

Consistent Trends in a Modified Climate Extremes Index in the United States, Europe, and Australia

AILIE J. E. GALLANT

School of Earth Sciences, University of Melbourne, Parkville, and School of Geography and Environmental Science, Monash University, Clayton, Victoria, Australia

DAVID J. KAROLY

School of Earth Sciences, University of Melbourne, Parkville, Victoria, Australia

KARIN L. GLEASON

National Climatic Data Center, Asheville, North Carolina

(Manuscript received 2 November 2012, in final form 28 October 2013)

ABSTRACT

The utility of a combined modified climate extremes index (mCEI) is presented for monitoring coherent trends in multiple types of climate extremes across large regions. Its usefulness lies in its ability to distill complex spatiotemporal fields into a simple, flexible nonparametric index.

Two versions of the mCEI are computed that incorporate changes in several annual- or daily-scale temperature-related and moisture-related extremes. Applying data from the contiguous United States, Europe, and Australia detects consistent and statistically significant increases in the spatial prevalence of climate extremes from 1950 to 2012. All three continental-scale regions show increasingly widespread warm annual- and daily-scale minimum and maximum temperature extremes, a decreasing spatial extent of cool annual- and daily-scale minimum and maximum temperature extremes, and increasing areas where the proportion of annual total precipitation falls on heavy-rain days. There were no statistically significant trends toward more widespread, annual-scale drought or moisture surplus in any region.

The dependence of annual extremes on the frequency of daily-scale extremes is highlighted by the strong covariations between annual- and daily-scale extremes in all regions. By the nature of construction of the combined indices, the differences in the trends of the mCEI and daily-scale mCEI (dmCEI) suggest that extremes in more areas are changing primarily because of a shift of temperature and daily rainfall distributions toward warm extremes and heavy-rainfall extremes.

1. Introduction

The attention devoted to the study of climate extremes and their changes over time stems largely from their potential to be detrimental to socioeconomic and biophysical systems. Climate extremes can be broadly defined as highly anomalous climatic conditions on sub-daily to annual or longer time scales (Karl et al. 1996; Frich et al. 2002; Alexander et al. 2006). Examples include heat waves, droughts, heavy rain, and severe winds,

but also specific phenomena such as hurricanes, tornadoes, or floods. Regardless of the type of event, past climate extremes have induced excessive mortality and increased hospital admissions (Whitman et al. 1997; Fouillet et al. 2006; Zhang et al. 2013). Extremes also impose considerable costs stemming from stresses and damage to infrastructure and direct impacts on commodities, such as loss or damage to crops and livestock (Meehl et al. 2000).

These adverse effects of climate extremes highlight the need for their effective monitoring. Over time, this requirement has increased for two reasons. The first is due to the expansion of human populations and associated infrastructure into vulnerable areas (Cardona et al. 2012). The second is that the characteristics of some

Corresponding author address: Dr. Ailie Gallant, School of Geography and Environmental Science, Monash University, VIC 3800, Australia.
E-mail: ailie.gallant@monash.edu

types of extremes, such as their frequency and severity, have changed since the beginning of the twentieth century (Alexander et al. 2006; Donat et al. 2013). There is increasing consensus that several of these changes are likely due to increases in anthropogenic greenhouse gases (Min et al. 2011; Hansen et al. 2012).

A summary of the current state of knowledge on changes in regional and global extremes, and their likely causes, can be found in a recent special report on climate extremes by the Intergovernmental Panel on Climate Change (IPCC) (Field et al. 2012). The report and the references therein describe increases in the incidence of hot weather events and decreases in cold weather events at many global locations (Brown et al. 2008; Donat et al. 2013). These include respective increases and decreases in multiday heating and cooling events (Alexander et al. 2006). The changes in precipitation-based extremes are mixed and so consistent signals over continental and larger areas are unclear (Donat et al. 2013). However, there are reports of increases in heavy-rain days and the proportion of total rainfall stemming from extreme 1-day events over substantial portions of the globe (Alexander et al. 2006; Min et al. 2011; Donat et al. 2013). This includes much of North America (Gleason et al. 2008; Peterson et al. 2008), western Europe during the boreal winter (Zolina et al. 2009), and large portions of Australia (Alexander et al. 2007; Gallant and Karoly 2010). The historical changes in drought conditions include large multidecadal variations. The longer-term trends in drought vary regionally and there is no consistent change over continental and larger-scale regions (Sheffield et al. 2012).

There are increasingly likely expectations that anthropogenic climate change has altered, and will alter, the frequency and severity of some types of climate extremes (Jones et al. 2008; Alexander and Arblaster 2009; Christidis et al. 2011; Donat et al. 2013; Field et al. 2012). For some extremes, there is already evidence of consistent changes over large-scale, continental, and hemispheric-scale regions (Alexander et al. 2006; Min et al. 2011; Donat et al. 2013; Hansen et al. 2012; Munasinghe et al. 2012). Therefore, the continued monitoring and attribution of changes in climate extremes is crucial.

Creating indices to detect and attribute large-scale, low-frequency changes in climatic extremes is a difficult task. The definitions of extremes vary (e.g., arbitrary thresholds, event-based, impact-based); there are changes in multiple types of extremes (e.g., those based on temperature, precipitation, or winds); and there is sometimes a lack of widespread appropriate data and/or spatially and temporally noisy signals in data.

Despite these challenges, coherent trends in climate extremes over large areas have been identified.

Alexander et al. (2006) and Donat et al. (2013) highlighted consistent changes in some extremes indices identified at the station and gridbox scale by computing global averages. Hansen et al. (2012) reported coherent, large-scale changes in seasonal temperature extremes by examining the percentage area of the globe affected. Munasinghe et al. (2012) detected global-scale changes in extreme temperatures by examining the occurrence of record-high or record-low temperatures.

The climate extremes index (CEI; Karl et al. 1996) and its variants (Gruza et al. 1999; Gleason et al. 2008; Gallant and Karoly 2010) are metrics that combine multiple types of extremes in order to assess large-scale, climatic changes in extremeness (Seneviratne et al. 2012). The term “extremeness” defines the degree to which climatic conditions are extreme. The CEI integrates several components that assess changes in temperature and moisture-related extremes and returns a percentage value representing the fractional area of a region affected. Although the CEI indices include more than one type of extreme from more than one variable, they remain imperfect. For example, the indices do not include multiday extremes, or many event-based extremes (e.g., floods or tornadoes) that are arguably more relevant for socioeconomic impacts (Seneviratne et al. 2012). However, the usefulness of the CEI lies in its ability to examine extremes from widely and readily available data that can be compared worldwide, which is crucial for examining large-scale and coherent changes across the globe.

Gleason et al.'s (2008) revised CEI is calculated operationally for the United States by the National Ocean and Atmospheric Administration (NOAA). The revised CEI comprises five components measuring the fraction of area of the contiguous United States experiencing extremes outside the 90th percentile and the 10th percentile of the following: annual maximum and minimum temperatures, annual Palmer drought severity index (PDSI; Palmer 1965), proportion of annual precipitation from heavy-precipitation days, and annual number of days with or without precipitation (Table 1). A sixth component representing landfalling-hurricane wind velocities has since been included in the operational version of the index (<http://www.ncdc.noaa.gov/extremes/cei/>).

The CEI was intended as a metric for monitoring low-frequency (i.e., multidecadal scale) changes in climate extremes. In a nonstationary climate, changes to the extremes of a climatic distribution can occur from a shift in the distribution, a change in variance of a distribution, a change in skewness of the distribution, or a combination of all three possibilities (Field et al. 2012; Seneviratne et al. 2012). The revised CEI from Gleason et al. (2008) adds the extremes from both tails of a

TABLE 1. The definitions of the components comprising the modified climate extremes index (mCEI), the daily modified climate extremes index (dmCEI), and the revised climate extremes index (CEI) of Gleason et al. (2008). The indices are calculated as the linear average of their components, where component 4 is doubled and shifted to have a mean of zero over the climatological base period (1950–2012). Each component is generated as some combination of the following extremes: $P90_x$, the percentage area where the average of variable x is above the 90th percentile, and $P10_x$, the percentage area where the average of variable x is below the 10th percentile, where x is defined in the table. A rain/wet day (dry day) is defined as a day with rainfall greater (less) than 1.0 mm. A heavy-rain day is defined as a day where the rainfall total exceeds the 90th percentile computed from all rain days. Cold days (nights) are defined as days (nights) where the daily maximum (minimum) temperature falls below the 10th percentile. Hot days (nights) are defined as days (nights) when the daily maximum (minimum) temperature exceeds the 90th percentile.

Component	CEI	mCEI	dmCEI
1	$x = \text{annual maximum temperature}$ $P10_x + P90_x$	$x = \text{annual maximum temperature}$ $P90_x - P10_x$	$x = \text{proportion of hot days in a year}$ $y = \text{proportion of cold days in a year}$ $P90_x - P90_y$
2	$x = \text{annual minimum temperature}$ $P10_x + P90_x$	$x = \text{annual minimum temperature}$ $P90_x - P10_x$	$x = \text{proportion of hot nights in a year}$ $y = \text{proportion of cold nights in a year}$ $P90_x - P90_y$
3	$x = \text{annual PDSI}$ $P10_x + P90_x$	$x = \text{annual PDSI}$ $P90_x - P10_x$	As in mCEI
4	$x = \text{proportion of heavy-rain days}$ in a year $P90_x$	As in mCEI	As in mCEI
5	$x = \text{number of wet days in a year}$ $y = \text{number of dry days in a year}$ $P90_x + P90_y$	$x = \text{number of wet days in a year}$ $y = \text{number of dry days in a year}$ $P90_x - P90_y$	As in mCEI

climatic distribution. Thus, the trends in the index are intended to highlight the prominence of changing climatic variance across a region. However, this index will also vary with shifts in a distribution. Gallant and Karoly (2010) modified this approach and instead subtracted the extremes from one tail in a distribution from those from the opposite tail. Thus, any trends in this modified CEI (mCEI) will tend to highlight shifts in the climatic distribution, or skewing toward a particular tail of the distribution.

