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ENSO forecasting based on noise sampling and low-frequency variability

Dmitri Kondrashov (1), Mickael Chekroun (1), Michael Ghil (1,2)

(1) University of California, Los Angeles, Department of Atmospheric and Oceanic Sciences and Institute of Geophysics and Planetary Physics, Los Angeles, United States (dkondras@atmos.ucla.edu), (2) Geosciences Department and Laboratoire de Meteorologie Dynamique (CNRS and IPSL), Ecole Normale Superieure, F-75231 Paris Cedex 05, FRANCE.

The El-Niño/Southern-Oscillation (ENSO) phenomenon dominates interannual climate signals in and around the Tropical Pacific Ocean and affects the atmospheric circulation and air–sea interaction over many parts of the globe. In particular, these effects are significant during ENSO's extreme phases, El Niño and La Niña, and include large anomalies in rainfall and temperatures. In practice, accurate long-term forecasting of ENSO beyond 6 months remains a challenge for current state-of-the art dynamical and statistical models.

Kondrashov et al. (2005) developed an Empirical Mode Reduction (EMR) model of ENSO based on monthly time series of sea surface temperature (SST) anomalies in a tropical belt spanning the three major ocean basins. EMR is a methodology for constructing stochastic models based on the observed evolution of selected climate fields; these models represent unresolved processes as multivariate, spatially correlated stochastic forcing. In EMR, multiple polynomial regression is used to estimate the nonlinear, deterministic propagator of the dynamics, as well as multi-level additive stochastic forcing, directly from the data set. The EMR-ENSO model has quite competitive forecast capabilities, which are due to its nonlinear dynamical operator's ability to capture ENSO's leading quasi-quadrennial and quasi-biennial oscillatory modes of low-frequency variability (LFV).

In this talk we develop a new procedure for forecasting based on the ENSO-EMR model. This procedure is based on two main ideas. The first idea is based on theoretical arguments that show — subject to suitable technical assumptions on the stochastic process that generates the noise — that, given a noise realization ω (t) of length L, each "continuous snippet" of length l of this realization, with l<L, corresponds to another realization ω'(t) of length l of the same stochastic process. Consider now the noise that is obtained during the inverse modeling procedure, which led to the EMR model in the first place; by making a copy of this noise in a sliding window of size l, we obtain a first set S of realizations (each of length l) that can potentially serve for driving the EMR model's dynamics in the future.

The second idea consists of refining further this subset S, by using the LFV present in the SST time series from past years. To do so, we use innovative ways to select SST patterns in the past that match best — in terms of correlation and rms error — the current SST pattern at the time from which a forecast is to be issued. A smaller subset S' is derived from the set S by using this LFV-compositing information in a systematic way.

Based on the EMR model that fits the 51 years of monthly mean SST data from January 1950 to December 2000, we test our approach for 12-month predictions. These hindcasts are carried out month-by-month, from January 2000 to December 2009, by using the refined subset S' derived herein. By using the small ensemble of selected realizations present in this subset, we are able to notably improve the prediction skill — especially at validation times of 6-to-12 months — compared with the previously used EMR forecasting driven by a much larger ensemble of purely random noise realizations. Extension of this method to other types of stochastic forecasting models will be discussed.