Parametric Sensitivity of E3SM in the Presence of Aleatoric, Observational, and Structural Uncertainty

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BACKGROUND

Many adjustable parameters in Earth System Models (ESMs) require calibration. An uncertainty in these parameters' values, especially those related to aerosol and cloud processes, can cause an Equilibrium Climate Sensitivity (ECS) spread that is equal to the uncertainty resulting from structural variations throughout climate models.

Recently, many US climate models have undertaken a research program to use Perturbed Physics Ensembles (**PPE**) to objectively calibrate ESM parameters. All the efforts have converged around a common, three-step framework called **Perturb parameters** θ_i , **Emulate,** and **Estimate** or **Calibrate**.

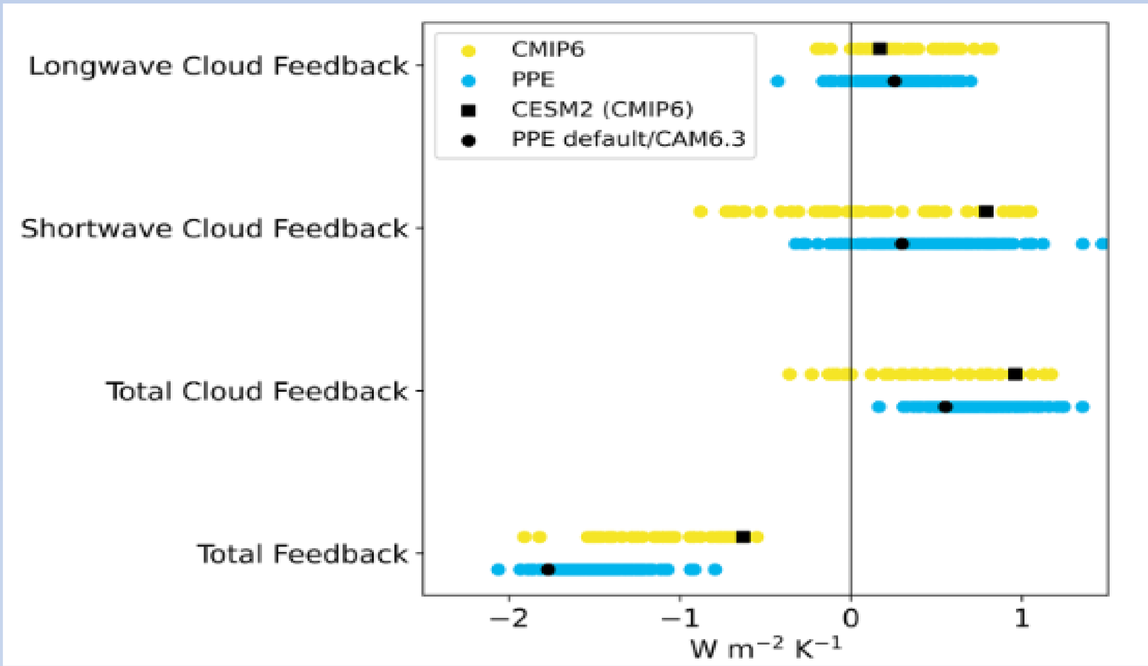

Figure 1 (Duffy et al., 2024), all CMIP6 ESMs are indicated by yellow dots. CESM2-CAM6 simulated values of the 45 tunable parameters (they are disrupted within logical physical limits selected by expert elicitation) denoted by blue dots.

As climate models are too expensive to undergo iterative optimization procedures, instead, a machine learning emulator, $Y_{Em} \approx Y_{Model}(\theta_i)$ is used that can map model parameters θ to subset Y_{Model} of model output.

$$\hat{\theta} = argmin|Y_{obs} - Y_{Em}|$$

Where $\hat{\theta}$ is the optimal value of parameter, by optimal, we mean that the model best matches observations when comparing a subset of model output Y_{Em} with the corresponding set of observations Y_{obs} .

METHODOLOGY

To tune the model, we plan to create 263 parameter sets using Latin hypercube sampling method, in which 45 parameters carefully selected from parameterizations associated with cloud processes, convection-precipitation, and aerosols. Table 1 shows an example of deep convection parameters we considered.

