Responses to Reviewers' Comments

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Manuscript title: Hyper-Resolution Land Surface Modeling for Farm-Scale Soil Moisture in India: Enhancing Simulations with Soil Vertical Heterogeneity

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The authors are grateful for the reviewer's suggestions. The review comments are in red, and our responses are highlighted in blue for clarity. Any text that is a part of the revised manuscript is written in blue italics. Line numbers refer to the original version of the manuscript.

Responses to the Comments from Reviewer #2

General comment and need for clarification: The paper presents the application of HydroBlocks hyper-resolution LSM in an Indian catchment with vertically heterogeneous and vertically homogeneous soil properties. The former model setup was also used for a global sensitivity analysis (GSA) to assess the influence of soil textural parameters on the model-simulated soil moisture. What is, however, not entirely clear is what are the key scientific contributions of the paper. That information may be already included, but as the authors use an existing model, contributions need to be very clear. In particular, the following aspects need to be clarified:

Comment 1: Is there a novelty in the work regarding the HydroBlocks LSM development, or does the work apply the model in its current setup? If the latter, then I would be cautious to put the focus in the paper on the modelling aspect, as implementing a model in a new case study is very difficult to justify as a scientific contribution.

Comment 2: If there is no novelty in the model development, then the novelty needs to be justified around data availability, model parameterisation and/or model use, which would change the focus of the paper. The application of GSA with the LSM is interesting, but then the literature review would need to cover that aspect to show what is novel about your work.

Response : The present study a) improves the model parameterization, b) examines the parameter sensitivity at hyperresolution scales, and c) applies the improved model in a new case study that has challenging landscape in terms of spatial heterogeneity. We discuss each of the three aspects in detail below:

a) Model improvements

Considering the landscape heterogeneities of Indian conditions, it is important to include drivers that account for these heterogeneities. Therefore, we modified the HydroBlocks to incorporate vertical heterogeneity in soil properties. The model version we selected originally considered vertically homogeneous soil, and we modified this model to incorporate soil vertical heterogeneity with the goal of improving rootzone soil moisture simulations. Although such an attempt has been made in the past, the goal of such studies was only to improve surface soil moisture simulations (Xu et al., 2023). Our focus on improving rootzone soil moisture simulations has direct implications in agriculture applications such as producing irrigation water advisories. Besides, unlike past studies, the soil data we used is globally available, which prompts wider applicability of our model in other regions.

b) Parameter sensitivity focused on agricultural applications

As mentioned earlier, one of the contributions of the present study is the incorporation of soil vertical heterogeneity of soil hydraulic parameters into the HydroBlocks model. This model improvement provides us an opportunity to understand the sensitivity of soil parameters along the soil profile at hyper-resolution scales focusing specifically on agricultural regions, which has not been attempted earlier. Previous studies have assessed soil parameter sensitivity in relation to runoff, evapotranspiration, heat fluxes, or soil moisture (Arsenault et al., 2018; Cuntz et al., 2016; Kishné et al., 2017; Bacelar et al., 2024). However, these studies have typically focused on either macroscale models or only the surface soil layer. Past studies also do not account for the effects of seasonal climatic variations on parameter sensitivity. Our study addresses these gaps by conducting a Global Sensitivity Analysis (GSA) to examine the sensitivity of soil parameters on soil moisture simulations in three key aspects: (1) at the field scale, (2) across all soil layers, including both surface and subsurface layers up to 100 cm depth, and (3) in a seasonal perspective.

c) New case study - Highly heterogeneous landscape

Majority of farmlands in India are small, typically less than 2 hectares (~142 m × 142 m). However, existing model simulations of rootzone soil moisture in India, provided by the government, are coarser (at ~5.5 km resolution https://bhuvan.nrsc.gov.in/nhp/). They use macroscale land surface model (VIC - Variable Infiltration Capacity) to produce simulations that do not consider the subgrid heterogeneity at fine resolution, thus limiting their applicability for agriculture applications. This work serves as a first attempt to address this limitation by applying the HydroBlocks model, which can produce the sub-grid heterogeneity necessary for farm-scale irrigation water management applications. This study also specifically discusses the added benefits of using hyperresolution LSM in fragmented agriculture systems to encourage government agencies and researchers to shift to using a hyperresolution LSM.

