Addressing compensating biases in EC-Earth4: the development of spatial tuning with ECtuner

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1. Introduction and Model configuration

Developing Earth System Models (ESMs) like **EC-Earth4** relies on parameterizations to represent subgrid-scale processes, which introduce significant **parametric uncertainty**. The **tuning procedure** is therefore a fundamental step to constrain these parameters and reduce systematic biases, ensuring that the model realistically reproduces the observed climate. (Hourdin et al. 2017, Mauritsen and Roeckner 2020, Mignot et al. 2021) However, traditional tuning can hide regional errors through compensating biases.

The EC-Earth4 climate model components:

- **OpenIFS-48r1** for the atmosphere
- **NEMO v4.2.2** (ORCA2 grid) for the ocean.

The **objectives** to be achieved through the tuning of EC-Earth4:

- minimizing biases in Net TOA radiation and component fluxes
- global Sea Surface Temperature (SST) distribution
- dynamics and circulation targets like the AMOC strength.

2. The AMIP tuning strategy

Calibration is performed across various stages, starting with standalone components (OIFS/NEMO), before final coupled system integration. The **atmospheric component** is specifically tuned to achieve radiative balance at the TOA using CERES observations.

The **ECtuner tool** (https://github.com/jhardenberg/ECtuner/tree/main) automates this process through a structured workflow:

1. **Sensitivity Analysis** (by using `sensitivity.py`): assess how target variables (e.g., radiative fluxes) respond to parameter perturbations.
2. **Define target fluxes and reference**: select the target radiative fluxes and the model's climate state computed via **ECmean**. These are compared against reference datasets to evaluate biases.
3. **Regional Weighting:** allows focusing on specific latitudinal bands (e.g., tropical vs. midlatitude) to correct regional biases.
4. **Optimization:** a global minimization algorithm (as **Dual annealing**) finds the parameter set that minimizes the cost function.

3. From global-mean to 2D spatial Tuning

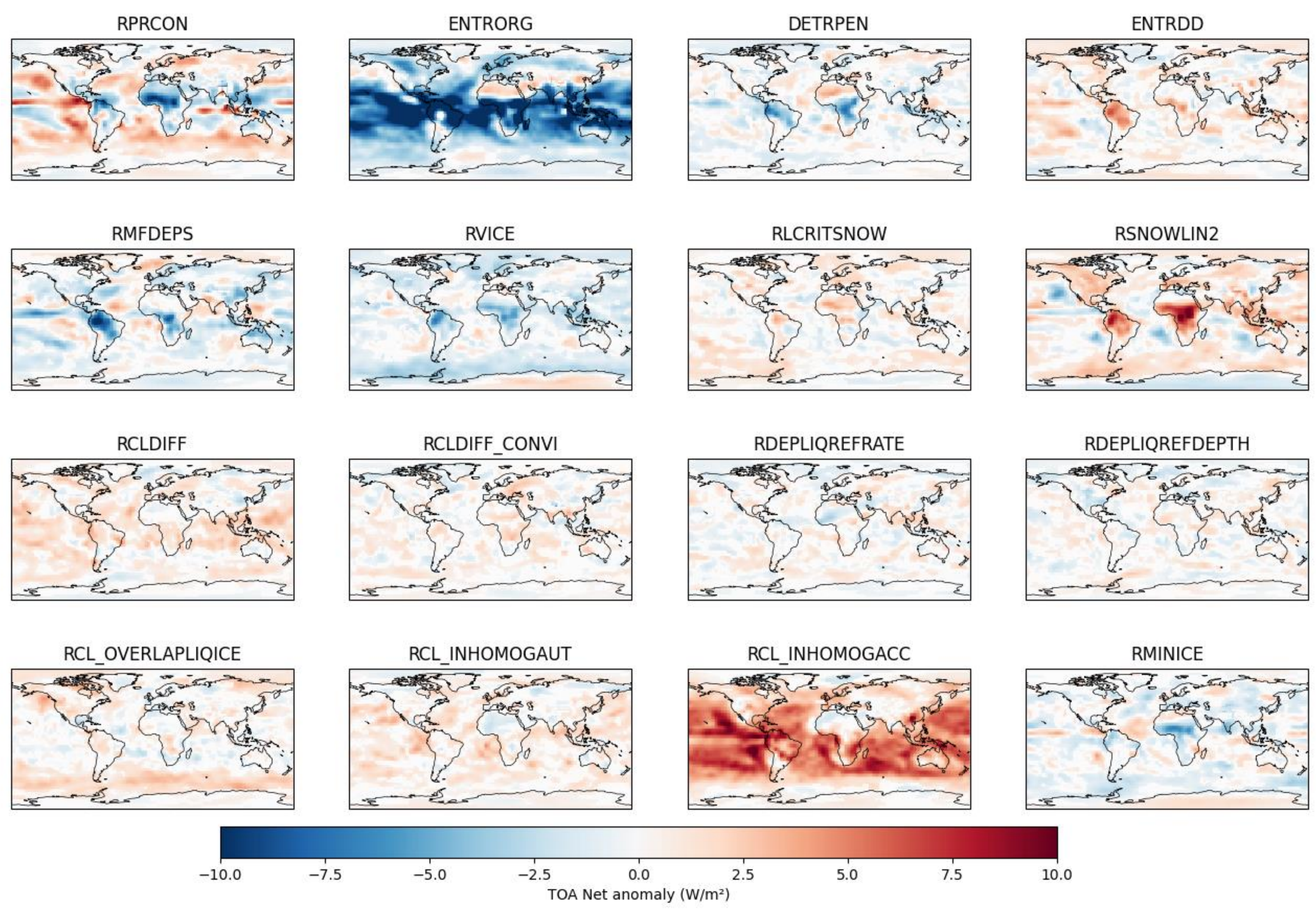
We evolve the traditional **ECtuner 1D** approach (based on latitudinal bands) to a **grid-point level (2D)** optimization to leverage localized "physics fingerprints" and mitigate **compensating biases**.

