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Estimating extremes from global ocean and climate models: A Bayesian hierarchical model approach

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ABSTRACT

Estimating oceanic and atmospheric extremes from global climate models is not trivial as these models often poorly represent extreme events. However, these models do tend to capture the central climate statistics well (e.g., the mean temperature, variances, etc.). Here, we develop a Bayesian hierarchical model (BHM) to improve estimates of extremes from ocean and climate models. This is performed by first modeling observed extremes using an extreme value distribution (EVD). Then, the parameters of the EVD are modeled as a function of climate variables simulated by the ocean or atmosphere model over the same time period as the observations. By assuming stationarity of the model parameters, we can estimate extreme values in a projected future climate given the climate statistics of the projected climate (e.g., a climate model projection under a specified carbon emissions scenario). The model is demonstrated for extreme sea surface temperatures off southeastern Australia using satellite-derived observations and downscaled global climate model output for the 1990s and the 2060s under an A1B emissions scenario. Using this case study we present a suite of statistics that can be used to summarize the probabilistic results of the BHM including posterior means, 95% credible intervals, and probabilities of exceedance. We also present a method for determining the statistical significance of the modeled changes in extreme value statistics. Finally, we demonstrate the utility of the BHM to test the response of extreme values to prescribed changes in climate.

1. Introduction

The recent "marine heat wave" recorded off Western Australia (Pearce and Feng, 2012; Wernberg et al., 2012) has focussed attention on marine extremes, a field that has received relatively less attention than atmospheric extremes. Extreme events can have significant impacts on the physical, chemical, and biological environment and it is not clear how they might change in a changing climate. Understanding the behavior of marine extremes in a changing climate is important for our understanding of the greater marine climate system as well as for predicting potential impacts on ecological habitats (Johnson et al., 2011; Wernberg et al., 2012).

Global climate models (GCMs) are indispensable tools for our understanding of the ocean and atmosphere climate system and how it may be changing under anthropogenic influences. GCMs perform well at capturing the general characteristics of the climate (e.g., the spatial distribution of mean temperatures) but underperform at capturing extreme events. For example, GCMs tend to underpredict the frequency and severity of heavy rainfall events and overpredict the extent of light drizzle (e.g., Perkins et al. (2007)). Despite the fact that GCMs poorly represent the extreme values it is still possible to glean information about the extremes from what the models represent well: the general climate.

Intuitively, the tails of probability distributions are related to the central moments of the distribution – at least for events which are "not too extreme". The shape of a distribution's tails can change significantly due to changes in the central statistics of the distribution, such as the mean or variance (e.g., Mearns et al. (1984) and Wigley (1985)), and one is reminded of the classic Intergovernmental Panel on climate change figure depicting the change in extreme hot and cold events due to changes in the temperature mean, variance, and skewness (Field et al., 2012). While it has been noted that trends in the statistics of extremes may not closely follow the trends of the mean (Katz, 2010) several studies have demonstrated that extreme value statistics can be well represented using the central statistics. For example, the frequency of air temperature extremes in the Asia–Pacific region were shown to be well-predicted by the mean temperature alone (Griffiths et al., 2005). Ballester et al. (2010) have shown that the changes in frequency, length, and intensity of air temperature extremes over Europe, in a climate change scenario, can be closely approximated using changes in the mean, variance and skewness simulated by an ensemble of GCM simulations. Simolo et al. (2011) modeled daily maximum and minimum temperature extremes in Europe using

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the first four L-moments (Hosking, 1990, 1992), showing that the change in the mean provided the best prediction for the changes in the extremes. Further, de Vries et al. (2012) showed that changes in the statistics of cold spells over Europe can be closely linked with changes in the mean and variance of air temperature.

Hierarchical models provide a framework for extreme events to be modeled using the climate statistics (e.g., Casson and Coles (1999), Cooley et al. (2007), and Sillmann et al. (2011)). A hierarchical model has multiple layers (or stages) where the parameters of one model layer are modeled by another layer. For example, a traditional linear regression model can be made hierarchical by allowing the regression coefficients to vary as a function of another set of variables, thereby adding another layer to the model. Here, we model marine extremes using an extreme value distribution (EVD) and in turn the EVD parameters are modeled as a function of some covariates (i.e., the marine climate statistics). This has the advantage that, if we assume the relationship between the covariates and extreme SSTs does not change in time, we can use projections of marine climate statistics under a climate change scenario and the fitted hierarchical model to model the extremes for the projected climate.

Bayesian estimation is particularly well-suited to hierarchical models and such models are called Bayesian hierarchical models (BHMs; Cressie and Wikle (2011)). In the Bayesian framework unknowns are modeled as random variables and so model inputs and outputs are both represented by probability distributions. Therefore, for all variables we can include or obtain estimates of their means and their uncertainty as well as inter-dependence (covariance). This implies that the construction of a model in a Bayesian framework relies on recognizing the inherent uncertainties and the model results reflect these uncertainties. BHMs allow for uncertainties at each level to be specified or modeled explicitly as a parameter (observational uncertainty, process model error, etc.). Several excellent introductions and reviews of Bayesian hierarchical methods in the atmospheric and ocean sciences are provided by Berliner et al. (1998), Cressie and Wikle (2011), and Wikle et al. (2013).