We acknowledge the reviewer's suggestion. We will briefly discuss the above aspects to emphasize the novelty (including parameter sensitivity) in the introduction section of the revised manuscript.

Comment 3: Another aspect mentioned in the challenge of data availability in India – again, the literature needs to support this argument and the novelty needs to justify either the use of datasets not typically applied for LSM parameterisation or how their data are processed so that they can inform the model's parameters.

Response: India does not have operational soil moisture measurement networks. For instance, the International Soil Moisture Network (Dorigo et al., 2011) has only one station within India, which was operational till 2012. The lack of soil moisture measurements prompted earlier studies to use or develop alternate evaluation techniques (Karthikeyan and Kumar, 2016; Nair and Indu, 2019). In recent years, scientists have demanded an increase in the soil moisture observation networks in India (https://science.thewire.in/environment/soil-moisture-monsoon-forecast-active-break-cycles-agriculture-irrigation/). To address this need, we initiated building the soil moisture network in the Upper Bhima basin, and future studies will definitely validate the results with existing data. We have discussed the lack of observational data in the manuscript in lines 107-109, 423-424, and 689-690. We will emphasize this further with literature citations in the revised manuscript.

Regarding soil parametrization, the model computes the soil-hydraulic parameters from the soil maps provided by the state-of-the-art SoilGrids 2.0 (Hengl et al., 2017) after processing them using pedotransfer functions (PTFs) (Saxton and Rawls, 2006). We have not used any specific dataset to 'calibrate' the model. Since soil data is provided as input, all the soil parameters are computed without any need for calibration. In addition to soil parameters, there are HRU decisive parameters and in-built parameters of Noah-MP model. These parameters have not been calibrated to local conditions to ensure the robustness of the model and carry out model validation independent of any observations. Furthermore, we envision this model to be used in other data-scarce regions in the future, so calibration should not impede such implementations.

Comment 4: The authors compare the model with a range of data, including in situ observations and remotely sensed products. Considering my comment about the novelty, it would be good to explain how the authors expect the model to behave against a range of data, and what is considered a good agreement (i.e., which data they consider most reliable for model testing).

Response: Field observations are the most suitable for validating any model simulation. However, the lack of an adequate soil moisture network has prompted us to evaluate the model performance with SMAP L3 satellite observations for satellite and SMAP L4 product for rootzone soil moisture. In the current study, we compared the model simulations to different coarse resolution (0.25 GLEAM, 0.1 ERA5-land, 9 km SMAP L3 and L4) soil moisture data products. Both ERA5-Land and SMAP-L3 observations are expected to have similar performances over India; however, ERA5-L shows higher wet bias during monsoon (Lal et al., 2022). Moreover, the SMAP soil moisture observations are widely used and tested against in situ observations across the globe (Chen et al., 2017; Colliander et al., 2022; Pan et al., 2016; Velpuri et al., 2016; Vergopolan et al., 2020, 2021). So, we expect SMAP L3 soil moisture to be the best data source available for the performance evaluation of the model simulation. Since SMAP L3 observations are assimilated into SMAP L4 for rootzone soil moisture data, we used the same for evaluating rootzone simulations. So, we expect the model to perform well based on two criteria:

1) error metrics indicate the accuracy when we compare 30 m soil moisture simulations from the model, upscaled to the native resolution of these reference datasets, with the corresponding soil moisture from the reference datasets.
2) Spatial heterogeneity in soil moisture simulations at 30 m resolution that reflects the land cover, topography, and soil variations.

Based on the above two criteria, we can analyze the model's agreement with macroscale datasets while maintaining the spatial heterogeneity expected from a hyperresolution model, as mentioned in lines 623-625. However, we will state the rationale explicitly in the methodology (Section 2.5) of the revised manuscript to improve clarity.

