Evaluating parametric sensitivity of climate feedback in the CNRM-CM6-1 model

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EGU General Assembly 2021

Introduction 1

The **Equilibrium Climate Sensitivity (ECS)** is the equilibrium warming in response to a doubling of carbon dioxide. Its values depend directly on **the climate feedback** strength. For almost 40 years, the ECS has been the primary metric of climate response to forcing and its uncertainty range remained broadly constant : [$1.5K$ – $4.5K$] [1].

However, in the short time since, **a number of significant questions have arisen from recent modeling activity** and a new ECS range was proposed, indicating a stronger constraint on ECS and lifting the low end of the range : [$2.3K$ - $4.5K$] [2].

In the 6th phase of CMIP, **1/3 of the GCMs have values of ECS exceeding 4.5K** [3]. These **high ECS values** are outside all of the uncertainty ranges previously assessed. **The parameters used to specify sub-grid processes** in climate models have a large impact on climate sensitivity [4]. A way to explore this parametric uncertainty is to create **Perturbed Physics Ensembles (PPE).**

Objectives : To explore the diversity and the plausibility of climate feedbacks in a perturbed physics ensemble (PPE) of the atmospheric-only simulations of CNRM-CM6-1.

Results 3

PPE feedback distribution :

In the PPE, we observed a large diversity of climate feedbacks, ranging from -1.7 to -0.7 $W.m^{-2}/K$, with the default model feedback falling at the center of the distribution (Figure 2).

This **feedback range is notably wider than the range observed in the multi-model CFMIP** ensemble and comparable to the results obtained in HadGEM3 atmosphere-only PPE [6].

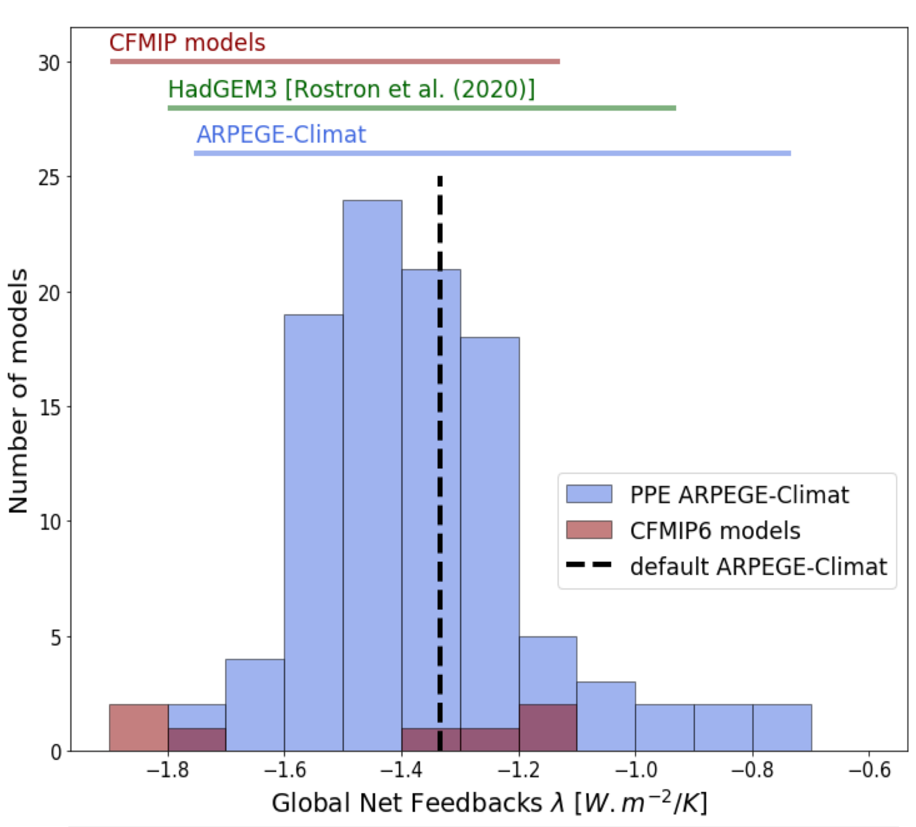

Figure 2 - Distribution of the feedback parameter $\lambda\,[W.m^{-2}.K^{-1}]$ in the PPE , the CFMIP models and the HadGEM3 ensemble.

