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*

$$\vec{x}^a = \vec{x}^b + H^T\left[\vec{y}^o - H\vec{x}^b\right] \qquad \vec{x}^b:$$ Background state from long "control" run of the model

- ***AI**: Assimilate obs anomalies on the model climate*

$$\vec{y}^{pso} = \vec{y}^o - \left(\overline{\vec{y}}^o - H\overline{\vec{x}}\right) \qquad \vec{x}^a = \vec{x}^b + H^T\left[\vec{y}^{pso} - H\vec{x}^b\right]$$

Pseudo-Observations

4. Least Square Initialization

- ***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.*

$$\vec{x}^a = \vec{x}^b + BH^T\left[HBH^T + R\right]^{-1}\left[\vec{y}^o - H\vec{x}^b\right]$$

with: $B = \alpha\overline{\left(\vec{x} - \overline{\vec{x}}\right)\left(\vec{x} - \overline{\vec{x}}\right)^T}$

4. Exploring Parameter Uncertainty

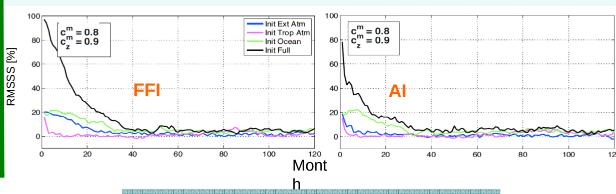
- ***EPU** provides an online correction of the drift based on a linear and short-time approximation of its evolution.*
- ***Work Hyp**: (1) Select Uncert. Param.; (2) Range of possible param.* $\left[\lambda_{\min}, \lambda_{\max}\right]$

$$\vec{x}^{un}(t_i) = \vec{x}(t_i) - \vec{b}(t_i) = \vec{x}(t_i) - \left.\frac{\partial F}{\partial \lambda}\right|_{\vec{x}(t_{i-1}),\vec{\lambda}} \delta\lambda_i \Delta T_{Bias}$$

- *The unknown parametric error is sampled using the assumed uniform distribution of possible parameter values*

5. Results – *Low Order Climate Model*

- *Model based on Lorenz (1963) introduced by Pena and Kalnay (2004)*
- *Three compartments: Extratropical/Tropical Atmospheres and Ocean*



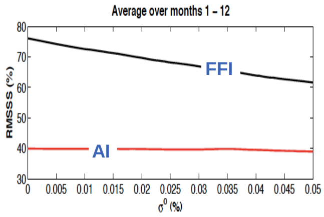
Nature: Solution to model equations with coupling strength $c=c_z=1$

Param Err in the coupling

10-yr long predictions are initialized each month for 30 yrs

Total of 360 startdates

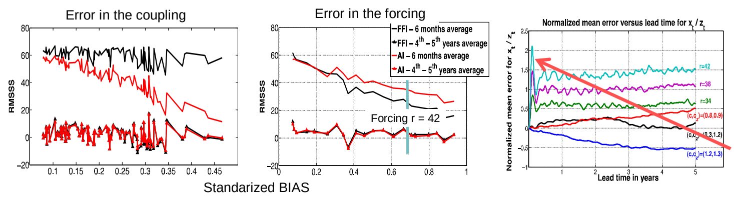
FFI vs AI as a function of Observation Accuracy



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

FFI vs AI as a function of Model Accuracy

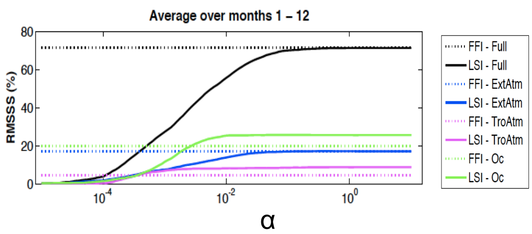


FFI gives the overall better results

The model configurations for which AI outperforms FFI are associated with a larger bias

Nevertheless, rather than the amplitude of the bias alone, it is the appearance of the **RAPID INITIAL DRIFT** that seems to favour AI

FFI vs FFI-LSI

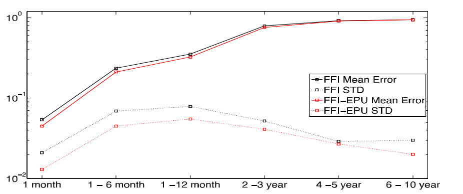


LSI improves the performance of FFI in all the situations when only a portion of the system's state is observed.

LSI operates an **EFFICIENT PROPAGATION OF INFORMATION FROM DATA-COVERED TO DATA-UNCOVERED AREAS** and to some extent reduces the initial error also far from the observational locations.

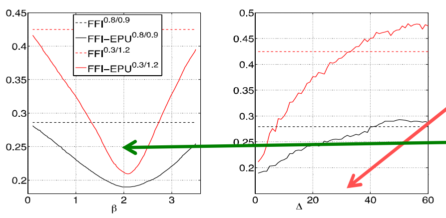
Estimating the background error covariance matrix using the statistics of the anomalies has therefore given proof of being a viable choice, in agreement with Smith and Murphy (2007), and extend them to the case of the estimation of cross-covariances between different model compartments.

FFI vs FFI-EPU



The use of EPU has clearly improved the skill of FFI within the first forecast year.

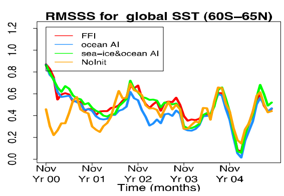
Later the limits of accuracy of the linear and short-time assumptions at the basis of EPU are approached, and only minor advantages over FFI are recorded.



Results have also demonstrated the robustness of EPU with respect to the two factors determining its implementation: **THE LENGTH OF THE DRIFT-CORRECTION INTERVAL** and the **ACCURACY OF OUR KNOWLEDGE OF THE ACTUAL RANGE OF POSSIBLE PARAMETERS.**

6. Future work

Preliminary Results with EC-Earth



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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