RESPONSE TO REVIEWER #1 FOR GEOSCIENTIFIC MODEL DEVELOPMENT: MANUSCRIPT EGUSPHERE-2025-713

We sincerely thank Reviewer #1 for their thorough and constructive feedback on our manuscript, "Soil Parameterization in Land Surface Models Drives Large Discrepancies in Soil Moisture Predictions Across Hydrologically Complex Regions of the Contiguous United States." The comments have significantly helped us identify areas for improvement, and we outline below how we will address each point in the revised manuscript to enhance clarity, robustness, and alignment with the standards of the hydrology and land surface modeling communities. Our responses to the suggestions are detailed below (in blue).

Silwimba et al. investigate the impact of different soil hydraulic parameter sets derived from various approaches on soil moisture variability across the contiguous United States (CONUS), using the Community Land Model version 5 (CLM5). The study employs Empirical Orthogonal Function (EOF) analysis to extract dominant spatiotemporal patterns in soil moisture and assesses how variability in soil hydraulic parameters influences hydrological processes.

The manuscript is generally well-written, with clearly articulated objectives and a methodologically sound design. The topic is timely and of interest to the hydrology and land surface modeling communities. The authors have presented the results in a clear and coherent manner. However, I have a few concerns and suggestions that, if addressed, could improve the clarity and robustness of the manuscript.

Major and Minor Comments

1. **Experimental Design Clarity:**

   The description of the experimental setup, particularly EXP1, EXP3, and EXP4a–4d, requires further clarification:

   a) For **EXP1**, how exactly does the use of uniform soil hydraulic parameters demonstrate a reduction in inter-model variability? A more detailed explanation of the hypothesis and expected behavior would be helpful.

      Response: We appreciate the reviewer's observation and agree that the original wording was potentially misleading. In the revised manuscript, we clarified that EXP1 is not designed to assess inter-model variability per se, since our study uses only CLM5. Instead, EXP1 serves as a baseline control simulation within CLM5, applying globally standardized soil hydraulic parameters derived from SP-MIP uniformly across the CONUS domain. By eliminating spatial variability in soil properties, this setup allows us to isolate CLM5's intrinsic response to a consistent parameter set. The objective is to establish a stable reference point against which the effects of varying parameterizations in other experiments (EXP2–EXP4) can be compared. We have removed references to inter-model variability and now explicitly define EXP1's role in highlighting intra-model sensitivity to soil parameter changes.

b) For **EXP3**, it is not entirely clear how this experiment isolates the intrinsic inter-model variability. Please elaborate.

Response: Thank you for highlighting this confusion. We have revised the description of EXP3 to clarify that it is not meant to isolate "inter-model" variability, but rather to assess CLM5's default behavior using its native parameter configuration. EXP3 uses CLM5's built-in soil maps and lookup tables to assign hydraulic properties, reflecting the model's operational configuration without externally imposed constraints. The goal is to establish a benchmark for CLM5's default performance, allowing us to compare its outputs with more controlled or hypothetical scenarios (e.g., EXP1 and EXP4a-4d). We have removed any mention of "intrinsic inter-model variability" and now focus on evaluating how CLM5's default parameter assumptions influence soil moisture outputs.

c) For **EXP4a–4d**, I find it difficult to understand how four different soil categories are implemented in the model. Do you run the model separately for each soil category? Are these scenarios simulated using four distinct parameter sets applied uniformly across the domain, or are they spatially varying? Clarifying how these simulations were configured in CLM5 is essential.

Response: We agree that the initial description of EXP4a–4d lacked sufficient detail. In the revised manuscript, we now clearly state that each of the four experiments (EXP4a–4d) involves a separate CLM5 simulation, in which a uniform set of soil hydraulic parameters corresponding to a specific USDA soil class (loamy sand, loam, clay, silt) is applied consistently across all grid cells in the CONUS. These parameter sets are sourced from SP-MIP and derived using standard PTFs. There is no spatial variation in soil properties within each experiment; the only difference across experiments is the texture class used. This design enables a clean comparison of how different soil textures influence soil moisture and energy balance outputs under identical meteorological conditions. We have revised the text to reflect this modeling setup and its role in evaluating texture-specific sensitivity within CLM5.

1. **Model–Observation Comparison**:
Have the authors considered validating the model outputs against observational soil moisture datasets? Including such comparisons would strengthen the findings and contextualize model performance.

