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

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Abstract: Estimation of field-scale surface and rootzone soil moisture (SM) is crucial for agriculture water management. When ground observations are not available, Land Surface Models (LSMs) aid in reconstructing historical dynamics and providing predictions. However, they often run at coarse resolution (in the order of tens of kilometers), overlook subgrid processes (e.g., lateral flow), and thus underestimating the SM spatial heterogeneity. Considering this limitation, we applied the Noah-MP LSM with the HydroBlocks hyper-resolution modeling framework to estimate surface and rootzone SM at field scale (effective 30 meters resolution) for the first time in India. Recognizing the importance of rootzone processes for agriculture, the present study attempts to improve high-resolution rootzone SM simulations by incorporating vertical heterogeneity in soil properties into HydroBlocks using the SoilGrids global soil database. The analysis is carried out in Upper Bhima Basin (a subbasin of Krishna Basin) for 2020 with ERA5-Land meteorological forcing.

HydroBlocks simulations, configured with vertically homogeneous (VHom) and vertically heterogeneous (VHet) soil properties, were compared against GLEAM, ERA5-Land, SMAP-L3, and SMAP-L4, revealing temporal consistency (correlation between 0.76 and 0.94) and improved sub-grid (up to 0.2 m^3m^{-3}) and spatial variability (σ_θ), in particular VHet ($\sigma_\theta = 0.093$ m^3m^{-3}) higher than VHom ($\sigma_\theta = 0.09$ m^3m^{-3}). Both HydroBlocks configurations show reasonable performance against in situ SM observations, with VHet showing systematic improvement compared to VHom by reducing the bias in all sub surface layers and a higher correlation (0.60) than VHom (0.59) at deeper layer (0-60 cm). Finally, we performed a Sobol sensitivity analysis to investigate the seasonal sensitivity of soil on HydroBlocks (VHet) SM simulations for the first five soil layers (up to 1 meter depth). Results revealed that soil parameters interact more prominently in the surface layer and during monsoons. Soil porosity (MAXSMC), Brooks-Corey parameter (BB), and SM at wilting point (WLTSMC) are significant parameters across seasons. Their order of significance changes from surface to deeper layers; however, they remain consistent beyond 30 cm depth. This study finds that the hyper-resolution LSM with vertical soil heterogeneity can enhance small-scale SM simulations by accounting for varying parameter importance, interactions, and seasonal effects within the soil column.

1. Introduction

Soil moisture is an important state variable in the energy and water cycles. It effectively controls sensible and latent heat fluxes at the land-atmosphere interface (Benson and Dirmeyer, 2021), playing a decisive role in land-atmospheric interactions (Schwingshackl et al., 2018; Sehgal et al., 2021; Goswami et al., 2023). Soil moisture available at the plant root zone (up to 1 m deep from the surface) represents the water availability to plants. Hence, rootzone soil moisture is significant in agriculture (Rigden et al., 2020; Tijdeman and Menzel, 2021). There is a notable spatial scale dependency on soil moisture variability, which is attributed to physical controls, including climatic factors like precipitation and land surface variability due to soil types, vegetation characteristics, and topography (Famiglietti et al., 2008; Gaur and Mohanty, 2016; Rosenbaum et al., 2012; Vergopolan et al., 2022). The dominance of these soil moisture controls varies significantly with changing spatial scales (Joshi and Mohanty, 2010; Vergopolan et al., 2022). With an increase in spatial resolution (from 25 km to ~1.6 km), drivers of soil moisture variability shift from vegetation, soil, and topography (Gaur and Mohanty, 2013, 2016) to mostly soil itself. Accordingly, the significance of scale and spatial variability may vary depending on the emphasis of different studies. The landscape heterogeneity is further enhanced by farming practices (irrigation, fertilizer application, tile drainage) (Vergopolan et al., 2021; Yang et al., 2024), particularly at the surface layer. This heterogeneity is not captured within a coarser grid resolution and is even more challenging to assess in a fragmented agrarian system (Vergopolan et al., 2021).

Land surface Models (LSMs) have advantages over satellite and point scale observations by providing temporally consistent hydrologic estimates over a large extent. Although LSMs are capable of accurate simulation of various land surface processes, traditional models are limited to macro scales (in the order of tens of kilometers), which are primarily intended to run synergistically with climate models (Ek et al., 2003; Lawrence et al., 2011; Niu et al., 2011). The coarse resolution can overlook many aspects of agricultural applications, including irrigation water management and crop yield prediction (Ray et al., 2022). However, traditional LSMs still overlook many subgrid processes, including subsurface lateral connectivity, which becomes significant when the model resolution becomes finer (Ji et al., 2017; Kim and Mohanty, 2016; Krakauer et al., 2014; Singh et al., 2015). To understand the soil moisture heterogeneity at the farm scale (in the order of a few meters), LSMs must accurately represent the complexity of various land surface processes at that scale. However, increasing complexity significantly increases computational expenses.

HydroBlocks (Chaney et al., 2016, 2021) is a semi-distributed hyper-resolution (< 1 km) LSM with Noah-MP at its core intended to simulate soil moisture at 30 m spatial resolution. One of the critical advantages of HydroBlocks is its incorporation of subsurface lateral connectivity between its computing units. Studies have been conducted to leverage the benefits of this semi-distributed modeling approach to simulate soil moisture at hyper-resolution without making the simulations computationally expensive (Torres-Rojas et al., 2022; Vergopolan et al., 2020, 2021). In India, fragmented agriculture prevails with 86% small or marginal holdings with farm sizes less than 2 hectares (Agriculture Census, 2015-16). Hence, considering the backdrop of small farm sizes prevalent in the country, representing sub-grid heterogeneity of soil, topography, and meteorological variables at the field scale is fundamental. High resolution soil moisture aids agricultural applications, including drought (Park et al., 2017; Vergopolan et al., 2021), crop yields (Vergopolan et al., 2021), precise irrigation and water management (Jalilvand et al., 2021, 2023; Zhou et al., 2024).

However, 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. The availability of digital soil maps at a finer spatial resolution and applying Pedo Transfer Functions (PTFs) for estimating soil-hydraulic properties can provide better results for surface soil moisture simulations compared to the traditional look-up table approach in the LSMs (Xu et al., 2023). Soil properties are dominant physical controls in soil moisture spatial heterogeneity

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

(Crow et al., 2012; Vergopolan et al., 2022). The importance of incorporating soil vertical heterogeneity in LSMs is emphasized in previous studies either through a simplified LSM considering a single soil column (Yang et al., 2005) or approximating effective hydraulic parameters (Zhu and Mohanty, 2003). 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. Incorporating soil vertical heterogeneity in the HydroBlocks LSM has improved field scale surface soil moisture simulation (Xu et al., 2023). However, the effects of incorporating soil vertical properties in the model to simulate rootzone soil moisture at the field scale are still unknown. With the greater significance of rootzone soil moisture in agriculture, a study on understanding the role of soil vertical properties on rootzone soil moisture simulations applied agriculture-dominant countries like India is needed

The soil hydraulic properties are parameterized in LSMs, and uncertainties in these soil parameters affect soil moisture simulations (Arsenault et al., 2018; Cai et al., 2014). Applying PTFs on digital soil maps and incorporating soil vertical properties offers a better representation of the spatial heterogeneity of soil parameters. Besides, HydroBlocks LSM, which accounts for subsurface lateral flow, can provide more accurate field scale soil moisture simulations (Vergopolan et al., 2022, 2020). However, the vertical and seasonal influence on these properties in soil moisture simulation at the field scale remains unknown. Hence, a detailed sensitivity analysis of soil parameters on soil moisture simulations at a field scale is required.

