Global observed changes in daily climate extremes of temperature and precipitation

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Abstract

A suite of climate change indices derived from daily temperature and precipitation data were calculated, primarily focusing on extreme events. By setting an exact formula for each index and using specially designed software, analyses done in different countries have been combined seamlessly. We present 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.

Probability distributions for a subset of approximately 200 temperature and 350 precipitation stations were analysed for the periods 1901-1950, 1951-1978 and 1979-2003. The analysis shows a significant warming throughout the 20th century. Temperature differences 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 timeseries are available shows that these changes occur for all seasons although they are least pronounced for September to November. Precipitation indices show a tendency towards wetter conditions.

Seasonal and annual indices for the period 1951 -2003 were gridded using an angular distance weighting technique and trends in the gridded fields were tested for significance. Results showed widespread significant changes in temperature extremes, 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. Changes in daily maximum temperature are less marked, implying that our world is becoming considerably less cold rather than considerably hotter. Precipitation changes were much less coherent but annual precipitation did show a widespread significant increase.

1. Introduction

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 datasets provide reasonable spatial coverage across the globe [*e.g. Jones and Moberg*, 2003, *New et al.,* 2000]. However, analyzing changes in extremes, such as changes in heatwave 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 previous "global" analysis of extreme indices by *Groisman et al.,* [2000] and *Frich et al.* [2002], there was 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.

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.

Another 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, conducted data quality control and computed indices using a standard procedure and software during the workshop. 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 2005 in South Africa [*New et al.*, 2005], Brazil [*Haylock et al.*, 2005; *Vincent et al.*, 2005], Turkey [*Sensoy et al.*, 2005; *Zhang et al.*, 2005a], Guatemala [*Aguilar et al.*, 2005] and India [*Peterson*, 2005; *Klein Tank et al.*, 2005] to provide additional coverage for Africa, southern South America, the Middle East, Central America and southwestern Asia respectively.

The objective of this paper is to provide the most comprehensive analysis of observed global temperature and precipitation extremes. To 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 co-authors 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

There are three international daily datasets freely available to the research community. They are 1) the GCOS Surface Network (GSN) dataset [*Peterson et al.*, 1997], 2) the European Climate Assessment (ECA) dataset [*Klein Tank et al.*, 2002] and 3) the

daily Global Historical Climatology Network (GHCN-Daily) dataset [*Gleason et al., 2002*]. The ECA data are used to cover Europe in this analysis, while GHCN-Daily data are used primarily for the USA. 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 [*e.g., New et al.*, 2005; *Haylock et al.*, 2005; *Vincent et al.*, 2005; *Sensoy et al.*, 2005; *Zhang et al.*, 2005a; *Aguilar et al.*, 2005; *Peterson*, 2005; *Klein Tank et al.*, 2005]. Data from the APN workshops [*Manton et al.*, 2001; *Griffiths et al.*, 2005] are also included.

Data have also been provided by the authors for some parts of the world. Though the level of development of high quality daily station datasets differs from one country to another, we included the best available datasets. Canada supplied carefully homogenised daily temperatures up to 2003 for 210 stations [*Vincent et al.*, 2002] and a high quality precipitation dataset [*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, 1999*]. Stations that were likely to be affected by urbanization were excluded, although recent studies [e.g. *Peterson*, 2003 and *Parker*, 2004] show that urbanization effects are minimal. Australian precipitation data also come from a high quality precipitation dataset [*Haylock and Nicholls*, 2000]. For some countries for which a national dataset did not necessarily exist e.g. Argentina [*Rusticucci and Barrucand, 2004*], China [*Zhai et al.*, 2005], India, Iran [*Rahimzadeh and Asghari, 2003*] and Mexico, the authors chose stations based on their knowledge of the best stations in their own country and/or recent analysis. The remaining data were supplied

primarily from the GHCN-Daily dataset and the Hadley Centre archives e.g. for Russia. 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

Irrespective of the data source, a similar quality control procedure was adopted to calculate the indices, predominantly using the RClimDex software. This package was written in R, a freely available statistical language and environment package.

The main purpose of the quality control procedure was to identify errors in data processing, such as errors in manual keying. The procedure automatically sets a daily precipitation amount to a missing value if it is less than zero and sets both daily maximum and minimum temperatures to missing values if daily maximum temperature is less than daily minimum temperature. The quality control procedure also identifies outliers in daily maximum and minimum temperature. 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 corrected on a case by case basis by workshop participants who are knowledgeable about their own daily data. Data processed outside of the workshops are similarly tested for outliers although access to metadata is not available in all cases. Statistical tests were not generally applied to precipitation data because of their non-normal distribution but any obvious outliers were identified and checked

manually. Local knowledge, an investigation of station histories or comparison with neighbouring stations can all be applied to determine whether an outlying precipitation value is erroneous. It is particularly important to identify multi-day precipitation accumulations that can appear erroneously in records of daily precipitation [*Viney and Bates*, 2004]. Even after data were processed and collated for this study, annual timeseries 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.

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 timeseries. It 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 of the stations used in this study. For ECA data, however, we use the most homogeneous stations defined by *Wijngaard et al.,* [2003] for both temperature and precipitation.

Note that we did not attempt to adjust inhomogeneous data. There are two main reasons for this. Firstly, there has been only limited success to date in adjusting daily

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temperatures [*e.g. Vincent et al.*, 2002]. Secondly, 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. It is

thus important to have access to station metadata. For example, the station

Eskdalemuir in Scotland exhibits a step change in 1984 (not shown) but no

documentary evidence supports a change of instrument, station relocation or any other

factor which would cause an artificial inhomogeneity. In cases like this, where

observing practices are well known and documented, we can only assume that the

break point identified reflects an actual variation in the climate and thus data from

these stations are retained in the analysis. However, where access to station metadata

is unavailable we either remove the station data or only use the data after the most

recent break point identified.

Inhomogeneities other than step changes, such as gradual changes in temperature, are

not accounted for. Such an inhomogeneity might occur through urbanization although

Peterson, [2003] and *Parker*, [2004] suggest that the effects of urbanization on data

averaged over an entire network of stations are minimal. The problem of such

inhomogeneities is also difficult to address though it could potentially be dealt with

by comparing data from neighbouring stations. However, our station network is not

usually dense enough for this approach to be adopted.

Figure 1 shows the locations of over 2000 temperature and over 2200 precipitation

stations used in this study. Although there are more precipitation stations, they are

generally distributed less uniformly than the temperature stations. All stations are

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 and 350 precipitation stations had enough data for changes throughout the entire 20th century to be analysed 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 The indices

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 (Table 1). 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. We chose to analyse all the indices except Rnn which is a user specific index and varies from region to region.

The indices can be divided into 5 different categories:-

- *percentile indices*

These indices sample the extreme ends of a reference period distribution. For temperature percentile indices include the occurrence of cold and warm days and cold and warm nights (TX10p, TX90p, TN10p and TN90p respectively). They 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 should capture the most extreme precipitation events in a year.

