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Anthropogenic influence on the changing likelihood of an exceptionally warm summer in Texas, 2011

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Abstract The impact of anthropogenic forcing on the probability of high mean summer temperatures being exceeded in Texas in the year 2011 was investigated using an atmospheric circulation model to simulate large ensembles of the world with 2011 level forcing and 5 “counterfactual” worlds under preindustrial forcing. In Texas, drought is a strong control on summer temperature, so an increased frequency in large precipitation deficits and/or soil moisture deficits that may result from anthropogenic forcing could magnify the regional footprint of global warming. However, no simulated increase in the frequency of large precipitation deficits, or of soil moisture deficits, was detected from preindustrial to year 2011 conditions. Despite the lack of enhancement to warming via these potential changes in the hydrological cycle, the likelihood of a given unusually high summer temperature being exceeded was simulated to be about 10 times greater due to anthropogenic emissions.

1. Introduction

Numerous investigations have aimed to quantify the role of anthropogenic greenhouse gases (GHG) on recent heat waves, some of which include the catastrophic heat waves in Russia, 2010 [Dole et al., 2011; Rahmstorf and Coumou, 2011; Otto et al., 2012]; in the USA, 2012 [Diffenbaugh and Scherer, 2013; Knutson et al., 2013]; in Australia, 2012/2013 [Ablaster et al., 2014; King et al., 2014; Knutson et al., 2014; Lewis and Karoly, 2014; Perkins et al., 2014]; and in central east China [Zhou et al., 2014], South/North Korea [Min et al., 2014], and Japan [Imada et al., 2014] in 2013. All but one of these studies [Dole et al., 2011] conclude that the probability of the event temperatures being equaled or exceeded had substantially increased due to the cumulative anthropogenic GHG emissions by the time of the event.

The heat wave of the summer of 2011 in Texas (plus portions of neighboring states and northern Mexico) is worthy of inclusion among the above in its extremity. This event was extraordinarily hot: 3.2°C warmer than average, whereas the previous hottest summer had been only 1.8°C above normal (baseline: 1960–2009 and period of record: 1895–2014) (Figure 1). The hot summer followed the third warmest spring on record and coincided with an exceptionally dry summer, as both the summer and preceding spring had the largest precipitation deficits on record (Figure 1). Compounded with a relative dry fall and winter leading up to the 2011 growing season, these rainfall deficits created a drought unprecedented in its intensity [Nielsen-Gammon, 2012].

The onset of drought in the fall of 2010 and its continuation through spring of 2011 has been linked to cooler than normal tropical Pacific sea surface temperatures (SSTs) [Hoerling et al., 2013; Seager et al., 2014], which historically have been concurrent with severe droughts [e.g., Seager and Hoerling, 2014]. Although the La Niña extended in a diminished state into summer 2011, the strength of teleconnections between tropical Pacific SSTs and the regional atmospheric circulation is weak in summer, and therefore, the persistence of the precipitation deficit appears to have been largely a consequence of internal atmospheric variability [Seager et al., 2014].

The summer heat wave of 2011 therefore was in large part a consequence of the precipitation deficit leading up to, and during, summer [Hoerling et al., 2013; Seager et al., 2014]. Primarily, two factors cause elevated temperatures during dry summers: (1) increased solar radiation reaching the surface because of diminished cloud cover and (2) less energy going toward changing the phase of soil water from liquid to vapor and more energy going toward increasing the air temperature, a consequence of the balancing of the energy budget through increased sensible heat flux and long-wave radiative cooling [e.g., Seager et al., 2014].
In addition to natural drivers of regional summer heat waves, anthropogenic warming can increase the intensity of such heat waves through various mechanisms. One is the direct greenhouse effect (the change in the downward infrared energy flux) operating at the regional level but excluding the effects of changes in the regional hydrological cycle. We refer to this as "base" warming. Two additional mechanisms can serve to intensify this base warming. The first, which we call "precipitation deficit" warming, is through a regional decrease in precipitation arising from changing atmospheric circulation patterns and a redistribution of the energy budget. The resulting decrease in precipitation coincides with generally less cloud cover and leads to a drier land surface and consequently higher temperature, driven by the two factors given previously. A second mechanism delivers positive feedback via an increase in potential evapotranspiration (PET) rate caused by an increase in temperature (and possibly by other means such as increased incoming short-wave radiation). The increased PET rate leads to faster drying of the soil and resulting higher summer temperatures as less energy is used to convert liquid water to vapor. We refer to this mechanism as "evapotranspiration (ET) enhancement" warming.

