Model Sensitivity-Determinate Multi-Parameter Estimation in Coupled Climate Models

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Abstract

While the information estimation theory based on Bayes' theorem is developed as various data assimilation algorithms for state estimation, it has also been applied to model parameter estimation. The resulted observation-estimated parameters can mitigate model bias. Parameter estimation is very promising for a coupled climate model to constrain its climate drift in climate simulation and prediction. However, given the existence of numerous model parameters, how to systematically perform parameter estimation is a research topic. Linking model sensitivities with the signal-to-noise ratio of parameter estimation, this study develops a physically-based methodology of simultaneous multiple parameter estimation for coupled climate models with biased physics. While either all the parameters within the biased physical scheme or only the most influential physical parameters being optimized, can greatly mitigate the model biases induced by biased physics, better results for climate estimation and climate prediction will be obtained when using this physically-based methodology of simultaneous multiple parameter estimation. These results provide a guideline when the real observations are assimilated into a coupled general circulation model that includes imperfect physical schemes for improving the performance of climate estimation and prediction by multiple parameter estimation.

Background

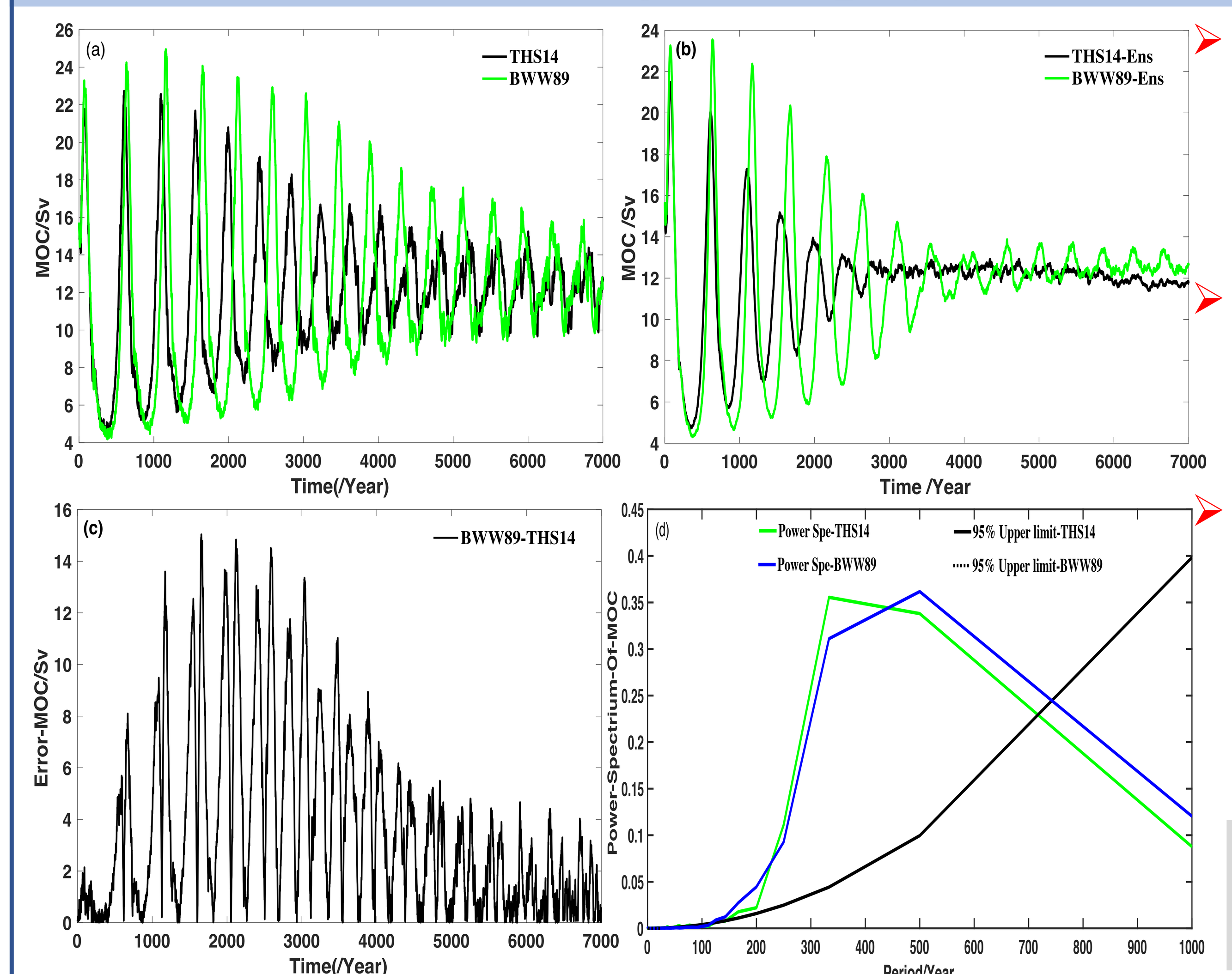
- Parameter estimation is very promising for a coupled climate model to constrain its climate drift in climate simulation and prediction.
- In traditional PO scheme, neither all parameters or the most sensitive one being simultaneously optimized can get the best results for climate estimation and prediction.
- Given the existence of numerous model parameters and linking the model sensitivities with signal-to-noise ratio, how to systematically perform parameter estimation is a research topic.