- *absolute indices*

These represent maximum or minimum values within a season or year. The temperature indices in this category are maximum daily maximum temperature (TXx), minimum daily maximum temperature (TXn), maximum daily minimum temperature (TNx) and minimum daily minimum temperature (TNn). Precipitation indices in this category are the maximum precipitation in a defined period falling over 1 day (RX1day) or 5 days (RX5day).

- *threshold indices*

These are defined as the number of days on which a temperature or precipitation value falls above or below a fixed threshold. They are not necessarily meaningful for all climates because they use fixed thresholds that 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 the annual occurrence of frost days (FD), the number of days on which minimum temperature falls below 0°C, have exhibited coherent trends over the mid-latitudes 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. As a result, we included the indices in our study, even though they may not provide truly "global" spatial coverage. The other temperature threshold indices are the annual occurrence of ice days (ID), summer days (SU) and tropical nights (TR) while the precipitation threshold indices are the number of days when the daily precipitation total was at least equal to 10mm (R10) or 20mm (R20).

- *duration indices*

These indices define periods of excessive warmth, cold, wetness or dryness or in the case of growing season length, periods of mildness. Many of the 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 take a value of zero [*Kiktev et al.*, 2002]. 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 (see Table 1). As this index only sampled daytime maxima we also chose to analyse spells of night time 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 extra-tropics.

- *other indices*

These include indices which do not fall into any of the above categories but changes in them could have significant societal impacts. They include total annual precipitation amount (PRCPTOT), diurnal temperature range (DTR) and a measure of the intensity of daily rainfall (SDII).

Some of the indices in Table 1 have the same name and definition as indices 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 period used to define the percentile based temperature indices, i.e. TN10p, TN90p, TX10p and TX90p, due to 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.

An added advantage of this study over previous "global" studies is that it analyses some indices, including the percentile indices, the absolute temperature indices and

DTR on a seasonal as well as an annual basis. This has been made possible because RClimDex provides monthly as well as annual results for some of the indices.

   3. Methodology

It is obvious from Fig. 1 that our stations are not evenly distributed across the global land area. The uneven distribution makes it difficult to assess global changes. A simple average of data from all available stations would result in a representation biased towards areas of higher station density. *Frich et al.* [2002] addressed this problem by thinning the station network so that there was one station every 250,000km^2. While this approach makes the network more or less even in terms of station density, it is at the cost of discarding a lot of otherwise useful information. Furthermore, 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 more climate data than we need. In addition, the choice of stations to be retained is somewhat subjective, especially in regions where the network is relatively dense. *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*, 1984]; a method also proposed by *New et al.* [2000]. *Kiktev et al.,* [2003] compared the gridded indices with those computed from the output of various global climate model simulations. *Caesar et al.* [2005] modified the *New et al.* [2003] and *Kiktev et al.* [2003] approaches to grid and analyze changes in daily maximum and minimum temperatures. We adopt the approach of *Caesar et al.* [2005], by weighting each station according to its distance and angle from the centre of a search radius.

The 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 timeseries for each station pairing within defined latitude bands and then average the correlations falling within each 100km bin. To reduce computation we only consider pairs of stations within 2000km of each other. We assume that at zero distance the correlation function is equal to one. A 2nd 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.*, 2005). Using the decorrelation length scale, *L*, we can define a correlation function, *f*, [*Jones et al.*, 1997] for station *i* as:-

$$ f_i = e^{-r_i / L} \tag{1} $$

where r_i is the distance of the *i*th station to the gridbox 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*:-

$$ \omega_i = f_i^{\,m} \left\{ 1 + \frac{\sum\limits_{k} f_k^{\,m} \left[1 - \cos(\theta_k - \theta_i) \right]}{\sum\limits_{k} f_k^{\,m}} \right\}, \quad i \neq k \tag{2} $$

where θ is the bearing of a station from the grid point. The weighting function (Eqn. [2]) 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 gridbox center. Fig. 2 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 we chose a value of 4 for this parameter since this value provides a reasonable compromise between reducing the RMS error and spatial smoothing, whilst still allowing some influence from more remote stations within the search radius [*Caesar et al.*, 2005]. 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 gridbox 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.

 Temperature variations are more coherent zonally than meridionally [*Jones et al.*, 1997] so we chose to calculate correlation decay distances for 4 non-overlapping 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 2. Although *Kiktev et al.* [2003] showed that trends in the indices were generally more coherent than the timeseries 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 timeseries of global results. We find that for most of the temperature indices, the values of L derived from the annual values are relatively large indicating widespread spatial coherent (see Table 2). However, most of the precipitation indices are generally much less coherent. Even given that there are a larger number of precipitation stations, we find that the gridded results contain much fewer grid points than for the temperature indices (Table 3). The most spatially coherent indices are the percentile indices for temperature; TN10p, TN90p, TX10p and TX90p (see Table 2). 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 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.,* [2005]. 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.

We conduct two different analyses of temporal changes in the indices. One compares empirical probability density functions (PDF) for various periods during the 20th century. The other examines trends in station and grid point data.

PDF's were produced for each station with sufficient data by binning annual values for various time periods. We also conducted a seasonal analysis by averaging the monthly index values for DJF, MAM, JJA and SON if at least 2 months out of 3 months of data 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 allowed us to assess temporal changes without having to allow for uncertainties arising from changes in the spatial coverage of the stations. We also want to determine if the distributions from each time period are significantly different from each other. This is done using a 2-tailed Kolmogorov-Smirnov test of the null hypothesis that two cumulative distribution functions are identical.

For analyzing trends we first grid the data using the ADW method described above and then estimate the trend for each grid box. Trends could have been estimated by fitting a straight line to the data using a least squares method. The statistical significance of such a trend can be determined by conducting a Student's t-test. However these simple methods are not robust and may not be reliable. The least squares estimate of a trend is very sensitive to outliers in the data. The t-test is valid only when the residuals of the series are independent and have a Gaussian distribution. This is not usually the case with the indices data. A Kendall's tau based slope estimator [*Sen*, 1968] has been used to compute the trends since this method does not

assume a distribution for the residuals and is robust to the effect of outliers in the series. We consider the serial correlation in the residuals when testing the statistical significance of trends, since a positive auto-correlation (which is usually present in timeseries of climate data) in the time series would make the test unreliable [*e.g. von Storch*, 1995; *Zhang and Zwiers*, 2004]. We use an iterative procedure, 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 in Appendix A of *Wang and Swail* [2001].

We would also like to assess the field significance of our results. *Livesey and Chen* [1983] described a method for assessing the collective significance of trends in a finite number of interdependent timeseries. *Kiktev et al.,* [2003] implemented this method by generating 1000 plausible fields of trends using a bootstrapping technique. We did likewise and calculated the residuals between the bootstrapped and actual trends in order to define a suitable set of trends that could have arisen through natural climate variability alone. The fields of residuals were used to estimate the 95% confidence interval for a zero trend at each grid point. 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.

Finally we analyse the global timeseries of results which are calculated as the average global land area sampled for each index in each season or year.

4. Results

Temporal changes in the indices are first considered by examining the distributions of each index for different time periods in the 20th century. 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. 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. We use a subset of about 200 temperature and 350 precipitation stations which cover the entire analysis period from 1901 to 2003 when comparing the three periods.

