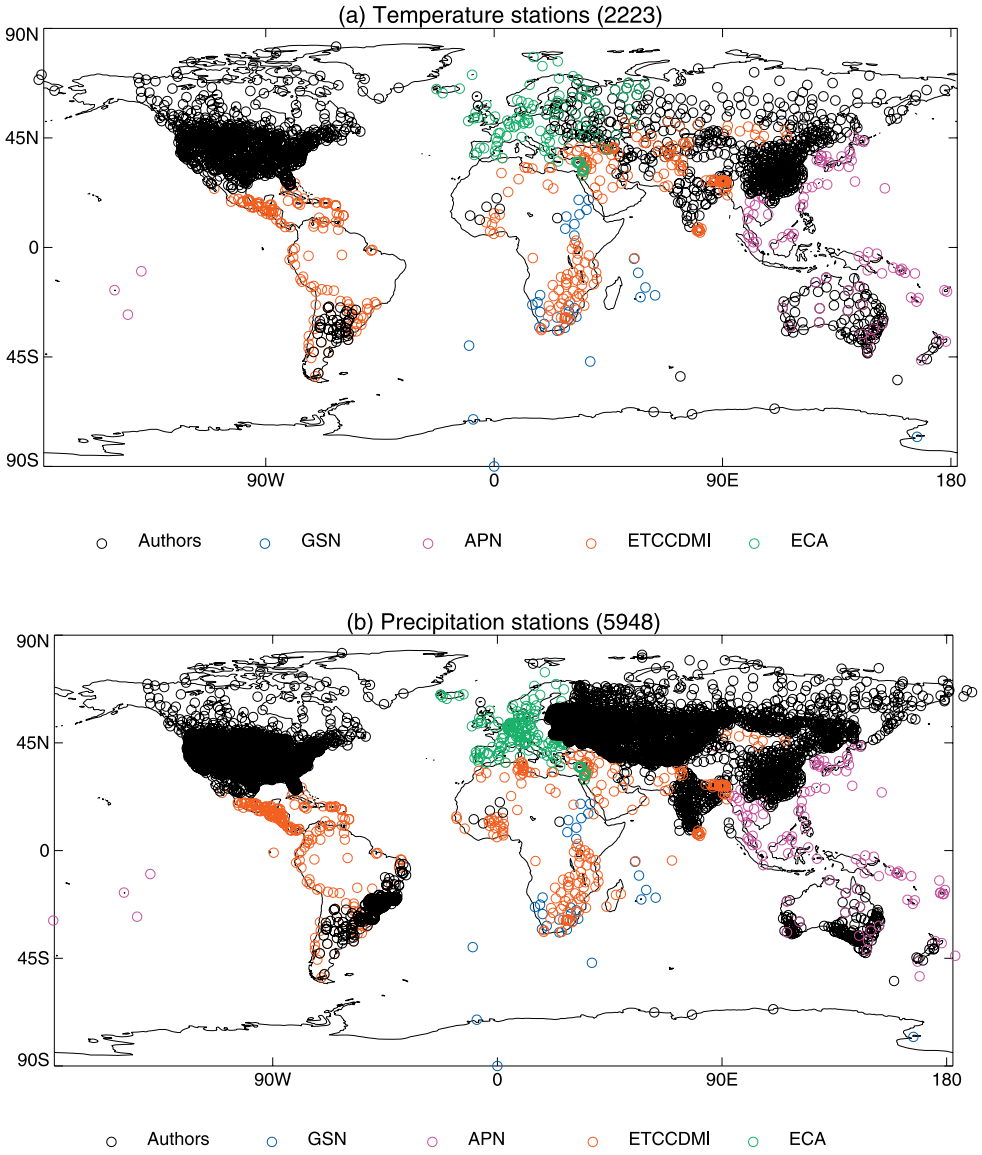

Figure 1. Locations of (a) temperature and (b) precipitation stations available for this study. The colors represent the different data sources that are described in the main text. Data for the United States and parts of Brazil were obtained by the authors from the GHCN-Daily data set. The numbers in brackets indicate the total number of stations.

potentially be dealt with by comparing data from neighboring stations. However, our station network is not usually dense enough for this approach to be adopted.

[13] Figure 1 shows the locations of the 2223 temperature and 5948 precipitation stations used in this study. Although there are more precipitation stations, they are generally distributed less uniformly than the temperature stations. All stations were used when gridding the indices. However, when calculating trends we chose only to consider grid boxes for which the data for the time period under consideration were at least 80% complete and ended no earlier than 1999. Most station networks contributing data to this study have good temporal coverage for the second half of the 20th century so we mostly focus on this period. However, a subset of around 200 temperature (depending on the index) and 608 precipitation stations had enough data for changes throughout the entire 20th century to be analyzed for at least one of the indices. We shall use these stations to put recent changes in the context of a century long timescale. The stations are primarily located in North America, Eurasia and Australia, although a few stations are located in Brazil and Sri Lanka.

2.3. Indices

[14] Sixteen of the 27 indices recommended by the ETCCDMI are temperature related and eleven are precipitation related. They are derived from daily maximum and minimum temperature and daily precipitation. A full descriptive list of the indices can be obtained from http://cccma.seos.uvic.ca/ETCCDMI/list_27_indices.html. One of the indices has a user-dependent threshold which we have chosen not to analyze in this study. The indices were chosen primarily for assessment of the many aspects of a changing global climate which include changes in intensity, frequency

and duration of temperature and precipitation events. They represent events that occur several times per season or year giving them more robust statistical properties than measures of extremes which are far enough into the tails of the distribution so as not to be observed during some years. The indices can be divided into 5 different categories:

[15] 1. Percentile-based indices include occurrence of cold nights (TN10p), occurrence of warm nights (TN90p), occurrence of cold days (TX10p), occurrence of warm days (TX90p), very wet days (R95p) and extremely wet days (R99p). The temperature percentile-based indices sample the coldest and warmest deciles for both maximum and minimum temperatures, enabling us to evaluate the extent to which extremes are changing. The precipitation indices in this category represent the amount of rainfall falling above the 95th (R95p) and 99th (R99p) percentiles and include, but are not be limited to, the most extreme precipitation events in a year.

[16] 2. Absolute indices represent maximum or minimum values within a season or year. They include maximum daily maximum temperature (TXx), maximum daily minimum temperature (TNx), minimum daily maximum temperature (TXn), minimum daily minimum temperature (TNn), maximum 1-day precipitation amount (RX1day) and maximum 5-day precipitation amount (RX5day).

[17] 3. Threshold indices are defined as the number of days on which a temperature or precipitation value falls above or below a fixed threshold, including annual occurrence of frost days (FD), annual occurrence of ice days (ID), annual occurrence of summer days (SU), annual occurrence of tropical nights (TR), number of heavy precipitation days > 10 mm (R10) and number of very heavy precipitation days > 20 mm (R20). These indices are not necessarily meaningful for all climates because the fixed thresholds used in the definitions may not be applicable everywhere on the globe. However, previous studies [e.g., *Frich et al.*, 2002; *Kiktev et al.*, 2003] have shown that temperature indices such as FD, the number of days on which minimum temperature falls below 0°C, have exhibited coherent trends over the midlatitudes during the second half of the 20th century. In addition, changes in these indices can have profound impacts on particular sectors of society or ecosystems. Therefore we included the indices in our study, even though some of them may not provide truly "global" spatial coverage or be truly extreme.

[18] 4. Duration indices define periods of excessive warmth, cold, wetness or dryness or in the case of growing season length, periods of mildness. They include cold spell duration indicator (CSDI), warm spell duration indicator (WSDI), growing season length (GSL), consecutive dry days (CDD) and consecutive wet days (CWD). Many of these indices were used in the near global analysis of *Frich et al.* [2002]. The heat wave duration index (HWDI) defined by *Frich et al.* [2002] has been found not to be statistically robust as it had a tendency to have too many zero values [*Kiktev et al.*, 2003]. This is because *Frich et al.* [2002] used a fixed threshold of 5°C above climatology to compute the index. This threshold is too high in many regions, such as the tropics, where the variability of daily temperature is low. To overcome this, the ETCCDMI replaced this index with the warm spell duration index (WSDI) which is calculated using a percentile based threshold. As this index only sampled daytime maxima we also chose to analyze spells of nighttime minima (CSDI). The CDD index is the length of the longest dry spell in a year while the CWD index is defined as the longest wet spell in a year. This category of indices also includes the length of the growing season (GSL) which is an index that is generally only meaningful in the Northern Hemisphere extratropics.

[19] 5. Other indices include indices of annual precipitation total (PRCPTOT), diurnal temperature range (DTR), simple daily intensity index (SDII), extreme temperature range (ETR) and annual contribution from very wet days (R95pT). They do not fall into any of the above categories but changes in them could have significant societal impacts. ETR and R95pT are not directly calculated by RClimDex but have been defined for this study as TXx−TNn and (R95p/PRCPTOT)*100 respectively.

[20] Some of the indices have the same name and definition as those used in previous studies [e.g., *Frich et al.*, 2002; *Klein Tank et al.*, 2002], but they may differ slightly in the way they are computed. Of particular importance is a recent finding that inhomogeneities exist at the boundaries of the climatological base period used to compute the thresholds for percentile based temperature indices, i.e., TN10p, TN90p, TX10p and TX90p, because of sampling uncertainty [*Zhang et al.*, 2005b]. A bootstrapping method proposed by *Zhang et al.* [2005b] has been implemented in RClimDex and is used to compute indices analyzed in this paper. The bootstrap procedure removes the inhomogeneities and thus eliminates possible bias in the trend estimation of the relevant indices.

[21] Unlike previous "global" studies, this paper also analyses seasonal values of some indices, such as the percentile indices, the absolute temperature indices and DTR whenever possible. This has been made possible because RClimDex and FClimDex also provide monthly values for those indices.

3. Methodology

[22] We conduct two different analyses of temporal changes in the indices. One examines trends in station and grid point data, and the other compares empirical probability distribution functions (PDF) for various periods during the 20th century. First we describe our method for gridding the station data.

3.1. Gridding the Indices

[23] The stations available for this study are not evenly distributed across the global land area. This uneven distribution makes it difficult to accurately compute global averages. A simple average of data from all available stations would result in a representation biased toward areas of higher station density. *Frich et al.* [2002] addressed this problem by thinning the station network so that there was approximately one station every 250,000 km^2. While this approach produces a more evenly distributed network, it is at the cost of discarding otherwise useful information. Maximizing the number of stations helps to reduce the impacts of random inhomogeneities. In fact, there is no place in the world for which we have too much climate data. In addition, the choice of stations to be retained is somewhat subjective, especially in regions where the network is

relatively dense. In order to compare observed indices with global climate model simulations, *Kiktev et al.* [2003] gridded some of the *Frich et al.* [2002] indices data onto a regular latitude-longitude grid, using a modified version of Shepard's angular distance weighting (ADW) algorithm [*Shepard*, 1968]. This algorithm is used because *New et al.* [2000] found it to be the most appropriate method for gridding irregularly spaced data when compared to several other methods. A modified approach of *New et al.* [2000] and *Kiktev et al.* [2003] has also been used to grid daily maximum and minimum temperatures [*Caesar et al.*, 2006]. We adopted this approach by gridding the indices onto a regular latitude-longitude grid by weighting each station according to its distance and angle from the centre of a search radius. A detailed description of the gridding methodology is given in Appendix A.

