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Multi-scale inverse modeling of precipitation: Model development and applications

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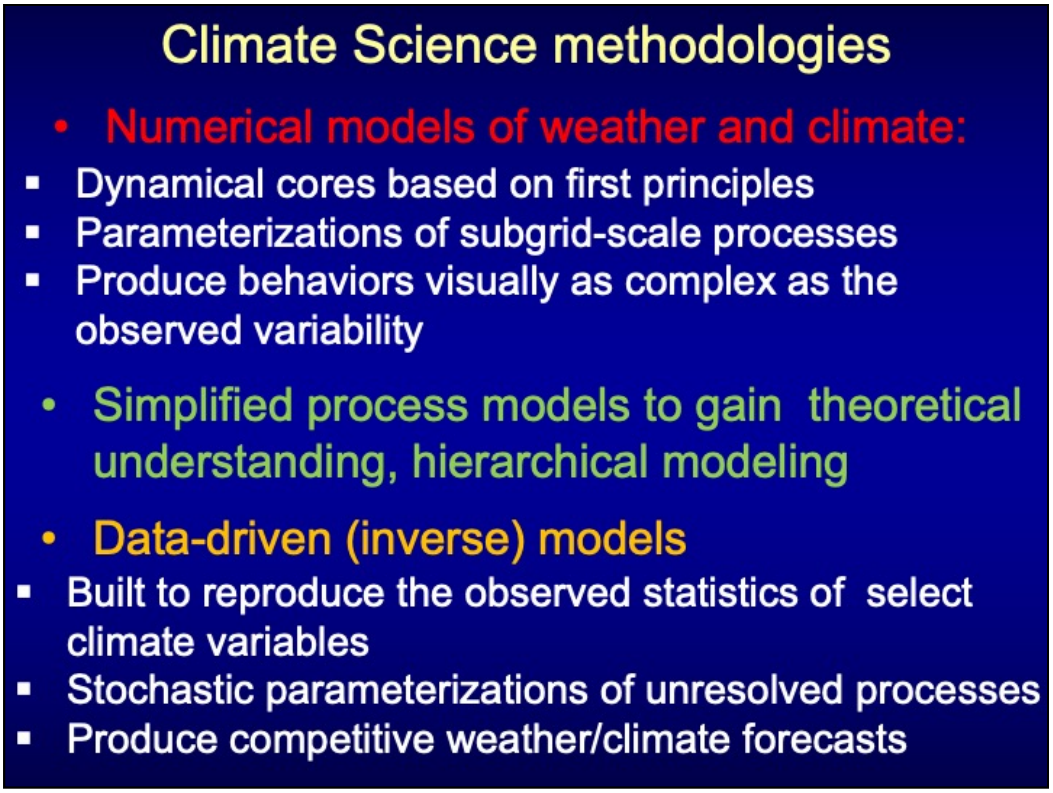
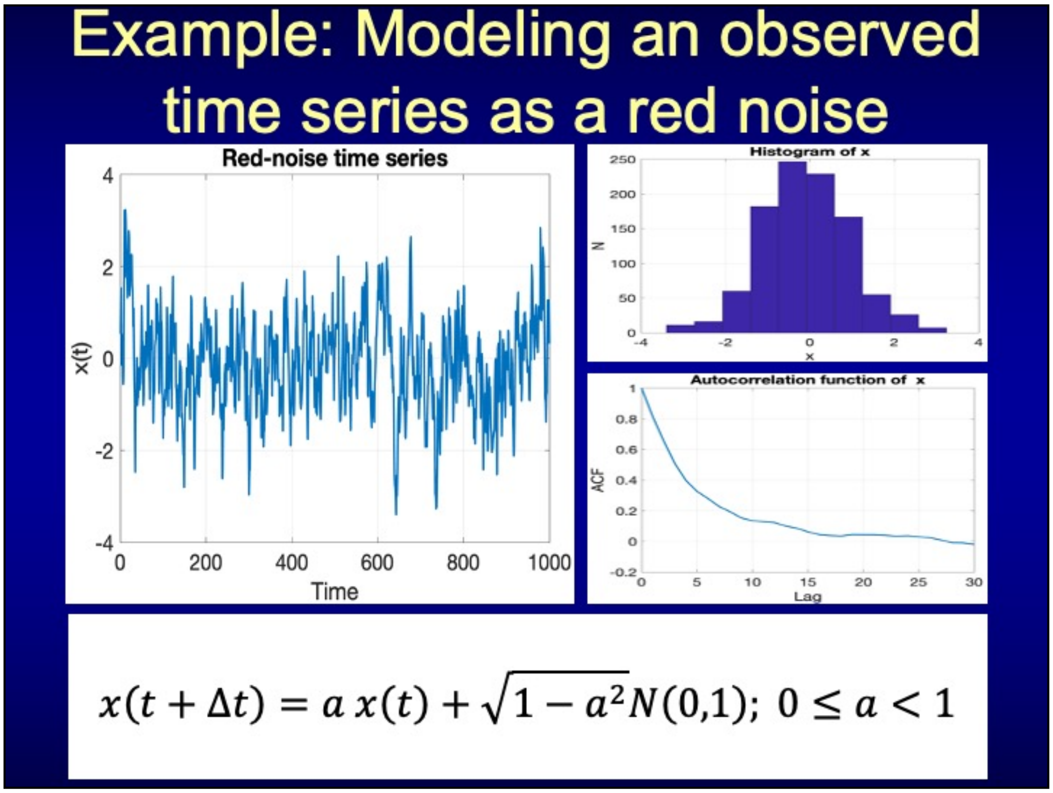
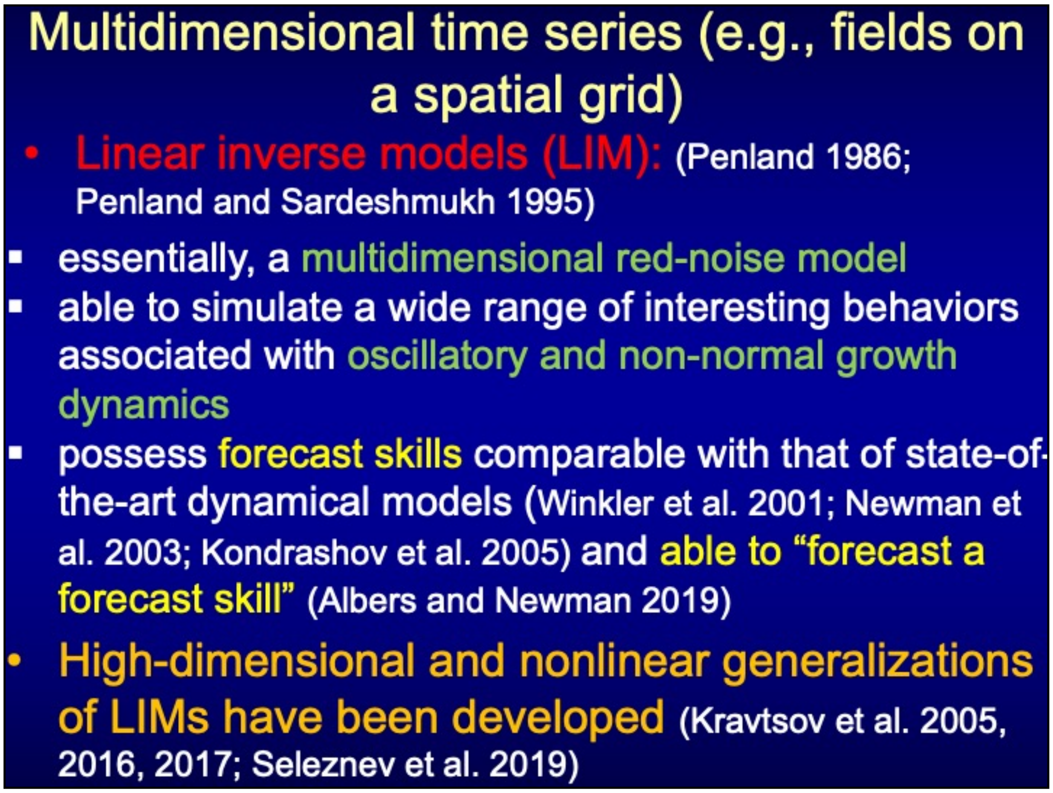


