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MODELING OF EXTREME RAINFALL PROJECTIONS OF INDIAN MONSOON UNDER CLIMATE CHANGE

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ABSTRACT

Extreme precipitations events are the most severe meteorological disasters and cause severe damages ecosystem, infrastructure, agricultural productivity. The Impacts of climate change are being investigated using General Circulation Models (GCMs). Since GCMs operate at coarse resolution, hence modified statistical downscaling is used for regional extreme projections at 0.25 degree resolution for Indian summer monsoon Rainfall (ISMR). Here, we use IPSL GCM from CMIP5 for extremes projections under RCP 8.5 scenario for future time periods (2020s, 2050s, and 2080s). We find spatially non uniform changes in future extremes projections under climate change for both Block maxima (BM) and Peak over Threshold (PoT) approaches. The study highlights the significance of managing the extremes in the future due to climate change and further studies are needed with usage of multiple GCMs for similar study.

KEYWORDS: Downscaling, CMIP5

Modeling of extremes is extremely a challenging research problem in hydrology considering the complexities involved in to it. As the factors affecting the extreme excesses are not clearly understood and methods for evaluation are still under developmental phase. Therefore, proper scientific study of extremes is necessary for proper planning and management of extremes events. Recent studies indicates occurrence of extremes have increased due to global warming/ anthropogenic activities [IPCC, 2013]. Although much progress in understanding the science of extremes modeling has been witnessing since the last two decades but there are still significant number of extremes are happening and causing huge losses to human life, infrastructure, industry, agriculture, ecosystem etc. at an unprecedented scales e.g. Mumbai floods in India 2005, Kedarnath (Uttarakhnad) floods in India 2013PROCEDURE FOR PAPER SUBMISSION

Considering the importance of extremes, several studies focused on understanding the nature and magnitude and frequency of extreme precipitation events using the General Circulation Models (GCMs) [Kharin and Zwiers, 2000; Kharin et al. 2007; IPCC, 2013]. However, GCMs ability to model extremes poses serious challenge [Mishra et al. 2014]. This is mainly attributed to the fact that GCMs operate at coarse spatial scales at which they are unreliable due to many reasons notably model convective parameter schemes [Westra et al. 2014]. Observations and climate model projections also reveal increases under warming climate for extremes [Kharin et al., 2007; Sillmann et al., 2013]. Since, changes in the frequency, duration and intensity (IDF) of extreme precipitation may have considerable impacts, therefore, accurate projections/predictions of future changes of extremes at local level are essential for policy interventions, decisions regarding mitigation and adaptation to climate change [Shashikanth et al. 2017].

There are two major downscaling techniques, viz dynamical and statistical approaches which are extensively employed by the researchers to extract the efficient final-resolution information from GCM outputs. Dynamical downscaling consists of running high resolution Regional Climate Models (RCMs) which makes use of lateral boundary conditions of GCMs, smaller scale physical processes to predict extremes (Schoof et al. 2013). The Dynamical downscaling is computationally intensive and whereas the statistical downscaling is highly preferred because of computational inexpensiveness and involves data driven philosophy for the establishment of statistical relationship between large scale predictors and predictand (observed rainfall). Although, both the downscaling techniques showed good skill in forecasting the mean precipitation, but for extreme precipitation, the skills are at lower side.

DATA AND METHODOLOGY

The data for the establishment of an empirical relationship between synoptic scale circulation patterns (predictors) and the local scale predictand is important for the realistic temporal projections of rainfall in the statistical downscaling (SD) method (Kannan and Ghosh, 2013). While modelling SD model, selection predictors of plays a very sensitive role. The guide lines issued by (Wilby et al 2004) are followed during the selection of predictors. Here, we use NCEP/NCAR reanalysis data (Kalnay et al 1996) as predictors and gridded rainfall provided by APHRODITE as predictand for establishing the relationship between

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predictors and predictand. The predictors are air temperature, wind velocities (U and V) at surface and 500 hpa pressure level and specific humidity 500hpa at pressure field and Mean sea level Pressure (MSLP). The rainfall projections are carried at 0.25 degree spatial resolution. In the current study, predictors based on works by Shashikanth et al. (2013), and Salvi et al. (2013) for Indian Summer monsoon Rainfall (hereafter, ISMR) are used.