3.2. Trend Analysis and Field Significance

[24] Some of the indices data do not have a Gaussian distribution and in these cases, a simple linear least squares estimation would not be appropriate. Therefore we used a nonparametric Kendall's tau based slope estimator [*Sen*, 1968] to compute trends since this method does not assume a distribution for the residuals and is robust to the effect of outliers in the series. However, a positive autocorrelation (which is usually present in time series of climate data) would make this test unreliable [e.g., *von Storch*, 1995; *Zhang and Zwiers*, 2004], so we also considered the serial correlation in the residuals when testing the statistical significance of trends. An iterative procedure was adopted, originally proposed by *Zhang et al.* [2000] and later refined by *Wang and Swail* [2001], to compute the magnitudes of trends and to test their statistical significance. Details of this method are given by *Wang and Swail* [2001, Appendix A]. This method was applied when calculating the trends and significance of the grid point time series. To provide an overall picture, global time series were also calculated by averaging available grids in each season or year. In this paper, a trend is considered to be statistically significant if it is significant at the 5% level.

[25] It is also important to assess the overall (field) significance of our results. *Livezey and Chen* [1983] showed that the collective significance of trends in a finite number of interdependent time series needs to be much larger than the nominal level, i.e., the 5% level in our case. We implement a similar technique to *Kiktev et al.* [2003] in determining whether our results are field significant. This involved creating 1000 bootstrapped fields using a moving block bootstrap resampling technique [*Wilks*, 1997] with a fixed block size of 2 for each index (see *Kiktev et al.* [2003, Appendix] for a detailed description of bootstrapping method). The null hypothesis is that the pattern of trends estimated from the actual station data is due to climate noise. We therefore estimate the difference between the 1000 bootstrapped fields and the actual trends derived from the station data to define a suitable set of plausible trends that could have arisen through natural climate variability alone. We use these residuals to estimate the 95% confidence interval that each grid point has a zero trend. For each field, the total area represented by grid points with significant trends was calculated. We then calculate the 95th percentile of these areas and if the area for the actual trends exceeds this, then our trends can be said to be field significant. Since this method is computationally expensive, field significance is only calculated for the annual indices.

3.3. Probability Distribution Functions

[26] PDFs were produced for each station with sufficient data by binning annual values for various time periods. A seasonal analysis was conducted by averaging the monthly index values for December–February, March–May, June–August and September–November if data from at least 2 months out of 3 were present. Because the number of such stations varies over time, we chose to analyze the same subset of stations during each of the time periods studied. This allows for the assessment of temporal changes without having to allow for uncertainties arising from changes in the spatial coverage of the stations. We also test whether the probability distributions of a particular index from different time periods are significantly different or not. This is done using a 2-tailed Kolmogorov-Smirnov test with a null hypothesis that two cumulative distribution functions computed for two periods are identical.

4. Results

[27] In this section, we first present trend analyses for the temperature indices followed by the precipitation indices. At the end of this section, changes in the probability distributions of the indices are presented.

4.1. Temperature Indices, 1951–2003

[28] When averaged over the globe, almost all of the temperature indices show significant changes over the 1951–2003 period. Trends in temperature indices, as detailed below, reflect an increase in both maximum and minimum temperature. There is also generally a much larger percentage of land area showing significant change in minimum temperature extremes than maximum temperature extremes. The magnitude of the trends is also generally greater for minimum temperature related extremes. This finding is in agreement with previous studies using monthly global data, e.g., *Jones et al.* [1999] and regional studies using daily data, e.g., *Yan et al.* [2002].

4.1.1. Absolute and Percentile-Based Temperature Indices

[29] Figure 2 shows the decadal trends in extremes between 1951 and 2003 for the percentile-based temperature indices. Although the definitions of the percentile-based temperature indices are calculated in percent, the units were converted into days for ease of understanding. From Table 1 we see that 74% (73%) of the land area sampled shows a significant decrease (increase) in the annual occurrence of cold nights (warm nights). Table 1 also shows that these changes are field significant for all the temperature indices except annual maximum daily maximum temperature (TXx). Annually the largest change in extremes corresponding to an increase in minimum temperature is over Eurasia (Figures 2a and 2b). *Klein Tank et al.* [2006] and *Yan et al.* [2002] showed that this warming has been occurring since the early 1900s. Additionally very large increases are seen in the annual occurrence of warm nights (a more than doubling of the frequency of this index) over North Africa and northern South America (Figure 2b).

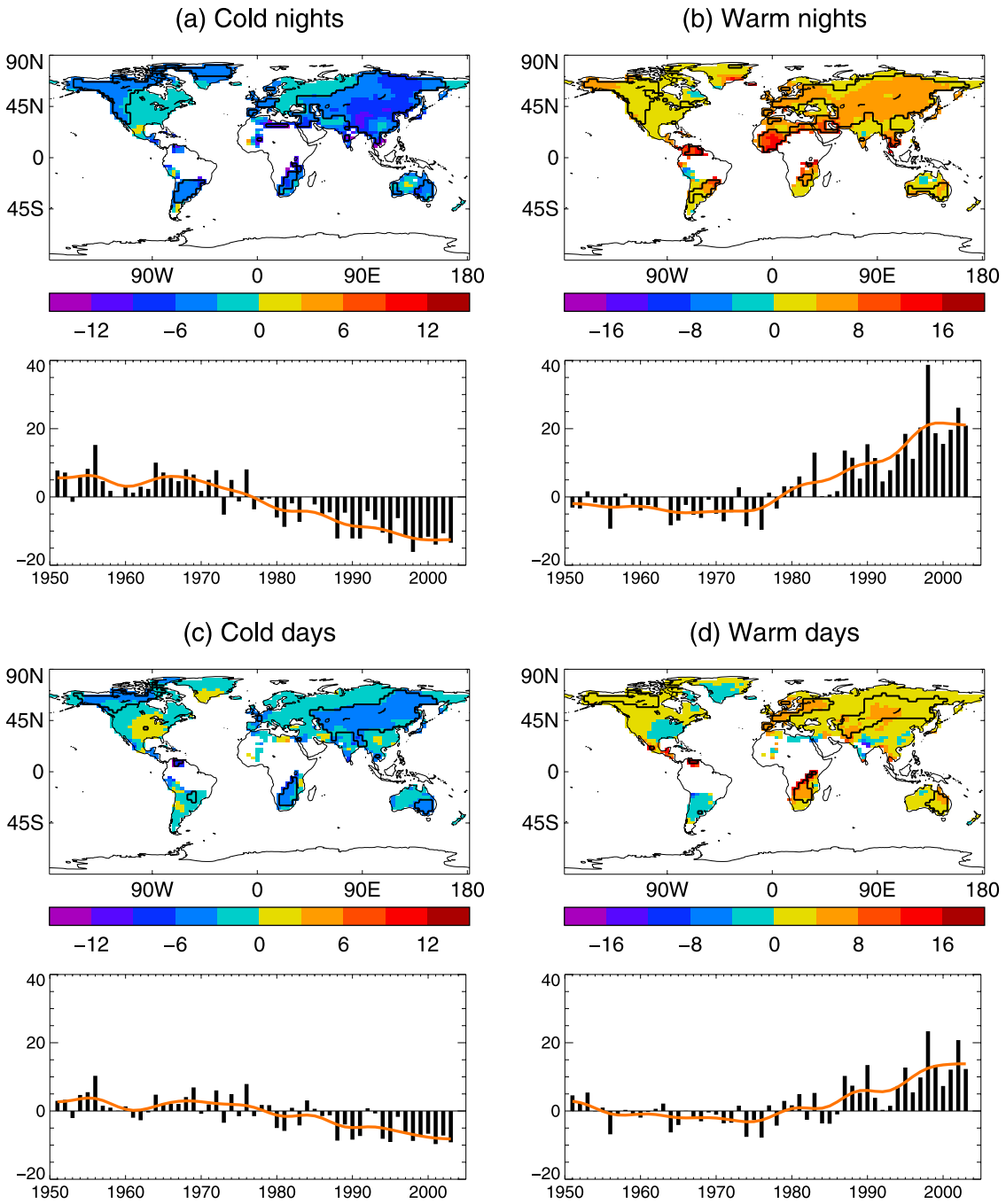

Figure 2. Trends (in days per decade, shown as maps) and annual time series anomalies relative to 1961–1990 mean values (shown as plots) for annual series of percentile temperature indices for 1951–2003 for (a) cold nights (TN10p), (b) warm nights (TN90p), (c) cold days (TX10p), and (d) warm days (TX90p). Trends were calculated only for the grid boxes with sufficient data (at least 40 years of data during the period and the last year of the series is no earlier than 1999). Black lines enclose regions where trends are significant at the 5% level. The red curves on the plots are nonlinear trend estimates obtained by smoothing using a 21-term binomial filter.

Asia also exhibits widespread warming in maximum temperature extremes although the trend patterns for maximum temperature are generally more mixed (Figures 2c and 2d). Some parts of the globe do exhibit changes in extremes corresponding to decreases in temperature although these are usually nonsignificant. An exception to this is a small part of central United States where a significant increase equivalent to approximately 2 days per decade is seen in the annual number of cold days (Figure 2c).

[30] Globally the annual number of warm nights (cold nights) increased (decreased) by about 25 (20) days since 1951 (Figures 2a and 2b). Trends in maximum temperature extremes showed similar patterns of change, although of smaller magnitude (Figures 2c and 2d). Changes in all these

Table 1. Percentage of Land Area Sampled Showing Significant Annual Trends for Each Indicator in Table 1[a]

Indicator	1951–2003		
	Total Grid Points	+ve Significant Trend, %	−ve Significant Trend, %
Maximum Tmax (TXx)	1028	11.6	2.7
Maximum Tmin (TNx)	997	**24.5**	1.1
Minimum Tmax (TXn)	1325	**29.3**	2.6
Minimum Tmin (TNn)	1379	**45.0**	1.9
Cold nights (TN10p)	1306	0.1	**74.0**
Cold days (TX10p)	1321	0.5	**46.0**
Warm nights (TN90p)	1404	**73.1**	0.1
Warm days (TX90p)	1275	**41.0**	0.9
Diurnal temperature range (DTR)	1024	4.2	**39.3**
Frost days (FD)	1039	0.2	**40.6**
Summer days (SU25)	957	**23.4**	3.7
Ice days (ID)	1017	1.3	**27.4**
Tropical nights (TR20)	1049	**27.6**	1.2
Growing season length (GSL)	761	**16.8**	0.3
Warm spell duration (WSDI)	871	**28.8**	0.6
Cold spell duration (CSDI)	1010	10.2	**26.0**
Maximum 1-day precip (RX1day)	824	7.0	2.7
Maximum 5-day precip (RX5day)	514	6.0	2.1
Simple daily intensity (SDII)	653	**14.6**	2.8
Heavy precipitation days (R10)	982	7.8	7.4
Very heavy precipitation days (R20)	775	11.7	5.0
Consecutive dry days (CDD)	816	4.0	6.9
Consecutive wet days (CWD)	323	3.1	4.6
Annual total precipitation (PRCPTOT)	1115	10.1	7.2
Very wet days (R95p)	653	11.2	2.5
Extremely wet days (R99p)	426	6.1	2.8

[a]The total number of global land grid points for the latitude-longitude grid chosen is 2291. Bold indicates field significance at 5% level.

percentile-based indices seem to have occurred around the mid 1970s which corresponds with changes in mean global temperature [*Folland et al.*, 2001]. Indeed every year since 1979 has been above the long-term average for the annual occurrence of warm nights and every year since 1977 has been below the long-term average for the annual occurrence of cold nights.