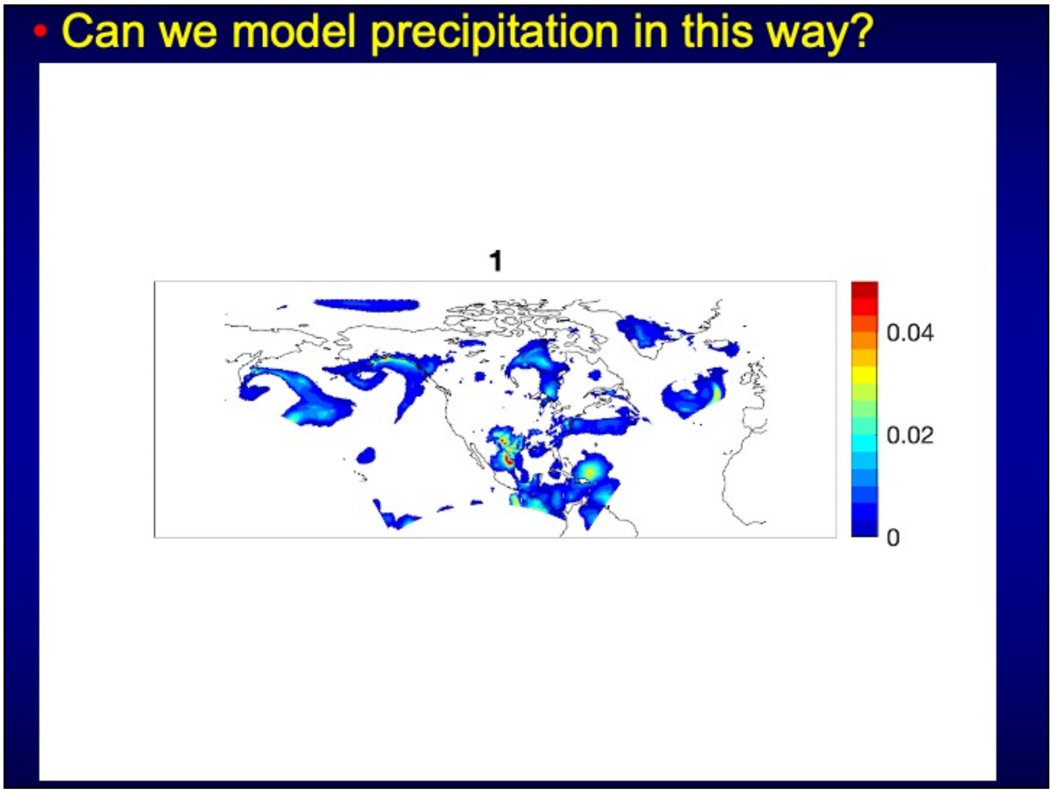
This talk will concentrate on some of the data-driven climate modeling methodologies.



