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Quantile-based bias correction and uncertainty quantification of extreme event attribution statements

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ABSTRACT

Extreme event attribution characterizes how anthropogenic climate change may have influenced the probability and magnitude of selected individual extreme weather and climate events. Attribution statements often involve quantification of the fraction of attributable risk (FAR) or the risk ratio (RR) and associated confidence intervals. Many such analyses use climate model output to characterize extreme event behavior with and without anthropogenic influence. However, such climate models may have biases in their representation of extreme events. To account for discrepancies in the probabilities of extreme events between observational datasets and model datasets, we demonstrate an appropriate rescaling of the model output based on the quantiles of the datasets to estimate an adjusted risk ratio. Our methodology accounts for various components of uncertainty in estimation of the risk ratio. In particular, we present an approach to construct a one-sided confidence interval on the lower bound of the risk ratio when the estimated risk ratio is infinity. We demonstrate the methodology using the summer 2011 central US heatwave and output from the Community Earth System Model. In this example, we find that the lower bound of the risk ratio is relatively insensitive to the magnitude and probability of the actual event.

1. Introduction

The summer of 2011 was extremely hot in Texas and Oklahoma, producing a record of 30.26 °C for the average June–July–August (JJA) temperature (3.24 °C above the 1961–1990 mean) as measured in the CRU observational dataset (CRU TS 3.21, Harris et al., 2014). In a previous study of the 2011 Texas heat wave by Hoerling et al. (2013), a major factor contributing to the magnitude of 2011 heat wave was the severe drought over Texas resulting from the La Niña phase of the ocean state. However, the analysis found a substantial anthropogenic increase in the chance of an event of this magnitude. As in most mid-latitude land regions, the probability of extreme summer heat in this region has increased due to human-induced climate change (Min et al., 2013). However, as Stone et al. (2013) note, depending on spatial extent of the region analyzed, observed summer warming is low in Texas in 2011 and traceable to the so-called "warming hole" (Meehl et al., 2012).

Extreme event attribution analyses attempt to characterize whether and how the probability of an extreme event has changed because of external forcing, usually anthropogenic, of the climate system. As with traditional detection and attribution of trends in climate variables (Bindoff et al., 2013), climate models must play an important role in the methodology due to the absence of extremely long observational records. The fraction of attributable risk (*FAR*) or the risk ratio (*RR*) are commonly-used measures that quantify this potential human influence (Palmer, 1999; Allen, 2003; Stott et al., 2004; Jaeger et al., 2008; Pall et al., 2011; Wolski et al., 2014). Following the notation used in Stott et al. (2004), let p_A be the probability in a simulation using all external (anthropogenic plus natural) forcings of an event of similar magnitude, location and season to the actual event and p_C be the probability of such an event under natural forcings. The *FAR* is defined as $FAR = 1 - p_C/p_A$ while the *RR* is defined as $RR = p_A/p_C$, with each quantity a simple mathematical transformation of the other. We note that the commonly used term "risk ratio" is more precisely a "probability ratio" (Fischer and Knutti, 2015) but we will stick to the *RR* nomenclature in this study —in part because *RR* is the well-established terminology.

In the seminal study of the 2003 European heat wave by Stott et al. (2004), their climate model did remarkably well in

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simulating both European mean summer temperature and its interannual standard deviation. However, this is not generally the case for the entirety of available climate model outputs nor for the wide range of extreme events of current interest (Peterson et al., 2012, 2013; Herring et al., 2014). Hence there is a need to correct model output, particularly in the tail of its distribution, to more realistically estimate both p_A and p_C. Quantile-based mapping is often used to reduce such climate model biases in statistical downscaling studies of future climate change projections. Such methods match quantiles of climate model outputs to observed data for monthly GCM temperature and precipitation (Wood et al., 2004). For instance, quantile-based corrections to the transfer function between the coarse mesh of the global models and the finer downscaled mesh have been obtained by using cumulative distribution functions (CDFs) to match percentiles between the model outputs and observations over a specified base period (Maurer and Hidalgo, 2008). Li et al. (2010) proposed an adjustment of the traditional quantile matching method (Panofsky and Brier, 1968) to account for time-dependent changes in the distribution of the future climate and suggested that the quantile-matching method is a simple and straightforward method for reducing the scale differences between simulations and observations, for the tails of the distribution as well. The quantile mapping approach of Li et al. (2010) has been previously used to empirically estimate annual and decadal maximum daily precipitation in an attribution study of an early season blizzard in western South Dakota (Edwards et al., 2014).

This paper is concerned with developing a formal statistical methodology using extreme value analysis combined with quantile mapping to adjust for model biases in event attribution analyses. We apply the methodology to the 2011 central US heatwave as a case study, using an ensemble of climate model simulations. In Section 2, we describe the observed and simulated data for the central US heatwave analysis. Section 3 presents our statistical methodology, describing the use of extreme value methods combined with the quantile bias correction to estimate the risk ratio. We describe several approaches for estimating uncertainty in the risk ratio, focusing on the use of a likelihood ratio-based confidence interval that provides a one-sided interval even when the estimated risk ratio is infinity. In Section 4 we present results from using the methodology for event attribution for the central US heatwave, showing strong evidence of anthropogenic influence.