4.1 Probability Density Functions

Fig. 3a-d shows the probability density functions (PDF's) for annual percentile based indices for temperature for each of the three periods. Comparing the differences between the distributions for the occurrence of cold nights and the occurrence of cold days (Figs. 3a & c) and the occurrence of warm nights and the occurrence of warm days (Figs. 3b & d), it is clear that extreme minimum temperatures have been warming at a faster rate than extreme maximum temperatures. Fig. 3a shows a marked reduction in the occurrence of cold night time temperatures over the 3 periods, particularly for the most recent 25-year period. There is also a marked increase in the occurrence of warm night time temperatures during the last century, again particularly in the last few decades (Fig. 3b). The coldest minimum temperature (TNn), the warmest minimum temperature (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).

For the other temperature indices, similar patterns emerge. Fig. 3e-h shows the PDF's for the occurrence of frost days (FD) and summer days (SU), warm spell duration index (WSDI) and cold spell duration index (CSDI). For the subset of stations under consideration, these indices are generally meaningful although they may be harder to analyse because the distributions are very non-Gaussian. For all the indices, except SU and WSDI, 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.

For the precipitation indices there are fewer clear signs of change (see Fig. 4), 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.

Most stations shown in Fig.1 have timeseries that are at least 80% complete during the period 1951-2003. Therefore we compared the latter time periods using this much larger set of stations. Fig.5 shows the results for a selection of the temperature indices. The distributions of all of the indices for this set of stations are significantly different between the two time periods. The minimum temperature percentile indices show the most marked increase. Changes in the absolute indices for temperature (TNn, TNx, TXX and TXn) are more complex to assess as they do not necessarily appear as a simple shift in the distribution. In addition, most of the remaining temperature and

precipitation indices are not normally distributed making them difficult to analyse. However, in general the latter period does appear warmer and wetter than the 1951-1978 period.

For nine of the temperature and two of the precipitation indices we are also able to assess changes in seasonal results. Warming of minimum temperature extremes is apparent during all seasons although changes between December and May are generally more pronounced, with least change in SON. An example of this is shown in Fig. 6. 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 reduction in DTR in all seasons during the second half of the 20th century (not shown). Interestingly the PDF's for the most recent time period for both maximum and minimum temperature also appear to exhibit a change in shape as well as scale. The maximum daily maximum temperature PDF for JJA is the only index which does not exhibit a significant change between 1951-1978 and 1979-2003.

The PDF's show that the distribution of most indices has changed significantly over the 20th century. In addition we would like to assess the regional significance of these changes. Firstly we look at the trends at a subset of individual stations and assess what percentage show significant change. We then grid the indices between 1951 and 2003 and assess the trends at individual grid points.

4.2 Trends in station data

For each index in Table 1, 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 Fig. 7. 122 temperature stations (60%) show a significant increase in minimum daily minimum temperature while over 50% of stations show a significant increase in maximum daily minimum temperature. Over 75% of stations show a significant increase in the occurrence of warm nights (Fig. 7b) while over 50% show a significant decrease in the occurrence of cold nights (Fig. 7a). The 10th and 90th percentiles of maximum temperature are not quite as coherent (Fig. 7c & 7d) but over 30% of stations show significant warming. Although the precipitation indices show a tendency towards wetter conditions with some regional significance there is little large scale significance in these indices. However, over 20% of stations do show a significant increase in annual total precipitation (not shown).

4.3 Spatial trend patterns

Fig. 8 shows the results of the trend analysis between 1951 and 2003 for the absolute and percentile temperature indices. Trends in temperature indices reflect an increase in both maximum and minimum temperature extremes, however generally a much larger percentage of land area shows significant change in minimum temperature extremes than maximum temperature extremes. The magnitude of the trends is also generally greater for minimum temperature related extremes. An exception to this is maximum daily minimum temperature (TNx) and minimum daily maximum temperature (TXn). Over 70% of the land area sampled shows a significant decrease (increase) in the annual occurrence of cold nights (warm nights). Table 3 shows that these changes are field significant for all the temperature indices except annual

maximum daily maximum temperature (TXx). Annually the largest percentage increase in minimum temperature extremes is over Eurasia. 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. Asia also exhibits widespread warming in maximum temperature extremes. The patterns for maximum temperature are generally more mixed. Eastern parts of the USA have seen a decrease in maximum daily maximum temperature (TXx), minimum daily maximum temperature (TXn) and the annual occurrence of warm days (TX90p) with an associated decrease in cold nights (TN10p) although these changes are not significant.

For the other temperature-based indices (not shown) there is widespread coherent warming. There are significant decreases in the annual occurrence of frost days over parts of western Europe and a large portion of Russia and China. This confirms the results of *Kiktev et al.,* [2003] although our results have less significance than theirs over western USA and Canada. Our results show the largest significant negative trend for frost days in the Tibetan Plateau. The annual occurrence of ice days are also significantly decreasing over central Russia and eastern and western China. There are significant positive trends in the annual number of tropical nights over central and southwest Asia, North Africa and southern 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 days are also significantly decreasing over a small part of eastern USA although there are significant increases in this index over parts of northern Canada, western Europe, the Middle East, central Asia, Australia and southern Brazil. The percentage of land area exhibiting a statistically significant decrease in the occurrence of annual cold spells is considerably larger than the

percentage of land area exhibiting a statistically significant increase in the annual occurrence of warm spells although both of these results are field significant (see Table 3). The significant decreases in cold spells occur predominantly in central and northern Russia, parts of China and northern Canada however there are some small areas showing a significant increase in cold spells over Spain, Turkey and the Caucasus. Almost 40% of the land area sampled shows a significant decrease in DTR (Table 3). These areas of significance are located over central and eastern Russia, much of China and eastern and central USA.

The precipitation indices show little significant change and only three of the precipitation indices cover more than 25% of the total global land area (Table 3). This is due to small correlation scales used in the gridding algorithm. The annual total precipitation index (PRCPTOT) has the best coverage and also has the largest significant increase of any of the precipitation indices. Fig. 9a shows that these increases are significant over parts of western Russia, central USA, Northern Canada and parts of eastern South America. However, annual total precipitation has decreased over South Africa, eastern Australia and China with a significant decrease over northern India. The annual number of consecutive dry days is shown in Fig 9b. The largest trends are decreases in this index over India although significant decreases are confined to small regions. The other precipitation indices, although generally smaller in spatial scale, do indicate enhanced precipitation between 1951 and 2003. However, there are only very small coherent regions of significant change and Table 3 shows that only annual total precipitation and simple daily intensity have field significant increases.

The observed warming and increased precipitation between 1951 and 2003 is apparent in all seasons. Fig. 10 shows decadal trends for the seasonal occurrence of cold nights and Fig. 11 shows the seasonal trends for maximum 5-day precipitation totals. From Table 4 we see that more land area shows significant changes in minimum temperature than maximum temperature. MAM has the most widespread significant change in the temperature indices with the least change usually occurring during SON. Fig. 10d shows that a large part of eastern and northern Europe, central North America and parts of South America exhibit non-significant increases in the annual occurrence of cold nights in SON.   Most of the significant warming in any season is occurring in Asia. Precipitation changes are most significant in DJF with least change in JJA, although compared to temperature there is much less coherence between regions with large areas showing both increasing and decreasing trends.

