EXPLAINING EXTREME EVENTS OF 2011 FROM A CLIMATE PERSPECTIVE

Thomas C. Peterson, Peter A. Stott and Stephanie Herring, Editors

Using a variety of methodologies, six extreme events of the previous year are explained from a climate perspective.

INTRODUCTION

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Every year, the Bulletin of the AMS publishes an annual report on the State of the Climate [e.g., see the Blunden and Arndt (2012) supplement to this issue]. That report does an excellent job of documenting global weather and climate conditions of the previous year and putting them into accurate historical perspective. But it does not address the causes. One of the reasons is that the scientists working at understanding the causes of various extreme events are generally not the same scientists analyzing the magnitude of the events and writing the State of the Climate. Another reason is that explaining the causes of specific extreme events in near-real time is severely stretching the current state of the science.

Our report is a way to foster the growth of this science. Other reports, such as those by the Intergovernmental Panel on Climate Change (IPCC), have focused on understanding changes over longer time scales and larger geographic regions. For example, assessing the state of the climate and science, IPCC (Field et al. 2012) concluded that "it is likely that anthropogenic influences have led to warming of extreme daily minimum and maximum temperatures at the global scale" and that "there is medium confidence[1] that anthropogenic influences have

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The abstract for this article can be found in this issue, following the table of contents.

DOI:10.1175/BAMS-D-12-00021.1

In final form 4 May 2012
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[1] Likely indicates probability greater than 66%; see IPCC guidance on uncertainty language (Mastrandrea et al. 2010), which also includes guidance on expression of levels of confidence.

contributed to intensification of extreme precipitation at the global scale".

This first edition of what is intended to be an annual report starts out with an assessment on causes of historical changes in temperature and precipitation extremes worldwide to provide a long-term perspective for the events discussed in 2011. That section also considers the use of the term "extreme" in climate science so as to provide a context for the extreme events discussed in the rest of the report. The report then goes on to examine only six extreme events assessed by teams of experts from around the world. We are not attempting to be comprehensive nor does our selection of extreme events reflect any judgment about the importance of the events discussed here relative to the many other extreme events around the world in 2011.

By choosing a few noteworthy events to analyze there could be a risk of selection bias if the events chosen are thought of as representative of the weather observed in 2011, which they are not. However, our purpose here is to provide some illustrations of a range of possible methodological approaches rather than to be comprehensive. We hope that the examples we have chosen will serve to stimulate the development of attribution science and lead to submissions that, in future years, look at different regions and a wider range of extreme events. Developing objective criteria for defining extreme weather and climate events ahead of time, and applying predetermined methodologies, should minimize the risk of bias resulting from selective choice of criteria based on what actually occurred (e.g., Stott et al. 2004).

Currently, attribution of single extreme events to anthropogenic climate change remains challenging (Seneviratne et al. 2012). In the past it was often stated that it simply was not possible to make an attribution statement about an individual weather or climate event. However, scientific thinking on this issue has moved on and now it is widely accepted that attribution statements about individual weather or climate events are possible, provided proper account is taken of the probabilistic nature of attribution (Nature Publishing Group 2011).

One analogy of the effects of climate change on extreme weather is with a baseball player (or to choose another sport, a cricketer) who starts taking steroids and afterwards hits on average 20% more home runs (or sixes) in a season than he did before (Meehl 2012). For any one of his home runs (sixes) during the years the player was taking steroids, you would not know for sure whether it was caused by steroids or not. But you might be able to attribute his increased number to the steroids. And given that steroids have resulted in a 20% increased chance that any particular swing of the player's bat results in a home run (or a six), you would be able to make an attribution statement that, all other things being equal, steroid use had increased the probability of that particular occurrence by 20%. The job of the attribution assessment is to distinguish the effects of anthropogenic climate change or some other external factor (steroids in the sporting analogy) from natural variability (e.g., in the baseball analogy, the player's natural ability to hit home runs or the configuration of a particular stadium).

There have been relatively few studies published in the literature that attempt to explain specific extreme events from a climate perspective and this report covers some of the main methodological approaches that have been published to date. A position paper produced for the World Climate Research Program (Stott et al. 2012) reviewed some of these studies including attribution assessments of the 2000 UK floods (Pall et al. 2011), the 2003 European heat wave (Stott et al. 2004), the cool year of 2008 in the United States (Perlwitz et al. 2009) and the 2010 Russian heat wave (Dole et al. 2011). Such studies have demonstrated how the changed odds of an individual extreme weather or climate event can be calculated and attributed—very likely more than doubled for the 2003 European heat wave. In other cases, such as the case of the cool year of 2008 in the United States, conditions apparently inconsistent with the expected effects of ongoing climate change can be explained by the interplay of human influence on climate decreasing the odds of such extremes and natural variability, La Niña in the case of the U.S. temperatures in 2008, increasing the odds.

This report also considers other approaches distinct from those that seek to apportion changed odds. Analyzing how temperatures within particular flow patterns have changed helps to illustrate how long-term climate change is altering the typical weather associated with a particular flow regime. Such a regime-based approach (Cattiaux et al. 2010a) has shown how the cold northwestern European winter of 2009/10, associated largely with a very negative North Atlantic Oscillation (NAO), would have been even colder were it not for a long-term warming associated with ongoing climate change. Other related approaches involve using statistical models or climate models to tease apart the effects of climate variability and long-term warming on the observed occurrence of particular extreme weather events. By not quantifying the link to human emissions, such analyzes do not fully answer the attribution question,

but they do help to put extreme events into a climate perspective.

While the report includes three examples of the odds-based attribution analyzes discussed earlier, the challenges of running models and analyzing data in time for this report have meant that only the final analysis (of the cold UK winter of 2010/11, section 8) has the climate model simulations available to explicitly calculate the change odds attributable to human influence. Therefore this new report is a step along the road towards the development of the regular near-real time attribution systems advocated by Stott et al. (2011) rather than the final product. While there may be an increasing focus on such near-real time attribution activities by operational centers around the world, there remains much underpinning science to be done in the development of such a service. An informal group of scientists, the Attribution of Climate-Related Events group (ACE; Schiermeier 2011), is meeting in September 2012 to discuss how to take such activities further (www.metoffice.gov.uk/research/climate/climate-monitoring/attribution/ace).

One important aspect we hope to help promote through these reports is a focus on the questions being asked in attribution studies. Often there is a perception that some scientists have concluded that a particular weather or climate event was due to climate change whereas other scientists disagree. This can, at times, be due to confusion over exactly what is being attributed. For example, whereas Dole et al. (2011) reported that the 2010 Russian heatwave was largely natural in origin, Rahmstorf and Coumou (2011) concluded it was largely anthropogenic. In fact, the different conclusions largely reflect the different questions being asked, the focus on the magnitude of the heatwave by Dole et al. (2011) and on its probability by Rahmstorf and Coumou (2011), as has been demonstrated by Otto et al. (2012). This can be particularly confusing when communicated to the public.

We hope that this new venture will help develop the means of communicating assessments of the extent to which natural and anthropogenic factors contribute to the extreme weather or climate events of a particular year. As such we seek your reactions to this report, which will be invaluable in determining how we should continue in future years. It will also help inform the dialog about how best to enable a wider public to appreciate the links between the weather they are experiencing and the effects of long-term climate change.

HISTORICAL CONTEXT

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The occurrence of high-impact extreme weather and climate variations invariably leads to questions about whether the frequency or intensity of such events have changed, and whether human influence on the climate system has played a role. Research on these questions has intensified in recent years, culminating in two recent assessments (Karl et al. 2008; Field et al. 2012), and in proposals to formalize "event attribution" as a global climate service activity (Stott et al. 2012). In order to provide historical context for later sections, this section discusses the extent to which human influence has caused long-term changes in the frequency and intensity of some types of extremes.

The nature of extreme events. The term "extreme" is used in a number of contexts in climate science. It refers to events that may in fact not be all that extreme, such as the occurrence of a daily maximum temperature that exceeds the 90th percentile of daily variability as estimated from a climatological base period, or it may refer to rare events that lie in the far tails of the distribution of the phenomenon of interest. A characteristic of extremes is that they are understood within a context—and thus seasonal or annual means may be "extreme" just as an unusual short-term event, such as a daily precipitation accumulation, may be extreme. Certain phenomena, such as tropical cyclones that have been classified on the Saffir–Simpson scale, or tornadoes that have been classified on the Fujita scale, are considered extreme as a class. The general definition of extremes that was adopted by the IPCC for its Special Report on Extremes (Field et al. 2012) applies to most extremes considered in this report, and across the range of space and time scales that are considered here. That definition describes an extreme as the "occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed

values of the variable." A full discussion of the definition of an extreme can be found in Seneviratne et al. (2012). In addition, Zwiers et al. (2012, unpublished manuscript) provide a discussion of the language surrounding extremes that is used in the climate sciences.

Challenges in detection and attribution of extremes. The discussion in this section reflects the fact that most detection and attribution research on long-term changes in the probability and frequency of extremes thus far has focused on short duration events that can be monitored using long records of local daily temperature and precipitation observations. These changes are generally captured as indices that document the frequency or intensity of extremes in the observed record rather than focusing on individual rare events. In contrast, many of the events considered in later sections of this report are individual events, often of longer duration than the extremes considered here, and are also usually events with longer return periods. Nevertheless, the finding that human influence is detectable in some types of short duration events that can be conveniently monitored from meteorological observations provides important context for the interpretation of other types of events. For example, feedbacks and physical processes that influence individual large events (Fischer et al. 2007; Seneviratne et al. 2010) will often also be at play in events that are reflected in indices. Thus, index-based studies are helpful for providing context for the attribution of individual events, and evaluate the ability of models to realistically simulate events that are affected by different feedbacks from those affecting mean climate.

While not discussed in this section, the detection and attribution of changes in the mean state of the climate system often also provides important context for the understanding of individual extreme events. An example is the European 2003 heat wave, which can be characterized both by very extreme warm daily maximum and minimum temperatures, and by an extremely warm summer season. The demonstration that human factors had influenced the climate of southern Europe in a quantifiable way over the latter part of the twentieth century was an important element in establishing that human influence had probably substantially increased the likelihood of an extreme warm summer like that experienced in the region in 2003 (Stott et al. 2004).

The frequency and intensity of extremes can be affected by both the internal variability of the climate system and external forcing, and the mechanisms involved can be both direct (e.g., via a change in the local energy balance) and indirect (e.g., via circulation changes). This makes the attribution of events to causes very challenging, since extreme events in any location are rare by definition. However, global-scale data make it possible to determine whether broadly observed changes in the frequency and intensity of extremes are consistent with changes expected from human influences, and inconsistent with other possibilities such as climate variability. Results from such detection and attribution studies provide the scientific underpinning of work determining changes in the likelihood of individual events.

Observed changes in extremes. We briefly consider historical changes in frequency and intensity of daily temperature and precipitation extremes. There is a sizable literature on such events, in part because reliable long-term monitoring data are gathered operationally by meteorological services in many countries. Many other areas remain understudied, such as whether there have been changes in the complex combinations of factors that trigger impacts in humans and ecosystems (e.g., Hegerl et al. 2011), or areas that are subject to greater observational and/or process knowledge uncertainty, such as the monitoring and understanding of changes in tropical cyclone frequency and intensity (e.g., Knutson et al. 2010; Seneviratne et al. 2012).

Changes in extreme temperature and the intensification of extreme precipitation events are expected consequences of a warming climate. A warmer climate would be expected to have more intense warm temperature extremes, including longer and more intense heat waves and more frequent record-breaking high temperatures than expected without warming. It would also be expected to show less intense cold temperature extremes and fewer record-breaking low temperatures than expected before. Both of these expected changes in the occurrence of record-breaking temperatures have indeed been observed (e.g., Alexander et al. 2006; Meehl et al. 2009). Further, a warmer atmosphere can, and does, contain more water vapor, as has been observed and attributed to human influence (Santer et al. 2007; Willett et al. 2007; Arndt et al. 2010). This implies that more moisture is available to form precipitation in extreme events and to provide additional energy to further intensify such events. About two-thirds of locations globally with long, climate-quality instrumental records [e.g., as compiled in the Hadley Centre Global Climate Extremes dataset (HadEX); Alexander et al. 2006] show intensification of extremes in the far tails of

the precipitation distribution during the latter half of the twentieth century (Min et al. 2011).

