Climate Extremes: Challenges in Estimating and Understanding Recent Changes in the Frequency and Intensity of Extreme Climate and Weather Events

Francis W. Zwiers, Lisa V. Alexander, Gabriele C. Hegerl, Thomas R. Knutson, James P. Kossin, Phillippe Naveau, Neville Nicholls, Christoph Schär, Sonia I. Seneviratne, and Xuebin Zhang

Abstract This paper focuses primarily on extremes in the historical instrumental period. We consider a range of phenomena, including temperature and precipitation extremes, tropical and extra-tropical storms, hydrological extremes, and transient extreme sea-level events. We also discuss the extent to which detection and attribution research has been able to link observed changes to external forcing of the climate system. Robust results are available that detect and often attribute changes in frequency and intensity of temperature extremes to external forcing. There is also some evidence that on a global scale, precipitation extremes have intensified due

---

Chapter Contributors M Donat, O Krueger, S Morak, TQ Murdock, M Schnorbus, V Ryabin, C Tebaldi, XL Wang

F.W. Zwiers (✉)
Pacific Climate Impacts Consortium, University of Victoria,
P.O. Box 1700 STN CSC, Victoria, BC V8W 2Y2, Canada
e-mail: fwzwiers@uvic.ca

L.V. Alexander
Climate Change Research Centre and ARC Centre of Excellence for Climate System Science,
The University of New South Wales UNSW, Sydney, NSW 2052, Australia
e-mail: l.alexander@unsw.edu.au

G.C. Hegerl
School of Geosciences, Grant Institute, University of Edinburgh,
The King's Buildings, West Mains Road, Edinburgh, EH9 3JW, UK
e-mail: Gabi.Hegerl@ed.ac.uk

T.R. Knutson
Geophysical Fluid Dynamics Laboratory, NOAA, Princeton University,
Forrestal Campus 201 Forrestal Road, Princeton, NJ 08540-6649, USA
e-mail: Tom.Knutson@noaa.gov

J.P. Kossin
NOAA's National Climatic Data Center, 151 Patton Avenue,
Asheville, NC 28801-5001, USA
e-mail: kossin@ssec.wisc.edu

G.R. Asrar and J.W. Hurrell (eds.), *Climate Science for Serving Society: Research, Modeling and Prediction Priorities*, DOI 10.1007/978-94-007-6692-1_13,

to forcing. However, robustly detecting and attributing forced changes in other important extremes, such as tropical and extratropical storms or drought remains challenging.

In our review we find that there are multiple challenges that constrain advances in research on extremes. These include the state of the historical observational record, limitations in the statistical and other tools that are used for analyzing observed changes in extremes, limitations in the understanding of the processes that are involved in the production of extreme events, and in the ability to describe the natural variability of extremes with models and other tools.

Despite these challenges, it is clear that enormous progress is being made in the quest to improve the understanding of extreme events, and ultimately, to produce predictive products that will help society to manage the associated risks.

Keywords Extremes • Extremes indices • Detection and attribution • Temperature and precipitation extremes • Extratropical storms • Tropical cyclones • Flood • Drought • Sea level

1 Introduction

This paper reviews some aspects of the current status of research on changes in climate extremes, identifying gaps and issues that warrant additional work. It focuses primarily on the historical instrumental period, giving a sense of the nature of the results that have been obtained and the challenges that arise from observational, methodological and climate modeling uncertainties. It also discusses the extent to which detection and attribution research has been able to link observed changes to external forcing of the climate system. In addition, the paper also very briefly

P. Naveau
Laboratoire des Sciences du Climat et l'Environnement (LSCE), CNRS,
Orme des Merisiers/Bat. 701 C.E. Saclay, Gif-sur-Yvette, 91191 Paris, France
e-mail: Philippe.Naveau@lsce.ipsl.fr

N. Nicholls
School of Geography and Environmental Science, Monash University,
Building 11, Clayton Campus, Wellington Road, Clayton, VIC 3800, Australia
e-mail: Neville.Nicholls@monash.edu

C. Schär • S.I. Seneviratne
Institute for Atmospheric and Climate Science, ETH Zurich,
Universitätstrasse 16, 8092, Zurich, Switzerland
e-mail: christoph.schaer@env.ethz.ch; sonia.seneviratne@env.ethz.ch

X. Zhang
Climate Research Division, Environment Canada, 4905 Dufferin Street,
Toronto, ON M3H 5T4, Canada
e-mail: Xuebin.Zhang@ec.gc.ca

discusses some aspects of projections for the twenty-first century, although this is not its primary focus. Extremes are not discussed on paleo time scales, in the context of the present (i.e., short term forecasting), or in the context of climate surprises (tipping points). These choices reflect our desire not to attempt too broad a review of the topic due to space constraints, as well as a view that high priority should be given to reducing uncertainty in the understanding of historical changes in extremes over the instrumental period as a prerequisite to confidently predicting changes over the next century. This includes the development of improved and comprehensive observational records, the development of better physical models, forcing data sets and more powerful statistical techniques, the development and refinement of the understanding of the physical processes that produce extremes, and continued improvement in the ability to attribute causes to those changes. Overall progress on understanding implications of ongoing and future changes in extremes will be strongly dependent upon the ability to document and understand changes in extremes during the period of history that has been (and continues to be) the most comprehensively and directly observed, which is why this is the topic of the present paper. While it is not the focus of this paper, it is clearly also very important to understand changes in extremes over longer periods of history, particularly where proxy data indicate larger extremes than observed during the modern instrumental period, such as for regional drought (e.g., Woodhouse and Overpeck 1998; Woodhouse et al. 2010).

Before beginning our review, it is worth taking a few minutes to think about the terminology that is used to describe extremes in climate science (see also Seneviratne et al. 2012, Box 3-1). Considerable confusion results from the various definitions of extremes that are in use. Part of this confusion occurs because the word *extreme* can be used to describe either a characteristic of a climate variable or that of an impact. In the case of a climate variable, such as surface air temperature or precipitation, the notion of an extreme is reasonably well defined and refers to values in the tails of the variable's distribution that would be expected to occur relatively infrequently. However, even in this case, there can be ambiguity concerning the definition of extremes. For example, a great deal of climate research on "extremes" deals with indicators of the frequency or intensity of events that, in fact, describe parts of the distribution that are not very extreme, such as warm events that occur beyond the 90th percentile of daily maximum temperature. Such events lie well within the observations that are collected each season, and they are typically studied by determining whether there are trends in their rates of occurrence. They are often referred to as "moderate extremes" in the literature (and we will also use that term occasionally below), but this term is not one that is used in statistical science to describe the upper part of a distribution, since the 90th percentile of daily values, for example, while in the upper tail would not necessarily be considered extreme in a statistical sense. The mechanisms involved in these 'moderate extremes' nevertheless should be similar to those involved in truly extreme events, and they are affected by different model biases from those for mean values (Hanlon et al. 2012a). There are also instances when the distribution of exceedances above the 90th percentile can be well approximated by an extreme value distribution. Nor does the term "moderate extremes" comprehensively describe the collection of ETCCDI[1] indices (Klein Tank et al. 2009) since they characterize various points in the distributions of daily temperature and precipitation observations, including diagnostics of daily variability that is not extreme, at least not everywhere, such as the annual number of frost days.

In addition to the literature on indices, or "moderate extremes" of climate variables, there is also a body of work that deals with rare values of climate variables that are generally not expected to recur each year. In this case the concept corresponds well to that used in the statistical sciences, and thus powerful statistical tools based on extreme value theory are available to aid in the analysis of historical and future extremes (e.g., Coles 2001; Katz et al. 2002). Such tools were originally developed to make statements about what might happen outside the range of the observed sample, such as the problem of estimating the 100-year return value on the basis of a 30- or 40-year sample. Hence, the notion of "extremes" in that context is defined as very high quantiles, such as the 95th, 99th or 99.9th percentiles of annual maximum values. An important aspect of this theory is to quantify the uncertainty of such extrapolations through the computation of suitably constructed confidence intervals. Increasingly, these tools are being used in the evaluation extreme events simulated in climate models (e.g., Kharin et al. 2007; Wehner et al. 2010; Wehner 2013). These tools are being further developed in the statistical sciences, and there is currently a very high level of interaction between that community and the climate sciences community on the development and application of methods that can be used in the climate sciences, such as the ExtREmes toolkit (see http://cran.r-project.org/web/packages/extRemes/).

In the case of extremes defined by their impacts, the concept of what constitutes an extreme may be less well defined, and this may affect the approaches that are available for analysis. For example, all tropical cyclones that are classified as Category 1–5 storms on the Saffir-Simpson scale are considered to be extreme because of their high potential to cause damage from high winds, rainfall, and/or storm surge flooding. These storms are an important component of the energetics climate system and occur in more or less constant numbers (globally) each year. They are more difficult to characterize statistically than, for example, extreme temperature events that are identified relative to variability recorded at fixed locations. The numbers of tropical cyclones within a region are not constant, the regions affected vary with time, and historical data that might be used to locate tropical cyclones in the tails of an appropriate probability distribution, while being constantly improved, often remain subject to substantial inhomogeneities due to the evolution of our observing systems (Knutson et al. 2010; Seneviratne et al. 2012).

[1] The joint World Meteorological Organization Commission on Climatology (CCl), World Climate Research Program Climate Variability and Predictability project (CLIVAR), and Joint Commission on Marine Meteorology (JCOMM) Expert Team on Climate Change Detection and Indices. See http://www.clivar.org/category/panels/etccdi

For the purpose of this article we consider "extreme events" to be well-defined weather or climate events (including tropical cyclones) that are rare within the current climate. With the term "well-defined" it is understood that these events may be defined in terms of measurable physical quantities such as temperature, precipitation, wind speed, runoff levels or similar; and the term "rare" is used to refer to values in the tails of the variable's distribution as discussed above, starting from the 90th percentile of the distribution to capture research on 'moderate' extremes.

It is important to note that the linkage between extreme events and extreme impacts (i.e. natural disasters) is not straightforward. Events that are rare from a statistical perspective may not necessarily lead to impacts if there is either no exposure or no vulnerability to the particular event. Also, the impact of an extreme event may depend on its season, its duration, and co-occurrence of further extremes, such as drought conditions with heat waves (Seneviratne et al. 2012). The occurrence of an extreme event does not necessarily imply monetary damages. Rather the occurrence of damages also depends upon whether there is any infrastructure at risk and its characteristics, population density, factors affecting the vulnerability of the population including whether emergency response measures are in place, etc (IPCC 2012). Conversely, not all damages from weather or climate events are related to extreme events as defined above. For instance, poor building practices may allow a "normal" or moderate event to generate extreme damages. For example, while the 2011 Thailand flood caused more than eight billion US dollars in insured damages, the amount of rain that fell in the region was not very unusual (van Oldenborgh et al. 2012). This issue is very familiar to the re-insurance industry, which uses damage models to link extreme events to impacts (e.g. Klawa and Ulbrich 2003; Watson and Johnson 2004). Extreme impacts in ecosystems may also occur following moderate events, e.g. when these are compounded with other climate events (see discussion in Hegerl et al. 2011 and Seneviratne et al. 2012).

The structure of the remainder of this paper is as follows. The paper begins in Sect. 2 with a discussion of the status of research on simple indices that are derived from daily (or occasionally more frequent) observations that are collected primarily at operational meteorological stations. The main focus here is on temperature and precipitation extremes, but wind extremes derived from station data are also discussed. Section 3 discusses storms (extra-tropical cyclones, tropical cyclones and tornadoes). This is followed by a discussion of hydrological extremes (droughts and floods) in Sect. 4, and extreme sea-levels (e.g., storm surge events) in Sect. 5. A summary and recommendations are presented in Sect. 6. Amongst other sources, the paper draws upon the IPCC 4th Assessment Report (IPCC 2007a, b), the US Global Change Program Special Assessment Product on extremes (i.e., CCSP 3.3, Karl et al. 2008), the recent WMO assessment on tropical cyclones (Knutson et al. 2010), a recently completed review of research on indices by Zhang et al. (2011), and on the IPCC Special Report on Extremes (Seneviratne et al. 2012).

2 Simple Indices Derived from Daily Data

2.1 Introduction

The indices that are discussed in this section are generally derived from daily observations of individual meteorological variables, such as temperature or precipitation. Indices calculated from daily data have appeal for a number of reasons, including the fact that they are relatively easy to calculate and that they summarize information on changes in variability compactly, and in a way that is accessible to a broad range of users.

Indices have been designed to characterize different parts of the distribution of a given variable. The indices that are of interest here are those that characterize aspects of the tails of the distribution (the "extremes") since these tend to be more relevant to society and natural systems than indices that characterize aspects of the distribution that occur more frequently, since extreme events are more likely to cause societal or environmental damage. However, a benefit of 'moderate' extremes is that they are better sampled and hence estimates of change in these kinds of extremes are less uncertain than estimates of changes in extremes that are further out in the tail of the distribution (Frei and Schär 2001).

Most indices of extremes tend to represent only "moderate extremes," i.e. those that typically occur at least once a year. In many cases, changes in the tails of the distribution, as indicated by changes in the indices, are essentially similar to those in other parts of the distribution (Fig. 1). However, even for temperature, changes may be seen that are not consistent between means and extremes, minimum and maximum, and upper and lower tail (e.g., Hegerl et al. 2004; Kharin et al. 2007) due to soil freezing, alterations in feedback processes, or energy balance constraints that may affect different parts of the distribution differently (e.g., Fischer and Schär 2009; Zazulie et al. 2010; Hirschi et al. 2011; Mueller and Seneviratne 2012). This can lead, for example, to strong changes where ice and snow-cover changes (Kharin and Zwiers 2005). Some indices for climate extremes can also be used for secondary inference; for example, statistical extreme value theory can be used to estimate long return period precipitation amounts from long time series of annual maximum

Fig. 1 (continued) Extremes are denoted by the *shaded areas*. In the case of temperature, changes in the frequencies of extremes are strongly affected by changes in the mean; a relatively small shift of the distribution to the right would substantially increase warm extremes and decrease cold extremes. In addition, the frequency of extremes can also be affected by changes in the shape of the tails of the temperature distribution, which could become wider or narrower, or could become somewhat skewed rather than being symmetric as depicted. In a skewed distribution such as that of precipitation, a change in the mean of the distribution generally affects its variability or spread, and thus an increase in mean precipitation would also likely imply an increase in heavy precipitation extremes, and vice-versa. In addition, the shape of the right hand tail could also change, affecting extremes. Furthermore, climate change may alter the frequency of precipitation and the duration of dry spells between precipitation events (From Zhang and Zwiers (2013), after Folland et al. (1995) and Peterson et al. (2008))

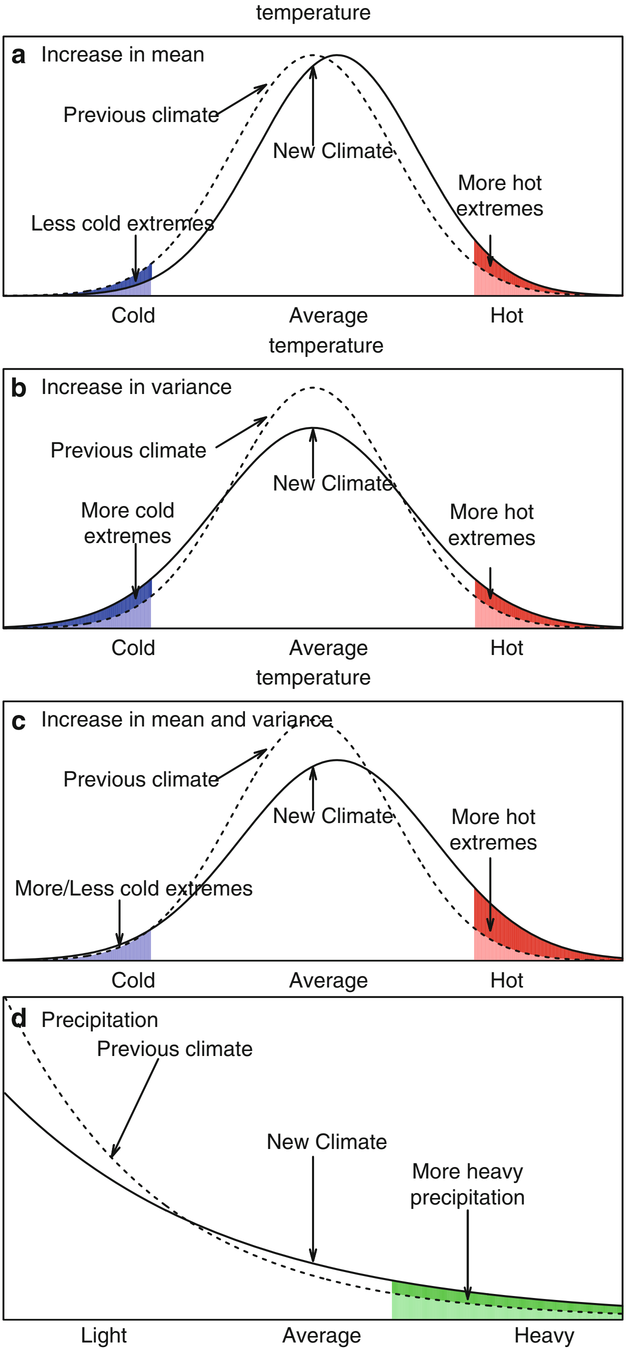

Fig. 1 Schematic representations of the probability distributions of daily temperature, which tends to be approximately Gaussian (exceptions can be caused by soil freezing, feedbacks, or energy balance constraints, see text), and daily precipitation, which has a skewed distribution.

daily precipitation amounts (Klein Tank et al. 2009). It should be noted that the estimation of return levels is often based on the assumption of spatial and/or temporal independence among sites or grid points (either on the raw data or conditionally on their distributional parameters). Consequently, uncertainties can be underestimated or these assumptions can be challenged. On the other hand, many studies also employ schemes that borrow information from adjacent locations to improve local parameter and return value estimates. Approaches range from simple averaging of key parameters across nearby grid points (e.g., Kharin and Zwiers 2000) to regional analysis approaches that derive spatial trends in distributional parameters estimated at different locations (e.g., Hanel et al. 2009).

In addition to indices that summarize various aspects of the tails of the daily variability of individual meteorological parameters, there have also been a variety of attempts to build indices that incorporate information from multiple parameters to summarize information related to impacts, such as fire weather indices that were first developed for operational use in wild fire risk management (e.g., Van Wagner 1987) and subsequently used to study the potential impacts of climate change on wild fire frequency and extent (e.g., Flannigan et al. 2005). Similar types of development are seen in a variety of indices (another example being health-related heat indices such as that described by Steadman 1979; Karl and Knight 1997; Fischer and Schär 2010; Sherwood and Huber 2010). Since these types of indices are impact specific, their construction must ultimately be informed by the characteristics and functioning of the system (ecological, social, or economic) or biological organism that is impacted (health, agriculture). This requires inter- and trans-disciplinary collaboration, and involves a range of potential compound indices far greater than would be required to monitor and understand change in the physical climate system.