4.4 Timeseries of global results

There is a significant increase in global total annual precipitation (PRCPTOT), number of days above 10mm (R10) and 20mm (R20), very wet days (R95p) and simple daily intensity index (SDII). However, of these only PRCPTOT and R10 provide reasonable spatial coverage across the globe. The results for R10 are shown in Fig. 12a. Annual global precipitation (PRCPTOT) has significantly increased by about 70mm between 1951 and 2003 (not shown). We combined two of the indices (PRCPTOT and R95p) to see if the contribution to total precipitation from days of heavy rain has increased. Fig. 12b shows that although the contribution has increased

the trend is not significant. The remaining precipitation indices show a tendency towards wetter conditions but the trends are not significant.

When averaged over the globe almost all of the temperature indices show significant changes over the 1951-2003 period. The minimum daily minimum temperature (TNn) has increased by nearly 5°C over this time, the greatest change in the absolute temperature indices. The annual occurrence of frost days has decreased by about 16 days and we see a significant negative trend in the annual occurrence of cold nights and a significant positive trend in the annual occurrence of warm nights. Fig. 13a-d shows the results plotted as annual anomalies for the percentile indices for temperature. The changes in minimum temperature related indices are generally greater than for maximum temperature related indices. Since the 1970s there has been a consistent decline in the occurrence of cold nights (Fig. 13a) and cold days (Fig. 13c) and a consistent increase in the occurrence of warm nights (Fig. 13b) and warm days (Fig. 13d). Indeed every year since 1983 has been above the long term average for the annual occurrence of warm nights and every year since 1980 has been below the long term average for the annual occurrence of cold nights. The seasonal results show that nearly all changes in temperature are significant between 1951 and 2003 except for maximum daily maximum temperature in DJF and JJA (not shown). Fig. 14 shows an example of the timeseries for the seasonal occurrence of warm nights (TN90p). Every year since 1986 has been above the long term average in both DJF and MAM for TN90p. In general the largest increases or decreases in the temperature indices occur during MAM.

5. Discussion

One of the unanswered questions posed by the climate community is whether the distribution of global temperature and precipitation is changing and if so how. Up until this point we have not had a satisfactory answer to this question because of lack of access to suitable data. Variations in global mean temperature are well known [*Jones and Moberg, 2003*] but it was unclear whether changes in the mean are affecting the variance of the whole distribution. There have been previous tantalising suggestions that the extremes of the temperature and precipitation distributions were also changing [*e.g. Frich et al., 2002*] and perhaps at a faster rate than the mean. However, although there are many regional studies which confirmed this [*e.g. Klein Tank and* Können*, 2003, Manton et al., 2001, Vincent and Mekis, 2005, Brunet et al., 2005*] we have not been able to provide the answer over the globe as a whole. Considerable time and effort is required to enable the study of climate extremes because of the reluctance of institutions to distribute daily climatic data to others outside their own country. Groups such as the ETCCDMI provide the means for individuals or institutions to contribute to a global analysis whilst still feeling they have ownership of their data. This has allowed us to study the extremes of maximum and minimum temperature and precipitation more closely.

While we see warming and coherent patterns of change in some of the temperature extremes indices, other indices show more complex behaviour. Although maximum temperature distribution tails appear to be warming, the tails of the minimum temperature distribution are increasing at a much faster rate. From our results we might conclude that rather than getting considerably hotter, the global climate is becoming considerably less cold. Annual precipitation is significantly increasing but

changes in precipitation extremes are much harder to assess because of their lack of global coherence. However we do see significant changes in the behaviour of extreme precipitation from the beginning to the end of the 20th century.

Although this study has shown that the changes in the extremes of temperature and precipitation are significantly changing, to adequately assess these changes properly we need to analyse the whole of the temperature and precipitation distributions. For this we would require access to global daily data.

6. Conclusions

Here we have used high quality global station data to analyse a previously unseen picture of changes in global temperature and precipitation extremes during the 20th century.

Using a subset of stations with data between 1901 and 2003, a significant increase in the extremes of the minimum temperature distribution is evident. A substantial rise in warm night time 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 show a similar shift. The maximum temperature distribution tails are also significantly warming but the rise is smaller in magnitude. 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 show a tendency towards wetter conditions with the distributions from the 1979-2003 period significantly different from the 1901-1950 reference period for every index. However

changes in precipitation are more complex to assess because of the nature of the distribution of precipitation.

Using all stations with data between 1951 and 2003 we find that all indices exhibit a significant change between 1951-1958 and 1979-2003. Warming is apparent in all seasons although March-May generally exhibits the largest change and September to November the smallest change.

Analysis of the gridded results from 1951-2003 shows that over 70% of the land area sampled shows a significant increase in warm nights with a similar proportion of significant decrease in cold nights. For the majority of the temperature indices over 20% of the land area sampled exhibits a statistically significant change and all but one is field significant. The spatial correlation for precipitation is low but around 20% of grid boxes show a significant increase in annual total precipitation.

The timeseries of global results show a significant change associated with a warming climate in all the temperature indices. Seasonally March-May exhibits the greatest warming. Five of the precipitation indices exhibit a significant increase associated with a wetter climate.

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 than minimum temperature extremes. Most precipitation indices show a tendency towards wetter conditions but not all show statistically significant changes.

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 organisers and participants.

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Figure captions

Fig. 1: Locations of (a) temperature and (b) precipitation stations available for this study. The colours represent the different data sources that are described in the main text.

Fig. 2: An example of how the decorrelation length scale, L (Eqn. [1] & [2]), is derived. The solid black line represents the correlation values for each 100km bin and the red line is a 2nd order polynomial fit to these data. The blue dashed and dotted line shows how the value of L is determined. The remaining lines represent the exponential weighting functions from Eqn. 2 varying the value of parameter m i.e. m=1 (dotted line), m=4 (dashed line), m=10 (dashed dotted line).

Fig 3: Annual probability density functions for a selection of temperature indices for a subset of approximately 200 stations with at least 80% complete data between 1901 and 2003 for 3 time periods: 1901-1950 (black), 1951-1978 (blue) and 1979 – 2003 (red). The x-axis represents (a)-(d) the percentage of time during the year when the indicators were below the 10th percentile or above the 90th percentile and (e)-(h) number of days. PDF bin sizes are (a)-(d) 1, (e)-(f) 20 and (g)-(h) 5.

Fig 4: As Fig. 3 but for a selection of precipitation indices and a subset of approximately 350 stations with at least 80% complete data between 1901 and 2003 for 3 time periods. The x-axis represents (a), (c) & (d) amount in (mm) and (b) annual number of days when precipitation is above 10mm. PDF bin sizes are (a) & (b) 10, (c) & (d) 50.