Methods

- A low-dimension analogue of the North Atlantic climate model, involving interaction between large-scale atmospheric circulation and ocean states driven by the variability of the Atlantic meridional overturning circulation (MOC). was used in this study. (Tardif et al. 2014)
- Different schemes for the volume averaged equivalent salt flux Q_S (a simplified representation of the hydrological cycle). THS14 scheme (Robert Tardif et al. 2014): A simple parameterization for Q_S is derived by assuming that runoff and mean transport terms are constant and by postulating that the eddy water vapor transport depends linearly on the eddy energy (Y^2+Z^2) as in Stone and Yao (1990): $Q_S = C_1 + C_2(Y^2+Z^2)$; BWW89 Scheme: the surface salinity flux is further simplified by replacing with $Q_S = m_{en}S_0$, $m_{en} = \frac{1}{2}\epsilon_s \frac{A_{O2}}{\rho_0 L_c} Q^O_{LH,2}$, $Q^O_{LH,2} = -\beta_0 + \beta_1 T_{*O2} + \beta_2 T_{s2}$ with $T_{s2} = A_2 + B_2 T_{*O2} + C_2 T_{*O1}$.
- DAEPC is employed to compute the model states and perform parameter optimization. $\Delta\mathcal{Y}^o_{k,i} = (\bar{\mathcal{Y}}^{\mathcal{U}}_k + \Delta\mathcal{Y}'_{k,i}) - \mathcal{Y}^{\mathcal{P}}_{k,i}$, $\Delta\mathcal{Z}_{i,j} = \frac{c^p_{j,k}}{(\sigma^p_{k,k})^2}\Delta\mathcal{Y}^o_{k,i} = \frac{Cov(\mathcal{Z}_j, \mathcal{Y}_k)}{(\sigma^p_{k,k})^2}\Delta\mathcal{Y}^o_{k,i}$.

Results

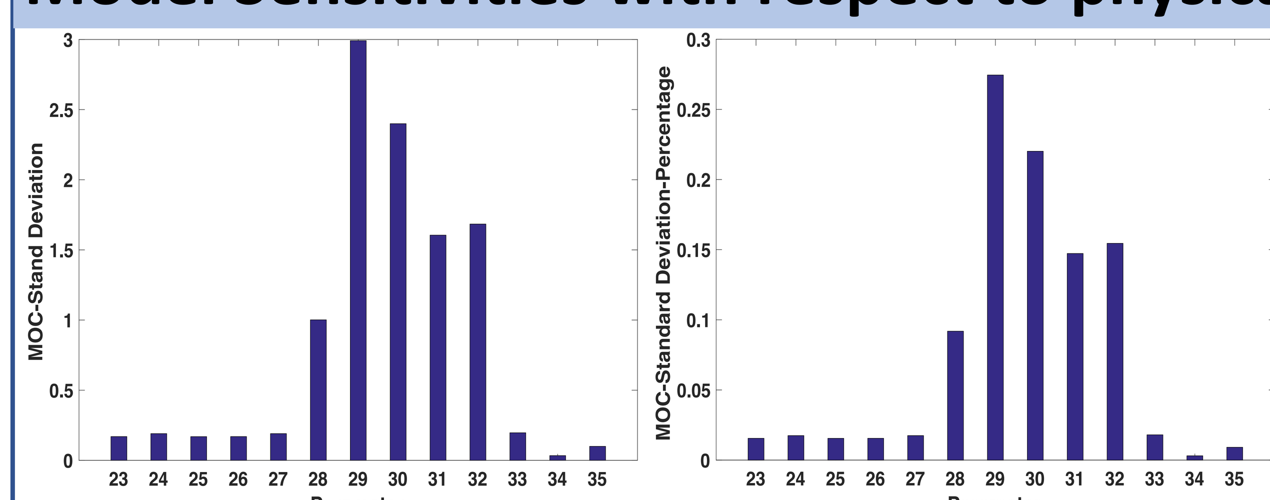
The model bias arising from physical schemes



- Similar as Tardif et al. 2014, initial condition condition are set such that the model solutions are in oscillatory mode, with an initial MOC strength of 15 Sv.
- Here the truth model uses the THS14 scheme, while the assimilation model uses the BWW89 scheme.
- Power spectrum of the MOC strength between 3000 and 4500 years assimilation starting from the initial condition with the THS14 and BWW89 scheme. And the characteristic variability time scales are about 300 and 500 years, respectively.

