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

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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 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 analysing 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.

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 modelling 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 discusses some aspects of projections for the 21st 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[10] 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 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, 2012). 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

[10] 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

improved, often remain subject to substantial inhomogeneities due to the evolution of our observing systems (Knutson et al., 2010; Seneviratne et al., 2012).

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 8 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 Section 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 Section 4, and extreme sea-levels (e.g., storm surge events) in Section 5. A summary and recommendations are presented in Section 6. Amongst other sources, the paper draws upon the IPCC 4th Assessment Report (IPCC 2007a, IPCC 2007b), 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

a. 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 (Figure 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 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).

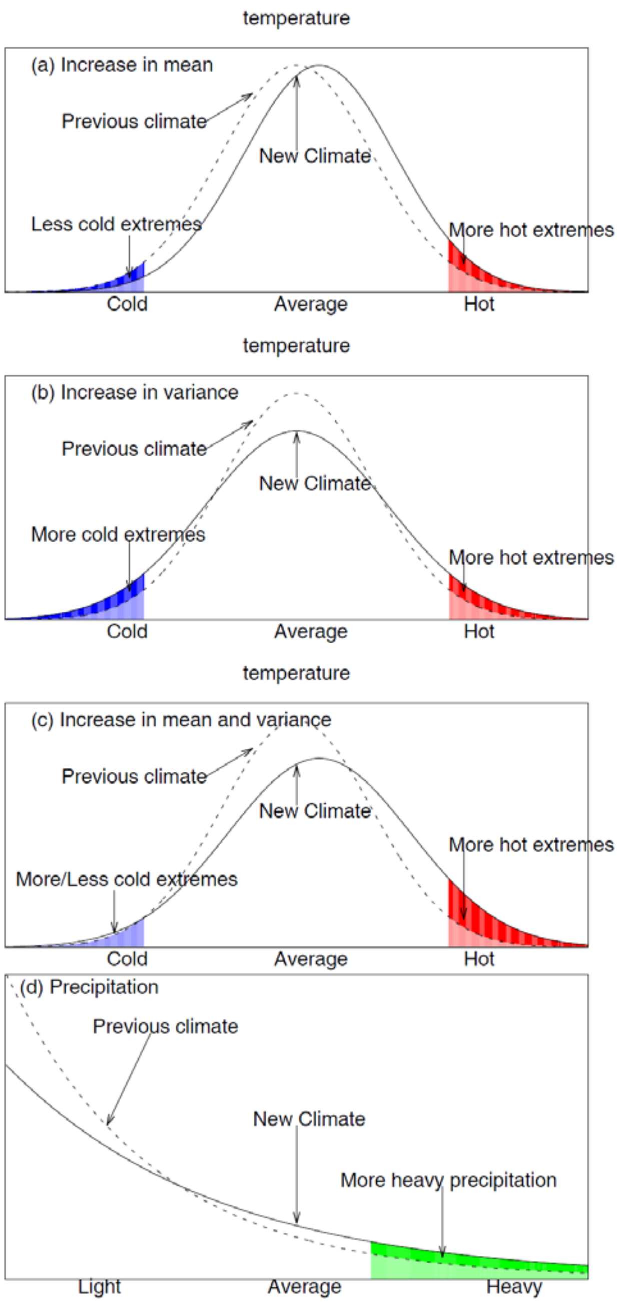

Figure 1: Schematic representations of the probability distributions of daily temperature, which tends to be approximately Gaussian (exceptions can be caused by soil freezing, feedbacks, or energy balance constraints, see text), and daily precipitation, which has a skewed distribution. Extremes are denoted 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 (2012), after Folland et al (1995) and Peterson et al (2008).

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.

b. Status

i) 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 1961-90; 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 (2012a, 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 because 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 focussed 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 Figure 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 Figure 2d), or vice-versa as in HadEX2 (blue curve in Figure 2d) or GHCNDEX (green curve in Figure 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). 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, 2012).

