Predictability associated with nonlinear regimes in an atmospheric model

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Introduction

Numerous previous studies addressed mid-latitude atmospheric flow patterns, or regimes, that persist for periods of time exceeding typical lifetimes of weather systems, that is, a few days (e.g., Koo et al. 2003; Kondrashov et al. 2004; Kravtsov et al. 2006, 2009). The enhanced persistence of regimes is due to their nonlinear dynamics. **In this study, we analyze output of a realistic atmospheric model to examine potential medium-range predictability associated with regime behavior.**

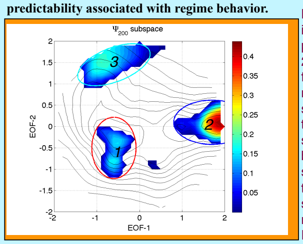

Fig. 1. Regime identification in the phase subspace of 200-mb stream-function EOFs. The model trajectories slowed down relative to those produced by simulations of benchmark linear stochastic models in three distinct phase space regions, later referred to as Regimes 1, 2 and 3.

Model and analysis methods

We have analyzed output from a long simulation of a three-layer quasi-geostrophic (QG3) model by Marshall and Molteni (1993). Probability density functions (PDFs) of raw and low-pass filtered data computed in the phase subspace of the leading Empirical Orthogonal Functions (EOFs) of either the streamfunction or zonally averaged zonal wind provided information about the regions in which the nonlinear QG3 model possessed enhanced probability of persistence relative to that of a linear empirical model constructed using the QG3 output (Kravtsov et al. 2005, 2009). For example, plotted in **Fig. 1** is the difference between QG3-based full-data–to–low-pass-filtered-data PDF ratio in the streamfunction EOF subspace and the 95th percentile of this quantity for the linear model simulations. This diagnostic identifies three distinct regime regions. Analogous considerations in the zonal-mean zonal wind EOF space identify three regimes as well; two of these regimes, however, turn out to be statistically identical to the corresponding streamfunction regimes. The composites associated with four statistically distinct regimes are plotted in **Fig. 2**.

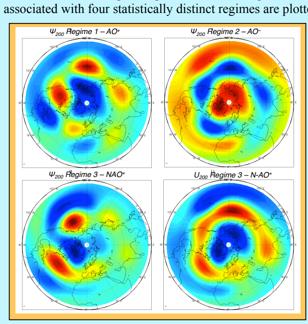

Fig. 2. 200-mb streamfunction anomalies associated with four statistically distinct regimes in the QG3 model. The top two regimes are associated with opposite phases of the Arctic Oscillation (AO); the bottom regimes are positive-phase North Atlantic Oscillation (NAO) and hybrid NAO/AO regime.

Behavior of QG3 trajectories prior to regime onset

The behavior of model trajectories prior to regime onset may yield information about regime precursors, which can in turn be used to improve the accuracy of medium-range weather forecasts. Kondrashov et al. (2004) verified the existence and outlined the topology of preferred transition paths between the QG3 regimes by computing regime-centered angular conditional PDFs. Schwartz (2009) analyzed lagged co-occurrences between the QG3 regimes and identified enhanced probability of transitions between at least two of the QG3 regimes (1 and 3) within a timescale of 10–20 days (not shown). The linear empirical models do not capture this feature (not shown), which further implicates the role of nonlinear processes in regime maintenance and transitions.

Our present analysis builds upon the above results, but explicitly recognizes the difference between regimes and their precursors. Hence, rather than studying transitions between regimes, we concentrate on the phase-space distribution of regime trajectories before regime occurrences. **Figure 3** shows such conditional PDFs of QG3 states that occur 12–18 days prior to each regime onset, along with the ratio of this PDFs to the full-data PDF. Similar figures were produced for trajectories generated by the linear statistical model (not shown).

The central feature of the PDFs shown in Fig. 3 is the presence of preferred residence zones for trajectories ending up in regime regions. Trajectories generated by the linear statistical model do not exhibit analogous preferred residence regions prior to occurrences of the states within regime regions — due to the lack of regime-generating nonlinear dynamics within this model (cf. Schwartz 2009). PDF ratios (Fig. 3, right) also exhibit distinctive regions for which the probability of a given regime occurrence within 12–18 days is elevated; the ratios are clearly very far from unity indicating high information content of the precursor-based data set. Analogous figures generated for the zonal wind metric exhibited similar phase-space patterns for lagged PDFs and PDF ratios.