Table 1: A description of deep convection parameters (Eidhammer et al., 2024)

Physics Scheme	Parameter Name	Description	Default	Min	Max
ZM	cldfrc_dp1	Parameter for deep convection cloud fraction	0.1	0.05	0.25
	cldfrc_dp2	Parameter for deep convection cloud fraction	500	100	1,000
	zmconv_c0_lnd	Convective autoconversion over land	0.0075	0.002	0.1
	zmconv_c0_ocn	Convective autoconversion over ocean	0.03	0.02	0.1
	zmconv_capelmt	Triggering threshold for ZM convection	70	35	350
	zmconv_dmpdz	Entrainment parameter	-1.0e-3	-2.0e-3	-2.0e-4
	zmconv_ke	Convective evaporation efficiency	5.0e-6	1.0e-6	1.0e-5
	zmconv_ke_lnd	Convective evaporation efficiency over land	1.0e-5	1.0e-6	1.0e-5
	zmconv_momcd	Efficiency of pressure term in ZM downdraft CMT	0.7	0	1
	mconv_momcu	Efficiency of pressure term in ZM updraft CMT	0.7	0	1
	zmconv_num_cin	Allowed number of negative buoyancy crossings	1	1	5
	zmconv_tiedke_add	Convective parcel temperature perturbation	0.5	0	2

There are several approaches to perturb parameters and the related study of parameter uncertainty. Every technique has a computational cost, which usually depends by the quantity of simulations run. For example, the "One At a Time" (OAT) technique is the conventional way for analyzing sensitivity to factors (Schmidt et al., 2017). However, OAT techniques typically produce ineffective results since they fail to take into consideration nonlinear interactions between various factors. In recent years, more objective and effective techniques for concurrently perturbing numerous moist physics and aerosol parameters have been devised (Eidhammer et al., 2024, Duffy et al., 2024).

METHODOLOGY
(cont.)

Here, we plan to conduct 3-years long simulation ensembles using the parameter samples using present day cyclic boundary conditions for the year 2010. We chose only 3-years long simulation because the recent study of Eidhammer et al., 2024 show 3-years and 5-years long simulations could be reproduce with similar RMSE for a given variable. The average monthly sea surface temperatures (SSTs) for 1995-2010 are used. All simulations use a resolution of 0.9◦ latitude × 1.1◦ longitude with 32 levels.

In this study we will use our 263 ensemble members to train and test the **Gaussian Processes** (**GP**), **Random forests** (**RF**), **Convolutional Neural Net** (**CNN**) emulator. In this case, we concentrate on the accuracy with which fast emulators can replicate particular model aspects, and we conclude with a brief illustration of their potential for model tuning. We make use of an open-source program called the Earth System Emulator (ESEm), which offers a comprehensive approach for simulating and evaluating a broad range of models and outputs (Watson-Parris et al., 2021).

Additionally, we have generated **10,000** parameters sets using the same Latin hypercube sampling method from 45 selected parameters. We generated prediction from trained GP, RF, CNN using these 10,000 sets. This large ensemble set allow us to fine tune the model without running the complex climate model 10,000 times.

E3SM CALIBRATION

We perform cross validation--the typical approach for dealing with overfitting in Machine Learning literature. Here, we leave out one or more of the CAM6 PPE members (as pseudo-observations) when training the emulator, and then evaluate how well the emulator is able to reproduce the value of the model output for those ensemble members that were not used in the emulator training. This process yields us the **optimal parameter set** (**$\hat{\theta}$**). Since the pseudo-observations are generated from the same model we are training and validating (e.g. CESM2-CAM6), we would call this a **perfect model** test. As of now we don't have the PPEs for E3SM and so we used the CESM2-CAM6 PPE from the study of Eidhammer et al., 2024.