2. Case study: summer 2011 central USA heatwave

For a representative case study of extreme temperature attribution, we define a central United States region bordered by 90°W to 105°W in longitude and 25°N to 45°N in latitude, chosen to encompass the Texas and Oklahoma heatwave that occurred in summer 2011 (see Fig. 1). For this region, we calculated summer (June, July, August [JJA]) average temperature anomalies for the time period 1901–2012 by averaging daily maximum temperatures for grid cells falling within the study region. Anomalies are computed using 1961–1990 as the reference period.

The observational data in this study are obtained from the gridded data product (CRU TS 3.21, Climatic Research Unit Time Series) available on a $0.5° \times 0.5°$ grid provided by the Climatic Research Unit (Harris et al., 2014). This dataset provides monthly average daily maximum surface air temperature anomalies. Similarly, monthly averaged daily maximum surface air temperatures were obtained from the CMIP5 database through the Earth System Grid Federation (ESGF) archive. For both the observations and model output, spatial averages over the cells covering the land surface of the region were calculated, resulting in simple 1-dimensional time series. In this study, we use a single climate model,

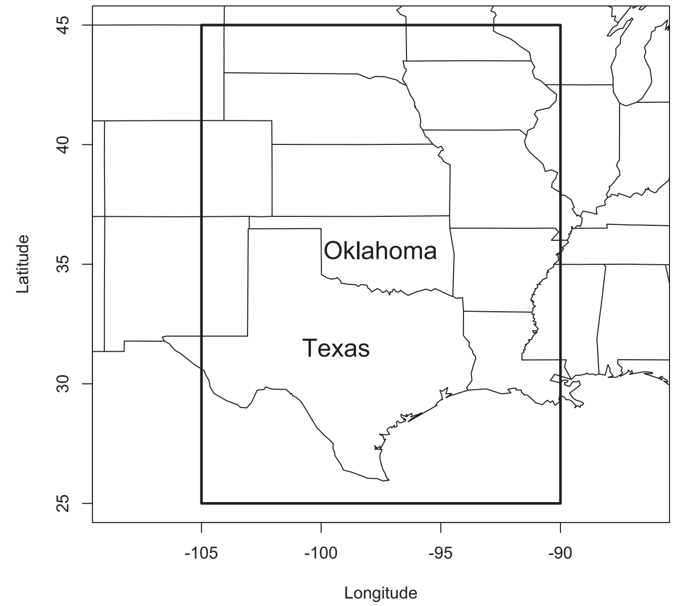

Fig. 1. Central United States region, 90°W to 105°W in longitude and 25°N to 45°N in latitude (bold rectangular area), covering the states of Texas and Oklahoma.

the fourth version of the Community Climate System Model (CCSM4) with a resolution of $1.25° \times 0.94°$ grid. To more fully explore the structural uncertainty in event attribution statements, additional models would need to be included in the analysis. While that topic is outside the scope of this paper, our methodology is also relevant for analyses that use multiple models that will each have their own biases.

The CCSM4 ensemble consists of multiple simulations, each initialized from different times of a control run; we treat the ensemble members as independent realizations of the model's possible climate state. For the actual scenario with all forcings included, we use an ensemble of five members, constructed by concatenating the period 1901–2005 from the CMIP5 “historical” forcings experiment and the period 2006–2012 from the matching RCP8.5 emissions scenario experiment. As a representation of a world without human interference on the climate system, we construct a counterfactual scenario by producing an ensemble of 12 100-year segments drawn from the preindustrial control run. In this scenario, greenhouse gases, aerosols and stratospheric ozone concentrations are set at pre-industrial levels, but other external natural forcings such as solar variability and volcanoes are not included. We use this counterfactual scenario as a proxy for the natural climate system without any external forcing factors.

An important consideration in event attribution analyses is whether the climate model(s) reasonably represent the magnitudes and frequencies of the event of interest (Christidis et al., 2013). Fig. 2 shows that summer temperatures vary more in the CCSM4 output than in the observations. The record observed extreme value in our central US region in 2011 was 2.467 °C above the 1961–1990 average (represented by the large black dot); even this extreme is somewhat lower than the observed values over just the states of Texas and Oklahoma. However, this value is not particularly rare in either model scenario dataset. Due to this scale mismatch in temperature variability, the climate model incorrectly estimates the probabilities of extreme events of this magnitude in both scenarios. In light of this model bias, a quantile mapping procedure to scale the extreme values of either the model or the observations to the other is warranted to more consistently relate the model's risk ratio to the real world. More precisely, we define the event according to observations, even in the presence of observational error, and calibrate the model to the observations with