GCM Data

For the present study IPSL-CM5A-LR-GCM has been used.

APHRODITE Data

The observed data for India at 0.25 degree resolution is obtained from Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation of Water Resources (hereafter APHRODITE), Japan is a daily gridded precipitation data covering more than 57 years of data (Yatagai et al. 2012).

Statistical Downscaling

Statistical Downscaling is a method which derives local to regional (10 to 50 km) information from the large scale climate predictors. In this method, the statistical relationship is established between large scale features (NCEP/NCAR) (Predictors) to regional-scale variables (Predictand in this case rainfall). Later, the same relation is used on GCM outputs to obtain predictand under the impacts of climate change for future. The present method utilizes the following methods to obtain the projections viz. Bias correction, K- mean clustering, classification and Regression trees (CART) and Kernel Regression (Kannan and Ghosh, 2013; Salvi et al. 2013). K-means clustering algorithm coupled with CART, is employed to for the generation of rainfall states using large scale synoptic scale circulation patterns. Conditional on the derived rainfall state, the kernel regression is employed for modeling the multisite rainfall (Kannan and Ghosh, 2013; Salvi et al. 2013). The methodology is applied separately to seven meteorologically homogeneous zones (Parthasarathy et al., 1995) in India.

The extreme rainfall projections are carried in the present study by means of two methods viz. Kernel Regression (KR) and Robust regression (RR), see the details in the Fig 1. The methodology developed by Shashikanth et al. (2017) and is used in the present study. Further details on the extreme rainfall projections can be found in the works of Shashikanth et al. (2017).

Kernel Regression

Generally, the relationships between extreme predictors (Climate predictors) and predictand (Extremes Rainfall) are highly nonlinear and to capture the relationship, nonparametric techniques such as K-nearest neighborhood (Mehrotra and Sharma, 2006) and kernel regression (Kannan and Ghosh, 2013, Salvi et al., 2013) are widely used. Here, we collect extreme series greater than the threshold (95% percentile) from each of grids (Ghosh et al. 2011; Vittal et al. 2013) and KR method only for extreme predictor-predictand combination series and project extremes.

Robust Regression

Robust regression is used when unusual or skewed/outliers are reported in the data set. Outliers are data points which do not follow the pattern of the other observations. The linear least squares estimate behaves badly in the presence of unusual data (Extremes) and the errors do not follow normal distribution. If the distribution of errors is asymmetric or prone to outliers, model assumptions are invalidated, and parameter estimates, confidence intervals, and other computed statistics become unreliable (Huber, 1972). Therefore, robust regression is employed which is not as vulnerable as least squares to heavy tailed data.

Extreme Value Theory (EVT)

The Extreme Value theory (EVT) is a strong statistical tool for analyzing hydrologic extremes (Coles et al. 2001). The two commonly used EVT methods viz. Block Maxima (Annual Maxima) using Generalized Extreme Value distribution (GEV) and Peak over Threshold (POT) using Generalized Pareto distribution (GP).

The block maxima approach in extreme value theory (EVT), consists of extraction maxima values based on annual maxima values. These annual maxima constitute a block maxima series. The block maxima method on the one hand misses some of these high observations and, on the other hand, retains some lower observations.

The main weakness of block maxima method is that it does not consider multiple occurrences of an extreme event over a particular threshold (Coles et al. 2001; Vittal et al. 2013). Therefore, POT method which takes in to account all extreme events crossing a threshold for the evaluation of 30 year return level flooding events. The peaks of extreme events (intensity) are analyzed using GP distribution.

