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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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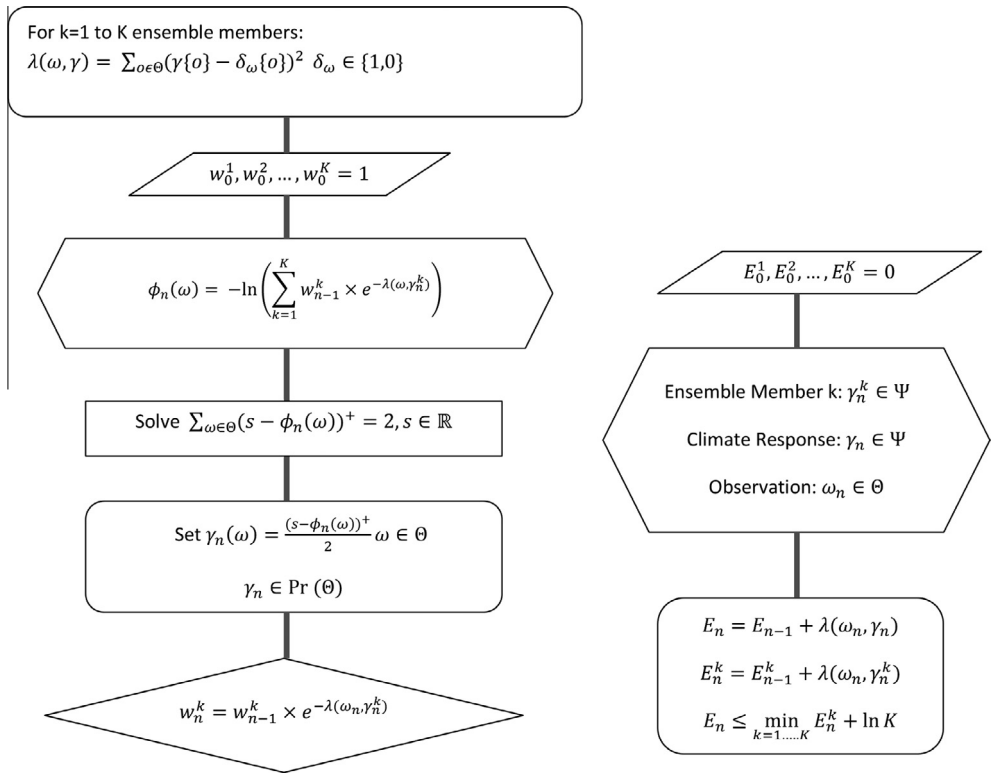

Fig. 1. The proposed algorithm for estimation of climate response weights (left), and cumulative error (right).

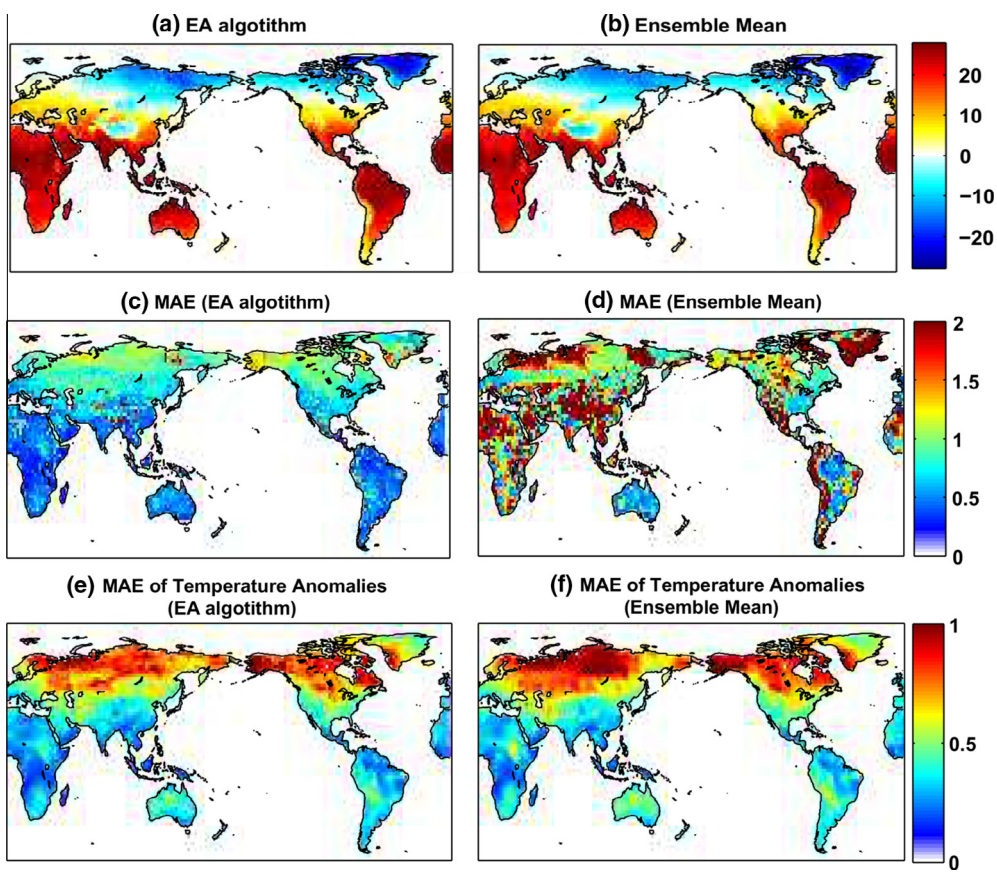

Fig. 2. The global annual mean temperature (1951–2005) based on the EA algorithm (a) and the multimodel ensemble mean (b), and their corresponding mean absolute error (MAE) maps relative to the CRU observations (MAE for absolute temperature values (c) and (d) and temperature anomalies (e) and (f)).

