Stochastic and deterministic aspects of observed seasonal-mean precipitation variations and extreme event occurrences over the United States

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Research questions
Where and when can we predict changes in climate better? Where and when is it fundamentally stochastic?

Premise
The observed interannual variance in monthly, seasonal, and annual precipitation occurrence is much higher than can be explained by purely stochastic, stationary processes. [1]. This unexplained variance suggests processes and drivers that have the potential to be separated from the stochastic part of precipitation: potential predictability [2,3].

Our approach is to separate and model the stationary stochastic components and then determine how much variance remains unexplained. By modeling each day of the year individually using weather station data, we can assess spatial and seasonal patterns in interannual variability.

Methods

Our historical record data is drawn from NCEP Reanalysis (Fig. 1) only stations that are more than 85% complete over at least 50 years are analyzed.

We use variable-order Markov chains to recreate the patterns of stochastic behavior in the observed data:

Ex: If it doesn’t rain Dec 7-8 in Tucson, how likely is it to rain on the 9th?
Ans: About 9%. If it does rain on the 8th, the likelihood increases to about 40%.

It is important to decide how many days of memory should be used. Additionally, to better determine transition probabilities between precipitation patterns and to better capture the likelihoods of rare events, it might be beneficial to pool the precipitation of neighboring days. To determine the appropriate chain order (memory) and pooling we use the Akaike Information Criterion (AIC) [5].

AIC and Models
By using the AIC to select model chain orders and pooling, model complexity can be determined without introducing artificial variance due to overfitting. For each day, models are created with different chain orders and pooling sizes, fit to the historical occurrence patterns, and the best model is selected using AIC. For each station 1000 simulated time series are then created using the appropriate (variable) memory transition probabilities, both of which are functions of the day of the year. Average daily occurrence frequencies are identical between the observed and simulated datasets, but variance is smaller for the stationary models. Figure 2 shows an example of the impacts of climatic forcings and long-term trends upon precipitation statistics.

Results
Potential predictability as defined by unexplained variance can be expressed in many ways. Here we present the unexplained variance as the number of wet days in a year, as well as the unexplained variances in the number of wet days for December-February and June-August.

Those areas with a high percentage of unexplained variance are poorly explained by a stationary model and thus are good candidates for improved predictability arising from long-term trends, period climate forcings, or internal feedbacks. The most notable areas of high potential predictability are those along the Great Lakes, Appalachian Mountains, and Four Corners regions. Also notable are the highly stochastic regions shown in the maps, particularly along the West Coast. In these areas, there may be little room for interannual prediction, although seasonal trends are clearly evident on shorter time-scales.

References

Additional information
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Questions related to the research are encouraged and can be directed to Dan Gianotti:
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