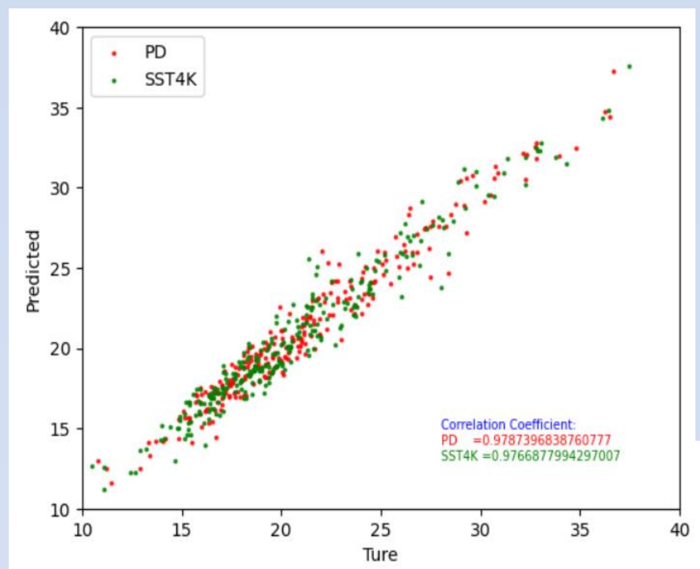

Figure 2 True vs Predicted by emulator. Red dots are for present day SST and green dots are for SST4K

- **In figure 2, it depicts the strength of the GP emulator because the true i.e., raw CESM2 LWCF vs GP predicted LWCF has a very strong positive linear relationship.**

- **In figure 3, as the emulated results of present day (PD) vs future (SST4K) also follows 1-to-1 relation i.e., correlation ~1 and so it is possible to predict climate by training the emulator with the present-day data!!!?**

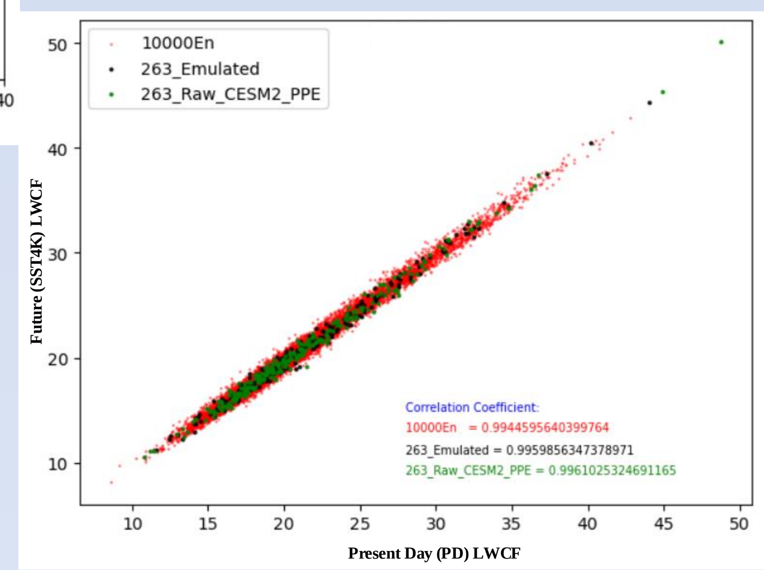

Figure 3 Present day SST vs 4k warming SST i.e., Future for Long wave cloud forcing (LWCF). The red dots are for 10,000 ensemble member emulated LWCF, black dots are for 263 ensemble member i.e., training set emulated LWCF, and green dots are for raw CESM2 model simulated LWCF.

E3SM CALIBRATION
(cont.)

To capture the structural uncertainty, we compare the RMSE of LWCF present day (PD) SST and SST4K for two different setup of model:

1. **CESM2 vs CESM1**
2. **CESM2 vs E3SMv2**.