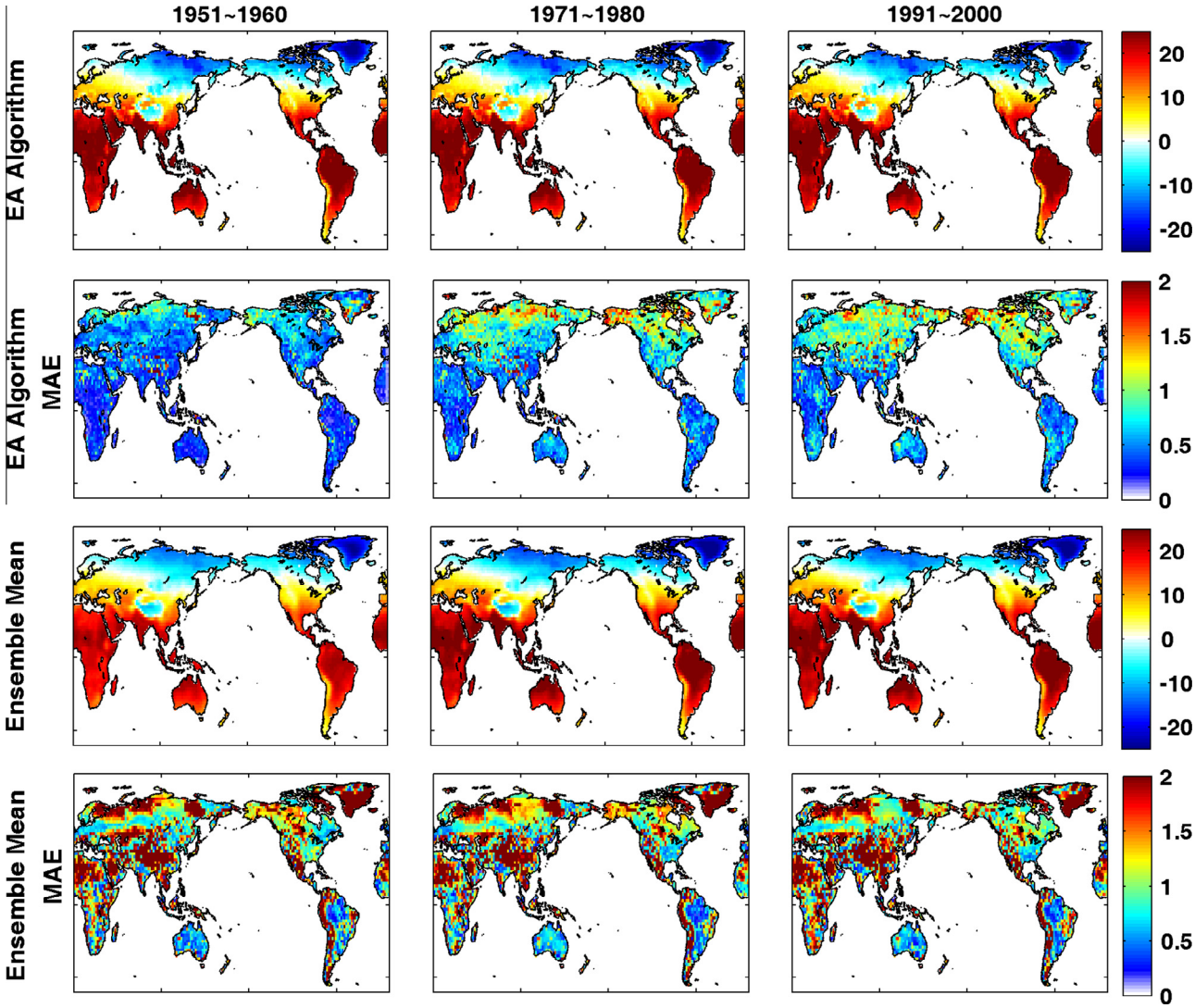

Fig. 3. The climate response of the global annual temperature based on the CMIP5 multimodel ensemble for three decades: 1951–1960, 1971–1980, and 1991–2000 (the 1st and 2nd row are based on the EA algorithm, and the 3rd and 4th rows are based on the ensemble mean).