- Sensitivities are now computed via **linear regression for every single pixel**.
- A ***R***^{2} **threshold** acts as a signal-to-noise filter: it masks pixel dominated only by internal model variability maintaining a geographical coverage sufficient to use local physical patterns.

The **hybrid objective function (*J*)** allows a controlled trade-off between pattern matching and global mean agreement:

$$J = (1 - \alpha) \times Cost_{spatial} + \alpha \times Cost_{global} + Penalty$$

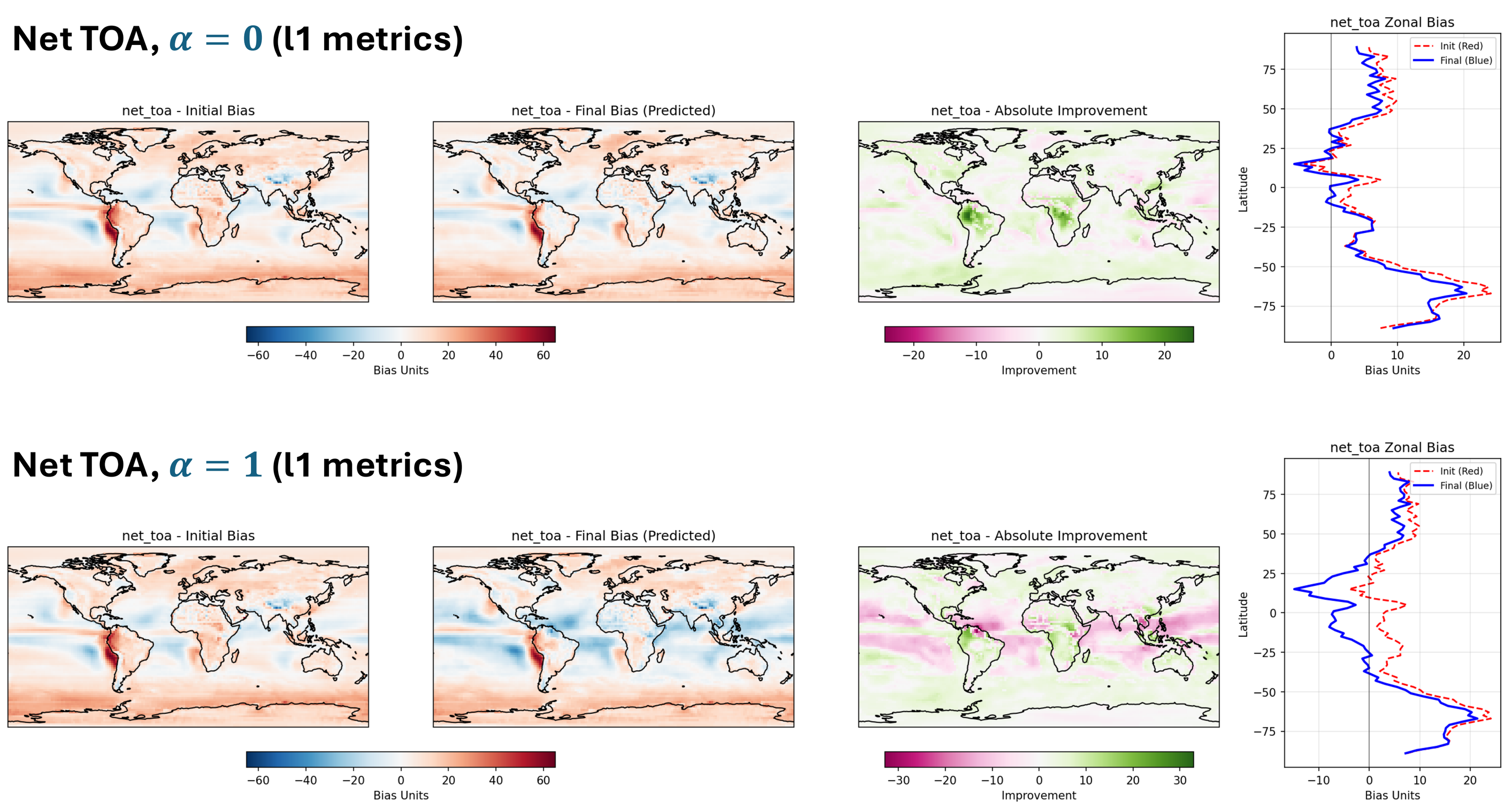
- α **parameter**: controls the balance: $\alpha = 0$ focuses purely on spatial patterns; $\alpha = 1$ targets only the global mean bias, mimicking the 1D tuner.