BHMs have been used in the geophysical literature for a number of years. Royle et al. (1999) estimated spatially regular wind fields from sparse scatterometer data using a BHM in which the covariance structure of the wind was conditional upon the atmospheric pressure field (using a hybrid physics–statistics model). This model allowed one to extrapolate the wind estimates where no observations existed, based on the wind–pressure relationship elucidated by the BHM. Berliner et al. (2003) jointly modeled atmospheric and oceanic variables as a function of independent measured data (i.e., scatterometer measurements, altimetry data) with a BHM, allowing for coupling of the atmosphere–ocean variables (air–sea interactions). Milliff et al. (2011) provided a BHM implementation for the generation of surface wind initial conditions for ensemble ocean forecasting, including a detailed explanation of the BHM algorithm. Bayesian methods, and in particular BHMs, have been used to model sea surface temperature variability over a range of time scales including high-frequency variability, the seasonal cycle, multi-decadal trends, and the mean (Higdon, 1998; Lemos and Sansó, 2009; Lemos et al., 2010). Bayesian techniques are also well-established in the ocean ecosystems modeling literature (e.g., Harmon and Challenor (1997)). For example, Fiechter et al. (2013) used a BHM in which the process layer is a Nutrient-Phytoplankton-Zooplankton-Detritus (NPZD) model and others have developed similar models using statistical emulators of NPZD mechanisms (Hooten et al., 2011; Leeds et al., 2013).

Using BHMs for extreme value analysis is a relatively recent development. Casson and Coles (1999) discussed the idea of pooling information on extreme values spatially thereby borrowing information across space to inform the model. The extremes were modeled site-wise in tandem with a latent spatial process model for the variation of parameter values in space. This model used Markov chain Monte Carlo techniques for estimating model parameter values, and it was demonstrated to be skillful by predicting the hurricane climate of the Atlantic and Gulf of Mexico regions. Cooley et al. (2007) developed a hierarchical model where extreme precipitation values observed at weather stations (i.e., point locations) were modeled using a peak-over-threshold extremes model (i.e., the Generalized Pareto Distribution). The parameters of the Generalized Pareto Distribution were then modeled using a latent spatial process. The latent spatial process was expressed using a set of covariates including latitude, longitude, mean precipitation, elevation, and terrain type. The fitted model was then used to interpolate extremes over locations covered by the covariates but for which observed extremes were not available. Similarly, Friederichs and Thorarinsdottir (2012) modeled peak wind using the Generalized Extreme Value distribution, the parameters of which were modeled as a function of covariates such as mean wind speed, wind speed variance, rain rate, atmospheric pressure, and the pressure tendency.

Generally, the parameters of a Bayesian hierarchical model are estimated using Markov chain Monte Carlo algorithms (Casson and Coles, 1999; Cooley et al., 2007; Sang and Gelfand, 2009; Schliep et al., 2010). However, we would like to note that there have also been many hierarchical models with parameter estimation performed by frequentist maximum-likelihood techniques. For example, Sillmann et al. (2011) related extreme air temperature minima over Europe are to atmospheric blocking patterns over the North Atlantic. Other examples include those by Abeysirigunawardena et al. (2009) and Zhang et al. (2010) who used indices of climate variability (e.g., the Southern Oscillation Index, the Pacific-North American teleconnection pattern) as predictors in models of extreme winds in Western Canada and extreme precipitation over North America, respectively.

In this paper we outline the BHM technique and how it can be used to improve estimates of extremes from global ocean and climate models. The basic idea is to fit the BHM to observed extremes using model output climate variables as covariates (mean, variance, etc.). Then by assuming stationarity of the model parameters and given simulated climate variables for a projected future climate we can model future extremes. In doing so we extend the technique of spatial interpolation of extremes (e.g., Cooley et al. (2007)) to include temporal extrapolation. This technique is demonstrated using dynamically downscaled ocean model simulations of global climate projections representing the 1990s and 2060s decades, under the A1B carbon emissions scenario (Nakicenovic et al., 2000). Essentially, this approach is a form of bias correction of the model simulated extremes. The present article focuses on developing a BHM methodology for extremes analysis of ocean temperatures using ocean climate model output data. While we provide a specific case study for the BHM development and its application, our BHM approach presented here is intended to be quite generic so that it can be readily applied in other ocean climate extremes' contexts. For more complete details of the climate change application of our technique developed here please see Oliver et al. (in press) which focusses on understanding changes in sea surface temperature extremes off southeastern Australia in response to future climate change scenarios.

This paper is structured as follows. Extreme value theory and methods of fitting extreme value distributions are presented in Section 2. The Bayesian hierarchical model approach is outlined in Section 3 and demonstrated for extreme sea surface temperatures off southeastern Australia in Section 4. A discussion and conclusions are presented in Section 5.