2.2 Status

2.2.1 Temperature and Precipitation Indices

Many indices have been defined (e.g., Frich et al. 2002; Klein Tank et al. 2009) for the purpose of monitoring changes in the moderately far tails of surface variables such as temperature and precipitation that are routinely observed on a daily, or more frequent, basis. These indices include: (i) absolute quantities such as the annual maximum and minimum temperature and the annual maximum precipitation; (ii) the frequency of exceedance beyond a fixed absolute threshold, such as the annual count of the number of days with precipitation amounts greater than 20 mm; (iii) the frequency of exceedance above or below fixed relative thresholds such as the 90th percentile of daily maximum temperature or the 10th percentile of daily minimum temperature where the threshold is determined from a climatological base period such as 1961–1990; and (iv) dimensionless indices, such as the proportion of annual precipitation that is produced by events larger than the 95th percentile of daily precipitation amounts, where the threshold is again determined from a fixed base period.

These indices are studied because they describe aspects of temperature and precipitation variability that have been linked, to greater or lesser degrees, to societal or ecological impacts. Relative indices also have the advantage that they can be applied across different climatic zones. Their calculation is actively coordinated by the CLIVAR/CCl/JCOMM Joint Expert Team on Climate Change Detection and Indices (ETCCDI). The state of development of these indices has recently been reviewed comprehensively by Zhang et al. (2011). Further, Sillmann et al. (2013a, b) have recently described the performance of climate models participating in the Coupled Model Intercomparison Project Phase 3 (Meehl et al. 2007b) and Phase 5 (Taylor et al. 2012) in simulating observed and projected changes in the suite of ETCCDI indices.

The calculation of indices requires high quality, high frequency (daily or better), homogeneous meteorological data. High quality data are available from hydro-meteorological services in many parts of the world, and are often freely available for scientific research at least nationally, if not on a fully open basis internationally, though various limitations to (mostly raw) data access remain an issue (see also point i below). Data availability is generally greater in developed countries than in developing countries, where resources and/or mandate sometimes limit the collection and dissemination of daily meteorological observations, although restricted data access also remains a problem in some developed countries. The ETCCDI has an ongoing program of open source software development and international workshops that are intended to train developing world scientists in the homogenization of data that are collected by their hydro-meteorological services, and in the subsequent calculation of indices (Peterson and Manton 2008). The calculated indices are published in the peer-reviewed literature (e.g., Aguilar et al. 2009) and are subsequently contributed to global scale index datasets such as HadEX (Alexander et al. 2006) and its updates (e.g. Donat and Alexander 2011; Alexander and Donat 2011), thereby helping to improve the global coverage of these datasets and consequently enabling more confident global scale monitoring and detection and attribution.

While the ETCCDI type of approach is helpful, there are nevertheless ongoing challenges. These include:

(i) Concerns about the reproducibility of the entire chain of index production. Currently the reproducibility of the full processing sequence cannot be guaranteed because, while methods and codes are freely available, the underlying daily station data are not always openly accessible to the international scientific community since regional data gathering organizations may not have the capacity or mandate to support open data dissemination.

(ii) Lack of access to daily station data also implies a lack of access to metadata describing the history of observing stations. This is an important concern because small changes in observing station location or exposure can affect both the mean and variability of the recorded data, leading to large artificial changes in extremes (Katz and Brown 1992). In the absence of station metadata, it is often difficult to determine if such issues have affected indices derived from the underlying data.

(iii) Lack of real-time updating, particularly for regions that are unable to contribute to the Global Historical Climate Network (GHCN, see http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/). This is a concern because maintaining and monitoring indices is not always part of the primary mandate of the developing world scientists who participate in the ETCCDI workshops and are involved in index development for their countries or regions. It should be noted however, that the Asia Pacific Network (APN; Manton et al. 2001), which has focused on a specific region, has been successful in running repeat workshops that have allowed for the updating of indices in that region.

(iv) While the indices provide much needed information on daily variability, some scientific information is lost when providing only a limited number of pieces of information about the distribution of daily temperature and precipitation. This is ameliorated somewhat by approaches to the analyses of indices (such as the annual extremes of daily minimum and maximum temperature) that are based on extreme value theory. Such methods can be used to make inferences about changes in extremes over time and are able to provide results for thresholds more extreme than that used to define the underlying index.

(v) Potential difficulties in characterizing the statistical distributions of some indices, particularly where extreme value theory cannot be directly applied, which makes it more difficult to make reliable statistical inferences about things such as the presence or absence of trend in a time series of annual indices.

(vi) Consideration of specific impacts often requires information that relies upon simultaneous values of several climate variables. For instance, health impacts from heat waves depend upon temperature and humidity (and additional factors), information that cannot be recovered from standard indices.

An additional challenge is that the spatial coverage of index datasets remains far from being truly global, with significant fractions of the globe still under-sampled, for example, in Africa and South America (see Fig. 2a–c). Further challenges in the production of global datasets are also related to the choice of gridding framework in addition to parameter choices that are made within a chosen gridding method (e.g. Donat and Alexander 2011). This adds additional uncertainty to long term variability measures and trend estimates. Nevertheless, even when different choices are made, trends are broadly similar, at least on a global scale and particularly for temperature extremes. Large differences in observed trends can be associated with data processing choices, such as whether the daily data are gridded first before the indices are calculated, as occurs when indices are derived from HadGHCND (red curve in Fig. 2d), or vice-versa as in HadEX2 (blue curve in Fig. 2d) or GHCNDEX (green curve in Fig. 2d). These sensitivities are addressed in some studies by using data that are processed in more than one way (Morak et al. 2011).

The index approach also has several scientific limitations. One such limitation, for which a solution has been found, is the possibility that inhomogeneities can be introduced into index time series unintentionally, such as can occur in the case of threshold crossing frequency indices when thresholds representative of the far tails are estimated from a fixed observational base period (e.g., Zhang et al. 2005).

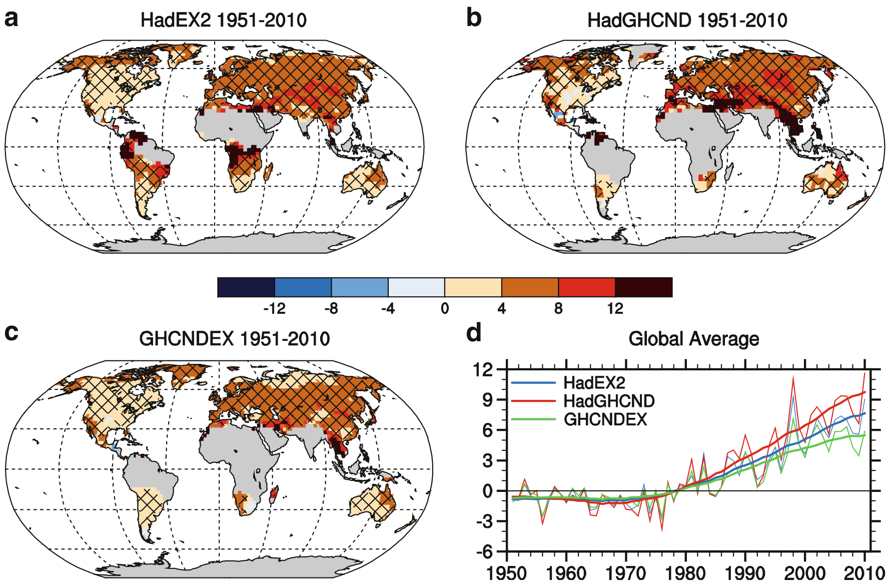

Fig. 2 Annual trends in warm nights (TN90p) using different datasets for the period 1951–2010 where at least 40 years are available. The datasets are (**a**) HadEX2 (Alexander and Donat 2011), (**b**) HadGHCNDEX (ETCCDI indices calculated from an updated version of HadGHCND (Caesar et al. 2006)) and (**c**) GHCNDEX (Donat and Alexander 2011). *Panel* (**d**) represents the global average time series plots for each of the three datasets presented as anomalies relative to the 1961–1990 with associated 21-year Gaussian filters

Another limitation, which can also be circumnavigated, is that differences in the recording resolution of observational data can cause non-climatic spatial variations in threshold crossing frequency and trends (e.g., Zhang et al. 2009). A third limitation is that in a changing climate, the number of exceedances of thresholds based on a climatological base climate may saturate, e.g. exceedances may never or almost always occur under strong climate change. Thus, percentage exceedance indices are only useful for characterizing change in a distribution that is not too far from the base period (see e.g. Portmann et al. 2009). A further limitation is that the nature of index data, which typically provides only one value per month (Alexander and Donat 2011), and in the earlier data, only one per year (Alexander et al. 2006), may limit the range of possible approaches that can be used to analyze change in certain types of extremes. For example, long return period extremes (e.g., the intensity of the 20-year extreme daily precipitation event) can be estimated from the annual extremes that are recorded in HadEX, but the analyst can only do so using the so-called block-maximum approach to extreme value analysis, which only considers the most extreme of a series of values observed within a block of a defined length (e.g. the annual maximum). In contrast, it is often argued by statisticians that the so-called peaks-over-threshold approach, by which all values exceeding a given threshold are used in the analysis, may result in more confident estimates of long period return values since it has the potential to utilize the information about extremes that is available in a long time series of daily values more effectively than the block-maximum approach. Dupuis (2012) gives a recent example of a peaks-over-threshold analysis for temperature extremes in several US cities. It should be noted however, that the peaks-over-threshold approach remains difficult to apply to large gridded datasets, such as the output from global climate models, because of the challenges associated with finding an automated procedure for reliably determining the appropriate threshold at each location in the grid. A further consideration is that most available index datasets do not currently provide the date (or dates) on which the extreme values were recorded. This creates a limitation when attempting to study the association between the occurrences of extremes in different variables or between climate extremes on the one hand and impacts on the other, and limits process based analyses of the conditions leading to recorded extremes. In contrast, the availability of monthly indices now makes it possible to study changes in the seasonality of extremes (see, for example, Morak et al. 2013).

As noted, methods have been developed to prevent inhomogeneities in indices that count exceedances beyond quantile based thresholds and to account for the effects of different data reporting resolutions (Zhang et al. 2005, 2009). Other limitations could be overcome by adding a modest number of additional indices to the "standard" ETCCDI list. For example, one could include within the suite of indices the r most extreme values observed annually for some small number $r > 1$ and not just the most extreme value annually, thereby enabling the application of the more efficient "r-largest" extreme value analysis techniques (e.g., Smith 1986; Zhang et al. 2004). Another example would be to store the dates of the annual occurrence of indices. In addition, it would be appropriate to redefine the ETCCDI indices such that they describe annual extremes and counts that pertain to a year that is defined in a climatologically appropriate manner, where the definition of the year would depend upon location and parameter, taking into account the form of the annual cycle for the specific aspect of the parameter that is relevant for each index. This may be challenging in regions with complex annual cycles, such as those with multiple wet and dry seasons. It should also be noted that the definition of the year has implications for many types of indices and not just annual extremes as discussed above. A specific example is CDD (consecutive dry days, see Klein Tank et al. 2009), an index that can show very large changes in climate models under future emissions scenarios (e.g. Tebaldi et al. 2006; Orlowsky and Seneviratne 2012). CDD calculated on the basis of the calendar year has a different interpretation in places where the climatological dry period spans the year boundary as opposed to places where the climatological dry period occurs in the middle of the year; while dry periods may be of comparable length in both types of places, CDD will tend to report them as being substantially shorter in the former. In contrast, a CDD index that was calculated from years that are defined locally in such a way that the climatological dry period occurs everywhere in the middle of the year would have a more uniform interpretation across different locations.

There are a number of factors that limit our ability to evaluate how well models simulate indices in comparison to observed indices. These include observational limitations, such as limited spatial and temporal coverage of observing stations, and the likelihood that there are few regions in the world where precipitation station density is sufficient to reliably estimate daily grid box mean precipitation on GCM and RCM scales (see discussion in Zhang et al. 2007). As a consequence, model evaluation often relies on proxies for direct observations, such as reanalysis products. This is a reasonable approach for variables such as surface temperature that are reasonably well constrained by observations in reanalyses, but it is more problematic in the case of variables such as precipitation (e.g. Lorenz and Kunstmann 2012) that are generally not observationally constrained in reanalyses (the North American Regional Reanalysis, Mesinger et al. 2006, is an exception; it uses precipitation observations to adjust latent heating profiles). Furthermore, the observational data streams assimilated in reanalysis data products are not consistent over time, e.g. because of the relatively short length of satellite data, which may affect their use for the assessment of climatic trends (e.g. Bengtsson et al. 2004; Grant et al. 2008; Lorenz and Kunstmann 2012; Sillmann et al. 2013a). Taking these various limitations into account, models are found to simulate the climatology of surface temperature extremes with reasonable fidelity (Kharin et al. 2007; Sillmann et al. 2013a) on global and regional scales when compared against reanalyses, although there are uncertainties associated with, for example, the representation of land-atmosphere feedback processes in models (Seneviratne et al. 2006). In contrast, intercomparisons between models, reanalyses, and large scale observational precipitation products such as CMAP (Xie et al. 2003) suggest large uncertainties in all three types of precipitation products; particularly in the tropics (e.g., see Figure 6 in Kharin et al. 2007).

Scaling issues (e.g., differences between the statistical characteristics and spatial representativeness of point observations from rain gauges or gridded observed precipitation versus that of grid box mean quantities simulated by climate models; Klein Tank et al. 2009; Chen and Knutson 2008), uncertainties in observational gridded products (Donat and Alexander 2011), and incomplete process understanding continue to limit the extent to which direct quantitative comparison can be made between station observations and models (Mannshardt-Shamseldin et al. 2010). It should be noted, however, that models of sufficiently high resolution may be capable of simulating precipitation extremes of comparable intensity to observed extremes. For example, Wehner et al. (2010) show the global model that they study produces precipitation extremes comparable to observed extremes at a horizontal resolution of approximately 60 km. In contrast, most global models continue to operate at lower resolutions, leading to ambiguities in the interpretation of projected changes in extremes. Nevertheless, precipitation change at large scales is determined primarily by changes in the global hydrological cycle that are reflected in changes in evaporation, atmospheric moisture content, circulation (which affects moisture transport and convergence), and energy and moisture budgets, providing a fundamental basis for the qualitative (in terms of the direction of change and its large scale features), if not quantitative (in terms of the absolute values of the changes and their detailed geographic patterns), interpretation of modeled precipitation changes. The scaling issue can sometimes be circumnavigated by transforming observed and simulated precipitation into dimensionless quantities that can more readily be intercompared, such as has been done by Min et al. (2011). A disadvantage of such transformations, however, is that the translation of extremes onto a probability or other type of relative scale may impede the physical interpretation of trends and variability. Also, the application of such transforms requires strong assumptions concerning the physical processes that generate extremes at different scales that are difficult to evaluate.

2.2.2 Wind Indices

To date, temperature and precipitation indices have been studied most intensively. Indices of wind extremes, while of enormous importance in engineering applications, have received less attention, in part because of the greater difficulty in obtaining homogeneous high-frequency wind data. Wind records are often affected by non-climatic influences, such as development in the vicinity of an observing station that alters surface roughness over time. It has also been postulated by Vautard et al. (2010) that large scale changes in vegetative cover over many land areas has altered surface roughness and that this may be an important contributor to the apparent stilling (reduction) of surface wind speeds in many mid-latitude regions (e.g., see also Zwiers 1987; Roderick et al. 2007).

An alternative to using direct anemometer observations of wind speeds is to consider a proxy that is based on pressure readings that are usually more homogeneous than wind speed observations. Several storm proxies currently being used are derived from pressure readings at single stations, such as the statistics of 24-hourly local pressure changes or of the frequency of low pressure readings. These single station proxies relate to synoptic experience and reflect storminess indirectly as they seek to detect atmospheric disturbances (e.g. Schmith et al. 1998; Hanna et al. 2008; Allan et al. 2009; Bärring and von Storch 2004; Bärring and Fortuniak 2009). Another approach to explore past storminess is to make use of the statistics of geostrophic wind speeds. Geostrophic wind speeds can be derived by considering mean sea-level pressure gradients in networks of reliable surface pressure records over homogenous mid-latitude domains, such as the north-east Atlantic and western Europe (e.g., Schmidt and von Storch 1993; Alexandersson et al. 1998). These records, which continue to be developed in the North Atlantic and European region (e.g., Wang et al. 2011) and are also being developed for south-eastern Australia (e.g., Alexander et al. 2011), are available for much longer periods of record than the more limited anemometer network. For the North Atlantic region for which they have been most extensively developed, they show predominately the effects of natural low frequency variability in atmospheric circulation on variations in storminess and extreme geostrophic wind speeds.

Recently Krueger and von Storch (2011) used a regional climate model to evaluate the underlying assumption that the extremes of geostrophic wind speed are indeed representative of surface wind speed extremes, and found good correspondence between the two. They also considered the sensitivity of the proxy to the density of stations in the network, concluding that higher density networks should give more reliable estimates of wind speed extremes. Work is currently underway to evaluate the robustness of such proxies to instrumental error in pressure readings and to inhomogeneity in one or more of the surface pressure records that are used to derive the geostrophic winds. Further, a study that evaluates how well a number of single-station pressure proxies represent storminess has recently been completed (Krueger and von Storch 2012) and concludes that all single-station pressure proxies considered were linearly related to storm activity, with absolute pressure tendency being most strongly correlated.

Another possibility for the construction of wind speed and storminess indices is provided by reanalyses, such as the NCEP (Kistler et al. 2001), ERA-40 (Uppala et al. 2005), or the twentieth century (20CR) reanalysis of Compo et al. (2011), which is based only on surface observations and covers the period 1871–2010. In contrast with wind speed observations and recent extreme wind speed reconstructions from surface pressure readings (e.g., Wang et al. 2011), all reanalyses appear to show an increase in European storm indicators during the last few decades of the twentieth century (Smits et al. 2005; Donat et al. 2011). For tropical cyclones, the intensities of the storms (i.e., maximum near-surface sustained 1-min wind speeds) can also be estimated globally using satellite data, at least since the early 1980s (Kossin et al. 2007; Elsner et al. 2008).

