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A methodology for deriving ensemble response from multimodel simulations

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SUMMARY

Multimodel ensembles are widely used to quantify uncertainties of climate model simulations. Previous studies have confirmed that a multimodel ensemble approach increases the skill of model simulations. However, one may need to know which ensemble member is more likely to be true, particularly when the ensemble is spread out over a wide area. Typically, ensemble response (climate response) is derived by taking the mean or median of ensemble members. However, strong similarities exist between models (members of an ensemble) which may cause biased climate response toward models with strong similarities. In this study, a model is proposed for deriving the climate response (ensemble response) of multimodel climate model simulations. The approach is based on the concept of Expert Advice (EA) algorithm which has been successfully applied to the financial sector. The goal of this methodology is to derive an ensemble response that at every time step is equal or better (less error) than the best model. The methodology is tested using the CMIP5 historical temperature simulations (1951–2005) and Climatic Research Unit observations, and the results show that the EA algorithm leads to smaller error compared to the ensemble mean.

1. Introduction

Several national and international efforts, such as the Intergovernmental Panel on Climate Change (IPCC; IPCC (2007)), provide data sets of historical and future climate. However, climate simulations are subject to uncertainties arising from uncertainties in boundary, and initial conditions, parameters and model structure (Reichler and Kim, 2008; Feddema et al., 2005; Brekke and Barsugli, 2013; Mehran et al., 2014; Liu et al., 2014; Liepert and Previdi, 2012; Wehner, 2013; John and Soden, 2007). Multimodel ensembles have been widely employed to quantify uncertainties of climate simulations (Meehl et al., 2007; Yun et al., 2003; Tebaldi and Knutti, 2007). Model simulations are also used to force hydrologic and land-surface models to derive hydrology projections. Previous studies have confirmed that a multimodel ensemble approach increases the skill of model simulations (Doblas-Reyes et al., 2003; Cantelaube and Terres, 2005). Regardless of the method of estimation, an ensemble consists of a number of realizations (individual climate simulations), each of which representing a probable climate condition that can occur. While a multimodel ensemble approach increases the skill of model simulations, one may need to know which ensemble member is more likely to be true, particularly when the ensemble is spread out over a wide area.

It is customary to derive the ensemble response or prediction quantity (hereafter, climate response) of multimodel ensembles by taking the arithmetic mean of simulated ensemble members (Min et al., 2007) where an equal weight is given to each ensemble member. Masson and Knutti (2011) stressed that strong similarities exist between several models (members of an ensemble) which may cause biased climate response toward models with strong similarities. One way to combine simulations of climate models is to weight ensemble members based on their performance in simulating past and present climate (e.g., Krishnamurti et al., 2000). Knutti et al. (2010) argues that while the ensemble mean provides useful information, there exist the need for more quantitative approaches to assess model simulations in order to maximize the value of multimodel ensemble climate simulations.

In recent years, Bayesian model averaging has also been used to derive the climate response of multimodel ensembles (e.g., Smith et al., 2009; Robertson et al., 2004; Tebaldi et al., 2004; Min et al., 2007). Limitations of the Bayesian methodology, when applied to climate projections, are addressed in Tebaldi and Knutti (2007). For a weighted average approach, quantifying the weights requires an index of model skill in order to estimate the weights accordingly.

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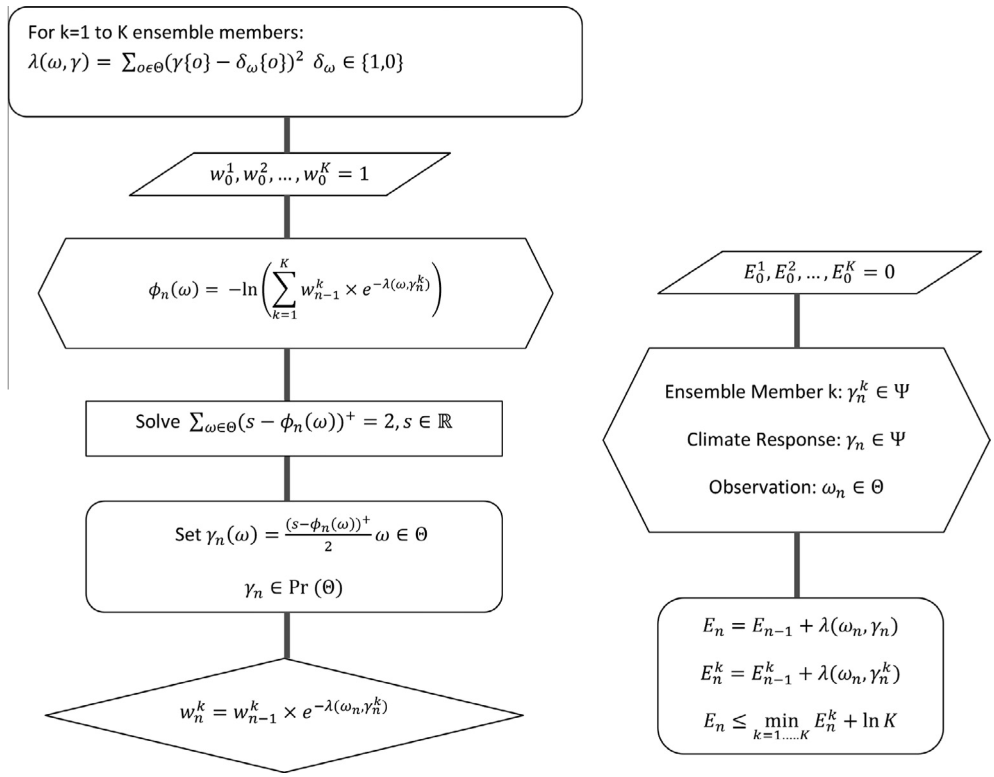