Detection and attribution of changes in intensity and frequency of extremes. A number of studies (e.g., Christidis et al. 2005, 2010; Zwiers et al. 2011; Morak et al. 2011, 2012) have now used various types of detection and attribution methods to determine whether the changes in temperature extremes predicted by climate models in response to historical greenhouse gas increases and other forcings are detectable in observations. The accumulating body of evidence on the human contribution to changes in temperature extremes is robust, and leads to the assessment that "it is likely that anthropogenic influences have led to warming of extreme daily minimum and maximum temperatures on the global scale" (Seneviratne et al. 2012). Results tend to show that the climate models used in studies simulate somewhat more warming in daytime maximum temperature extremes than observed, while underestimating the observed warming in cold extremes in many locations on the globe. It remains to be determined if this model-data difference occurs consistently across all models, or whether it is specific to the small set of phase 3 of the Coupled Model Intercomparison Project (CMIP3) climate models used in the studies.

Heavy and extreme precipitation events have also received a considerable amount of study. Heavy precipitation has been found to contribute an increasing fraction of total precipitation over many of the regions for which good instrumental records are available (Groisman et al. 2005; Alexander et al. 2006; Karl and Knight 1998; Kunkel et al. 2007; Peterson et al. 2008; Gleason et al. 2008), indicating an intensification of precipitation extremes. Direct examination of precipitation extremes, such as the largest annual 1-day accumulation, or the largest annual 5-day accumulation, also shows that extreme precipitation has been intensifying over large parts of the global landmass for which suitable records are available (Alexander et al. 2006; Min et al. 2011; Figs. 1 and 2), with an increase in the likelihood of a typical 2-yr event of about 7% over the 49-yr period from 1951 to 1999 (Min et al. 2011). It should be noted, however, that the spatial extent of regions for which long records of daily and pentadal precipitation accumulations are available is still severely limited (e.g., Alexander et al. 2006; see also Fig. 1), and that spatial patterns of change are still noisy.

The intensification of extreme precipitation is an expected consequence of human influence on the climate system (e.g., Allen and Ingram 2002; Trenberth et al. 2003) and is simulated by models over the latter half of the twentieth century in response to anthropogenic forcing, albeit with weaker amplitude than observed, which is at least partly due to differences in the spatial scales resolved by climate models and station-based local records (Chen and Knutson 2008). Nevertheless, Min et al. (2011) recently showed, using an ensemble of models and an index of extreme precipitation that is more comparable between models and data than records of intensity of events, that the observed large-scale increase in heavy precipitation cannot be explained by natural internal climate variability, and that human influence on climate provides a more plausible explanation. The body of research available on precipitation extremes is in an earlier stage of development than for temperature extremes, and thus Seneviratne et al. (2012) did not give a quantified likelihood assessment concerning precipitation extremes, but rather stated that "there is medium confidence[2] that anthropogenic influences

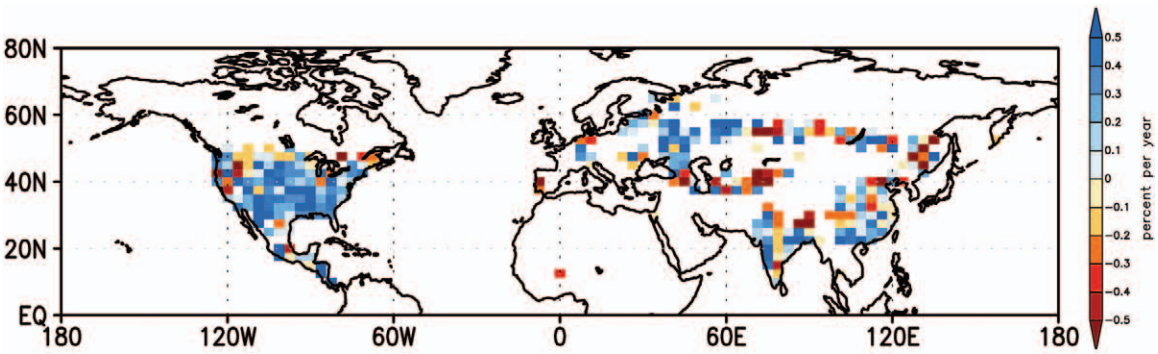

Fig. 1. Geographical distribution of trends of probability-based indices (PI) of extreme precipitation during 1951–99 for 1-day precipitation accumulations. Annual extremes of 1-day accumulations were fitted to the Generalized Extreme Value distribution, which was then inverted to map the extremes onto a 0%–100% probability scale. Blue colors indicate intensification of extreme precipitation, which is observed at about two-thirds of locations. From Min et al. (2011).

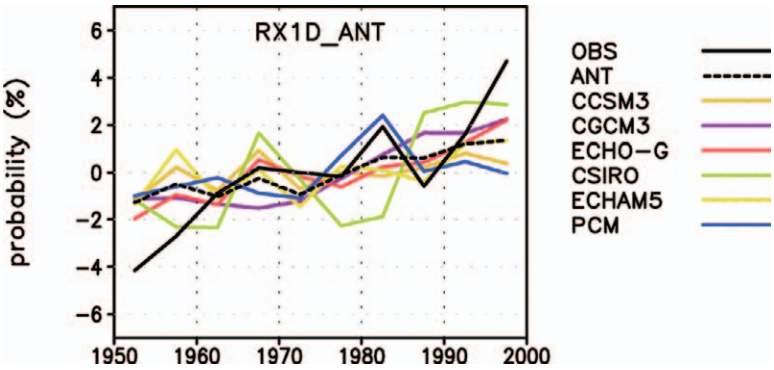

Fig. 2. Time series of five-year mean area-averaged PI (as defined in Fig. 1) anomalies (%) for 1-day annual extreme precipitation anomalies over Northern Hemisphere land during 1951–99. Black solid line represents observations and the dashed line represents the multi-model mean for the models indicated in the legend. Model simulations were run with anthropogenic forcings. Colored lines indicate results for individual model averages [see Supplementary Table 1 of Min et al. (2011) for the list of climate model simulations and Supplementary Fig. 2 of Min et al. (2011) for time series of individual simulations]. Each time series is represented as anomalies with respect to its 1951–99 mean.

have contributed to intensification of extreme precipitation on the global scale."

Few detection and attribution studies that include observations of temperature or precipitation extremes in the first decade of the twenty-first century have yet been performed (exceptions include Morak, et al. (2011, 2012, manuscript submitted to *J. Climate*), who detect anthropogenic influence in the frequency of occurrence of temperature extremes in data that extend to 2005]. However, studies of changes in extremes that include more recent observations show that ongoing changes in temperature extremes are regionally consistent with those observed in the latter half of the twentieth century. Examples include studies of the frequencies of warm and cold days and nights in North America (Peterson et al. 2008); the frequency of record breaking temperatures in the United States (Meehl et al. 2009); and the frequency of temperature extremes in multiple regions globally (Morak et al. 2011, 2012, manuscript submitted to *J. Climate*). Results from recent studies of precipitation extremes are more mixed. Some studies do show changes consistent

[2] See Mastrandrea et al. (2010) for a description of IPCC confidence language used in the IPCC Fifth Assessment, including the Special Report on Extremes (Field et al. 2012).

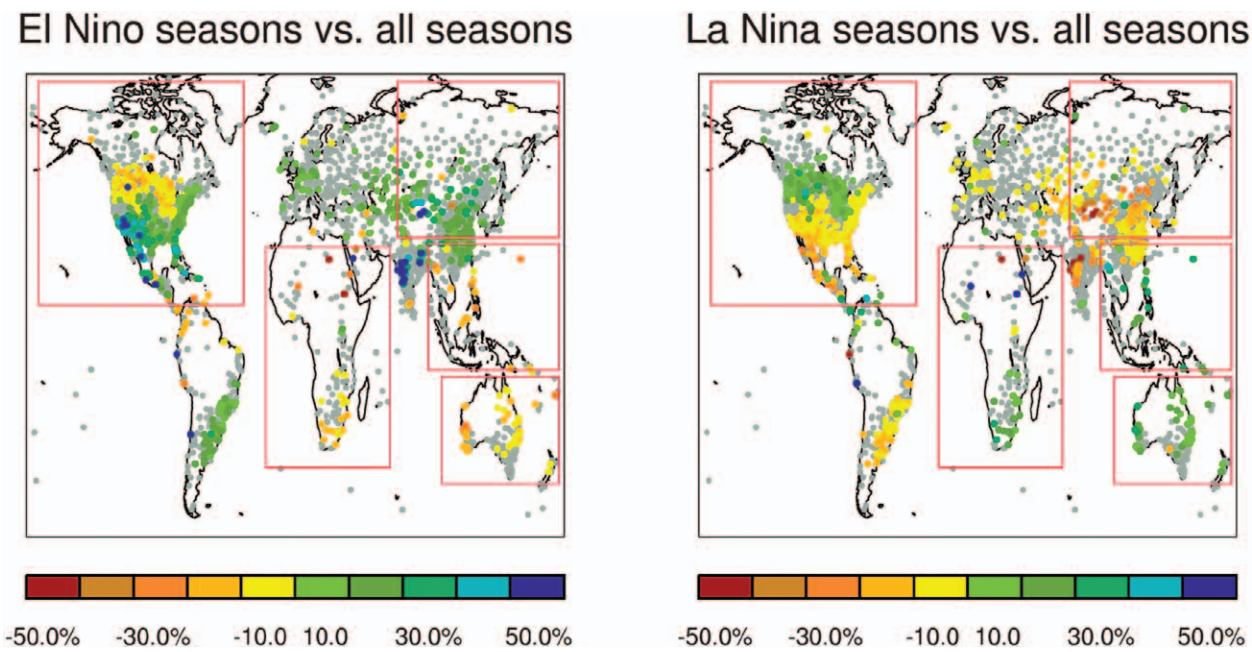

Fig. 3. Impact of (left) El Niño and (right) La Niña on the intensity of the largest 1-day precipitation event monthly in the November–April half of the year. Based on station data from the Global Historical Climatology Network-Daily (GHCN-D) for 1949–2003. From Kenyon and Hegerl (2010).

with those observed in the latter part of the twentieth century [e.g., the fraction of U.S. land area affected by extreme precipitation (Gleason et al. 2008), change in various extreme precipitation indicators in North America (Peterson et al. 2008), and heavy precipitation in Europe (Zolina et al. 2010)], while others do not demonstrate evidence of statistically significant trends [e.g., Choi et al. (2009) for the Asia-Pacific region and Aguilar et al. (2009) for central Africa; see also the assessment of Seneviratne et al. (2012)]. Overall, changes in precipitation remain regionally mixed, testifying to the high spatial variability of precipitation.

Natural low frequency internal variability of the climate system also affects the intensity and frequency of temperature and precipitation extremes, generally with a mixed pattern of increasing and decreasing responses depending on regions and seasons. For example, El Niño strongly influences both temperature and precipitation extremes globally (Kenyon and Hegerl 2008, 2010; see Fig. 3) and can alter the likelihood of rare damaging wintertime precipitation events by more than a factor of 4 in some parts of the United States, particularly in the southwest (Zhang et al. 2010). Any human influence on extreme weather risk combines with these episodic variations and the chance fluctuations that are inevitable when dealing with rare events; hence we should not assume that, if human influence is making a particular type of event more likely over time, it will necessarily occur with greater than average likelihood every year.

THE ABSENCE OF A ROLE OF CLIMATE CHANGE IN THE 2011 THAILAND FLOODS

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Thailand experienced severe flooding in 2011. During and after an unusually wet monsoon (July–September) in northern Thailand, rivers on the flood plains in the center and the south flooded their banks and inundated large parts of the country, including the former capital Ayuttha and neighborhoods of the present capital Bangkok. Large-scale industrial estates were submerged by 2.5 m of water for nearly 2 months and the economic damage was considerable. The reinsurer SwissRe estimated an insured damage between 8 and 11 billion U.S. dollars (USD) (SwissRe 2011). The total damage is much more uncertain, the World Bank estimates a value of 45 billion USD (World Bank 2011).

Flooding events are not uncommon in Thailand. However, the scale of the 2011 event was unprecedented. In this article we perform a first analysis of the meteorological component of the flood: how unusual was the rainfall in the catchment of the Chao Phraya river in northwestern Thailand, and are future monsoon rainfall trends expected due to climate change? It should be emphasized, however, that nonmeteorological factors were much more important in setting the scale of the disaster. Examples are the changing hydrography of the river (the levels of the Chao Phraya were in some places more than 0.5 m higher than in 1995 for even a slightly lower discharge), conversion of agricultural land to much more vulnerable industrial usage, and reservoir operation policies.