Fig 5: Annual probability density functions for global stations in Fig. 1 with at least 80% of data for the indicators shown between 1951 and 2003 for 2 time periods: 1951-1978 (blue) and 1979–2003 (red). The x-axis represents (a)-(b) °C, (c)-(d) the percentage of time during the year when minimum temperature was below the 10th percentile and maximum temperature was above the 90th percentile respectively. PDF bin sizes are (a)-(b) 5 and (c)-(d) 1.

Fig 6: Seasonal probability density functions for occurrence of warm nights for (a) Dec-Feb, (b) Mar-May, (c) Jun-Aug and (d) Sep-Nov. Blue lines represent the period 1951-1978 and red lines 1979–2003.

Fig 7: 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. Black circles indicate a non-significant change. Red (blue) filled circles indicate a significant increase (decrease) at the 5% level.

Fig 8: Observed trends per decade for 1951 to 2003 for the extreme and percentile temperature indices. Trends were only calculated for stations which had at least 40 years of data during this period and had data until at least 1999. Black lines enclose regions where trends are significant at the 5% level using the method of *Wang and Swail,* [2001].

Fig 9: Observed trends per decade for 1951 to 2003 for two precipitation indices i.e. total annual precipitation (PRCPTOT) and annual number of consecutive dry days. Criteria for trend calculation as Fig 8.

Fig 10: Observed percentage decadal trends in the seasonal occurrence of cold nights between 1951 and 2003. Criteria for trend calculation as Fig 8.

Fig 11: Observed decadal trends (mm) in the seasonal occurrence of maximum 5-day precipitation between 1951 and 2003. Criteria for trend calculation as Fig 8.

Fig 12: The globally averaged timeseries of (a) the annual number of days when precipitation was greater than or equal to 10mm (expressed as an anomaly from the 1961-1990 reference period) and (b) the percentage contribution to total annual precipitation from very wet days. The smoothed line is a 21-term binomial fit to the data to show decadal variations.

Fig 13: Global annual timeseries anomalies (with respect to 1961-1990) for (a) cold nights (TN10p), (b) warm nights (TN90p), (c) cold days (TX10p), (d) warm days (TX90p). The red line shows a 21-term binomial fit to the data to show decadal variations. Trends are significant at the 5% level for all the indices shown using a modified Kendall tau test (*Wang and Swail*, [2001]).

Fig 14: As Fig 13 but for seasonal timeseries of results for warm nights (TN90p).

Tables

ID	Indicator name	Indicator definitions	UNITS
TXx	Max Tmax	Let Tx_{kj} be the daily maximum temperatures in month k, period j. The maximum daily maximum temperature each month is then $TXx_{kj} = \max(Tx_{kj})$	°C
TNx	Max Tmin	Let Tn_{kj} be the daily minimum temperatures in month k, period j. The maximum daily minimum temperature each month is then $TNx_{kj} = \max(Tn_{kj})$	°C
TXn	Min Tmax	Let Tx_{kj} be the daily maximum temperatures in month k, period j. The minimum daily maximum temperature each month is then $TXn_{kj} = \min(Tx_{kj})$	°C
TNn	Min Tmin	Let Tn_{kj} be the daily minimum temperatures in month k, period j. The minimum daily minimum temperature each month is then $TNn_{kj} = \min(Tn_{kj})$	°C
TN10p	Cold nights	Let Tn_{ij} be the daily minimum temperature on day i in period j and let $Tn_{in}10$ be the calendar day 10th percentile centred on a 5-day window (Zhang et al., 2005b). The percentage of time is determined where $Tn_{ij} < Tn_{in}10$	Days
TX10p	Cold days	Let Tx_{ij} be the daily maximum temperature on day i in period j and let $Tx_{in}10$ be the calendar day 10th percentile centred on a 5-day window (Zhang et al., 2005b). The percentage of time is determined where $Tx_{ij} < Tx_{in}10$	Days
TN90p	Warm nights	Let Tn_{ij} be the daily minimum temperature on day i in period j and let $Tn_{in}90$ be the calendar day 90th percentile centred on a 5-day window (Zhang et al., 2005b). The percentage of time is determined where $Tn_{ij} > Tn_{in}90$	Days
TX90p	Warm days	Let Tx_{ij} be the daily maximum temperature on day i in period j and let $Tx_{in}90$ be the calendar day 90th percentile centred on a 5-day window (Zhang et al., 2005b). The percentage of time is determined where $Tx_{ij} > Tx_{in}90$	Days
DTR	Diurnal temperature range	Let Tx_{ij} and Tn_{ij} be the daily maximum and minimum temperature respectively on day i in period j. If I represents the number of days in j, then $$DTR_j = \frac{\sum_{i=1}^{I}(Tx_{ij} - Tn_{ij})}{I}$$	°C
FD0	Frost days	Let Tn_{ij} be the daily minimum temperature on day i in period j. Count the number of days where $Tn_{ij} < 0°C$	Days
SU25	Summer days	Let Tx_{ij} be the daily maximum temperature on day i period j. Count the number of days where $Tx_{ij} > 25°C$	Days
ID0	Ice days	Let Tx_{ij} be the daily maximum temperature on day i in period j. Count the number of days where $Tx_{ij} < 0°C$	Days
TR20	Tropical nights	Let Tn_{ij} be the daily minimum temperature on day i in period j. Count the number of days where $Tn_{ij} > 20°C$	Days
GSL	Growing season Length	Let T_{ij} be the mean temperature on day i in period j. Count the number of days between the first occurrence of at least 6 consecutive days with $T_{ij} > 5^oC$ and the first occurrence after 1st July (1st January in SH) of at least 6 consecutive days with $T_{ij} < 5^oC$	Days
WSDI*	Warm spell duration indicator	Let Tx_{ij} be the daily maximum temperature on day i in period j and let $Tx_{in}90$ be the calendar day 90th percentile centred on a 5-day window (Zhang et al., 2005b). Then the number of days per period is summed where, in intervals of at least 6 consecutive days:- $Tx_{ij} > Tx_{in}90$	Days