Recent studies found weak [Rupp et al., 2012] or no [Hoerling et al., 2013; Seager et al., 2014] evidence of human influence on the probability of extremely low precipitation in Texas as of recent years, implying that precipitation deficit warming has not been enhanced by increased anthropogenic GHG concentrations. This would leave base warming and ET enhancement warming as two potential drivers of increased probability of heat waves.

A few attempts have been made to quantify human-induced change in heat wave magnitudes and likelihood in Texas. Rupp et al. [2012] found an approximately 1°C increase in simulated extreme summer temperature by 2008 as compared to the 1960s and estimated that the likelihood of a heat wave of a given temperature had increased by over 1 order of magnitude during the intervening decades. However, although the influence of the Pacific Ocean was somewhat accounted for in their study, the relative roles of anthropogenic
forcing and other oceanic variability were not clearly separated. Hoerling et al. [2013] estimated that anthropogenic warming over the three decades preceding 2011 accounted for approximately 0.6°C or 20% of the total 2011 summer temperature anomaly. The remaining 80% was attributed to anomalous SSTs and natural atmospheric variability. They also estimated a mere doubling of the event likelihood, in contrast to Rupp et al. [2012]. Lastly, Seager et al. [2014] concluded that the summer temperature in 2011 over Texas and Northern Mexico was consistent with the known inverse relationship between precipitation and temperature in summer and “not necessarily outside the range expected from this relation alone.”

In this study, we aim again to quantify changes in Texas heat wave probabilities by the year 2011, given the differing conclusions of the above studies. We compare simulated heat wave probabilities in 2011 with those in a set of what are referred to as “counterfactual” worlds, in which we include the natural forcings present in 2011 but maintain anthropogenic forcing at levels existing in 1900. Like Rupp et al. [2012], we generate a very large number of simulations per scenario (>800 ensemble members, differing only by their initial conditions), which permit explicit representation of the tails of distributions, without fitting arbitrary functions to relatively small samples to estimate probabilities of extremes. However, this study differs from Rupp et al. [2012] and Hoerling et al. [2013], who examined changes since a more recent past, by considering the greater impact of accumulated GHG emissions since the near-preindustrial era. It also differs from these two studies by estimating changes in probabilities of extreme soil moisture deficits with the goal of determining the indirect role of changing PET rate on heat wave likelihood by increasing drought severity.

2. Data and Methods

Values of observed monthly temperature and precipitation spatially averaged over Texas for the years 1895–2014 were obtained from the U.S. National Climatic Data Center Climate at a Glance data set (ftp://ftp.ncdc.noaa.gov/pub/data/cirs/).

We used the U.K. Meteorological Office’s Hadley Centre atmospheric general circulation model 3P (HadAM3P) [Pope et al., 2000; Gordon et al., 2000; Massey et al., 2014] (1.875°×1.25°, 19 levels, 15 min time step) to simulate the atmospheric and land surface climates from December 2010 to November 2011 under six scenarios, each with a unique set of boundary conditions and atmospheric gas concentrations, though with identical solar irradiance and land surface climates. The first scenario (referred to as “all forcings”) used observed GHG and nonvolcanic SO2 concentrations with prescribed sea surface temperature (SST) and sea ice boundary conditions from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) [Stark et al., 2007].

The remaining five scenarios were variations on a counterfactual world in 2011 absent increased anthropogenic GHGs. All five “natural forcing” scenarios were identical inasmuch that they assumed preindustrial era (circa 1900) GHG and nonvolcanic SO2 concentrations. Three of the five natural forcing scenarios varied in their SSTs. The “natural” world SSTs were generated using global climate model (GCM) simulations of the Coupled Model Intercomparison Project phase 5 (CMIP5) [Taylor et al., 2012]. SST changes due to anthropogenic emissions were estimated by differencing temporally smoothed SSTs from three GCMs (Centre National de Recherches Météorologiques coupled global climate model, version 5 (CNRM-CM5), Hadley Centre coupled model, version 3 (HadCM3), and Hadley Centre Global Environmental Model, version 2 Earth System configuration (HadGEM2-ES), ensemble member “r1i1p1″). For HadGEM2-ES, current era SSTs were obtained by concatenating the “Historical” experiment (ending in 2005) with the Representative Concentration Pathway 8.5 future forcing experiment. These SSTs were differenced from the “HistoricalNat” experiment extending to 2019, which excludes anthropogenic forcing but is otherwise identical to the Historical experiment. For CNRM-CM5 and HadCM3, we differenced the years from the last decade of the Historical simulation with the initial decade of the Historical experiment beginning in 1850 due to data availability at the time the SST boundary conditions were generated. The SST differences were then spatially smoothed with a Gaussian filter, and the results were subtracted from the observed OSTIA SSTs. The final counterfactual SST patterns may be considered to be functions of both the model’s global transient climate response (Table S1 in the supporting information), its regional responses, and of its internal variability, although the applied temporal smoothing reduces the internal variability. The changes in SST from the all forcing to the natural forcing scenarios, averaged over December 2011 to
August 2012 and 70°S to 70°N, were \(-0.34, -0.35, \text{and} -0.62°C\) for CNRM-CM5, HadCM3, and HadGEM2-ES. Figures S1 and S2 in the supporting information, respectively, show the imposed SST-differenced spatial patterns and SST anomalies by season.