The current study deploys digital soil maps combined with PTFs to estimate soil properties for each vertical soil layer in HydroBlocks and soil moisture at the farm scale (30 m spatial resolution). Although the primary goal of this study is to understand the effect of soil vertical properties in rootzone soil moisture, a study emphasizing the importance of having hyper-resolution LSM in India is still missing. For the first time, a hyper-resolution LSM simulations were set up over an Indian catchment, the Upper Bhima basin, a sub-basin of Krishna, in Maharashtra.. Although focused on a single catchment, this research holds global relevance, particularly considering that 84% of the world's farmers are smallholders.

The current study evaluates the performance of surface and rootzone soil moisture simulations obtained from two configurations of HydroBlocks – the first configuration with vertically heterogeneous soil properties and the second with vertically homogeneous soil properties. The soil moisture simulations from the model are evaluated using available in situ soil moisture station data in the basin at multiple soil depths. Because India does not have a well-monitored soil moisture network to evaluate the simulations, we also assessed the performance using satellite and reanalysis of soil moisture products. We also did an intercomparison between two HydroBlocks configurations at multiple layers (up to 1 m deep) to simulate soil moisture at each layer. Besides, a comprehensive understanding of the significance of soil parameters in hyper-resolution modeling of soil moisture for each soil layer and their seasonal variability remains unknown. Hence, for the first time, we performed a global sensitivity analysis test using the HydroBlocks, which considers soil vertical heterogeneity, on five soil layers (up to 1 meter depth) to assess the influence of soil textural parameters on the model simulated soil. In this process, we also evaluated the seasonal variability of parameter sensitivity. Through this research, we aim to address the following research questions:

- What are the benefits of a hyper-resolution LSM in generating soil moisture at the surface and rootzone over an agriculture-dominant landscapes in India?

- What changes does the integration of vertical soil heterogeneity into the model bring in the simulation of surface and rootzone soil moisture?
- What are the sensitive soil parameters toward soil moisture in each soil layer?
- Is there a seasonal influence on the soil parameter sensitivity?

2. Data and Methods

2.1 Study Area

The present study is carried out in the Upper Bhima basin, as shown in Fig.1, a subbasin of the Krishna Basin in India. The Upper Bhima basin has a spatial extent spread around 45,790 km^2 between 73.3° and 76.10° longitudes and 16.85° and 19.40° latitudes. The terrain is characterized by high elevation (353 m -1479 m) with steep slopes towards the west and flat land towards the east. The subbasin is identified with seven land cover classes according to IGBP standards of land cover classification, as shown in Fig.1. The majority of the basin area is occupied by croplands with more than 77%, followed by grasslands (12%), urban and built-up areas (6%), water bodies (2.5%), mixed forests (1.8%), with the remainder 0.7% for barren lands and permanent wetlands.

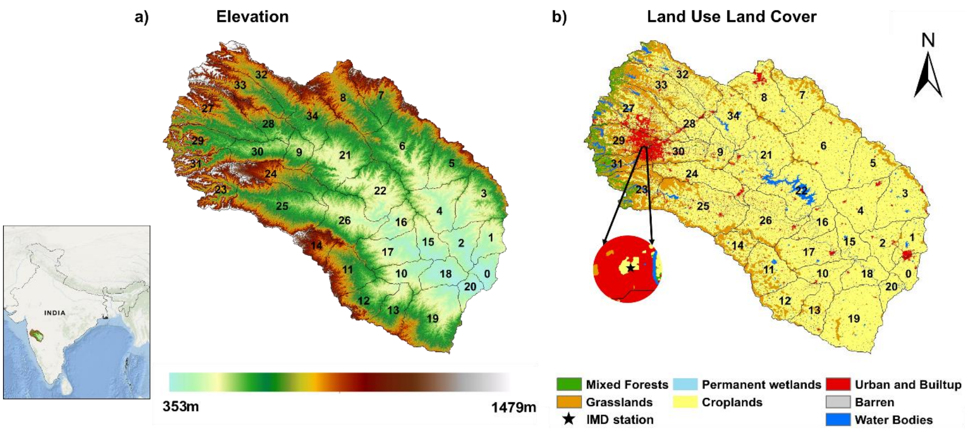

Figure 1: The Upper Bhima Basin (a) elevation in meters and (b) land use land cover (LULC) according to IGBP classification. The basin is divided into 35 subwatersheds modeled independently. The inset shows the location of the IMD station for in situ soil moisture observations.

The entire study area is subdivided into 35 watersheds (Lehner and Grill, 2013), with area varying between 490 km2 and 2883 km2 to make the simulations computationally feasible. The climate of the Upper Bhima River Basin is marked by a high degree of variability due to the interplay between the monsoon and the Western Ghat mountain range (Gunnell, 1997) The average annual rainfall for the basin is 653 mm, which is distributed non-uniformly across space and time (Garg et al., 2012). The Western Ghats zone receives heavy rainfall, with a maximum of 5000 mm per year. However, the rainfall decreases significantly towards the eastern slopes and plateau areas, falling below 500 mm per year (Pavelic et al., 2012).

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

2.2 Data

2.2.1 ERA5-Land

ERA5-Land is the fifth-generation global reanalysis product, providing hourly data for the land component of ERA5 at a spatial resolution of 9 km from 1950 onwards (Muñoz-Sabater et al., 2021). The model assimilates data from satellite sensors like Soil Moisture Ocean Salinity (SMOS), Advanced Microwave Scanning Radiometer-2 (AMSR-2), Tropical Rainfall Measuring Mission Microwave Imager (TRMM-MI), Active microwave instrument scatterometer onboard ERS1/2 and meteorological operational satellite for soil moisture product. Soil moisture data available at three soil layer depths (0-7 cm, 7-28 cm, and 28-100 cm) at 3-hour intervals were used in the current study for comparison with the model simulated soil moisture data.

2.2.2 GLEAM

GLEAM is a set of algorithms that estimate the main components of evapotranspiration based on satellite observations (Martens et al., 2017). In the current study, we have used GLEAM v3.6a – a global dataset spanning 42 years with a spatial resolution of 0.25° and a temporal resolution of 1 day. This dataset is based on the reanalysis radiation and air temperature, a combination of gauge-based reanalysis and satellite-derived precipitation and satellite derived vegetation optical depth. Soil moisture data from this product is available for surface (0-10 cm) and (0-100cm)

2.2.3 SMAP enhanced L3

The Soil Moisture Active Passive (SMAP) enhanced Level 3 product is a daily composite based on SMAP enhanced Level 2 product (O'Neill et al., 2021), providing global soil moisture data at a spatial resolution of 9 km available from 2015 onwards. In the current study, we have used daily SPL3SMP_E, Version 5 soil moisture data (0- 5 cm) for the study area.

2.2.4 SMAP L4

The level-4 SMAP is a global product that merges SMAP observations into the NASA Catchment Land Surface Model (Reichle et al., 2014) using an Ensemble Kalman filter. Hence, it provides data at a deeper layer, facilitating rootzone soil moisture estimates. For the current study, we have used rootzone (0-100 cm) soil moisture estimates of SMAP L4 product at a spatial resolution of 9 km and temporal resolution of 3 hours.

