Advanced Review

Indices for monitoring changes in extremes based on daily temperature and precipitation data

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Indices for climate variability and extremes have been used for a long time, often by assessing days with temperature or precipitation observations above or below specific physically-based thresholds. While these indices provided insight into local conditions, few physically based thresholds have relevance in all parts of the world. Therefore, indices of extremes evolved over time and now often focus on relative thresholds that describe features in the tails of the distributions of meteorological variables. In order to help understand how extremes are changing globally, a subset of the wide range of possible indices is now being coordinated internationally which allows the results of studies from different parts of the world to fit together seamlessly. This paper reviews these as well as other indices of extremes and documents the obstacles to robustly calculating and analyzing indices and the methods developed to overcome these obstacles. Gridding indices are necessary in order to compare observations with climate model output. However, gridding indices from daily data are not always straightforward because averaging daily information from many stations tends to dampen gridded extremes. The paper describes recent progress in attribution of the changes in gridded indices of extremes that demonstrates human influence on the probability of extremes. The paper also describes model projections of the future and wraps up with a discussion of ongoing efforts to refine indices of extremes as they are being readied to contribute to the IPCC's Fifth Assessment Report.

How to cite this article:
WIREs Clim Change 2011. doi: 10.1002/wcc.147

INTRODUCTION

According to an old saying, a person standing with one foot on a hot stove and the other on a block of ice is comfortable on average. The corollary in climate science is that monthly averages smooth over a lot of important information such as that which characterizes the behavior of extremes that are usually responsible for impacts. Indices derived from daily data are an attempt to objectively extract information from daily weather observations that answers questions concerning extremes that affect many human and natural systems. These questions include: has the heaviest daily precipitation event in a year changed significantly over time, have the number of days below freezing decreased, or are heat waves

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becoming longer or more intense? This paper reviews practice and research pertaining to a wide variety of such indices.

Two types of indices not addressed in this paper are those dealing with drought and tropical cyclones. In both cases, there are specific, complex issues that affect indices describing these phenomena and the underlying data from which the indices are derived. Also, in both cases there is a well developed literature that has been summarized in recent authoritative review articles.[1–3]

CLIMATE INDICES FROM DAILY DATA

Rationale for the Use of Indices

As many aspects of climate are well represented by monthly means, most indices derived from daily data generally focus on extremes. Figure 1[4,5] shows a stylized representation of extremes. Two main differences in various indices of extremes are (1) how the distribution was defined, and (2) how far into the tails of the distribution the index threshold is located. Generally speaking, indices that characterize aspects of the far tails of the distribution tend to be more relevant to society and natural systems than indices that characterize aspects of the distribution that occur more frequently. This is because the more extreme an event, the more likely it is to cause societal or environmental damage. However, analyses of changes in the frequency or intensity of extremes that are further out in the tail of the distribution are inherently more uncertain because such events occur less frequently, with the result that less data are available to identify and characterize possible changes. For example, with 50 years of daily data, which is the typical length of daily temperature or precipitation records at meteorological stations, it is difficult, if not impossible, to estimate changes in the frequency of events with a 50-year return period. Therefore a compromise must be made between uncertainty and the rarity of events that indices represent.

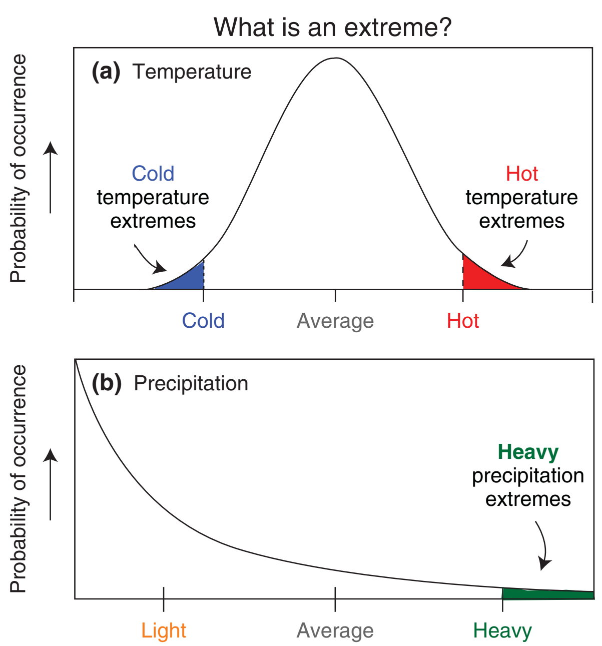

FIGURE 1 | The probability distributions of daily temperature and precipitation. The higher the black line, the more often weather with those characteristics occurs. Extremes are denoted by the shaded areas. (Reprinted with permission from Ref 4. Copyright 2005 Intergovernmental Panel on Climate Change)

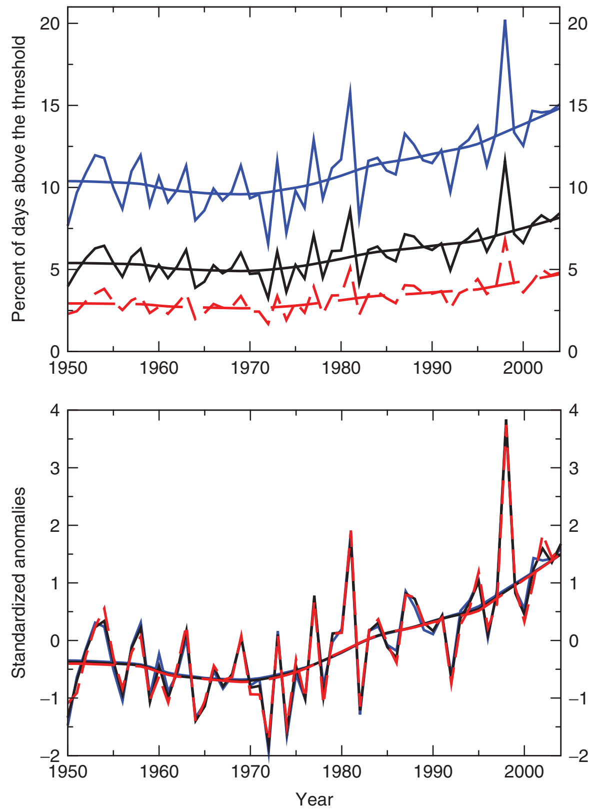

FIGURE 2 | Top: Percent of days exceeding the 90th (blue), 95th (black) and 97.5th (red dashed line) percentiles North American minimum temperature. Bottom: Standardized anomalies of the time series in the top panel. The thick smoothed lines are from a LOWESS filter applied to the annual time series. The climate change signal averaged over North America is essentially identical for each of these three thresholds for extremes. (Reprinted with permission from Ref 6. Copyright 2008 American Geophysical Union)

Most indices of extremes tend to examine only 'moderate extremes', that is, those that are typically occurring at least once a year. Interestingly, as shown in Figure 2,[6] indices that consider different points in the tails of the distribution sometimes reveal very similar climate signals. However, even for temperature, changes may be seen that are not consistent between means and extremes, minimum and maximum, and upper and lower tail.[7,8] Some indices for climate extremes can also be used for secondary inference; for example, statistical theory on extreme values can be used to estimate long return period precipitation amounts, such as the 1-in-20 year daily precipitation amount, from time series of annual maximum daily precipitation[9] that are sufficiently long.

Historical Use of Metrics of Extremes

Information about certain types of extremes has been collated for many years. Information about the number of days with frost, and/or the date of the first autumn and last spring frost, has been collected in some areas since mediaeval times. In some areas such collections form part of the documentary record from which information about climate in the preinstrumental period is inferred.[10] A related variable, the growing season length (defined as the length of time between the first and last occasions in a year when the temperature is warm enough for plants to grow), has also been of interest for many years. These indices are almost invariably based on fixed, rather than relative, thresholds (such as the occurrence of a temperature below 0 °C), where the threshold may be dependent upon the particular type of plant of interest since different types of plants begin to grow at different temperature thresholds.