For example, if an observed time series has an estimated PDF and ACF like the ones shown in this slide (Gaussian-like PDF, exponentially decaying ACF), it can be modeled as a red-noise process driven by a Gaussian white noise. This equation, if trained on a fraction of data, can be used for out-of-sample prediction of the remaining (or future) data. Red noise turns out to be a good zero-order model for the variability associated with many climatic phenomena.



The idea of parametric stochastic modeling of observed time series has been further developed and applied to multidimensional data.

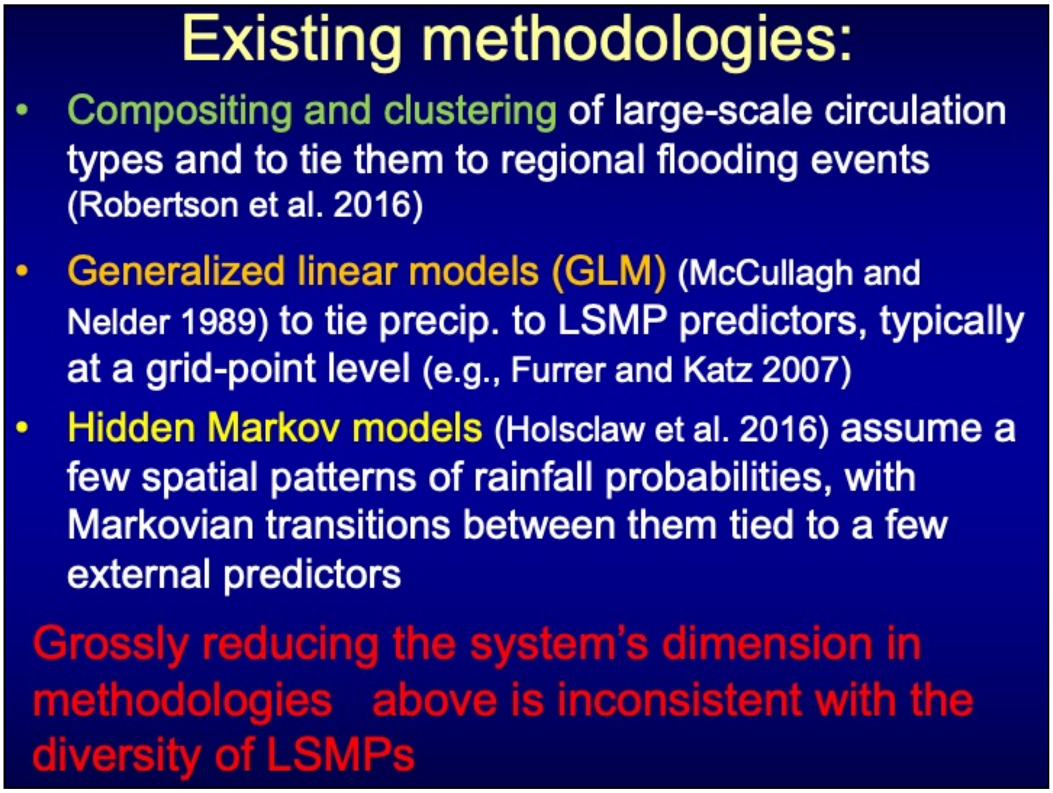


The LIMs above have been successfully applied to model fields with “continuous” time series, such as temperature or streamfunction. The possibility of a direct application of this technique to model positive definite, intermittent precipitation field is not obvious. The animation of this slide illustrates the observed evolution of daily precipitation around North America in the summer of 1979.

