Fidelity of Precipitation Extremes in High Resolution Global Climate Simulations.

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Abstract
Precipitation extremes have tangible societal impacts. Here, we assess if current state of the art global climate model simulations at high spatial resolutions (0.35°x0.35°) capture the observed behavior of precipitation extremes in the past few decades over the continental US. We design a correlation-based regionalization framework to quantify precipitation extremes, where samples of extreme events for a grid box may also be drawn from neighboring grid boxes with statistically equal means and statistically significant temporal correlations. We model precipitation extremes with the Generalized Extreme Value (GEV) distribution fits to time series of annual maximum precipitation. Non-stationarity of extremes is captured by including a time-dependent parameter in the GEV distribution. Our analysis reveals that the high-resolution model substantially improves the simulation of stationary precipitation extreme statistics particularly over the Northwest Pacific coastal region and the Southeast US. Observational data exhibits significant non-stationary behavior of extremes only over some parts of the Western US, with declining trends in the extremes. While the high resolution simulations improve upon the low resolution model in simulating this non-stationary behavior, the trends are statistically significant only over some of those regions.

Keywords: climate extremes, non-stationarity of extremes, high resolution climate modeling

1 Introduction

With increases in computational power and recent advances in climate modeling, multidecadal simulations with high resolution global climate models are being integrated more often. Most significant improvements with high resolution models are noted in the realism of reproducing intense storms and in the simulations of mean climate over regions strongly influenced by orography [23]. Early analyses of these simulations reveal that while simulated mean precipitation may improve with increase in resolution [13], the result may be model sensitive [1]. Further,
long-standing model biases like the double Inter-Tropical Convergence Zone (ITCZ) over the tropical Pacific continue to exist in these high-resolution models.

Recent observational studies suggest that there has been a significant increase in regional surface temperature and precipitation extremes over the past few decades [25, 5, 3, 9], with some studies formally attributing the changes in climate extremes to anthropogenic activities [5, 18]. Over the US, recent studies have found evidence of increasing extremes of precipitation averaged over the whole continental US [17, 15], although not all datasets show significant trends. Further, multi-model global climate model projections suggest an increasing trend in future precipitation extremes [17, 20], but with a large regional ensemble spread, particularly over the tropics.

However, the observed extremes as well as the trend of extreme precipitation over the past few decades is not well simulated by typical low resolution global climate models [14]. Recent studies suggest that increase in horizontal resolution can also improve simulations of extreme precipitation over land [24, 23]. As an example, Figure 1 shows the 99.9 percentile of precipitation, a familiar metric of extremes, for a high-resolution (0.25°x0.25°) gauge based analysis from the National Oceanic and Atmospheric Administration’s (NOAA) Climate Pre-
diction Center (CPC), a high resolution reanalysis (0.5°x0.67°) from National Aeronautics and Space Administration (NASA) called the Modern-Era Retrospective Analysis for Research and Applications (MERRA) and single simulations with a low resolution (1.4°x1.4°) and a high resolution (0.35°x0.35°) model version of the Community Earth System Model (CESM1.0). Distinct improvements with resolution are seen over the Northwest Pacific coast, Sierra Nevada mountains and the Southeast US, where the spatial pattern and magnitude of precipitation extremes are much closer to the observed values in the high resolution simulation, as noted in other model validation studies [24, 23]. High-resolution MERRA, which does not assimilate gauge data, also captures the extremes over the Western US. However, it fails to capture the extremes over the Southeastern US, where it is known to exhibit low variance [2].

Here, we assess further if the fidelity of the high resolution CESM1.0 in simulating stationary and non-stationary precipitation extremes has improved as compared to its inexpensive low resolution version, using a regionalization framework to quantify extremes. We describe our simulations and validation data used here in the next Section followed by a description of our methodology to quantify extremes in Section 3. We present our results in Section 4 and provide a brief summary and our future plans for the analysis of the simulation of climate extremes in high resolution global climate models in Section 5.