CSDI*	Cold spell duration indicator	Let Tn_{ij} be the daily minimum temperature at day i in period j and let $Tx_{in}10$ be the calendar day 10th percentile centred on a 5-day window (Zhang et al., 2005b). Then the number of days per period is summed where, in intervals of at least 6 consecutive days:- $$Tn_{ij} < Tn_{in}10$$	Days
RX1day	Max 1-day precipitation amount	Let RR_{ij} be the daily precipitation amount on day i in period j. Then the maximum 1-day values each month is $Rx1day_j = \max(RR_{ij})$	Mm
RX5day	Max 5-day precipitation amount	Let RR_{kj} be the precipitation amount for the 5-day interval ending k, period j. Then maximum 5-day values for period j are $Rx5day_j = \max(RR_{kj})$	Mm
SDII	Simple daily intensity index	Let RR_{wj} be the daily precipitation amount on wet days, $w(RR \geq 1mm)$ in period j. If W represents number of wet days in j, then $$SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W}$$	Mm/day
R10	Number of heavy precipitation days	Let RR_{ij} be the daily precipitation amount on day i in period j. Count the number of days where $RR_{ij} \geq 10mm$	Days
R20	Number of very heavy precipitation days	Let RR_{ij} be the daily precipitation amount on day i in period j. Count the number of days where $RR_{ij} \geq 20mm$	Days
CDD*	Consecutive dry days	Let RR_{ij} be the daily precipitation amount on day i in period j. Count the largest number of consecutive days where $RR_{ij} < 1mm$	Days
CWD*	Consecutive wet days	Let RR_{ij} be the daily precipitation amount on day i in period j. Count the largest number of consecutive days where $RR_{ij} \geq 1mm$	Days
R95p	Very wet days	Let RR_{wj} be the daily precipitation amount on a wet day $w(RR \geq 1.0mm)$ in period j and let $RR_{wn}95$ be the 95th percentile of precipitation on wet days in the 1961-1990 period. If W represents the number of wet days in the period, then $$R95p_j = \sum_{w=1}^{W} RR_{wj} \text{ where } RR_{wj} > RR_{wn}95$$	Mm
R99p	Extremely wet days	Let RR_{wj} be the daily precipitation amount on a wet day $w(RR \geq 1.0mm)$ in period j and let $RR_{wn}99$ be the 99th percentile of precipitation on wet days in the 1961-1990 period. If W represents number of wet days in the period, then $$R99p_j = \sum_{w=1}^{W} RR_{wj} \text{ where } RR_{wj} > RR_{wn}99$$	mm
Rnn	Number of days above nn mm	Let RR_{ij} be the daily precipitation amount on day i in period j. If nn represents any reasonable daily precipitation value then, count the number of days where $RR_{ij} \geq nnmm$	Days
PRCPTOT	Annual total wet-day precipitation	Let RR_{ij} be the daily precipitation amount on day i in period j. If I represents the number of days in j, then $$PRCPTOT_j = \sum_{i=1}^{I} RR_{ij}$$	mm

Table 1. Extreme temperature and precipitation indices recommended by the ETCCDMI. See also http://cccma.seos.uvic.ca/ETCCDMI/list_27_indices.html. For

spell/duration indices (marked with a *), a spell can continue into the next year and is

counted against the year in which the spell ends.

Indicator	60N-90N	30N-60N	0-30N	0-30S	30S-90S
TNn	1067	1391	1330	707	580
TNx	804	596	185	448	393
TXx	717	794	239	555	583
TXn	1219	1037	1165	598	608
TN10p	1466	2000	674	809	581
TN90p	1536	1493	2000	728	866
TX10p	1554	1926	855	947	1091
TX90p	1552	1271	764	1051	910
R10	363	382	340	601	353
R20	253	187	232	586	266
CDD	463	278	459	277	208
CWD	318	284	140	422	122

Table 2. Annual decorrelation length scales (in km) for the absolute and percentile

temperature indices and the threshold and duration precipitation indices. A value of

2000km means that the fitted function did not fall below $1/e$ (see text).

Indicator	1951-2003		
	Total grid points	+ve significant trend (%)	-ve significant trend (%)
Maximum Tmax (TXx)	1036	10.8	2.4
Maximum Tmin (TNx)	994	**24.1**	0.8
Minimum Tmax (TXn)	1342	**27.5**	2.9
Minimum Tmin (TNn)	1369	**41.3**	1.5
Cold nights (TN10p)	1312	0.1	**76.3**
Cold days (TX10p)	1353	0.2	**46.0**
Warm nights (TN90p)	1459	**72.2**	0.1
Warm days (TX90p)	1298	**39.5**	0.5
Diurnal temperature range (DTR)	1030	4.2	**38.6**
Frost days (FD0)	1062	0.3	**39.8**
Summer days (SU25)	978	**23.3**	3.1
Ice days (ID0)	1016	1.3	**24.6**
Tropical nights (TR20)	1079	**31.3**	1.3
Growing season length (GSL)	877	**17.8**	1.1
Warm spell duration (WSDI)	889	**19.3**	0.3
Cold spell duration (CSDI)	1048	3.6	**33.0**
Maximum 1-day precip (RX1day)	155	5.1	2.6
Maximum 5-day precip (RX5day)	356	7.3	1.7
Simple daily intensity (SDII)	375	**11.7**	1.6
Heavy precipitation days (R10mm)	784	11.7	3.4
Very heavy precipitation days (R20mm)	380	12.6	2.6
Consecutive dry days (CDD)	643	2.0	9.8
Consecutive wet days (CWD)	488	6.1	3.1
Annual total precipitation (PRCPTOT)	1032	**20.7**	4.4
Very wet days (R95p)	376	9.3	1.3
Extremely wet days (R99p)	128	4.7	1.6

Table 3: The percentage of land area sampled showing significant annual trends for each indicator in Table 1. The total number of global land grid points for the latitude-longitude grid chosen is 2291. Bold indicates field significance.

1951-2003	DJF			MAM			JJA			SON		
Indicator	N	+ve	-ve	N	+ve	-ve	N	+ve	-ve	N	+ve	-ve
TXx	1325	21.1	4.7	1300	23.2	2.3	1315	16.5	3.1	1278	12.0	2.0
TNx	1284	34.5	3.3	1334	39.0	2.0	1278	30.6	0.6	1178	21.6	0.9
TXn	1387	29.1	2.5	1391	31.2	2.4	1258	13.0	3.5	1385	19.0	2.0
TNn	1381	40.5	1.3	1378	54.0	1.3	1298	34.4	1.5	1440	35.8	0.3
TN10p	1373	0.1	42.0	1296	0.2	62.2	1259	0.6	44.6	1376	0.4	43.4
TX10p	1270	0.5	25.8	1295	0.5	35.4	1250	2.5	18.1	1252	1.0	7.7
TN90p	1392	37.5	0.5	1342	49.6	0.5	1294	41.0	0.1	1205	29.5	0.33
TX90p	1275	20.9	2.7	1281	24.3	2.7	1149	16.0	1.4	1147	5.8	0.0
DTR	1225	2.9	38.4	1165	4.2	34.2	984	5.3	20.1	1079	1.8	26.5
RX1day	752	10.6	3.2	584	7.2	1.0	599	4.5	1.8	737	9.2	2.0
RX5day	924	14.9	3.0	767	10.8	1.4	737	5.4	2.2	772	10.0	1.4

Table 4: The 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. The number of gridboxes sampled for each index and season is denoted by N.

Figures

(a) Temperature stations

(b) Precipitation stations

Fig. 1: Locations of (a) temperature and (b) precipitation stations available for this study. The colours represent the different data sources that are described in the main text.

Fig. 2: An example of how the decorrelation length scale, *L* (Eqn. [1] & [2]), is derived. The solid black line represents the correlation values for each 100km bin and the red line is a 2nd order polynomial fit to these data. The blue dashed and dotted line shows how the value of *L* is determined. The remaining lines represent the exponential weighting functions from Eqn. 2 varying the value of parameter m i.e. m=1 (dotted line), m=4 (dashed line), m=10 (dashed dotted line).