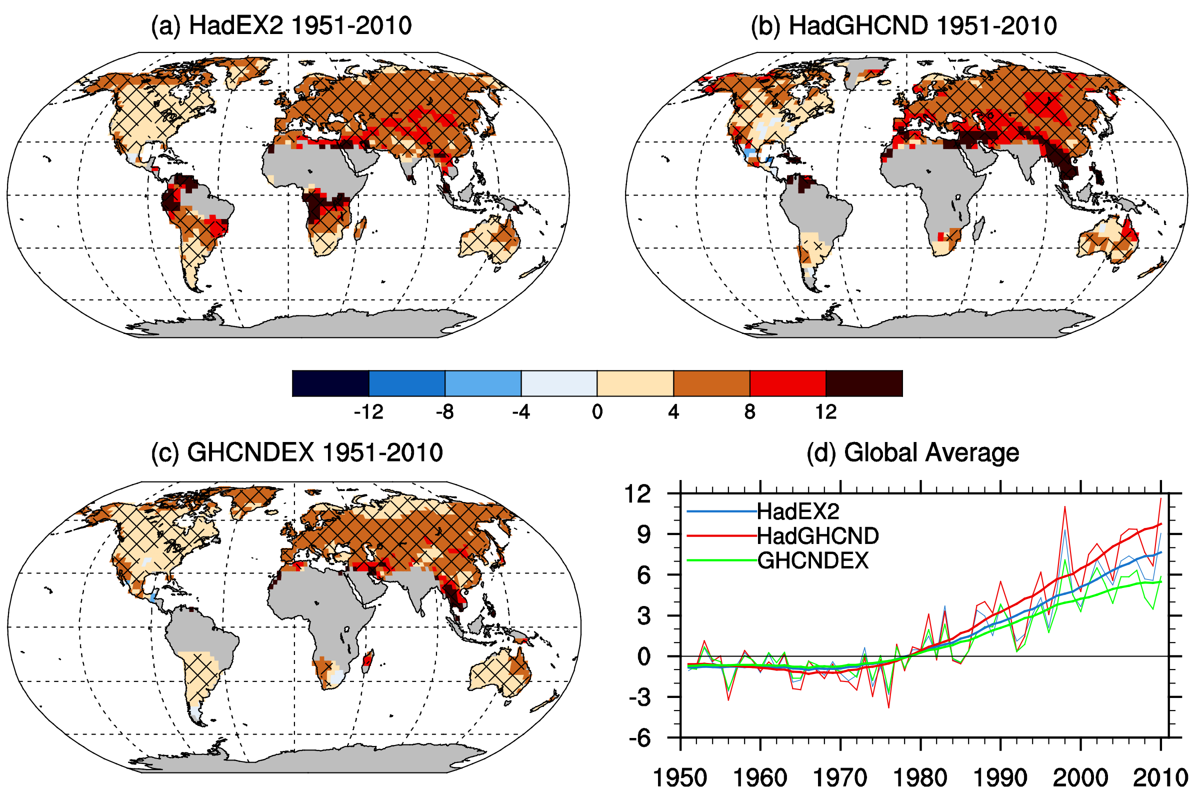

Figure 2: Annual trends in warm nights (TN90p) using different datasets for the period 1951 to 2010 where at least 40 years are available. The datasets are (a) HadEX2 (Alexander and Donat 2011), (b) HadGHCNDEX (ETCCDI indices calculated from an updated version of HadGHCND (Caesar et al. 2006)) and (c) 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.

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 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., 2012a). 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., 2012a) 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 substantially 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 modelled 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 at el (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.

ii) 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 20^{th} Century (20CR) reanalysis of Compo et al (2011), which is based only on surface observations and covers the period 1871-2008. 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 20^{th} century (Smits et al, 2005; Donat et al, 2011). For tropical cyclones, the intensities of the storms (i.e., maximum near-surface sustained one-minute wind speeds) can also be estimated globally using satellite data, at least since the early 1980s (Kossin et al. 2007; Elsner et al. 2008).

c. Role of external influences

i) 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; Figure 3, which also shows that human influence can be detected in the frequency of warm nights in most regions; Morak et al.,

2012) 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, 2012) 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 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 modelling 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; Schlatter, 2002; Vannitsem and Naveau, 2007; Blanchet and Davison, 2011)[11]. 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 modelling 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

[11] 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 is max-stable.

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.