2.2.5 In-situ soil moisture data

The India Meteorological Department (IMD) Agromet Division provides weekly soil moisture measurements for 41 stations across India at various depths: 5 cm, 7.5 cm, 15 cm, 30 cm, 45 cm, and 60 cm based on gravimetric measurements. The Upper Bhima basin has only one station at 18.5385° N, 73.8429° E (Fig.1). However, during 2020, due to the COVID-19 pandemic, soil moisture was recorded for only 34 weeks. Despite limited data, this comprises the best ground truth estimation of soil moisture in the domain.

2.2.6 Data used in the HydroBlocks

We use ERA5-Land (Muñoz-Sabater et al., 2021) as meteorological forcings, which include precipitation, air temperature, longwave and shortwave radiations, surface air pressure, wind speed, and specific humidity derived from 2 m dew point temperature at 0.1° spatial resolution and 3-h time intervals over a time period 2015-2020. Besides, the model also requires static data about soil characteristics, topography, and land cover regridded to 30 m spatial resolution. We used the SoilGrids dataset (Hengl et al., 2017) at 250 m resolution and PTFs (Saxton and Rawls, 2006) to estimate other soil hydraulic properties. These include porosity, pore size distribution parameters, soil moisture at the wilting point, field capacity, saturated hydraulic conductivity, soil water diffusivity at saturation, and saturated soil matric potential. The land use land cover data is obtained from ESRI (Karra et al., 2021), available at 10 m resolution. Further, the land cover classes are reclassified based on IGBP classification as per the model requirement using the nearest neighbor for each 30m grid cell. The elevation data for topography is obtained from the ASTER Global Digital Elevation Model, available at a resolution of 30 m.

2.3 HydroBlocks Model

HydroBlocks (Chaney et al., 2016, 2021) is a semi-distributed hyper-resolution LSM that clusters areas of hydrologic similarity into Hydrologic Response Units (HRU). The HRUs form the domain's computing units and enable simulating land surface processes at an effective 30m spatial resolution. At its core, HydroBlocks applies Noah-MP to solve land surface processes within each HRU. The present study uses the HydroBlocks model version using Darcy's equation to maintain the lateral connectivity between HRUs at the subsurface (Chaney et al., 2021). HydroBlocks was validated over the United States and have been demonstrated to provide accurate and computationally feasible simulations of soil moisture at a farm scale (Vergopolan et al., 2021, 2020).

2.4 HydroBlocks Model with Vertically Heterogenous Soil Parameterization for Soil Moisture Profile Simulations

For computational efficiency, the basin was discretized into 35 sub-watersheds. For each sub-watersheds, we simulated soil moisture at 30 m resolution at the surface (0 – 5 cm) and the rootzone (0 – 100 cm) for the year 2020 at a temporal resolution of 3 hours. We spin up the model from 2015 to 2019. In an attempt to improve the soil moisture profile simulations, the HydroBlocks model is modified to incorporate vertical heterogeneity in soil properties. The schematic of vertical heterogeneity implemented in HydroBlocks is shown in Fig.2. The vertical heterogeneity of soil properties corresponds to soil depth information as in SoilGrids, which are 0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm, and 100-200 cm. From this point forward, vertical heterogeneity (of soil properties) incorporated in HydroBlocks is referred to as HydroBlocks Vertically Heterogeneous (VHet) version. In the case of the existing model of HydroBlocks, the soil profile is assumed to be vertically homogeneous (VHom), wherein the surface layer soil properties are utilized for the entire soil column. Both model configurations are run at Noah-MP parameterization schemes, as shown in Table 1.

https://doi.org/10.5194/hess-2024-339
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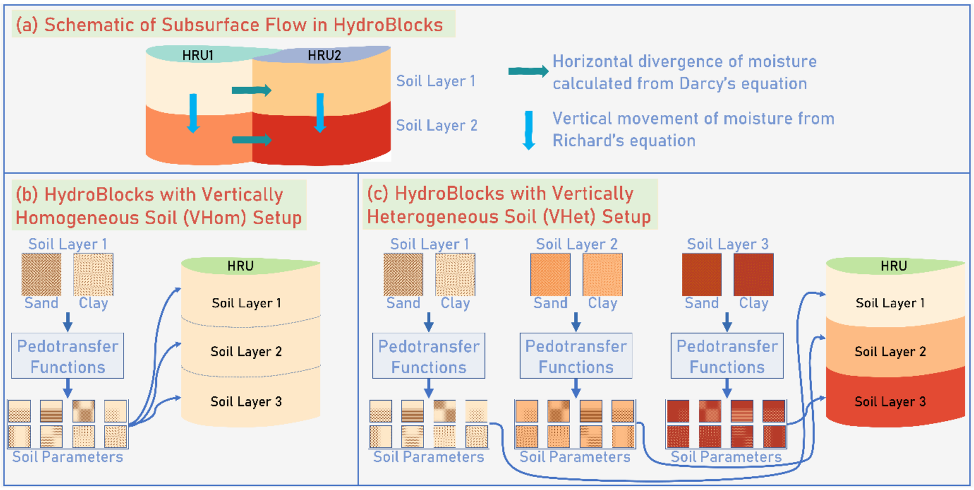

Figure 2: Schematics depicting HydroBlocks LSM setups. a) HydroBlocks updates soil moisture between different soil layers after incorporating vertical flow between layers and lateral flow between the HRUs at the subsurface layer for every timestep. The lateral subsurface flow is defined by Darcy's equation. b) HydroBlocks model setup with vertically homogeneous (VHom) soil and after incorporating vertical heterogeneous (VHet) soil. Soil properties for each layer are defined by sand clay and organic matter content using PedoTransfer Functions (PTFs). Each small square represents soil parameters for each soil layer. Hence, the VHet setup has eight soil parameters stacked for three soil layers (represented by three colours). In the VHom setup, the eight soil parameters corresponding to the surface layer are used in the entire soil column.

Table 1. Description of the selected Noah-MP schemes

Parametrization	**Schemes selected**
Dynamic vegetation	Off
Canopy stomatal resistance	Ball-Berry
Soil moisture factor for stomatal resistance	Noah type
Runoff and groundwater	TOPMODEL-based scheme with the equilibrium water table
Surface layer drag coefficient	Monin-Obukhov-based
Supercooled liquid water in frozen soil	Koren99 scheme
Frozen soil permeability	Koren99 scheme
Radiation transfer	Modified two-stream
Ground snow surface albedo	CLASS
Snow/soil temperature time scheme (layer 1)	Semi implicit scheme

2.5 Performance Evaluation

To compare model simulations with IMD in situ soil moisture observations, we selected common depths (5 cm, 15 cm, 30 cm, and 60 cm). Soil moisture simulations from the model are hence calculated corresponding to layers 0- 5cm, 0-15 cm, 0-30 cm, and 0-60 cm after assigning weights based on the model layers 0-5 cm, 5-15 cm, 15-30 cm, and 30-60 cm. VHet and VHom simulations are evaluated against in situ observations using bias, unbiased Root Mean Square Error (ubRMSE), Pearson's correlation (R), and Spearman's rank (R_{sp}) correlations.
Due to the limited availability of in situ soil moisture observations over the study area, HydroBlocks simulated soil moisture is also compared with existing satellite and reanalysis products. These products include SMAP L3