"*Considering the limited availability of in situ soil moisture measurements, we selected SMAP L3 surface soil moisture data, which are satellite observations, for evaluating surface soil moisture simulations. SMAP L3 soil moisture product has been extensively validated against in situ observations across the globe (Chen et al., 2017; Colliander et al., 2022; Pan et al., 2016; Velpuri et al., 2016; Vergopolan et al., 2020, 2021). Therefore, we selected SMAP L3 for surface soil moisture assessment. Further, we selected SMAP L4 for evaluating rootzone simulations since it is an assimilated product. By comparing with the macroscale reference dataset, we aim to ensure that the HydroBlocks simulations offer improved sub-grid heterogeneity while maintaining temporal consistency with these datasets. The performance metrics (bias, ubRMSE, and correlation) can reveal the accuracy and consistency at upscaled resolution (9 km) while sub-grid spatial standard deviation reveals the model's ability to capture the soil moisture variability resulting from land heterogeneity.*"

Comment 5: Two HydroBlocks configurations do not seem to show significant differences in simulations (Fig. 3). The same conclusion can be drawn from Fig. 5b as well, as the maps for the two configuration differences look very similar. However, the results in Section 3.3 indicate that there are differences in some catchments. Please comment on that as it is a key focus of the paper. I am also wondering if the comparison between the two configurations should come before the comparison with the observed data.

Response: Figures 3 and 5 represent 'surface' soil moisture simulations for both HydroBlocks configurations (VHet and VHom). Since both configurations use identical soil-hydraulic properties at the surface level, minimal differences are observed with negligible bias across most watersheds during intercomparison. However, ubRMSD highlights certain differences between the configurations in the surface layer, indicating the influence of subsurface soil layers. A closer look at Figure 3 shows that both HydroBlocks simulations differ during the monsoon season as they approach saturation. For these four watersheds shown in Figure 3, the average ubRMSD between the corresponding HRUs of the two configurations during monsoons is 0.016 m^3m^{-3}.

It may be noted that the vertical flow between layers is solved using the one-dimensional Richards equation, which depends on the soil-hydraulic properties of adjacent layers. We expect a change in surface soil moisture due to the vertical flow of moisture from subsurface layers under saturated conditions (expected during monsoons). Under saturated conditions, there is also subsurface lateral flow between adjacent HRUs in both versions. Lateral subsurface flows are prominent in regions with highly variable terrain conditions (Singh et al., 2015). The changes in surface soil moisture due to vertical and lateral movement of water are predominantly controlled by the textural properties of the soil profile. In the VHet configuration, the differences in soil properties across soil layers affect the vertical flow and, subsequently, the lateral flow of moisture, resulting in above noted differences during the monsoon season. These differences are particularly observed in watersheds with steep terrains in the study area (e.g., watersheds 23, 27, and 29).

We will include the above discussion in the revised manuscript to highlight the differences in surface soil moisture simulations between the two model versions.

Regarding the manuscript structure: It is important to note that besides model improvements, this work serves as the first attempt to establish a hyperresolution LSM in Indian conditions to serve the needs of marginal farmers. Past attempts have only used macroscale LSMs at coarse resolution under these conditions. So, there was a need to examine the benefits and validity of hyperresolution LSM simulations before we discussed the model improvements. Furthermore, the parameter sensitivity analysis is designed to go hand-in-hand with the model intercomparison section. Given these considerations, the results and discussion section is structured as 1) assessing the benefits of using hyper-resolution LSM in terms of sub-grid heterogeneity, validation with in-situ data, and consistency with coarse resolution datasets, 2) analyzing the improvements made in HydroBlocks through VHet configuration, and 3) detailed examination of the VHet configurations through parameter sensitivity experiments.

Therefore, we decided not to alter the present structure of the results and discussion section.