Observed rainfall anomaly and return time. We use the Global Precipitation Climatology Centre (GPCC) V5 1° rainfall analyzes (Schneider et al. 2011) to estimate historical rainfall over Thailand. This dataset nominally starts in 1901, but up to 1915 there are very few reporting stations in Thailand. The number of stations included rises from 35 in 1915 to 80 in recent years (A. Becker 2011, personal communication). We therefore start our analysis in 1915. For 2010 and 2011 the dataset was extended using the GPCC monitoring product. On the overlap period 1986–2010 the correlation is 0.99 but the monitoring dataset has a slightly lower mean and variability. A linear correction for the mismatch leads to a 2.7% increase in the values for 2010 and 2011.

Figure 4a shows the time series of rainfall in the middle and upper Chao Phraya basin, approximated by the region 15°–20°N, 99°–101°E, which is shown by the box in Fig 5. In this estimate the monsoon season 2011 is the wettest in the record, but comparable to 1995. To estimate the return time we fitted a

generalized Pareto distribution (GPD; Coles 2001) to the highest 80% of the distribution before 2011. This gives a central estimate of a return value of 140 years although the 95% confidence interval encompasses a range from 50 to several thousand years. In terms of large-scale meteorology, the 2011 monsoon was not very different from previously observed seasons.

La Niña has a statistically significant but small effect of rainfall in the area: the linear correlation coefficient with the Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST1) Niño-3.4 index is about −0.25 (between −0.07 and −0.39 with 95% confidence), slightly weaker than the spring teleconnection to the Netherlands (van Oldenborgh et al. 2000). Under the assumption that the empirical distribution shifts linearly with the Niño-3.4 index, the observed weak La Niña (Niño-3.4 = −0.5) implies an increase of the probability of "above-normal" precipitation from 33% to 45% in July–September 2011. From the scatterplot Fig. 4b one can see that all extreme rainfall events in the past occurred at neutral or La Niña conditions. However, the return time of the 2011 event was not lower relative to the regression line than the 140 years quoted above. The extra 17 ± 13 mm (2σ error) explained by the weak La Niña is counteracted by other changes in the tail within the large uncertainties of the empirical distribution function.

Have Thailand rainfall extremes become more likely due to climate change? One method to answer this question is to analyze the observations only. Given the intrinsic rarity of extreme events, this implies that one has to make statistical assumptions on the distribution of the data. One possibility is the assumption that the probability distribution function of monsoon rainfall does not change shape but is shifted to higher or lower values by the changing climate (van Oldenborgh 2007). The trend of the time series in Fig. 4 is not significantly different from zero: the mean precipitation has not changed beyond the natural variability. The 20-yr running mean and standard deviation also do not show significant variations.

The second method is to use climate models rather than statistical models, which in principle can give a physics-based estimate of the change in PDF. A full analysis would have to involve a validation of the representation of the Southeast Asian monsoon in these models. Here we simply note that the 17 climate models available in the CMIP5 archive (Taylor et al. 2012) at the time of writing

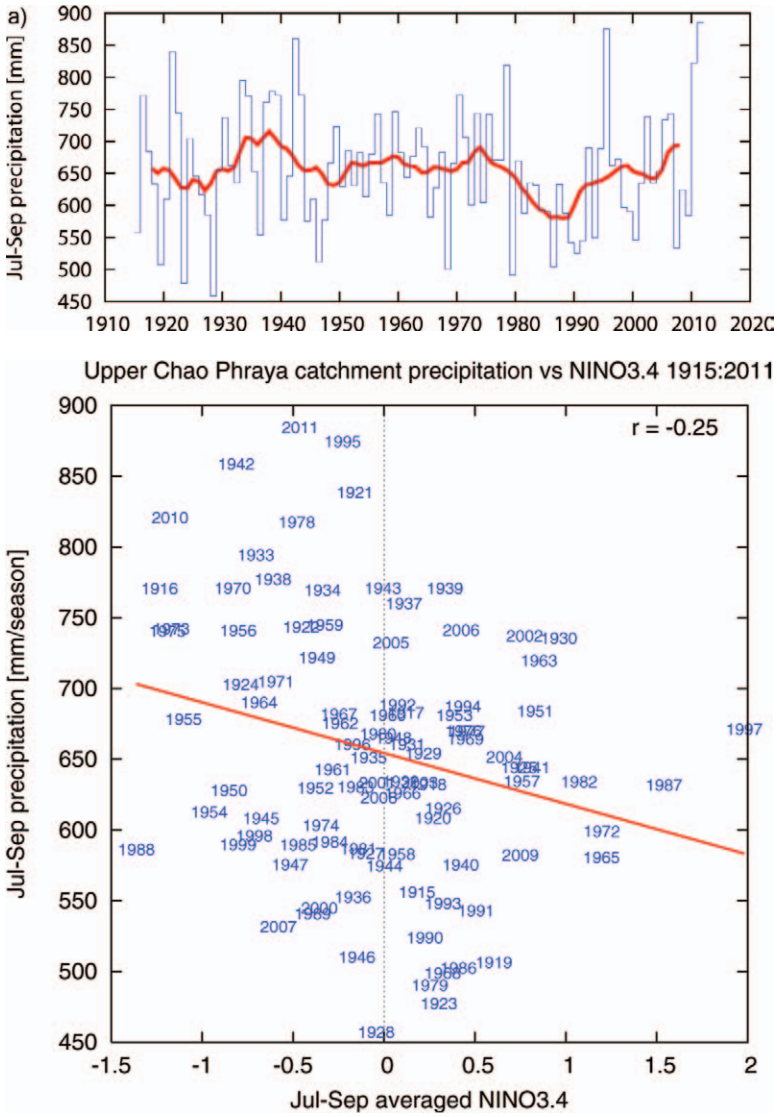

Fig. 4. (a) July–September precipitation (mm) in the upper catchment of the Chao Phraya river that flooded in 2011. The rainfall has been approximated by the 10 grid boxes in 15°–20°N, 99°–101°E in the GPCC V5 1° analysis 1915–2009, extended with the GPCC monitoring analysis linearly adjusted to agree on the overlap period. The red line denotes a 10-yr running mean. (b) Scatterplot of this precipitation against the HadISST1 Niño-3.4 index. The least squares regression line has been drawn red.

show no trend in the region of the catchment of the Chao Phraya up to 2011 in either mean or variability. They do show an increase of 10%–20% in both mean and standard deviation by 2100, indicating that the frequency of very active monsoons is projected to increase in the future by these models. We again stress that the credibility of any projected change depends on the simulation of climatology of the Asian monsoon, which is as yet untested in this ensemble and has been shown to be highly variable across models (Kim et al. 2008).

Conclusions. Although the damage caused by the 2011 floods on the Chao Phraya river in Thailand was unprecedented, the available data show that the amount of rain that fell in the catchment area was not very unusual. Other factors such as changes in the hydrography and increased vulnerability were therefore more important in setting the scale of the disaster. Neither in the precipitation observations nor in climate models is there a trend in mean or variability up to now, so climate change cannot be shown to have played any role in this event. Current models do project increases in both mean and variability in the future that would increase the probability of extremes. It may be advisable to take this into account when addressing current vulnerabilities.

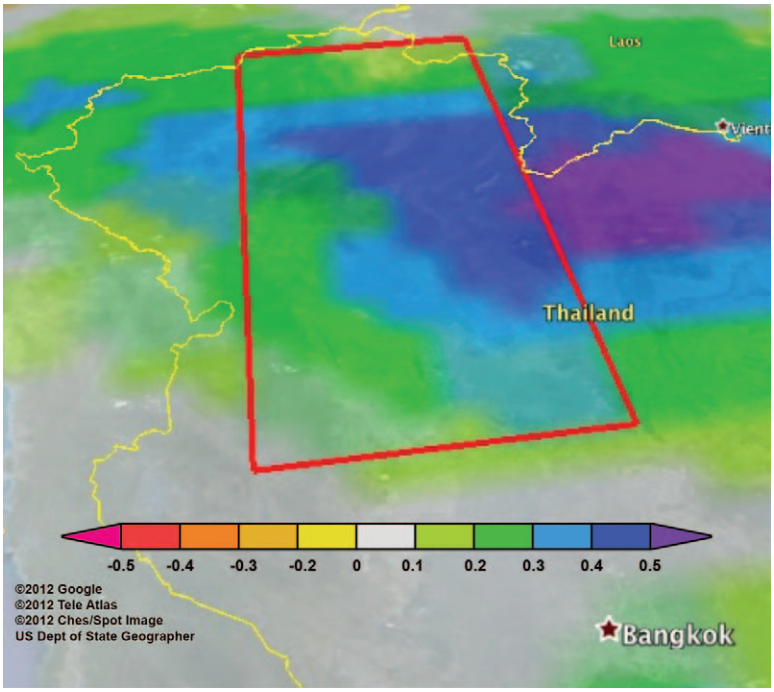

Fig. 5. Relative precipitation anomalies in Southeast Asia during July–September 2011. The value 0.5 means 50% more precipitation than normal in this season. The red box denotes our approximation of the middle and upper catchment basin of the Chao Phraya River, which runs south through Bangkok to the Gulf of Thailand. Data: GPCC V5 plus monitoring datasets at 1° resolution.

EXCEPTIONAL WARMING IN THE WESTERN PACIFIC–INDIAN OCEAN WARM POOL HAS CONTRIBUTED TO MORE FREQUENT DROUGHTS IN EASTERN AFRICA

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In 2011, East Africa faced a tragic food crisis that led to famine conditions in parts of Somalia and severe food shortages in parts of Ethiopia and Somalia. While many nonclimatic factors contributed to this crisis (high global food prices, political instability, and chronic poverty, among others) failed rains in both the boreal winter of 2010/11 and the boreal spring of 2011 played a critical role. The back-to-back failures of these rains, which were linked to the dominant La Niña climate and warm SSTs in the central and southeastern Indian Ocean, were particularly problematic since they followed poor rainfall during the spring and summer of 2008 and 2009. In fact, in parts of East Africa, in recent years, there has been a substantial increase in the number of below-normal rainy seasons, which may

be related to the warming of the western Pacific and Indian Oceans (for more details, see Funk et al. 2008; Williams and Funk 2011; Williams et al. 2011; Lyon and DeWitt 2012). The basic argument of this work is that recent warming in the Indian–Pacific warm pool (IPWP) enhances the export of geopotential height energy from the warm pool, which tends to produce subsidence across eastern Africa and reduce onshore moisture transports. The general pattern of this disruption has been supported by canonical correlation analyzes and numerical experiments with the Community Atmosphere Model (Funk et al. 2008), diagnostic evaluations of reanalysis data (Williams and Funk 2011; Williams et al. 2011), and SST-driven experiments with ECHAM4.5, ECHAM5, and the Community Climate Model version 3 (CCM3.6) (Lyon and DeWitt 2012).

An increased frequency of East African droughts. Here we present 1979–2010 GPCP data (Adler et al. 2003), augmented by 2011 estimates based on the Climate Prediction Center's RFE2 (Xie and Arkin 1997) dataset (the RFE2 data were regressed against the GPCP data and used to fill in 2011, which is not included in the current GPCP archive).

Dry areas, based in the 1999–2011 anomalies, were identified for the March–June and June–September seasons. These regions are shown with brown (March–June) and blue (June–September) polygons in Fig. 6a. The background shading in Fig. 6a shows 2005 Gridded Population of the World population densities. The region impacted is one of the most densely populated areas of Africa. The population density and population for the March–June region shown in Fig. 6a are 44 people km^{-2} and 28.5 million people. The population density and population of the June–September dry region is 49 people km^{-2} and 30.5 million people. These regions also have large chronically undernourished and food-insecure populations. As Fig. 6b shows, these highly vulnerable regions have experienced a large number of below-normal rainfall seasons, especially since 1999.