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

Hydrology and Earth System Sciences
Discussions

Enhanced (9 km resolution), SMAP L4 (9 km resolution), ERA5-Land (0.1° resolution) and GLEAM (0.25° resolution). The evaluation of surface and rootzone soil moisture simulations is carried out in two ways. First, consistency with respect to satellite and reanalysis datasets is carried out in terms of temporal and spatial variations. Time variations are assessed in four randomly selected watersheds (Fig.S1). Spatial variations are evaluated in terms of daily soil moisture and spatial standard deviations (to analyze the subgrid heterogeneity). Spatial standard deviation is computed using the HydroBlocks simulations from grid cells falling within the coarser resolution grids of each reanalysis and satellite data. Second, a quantitative comparison is carried out by upscaling HydroBlocks soil moisture simulations to a reference macroscale product. We use bias, Pearson Correlation, and ubRMSE for this purpose. For the surface layer, spatio-temporal comparisons are carried out with SMAP L3, ERA5-Land, and GLEAM surface soil moisture. For the rootzone, SMAP L4, ERA5-Land, and GLEAM rootzone soil moisture are used for this purpose. In both cases, one SMAP grid cell is randomly identified within the four selected watersheds (Fig.S1), and soil moisture corresponding to the grid cell is considered from all datasets. A quantitative comparison is carried out using SMAP L3 and SMAP L4 as references for surface and rootzone soil moisture simulations.

2.6 Sensitivity Analysis

Soil moisture has high spatial-temporal variability. Understanding this variability in the context of the influence of soil textural properties requires a careful study of their role under varying climatic conditions. Although soil textural properties have been shown to drive the soil moisture variability at hyper-resolutions (Vegropolan et al., 2022), the vertical and seasonal influence on these properties in soil moisture simulation at this scale remains unknown. Hence, a Sobol sensitivity analysis (Sobol, 1993) is performed on the soil parameters of HydroBlocks (parameters used in Noah-MP) at the HRU scale and at every timestep. Eight soil parameters are considered, which include the Brooks-Corey parameter (BB), wilting point (WLTSMC), porosity (MAXSMC), field capacity (REFSMC), soil moisture limiting direct evaporation (DRYSMC), saturation soil matric potential (SATPSI), saturated hydraulic conductivity (SATDK) and saturated soil-water diffusivity (SATDW). To minimize the computational time, we selected a small watershed of 402.1 km^2 within the basin to perform the sensitivity test across all of its HRUs. The watershed is predominantly cropland (96%), waterbodies (2.3%), and with the remainder 1.7% for urban and mixed forest. The watershed has flat terrain with elevation range between 376m and 548m and clay content (30% to 42.6%). To assess the sensitivity of soil parameters with respect to depth, Sobol analysis is carried out on soil moisture simulations obtained from HydroBlocks VHet version at each soil layer and each timestep across all HRUs in the selected watershed. We considered a variability of one standard deviation for each soil parameter in the sensitivity analysis. The Sobol analysis is carried out using the Python package SALib (Herman and Usher, 2017). In this test, HRUs under urban land cover are omitted due to the lack of information and variability of soil parameters in these regions. This test decomposes the total variance V of the model output as a combination of variances of each input parameter as V_i and as variances of its interactions with other parameters.

$$\mathrm{V} = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + V_{12,\dots,n} \quad (1)$$

V_{ij} is the variance in the model output corresponding to the interaction between parameters i and j, and hence $V_{12,\dots,n}$ represents all the interactions higher than the third order.

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

S_i is the first-order Sobol index representing the contribution of each parameter without considering its interaction with other parameters. The total contribution from parameter i., including its interaction with other parameters, is defined by the total order of Sobol index S_{Ti}. This can also be written in terms of total variance, V when the sum of all variances where every parameter is varied except the parameter i as $V_{\sim i}$. Hence, the first-order Sobol index S_i and total-order Sobol index S_{Ti} are as follows.

$$S_i = \frac{V_i}{V}, \quad (2)$$

$$S_{Ti} = 1 - V_{\sim i}/V \quad (3)$$

Soil moisture generated from the model is a time series data. Hence, Sobol indices are calculated at each timestep for all parameters under consideration. Further, following (Cuntz et al., 2016), the $V_{12,\dots,n}$ arithmetic mean of Sobol indices is calculated over all time steps as given below. The time series of sensitivity is utilized to assess the role of seasonality in influencing soil parameter sensitivity on soil moisture profile simulations.

$$\bar{S_i} = \frac{1}{T}\sum_{t=1}^{T} S_i(t) = \frac{1}{T}\sum_{t=1}^{T} \frac{V_i(t)}{V(t)} \quad (4)$$

$$\bar{S_{Ti}} = \frac{1}{T}\sum_{t=1}^{T} S_{\mathrm{Ti}}(t) = 1 - \frac{1}{T}\sum_{t=1}^{T} \frac{V_{\sim i}(t)}{V(t)} \quad (5)$$

3. Results and Discussion

3.1 The capabilities of hyper-resolution simulations for characterizing the soil moisture dynamics

3.1.1 Temporal dynamics of surface soil moisture

Fig.3 shows the temporal variation of surface soil moisture of different products: HydroBlocks VHet and VHom, SMAP L3, GLEAM, and ERA5-Land for four watersheds. The HydroBlocks model configurations (VHet and VHom) are shown at a location corresponding to an SMAP grid. During dry seasons (October to May), the soil moisture spatial variability of HydroBlocks simulations are consistent, as shown in terms of its standard deviation in shades. From all the data products, only ERA5-Land is drier than HydroBlocks simulations in the dry period. During the monsoon season, HydroBlocks simulations showed less spatial variability (black and maroon shades in Fig.3); however, less consistency than during the dry periods. Considering that the only difference between the two HydroBlocks model configurations is the vertical heterogeneity of subsurface soil layers, the observable differences in surface soil moisture during the monsoon can be attributed to the influence of soil properties at the deeper layers, especially during active wetting/drying conditions. Compared to other data products, ERA5-Land exhibits sudden wetups with increased precipitation towards the onset of the monsoon and steeper drydown as the monsoon recedes. During monsoon, ERA5-Land shows high wet bias compared to other data products. Despite using the same meteorological forcing as ERA5-Land, HydroBlocks simulations were more consistent and able to better represent the temporal dynamics of SMAP L3 surface soil moisture. There are several differences between the HydroBlocks and ERA5-Land in terms of soil hydrology processes (e.g., accounting for lateral connectivity), modeling resolution, parameterizations, and supporting datasets. ERA5-Land defines soil properties based on soil texture information derived from soil depth (30-100 cm) of FAO Digital Soil Map of World at 9 km resolution (Muñoz-Sabater et al., 2021). This soil data ignores horizontal and vertical spatial variability of soil properties at the field scale in the study region (Dai et al., 2019; Poggio et al., 2021). Further, HydroBlocks used in this study do not account for surface channel routing, whereas ERA5-land does, which can also influence soil moisture variations.