Fig 1. Difference of MOC strength and Power Spectrum between the models using the THS14 and BWW89 hydrological cycle.

Model Sensitivities with respect to physical parameters

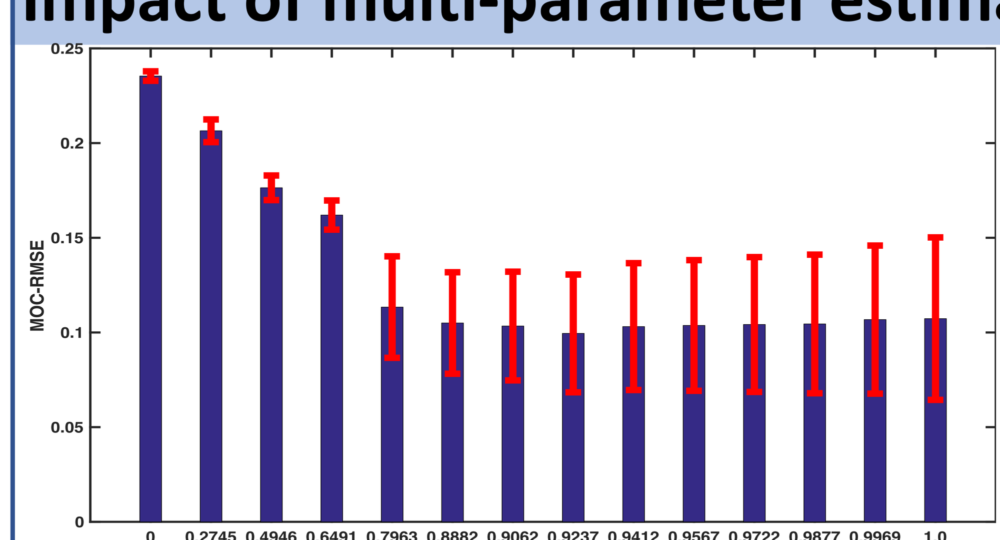


	28	29	30	31	32
Percentage	0.0919	0.2745	0.2201	0.1472	0.1545
	23	24	25	26	27
Percentage	0.0155	0.0175	0.0155	0.0155	0.0175
Stand Devi	0.1693	0.1903	0.1689	0.1694	0.1904
	33	34	35		
Percentage	0.0180	0.0031	0.0091		
Stand Devi	0.1964	0.0335	0.0995		

- For each parameter, the standard deviation of perturbation is 5% of the default value. All 100 ensemble model runs are started from the biased initial condition, the assimilation model is integrated for 100 years and sensitivity are calculated using the outputs from the last 50 years.
- The most sensitive parameters are including in calculation of $Q^O_{LH,2}$, which represents the latent heat flux to the atmosphere from the surface of low-latitude ocean.

Fig 2. The time-averaged sensitivity and its percentage of the MOC strength with respect with all 13 parameters including in BWW89 scheme for Qs.

Impact of multi-parameter estimation on MOC strength estimation



	RMSE	Percentage	Spread
MPP	0.2354	0.0 (assuming)	0.0025
29	0.2065	0.2745	0.0060
29-30	0.1764	0.4946	0.0065
29-30-32	0.1620	0.6491	0.0077
29-30-32-31	0.1134	0.7963	0.0268
28-29-30-31-32	0.1050	0.8882	0.0268
28-29-30-31-32-33	0.1034	0.9062	0.0287
27-28-29-30-31-32-33	0.0995	0.9237	0.0311
24-27-28-29-30-31-32-33	0.1031	0.9412	0.0335
29 ,30,32,31,28,33 , 27,24,26	0.1037	0.9567	0.0345
29 ,30,32,31,28,33, 27,24, 26,23	0.1042	0.9722	0.0356
29 ,30,32,31,28,33, 27,24, 26,23,25	0.1045	0.9877	0.0366
29 ,30,32,31,28,33, 27,24, 26,23,25,35	0.1068	0.9969	0.0391
13-param	0.1073	1.0	0.0429
CTL	1.7018		1.2885
SEO	0.3733		0.0999

- In order to mitigate the dependence of the results on the initial condition, each parameter optimization experiment will be repeated for 20 times starting from 20 different initial conditions.
- 0 represent that all of the parameters within the biased physical scheme are perturbed but not estimated. And 1 denotes that all these parameters are simultaneously perturbed and estimated.
- The parameters whose sensitivities account nearly 90% of the sensitivities being estimated can get the lowest RMSEs of MOC strength estimation.