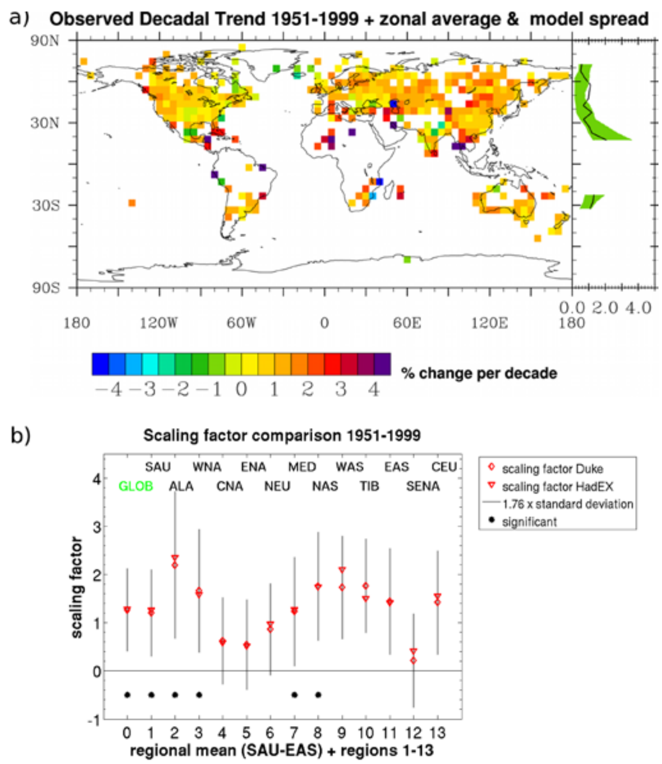

Figure 3: (a) 1951–1999 observed decadal trend of TN90 (in % change per decade) based on a combination of HadEX (Alexander et al, 2006) and additional index data from Kenyon and Hegerl (2008). The zonal average of the observations (black line) and the spread of trends in an ensemble of CMIP3 [12]"ALL" forcings model simulated trends 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 (labelled 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).

A limitation of many studies that have been conducted to date is that they have been confined to the 20th 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 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 21rst century (e.g. Morak et al., 2012). 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, modelling 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

[12] Coupled Model Intercomparison Project Phase 3, see http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php

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 modelling 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 modelled. 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.

ii) 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 behaviour (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 behaviour 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 behaviour between observed and climate model simulated extreme precipitation in the model they study. Averaging in space and time smoothes the tail behaviour 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., 2012) 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 20th 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 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 Figure 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 20th 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.

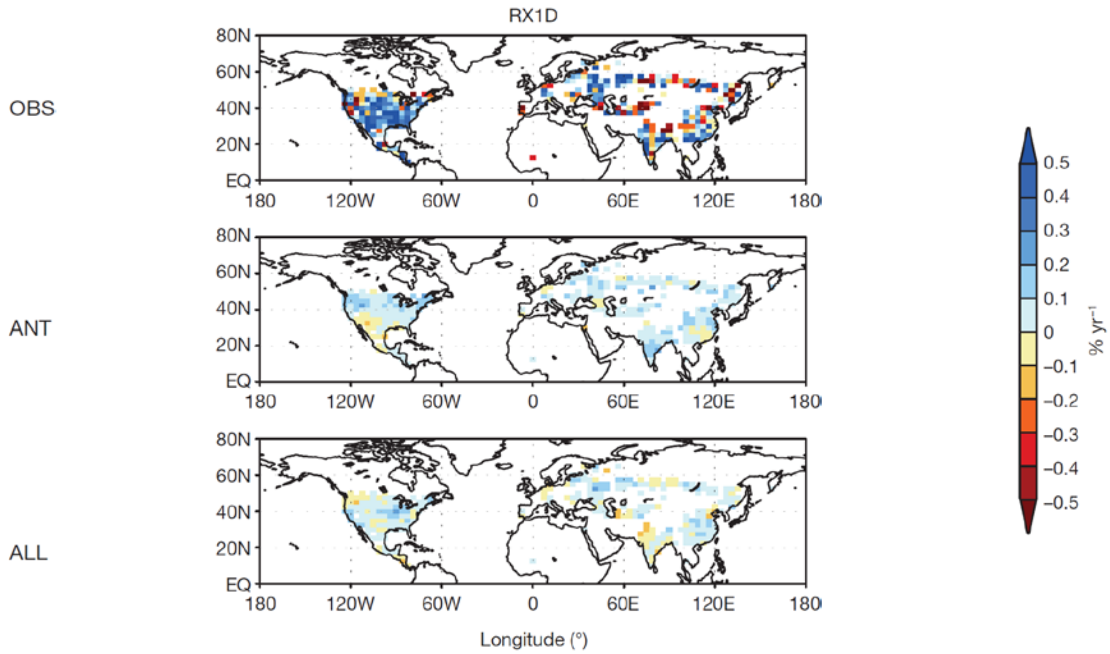

Figure 4: Geographical distribution of trends of extreme precipitation indices (PI) for annual maximum daily precipitation amounts (RX1D) during 1951–99. Observations (OBS); model simulations with anthropogenic (ANT) forcing; model simulations with anthropogenic plus natural (ALL) forcing. For models, ensemble means of trends from individual simulations are displayed. Units: per cent probability per year. From Min et al (2011; see paper for details).