2 Experiments and Data

2.1 Global Climate Model Simulations

We conduct two sets of experiments with Community Earth System Model (CESM1.0) using the spectral dynamical core [19] and Community Atmosphere Model 4 (CAM4) atmospheric physics parameterizations of radiative transfer, moist physics and turbulence configured to run with prescribed observed ocean and sea-ice conditions. The two versions of the model simulate a reasonable climate [7, 12] with the high resolution model also capturing the teleconnections between the tropical Pacific and Northwest Pacific coast [12]. We configure the model at two horizontal resolutions: T85 (1.4°x1.4°) and T341 (0.35°x0.35°). The model is forced with observed greenhouse gases, aerosols, ozone, sea surface temperatures and sea-ice conditions for the period 1979-2005. The analysis presented below is based on an ensemble of five integrations for each model configuration. Each ensemble member integration starts with a different initial condition of the atmosphere. Previous studies with the T85 model suggest that the model captures the stationary and non-stationary components of extremes in surface temperature fairly well globally, when compared to MERRA reanalysis [7]. Figure 1c, d show the precipitation extremes simulated by these two model versions over the US.

2.2 Observational Data for Model Validation

We validate our results with the NOAA CPC gauge analysis product over the US [26]. The gauge analysis is created using an optimal interpolation method and also corrects for the biases caused by orographic effects. We also compare CPC data and our model results against the NASA MERRA reanalysis, which incorporates satellite measurements from the period 1979 to present including the NASA Earth Observing System (EOS) data, in addition to surface based observations [21]. It simulates the global hydrologic cycle and the water vapor climatology well, particularly over the tropical oceans as compared to other reanalysis products [21], but exhibits biases over land, for example over the Southeast US where it exhibits a low precipitation bias [2]. An artifact of this bias is also seen in the simulation of extremes over the region (Figure 1).
However, it is one of the few observationally based high-resolution products that can be used to evaluate high resolutions simulations globally.

3 Methods

3.1 Generalized Extreme Value Distribution

We apply Generalized Extreme Value (GEV) distribution as a model of the annual maximum of daily precipitation extremes at each grid point separately. The time series of annual maximum daily precipitation (with 27 data points for the period 1979-2005) is used to compute the parameters of a GEV using the maximum log-likelihood method. The block maximum (annual maximum in our case) of independently and identically distributed samples, regardless of the distribution of the population, follow the three parameter GEV distribution, \( G(\mu, \sigma, \xi) \), which is represented as:

\[
G(z) = \exp \left\{ -\left[1 + \frac{z - \mu}{\sigma} \right]^{-1/\xi} \right\}
\]

where \( \mu, \sigma \) and \( \xi \) represent the location, scale and shape parameter respectively of the distribution. For situations where \( \xi = 0 \), the function is interpreted as the limit of the equation as \( \xi \to 0 \) [6]. These parameters can be easily inverted to compute the more familiar return periods of extremes [6]. Here, we focus only on the location parameter of the GEV model.

Trends in extremes are generally established using non-parametric tests like the Mann-Kendall test [25], bootstrapping [17] or by modeling non-stationary GEV [3]. We use the latter method here. To represent non-stationarity in extremes in the GEV model of extremes, we introduce a time dependent term in the location parameter \( (\mu = \mu_0 + \alpha t) \) represented as \( G(\mu_0 + \alpha t, \sigma, \xi) \), where \( t \) represents a time index. The additional parameter, \( \alpha \), is also estimated with the maximum log-likelihood method along with the other three parameters. Previous studies have found that the non-stationarity of scale and shape parameters for climate extremes is not statistically significant [3], and we do not explore these here. The approximate distribution of GEV parameters is multivariate normal [6]. We thus use the standard error of parameter estimates to establish the significance of the linear trend (\( \alpha \)) in the location parameter using the two-tailed Student’s t-test.