Has ocean warming led to decreased East African rainfall during La Niña episodes? While the La Niña event of 2010/11 played a central role in triggering the 2010/11 food crisis, it is impossible to unambiguously attribute a single event to anthropogenic climate change. There has been recent research, however, that has emphasized that the long-term trend in IPWP SSTs (Williams and Funk 2011), rainfall, and winds could interact dangerously with interannual La Niña climate events. The latter observation helped trigger effective early warning of the 2011 East African food crisis (Ververs 2012; Funk 2011). More recent SST-driven climate simulations have emphasized the important role of post-1999 warming in the Pacific in driving the 2011 drought (Lyon and DeWitt 2012).

How much has the IPWP been warming? Figure 7 shows the recent IPWP warming, as measured by SSTs and an air temperature index. Also shown is a new CMIP5 multimodel ensemble IPWP SST average, based on 55 simulations from five models running the historical climate experiment (Taylor et al. 2011). In the historical experiment models are initialized in

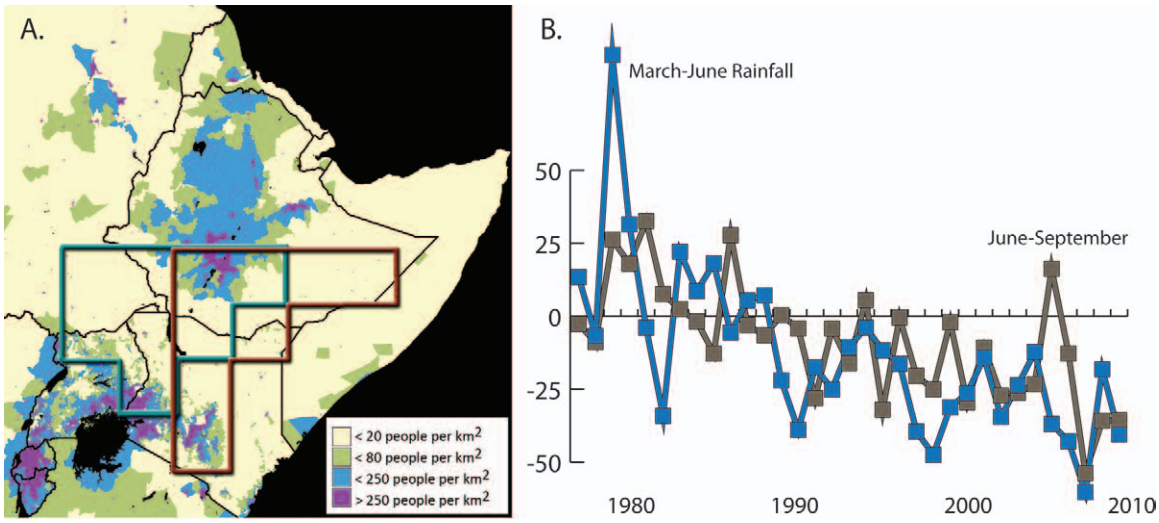

Fig. 6. (a) 2005 gridded population of the world overlain with polygons showing locations where recent GPCP rainfall values have declined substantially. (b) Time series of GPCP March–June and June–September rainfall anomalies (%) for these locations.

1850, and the coupled ocean–atmosphere models run through 2005, with the primary forcing being changes in greenhouse gases and aerosols. Annual 2001–11 IPWP SSTs have been very warm (Fig. 7), 28.4°C, which is 0.7°C greater than their 1900–50 mean. The interannual variability in the IPWP SST time series is very low (0.25°C). A 0.7°C increase represents a large change, vis-à-vis the IPWPs historic variability, as measured by the 1890–1970 standard deviation of decadal SSTs (0.10°C).

We can confirm the exceptional warming in the IPWP with an independent index we computed by averaging selected long-running GHCN v3 (Lawrimore et al. 2011) air temperature stations.[3] The 2001–11 air temperature index recorded a 0.5°C increase since 1950, a large increase when compared with the 1890–1970 standard deviation of decadal averages of the air temperature index. Both SSTs and terrestrial station data converge on substantial warming.

Between 1864 and 2011, 10-yr running averages of the IPWP SSTs are highly correlated with global National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS) (Hansen et al. 2010) temperatures (r = 0.99; Fig. 7). Over the past 160 years, the simulated IPWP SSTs have also covaried strongly with the simulated global temperatures in the CMIP5 archive. While formal attribution studies have been made for the southern and northern Indian and Pacific Oceans (Barnett et al. 2005; Pierce et al. 2006), specific attribution of the IPWP has not been made. It is interesting, however, to note how closely the magnitude of warming in the 12-member CMIP5 ensemble matches the observations (Fig. 7).

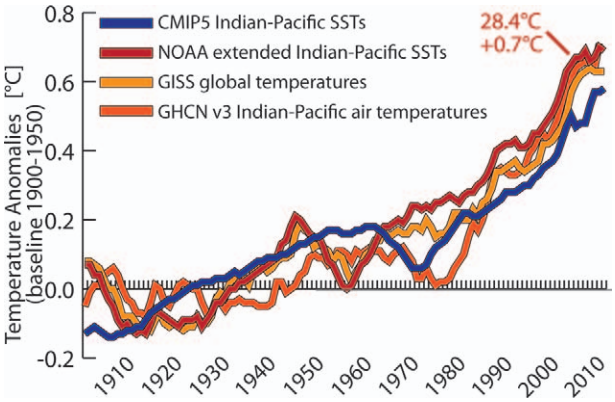

Fig. 7. Long time series of smoothed temperature indices for the IPWP CMIP5 SSTs, IPWP National Oceanic and Atmospheric Administration (NOAA) extended v3 SSTs, NASA GISS global air temperatures, Wilson tropical coral SST reconstruction, and a GHCN IPWP air temperature index.

Conclusions. The ~0.7°C IPWP warming, given the already warm state of the region, is likely to have had substantial dynamic impacts, as supported by recent modeling experiments (Lyon and DeWitt 2012). The relationship between rainfall and SSTs is nonlinear. Between 26° and 29°C average rainfall rates increase by a factor of 5, and observational studies based on GPCP data suggest that a change from mean SSTs of 27.7°–28.4°C might be associated with a change of rainfall rates from 3.4 to 5.5 mm day^{-1} (Folkins and Braun 2002); and this rate of change is similar to recent analyzes of GPCP data within the rising portion of the Pacific Walker circulation, which identified an increase of ~1 mm day^{-1} decade^{-1} (Zhou et al. 2011).

It is interesting to note that while SST-driven simulations of the 2011 March–May (MAM) season clearly show the important role played by the warm western Pacific (Lyon and DeWitt 2012), and while the new CMIP5 SSTs exhibit substantial warming during the 1990s and 2000s, these increasing SSTs do not appear to produce corresponding large changes in evaporation or rainfall over eastern Africa or the IPWP oceans. While Held and Soden (2006) suggested that the coupled models' weak hydrologic response to warming could help explain their predictions of a weakening of Walker circulation and more El Niño–like weather, recent observations indicate increases in evaporation and rainfall (Yu and Weller 2006; Zhou et al. 2011). An intensification of these hydrologic responses and the southeast trade winds across the Pacific, potentially associated with more La Niña-like climate, might help explain the differences between the observations and model projections. In any event, recent research has suggested that continued warming in the IPWP will likely contribute to more frequent East African droughts during the boreal spring and summer (Funk et al. 2008; Williams et al. 2011).

[3] Bombay/Mombassa, Madras, Port Blair, Mannar, Trincomalee, Puttalam, Colombo, Nuwara Eliya, and Sandaka.

DID HUMAN INFLUENCE ON CLIMATE MAKE THE 2011 TEXAS DROUGHT MORE PROBABLE?

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In 2011, the state of Texas experienced an extraordinary heat wave and drought. The 6-month growing season of March–August (MAMJJA) and the three summer months of June–August (JJA) were both, by wide margins, the hottest and driest in the record that dates back to 1895 (Fig. 8). (See also Nielsen–Gammon, Office of the State Climatologist Report: The 2011 Texas drought, a briefing packet for the Texas Legislature, Oct. 21, 2011).

As with other extreme events discussed in this volume, we pose this question: Was the likelihood of either the heat wave or the drought altered by human influence on global climate? This question is portentous because an affirmative answer implies that such events, with their severe impacts on ecosystems and economics, may become more frequent. Here we endeavor to quantify the change in the likelihood of the heat wave and drought since the 1960s to the present, a period during which there has been a significant anthropogenic influence on climate. We analyze a very large ensemble of simulations from a global climate model (GCM), with greenhouse gas concentrations and other climate forcings representative of the 1960s and present day (Pall et al. 2011; Otto et al. 2012). Through the use of public volunteered distributed computing (Allen 1999; Massey et al. 2006), we obtain an ensemble size that is large enough to examine the tails of the distribution of climate variables (see the later section on the changing odds of warm Novembers and cold Decembers in England for more details).

Along with anthropogenic greenhouse gases and other climate forcings, natural sources of interannual variability will result in differences in probability distributions between years. The El Niño–Southern Oscillation (ENSO), for one, is considered to be a key driver of drought conditions in the central United States (Trenberth et al. 1988; Palmer and Brankovic 1989; Atlas et al. 1993; Hong and Kalnay 2000). Hence, to assess the role of multidecadal trends on the 2011 heat wave and drought, we compared years with similar La Niña conditions, separated by four decades, to evaluate how the probability of hot/dry conditions differed between them. The years were 1964, 1967, 1968, and 2008, with 2008 serving as a proxy for 2011 because simulations for 2011 were not available.

Data and methods. Values of observed monthly temperature and precipitation for the years 1895–2011 and spatially averaged over the state of Texas were obtained from the U.S. National Climatic Data Center (NCDC) Climate at a Glance dataset (www.ncdc.noaa.gov/oa/climate/research/cag3/cag3.html).

The atmospheric and land surface climate of the decades 1960–70 and 2000–10 were simulated with the UK Meteorological Office's Hadley Center Atmospheric General Circulation Model 3P (HadAM3P) with SST and sea–ice fraction taken from the HadISST observational dataset (Rayner et al. 2003) and using observed greenhouse gas concentrations. A large ensemble of runs with varying initial conditions was completed, resulting in many plausible realizations of the climate of these decades. See the later section on the changing odds of warm Novembers and cold Decembers in England for more information on the modeling and the climate forcings used.

Because simulations under 2011 forcing conditions were not available, we chose 2008 as a proxy for 2011, and compared it to the years 1964, 1967, and 1968. The years 1964 and 2008 were similar with respect to sea surface temperature patterns in the tropical and northern Pacific, as given by the Niño-3.4 and Pacific decadal oscillation (PDO) indices, respectively. The years 1967 and 1968 were also La Niña years (though weaker than 1964) and had negative values of the PDO index. The inclusion of three La Niña years from the 1960s allows us to examine interannual variability not driven by ENSO alone. Moreover, any influence of the Mt. Agung volcanic eruption (Indonesia,

18 February 1963) on Texas climate would have been greatly reduced by 1967 (Robock 2000).

A spatial, weighted average was calculated from the 27 GCM grid boxes that fell within Texas, with weights proportional to the cosine of the latitude. Surface air temperature and cumulative precipitation were also averaged over MAMJJA and JJA and the return period for each value from each ensemble member was calculated. Totals of 171, 1464, 522, and 1087 ensemble members were analyzed for 1964, 1967, 1968, and 2008, respectively. We attempted no model bias correction because our objective was to examine changes in the entire modeled probability distribution between the 1960s and 2008, and not to estimate the actual return period of the 2011 heat wave in a nonstationary setting.

Results. The GCM captured the inverse correlation between temperature and precipitation that is evident in the observations (Fig. 8), though the model in general generated a climate that was too dry and too warm. Between 1964 and 2008, the simulated ensembles show shifts towards warmer and slightly drier conditions (Fig. 8). The relationship is similar between 1967–68 and 2008 (not shown).

The return period for a given low precipitation event was slightly longer for the years in the 1960s than for 2008 (Fig. 9, top; e.g., a simulated 100-yr return period MAMJJA precipitation under 1964 conditions has a 25-yr return period under 2008 conditions). This may indicate an increased contribution of precipitation deficit to drought conditions in 2008, but larger sample sizes and a more in depth analysis including looking at other years are required before firmer conclusions can be drawn.

For extreme heat events, the difference between the years in the 1960s and 2008 was much more pronounced, with the return period of a particular extreme heat event being more than an order of magnitude shorter for 2008 than for any of the 3 years from the 1960s (Fig. 9, lower panel). As an example, 100-yr return period MAMJJA and JJA heat events under 1964 conditions had only 5- and 6-yr return periods, respectively, under 2008 conditions.