Response: We thank the reviewer for this thoughtful suggestion. In the current study, we compare CLM5 outputs to the ERA5-Land reanalysis product, which assimilates a wide range of observational and model-derived inputs to produce a spatially and temporally consistent estimate of soil moisture across CONUS. ERA5-Land was selected for its comprehensive coverage, high temporal resolution, and comparability with the spatial resolution of our CLM5 simulations. The purpose of this comparison is to examine similarities and differences between the modes of soil moisture variability from the SP-MIP numerical experiments and those of a reanalysis dataset. To carry out this comparison, we use multiple statistical metrics, including Euclidean distance, Taylor Diagrams, and EOF-based analyses (Sections 3.1–3.4), to systematically assess the agreement between CLM5 simulations and ERA5-Land data.

We fully agree, however, that incorporating direct observational datasets such as in-situ measurements from soil moisture monitoring networks or remote sensing products like the Soil Moisture Active Passive (SMAP) mission would provide an additional layer of comparison and help benchmark model performance more rigorously. We underscore that the primary purpose of this comparison is not so much a validation of the model performance, but rather an assessment of the degree to which the ranges of variability in SP-MIP experiment soil moisture response compares with those seen in observational datasets. We admit that some of the comparison metrics we used are commonly used in more strict model validation studies, where benchmarking against multiple datasets is important to evaluate the veracity of model predictions. However, we believe that introducing additional comparisons with observational data may unnecessarily expand the scope of the current work, which seeks primarily to assess the sensitivity of the model to soil parameters.

However, in acknowledgment that the previous version of the manuscript may not have been clear about the purpose of this work, we have added a paragraph in the revised Section 4 acknowledging the narrow scope of our work and emphasizing the value of integrating direct observational datasets in future works, which might seek to more deliberately calibrate soil parameters within a global land model. We note that upcoming efforts will focus on leveraging SMAP and in-situ data to complement reanalysis-based validation and further improve the robustness and interpretability of soil moisture simulations in CLM5. This will support more comprehensive model evaluation and enhance confidence in land surface model applications.

2. **Figure Reference – Line 328:**
   The text refers to Figure 6, but the description seems to match the content of Figure 8. Please verify and correct this reference.

   We thank the reviewer for pointing out the incorrect figure reference on line 328. The text description corresponds to Figure 8, not Figure 6. We have corrected the reference in the revised manuscript to ensure consistency between the narrative and the associated figure.

3. **Regional Subdivisions of CONUS:**
   While the manuscript defines subregions within CONUS, the analysis appears to be conducted solely at the national scale. What is the purpose of introducing these subdivisions if no region-specific results are discussed?

   Response: To adrress the reviewer's concern regarding the relevance of regional subdivisions, we have revised Section 2.1 to explicitly clarify the role of the CONUS subregions Western North America (WNA), Central North America (CNA), Eastern North America (ENA), and North Central America (NCA) in our analysis. These subdivisions, based on Giorgi and Francisco (2000), now serve as a physically meaningful framework for interpreting region-specific patterns in soil moisture variability identified through EOF analysis. The revised text emphasizes how each region captures distinct hydroclimatic characteristics, supporting a spatially disaggregated evaluation of model sensitivity to soil hydraulic parameters. By linking EOF-derived spatial modes and observed model-observation discrepancies (e.g., higher soil moisture in ENA and lower model agreement in CNA) to these macro-regions, the updated section enhances both the interpretability and process-level insights of the results. This regionalization strengthens the methodological coherence of the study and directly supports our objective of understanding spatially heterogeneous parameter impacts across the CONUS domain.

4. **Motivation for EOF Analysis:**
   The rationale for employing EOF analysis to study soil moisture variability is not clearly justified. What specific insight does EOF provide in this context that other metrics might not? Please expand on the scientific motivation for this methodological choice.

   Response: To address the reviewer's request for a stronger justification of the EOF analysis, we have substantially revised Section 2.3 to clarify the rationale, methodological advantages, and contextual relevance of using EOFs to study soil moisture variability. The revised section now emphasizes that EOF analysis, implemented via Singular Value Decomposition (SVD), is particularly suited to extracting dominant spatiotemporal patterns from high-dimensional soil moisture datasets, enabling robust comparisons across experiments and observational benchmarks. We explicitly link this technique to our study's objective of evaluating how soil hydraulic parameterizations influence moisture dynamics across diverse hydroclimatic regions in CONUS. The revised text also highlights EOFs' utility in diagnosing interactions with large-scale climate drivers (e.g., ENSO, PDO), their role in identifying parameter-sensitive regions, and their advantage over simpler metrics such as RMSE or bias. Furthermore, we acknowledge the method's limitations, such as its reliance on orthogonality, and describe how we address these using supplementary diagnostics (e.g., Taylor diagrams, Euclidean distance). Lastly, we clarify that all EOF analyses were conducted using the open-source eofs (Dawson, 2016) Python package, ensuring transparency and reproducibility.