Information on the number of days above or below certain fixed thresholds in a given month/year has been published routinely since the 19th century (see, e.g., Ref 11). For much of the 20th century, information reported on such extremes was often in climatological form—such as long-term averages of the number of days on which a threshold was reached in particular locations. Climatologies of this type were particularly common for frost[12–15] but were also produced for extreme hot days[16,17] or other extremes.

Lamb[18] reported on changes in the length of the growing season in England over the 1900–1975 period, but otherwise analyses of changes in metrics of extremes were virtually nonexistent in the international literature until the 1990s. The IPCC First Assessment Report[19] reported no information on extremes at daily or similar timescales; the only extremes considered were those at seasonal and longer timescales. By the time of the IPCC Second Assessment Report[20] (SAR), a limited number of studies had begun to appear (see, e.g., Ref 21), although larger-scale regional analyses were still generally lacking. Furthermore, whilst the use of relative thresholds for analysis of extremes of monthly or seasonal mean temperature extends back to the 1970s[22] (and even earlier for drought indices), it was not until the second half of the 1990s that the first papers, many of which arose from the 1997 Asheville workshop (see below), appeared using relative thresholds for daily extremes.

The Use of Indices for Monitoring Changes in Climate Extremes

While much progress has been made in recent decades, the lack of high-quality analyses and credible data has been a major obstacle to assessing changes in extremes.[23] In 1995, the SAR noted that 'the data on climate extremes and variability are inadequate to say anything about global changes', even though changes in extreme weather events were observed in some regions where sufficient data were available.[24] As a result, the assembly of high-quality and credible historical time-series of key variables clearly became the first step towards the detection and attribution of changes in climate extremes. To this end, the World Meteorological Organization (WMO) CLIVAR[a]/GCOS[b] organized an international Workshop on Indices and Indicators for Climate Extremes in Asheville, North Carolina, 3–6 June 1997, to encourage the development of data sets, and analysis techniques, to determine whether such extreme events are becoming more extreme or variable.[25] The ideas discussed during the workshop and the recommendations that were made resulted in many international projects that have produced much better analyses on extremes both at global[26] and regional[27] scales. As a result, there was much more to say on extremes in the IPCC 4th Assessment Report.[28]

At the November 1999 meeting of what is now known as the joint CCl[c]/CLIVAR/JCOMM[d] Expert Team on Climate Change Detection and Indices (ETCCDI), it was recognized that a two-pronged approach was needed to promote further work on the monitoring and analysis of daily climate records to identify trends in extreme climate events.[27] First, it was recognized that it was important to document the exact formulation of an internationally agreed suite of indices of climate extremes from daily precipitation and temperature data. The use of agreed indices allows comparison of analyses conducted in any part of the world and seamless merging of index data to produce a global picture as well. The second prong was to promote the analysis of extremes around the world, particularly in less developed countries, by organizing regional climate-change workshops that provided training for the local experts and conducted data analysis. These series workshops were modelled from the pioneering December 1998 Asia-Pacific Network for Global Change Research (APN) meeting in Melbourne. See Section 4 for more detail on the workshops.

Unfortunately very few of the participants were able to release their country's daily data at that time (although data availability has gradually improved over the last 15 years) but many were willing to release the indices derived from their data. The station time series of 27 indices from daily data produced by workshops or computed from global historical climate network (GHCN) daily data are available from http://cccma.seos.uvic.ca/ETCCDI/. These series allow assessments of how extremes are changing in many parts of the world, with the caveat that these assessments are only as good as the processing of the underlying daily data (such as homogeneity adjustments), and that the data are still often not openly available. Nevertheless, this is a significant step forward in providing answers to the question of whether the climate has become more variable or extreme.

THE CURRENTLY USED CLIMATE INDICES

In order to detect changes in climate extremes, it is important to develop a set of indices that are statistically robust, cover a wide range of climates, and have a high signal-to-noise ratio. Internationally agreed indices derived from daily temperature and precipitation allow results to be compared consistently across different countries and also have the advantage of overcoming most of the restrictions on the dissemination of daily data that are applied in many countries. It should be recognized that in addition to the agreed ETCCDI indices, individual groups have developed different, though sometimes overlapping, sets of indices in response to different objectives.[29–32]

The Current ETCCDI Indices

Frich et al.[33] defined a suite of indices that have subsequently become known as the 'ETCCDI' indices and that were based on the European Climate Assessment (ECA) indices[29] to analyze trends for the second half of the 20th century. These indices were chosen to sample a wide variety of climates and included indicators such as the total number of days annually with frost and the maximum number of consecutive dry days in a year. They also included a definition of heat waves with at least five consecutive days where daily maximum temperature was greater than a fixed threshold of 5 °C above a 1961–1990 base period mean. It is now recognized that this definition is difficult to apply in places where day-to-day variability in temperature is very small, such as tropical regions, and a more flexible indicator of heat waves has therefore been proposed.[34] ETCCDI adopted most of the ECA indices,[29] but modified those that appeared problematic when applied to a wide range of areas. In total, 27 indices were defined (see Table 1). ETCCDI also developed new methods to address inhomogeneity issues inherent in the original calculation of some ECA indices.

One type of index measures the monthly and/or annual maxima or minima of daily temperature or maximum amount of daily precipitation. These types of extremes indices have been widely used in engineering applications to infer design values for engineering structures. Another type of index involves the calculation of the number of days in a year exceeding specific thresholds that have fixed values or thresholds that are relative to a base period climate. Some other indices are defined to measure periods of dryness, wetness, heat or cold, or periods of mildness as in the case of growing season length periods.

Examples of 'day-count' indices with fixed thresholds are the number of days with daily minimum temperature below 0 °C (i.e., frost days) or the number of days with rainfall amount higher than 20 mm. These indices are less suitable for spatial comparisons of extremes than those based on percentile thresholds. The reason is that, over large areas, day-count indices based on fixed thresholds may sample very different parts of the temperature and precipitation distributions. For example, while the number of days with a minimum temperature below 0 °C may be a good indicator of extreme cold in many mid-latitude climates, at higher latitudes, where nearly all winter nights are below 0 °C even in mild winters, variability in the annual number of nights below 0 °C is driven largely by conditions in spring and autumn. Furthermore, an index such as the number of summer days above 25 °C may be an indicator of abnormal warmth in a climate where the mean summer maximum temperature is 18 °C, but, in effect, one of abnormal cold in a climate where the mean summer maximum temperature is 35 °C.

An example of a 'day-count' index with thresholds relative to base period climatology is the number of days with minimum temperature below the long-term 10th percentile of the 1961–1990 base period. Many ETCCDI indices are based on percentiles with thresholds set to assess moderate extremes that typically occur a few times every year rather than high impact, once-in-a-decade weather events. For temperature, the percentile thresholds in the ETCCDI indices are calculated from five-day windows centered on each calendar day to account for the mean annual cycle. For

TABLE 1 | The Extreme Temperature and Precipitation Indices Recommended by the ETCCDI (Some User Defined Indices are Not Shown)

