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Statistical downscaling of regional climate model output to achieve projections of precipitation extremes

Eric M. Laflamme [a,*], Ernst Linder [b], Yibin Pan [b]

[a] Department of Mathematics Plymouth State University, MSC 29, 17 High Street Plymouth, NH 03264, United States
[b] Department of Mathematics and Statistics University of New Hampshire, W383 Kingsbury Hall, 33 Academic Way Durham, NH 03824, United States

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ABSTRACT

In this work we perform a statistical downscaling by applying a CDF transformation function to local-level daily precipitation extremes (from NCDC station data) and corresponding NARCCAP regional climate model (RCM) output to derive local-scale projections. These high-resolution projections are essential in assessing the impacts of projected climate change. The downscaling method is performed on 58 locations throughout New England, and from the projected distribution of extreme precipitation local-level 25-year return levels are calculated. To obtain uncertainty estimates for return levels, three procedures are employed: a parametric bootstrapping with mean corrected confidence intervals, a non-parametric bootstrapping with BCa (bias corrected and acceleration) intervals, and a Bayesian model. In all cases, results are presented via distributions of differences in return levels between predicted and historical periods. Results from the three procedures show very few New England locations with significant increases in 25-year return levels from the historical to projected periods. This may indicate that projected trends in New England precipitation tend to be statistically less significant than suggested by many studies. For all three procedures, downscaled results are highly dependent on RCM and GCM model choice.

1. Introduction

There is great societal interest in assessing the impacts of projected climate change, and more specifically, there is an intense interest in the impact of change in variability and extreme events that could accompany global climate change predictions (Tebaldi et al., 2006). Increases in these extremes have already been observed as precipitation events, heat waves, and drought are occurring with greater intensity and frequency over the past few decades (U.S. Climate Change Science Program (USCCSP), 2008). Other analyses have provided additional evidence that precipitation extremes are becoming more extreme and will continue to do so in the future (e.g. Zwiers and Kharin, 1998; Groisman et al., 1999; Meehl et al., 2000; Tank and Konnen, 2003; Karl and Knight, 1998; Kharin and Zwiers, 2005). In their survey of recent projections of climate extremes provided by global circulation models (GCMs), Tebaldi et al. (2006) concluded that models agree with observations over the historical period and that there is a trend towards a world characterized by intensified precipitation, with a greater frequency of heavy-precipitation and extreme events.

Precipitation extremes are a primary concern as these events are typically more impactful than precipitation events alone and are responsible for a disproportionately large part of climate-related damages (Kunkel et al., 1999; Easterling et al., 2000; Meehl et al., 2000). Natural systems may also be affected by changes in precipitation extremes, as these events have been shown to cause shifts in ecosystem distributions, to trigger extinctions, and to alter species morphology and behavior (Parmesan et al., 2000). Furthermore, extreme rainfall often translates into extreme flooding and consequently great material and economic losses, erosion and damage to crops, collapse of lifeline infrastructure, the breakdown of public health services (Douglas and Fairbank, 2011), fatalities (Kunkel et al., 1999), and structural damage to dams, bridges, and coastal roads.

In this work, we outline a procedure to examine potential change in precipitation extremes in New England. In the following section (Section 2), we discuss methods of statistical/probabilistic downscaling as well as some elements of extreme value theory germane to our analysis. In Section 3, we describe our data: precipitation observations for locations throughout New England, historical climate model output, and projected series for future precipitation. Section 4 outlines our downscaling approach and discusses all details of our methods. Section 5 presents our

* Corresponding author.
E-mail addresses: emlaflamme@plymouth.edu (E.M. Laflamme), elinder@unh.edu (E. Linder), ybj3@unh.edu (Y. Pan).

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downscaling results. Lastly, in Section 6, a discussion and conclusion is presented.

2. Downscaling

Atmosphere-ocean general circulation models, or AOGCMs, are coupled atmosphere and ocean models that simulation weather at a global scale. AOGCMs are the main component of global climate models (GCMs) which are the primary tools used to quantify and assess climate change impacts (Wilby and Harris, 2006). However, because global weather simulation is so computationally expensive, these models provide predictions at an extremely coarse scale (250 KM by 250 KM, in most cases). The issue is that environmental impact models are sensitive to local climate characteristics, and the drivers of local climate variation are not captured at the coarse scales of GCMs (Maurer and Hidalgo, 2008). That is, GCMs do not provide an accurate description of local climate. To overcome this discrepancy, methods of 'downscaling' are applied to produce local-scale climate predictions based on corresponding GCM scenarios.

Downscaling appears in two forms: Dynamical and statistical downscaling (or empirical statistical downscaling, ESD). Dynamical downscaling is a computationally-intensive technique which makes use of the lateral boundary conditions combined with regional-scale forcings such as land-sea contrast, vegetation cover, etc., to produce regional climate models (RCMs) from a GCM. RCM outputs are typically produced over regular geographic grids with scales in the tens of kilometers.