Selection of optimal parametrizations along feedback range :

The optimization of the emulators allowed to find the sub-set of parametrizations with the lowest error covering the entire feedback range (black line, Figure 3). A selection of nine parametrizations is selected from this sub-set and used to produce nine candidate versions of ARPEGE-Climat, discretely sampling the range of net feedback (triangles, Figure 3).

The MLR proved efficient in the prediction of the climatic fields and its optimization allowed the **successful identification of better performing versions of the model** for the variables considered.

Six versions are found to have comparable or lower aggregated metric than the default, with estimated **climate sensitivities ranging from 3.8K to 10K**.

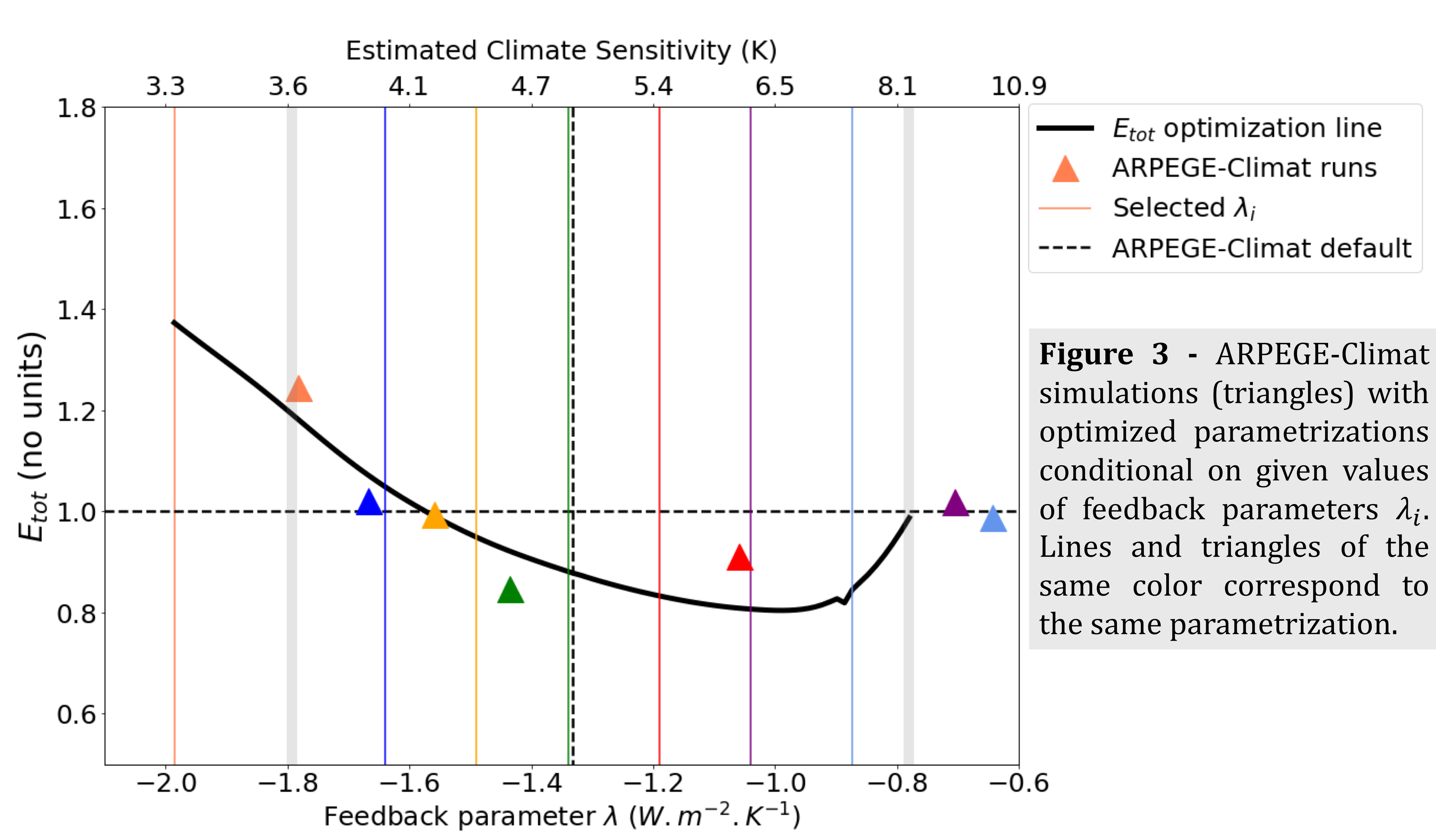

Figure 3 - ARPEGE-Climat simulations (triangles) with optimized parametrizations conditional on given values of feedback parameters λ_i. Lines and triangles of the same color correspond to the same parametrization.

Methods 2

Climate simulations :

- Atmospheric component of CNRM-CM6-1 : ARPEGE-Climat 6.3
- Control : **amip**
- Forced : **amip-future4K** (global mean SST increase is +4K in average)
- Three years long with prescribed CO_2 from 1979 to 1981

Perturbed Physics Ensemble (PPE) :

- 30 parameters selected