ID	Indicator Name	Indicator Definitions	Units
TXx	Max Tmax	Monthly maximum value of daily max temperature	°C
TNx	Max Tmin	Monthly maximum value of daily min temperature	°C
TXn	Min Tmax	Monthly minimum value of daily max temperature	°C
TNn	Min Tmin	Monthly minimum value of daily min temperature	°C
TN10p	Cool nights	Percentage of time when daily min temperature < 10th percentile	%
TX10p	Cool days	Percentage of time when daily max temperature < 10th percentile	%
TN90p	Warm nights	Percentage of time when daily min temperature > 90th percentile	%
TX90p	Warm days	Percentage of time when daily max temperature > 90th percentile	%
DTR	Diurnal temperature range	Monthly mean difference between daily max and min temperature	°C
GSL	Growing season length	Annual (1st Jan to 31st Dec in NH, 1st July to 30th June in SH) count between first span of at least 6 days with TG>5 °C and first span after July 1 (January 1 in SH) of 6 days with TG<5 °C	days
FD0	Frost days	Annual count when daily minimum temperature < 0 °C	days
SU25	Summer days	Annual count when daily max temperature > 25 °C	days
TR20	Tropical nights	Annual count when daily min temperature > 20 °C	days
WSDI	Warm spell duration indicator	Annual count when at least six consecutive days of max temperature > 90th percentile	days
CSDI	Cold spell duration indicator	Annual count when at least six consecutive days of min temperature < 10th percentile	days
RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
RX5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
SDII	Simple daily intensity index	The ratio of annual total precipitation to the number of wet days (≥ 1 mm)	mm/day
R10	Number of heavy precipitation days	Annual count when precipitation ≥ 10 mm	days
R20	Number of very heavy precipitation days	Annual count when precipitation ≥ 20 mm	days
CDD	Consecutive dry days	Maximum number of consecutive days when precipitation < 1 mm	days
CWD	Consecutive wet days	Maximum number of consecutive days when precipitation ≥ 1 mm	days
R95p	Very wet days	Annual total precipitation from days > 95th percentile	mm
R99p	Extremely wet days	Annual total precipitation from days > 99th percentile	mm
PRCPTOT	Annual total wet-day precipitation	Annual total precipitation from days ≥ 1 mm	mm

Precise definitions are given at http://cccma.seos.uvic.ca/ETCCDI/list_27_indices.html.

precipitation, the percentile thresholds in the ETCCDI indices are calculated from the sample of all wet days in the base period without consideration of the annual cycle. Such indices allow straightforward monitoring of trends in the frequency or intensity of events, which, while not particularly extreme, would nevertheless potentially cause stress to humans or the environment. The reason for choosing percentile thresholds is that the number of days exceeding percentile thresholds is more evenly distributed in space and is meaningful in every region. The thresholds are set so that the frequency of threshold crossing during the base period, such as 10% of all recorded days, is fixed. Such indices allow for spatial comparisons over large regions with complex topography because they sample the same part of the probability distribution of temperature and precipitation at each location. They also can account for isolated missing values in a relatively straightforward fashion.

Comparison of Indices Defined by Different Groups

Indices defined by different groups may be similar and may have similar names. However, the way in which they are defined and how they are calculated can be quite different. This is particularly the case for the percentile-based temperature indices that include exceedance rates of temperature smaller than the 10th percentile or larger than 90th percentile, as well as heat wave or cold spell related indices. Haylock and Goodess[30] computed the 10th and 90th percentiles based on all available data, summer and winter, within the base period. This creates challenges for the interpretation of these indices from an extremes perspective because the 10th and 90th percentiles of annual daily temperature are close to the medians of winter and summer temperatures respectively in many climates. The long-term changes in the 10th and 90th percentile exceedance would therefore largely reflect mean winter and summer temperature changes, respectively, at most locations except those at very low latitudes or some coastal regions. On the other hand, the percentile-based thresholds in the ETCCDI/ECA approach are computed for each calendar day using data for a consecutive 5-day moving windows centered on that calendar day from the base period. The data sample is relatively small and biases in the exceedance rates need to be considered. As the threshold changes within the year, cold spells or heat waves that are defined as daily temperatures away from those thresholds are defined only in a relative sense. This latter approach means, for example, that a location could experience what would be classified as a heat wave in the middle of winter. Thus the choice of index may be influenced by the application—an absolute annual index may be most suitable for many impacts applications, whereas relative indices may be best for assessing changes in synoptic situations favourable for extreme temperatures. Hence the term heat wave can mean very different things depending on the index formulation. Note that seasonal splicing of index data can be helpful for both impacts studies and to characterize variations in extremes due to climate dynamics (see, for example, Refs 35 and 36).

The ETCCDI set of indices form a core set of indices that can be calculated in a similar way everywhere. Additional locally defined indices have also been calculated in various parts of the world to highlight particular characteristics of climate change in those regions or changes in variables other than temperature or precipitation.[29–32]

CONSIDERATIONS IN COMPUTING INDICES

Requirement for Homogeneity Assessment of Underlying Data

Homogeneity implies consistency of a series through time and is an obvious requirement for the robust analysis of climate time series. While many of the time series that are used for indices calculations have been adjusted to improve homogeneity, some aspects of these records may remain inhomogeneous, and this should be borne in mind when interpreting changes in indices. For example, most methods for assessing homogeneity do not consider changes in day-to-day variability or changes in how the series has been derived. It is possible for a change of variance to occur without a change in mean temperature. Two examples of ways in which this could occur are where a station moves from an exposed coastal location to a location further inland, increasing maximum temperatures and decreasing minimum temperatures, or where the number of stations contributing to a composite series changes. For example, Yan et al.[37] found that the daily variance structure in the daily Central England Temperature series[38,39] changed in 1878 when the data set changed from being based on a single station to the average of three stations.

Gridded daily data have similar deficiencies related to the changing density of networks. The sparser the station network, the smoother will be the interpolated values at grid points/boxes. This is discussed further in section on ‘Production of Gridded Indices for Model Comparison’. Monthly gridded datasets can be adjusted for these problems (e.g., Refs 40 and 41) so that time series for individual boxes are not affected by changing station numbers,[42] but no such adjusted global data set currently exists for gridded daily data.

Homogeneity adjustment of daily data is difficult because of high variability in the daily data when compared with monthly or annual data, and also because an inhomogeneity due to a change in station location or instrument may alter behavior differently under different weather conditions. Homogeneity adjustment of daily data is a very active field of research. Vincent and Mekis[31] adjusted daily temperature data by assigning change factors interpolated from monthly values. This was shown to improve the data homogeneity in general, particularly in climates with large seasonal temperature variations.

Differences in inhomogeneities under different weather conditions may also be considered (e.g., Ref 43) but this usually requires detailed metadata, and may depend on other elements (e.g., cloud cover, wind speed) that are not necessarily available at all temperature stations. Recent improvement has involved quantile matching methods for daily temperature that can be conducted with reference stations[44] or without reference stations.[45]

To Use or Not to Use Reanalysis?

Reanalyses are essentially very short term weather forecasts that are updated each 6 or 12 h based on *in situ* and satellite observations that are assimilated into the model in a consistent manner over the length of the reanalysis period.[46,47] An advantage of reanalyses is that they provide data that cover the entire world (or region of interest in the case of a regional reanalysis, such as the North American Regional Reanalysis[48]), thereby making reanalyses a potentially useful source of information for monitoring long-term changes in extremes in data-sparse regions. Reanalyses have some well-known precipitation biases, which are generally a product of the reanalysis model and are usually not directly constrained by observations. These may be alleviated somewhat when precipitation data are assimilated (e.g., Ref 48). Reanalyses are also affected by inhomogeneities from changes over time in the global observing system. Nevertheless, for daily/monthly mean *temperature* reanalyses have generally been shown to be reliable when compared to good station data,[47,49] suggesting that they have potential for extending the monitoring of extremes to those regions where station data are sparse or unreliable. Reanalyses have not yet been used in conjunction with the indices discussed above, but it is probably only a matter of time before they are. In conclusion, trends in extremes indices from reanalysis data have to be treated with caution, particularly for precipitation.