[31] The absolute temperature indices exhibit a similar pattern (not shown) with large negative change in the 1950s for minimum daily minimum temperature and minimum daily maximum temperature. However, larger errors are likely in the earlier part of the record in part because of the sensitivity of these particular indices to spatial coverage. At the start of the record, the global anomalies are dominated by extratropical regions where minimum and maximum daily temperatures are generally cooler. The minimum daily minimum temperature (TNn) increased by nearly 5°C between 1951 and 2003, the greatest change in the absolute temperature indices. However, this is dominated by the very large negative anomalies in the 1950s when there was increased sampling uncertainty.

4.1.2. All Other Temperature Indices

[32] The annual occurrence of cold spells significantly decreased (Figure 3a) while the annual occurrence of warm spells significantly increased (Figure 3b). Both of these results are field significant (see Table 1). However, the trend in warm spells is greater in magnitude and is related to a dramatic rise in this index since the early 1990s. The significant decreases in cold spells occurred predominantly in central and northern Russia, parts of China and northern Canada, however a large part of the United States showed a significant increase in this index. Significant increases in warm spells were seen over central and eastern United States, Canada and parts of Europe and Russia. This general increase in warm spells was highlighted in previous studies such as *Frich et al.* [2002] and *Klein Tank et al.* [2002] although the definition of these indicators varies between each study. Figure 3c shows there are significant decreases in the annual occurrence of frost days over parts of western Europe and a large portion of Russia and China. These results compare well with the results of *Kiktev et al.* [2003] although the areas of significance vary in some regions. The largest significant negative trend for frost days appears in the Tibetan Plateau (Figure 3c). The annual occurrence of frost days have decreased by approximately 16 days on average (Figure 3c) over those parts of the globe where this index can be defined. The annual occurrence of ice days is also significantly decreasing over central Russia and eastern and western China (not shown).

[33] For comparison with *Frich et al.* [2002], we create the extreme temperature range index (ETR) from the difference between the annual maximum daily maximum temperature and minimum daily minimum temperature (Figure 3d). Although both studies confirm a significant downward trend in ETR, our improved global coverage suggests that decreases in ETR might be greater than were suggested by *Frich et al.* [2002] who had no data over most of the tropics, South America or Africa. However, our study may be affected by sampling uncertainties primarily in the 1950s.

[34] For the other temperature-based indices (not shown) there is widespread coherent warming. There are significant positive trends in the annual number of tropical nights over central and southwest Asia, North Africa and southern

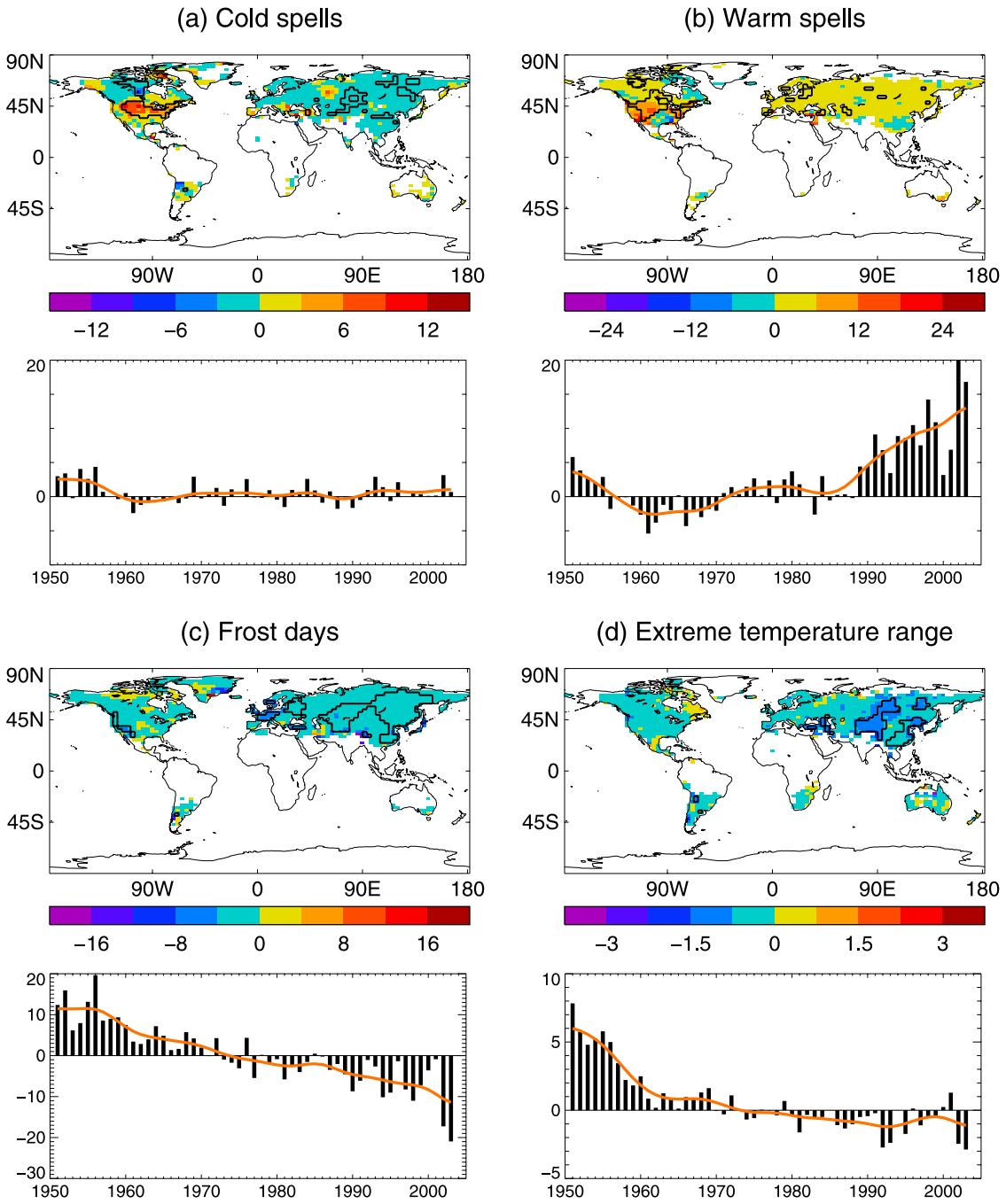

Figure 3. As Figure 2 but for indices (a) CSDI in days, (b) WSDI in days, (c) FD in days, and (d) ETR (i.e., TXx-TNn) in °C.

Brazil. However, there are negative trends (although non-significant) in this index and the annual number of summer days over a large part of India. Summer day counts show significant increases in this index over parts of northern Canada, western Europe, the Middle East, central Asia, Australia and southern Brazil, although it has significantly decreased over a small part of eastern United States. Almost 40% of the land area sampled shows a significant decrease in DTR (Table 1) for the period 1951 to 2003, consistent with minimum temperatures warming faster than maximum temperatures. These areas of significance are located over central and eastern Russia, much of China and eastern and central United States.

4.1.3. Seasonal Results

[35] Warming is observed in all seasons. Figures 4 and 5 show decadal trends and time series of global anomalies for the seasonal occurrence of cold and warm nights, respectively. In all seasons and for both indicators we again see a strong change in climate around the mid 1970s. Table 2 shows that seasonally more land area exhibits significant changes in minimum temperature than maximum temperature. MAM has the most widespread significant change in

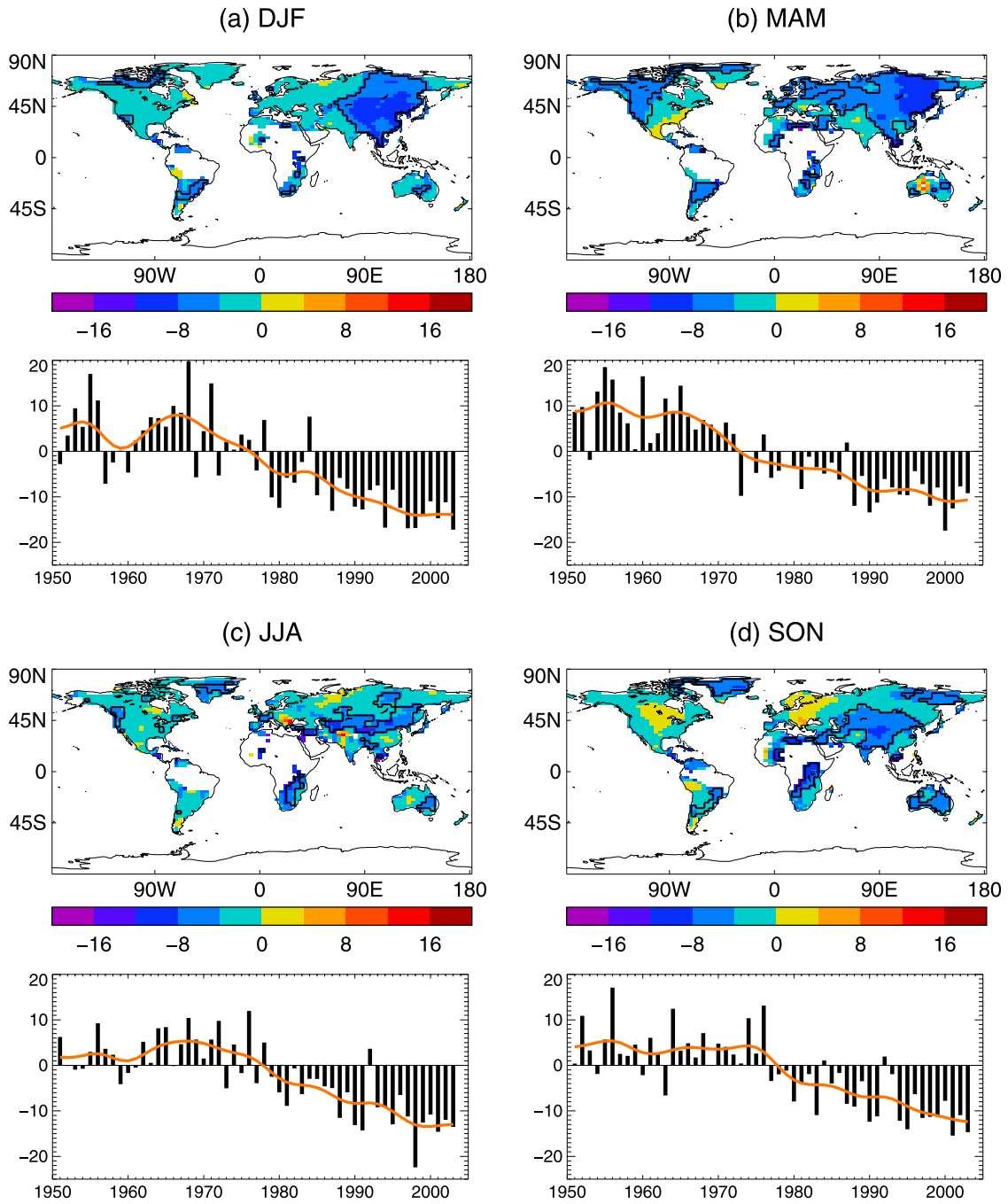

Figure 4. As Figure 2 but for the seasonal occurrence of cold nights (TN10p) in days for (a) December–February, (b) March–May, (c) June–August, and (d) September–November.

