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DAILY SCALE MEMORY IN PRECIPITATION FOR IMPROVED CLIMATIC NULLS

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***Abstract*—Weather and climate prediction rely on inherently different predictors at different time scales. Some of the variability in precipitation on climate time-scales (i.e., interannual) could be attributed to accumulated noise on weather (i.e., daily) time-scales. To determine a lower bound on how much climate variability is due to processes at climate time-scales, weather generator models with no mechanism for interannual variability aside from short term (weather-scale) memory structure are created as nulls against which to compare the observational record of precipitation variability. These models can then be used to assess potential predictability in the observational record as well as in Global Climate Models, even at different spatial scales. Initial comparisons are presented.**

I. MOTIVATION

The predictors of future precipitation at weather (hours to weeks) and climate (years to centuries) time-scales are quite different, due to the strong persistence of atmospheric conditions at weather time-scales and the chaotic trajectories of atmospheric systems on climate time-scales [1]. Processes that are somewhat predictable in either time-scale may be modeled as stochastic noise at another; for example, the empirical climatology of ENSO states that might be used in a daily weather generator model (WGM) or a binomial distribution of annual wet days that might be used for climate simulation.

When attempting to determine the relative influences of weather time-scale processes and climate time-scale processes on the total variability of precipitation, we are often limited at the low-frequency end by lack of data to differentiate trends and quasi-periodic processes. At weather time-scales, however, the observational record of the last century provides sufficient data for fairly sophisticated models of precipitation and its memory structure. We make use of this rich data source to create models of precipitation variability at weather time-scales under the (false) assumption of a stationary climate [2]. Discrepancies between our "no climate" models and the observational data used to fit those models give us a metric for how poor that assumption is, and thereby a means for estimating the contribution of weather-scale and climate-scale processes to the total variability of precipitation.

Beyond simply classifying the weather/climate variability fractions at locations with surface observations, this separation of time-scales gives a means for calculating potential predictability of precipitation on climate time-scales (akin to signal-to-noise comparisons) [2], [3], and for comparing the relative strength of weather-scale processes and climate-scale processes in the observational record as compared to simulations from global climate models.

II. METHOD

To determine the memory structure of local, climate-stationary precipitation, a suite of probabilistic models are designed to represent the joint probability of multi-day precipitation events. As a generalization of the autoregressive framework, daily precipitation is assumed to vary probabilistically with previous days' precipitation values (see Figure 1). By representing probability densities as Gaussian Mixture Models (GMMs), analytic solutions to marginal and conditional densities can be determined as well for easy fitting and simulation. Two methods are attempted–one in which GMM components are truncated to force non-negative values and zero-variance (delta function) components are used to represent dry days, and one in which precipitation is transformed through an empirical inverse cumulative density function (CDF) transformation and then fit using more typical GMMs to reduce the number of necessary parameters.

Models are fit for each day of the year, with values pooled in a window around the day in question to increase data volume, and for each location in the United States Historical Climatology Network [4]. Model selection and appropriate memory structure is determined using the Akaike Information Criterion [5]. Simulations of the observed record of daily precipitation are then created using the model which recreate the observed

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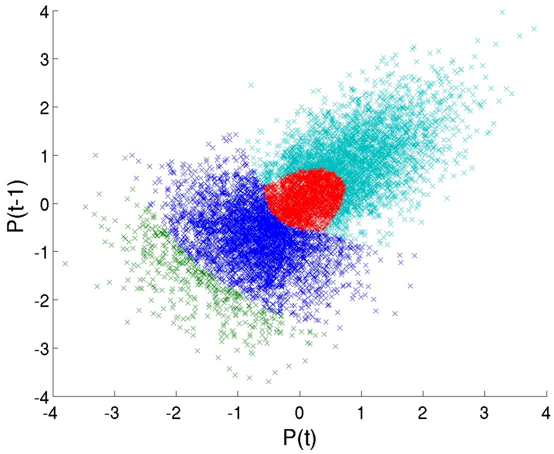

Fig. 1. CDF-transformed precipitation represented as a mixture of jointly Gaussian PDFs for a single day's rain and the previous day's rain. This represents a 1-lag model, similar to an AR(1) process, but with more opportunity to represent complex temporal dependence.

memory structure and the observed daily statistics (mean, variance) for each day of the year. Because of the interannual stationarity assumption, however, the model underestimates the interannual variability of accumulated precipitation at periods longer than the memory of the model (i.e., seasonal to annual totals). The difference between the interannual variability of seasonal totals from ensembles of simulated precipitation and the observed record then shows what portion of interannual variability could, as a null assumption, be attributed to high-frequency, weather-scale processes, and what additional variability–not represented in the model–must be due to lower frequency processes.

III. EVALUATION

After comparing the two methods, we find that the CDF transformed mixture model framework can capture the full temporal structure of the more complex truncated GMM model by allowing more mixture components due to increased degrees of freedom. Both models are designed to allow comparison of datasets with vary different rates of precipitation occurrence, and so are particularly useful in comparing data across measurement scales (i.e., station data with gridded products and GCM simulations). We present scale comparisons as well as comparisons of potential predictability from observational data with GCM historical run output.

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