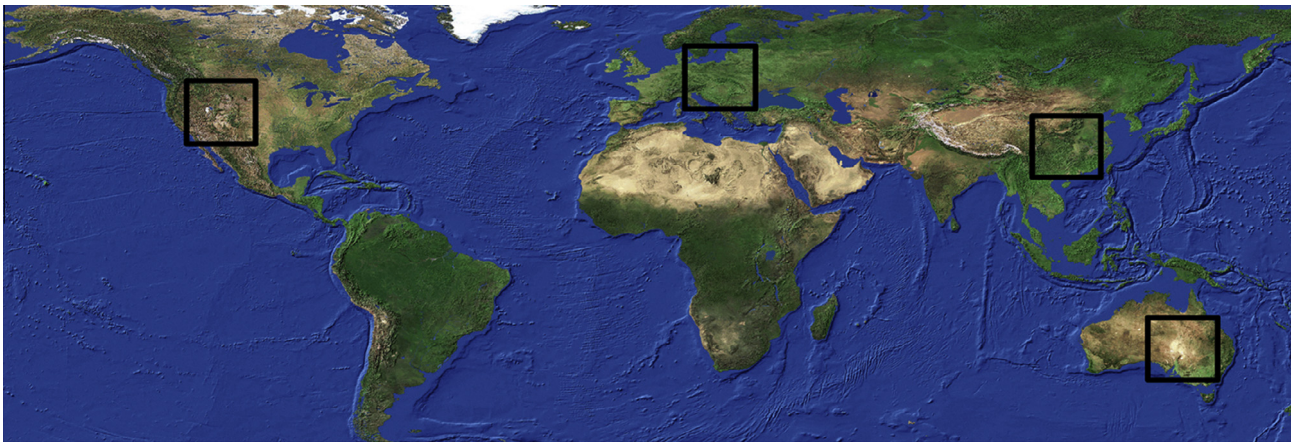

Fig. 4. Selected regions for time series analysis.

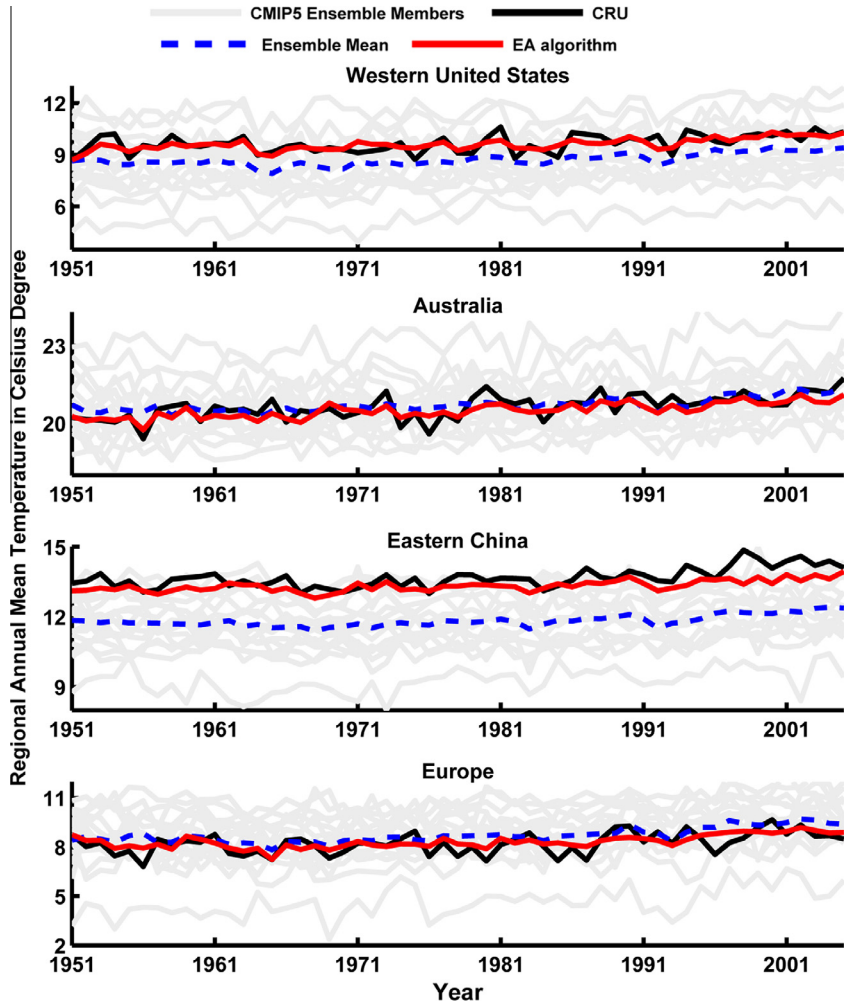

Fig. 5. Time series of the CMIP5 annual mean temperature, and the ensemble response based on the arithmetic mean and the EA algorithm for the western United States, Europe, eastern China and eastern Australia. The solid black line represents the CRU annual mean temperature, whereas the gray lines show the individual CMIP5 ensemble members (17 models). The dashed blue and solid red lines respectively show the ensemble mean and the EA algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Several studies have tackled this issue and contradicting results are presented on the best method to combine climate model projections (see Tebaldi and Knutti (2007) and references therein). Among many reasons, the choice of model skill, and strong dependencies and similarities of ensemble members are the main challenges in deriving a meaningful climate response.

In order to resolve this limitation, a model is proposed for deriving the climate response of climate model simulations. In the proposed method, ensemble members are weighted based upon their performance in simulating observations using the so-called Expert Advice algorithm (Cesa-Bianchi and Lugosi, 2006). The goal of this methodology is to derive the weights (predicting models) such that at every time step the climate response is equal or better (less error) than the best model.