Conclusions. We are assessing how the combined impact of changing atmospheric composition and surface temperatures have affected the risk of extreme hot and dry conditions in Texas: since most of the large-scale warming that has occurred over the past 50 years is thought to be attributable to the anthropogenic increase in greenhouse gas levels, this provides one component of a multistep attribution process (Hegerl et al. 2010) relating the 2011 event to human influence.

We found that extreme heat events were roughly 20 times more likely in 2008 than in other La Niña years in the 1960s and indications of an increase in frequency of low seasonal precipitation totals. With 2008 serving as our proxy for 2011, this suggests that conditions leading to droughts such as the one that

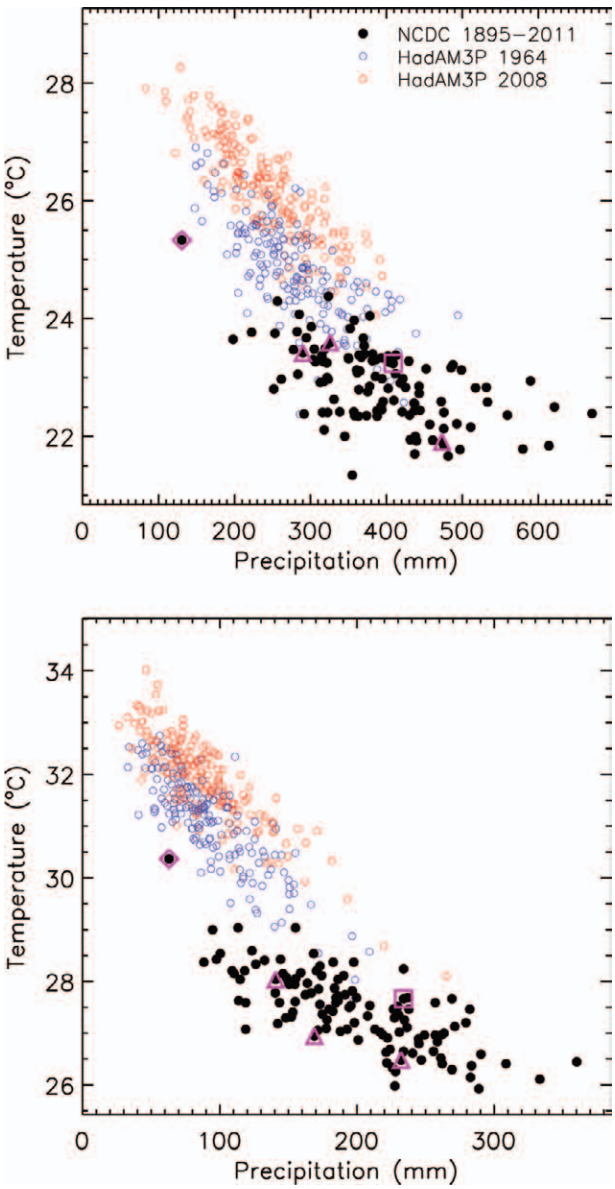

Fig. 8. Texas mean temperature against total precipitation for (top) MAMJJA and (bottom) JJA from NCDC and the HadAM3P ensembles. The observed years 1964, 1967, and 1968 are highlighted by the magenta triangles, and the observed years 2008 and 2011 are highlighted by the magenta square and diamond, respectively. To facilitate comparison between model years, only a random sample of the HadAM3P 2008 dataset, equal in size to the 1964 dataset, is shown.

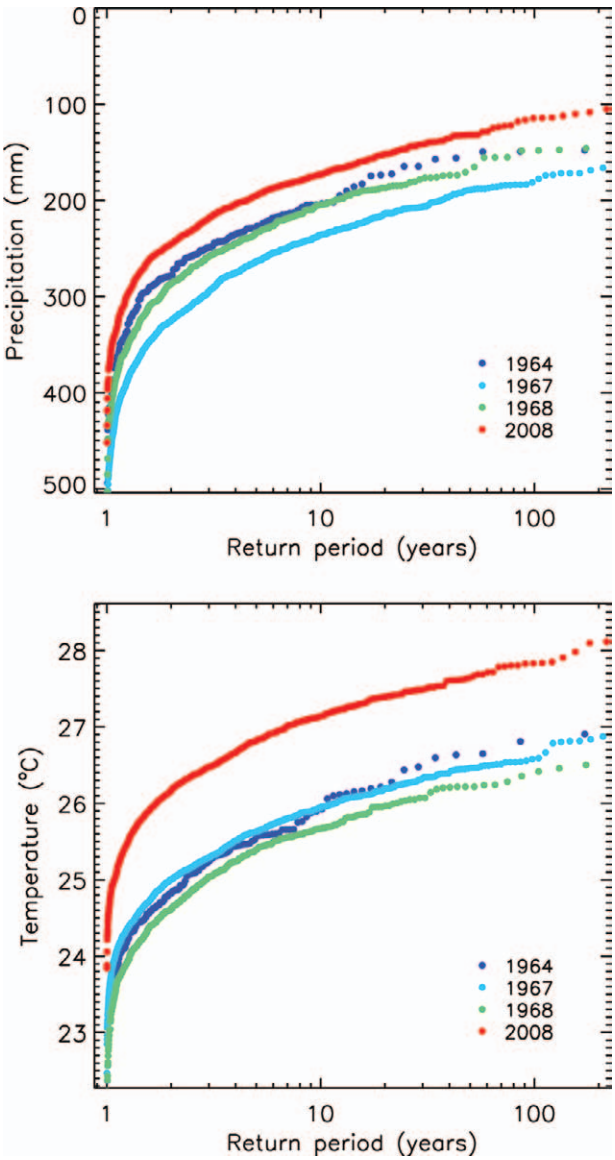

Fig. 9. Return periods of (top) total precipitation and (bottom) mean temperature, Texas, MAMJJA, 1964, 1967, 1968, and 2008, from HadAM3P ensembles.

occurred in Texas in 2011 are, at least in the case of temperature, distinctly more probable than they were 40–50 years ago.

However, there are two main factors in the model driving the differences in the 1960s and 2008 probability distributions of precipitation and temperature. One factor is the effects of external climate forcings, dominated by the increase in greenhouse gas concentrations due principally to anthropogenic emissions. The second factor is the difference in the SST/sea–ice-fraction fields between the years. However, the difference in SST/sea–ice-fraction fields itself has a contribution from increased anthropogenic greenhouse gases, and a second contribution that is due to natural variability. We chose to compare years with similar values of the Niño-3.4 and PDO in order to reduce the contribution due to natural variability; however, other SST patterns may have played significant roles (e.g. McCabe et al. 2004; Schubert et al. 2009).

Progress toward quantifying attribution will include analysis of more years to further evaluate the natural variability and test the robustness of the results presented here. Furthermore, we will explore uncertainty in atmospheric response using perturbed physics ensembles.

Modeling studies such as this allow us to quantify how much the probability of extreme hot and dry conditions in Texas has changed. Quantifying the absolute probability of such extreme conditions is much more difficult, since the models we use are subject to bias, particularly affecting tails of distributions, and data records are too short to quantify absolute probabilities empirically. Hence, while we can provide evidence that the risk of hot and dry conditions has increased, we cannot say that the 2011 Texas drought and heat wave was "extremely unlikely" (in any absolute sense) to have occurred before this recent warming.

CONTRIBUTION OF ATMOSPHERIC CIRCULATION TO REMARKABLE EUROPEAN TEMPERATURES OF 2011

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Western Europe witnessed remarkable temperature events during the year 2011. Hot and dry spring and autumn (the warmest and second warmest in France, respectively) have contrasted with an uneven summer and a cold and snowy winter 2010/11 (including cold records over the United Kingdom in December 2010). Our scientific challenge consists in putting such regional events into the context of climate change, either by evaluating anthropogenic fingerprints on each event [e.g. with calculations of fractions of attributable risk (Stott et al. 2004)] and/or by understanding how climate change affects physical processes at regional scales. The second approach is taken in this paper. In Europe,

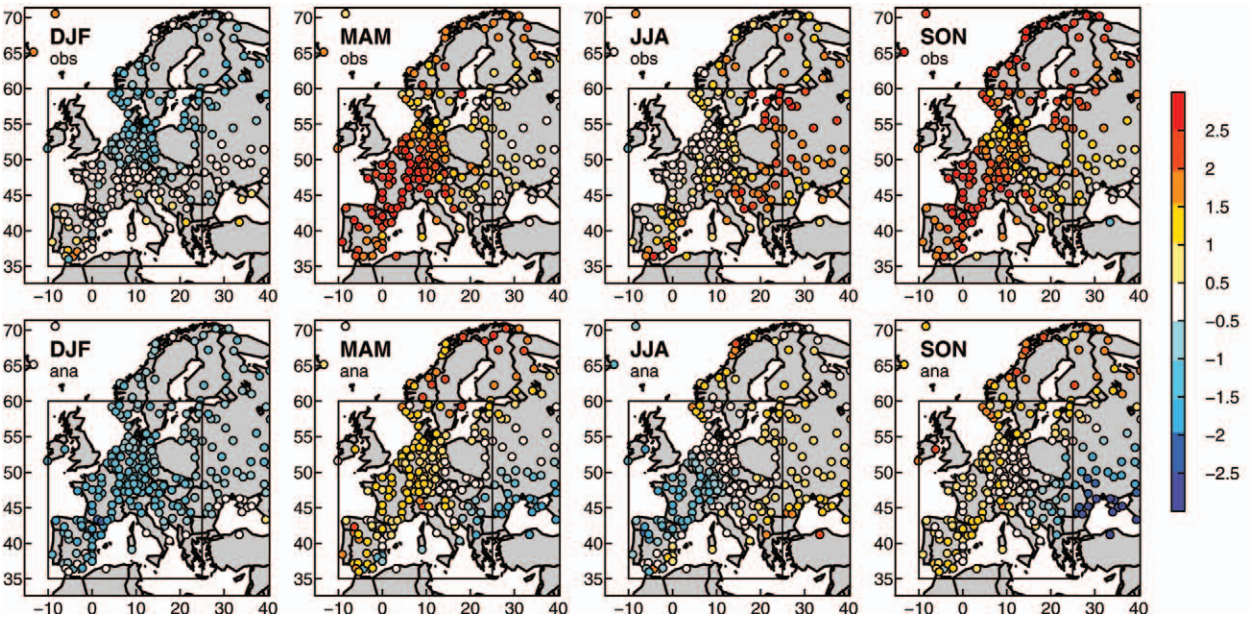

Fig. 10. (top) Observed temperatures of December–February (DJF), March–May (MAM), June–August (JJA), and September–November (SON) 2010/11, represented as normalized anomalies (σ levels) relative to 1971–2000 climatologies at each station. The box over western Europe encompasses the area retained for the regionally averaged statistics along the paper (171 stations over 306). (bottom) As at top, but for analog temperatures. Observed temperatures are quasi-systematically higher than analog ones, while spatial patterns are well correlated (Table 1).

studies have highlighted that recent temperatures have been systematically warmer than expected from the North Atlantic dynamics, which controls their intraseasonal to interannual variability (e.g., Cattiaux et al. 2010b; Vautard and Yiou 2009). Here we investigate the contribution of large-scale circulations to temperatures anomalies of 2011 using the same flow-analogue approach as in the analysis of winter 2009/10 by Cattiaux et al. (2010a, C10 hereafter).

Were 2011 temperatures anomalously warm compared to those expected from their flow analogues? We use in situ measurements provided by the European Climate Assessment dataset at more than 2500 stations over the period 1948–2011 (Klein-Tank et al. 2002). Similarly to C10, 306 stations are selected on the basis of (i) an altitude lower than 800 m, (ii) the availability of more than 90% of daily values between 1 January 1948 and 31 December 2011, and (iii) only one station per 0.5° × 0.5° latitude/longitude box for spatial homogeneity. We compute anomalies relative to 1971–2000 climatological standards [mean and standard deviation σ].