2.3 Role of External Influences

2.3.1 Temperature Extremes

Considerable progress has been made in the detection and attribution of externally forced change in surface temperature extremes since the feasibility of such studies was first demonstrated by Hegerl et al. (2004). Studies that detect human influence on surface temperature extremes are available on the global and regional scale and use a range of indices that probe different aspects of the tails of the surface temperature distribution. This includes studies of changes in the frequency moderately extreme temperature events (e.g., Morak et al. 2011; Fig. 3, which also shows that human influence can be detected in the frequency of warm nights in most regions; Morak et al. 2013) and the magnitude (e.g., Christidis et al. 2005, 2011; Zwiers et al. 2011) of extreme surface temperature events. Results are robust across a range of methods and across both types of indices. Some studies use methods that rely on extreme value theory (e.g., Christidis et al. 2011; Zwiers et al. 2011), and are therefore best suited for studying change in the far tails of the temperature distribution, whereas other studies that consider less extreme parts of the distribution (Christidis et al. 2005; Morak et al. 2011, 2013) appropriately use standard fingerprinting approaches (e.g., Hegerl et al. 2007). Some studies (e.g., Christidis et al. 2011) are also able to separate and quantify the responses to anthropogenic and natural external forcing from observed changes in surface temperature extremes, thereby increasing

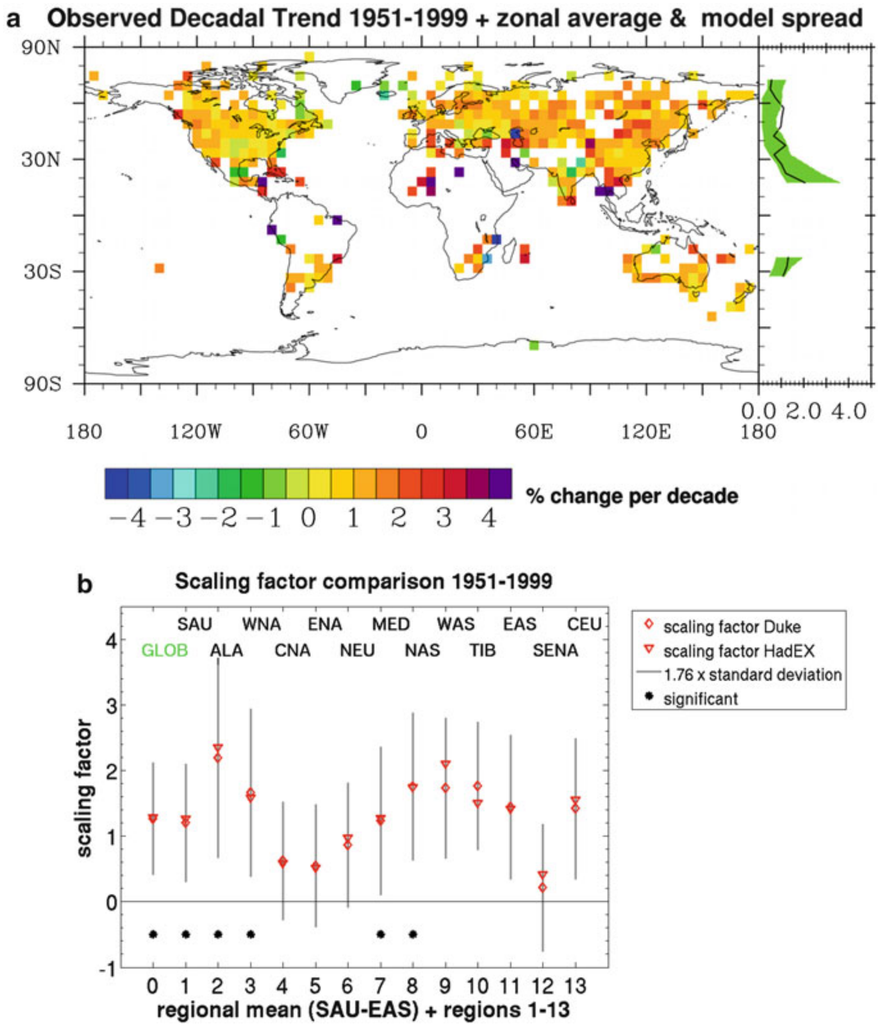

Fig. 3 (**a**) 1951–1999 observed decadal trend of TN90 (in % change per decade) based on a combination of HadEX (Alexander et al. 2006) and additional index data from Kenyon and Hegerl (2008). The zonal average of the observations (*black line*) and the spread of trends in an ensemble of CMIP3 (Coupled Model Intercomparison Project Phase 3, see http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php) "ALL" forcings model simulations for the same period (*green shaded area*) is shown on the side of the plot. (**b**) The scaling factors (*red markers*) of observed changes projected onto the multi-model mean fingerprint for the period 1951–1999. The "*diamonds*" indicate scaling-factors based the Kenyon and Hegerl (2008) dataset (labeled Duke in the legend), and the "*triangles*" indicate scaling-factors based on HadEX. *Grey bars* indicate 5–95 % uncertainty ranges. Regions in which results are detectable at the 5 % significance level and where model simulated internal variability is consistent with regression residuals are indicated with an asterisk. Results indicate broad increases in the frequency of warm nights, as well as the detection of anthropogenic influence in the pattern of observed increases globally and in several regions (From Morak et al. 2011)

confidence in the attribution of a substantial part of the observed changes to external forcing on global scales. Other studies use indirect evidence for attributing significant changes to forcing, such as the tight link between changes in mean and extreme temperatures in a multi-step attribution method (Morak et al. 2011; see Hegerl et al. 2010).

There is the potential to further develop techniques in order to be able to conduct the analysis more fully within the framework of extreme value theory and more confidently separate signals by utilizing recent developments in the statistical modeling of extremes that account for their spatial dependence properties. One approach would be to model extremes spatially via so-called max-stable processes (e.g., Smith 1990; Schlather 2002; Vannitsem and Naveau 2007; Blanchet and Davison 2011).[2] Other approaches are also actively being considered. By working within the framework of extreme value theory, as has already been done in the recent studies of Christidis et al. (2011) and Zwiers et al. (2011), it should become possible to attribute changes in the *likelihood* of extreme events to external causes, thereby contributing to the scientific underpinnings that will be required for event attribution (see Stott et al. 2012). For example, Zwiers et al. (2011) provide rough estimates of circa 1990s expected waiting times for events that nominally had a 20-year expected waiting time in the 1960s, showing that cool temperature extremes have become substantially less frequent globally, whereas warm temperature extremes have become modestly more frequent. Approaches such as that of Zwiers et al. (2011), which considers grid points or stations independently of each other, could be made more efficient if the spatial dependence between extremes could be taken into account. Statistical space-time modeling can account for spatial dependence between parameters of extreme value distributions, for example, by setting prior expectations of spatial dependence that are updated with data. These methods can account for complex space-time structure of extremes and make use of information in data more completely (e.g., Sang and Gelfand 2009, 2010; Heaton et al. 2010). Climatologists will need the assistance of statisticians to fully realize the benefits from these types of approaches. It should be noted that several of the detection and attribution techniques currently applied to extremes are able to take spatial dependence into account (e.g., Hegerl et al. 2004; Christidis et al. 2005, 2011; Min et al. 2011; Morak et al. 2011) by casting the problem in such a way that the Gaussian assumption should hold approximately.

A limitation of many studies that have been conducted to date is that they have been confined to the twentieth century, in part due to the design of the CMIP3 experiment which ended the historical simulations and the single forcing runs at 1999 or 2000, but more importantly, because suitable observational datasets providing broad

---

[2] A probability distribution is said to be *stable* when the average of a sample of independently drawn values from that distribution has a distribution belonging to the same family of distributions (Feller 1971). The Gaussian distribution is an example of a stable distribution. Stability can also be defined in terms of some other types of operations that may be applied to a sample. In particular, *max-stable* distributions have the property that the maximum value of such a sample again has a distribution within the same family of distributions. The generalized extreme value distribution is max-stable.

coverage of annual temperature extremes have not yet been updated to the more recent decade (e.g., Alexander et al. 2006), although recent studies extend into the twenty-first century (e.g. Morak et al. 2013). Initiatives to expand these datasets, including updating them in near-real time are currently underway or finished (Donat and Alexander 2011; Alexander and Donat 2011). Also, modeling groups participating in CMIP3 generally were not able to make available large volumes of high frequency (daily or higher) output or ensembles of historical single forcing runs (e.g., runs with historical greenhouse gases or aerosol forcing only). Consequently, currently available studies that separate signals have only been performed with single climate models rather than with multi-model ensembles. All of these problems are presently being alleviated at least to some extent with the advent of updated research quality datasets, such as HadEX2 (Alexander and Donat 2011), and the growing availability of CMIP5 simulations (Taylor et al. 2012) that are currently being analyzed by the climate modeling community and are making available high frequency output more broadly than their predecessors in CMIP3, enabling a more thorough exploration of model uncertainties (for example, Hanlon et al. 2012b show results for a multi-model detection analysis for temperature extremes over Europe).

The studies available to date use only a limited number of models. Across many of these studies results suggest that the climate model simulated pattern of the warming response to historical anthropogenic forcing in cold extremes fits observations best when its amplitude is scaled by a factor greater than one (i.e., when the simulated warming signal is scaled up). Conversely, the expected warming signal in warm daily maximum temperature extremes generally needs to be scaled down, and in fact, has only recently been detected in observations through the use of more sophisticated statistical techniques (Christidis et al. 2011; Zwiers et al. 2011). These results point to the possibility that the forcing and/or response mechanisms, including the possibility of feedbacks that operate differently during the warm and cold seasons and during different parts of the diurnal cycle (day versus night), may not be fully understood (e.g. Portmann et al. 2009) or accurately modeled. Recent examples include work by Seneviratne et al. (2006, 2010) and Nicholls and Larsen (2011) concerning the role of land-atmosphere feedbacks in the development of temperature extremes, by Sillmann et al. (2011) on the role of blocking in the development of cold temperature extremes in winter over Europe, and by Hohenegger et al. (2009) on the role of the soil-moisture precipitation feedback.

2.3.2 Precipitation Extremes

As is also the case with change in the mean state, in comparison with surface air temperature only limited progress has been made in determining the extent to which external influences on the climate system have influenced changes in the intensity or frequency of heavy or extreme precipitation. Various observational studies have found that extreme precipitation can have heavy tailed behavior (with a shape parameter in the range of approximately 0–0.2 when annual maxima of daily precipitation are fitted with a generalized extreme value distribution, e.g., Fowler et al. 2010).

While climate models simulate substantial precipitation extremes, it is not clear that they simulate daily intensities that are as heavy-tailed as observed, nor is it clear that they do so given the different scales represented by observed point values and simulated grid-box values. For example, Kharin and Zwiers (2005) do not find strong evidence for heavy tailed behavior in the model that they studied, estimating shape parameters that are positive, but near zero. Fowler et al. (2010) similarly find a discrepancy in tail behavior between observed and climate model simulated extreme precipitation in the model they study. Averaging in space and time smoothes the tail behavior recorded at weather stations but this reduces the applicability for impact studies. In addition, it is a real challenge to detect and attribute changes whenever the variable of interest has a positive shape parameter, indicating unbounded growth in return values as return periods become very long. In such cases, uncertainties grow rapidly with a slight change in the shape parameter and consequently very long time series are necessary. Thus there are substantial statistical challenges associated with the detection and attribution of the precipitation response to external forcing.

Nevertheless, there is a modest body of literature that has investigated whether there is evidence that natural or anthropogenic forcing has affected global land mean precipitation (e.g., Gillett et al. 2004; Lambert et al. 2005), the zonal distribution of precipitation over land (e.g., Zhang et al. 2007; Noake et al. 2011; Polson et al. 2013) and the quantity of precipitation received at high northern latitudes (Min et al. 2008). Since the variability of precipitation is related to the mean (there is greater short term precipitation variability in regions that receive more precipitation), the detection of human influence on the mean climatological distribution of precipitation should imply that there has also been an influence on precipitation variability, and thus extremes. Hegerl et al. (2004) found in a model-study that changes in moderately extreme precipitation may be more robustly detectable than changes in mean precipitation since models robustly expect extreme precipitation to increase across a large part of the globe while the pattern of increase and decrease in annual total precipitation is more sensitive to model uncertainty.

Min et al. (2011) recently investigated this possibility, finding evidence for a detectable human influence in observed changes in precipitation extremes during the latter half of the twentieth century. This was accomplished by transforming the tails of observed and simulated distributions of annual maximum daily precipitation amounts into a probability based index (PI) before applying an optimal detection formalism, thereby partly circumnavigating the scaling issues that are associated with precipitation. It should be noted however, that some strong assumptions are implicit in such transformations that are not necessarily verifiable. For example, it is implicitly assumed that forced changes in precipitation extremes result in comparable changes in PI at different scales, even though the mechanisms that generate extreme precipitation locally may be quite different from those that determine extreme events on climate model grid box scales and larger. Even with the transformation, it was found that a best fit with observations required that the magnitude of the large-scale climate model simulated responses to external forcing be increased by a considerable factor, with a greater increase in magnitude being required in the

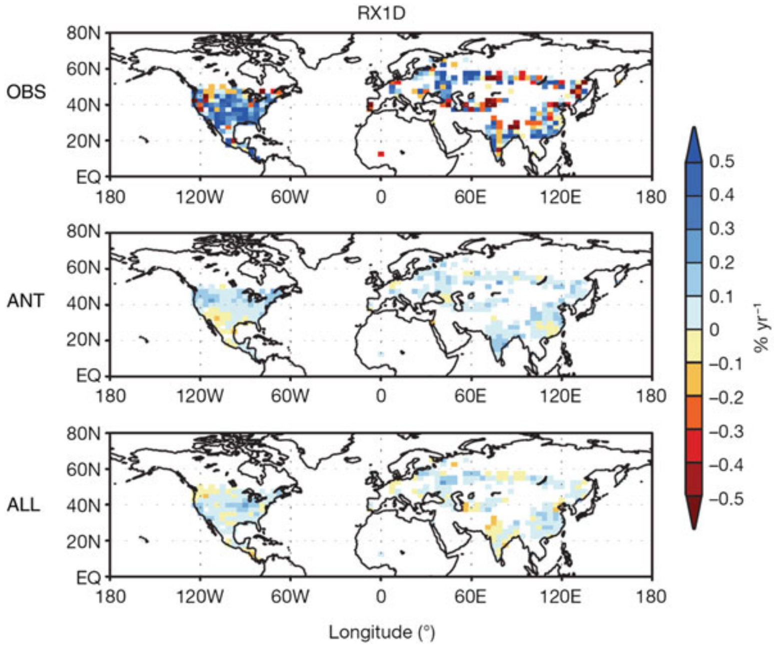

Fig. 4 Geographical distribution of trends of extreme precipitation indices (*PI*) for annual maximum daily precipitation amounts (*RX1D*) during 1951–1999. Observations (*OBS*); model simulations with anthropogenic (*ANT*) forcing; model simulations with anthropogenic plus natural (*ALL*) forcing. For models, ensemble means of trends from individual simulations are displayed. Units: per cent probability per year (From Min et al. (2011; see paper for details))

case of historical simulations that take into account a combination of anthropogenic and natural forcing (ALL forcing), than for simulations accounting only for the former (ANT forcing; see Fig. 4). The discrepancy between scaling factors for ALL and ANT forcing is understandable given that the anthropogenically forced signal is still small, and that natural forcing (from changes in solar and volcanic activity) would have offset some of the response to ANT forcing, thereby weakening the ALL signal during the latter part of the twentieth century. This leads to smaller expected changes in the ALL fingerprint, which are more strongly affected by noise and thus more difficult to detect, than the 'cleaner' signal from ANT forcing. The on-line supplementary information accompanying Min et al. (2011) includes an extensive set of sensitivity analyses that consider a broad range of uncertainties affecting their results.

The cause of the discrepancies between observed and simulated changes in both mean and extreme precipitation remains to be fully understood. Explanations could include uncertainties in observations, forcing, or the representation of moist processes in models. The observations used in detection studies to date have been limited to the twentieth century, extending to the early twenty-first century in some recent cases, and have been based exclusively on station data. Noake et al. (2011)

suggest that the scale problem (see below) may be part of the model-data mismatch, as it reduces when precipitation changes are expressed in percent. Polson et al. (2013) find that while detection in some seasons is robust to data uncertainty, CMIP5 models and data agree within data and sampling uncertainty for most seasons. Nevertheless, coverage is limited to land areas only and in many regions, is inadequate due to limitations in observing network density, access to existing observations for the purposes of scientific research, or lack of capacity or mandate to facilitate the dissemination of observations. Remote sensing products may eventually solve these problems, but they have not yet been used in detection and attribution studies due to homogeneity concerns and lack of sufficiently long records, although they have been used in some cases for model evaluation (e.g., Kharin et al. 2007). Without broader coverage it is difficult to assess, for example, whether discrepancies in changes between models and observations are a global phenomenon or whether they are regional in nature, reflecting, for example, differences in moisture transport between models and the observed world. Topography, land-atmosphere coupling, and the representation of teleconnected patterns of variability all affect precipitation and are subject to uncertainty due to limited resolution in climate models or lack of complete process knowledge. In addition, wide uncertainty also remains in aerosol forcing (e.g., Forster et al. 2007), aerosol transport, the effect of aerosols upon the production of precipitation, and so on, which may affect both temperature extremes and precipitation extremes. Further, there are differences in the mechanisms of response to long- and short-wave forcing (e.g., Mitchell et al. 1987; Allen and Ingram 2002) and thus the possibility that models may over- or under-simulate the response to one or the other type of forcing.

3 Storms

High energy cyclonic phenomena driven by latent heat release occur in the atmosphere on a number of scales, ranging from individual tornadoes to mesoscale convective complexes to extra-tropical and tropical cyclones. They often cause extensive damage directly by high wind speeds and/or heavy precipitation, and this may be compounded by the effects of flying debris, drifting snow, storm surges and high waves, and wind driven ice movements and other associated events.

3.1 Extra-Tropical Cyclones

Extratropical cyclones (synoptic-scale low pressure systems) exist throughout the mid-latitudes and are associated with extreme winds, sea levels, waves and precipitation. Climate models project changes in the large scale flow and reduced meridional temperature gradients as a consequence of greenhouse gas forcing, both of which affect extra-tropical cyclone development, and consequently produce changes in their number distribution (Lambert and Fyfe 2006) and in the positioning of extra-tropical storm tracks (Bengtsson et al. 2006).

Climate models represent the general structure of the storm track pattern reasonably well (Bengtsson et al. 2006; Greeves et al. 2007; Ulbrich et al. 2008; Catto et al. 2010) although models tend to have excessively zonal storm tracks (Randall et al. 2007). Detecting changes in extra-tropical cyclone numbers, intensity, and activity based on reanalysis remains challenging due to concerns about inhomogeneity that is introduced through changes over time in the observing system, particularly in the southern hemisphere (Hodges et al. 2003; Wang et al. 2006, 2012). Even though different reanalyses correspond well in the Northern Hemisphere (Hodges et al. 2003; Hanson et al. 2004; Wang et al. 2012), changes in the observing system over time may also have affected the fidelity with which cyclone characteristics are represented in reanalyses there as well (Bengtsson et al. 2004).

Numerous studies using reanalyses suggest that the main northern and southern hemisphere storm tracks have shifted polewards during the last 50 years (e.g., Trenberth et al. 2007). Idealized modeling studies (e.g., Brayshaw et al. 2008; Butler et al. 2010) suggest that radiative forcing from increases in well mixed greenhouse gases and decreases in stratospheric ozone may have played a role in these shifts. However, Sigmond et al. (2007) note that the response of the extratropical circulation to global warming is not necessarily robust across different models even for a common SST change pattern, and for a given model and SST change the extratropical response can depend on the horizontal resolution and on certain poorly constrained tuning parameters. For the moment, observational studies of pressure-based indices (discussed above; e.g., Wang et al. 2011 for the European/North Atlantic region, see Fig. 5; Alexander et al. 2011 for south-eastern Australia) are not able to provide corroborating evidence of a poleward shift in the principal storm track locations, since in both hemispheres, the domain over which pressure triangles needed to produce these indices is rather limited. Ongoing work with single station pressure proxies may help to alleviate this situation in the future. For example, a regional study over Canada that considered changes in observed cyclone deepening rates based on pressure tendencies at stations (Wang et al. 2006) found qualitative agreement between reanalyses and station data suggesting a northward shift of the winter storm track over Canada.