In most studies that rely on climate model simulations, simulated anomalies are used instead of the absolute values to remove biases in individual model simulations (e.g., Collins et al., 2011). However, in hydrology and water resources studies, often the absolute values of model simulations are necessary. For example, to run a hydrologic model with climate simulations as forcing (e.g., Ficklin et al., 2009), the original model simulations are used and not the anomalies. Similarly, absolute values of temperature and/or precipitation simulations are used for multivariate analysis (Hao et al., 2013), climate impact assessment (Madani and Lund, 2010), drought analysis (Madadgar and Moradkhani, 2011), and water-energy-climate nexus studies (Tarroja et al., 2014a), etc. The suggested algorithm can be applied to both original ensemble simulations and their anomalies.

2. Data

2.1. Climate model simulations

In this study, 41 Coupled Model Intercomparison Project Phase 5 (CMIP5) historical annual temperature simulations from 1951 to 2005 are considered. For the same model family, one is selected which contributes a subset of 17 models used to derive the climate response. These data sets represent the most extensive and ambitious multi-model simulations that contribute to the World Climate Research Programme's CMIP multi-model dataset (Meehl and Bony, 2011; Taylor et al., 2012). For an overview of the climate models and the experiment, the interested reader is referred to Taylor et al. (2012).

2.2. Ground-based observations

Annual observations of temperature provided by the Climatic Research Unit (CRU, Mitchell and Jones, 2005; New et al., 2000),

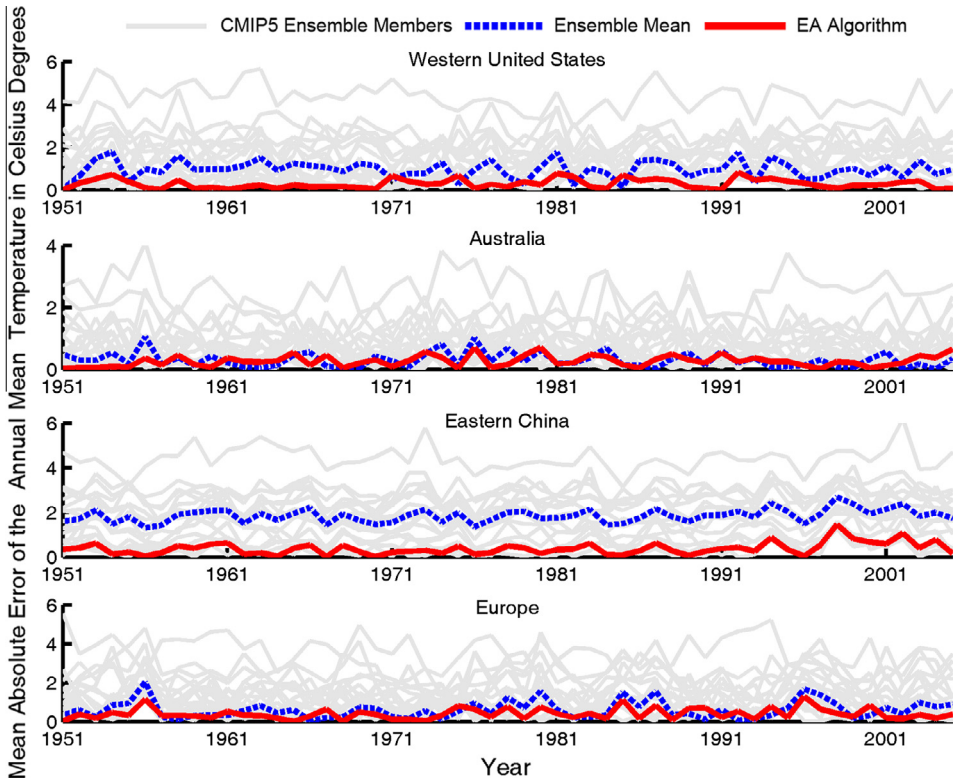

Fig. 6. Mean absolute error (temperature °C) values for the ensemble arithmetic mean and EA algorithm shown in Fig. 5.

Table 1
Mean absolute error (MAE), and Mean Square Error (MSE) of the ensemble mean (EM) and EA algorithm (EAA) for temperature simulations across the selected regions in the western United States, Australia, eastern China and Europe.

	MAE		MSE	
	EM	EAA	EM	EAA
Western U.S.	0.94	0.28	1.07	0.13
Australia	0.30	0.26	0.15	0.10
Eastern China	1.84	0.37	3.48	0.21
Europe	0.60	0.40	0.56	0.24

available in a 0.5° spatial resolution, are used as reference data. The CRU gridded temperature data are based on an archive of monthly mean temperatures provided by more than 4000 weather stations distributed across the globe. CRU observations have been validated and used in numerous studies of historical climate variability (e.g., Tanarhte et al., 2012). For consistency, the CMIP5 model simulations and CRU observations all are gridded to a common 2×2-degree resolution. This study focuses on global land areas (excluding Antarctica) for which the CRU observations are available.