Winter 2010/11 was particularly cold in northern Europe, falling below −1σ at most of stations above 50°N (Fig. 10, top). Over western Europe (defined by the insert box in Fig. 10), it ranks as the nineteenth coldest winter of the whole period 1949–2011 (Table 1) and the fifth coldest of the last 25 years (after 1987, 1996, 2010, and 2006). It was followed by exceptionally warm anomalies from March to May 2011, especially over western Europe where seasonal temperatures locally exceeded 2.5σ, making 2011 the second hottest spring between 1948 and 2011 (after 2007). In this region, the temperature rise initiated in March climaxed during April, with respectively 25 of 30 and 14 of 30 days above 1 and 2σ (Fig. 11a). As shown in recent studies, dry soils in early summer are a necessary, but not sufficient, condition for the genesis of heat waves such as those experienced in 1976 and 2003 (e.g., Vautard et al. 2007).

In 2011, despite important deficits in soil moisture at the end of spring (comparable to those that preceded summer 2003 heat waves), summer temperatures turned out to be close to normal over most of western Europe. With a cool July and a warm spell at the end of August, it ranks as the fourteenth warmest summer of the period 1948–2011 but the third coolest since 2000 (after 2004 and 2005). The rest of the year was marked by anomalously mild temperatures over all of Europe, punctuated by a few moderate cold spells. Seasonal anomalies of autumn 2011 exceeded 2.5σ in most stations of western Europe, especially during September with respectively 17 of 30 and 9 of 30 days above 1 and 2σ, making 2011 the second warmest autumn of 1948–2011 (after 2006). Overall, the calendar year 2011 (January to December) is the

Table 1. Normalized anomalies of observed and analog temperatures averaged over western Europe (171 stations inside the box in Fig. 10), for DJF, MAM, JJA, and SON 2010/11 and the whole year 2011, with corresponding rankings in superscripts. Spatial (patterns in Fig. 10), intraseasonal (series in Fig. 11a), and interannual (series in Fig. 11b) correlations between observed and analog temperatures are all significant at 5%. Flow-analogues quality, as evaluated from mean correlations between observed and analog SLP.

	DJF	MAM	JJA	SON	Year (J–D)
Observed anomaly	-0.8^{45}	2.4^{2}	1.1^{14}	2.5^{2}	2.1^{1}
Analog anomaly	-1.3^{51}	0.9^{12}	-0.5^{36}	0.5^{15}	0.7^{10}
Spatial correlation	0.5	0.55	0.63	0.72	—
Intraseasonal correlation	0.59	0.57	0.44	0.24	0.55
Interannual correlation	0.85	0.70	0.60	0.58	0.75
Flow-analogues quality	0.72	0.68	0.63	0.67	0.68

warmest year over western Europe in our dataset (2.1σ, Fig. 11b). However, the hottest 12-month-long period remains July 2006–June 2007, which contains three seasonal warm records (autumn, winter, and spring) and an anomaly that reaches 3.8σ.

The contribution of the large-scale dynamics to temperature anomalies of 1948–2011 is estimated from the same flow-analogue approach as used in C10. For each day, we selected the 10 days with the most correlated atmospheric circulation among days of other years but within a moving window of 31 calendar days (for details, see Lorenz 1969; Yiou et al. 2007). The following results are insensitive to (i) the number of selected days (here 10) and (ii) the metrics used for assessing analogy (here Spearman's rank correlation). Further methodological details can be found in C10 and Vautard and Yiou (2009). Circulations are derived from sea level pressure (SLP) anomalies of National Centers for Environmental Prediction (NCEP)–National Center for Atmospheric Research (NCAR) reanalyzes (Kistler et al. 2001) and considered over the period 1948–2011 and the area (22.5°–70°N, 80°W–20°E). The quality of flow analogues for 2011 was checked by verifying that mean correlations between observed and analog SLP indicated in Table 1 were close to the 1948–2010 mean (not shown).

For all seasons of 2011, mean analog temperatures (i.e., averaged over the 10 analog days) were lower than observed ones at respectively 76%, 88%, 86%, and 89% of western Europe

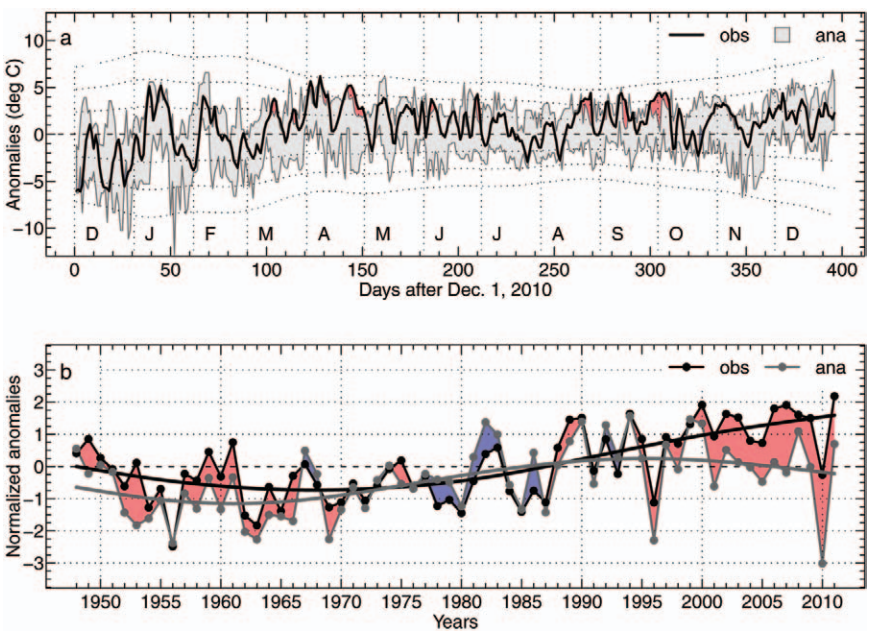

Fig. 11. (a) Daily anomalies (°C) of observed (black line) and analog (gray spread encompassing the 10 values) temperatures from December 2010 to December 2011. Dashed lines indicate climatological σ levels (higher variability in winter than in summer), and red (blue) indicates days with observed temperatures above (below) the 10 analog values. (b) Yearly observed (black) and analog (gray) temperatures averaged over western Europe, represented as normalized anomalies relative to the period 1971–2000. Smoothing by splines with 4 degrees of freedom is added, and red (blue) indicates years with observed temperatures above (below) analog ones. The recent tendency for observed temperatures to be warmer than analog temperatures is particularly prominent in both 2010 (cold record in analogues while close to normal in observations) and 2011 (warm record in observations while <1σ in analogues).

stations (Fig. 10, bottom, and Table 1). The persistence of a strong negative phase of the North Atlantic Oscillation in December 2010 could have made 2010/11 the thirteenth coldest winter since 1948 if large-scale dynamics was the sole driver of temperature variations. During this particular season the difference between observed and analog temperatures peaks over southwestern Europe, suggesting that local processes may have inhibited the maintenance of cold anomalies in this region. For all other seasons, spatial patterns of observed and analog anomalies are better correlated. In particular, large-scale circulations contributed to both exceptionally warm spring and autumn over western Europe, up to respectively ~40% and ~20% of observed anomalies. Summer dynamics were rather favorable to cold weather over France and Spain, thus preventing the development of a potential heat wave that dry conditions at the end of spring could have nurtured.

At the intraseasonal time scale, observed temperatures of 2011 were 29% of the time above the maximum of the 10 analog temperatures, and 77% above the median (Fig. 11a). This is significantly higher than the expected statistical values, respectively 1/11 = 9% (2.5–20%) and 1/2 = 50% (35%–65%) (brackets indicate 95% confidence intervals obtained from binomial quantiles assuming 40 independent days among the 396 of Fig. 11a). The heat waves of late April, late August, and late September were largely underestimated by the analogues, despite relatively high correlations between observed and analog SLP during these three periods (not shown). Overall, the analog temperature of year 2011 reaches 0.7σ, suggesting that large-scale circulations contributed to ~33% of the observed anomaly (Fig. 11b).

Conclusions. 2011 fits into the pattern of recent years where observed temperatures are distinctly warmer than analog temperatures. This is true for seasons with cold anomalies which are not as cold as expected from flow-analogues (e.g., winter 2009/10; see C10) and warm seasonal anomalies, that are hotter than the corresponding analog seasons (e.g., autumn–winter 2006/07; see Yiou et al. 2007). In addition, high interannual correlations between observed and analog temperatures confirm that the North Atlantic dynamics remains the main driver of European temperature variability, especially in wintertime.

HAVE THE ODDS OF WARM NOVEMBER TEMPERATURES AND OF COLD DECEMBER TEMPERATURES IN CENTRAL ENGLAND CHANGED?

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The Central England Temperature (CET) data set is the oldest continuously running temperature dataset in the world (Manley 1974) and records temperatures over a central area of England stretching between Lancashire, Bristol, and London. The decade of 2002–11 has been a particularly interesting one for CETs, with a number of warm autumns (2009, 2011), along with a number of cold winters (2009/10, 2010/11).

The emergent science of probabilistic event attribution is becoming an increasingly important method of evaluating the extent of how this human-influenced climate change is affecting localized weather events. Studies into the European heat wave of 2003 (Stott et al. 2004), the England and Wales floods of 2000 (Pall et al. 2011), and the Russian heat wave of 2010 (Dole et al. 2011; Rahmstorf and Coumou 2011; Otto et al. 2012) have sought to determine to what extent the risks of these events occurring have increased because of anthropogenic global warming.

We follow a similar methodology to Pall et al. (2011), which uses very large ensembles of global climate models (GCMs) to assess the change in risk of autumn flooding in the United Kingdom under two

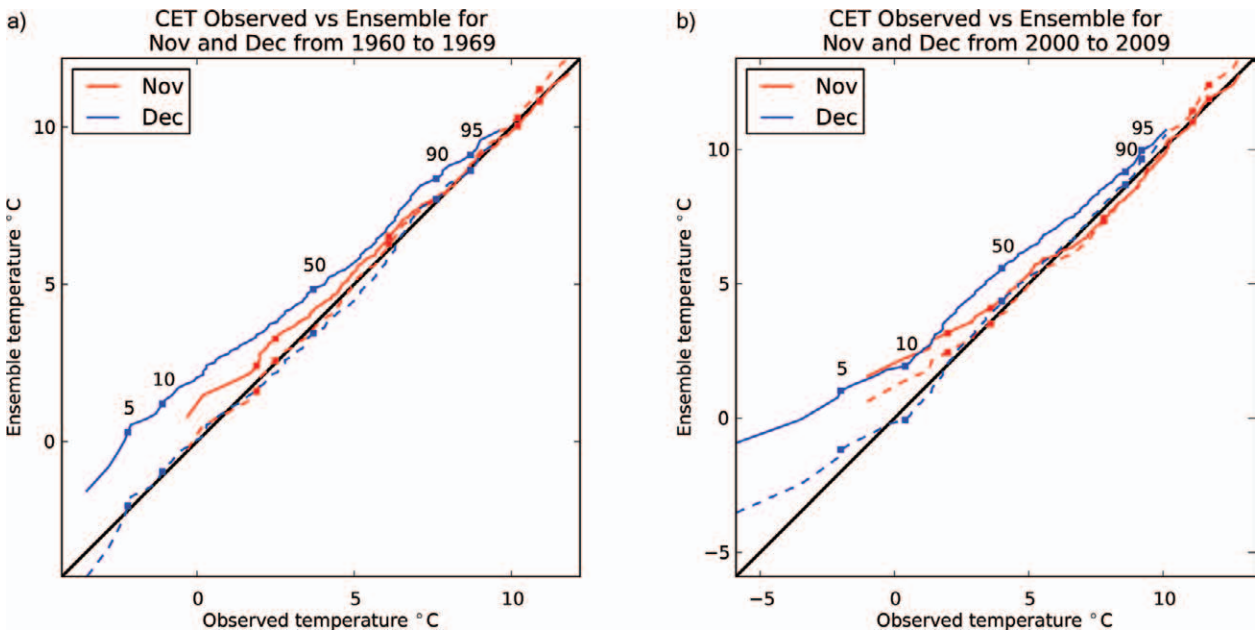

Fig. 12. (a) Quantile-quantile plot for November and December of the 1960–1969 decade. Uncorrected ensemble data are shown with a solid line, whereas the same ensemble data corrected for bias in the mean and standard deviation are shown with a dashed line. The squares denote the 5th, 10th, 50th, 90th, and 95th percentiles. (b) As in (a), but for the 2000–2009 decade.

different climate scenarios: observed autumn 2000 and a natural-only forcing autumn 2000. However, our two climate scenarios are based both on observations, one scenario for the 1960s decade and one for the 2000s. The method of Pall et al. (2011) decouples the anthropogenic signal from the natural variability by ensuring that the natural variability is the same in both scenarios. Although our method does not permit decoupling, using decadal long scenarios reduces some of the effects of natural variability and allows both scenarios to be validated against observed data. We have also expanded the method to use a regional climate model (RCM) embedded within a GCM. The increased resolution of the RCM results in a more realistic simulation of localized weather events, including cold and warm temperatures (Jones et al. 2004).