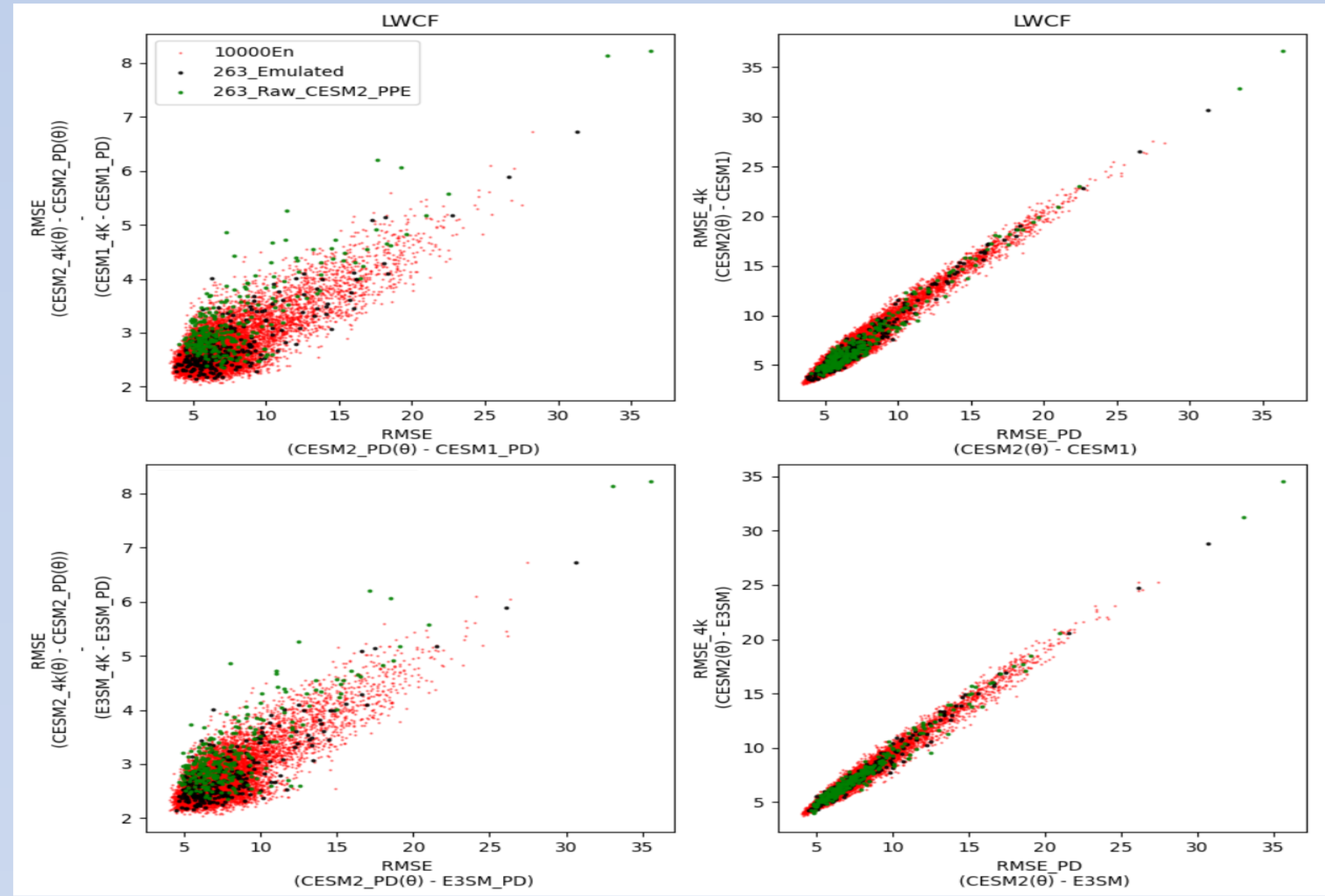

*Figure 4 Root mean square error (RMSE) of LWCF for SST4K vs PD. Upper panel is for the **CESM2-CESM1** comparison and lower panel is for **CESM2-E3SM** comparison. The left panel is for the total RMSE difference between CESM2 and CESM1 for SST4K to SST PD where the right panel is straightforward RMSE difference of CESM2 and CESM1 for SST4K.*

- In figure 4, as there is not much difference between top and bottom panel i.e., the role of structural uncertainty is negligible, we may use E3SM calibrated to pseudo-observations from historical CAM6 simulations to predict future climate in CAM6.

CONCLUSIONS

- In comparison to parametric uncertainty, structural uncertainty has relatively little influence.
- The prediction of future climate is possible with the help of ML and PD/historical pseudo-observations from CESM2-CAM6

FUTURE WORK

- In the future, we will train the emulator while taking weather and observational uncertainties into account by using the current gaussian process emulators and creating a hierarchical Bayesian framework.

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