https://doi.org/10.5194/hess-2024-339
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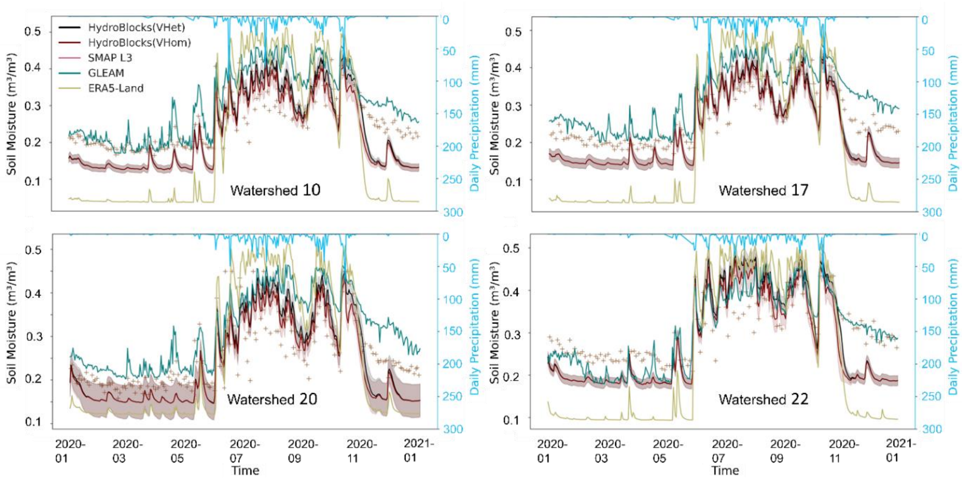

Figure 3: Time series of surface soil moisture simulations from HydroBlocks (VHet and VHom configurations) compared with SMAP L3, ERA5-Land, GLEAM surface soil moisture (m^3m^{-3}), and ERA5-Land daily precipitation (mm). Soil moisture values considered from all datasets for the year 2020 correspond to a randomly identified SMAP L3 grid in each of the four watersheds. Both HydroBlocks simulations are represented by the mean soil moisture from all 30 m grids within the SMAP L3 grid, with one spatial standard deviation shown as a light-coloured band around the mean.

During the dry season (October to May), HydroBlocks VHom and VHet surface soil moisture simulations are consistent with SMAP L3 observations with the exception of dry bias of -0.056 m^3m^{-3}.and -0.051 m^3m^{-3}, respectively. Conversely, during the monsoon, HydroBlocks simulations have a wet bias of 0.015 m^3m^{-3} and 0.032 m^3m^{-3} compared to SMAP L3. However, during saturated conditions, where soil moisture is around 0.45 m^3m^{-3}, there is a convergence between HydroBlocks VHet and VHom simulations and SMAP soil moisture. In HydroBlocks, the saturated soil moisture conditions are limited by soil porosity, which is computed through PTFs. Consistency with satellite observed saturation levels confirms that properties computed using digital soil maps and PTFs can improve soil moisture modeling performance than those obtained from the look-up table, as also shown in (Xu et al., 2023).

HydroBlocks surface soil moisture simulation, compared to that of GLEAM data at 0.25° spatial resolution, shows minimal temporal variability with steeper drydown towards the end of the monsoon. HydroBlocks represents surface soil moisture at 5 cm depth and uses Richards equations in Noah-MP to account for the vertical flow of soil water. In contrast, GLEAM represents soil moisture for a 10 cm profile and uses a simplified drainage scheme independent of soil properties except for wilting point and soil porosity (Martens et al., 2017). This simplification is beneficial for enhancing computational efficiency (Martens et al., 2017); however, it ignores various subgrid processes and is hence not suitable for field-scale application.

3.1.2 Temporal dynamics of rootzone soil moisture

Fig.4 shows the temporal variation of rootzone soil moisture (1 meter deep) for different products, including two HydroBlocks model configurations at a location corresponding to an SMAP pixel in four different watersheds. Results show a wet bias of 0.03 m^3m^{-3} between HydroBlocks (VHet) and HydroBlocks (VHom). During the dry period from January to May, neither model configuration depicts a noticeable drydown except for later months in the period. Precipitation events were limited and of low magnitude, causing low evaporation. However, other soil moisture data products show a consistent drydown pattern throughout the period. HydroBlocks simulations do not depict a prominent drydown since the monthly LAI values are zero from the Noah-MP parameter table, MPTABLE.TBL, thus, indicates no transpiration till April. Towards the end of April, as LAI increases, transpiration also increases, causing a discernible drydown pattern in both HydroBlocks configurations. To address this limitation, we expect that incorporating dynamic LAI as an input in Noah-MP parameterization improves vegetation accountability and transpiration estimation. However, implanting dynamic vegetation in hyper-resolution scales increases the complexity and is beyond the purview of current work. Such a modification shall be included in future versions of the model.

During the monsoon, with the increase in precipitation events and their intensities, soil moisture variability increases in all data products. HydroBlocks VHet and VHom rootzone soil moisture values were consistent with SMAP L4 and GLEAM; however, they showed a significant dry bias of -0.056 m^3m^{-3} and 0.08 m^3m^{-3} compared to ERA5-Land during the monsoon. Unlike HydroBlocks rootzone soil moisture, which saturates at 0.4 m^3m^{-3}, ERA5-Land data saturates at 0.5 m^3m^{-3} in monsoon.

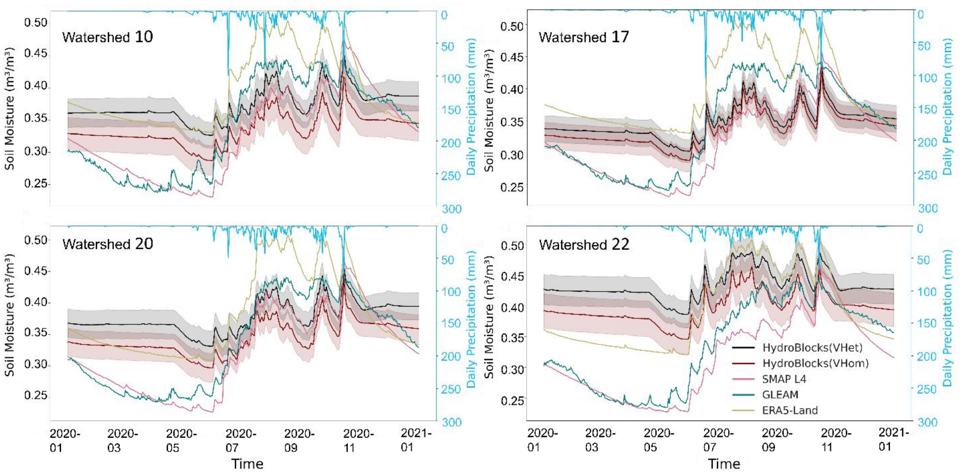

Figure 4: Time series plots of rootzone soil moisture simulations from HydroBlocks (VHet and VHom configurations) compared with SMAP L4, ERA5-Land, GLEAM rootzone soil moisture (m^3m^{-3}), and ERA5-Land daily precipitation (mm). Soil moisture values considered from all datasets for the year 2020 corresponded to a randomly identified SMAP L4 pixel in each of the four watersheds. HydroBlocks rootzone soil moisture simulations are represented by the mean soil moisture from all 30 m grids within the SMAP L4 pixel, with one standard deviation shown as a light-colored band around the mean.

3.1.3 Spatial dynamics of surface soil moisture

The spatial distribution of surface soil moisture estimates for GLEAM, ERA5-Land, SMAP L3, and HydroBlocks (VHom and VHet) are shown in Fig. 5(a). HydroBlocks and SMAP L3 soil moisture data show a transition from wetter in the west to drier soil conditions in the east, reflecting the spatial pattern of precipitation across the basin. Compared to HydroBlocks simulations, SMAP L3 soil moisture data shows a smoother transition, which can be attributed to the effect of interpolation of original SMAP retrieval at 36 km to 9km (Chaubell et al., 2016). As expected, the HydroBlocks surface soil moisture shows substantial spatial variability (represented by the spatial standard deviation σ_θ, of VHet = 0.088 m^3m^{-3} and VHom =0.084 m^3m^{-3}) compared to macroscale products (σ_θ of SMAP L3 = 0.054 m^3m^{-3}, ERA5-Land = 0.033 m^3m^{-3}, and GLEAM = 0.017 m^3m^{-3}). The spatial variability of HydroBlocks surface soil moisture is shown for each coarse resolution pixel corresponding to the coarser scale products in Fig.5(b). The dry soil conditions in urban areas of some watersheds result in high soil moisture variability with a spatial standard deviation exceeding 0.16 m^3m^{-3} at all the macroscale product resolutions. However, this behavior is likely a response to how urban areas are parametrized in the model rather than only the soil hydrologic process. Further, drier watersheds in the south exhibit a low standard deviation (~0.02 m^3m^{-3}) in this region.