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 20th century, extending to the early 21st 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. (2012) 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.

a. 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 changes in their number distribution (Lambert and Fyfe, 2006) and in the positioning of extra-tropical storm tracks (Bengsston 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 modelling 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 Figure 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.

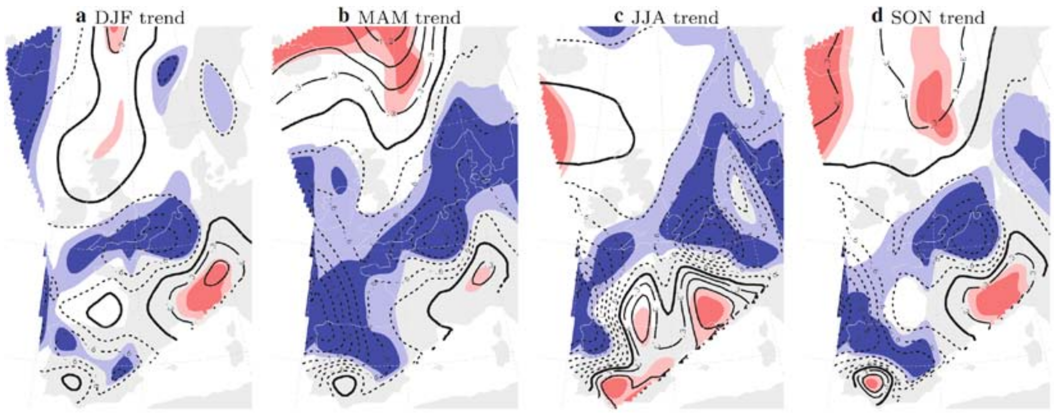

Figure 5: Example of an analysis of trends in seasonal storm indices derived from long surface pressure records. This figure shows contour maps of Theil-Sen (also sometimes know as Kendall's) linear trend estimates (in unit per century) in seasonal storm indices defined as the 99th percentile of sub-daily geostrophic wind speed estimated from pressure triangles for the period 1902–2007 in a domain the 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).

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, is 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 that would not formally be considered to 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.

b. 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 Figure 6).