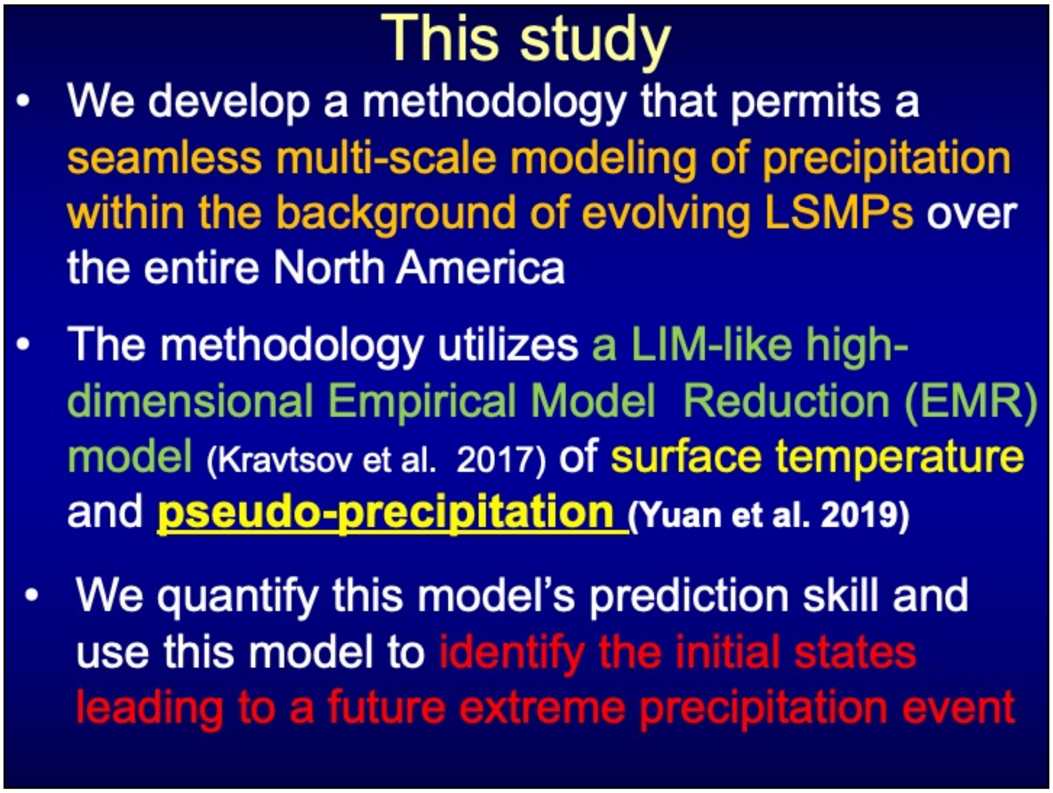
Statistical modeling of precipitation

- A snapshot of daily precipitation is a sparse map with a lot of empty space and embedded multi-scale features
- A time series of precipitation at a point is intermittent; the associated PDF is strongly non-Guassian
- Statistical prediction of precipitation is based on the association between extreme precipitation and recurrent large-scale meteorological patterns (LSMP) (Grotjahn et al. 2016). A great diversity of LSMPs exists over North America (Barlow et al. 2019)

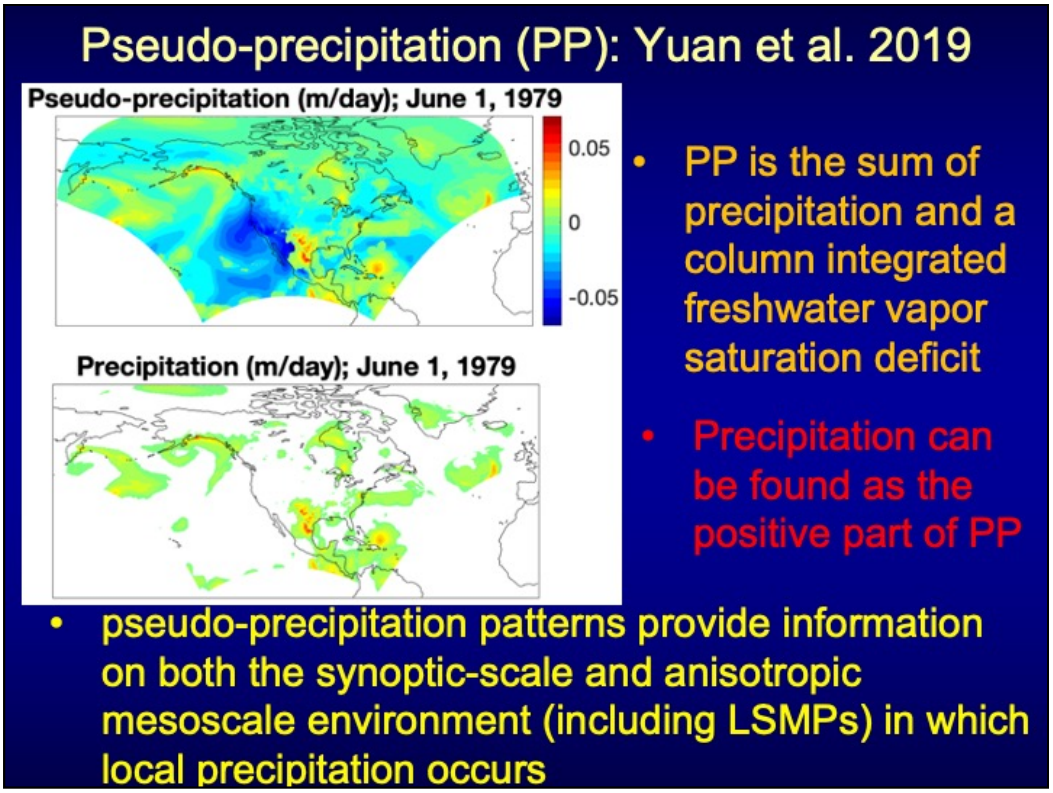
Statistical modeling of precipitation is a challenging multi-scale problem.



The existing methodologies for statistical modeling of precipitation involve, in one way or another, a built-in gross reduction of the system's dimension, inconsistent with a great diversity of precipitation systems and LSMPs. This essentially enforces the application of these models at a local-to-small-region level. We propose an alternative methodology, which permits a seamless multi-scale modeling of precipitation within the background of evolving LSMPs over the entire North America.



