Response to Reviewer #1

We sincerely thank Reviewer #1 for the constructive and detailed comments. We have carefully revised the manuscript and addressed each point below. Reviewer comments are reproduced in **bold**, followed by our responses.

Comment 1

General comments: This study presented a linear optimization methodology to improve ENSO fidelity in the ICON XPP Earth System Model. The authors firstly assessed the sensitivity of ENSO metrics to 21 atmospheric parameters in atmosphere-only simulations. Then, six parameters were identified as most impactful and were subsequently tuned in fully coupled simulations, yielding moderate improvements in various ENSO metrics. Overall, the results demonstrated that the newly proposed method can effectively optimize key atmospheric parameters to improve representation of critical ENSO characteristics and feedback-process fidelity within a climate model. However, some aspects related to the optimization methodology should be improved before the paper is suitable for publication.

Major comment: As stated by the authors, one of the novelties of this work is that they provided a newly proposed optimization method. However, the motivation to develop such a new method is unclear. Many previous studies focusing on parametric sensitivity or parameter calibration have been conducted in the past two decades. The limitations of the methodologies in previous studies and the advantage of the new method provided here (e.g., linear vs nonlinear; direct tuning vs using surrogate model) should be discussed in more detail.

Response: Thank you for this important comment. We fully agree and revised the manuscript following the two parts of your comment.

(1) Motivation and novelty positioning. We added a broader review of previous climate-model tuning and calibration studies in the **Introduction**, and we clarified that our novelty is *not* proposing parameter tuning in general. Instead, we emphasize that this framework was designed for *direct ENSO-targeted tuning* in a comprehensive fully coupled ESM. We therefore changed the wording from "a newly proposed optimization method" to a more precise framing: a linear optimization framework designed for direct optimization of ENSO climatology, variability, and feedback metrics in coupled simulations.

(2) Limitations and advantages of the present method. We agree that our current framework is based on a first-order linear approximation and does not explicitly resolve higher-order nonlinear interactions. To address this directly, we added discussion in the **Summary and Discussion** section that (i) acknowledges this limitation, (ii) explains why a linear approach is still useful and effective for current high-cost coupled simulations, and (iii) states clearly that a more comprehensive nonlinear optimization strategy is planned as future work.

What was changed in the manuscript:

- **Introduction:** expanded literature review of existing parameter sensitivity/tuning/calibration approaches and clarified the motivation for this study.
- **Introduction and Abstract wording:** reframed novelty from "newly proposed optimization method" to direct ENSO-targeted tuning in a fully coupled ESM.

- **Summary and Discussion:** added explicit discussion of the linear-method limitation (nonlinear interactions not fully represented), practical value of linear optimization, and planned future nonlinear optimization work.

Literature now cited/discussed to address this comment:

- Hourdin, F., Mauritsen, T., Gettelman, A., et al. (2017): The art and science of climate model tuning. *Bulletin of the American Meteorological Society*, 98, 589–602. https://doi.org/10.1175/BAMS-D-15-00135.1
- Murphy, J. M., Sexton, D. M. H., Barnett, D. N., et al. (2004): Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, 430, 768–772. https://doi.org/10.1038/nature02771
- Severijns, C. A., and Hazeleger, W. (2005): Optimizing parameters in an atmospheric general circulation model. *Journal of Climate*, 18, 3527–3535. https://doi.org/10.1175/JCLI3482.1
- Tett, S. F. B., Rowlands, D. J., Mineter, M. J., et al. (2017): Calibration of climate models using observational data. *Geoscientific Model Development*, 10, 3567–3589. https://doi.org/10.5194/gmd-10-3567-2017
- Williamson, D., Goldstein, M., Allison, L., et al. (2013): History matching for exploring and reducing climate model parameter space using observations and a large perturbed physics ensemble. *Climate Dynamics*, 41, 1703–1729. https://doi.org/10.1007/s00382-013-1896-4
- Watson-Parris, D., Williams, M. L., Deaconu, L., et al. (2021): Uncertainty quantification and learning in climate modeling using machine learning. *Nature Reviews Earth & Environment*, 2, 287–299. https://doi.org/10.1038/s43017-021-00156-5
- Lguensat, R., Fablet, R., Chapron, B., et al. (2023): Learning to tune coupled climate models with machine learning. *Journal of Advances in Modeling Earth Systems*, 15, e2022MS003367. https://doi.org/10.1029/2022MS003367
- Zhang, X., Duan, W., and Zebiak, S. E. (2015): Parameter optimization for an intermediate coupled model using ENSO dynamics. *Journal of Climate*, 28, 193–214. https://doi.org/10.1175/JCLI-D-14-00348.1

Comment 2

For both atmosphere-only and fully coupled experiments, the cost functions are rescaled by the parameter setting in the control runs. This helps prevent the optimized parameter values from deviating excessively from their control-run settings, thereby ensuring physical plausibility (Line 408). However, the default settings are different in the atmosphere-only and in the fully coupled experiments. One may ask which setting has more physical plausibility?