Detection and attribution studies examining whether human influence has played a role in changes in cyclone number, intensity or distribution have not yet been conducted. However, human influence has been detected in the global sea level pressure (Gillett et al. 2005; Gillett and Stott 2009) and in one study, in geostrophic wind energy derived from sea level pressure records (Wang et al. 2009b). Gillett and Stott (2009) show that observed patterns of trends, which indicate decreases in high latitude sea level pressure and increases elsewhere, are robust when calculated from data for 1949–2009. Observed changes were consistent with expectations based on the model (HadGEM1) used in that study, suggesting that anthropogenic influence has contributed to both pressure decreases at high latitudes and increases at low latitudes. The mechanism for the latter is not well understood. Using an approach

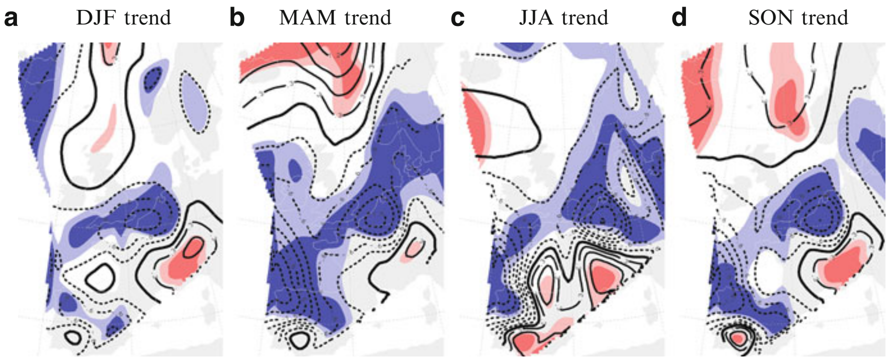

Fig. 5 Example of an analysis of trends in seasonal storm indices derived from long surface pressure records. This figure shows contour maps of Theil-Sen (also sometimes know as Kendall's) linear trend estimates (in unit per century) in seasonal storm indices defined as the 99th percentile of sub-daily geostrophic wind speed estimated from pressure triangles for the period 1902–2007 in a domain that covers western Europe and the eastern North Atlantic. The contour interval is 0.3. The zero contours are shown in *bold*. Positive trends are shown in *thin solid contours*, and *reddish* shadings indicate at least 20 % significance; and negative trends in *dashed contours* and *bluish shadings*. The *darker shadings* indicate areas with trends that are significant at the 5 % level or lower. Significance is determined using the Mann-Kendall trend test (From Wang et al. (2011). The statistical methods are described in Wang and Swail (2001))

that would not formally be considered as a detection and attribution method, Fogt et al. (2009) find that both coupled climate model simulated trends and observed trends in the Southern Annular Mode (SAM) lie outside the range of internal climate variability during the austral summer, suggesting that human influence has contributed to the observed SAM trends.

3.2 *Tropical Cyclones*

About 90 tropical cyclones have been observed annually since the introduction of geostationary satellites. The global frequency has remained more or less constant over this period, albeit with substantial variability in the frequency of tropical cyclones and locations of their tracks within individual ocean basins (e.g., Webster et al. 2005; Kossin et al. 2010).

Tropical cyclones are typically classified in terms of their intensity according to the Saffir-Simpson scale as indicated by near-surface wind speed or central pressure. Long-term records of the strongest storms are potentially less reliable than those of tropical cyclones in general (Landsea et al. 2006). In addition to intensity, other impact-relevant characteristics of tropical cyclones include frequency, duration, track, precipitation, and the structure and areal extent of the wind field in tropical cyclones, the latter of which can be very important for damage through storm surge as well as the direct wind-related damage.

Forming robust physical links between changes in tropical cyclone characteristics and natural or human-induced climate changes is a major challenge. Historical tropical cyclone records are known to be heterogeneous due to changing observing technology and reporting protocols (e.g., Landsea et al. 2004) and because data quality and reporting protocols vary substantially between regions (Knapp and Kruk 2010). The homogeneity of the global record of tropical cyclone intensity derived from satellite data has been improved (Knapp and Kossin 2007; Kossin et al. 2007), but these records represent only the past 30–40 years. Statistically significant trends have not been observed in records of the global annual frequency of tropical cyclones (e.g., Webster et al. 2005). Century-scale trends in frequency have been identified in the North Atlantic, but are contested (see below). Increasing century-scale frequency trends have not been identified in other basins although a declining trend in the frequency of land-falling tropical cyclones has recently been identified in a new long-term dataset for eastern Australia (Callaghan and Power 2011). Power dissipation has increased sharply in the North Atlantic and more weakly in the western North Pacific over the past 25 years (Emanuel 2007), but the interpretation of longer-term trends is constrained by data quality concerns as well as uncertainties on the potential role of natural climate variability in the observed increases. Satellite-based records of extreme precipitation associated with tropical cyclones also appear to have substantial homogeneity issues due to satellite changes (Lau et al. 2008). It remains difficult to robustly place tropical cyclone metrics for recent decades into a longer historical context (Knutson et al. 2010) because pre-satellite records are incomplete and therefore require the use of methods to estimate storm undercounts and other biases; these methods have provided mixed conclusions to date (e.g., for the North Atlantic basin, see Holland and Webster 2007; Landsea 2007; Mann et al. 2007; Vecchi and Knutson 2008; Landsea et al. 2009; Knutson et al. 2010; see also Fig. 6).

Our understanding of the factors that affect tropical cyclone metrics and their variation is improving but remains incomplete. Anthropogenic forcing has been identified as a cause of SST warming in tropical cyclogenesis regions (e.g., Santer et al. 2006; Gillett et al. 2008). Potential intensity theory (Bister and Emanuel 1998) links changes in the mean thermodynamic state of the tropics to cyclone potential intensity and implies that a greenhouse warming could induce a shift towards greater intensities. This has received some support from dynamical hurricane model simulations (summarized in Knutson et al. 2010, Table S2). Results suggest that human influence could have altered tropical cyclone intensities over the twentieth century. However, as noted above, the available evidence concerning historical trends and detectable anthropogenic influence on tropical cyclone characteristics is mixed. A global analysis of trends in satellite-based tropical cyclone intensities has identified an increasing trend that is largest in the upper quantiles of the distribution (Elsner et al. 2008), and most pronounced in the Atlantic basin. However, this record extends back only to 1981 which is regarded as too short to distinguish a long-term trend from the pronounced multi-decadal variability in the Atlantic basin. Historical data show that tropical cyclone power dissipation is related to sea surface temperatures (SSTs), near-tropopause temperatures and vertical wind shear (Emanuel 2007),

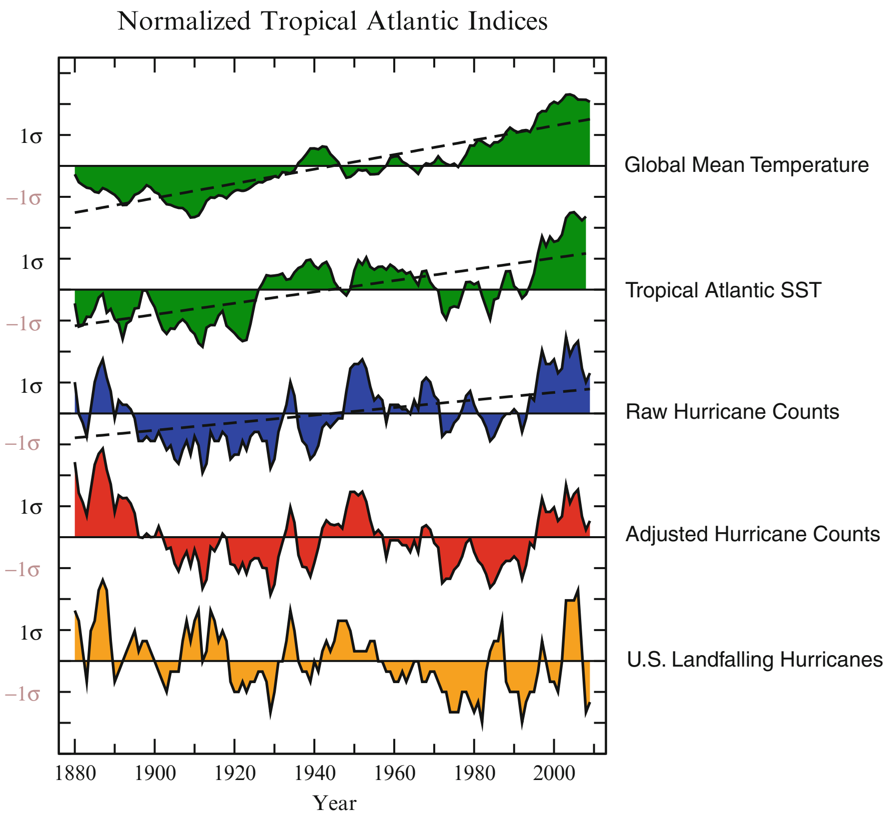

Fig. 6 Five-year running means of tropical Atlantic indices. *Green curves* depict global annual-mean temperature anomalies (*top*) and August–October Main Development Region (MDR, defined as 20–80 W, 10–20 N) SST anomalies (second from *top*). *Blue curve* shows unadjusted Atlantic hurricane counts. *Red curve* shows adjusted Atlantic hurricane counts that include an estimate of "missed" hurricanes in the pre-satellite era. *Orange curve* depicts annual U.S. landfalling hurricane counts. *Vertical axis tic marks* denote one standard deviation intervals (shown by the σ symbol). *Dashed lines* show linear trends. Only the top three curves have statistically significant trends (Source: Adapted from Vecchi and Knutson 2011)

but it has been suggested that the spatial pattern of SST variation in the tropics may exert an even stronger influence on Atlantic hurricane activity than absolute local SSTs (Swanson 2008; Vecchi and Soden 2007; Ramsay and Sobel 2011). This would have important implications for the interpretation of climate model projections (Vecchi et al. 2008). Related to this, a growing body of evidence suggests that the SST threshold for tropical cyclogenesis (currently about 26 °C) would increase at about the same rate as tropical SSTs due to greenhouse gas forcing (e.g., Ryan et al. 1992; Knutson et al. 2008; Johnson and Xie 2010). This means, for example, that the areas of simulated tropical cyclogenesis would not expand along with the 26 °C isotherm in climate model projections. The most recent assessment by the World

Meteorological Organization (WMO) Expert Team on Climate Change Impacts on Tropical Cyclones (Knutson et al. 2010) concluded that it remains uncertain whether past changes in any measure of tropical cyclone activity (frequency, intensity, rainfall) exceeds the variability expected through natural causes, after accounting for changes in observing capabilities over time. Seneviratne et al. (2012) drew essentially the same conclusion, stating that "The uncertainties in the historical tropical cyclone records, the incomplete understanding of the physical mechanisms linking tropical cyclone metrics to climate change, and the degree of tropical cyclone variability provide only *low confidence* for the attribution of any detectable changes in tropical cyclone activity to anthropogenic influences". However, recent advances in understanding and phenomenological evidence for shorter-term effects on tropical cyclones from aerosol forcing are providing increasing confidence that anthropogenic forcing has had a measurable effect on tropical cyclone activity in certain regions (Mann and Emanuel 2006; Evan et al. 2009, 2011; Booth et al. 2012; Villarini and Vecchi 2013) although the relative influence of aerosols vs. natural variability on recent multidecadal variability in the Atlantic basin remains uncertain (e.g., Ting et al. 2009; Zhang and Delworth 2009; Camargo et al. 2013; Villarini and Vecchi 2013). Thus, when assessing changes in tropical cyclone activity, it is clear that detection and attribution aimed simply at long-term linear trends forced by increasing well-mixed greenhouse gasses is not adequate to provide a complete picture of the potential anthropogenic contributions to the changes in tropical cyclone activity that have been observed.

Based on a variety of model projections of late twenty-first century climate, it is expected that global tropical cyclone frequency will either decrease or display little change as a consequence of greenhouse warming, but that there will be an increase in mean wind speed intensity and in tropical cyclone rainfall rates over the twenty-first century (Meehl et al. 2007a; Knutson et al. 2010). Projected changes for individual basins are more uncertain than global mean projections, as they show large variations between different modeling studies. Studies that have compared tropical cyclone projections downscaled from different climate models using a single downscaling framework (e.g., Zhao et al. 2009; Sugi et al. 2009) suggest that at the regional scale, the uncertainties in tropical cyclone projections due to differences in projected SST patterns are substantial. Concerning detection and attribution of tropical cyclone changes, in addition to the substantial uncertainty in historical records, a further challenge for identifying such an anthropogenic change signal in observations is that the projected changes are typically small compared to estimated observed natural variability. Modeling studies (e.g. Knutson and Tuleya 2004; Bender et al. 2010) suggest, on the basis of idealized simulations, that unambiguous detection of the effect of greenhouse gas forcing on Atlantic tropical cyclone characteristics may still be decades off. Other studies that have considered projected changes in tropical cyclone-related damage and loss under the A1B emissions scenario (Crompton et al. 2011; Emanuel 2011; Mendelsohn et al. 2012) predict a broad range of emergence time-scales from decades to centuries. However, it should again be emphasized that regional forcing by agents other than greenhouse gases, such as anthropogenic aerosols, is known to affect the regional climatic conditions differently (e.g. Villarini and Vecchi 2013), and that there is evidence that anthropogenic aerosol pollution has affected tropical cyclone activity in some regions. Thus it seems likely that the emergence time-scales projected under A1B warming are sensitive to the A1B aerosol forcing projections, which are known to be highly uncertain (Forster et al. 2007; Haerter et al. 2009).

3.3 Tornadoes and Other Types of Small Scale Severe Weather

Tornadoes typically occur during severe thunderstorms in which rapid vertical motion and the resulting convergence of angular momentum produces the potential for very high local vorticity. While our understanding of tornadoes has increased in recent years (e.g., Trapp et al. 2005), the body of research that is available globally on changes in tornado frequency and intensity remains limited. This is in part because the available data are inhomogeneous in time (e.g., Brooks 2004) due to changes in reporting practices as well as changes in population and public awareness, and the introduction of technology such as Doppler radar, all of which undoubtedly affect detection rates. The assessments of Trenberth et al. (2007) and Karl et al. (2008) contain brief sections summarizing available research on tornadoes and other types of small scale severe weather. The scale of these phenomena implies that there are only limited opportunities for interpretation of the observed record using models. At present, any change in their likelihood of occurrence can only be inferred indirectly from models by considering changes in atmospheric conditions such as stability and vertical shear that affect their occurrence. For this reason, as well as the inadequacy of the observational record, detection and attribution studies have not been attempted. Projections of future changes in the incidence and intensity of tornadoes due to greenhouse warming and other climate forcings also remain uncertain, partly because competing influences on tornado occurrence and intensity might change in different ways. Thus, on the one hand, greenhouse gas induced warming may lead to greater atmospheric instability due to increases in temperature and moisture content, suggesting a possible increase in severe weather, but on the other hand, vertical shear may decrease due to reduced pole-to-equator temperature gradients (Diffenbaugh et al. 2008).

4 Hydrological Extremes

We discuss here floods and droughts, which are complex phenomena with large impacts that affect large numbers of people each year. Space and time scales can be large, particularly in the case of droughts which can occur on sub-continental to continental scales and have extended durations of years or longer. In contrast, some types of flooding can be localized and of short duration, although flooding may also occur in large basins over an extended period of time (months). While floods and droughts generally represent opposite ends of the spectrum of variability in a region's hydrological balance, it should be noted that the two phenomena are not completely mutually exclusive. For example, extreme precipitation events, with the possibility of local flash flooding, can occur during drought (e.g., Hanesiak et al. 2011).

4.1 Floods

Floods are affected by various characteristics of precipitation. For example, freshet flooding is driven by meteorological and synoptic characteristics that control the timing and magnitude of energy fluxes into the snowpack, possibly confounded by the occurrence of rainfall. The frequency and intensity of floods can be altered by natural and human engineered and non-engineered land use effects on drainage basins, which makes the detection of climatic influences difficult. Human engineering-induced effects include the possibility that the impoundment of water may alter the local precipitation climatology (Hossain et al. 2009). Storm surge events can cause coastal flooding, which may be exacerbated in estuaries if a storm surge event coincides with heavy discharge. Sea level rise (Sect. 5) can also interact with storm surge events to increase the risk of coastal flooding (Abeysirigunawardena et al. 2009).

The IPCC AR4 (Rosenzweig et al. 2007) and the IPCC Technical Paper VI based on the AR4 (Bates et al. 2008) concluded that documented trends in floods show no evidence for a globally widespread change in flooding (see also, for example, Kundzewicz et al. 2005), although there was abundant evidence for earlier spring peak flows and increases in winter base flows in basins characterized by snow storage. They also noted that there was some evidence of a reduction in ice-jam floods in Europe (Svensson et al. 2006). As highlighted in the SREX (Seneviratne et al. 2012), subsequent research, which continues to be hampered by the limited availability and coverage of river gauge data, provides mixed results. Some studies suggest that there has been an increase in flooding over time in some basins (e.g., some basins in south-east Asia, Delgado et al. 2009; Jiang et al. 2008; and South America, Barros et al. 2004). Another study tentatively concluded that a significant increase was detectable in "great floods"—referring to floods with discharges exceeding 100-year levels in basins larger than 200,000 km^2 (Milly et al. 2002). However, many other studies suggest no climate-driven change (e.g., in northern Asia, Shiklomanov et al. 2007; North America, Cunderlik and Ouarda 2009; Villarini et al. 2009) or provide regionally inconsistent findings (e.g., in Europe, Allamano et al. 2009; Hannaford and Marsh 2008; Mudelsee et al. 2003; and Africa, Di Baldassarre et al. 2010), or a change in the characteristics of flooding such as might be expected when a snowmelt driven flood regime switches, with warming, to a mixed snowmelt-rainfall regime (e.g., Cunderlik and Ouarda 2009).

River discharge simulation under a changing climate scenario is generally undertaken by driving a hydrological model with downscaled, bias-corrected climate model outputs. However, bias-correction and statistical downscaling tend to ignore the energy closure of the climate system, which could be a non-negligible source of uncertainty in hydrological projections (Milly and Dunne 2011). Most hydrological models must first be tuned on a basin-by-basin basis to account for sub-grid-scale characteristics such as basin hypsometry, the degree of watercourse meander and other channel characteristics. Hydrologic modeling is therefore subject to a cascade of uncertainties from climate forcing, climate models, downscaling approach, tuning, and hydrological model uncertainty that remain difficult to quantify comprehensively.

