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Approaches for Estimating Seasonal Predictability: Where are We with Current Estimates?

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1. Introduction

Estimating limits of seasonal predictability, while important, continues to be a controversial issue. A National Research Council report on the "Assessment of Intraseasonal to Interannual Climate Prediction and Predictability" (2010) stated that "The true limits of predictability cannot be quantified with any certainty because there is no way of estimating predictability without models or, in the case of observational data, ad hoc assumptions." However, there are various methodologies based on observational data and model simulations that can be used to provide estimates of seasonal predictability, and further, these methods follow a hierarchy of approximations. An overview of predictability estimates spanning last 40-years is presented to assess where we currently stand on our estimates of seasonal climate predictability, and what gaps remain.

2. Historical review of estimate of predictability

Given the observational data, one can estimate the total variability of seasonal means, for example, based on the reanalysis data extending back to 1950s, an estimate of variability in December-January-February (DJF) seasonal mean can be made (Fig. 1). In the context of what fraction of observed variability is predictable, either as an initial value or boundary value problem, has been a focus of analysis in last 40-years. The fundamental problem in estimating predictability is estimating the fraction of total observed variance that can be linked to external causes such as slowly evolving boundary conditions or to the initial conditions.

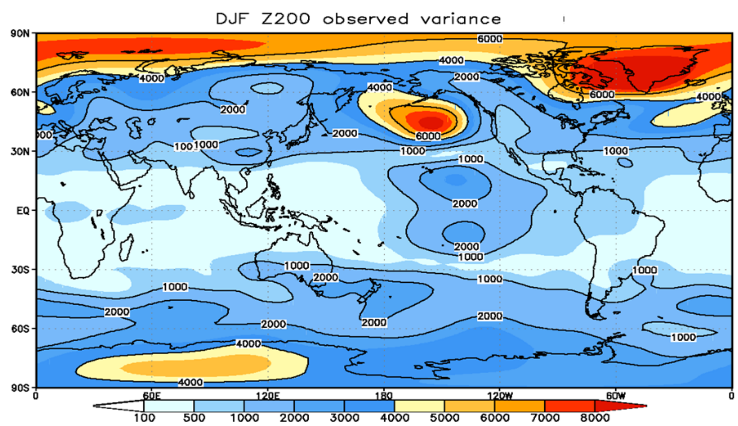

Fig. 1 Total variability of the observed December-January-February (DJF) seasonal mean heights estimated from the NCEP/NCAR reanalysis over 1979-2010 period. Estimating seasonal predictability entails partitioning observed seasonal variability into causes that are external (and can potentially be predicted), and causes that are related to initial perturbations that grow with lead time during model integrations.

The methods for estimating predictable component of seasonal variability can be grouped into based entirely on the observational data or based on model simulations (or a combination of the two). Based on observational data, Madden (1976) presented an estimate of predictable component of seasonal mean variability in surface pressure and surface temperature and concluded that over the continental US, about 20% of seasonal mean variability can be predicted at certain geographical locations. Based on this estimate, the author concluded that low fraction of variance that can be predicted "places important limitations on our ability to make long-range predictions." Horel and Wallace (1981) based on a regression analysis of 700 hPa seasonal mean heights reached a similar conclusion for a low estimate of predictability.

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Robust estimates of seasonal predictability can be made from ensemble of model simulations and initialized predictions. The basic premise of model based estimates is based on the assumption that among an ensemble of simulations the common variability (defined as the variability of ensemble mean) is the predictable component of seasonal variability while the variability different from ensemble mean is the unpredictable component. One of the earliest model estimates of seasonal mean predictability of wintertime 200 hPa heights was made by Kumar and Hoerling (1995), and the results were consistent with the estimates of low predictability of Madden (1976) and Horel and Wallace (1981) in extratropical latitudes. Kumar and Hoerling (1995) also demonstrated that the predictability was largest in the tropical latitudes (and was associated with interannual variability of sea surface temperatures), and decreased monotonically in extratropical latitudes.

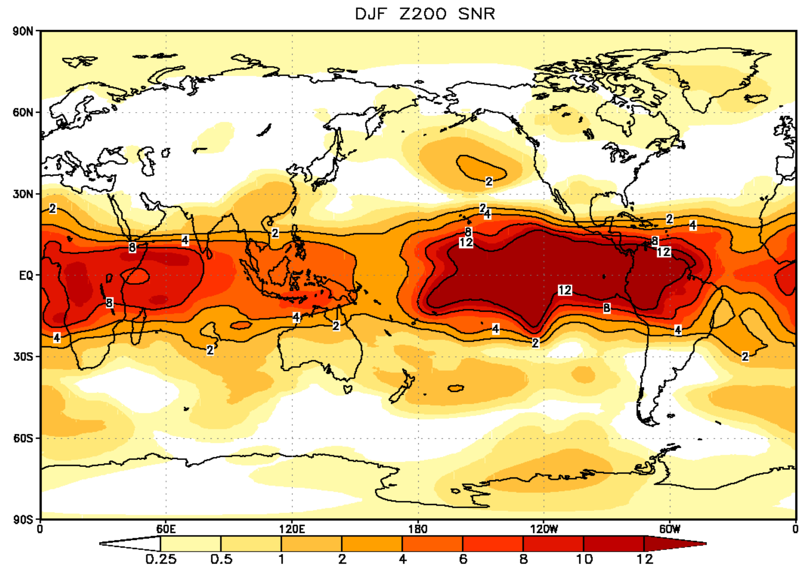

Fig. 2 Estimate of signal-to-noise (SNR) ratio for December-January-February (DJF) seasonal mean heights estimated from North American Multi-Model Ensemble (NMME). SNR is the ratio of predictable and unpredictable component of the total seasonal variability. Larger (smaller) values of SNR indicate higher (lower) predictability. Predictability is higher (lower) in tropical (extratropical) latitudes.

The predictability estimate of Kumar and Hoerling (1995) was based on the analysis of a single model and which could be erroneous due to model biases. To rectify this issue, Kumar *et al.* (2007) presented an analysis based on simulations from multiple models. More recently this estimate based on this approach was updated based on initialized forecasts from the North American Multi-Model Ensemble (NMME) (Kirtman *et al.* 2014). The latest estimate of predictability (Fig. 2) still corroborate results from Madden (1976) and Horel and Wallace (1981) in that the predictability in the extratropical latitudes is only a small fraction of total variability. These results are consistent with the low skill of seasonal predictions in extratropical latitudes (Peng *et al.* 2012).

3. Summary

Over last 40 years, vigorous research efforts have gone into estimating the predictable component of the observed seasonal variability. These estimates are based on observational data and ensemble of model simulations. Further, different methods rely on different level of sophistication with estimates based on methods ranging from linear to non-linear procedures. Irrespective to the methodologies used, however, the general conclusions have remained quite robust – largest predictability in seasonal means is in tropical latitudes and decreases monotonically towards the extratropical latitudes; a large fraction of variability in extratropical latitudes, consistent with the growth of initial forecast perturbations, is unpredictable. A continued update in estimates of predictability based on newer generation of seasonal forecast systems will be useful in the validation for the current estimates of predictability.

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