- **Norm flexibility**: the tool supports both **quadratic (*L2*)** metrics, to penalize large local outliers and **linear (*L1*)** metrics, providing a more robust estimation against extreme values.



2D Sensitivity maps (slopes) showing the localized influence of cloud and convection parameters on Net TOA radiation. Grey areas indicate regions where the linear relationship is weak (R2 < 0.3) and are excluded from the optimization.

4. Compensating biases

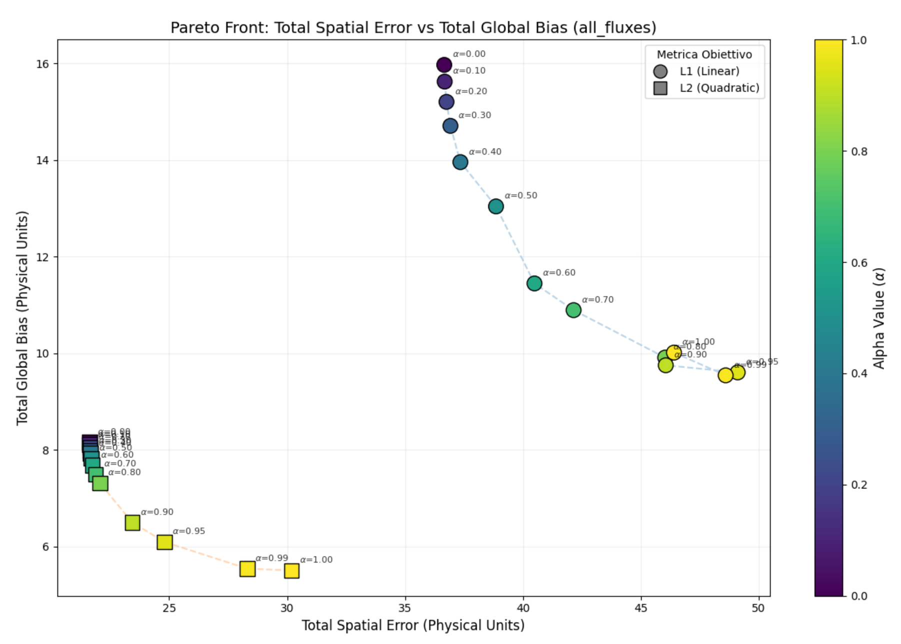
Optimisation based on the global mean ($\alpha = 1$) can cause the model to generate **compensatory biases**: **regional errors of opposite sign cancel each other out**, resulting in a global balance that appears perfect but is physically distorted. Spatial tuning ($\alpha \to 0$) forces the model to improve geographical patterns, revealing the effectiveness of the parameterisations.