the temperature indices with the least change usually occurring during SON. This is still valid even if we analyze each hemisphere separately.

[36] Increases in the seasonal occurrence of cold nights are generally nonsignificant. Similarly decreases in the seasonal occurrence of warm nights are generally nonsignificant. Most of the significant warming in any season is occurring in Asia. Seasonal results show that nearly all changes in temperature indicating warming are significant between 1951 and 2003 (not shown). Every year since 1985 has been above the long-term average of the occurrence of warm nights in both DJF and MAM (Figures 5a and 5b). Similarly every year since 1988 has been below the long-term average of the occurrence of cold nights for both these seasons (Figures 4a and 4b).

4.2. Precipitation Indices, 1951–2003

[37] We find a general increase in the precipitation indices. When compared with temperature changes, we see a less spatially coherent pattern of change and a lower level of statistical significance. Other studies have asserted that there have been increases in extreme precipitation. Most notably, *Groisman et al.* [2005] found widespread increases in very intense precipitation (defined as the upper

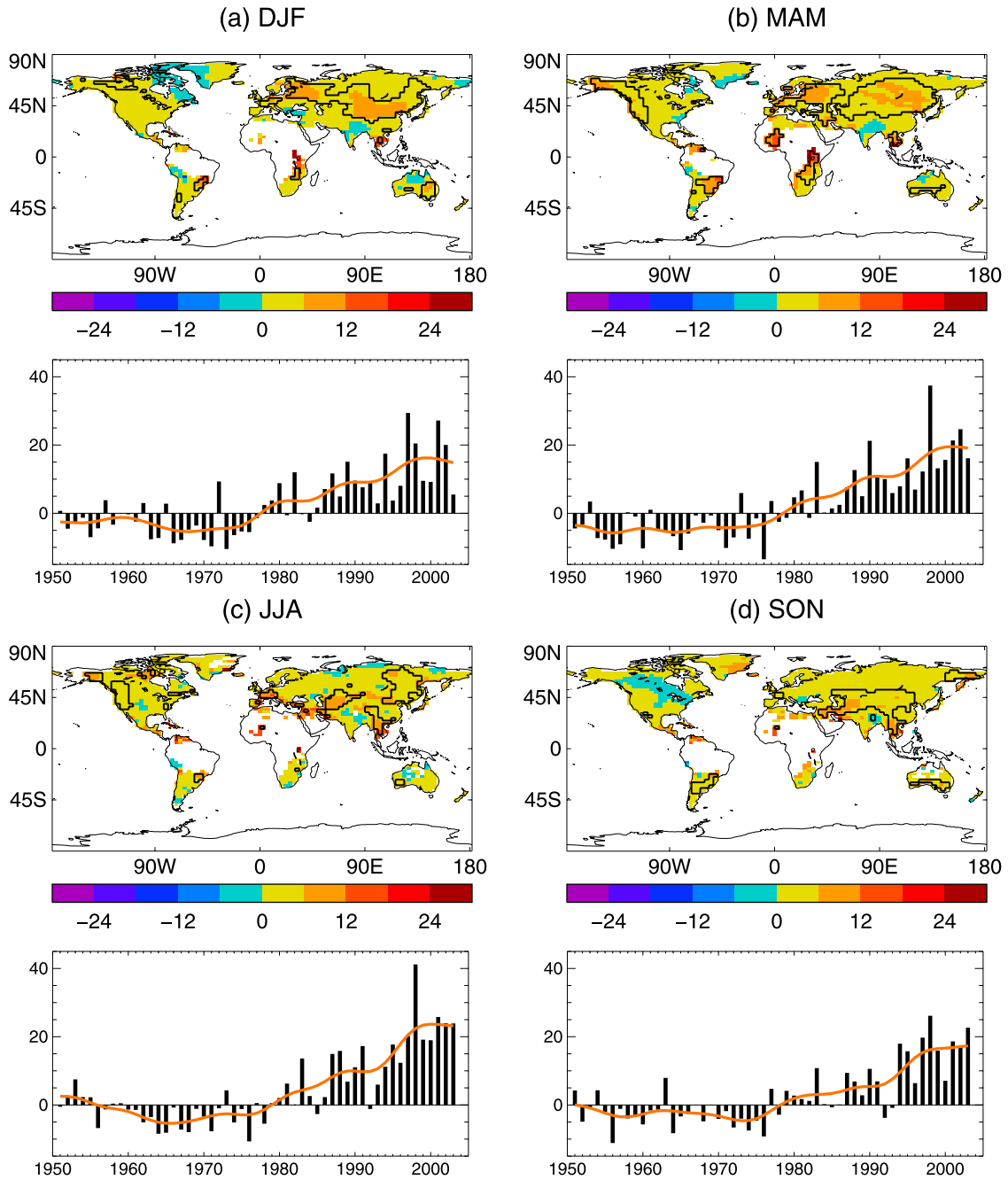

Figure 5. As Figure 2 but for the seasonal occurrence of warm nights (TN90p) in days for (a) December–February, (b) March–May, (c) June–August, and (d) September–November.

0.3% of daily precipitation events) across the midlatitudes. However, their index is much more "extreme" than any of the indices that we have studied and therefore a direct comparison is not possible between the two studies.

4.2.1. Annual Results

[38] Because of small correlation scales, the gridded precipitation indices have a much smaller spatial coverage when compared with temperature indices. Trends computed on the grids show little significance (Table 1). However, when averaged across the globe, we see a significant increase in most of the precipitation indices except for consecutive dry days (CDD) and consecutive wet days (CWD), reflecting the filtering of noise that makes it easier to detect a significant trend. Note that trends in these indices are dominated by the wetter regions. *Kiktev et al.* [2003] and *Frich et al.* [2002] also found significant increases in R10 but neither of those studies found a significant increase in SDII.

[39] The annual total precipitation has the best spatial coverage. However, the analysis of total precipitation change is not the main objective of this study since

Table 2. Percentage of Land Area Showing Significant Trends at the 5% Level for Each Season Between 1951 and 2003 for Indices That Can Be Calculated Seasonally[a]

	DJF			MAM			JJA			SON		
Indicator	N	+ve	−ve	N	+ve	−ve	N	+ve	−ve	N	+ve	−ve
TXx	1295	24.2	4.1	1243	23.0	2.6	1259	16.2	3.6	1272	12.3	2.1
TNx	1281	39.0	3.2	1296	38.0	2.4	1190	27.5	0.8	1249	25.1	1.3
TXn	1330	34.5	2.7	1344	33.9	2.6	1211	13.7	4.8	1414	20.7	2.7
TNn	1493	48.6	2.0	1376	53.8	1.2	1313	33.5	1.5	1445	36.2	1.1
TN10p	1328	0.1	43.0	1335	0.1	66.9	1285	0.5	40.9	1421	0.3	46.2
TX10p	1302	1.2	26.3	1336	0.5	38.4	1245	3.3	17.8	1347	1.4	9.4
TN90p	1298	40.4	0.3	1367	54.3	0.3	1232	39.0	0.1	1252	32.4	0.6
TX90p	1352	24.7	2.3	1302	23.7	2.5	1194	18.0	2.1	1226	9.1	0.2
DTR	1183	3.1	35.8	1176	4.4	32.6	1128	4.9	22.8	1168	3.3	26.1
RX1day	704	8.8	2.7	634	7.7	2.1	756	4.1	3.6	824	7.0	2.7
RX5day	964	12.1	5.3	809	9.1	2.2	912	3.6	3.5	878	8.9	2.6

[a]The number of grid boxes sampled for each index and season is denoted by N.

many other studies [e.g., *New et al.*, 2000] have analyzed this variable using monthly data and have better spatial coverage. Our interest was to use daily data to analyze a range of the more extreme or intense precipitation events in a season or year. Figure 6 shows that when averaged across the globe the more extreme precipitation events in a year have been increasing. Figure 6a shows that there have been significant increases of up to 2 days per decade in the number of days in a year with heavy precipitation in south-central United States and parts of South America. The percentage contribution from very wet days to the annual precipitation total has slightly increased (by 1% since 1951; Figure 6b) although the trend is not significant and there is little significance at the grid box level in this indicator.

[40] Changes in the annual number of consecutive dry days are shown in Figure 6c. The largest trends are decreases in this index over India although significant decreases are confined to small regions. There has been a steady decline in consecutive dry days since the 1960s. This generally agrees with the earlier studies of *Frich et al.* [2002] and *Kiktev et al.* [2003] who used station data with poorer coverage. Decadal trends in the simple daily intensity index (Figure 6d) also agree well with the results from *Kiktev et al.* [2003] although unlike *Kiktev et al.* [2003] the decreasing intensity in the western United States is not identified to be statistically significant in this study.

[41] The other precipitation indices, although generally covering smaller regions, do indicate enhanced precipitation between 1951 and 2003. However, there are only very small coherent regions of significant change. Compared to temperature there is much less spatial coherence between regions, with large areas showing both increasing and decreasing trends.

4.2.2. Seasonal Results

[42] Only two of the precipitation indices have been calculated seasonally: maximum 1-day precipitation totals (RX1day) and maximum 5-day precipitation totals (RX5day). The spatial coverage of RX5day is better than RX1day because of the fact that it has a larger decorrelation length scale (see Appendix A). Figure 7 shows the seasonal trends for RX5day. In nearly all seasons there is an increase in this index although it is not so clear in June–August (Figure 7c). There are very few areas of significant change except for significant increases over south-central United States and northern Russia and Canada in December–January (Figure 7a), northern India and southern Brazil in March–May (Figure 7b) and southeastern United States and a few other small regions in the United States and Europe in September–November (Figure 7d).