3.2 Regionalization Framework

Statistical modeling of extremes suffers from small sample size. However, data from surrounding regions can potentially provide more samples given a homogeneous regional climate. We use a flexible region of influence approach as our regionalization method. Such regionalization frameworks have been used in flood assessment modeling, and have been described in detail in previous works [4]. Regionalization studies that exploit climate homogeneity to increase their sample size for precipitation extremes have focused primarily on weather station data [16, 8]. Here, we use a regionalization methodology loosely based on these previous studies but in the context of gridded model output and reanalysis data, where data from surrounding grid boxes, which may not be adjacent but with homogeneous climate are pooled with the grid box data for each year. The annual maximum for that grid point is then computed as the maxima of that entire pool. Thus, the annual maximum for a grid box with \( n \) contributing surrounding grid boxes is computed as a maximum of \( nx365 \) data points instead of just 365 daily values for
a non-leap year. A new data pool is generated for each grid box, thus obviating the need for creating fixed climate zones.

We define climate homogeneity of two grid boxes based on two metrics. A surrounding grid box is allowed to contribute to the pool of a grid box if their means are statistically equal (based on a two-tailed Student’s t-test at the 95% confidence level) and if their daily time series display a statistically significant linear correlation after removal of the annual cycle. Since precipitation is highly intermittent, we only use days where the precipitation is greater than 0.5mm/day to compute the mean and the serial correlation. We search for homogenous grid boxes within a 300km radius of the grid box, based on recent studies that suggest that daily precipitation has a length scale of a few hundred kilometers [11]. It should be noted, however, that individual intense precipitation events have a much smaller radius of correlation [9], but we here are only interested in gathering samples of potential extreme events.

High resolution model output of several years of simulation comprises a very large dataset (>20GB for global daily precipitation from a 25 year simulation). However, the regionalization framework is easy to execute in parallel as regionalization for each grid point can be conducted independently. We implemented such an algorithm in Python using the ‘mpi4py’ module for the above computation to effectively use a compute cluster. The GEV parameters were computed using the ’evd’ package in R.

4 Results

4.1 Stationary Extremes

Figure 2 shows the location parameter ($\mu$) of the GEV distribution for CPC, MERRA, T85 model ensemble mean and the T341 model ensemble mean. The location parameter represents the center of the GEV distribution from the origin. GEV parameters are estimated separately for each ensemble member and then aggregated to generate the ensemble mean. The largest extremes, as represented by the location parameter, are observed over the Northwest Pacific coast regions, the Sierra Nevada mountains and the Southeastern coastal regions. MERRA captures the extremes in the Northwest Pacific coast region but also displays larger extremes inland of the coast. It fails to capture the magnitude of the extremes in the Southeast US, as also noted in Fig. 1.

The T85 model captures the broad spatial pattern of the location parameters, but severely underestimates the magnitude of extremes over the Northwestern and Southeastern regions. The T341 model provides a significant improvement over the T85 model in capturing the magnitude of extremes over these regions. While it exhibits stronger extremes in the Northwest Pacific and Southeast US, it is still weaker than CPC data in some parts of those regions. Moreover, it is positively biased both inland of the Pacific coast similar to MERRA. It also overestimates the magnitude of extremes over the eastern half of the US. The overestimate in precipitation extremes over the eastern half of the US also exists in several high resolution regional models [22]. A similar bias also exists in a different version of the model used here (CAM5.0) which uses a different dynamical core and several different sub-grid parameterizations [23], but share the same deep convective precipitation parameterization, which was found to be over-sensitive to horizontal resolution [23].

The low resolution model represents the spatial average of precipitation over its grid box which is much larger than the CPC data and T341 model grid box. It thus does not represent the variability observed in high resolution data, but rather a spatially smoothed variability. Fig. 3 shows the GEV location parameters for the CPC data and T341 model ensemble aggregated
to the T85 model resolution. We conservatively map the precipitation data to the T85 grid before computing the GEV parameters. The T85 model captures the aggregated precipitation over the Northwest Pacific. But, over the Southeastern US the model underestimates the magnitude. The magnitude of extremes increase in the T341 model, improving on the T85 model over the Southeast but overestimating it over the Northwest, Central and Northeast US. Previous studies have found that precipitation extremes do not converge even as the resolution is increased to 0.25km [24], progressively increasing with resolution.