Table 1 describes the differences in the computation of the CEI, the mCEI, and a third index, the dmCEI. The dmCEI includes daily-scale, rather than monthly-scale, temperature extremes. Whether the CEI or mCEI is computed is an arbitrary choice and depends on the desired application of the index. The mCEI will better describe the sign of any changes in extremes (e.g., from cold to hot, dry to wet, etc.), which is additional and useful information compared with the CEI. Thus, this study mostly presents results from the mCEI. However, the CEI and mCEI are compared in section 6.

The CEI, mCEI, and dmCEI share common characteristics that make them effective tools for monitoring and communicating changes in aspects of climate extremeness, and potentially for attributing causes in these changes. The indices include multiple types of extremes that are relevant for socioeconomic and physical impacts and for which there are widely available data. These features make the indices relevant, calculable, and comparable for multiple regions of any size (e.g., state or

country scale to global scale). Simple indices most effectively communicate climate changes. The CEI metrics distill a suite of complex information into a simple index that informs the user whether an area is becoming more or less extreme and, if desired, the sign of these changes (e.g., colder and drier or warmer and wetter). The combined index is likely to be affected less by natural climate variability than the individual components and therefore may be better suited for identifying longer-term trends. The mCEI is flexible in its construction, so the components comprising the index could be combined in a way that illustrated hot-to-cold or wet-to-dry extremes also. The simple nature of the index is useful for attribution studies as it conveys large-scale information about changes in climate extremes. Furthermore, the CEI can be more easily compared with output from a climate model compared to other extremes indices as the CEI is nonparametric.

This study uses the mCEI to demonstrate that there have been consistent, long-term changes in climate extremes for three near-continental-scale regions, namely the United States, Europe, and Australia, since the mid-twentieth century. These regions were selected as they contained sufficient spatially dense networks of high-quality data. Data show near-continental-scale trends in the prevalence of warm extremes, and some wet extremes, from 1950 to 2012 (section 4). The mCEI and revised CEI are compared and assessed in further detail in section 5 and a sensitivity analysis is performed in section 6.

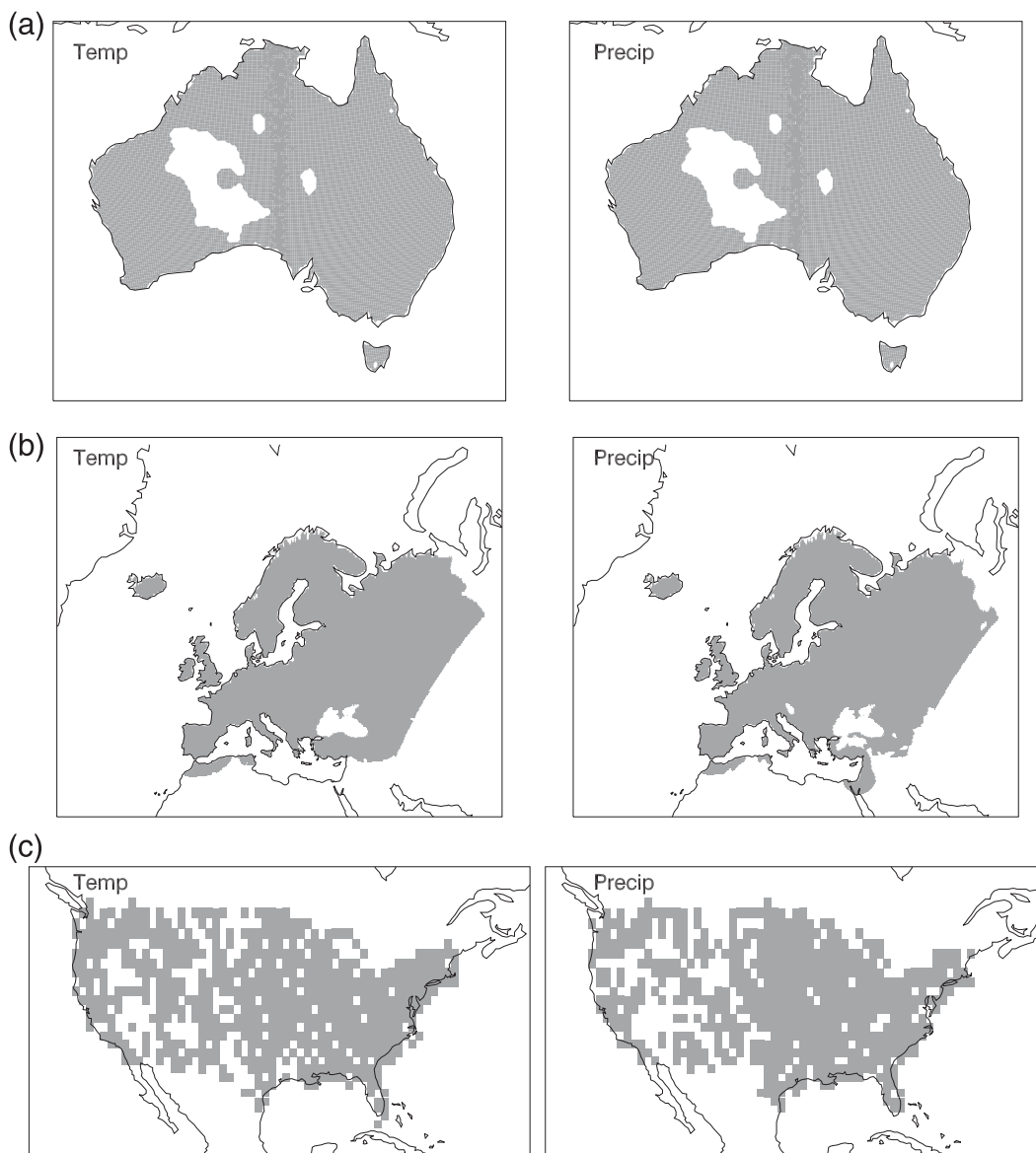


FIG. 1. The shading represents those areas that are included as part of (a) Australia, (b) Europe, and (c) the contiguous United States for computation of the mCEI and dmCEI, described in Table 1.

2. Data

The computation of the mCEI and dmCEI requires daily and/or monthly temperature and precipitation data, and monthly Palmer drought severity index data. Datasets of suitable quality and spatial coverage for climate change and extremes analysis were available for Australia, Europe, and the continental United States from 1950 to 2012. Figure 1 shows the coverage of these data, which contain some missing areas due to lack of data, reduced data quality, and/or short data records.

a. Temperature and precipitation data

Regularly gridded daily and monthly minimum and maximum temperature and precipitation data are available from the Australian Bureau of Meteorology (Jones et al. 2009). These products interpolate data from approximately 60 to over 700 temperature stations, and from approximately 3000 to over 7000 precipitation stations onto a grid with $0.05^\circ \times 0.05^\circ$ resolution, with the number of available stations generally increasing with time. Station data were first separated into a monthly climatological average and an anomaly component and

each were interpolated onto a regular grid using three-dimensional smoothing splines and the Barnes successive-correction method, respectively. Data at every fifth grid point only were used in order to make the Australian grid comparable with the European region, effectively making its resolution $0.25^\circ \times 0.25^\circ$. Gallant and Karoly (2010) showed that computing the mCEI and dmCEI metrics at this resolution produces comparable results to those computed from high-quality station data.

Regularly gridded daily maximum and minimum temperature and precipitation data for Europe were available from the Ensemble-Based Predictions of Climate Changes and their Impacts (ENSEMBLES) observations (E-OBS) gridded dataset (Haylock et al. 2008). The grids have $0.25^\circ \times 0.25^\circ$ resolution and were generated from up to 2316 stations, although this number varied with time. Quality-control tests included testing for statistical outliers and flagging suspect prolonged-precipitation events. Stations were correlated against the 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) dataset and were adjusted at leads and lags of up to 1 day to account for differences in measuring times between stations. As at the Australian stations, data were separated into a monthly-mean and a daily-anomaly component prior to gridding. The monthly means were interpolated using thin-plate splines and following that kriging was applied to the daily anomalies. Full details of their method can be found in Haylock et al. (2008).

The components for the mCEI only were provided by the National Climatic Data Center. These were computed from a gridded dataset described in detail in Gleason et al. (2008). 1100 monthly temperature stations from the U.S. Historical Climatology Network (HCN) (Karl et al. 1990), and 900 daily precipitation stations (both HCN and non-HCN), were linearly averaged into $1^\circ \times 1^\circ$ grid cells across the contiguous United States.

b. Palmer drought severity index data

Developed in the United States, the Palmer drought severity index estimates relative magnitudes of anomalous wet and dry conditions, primarily to examine drought or moisture surplus. The index incorporates the effects of precipitation, evaporation, runoff, recharge, and loss (Palmer 1965) and effectively describes water balance in the soil using a simple two-layer bucket model. All processes are derived from three inputs only: mean monthly temperature, precipitation accumulation, and the subsoil available water capacity of the soil. The upper soil layer is assumed to have a capacity of 25 mm.