Land surface initial conditions for each of these three natural forcing scenarios were taken as the final conditions from simulations using one of the natural SST sets (CNRM-CM5, HadCM3, and HadGEM2-ES) but for the prior year.

Beginning each scenario with a different land surface initial condition complicates the analysis of soil moisture because of soil moisture’s longer dependency on the initial state. Thus, to compare changes in soil moisture more directly, we simulated a fourth natural forcing scenario that used the identical initial land surface conditions as the all forcing scenario but with the same SSTs derived from the HadCM3 simulations. We refer to this scenario as “natural HadCM3 alt. I.C.,” where I.C. stands for initial conditions.

The four natural forcing scenarios described above used sea ice fraction from the years in the OSTIA record (1985–2010) with the largest mean annual Arctic and Antarctic sea ice extents: 1986.12–1987.11 and 2007.12–2008.11, respectively. We chose to sample directly from the observed sea ice record because of complications in generating sea ice using the straightforward differencing method applied for SSTs. The net increase in Arctic sea ice extent between the observed 2011 sea ice and the natural scenario was 15, 13, and 49% in December-January-February (DJF), March-April-May (MAM), and June-July-August (JJA), respectively.

The fifth natural forcing scenario used an alternative sea ice extent along with the HadCM3 SST pattern to gauge the sensitivity to our particular sea ice selection. (We refer to this scenario as “natural HadCM3 alt. S. Ice.”) Changes in Arctic sea ice extent are not expected to have an appreciable effect on weather patterns over North American midlatitudes during the summer [Sewall and Sloan, 2004; Singarayer et al., 2006; Francis and Vavrus, 2012; Screen and Simmonds, 2013; Screen et al., 2014; Peings and Magnusdottir, 2014], although it has been suggested that Arctic amplification due to retreating sea ice during the cold season has caused higher-amplitude pressure waves that progress more slowly across North America, which could result in the intensification of cold season extreme events [e.g., Singarayer et al., 2006; Francis and Vavrus, 2012]. Hadley Centre Sea Ice and Sea Surface Temperature Data Set, version 1 (HadISST1) sea ice fraction [Rayner et al., 2003] for the period of 1968.12–1969.11 was chosen as it had the largest mean annual Arctic sea ice extent in the HadISST1 record (though not the largest Antarctic extent). The net increases in Arctic sea ice extent between the observed 2011 sea ice and the alternative sea ice scenario were 22, 19, and 75% in DJF, MAM, and JJA, respectively.

Finally, to generate a large ensemble of simulations per scenario, the baseline initial conditions of potential temperature were perturbed by adding next-day differences, generated from a single year of the model run, to the full field of potential temperature. Simulations used from 839 to 906 sets of initial conditions per scenario and were retrieved from remote volunteers’ computers as part of the Climateprediction.net program [Allen, 1999; Massey et al., 2006].

Model output was spatially averaged over the 27 model grid cell centers that fell within Texas, weighted proportionally by the cosine of the latitude. What we call “conditional” return periods were calculated for each season for each variable and for each forcing ensemble. The return periods are conditional in that they are dependent on the particular SST patterns and forcings at a particular time (e.g., summer 2011). Bootstrapping was used to estimate the 5% to 95% confidence interval.

Statistics of simulated seasonal temperature and precipitation over the period of 1960–2010 were calculated from an existing ensemble of simulations using HadAM3P with observed forcing and HadISST1 SSTs and sea ice fractions. Twenty ensemble members for each year varying by their initial conditions were used for this study.