4.3. Distribution Changes and Trends, 1901–2003

[43] In order to put the above results in a historical context, we examine temporal changes in the indices for a subset of stations with complete coverage for 1901–2003. We compare the probability distributions of each index for different time periods in the 20th century and also compute trends for the same period. In the first half of the 20th century there are far fewer (by about a factor of 10) stations than in the latter half of the century. There are about 200 temperature stations (depending on the index) and 608 precipitation stations across the globe. We split the data up into one 50-year period and two approximately 25-year periods, i.e., 1901–1950, 1951–1978 and 1979–2003. The start year of the most recent period was chosen because it coincides with the start of the satellite era. This will be important for future comparison with reanalysis data.

4.3.1. Probability Distribution Functions Using Station Data: 1901–2003

[44] Figures 8a–8d show the PDFs for annual values of percentile-based temperature indices for each of the three periods. The differences between the distributions for the occurrence of cold nights and the occurrence of cold days (Figures 8a and 8c) and the occurrence of warm nights and the occurrence of warm days (Figures 8b and 8d) clearly indicate that extreme minimum temperature occurrences have been increasing at a faster rate than that of extreme maximum temperature. Figure 8a shows a marked reduction in the occurrence of cold nighttime temperatures over the 1901–2003, particularly for the most recent 25-year period. There is also a marked increase in the occurrence of warm nighttime temperatures during the last century, again with strongest change in the last few decades (Figure 8b). The coldest minimum temperature (TNn), the warmest minimum temperature

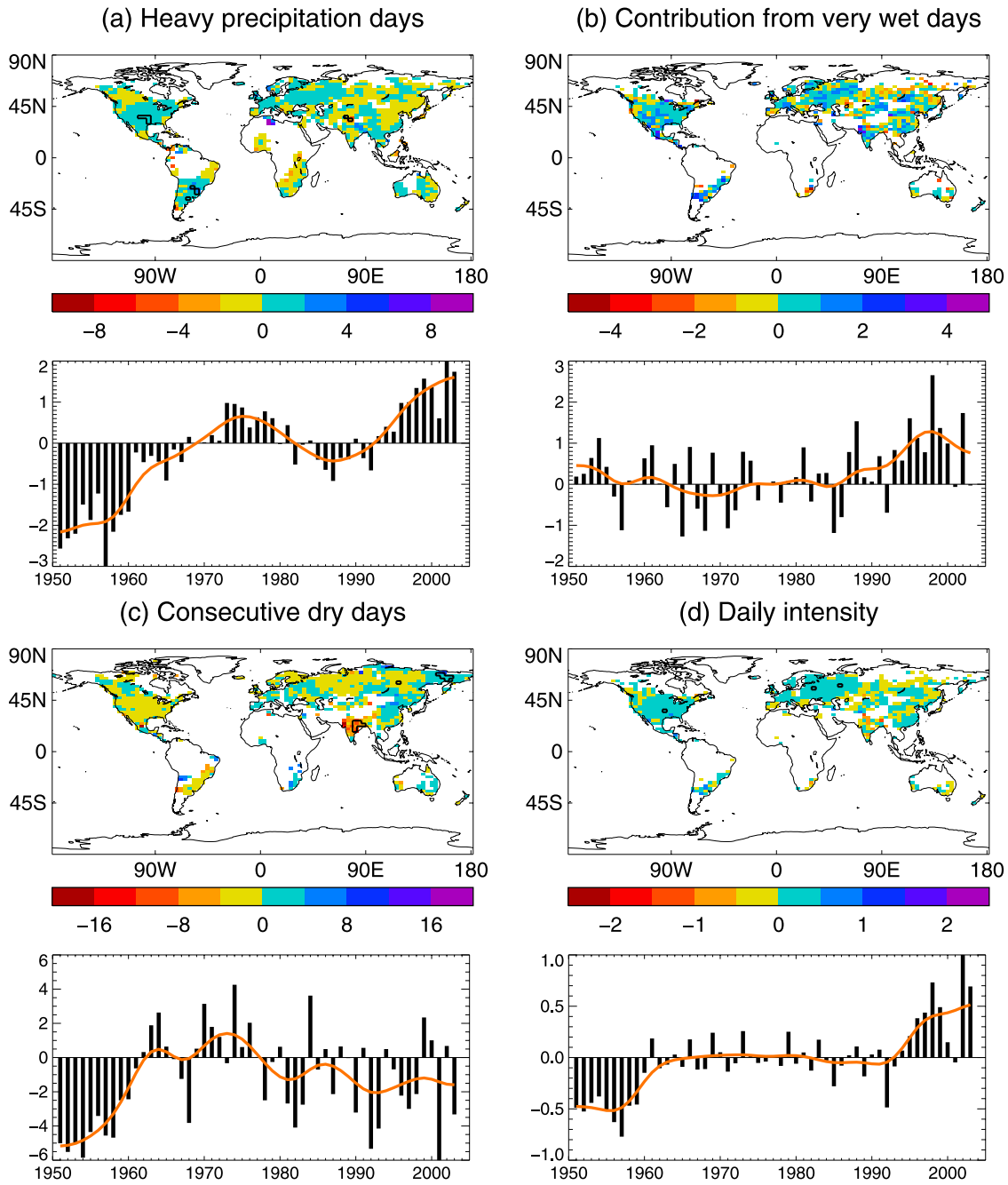

Figure 6. As Figure 2 but for precipitation indices (a) R10 in days, (b) R95pT (i.e., (R95p/PRCPTOT)*100) in %, (c) CDD in days, and (d) SDII in mm/day.

(TNx), the coldest maximum temperature (TXn) and the hottest maximum temperature (TXx) have also increased in the latter half of the 20th century but the difference between the 1951–1978 and 1979–2003 time periods is less obvious (not shown).

[45] Similar patterns of change emerge for the other temperature indices (not shown). However, the remaining indices are harder to analyze because the distributions are very non-Gaussian. For all the indices, except the annual occurrence of summer nights and warm spell duration index, the PDF for the most recent time period is significantly different from that for the first half of the 20th century. Also the 1979–2003 PDF is significantly different from the 1951–1978 PDF for all of the temperature indices studied, indicating a shift toward warmer conditions in the most recent decades.

[46] For the precipitation indices there are fewer clear signs of change (see Figure 9), although the most recent time period is significantly different from the 1901–1950 period for every index. In general statistical tests show changes in the precipitation indices that are consistent with a wetter climate. However, these results are difficult to

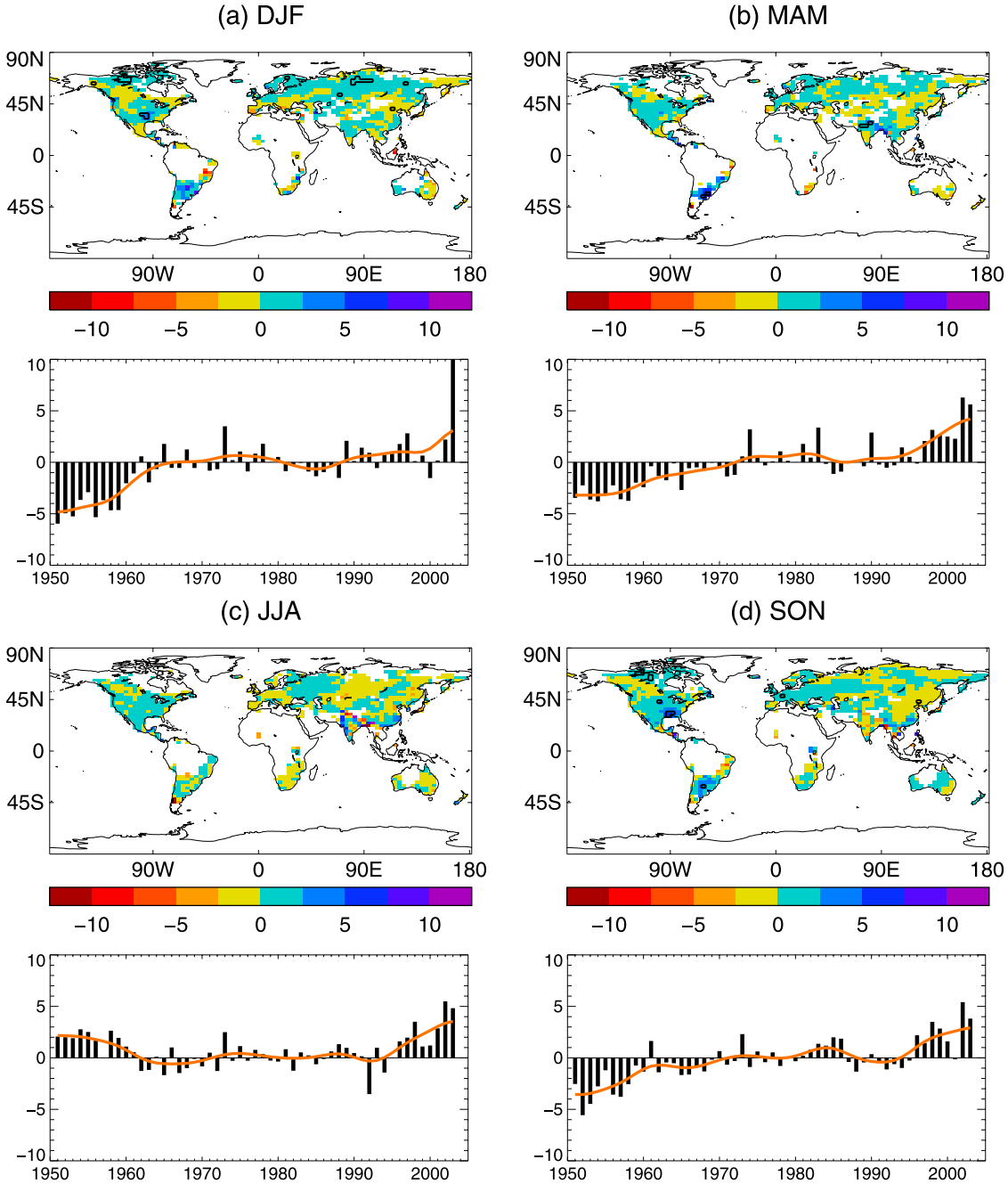

Figure 7. As Figure 2 but for the seasonal maximum 5-day precipitation amount (RX5day) in mm for (a) December–February, (b) March–May, (c) June–August, and (d) September–November.

quantify and their significance may be affected by the very non-Gaussian nature of the precipitation indices.