Statistical downscaling (SD), on the other hand, is a computationally less demanding alternative that may be applied to achieve a variety of results. Essentially, statistical downscaling is a two-step process consisting of 1) the development of statistical relationships between local climate variables and large-scale predictors, and 2) the application of such relationships to the output of large-scale output to simulate local climate characteristics in the future (Hoar and Nychka, 2008). Statistical downscaling is a realistic approach to develop a specific, local-level climate prediction. Typically, SD methods are applied to GCM projections, but may also be applied to RCM output as these results may not be representative for the local climate (Skaugen et al., 2002; Engen-Skaugen, 2004). Furthermore, RCM output may simply have inadequate spatial resolution for some impact studies, and hence additional statistical downscaling must be applied to the dynamical model results (Benestad et al., 2007).

2.1. Probabilistic downscaling

This analysis focuses on a method of 'probabilistic downscaling' to project a single variable, extreme precipitation, into the future. While traditional ESD models the link between large- and local-scale variables, probabilistic downscaling is a type of statistical downscaling that models the relationship between large- and local-scale statistical entities. In this case, the statistical entities are the corresponding cumulative distribution functions (CDFs) of the large- and local-scale precipitation extremes. In this way, probabilistic downscaling techniques do not retain the chronology, or exact ordering, of events. However, accurate descriptions of future climate distributions are themselves sufficient predictions as we do not aim to predict weather, but rather the distribution of a weather variable (precipitation extremes).

When working exclusively with cumulative distribution functions, the simplest form of downscaling is what is referred to as 'quantile mapping' or 'quantile matching'. This non-parametric technique downscales a large-scale value x by selecting a local-scale value y based on the following:

$$F_Y(y) = F_X(x) \text{ with } y = F_Y^{-1}(F_X(x))$$

where F is a CDF of a climate random variable. Once a mapping has been defined, it is then applied to large-scale dataset to create a local-scale prediction. The method does not take into account the information of the distribution of the future modeled dataset (Michelangeli et al., 2009). Furthermore, the method of quantile mapping cannot provide local-scale quantiles outside the range of the historical observations (Michelangeli et al., 2009). Proposed by Wood et al. (2004), the technique was applied to downscale monthly precipitation and temperature output from a GCM, and became known as bias-correction and spatial downscaling (BCSD).

To overcome the shortcomings of the quantile matching methodology, Michelangeli et al. (2009) proposed an extension to this mapping called the CDF-t. The CDF-t is similar to quantile mapping as it compares local- and large-scale distributions, but it accounts for changes in the large-scale CDF between historical and future periods. Let X denote a variable from climate model output and let X_C denote the series of the variable over the current, or calibration, period. Then, X_P denotes the variable projected into the future, the time series from runs of the climate model in the future. Similarly, let Y_C and Y_P denote the current and future series for the local-level station. We note that while Y_C is observed, Y_P will need to be predicted or downscaled. Finally, a transformation, $T(\bullet)$, is assumed to exist between the large- and local-scale variable such that $T(\bullet){:}[0,1]\to[0,1]$. We then have the relationship:

$$F_{Y_P}(x) = T\left(F_{X_P}(x)\right) = F_{Y_C}\left(F_{X_C}^{-1}\left(F_{X_P}(x)\right)\right) \tag{1}$$

where F_{Y_P} and $F_{X_P}$are the respective empirical CDFs for the local- and large-scale prediction, and F_{Y_C} and F_{X_C} are the respective CDFs of observed (historical) local-level data and observed large-scale, or regional data. For further details see Michelangeli et al. (2009). The improvement over quantile mapping is that the future, local-scale distribution is a function of both historical observations and large-scale information that may be distributed differently between calibration and projection periods.

However, for precipitation data, we are more concerned with the extreme events. In these cases, where the tails, which correspond to the extremes or high quantiles, are of primary interest, the non-parametric CDF-t is not ideal. Generally speaking, these rare, extreme values result in empirical CDFs for precipitation that are heavy-tailed. With few data at the extreme ends of the distribution, non-parametric quantile estimates in these tails have large variance and they may be strongly influenced by a single extreme event. Also, observations of historical changes, as well as future projections, confirm that changes in the distributional tails of precipitation (extremes) may not occur in proportion to changes in the mean and may not be symmetric in nature (Kharin and Zwiers, 2005; Robeson, 2004; Tank and Konnen, 2003; Easterling et al., 2000).

In light of this, Kallache et al. (2011) proposed the XCDF-t technique to downscale the distribution of extremes exclusively. The technique is analogous to the CDF-t technique of Michelangeli et al. (2009) in that is makes use of the same transformation function form (see Eq. (1)) to link large- and local-scale distributions of climate variables. Unlike the CDF-t method, however, the XCDF-t links estimated parametric distributions of large- and local-scale extremes only. To do this, 'exceedances over a threshold' based on extreme value theory (EVT) are used to fit appropriate distributions to extremes based on limiting properties of max-stable processes (See, for example, Coles, 2001). The framework of EVT allows for more precise estimation of the extreme portions of distributions.

For the XCDF-t, F_{X_P}, F_{Y_C}, and F_{X_C} are cumulative Generalized Pareto distribution (GPD) for the extremes of the modeled