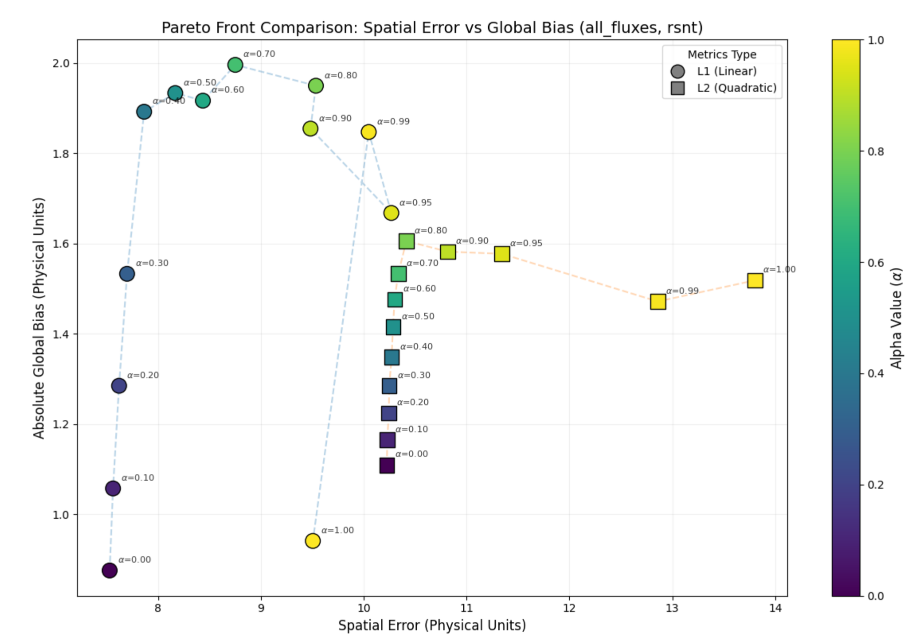
Comparison of Net TOA bias maps. Global tuning ($\alpha = 1$) results in zero global biases, but hides regional errors through compensation, whereas spatial tuning ($\alpha = 0$) highlights and mitigates local biases. L1 metric is used because it does not penalise individual pixels with extreme errors excessively.

Target flux	Initial cost (Global/Spatial)		Final cost (Global/Spatial) (predicted)
Net TOA	5.63 / 8.73	$\alpha = 0$	3.96 / 7.41
		$\alpha = 1$	0.0 / 9.35
rsnt	1.31 / 7.81	$\alpha = 0$	0.87 / 7.53
		$\alpha = 1$	0.94 / 9.5

Quantitative Comparison of Predicted Bias Reduction (W/m²). Final values are predicted based on the linear sensitivity of the model to parameter perturbations.



Evolution of the total all-flux cost: as α increases, the overall cost decreases at the expense of spatial error for both metrics.



Focus on RSNT: it seems that L1 metric maintains greater stability than L2.

5. Outlook

The results presented here are based on **present-day AMIP** experiments, where the tuning outcome has been assessed primarily through final cost predictions. To validate these findings, the next step involves running new present-day simulations to verify the effective impact of spatial tuning on the model's climatology.

Next step: What's the impact of bias compensation on future projections?

We will repeat the spatial tuning experiment using future climate projections, inspired by the **amip-future/amip-future4K** protocol followed for example by Qin et al. 2022. This will allow us to assess how regional bias compensation affects climate sensitivity and the robustness of future projections.

Reference

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The research reported in this work was supported by the contract "MC-FORUM" funded by ASI and by OGS and CINECA under HPC-TRES program award number 2024-04.

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