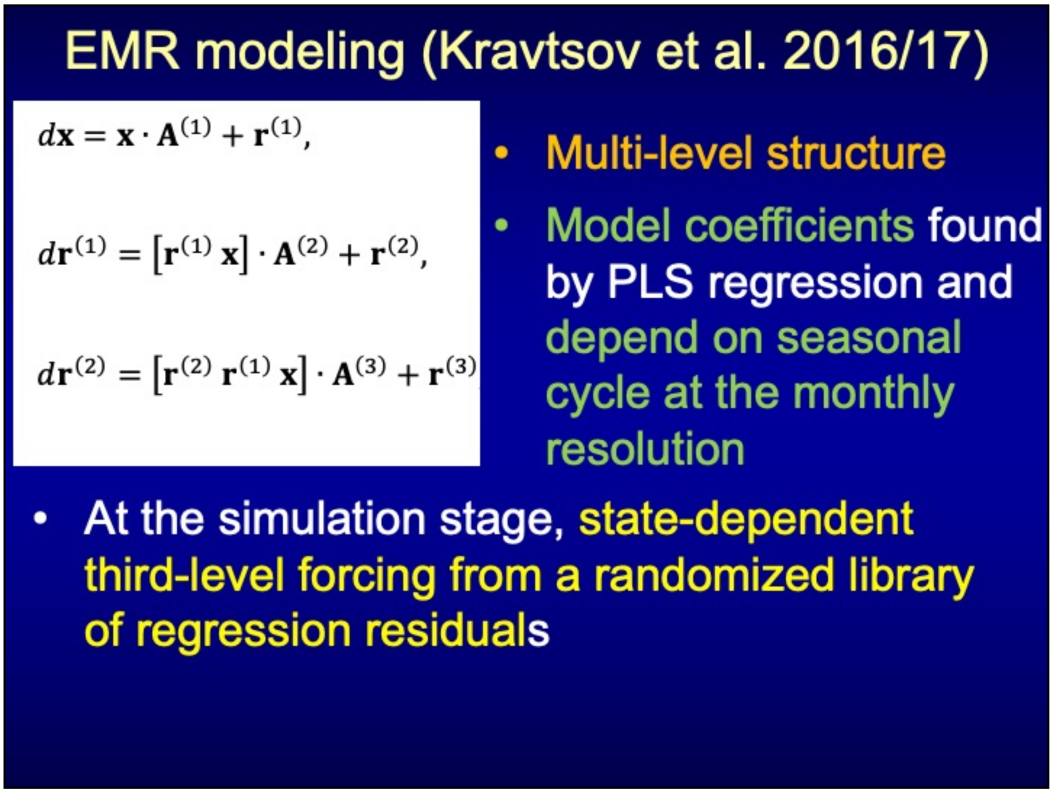
We utilize a previously developed LIM-like high-dimensional EMR model to model precipitation. The key idea is to replace the precipitation field with the so-called pseudo-precipitation.



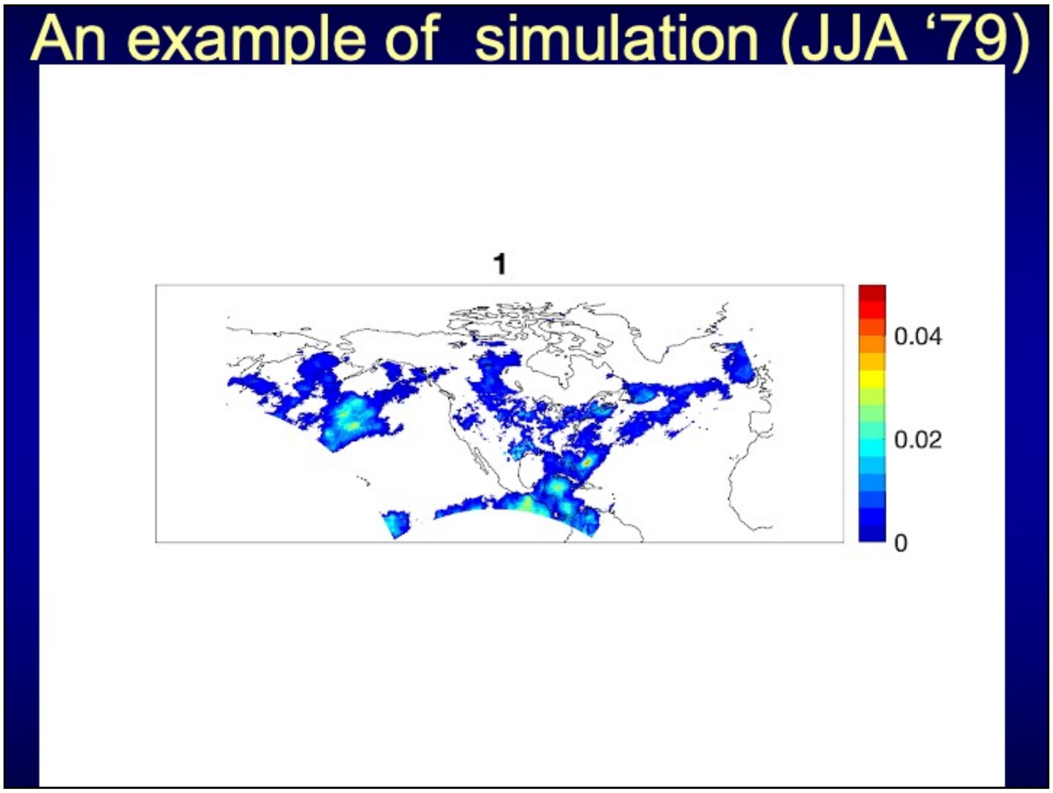
The PP field incorporates the information about both precipitation, which can exhibit small-scale intermittent structures, and multi-scale synoptic environment; it thus provides a promising, yet unexplored way to characterize and predict, statistically, wet and dry weather conditions. One of its attractive features is that the distribution of PP, unlike that of Pr, is a single-mode, two-tailed distribution, which makes PP more similar to other dynamical and thermodynamic variables describing atmospheric state. *This opens up a possibility for using standard methodologies developed previously for temperature and flow-field analysis and modeling (CCA, LIMs) to analyze and model pseudo-precipitation and, hence, its positive part associated with the actual precipitation.* The figure in this slide is based on NARR reanalysis (http://www.esrl.noaa.gov/psd/data/gridded/data.narr.html); Messinger et al. (2006).

