Decadal Climate Predictions Using Sequential Learning Algorithms

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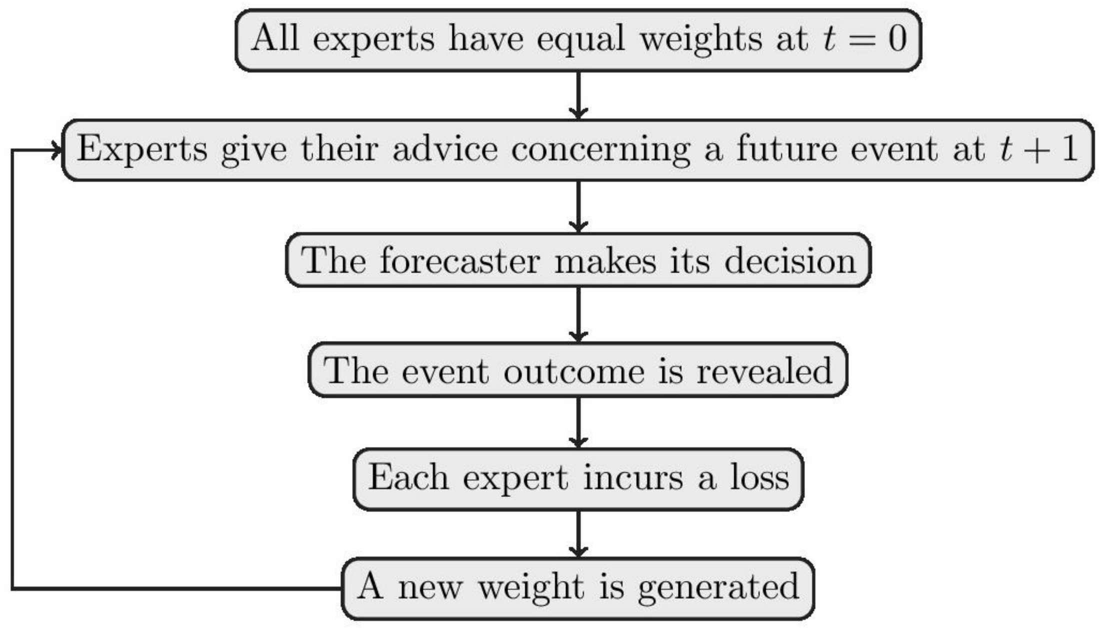
1. INTRODUCTION

Decadal climate predictions are aimed at providing information about the evolution of the climate system during the next ten to thirty years. The main tool used to generate these predictions are global climate models. However, the predictions of these models are not sufficiently accurate and are subjected to large uncertainties. One way to improve the prediction skill is to use a weighted ensemble of climate models. Here, a new method from the field of decision-making is used to weight climate models. The weights of the models are generated by comparing, during a learning period, their predictions with reanalysis data (considered here as true values). The weighted average and weighted standard deviations of the model ensemble are used as a new suggested improved forecast. It is shown that this method can improve the predictions of global climate models and reduces their uncertainties.

2. BASIC CONCEPT

The forecaster is a mathematical algorithm that takes advantage of several available model predictions (experts) and the knowledge of their past performance to generate a set of improved predictions in a sequential manner



The forecaster's goal is to minimize the cumulative regret with respect to each one of the climate models. This is defined, for expert E, by the quantity:

$$R_{E,n} \equiv \sum_{t=0}^{n} \left(l(\hat{p}_t, y_t) - l(f_{E,t}, y_t) \right) \equiv L_n - L_{E,n}$$

l - loss function, a measure of the difference between the predicted and the true values.

y_t - true value at time t.

$\hat{p}_t$ - predicted value by the forecaster at time t.

$f_{E,t}$ - predicted value by the expert E at time t.

L - cumulative loss function.

The outcome of the forecaster is a weighted average of the climate models in the ensemble, that is:

$$\hat{p}_n \equiv \sum_{E=1}^{N} W_{E,n-1} \cdot f_{E,n}$$

$W_{E,t-1}$ - weight of expert E based on the regret up to time $n-1$.

3. EXPERIMENTAL SETUP

- Multi-model ensemble of eight global climate model simulations from the CMIP5 decadal experiments.
- Thirty-year (1981-2011) simulation.
- NCEP reanalysis data considered as true values.
- Monthly averages of surface temperature.
- Twenty years of the learning period (the weights are updated every month).
- Ten years of validation of the forecasters (the weights are constant).