3. Methodology and results

The concept of estimation using Expert Advice (EA) algorithm (Cesa-Bianchi and Lugosi, 2006) has been successfully applied in the financial sector and game theory (e.g., DeSantis et al., 1988). The original model was designed for categorical predictions based on multiple predictors. Here, the concept of expert advice has been modified so that it can be applied to climate variables (i.e., continuous time series). This study focuses on ensemble climate model simulations. The goal of the methodology is to weight the predictors (ensemble members) such that at any given time, the composite climate response is superior to the best model plus and acceptable error term which is a function of the ensemble size. Let's assume that Θ is a finite set of climate observations, and Ψ is a set of climate simulations over the period for which observations are available. In other words, Ψ is the set of all probability measures on Θ:

$$\Psi := Pr(\Theta) \tag{1}$$

After Vovk and Zhdanov (2009), an error (loss) function $\lambda(\omega, \gamma)$ is defined as:

$$\lambda(\omega, \gamma) = \sum_{o \in \Theta} (\gamma\{o\} - \delta_\omega\{o\})^2 \tag{2}$$

where

ω = individual variables in observations space Θ
γ = individual variables in climate simulations space Ψ
$\delta_\omega \in Pr(\Phi)$ = probability measure concentrated at ω
$\gamma\{o\}$ = difference $(\Psi - \Theta)$
$\delta_\omega\{\omega\}$ = 1 for $o = \omega$, meaning $\gamma\{o\} = 0$
$\delta_\omega\{o\}$ = 0 for $o \neq \omega$, meaning $\gamma\{o\} \neq 0$

Having a finite number (n time steps) of observations ($\omega_n \in \Theta$), the objective of EA algorithm is to derive the best predictor (γ_n, climate response) given $k = 1, 2, \ldots, K$ climate simulations ($\gamma_n^k \in \Psi$). Throughout this paper, a common statistical convention is used in which uppercase and lowercase characters denote random variables and their specified variables, respectively. Fig. 1 displays the flowchart of the proposed algorithm. As shown, first the loss function is computed (Eq. (2)). Then, the initial values of weights at the beginning are set to 1: $w_0^1, \ldots, w_n^K = 1$, where $w_0^1, \ldots, w_n^K$ are weights corresponding to $k = 1, 2, \ldots, K$ climate simulations (ensemble members). In other words, at the beginning of the analysis, the model assumes all climate simulations are as equally representative, and thus a similar weight will be assigned to each ensemble member. Then, the EA algorithm decreases the weights (w_n^k) of