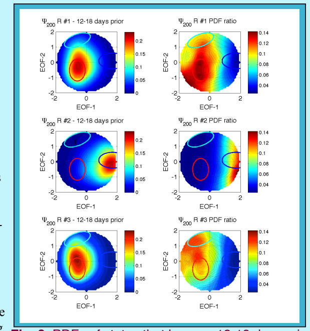

Fig. 3. PDFs of states that happen 12-18 days prior to occurrence of streamfunction regimes (left). Ratios of these PDFs to full-data PDF (right).

Assessment of linear stochastic model forecast skill

The multi-level linear stochastic model we used to assess statistical significance of regimes in preceding sections is in fact a fairly skillful overall predictor of the QG3 model's low-frequency variability, which beats benchmark damped persistence forecasts at lead times exceeding 2 days (not shown). Along similar lines, Winkler et al. (2001) have shown that a linear empirical model trained on the observed data possesses the week-2 skill in predicting the mid-latitude flow comparable to that of a state-of-the-art weather prediction model. Is there room for improving the linear model forecasts?

To address this issue, we examine the distribution of linear model forecast skill in terms of the phase-space structure of the 5-day forecast error root-mean-square (rms) averaged over the ten-dimensional EOF subspace in which the linear model operates. We defined *persistently good forecasts* as the episodes of the anomalously low forecast error (lower than 25th percentile of all forecast errors) that persist for the period of time longer than 75th percentile of duration for all such episodes. The regions in which PDFs of persistently good forecasts exceeds 95th percentile of bootstrap-generated surrogate "good forecasts" for the streamfunction-metric-based and zonal-mean-zonal-wind-based linear models are shown in **Figs. 4** and **5**, respectively. Left panels show the results based on the QG3-generated data, while the right panels address the linear-model self-forecasts.

It is immediately obvious that there is a marked correspondence between the phase-space regions of good forecasts (left panels of Figs. 4 and 5) and the QG3 model regimes defined in Figs. 1 and 2. In particular, within the streamfunction metric, a statistically distinct region of good forecasts overlaps with Regime 1, with initialization days originating outward from the origin, and forecasted trajectories ending up closer to the origin, while there are no good forecast anomalies associated with Regimes 2 and 3. Within the zonal-wind metric, both Regimes 1 and 2 (and not the Regime-3) are better forecasted, with the same inward tendency of forecasted trajectories. *However, the linear model self-forecasts do not exhibit preferred regions*. Furthermore, the phase-space distribution of persistence forecasts (not shown) is very similar to that of the linear model forecasts for QG3 trajectories in Figs. 4 and 5.

The combination of these facts demonstrates that it is not the linear model's (or persistence model) being particularly skillful within the good-forecast regions, but rather the enhanced persistence of the QG3 trajectories there that defines the phase-space non-uniformity of the linear model (and persistence) forecast skill. **The truly useful medium-range prediction model that puts the potential predictability associated with persistence of the QG3 model's nonlinear regimes to best use needs to be able to skillfully forecast regime occurrences conditioned on the appearance of the precursors identified in Fig. 3.**

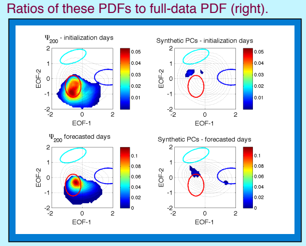

Fig. 4. Spatial distribution of linear model 5-day forecast skill based on streamfunction-metric rms error. Color shading identifies statistically significant regions of enhanced skill. Left: QG3 initializations. Right: linear model self-forecast.

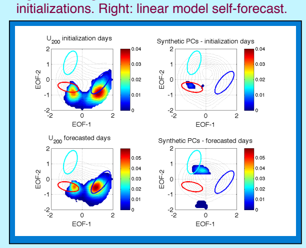

Fig. 5. Same as Fig. 4, but for the zonal-mean zonal wind metric.

Discussion

We have demonstrated the presence of characteristic precursors and preferred trajectory paths that lead to the onset of anomalously persistent flow states (regimes) in an idealized but realistic atmospheric model. While in existence, the regimes can be well forecasted by these empirical models that lack explicit nonlinear dynamics; because of that, the latter models, however, fail to simulate regime precursors and preferred transition paths.

In future work, we aim to improve the performance of linear models by conditioning their coefficients on the occurrence of the regime precursors and regimes, which will hopefully improve the model capabilities to forecast regime onsets and breaks, as well as the transitions between the regimes. Pending the success of such a procedure to forecast the QG3 based trajectories, we will attempt to construct an improved empirical scheme to predict real, nature generated data sets.

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For further information

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