4.3.2. Probability Distribution Functions Using Gridded Data: 1951–2003

[47] Between 1951 and 2003 there is much better spatial coverage of the data. When comparing PDFs within this period, we use a larger data sample. Gridded indices have been used to calculate PDFs. To minimize sampling error due to different spatial coverage in different periods (see section 4.1.1), a fixed set of grid boxes which have no missing data over this period have been used. These results were also compared with the PDFs computed from grid boxes that had 80% of complete data and ended no later than 1999. Results indicate that the varying sample made little difference to the result for the percentile-based temperature indices, but had a much larger effect for some of the other indices, particularly the absolute indices. This is because the percentile-based temperature indices are calculated with respect to the local climate (with an expected outcome of 10% during the base period regardless of regional climate) while some of the other indices can differ significantly between

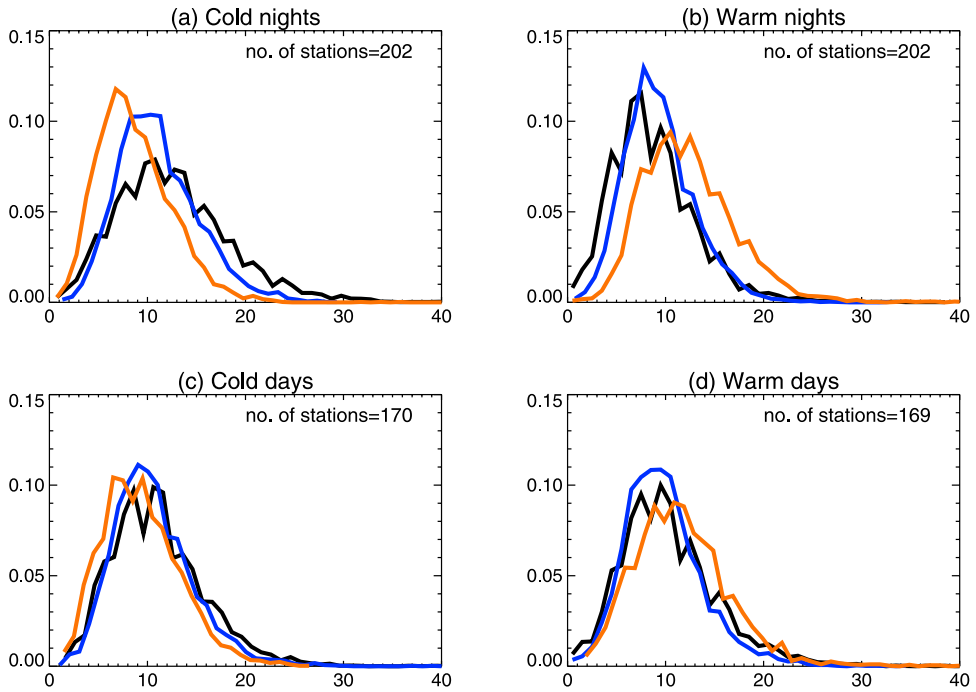

Figure 8. Annual probability distribution functions for (a) cold nights, (b) warm nights, (c) cold days, and (d) warm days for a subset of stations with at least 80% complete data between 1901 and 2003 for three time periods: 1901–1950 (black), 1951–1978 (blue), and 1979–2003 (red). The *x* axis represents the percentage of time during the year when the indicators were below the 10th percentile or above the 90th percentile. PDF bin sizes are 1. The number of stations in each case is given in the top right-hand corner.

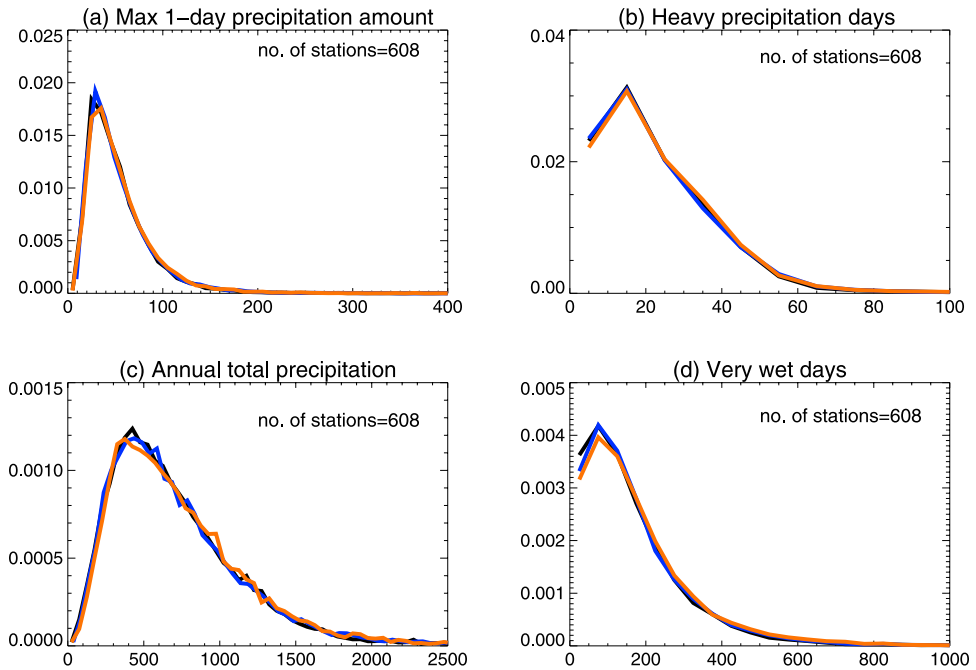

Figure 9. As Figure 8 but for (a) maximum 1-day precipitation amount, (b) heavy precipitation days, (c) annual total precipitation, and (d) very wet days and a subset of stations with at least 80% complete data between 1901 and 2003 for three time periods. In Figures 9a, 9c, and 9d the *x* axis represents amount (in mm), and in Figure 9b it represents the annual number of days when precipitation is above 10 mm. PDF bin sizes are 10 for Figures 9a and 9b and 50 for Figures 9c and 9d. The number of stations in each case is given in the top right-hand corner.

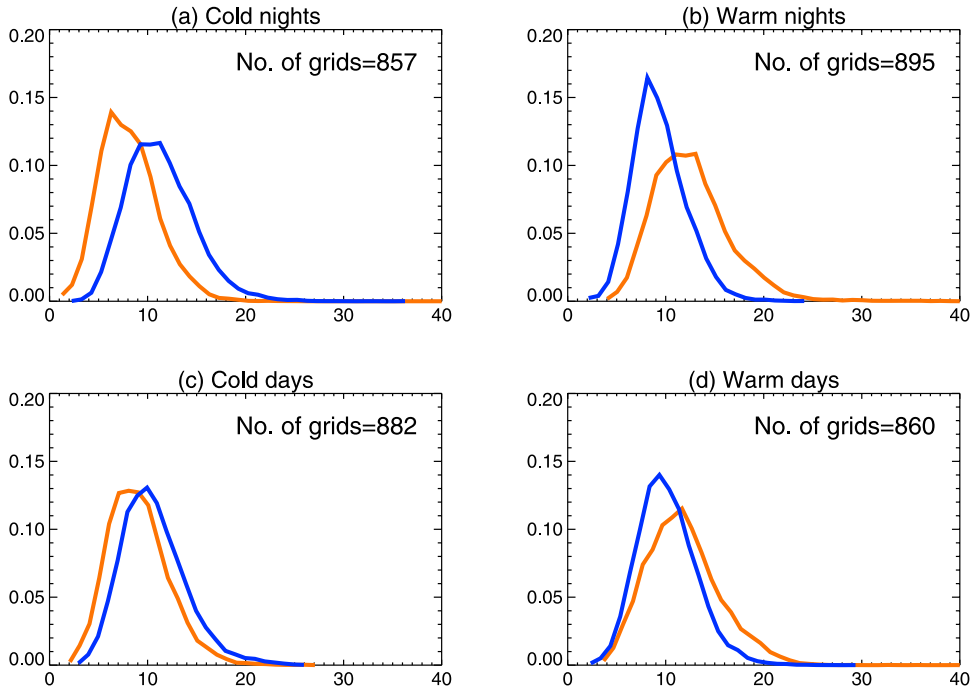

Figure 10. Annual probability distribution functions for grid boxes in Figure 2 with no missing data between 1951 and 2003 for two time periods: 1951–1978 (blue) and 1979–2003 (red). The *x* axes represent the percentage of time during the year when (a and b) minimum temperature and (c and d) maximum temperature were below (above) the 10th (90th) percentile respectively. PDF bin sizes are 1. The number of grid boxes in each case is given in the top right-hand corner.

different climatic regions. Also varying spatial coverage at the start and end of the time period, e.g., lack of data in the tropics in the 1950s, changes the composition of the PDFs for some of the indices. For this reason we only show the percentile-based temperature indices in Figure 10. The distributions of these indices using the fixed grids are significantly different between the two time periods, with very notable shifts in the distribution; the minimum temperature percentile-based indices show the most marked shifts toward less cold nights and more warm nights. Changes in the absolute temperature indices (not shown) are more complex to assess as they do not necessarily appear as a simple shift in the distribution. However, in general the latter period does appear warmer and wetter than the 1951–1978 period.

[48] For nine of the temperature and two of the precipitation indices we are also able to assess changes in seasonal values. Warming of minimum temperature extremes is apparent during all seasons although changes between December and May are generally more pronounced, with least change generally in September–November. Figure 11 shows the seasonal results for the annual occurrence of cold nights and warm nights. Maximum temperatures exhibit a similar pattern of change although the magnitude of warming is much smaller in all seasons. This has led to a significant decrease in DTR during the last half of the 20th century. The maximum daily maximum temperature PDF for JJA is the only index which does not exhibit a significant change between these time periods.

4.3.3. Trends in Station Data

[49] For each index we calculated trends for the period 1901–2003 for those stations that had sufficient data for that period. An example of such trends is given in Figures 12 and 13 for temperature and precipitation indices, respectively. Extreme minimum temperature increases are relatively widespread and coherent (Figures 12a and 12b) and while we also see an overall warming of maximum temperatures extremes since 1901, the pattern is not so coherent (Figures 12c and 12d). 77% of stations showed a significant increase in the occurrence of warm nights (Figure 12b) while 51% showed a significant decrease in the occurrence of cold nights (Figure 12a). Although the precipitation indices show a tendency toward wetter conditions with some regional significance, there is less large-scale significance in these indices. However, analysis of maximum 1-day rainfall, maximum 5-day rainfall, very wet days and extremely wet days (Figure 13), showed that 28%, 25%, 28% and 13% of stations have exhibited significant increases respectively. The largest change in any precipitation index is a significant increase in the annual precipitation total at 37% of stations between 1901 and 2003. The results indicate that the widespread global warming and wetting that we have seen in the past 50 years or so is likely to be part of a much longer term trend.