At a watershed scale, represented by the inset of Fig.5(a), we can observe higher spatial heterogeneity in HydroBlocks VHet and VHom simulations than in SMAP L3, ERA5-Land, and GLEAM soil moisture data. HydroBlocks simulations in this watershed, although spatially consistent with SMAP L3 observations, reveal a detailed variation. We can observe wet soil patches near streams or dry soil in higher elevations to the south of this watershed. Similar spatial heterogeneity is not observed in the estimates of other datasets because of their coarse resolution. Besides, this watershed has a spatial extent less than GLEAM's 0.25° grid resolution. Improvement in spatial variability at a localized scale is a response to the combined interactions between the meteorological forcing, topography, land cover types, and soil properties (Vergopolan et al., 2022).

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Preprint. Discussion started: 6 December 2024

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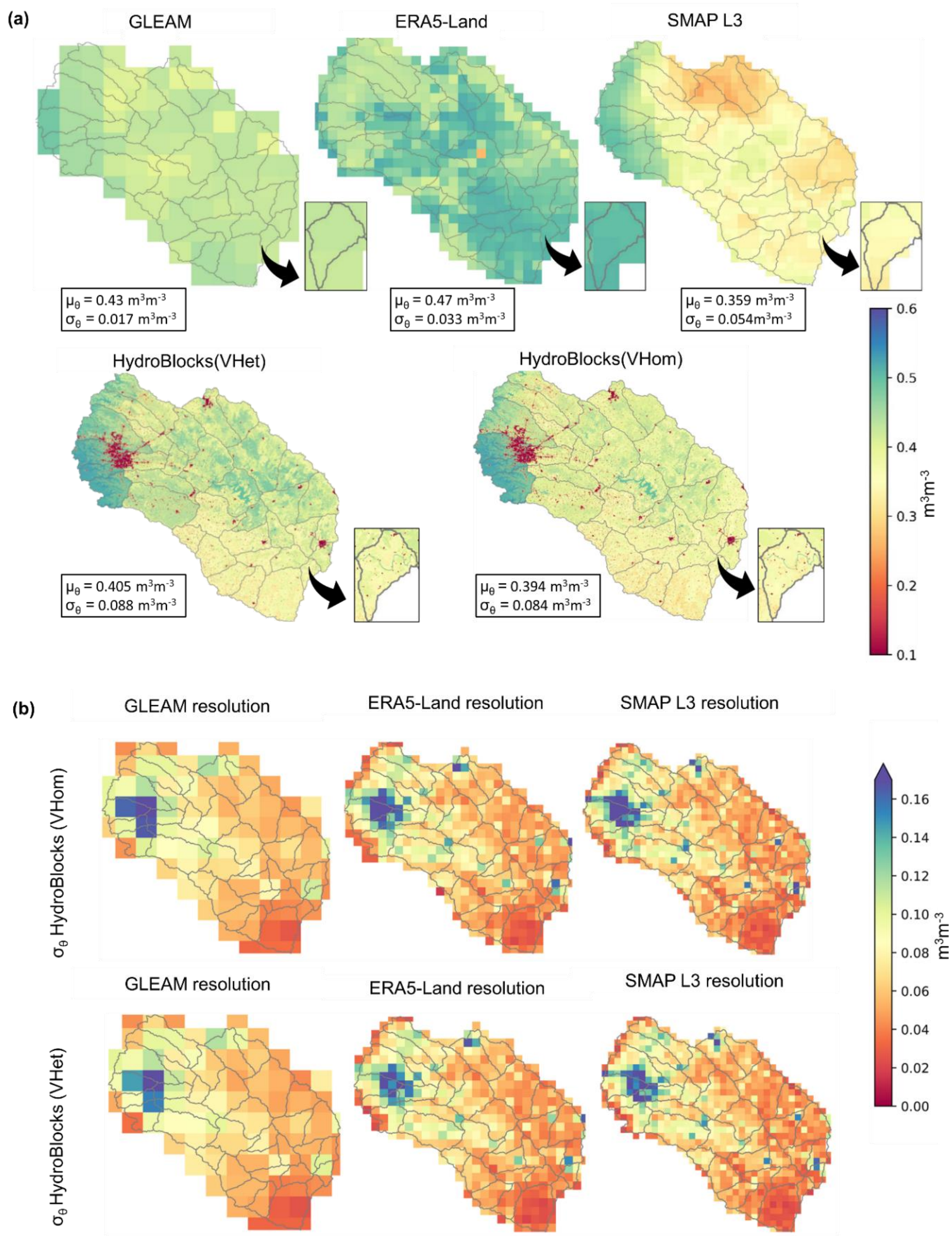

Figure 5: (a) The spatial maps of surface soil moisture on August 6, 2020, were obtained from HydroBlocks simulations compared with ERA5-Land, GLEAM, and SMAP L3 data. The soil moisture mean (μ_θ) and spatial standard deviation (σ_θ) of the entire basin for each data product are also shown. The inset shows the simulations at a watershed scale (watershed 20 with an area of 402 km^2). (b) Spatial standard deviations (σ_θ) of HydroBlocks (VHet and VHom configurations) surface soil moisture (at 30 m resolution) estimates within coarser resolution pixels of different macroscale products.

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

Hydrology and Earth System Sciences
Discussions

3.1.4 Spatial dynamics of rootzone soil moisture

Fig.6(a) shows the spatial maps of the rootzone soil moisture estimates on August 6, 2020, across the whole basin from GLEAM, ERA5-Land, SMAP L4, and HydroBlocks VHet and VHom. As for the surface, HydroBlocks rootzone soil moisture shows higher spatial variability (σ_θ, of VHet = 0.093 m^3m^{-3} and VHom =0.09 m^3m^{-3}) than other macroscale products (σ_θ of SMAP L3 = 0.052 m^3m^{-3}, ERA5-Land = 0.032 m^3m^{-3}, and GLEAM = 0.018 m^3m^{-3}). However, the rootzone variability is higher than the surface soil moisture variability. HydroBlocks simulations show wet soil in most of the basin, except for watersheds 11, 12, 13, and 19 in the south, where soil is dry. The spatial pattern of HydroBlocks simulations is not consistent with any of the macroscale data at a basin scale. However, at a regional scale, soil moisture simulations from HydroBlocks and other products show similarities, although HydroBlocks simulations demonstrate high spatial variability. For example, in Watersheds 5, 6, 7, and 8, simulations of HydroBlocks (both configurations) and ERA5-Land show the influence of topography where the soil is drier at the ridges and wet in the foothills. However, HydroBlocks simulation shows better spatial variability, which is evident from its spatial standard deviation within the corresponding ERA5-Land grid cells (Fig.6(b)). Watersheds 23, 29, and 31 towards the west of the basin receive high precipitation and have numerous tributaries, causing the soil to be wet with more spatial variability in HydroBlocks simulations than SMAP L4 data. Figure 6(b) shows the spatial standard deviation of rootzone soil moisture simulated by HydroBlocks (VHom) and HydroBlocks (VHet) for each coarser resolution pixel of the macroscale products. HydroBlocks could simulate the dryness in soil moisture in the urban area, causing a high standard deviation (~0.2 m^3m^{-3}) within the corresponding coarse resolution grid cells. Macroscale products like GLEAM have wide applicability in hydroclimatic studies (Baker et al., 2021), particularly due to their improved accuracy in estimating evapotranspiration (Ding and Zhu, 2022; Zhu et al., 2022). However, macroscale products overlook the sub-grid scale process, including lateral connectivity and heterogeneity in land cover types at the field scale (Wood et al., 2011). Agricultural applications require spatial heterogeneity of rootzone soil moisture at the field scale (Vergopolan et al., 2021).