Sampling Uncertainty and Problems Associated with Indices Definitions

Some indices may be challenging to compute even though they have simple definitions. Percentile-based temperature indices are an example. In the ETCCDI indices set, they are calculated by counting the number of days in a year, or season, for which daily values exceed a time-of-year-dependent threshold. The threshold is defined as a percentile of daily observations for a 5-day window centred upon the calendar day of interest during a base period which is fixed to a common period (such as 1961–1990) to allow comparison of indices across stations with different record lengths, and for easy updating as new daily data become available. The estimation of such thresholds is subject to sampling uncertainty, and threshold crossing rates may differ from that which nominally corresponds to the percentile level.[50,51] Threshold crossing rates may also display inhomogeneity, with the rate being different within the base period, which is used for threshold estimation, than outside the base period. These inhomogeneities come about for two reasons. First, the estimated thresholds are subject to sampling error. This implies that while thresholds can usually be estimated so that exceedance rates within the base period are by definition exactly 10% (in the case of the 90th percentile), exceedance rates outside the base period used to obtain the percentile thresholds will be different, creating step changes in the time series of annual day counts at the beginning and end of the base period. Second, in most cases threshold crossing rates for high quantiles are positively biased even when quantile estimates are unbiased because the right hand tail of the probability density function of daily values decreases monitonically with increasing values for most variables. This inhomogeneity is larger in index series that correspond to thresholds corresponding to rarer events that occur farther from the center of the distribution. Depending on the location of the reference period in the time series and rarity of the events, the effect of the step changes can be sufficiently large to affect trend calculations, especially if a trend analysis is conducted on regionally or large-scale averaged series (Figure 3, see also Ref 51). When using a fixed base period, the inhomogeneity can be effectively removed by using a bootstrap procedure such that values estimated for the base period are unbiased relative to those that are outside of the base period.[51] This is done by not using any data from a particular year within the base period to calculate the index threshold applied to data for that year.

Although temperature is a variable with values in a continuous range, temperature records contain only a discrete set of values because temperature measurements can be read and/or recorded only to a certain precision. This leads to multiple readings of identical values, particularly for low-precision data. The comparison of the discrete observed records with estimated thresholds in the calculation of percentile indices may result in unexpected problems in the mean and trends of these indices when data precision is poor or varies over time. The WMO recommends that temperatures be recorded to the nearest 0.1 °C. However, this is often not followed in practice (e.g., many American stations record to the nearest 0.5 °F, and many non-principal Canadian stations to the nearest 0.5 °C[52]),

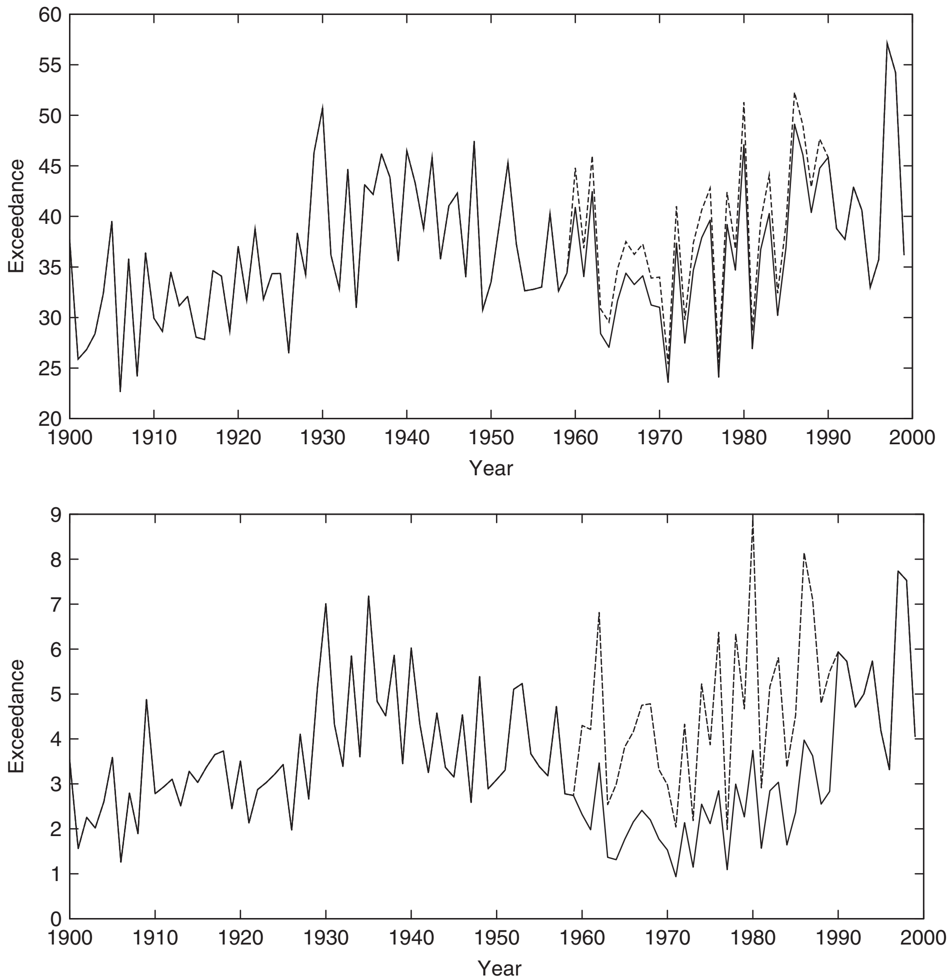

FIGURE 3 | Number of days on which daily temperature exceeds its (top) 90th and (bottom) 99th percentiles averaged over 210 Canadian stations. Rates for the in-base period computed with the bootstrap resampling procedure of Zhang et al.[51] are shown with the dashed lines. Trend estimation for the 99th percentile index would be affected by the step changes. (Reprinted with permission from Ref 51. Copyright 2005 American Meteorological Society)

and even where data precision is nominally to 0.1 °C, observers may have a tendency to round values.[53] Changes in data precision have also arisen in countries which have changed measurement systems for example from Fahrenheit to Celsius.[53]

The extent of any bias arising from data precision depends on the exact method of index calculation, and on the level of daily temperature variability compared to data precision. For example, the occurrence of daily temperature greater than its 90th percentile would be biased low (frequency less than 10%) compared with its expected level of 10% if 'greater than' is used to count exceedances but it would be biased high if the exceedance also includes values that are equal to the threshold. This bias also affects trend analysis. For example, Zhang et al.[52] showed that significant trends are detected less frequently in lower precision data than higher precision data when 'greater than' is used to count exceedances in a Monte-Carlo simulation. The extent of the bias is likely to be particularly large at stations with very low day-to-day temperature variations, such as tropical islands; at such locations, substantial differences can be observed between the expected and actual frequency of events even when data have 0.1 °C precision. This problem can be addressed when the loss of precision is not overly severe by adding a small random number to artificially restore data precision. While these adjustments do not improve the accuracy of individual observations, the exceedance rates that are computed from data adjusted in this way have properties, such as long-term mean and trend, that are similar to those directly estimated from data that are originally of the same precision as the adjusted data.[52]

Another issue that has been identified in relation to the definition of indices pertains to biases that can be introduced from the under-reporting of small rainfall amounts.[54,55] For this reason a 'wet day' is usually defined only for those days where daily precipitation equals or exceeds 1 mm.

REGIONAL EXTREMES WORKSHOPS

Hands-on Analysis

In many instances 'workshops' might be more appropriately named 'talking shops'. The ETCCDI regional workshops are different. They are modelled after the APN workshop approach that brought together world-recognized experts in climate change analysis to guide participants from a dozen countries in the Asia-Pacific region (e.g., Ref 56). Participants spend the majority of their time performing 'hands-on' analysis of their data which they have brought along from their countries. Under the tutelage of the experts they analyze their data, often for the first time. They have heard about the importance of digitizing their data for years but it is the hands-on analysis at the workshops that allows them to fully appreciate the true value of digital daily data. As a result, upon returning home some participants undertake additional digitization efforts as illustrated by Figure 4.[57]

Workshop Format

As noted, the core activity is the hands-on analysis of national data from neighbouring countries in a region. The first step in the analysis is basic quality control (QC) involving a variety of graphical and statistical analyses. However, these routines require human intervention. For example, the basic test of maximum temperature being less than minimum temperature may identify the existence of a problem, but the participant must examine the actual data to determine the exact nature of the problem and its possible solution.