5. Discussion

[50] One of the unanswered questions posed by the climate community is whether the distribution of observed

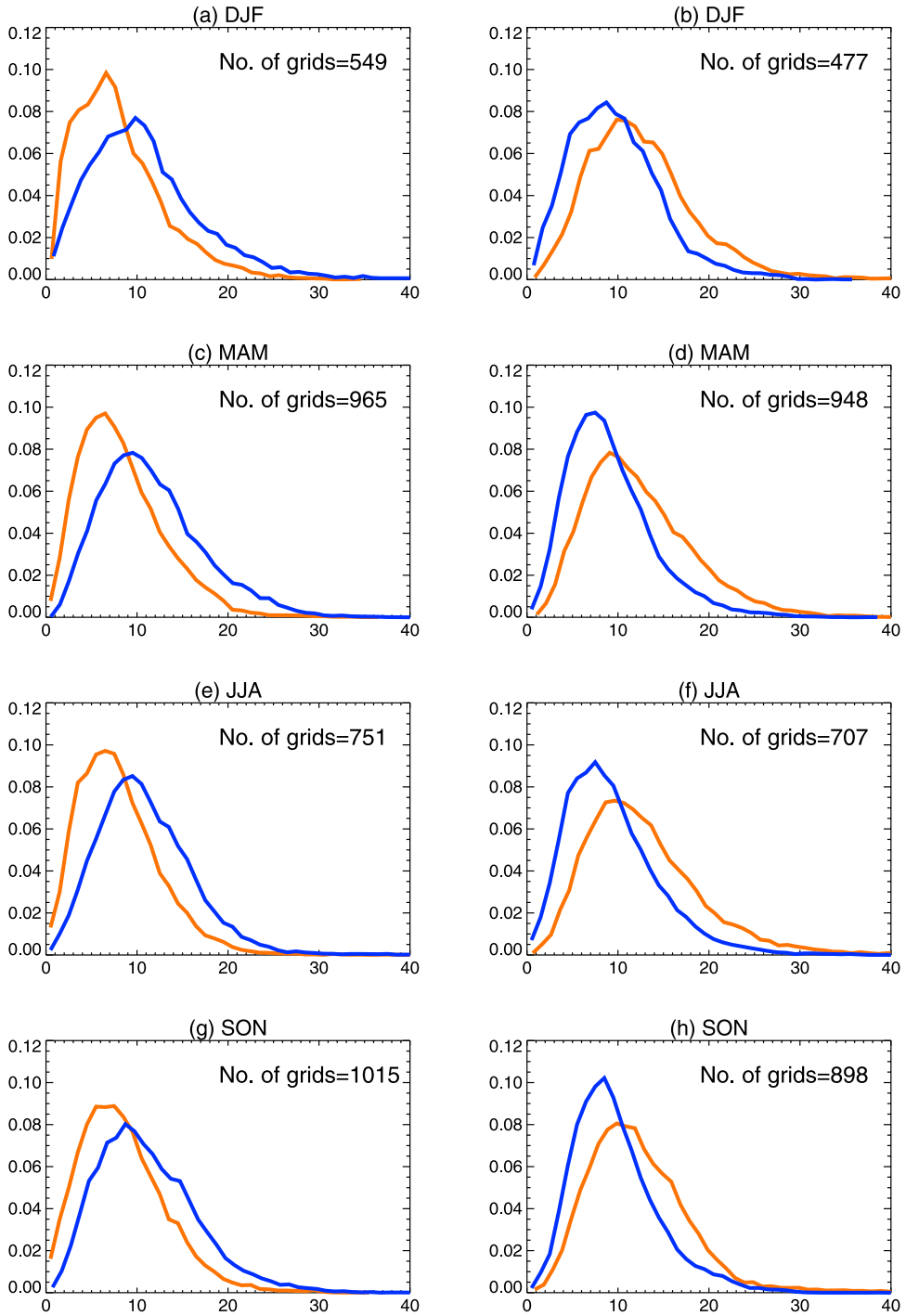

Figure 11. As Figure 10 but for seasonal results for (left) cold nights and (right) warm nights.

global temperature and precipitation is changing and if so how. The changes in temperature extremes documented here are what one would generally expect in a warming world: decreases in cold extremes and increases in warm extremes. As the decreases in extreme minimum temperatures are greater than the increases in extreme maximum temperature, these results agree with earlier global studies [e.g., *Jones et al.*, 1999] and regional studies [e.g., *Klein Tank and Können*, 2003; *Manton et al.*, 2001; *Vincent and Mekis*, 2006; *Yan et al.*, 2002; M. Brunet et al., Spatial and temporal temperature variability and change over Spain during 1850–2003, submitted to *Journal of Geophysical Research*, 2005] which imply that rather than viewing the world as getting hotter it might be more accurate to view it as getting less cold. Combined with the results of other studies, the asymmetry in the changes in cold versus warm extremes that are seen in this study, hints at potential changes in the shape and/or scale of the

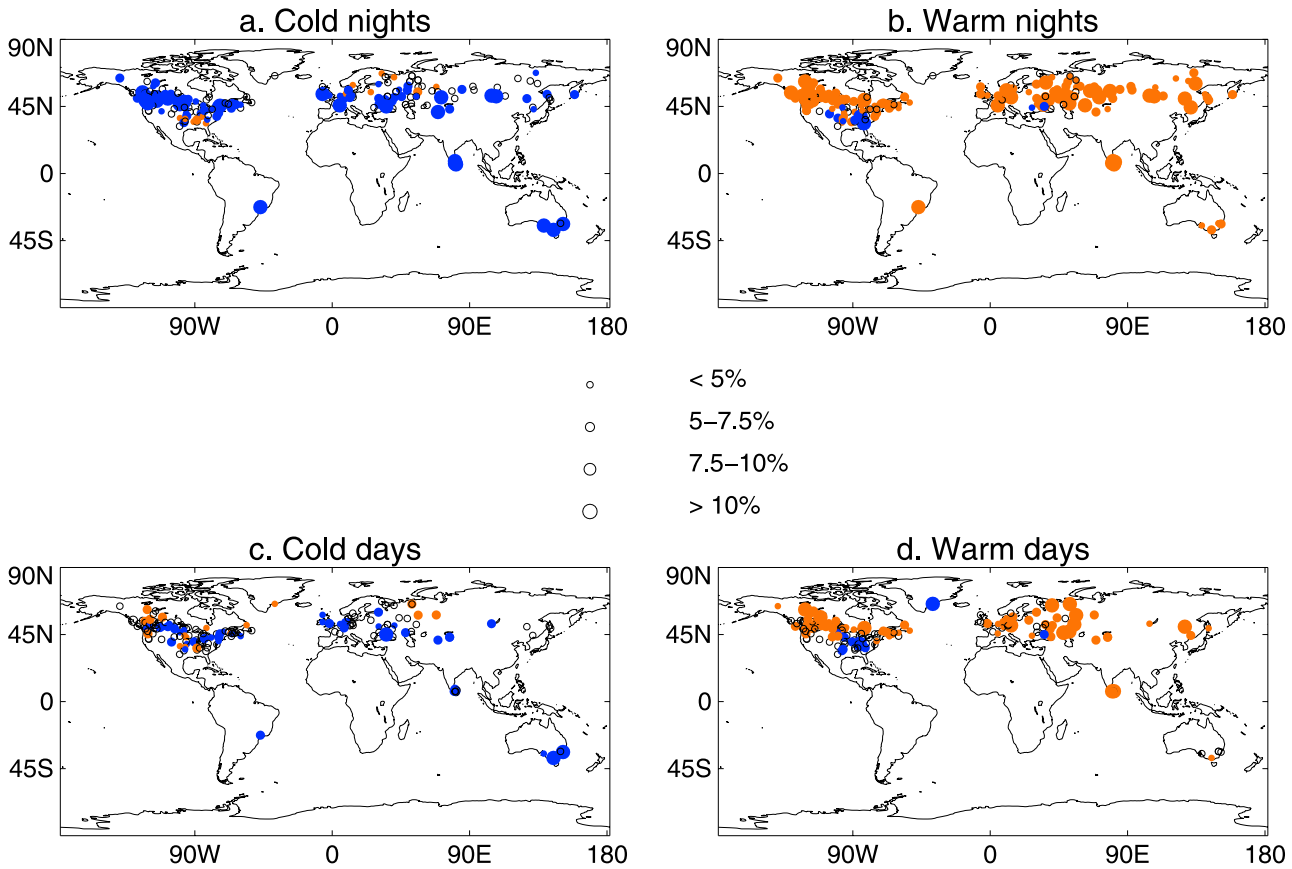

Figure 12. The 100-year trends for the percentile temperature indices for the period 1901–2003 for a subset of stations with at least 80% complete data between 1901 and 2003 for (a) cold nights, (b) warm nights, (c) cold days, and (d) warm days. Black circles indicate a nonsignificant change. Red (blue) solid circles indicate a significant increase (decrease) at the 5% level.

distribution of temperature observations. In addition, the evidence suggests complex changes in precipitation extremes but which supports a generally wetter world. However, to accurately assess potential changes in the shape of the distribution of temperature and precipitation observations requires additional rigorous analysis beyond the scope of this paper.

6. Conclusions

[51] Using global station data which have become available for the first time as a result of intense international collaboration, we have presented a previously unseen global picture of changes in temperature and precipitation extremes during the 20th century. We show the following:

[52] 1. Between 1951 and 2003, over 70% of the land area sampled showed a significant increase in the annual occurrence of warm nights while the occurrence of cold nights showed a similar proportion of significant decrease. For the majority of the other temperature indices, over 20% of the land area sampled exhibits a statistically significant change and all but one is field significant.

[53] 2. Using a fixed set of complete grid boxes, we find that all indices exhibit a significant change between 1951–1978 and 1979–2003. Warming is apparent in all seasons although March to May generally exhibits the largest change and September to November the smallest change. Over nearly all parts of the globe both tails of the minimum temperature distribution have warmed at a similar rate. Maximum temperature extremes have also increased but to a lesser degree. Most precipitation indices show a tendency toward wetter conditions but not all show statistically significant changes.