Response: Thank you for this insightful comment. We agree that the use of control parameter values as a reference in the cost function requires clarification, particularly because the default parameter settings differ between atmosphere-only and fully coupled configurations.

The purpose of including the parameter-deviation term in the cost function is not to define a physically "correct" reference state, but to provide a regularization constraint that prevents the optimization from exploring unrealistic regions of parameter space. In both configurations, the control parameter sets represent numerically stable and previously calibrated baseline states, rather than physically optimal solutions.

The difference between atmosphere-only and coupled default parameter values reflects that these two configurations are tuned separately to achieve stable and realistic mean climate states under different boundary conditions and coupling regimes. Therefore, neither configuration should be interpreted as inherently more physically plausible than the other.

Instead, the parameter constraint acts as a locality condition, ensuring that the optimization remains within a physically meaningful neighborhood of the corresponding baseline configuration. This is particularly important in high-dimensional parameter spaces, where unconstrained optimization may lead to unrealistic fluxes or unstable model behavior.

In practice, we find that optimized parameter values remain within a limited range of the control values, indicating that the optimization does not rely on large departures from the baseline state.

We have clarified this point in the revised manuscript (cost-function section), emphasizing that reference parameter values serve as practical constraints for stability and realism, rather than as an absolute measure of physical plausibility.

Comment 3

In section 3.4, the ENSO metric is estimated by using Eq. 11, which is based on the pre-calculated parameter sensitivities. However, the lefthand side of Eq. 11 (i.e., Δ_m) is expressed as a quadratic function of a physical variable which measures the difference between simulation and observation (according to Line 386), while the righthand side of Eq. 11 is just a linear function with no observation information included (according to Line 323). So it is unclear to me what are the physical meaning and theoretical basis of Eq. 11?

Response: Thank you for this important and technically insightful comment. We agree that the interpretation of Eq. (11) needed clearer explanation.

Eq. (11) is not intended as an exact reformulation of the ENSO metric itself. Instead, it is a first-order approximation of how the model–observation misfit changes under parameter perturbations. The ENSO metric is defined from model–observation differences (e.g., RMSE) and is therefore nonlinear. In contrast, the right-hand side of Eq. (11) represents a linearized estimate of model-response changes, based on pre-computed sensitivities.

Conceptually, the procedure is: (i) approximate the parameter-induced change in model variables by linear sensitivities around a reference state; (ii) evaluate how this linearized model change modifies the model–observation misfit, with observations kept fixed; and (iii) use this as a first-order surrogate for optimization. Therefore, Eq. (11) should be interpreted as a linearized misfit-change estimate, not as an exact identity for the nonlinear metric.

We also acknowledge the limitation directly: this approximation neglects higher-order nonlinear effects (both in model response and in metric definition), and is expected to be most accurate for moderate parameter perturbations.

Regarding the related question of why sensitivities are computed with respect to the control simulation rather than observations: parameter sensitivities are properties of the model response, i.e., derivatives of model output with respect to model parameters. Observations do not depend on model parameters and therefore cannot directly provide such derivatives. The control simulation is used as a numerically stable baseline state around which sensitivities are evaluated, while observations are used to define the optimization target (the misfit/cost function).

We have clarified these points in the revised manuscript by explicitly stating that Eq. (11) is a first-order approximation and by clarifying the distinct roles of model sensitivities (response operator) and observations (optimization target).

Comment 4 (Minor Comments)

Response: Thank you for these helpful minor comments. We revised the manuscript accordingly:

1. **Line 267 (Eq. 3), ϕ_l or ϕ_i? Same for Line 276.**
   We confirmed this should be ϕ_i. We revised the notation in the manuscript to make this explicit.

2. **Line 352, correlation in Figure 4 heading.**
   Thank you for catching this misleading wording. We revised the caption to: "The correlation between the pair of sensitivities is -0.83 in (a) and -0.55 in (b)."

3. **Line 372, left X-axis, RMSE?**
   We clarified the caption: the x-axis shows parameter names, and the y-axis shows RMSE-based sensitivity values.

4. **Line 402 (Eq. 9), np_i or np_k?**
   Thank you. This should be np_k, and we corrected Eq. (9) accordingly.

5. **Line 409, physical bounds and sampling algorithm.**
   We clarified that Δ_{limit} enforces positivity constraints for relevant parameters. During optimization, any candidate parameter combination with out-of-bound (e.g., negative) values is discarded, and the search continues until a physically valid combination with lower cost is found.

6. **Line 695, wording of "although".**
   We revised the sentence to: "The ENSO phenomenon has distinct impact on global climate patterns and extreme weather events. Therefore, accurate model representation of ENSO phenomenon is paramount for climate research and prediction."
