Assessing Human Influence on Changes in Extremes

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The term "extremes" refers to a range of weather and climate phenomena that are rare within the context in which they occur. Extremes can be differentiated according to the temporal and spatial scales of the phenomenon of interest, weather extremes being events that are rare at a particular place and time of year (IPCC, 2007; CCSP, 2008), and climate extremes being rare events that persist over a period of time, such as a season. The term as used in the climate literature includes phenomena that span from the range from those that are not all that rare or intense, albeit likely stressful, such as exceedance of the 90th percentile of daily maximum temperature, to those that are unprecedented in impact and in the instrumental climatic record.

The approaches used to analyse changes in extremes vary according to the type of phenomenon. In the case of very intense, short duration phenomena, such as tornadoes (Brooks and Dotzek, 2008; CCSP, 2008), where records are short or may not have sufficient reliability, process studies may be the only viable option for gaining insight into the factors that control their occurrence and intensity. Similarly, process studies may also be required to interpret events that are unprecedented in the instrumental record, such as the European 2003 heat wave (Schär, et al, 2004; Stott, et al, 2004). On the other hand, a variety of statistical and modelling approaches may be useful when data are reliable and homogeneous, and are available on an annual basis. In this case approaches range from the analysis of simple indices of extremes, such as those defined by the Expert Team on Climate Change Detection and Indices and the Asia-Pacific Network (ETCCDI and APN respectively, Peterson and Manton, 2008), to the application of extreme value theory (eg, Kharin et al, 2007).

The ETCCDI and APN have approached the data problem by organizing a worldwide series of capacity building workshops that have trained developing world scientists in the basic quality control of climatic data, its homogenization, and in its subsequent application for the calculation and analysis of climatic indices. As a result, it has been possible to engage developing world scientists in studies of changes in moderately intense extremes, and to greatly expand the domain over which indices for monitoring extremes are available (eg, Alexander et al, 2006). These types of indices have subsequently been used to assess whether human influence is detectable in observed changes in temperature extremes (eg, Christidis et al, 2005) and to assess changes in extremes simulated by climate models (eg, Tebaldi et al, 2006; Meehl et al, 2007).

Despite their simplicity, indices are not without their pitfalls, even when the available data are reliable and homogeneous. For example, indices that use a fixed threshold, such the so-called

R10mm index that counts the number of days per year with rainfall greater than 10 mm, may not consistently provide counts of events that are equally "extreme" in all regions. In particular, R10mm counts events that are quite rare in dry Arctic climates but are very common in moist tropical climates. This problem can be avoided with indices that use thresholds specific to the local climate, such as TX90p, which counts the percentage of days each year with daily maximum temperature above the 90th percentile of daily maximum temperatures. However, great care is required to estimate the percentile thresholds to ensure that inhomogeneities are not introduced into the index time series at the boundaries of the base periods that are used to determine the thresholds (Zhang et al, 2005). A further difficulty that has been encountered in the calculation of percentile indices relates to the recording resolution of the climate archive from which the indices are calculated. Practice has varied considerably around the world, with some jurisdictions recording temperature to within the nearest 0.1°C while others have recorded historical temperature data at much coarser resolutions, such as 0.5°C or 1°F. This, together with the fact that recording resolution is not constant over time at all stations, poses difficulties for percentile index calculations, particularly in areas with low climatic variability. Fortunately, data adjustments can be made to place index calculations, and the subsequent derivation of trends, on a sound footing (Zhang et al, 2008).

An advantage of the indices approach is that standard methods of trend and detection analysis can generally be applied, although some statistical approximations concerning the distributions of the indices may be required. This has allowed the application of the optimal detection technique (eg, Hasselmann, 1997; Allen and Tett, 1999) to observed indices of extremes, enabling the identification of human influence at global scales on the temperature of extreme cold days, cold nights, and warm nights (Christidis et al, 2005; Hegerl et al, 2007).

