Attribution of Climate Change and Climate Variability to Extreme Rainfall Frequency in Contagious United States

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ABSTRACT

This study relies on a systematic analysis to investigate the time space structure of extreme events, over 115 years of rainfall data, in 1244 high quality stations across the United States. The random variable applied in the model is the number of days with a rainfall above 95-percentile of the whole period of record. In this study, a Bayesian multilevel model which is hierarchically characterized by regional properties of each stations is employed to examine a series of hypotheses and explain the trend in rainfall extremes using Global near Surface Temperature (GST) as a proxy of climate change and combination of four different cyclical climate modes (i.e. ENSO, NAO, PDO, AMO).

INTRODUCTION

The casual learning structure shapes this study to identify the different modes of oscillation and their corresponding spatial influence, through the gradual inclusion of climate variables into the inference of Bayesian model. Within each stage of modeling, de-trending the natural cycles help to find the footprint of climate change on the residual noise. It is also implying an intensive signal analysis along with the application of Principal Component Analysis (PCA) to identify the major areas of climate influence, temporally and spatially across the U.S. and correspondingly compare them with the output of the model. Such an approach was adopted to bring the fourfold objectives to the focus of interest: (1). To compare the contribution of climate change and modes of variability in each climate region, (2). To understand the role of each mode of oscillation in a hierarchical structure, (3). To describe and visualize the main external and internal mechanism in extreme rainfall frequency, (4). To build a framework for frequency analysis, and integrate the signal analysis with quantitative approach. The random variable applied in the model is the number of days with rainfall more than 95-percentile of the whole period of record (hereinafter, Count Analysis).

METHODOLOGY : FREQUENCY INDEX

Extreme Event Frequency Index. Following the practice applied by Cioffi et al., this study adopted a fixed-percentile threshold over total daily precipitation data of each station, considering only non-zero values:

$$f_{jt} = \sum_{i=1}^{ny} I(P_{ijt} > Th_j)$$

Here j , t and ny index the station, year and the number of days in the year, respectively. P_{ijt} is the daily rainfall and Th_j the threshold in station j. $I(\,)$ takes the value 1 if the argument is true and 0 otherwise.

Figure 1. the location of station, and their size distribution

METHODOLOGY : SYNTHETIC DATA EXPERIMENT

we set up an experiment and examined the trend training in a causal learning framework. Four different waves with periodical cycles of 4, 10, 30 and 100 years were considered and a 10000-size data was produced:

$$\lambda = \alpha + \beta_1.T + \beta_2.W_{T=4} + \beta_3.W_{T=10} + \beta_4.W_{T=30} + \beta_5.W_{T=100} + error$$

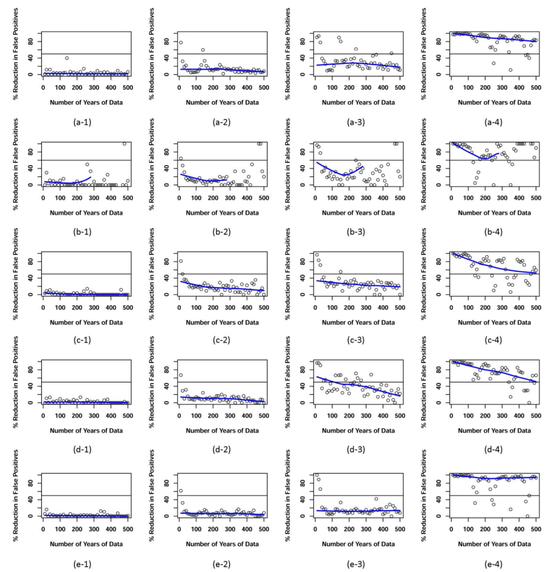

Figure 2. The rows refer to different scenarios to generate the synthetic data; (a). if the coefficients for all of the cycles is equal, (b). if the impact of 4-years cycles is twice the others. (c). if the impact of 10-years cycles is twice the others. (d). if the impact of 30-years cycles is twice the others. (e). if the impact of 100-years cycles is twice the others. Also, the columns present the decomposition of different cycles; (1). Only 100-years cycle, (2). 30+100-years cycles, (3). 10+30+100-years cycles and (4). All the cycles. The blue line represents the overall trend in reduction rate. The black line is a reference line to compare effects of decomposition.

METHODOLOGY : MODEL DEVELOPMENT

$$Data\ Level:\ Y(j,t) \sim Poisson(\lambda_t^j)$$

where $Y(j,t)$ is the observation of the count analysis at station j at time t and λ_t^j is Poisson regression coefficient; j indexes the station and t the year. The structure levels of model was defined as following:

$$log(\lambda_t^j) = [\alpha_j + \beta_j^1.T + \beta_j^{2:5}.X_t\,]$$

$$X_t = [ENSO\,, NAO\,, AMO\,, PDO]_t$$

The values for $\beta_j^{2:5}$ is updated by using a multivariate normal distribution.

$$\beta_j^i \sim MVN(\mu_\beta^i, \Sigma_\beta) \mid \Sigma_\beta = Inv - Wishart_\nu(\Lambda)$$

$$\beta_j^i \sim MVN(\mu_\beta^i, \Sigma_\beta) \mid \mu_\beta^i = a_2 + b_1^i.Elev_j + b_2^i.\overline{P}_j + b_3^i.CV_j$$

RESULTS : CASUAL LEARNING - ONLY TIME TREND

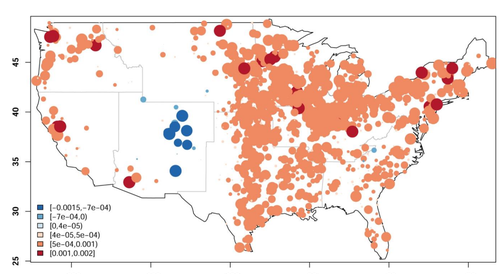

Figure 3. The median of β_1^i values (Time-Trend association)

Under H_0 scenario, it is assumed that there is a time-trend in frequency of extreme events and the Bayesian model is not informed with any climate index. To validate the first hypothesis, a number of PCA/Wavelet analysis are performed and compare with the results of model. Obviously, the exogenous effect of climate change, replicated in time-trend association of the model, can be partly or fully justified with large climate mechanisms. Under a series of new hypotheses, this supposition is examined and the model is gradually getting informed about different modes of climate.