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Preprint. Discussion started: 6 December 2024

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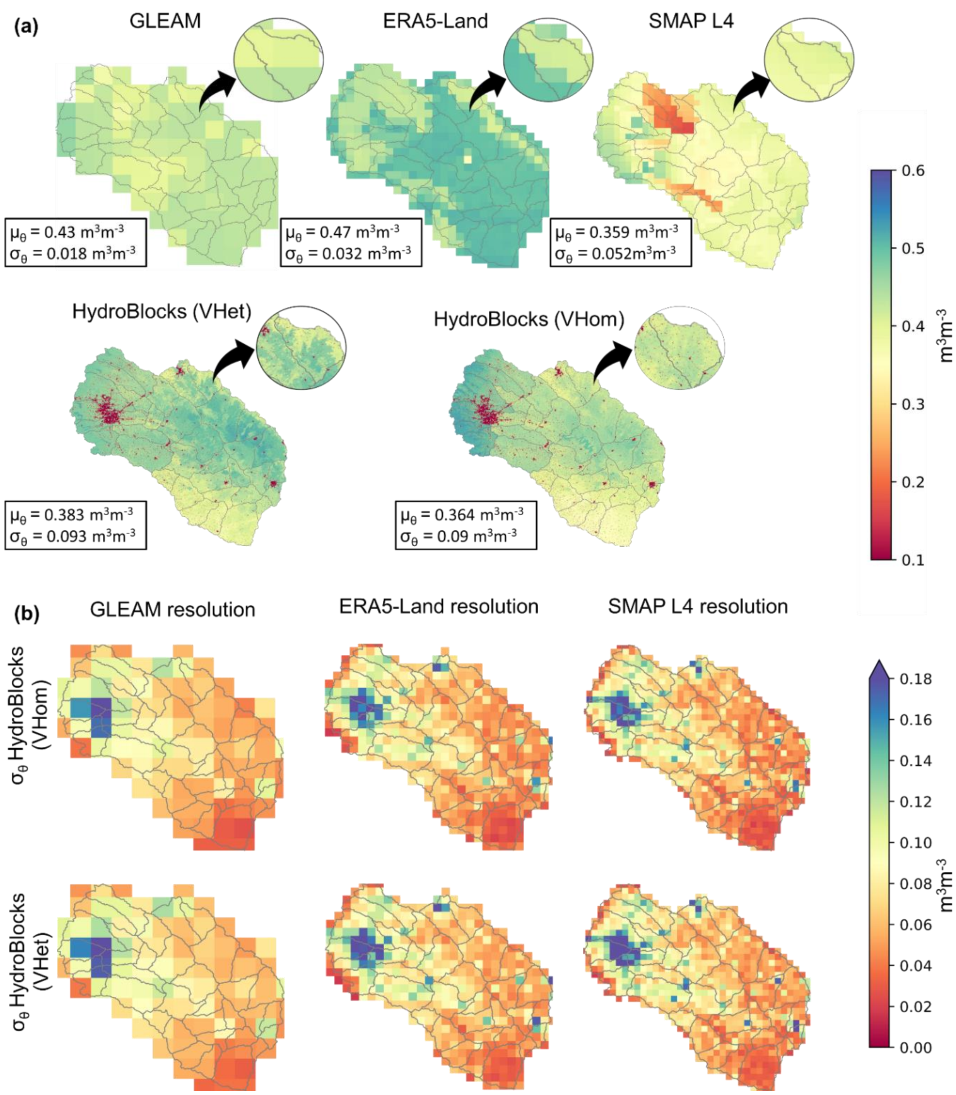

Figure 6: (a) The spatial maps of rootzone soil moisture on August 6, 2020, were obtained from HydroBlocks simulations compared with ERA5-Land, GLEAM, and SMAP L4 data. The soil moisture mean (μ_θ) and spatial standard deviation (σ_θ) of the entire basin for each data product are also shown. The insets reveal the spatial details of the simulations at a local scale. (b) Spatial standard deviations (σ_θ) of HydroBlocks (VHet and VHom configurations) rootzone soil moisture (at 30 m resolution) estimates within coarser resolution pixels of different macroscale products.

Further comparing the two model configurations, HydroBlocks (VHet) simulations show soil to be wet in plain topography and drier in hilly areas to the west of the basin than HydroBlocks (VHom) simulations. At field scale, HydroBlocks (VHet) offers higher spatial variability than HydroBlocks (VHom) in both surface and rootzone soil moisture simulations. A farm-scale soil moisture simulation with improved sub-grid variability is valuable for

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

precision irrigation and water resources management (Peng et al., 2021). Root zone soil moisture indicates water availability to plants, and its spatial variability significantly impacts crop yield and their predictions (Holzman et al., 2014). However, both model configurations of HydroBlocks could simulate soil moisture with higher spatial variability than in macroscale products. We further evaluated the performance of HydroBlocks, and the results are discussed in the next section.

3.2 Model Performance

3.2.1. Validation with IMD in-situ observations

In-situ monitoring of soil moisture is a challenge in agriculture dominant countries like India, which have fragmented farming systems (Karthikeyan and Kumar, 2016; Vergopolan et al., 2021). In view of these limitations, we could validate HydroBlocks VHet and VHom simulations with in-situ soil moisture data at only one location. Fig.7 presents the timeseries and scatterplots of VHet and VHom simulations of an HRU corresponding to location where in-situ station is situated in watershed 29. Fig. 7(a) corresponds to the surface layer (0-5 cm), Fig. 7(b) corresponds to layer 2 (0-15 cm), Fig. 7(c) coreesponds to layer 3 (0-30 cm) and Fig 4 corresponds to layer 4 (0-60 cm) ; Table 2 presents the layer-wise performance VHet and VHom simulations. In the case of surface soil moisture, results reveal that both HydroBlocks configurations exhibited similar performance. Both VHet and VHom configurations have low bias (-0.001 m^3m^{-3} 0.003 m^3m^{-3}) with similar ubRMSE (0.096 m^3m^{-3} and 0.097 m^3m^{-3}) and correlation (R = 0.66;0.66 and R_{sp} = 0.66;0.67) when compared to in-situ observations.