Pre-computed PDSI data as in Karl (1986), and applied to the CEI as in Gleason et al. (2008), were used to generate component 3 for the United States (Table 1).

The PDSI in Australia and Europe was calculated using an algorithm developed at the University of Nebraska (<http://greenleaf.unl.edu>). Note that the PDSI, not the self-calibrating PDSI, was calculated so that the drought-moisture surplus metric remained consistent across all regions. The temperature and precipitation inputs for these PDSI calculations were those data previously described in section 2a. The subsoil available water capacities for the Australian and European regions, measured in millimeters, were extracted from the Global Gridded Surfaces of Selected Soil Characteristics dataset, part of the International Geosphere-Biosphere Programme Data Information Systems (IGBP-DIS; Global Soil Data Task Group 2000).

3. Methods

The mCEI and dmCEI components were computed using the same techniques as in Gallant and Karoly (2010). These components were described in section 1 and are shown in Table 1. The mCEI and dmCEI components were combined to show variations between cold and dry environments and warm and wet environments, which were represented as negative and positive values, respectively. This choice of combination was chosen to highlight the strongest trends in all regions. However, there is flexibility in the combination of the components in Table 1. This flexibility is particularly useful for seasonal and/or more regional examinations where, for example, dry extremes may be more prominent.

All components and combined indices were calculated for the January–December year. The extremes were calculated as a highly abnormal value of each component, namely above the 90th or below the 10th percentile, compared with the climatological average period of 1950–2012. An mCEI or a dmCEI of zero indicates that extremes in a region are not abnormally prominent compared with climatology.

Positive values for temperature-based components indicate a larger-than-normal fractional area with hot extremes compared to cool extremes, and a negative value indicates a larger-than-normal fractional area of cool extremes compared to hot extremes. Positive values in the PDSI-based component 3 indicate larger-than-normal areas of moisture surplus and the negative values indicate larger areas of moisture deficit (i.e., drought). Component 4 is always positive and represents the extreme upper tail only of the daily rainfall distribution. As all other components represent extremes in both tails, component 4 is doubled when it is included in the mCEI and dmCEI. The doubling avoids underweighting component 4 in the combined index compared to other types of extremes (Karl et al. 1996). When included in

the mCEI/dmCEI calculation, component 4 is shifted to have a mean of zero relative to the climatological base period so that the combined index is not biased toward positive values. Last, component 5 is positive or negative when a larger proportion of a region is affected by an extreme number of wet days or dry days, respectively.

Changing the percentile thresholds for each component of the mCEI and dmCEI tested whether the statistical significance of the trends were sensitive to the choice of threshold for extreme. The thresholds were increased or decreased for each component to the 95th and 97th, and 5th and 3rd percentiles, respectively, and the mCEI and dmCEI were recomputed. The largest and smallest thresholds (97th and 3rd percentiles) were selected in order to ensure that at least one of the 63 years of data from 1950 to 2012 was counted as extreme. A comparison between the mCEI and the CEI was performed for all regions and so the revised CEI of Gleason et al. (2008) was also computed (Table 1). The differences in the trends between the mCEI and the CEI can highlight how changes to the distribution of climate variables are changing extremes.

The Australian data grids are complete and contain no missing data. However, several areas in central and western Australia were removed from analysis as in Gallant and Karoly (2010) because of temporally varying station networks that introduce spurious climatic trends (Jones et al. 2009; King et al. 2013a). Less than 1% of the European grids contain more than 5% missing data; these grids are still included in the analysis and the missing data do not affect the results. For the United States, station records for each variable were used only if they were 90% complete within the analysis period and for the period of record. Thus, the $1^\circ \times 1^\circ$ grid box covered approximately 70% of the contiguous United States for temperature and approximately 80% for precipitation. All of the United States is represented by the PDSI, which was computed for larger climate divisions rather than at the station/grid box level (Karl et al. 1996). A complete discussion of the data used to generate the U.S. indices can be found in Gleason et al. (2008).

Uncertainties in the time series of the mCEI, dmCEI, and its components, and the resulting uncertainties in the trends of these time series, were estimated using a block-jackknife technique. Ten years of data, comprising two independent 5-yr blocks, were systematically removed from the climatological base period (1950–2012) and the percentiles and time series were recomputed. Given the reduced sample size used for recalculation of the indices, this methodological design computes a more conservative estimate of uncertainty compared to a block-bootstrap. Simultaneously, the method incorporates

an estimation of the uncertainty associated with the choice of climatological base period for standardization. The technique resulted in 55 unique replicates of each time series from which two-tailed 90% confidence intervals were generated for the annual value of each time series and for the trends.

The magnitudes of the long-term (1950–2012) trends were computed using linear regression and are described in the units of percentage per decade. The significance of these trends was determined using a modified non-parametric Mann–Kendall test that accounted for persistence in the time series (Hamed and Rao 1998). Any autocorrelation in the data inflates the variance of the null distribution and so can lead to an increase in type I errors (i.e., false positives) (Hamed and Rao 1998; Hamed 2008). Statistical significance is defined at the two-tailed 5% level unless otherwise stated.

4. Regional trends in mCEI components

The trends in the annual mCEI components are now presented for the United States, Europe, and Australia from 1950 to 2012. An analysis of the annual dmCEI is also included for the two latter regions for which daily temperature data were available. This is the first time the mCEI and dmCEI have been calculated for Europe and the United States, while the Australian indices represent an update from 2008. Moreover, this study represents the first multiregion comparison of the mCEI and dmCEI.

a. United States

The temperature-based components (1 and 2) of the United States mCEI over 1950–2012 are shown in Figs. 2 and 3. The positive trends in these components showed a statistically significant change from more spatially prevalent cool extremes toward more prevalent warm extremes. These trends are consistent with the increases in warm extremes and decreases in cool extremes reported in other studies (DeGaetano and Allen 2002; Donat et al. 2013; Hansen et al. 2012). Using the mCEI, we found a statistically significant increase in component 1 of 5.1% decade⁻¹ and in component 2 of 8.0% decade⁻¹ from 1950 to 2012. Thus, the trends in minimum-temperature extremes were stronger than for maximum-temperature extremes.

Components 3, 4, and 5 describe variations in the spatial prominence of moisture-related extremes and are shown in Figs. 4 and 5. All extreme-daily-rainfall trends (components 4 and 5) showed that the area of the contiguous United States experiencing very wet extremes increased from 1950 to 2012 (Groisman et al. 2005). Component 4 (heavy-rain days) showed an

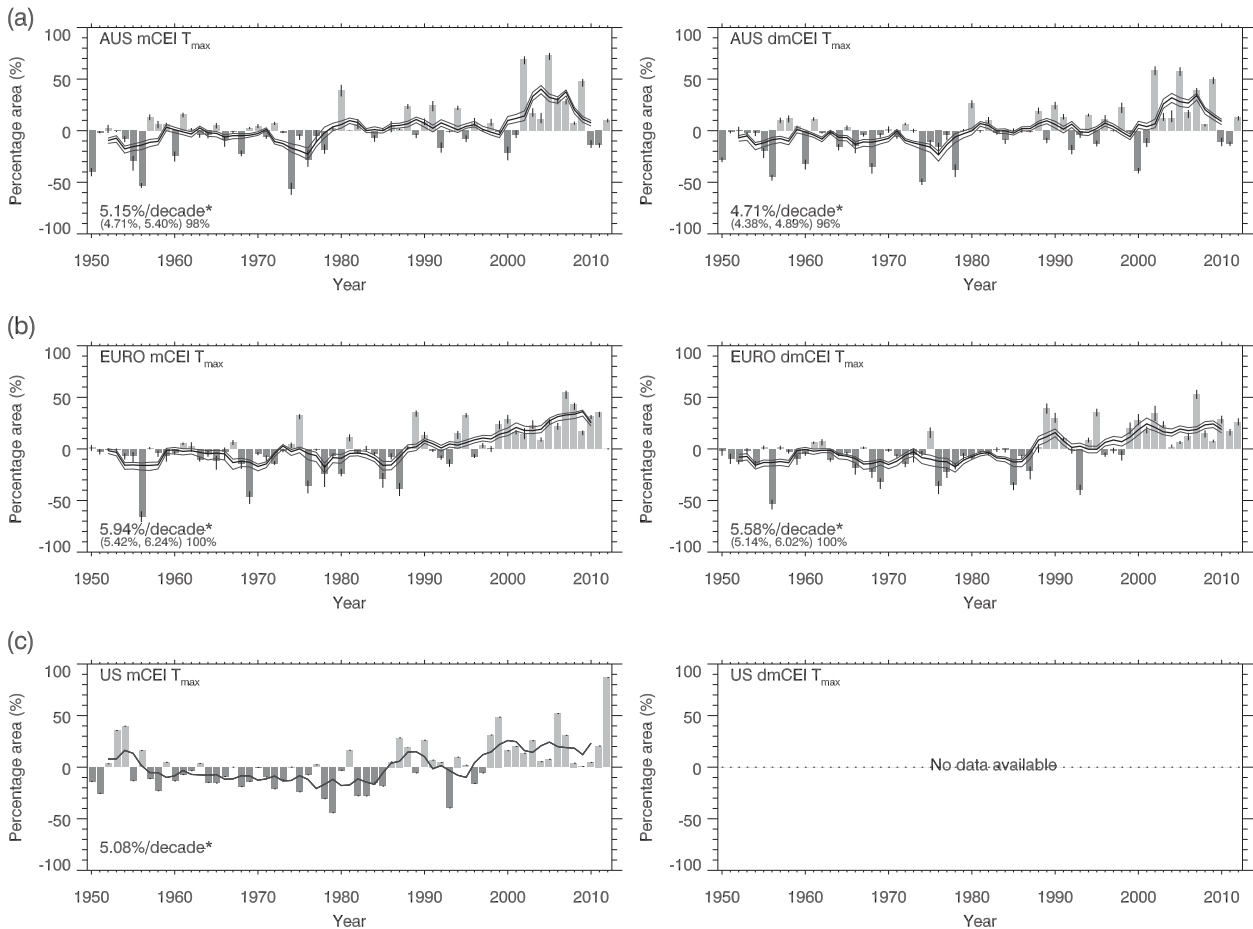


FIG. 2. This component represents variations in the areal extent of the extremes of annual and daily maximum temperatures. See Table 1 for a precise definition. It shows component 1 of the (left) mCEI and (right) dmCEI, computed for (a) Australia, (b) Europe, and (c) the contiguous United States. The interannual (bars) and 5-yr averaged (line) variations are shown from 1950 to 2012. The linear trends for each time series are inset on each plot and statistical significance (two-tailed 5% level) is denoted by an asterisk. The 90% confidence interval of the trend based on block-jackknife replicates is provided in parentheses. The adjacent percentage is the proportion of these replicates that are statistically significant.