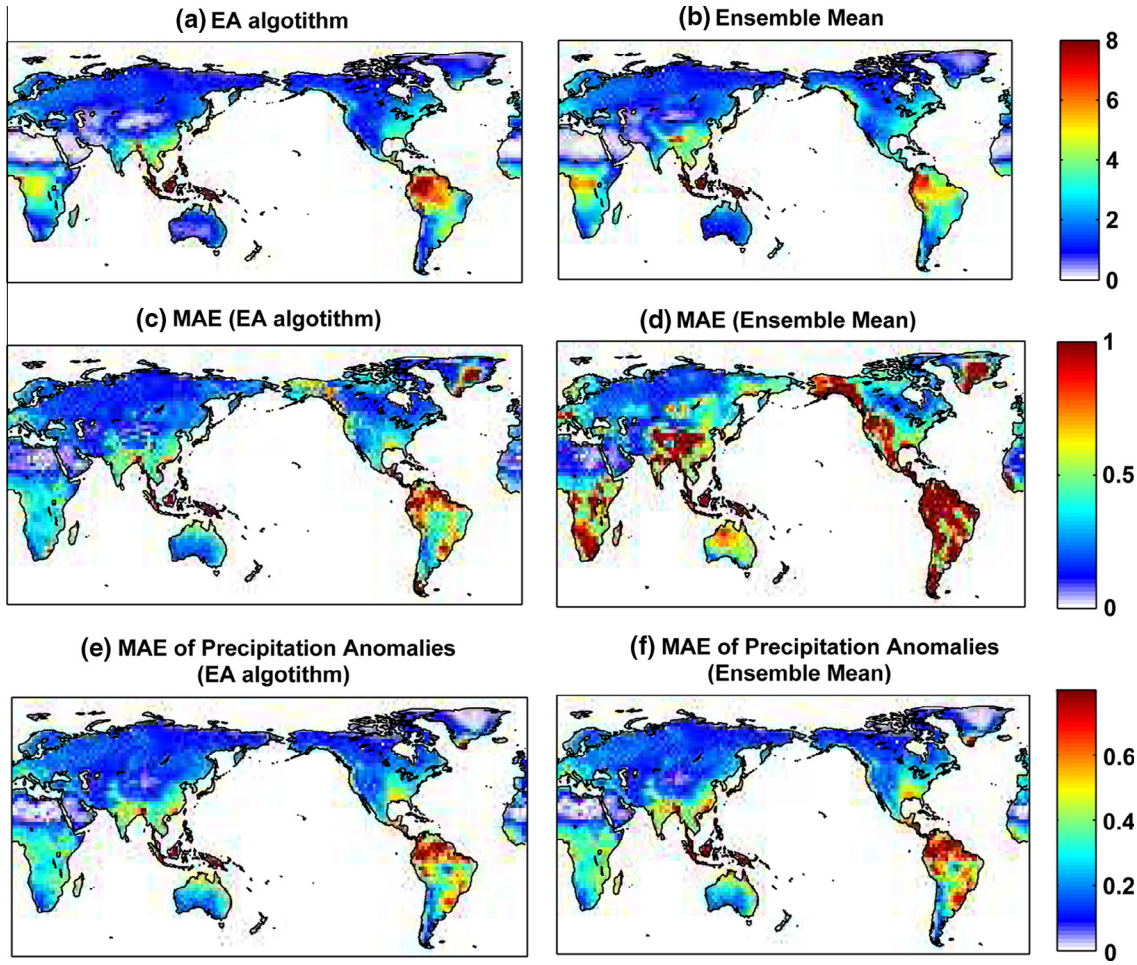

Fig. 7. The global annual mean precipitation (1951–2005) based on the EA algorithm (a) and the multimodel ensemble mean(b) in mm/day, and their corresponding mean absolute error (MAE) maps relative to the CRU observations (MAE for absolute precipitation values (c) and (d) and precipitation anomalies (e) and (f)).

ensemble members ($k = 1, 2, \ldots, K$) exponentially with the increase of error (loss) function ($\lambda(\omega_n, \gamma_n^k)$). The weight function ($\Phi_n(w)$) can be expressed as:

$$\Phi_n(w) = -\ln\left(\Sigma_{k=1}^{K} w_{n-1}^k \times e^{-\lambda(\omega_n, \gamma_n^k)}\right) \tag{3}$$

where w_n^k and w_{n-1}^k refer to weights of ensemble member k at time steps n and $n-1$, respectively. Vovk (2001) mathematically proves that there is a unique s (Fig. 1) that can be derived through optimizing $\gamma_n(\omega)$. Then, the weighting factors (w_n^k) at time step n can be obtained for each ensemble member based on the performance of climate simulations with respect to observations up to time step $n-1$:

$$w_n^k = w_{n-1}^k \times e^{-\lambda(\omega_n, \gamma_n^k)} \tag{4}$$

This indicates that EA algorithm learns from the past and adjusts itself to derive the best ensemble response. In this approach, each ensemble member (e.g., Kth member of the ensemble) would have its own cumulative error function (E_n^K). Having K expert advice (climate simulations or ensemble members), the objective of the algorithm is to obtain the best prediction at time step n with the least cumulative error over the past $n-1$ time steps (E_{n-1}) where observations are available.

$$E_n^k = E_{n-1}^k + \lambda(\omega_n, \gamma_n^k) \tag{5}$$

As shown in Fig. 1 (right flowchart), the initial values of error (loss) functions are set to zero (i.e., $E_0^1, \ldots, E_0^K = 0$). The cumulative loss (error) for each ensemble member at time step n can then be obtained by accumulating the error (loss) function in the past $n-1$ time steps (see Fig. 1 (right flowchart)). The algorithm guarantees that for all $n = 1, 2, \ldots,$ the cumulative error function (E_n) will be less or equal to the best model plus a constant – depending on the number of climate simulations (Vovk, 2001):

$$E_n \leqslant \min_{k=1,\ldots,K} E_n^k + \ln K \tag{6}$$

The proposed methodology is used to derive the climate response of the multimodel CMIP5 temperature simulations. Fig. 2 displays the global annual mean temperature (1951–2005) based on (a) EA algorithm; and (b) the multimodel ensemble mean. Both Fig. 2a and b are derived using 17 CMIP5 historical temperature simulations. One can see the spatial patterns of both are very similar. However, the EA algorithms leads to smaller mean absolute error (MAE) compared to the ensemble mean (compare Fig. 2c and d). As shown, the MAE of the ensemble mean exceeds 2 °C over certain regions, while the MAE of the EA algorithm remains primarily below 1 °C.

In most climate change and variability studies, anomalies are used instead of the absolute values of, here, temperature, to account for biases in climate model simulations (e.g., Collins et al., 2011). Fig. 2e and f display the MAE of the EA algorithm and ensemble mean, respectively. In these figures, CMIP5 temperature anomalies are derived based on CRU observations (1951–2005). As shown, even considering the temperature anomalies, the EA algorithm leads to a smaller error than the ensemble mean.