[54] 3. A subset of stations with near-complete data between 1901 and 2003 and covering a very large area of the Northern Hemisphere midlatitudes show significant shifts associated with warming in the probability distribution of temperature indices. A substantial rise in warm nighttime temperatures is apparent over the 25 year period between 1979 and 2003 when compared to the rest of last century. The cold tails of minimum temperature indicate a similar shift. The maximum temperature indices show similar changes but with smaller magnitudes. The distributions of all but 2 of the temperature indices are significantly different when the period between 1979 and 2003 is compared with 1901–1950. Precipitation indices derived from a subset of stations with near-complete data between 1901 and 2003 and covering the Northern Hemisphere midlatitudes and parts

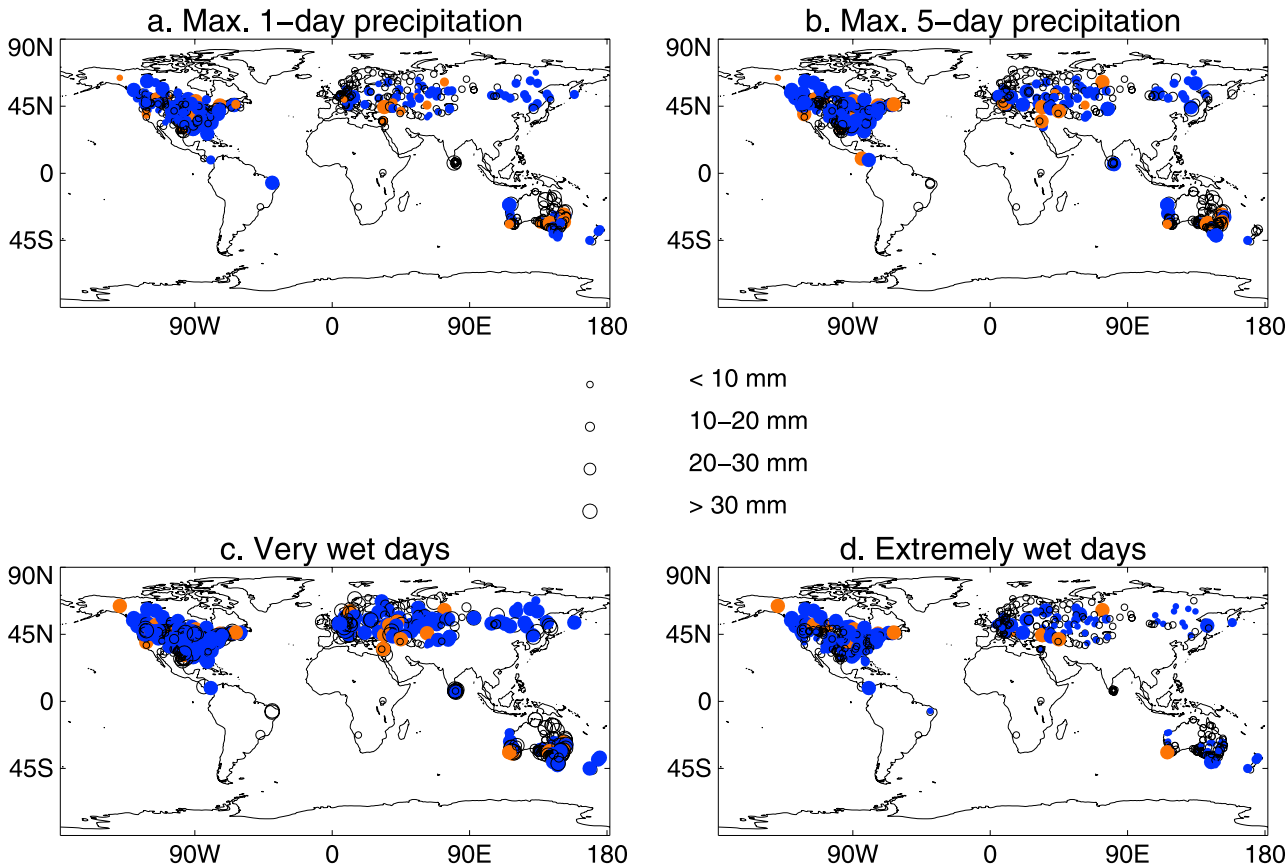

Figure 13. The 100-year trends for a selection of precipitation indices for the period 1901–2003 for a subset of stations with at least 80% complete data between 1901 and 2003. Black circles indicate a nonsignificant change. Blue (red) solid circles indicate a significant increase (decrease) at the 5% level.

of Australia display a tendency toward wetter conditions with the distributions from the 1979–2003 period significantly different from the 1901–1950 period for every index.

[55] Most of the indices used in this study are available to the international research community at the ET's website http://ccma.seos.uvic.ca/ETCCDMI through the effort and willingness of the regional climate change workshop organizers and participants. Gridded data sets are also available from http://www.hadobs.org.

Appendix A: Gridding Methodology

[56] The angular distance weighting (ADW) method of calculating grid point values from station data requires knowledge of the spatial correlation structure of the station data, i.e., a function that relates the magnitude of correlation to the distance between the stations. To obtain this we correlate time series for each station pairing within defined latitude bands and then average the correlations falling within each 100 km bin. To optimize computation only pairs of stations within 2000 km of each other are considered. We assume that at zero distance the correlation function is equal to one. This may not necessarily be the best assumption for the precipitation indices because of their noisy nature but it does provide a good compromise to give better gridded coverage. A second-order polynomial function is then fitted to the bin averages in order to smooth the data. We define the decorrelation length scale or correlation decay distance as the distance at which the mean correlation from the fitted function falls below $1/e$ [see *Caesar et al.*, 2006]. Using the decorrelation length scale, L, we can define a correlation function, f [*Jones et al.*, 1997], for station i as

$$f_i = e^{-r_i/L} \tag{A1}$$

where r_i is the distance of the ith station to the grid box center. From this we are able to determine a weighting function for each station, i, that depends on the locations of the other contributing stations, k,

$$\omega_i = f_i^m \left\{ 1 + \frac{\sum_k f_k^m [1 - \cos(\theta_k - \theta_i)]}{\sum_k f_k^m} \right\}, \quad i \neq k \tag{A2}$$

where θ is the bearing of a station from the grid point. The weighting function (equation (A2)) also contains a parameter, m, which adjusts how steeply the exponential function decays and thus how much weighting each station obtains the further it is away from the grid box center. Figure A1 shows an example of how the correlation decay distance is obtained along with plots of the exponential weighting functions using several values of m. In all cases

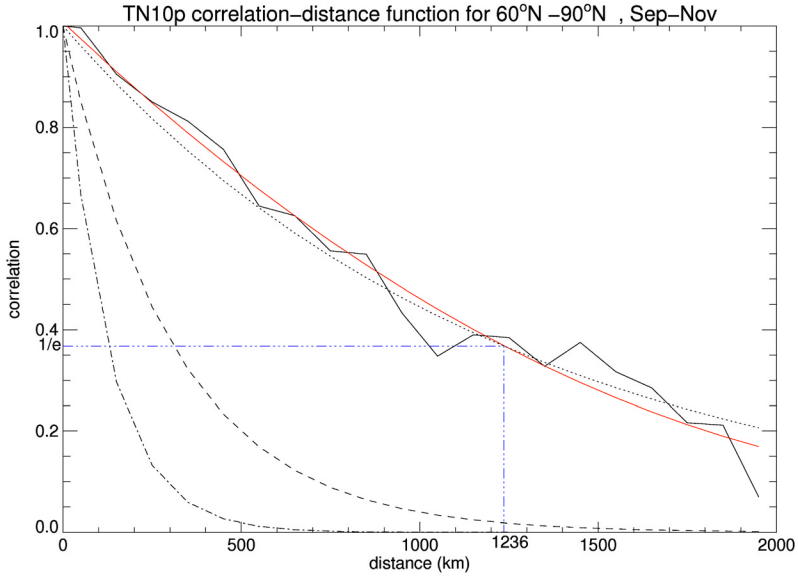

Figure A1. An example of how the decorrelation length scale, L (equations (A1) and (A2)), is derived. The solid black line represents the correlation values for each 100 km bin, and the red line is a second-order polynomial fit to these data. The blue dash-dotted line shows how the value of L is determined. The remaining lines represent the exponential weighting functions from equation (A2) varying the value of parameter m, i.e., m = 1 (dotted line), m = 4 (dashed line), m = 10 (dash-dotted line).

we chose a value of 4 for this parameter since this value provides a reasonable compromise between reducing the RMS error and spatial smoothing, while still allowing some influence from more remote stations within the search radius [*Caesar et al.*, 2006]. The minimum number of stations required to calculate a grid point value is 3. Because stations at a distance greater than L from a grid point are unlikely to contribute any useful information to the grid point estimate [*New et al.*, 2000], we use the distance of the decorrelation length scale as our search radius. We therefore do not limit the maximum number of stations to calculate a grid box value so long as they fall within the radius of influence. The grid size 2.5 degrees of latitude by 3.75 degrees of longitude was chosen as this will be convenient for future comparison with output from Hadley Centre models and provides a good compromise between regional detail and available station density.

[57] Temperature variations are more coherent zonally than meridionally [*Jones et al.*, 1997] so we chose to calculate correlation decay distances for four nonoverlapping zonal bands of 30° latitude between 90°N and 30°S, plus a 60° band spanning the data-sparse 30 to 90°S latitudes. For convenience we also chose these bands for the precipitation indices. To avoid discontinuities at the band boundaries, the correlation decay distances were linearly interpolated to each grid point from the center of each band. The spatial relationships between stations vary with season as well as latitude. For this reason we calculate separate values of L for each index and each season, i.e., December–February (DJF), March–May (MAM), June–August (JJA) and September–November (SON). The annual decorrelation length scales for a selection of indices are shown in Table A1. Although *Kiktev et al.* [2003] showed that trends in the indices were generally more coherent than the time series of annual values from which they were calculated, we chose to grid the actual values rather than the trends since we are interested in analyzing the time series of global results. For most of the temperature indices, the values of L derived from the annual values are relatively large indicating widespread spatial coherent (see Table A1). However, most of the precipitation indices are generally much less coherent. Even given that there are a larger number of precipitation stations, the gridded results contain much fewer grid points than for the temperature indices (Table 1). The most spatially coherent indices are the percentile indices for temperature; TN10p, TN90p, TX10p and TX90p (see Table A1). This is to be expected since they are defined relative to the local climate. Of the indices that can be defined seasonally, maximum daily minimum temperature (TNx), maximum daily maximum temperature (TXx) and diurnal temperature range (DTR) are the least

Table A1. Annual Decorrelation Length Scales (in km) for the Absolute and Percentile Temperature Indices and the Threshold and Duration Precipitation Indices[a]

Indicator	60°N–90°N	30°N–60°N	0–30°N	0–30°S	30°S–90°S
TNn	1067	1410	1082	707	565
TNx	804	491	266	448	397
TXx	717	622	313	555	553
TXn	1219	1180	796	598	642
TN10p	1528	961	674	809	577
TN90p	1536	837	1307	728	896
TX10p	1554	985	600	947	1043
TX90p	1552	974	530	1051	881
R10	323	356	639	656	355
R20	248	250	513	591	267
CDD	553	221	327	357	205
CWD	100	139	202	364	126

[a]Length scales are in km.

spatially coherent and, as expected, GSL is not defined at all outside the Northern Hemisphere extratropics. Although the annual values of L are generally larger than for any individual month or season (not shown), the seasonal indices data are still quite spatially coherent, particularly for the temperature indices. The decorrelation length scales are generally higher for the Northern Hemisphere extratropics. Seasonal results show that for both hemispheres the correlations for temperature are higher in winter than in summer. This is consistent with the results of *Caesar et al.* [2006]. The absolute indices for precipitation, RX1day and RX5day, can be defined seasonally but, although the seasonal indices are more spatially coherent than the annual indices, the spatial coverage remains relatively poor.

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