increase of $1.1\% \text{ decade}^{-1}$ that was statistically significant (Fig. 5). The trend in component 5 (wet or dry days) of $2.1\% \text{ decade}^{-1}$ was statistically significant at the two-tailed 6% level ($p = 0.03$) (Fig. 4). Large interdecadal variations are evident in component 3 and so trends were insignificant. There was no net change in the spatial extent of drought or moisture surplus across the contiguous United States from 1950 to 2012.

b. Europe

There was an increase in the spatial prevalence of warm extreme-minimum and -maximum temperatures in Europe from 1950 to 2012, and a concurrent decrease in the spatial extent of cool extremes (Moberg and Jones 2005; Moberg et al. 2006). Minimum-temperature extremes (component 1) showed larger trends than maximum-temperature extremes (component 2). The

positive trends in components 1 and 2 were over 5% and $6\% \text{ decade}^{-1}$, respectively. All trends were statistically significant and remained so when uncertainty in the trend was included.

The moisture-related components of the European mCEI and dmCEI had weaker trends and larger variations compared to the temperature-based components (Figs. 4 and 5). There was no significant trend in component 3 (drought or moisture surplus) from 1950 to 2012 and interdecadal variation in the time series was large compared to the other components. The trends in the daily-scale moisture-related extremes were positive, indicating an increasing spatial prevalence of daily-scale wet extremes, compared to dry extremes. Component 4 (heavy-rain days) had a statistically significant trend of $0.9\% \text{ decade}^{-1}$ from 1950 to 2012. Component 5 (extreme proportion of wet-dry days) had positive trend

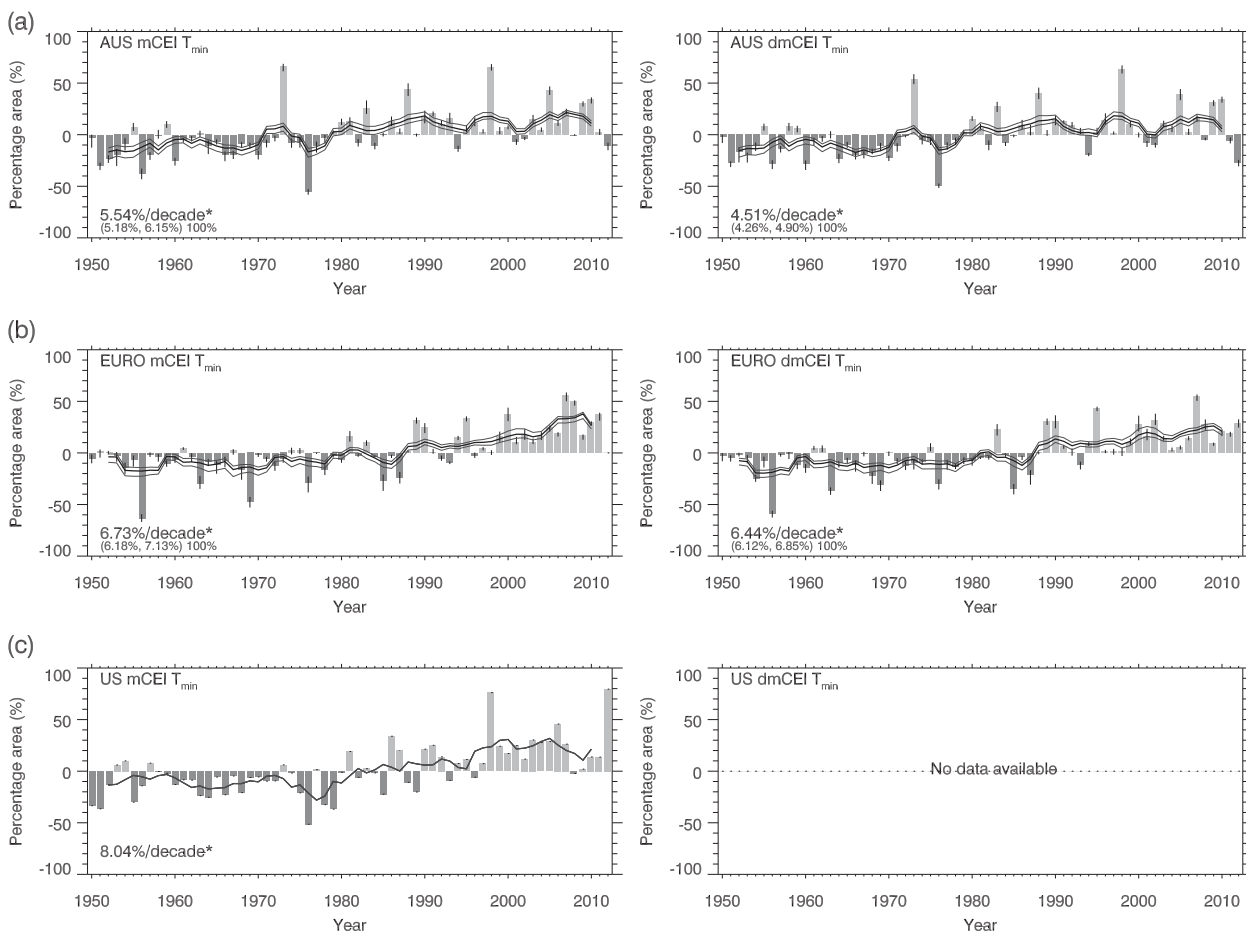


FIG. 3. As in Fig. 2, but for component 2. This component represents variations in the areal extent of the extremes of annual and daily minimum temperatures. See Table 1 for a precise definition.

of $2.1\% \text{ decade}^{-1}$ that was also statistically significant. These results highlight statistically significant changes in daily-scale extreme-rainfall events (Moberg and Jones 2005), but not in annual-scale moisture-based extremes in Europe.

c. Australia

In Australia, changes to the spatial prevalence of maximum-temperature extremes (component 1) were of similar magnitude to the changes in minimum-temperature extremes (component 2). Like other regions, these components showed statistically significant positive trends over the period 1950–2012 (Figs. 2 and 3). The statistically significant trends in component 1 illustrate that an increasing area of Australia experienced a combined increase in warm extremes, and a decrease in cool, annual, and daily maximum-temperature extremes from 1950 to 2012. These changes occurred at a rate of $5.2\% \text{ decade}^{-1}$ and $4.7\% \text{ decade}^{-1}$, respectively. Minimum-temperature extremes (component 2) were

also statistically significant and showed rates of change of 5.5% and $4.5\% \text{ decade}^{-1}$ for annual and daily data, respectively.

As for the other regions, the interdecadal variations in the moisture-related components were more prominent than in the temperature-related components in Australia. The particularly large variations in components 3 and 5 meant that their trends were not statistically significant (Fig. 4). However, an increasing trend in heavy-rain days (component 4) of $0.9\% \text{ decade}^{-1}$ was statistically significant.

5. Regional comparison

The contiguous United States, Europe, and Australia showed consistent changes in the direction and significance of all mCEI and dmCEI components (Table 1).