- Latin Hypercube sampling (parameters are varying simultaneously)
- 102 members

Control climate performance assessment :

Four variables (s) from amip simulation, temporally averaged :

- TOA radiative fluxes (SW, LW)
- Surface temperature (tas)
- Precipitations (pr)

- EOF analyse where the temporal dimension is replaced by the ensemble itself. In the present study, the EOFs were truncated after the 5th mode, explaining most of the variance.
- Projection of the observations (CERES, BEST and GPCP datasets) on the EOF basis .
- Root Mean Square Error (RMSE) between the principal component (w) for each member and the projection of the observations (o), with i varying from 1 to N, the number of modes considered ($N = 5$) :

$$E_s = \sqrt{\Sigma_i^N \frac{(w_{is} - o_{is})^2}{N}}$$

- E_s is standardized by the error associated with a simulation using the default parametrisation ($E_{DEF,s}$). Then we averaged all the errors and estimated the aggregated metric : $E_{tot} = \Sigma_s^P \left(\frac{E_s}{E_{DEF,s}}\right) \times \frac{1}{P}$ with $P = 4$.

Predictions with regression techniques :

Finite computational resources limit our capacity to run more members with the climate model.

We used a Multi Linear Regression (MLR) to predict the control climate and the feedbacks based on the perturbed parameter (Figure 1).