Detailed comments:

Comment 6: Line 56: Be careful about the statement that LSMs "are primarily intended to run synergistically with climate models", as there are many applications of running LSMs in isolation. Please clarify how this statement links with your work.

Response: We agree with the reviewer's comment that LSMs could be run in isolation. With these lines, we intended to convey that LSMs were originally developed to solve the atmospheric processes in weather and atmospheric models by providing lower boundary conditions to the atmosphere, which does not solve the hydrological process on the land surface (Wood et al., 2011). Accordingly, the LSMs, including Noah-MP, in general run at ~25 km spatial resolution (Yang et al., 2021), and the sub-grid processes (e.g., lateral flow) are either parameterized or not accounted for. We will clarify that LSMs can be run with or without being coupled to the atmosphere or oceans as follows:

*"LSMs were originally developed for providing lower boundary conditions to the atmosphere in weather and atmosphere models and focusing on partitioning radiation at the land surface than solving the hydrological process on the land surface, thus traditional LSMs operating at macroscale resolution (>5 km) (*Vergopolan et al., 2020; *Wood et al., 2011). However, LSMs have evolved by incorporating components representing vegetation, soil moisture, plant phenology, surface water, groundwater, lateral flow as well as irrigation (Fisher and Koven, 2020; Liu et al., 2020; Niu et al., 2011). With increased complexity, LSMs were able to run independently to solve land surface states and fluxes (Nie et al., 2022; Shrestha et al., 2020; Su et al., 2024). However, many LSMs, including Noah-MP, mostly operate at ~25 km spatial resolution (Yang et al., 2021) over the continental extent, and the sub-grid processes (e.g. lateral flow) are either parameterized or not accounted for (Beven and Cloke, 2012; Fisher and Koven, 2020)."*

Comment 7: Line 75: "One of the critical challenges to extending the applicability of a hyper-resolution LSM is the availability of high-resolution input data as well as point scale observations for validation" of hyper-resolution (< 1 km) LSMs. Please expand on what the challenges are.

Response: We thank the reviewer for raising the concern. Some key challenges for hyper-resolution modelling are as follows:

a) **High-resolution input data:** To capture the field scale variations of hydrological fluxes and states, it is necessary to capture the field scale variations of physical controls affecting them. Challenges associated with the availability of meteorological forcing and land information (soil, topography, and land cover) at fine resolution hinder the accuracy of high-resolution model simulations (Hoch et al., 2023).

b) **Epistemic uncertainty:** The models are developed by our understanding of various processes, assumptions, and parameterisation. However, our understanding of these processes is limited by the spatial scale (Beven and Cloke, 2012; Wood et al., 2012). Field-scale processes that decide the subgrid heterogeneity within coarse resolution (>5 km) grid cells are not adequately represented in these models because of the epistemic uncertainty (Fisher and Koven, 2020).

c) **Computational demands:** Hyperresolution modelling at a global scale (<1 km resolution) or continental scale (~100 m resolution), with representation of various field-scale processes in the model, requires significant computational power. Therefore, improving the model's computational efficiency remains a challenge despite recent attempts to implement high-resolution land surface models (1 km) at a global scale (van Jaarsveld et al., 2025).

d) **Validation:** Modelling at hyperresolution scales demands validation with in-situ observations. Developing countries, including India, have sparse in situ soil moisture networks, which limits the validation of the model simulations (Karthikeyan and Kumar, 2016; Roy et al., 2023; Vergopolan et al., 2021).

In the revised manuscript, we will briefly provide details about the challenges associated with hyperresolution LSMs as follows:

"However, some of the critical challenges to extending the applicability of a hyper-resolution LSM include: (a) availability of high-resolution input data to capture the field scale variations of physical controls (meteorology, soil, topography, and landcover) affecting hydrological fluxes and states at field scale (Hoch et al., 2023), (b) epistemic uncertainty involved in our understanding of various physical processes at field scale (Beven and Cloke, 2012; Fisher and Koven, 2020; Wood et al., 2012), significant computational requirements for solving various physical processes in numerous grids over continental extent and availability of point scale observations for validation in particular at developing countries which are having sparse soil moisture networks (Karthikeyan and Kumar, 2016; Roy et al., 2023; Vergopolan et al., 2021)."