Once the data have passed the QC tests, participants assess the temporal homogeneity of the data. Changes in instruments or observing sites often cause inhomogeneities, and so the station history metadata are vital for resolving such problems. Data gathered before such artificial changes are removed from the analysis because the use of more advanced adjustment techniques is beyond the current scope of the workshops.

Participants are then able to use a software package that is maintained by the ETCCDI to calculate the suite of indices for each station in their country. An expert collates all the results and gives an overview of the trends and variability in extremes across the whole region. The benefits of working across national borders become obvious when similar results from neighbouring countries verify the analyses.

The painstaking task of preparing a peer-reviewed paper about extremes in the region requires access to the data after the workshop. Almost all participants have allowed time series of their indices to be publicly shared (see http://cccma.seos.uvic.ca/ETCCDI for available calculated station level indices as well as the indices software).

Past and Future of the Workshops

The ETCCDI workshop approach has been very successful and has produced a slew of peer-reviewed publications written by participants.[58–67] These have contributed significantly to analyses in data sparse

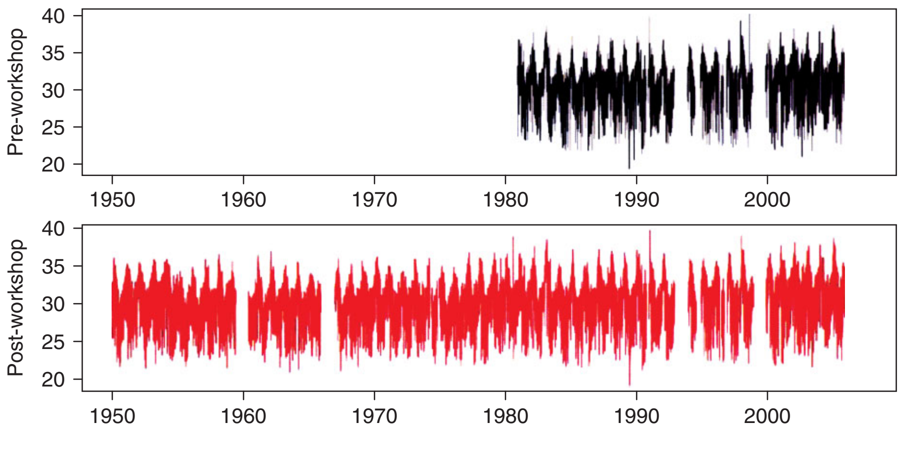

FIGURE 4 | Digital daily maximum temperature from Berberati, Central African Republic. Black indicates before the regional climate change workshop and red indicates a few months after the workshop. The improvements are a result of a digitization effort. (Reprinted with permission from Ref 57. Copyright 2009 American Geophysical Union)

regions of the globe. Alexander et al.[26] were able to use results from the workshops available at the time and made important improvement in spatial coverage over the Frich et al.[33] analysis. Spatial coverage of analyses is further improved by more recent workshops in Congo,[57] Vietnam,[65] Korea,[67] and the western Indian Ocean islands.[66] There have also been additional workshops in South America and Indonesia though the results from those workshops have not been published yet.

The new studies for other regions of the world generally support the findings in Alexander et al.[26] In all regions, warm extremes, particularly at night, are increasing and cold extremes are decreasing. Precipitation indices, however, have shown a much more mixed pattern of change. While Alexander et al.[26] indicated a general increase in heavy precipitation globally, some regional results, for example, Central Africa and the Indo-Pacific region, show no clear indication for an increasing trend. The analyses of the index data generally include the analysis of trends in the time series of indices; some of the analyses also examine potential driving mechanisms of these extremes. For example, there is a clear indication that sea surface temperature patterns are influencing temperature and rainfall indices in the Indo Pacific region,[66] in Central America[63] and in the Asia-Pacific.[65] Caesar et al.[66] indicate that for the Indo Pacific region an ENSO-like correlation pattern exists between sea surface temperatures (SSTs) and precipitation indices while some temperature indices appear more related to local SSTs. Figure 5(a) shows that there are positive correlations in the South China Sea and Bay of Bengal between SSTs and warm nights with little evidence of an ENSO influence, while Figure 5(b) indicates negative SST anomalies in the equatorial Pacific (i.e., La Niña conditions) are highly correlated with increased heavy precipitation days. Vincent et al.[68] also showed that the Pacific Decadal Oscillation (PDO) has a significant influence on temperature indices in the South American region. However, a statistically significant trend in temperature indices, which is consistent with warming, is still present after the PDO effect is considered. Such analyses have only been possible through the ETCCDI workshops.

A limitation of the ETCCDI workshops is that it has not been possible to repeat them in the same regions over time to ensure continuity. The APN workshops have been successful in this respect, which enables additional analysis to be performed as each workshop progresses. In the future, ETCCDI workshops may follow a similar model. It is also possible to have the indices updated on a regional website by a regionally responsible host.

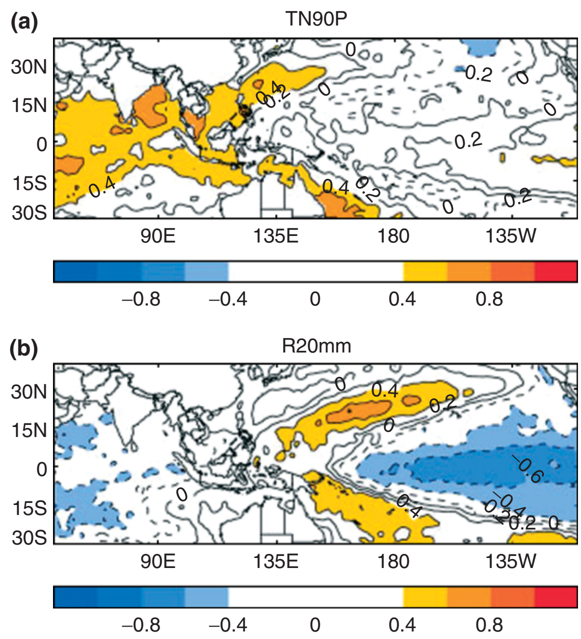

FIGURE 5 | Correlation between de-trended Indo-Pacific region annual series of (a) TN90p and (b) R20mm, and sea surface temperature dataset HadISST. (Reprinted with permission from Ref 65. Crown copyright 2011 The Met Office)

PRODUCTION OF GRIDDED INDICES FOR MODEL COMPARISON

Point Observations versus Grid Boxes

It is only in the last decade or so that there have been serious attempts at model evaluation at daily time scales.[69–71] Modellers are most likely to use observed datasets that are gridded to the resolution of the climate models (e.g., see Ref 72). To adequately compare observations and models, both the spatial and temporal scales of observations and model data need to be comparable. This is not always the case; observations are generally collected at observation sites (points) while climate model output typically represents grid box mean values. This scale mismatch (sometimes referred to as the 'problem of a change in support' in the statistical community) is typically more of a problem for less continuous fields (e.g., precipitation) and for small temporal scales (e.g., daily or sub-daily data and extremes). For example, it is incorrect to interpret climate model simulated precipitation at a grid as a point estimate[73] (see also Ref 74 and references therein) while precipitation observed at a station usually represents only a very small surrounding region. Hydrologists use areal reduction factors to describe the relationship between rainfall extremes at a point with those measured over an area.[75] This concept has also been applied in comparisons of extreme precipitation simulated by climate models at different resolutions,[73] and in climate model evaluation.[76] Some indices, such as percentile-based indices or indices based on the probability distribution of extremes distributions, may be less affected by the scale mismatch (e.g., Refs 77 and 78).