The comparable magnitudes of the linear trends of component 1 (maximum temperature) across all three regions mask some differences in their evolution over

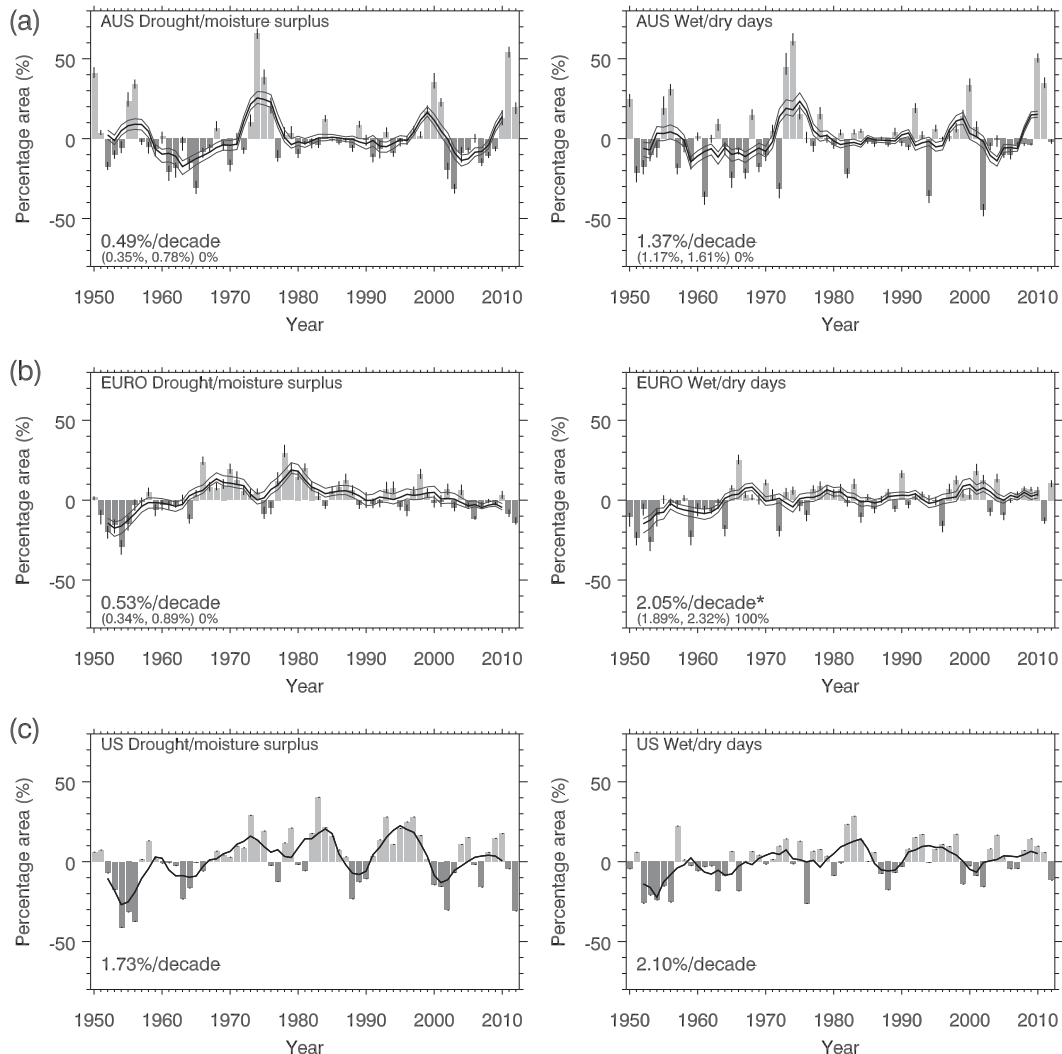


FIG. 4. As in Fig. 2, but for components (left) 3 and (right) 5. Component 3 represents variations in the areal extent of drought and moisture surplus. Component 5 represents the areal extent of the region experiencing an extreme number of wet days or an extreme number of dry days. See Table 1 for a precise definition.

time. There was a relatively constant rate of change from 1950 to 2012 in the United States and Europe. However, in Australia there was a weak trend through most of the time series, followed by a relatively abrupt increase at the turn of the twenty-first century (Fig. 2). The positive trends in heavy-rain days (component 4) were consistent in magnitude across all three regions and all were statistically significant. The uncertainties in the magnitudes of the trends in components 1, 2, and 4 were on the order of around 0.5% or less, and statistical significance was robust to this uncertainty. The insignificance of the trends in components 3 (drought or moisture surplus) and 5 (wet or dry days) in the United States and Australia, and component 3 only in Europe, was a result of the large interdecadal variations in these time series (Fig. 4).

In all regions, there were strong covariations between the components based on annual and daily data. In Australia, the correlation between component 1 computed using annual maximum temperatures and component 1 computed using daily maximum temperatures was 0.94. For minimum temperature extremes (component 2), this correlation was 0.97. In Europe, the correlations between the temperature components based on annual and daily data were above 0.87. Daily data were not available for the United States and so such a comparison could not be performed here.

Strong covariations were also observed between some annual and daily moisture-related components (Fig. 4). The spatial extent of extreme drought or moisture surplus (component 3) varied in a similar manner to the

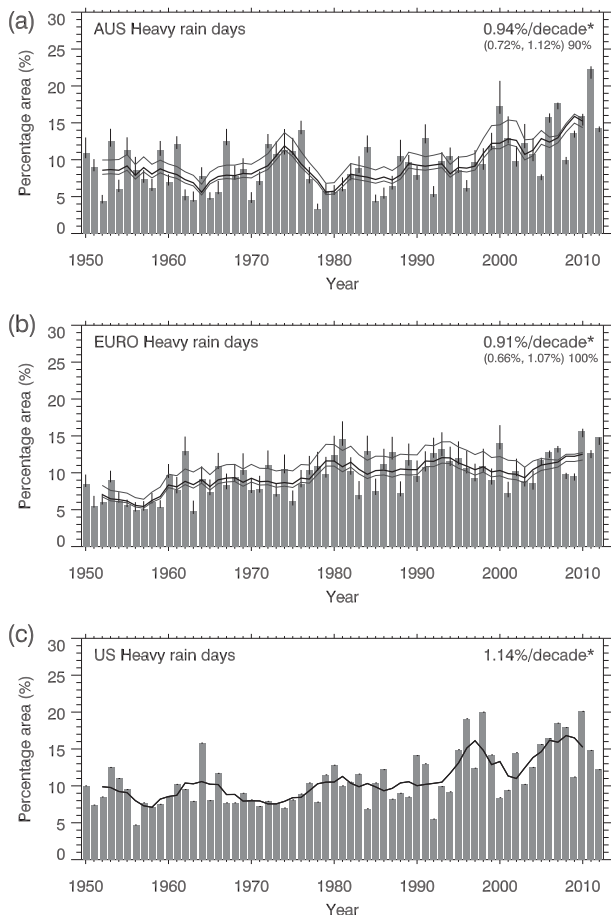


FIG. 5. As in Fig. 2, but for component 4. This component represents variations in the percentage area of a region experiencing an extreme proportion of the annual precipitation accumulation stemming from heavy 1-day events. See Table 1 for a precise definition. Note that when combined in the mCEI or dmCEI, this component is converted to an anomaly relative to the period 1950–2012, and then doubled (see section 1).

extremes in the number of wet or dry days (component 5). This relationship was stronger in the United States and Australia, where correlations were above 0.74, and weaker in Europe, where the correlation was 0.54.

Annual data are a construct of the frequency and intensity of daily data. The strong relationship between annual and daily temperature and some moisture-related components suggests that annual extremes are strongly linked to the frequency of daily extremes, rather than to the intensity. For the moisture-related components, this result is further supported by weaker correlations between heavy-rain days (component 4), which represent a measure of daily rainfall intensity, and drought or moisture surplus (component 3). These components had correlations of 0.42, 0.22, and -0.05 in Australia, Europe, and the United States, respectively.

As a result of the similarities in the trends of the components across all regions, when combined, the mCEI and dmCEI showed changes from 1950 to 2012 that were consistent in sign and magnitude for the contiguous United States, Europe, and Australia (Fig. 6). These trends provide evidence of increasingly widespread areas of warmer and wetter extremes, and a reduction in areas affected by cooler extremes. There was little change to dry extremes in any region (Sheffield et al. 2012). These results were insensitive to the differences in grid resolution between the United States (1.00°) and Europe and Australia (0.25°), which was examined by smoothing the finer-resolution grid to a $1.00^\circ \times 1.00^\circ$ surface and comparing the resulting component time series with the original. The two time series were almost indistinguishable.

The trends in the mCEI (which uses annual temperature data) occurred at rates of 2.9%, 3.4%, and 3.9% decade $^{-1}$ for Australia, Europe, and the United States, respectively, and all trends were statistically significant. The dmCEI was computed for Europe and Australia only (see section 3) and the trends were consistent in sign and magnitude to the mCEI. There were statistically significant trends of 2.6% and 3.3% decade $^{-1}$ for Australia and Europe, respectively. The similarities between trends based on annual and daily extremes were again highlighted in the combined indices, with the correlations between the mCEI and the dmCEI exceeding 0.92 for Australia and Europe.

The consistency between the magnitudes and statistical significance of the 63-yr trends in the mCEI and dmCEI in all regions suggests there is potentially a common cause of the trends on this time scale. For comparison, we now test whether this is also the case for their year-to-year variations. Linearly detrending the mCEI and dmCEI time series to retain the high-frequency variations only (e.g., interannual to multi-year) and correlating the regional indices illustrate any difference between climatic variations in extremes in these regions on different time scales (Table 2). The correlations between the regional mCEI indices ranged between 0.06 and 0.18, and there was a correlation of 0.01 between the Australian and European dmCEI. The detrended correlations between the components comprising the mCEI and dmCEI were also insignificantly correlated between regions except in two cases (Table 2). The lack of statistically significant correlations on the interannual time scale suggests that either the processes causing widespread extremes on each landmass are different on the interannual time scale, or that the effects of some common cause (e.g., some large-scale climate mechanism with teleconnections to all regions) are different and nonlinear for each landmass.