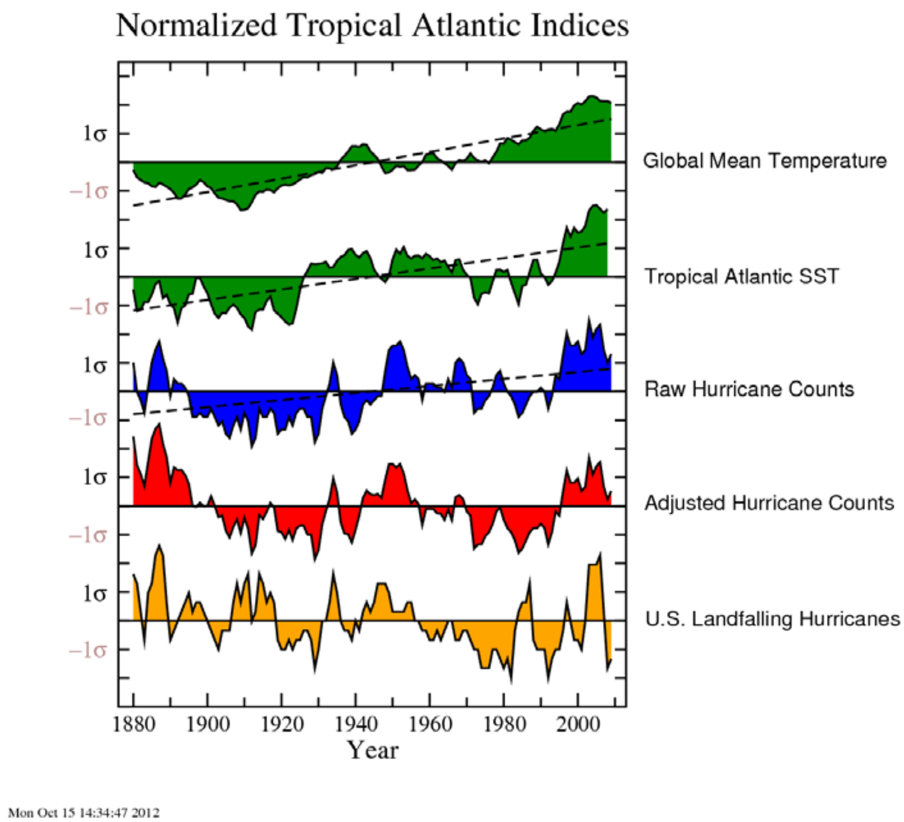

Figure 6: Five-year running means of tropical Atlantic indices. Green curves depict global annual-mean temperature anomalies (top) and August- October Main Development Region (MDR, defined as 20W-80W, 10N-20N) SST anomalies (second from top). Blue curve shows unadjusted Atlantic hurricane counts. Red 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).

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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 20th 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), 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 cyclogensis (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^{o}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 2012, submitted for publication)) 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. 2012; Villarini and Vecchi 2012, submitted for publication). 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 21st 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 21st 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 modelling 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. Modelling 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 Vechhi, 2012, submitted for publication], 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).

c. 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., Hannesiak et al, 2011).

a. 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 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 (section 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-yr 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 modelling 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 (2012), 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).

b. 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/analysed via statistical analysis of discharge records (see e.g., Fleig et al, 2006).

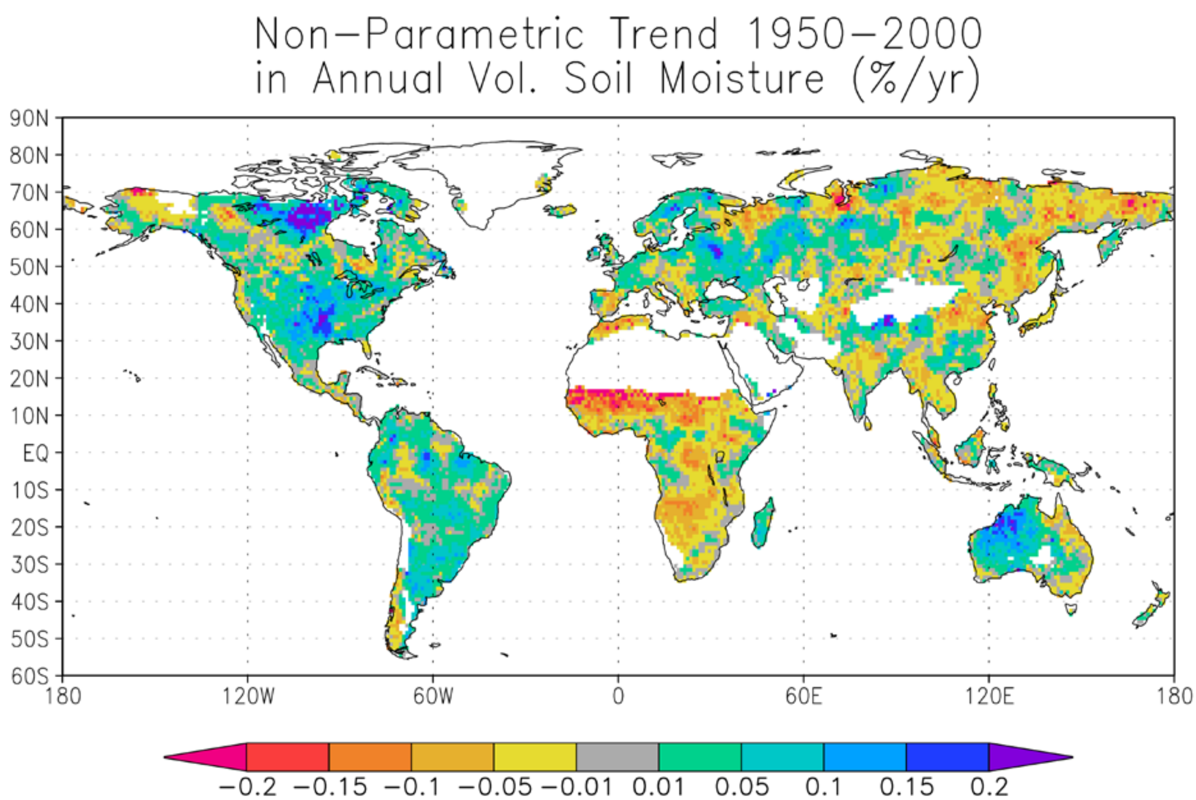

Figure 7: Global distribution of linear trends in annual mean volumetric soil moisture for 1950-2000 obtained from the Variable Infiltration Capacity (VIC) hydrologic model when driven with observationally based forcing. The trends are calculated using the Theil-Sen estimator and evaluated with the Mann–Kendall 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; Figure 1).

