Quantifying the Uncertainties in an Ensemble of Decadal Climate Predictions Ehud Strobach^{1,2} and Golan Bel^{3,4}

¹University of Maryland, ²NASA Goddard Space Flight Center, ³Ben-Gurion University of the Negev, ⁴Los Alamos National Laboratory

1. Introduction

Meaningful climate predictions should be accompanied by the corresponding uncertainty range. Common methods for estimating the uncertainty range are based on the spread of ensemble predictions. However, a simulation ensemble is not necessarily a proper sample of the real distribution of the climate, and therefore, the ensemble spread cannot be interpreted as the actual uncertainty.

We propose a new method that links between the ensemble spread and the uncertainty without relying on any assumptions regarding the distribution of the ensemble predictions. The method is tested using CMIP5 1981–2010 decadal predictions and is shown to outperform other common methods.



. Metl	hods	$\begin{array}{c} + & + \\ + & - & - \\ + & + \\ \end{array}$	\rightarrow time \rightarrow
Institute ID	Model name	Modeling center (or group)	Grid (latitude × longitude)
BCC	BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration	64 × 128
CCCma	CanCM4	Canadian Centre for Climate Modelling and Analysis	64 × 128
CNRM-CERFACS	CNRM-CM5	Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	128 × 256
LASG-IAP	FGOALS-s2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences	108×128
IPSL	IPSL-CM5A-LR	Institute Pierre-Simon Laplace	96 × 96
MIROC	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo),	128 × 256
	MIROC4h	National Institute for Environmental Studies, and Japan Agency	320 × 640
		for Marine-Earth Science and Technology	
MRI	MRI-CGCM3	Meteorological Research Institute	160 × 320

Weighted ensemble

$$P_t \equiv \sum_{E=1}^N W_{E,t} \cdot f_{E,t}$$

Models are weighted based on their past performance using the EGA machine learning algorithm (Strobach and Bel, 2015, Strobach and Bel, 2016)

Uncertainty range for confidence level c

 $\Pr\{(\mathbf{p}_{t} - \gamma_{d} \cdot \delta_{G} \cdot \sigma_{t}) \leq y_{t} \leq (\mathbf{p}_{t} + \gamma_{u})\}$ Normal distribution (no correction): γ_{μ}

- RMSE-corrected method: $\gamma_u = \gamma_d = \gamma_d$
- Asymmetric range method: $\gamma_u = \inf \left\{ \gamma_u \in \Re: \frac{1}{n} \sum_{t=1}^n \Theta((p_t + \gamma_u \cdot \sigma_t) - \right\}$ $\gamma_d = \inf \left\{ \gamma_d \in \Re: \frac{1}{n} \sum_{t=1}^n \Theta(y_t - (p_t - \gamma_d \cdot p_t)) \right\}$



$$\begin{aligned} & \{ \cdot \delta_G \cdot \sigma_t \} \\ & = \gamma_d = 1 \\ \hline \frac{\sum_{t=1}^n (p_t - y_t)^2}{\sum_{t=1}^n \sigma_t^2} \end{aligned}$$

$$(y_t) \ge \frac{1+c}{2}$$

 $(\sigma_t)) \ge \frac{1+c}{2}$

3. Results: monthly surface temperature (1991-2010)

a. Predicted minus observed confidence level



The spatial distribution of the difference between the fraction of observations that were outside the predicted range of the c=0.9 confidence level and the predicted 0.1 fraction, for the surface temperature.

c. Ratio between the uncertainty ranges estimated using different methods



The log of the ratio between the uncertainty ranges of the monthly surface temperature with a confidence level of 0.9 as estimated by the RMSEcorrected and asymmetric methods and those estimated by the Gaussian method. The two left panels show the ratio for the predictions of an equally weighted ensemble, and the two right panels show it for a weighted ensemble (EGA forecaster).

$$\delta_G = \sqrt{2} \operatorname{erf}^{-1}(\mathbf{c}), \ \operatorname{erf}(s) \equiv \frac{1}{\sqrt{\pi}} \int_{-s}^{s} e^{-x^2} dx$$













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b. Observed vs. estimated frequency

4. Conclusions

Without correction, the CMIP5 ensemble is over-confident (the variance is smaller than the mean squared error).

The asymmetric method improves the ensemble forecast reliability without relying on any assumption regarding the distribution of the predictions.