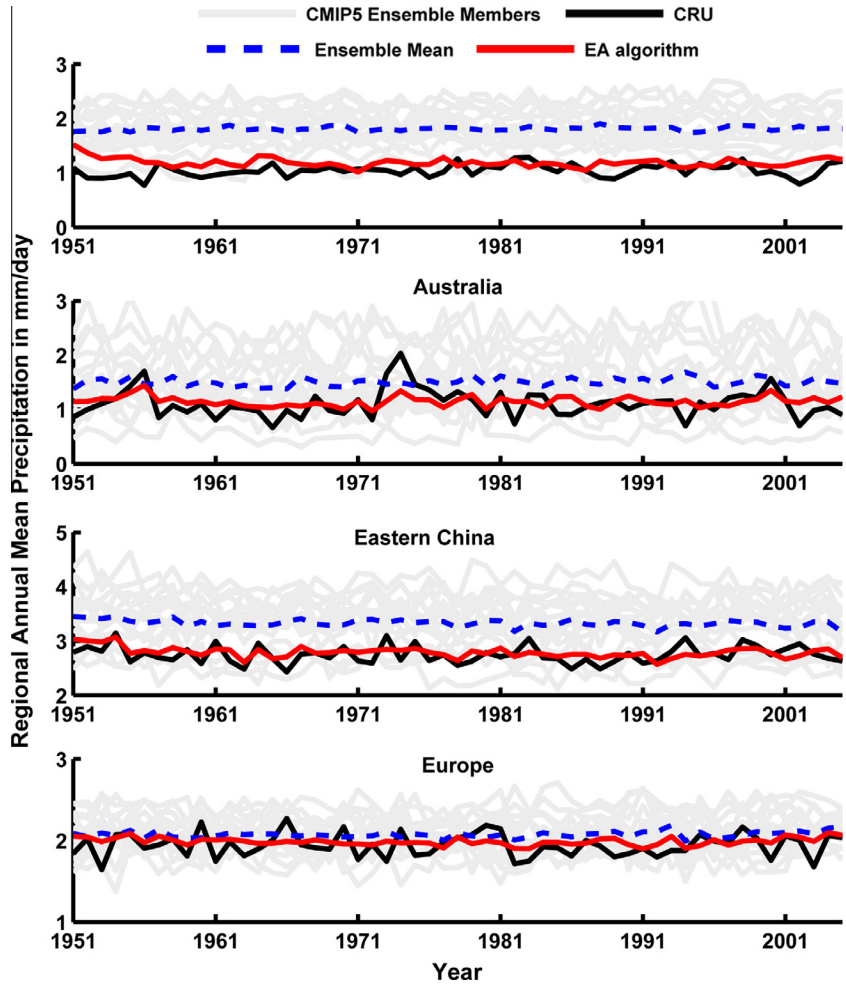

Fig. 8. Time series of the CMIP5 annual mean precipitation, and the ensemble response based on the arithmetic mean and the EA algorithm for the western United States, Europe, eastern China and eastern Australia. The solid black line represents the CRU annual mean precipitation, whereas the gray lines show the individual CMIP5 ensemble members (17 models). The dashed blue and solid red lines respectively show the ensemble mean and the EA algorithm (similar to Fig. 5, but for precipitation). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 3 shows the climate response of the global annual temperature based on the CMIP5 multimodel ensemble for three decades: 1951–1960, 1971–1980, and 1991–2000. The first and second rows in the figure display the results using the EA algorithm and the corresponding error, respectively. In Fig. 3, the third and fourth rows show the same result for the ensemble mean. Similar to the results presented in Fig. 2, at the three time steps, the EA algorithm leads to a smaller error compared to the ensemble mean.

To further investigate the performance of the proposed climate response algorithm, the time series of the CMIP5 ensemble members, and the ensemble response based on the arithmetic mean and the EA algorithm are provided for the western United States, Europe, eastern China and eastern Australia (see the highlighted regions in Fig. 4). In Fig. 5, the solid black line represents the CRU annual mean temperature, whereas the gray lines show the individual CMIP5 ensemble members (17 models). The dashed blue and solid red lines respectively show the ensemble mean and the EA algorithm. As shown, the EA algorithm is in much better agreement with the observed historical data compared to the ensemble mean, especially in the western United States and eastern China. In the EA algorithm, the ensemble members that are in better agreement with observations and lead to the smaller cumulative loss function receive higher weights in estimating the climate response. Fig. 6 plots the mean absolute error (temperature °C) values for the ensemble arithmetic mean and EA algorithm. The figure confirms that the EA algorithm leads to less error with respect to observed historical data. For the selected regions, Table 1 summarizes the MAE and mean squared error (MSE). As shown, the metrics confirm that the EA algorithm is superior to the ensemble mean in the selected regions.

Technically, the proposed algorithm can be used with different data sets. Application of the algorithm to CMIP5 precipitation data is presented in Figs. 7–9. As shown the behavior of the EA algorithm relative to the ensemble median is similar to temperature data (compare Figs. 8 and 9 with Figs. 5 and 6). It should be noted that CMIP5 simulations are not forced with the observed sea surface temperature, and hence their daily, monthly or annual values (especially extremes) are not expected to match with the observations. We do not claim that this method leads to a climate response that can represent the observed monthly or interannual variability. Neither do we claim that the proposed algorithm would remove the underlying biases. The suggested algorithm provides an ensemble response consistent with the average statistics of the observations. The final product should be used and interpreted the way climate model simulations are used in the literature. That is, understanding the long-term means, statistics, trends, responses to changes in forcing, etc.

Finally, the application of this algorithm is not limited to climate model simulations and is not designed for a specific data