It should be noted that the comparison between models and observations may also be affected by similar representativeness questions temporally, particularly at very short, sub-diurnal, durations. Klein Tank et al.[9] note that the spatial resolution of climate models is not yet sufficient to easily provide detail on extremes at local and regional levels. They also note that being aware of these scaling issues is important in avoiding the misinterpretation of the results of observed and modelled extremes. While at present it may be difficult to produce observational datasets that are fully comparable with model output, Klein Tank et al.[9] and others have aimed to provide a set of guidelines and suggestions for the modelling and observational communities that will hopefully make comparison easier in future.

Gridded Daily Data

Nevertheless, Haylock et al.[79] developed the E-OBS gridded daily dataset for Europe. Although developed for regional climate model evaluation (see, e.g., Ref 80), E-OBS is also being used for climate monitoring. It is updated in near- real time, so the extent of some recent extremes such as the Russian heat wave in July 2010[81] can be compared to historical data. As discussed further below, gridded datasets may have different properties depending upon their intended use, and thus they should only be applied in other circumstances with caution.

Because of the discontinuous nature of daily precipitation in both time and space, precipitation occurs more frequently within an area than at a point. As a result, there are more days with precipitation over an area than over a point, and in general, lower precipitation intensity over an area than a point, so gridded precipitation data sets (which are, in effect, weighted averages over grid boxes) will tend to have more wet days and a smaller mean amount of precipitation per wet day than point data (see, e.g., Figure 10 of Osborn and Hulme[74]). Low station density over most parts of the world makes it impossible to produce a gridded daily precipitation data set that is truly comparable with climate model simulations. Differences in station density across the space also result in different degrees of representativeness of gridded values for an area, resulting in spatial inconsistency.

Shen et al.[82] addressed this issue by developing a hybrid method involving inverse-distance weighting and nearest-station assignment for interpolating the precipitation data to ensure a match between gridded values and station observations not only in the number of precipitation days per month, but also the precipitation amount for a day. Haylock et al.[79] includes an extra conditional interpolation (wet or dry) to ensure that gridded products have the same wet/dry characteristics as the original station data. While, with these approaches, gridded values are made to match with those observed at stations, it is difficult to precisely interpret the meaning of such gridded products as they do not represent the area mean.

Apart from the resolution of the grid, there are a number of other choices that have to be made when developing a gridded dataset appropriate for the analysis of extremes. These include the choice of interpolation software, whether to transform the variable, and choice of transformation, the simplest of the latter being the use of anomalies rather than absolute values. Hofstra et al.[83] compared a number of the subjective choices made in the development of E-OBS. The final gridded values are robust to most of the choices, but as expected the choices become more important when the network is sparser. Of particular importance to extremes, the approaches taken in the gridding ensured that the gridded dataset represents areal as opposed to point values. This was achieved by gridding to a much higher resolution than the final grid-box size, and then averaging all the values within each grid box. The success of this approach is nevertheless dependent on the station density, with the result that there may not be enough information in data-sparse areas to construct gridded values of areal representation.

Gridded Indices

Two methods have been used to obtain gridded indices. One is to compute the indices at individual stations and then grid the indices, the other is to grid the station daily data first and then to compute the indices at the grids. The difference in the order of calculation has an impact on the gridded indices and their interpretation. In the first case, what is produced is a grid box value that is representative of point values of indices within the box, while in the second case, the grid box value is an index that describes an aspect of the behavior of the daily grid box mean values of the climate variable of interest. The former may not be easily comparable with indices produced from climate model simulated grid box values. The latter would be expected to correspond more closely to climate model simulated grid box values provided the observation network is sufficiently dense, although, as station density changes across different regions, it is difficult to make the indices consistent across the space.

Haylock et al.[79] estimated extreme indices from the grid, and also calculated the indices from the stations and then interpolated the results. As expected, the two approaches did not lead to the same results. Indices calculated at the stations are more extreme, particularly so for the more severe extremes. The 1-in-10 year maximum daily temperature computed from gridding the daily data then calculating indices is about 1 °C cooler than that by gridding indices calculated at stations. The 1-in-10 year maximum daily precipitation over a grid is about 30–50% smaller than point estimations. This is qualitatively consistent with other studies (e.g., Refs 73, 74, and 76). The exact results depend heavily on the density of the network and the orography.

APPLICATIONS OF THE INDICES

Observed Changes in Indices

One of the main advantages of the ETCCDI indices and other similar indices has been the ability to combine regional information into a global product. Figure 6, which is from the compilation by Alexander et al.,[26] shows estimated trends in a few temperature related indices. It is evident that there has been a clear increase in the number of warm days and warm nights, and a decrease in the number of cold days and cold nights, consistent with what would be expected from warming in the mean temperature. These results illustrate the widespread significant changes in temperature extremes associated with the warming since 1950, especially for those indices derived from daily minimum temperature. Over 70% of the global land area sampled shows a significant decrease in the annual occurrence of cold nights and a significant increase in the annual occurrence of warm nights. Daily maximum temperature indices showed similar changes but with smaller magnitudes.

Figure 7 shows observed trends for several precipitation indices, again from Alexander et al.[26] While the changes are much less spatially coherent, there is a general increase in the number of heavy precipitation days, an increase in the heavy daily precipitation contribution to annual total precipitation amount, and a reduction in the number of consecutive dry days. The Alexander et al.[26] analysis, along with numerous regional analyses, provided an important foundation for the IPCC 4th Assessment statement that 'changes in extremes of temperatures are also consistent with warming' and that 'substantial increases are found in heavy precipitation' in many regions, particularly in middle and high latitudes.[84]

Attributing Observed Changes in Indices to Causes

There has been quite a bit of work that attempts to attribute causes to observed changes in indices. Kiktev et al.[85] compared six indices from the updated dataset of Frich et al.[33] with those computed from a three member ensemble simulation of an atmosphere-only global climate model (GCM) forced by observed SSTs and a combination of anthropogenic forcings. They found that the inclusion of anthropogenic effects in the model integrations (especially increases in greenhouse gases) significantly improves the simulation of changing extremes in temperature, while changes in precipitation appeared to be more dominated by climate variability. More recent studies have compared trends in indices from observations with those from the ECHAM5/MPI-OM model (e.g., Refs 86 and 87) or with a selection of multimodel ensembles from CMIP3 datasets over the globe[88,89] or on a regional basis.[90,91] Portmann et al.[7] focused on changes over the US in an index that is very similar to that of the number of warm days and nights, namely the number of exceedances of the 90th percentile of daily temperatures, but with thresholds calculated over the last 50 years rather than 1961–1990. They show that regions of decreases in the number of exceedances coincide with regions with stronger climatological precipitation in May and June, and suggested the possibility of a link with vegetation in the observed change.

In general, model simulations with external forcing yield reasonable skill in reproducing observed patterns of trends in temperature indices. Christidis et al.[92] performed a detection and attribution analysis on a suite of temperature indices, including the hottest day (maximum annual daily maximum temperature), coldest day (minimum annual daily maximum temperature), hottest night (maximum annual daily minimum temperature), and coldest night (minimum annual daily minimum temperature). They found that the model simulated pattern of response to human influence was detectable in the observed changes in the cold tail of the distribution (coldest night and coldest day annually) but that the amplitude of the pattern was greater in observations than simulated by the model, suggesting that the model had underestimated the effect of anthropogenic forcing on cold tail temperatures. Human influence was also detected in the observed change in the warmest night annually, but not in the warmest day annually, in which case the models seemed to overestimate the expected change.