3. Results and Discussion

A reliable assessment of precipitation deficit warming in a modeling framework requires that the climate model adequately reproduce the observed relationship between temperature and precipitation, particularly in summer. The observed Pearson correlation coefficients of mean seasonal temperature and precipitation in Texas are \(-0.22, -0.29, -0.76, \text{and} -0.27\) in DJF, MAM, JJA, and September-October-November, respectively.
From the HadAM3P 1960–2010 ensemble, the correlations are \(0.30\), \(0.52\), \(0.71\), and \(0.46\) for the same seasons. The observed and simulated correlations are very similar in summer, the season with the strongest association between temperature and precipitation. For the remaining seasons, the simulated correlations are slightly stronger than the observed correlations, but the differences are not statistically significant (significance level = 0.95, two-sided test). Figure S3 in the supporting information further illustrates how HadAM3P reproduces the observed strength of the relationship between temperature and precipitation.

The influence of anthropogenic forcing on extreme temperatures is illustrated by comparing return period curves of seasonal temperatures in the all forcing ensemble with temperatures from all five natural forcing ensembles (Figure 2). For example, at the 100 year conditional return period for summer temperature, the all forcing scenario is \(0.5–1.0\)°C warmer than the natural forcing scenarios. Confidence intervals do not overlap between the all forcing and natural forcing scenarios at, and below, the 200 year conditional return period, implying that the differences are significantly different.

While the all forcing scenario stands apart from each of the natural forcing scenarios, there is some significant variability among the natural forcing scenarios themselves. Most evident is the overall cooler ensemble generated using SSTs derived from HadGEM2-ES, which are cooler than the SSTs derived from HadCM3 and CNRM-CM5. In summer, natural forcing HadGEM2-ES scenario is significantly different from the other natural forcing scenarios only for return periods less than 40 years. Still, it highlights the importance of not relying on a single scenario of a counterfactual world when conducting modeling experiments such as this one.

**Figure 2.** Conditional return period of simulated mean (a) spring and (b) summer temperature anomalies and total (c) spring and (d) summer precipitation anomalies in Texas, 2011, for the all forcing and five natural forcing scenarios (baseline: 1960–2009 with all forcing ensemble). The vertical and horizontal lines indicate the inner 90th percentiles.
Curiously, the scenario using the largest Arctic sea ice extent (HadCM3 alt. S. Ice) appears to be the warmest of the natural forcing ensembles. However, the separation between the return period curves with the two different sea ice extents but identical SSTs is not statistically significant. With only one alternate sea ice scenario, we hesitate to draw any firm conclusion about the role of sea ice other than that sensitivity to sea ice merits further investigation.

In contrast to temperature, return periods for precipitation deficits are generally indistinguishable between the all forcing and natural forcing scenarios. For any particular precipitation deficit, the all forcing confidence intervals on the conditional return period overlap with at least one of the natural forcing confidence intervals. At the longer return periods, the all forcing scenario overlaps with most, if not all, of the natural forcing scenarios. These results are consistent with Rupp et al. [2012, 2013] and Hoerling et al. [2013] that do not show

Figure 3. Conditional return periods of simulated mean (a) winter, (b) spring, and (c) summer soil moisture anomalies and (d) winter, (e) spring, and (f) summer precipitation anomalies in Texas, 2011, for the all forcing scenario and the natural forcing HadCM3 alt. I.C. scenario (baseline: 2011 all forcing ensemble).
current anthropogenic GHGs leading to increased frequency in large precipitation deficits in Texas and neighboring states.

Despite the lack of significant separation between the conditional return period curves of precipitation among the scenarios, the effect of anthropogenic forcing within HadAM3P is to reduce summer precipitation on average: the change in mean summer precipitation from the natural forcing to the all forcing scenario ranges from $-4\%$ to $-12\%$. However, as noted above, this difference is not detectable through the lower tail of the precipitation distribution, implying that the decrease in the mean precipitation rate is not due to an increase in the frequency of the driest summers.

No significant differences are apparent in the longer conditional return periods of soil moisture deficit in either spring or summer (Figure 3). In fact, on average, soil moisture deficits are somewhat greater in the natural forcing ensemble. Spring soil moisture is slightly higher in the all forcing ensemble as a result of the slightly higher precipitation in spring (+2%), relative to the particular natural forcing ensemble used to investigate changes in soil moisture. These wetter soil moisture conditions in the all forcing scenario appear to persist through summer despite the slightly higher summer precipitation deficits in all forcing relative to natural forcing. This may be because spring is the wettest season in Texas, with simulated spring precipitation being about 80% greater than summer precipitation, and so the wet spring sustains higher soil moisture well into the summer season.