Recently, several studies have detected the influence of anthropogenically-induced climate change in variables that may affect floods. These include Zhang et al. (2007), Noake et al. (2011) and Polson et al. (2013), who detected human influence in observed changes in zonally averaged land precipitation, Min et al. (2008), who detected human influence in northern high-latitude precipitation and Min et al. (2011), who detected human influence in observed global scale change in precipitation extremes. Nevertheless, the extent to which such changes in precipitation may lead to changes in flooding depend on the regional climate characteristics of the respective river catchments, as well as on changes in other climate variables such as soil moisture content. While human influence has not yet been detected in the magnitude/frequency of floods, at least two studies using detection and attribution methodologies that incorporated output from hydrologic models driven with downscaled climate model output have suggested that human influences have had a discernable effect on the hydrology of the regions that they studied. Barnett et al. (2008) detected anthropogenic influence in western US snowpack and the timing of peak-flow (see also Hidalgo et al. 2009), and Pall et al. (2011) estimated that human influence on the climate system increased the likelihood of a fall 2000 flooding event that occurred in the southern part of the UK.

Uncertainty is still large in the projected changes in the magnitude and frequency of floods. The largest source of uncertainties in hydrological projections is from differences between the driving climate models, but the choice of future emission scenarios, downscaling method, and hydrologic model also contribute uncertainty (e.g., Kay et al. 2009; Prudhomme and Davies 2009; Shrestha et al. 2011; Taye et al. 2011). The relative importance of downscaling, bias-correction and the choice of hydrological models as sources of uncertainty may depend on the selected region/catchment, the selected downscaling and bias-correction methods, and the selected hydrological models (Wilby et al. 2008). Chen et al. (2011) demonstrated considerable uncertainty was caused by the choice of downscaling method used to make hydrological projections for a snowmelt-dominated Canadian catchment. Downscaling and bias-correction are also a major source of uncertainty in rain-dominated catchments (van Pelt et al. 2009).

4.2 Droughts

Drought is affected by multiple climate variables on multiple times scales, including atmospheric circulation, precipitation, temperature, wind speed, solar radiation, and antecedent soil moisture and land surface conditions. It can feed back upon the atmosphere via land-atmosphere interactions, potentially affecting the extremes of temperature, precipitation and other variables (e.g., Seneviratne et al. 2010; Nicholls and Larsen 2011). It can take multiple forms including meteorological drought (lack of precipitation), agricultural (or soil moisture) drought and hydrological drought (runoff or streamflow). There are few direct observations of drought-related variables (e.g., Trenberth et al. 2007), including soil moisture, and hence drought proxies such as the Palmer Drought Severity Index (PDSI – Palmer 1965; Dai et al. 2004; Heim 2002), the Standardized Precipitation Index (SPI – McKee et al. 1993; Heim 2002) and the Standardized Precipitation Evapotranspiration Index (SPEI – Vicente-Serrano et al. 2010) are often used to monitor and study changes in drought conditions. However, the use of these indirect indices results in substantial uncertainties in the resulting analyses; in particular the PDSI has been criticized as having several limitations (see discussion in Seneviratne et al. 2012). In contrast, hydrologic drought can be observed/analyzed via statistical analysis of discharge records (see e.g., Fleig et al. 2006).

Global assessments of changes in drought remain uncertain. Trenberth et al. (2007), using the Dai et al. (2004) dataset, found large increases in dry areas as indicated by the PDSI. However, it has been noted that the PDSI may not be comparable between diverse climatological regions (e.g., Karl 1983; Alley 1984). The self-calibrating (sc-) PDSI introduced by Wells et al. (2004) attempts to alleviate this problem by replacing fixed empirical constants with values based on the local climate. Using the sc-PDSI, van der Schrier et al. (2006) show that twentieth century soil moisture trends in Europe are not statistically significant. Using a more comprehensive land surface model than that implicit in either the PDSI or sc-PDSI, together with observation-based forcing, Sheffield and Wood (2008) inferred that decreasing trends in drought duration, intensity and severity were prevalent globally during 1950–2000 (Fig. 7). However, they also noted strong regional variation and increases in drought indicators in some regions, consistent with some regional studies. For example, Andreadis and Lettenmaier (2006), using a similar approach, found increasing trends in soil moisture and runoff in much of US in the latter half of twentieth century. On the other hand, Dai (2011) found a global tendency for increases in drought based on various versions of the PDSI including the sc-PDSI and soil moisture from a land surface model driven with observation-based forcing. Patterns of change obtained with those different techniques were largely consistent, with substantial spatial variability being a dominant characteristic. Nevertheless, inconsistencies between studies and indicators demonstrate that there remain large uncertainties with respect to global assessments of past changes in droughts, making it difficult to confidently attribute observed changes to external forcing on the climate system (Seneviratne et al. 2012).

Characterizing hydrologic (i.e. runoff and streamflow) drought globally and regionally is also challenging due to difficulties in establishing robust and/or standardized quantitative drought descriptions over varied hydrologic regimes (e.g., Fleig et al. 2006). Some recent examples regarding analysis of streamflow records for detection of possible trends in low flow include work in Europe (Stahl et al. 2010), Canada (Ehsanzadeh and Adamowksi 2007) and the UK (Hannaford and Marsh 2006).

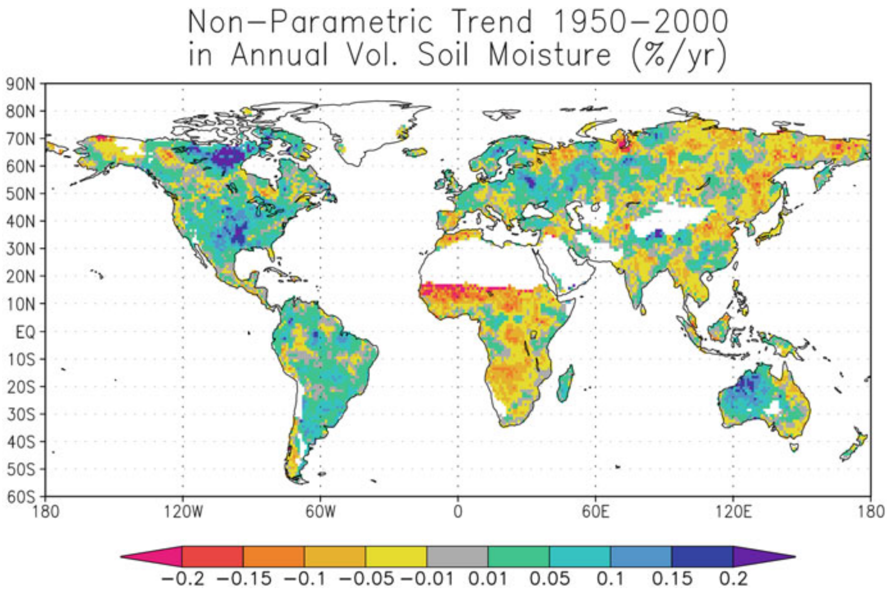

Fig. 7 Global distribution of linear trends in annual mean volumetric soil moisture for 1950–2000 obtained from the Variable Infiltration Capacity (*VIC*) hydrologic model when driven with observationally based forcing. The trends are calculated using the Theil-Sen estimator and evaluated with the Mann–Kendall nonparametric trend test. Regions with mean annual precipitation less than 0.5 mm day^{-1} have been masked out because the VIC model simulates small drying trends in desert regions that, despite being essentially zero, are identified by the nonparametric test (From Sheffield and Wood (2008; Fig. 1))

Despite these uncertainties in global scale studies, there is often more agreement amongst regional studies of historical and current drought, consistent with the notion that circulation changes should induce regionally coherent shifts in drought regimes. For example, precipitation is strongly affected by the El Niño/Southern Oscillation in many parts of the world (Ropelewski and Halpert 1987), including extremes (Alexander et al. 2009; Kenyon and Hegerl 2010; Zhang et al. 2010), and the resulting teleconnected circulation responses are often linked to the occurrence of precipitation deficits and drought in different regions (e.g., Folland et al. 1986; Hoerling and Kumar 2003; Held et al. 2005; Hoerling et al. 2006; Giannini et al. 2008; Schubert et al. 2009) although internal atmospheric variability that is not forced by slowly changing boundary conditions can also create drought (e.g., Hoerling et al. 2009). Also, progress is being made in understanding the role of land-atmosphere feedbacks that affect surface conditions (e.g., Koster et al. 2004; Seneviratne et al. 2006, 2010; Fischer et al. 2007), although the rate of advance is limited by the availability of observational data.

Christensen et al. (2007) provide an assessment of regional drought projections based on simulations that were performed for CMIP3, noting consistency across models in projected increases in droughts particularly in subtropical and mid-latitude areas. Uncertainty in drought projections stems from multiple sources. Perhaps the most fundamental of these is the uncertainty in the pattern of sea-surface temperature response to forcing, which is “El Niño like” in many models (Meehl et al. 2007a), and which therefore cascades to other aspects of model behavior through the teleconnected responses to SST change. A second source of uncertainty is associated with the possible alteration of land-atmosphere feedback processes, both as a consequence of change in the physical climate system and change in the terrestrial biosphere. A third source of uncertainty arises because the complexities of drought are at best incompletely represented in commonly used drought indices, leading to potential discrepancies of interpretation. For example, Orlowsky and Seneviratne (2012) show, using a more complete ensemble of CMIP3 simulations than was available at the time of Christensen et al. (2007), that ensemble projections based on meteorological and agricultural drought indices can be quite different, particularly at higher latitudes. Also, Burke and Brown (2008), considering several drought indices and two different ensembles of climate model simulations, show little change in the proportion of the land surface that is projected to be in drought based on the SPI, whereas indices that account for change in the atmospheric demand for moisture showed significant increases in the global land area affected by drought. It has been suggested that inferences based on climate model simulated soil moisture may be more robust than those based on other types of drought indicators. This is because model results are often found to be consistent after simple scaling (e.g., Koster et al. 2009; Wang et al. 2009a).

5 Sea Level

Transient sea level extremes caused by severe weather events such as tropical or extratropical cyclones can produce storm surges and extreme wave heights at the coast. Extreme sea levels may change in the future as a result of both changes in atmospheric storminess and mean sea level rise, neither of which will be spatially uniform across the globe. Sea level change along coast lines may also be affected by some additional factors including glacial isostatic adjustment, coastal engineering, and changes in the Earth’s gravitational field (e.g., Mitrovica et al. 2010) arising from glacial and ice-sheet melting. Global mean sea level rose at an average rate of 1.7 [1.2–2.2] mm year^{-1} over the twentieth century, 1.8 [1.3–2.3] mm year^{-1} over 1961–2003, and at a rate of 3.1 [2.4–3.8] mm year^{-1} over 1993–2003 (Bindoff et al. 2007). Externally induced sea level rise occurs against a backdrop of natural variability in sea level that must be taken into account when attributing causes to observed changes. For example, natural modes of variability such as the El Niño/Southern Oscillation (Menéndez and Woodworth 2010), the Pacific Decadal Oscillation (Abeysirigunawardena and Walker 2008), the North Atlantic Oscillation (Marcos et al. 2009) and the position of the South Atlantic high (Fiore et al. 2009) all have transient effects on extreme sea levels. It is *very likely* that humans contributed to sea level rise during the latter half of the twentieth century (Hegerl et al. 2007),

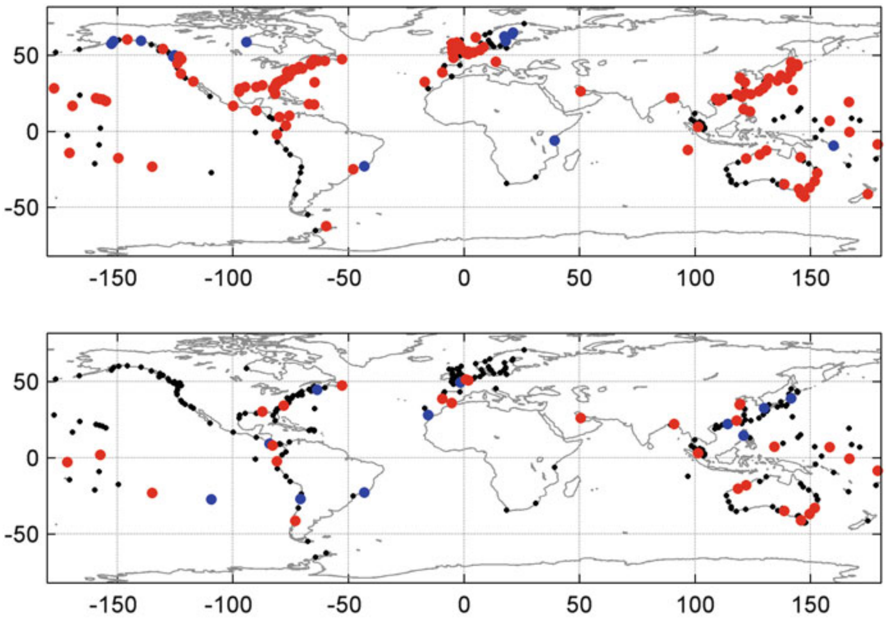

Fig. 8 Estimated trends in (*upper*) annual 99th percentile of sea level based on monthly maxima of hourly tide gauge readings from 1970 onwards, and (*lower*) 99th percentile after removal of the annual medians of hourly readings. Only trends significant at the 5 % level are shown in color: *red* for positive trends and *blue* for negative trends. Linear trends were estimated via least-squares regression taking the interannual perigean tidal influence into account (From Menéndez and Woodworth 2010). The figure shows that extreme sea levels have risen broadly, and that the dominate influence on that rise is from the increase in mean sea level

and therefore *more likely than not* that humans contributed to the trend in extreme high sea levels (Solomon et al. 2007). Both mean and extreme sea level has continued to rise since the AR4 (Church et al. 2011; Menéndez and Woodworth 2010; Woodworth et al. 2011; see Fig. 8).

Meehl et al. (2007a) projected model based 90 % ranges for sea level rise for 2090–2099 relative to 1980–1999 that varied from 18 to 38 cm in the case of the SRES B1 scenario to 26–59 cm in the case of the A1FI scenario. These estimates accounted for ocean thermal expansion, glaciers and ice caps, and modeled aspects of ice sheets. It was also estimated that an acceleration of the flow of ice from Greenland and Antarctic could increase the upper ends of these ranges by 10–20 cm, and it was noted that insufficient understanding of ice sheet dynamics meant that a larger contribution could not be ruled out. Subsequent studies that use statistical models to extrapolate sea level changes based on historical relationships between temperature and sea level have suggested somewhat higher ranges, for example, 0.75–1.90 m (Vermeer and Rahmstorf 2009, based on SRES B1 to A1FI scenarios), and 0.90–1.30 m (Grinsted et al. 2010, based on the SRES AIB scenario only).

Projections of extreme sea level can be produced regionally in several ways. Often, such studies involve a combination of downscaling and hydrodynamic modeling (e.g., Debernard and Roed 2008, who consider the European region and projected both decreases and increases depending upon location). Lin et al. (2012) used a statistical-dynamical hurricane simulation model together with a dynamical model of storm surge to project large reductions in the return periods of tropical cyclone-related surge events in New York City over the twenty-first century. Such approaches may not be feasible in all locations if the driving climate model does not simulate the phenomena that are likely to cause storm surge in a given region (e.g., tropical cyclones). In such cases it may be possible to construct statistical or idealized models of tropical cyclone characteristics from observations that can then be perturbed to represent future conditions and to drive hydrodynamic models (e.g., McInnes et al. 2003; Harper et al. 2009; Mousavi et al. 2011). A further approach is to conduct sensitivity analyses to assess the relative impacts on mean sea level rise and wind speed increase (e.g., McInnes et al. 2009).

6 Summary and Recommendations

In this paper we have reviewed some, but not all, aspects of the current status of research on changes in climate extremes. We have focused primarily on the historical instrumental record, noting results and challenges that arise from observational, methodological and climate modeling uncertainties. The choice to focus on the historical instrumental record reflects our view that high priority should be given to reducing uncertainty in our understanding of historical changes in extremes over the instrumental period as a prerequisite to confidently predicting changes over the next century. This includes the development of improved and comprehensive observational records, improvement in our ability to confidently detect changes in observations through the development of better physical models, forcing data sets and more powerful statistical techniques, the development and refinement of our understanding of the physical processes that produce extremes, and continued improvement in our ability to attribute causes to those changes. This does not imply that research on other aspects of extremes is of lesser importance, but rather that overall progress on understanding the implications of ongoing and future changes in extremes will be strongly dependent upon our ability to document and understand changes in extremes during the period of history that has been (and continues to be) the most comprehensively and directly observed.

Despite the limited scope of this review, it is apparent that a number of substantive challenges remain that impede the advancement of our understanding of extreme phenomena. We will discuss several in the following paragraphs.

The most fundamental of all of these challenges is simply *the state of the historical observational record* itself. Irrespective of the state of our process knowledge and our ability to integrate that knowledge into climate and weather prediction models, it is difficult to have confidence in predictions or projections if we do not have adequate historical data to reliably document how the extremes behavior of the climate system has changed over the past century and to evaluate both model variability and model behavior under historical forcing. While progress has been made in improving datasets, much remains to be done to improve access to even basic daily meteorological observations. The current situation, improved somewhat through the efforts of the ETCCDI and APN[3] (but at the loss of complete reproducibility of all calculations involved in the derivation of extremes indices, and at the cost of large delays in the construction of research-quality datasets), is far from satisfactory as is clearly evident by the far less than global coverage of available datasets of temperature and precipitation extremes. We cannot state strongly enough the importance of continuing and enhancing such efforts to develop datasets of high-frequency in situ observations that are as spatially and temporally complete as possible, as homogenous as possible, and that are accompanied by as much metadata as possible concerning the history of each observing system or station. The lack of metadata describing changes in the exposure and location of observations and in observing procedures is arguably the greatest uncertainty in any work regarding instrumentally observed changes in extremes. With such metadata we know we can remove many of the non-climate influences of changes in instrumentation or location – but these metadata are simply not available for most of the world. This applies to floods, droughts, extreme temperature and precipitation, and tropical cyclones. An additional concern is that there remains a great deal of historical high-frequency data in hard-copy that has yet to be digitized. Much of this data is under threat, thus additional programs (such as the US NOAA Forts Program[4]) are needed to ensure the archival and digitization of such data (see also Page et al. 2004). The limitations of current datasets, whether they are derived directly from the available observational record or interpret observations using models of various complexities (e.g., drought indicators), severely limit our ability to answer key policy-relevant questions about the historical record, such as whether humans have influenced the intensity of extreme precipitation, or whether they have contributed to any perceived change in tropical cyclone behavior.

An important effort with regard to surface temperature is the International Surface Temperature Initiative[5] which seeks to assemble a comprehensive, open, transparent and traceable international data base of surface temperature observations with temporal resolution ranging from hourly upwards, and including associated metadata. A similar effort for precipitation observations, and other key variables such as surface pressure and wind observations, would also be exceedingly valuable. An innovative and promising development with regard to the improvement of climate datasets is the use of "crowd-sourcing"[6] for the digitization and analysis

[3] Asia-Pacific Network for Global Change Research.