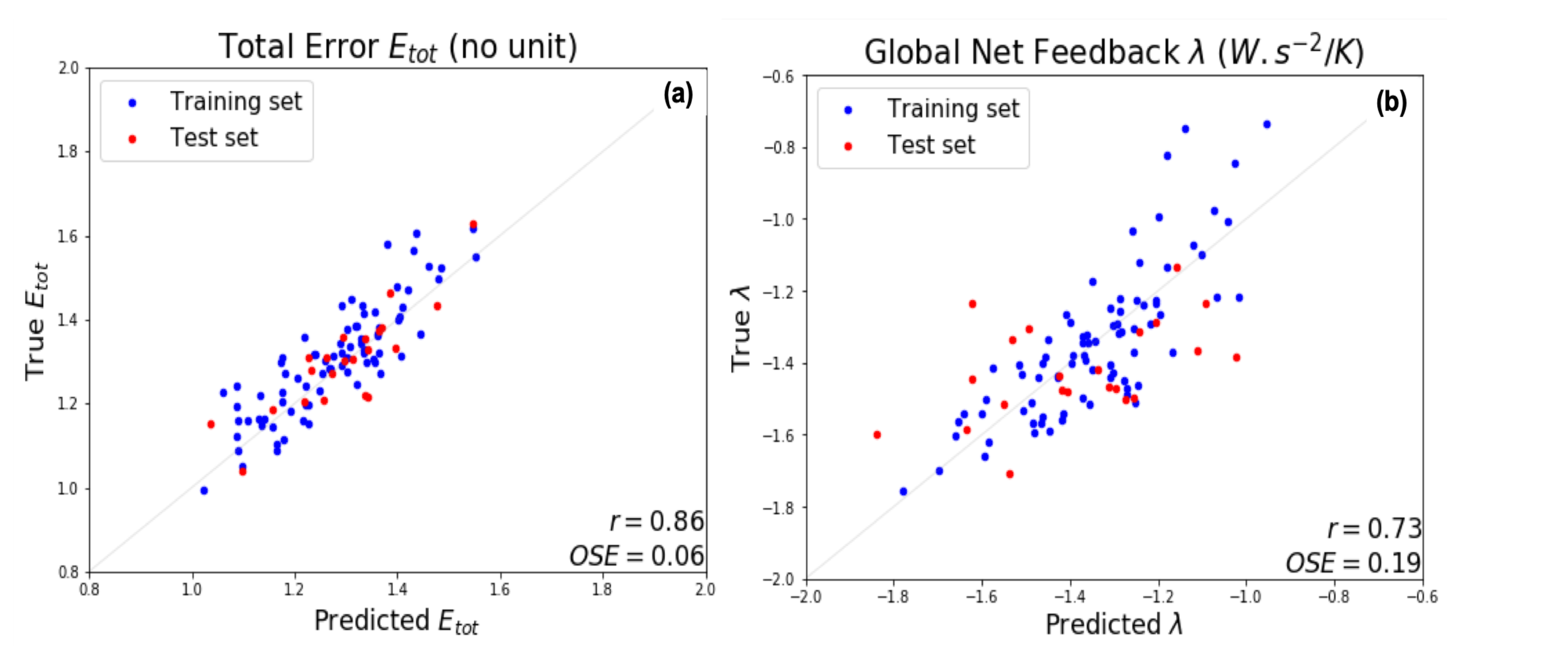

Figure 1 - Correlation between emulated and actual values of total error *Etot* and global net feedback.

Optimization with constraints :

Optimization of the emulators to minimize E_{tot} conditional on a global net feedback value predicted to lie within a chosen bin

→ Minimization with constraint to find optimal parametrizations

→ Sequential Least Squares Progamming (SLSQP) [5]

Conclusions 4

The climatological constraints considered suggest **the existence of model variants with comparable climatological performance** to the release version of CNRM-CM6 **with both lower and higher net feedback strengths.**

In the new generation of models, many members exhibited **values of ECS outside of the observed range**. Our model optimization exercise suggests that optimal model configurations may exhibit **even higher values of ECS**. Understanding how these findings integrate into a **general assessment of ECS is a priority for future research.**

Perspectives : The method developped here will be used to find candidates for fully coupled simulations. Further study will explore the relationship between some parameters and the change in climate sensitivities. Trade-offs between performance in different variables will be investigate.

[1] Charney, J. G. et al. (1979). *Carbon dioxide and climate: a scientific assessment.*
[2] Sherwood et al. (2020). *An assessment of Earth's climate sensitivity using multiple lines of evidence.*
[3] Zelinka et al. (2020). *Causes of higher climate sensitivity in CMIP6 models.*
[4] Sanderson et al. (2008). *Constraints on model response to greenhouse gas forcing and the role of subgrid-scale processes.*
[5] Kraft (1988). *A software package for sequential quadratic programming.*
[6] Karmalkar et al. (2019). *Finding plausible and diverse variants of climate model.*