4. FORECASTERS

EWA
Exponential Weighted Average
Converges to the best model

$$\hat{p}_n \equiv \frac{\sum_{E=1}^{N} e^{-\eta L_{E,n-1}} \cdot f_{E,n}}{\sum_{i=1}^{N} e^{-\eta L_{i,n-1}}}$$

$$l(f_{E,t}, y_t) = \left(f_{E,t} - y_t\right)^2$$

$$L_{E,n} = \sum_{t=1}^{n} l(f_{E,t}, y_t)$$

EGA
Exponentiated Gradient Average
Converges to the measurements

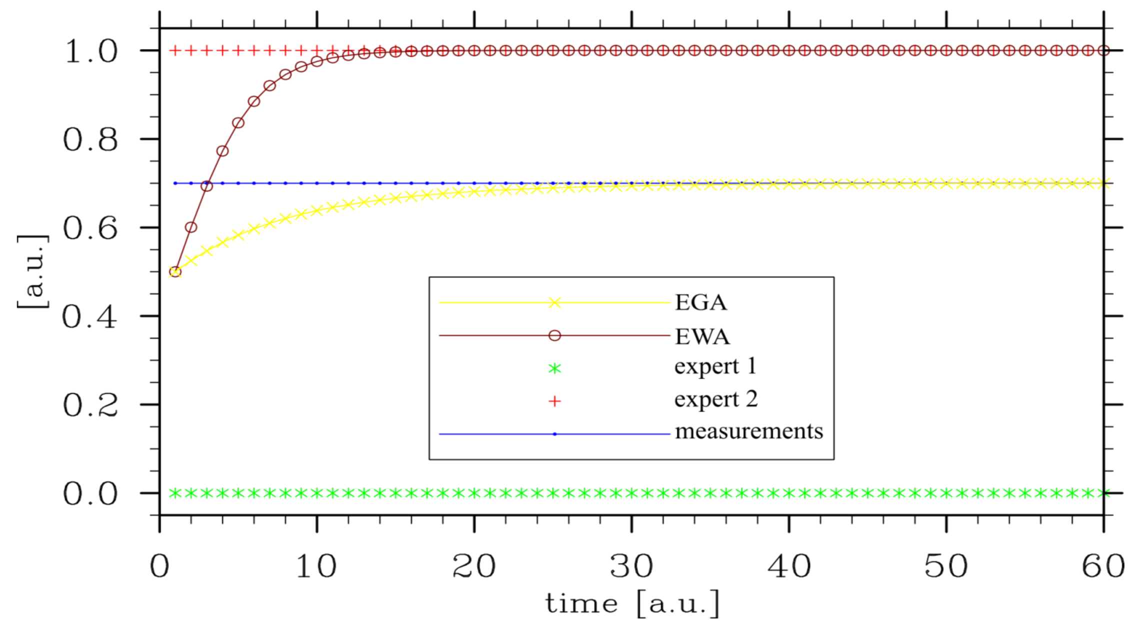
$$\hat{p}_n \equiv \frac{\sum_{E=1}^{N} e^{-\eta L'_{E,n-1}} \cdot f_{E,n}}{\sum_{i=1}^{N} e^{-\eta L'_{i,n-1}}}$$

$$l'(f_{E,t}, y_t) = 2(\hat{p}_t - y_t) \cdot f_{E,t}$$

$$L'_{E,n} = \sum_{t=1}^{n} l'(f_{E,t}, y_t)$$

η – Learning parameter, large η fast learning.

EWA to EGA Comparison



It can be shown that:

$$\max_{E=1,\ldots,N} R_{E,n} \xrightarrow{n\to\infty} 0$$

meaning that the forecaster will be at least as good as the best model during the learning period.

