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Decadal Climate Predictions Using Sequential Learning Algorithms

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Ensembles of climate models may improve future climate predictions and reduce their uncertainties. We adopt two Sequential Learning Algorithms (SLAs) in order to establish a weighted ensemble of models based on their past performance. The method has several advantages, including the lack of a priori assumptions regarding the ensemble members; the weight of the ensemble members can be updated upon the arrival of new measurements; and it can be proved that the prediction of the weighted ensemble is at least as good as the prediction of the best model if the learning period is long enough. Using this method, we aim to achieve two main goals - provide better future climate predictions and reduce their uncertainties.

The goal of SLAs is to minimize the *cumulative regret* with respect to each one of the climate models. This is defined, for expert E, after n time steps, by the quantity:

$$R_{E,n} \equiv \sum_{t=1}^{n} l(p_t, y_t) - l(f_{E,t}, y_t) \equiv L_n - L_{E,n} \tag{1}$$

where, l is the *loss function* - a measure of the difference between the predicted and the true values; y_t is the true value at time t; p_t is the predicted value by the algorithm at time t; $f_{E,t}$ is the predicted value by the expert E at time t; and L is the *cumulative loss function*. The outcome of the algorithm is a weighted average of the climate models in the ensemble, that is:

$$p_t \equiv \sum_{E=1}^{N} W_{E,t-1}(R_{E,t-1}) \cdot f_{E,t} \tag{2}$$

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

We adopted one 30-year CMIP5 experiment (between 1981-2011) to demonstrate the ability of the SLAs to fulfill the two goals. Four variables were considered – monthly averages of surface temperature, U and V components of 10m wind speed, and surface pressure. The CMIP5 hindcast data was divided to a learning period in which the weight of the models was updated in each time step and a verification period in which the weights of the models are constant and the weighted average of the models was tested against measurements.

It will be shown that one of the two algorithms is more suitable for decadal climate predictions. This algorithm has the ability to improve climate predictions by a few percent, compared to the predictions made according to a reference climatology as well as predictions generated by the the commonly used regression method. Also, the algorithm has the ability to reduce the uncertainties associated with the predictions by more than 50% compared to the simple average of the model results.