Data and procedure

- North American regional reanalysis (NARR) (Messinger et al. 2006) **daily** T2 and PP data 1979–2020
- Data compression: 3000 leading common EOFs of T2/PP accounting for >95% of total variance of the **1979–1999 anomalies** with respect to seasonal cycle
- Build EMR model, produce surrogate precip. sequences for 1979–1999, compare statistics
- Produce precip. hindcasts for 2000–2020 period, estimate skill.



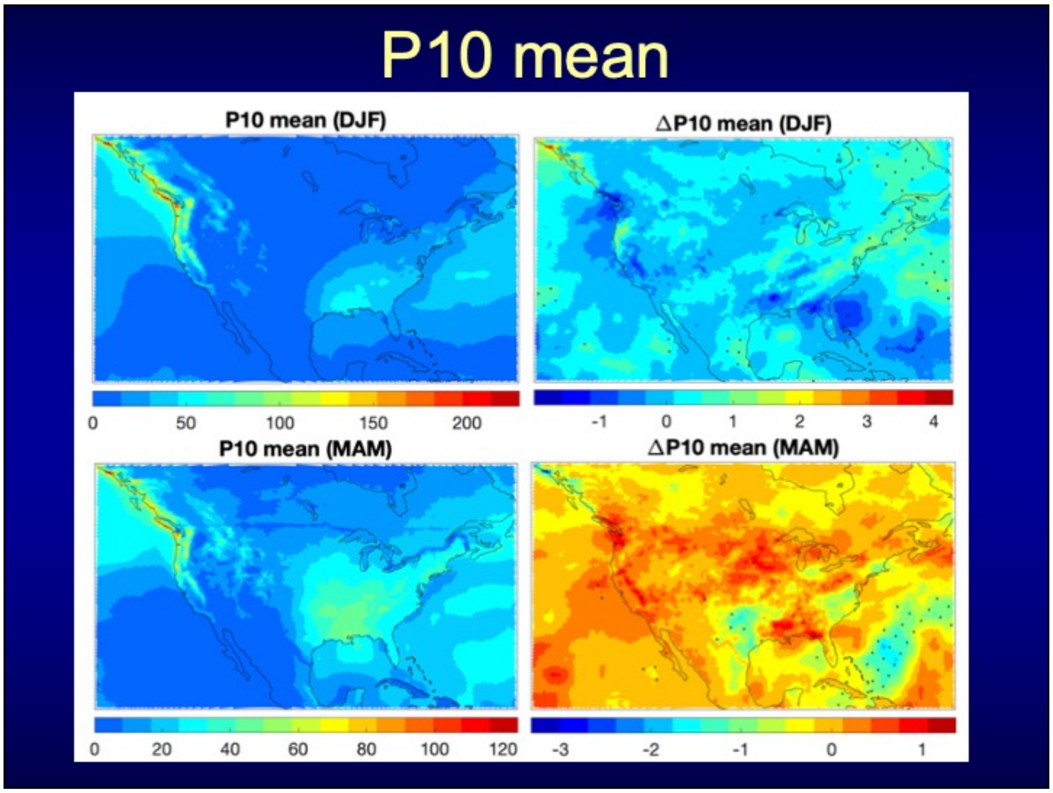
With x denoting the state vector to be modeled (in our case, 3000 PCs of T2/PP), the EMR model features a multi-level structure with hidden variables formed by a given level's regression residuals, seasonally dependent propagator and a state-dependent random forcing.