Comment 8: Line 83: "While those approaches were valuable in advancing our understanding, their application in simulating soil moisture at a heterogeneous land surface at field scales covering large spatial extent remains limited." Please clarify what the limitations include.

Response: The concerned sentence is written while citing two specific works e.g., Zhu and Mohanty, (2003) and Yang et al., (2005). Zhu and Mohanty (2003) assumed heterogeneous soil as an equivalent homogeneous soil producing the same total flux and pressure head as the heterogenous profile and derived depth-dependent effective hydraulic parameters. However, their study shows that effective parameters cannot be computed in Brook's Correy model, which is widely used in hydrological models, including Noah-MP and Variable Infiltration Capacity (VIC) models. More importantly, their study was carried out under controlled conditions and was not applied to any LSM over any region.

Yang et al., (2005) incorporated vertical heterogeneity of soil parameters in a single source LSM. However, a single source LSM does not distinguish between vegetation and bare surface within a grid, which limits its practical applicability. Hence, the study is done over a region with sparse vegetation with minimal land cover heterogeneity.

Our study advances hyperresolution land surface modeling by building on the above studies in terms of incorporating soil vertical heterogeneity in HydroBlocks, with Noah-MP (a dual source

LSM) at its core, and testing its practical applicability at a regional scale in a heterogeneous landscape.

We will clarify these discussions in the revised manuscript as follows.

"The importance of incorporating soil vertical heterogeneity in LSMs is emphasized in previous studies (Yang et al., 2005; Zhu and Mohanty, 2003). Through a set of synthetic experiments, Zhu and Mohanty (2003) generated depth-varying effective hydraulic parameters for different hydraulic conductivity models. However, their study does not include application to any LSM over a region, as well as showed that effective parameters cannot be computed in Brook's Correy model, which is widely used in hydrological models, including Noah-MP and Variable Infiltration Capacity (VIC) models. Later, Yang et al. (2005) revealed the necessity for considering soil vertical heterogeneity in LSMs; however, they deployed a single source LSM over a sparsely vegetated region with minimal land cover heterogeneity. While those approaches were valuable in advancing our understanding, their application in simulating soil moisture at a heterogeneous land surface at field scales covering large spatial extent remains limited."

Comment 9: Fig 3. It is not clear what the data in the plot represented by crosses are – please add in the legend. Also, in the figure caption explain what the shaded area in the plot represents.

Response: We apologize for the confusion. The crosses represent SMAP L3 observations for surface soil moisture. It was a mistake in the legend. The shaded area represents one standard deviation of soil moisture from all the 30 m HydroBlocks grids within a SMAP grid. We have already mentioned it in the caption in lines 306-308.

We will update the legend of Figure 3 in the revised manuscript.

Comment 10: Line 280: Explain which data you would expect the model to agree with and why.

Response: We expect SMAP L3 (represented as crosses) to agree with the model simulations, as it comprises satellite observations that have been extensively validated worldwide. A detailed explanation is provided in the comment 4.

Comment 11:. Line 328: You say that in Fig 4. "Results show a wet bias" of the HydroBlocks simulations in a dry period. However, from the plot, it seems that model results agree well with ERA5-Land data. Please comment on that.

Response: We would like to clarify that the concerned line highlights the wet bias between VHet and VHom configurations' soil moisture simulations. Comparison with ERA5-Land is carried out later in the same section (in lines 341-343).

Commet 12: Line 421. I would suggest moving section 3.2.1 earlier in the text, as it shows the performance of the model against observations.

Response: We thank the reviewer for the suggestion. The reviewer made a similar comment earlier regarding the manuscript structure (Comment 5). We are repeating the same response below for the reviewer's convenience.