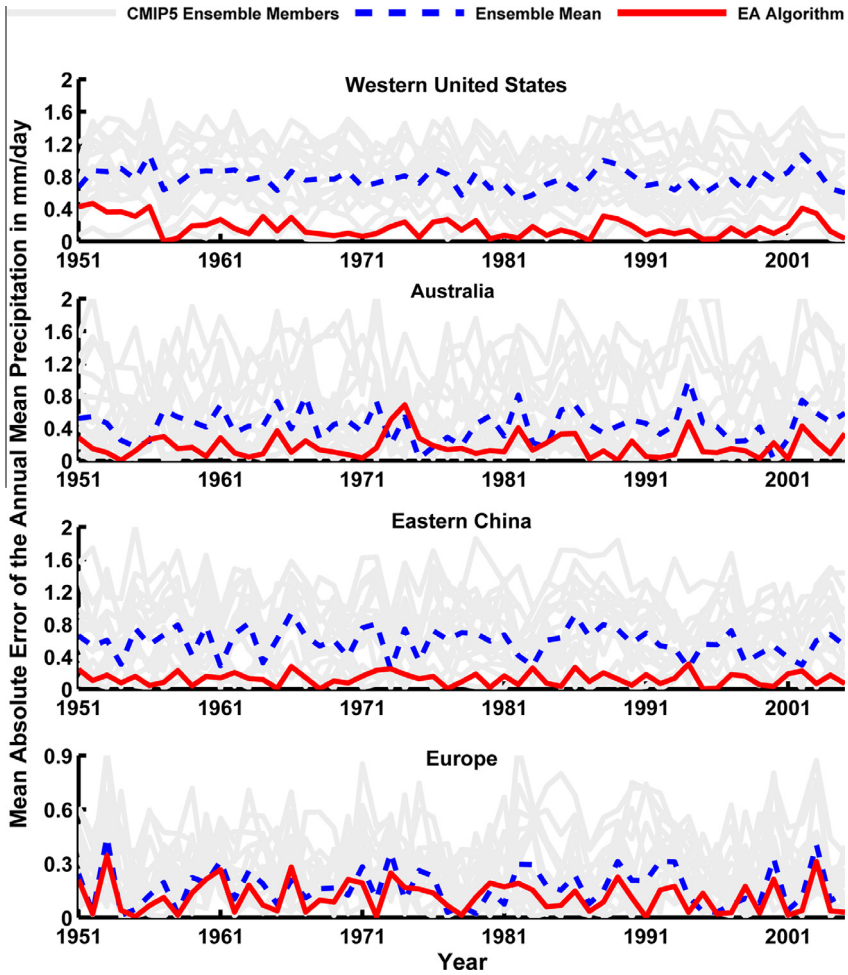

Fig. 9. Mean absolute error (precipitation in mm/day) values for the ensemble arithmetic mean and EA algorithm shown in Fig. 8 (similar to Fig. 6, but for precipitation).

set or variable. It can potentially be applied to other applications including deriving ensemble response of persistence-based drought prediction models (AghaKouchak, 2014a; Lyon et al., 2012; Madadgar and Moradkhani, 2013; Hao et al., 2014), multi-model streamflow forecasting (Wood and Schaake, 2008; Moradkhani et al., 2006; Najafi et al., 2012); persistence-based ensemble predictions (AghaKouchak, 2014b); post-processing of hydrologic forecast ensembles (Madadgar et al., 2014), water availability and energy production (Tarroja et al., 2014b), and multi-model hurricane tracks (Zhang and Krishnamurti, 1997). Specifically, this model can be useful for slow changing processes such as drought in which the state variables do not change substantially from one time step to another.

4. Conclusions and discussion

In this paper, a methodology is proposed for deriving the climate response of multimodel climate simulations. The suggested approach is an alternative to the arithmetic mean of ensemble members. The methodology is based on the concept of Expert Advice (EA) algorithm that has been widely used in the financial sectors. The objective of the EA algorithm is to derive weights of predictors (here, individual ensemble members) such that at every time step the ensemble response (here, climate response) is equal or better than the best model. The model was tested using the CMIP5 historical temperature simulations (1951–2005), and the results showed that the EA algorithm led to smaller mean absolute error (MAE) values compared to the ensemble mean. The MAE values were smaller for both the original simulations and the temperature anomalies derived based on CRU observations.

The suggested climate response model could also be used with climate projections, assuming that the performance of the models in future will be the same as in the past. That is, the final set of weights obtained based on historical data would be used for deriving ensemble response of projections. The authors acknowledge that modeling observed historical data accurately does not guarantee that the model can produce reliable climate response. Nonetheless, the importance of representing historical observations cannot be ignored. It is worth mentioning that the proposed methodology is more suitable when absolute values of climate model simulations are needed. Using anomalies one can avoid biases and look into relative changes simulated by individual models. However, for practical applications such as climate change impact assessment on the water cycle and ecosystem, one needs the absolute values of climate variables.

It is well-known that the multimodel ensembles are not necessarily symmetrical around observations. The proposed algorithm can capture the asymmetries in the ensemble, leading to a response that matches the observations best rather than a response in the center of the ensemble. In most studies, uncertainties of climate projections are described/quantified by a measure of spread across the ensemble mean (Furrer et al., 2007; Tebaldi and Knutti, 2007; Masson and Knutti, 2011; Lopez et al., 2006). For example, in a review study, Knutti et al. (2008) describes the uncertainty of the global temperature projections as one standard deviation of the multimodel response ensemble around the ensem-

ble mean. In other words, most uncertainty models, assume a symmetrical uncertainty space around the climate response. However, there is no reason to believe that uncertainty space of future projections is symmetrical around a given ensemble mean (climate response). While the Gaussian assumption of uncertainty is widely being used mainly due to its simplicity, the distribution of uncertainty space is completely arbitrary. Current efforts are underway by the authors to use a non-Gaussian uncertainty model based on AghaKouchak et al. (2010) around the suggested climate response model (EA algorithm). This would allow deriving the probability of exceedance of a certain condition above/below the climate response given an asymmetrical spread of the uncertainty (ensemble).

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