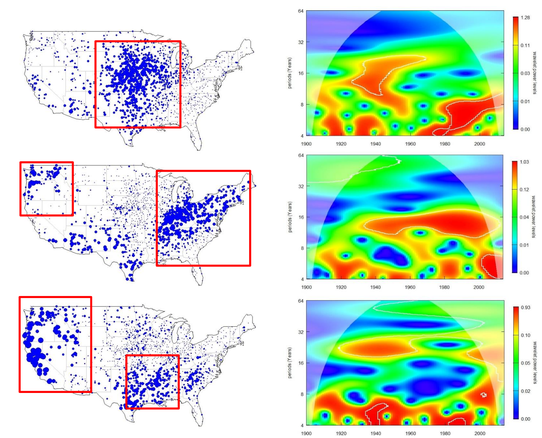

Figure 4. the eigenvectors for PC1, PC2 and PC3 and their Wavelet power spectrum (from top to bottom)

RESULTS : CASUAL LEARNING- CLIMATE INFORMED

The climate inclusion, from higher frequency to lower frequency: With H1 hypothesis, only ENSO, With H_2 hypothesis, ENSO and NAO, With H_3 hypothesis, ENSO, NAO and AMO, With H_4 hypothesis, ENSO, NAO, AMO and PDO climate index are added. Consequently, the reduction of time-trend respond, compared to only time-trend scenario (H_0) is evaluated.

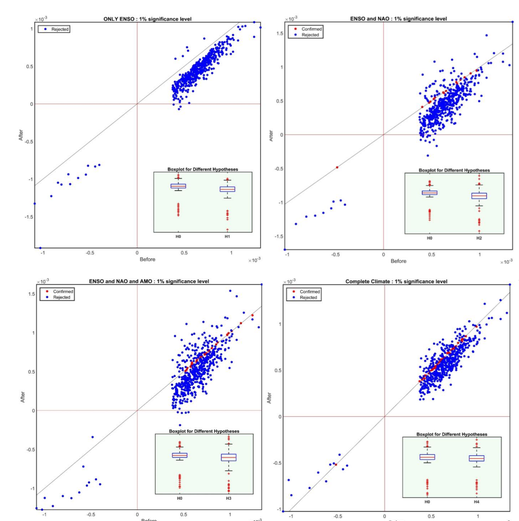

Figure 5. The reduction in respond of the model to the time, under H_1, H_2, H_3,H_4 hypothesis

SUMMARY

we performed two groups of analysis: qualitative trend analysis of rainfall extreme frequency and quantitative evaluation of time trend respond, in a hierarchically structured model; to recognize spatial grouping of stations across the US, secondly facilitates the study to rank the different mechanism regarding their contribution to the different sources of variability.

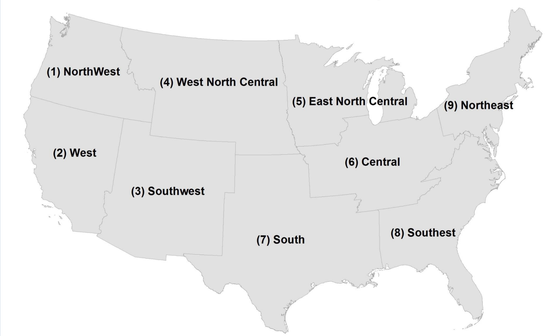

Figure 6. Different climate region of United States

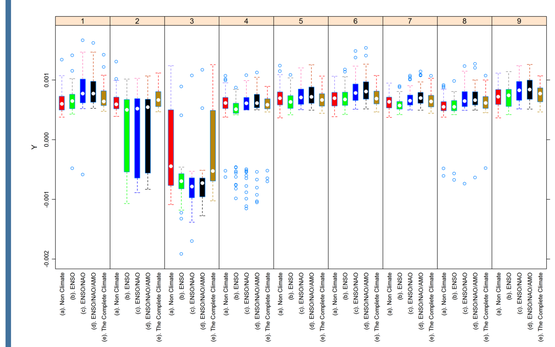

Figure 7. to compare the time-trend association for stations in each climate region. Each block presents the alteration in the median of β_1^i , once the model is driven under different hypotheses.

- Except for Northwest and Southeast, in all the other climate regions, the addition of ENSO reduces the time-trend responds. As per our preliminary results on PCA time-trend analysis suggest, any time dependent trend in extreme rainfall events, partly shares explanation with variability of ENSO.
- In West, while the effect of ENSO expands the range of time trend and significantly lower the values, PDO show a counter effect and moderate the respond. For Southwest, the same duality is evident in the reverse order, where ENSO moderates the coefficients and PDO interrupts the uniformity of region's respond once again and increase the overall values.
- The addition of NAO and AMO in the near Atlantic regions (Northeast, Southeast, Central) increase the time association and in near Pacific regions, where they are negatively associated to extreme frequency, reduce the values.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge support from NOAA under grants NA11SEC4810004, NA12OAR4310084 and NA15OAR4310080. All statements made are the views of the authors and not the opinions of the funding agency or the U.S. government.