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Data-Driven Model Reduction and Climate Prediction: Nonlinear Stochastic, Energy-Conserving Models With Memory Effects

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Comprehensive dynamical climate models aim to simulate past, present and future climate; more recently, they also attempt to predict climate on longer and longer time scales. These models, commonly known as general circulation models or global climate models (GCMs) represent a broad range of time and space scales and use a state vector that has many millions of degrees of freedom. Considerable work, both theoretical and data-based, has shown that much of the observed climate variability can be represented with a substantially smaller number of degrees of freedom.

While detailed weather prediction out to a few days requires high numerical resolution, it is fairly clear that a major fraction of climate variance can be predicted in a much lower-dimensional phase space. Low-dimensional models (LDMs) can simulate and predict this fraction of variability, provided they are able to account for (i) linear and nonlinear interactions between the resolved high-variance climate components; and (ii) the interactions between the small number resolved components and the daunting number of unresolved ones.

Here we will present applications of a particular data-driven LDM approach, namely an energy-conserving formulation of empirical model reduction (EMR). As an operational methodology, EMR constructs a low-order nonlinear system of prognostic equations driven by stochastic forcing; it estimates both the dynamical operator and the properties of the driving noise directly from observations or from a high-order model's simulation. The multi-level EMR structure for modeling the stochastic forcing allows one to capture feedback between high- and low-frequency components of the variability, thus parameterizing the "fast scales," often referred to as the "noise," in terms of the memory of the "slow" scales, referred to as the "signal."

In real-time ENSO prediction, EMR already proved to be highly competitive among state-of-the art dynamical and statistical models. New opportunities for EMR prediction will be illustrated in the framework of "Past Noise Forecasting", by utilizing on the one hand the EMR-estimated history of the driving noise, and on the other hand the phase of low-frequency variability estimated by advanced time series analysis.