[4] See http://www.ncdc.noaa.gov/oa/climate/cdmp/forts.html

[5] http://www.surfacetemperatures.org/

[6] The use of unpaid volunteers, often solicited via the internet.

of climate data, as is being done at US National Climatic Data Centre for both surface temperature data rescue and ongoing tropical cyclone reanalysis.[7]

A second set of challenges concerns *the state of our tools for analyzing observed changes in extremes*. It should be acknowledged that a great deal of progress has been achieved using available tools. For example, there is now a large body of research on more "moderate" extremes because more data tend to be available, signal-to-noise ratios tend to be higher, and because changes in their characteristics can often be successfully studied with more or less standard statistical techniques. However, further progress could be made by improving our tools.

One basic tool is the language that is used to describe extremes, and in this case it is clear that there is a lack of precision in the language that is used in climatology. This lack of precise language hinders advances in research on extremes because it makes the job of clearly articulating hypotheses and objects for analysis all the more difficult. In climatology, the term "extreme" can refer to occurrences of high impact phenomena (e.g., droughts, floods, tropical cyclones) that may or may not be characterized by rare values of the underlying meteorological variables, events that are in fact not very rare (e.g., exceedance of the 90th percentile of temperature or precipitation), or rare events that occur in the far tails of the distributions of clearly defined hydro-meteorological variables such as temperature, precipitation, wind speed, stream flow, and so on. While statistical reasoning and methods are useful in all three cases, the powerful extreme value theory of statistical science can only be brought to bear on the latter, and even in this case, there are clear limitations in practice and in the available theory that impede progress in the analysis of climatological extreme values. Some of these challenges include,

- The need for improvements in the reliability of estimators of the attributes of heavy-tailed variables, and in methods to determine whether these attributes are changing over time.
- A need for the further development of methods or concepts to realistically represent the spatial dependence of extreme values. Currently available approaches based on max-stable processes (e.g., Smith 1990; Schlather 2002) remain difficult to use, do not appear to provide a sufficient broad set of models to represent the heterogeneity and anisotropy of the spatial dependence of extremes that is seen in the real world, and do not provide an obvious approach to dimension reduction, which is a more or less essential component of standard detection and attribution methods.
- The development of methods that would allow for the automated application of so-called peaks-over-threshold approaches to extreme value analysis. If this could be achieved with suitable statistical rigor, it would represent a highly desirable development for the analysis of large collections of station data and gridded datasets since peaks-over-threshold approaches arguably use the available data

[7] http://www.cicsnc.org/corp/presentations/Scott%20Hausman.pdf (presentation made to the 30th Conference on Hurricanes and Tropical Meteorology, Ponte Verde, Florida, USA, 15–20 April 2012).

more efficiently than the more frequently used block-maximum approach. It should be noted however, that such a development would only be beneficial if the underlying high-frequency weather data were available for analysis; indices defined on fixed thresholds or annual blocks, such as those that result from the work of the ETCCDI, would not be suitable.

- Development of methods that are able to combine information on extremes from observations and models, suitably representing uncertainty in the analysis that arises from multiple sources, including uncertainties in the responses to external forcing that are present in extremes and uncertainty associated with the forcing, the climate models themselves, and the internal variability that they simulate.

A third set of challenges concerns *continuing deficiencies in the state of our understanding of the processes that are involved in the production of extreme events*, which limits our confidence in the interpretation of observed extreme events and in observed changes in the frequency and intensity of extreme events. This type of challenge is evident in a number of different ways. A very fundamental aspect is apparent when comparing observed and model-simulated precipitation extremes; due to limited resolution, current global climate models do not simulate precipitation extremes that are of the same intensity as those that are observed in station data (Chen and Knutson 2008). Climatologists refer to this in the literature as a "scaling" issue, and statisticians refer to it as a "change of support" problem. One approach that has been used in detection and attribution research (e.g., Min et al. 2011) is to use probability integral transforms to convert model-simulated and observed precipitation extremes to a common dimensionless scale. While this formally allows comparison between the two, it does not at all resolve the question of whether the physical processes that lead to extreme precipitation on a climate model grid-point scale are the same as those that lead to extreme precipitation at the local scale. While this problem will become less severe as climate model resolution improves, it will still challenge, particularly the interpretation of warm season convective heavy precipitation.

Another area in which the importance of process knowledge is increasingly apparent is in the understanding and interpretation of temperature extremes, where there is a growing understanding of the role of feedback processes in determining the amplitude, duration and extent of extreme events (e.g., Seneviratne et al. 2006; Fischer et al. 2007; Sillmann et al. 2011; Mueller and Seneviratne 2012). It is also increasingly apparent that large scale low-frequency variability plays an important role in altering the likelihood of extreme events, including the effects of ENSO on the intensity and frequency of extreme precipitation (e.g., Alexander et al. 2009; Kenyon and Hegerl 2010; Zhang et al. 2010) and the effects of tropical SST anomalies on drought in regions such as the Sahel (e.g., Held et al. 2005; Hoerling et al. 2006) and southwestern North America (Cook et al. 2007). As is evident from the example of North American drought, it is often only through the study of paleoclimate data that we become aware of the role of low-frequency climate variability in the occurrence of extremes. In the case of tropical cyclones, there are some very specific improvements in process knowledge that would increase our confidence in both historical changes and future projections. These include improvements in the understanding of historical and future changes in tropical tropospheric lapse rates, up to and including the tropopause transition layer, which is important for determining tropical cyclone potential intensity (Emanuel 2010). An important question that remains unresolved is whether projections of relative SST (i.e., regional SST relative to the tropical mean) can be used as proxy for future potential intensity (Emanuel et al. 2013), since relative SST is generally not shown to increase substantially in the next century (Vecchi and Soden 2007). Another presently unresolved question is what portion of the observed multi-decadal climate variability in the tropical Atlantic (which tropical cyclones are observed to substantially respond to) is due to natural variability versus external forcing by greenhouse gasses and anthropogenic aerosols. Understanding changes in the frequency and intensity of extremes both due to external forcing and internal climate variability is further only possible if seasonally resolved information on changes in extremes is available and analyzed. For example, circulation (some of aspects of which are predicted to change in a changing climate) impacts both temperature and precipitation extremes differently in different seasons (Kenyon and Hegerl 2008, 2010). This can only be captured if indices of extremes are resolved at seasonal or shorter time scales.

A topic that has not been explicitly discussed in this paper, which poses a challenge that cuts across definitional issues, our state of process understanding in the physical climate system, and our state of understanding of the impacts of extremes, is the analysis of compound or multi-variable climate extremes; that is, events where the combined effect of, for example, temperature, wind speed and precipitation produces extreme impacts where perhaps the individual temperature, wind or precipitation readings would not be considered to be particularly extreme. While much discussed, there has as yet been relatively little research to investigate such events. That said, research on recognized phenomena such as heat waves, drought, or tropical and extra-tropical cyclones does fit into this category, as does recent event attribution research (e.g., see Stott et al. 2004; Fischer et al. 2007; Pall et al. 2011; Stott et al. 2012; see also Peterson et al. 2012 and Otto et al. 2012). Also, there have been a few attempts to develop multi-indicator extremes indices for monitoring the extent to which a large region is being affected by extremes (e.g., such as introduced by Karl et al. 1996 and revised by Gleason et al. 2008). This situation comes about in part because of the state of available data resources, which remains limited, but also because there is insufficient process and impacts knowledge to rigorously describe multi-variable events in a manner that avoids selection bias.

Finally, the reliable detection and attribution of changes in extremes, regardless of the specific type of phenomenon of interest, depends heavily upon *the ability of models to simulate the natural background variability of the climate system*. In the case of tropical cyclones, this means simulating tropical SSTs patterns and their variability correctly, as well as simulating the variability of the vertical structure of the tropical atmosphere correctly. More generally, it means ensuring that the large scale modes of variability, such as the El-Niño/Southern Oscillation, the Pacific Decadal Oscillation and the Atlantic Multi-decadal Oscillation, are well understood from an observational perspective and well simulated from a modeling perspective.

While extremes represent the tail behavior of climate and weather variables, a growing body of research indicates that their likelihood and intensity is very much influenced by behavior that is more central to the distribution of climate and weather states.

While we have focused on the challenges that are faced by those who attempt to undertake research on extremes, it is also evident that this is an area in which enormous progress has been made, as is discussed by Nicholls and Alexander (2007) and as is clearly evident from recent assessments, including IPCC (2007a), Karl et al. (2008) and particularly Seneviratne et al. (2012). This is an area with very significant momentum and in which the potential exists for the development of applied climate science in terms of predicting or identifying the predictability of extremes. There is considerable potential for developing useful products, for example, which may be able to provide predictions or projections of changes in the likelihood of extremes, either through modeling the influence of seasonal to multi-decadal climate variability on the frequency and/or intensity of extremes, or modeling the direct or indirect impact of external forcing on the properties of extremes. Their interpretation and possible predictive utility may be instrumental for the development of useful climate services and the user interface for those services, for example, as envisioned through the WMO Global Framework for Climate Services.

References

Abeysirigunawardena DS, Walker IJ (2008) Sea level responses to climatic variability and change in northern British Columbia. Atmosphere-Ocean 46:277–296

Abeysirigunawardena DS, Gilleland E, Bronaugh D, Wong W (2009) Extreme wind regime responses to climate variability and change in the inner south coast of British Columbia, Canada. Atmosphere-Ocean 47:41–62

Aguilar E et al (2009) Changes in temperature and precipitation extremes in western Central Africa, Guinea Conakry and Zimbabwe, 1955–2006. J Geophys Res 114, D02115. doi:10.1029/2008JD011010

Alexander L, Donat M (2011) The CLIMDEX project: creation of long-term global gridded products for the analysis of temperature and precipitation extremes. In: WCRP Open Science conference, Denver, Oct 2011

Alexander LV et al (2006) Global observed changes in daily climate extremes of temperature and precipitation. J Geophys Res 111, D05109. doi:10.1029/2005JD006290

Alexander LV, Uotila P, Nicholls N (2009) The influence of sea surface temperature variability on global temperature and precipitation extremes. J Geophys Res-Atmos 114, D18116. doi:10.1029/2009JD012301

Alexander LV, Wang XL, Wan H, Trewin B (2011) Significant decline in storminess over southeast Australia since the late 19th century. Aust Meteorol Oceanogr J 61:23–30

Alexandersson H, Schmith T, Iden K, Tuomenvirta H (1998) Long term variations of the storm climate over NW Europe. Glob Atmos Ocean Syst 6:97–120

Allamano P, Claps P, Laio F (2009) Global warming increases flood risk in mountainous areas. Geophys Res Lett 36, L24404

Allan R, Tett S, Alexander LV (2009) Fluctuations of autumn-winter severe storms over the British Isles: 1920 to present. Int J Climatol 29:357–371. doi:10.1002/joc.1765

Allen MR, Ingram WJ (2002) Constraints on future changes in climate and the hydrologic cycle. Nature 419:224–232
Alley WM (1984) The palmer drought severity index: limitations and assumptions. J Clim Appl Meteorol 23:1100–1109
Andreadis KM, Lettenmaier DP (2006) Trends in 20th century drought over the continental United States. Geophys Res Lett 33, L10403. doi:10.1029/2006GL025711
Barnett TP et al (2008) Human-induced changes in the hydrology of the western United States. Science 319:1080–1083
Bärring L, Fortuniak K (2009) Multi-indices analysis of southern Scandinavian storminess 1780–2005 and links to interdecadal variations in the NW Europe-North Sea region. Int J Climatol 29:373–384
Bärring L, von Storch H (2004) Scandinavian storminess since about 1800. Geophys Res Lett 31:1790–1820
Barros V, Chamorro L, Coronel G, Baez J (2004) The major discharge events in the Paraguay river: magnitudes, source regions, and climate forcings. J Hydrometeorol 5:1161–1170
Bates BC, Kundzewics ZW, Wu S, Palutikof JP (2008) Climate change and water. Technical paper of the Intergovernmental Panel on Climate Change. IPCC Secretariat, Geneva, 210 pp
Bender MA, Knutson TR, Tuleya RE, Sirutis JJ, Vecchi GA, Garner ST, Held IM (2010) Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. Science 327:454–458
Bengtsson L, Hagemann S, Hodges KI (2004) Can climate trends be calculated from reanalysis data? J Geophys Res 109, D11111. doi:10.1029/2004JD004536
Bengtsson L, Hodges KI, Roeckner E (2006) Storm tracks and climate change. J Clim 19:3518–3543
Bindoff NL et al (2007) Observations: oceanic climate change and sea level. In: Solomon S et al (eds) The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York
Bister M, Emanuel KA (1998) Dissipative heating and hurricane intensity. Meteorol Atmos Phys 65:233–240
Blanchet J, Davison AC (2011) Spatial modeling of extreme snow depth. Ann Appl Stat 5:1699–1725. doi:10.1214/11-AOAS464
Booth BBB, Dunstone NJ, Halloran PR, Andrews T, Bellouin N (2012) Aerosols implicated as a prime driver of twentieth-century North Atlantic climate variability. Nature 484:228–232
Brayshaw DB, Hoskins B, Blackburn M (2008) The storm-track response to idealized SST perturbations in an aquaplanet GCM. J Atmos Sci 65:2842–2860
Brooks HE (2004) On the relationship of tornado path length and width to intensity. Weather Forecast 19:310–319
Burke EJ, Brown SJ (2008) Evaluating uncertainties in the projection of future drought. J Hydrometeorol 9:292–299
Butler AH, Thompson DW, Heikes R (2010) The steady-state atmospheric circulation response to climate change-like thermal forcings in a simple general circulation model. J Clim 23:3474–3496. doi:10.1175/2010JCLI3228.1
Caesar J, Alexander L, Vose R (2006) Large-scale changes in observed daily maximum and minimum temperatures: creation and analysis of a new gridded data set. J Geophys Res 111, D05101. doi:10.1029/2005JD006280
Callaghan J, Power SB (2011) Variability and decline in the number of severe tropical cyclones making land-fall over eastern Australia since the late nineteenth century. Clim Dyn 37:647–662. doi:10.1007/s00382-010-0883-2
Camargo S, Ting M, Kushnir Y (2013) Influence of local and remote SST on North Atlantic tropical cyclone potential intensity. Clim Dyn 40:1515–1529
Catto JL, Shaffrey LC, Hodges KJ (2010) Can climate models capture the structure of extratropical cyclones? J Clim 23:1621–1635
Chen C-T, Knutson TR (2008) On the verification and comparison of extreme rainfall indices from climate models. J Clim 21:1605–1621. doi:10.1175/2007JCLI1494.1
Chen J, Brissette FP, Leconte R (2011) Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. J Hydrol 401:190–202

Christensen JH et al (2007) Regional climate projections. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds) Climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp 847–940
Christidis N, Stott PA, Brown SJ, Hegerl GC, Caesar J (2005) Detection of changes in temperature extremes during the second half of the 20th century. Geophys Res Lett 32, L20716
Christidis N, Stott PA, Brown SJ (2011) The role of human activity in the recent warming of extremely warm daytime temperatures. J Clim 24:1922–1930
Church JA, Gregory JM, White NJ, Platten SM, Mitrovica XJ (2011) Understanding and projecting sea level change. Oceanography 24:130–143
Coles S (2001) An introduction to the statistical modeling of extreme values. Springer, London, 208 pp. ISBN ISBN 1-85233-459-2
Compo GP, Whitaker JS, Sardeshmukh PD, Matsui N, Allan RJ et al (2011) The twentieth century reanalysis project. Q J R Meteorol Soc 137:1–28. doi:10.1002/qj.776
Cook ER, Seager R, Cane MA, Stahle DW (2007) North American drought: reconstructions, causes and consequences. Earth Sci Rev 81:93–134. doi:10.1016/j.earscirev.2006.12.002
Crompton RP, Pielke RA Jr, McAneney KJ (2011) Emergence timescales for detection of anthropogenic climate change in US tropical cyclone loss data. Environ Res Lett 6:014003. doi:10.1088/1748-9326/6/1/014003
Cunderlik JM, Ouarda TBMJ (2009) Trends in the timing and magnitude of floods in Canada. J Hydrol 375:471–480
Dai A (2011) Drought under global warming: a review. Wiley Interdiscip Rev Clim Change 2:45–65
Dai A, Trenberth KE, Qian T (2004) A global data set of palmer drought severity index for 1870–2002: relationship with soil moisture and effects of surface warming. J Hydrometeorol 5:1117–1130
Debernard JB, Roed LP (2008) Future wind, wave and storm surge climate in the Northern Seas: a revisit. Tellus A 60:427–438
Delgado JM, Apel H, Merz B (2009) Flood trends and variability in the Mekong river. Hydrol Earth Syst Sci 6:6691–6719
Di Baldassarre G, Montanari A, Lins H, Koutsoyiannis D, Brandimarte L, Blöschl G (2010) Flood fatalities in Africa: from diagnosis to mitigation. Geophys Res Lett 37, L22402
Diffenbaugh NS, Trapp RJ, Brooks H (2008) Does global warming influence tornado activity? Eos Trans Am Geophys Union 89:553
Donat M, Alexander L (2011) Uncertainties related to the production of gridded global data sets of observed climate extreme indices. In: Abstract for WCRP Open Science conference, Denver, Oct 2011
Donat MG, Renggli D, Wild S, Alexander LV, Leckebusch GC, Ulbrich U (2011) Reanalysis suggests long term upward trends in European storminess since 1871. Geophys Res Lett 38, L14703. doi:10.1029/2011GL047995
Dupuis DJ (2012) Modeling waves of extreme temperature: the changing tails of four cities. J Am Stat Assoc 107(497):24–39. doi:10.1080/01621459.2011.643732
Ehsanzadeh E, Adamowksi K (2007) Detection of trends in low flows across Canada. Can Water Resour J 32:251–264
Elsner JB, Kossin JP, Jagger TH (2008) The increasing intensity of the strongest tropical cyclones. Nature 455:92–95
Emanuel KA (2007) Environmental factors affecting tropical cyclone power dissipation. J Clim 20:5497–5509
Emanuel K (2010) Tropical cyclone activity downscaled from NOAA-CIRES reanalysis, 1908–1958. J Adv Model Earth Syst 2:1. doi:10.3894/JAMES.2010.2.1
Emanuel K (2011) Global warming effects on U.S. hurricane damage. Weather Clim Soc 3:261–268
Emanuel K, Solomon S, Folini D, Davis S, Cagnazzo C (2013) Influence of tropical tropopause layer cooling on Atlantic hurricane activity. J Clim 26:2288–2301. doi:10.1175/JCLI-D-12-00242.1