Using an improved approach, Christidis et al.[93] recently found that human influence could be detected in changes in the location parameter of the generalized extreme value (GEV) distribution when a

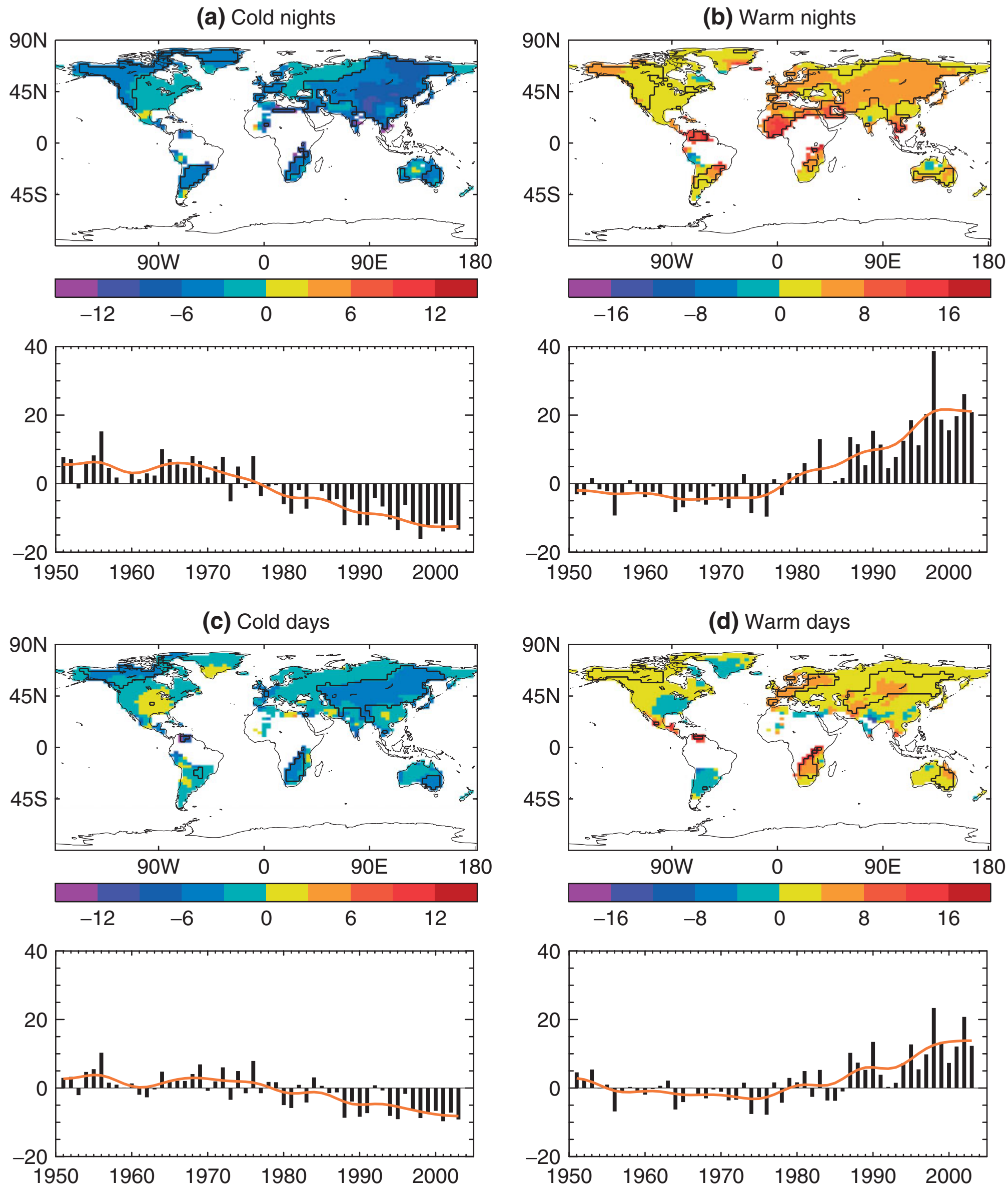

FIGURE 6 | Trends (in days per decade, shown as maps) and annual time series anomalies relative to 1961–1990 mean values (shown as plots) for annual series of percentile temperature indices for 1951–2003 for (a) cold nights (TN10p), (b) warm nights (TN90p), (c) cold days (TX10p), and (d) warm days (TX90p). 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. (Reprinted with permission from Ref 26. Copyright 2006 American Geophysical Union)

non-stationary version of that distribution was fitted to the temperatures of the warmest day annually, although the model used in their study, HadCM3, appears to have over-estimated the response to anthropogenic forcing in the temperatures of the warmest day annually. Using a similar approach, Zwiers et al.[94] detect human influence in the annual minimum and maximum extremes of daily minimum and maximum temperatures, again using the GEV distribution and taking non-stationarity in the location parameter into account, but using fingerprints from several climate models. Consistent with previous studies, it was found that the model-simulated response to anthropogenic forcing had to be scaled down to best fit observed changes in extremes in the case of the temperature of the warmest day annually, and scaled up to best fit the observed changes in extremes of the coldest night annually. This study also showed that the magnitude

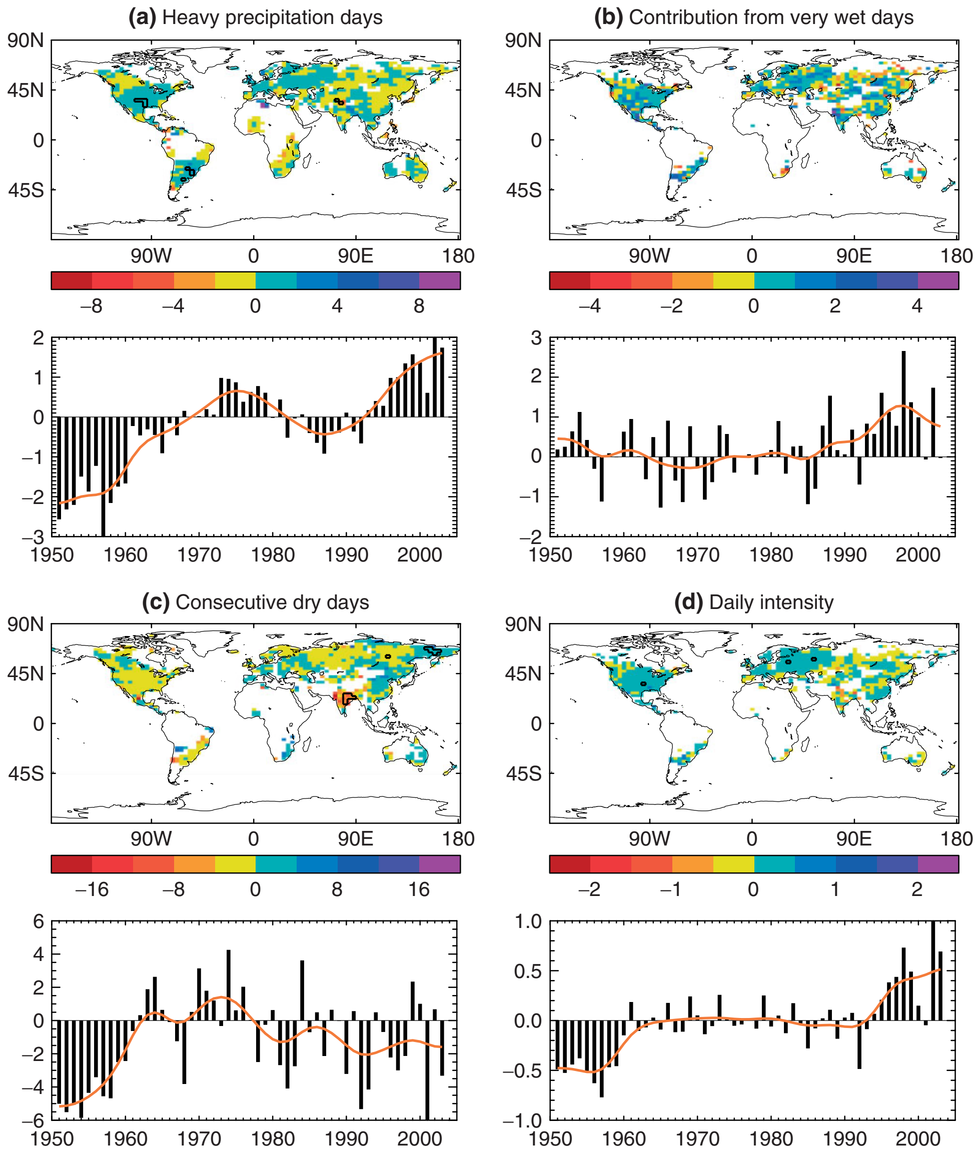

FIGURE 7 | As Figure 6 but for precipitation indices (a) R10 in days, (b) R95pT (i.e., (R95p/PRCPTOT) * 100) in %, (c) CDD in days, and (d) SDII in mm/day. (Reprinted with permission from Ref 26. Copyright 2006 American Geophysical Union)

of model-simulated changes in the coldest day annually and warmest night annually accorded well with observed changes. They estimate that the waiting times for circa 1960s 20-year extreme warm temperature events had been reduced to approximately 10- to 15-years for the warmest night annually and the warmest day annually respectively by the 1990s due to anthropogenic forcing of the climate system. They similarly estimated that return times for the 20-year extremes of the coldest night annually and coldest day annually had increased to approximately 35- and 30-years respectively.