RESULTS AND DISCUSSION

The statistical downscaling model developed by Kannan and Ghosh (2013) and Salvi et al. (2013) is used for the multisite rainfall projections on daily scale. The mean rainfall projections are very well modelled by the present method. Since all statistical downscaling models fail to model day to day variability that well and hence extremes are not well simulated by them. Therefore slight modifications are suggested for modelling of extremes (Fig 1).

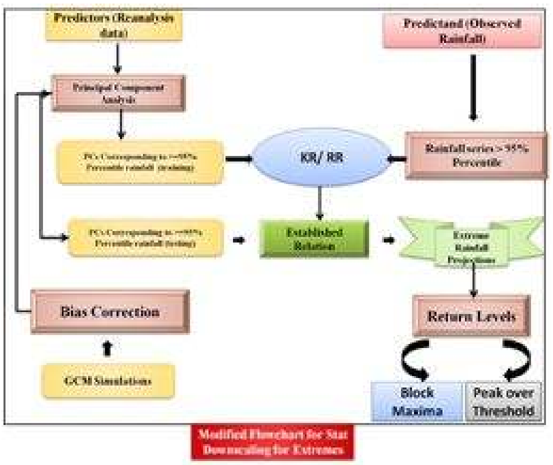

Figure 1: Algorithm for the simulation of extremes using two well known statistical robust methods BM and PoT.

In this methodology the extreme excesses of greater than 95% percentile are separated and an empirical relationship is established between extreme NCEP/NCAR extreme predictors and predictand (in this extreme rainfall). We followed the definition of extreme as rainfall exceeding 95 percentile rainfall values [Vittal et al. 2013; Ghosh et al. 2011]. The Kernel Regression technique is applied on the extreme predictors and extreme rainfall for the simulation of extremes, similar to as mentioned above. Assuming the relation holds good for future, the future simulations of the extremes derived using GCM predictors.

Secondly, we have also used Robust Regression (RR) technique for the simulation of extremes. In the RR method also, a relationship is established between large scale features of NCEP/NCAR predictors and regional scale predictand corresponding to extremes. Assuming the same relation holds good for future and extremes are projected with RLs are determined using block maxima and peak over threshold methods.

Hence, by fixing the minimum absolute percentage of criteria from KR and RR methods, revised estimates of NCEP/NCAR simulated extremes at 30 year return level show results being improved considerably/ reasonably [Fig 2 (b, d)] for BM and PoT methods with that of observed extremes for the corresponding 30 year return levels. Based on the same approach, we have regenerated the GCM simulated extremes with 30 year RL [Fig 3]. The absolute percentages of errors [Fig 3 (b, d)] results show good improvements. However, the absolute percentages of errors in the case of PoT method at some of nodes errors are high.

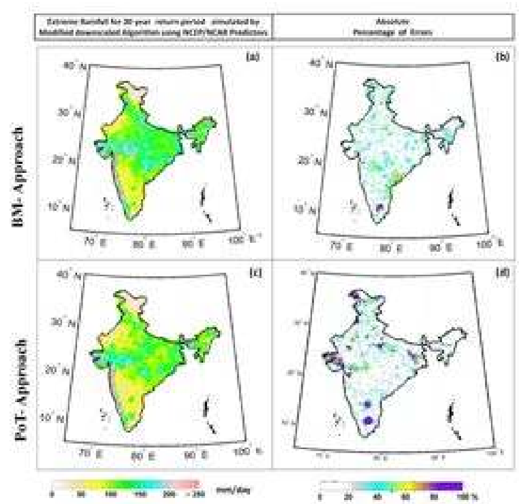

Figure 2: Spatial variation of simulated extremes using modified statistical downscaling using NCEP/NCAR predictors using BM and PoT approach.