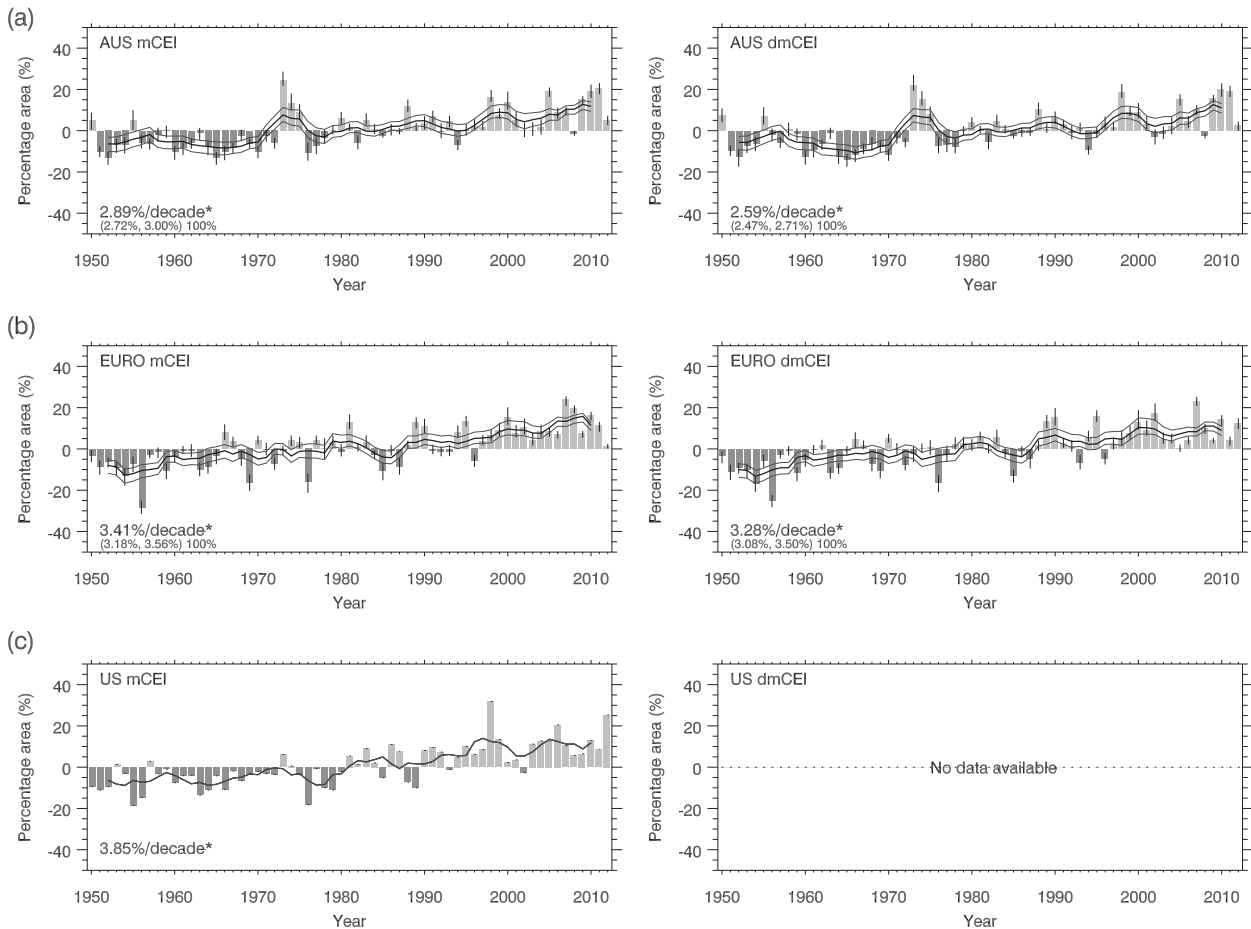


FIG. 6. The combined extremes indices, (left) mCEI and (right) dmCEI, for the three regions. These are the linear combinations (simple average) of those presented in Figs. 2–5, except that component 4 (Fig. 5) has been doubled and shifted to have a mean of zero over the period 1950–2012. See Table 1 for precise definitions of the mCEI and dmCEI.

This second possibility was briefly examined by correlating the Niño-3.4 index (Trenberth 1997) with each of the components. In Australia, these correlations were statistically significant at the two-tailed 2% level for all components except those based on minimum temperatures (component 2). The sign of these correlations indicated that Australia experiences more widespread warm maximum-temperature extremes, more widespread drought, less widespread heavy-precipitation extremes, and more widespread extreme number of dry days during El Niño events and vice versa for La Niña (Min et al. 2013). These results are consistent with an increased likelihood of warm and dry average conditions during El Niño and cool and wet conditions during La Niña across much of Australia (Power et al. 1998) and suggests that there are similar relationships for the temperature- and moisture-based extremes (Arblaster and Alexander 2012; King et al. 2013b; Min et al. 2013).

The European temperature-related components had statistically significant inverse correlations at the two-tailed 5% level with the Niño-3.4 index, indicating more widespread cool extremes and less widespread warm extremes during El Niño events. However, the statistical significance of these relationships was borderline, and other studies report few statistically significant relationships between ENSO and temperature extremes in Europe (Kenyon and Hegerl 2008). Only component 5 (extreme wet or dry days) showed a statistically significant relationship with the Niño-3.4 index in the United States. The sign of this relationship suggested an increase in extreme wet days across more of the region during El Niño events.

The results presented above suggest that any consistencies between the regional mCEI and dmCEI time series are reflections of similarities in the long-term trends in extremes, rather than their year-to-year variations.

TABLE 2. The detrended correlations between interannual mCEI and dmCEI indices and their components (Table 1). All data were detrended using linear regression. Boldface values indicate a statistically significant correlation at the two-tailed 5% level. The significance testing incorporates adjustments for autocorrelated data as in Bretherton et al. (1999). N/A indicates no daily data availability in the United States for the dmCEI and its daily temperature components.

Component	$r_{(\text{US,Europe})}$	$r_{(\text{US,Australia})}$	$r_{(\text{Europe,Australia})}$
1 (mCEI)	0.08	0.03	0.12
1 (dmCEI)	N/A	N/A	0.17
2 (mCEI)	0.03	0.27	0.10
2 (dmCEI)	N/A	N/A	0.04
3	0.35	0.01	-0.11
4	0.09	0.02	-0.02
5	-0.03	0.01	0.10
mCEI	0.06	0.18	0.11
dmCEI	N/A	N/A	0.01

6. CEI variants and sensitivity to the definition of “extreme”

Throughout this study, we have assessed changes in extremes from cool and dry to warm and wet (or vice versa), which depended on the construction of the mCEI and dmCEI. Although these definitions are arbitrary choices, they were selected as the most significant changes to extremes were illustrated by combining the components in this way.

A possible issue with this choice of combination is that it dampens any signal of changes to cool or dry extremes that might be occurring concurrently. There were some differences in the variations of the time series that might support dry extremes being included as a positive value in the index. For example, the increases in the CEI in the early 1990s and early 2000s in Australia and during the mid-1950s in Europe and the United States were all associated with reductions in the mCEI. In turn, these were associated with increases in drier extremes in at least one of the three moisture-based components (Figs. 4 and 5).

The sensitivity of the mCEI construction to dry extremes was tested. Component 3 is an indicator of widespread drought (negative values) or widespread moisture surplus (positive values). The sign of the component was reversed so that positive values represented drought conditions and the mCEI was recomputed. The changes in trends of the resulting mCEI in Australia and Europe were of order 0.01%, and of order 0.1% in the United States, and all trends in the mCEI and dmCEI remained statistically significant. Thus, low-frequency changes in extremes were insensitive to the definition of this component in all regions, probably because the trends in component 3 were insignificant. Recent work has

demonstrated that caution must also be exercised in the use of the PDSI for detecting changes in drought and moisture surplus. For example, Sheffield et al. (2012) demonstrated that the PDSI overinflates trends in warming environments because of its strong dependence on temperature as a proxy for evaporation. Thus, other metrics for drought or moisture surplus should be considered for application to component 3 in future work.

As discussed in section 1, differences in the trends of the CEI and the mCEI can highlight the types of changes in climatic distributions that are leading to changes in extremes (e.g., a shift of the distribution or change in variance). So, the CEI was computed for all regions and compared to the mCEI. Figure 7 shows that the strong trend in the mCEI time series is not mirrored in the CEI. This was also true for the components of the combined index. Recall that the CEI adds the extremes of both tails, while the mCEI subtracts the lower tail from the upper tail. Thus, the stronger trends in the mCEI compared to the CEI suggest that changes in extremes over increasingly larger areas of Europe, the United States, and Australia are more closely associated with shifts in climatic distributions compared to changes in their variance (Alexander et al. 2007), although both may play a role (Hansen et al. 2012). The differences in the mCEI and CEI indices imply that combining the components should be not be done indiscriminately and that the resulting choices for combination are purpose-dependent.

The mCEI and dmCEI definitions are sensitive to the percentile thresholds used to define what is “extreme” (Table 1). For all components, extremes were defined as those events in the top or bottom 10% of the distribution. Using the Australian region as a case study, we tested the sensitivity of the significance of the trends in the mCEI and dmCEI to this definition, shown in Fig. 8. Applying a stricter percentile threshold to define an extreme reduced the magnitude of the variability in the recomputed mCEI and dmCEI time series and also reduced the magnitude of the trend. These differences were expected as the definition of an extreme moved to increasingly rare events with decreasing and increasing percentiles. However, the significance of the trend remained insensitive to the definition.