Fig 3: Annual probability density functions for a selection of temperature indices for a

subset of approximately 200 stations with at least 80% complete data between 1901

and 2003 for 3 time periods: 1901-1950 (black), 1951-1978 (blue) and 1979 – 2003

(red). The x-axis represents (a)-(d) the percentage of time during the year when the

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indicators were below the 10th percentile or above the 90th percentile and (e)-(h) number of days. PDF bin sizes are (a)-(d) 1, (e)-(f) 20 and (g)-(h) 5.

Fig 4: As Fig. 3 but for a selection of precipitation indices and a subset of approximately 350 stations with at least 80% complete data between 1901 and 2003 for 3 time periods. The x-axis represents (a), (c) & (d) amount in (mm) and (b) annual number of days when precipitation is above 10mm. PDF bin sizes are (a) & (b) 10, (c) & (d) 50.

Fig 5: Annual probability density functions for global stations in Fig. 1 with at least 80% of data for the indicators shown between 1951 and 2003 for 2 time periods: 1951-1978 (blue) and 1979–2003 (red). The x-axis represents (a)-(b) °C, (c)-(d) the percentage of time during the year when minimum temperature was below the 10th percentile and maximum temperature was above the 90th percentile respectively. PDF bin sizes are (a)-(b) 5 and (c)-(d) 1.

Fig 6: Seasonal probability density functions for occurrence of warm nights for (a) Dec-Feb, (b) Mar-May, (c) Jun-Aug and (d) Sep-Nov. Blue lines represent the period 1951-1978 and red lines 1979–2003.

Fig 7: 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. Black circles indicate a non-significant change. Red (blue) filled circles indicate a significant increase (decrease) at the 5% level.

Fig 8: Observed trends per decade for 1951 to 2003 for the extreme and percentile temperature indices. Trends were only calculated for stations which had at least 40 years of data during this period and had data until at least 1999. Black lines enclose

regions where trends are significant at the 5% level using the method of *Wang and Swail,* [2001].

Fig 9: Observed trends per decade for 1951 to 2003 for two precipitation indices i.e. total annual precipitation (PRCPTOT) and annual number of consecutive dry days. Criteria for trend calculation as Fig 8.

Decadal trends (%) in occurrence of cool nights (TN10p)

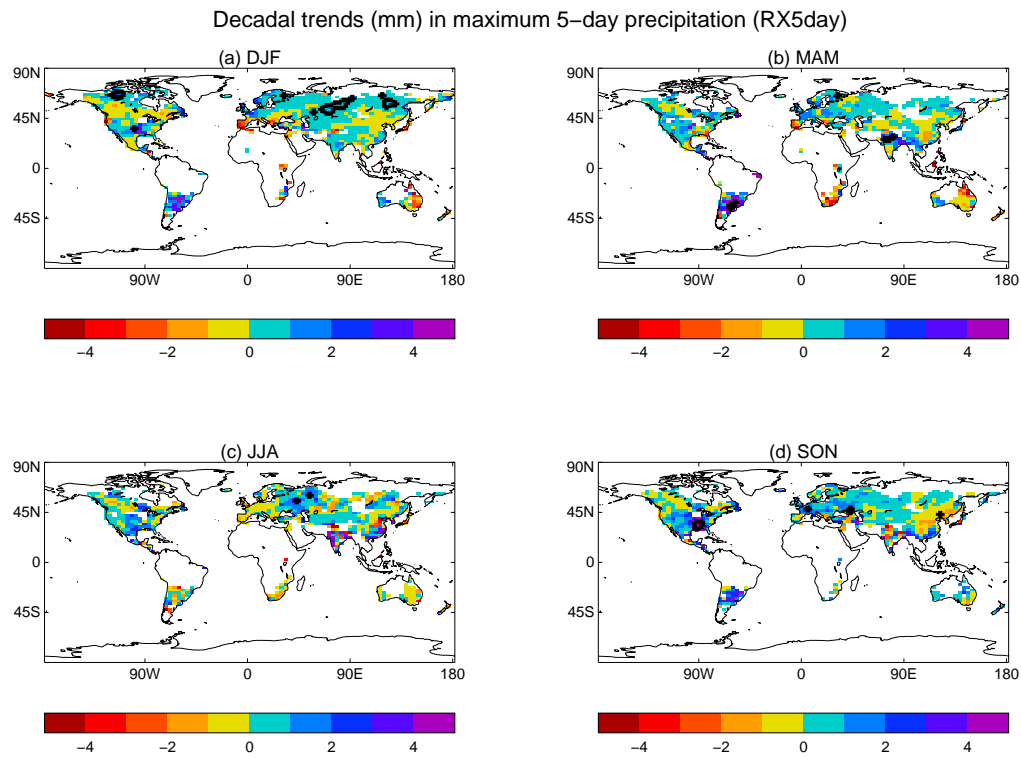Fig 10: Observed percentage decadal trends in the seasonal occurrence of cold nights between 1951 and 2003. Criteria for trend calculation as Fig 8.

Decadal trends (mm) in maximum 5–day precipitation (RX5day)