While the work discussed above focuses on changes in the intensity of warm and cold extremes, results are also available on changing frequency of temperature extremes. The number of warm nights per year (TN90), defined as the number of nights with minimum temperature above the 90th percentile, has also been recently analyzed over large regions. Morak et al.[95] show that this index shows detectable changes over the second half of the 20th century that are consistent with the expected change due to greenhouse gas increases both globally, and over many regions considered. They also show that most of this trend can be predicted from changes in monthly mean temperature based on the regression relationship between both for de-trended data. Similarly, changes in the number of hot days, and cold nights are detectable in some regions and generally on global scales.[95]

Similarities in the observed and simulated trend patterns for precipitation indices are generally poor. However, Min et al.[78] show that the pattern of change in the wettest day of the year, analyzed by mapping it onto a local GEV distribution, detect human influence in the observed widespread tendency towards more intense extreme precipitation over those parts of the world considered (largely in the Northern Hemispheric extra-tropics). The observed change appears to be larger than simulated by the models, but uncertainties are large.

Projected Future Changes in Indices

Indices have also been computed and analyzed for projected future climate.[86,87,89,90,96,97] Extreme precipitation and extreme warm temperature are both projected to increase while extreme cold temperatures will become more moderate. Russo and Sterl[87] showed that for daily temperatures simulated by ECHAM5/MPI-OM for 2070-2099, the 90th percentile computed from the 1961–1990 base period was exceeded 70% of the time in some regions.

CONTINUING DEVELOPMENTS

A limitation of the current suite of ETCCDI indices is that none of the temperature indices consider the effects of humidity and wind on the apparent temperature that is felt by humans. One possibility is to include humidity and wind information alongside temperature data to form a single index, though this would be limited by the availability of the humidity and wind data. Indices that combine temperature and precipitation information in a single index have been proposed by some groups.[98–100]

The development of indices to assess multiday temperature extremes (e.g., prolonged heat waves) has been particularly challenging, as the occurrence of such events depends not just on the frequency distribution of daily temperatures, but also on their persistence from day to day. The existing indices in widespread use, such as the maximum number of consecutive days during events with six or more consecutive days above a specified percentile value or anomaly, vary widely in frequency across climates, describe events that occur rarely or not at all in many climates, and are poor discriminators of extreme events such as the 2003 central European heat wave.[34] A new range of indices has been developed[34] that is instead based on the highest temperature in a year to be exceeded on a specified number of consecutive days. This range of indices is defined in all climates and has a number of other desirable statistical properties, such as being approximately normally distributed in many climates.

In many parts of the world, there are distinctive wet and dry seasons. The timing of the onset of wet or dry seasons is important for both human systems such as agriculture and natural ecosystems. Yet monitoring of long-term changes in the timing of the rainy season is difficult, as it is difficult to precisely define the onset or end of the rainy season. Outgoing long-wave radiation has been used as a proxy to define onset of the rainy season for South America.[101,102] Rainfall data have also been used to determine the onset of the rainy season for South America.[103–105] A similar approach has been used to define the onset of the Indian monsoon. While remote sensing approaches may be able more precisely define the onset of monsoons under such circumstances, due to their ability to assess not just temporal, but also spatial variability of characteristic features, a limitation is that time series of onset dates are necessarily limited to the periods when appropriate instruments are available during the satellite era. Consequently, trends can only be calculated over limited periods. Lack of homogeneity, resulting from the fact that the satellite records are necessarily developed from a succession of relatively short lived and technologically evolving instruments, may also be a concern for some types of indices derived from remotely sensed data.

CONCLUSIONS

Monthly means provide useful and simple metrics that can be used to track relatively slow climate variations and change. However, impacts are often the result of short term excursions into the tails of the distributions of daily data; a comprehensive suite of indices provides a means to synthesize information about these excursions. The ETCCDI, and related, indices were developed to provide scientifically robust measures of daily variability, primarily of extremes, that are easily calculated and understood by the climate community. The indices are designed to enable the ongoing monitoring of changes in the frequency and/or intensity of 'moderately' extreme events, by focusing on events that typically occur several times per year. In addition, some indices, such as the annual maximum of daily maximum temperature (TXx) or the annual maximum 1-day precipitation accumulation (RX1D), also provide the basic information that can be used to make inferences about changes in long-return period extreme events in observations[78,94] and models.[96] The dissemination of free ETCCDI supported software to calculate indices has contributed to capacity development across many regions of the world where previously analysis of climate extremes had been limited. The analyses of the indices computed from different parts of the world show clear changes in extremes, especially in temperature extremes. Furthermore, recent detection and attribution studies of observed changes in a range of indices[7,8,78,92–95] demonstrate that human induced changes in greenhouse gas concentrations appear to be a factor in the observed changes in extremes.

Despite their many advantages, the experience that has been gathered through the application and analysis of indices has also uncovered some weaknesses. For example, in some instances it has been difficult to define indices that provide useful information across the broad range of climates that exist within the Earth system, and that would continue to provide useful information under future forcing conditions. Even where indices are robustly defined, the details of their calculation, or the particular characteristics of the data that are used for their calculation, may inadvertently introduce temporal[51] or spatial[52] inhomogeneities. The definition and application of indices of the type described in this paper will, no doubt, continue to evolve as needs and the understanding of current indices further develop. A logical progression would be the inclusion of multi-parameter indices in the ETCCDI suite, including those that describe longer time-scale high impact phenomena, such as drought indices that are based on precipitation and temperature data. Past effort focused primarily on the most commonly exchanged variables of daily maximum and minimum temperature and total precipitation. But future indices, data exchange permitting, could also focus on other parameters such as wind speed or specific humidity, both of which are GCOS Essential Climate Variables.[106] The availability of new variables would also allow new multi-parameter indices such as moist enthalpy or apparent temperature which requires both temperature and humidity data.

NOTES

[a]CLIVAR: World Climate Research Programme (WCRP) project for climate variability and predictability.
[b]GCOS: Global Climate Observing System.
[c]CCl: World Meteorological Organization (WMO) Commission for Climatology.
[d]JCOMM: Joint WMO–IOC [United Nations Educational, Scientific and Cultural Organization (UNESCO) Intergovernmental Oceanographic Commission] Technical Commission for Oceanography and Marine Meteorology.

ACKNOWLEDGMENTS

L. Alexander is supported by Australian Research Council grants LP100200690 and CE110001028. P.D. Jones is supported by a US Department of Energy grant (DE-SC0005689). G.C. Hegerl is supported by NERC (NE/H003533/1) and by the National Science Foundation (Grant ATM-0296007). P.D. Jones, X. Zhang, F.W. Zwiers, and G.C. Hegerl are also supported by the US Department of Energy's Office of Science, Office of Biological and Environmental Research, and the National Oceanic and Atmospheric Administration's Climate Program Office through the International ad-hoc Detection and Attribution Group (IDAG) group.

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