Regarding the manuscript structure: It is important to note that besides model improvement done in this work, this work serves as the first attempt to establish a hyperresolution LSM in Indian conditions to serve the needs of marginal farmers. Past attempts have only used macroscale LSMs at coarse resolution under these conditions. So, we felt there is a need to examine the benefits and validity of hyperresolution LSM simulations before we discuss the model improvements. Furthermore, the parameter sensitivity analysis is designed to go hand-in-hand with the model intercomparison section. Given these considerations, the results and discussion section is structured as 1) assessing the benefits of using hyper-resolution LSM in terms of sub-grid heterogeneity, validation with in-situ data, and consistency with coarse resolution datasets, 2) analyzing the improvements made in HydroBlocks through VHet configuration, and 3) detailed examination of the VHet configurations through parameter sensitivity experiments.

Comment 13: Line 460: I would suggest moving section 3.2.2 into an Appendix.

Response: We agree with the reviewer's suggestion. We will move Section 3.2.2 into the Appendix of the revised manuscript.

Comment 14: Line 552: The SA analysis results are interesting, but more explanation needs to be added around the values of soil layer parameters – has the model been calibrated first? What are the default values of selected parameters and how their ranges were selected?

Response: We thank the reviewer for raising the concern. As mentioned earlier, the model has not been calibrated in this study to ensure its robustness and subsequently make model validation independent of any observations. The following steps are implemented for sensitivity analysis:

1) We segregated HRUs based on land cover classes and masked out the urban area.
2) The standard deviation of each of the eight soil parameters is computed across HRUs belonging to a particular land cover class. These standard deviations are used to define the upper and lower bounds of soil parameters at each of the HRUs. For instance, sampling bounds of MAXSMC of an HRU, say HRU_1, are determined by first identifying the land cover class of HRU_1 and computing the standard deviation (σ_{lc1}) of MAXSMC values for all HRUs belonging to the same land cover class. Hence, the sampling bounds of MAXSMC at HRU_1 will be $(x - \frac{\sigma_{lc1}}{2}, x + \frac{\sigma_{lc1}}{2})$, where x is the value of MAXSMC at HRU_1.
3) For each HRU, we selected 2,048 randomly generated values within the respective bounds of each soil parameter. Considering computational demands, we only considered first-order and total-order Sobol indices. This step resulted in a total of 20,480 parameter combinations, and accordingly 20,480 model simulations for the entire watershed.

4) The soil moisture simulations resulting from the above step are used to estimate the Sobol indices for each of the eight soil parameters. These Sobol indices are aggregated temporally at a seasonal scale at each HRU and soil layer.

This analysis was run over a period of 9 days with four nodes (128 CPUs in each node) in an HPC. We will provide the above procedure in Supplementary Material and will refer to it in the main manuscript in Sect 2.6.

Comment 15: Line 660: The numbers obtained as evidence that VHet conceptualisation is very similar (0.088 vs 0.084, which is less than 5% difference). Please comment on the significance of these results.

Response: The spatial standard deviation values mentioned are calculated for different soil moisture products on a specific day across the entire basin (and not an average of sub-grid spatial standard deviation). Although these values have similar magnitude, they result in significant spatial variations in soil moisture at a local (or HRU) scale, given that soil moisture is a strictly bounded variable. The differences in the soil moisture simulations become evident in subsequent analyses of the study. For instance, their surface soil moisture simulations show notable differences in certain watersheds (5, 6, 7, 8, 21, 22) at the local scale, as shown in Figure 5a. In the case of rootzone soil moisture simulations, the difference is more prominent, as shown in Figure 6a. Furthermore, comparison with in situ data also reveals that VHet configuration systematically improves soil moisture simulations over VHom by reducing the bias by 14.7 % on average across all sub-surface layers, as provided in Table 2 (Line 443). We find that the inclusion of soil heterogeneity affects the distribution of soil moisture within the watershed at an HRU scale, which is further evident in the analysis discussed in Sect 3.3 with Figure 10 and Figure 11.

We will include the above discussion in the revised manuscript.

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