Fig 11: Observed decadal trends (mm) in the seasonal occurrence of maximum 5-day precipitation between 1951 and 2003. Criteria for trend calculation as Fig 8.
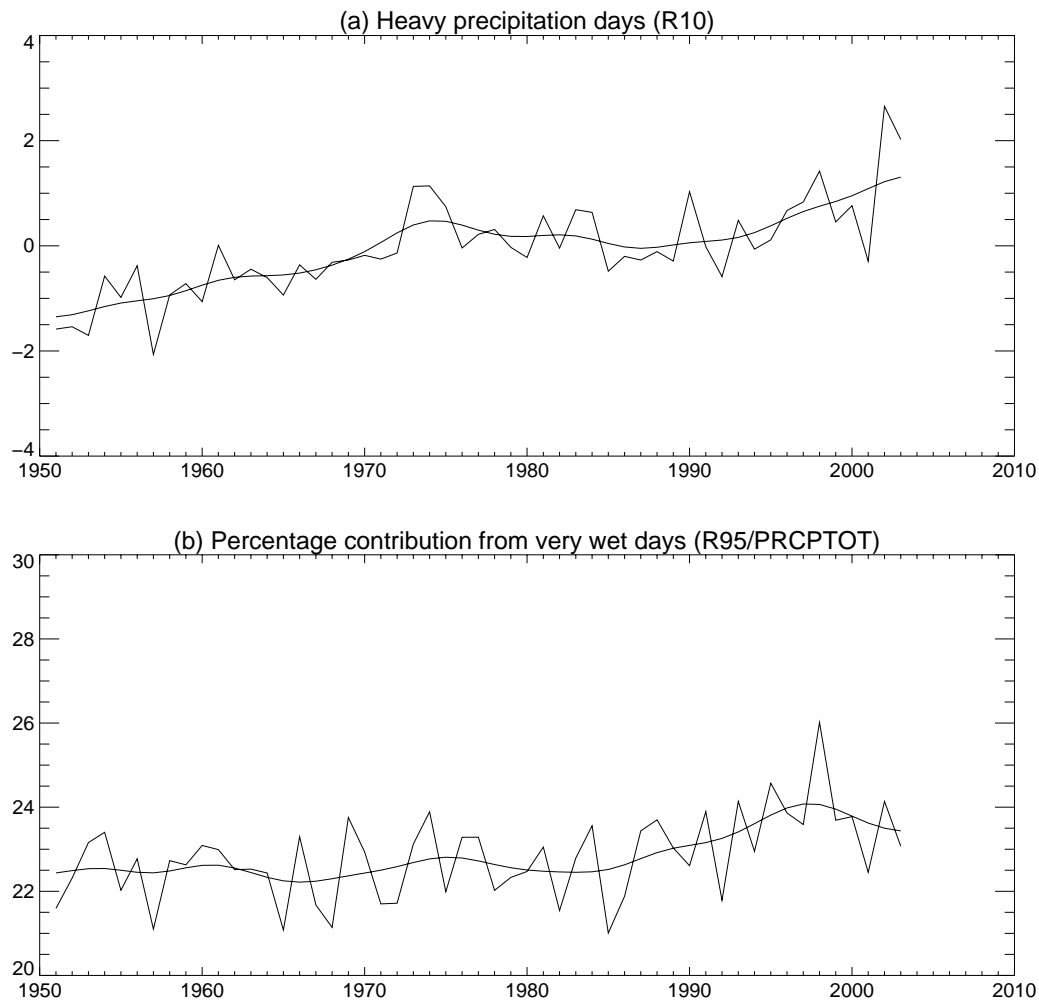
Fig 12: The globally averaged timeseries of (a) the annual number of days when precipitation was greater than or equal to 10mm (expressed as an anomaly from the 1961-1990 reference period) and (b) the percentage contribution to total annual precipitation from very wet days. The smoothed line is a 21-term binomial fit to the data to show decadal variations.
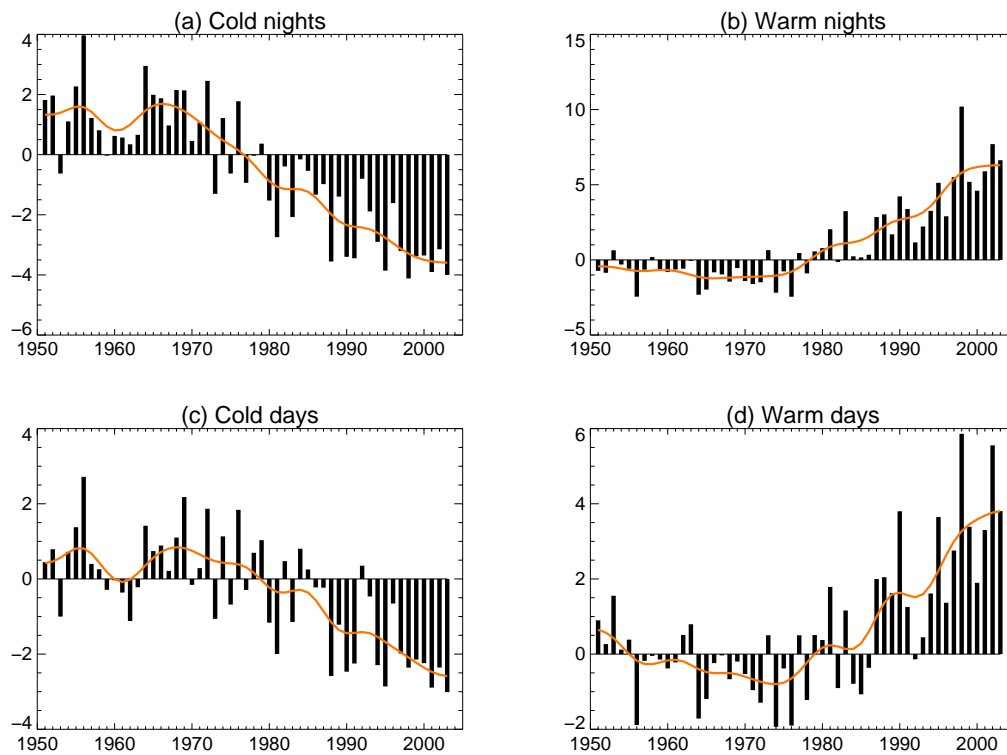
Fig 13: Global annual timeseries anomalies (with respect to 1961-1990) for (a) cold nights (TN10p), (b) warm nights (TN90p), (c) cold days (TX10p), (d) warm days (TX90p). The red line shows a 21-term binomial fit to the data to show decadal variations. Trends are significant at the 5% level for all the indices shown using a modified Kendall tau test (*Wang and Swail*, [2001]).
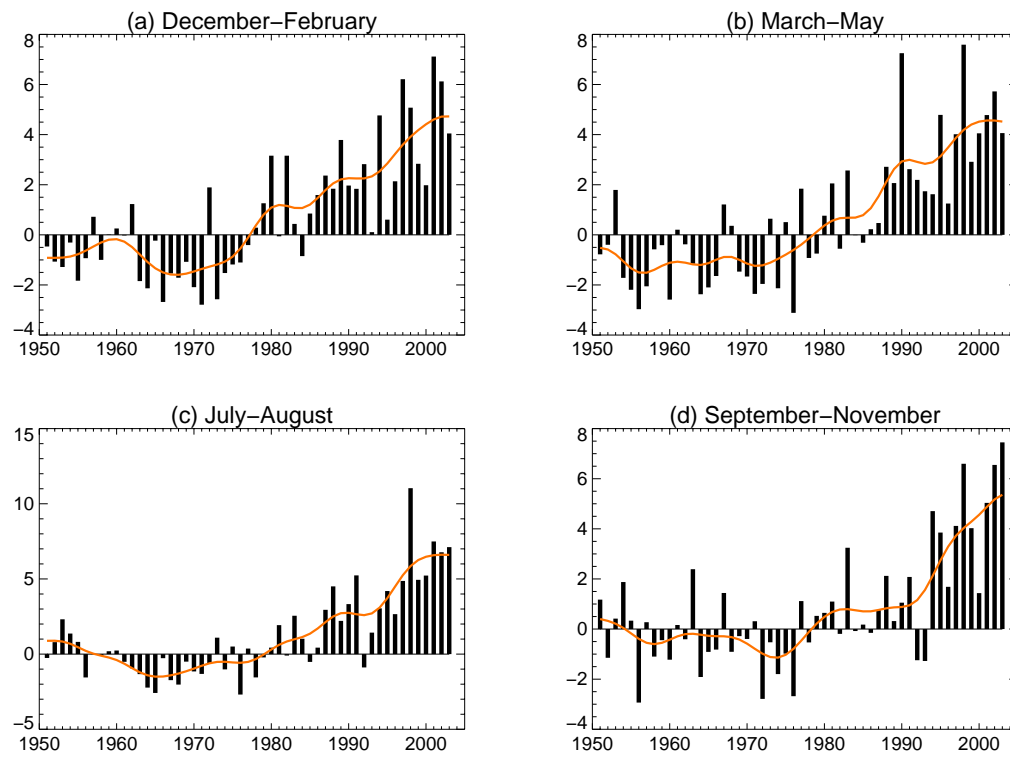
Fig 14: As Fig 13 but for seasonal timeseries of results for warm nights (TN90p).