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 20th 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 (Figure 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 20th 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).

Characterising hydrologic (i.e. runoff and streamflow) drought globally and regionally is also challenging due to difficulties in establishing robust and/or standardised 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).

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 behaviour 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 to 2.2] mm yr^{-1} over the 20^{th} century, 1.8 [1.3 to 2.3] mm yr^{-1} over 1961 to 2003, and at a rate of 3.1 [2.4 to 3.8] mm yr^{-1} over 1993 to 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 20^{th} century (Hegerl et al, 2007), 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; Menendez and Woodworth, 2010; Woodworth et al, 2011; see Figure 8).

Meehl et al (2007a) projected model based 90% ranges for sea level rise for 2090–2099 relative to 1980–1999 that varied from 18–38 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 modelled 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 modelling (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 21^{st} 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).

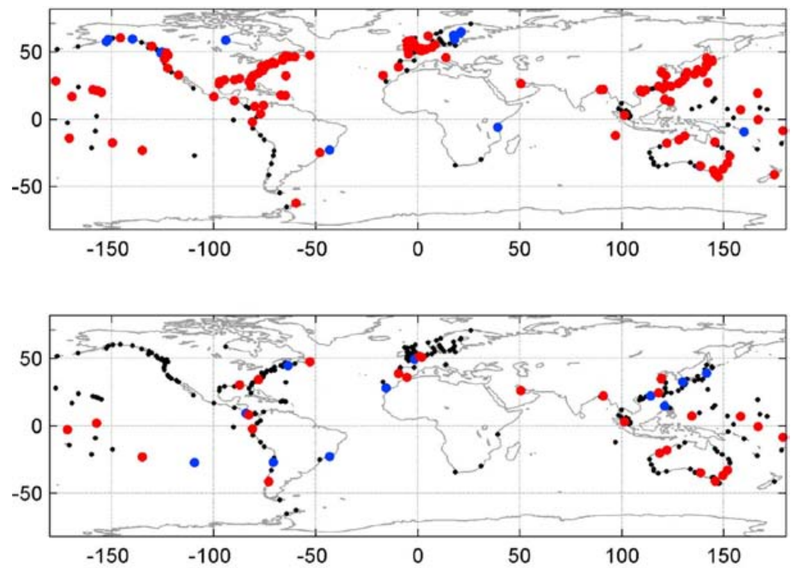

Figure 8: Estimated trends in (upper) annual 99th percentile of sea level based on monthly maxima of hourly tide gauge readings from 1970 onwards, and (lower) 99th percentile after removal of the annual medians of hourly readings. Only trends significant at the 5% level are shown in colour: red for positive 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.

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 focussed primarily on the historical instrumental record, noting results and challenges that arise from observational, methodological and climate modelling 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 behaviour of the climate system has changed over the past century and to evaluate both model variability and model behaviour 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[13] (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

[13] Asia-Pacific Network for Global Change Research

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[14]) are needed to ensure the archival and digitisation 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 behaviour.

An important effort with regard to surface temperature is the International Surface Temperature Initiative[15] 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"[16] for the digitization and analysis of climate data, as is being done at US National Climatic Data Centre for both surface temperature data rescue and ongoing tropic cyclone reanalysis[17].

A second set of challenges concerns *the state of our tools for analysing 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

[14] See http://www.ncdc.noaa.gov/oa/climate/cdmp/forts.html
[15] http://www.surfacetemperatures.org/
[16] The use of unpaid volunteers, often solicited via the internet.
[17] 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

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 rigour, 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 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 paleo-climate data that we become aware of the role of low-frequency climate variability in 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. 2012), 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; Fisher 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 modelling perspective. While extremes represent the tail behaviour of climate and weather variables, a growing body of research indicates that their likelihood and intensity is very much influenced by behaviour that is more central to the distribution of climate and weather states.

While we have focussed 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 modelling the influence of seasonal to multi-decadal climate variability on the frequency and/or intensity of extremes, or modelling 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.

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