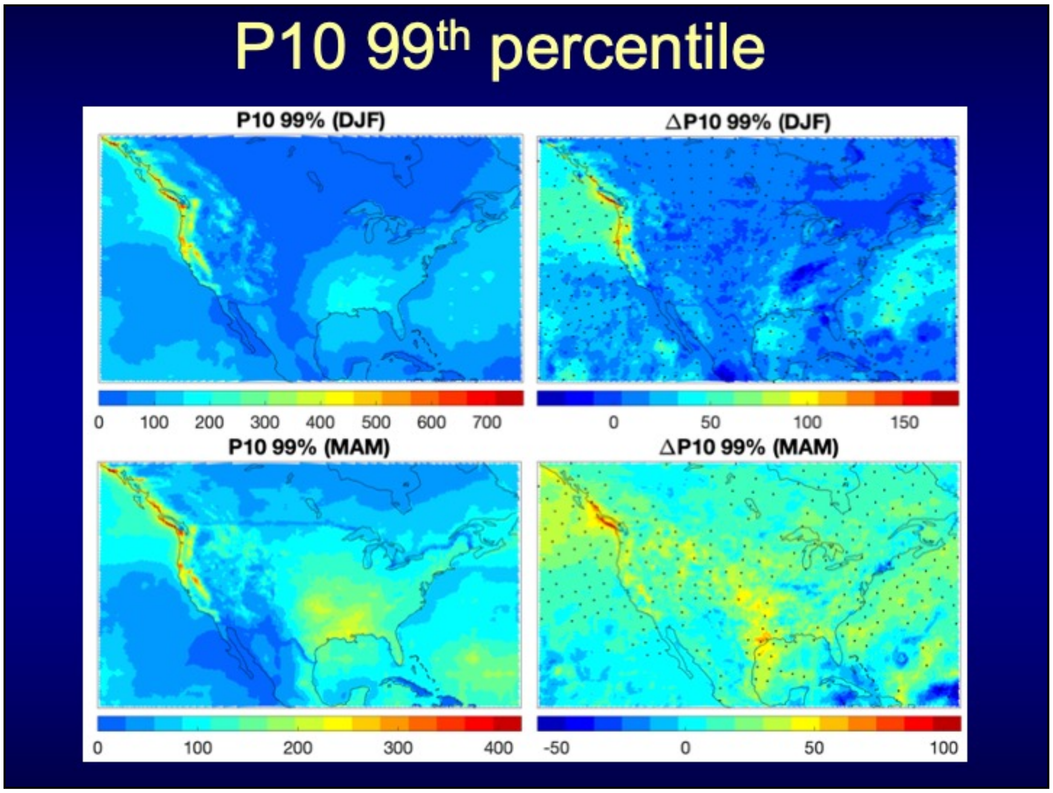
The simulated precipitation fields look fuzzier than the NARR output but are otherwise visually similar in terms of spatial scales and propagation sequences.

Properties of simulated 0–10-day total precipitation (P10)

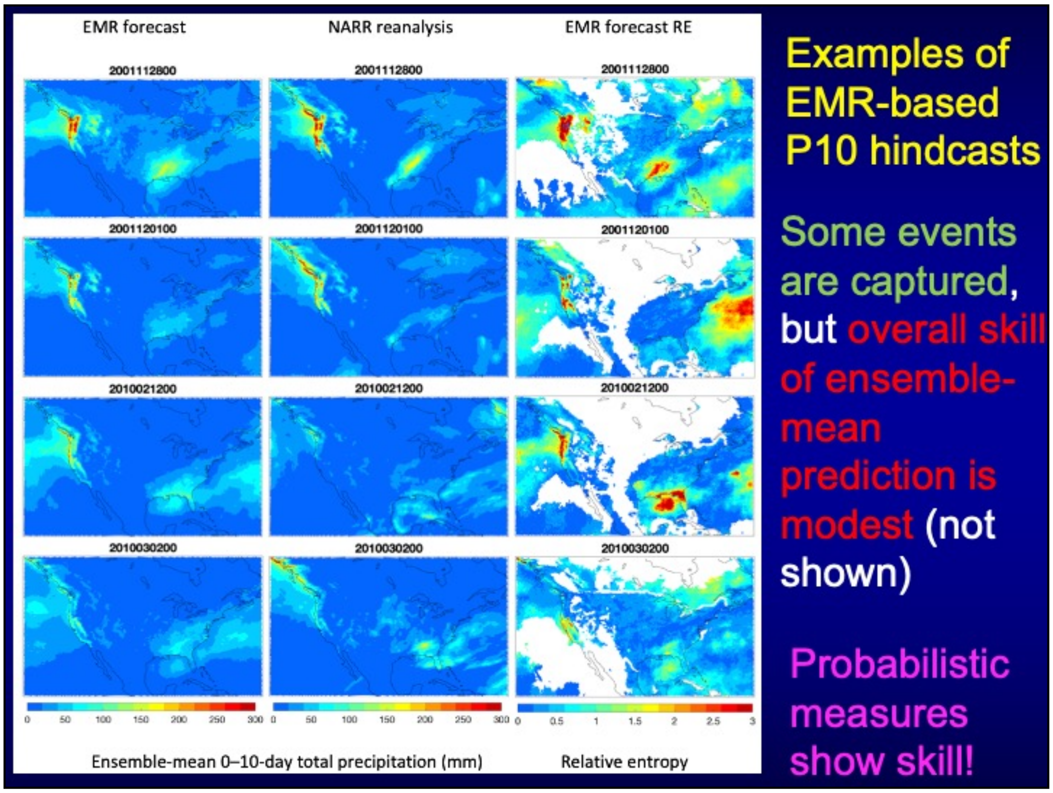
- We'll further concentrate on the P10 quantity, which is a proxy for a high-risk flooding event
- The PDFs of 1979–1999 simulated P10 are a good match to observed distributions (next two slides)
- We will also discuss, after that, EMR's P10 hindcasts over 2000–2020 period