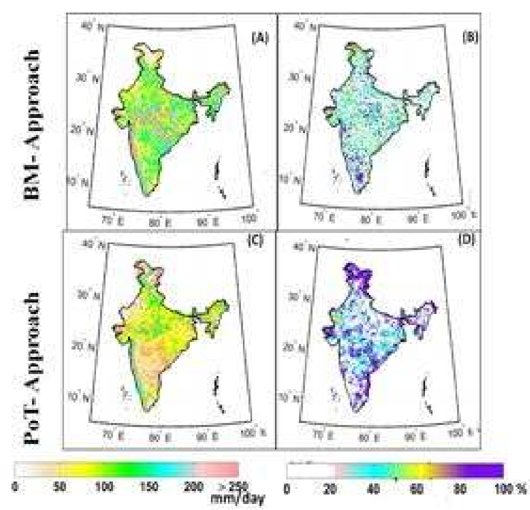

Figure 3: The simulated extremes using modified statistical downscaling algorithm (Shashikanth et al. 2017) for GCM predictors.

To consider the plausible changes in future extremes, we consider the worst case scenarios for IPSL CMIP5 model under RCP 8.5 scenario (Fig 4). The spatial patterns of changes in extremes are presented in Figure 4. We find the non-uniform increase in extremes for future period [2081-2099] with respect base line period [1981-2000]. The future changes in extremes do not show uniform increases but are limited to few regions in India and the results is in consistent with Ghosh et al. [2011] Mondal and Mujumdar [2015]; IPCC [2013]. We notice from the results (Fig 4) that Block Maxima (BM) shows increase in extremes in central, South, Gujarat, West Bengal and North east India and West coast of India.

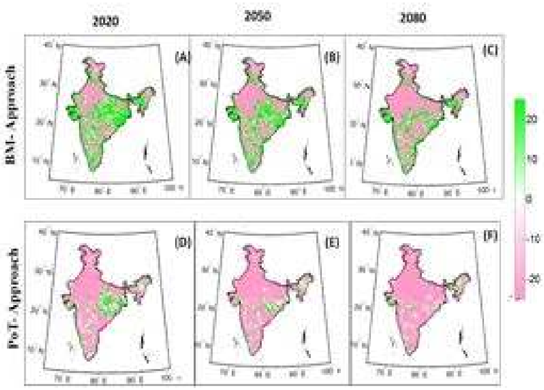

Figure 4: The Changes in 30year RL extreme precipitation during historical (198-2000) and future (2081-2100) for BM and POT approaches using modified statistical downscaling for IPSL GCM.

The results of changes in extremes for different time windows 2020s (2010-2040), 2050s (2041-2070) and 2080s (2071-2100) suggests decreases changes in extremes from 2020s to 2080s. This needs to be further explored. Since the usage of single GCM in climate trajectory projections may sometimes produce misleading information (Ghosh and Mujumdar, 2006). However, this is the main limitation of the present work. Similarly, the projected changes in return levels as obtained with PoT (Fig 4 D, E, F) exhibit spatially non-uniform changes as those obtained with BM (Fig. 4 A, B, C). Here, the increase is less prominent compared to BM. The differences in the results obtained from BM and PoT show that Block maxima probably do not consider the extremes occurring in the entire season and consideration of such cases needs PoT approach. Significantly, the extreme projections for different time windows 2020s (2010-2039), 2050s (2040-2069) and 2080s (2070-2099) are gradually decreases with the lead time (Fig. 4). Although, with increase in global warming, no doubt increases extremes [IPCC, 2007] are limited to few regions in India, but No uniform increases are found in the current study (Shashikanth et al. 2017).

CONCLUSION

Projections of rainfall extremes are a major research challenge in climate science considering the challenges it poses and still it is even more complex for ISMR. The results from the present work can provide some basic strategies in countering the menace of extremes. In the downscaling of the extremes, the local factors such as urbanization and deforestation which play significant role have not been considered and would form the future scope of study from the present work.

The results show that in the future the extremes are heterogeneously poised across Indian region and this will form a valuable input to study the impact of climate change on local hydrology for the management of extremes.

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