Evan AT, Vimont DJ, Heidinger AK, Kossin JP, Bennartz R (2009) The role of aerosols in the evolution of tropical North Atlantic ocean temperature anomalies. Science 324:778–781
Evan A, Kossin J, Chung C, Ramanathan V (2011) Arabian Sea tropical cyclones intensified by emissions of black carbon and other aerosols. Nature 479:94–97
Feller W (1971) An introduction to probability theory and its applications, vol 2. Wiley, New York, 704 pp
Fiore MME, D'Onofrio EE, Pousa JL, Schnack EJ, Bertola GR (2009) Storm surges and coastal impacts at Mar del Plata, Argentina. Cont Shelf Res 29:1643–1649
Fischer EM, Schär C (2009) Future changes in daily summer temperature variability: driving processes and role for temperature extremes. Clim Dyn 33:917–935
Fischer EM, Schär C (2010) Consistent geographical patterns of changes in high-impact European heatwaves. Nat Geosci 3:398–403
Fischer EM, Seneviratne SI, Vidale PL, Lüthi D, Schär C (2007) Soil moisture – atmosphere interactions during the 2003 European summer heatwave. J Clim 20:5081–5099
Flannigan M, Logan K, Amiro B, Skinner W, Stocks B (2005) Future area burned in Canada. Clim Chang 72:1–16
Fleig AK, Tallasken LM, Hisdal H, Demuth S (2006) A global evaluation of streamflow drought characteristics. Hydrol Earth Syst Sci 10:535–552
Fogt RL, Perlwitz J, Monaghan AJ, Bromwich DH, Jones JM, Marshall GJ (2009) Historical SAM variability. Part II: twentieth-century variability and trends from reconstructions, observations, and the IPCC AR4 models. J Clim 22:5346–5365
Folland CK, Palmer TN, Parker DE (1986) Sahelian rainfall and worldwide sea temperatures 1901–1985. Nature 320:602–607
Folland CK et al (1995) Observed climate variability and change. In: Houghton JT et al (eds) Climate change 1995: the science of climate change. Cambridge University Press, Cambridge, pp 99–181
Forster P et al (2007) Changes in atmospheric constituents and in radiative forcing. In: Solomon S et al (eds) Climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York
Fowler HJ, Cooley D, Sain SR, Thurston M (2010) Detecting change in UK extreme precipitation using results from the climateprediction.net BBC climate change experiment. Extremes 13:241–267
Frei C, Schär C (2001) Detection probability of trends in rare events: theory and application to heavy precipitation in the Alpine region. J Clim 14:1568–1584
Frich P, Alexander LV, Della-Marta P, Gleason B, Haylock M, Klein Tank AMG, Peterson T (2002) Observed coherent changes in climatic extremes during the second half of the twentieth century. Clim Res 19:193–212
Giannini A, Biasutti M, Verstraete MM (2008) A climate model-based review of drought in the Sahel: desertification, the re-greening and climate change. Glob Planet Chang 64:119–128
Gillett NP, Stott PA (2009) Attribution of anthropogenic influence on seasonal sea level pressure. Geophys Res Lett 36, L23709
Gillett NP, Weaver AJ, Zwiers FW, Wehner MF (2004) Detection of volcanic influence on global precipitation. Geophys Res Lett 31, L12217. doi:10.1029/2004GL020044
Gillett NP, Allan RJ, Ansell TJ (2005) Detection of external influence on sea level pressure with a multi-model ensemble. Geophys Res Lett 32, L19714
Gillett NP, Stott PA, Santer BD (2008) Attribution of cyclogenesis region sea surface temperature change to anthropogenic influence. Geophys Res Lett 35, L09707
Gleason KL, Lawrimore JH, Levinson DH, Karl TR, Karoly DJ (2008) A revised U.S. climate extremes index. J Clim 21:2124–2137. doi:10.1175/2007JCLI1883.1
Grant AN, Bronnimann S, Haimberger L (2008) Arctic warming vertical structure contested. Nature 455:E2–E3. doi:10.1038/nature07257
Greeves CZ, Pope VD, Stratton RA, Martin GM (2007) Representation of Northern Hemisphere winter storm tracks in climate models. Clim Dyn 28:683–702

Grinsted A, Moore AJ, Jevrejeva S (2010) Reconstructing sea level from paleo and projected temperatures 200 to 2100 AD. Clim Dyn 34:461–472
Haerter JO, Roeckner E, Tomassini L, von Storch JS (2009) Parametric uncertainty effects on aerosol radiative forcing. Geophys Res Lett 36, L15707
Hanel M, Buishand TA, Ferro CAT (2009) A nonstationary index flood model for precipitation extremes in transient regional climate model simulations. J Geophys Res 114, D15107. doi:10.1029/2009JD011712
Hanesiak JM et al (2011) Characterization and summary of the 1999–2005 Canadian Prairie drought. Atmosphere-Ocean 49:421–452. doi:10.1080/07055900.2011.626757
Hanlon H, Hegerl GC, Tett SFB, Smith DM (2012a) Can a decadal forecasting system predict temperature extreme indices? J Clim, in press. doi10.1175/JCLI-D-12-00512.1
Hanlon H, Morak S, Hegerl GC (2012b) Detection and prediction of mean and extreme European summer temperatures with a CMIP5 multi-model ensemble. J Geophys Res, submitted
Hanna E, Cappelen J, Allan R, Jonsson T, Le Blancq F, Lillington T, Hickey K (2008) New insights into North European and North Atlantic surface pressure variability, storminess, and related climatic change since 1830. J Clim 21:6739–6766
Hannaford J, Marsh T (2006) An assessment of trends in UK runoff and low flows using a network of undisturbed catchments. Int J Climatol 26:1237–1253
Hannaford J, Marsh TJ (2008) High-flow and flood trends in a network of undisturbed catchments in the UK. Int J Climatol 28:1325–1338
Hanson CE, Palutikof JP, Davies TD (2004) Objective cyclone climatologies of the North Atlantic – a comparison between the ECMWF and NCEP reanalyses. Clim Dyn 22:757–769
Harper B, Hardy T, Mason L, Fryar R (2009) Developments in storm tide modelling and risk assessment in the Australian region. Nat Hazard 51:225–238
Heaton MJ, Katzfuss M, Ramachandar S, Pedings K, Gilleland E, Mannshardt-Shamseldin E, Smith RL (2010) Spatio-temporal models for large-scale indicators of extreme weather. Environmetrics 22:294–303
Hegerl GC, Zwiers FW, Stott PA, Kharin VV (2004) Detectability of anthropogenic changes in annual temperature and precipitation extremes. J Clim 17:3683–3700
Hegerl GC, Zwiers FW, Braconnot P, Gillett NP, Luo Y, Marengo Orsini JA, Nicholls N, Penner JE, Stott PA (2007) Understanding and attributing climate change. In: Solomon S et al (eds) The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York
Hegerl GC, Hanlon H, Beierkuhnlein C (2011) Elusive extremes. Nat Geosci 4:142–143
Hegerl GC, Hoegh-Guldberg O, Casassa G, Hoerling MP, Kovats RS, Parmesan C, Pierce DW, Stott PA (2010) Good practice guidance paper on detection and attribution related to anthropogenic climate change. In: Stocker TF, Field CB, Qin D, Barros V, Plattner G-K, Tignor M, Midgley PM, Ebi KL (eds) Meeting report of the Intergovernmental Panel on Climate Change expert meeting on detection and attribution of anthropogenic climate change. IPCC working group I technical support unit, University of Bern, Bern
Heim RR (2002) A review of twentieth-century drought indices used in the United States. Bull Am Meteorol Soc 83:1149–1165
Held IM, Delworth TL, Lu J, Findell KL, Knutson TR (2005) Simulation of Sahel drought in the 20th and 21st centuries. Proc Natl Acad Sci USA 102:17891–17896. doi:10.1073_pnas.0509057102
Hidalgo HG et al (2009) Detection and attribution of streamflow timing changes to climate change in the Western United States. J Clim 22:3838–3855
Hirschi M, Seneviratne SI, Alexandrov V, Boberg F, Boroneant C, Christensen OB, Formayer H, Orlowsky B, Stepanek P (2011) Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. Nat Geosci 4:17–21. doi:10.1038/ngeo1032
Hodges KI, Hoskins BJ, Boyle J, Thorncroft C (2003) A comparison of recent reanalysis datasets using objective feature tracking: storm tracks and tropical easterly waves. Mon Weather Rev 131:2012–2037
Hoerling MP, Kumar A (2003) The perfect ocean for drought. Science 299:691–694

Hoerling MP, Hurrell J, Eischeid J, Phillips A (2006) Detection and attribution of twentieth-century Northern and Southern African rainfall change. J Clim 19:3989–4008
Hoerling M, Quan X, Eischeid J (2009) Distinct causes for two principal US droughts of the 20th century. Geophys Res Lett 36, L19708. doi:10.1029/2009GL039860
Hohenegger C, Brockhaus P, Bretherton CS, Schär C (2009) The soil moisture-precipitation feedback in simulations with explicit and parameterized convection. J Clim 22:5003–5020
Holland GJ, Webster PJ (2007) Heightened tropical cyclone activity in the North Atlantic: natural variability or climate trend? Philos Trans R Soc A 365:2695–2716
Hossain F, Jeyachandran I, Pielke R Jr (2009) Have large dams altered extreme precipitation patterns. Eos Trans Am Geophys Union 90:453
IPCC (2007a) Climate change 2007: the physical science basis. In: Solomon S et al (eds) Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York, 996 pp
IPCC (2007b) Climate change 2007: impacts, adaptation and vulnerability. In: Parry ML et al (eds) Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 976 pp
IPCC (2012) Summary for policymakers. In: Field CB, Barros V, Stocker TF, Qin D, Dokken DJ, Ebi KL, Mastrandrea MD, Mach KJ, Plattner G-K, Allen SK, Tignor M, Midgley PM (eds) Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of working groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York, pp 1–19
Jiang T, Kundzewicz ZW, Su B (2008) Changes in monthly precipitation and flood hazard in the Yangtze River Basin, China. Int J Climatol 28:1471–1481
Johnson NC, Xie S-P (2010) Changes in the sea surface temperature threshold for tropical convection. Nat Geosci 3:842–845
Karl TR (1983) Some spatial characteristics of drought duration in the United States. J Clim Appl Meteorol 22:1356–1366
Karl TR, Knight RW (1997) The 1995 Chicago heat wave: how likely is a recurrence? Bull Am Meteorol Soc 78:1107–1119
Karl TR, Knight RW, Easterling DR, Quayle RG (1996) Indices of climate change for the United States. Bull Am Meteorol Soc 77:279–292
Karl TR, Meehl GA, Christopher DM, Hassol SJ, Waple AM, Murray WL (2008) Weather and climate extremes in a changing climate. Regions of focus: North America, Hawaii, Caribbean, and U.S. Pacific Islands. A report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research, Washington, DC, 164 pp
Katz RW, Brown BG (1992) Extreme events in a changing climate: variability is more important than averages. Clim Chang 21:289–302
Katz R, Parlange M, Naveau P (2002) Extremes in hydrology. Adv Water Resour 25:1287–1304
Kay AL, Davies HN, Bell VA, Jones RG (2009) Comparison of uncertainty sources for climate change impacts: flood frequency in England. Clim Chang 92:41–63
Kenyon J, Hegerl GC (2008) Influence of modes of climate variability on global temperature extremes. J Clim 21:3872–3889
Kenyon J, Hegerl GC (2010) Influence of modes of climate variability on global precipitation extremes. J Clim 23:6248–6262
Kharin VV, Zwiers FW (2000) Changes in the extremes in an ensemble of transient climate simulation with a coupled atmosphere–ocean GCM. J Clim 13:3760–3788
Kharin VV, Zwiers FW (2005) Estimating extremes in transient climate change simulations. J Clim 18:1156–1173
Kharin VV, Zwiers FW, Zhang X, Hegerl GC (2007) Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. J Clim 20:1419–1444
Kistler R et al (2001) The NCEP-NCAR 50-year reanalysis: monthly means CD-ROM and documentation. Bull Am Meteorol Soc 82:247–267
Klawa M, Ulbrich U (2003) A model for the estimation of storm losses and the identification of severe winter storms in Germany. Nat Hazard Earth Syst Sci 3:725–732

Klein Tank AMG, Zwiers FW, Zhang X (2009) Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation (WCDMP-72, WMO-TD/No.1500), 56 pp
Knapp KR, Kossin JP (2007) A new global tropical cyclone data set from ISCCP B1 geostationary satellite observations. J Appl Remote Sens 1:013505
Knapp KR, Kruk MC (2010) Quantifying inter-agency differences in tropical cyclone best track wind speed estimates. Mon Weather Rev 138:1459–1473
Knutson TR, Tuleya RE (2004) Impact of CO2-induced warming on simulated hurricane intensity and precipitation: sensitivity to the choice of climate model and convective parameterization. J Clim 17:3477–3495
Knutson TR, Sirutis JJ, Garner ST, Vecchi GA, Held IM (2008) Simulated reduction in Atlantic hurricane frequency under twenty-first- century warming conditions. Nat Geosci 1:359–364
Knutson TR, McBride JL, Chan J, Emanuel K, Holland G, Landsea C, Held I, Kossin JP, Srivastava AK, Sugi M (2010) Tropical cyclones and climate change. Nat Geosci 3:157–163
Kossin JP, Knapp KR, Vimont DJ, Murnane RJ, Harper BA (2007) A globally consistent reanalysis of hurricane variability and trends. Geophys Res Lett 34, L04815. doi:10.1029/2006GL028836
Kossin JP, Camargo SJ, Sitkowski M (2010) Climate modulation of North Atlantic hurricane tracks. J Clim 23:3057–3076
Koster RD et al (2004) Regions of strong coupling between soil moisture and precipitation. Science 305:1138–1140
Koster RD, Guo ZC, Yang RQ, Dirmeyer PA, Mitchell K, Puma MJ (2009) On the nature of soil moisture in land surface models. J Clim 22:4322–4335
Krueger O, von Storch H (2011) Evaluation of an air pressure based proxy for storm activity. J Clim 24:2612–2619
Krueger O, von Storch H (2012) The informational value of pressure-based single-station proxies for storm activity. J Atmos Ocean Technol 29(4):569–580
Kundzewicz ZW et al (2005) Summer floods in central Europe: climate change track? Nat Hazard 36:165–189
Lambert SJ, Fyfe JC (2006) Changes in winter cyclone frequencies and strengths simulated in enhanced greenhouse warming experiments: results from the models participating in the IPCC diagnostic exercise. Clim Dyn 26:713–728
Lambert FH, Gillett NP, Stone DA, Huntingford C (2005) Attribution studies of observed land precipitation changes with nine coupled models. Geophys Res Lett 32, L18704. doi:10.1029/2005GL023654
Landsea CW (2007) Counting Atlantic tropical cyclones back to 1900. Eos Trans Am Geophys Union 88:197–202
Landsea CW, Anderson C, Charles N, Clark G, Dunion J, Fernandez-Partagas J, Hungerford P, Neumann C, Zimmer M (2004) The Atlantic hurricane database re-analysis project: documentation for the 1851–1910 alterations and additions to the HURDAT database. In: Murnane RJ, Liu KB (eds) Hurricanes and Typhoons: past, present and future. Columbia University Press, New York, pp 177–221
Landsea CW, Harper BA, Hoarau K, Knaff JA (2006) Can we detect trends in extreme tropical cyclones? Science 313:452–454
Landsea CW, Vecchi GA, Bengtsson L, Knutson TR (2009) Impact of duration thresholds on Atlantic tropical cyclone counts. J Clim 23:2508–2519. doi:10.1175/2009JCLI3034.1
Lau KM, Zhou YP, Wu HT (2008) Have tropical cyclones been feeding more extreme rainfall? J Geophys Res 113, D23113. doi:10.1029/2008JD009963
Lin N, Emanuel K, Oppenheimer M, Vannarcke E (2012) Physically based assessment of hurricane surge threat under climate change. Nat Clim Change 2:462–467. doi:10.1038/NCLIMATE1389
Lorenz C, Kunstmann H (2012) The hydrological cycle in three state-of-the-art reanalyses: intercomparison and performance analysis. J Hydrometeorol 13(5):1397–1420. doi:10.1175/JHM-D-11-088.1
Mann ME, Emanuel KA (2006) Atlantic hurricane trends linked to climate change. Eos Trans Am Geophys Union 87:233–241

Mann ME, Emanual KA, Holland GJ, Webster PJ (2007) Atlantic tropical cyclones revisited. Eos Trans Am Geophys Union 88:349–350

Mannshardt-Shamseldin EC, Smith RL, Sain SR, Mearns LD, Cooley D (2010) Downscaling extremes: a comparison of extreme value distributions in point-source and gridded precipitation data. Ann Appl Stat 4:484–502

Manton MJ et al (2001) Trends in extreme daily rainfall and temperature in southeast Asia and the South Pacific: 1916–1998. Int J Climatol 21:269–284

Marcos M, Tsimplis MN, Shaw AGP (2009) Sea level extremes in southern Europe. J Geophys Res 114, C01007

McInnes KL, Walsh KJE, Hubbert GD, Beer T (2003) Impact of sea-level rise and storm surges on a coastal community. Nat Hazard 30:187–207

McInnes KL, Macadam I, Hubbert GD, O'Grady JG (2009) A modelling approach for estimating the frequency of sea level extremes and the impact of climate change in southeast Australia. Nat Hazard 51:115–137

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. Preprints, Eighth conference on applied climatology, American Meteorological Society, Anaheim, pp 179–184

Meehl GA et al (2007a) Global climate projections. In: Solomon S et al (eds) The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Meehl GA et al (2007b) The WCRP CMIP3 multi-model dataset: a new era in climate change research. Bull Am Meteorol Soc 88:1383–1394

Mendelsohn R, Emanuel K, Chonabayashi S, Bakkensen L (2012) The impact of climate change on global tropical cyclone damage. Nat Clim Change 2:205–209. doi:10.1038/nclimate1357

Menéndez M, Woodworth PL (2010) Changes in extreme high water levels based on a quasi-global tide-gauge dataset. J Geophys Res 115, C10011

Mesinger F et al (2006) North American regional reanalysis. Bull Am Meteorol Soc 87:343–360. doi:10.1175/BAMS-87-3-343

Milly PCD, Dunne KA (2011) On the hydrologic adjustment of climate-model projections: the potential pitfall of potential evapotranspiration. Earth Interact 15:1–14

Milly PCD, Wetherald RW, Dunne KA, Delworth TL (2002) Increasing risk of great floods in a changing climate. Nature 415:514–517

Min SK, Zhang X, Zwiers FW (2008) Human induced Arctic moistening. Science 320:518–520

Min SK, Zhang X, Zwiers FW, Hegerl GC (2011) Human contribution to more-intense precipitation extremes. Nature 470:378–381. doi:10.1038/nature09763

Mitchell JFB, Wilson CA, Cunnington WM (1987) On CO_2 sensitivity and model dependence of results. Q J R Meteorol Soc 113:293–322

Mitrovica JX, Tamisiea ME, Ivins ER, Vermeersen LLA, Milne GA, Lambeck K (2010) Surface mass loading on a dynamic earth: complexity and contamination in the geodetic analysis of global sea-level trends. In: Church JA et al (eds) Understanding sea-level rise and variability. Wiley-Blackwell, Chichester, pp 285–325

Morak S, Hegerl GC, Kenyon J (2011) Detectable regional changes in the number of warm nights. Geophys Res Lett 38, L17703. doi:10.1029/2011GL048531

Morak S, Hegerl GC, Christidis N (2013) Detectable changes in temperature extremes. J Clim 26:1561–1574