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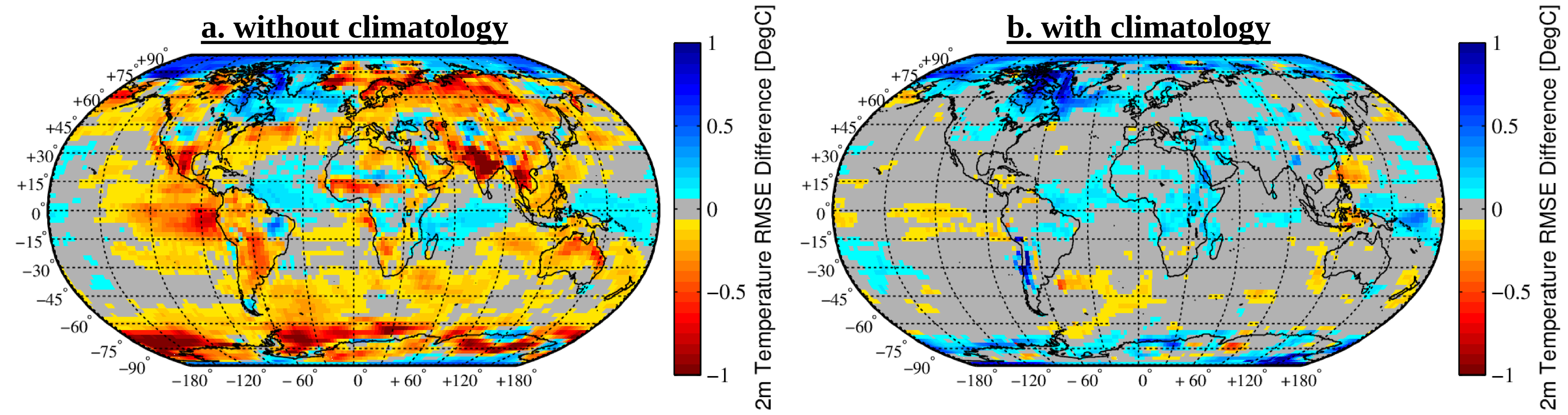
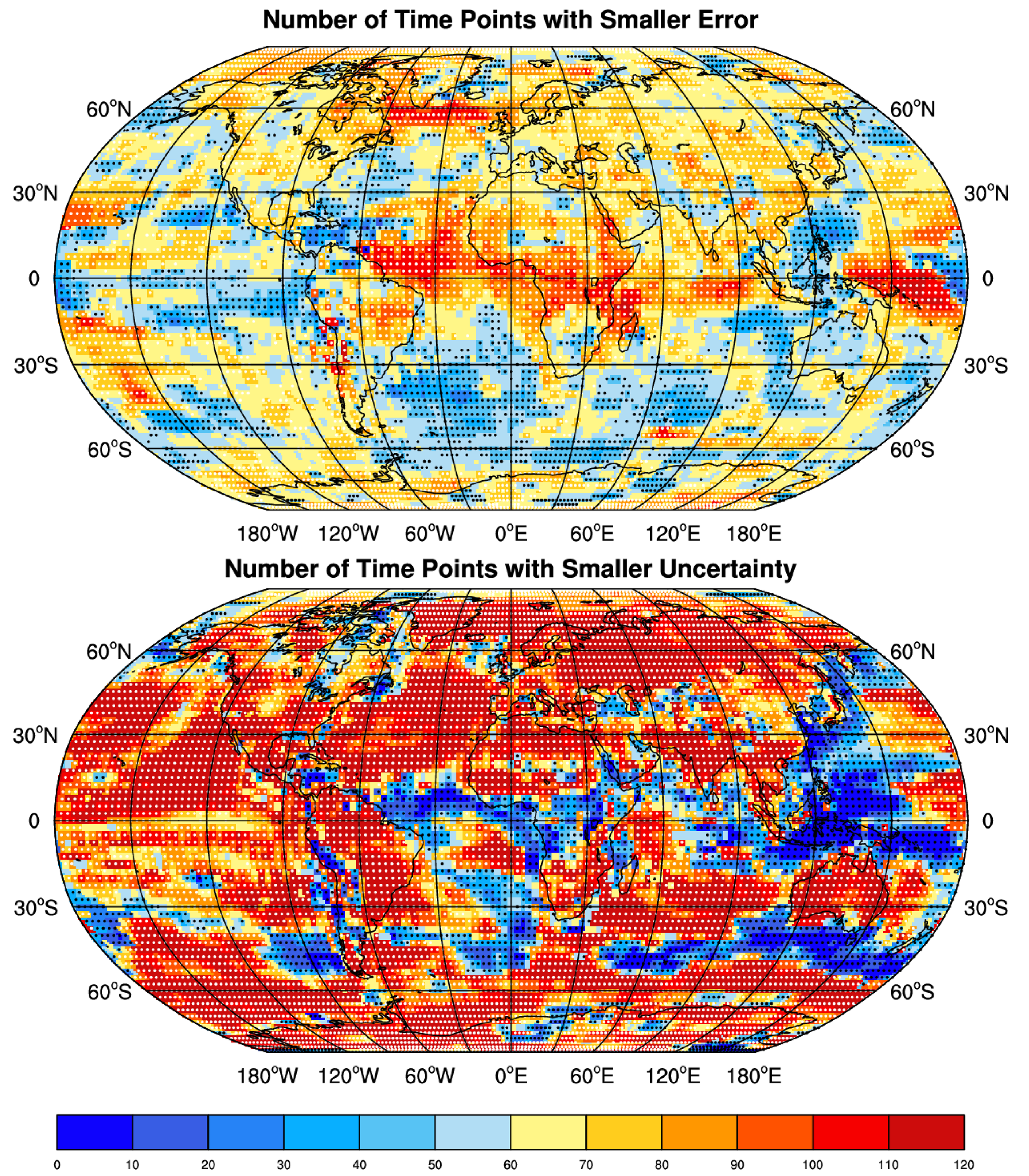
5. CLIMATOLOGY AS AN ADDITIONAL EXPERT



The difference between the 10-year validation period average 2-m-temperature RMSE of the climatology and the EGA forecaster, (a) EGA with an ensemble that includes eight models, (b) EGA with an ensemble that includes the same eight models and also the climatology of the learning period as an additional model. **The results demonstrate that when the ensemble includes the climatology, the EGA forecaster has higher skill.**