While the index approach has proven to be practical and useful, the types of extremes that have significant impacts, and which are important for the design of infrastructure such as storm water handling systems, occur farther out in the tails than can typically accessed via simple analyses of indices. In the case of rare events that recur only infrequently, such as the 20- or 100-yr event, it becomes necessary to analyse extremes using statistical extreme value theory (eg, Smith, 2002; Kharin et al, 2007). Two approaches have been defined; the so-called peaks-over-threshold approach and the block maximum approach. The latter, which is typically used to analyze the behaviour of annual extremes, such as the annual maximum daily maximum temperature at a given location, or the annual maximum of daily precipitation amounts at a location, is the more commonly used in climatology. A typical product of the application of extreme value theory is an estimate of a long-period return value, such as the daily rainfall amount that would be expected to be exceeded only once every 20- or 100-years, on average. A strength of the extreme value theory approach is that the method can account for non-stationarity in the behaviour of extremes thereby providing a means to quantify changes in the risks of extremes that are associated with external influences, such as anthropogenic influence on the climate, and with internal variability such as ENSO (eg., Klein-Tank et al, 2009; Kharin and Zwiers, 2005; Zhang et al, 2009). For example, Zhang et al (2009) demonstrate that the risk of an extreme precipitation event is strongly dependent upon the state of ENSO over much of North America.

To date, only a few detection and attribution studies have used diagnostics obtained by applying extreme value theory to time series of annual extremes. One recent study (Brown et al, pers. comm., 2009) demonstrates that this more powerful approach makes it possible to detect human influence on extreme warm days as well as on extreme cold days, cold nights and warm nights as has previously been obtained by Christidis et al (2005). Another recent study (Wang et al, 2008) uses extreme value theory in a downscaling approach to demonstrate that the combined influence of natural and anthropogenic forcing is likely detectable in extreme significant wave height in the northern hemisphere in boreal winter. Continued development of this approach, whereby detection and attribution is conducted within the framework of extreme value theory, should allow detection of external influence farther out in the tails of observable quantities, and should allow observational constraints to be placed on estimates of changes in the probability of extremes (termed *risk*) that are attributable to human influence. This is not possible with current approaches to estimating attributable risk, such as that used by Stott et al (2004).

The IPCC 4th Assessment Report (2007) summarized in Table SPM-2 the then current assessments of the likelihood that observed trends in extremes were, in part, the result of human influence on the climate system. Those assessments were based either on formal detection and attribution studies, where available, or on expert judgement in the absence of such studies. That table can now be modestly updated, based both on the formal detection studies on extremes such as those cited above, but also on further corroborating evidence that external influence has affected the base state in instances where studies on extremes continue to be unavailable. For example, detection studies now demonstrate that sea-surface temperature changes in key tropical cyclogenesis regions are in part attributable to human influence (Santer et al, 2006; Gillett et al, 2008). Similarly, there are now several studies that indicate human influence on the base state of the hydrological cycle; they further support the assessment that human influence has more likely than not affected the intensity of heavy precipitation events. These studies show that human influence has affected the meridional distribution of precipitation on land (Zhang et al, 2007) and column integrated atmospheric water vapour over the oceans (Santer et al, 2007). In addition, human influence has been detected in changes in the distribution of high latitude precipitation (Min et al, 2008), and in the western U.S. hydrological cycle (Barnett et al, 2008).

A constraint on progress in quantifying the effects of external influences on weather and climate, which is additional to that imposed by the quality and availability of data, is the ability of climate models to simulate the climatological intensity and frequency of extremes. Kharin et al (2007) recently compared the ability of the CMIP3 models that provided daily data to the PCMDI multi-model archive to simulate long-period return values of extreme maximum and minimum temperature, and of daily precipitation amounts. Their results demonstrate that models simulate surface air temperature extremes plausibly. On the other hand, they tend to under-simulate precipitation extremes in the extra-tropics (in part because of differences in the scales that are represented by observed and simulated precipitation amounts) and the representation of tropical precipitation extremes is highly variable between models. Nevertheless, the models showed reasonably consistent behaviour in simulating changes in precipitation extremes under the SRES forcing scenarios from one model to the next, at least on large regional scales, indicating that there is some potential for the detection of changes in precipitation extremes (see also, Hegerl et al, 2004). Min et al (2009), using a Bayesian decision analysis formalism, support this conclusion in a perfect model potential detectability study, although they find that this conclusion is sensitive to the structural uncertainty in models.

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