4.2 Non-stationary Extremes

Figure 4 shows the trend in the location parameters represented by $\alpha$ in the GEV model. For the model ensembles, the ensemble mean of $\alpha$ is shown. The null hypotheses that $\alpha$ is not significantly different from zero is tested based on a two-tailed Students t-test, and the regions where the null hypothesis is rejected at the 95% confidence level are hatched. The CPC gauge analysis only shows significant non-stationarity in the extremes over some regions in the
Western half of the US with parts of Nevada, Southern California, Northwest Pacific coastal regions, central Montana and Southern New Mexico exhibiting a negative trend. Significant positive trend is observed in Northern Idaho and parts of Western California. The MERRA reanalysis fails to capture the trend observed in the gauge analysis in the Western half of the US. However, it exhibits significant positive trends over large swaths of Central and Eastern US, where it is negatively biased in the mean as well as the extremes. CPC gauge analysis also exhibits these trends in most grid boxes, but these trends are not significant. A recent study finds similar trends in the observations with the eastern half showing largely positive trends and the parts of Western US showing positive trends [18]. A number of previous studies of trends in precipitation extremes over the US are largely based on large domain averages, where the conterminous US is divided into climate regions based on empirical orthogonal functions, and trends are evaluated based on century long data records. Thus, the results here are not directly comparable to those studies. On the centennial time-scales, those studies do not find a significant trend in the extremes over the Northwest region [10, 17]. However, significant trends were found over the Southern US [10, 17].

The T85 model exhibits weak non-stationarity over the US but does simulate the negative trend over parts of California and Nevada but these are not significant. The T341 model simulates stronger trends in these regions which are also statistically significant, particularly over Southern California, Southern Nevada and Western Arizona comparing well the CPC gauge analysis. The T341 model also simulates significant positive trends over parts of Texas, where CPC and MERRA also exhibit a positive trend. Over the Eastern US the model simulates weak negative trends, where MERRA exhibits significant positive trends.

5 Summary and Discussion

We examine the fidelity of high resolution climate models in simulating the extremes of precipitation over the continental US. We use a regionalization framework to compute the annual maximum precipitation time series for each grid box pooling data from temporally correlated neighboring grid points that are also statistically similar. Our analysis reveals that high resolution models substantially improves the representation of stationary extremes of precipitation over the Northwest Pacific and Southeast US, where the coarse resolution model simulates much weaker extremes than observed. Over the US, the high resolution model captures the declining
trends in the extremes over the Southwest US where the observations also show significant trends. The low resolution model displays weaker trends in the region. When compared to MERRA globally (not shown), the high resolution model only captures the non-stationarity over parts of the Indian sub-continent and Northern Australia, where they improve upon the weak positive trends in the low-resolution model. However, extreme precipitation estimates from observational data are only reliable for regions with dense station networks, like over the US.

Several climate phenomenon like El Nino, North Atlantic Oscillation, etc. are statistically related to remote climate extremes [3]. These teleconnections can be represented in the GEV distributions. Global climate models have the advantage of explicitly simulating global climate teleconnections as opposed to downscaling efforts with high resolution regional climate models. We plan to include indices of various climate phenomenon in the GEV distribution model in our fidelity examinations of the high-resolution climate models in the future and conduct a more global analysis using other global observational data like the CPC global data, Tropical Rainfall Measuring Mission (TRMM) data as well as reanalysis products. Further, threshold based GEV models also help to increase the extreme sample size as compared to the block maximum approaches used here. We plan to investigate these models in the future.

Figure 4: Non-stationary extremes. Same as Fig. 2 but for the linear trend in the location parameter of the non-stationary GEV model. Regions where the trend is statistically significant, based on a two-tailed t-test, are hatched.
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