In this section we use large ensembles of the two climate scenarios to evaluate whether the frequency of warm Novembers and cold Decembers occurring has altered between the 1960s and 2000s, this being the period during which there has been a significant anthropogenic influence on climate.

Method. Weatherathome is a volunteer-distributed computing project that uses idle computing time from a network of "citizen scientists" home computers to run an RCM embedded within a GCM. The models used are HadAM3P, an atmosphere only, medium-resolution (1.875° × 1.25°, 19 levels, 15-min time step) GCM and HadRM3P, a high-resolution (0.44° × 0.44°, 19 levels, 5-min time step) RCM. Both models have been developed by the UK Met Office and are based upon the atmospheric component of HadCM3 (Pope et al. 2000; Gordon et al. 2000) with some improvements to the sulfur cycle and cloud parameterizations (Jones et al. 2004). The coupling between the models is performed every 6 h when the lateral boundary conditions of the RCM are relaxed to the GCM across four perimeter grid boxes (Jones et al. 2004)

Each volunteer's computer runs both models for a model year at a time, with initial conditions being provided by model runs previously completed by other volunteers. In this way, very large ensembles of RCMs can be computed, on the order of thousands, which in turn allows greater confidence when examining the tails of the distribution of climate variables.

The results examine the changing frequency of warm Novembers and cold Decembers since the 1960s. Two periods are analyzed, the 2000s and the 1960s which both use sea surface temperatures (SST) and sea ice fractions (SIF) from the HadISST observational dataset (Rayner et al. 2003). Atmospheric gas concentrations, including CO_2, N_2O, CH_4, O_3, and the halocarbons, are taken from observations and Special Report on Emissions Scenarios (SRES) scenario A1B (Nakicenovic and Swart 2000). Natural

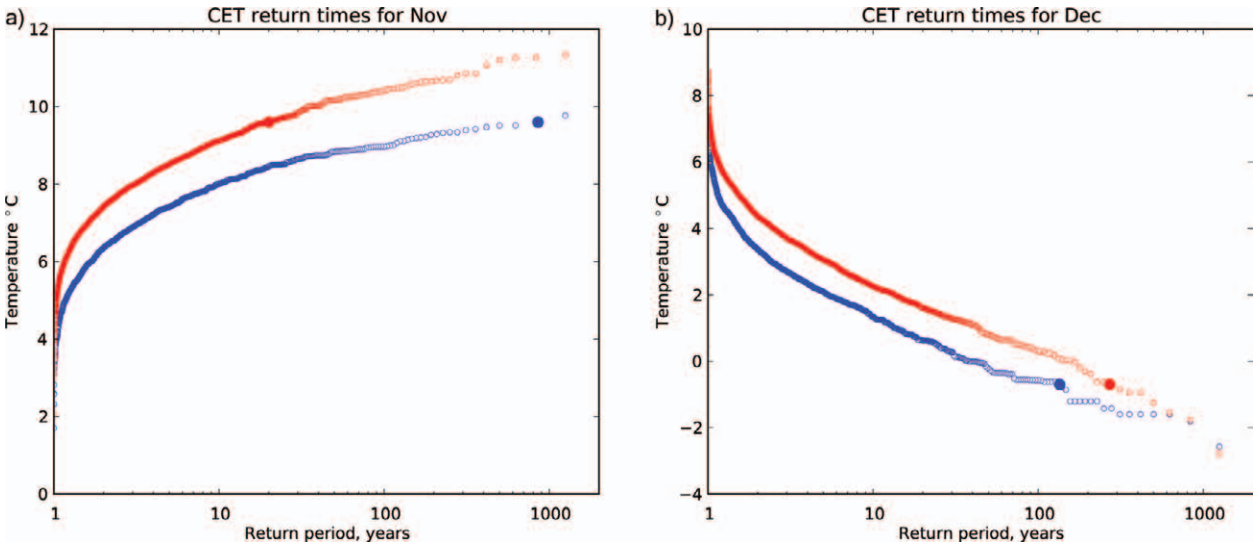

Fig. 13. (a) Return times of temperatures for November in the 1960–1969 decade (blue curve) and the 2000–2009 decade (red curve). The observed value for the warm November 2011 of 9.6°C is shown on both curves as a solid, larger circle, with a return period in 1960–1969 of 1250 years and in 2000–2009 of 20 years. (b) Return times of temperatures for December in the 1960–1969 decade (blue curve) and the 2000–2009 decade (red curve). The observed value for the cold December 2010 of –0.7°C is again shown as a solid, large circle, with a return period in 1960–1969 of 139 years and in 2000–2009 of 278 years.

volcanic emissions are assigned values from Sato et al. (2011). Finally, a modification to the model allows a variable solar forcing, which is taken from Krivova et al. (2007) and Lockwood et al. (2011). The topography and land use remain unchanged between scenarios.

Validation and bias correction. To analyze the results from the regional modeling experiment, four separate ensembles are formed from the data. Each data point in each ensemble is the mean of 27 grid boxes from the regional model, corresponding to 9 grid boxes centered over London, 9 over Bristol, and 9 over Manchester, which replicates the spatial distribution of the CET. The four ensembles are: all the Novembers occurring in the 1960s, all Decembers in the 1960s, all Novembers in the 2000s, and all Decembers in the 2000s. To ensure that the distribution of temperatures in these ensembles are representative of the distribution of the observed Central England Temperature, a validation exercise is performed.

Figure 12a shows quantiles of temperatures in the ensembles of 1960s Novembers and Decembers against the corresponding quantiles in the CET dataset. Figure 12b shows the same for the 2000s ensembles. The solid lines are the raw ensemble data, whereas the dashed lines are the result of applying a simple bias correction to ensure the means and standard deviations of the ensembles match the means and standard deviations of the observed CET dataset. The same bias correction is applied to both the 1960s and 2000s.

After the bias correction, there is good agreement between the ensembles and observations, giving confidence that any change in return time is representative of the change in return time in the observations.

Results and conclusions. Figure 13a shows the return times of warm temperatures in November in both the 1960s ensemble (blue) and 2000s ensemble (red). The temperature of a 100-yr event in Novembers in the 2000s has increased to 10.42°C from 8.97°C. The warm November of 2011, which is the second warmest in the CET, has a monthly mean temperature of 9.6°C. This corresponds to a return period of 20 years in the 2000s, but a return period of 1250 years in the 1960s, an approximately 62 times increase in occurrence.

Figure 13b shows the return times of cold temperatures in December in both the 1960s and 2000s. Although the occurrence of a cold December in the 2000s has decreased from the 1960s, the difference in temperature of the 100-yr event is 0.87°C. The cold December of 2010, which is the second coldest December and coldest since 1890, has a monthly mean temperature of –0.7°C, which has a return period of 139 years in the 1960s and a return period of 278 in the 2000s. Therefore, a cold December of –0.7°C is half as likely to occur in the 2000s when compared to the 1960s.

LENGTHENED ODDS OF THE COLD UK WINTER OF 2010/11 ATTRIBUTABLE TO HUMAN INFLUENCE

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The winter of 2010/11 began with the coldest December in the UK series dating back to 1910 and the second coldest December in the Central England Temperature (CET) record dating back to 1659 (Manley 1974), with a –5.3°C anomaly in the monthly average temperature relative to the 1961–90 mean. There were many adverse consequences of the extreme temperatures, including closed airports and schools. There was also the novel experience for many children, wherever they lived in the United Kingdom, of a white Christmas. Here we put the cold winter of 2010/11 into the long-term context of climate variability and change through an analysis of the 353 yr central England temperature record and the application of a new modeling system for attribution of extreme weather- and climate-related events. Because February was much milder, with a positive temperature anomaly of 2.6°C, we concentrate in this paper on the first two months of winter.

Figure 14 shows how the early part of the 2010/11 winter compares to the other winters in the central England temperature record. Both the combined 2-month mean temperature for December and January and the mean December 2010 temperature stand out as exceptionally cold, although in neither case was the temperature unprecedented in this unique multi-century instrumental record. The question we seek to answer is whether the chances of such cold winter temperatures were greater or less in 2010/11 as a result of human influence on climate.

Has human influence on climate changed the chances of cold winters? The main tool we use to address this question is the Met Office Hadley Centre attribution system (Christidis et al. 2012, manuscript submitted to *J. Climate*). This is based on HadGEM3-A, the atmospheric component of the model used for seasonal forecasting at the Met Office (Arribas et al. 2011) and which has a resolution of 1.25° longitude by 1.875° latitude and 38 vertical levels. We compare a 100-member ensemble of model simulations forced with observed SSTs and sea ice and current levels of greenhouse gases with two alternative 100-member ensembles in which human influence has been subtracted from the SSTs and sea ice and in which greenhouse gases and aerosols are reduced to preindustrial levels following a similar methodology to that of Pall et al (2011). Here, estimates of the change in SST due to human influence are derived from transient simulations of three coupled climate models, HadGEM1, HadGEM2-ES, and HadCM3. Further details of the attribution system are given in Christidis et al (2012, manuscript submitted to *J. Climate*).

Verification of model statistics against observations helps assess the trustworthiness of the attribution system. Based on a five-member ensemble of simulations forced with observed SSTs from 1960 to 2010, Christidis et al. (2012, manuscript submitted to *J. Climate*) concluded that the model has a realistic representation of UK temperature variability although its reliability in capturing the predictability of UK temperatures is not as high as for temperatures over the region affected by the Russian heat wave of 2010 (Christidis et al. 2012, manuscript submitted to *J. Climate*). Nevertheless the model is expected to produce a reliable estimate of the overall changed odds of cold winters in the United Kingdom due to human influence, all other factors being equal, even if the odds could additionally have been affected in recent years by factors we do not calculate here such as the recent minimum in solar activity (Ineson et al. 2011). As a further check on the robustness of the model-based results, we determine whether they are broadly consistent with observational estimates derived from the multicentury CET record.

Change of odds in the model. The change of odds of cold December and January temperatures in 2010/11 attributable to climate change can be seen in Fig. 15 (top), which shows the ratio of the probability of such cold temperatures in the current world (P1) to the world had human influence not affected climate (P0). The three estimates, based on attributable SST changes derived from the HadGEM1, HadGEM2-ES, and HadCM3 models, have median values of approximately 0.5, indicating that human influence has halved the probability of temperatures as cold as seen in 2010/11 with 5th–95th-percentile uncertainty ranges of 0.24–0.80, 0.25–0.70, and 0.26–0.82 depending on which coupled model is used to define the change in SSTs. In summary, model results indicate that human influence has reduced the odds by at least 20% and possibly by as much as 4 times with a best estimate that the odds have been halved.