The absence of an increase in the frequency of very low precipitation totals under the all forcing scenario implies that anthropogenically driven precipitation deficit warming is not contributing to the increase in the frequency of high summer temperatures. Furthermore, the simulations do not reveal an increase in the frequency of large soil moisture deficits, which is contrary to what we would expect if ET was increased while precipitation was largely unchanged. The implication is that ET enhancement warming is also not a significant component of the total anthropogenic warming. This leaves the base warming as the dominant cause of an increased frequency of exceptionally warm summers.

To quantify the change in the likelihood of warm summers, we interpolated, for a vector of given temperature anomalies, the conditional return periods for the all forcing and natural forcing ensembles. Prior to interpolation, the five natural forcing ensembles were combined into a single ensemble, which assumes equal likelihood of each scenario. Figure 4 shows the natural forcing versus the all forcing conditional return periods. For temperature anomalies having return periods between 10 and 100 years in the all forcing scenario, the corresponding natural forcing return periods are about 10 to 20 times greater and no less than 7 times greater.

This change in likelihood is substantially higher than the factor of $\sim2$ estimated by Hoerling et al. [2013] from an analysis of CMIP5 simulations. However, Hoerling et al. [2013] also compared 2011 to the period of 1981–2010, so one would expect their reported changes to be smaller on that account alone since anthropogenic GHG concentrations had substantially increased by that period. Rupp et al. [2012] estimated a 100 year return period anomaly in the 1960s becoming roughly a 5 year return period anomaly in 2008, a 20-fold increase in likelihood, whereas Figure 4 indicates a 7 to 14-fold increase between the preindustrial era and year 2011. This suggests that Rupp et al.’s [2012] results were driven not only by anthropogenic GHGs but also by natural variability in SST patterns, given that they used the same atmospheric climate model as done here.

Although it is tempting to assign a conditional return period to the actual 2011 mean summer temperature within the context of the HadAM3P simulations, biases in the modeled return period curves preclude direct estimation of a return period. Although simulated summer temperatures ($\sigma = 1.18^\circ$C) are more variable than observed temperatures ($\sigma = 0.75^\circ$C), if we could assume a Gaussian probability distribution for both

![Figure 4](image-url)

**Figure 4.** Return period in the combined natural forcing scenarios to the return period in the all forcing scenario for mean summer temperature, Texas, 2011. The shaded area shows the inner 90th percentile.
observed and simulated temperatures, a simple rescaling of the temperature anomalies by the ratio of the simulated to observed standard deviations could be done. However, while the observations and simulations are close to Gaussian through most seasons (see Figure 54 in the supporting information), the simulations deviate somewhat from Gaussian in summer. Moreover, the 2011 summer temperature is clearly a departure from the Gaussian-like distribution of the remaining observations.

We may, however, estimate a lower bound on the return period by examining the second highest summer anomaly on record (1.78°C) and using quantile mapping to adjust for bias. The result is a corresponding simulated anomaly of 2.2°C, which has a conditional return period in 2011 of approximately 10 years. In the natural forcing scenarios, this anomaly would have a conditional return period of roughly 100 years (Figure 4). Of course, the conditional return period of the actual 2011 value will possibly be very much higher than 10 years, so we remain far from being able to reliably estimate the probability of surpassing the summer 2011 temperature in the next few decades.

4. Conclusions

In a numerically simulated environment, anthropogenic warming since the end of the nineteenth century increased, by an order of magnitude, the likelihood of exceeding some arbitrarily high mean summer temperature in Texas in 2011. This change corresponds to a simulated 0.5–1.0°C increase over preindustrial conditions, although the actual change may be smaller because the simulated summer temperatures are more variable than observations.

We can compare these estimates for those of recent notable heat waves to provide a global context, even though the particulars of the varying methodologies used may explain more variability among studies than differences in the events themselves. Otto et al. (2012), for one, estimated a threefold increase in likelihood for the 2012 Russian heat wave due to anthropogenic GHGs. Diffenbaugh and Scherer (2013) calculated at least a fourfold increase for the 2012 U.S. heat wave, while Knutson et al. (2013) estimated that the likelihood grew by a factor of 12 for the months of March–May. For the 2013 Australian heat wave, estimates range more widely, from 3 [Perkins et al., 2014] to 23 [King et al., 2014] times greater. Lastly, the likelihood of a heat wave such that struck east Asia in 2013 was calculated to have increased by 2.5 times over central east China [Zhou et al., 2014] and 10 times over South/North Korea [Min et al., 2014] and Japan [Imada et al., 2014]. Our estimates for the 2011 Texas heat wave fall within the ranges given above, although we emphasize that the results are dependent on methodology, the climate model, and model parameters implemented.

Further work using other models and/or parameter sets would test the robustness of these conclusions.

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