Fig 3. The RMSEs of the MOC value for different PO experiments using different sensitivity percentages. Here the blue bar represents the mean value of the RMSEs of the 20 cases starting from 20 different initial conditions. And red bar stands for the upper/lower level of the uncertainty of RMSEs (standard deviation of 20 cases).

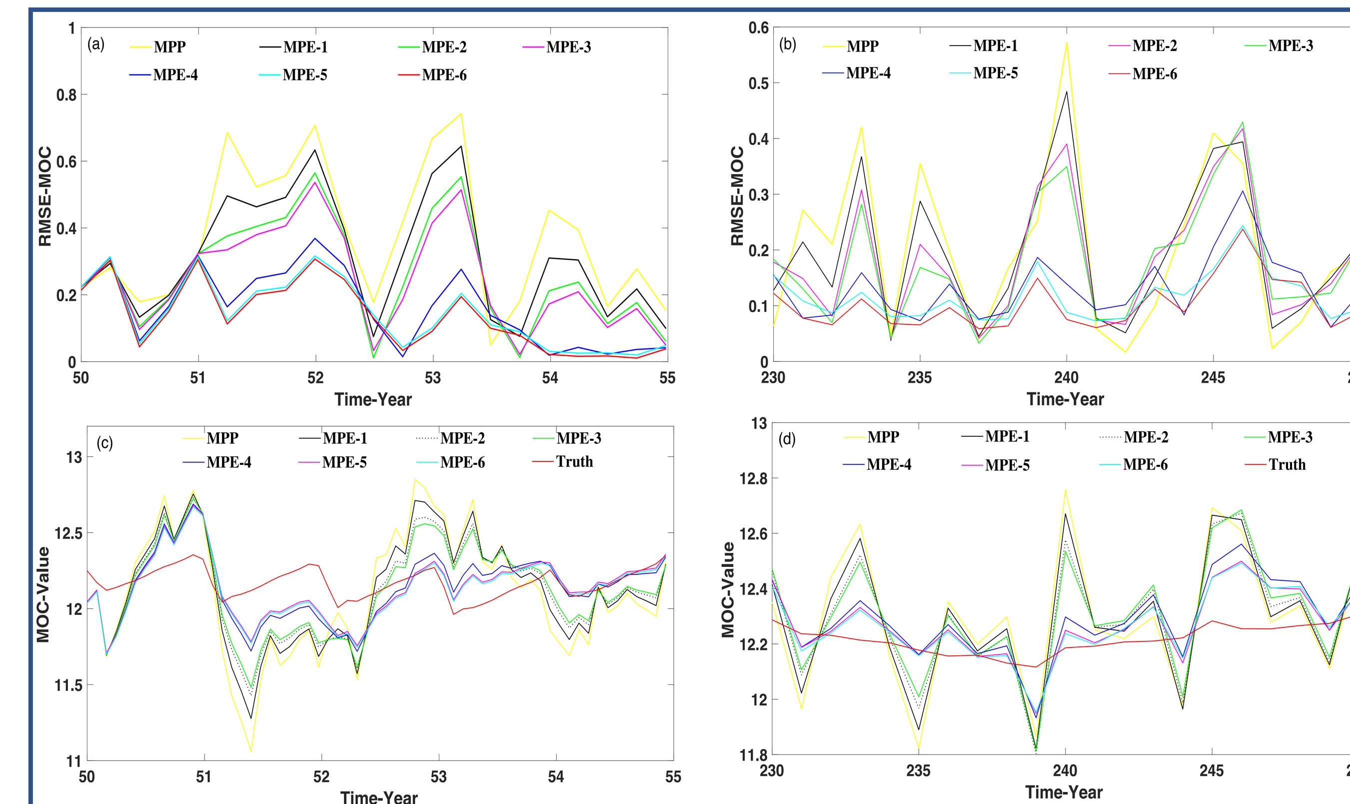


Fig 4. Time series of the RMSEs or MOC strength during 50 to 55 years and 230 to 250 years for different PO experiments. (The results of MPE7~MPE13 are very closely to that of MPE6 and not shown.)

Conclusion

- Parameter optimization is able to mitigate the model biases induced by biased physics and enhance the performance of AMOC analyses.
- While either all the parameters within the biased physical scheme or only the most influential physical parameters being optimized, can greatly mitigate the model biases induced by biased physics, better results for climate estimation and climate prediction will be obtained when using this physically-based methodology of simultaneous multiple parameter estimation.
- In this Low-order coupled model case, the parameters whose sensitivities account nearly 90% of the sensitivities of the MOC strength with all 13 parameters being estimated can get the optimal results. Also in order to mitigate the dependence of the results on the model, we are testing this method on an intermediate coupled model and a CGCM.

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