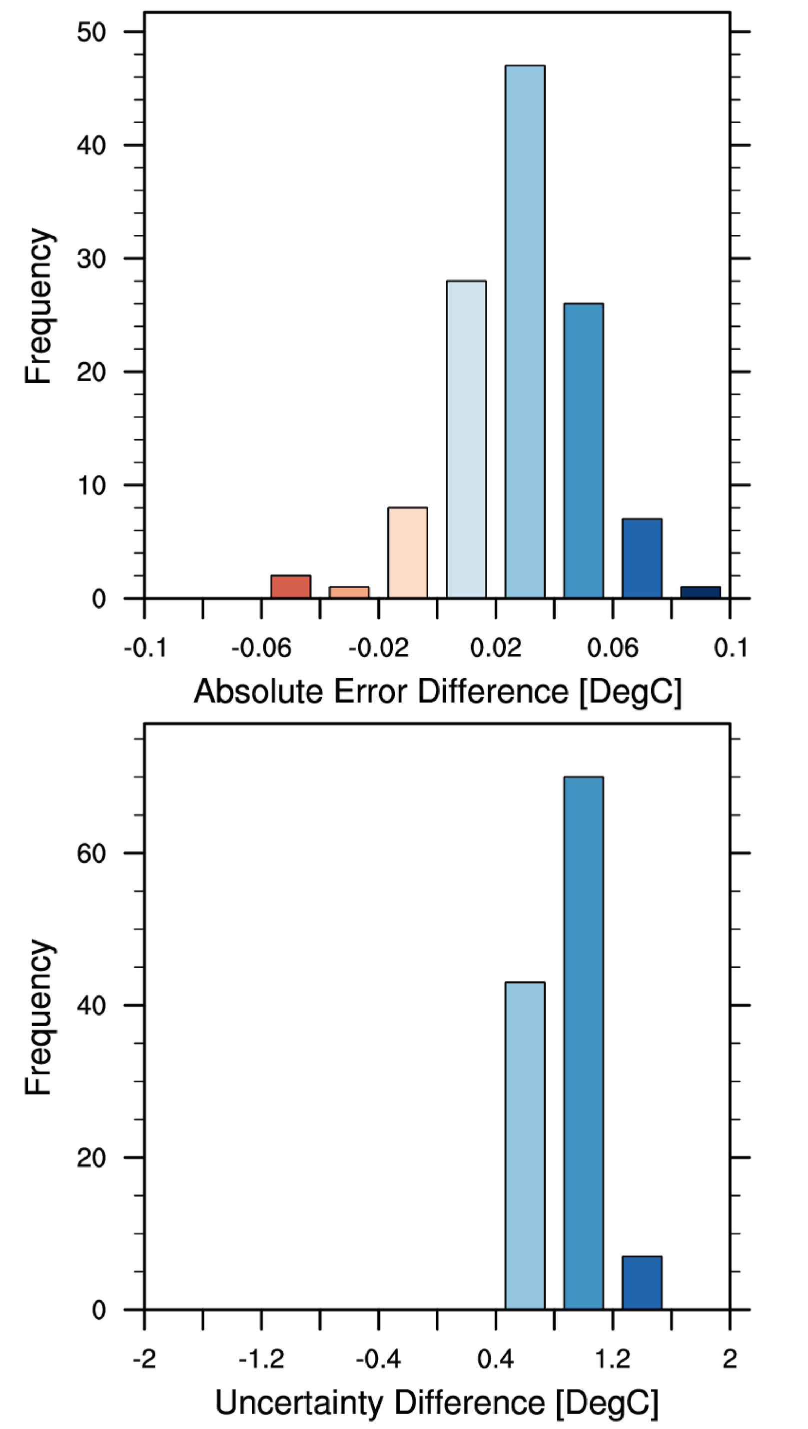
6. STATISTICAL SIGNIFICANCE

REGIONAL



The number of time points in which the EGA forecaster performs better. The upper panel shows the spatial distribution of the number of time points in which the absolute error of the EGA forecaster is smaller than that of the climatology. The lower panel shows the spatial distribution of the number of time points in which the uncertainty of the EGA weighted ensemble is smaller than that of the equally weighted ensemble. White circles represent significant improvement by the EGA forecaster, and black circles represent its significantly poorer performance. **Both quantities show better performance of the EGA forecaster over most of the globe.**

GLOBAL



The histograms of the globally averaged differences of absolute error and uncertainty. The upper panel shows the histogram of the globally averaged difference between the absolute error of the climatology and that of the EGA forecaster. The lower panel shows the histogram of the difference between the uncertainties of equally weighted and EGA-weighted ensembles. **Both quantities show significantly improved performance of the EGA forecaster.**