The magnitudes and significance of the trends in the mCEI, dmCEI, and their comprising components were also insensitive to sampling, which were tested using block-jackknife replicates (section 3). As each replicate was constructed from a subset of approximately 80% of the complete dataset, it effectively highlights the insensitivity to the choice of climatological base period from which the percentiles were

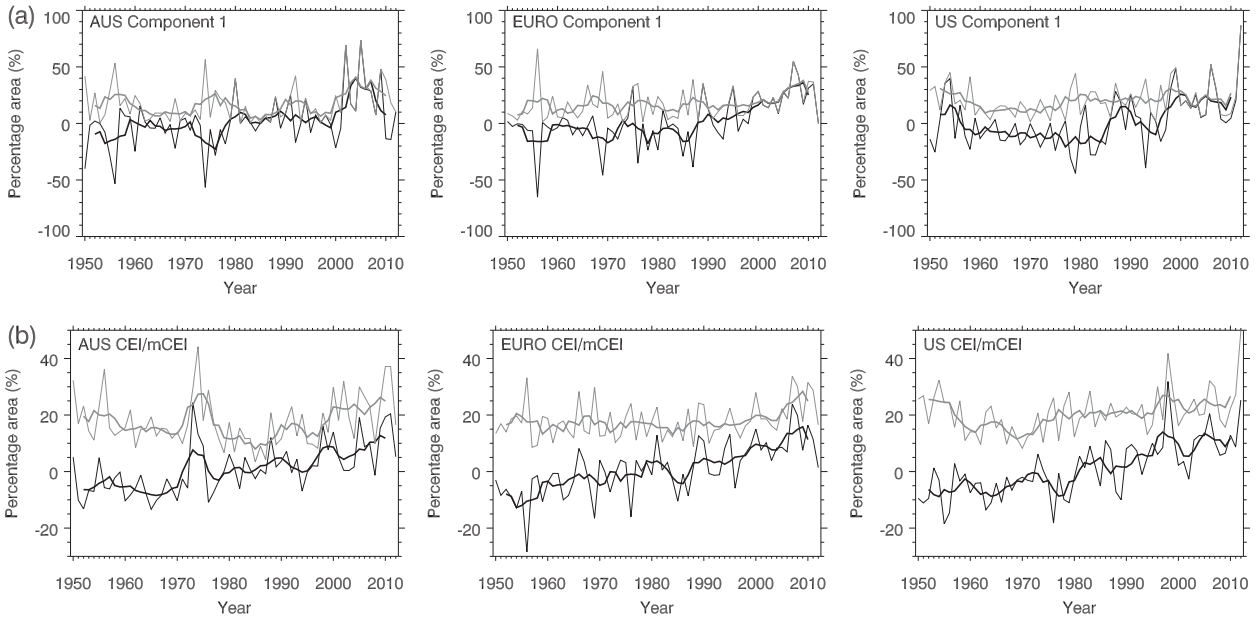


FIG. 7. (a) The interannual (thin line) and 5-yr (thick line) variations in component 1 computed using the technique for the mCEI (black) and the revised CEI (gray). (b) As in (a), but for the combined indices [i.e., mCEI (black) and dmCEI (gray)]. The time series are shown for (left) Australia, (center) Europe, and (right) the contiguous United States. The components comprising these indices differ in that the mCEI computes the difference between the upper and lower extremes, while the CEI computes their additive effect (see Table 1).

generated, which has been a past criticism of the CEI. In all cases, the jackknifed trends remained statistically significant for at least 90% of the replicates indicating insensitivity in the trends to the climatological base period.

The above results have highlighted that the trends in the mCEI and dmCEI, and their comprising components, are robust and unusual when compared to a stationary climate.

7. Discussion

The similarity in the magnitudes and significance of the trends in the mCEI, dmCEI, and their comprising components in all regions warrants further investigation to determine if there is a common cause. The interannual variations in the indices showed no significant similarities between the regions, likely because the physical processes causing climatic variations are different for each.

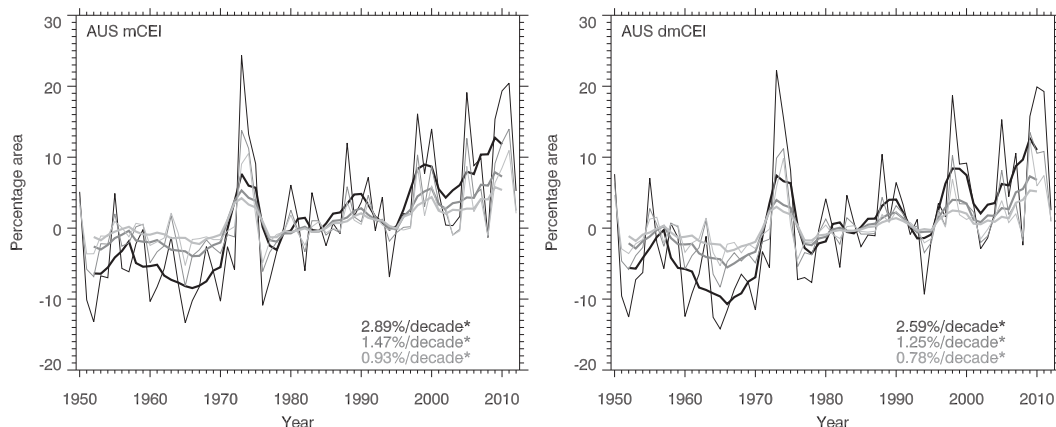


FIG. 8. The interannual (thin line) and 5-yr (thick line) variations in the (left) mCEI and (right) dmCEI are shown for the Australian region. The comprising components have been generated using the 10th and 90th percentiles (black), 5th and 95th percentiles (gray), and the 3rd and 97th percentiles (light gray) to define extremes. The trends in the indices for each threshold case are inset and are shown in the same color scheme as for the time series.

Although individual extremes are caused by weather events, various environmental states of the atmosphere and oceans have been linked with probabilistic changes to the types of weather systems that occur and, subsequently, to the extreme events from which they stem (Kenyon and Hegerl 2008; Min et al. 2013). For example, modes of climate variability, such as ENSO and the northern annular mode, have been linked to variations in maximum- and minimum-temperature extremes within all three regions examined here (Kenyon and Hegerl 2008; Arblaster and Alexander 2012; Min et al. 2013).

The Niño-3.4 index, an indicator of ENSO, showed statistically significant relationships with some components, particularly in Australia. ENSO has a relationship with interannual to interdecadal variations in some Australian temperature and precipitation extremes (Arblaster and Alexander 2012; King et al. 2013b). However, there is little evidence of long-term changes in ENSO that could be associated with the long-term trends reported here (Nicholls 2008). Furthermore, any relationships that existed between the Niño-3.4 index extremes were opposing between regions. In short, there are no known natural mechanisms that include a long-term trend that could be responsible for such similar and significant trends in these three continental-scale regions.

Projections from coupled general circulation models suggest that extremes should change in a similar manner to those observed trends described here for large parts of Europe, Australia, and the United States associated with increases in anthropogenic greenhouse gases. Moreover, observed increases in regional warm extremes (Alexander and Arblaster 2009; Morak et al. 2011; Stott et al. 2011) and heavy-precipitation events (Min et al. 2011; Pall et al. 2011) have been linked to anthropogenic climate change in some of the regions examined here. This study was designed to identify large-scale coherent changes in extremeness only and did not involve attribution. However, given the similarities in the regional trends and what is expected from anthropogenic climate change, future research should examine whether any anthropogenic contribution can be identified from these indices. Regardless of their cause, ongoing monitoring is important to determine any continuation of the trends toward increasing areas of continental-scale regions being affected by extremes.

8. Conclusions

The mCEI and dmCEI were computed for the three near-continental-size landmasses of the contiguous United States, Europe, and Australia. The mCEI and dmCEI were demonstrated as useful for monitoring trends in

extremeness because of their ability to distill complex spatiotemporal information on extremes into a simple, nonparametric index. Although temperature- and moisture-based variables only were examined, the mCEI and dmCEI could be developed to include other types of extremes when widespread, reliable data become available.

Coherent and robust changes in temperature and daily rainfall extremes have occurred across three continental-scale regions located in the Northern and Southern Hemispheres. The mCEI and dmCEI in all regions increased by at least 2.6% decade⁻¹. These changes stemmed from increasing areas of warm extremes, and decreasing areas of cool, maximum, and minimum annual and daily temperature extremes, and increasing areas where the proportion of annual total precipitation falls on heavy-rain days. There were no statistically significant trends toward more widespread, annual-scale drought or moisture surplus in any region. The differences between the mCEI and revised CEI suggest that increasing proportions of Europe, the United States, and Australia are being affected by climate extremes primarily because of shifts in climatic distributions, rather than changes in variance.

There is strong potential for the types of extreme events comprising the mCEI and dmCEI to be associated with negative socioeconomic and biophysical effects. Thus, the changes in extremes in these regions must continue to be monitored and attribution studies undertaken to determine the possible causes of these trends.

Acknowledgments. We thank the National Climatic Data Center for providing the CEI components for the United States and to the University of Nebraska for the PDSI code. We also acknowledge the E-OBS dataset from the EU-FP6 project ENSEMBLES (<http://ensembles-eu.metoffice.com>) and the data providers in the ECA&D project (<http://www.ecad.eu>). Funding for this research was provided by the Australian Research Council Centre of Excellence for Climate System Science Grant CE11E0098 and the Australian Research Council Linkage Grant LP100200690.

REFERENCES

- Alexander, L. V., and J. M. Arblaster, 2009: Assessing trends in observed and modelled climate extremes over Australia in relation to future projections. *Int. J. Climatol.*, **29**, 417–435.
- , and Coauthors, 2006: Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.*, **111**, D05109, doi:10.1029/2005JD006290.
- , P. Hope, D. A. Collins, B. Trewin, A. H. Lynch, and N. Nicholls, 2007: Trends in Australia's climate means and extremes: A global context. *Aust. Meteor. Mag.*, **56**, 1–18.

