Full-Field and Anomaly Initialization using a low-order climate model: a comparison and proposals for advanced formulations

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1. Introduction

Current initialization techniques for seasonal-to-decadal climate predictions fall into two main categories, namely Full Field Initialization (FFI) and Anomaly Initialization (AI). In FFI the initial model state is replaced by the best possible available estimate of the real state. The initial error is efficiently reduced but, due to the unavoidable presence of model deficiencies, the prediction drifts away from the observations no matter how small the initial error is. This problem is partly overcome with the AI where the aim is to forecast future anomalies by assimilating observed climate anomalies on an estimate of the model mean climate. In this way, the initial model state is kept on (or closer to) its own attractor. The large variety of experimental setups, models and observational networks adopted in the studies appeared to date makes difficult to draw firm conclusions on the respective advantages and drawbacks of the FFI and AI, let alone identifying distinctive lines for improvement. The lack of a unified mathematical framework adds an additional difficulty toward the design of adequate initialization strategies that fit the desired forecast horizon, observational network and model at hand.

2. Objectives

1. Compare FFI and AI for a range of different observational and model error scenarios using an idealized coupled dynamics

2. Introduce and study two advanced formulations: Least-Square-Initialization (LSI) and Exploring-Parameter-Uncertainty (EPU)

3. DA formulation of FFI and AI

• FFI: Model state is replaced by the best-possible available estimate of the actual state

\[ \tilde{x}(t) = \tilde{x} + H[T]\tilde{y}(t) - H\tilde{x}] \]

• Background state from long "control" run of the model

• AI: Assimilate obs anomalies on the model climate

\[ \tilde{y} = \tilde{y}^o - H\tilde{x} \]

4. Exploring Parameter Uncertainty

• EPU provides an online correction of the drift based on a linear and short-time approximation of its evolution.

\[ \tilde{y}(t) = \tilde{x}(t) - T \frac{\partial \tilde{y}(t)}{\partial \tilde{x}(t)} \tilde{x}(t) \]

The analysis of their error scaling properties suggests the use of FFI when a good observational network is available and reveals the direct relation of its skill with the observational accuracy.

AI seems almost insensitive to observation accuracy

5. Results – Low Order Climate Model

• LSI improves the fit to the observations allowing for their informational content to be propagated to the entire model domain.

• LSI merges observation and model, and the model error covariance is estimated using the statistics of the anomalies.

\[ \tilde{x} = \tilde{x} + H[T]B[H[T]R[T]B[H[T]\tilde{y} - H\tilde{x}] \]

6. Future work

Two main lines of research have been undertaken as follow-up activities:

(1) with state-of-the-art climate models we are studying the effect of initializing different areas using FFI in a multiyear prediction horizon;

(2) extend the analysis presented in this study to a larger set of uncertain parameters and to study the use of LSI in coupled climate models of intermediate complexity.

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