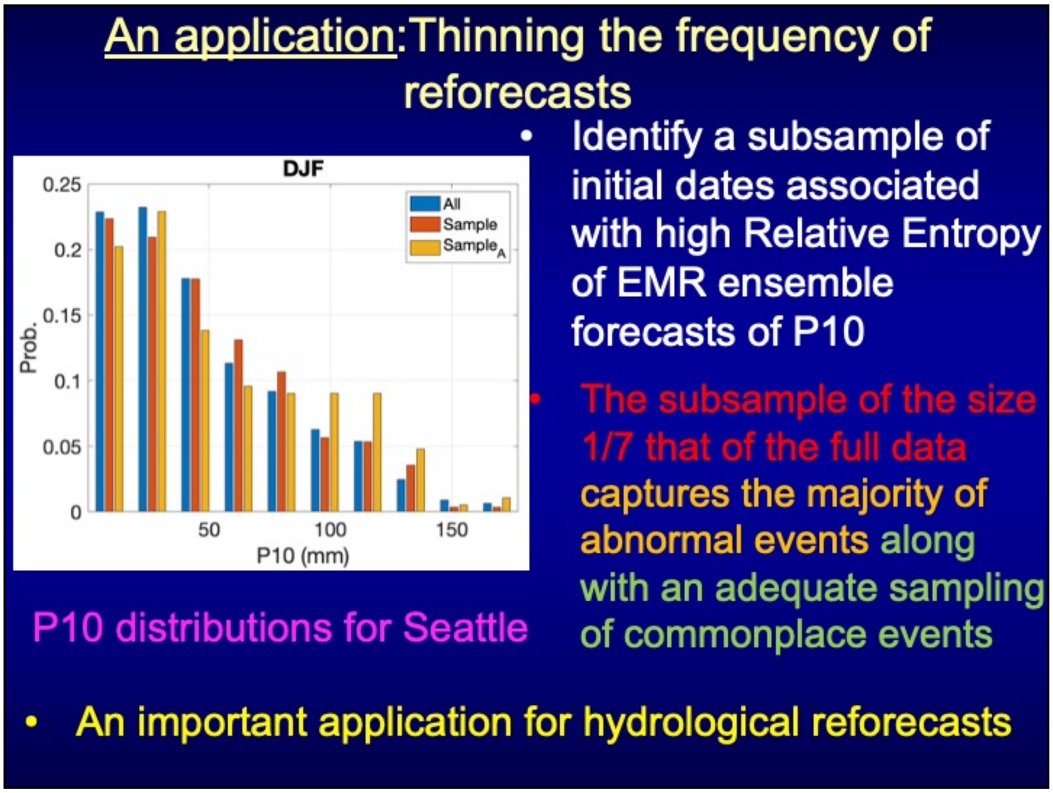
The means of the observed (left column) and simulated P10 distributions are statistically indistinguishable (the difference is shown on the right).



The 99th percentile of P10 tends to be slightly overestimated in the EMR simulations, perhaps indicating a more slowly propagating, somewhat overly persistent precipitation sequences.



EMR model is able to forecast some significant P10 events in the ensemble-mean (of 100 forecasts): see left and middle columns. Most importantly, the large number of forecasts (possible to achieve due to numerical efficiency of the EMR model) makes it possible to compute probabilities of forecast precipitation events and, as a particular example, identify the occurrences of potentially abnormal P10 episodes. One probabilistic measure of forecast utility is a relative entropy (Kleeman 2002), which shows how different the distribution of forecasts is from the climatological distribution (right column).



In the figure, blue histogram is based on the entire 2000–2020 data, red is from a small subsample based on selection using EMR P10 forecasts' relative entropy, and yellow — from a small subsample based on an alternative methodology focusing directly on the large magnitude of P10 in ensemble-mean forecasts. The EMR-RE based sample captures well the P10 distribution associated with the full P10 sample (here and at other locations: not shown), which allows one to utilize this subsample to dramatically increase the numerical efficiency of hydrological reforecasts (future work).

Summary

- We developed a novel methodology for multi-scale statistical modeling of precipitation
- Central to this methodology is the usage of pseudo-precipitation as the input to previously developed LIM-like EMR model
- The model produces statistically accurate surrogate realizations of the 1979–1999 precip. and skillful forecasts over the 2000–2020 period
- Large ensemble size (due to numerical efficiency) permits accurate estimation of forecasts’ PDFs
- A successful application to the problem of thinning the frequency of hydrological reforecasts

Discussion

Our new EMR methodology for statistical modeling of precipitation is fundamentally different from more traditional techniques (which typically work with individual precipitation records at a local level and/or postulate *ad hoc* connections with a limited number of large-scale predictors) in that it automatically accounts for spatiotemporal multi-scale structure of precipitation dynamics, thereby providing a unified framework to model diverse precipitation environments.

The main limitation associated with the present methodology is the need for continuous data set for the temperature and humidity throughout the atmospheric column to compute pseudo-precipitation, which makes it necessary to rely on reanalysis data (rather than raw observations of these quantities)

Acknowledgements

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