- Arblaster, J. M., and L. V. Alexander, 2012: The impact of the El Niño–Southern Oscillation on maximum temperature extremes. *Geophys. Res. Lett.*, **39**, L20702, doi:10.1029/2012GL053409.
- Bretherton, C. S., M. Widmann, V. P. Dymnikov, J. M. Wallace, and I. Blade, 1999: The effective number of spatial degrees of freedom of a time-varying field. *J. Climate*, **12**, 1990–2009.
- Brown, S. J., J. Caesar, and C. A. T. Ferro, 2008: Global changes in extreme daily temperature since 1950. *J. Geophys. Res.*, **113**, D05115, doi:10.1029/2006JD008091.
- Cardona, O. D., and Coauthors, 2012: Determinants of risk: Exposure and vulnerability. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, C. B. Field et al., Eds., Cambridge University Press, 65–108.
- Christidis, N., P. A. Stott, and S. J. Brown, 2011: The role of human activity in the recent warming of extremely warm daytime temperatures. *J. Climate*, **24**, 1922–1930.
- DeGaetano, A. T., and R. J. Allen, 2002: Trends in twentieth-century temperature extremes across the United States. *J. Climate*, **15**, 3188–3205.
- Donat, M., and Coauthors, 2013: Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The HadEX2 dataset. *J. Geophys. Res.*, **118**, 2098–2118, doi:10.1002/jgrd.50150.
- Field, C. B., and Coauthors, Eds., 2012: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. Cambridge University Press, 582 pp.
- Fouillet, A., and Coauthors, 2006: Excess mortality related to the August 2003 heat wave in France. *Int. Arch. Occup. Environ. Health*, **80**, 16–24.
- Frich, P., L. V. Alexander, P. Della-Marta, B. Gleason, M. Haylock, A. M. G. Klein Tank, and T. Peterson, 2002: Observed coherent changes in climatic extremes during the second half of the twentieth century. *Climate Res.*, **19**, 193–212.
- Gallant, A. J. E., and D. J. Karoly, 2010: A combined climate extremes index for the Australian region. *J. Climate*, **23**, 6153–6165.
- Gleason, K. L., J. H. Lawrimore, D. H. Levinson, T. R. Karl, and D. J. Karoly, 2008: A revised U.S. climate extremes index. *J. Climate*, **21**, 2124–2137.
- Global Soil Data Task Group, cited 2000: Global gridded surfaces of selected soil characteristics (IGBP-DIS). Oak Ridge National Laboratory Distributed Active Archive Center. [Available online at http://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=569.]
- Groisman, P. Ya., R. W. Knight, D. R. Easterling, T. R. Karl, G. C. Hegerl, and V. N. Razuvaev, 2005: Trends in intense precipitation in the climate record. *J. Climate*, **18**, 1326–1350.
- Gruza, G., E. Rankova, V. Razuvaev, and O. Bulygina, 1999: Indicators of climate change for the Russian Federation. *Climatic Change*, **42**, 219–242.
- Hamed, K. H., 2008: Trend detection in hydrologic data: The Mann-Kendall trend test under the scaling hypothesis. *J. Hydrol.*, **349**, 350–363.
- , and A. R. Rao, 1998: A modified Mann-Kendall trend test for autocorrelated data. *J. Hydrol.*, **204**, 182–196.
- Hansen, J., M. Sato, and R. Ruedy, 2012: Perception of climate change. *Proc. Natl. Acad. Sci. USA*, **109**, E2415–E2423, doi:10.1073/pnas.1205276109.
- Haylock, M. R., N. Hofstra, A. M. G. Klein Tank, E. J. Klok, P. D. Jones, and M. New, 2008: A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *J. Geophys. Res.*, **113**, D20119, doi:10.1029/2008JD010201.
- Jones, D. A., W. Wang, and R. Fawcett, 2009: High-quality spatial climate data-sets for Australia. *Aust. Meteor. Oceanogr. J.*, **58**, 233–248.
- Jones, G. S., P. A. Stott, and N. Christidis, 2008: Human contribution to rapidly increasing frequency of very warm Northern Hemisphere summers. *J. Geophys. Res.*, **113**, D02109, doi:10.1029/2007JD008914.
- Karl, T. R., 1986: The sensitivity of the Palmer drought severity index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. *J. Climate Appl. Meteor.*, **25**, 77–86.
- , C. N. Williams Jr., F. T. Quinlan, and T. A. Boden, 1990: United States Historical Climatology Network (HCN) serial temperature and precipitation data. ORNL/CDIAC-30, NDP-019/R1, Department of Energy, 389 pp.
- , R. W. Knight, D. R. Easterling, and R. G. Quayle, 1996: Indices of climate change for the United States. *Bull. Amer. Meteor. Soc.*, **77**, 279–292.
- Kenyon, J., and G. C. Hegerl, 2008: Influence of modes of climate variability on global temperature extremes. *J. Climate*, **21**, 3872–3889.
- King, A. D., L. V. Alexander, and M. Donat, 2013a: The efficacy of using gridded data to examine extreme rainfall characteristics: A case study for Australia. *Int. J. Climatol.*, **33**, 2376–2387, doi:10.1002/joc.3588.
- , —, and —, 2013b: Asymmetry in the response of eastern Australia extreme rainfall to low-frequency Pacific variability. *Geophys. Res. Lett.*, **40**, 2271–2277, doi:10.1002/grl.50427.
- Meehl, G. A., and Coauthors, 2000: An introduction to trends in extreme weather and climate events: Observations, socioeconomic impacts, terrestrial ecological impacts, and model projections. *Bull. Amer. Meteor. Soc.*, **81**, 413–416.
- Min, S.-K., X. B. Zhang, F. Zwiers, and G. C. Hegerl, 2011: Human contribution to more-intense precipitation extremes. *Nature*, **470**, 378–381.
- , W. Cai, and P. Whetton, 2013: Influence of climate variability on seasonal extremes over Australia. *J. Geophys. Res.*, **118**, 643–654.
- Moeborg, A., and P. D. Jones, 2005: Trends in indices for extremes in daily temperature and precipitation in central and western Europe, 1901–1999. *Int. J. Climatol.*, **25**, 1149–1171.
- , and Coauthors, 2006: Indices for daily temperature and precipitation extremes in Europe analyzed for the period 1901–2000. *J. Geophys. Res.*, **111**, D22106, doi:10.1029/2006JD007103.
- Morak, S., G. C. Hegerl, and J. Kenyon, 2011: Detectable regional changes in the number of warm nights. *Geophys. Res. Lett.*, **38**, L17703, doi:10.1029/2011GL048531.
- Munasinghe, L., T. Jun, and D. H. Rind, 2012: Climate change: A new metric to measure changes in the frequency of extreme temperatures using record data. *Climatic Change*, **113**, 1001–1024.
- Nicholls, N., 2008: Recent trends in the seasonal and temporal behaviour of the El Niño–Southern Oscillation. *Geophys. Res. Lett.*, **35**, L19703, doi:10.1029/2008GL034499.
- Pall, P., T. Aina, D. A. Stone, P. A. Stott, T. Nozawa, A. G. J. Hilberts, D. Lohmann, and M. R. Allen, 2011: Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature*, **470**, 382–385, doi:10.1038/nature09762.
- Palmer, W. C., 1965: Meteorological drought. Department of Commerce Research Paper 45, 58 pp.
- Peterson, T. C., X. Zhang, M. Brunet-India, and J. L. Vázquez-Aguirre, 2008: Changes in North American extremes derived from daily weather data. *J. Geophys. Res.*, **113**, D07113, doi:10.1029/2007JD009453.

- Power, S., F. Tseitkin, S. Torok, B. Lavery, R. Dahni, and B. McAvaney, 1998: Australian temperature, Australian rainfall and the Southern Oscillation, 1910–1992: Coherent variability and recent changes. *Aust. Meteor. Mag.*, **47**, 85–101.
- Seneviratne, S., and Coauthors, 2012: Changes in climate extremes and their impacts on the natural physical environment. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, C. B. Field et al., Eds., Cambridge University Press, 109–230.
- Sheffield, J., E. F. Wood, and M. L. Roderick, 2012: Little change in global drought over the past 60 years. *Nature*, **491**, 435–438.
- Stott, P. A., G. S. Jones, N. Christidis, F. Zwiers, G. C. Hegerl, and H. Shiogama, 2011: Single-step attribution of increasing frequencies of very warm regional temperatures to human influence. *Atmos. Sci. Lett.*, **12**, 220–227.
- Trenberth, K. E., 1997: The definition of El Niño. *Bull. Amer. Meteor. Soc.*, **78**, 2771–2777.
- Whitman, S., G. Good, E. R. Donoghue, N. Benbow, W. Y. Shou, and S. X. Mou, 1997: Mortality in Chicago attributed to the July 1995 heat wave. *Amer. J. Public Health*, **87**, 1515–1518.
- Zhang, Y., M. Nitschke, and P. Bi, 2013: Risk factors for direct heat-related hospitalization during the 2009 Adelaide heat-wave: A case crossover study. *Sci. Total Environ.*, **442**, 1–5.
- Zolina, O., C. Simmer, K. Belyaev, A. Kapala, and S. Gulev, 2009: Improving estimates of heavy and extreme precipitation using daily records from European rain gauges. *J. Hydrometeorol.*, **10**, 701–716.

Copyright of Journal of Climate is the property of American Meteorological Society and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.