Change of odds estimated from the CET record. An observationally based consistency check of these numbers is obtained by calculating empirically the number of times prior to 1910 CET was colder than 2010/11 (28 times) and comparing this to the number of times CET would have been colder than observed in 2010/11 if CET had warmed between 0.3 and 1 K because of human influence on climate (between 20 and 7 times, respectively). These representative values for CET human-induced warming span the range of human-induced SSTs in the vicinity of the United Kingdom according to the HadGEM1, HadGEM2-ES, and HadCM3 models. This corresponds to a reduction of probability of between 0.25 and 0.71 consistent with the estimates obtained from the model. A more direct but more approximate calculation (given the fewer number of data points available for the calculation) is to note that whereas temperatures colder than 2010/11 were observed only once in the last 30 years (P1 = 1/30) and temperatures as cold or colder twice (P = 2/30), colder temperatures were observed from 1 to 6 times in samples of 30-yr periods taken from the CET record before 1910. This difference in probabilities corresponds to a ratio of

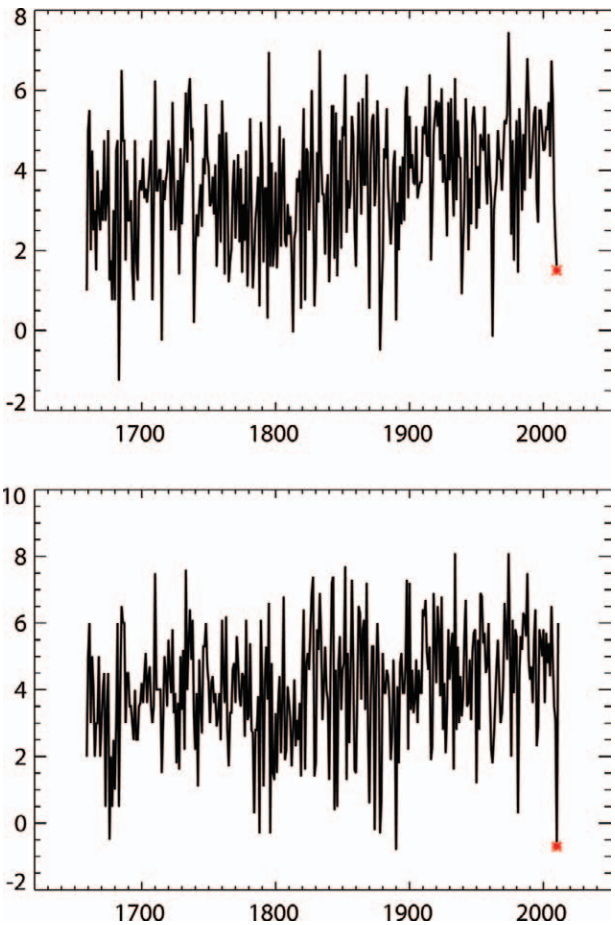

Fig. 14. Central England temperature averaged over (top) December and January combined and (bottom) December. Winter of 2010/11 shown as red stars. December/January 2010/11 was the thirty-fourth coldest December/January in the record and December was the second coldest December in the record.

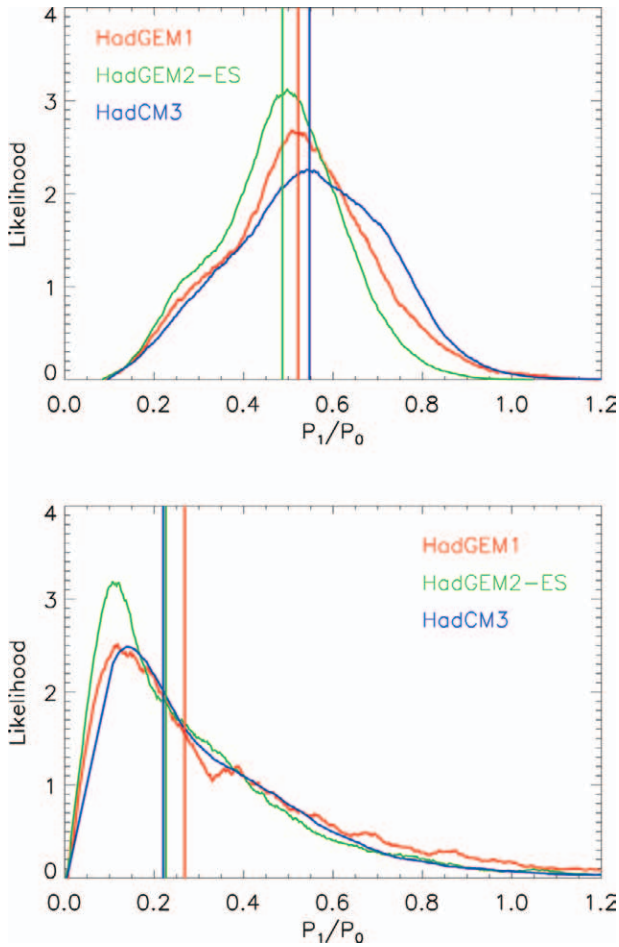

Fig. 15. Attributable change in probability (P1/P0) of (top) December/January temperatures as cold as observed in 2010/11 and (bottom) December temperatures as cold as observed in 2010, where P1 is the probability of a temperature as cold as that observed in the winter of 2010/11 in the current climate, and P0 is the probability of such cold temperatures had human influence not affected the climate of 2010/11. The uncertainty in this number is shown as likelihood distributions representing modeling uncertainty estimated by a bootstrap procedure (Christidis et al. 2012, manuscript submitted to *J. Climate*). Likelihood distributions are calculated for three specifications of alternative SSTs (red, green, and blue curves) estimated from simulations of the HadGEM1, HadGEM2-ES, and HadCM3 coupled climate models. The vertical lines mark the median values. A value of 0.5 indicates that the probability has halved and a value of 1.0 indicates there is no change.

probabilities of from 0.17 to 1 with a median value of 0.5, also consistent with the model-based estimates but with a larger range (due to the greater sampling uncertainty). In this calculation we assume P1 is equally likely to be 1/30 or 2/30 and we treat each overlapping 30-yr segment of CET before 1910 as equally representative of preindustrial temperatures.

For the single month of December 2010, the HadGEM3-A-based attribution system estimates that the ratio of probabilities P1/P0 lies between 0.06 and 1.00 (5th–95th percentiles) with a median of 0.27 when HadGEM1 SSTs are used and between 0.05 and 0.79 with a median of 0.23 when HadGEM2-ES SSTs are used and between 0.05 and 0.74 with a median of 0.22 when HadCM3 SSTs are used (Fig. 15, bottom). The larger uncertainties than for December and January combined are associated with a more extreme temperature excursion. Given the rare nature of this event in the observational record—only two occurrences of temperatures as cold as December 2010 have been seen since 1659 (Fig. 14)—it is not possible to make the same direct observationally based empirical calculation of the change in odds as was done for the combined December/January temperatures.

Conclusions. The winter of 2010/11 was a rare weather event, even in the context of the 352 years of the central England temperature record. Yet while the odds of such an event have lengthened as a result of human influence on climate, such unlikely events can still happen, as the winter of 2010/11 demonstrated. Further refinements of such calculations could include calculations of how the risk of extremely cold temperatures in a specific winter might vary as a result of natural factors, such as a minimum in the solar cycle (Ineson et al. 2011).

CONCLUSIONS

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"Climate is what a boxer trains for but weather throws the punches" (D. Arndt 2012, personal communication). Attribution analyzes, such as those in this article, have the potential to inform the necessary training and adaptation options for societies in dealing with the punches weather and climate extremes throw their way.

The section on historical context summarizes the evidence that human influence has affected trends and long-term behavior of temperature and precipitation extremes around the globe, thus altering the types and frequencies of punches for which our boxer must train. This is to be anticipated from theoretical expectations of a warmer world. The recent IPCC SREX report (Field et al. 2012) concluded that "it is likely that anthropogenic influences have led to warming of extreme daily minimum and maximum temperature at the global scale" and that "there is medium confidence that anthropogenic influences have contributed to intensification of extreme precipitation at the global scale." But even if human influence is making a particular type of event more likely on average, because of natural variability it does not necessarily follow that its likelihood is greater every year. So while it has been argued that in the anthropocene[4] all extreme weather or climate events that occur are altered by human influence on climate (Trenberth 2011), and although it is difficult to prove that a particular extreme weather or climate event was not in some way influenced by climate change, this does not mean that climate change can be blamed for every extreme weather or climate event. After all, there has always been extreme weather.

The contributions in this article examining some of the specific extreme weather or climate events of 2011 demonstrate the importance of understanding the interplay of natural climate variability and anthropogenic climate change on their occurrence. We should not expect that climate change plays the major role in every extreme weather or climate event and indeed the rainfall associated with the devastating Thailand floods was not especially unusual. In this case, nonclimatic factors such as changes in land use and water management probably played a bigger role in the disaster. Thus attribution of the impacts of weather-related events to climate variability and change requires careful consideration

[4] The anthropocene is the most recent geological era in which human activities have had a significant global impact on the Earth's ecosystems (Crutzen 2002).

of possible confounding factors not related to climate (Hegerl et al. 2010).

The development of a regular attribution service whose results are available shortly after the month or season in question depends on the implementation of an established methodology. For example, the same circulation regime–based technique used to analyze the very cold northwestern European winter of 2009/10 (Cattiaux et al. 2010a) was used to investigate European seasonal temperatures in 2011. All four seasons were warmer in many parts of Europe than would be expected from the average of previous years with similar atmospheric flow conditions. While 2011 had the warmest annual mean temperatures in western Europe since the start of the analysis in 1948, temperatures expected from the observed atmospheric flow conditions would not have been unusual. The implication is that without long-term warming, 2011 would not have been a record breaker by this measure.

Another approach that supports a regular attribution service is based on estimating the changed probabilities of extreme weather or climate events from ensembles of atmosphere only climate models with different sea surface temperatures (SSTs) and altered concentrations of greenhouse gases and other climate forcings. This technique has been used to show that human-induced greenhouse gas emissions have increased the risk of the UK flooding seen in 2000 (Pall et al. 2011). A similar analysis of the cold UK winter of 2010/11 determined that temperatures as cold as seen in the early part of the winter were less likely as a result of human influence on climate and when looking at combined December/January temperatures they were half as likely. Examining the unique multicentury record of central England temperatures allows a simple verification of such statistics for the United Kingdom.

An important future development of such attribution systems is to allow the changed risk of extreme weather or climate events to be calculated quickly and disseminated on a regular basis. The Weather Risk Attribution Forecast (WRAF) system, which is based on a seasonal forecasting modeling system, has been trialled in this way, providing regularly updated estimates of risks of temperature and precipitation extremes. It will be crucial to understand the strength and limitations of such systems for the weather and climate events to which they are being applied. This should include an assessment of the reliability of the models being used (Christidis et al. 2012, manuscript submitted to *J. Climate*).

Providing such attribution results in time for this issue has proved extremely challenging given the delays involved in collecting observations, running models and analyzing data. Two analyzes presented here used preexisting climate model simulations to compare event statistics for recent years with years from the 1960s. While this approach does not explicitly calculate the extent of changes attributable to human influence because natural external forcing and natural internal variability could have contributed to the change in the likelihood of events since the 1960s, it does address how the long-term warming trend has affected weather odds. By carefully choosing years with patterns of SSTs similar to those of 2011, it was possible to determine that heat waves such as the one that affected Texas have become distinctly more likely than they were 40 years ago. In the United Kingdom there has been a much greater increase in the likelihood of the very warm November temperatures seen in 2011 than the reduction in likelihood of the very cold December temperatures seen the previous winter. This interesting seasonal asymmetry in the change of extreme climate and weather odds seems worthy of further investigation.

It has been questioned whether attribution studies might neglect many of the regions most vulnerable to extreme weather because of the greater difficulties of collecting climate observations and undertaking climate modeling in developing countries (Hulme 2011). Therefore the analysis of the East African drought of 2011 is particularly interesting because it demonstrates the potential for attribution in tropical regions that lack robust international exchange of climate observations. Low-latitude regions generally have higher ratios between the signal of climate change in temperature and variability than other regions (Mahlstein et al. 2011) and there appears to be potential skill in seasonal forecasting of impact-relevant metrics such as the onset of seasonal rains in Africa (Graham and Biot 2012). While La Niña had a large role to play in the failure of the rains in East Africa, there is evidence that warming in the western Pacific–Indian Ocean warm pool has contributed to an increased frequency of droughts in this region. While such a conclusion is supported by a deeper body of literature, the hypothesis of a link between ocean warming and a greater risk of drought in this region remains controversial. All attribution assessments are necessarily subject to change as science advances. A key challenge for attribution assessments remains to accurately characterize their levels of confidence given current understanding.

2011 was a year during which the weather threw plenty of punches [see Blunden and Arndt's (2012)

supplement to this issue]. While much work remains to be done in attribution science, to develop better observational datasets, to improve methodologies, to make further progress in understanding and to assess and improve climate models, the contributions in this article demonstrate the potential that already exists for meaningful assessments of the connection between specific extreme weather or climate events that occurred in a particular year and climate change. Whether readers react with excitement at the possibilities already demonstrated, or with irritation at the gaps and limitations still present, our hope as editors is that this initial selection of investigations encourages further development of the capability to produce timely and reliable assessments of recent extreme weather or climate events. Such an enterprise is much further advanced for climate monitoring—as shown by the maturity of the annual State of the Climate report (e.g., Blunden and Arndt 2012)—but even there important uncertainties exist and new assessments of past years will emerge, just as they will for attribution as understanding develops. By developing the scientific underpinning, the ability to put recent extreme weather or climate events into the longer-term context of climate change should improve as each year goes by.

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