5. **Conclusion Structure:**
   The manuscript introduces two central research questions related to the influence of Soil hydraulic parameters on spatial soil moisture patterns and their temporal evolution during climate extremes. However, the conclusion section does not clearly revisit or synthesize findings in response to these questions. I recommend revising the conclusion to directly address the key research objectives and summarize how the results support them.

   Response: To address the reviewer's concern regarding the structure and focus of the conclusion, we have significantly revised Section 4 to explicitly revisit and synthesize the study's two primary research questions: (1) how soil hydraulic parameters influence spatial soil moisture distributions, and (2) how these parameters affect temporal dynamics during climate extremes. The updated section now integrates findings from the EOF and principal component analyses to demonstrate how parameter choices influence both spatial gradients, particularly in regions like ENA and CNA, and the temporal evolution of moisture anomalies associated with events such as ENSO phases. In addition, we have expanded the conclusion to include a targeted set of practical recommendations for improving soil moisture simulation in CLM5. These include refining parameter estimation using advanced pedotransfer functions and machine learning methods, leveraging high-resolution satellite and in situ datasets (e.g., SMAP), and conducting region-specific parameter calibrations. We also emphasize the importance of accounting for vegetation–soil moisture feedbacks and linking modeled variability to large-scale climate drivers, such as ENSO, to enhance model realism and forecasting capability. These additions directly align the conclusion with the study's original objectives while offering clear directions for future land surface model development and application.

6. **Sensitivity of Hydraulic Parameters:**
It would be valuable for the reader to understand which specific Soil hydraulic parameters (e.g., saturated hydraulic conductivity, porosity, van Genuchten parameters) are most influential in controlling soil moisture dynamics across the simulations. A sensitivity analysis or discussion on this point would enhance the study's relevance for land model parameterization efforts.

Response: We appreciate the reviewer's suggestion to include a sensitivity analysis of individual soil hydraulic parameters. We agree that understanding the relative influence of specific parameters such as saturated hydraulic conductivity, porosity, and van Genuchten coefficients would provide valuable insights for model parameterization. However, this level of diagnostic analysis is beyond the scope of the present study. Our analysis is based on pre-run CLM5 simulations using prescribed parameter sets from SP-MIP, and we did not have access to the exact individual parameter values used within the model configurations for each experiment. As such, we were unable to systematically perturb or isolate individual parameters for a formal sensitivity analysis.

Instead, the study adopts a comparative experimental design outlined in Section 2.2.1, where each simulation applies a distinct parameter set derived from known pedotransfer functions or soil texture classes (e.g., EXP1 with standardized values, EXP4a–4d with uniform soil textures). Through this approach, we evaluated the aggregate effects of different parameter configurations on soil moisture variability, which were further decomposed using EOF analysis. While we acknowledge that this limits our ability to attribute responses to specific parameter changes, the results nonetheless highlight the substantial impact of parameter-driven variability on both spatial and temporal soil moisture patterns, especially in hydroclimatically complex regions such as the Great Plains.

We view this as an important direction for future research and have added to the revised manuscript (Section 4, see below), recommending that subsequent studies conduct targeted sensitivity analyses using parameter perturbation techniques or machine learning frameworks to systematically rank the influence of individual hydraulic properties on land surface model outputs.

"….While our comparative framework assessed the aggregate effects of parameter set differences, we did not perform a formal sensitivity analysis to isolate the influence of individual soil hydraulic properties (eg., saturated hydraulic conductivity, porosity, van Genuchten parameters), which remains an important area for future investigation "

Reference

Giorgi, F. and Francisco, R.: Evaluating uncertainties in the prediction of regional climate change, Geophysical Research Letters, 27, 1295– 1298, 2000.

Dawson, A.: eofs: A library for EOF analysis of meteorological, oceanographic, and climate data, Journal of Open Research Software, 4, 2016.