Fig. 1. The proposed algorithm for estimation of climate response weights (left), and cumulative error (right).

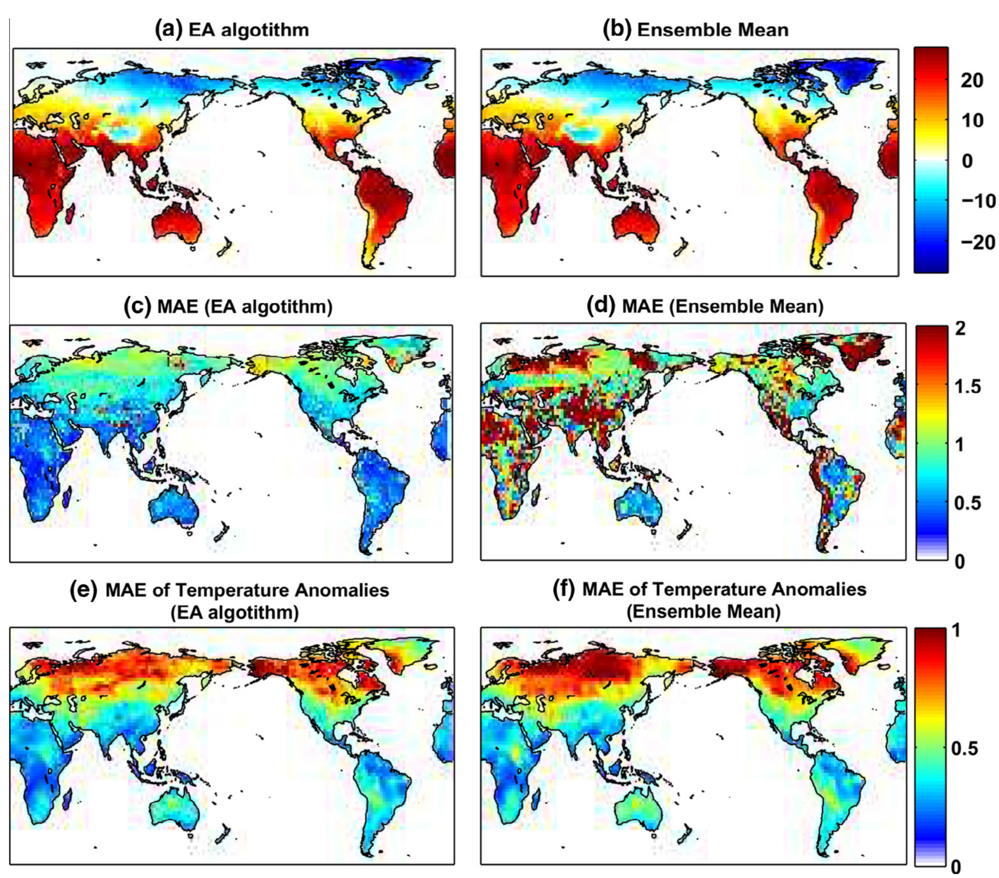

Fig. 2. The global annual mean temperature (1951–2005) based on the EA algorithm (a) and the multimodel ensemble mean (b), and their corresponding mean absolute error (MAE) maps relative to the CRU observations (MAE for absolute temperature values (c) and (d) and temperature anomalies (e) and (f)).