Mousavi ME, Irish JL, Frey AE, Olivera F, Edge BL (2011) Global warming and hurricanes: the potential impact of hurricane intensification and sea level rise on coastal flooding. Clim Chang 104:575–597. doi:10.1007/s10584-009-9790-0

Mudelsee M, Borngen M, Tetzlaff G, Grunewald U (2003) No upward trends in the occurrence of extreme floods in central Europe. Nature 425:166–169

Mueller B, Seneviratne SI (2012) Hot days induced by precipitation deficits at the global scale. Proc Natl Acad Sci USA 109:12398–12403. doi:10.1073/pnas.1204330109

Nicholls N, Alexander L (2007) Has the climate become more variable or extreme? Progress 1992–2006. Prog Phys Geogr 31:1–11

Nicholls N, Larsen S (2011) Impact of drought on temperature extremes in Melbourne, Australia. Aust Meteorol Oceanogr J 61:113–116

Noake K, Polson D, Hegerl GC, Zhang X (2011) Changes in seasonal land precipitation during the latter twentieth century. Geophys Res Lett 39, L03706

Orlowsky B, Seneviratne SI (2012) Global changes in extremes events: regional and seasonal dimension. Clim Chang 110:669–696. doi:10.1007/s10584-011-0122-9

Otto FE, Massey N, van Oldenburg GJ, Jones RG, Allen MR (2012) Reconciling two approaches to attribution of the 2010 Russian heat wave. Geophys Res Lett 39, L04702. doi:10.1029/2011GL050422

Page CM, Nicholls N, Plummer N, Trewin BC, Manton MJ, Alexander L, Chambers LE, Choi Y, Collins DA, Gosai A, Della-Marta P, Haylock MR, Inape K, Laurent V, Maitrepierre L, Makmur EEP, Nakamigawa H, Ouprasitwong N, McGree S, Pahalad J, Salinger MJ, Tibig L, Tran TD, Vediapan K, Zhai P (2004) Data rescue in the South-east Asia and South Pacific region: challenges and opportunities. Bull Amer Meteorol Soc 85:1483–1489

Pall P, Aina T, Stone DA, Stott PA, Nozawa T, Hilbberts AGJ, Lohmann D, Allen MR (2011) Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470:382–385

Palmer WC (1965) Meteorological drought. Research paper 45, US Department of Commerce, Weather Bureau, Washington, DC, 58 pp. Available from NOAA Library and Information Services Division, Washington, DC, 20852

Peterson TC, Manton MJ (2008) Monitoring changes in climate extremes: a tale of international collaboration. Bull Am Meteorol Soc 89:1266–1271

Peterson TC, Anderson D, Cohen SJ, Cortez M, Murname R, Parmesan C, Phillips D, Pulwarty R, Stone J (2008) Why weather and climate extremes matter. In: Karl TR et al (eds) Weather and climate extremes in a changing climate. Regions of focus: North America, Hawaii, Caribbean, and U.S. Pacific Islands. U.S. Climate Change Science Program and the Subcommittee on Global Change Research, Washington, DC, pp 11–33

Peterson TC, Stott PA, Herring S (eds) (2012) Explaining extreme events of 2011 from a climate perspective. Bull Am Meteorol Soc 93:1041–1066. doi:10.1175/BAMS-D-12-00021.1

Polson D, Hegerl GC, Zhang X, Osborn T (2013) Causes of robust seasonal land precipitation changes. J Clim, in press, doi:10.1175/JCLI-D-12-00474.1

Portmann RW, Solomon S, Hegerl GC (2009) Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. Proc Natl Acad Sci USA 106:7324–7329. doi:10.1073_pnas.0808533106

Prudhomme C, Davies H (2009) Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate. Clim Chang 93:197–222

Ramsay HA, Sobel AH (2011) The effects of relative and absolute sea surface temperature on tropical cyclone potential intensity using a single column model. J Clim 24:183–193

Randall DA et al (2007) Climate models and their evaluation. In: Solomon S et al (eds) The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Roderick ML, Rotstayn LD, Farquhar GD, Hobbins MT (2007) On the attribution of changing pan evaporation. Geophys Res Lett 34, L17403. doi:10.1029/2007GL031166

Ropelewski CF, Halpert MS (1987) Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. Mon Weather Rev 115:1606–1626

Rosenzweig C et al (2007) Assessment of observed changes and responses in natural and managed systems. In: Parry ML et al (eds) Impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Ryan BF, Watterson IG, Evans JL (1992) Tropical cyclone frequencies inferred from Gray's yearly genesis parameter – validation of GCM tropical climates. Geophys Res Lett 19:1831–1834

Sang H, Gelfand AE (2009) Hierarchical modeling for extreme values observed over space and time. Environ Ecol Stat 16:407–426

Sang H, Gelfand AE (2010) Continuous spatial process models for spatial extreme values. J Agric Biol Environ Stat 15:49–65
Santer BD et al (2006) Forced and unforced ocean temperature changes in Atlantic and Pacific tropical cyclogenesis regions. Proc Natl Acad Sci USA 103:13905–13910
Schlather M (2002) Models for stationary max-stable random fields. Extremes 5:33–44
Schmidt H, von Storch H (1993) German Bight storms analysed. Nature 365:791
Schmith T, Kaas E, Li T-S (1998) Northeast Atlantic winter storminess 1875–1995 re-analysed. Clim Dyn 14:529–536
Schubert S et al (2009) A US CLIVAR project to assess and compare the responses of global climate models to drought-related SST forcing patterns: overview and results. J Clim 22:5251–5272
Seneviratne SI, Lüthi D, Litschi M, Schär C (2006) Land-atmosphere coupling and climate change in Europe. Nature 443:205–209
Seneviratne SI, Corti T, Davin EL, Hirschi M, Jaeger E, Lehner I, Orlowsky B, Teuling AJ (2010) Investigating soil moisture-climate interactions in a changing climate: a review. Earth Sci Rev 99:125–161
Seneviratne SI, Nicholls N, Easterling D, Goodess CM, Kanae S, Kossin J, Luo Y, Marengo J, McInnes K, Rahimi M, Reichstein M, Sorteberg A, Vera C, Zhang X (2012) Changes in climate extremes and their impacts on the natural physical environment. In: Field CB, Barros V, Stocker TF, Qin D, Dokken D, Ebi KL, Mastrandrea MD, Mach KJ, Plattner G-K, Allen SK, Tignor M, Midgley PM (eds) Intergovernmental Panel on Climate Change special report on managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge/New York
Sheffield J, Wood EF (2008) Global trends and variability in soil moisture and drought characteristics, 1950–2000, from observation-driven simulations of the terrestrial hydrologic cycle. J Clim 21:432–458
Sherwood SC, Huber M (2010) An adaptability limit to climate change due to heat stress. Proc Natl Acad Sci USA 107(21):9552–9555
Shiklomanov AI, Lammers RB, Rawlins MA, Smith LC, Pavelsky TM (2007) Temporal and spatial variations in maximum river discharge from a new Russian data set. J Geophys Res 112:G04S53
Shrestha RR, Berland AJ, Schorbus MA, Werner AT (2011) Climate change impacts on hydroclimatic regimes in the Peace and Columbia watersheds, British Columbia, Canada. In: Pacific climate impacts consortium, University of Victoria, Victoria, 37 pp. Available from http://pacificclimate.org/sites/default/files/publications/Shrestha.Synthesis.FinalReport.Apr2011.pdf
Sigmond M, Kushner PJ, Scinocca JF (2007) Discriminating robust and non-robust atmospheric circulation responses to global warming. J Geophys Res 112, D20121. doi:10.1029/2006JD008270
Sillmann J, Croci-Maspoli M, Kallache M, Katz RW (2011) Extreme cold winter temperature in Europe under the influence of North Atlantic atmospheric blocking. J Clim 24:5899–5913. doi:10.1175/2011JCLI4075.1
Sillmann J, Kharin VV, Zhang X, Zwiers FW, Bronaugh D (2013a) Climate extreme indices in the CMIP5 multi-model ensemble. Part 1: model evaluation in the present climate. J Geophys Res 118, doi:10.1002/jgrd.50203
Sillmann J, Kharin VV, Zwiers FW, Zhang X, Bronaugh D (2013b) Climate extreme indices in the CMIP5 multi-model ensemble. Part 2: future climate projections. J Geophys Res 118, doi:10.1002/jgrd.50188
Smith RL (1986) Extreme value theory based on the r-largest annual events. J Hydrol 86:27–43
Smith RL (1990) Max-stable processes and spatial extremes. Unpublished manuscript. Available at http://www.stat.unc.edu/postscript/rs/spatex.pdf
Smits A, Klein Tank AMG, Können GP (2005) Trends in storminess over the Netherlands, 1962–2002. Int J Climatol 25:1331–1344. doi:10.1002/joc.1195
Solomon S et al (2007) Technical summary. In: Solomon S et al (eds) Climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Stahl K, Hisdal H, Hannaford J, Tallaksen LM, van Lanen HAJ, Sauquet E, Demuth S, Fendekova M, Jodar J (2010) Streamflow trends in Europe: evidence from dataset of near-natural catchments. Hydrol Earth Syst Sci 14:2367–2382

Steadman RG (1979) The assessment of sultriness. Part I: a temperature-humidity index based on human physiology and clothing science. J Appl Meteorol 18:861–873

Stott PA, Stone DA, Allen MR (2004) Human contribution to the European heatwave of 2003. Nature 432:610–614. doi:10.1038/nature0308

Stott PA et al (2012) Attribution of weather and climate-related extreme events. In: WCRP Open Science conference: climate research in service to society, World Climate Research Programme, Denver (this volume)

Sugi M, Murakami H, Yoshimura J (2009) A reduction in global tropical cyclone frequency due to global warming. SOLA 5:164–167. doi:10.2151/sola.2009-042

Svensson C, Hannaford J, Kundzewicz ZW, Marsh TJ (2006) Trends in river floods: why is there no clear signal in observations? IAHS/UNESCO Kov Colloq: Front Flood Res 305:1–18

Swanson KL (2008) Non-locality of Atlantic tropical cyclone intensitites. Geochem Geophys Geosyst 9:Q04V01

Taye MT, Ntegeka V, Ogiramoi NP, Willems P (2011) Assessment of climate change impact on hydrological extremes in two source regions of the Nile River Basin. Hydrol Earth Syst Sci 15:209–222

Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. Bull Am Meteorol Soc 93(4):485–498

Tebaldi C, Hayhoe K, Arblaster JM, Meehl GA (2006) Going to the extremes—an intercomparison of model-simulated historical and future changes in extreme events. Clim Change 79:185–211

Ting M, Kushnir Y, Seager R, Li C (2009) Forced and internal 20th century SST trends in the North Atlantic. J Clim 22:1469–1481. doi:10.1175/2008JCLI2561.1

Trapp RJ et al (2005) Tornadoes from squall lines and bow echoes. Pt I: climatological distribution. Weather Forecast 20:23–34

Trenberth KE et al (2007) Observations: surface and atmospheric climate change. In: Solomon S et al (eds) The Physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Ulbrich U, Pinto JG, Kupfer H, Leckebusch GC, Spangehl T, Reyers M (2008) Changing northern hemisphere storm tracks in an ensemble of IPCC climate change simulations. J Clim 21:1669–1679

Uppala SM et al (2005) The ERA-40 re-analysis. Q J R Meteorol Soc 131:2961–3012. doi:10.1256/qj.04.176

van der Schrier G, Briffa KR, Jones PD, Osborn TJ (2006) Summer moisture variability across Europe. J Clim 19:2818–2834

van Oldenborgh GJ, van Urk A, Allen M (2012) The absence of a role of climate change in the 2011 Thailand floods. In: Peterson TC et al (eds) Explaining extreme events of 2011 from a climate perspective. Bull Am Meteor Soc 93:1041–1067. doi:10.1175/BAMS-D-12-00021.1

van Pelt SC, Kabat P, ter Maat TW, van den Hurk BJJM, Weerts AH (2009) Discharge simulations performed with a hydrological model using bias corrected regional climate model input. Hydrol Earth Syst Sci 13:2387–2397

Van Wagner C (1987) Development and structure of the Canadian forest fire weather index system. Technical report #35, Canadian Forest Service

Vannitsem S, Naveau P (2007) Spatial dependences among precipitation maxima over Belgium. Nonlinear Process Geophys 14:621–630

Vautard R, Cattiaux J, Yiou P, Thepaut J-N, Ciais P (2010) Northern Hemisphere atmospheric stilling partly attributed to an increase in surface roughness. Nat Geogr 3:756–761. doi:10.1038/NGEO979

Vecchi GA, Knutson TR (2008) On estimates of historical North Atlantic tropical cyclone activity. J Clim 21:3580–3600

Vecchi GA, Knutson TR (2011) Estimating annual numbers of Atlantic hurricanes missing from the HURDAT database (1878–1965) using ship track density. J Clim 24:1736–1746. doi:10.1175/2010JCLI3810.1
Vecchi GA, Soden BJ (2007) Effect of remote sea surface temperature change on tropical cyclone potential intensity. Nature 450:1066–1070
Vecchi GA, Swanson KL, Soden BJ (2008) Whither hurricane activity. Science 322:687–689
Vermeer M, Rahmstorf S (2009) Global sea level linked to global temperature. Proc Natl Acad Sci USA 106:21527–21532
Vicente-Serrano SM, Begueria S, Lopez-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim 23(7): 1696–1718
Villarini G, Vecchi GA (2013) Projected increases in North Atlantic tropical cyclone intensity from CMIP5 models. J Clim 26:3231–3240. doi:10.1175/JCLI-D-12-00441.1
Villarini G, Serinaldi F, Smith JA, Krajewski WF (2009) On the stationarity of annual flood peaks in the continental United States during the 20th century. Water Resour Res 45, W08417
Wang XL, Swail VR (2001) Changes of extreme wave heights in Northern Hemisphere oceans and related atmospheric circulation regimes. J Clim 14:2204–2221
Wang XL, Wan H, Swail VR (2006) Observed changes in cyclone activity in Canada and their relationships to major circulation regimes. J Clim 19:896–915
Wang AH, Bohn TJ, Mahanama SP, Koster RD, Lettenmaier DP (2009a) Multimodel ensemble reconstruction of drought over the continental United States. J Clim 22:2694–2712
Wang XL, Swail VR, Zwiers FW, Zhang X, Feng Y (2009b) Detection of external influence on trends of atmospheric storminess and northern oceans wave heights. Clim Dyn 32:189–203
Wang XL, Wan H, Zwiers FW, Swail VR, Compo GP, Allan RJ, Vose RS, Jourdain S, Yin X (2011) Trends and low-frequency variability of storminess over western Europe, 1887–2007. Clim Dyn 37:2355–2371. doi:10.1007/s00382-011-1107-0
Wang XL, Feng Y, Compo GP, Swail VR, Zwiers FW, Allan RJ, Sardeshmukh PD (2012) Trends and low frequency variability of extra-tropical cyclone activity in the ensemble of twentieth century reanalysis. Clim Dyn. doi:10.1007/s00382-012-1450-9
Watson CC, Johnson ME (2004) Hurricane loss estimation models: opportunities for improving the State of the Art. Bull Am Meteorol Soc 85:1713
Webster PJ, Holland GJ, Curry JA, Chang HR (2005) Changes in tropical cyclone number, duration, and intensity in a warming environment. Science 309:1844–1846
Wehner MF (2013) Very extreme seasonal precipitation in the NARCCAP ensemble: model performance and projections. Clim Dyn 40(1–2):59–80. doi:10.1007/s00382-012-1393-1
Wehner MF, Smith RL, Bala G, Duffy P (2010) The effect of horizontal resolution on simulation of very extreme precipitation events in a global atmospheric model. Clim Dyn 34:241–247. doi:10.1007/s00382-009-0656-y
Wells N, Goddard S, Hayes MH (2004) A self-calibrating Palmer drought severity index. J Clim 17:2335–2351
Wilby RL, Beven KJ, Reynard NS (2008) Climate change and fluvial flood risk in the UK: more of the same? Hydrol Process 22:2511–2523
Woodhouse CA, Overpeck JT (1998) 2000 years of drought variability in the central United States. Bull Am Meteorol Soc 79:2693–2714
Woodhouse CA, Meko DM, MacDonald GM, Stahle DW, Cook ER (2010) A 1200-year perspective on 21st century drought in southwestern North America. Proc Natl Acad Sci USA 107:21283–21288. doi:10.1175/2011JCLI4075.1
Woodworth PL, Gehrels WR, Nerem RS (2011) Nineteenth and twentieth century changes in sea level. Oceanography 24:80–93. doi:10.5670/oceanog.2011.29
Xie P, Janowiak JE, Arkin PA, Adler R, Gruber A, Ferraro R, Huffman GJ, Curtis S (2003) GPR pentad precipitation analyses: an experimental dataset based on gauge observations and satellite estimates. J Clim 16:2197–2214
Zazulie N, Rusticucci M, Solomon S (2010) Changes in climate at high southern latitudes: a unique daily record at orcadas spanning 1903–2008. J Clim 23:189–196. doi:10.1175/2009JCLI3074.1

Zhang R, Delworth T (2009) A new method for attributing climate variations over the Atlantic Hurricane Basin's main development region. Geophys Res Lett 36, L06701. doi:10.1029/2009GL037260

Zhang X, Zwiers FZ (2013) Statistical indices for diagnosing and detecting changes in extremes. In: Agha Kouchak et al (eds) Extremes in a changing climate. Water Science and Technology Library 65. Springer, Dordrecht. doi:10.1007/978-94-007-4479-0-1

Zhang X, Zwiers FW, Li G (2004) Monte Carlo experiments on the detection of trends in extreme values. J Clim 17:1945–1952

Zhang X, Hegerl GC, Zwiers FW (2005) Avoiding inhomogeneity in percentile-based indices of temperature extremes. J Clim 18:1641–1651

Zhang X, Zwiers FW, Hegerl GC, Lambert FH, Gillett NP, Solomon S, Stott PA, Nozawa T (2007) Detection of human influence on twentieth-century precipitation trends. Nature 448:461–465

Zhang X, Zwiers FW, Hegerl G (2009) The influence of data precision on the calculation of temperature percentile indices. Int J Climatol. doi:10.1002/joc.1738

Zhang X, Wang J, Zwiers FW, Groisman PY (2010) The influence of large scale climate variability on winter maximum daily precipitation over North America. J Clim 23:2902–2915

Zhang X, Alexander LV, Hegerl GC, Klein Tank A, Peterson TC, Trewin B, Zwiers FW (2011) Indices for monitoring changes in extremes based on daily temperature and precipitation data. Wiley Interdiscip Rev Clim Change 2:851–870. doi:10.1002/wcc.147

Zhao M, Held I, Lin S-J, Vecchi GA (2009) Simulations of global hurricane climatology, interannual variability, and response to global warming using a 50 km resolution GCM. J Clim 22:6653–6678. doi:10.1175/2009JCLI3049.1

Zwiers FW (1987) An extreme value analysis of wind speed at 5 Canadian locations. Can J Stat 15:317–327

Zwiers FW, Zhang X, Feng Y (2011) Anthropogenic influence on long return period daily temperature extremes at regional scales. J Clim 24:881–892