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Preprint. Discussion started: 6 December 2024

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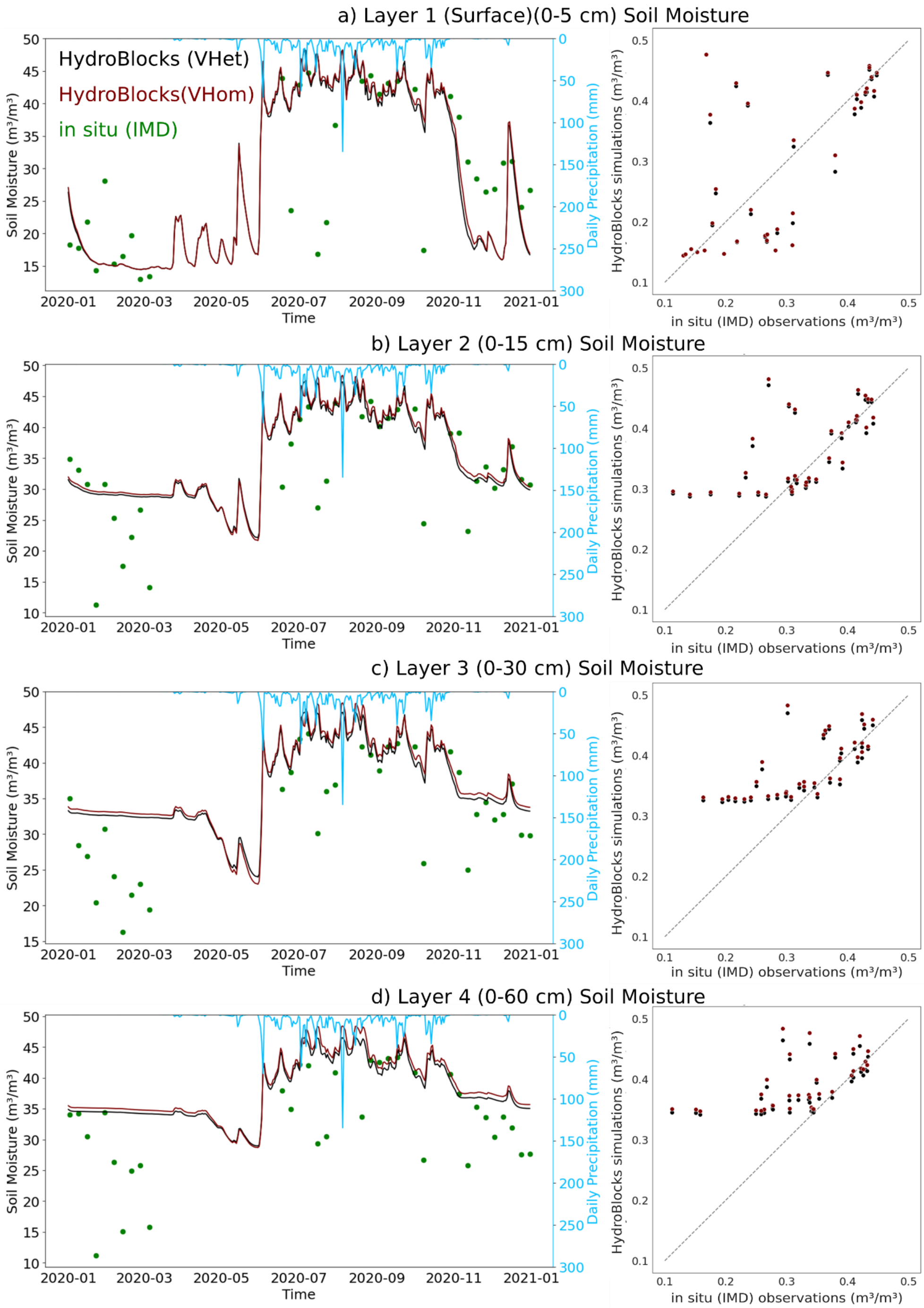

Figure 7: Time series of HydroBlocks (VHet and VHom configurations) simulations of soil moisture at different layers ((a) 0-5 cm (surface), (b) 0-15 cm, (c) 0-30 cm, (d) 0-60 cm with ERA5-Land daily precipitation (mm),

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

which is used as the forcing in the model, are compared with IMD in situ soil moisture observations at watershed 29. Scatterplots comparing the HydroBlocks simulations and in situ observations are also included beside layerwise soil moisture time series. HydroBlocks simulations are converted to daily timescale before comparing against insitu observations.

Table 2. Performance metrics of layer wise simulations of HydroBlocks VHet and VHom configurations against IMD in situ observations.

	Layer 1 (Surface) (0-5 cm)		**Layer 2 (0-15 cm)**		**Layer 3 (0-30 cm)**		**Layer 4 (0-60 cm)**	
	VHom	VHet	VHom	VHet	VHom	VHet	VHom	VHet
Bias (m^3m^{-3})	0.003	-0.001	0.036	0.030	0.051	0.044	0.067	0.059
ubRMSE (m^3m^{-3})	0.096	0.097	0.067	0.067	0.055	0.055	0.066	0.066
R	0.66	0.66	0.63	0.63	0.70	0.70	0.59	0.60
R_{sp}	0.67	0.66	0.67	0.67	0.80	0.80	0.67	0.68

In the case of subsurface layers, soil moisture simulations from VHet slightly outperformed VHom, particularly by reducing the bias. In all the sub surface soil layers at different depths (0-15 cm ,0-30 cm, 0-60 cm), VHet simulations show lower bias (0.030 m^3m^{-3}, 0.044 m^3m^{-3} and 0.059 m^3m^{-3}) than VHom (0.036 m^3m^{-3}, 0.051 m^3m^{-3} and 0.067 m^3m^{-3}). However, there is no change in ubRMSE values (~0.067 m^3m^{-3}, 0.055 m^3m^{-3}, and 0.066 m^3m^{-3}). This indicates that incorporating soil vertical properties into the model has brought a systematic improvement (thus, the difference in bias) in deeper layers. VHet configuration also show a marginal improvement in the correlation values in the deeper layer (at depth 0-60cm) with R and R_{sp} (0.60 and 0.68) than VHom's values (0.59 and 0.67, respectively) at the site. Both VHet and VHom configurations show similar correlation values in other sub surface layers – R = 0.67 and R_{sp} = 0.67 for layer (0-15 cm) and R = 0.7;R_{sp} = 0.80 for layer (0-30 cm). VHet simulations have shown good agreement with in situ soil moisture during the monsoon season (Fig. 7 (b,c,d)). Furthermore, the wetup and drydown patterns of both configurations are largely consistent with in situ observations and precipitation. It is important to note that there could be uncertainties due to the lack of dense network of observations, which can affect the performance (Chen et al., 2017). Despite uncertainties, VHet followed by VHom simulations are reasonably accurate when compared to the ground truth. To gain further confidence on the quality of simulations and account for land surface heterogeneity, we evaluated the model simulations against SMAP L3 and SMAP L4 soil moisture data and discussed in Sect 3.2.2.

3.2.2 Comparison with SMAP L3 and L4 soil moisture data

The boxplots shown in Fig. 8 explain the quality of HydroBlocks VHet and VHom surface soil moisture simulations with respect to SMAP L3 observations. Only those SMAP L3 pixels that have recommended retrieval quality are considered during this analysis. Performance is assessed using bias, ubRMSE, and Pearson correlation. Most of the watersheds have a dry bias compared to SMAP L3. Exceptions are there, with some watersheds having a marginal wet bias, however, less than 0.025 m^3m^{-3}. The average median bias values, across the basin, for

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Preprint. Discussion started: 6 December 2024

Hydrology and Earth System Sciences
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HydroBlocks VHet and VHom simulations are -0.02 m^3m^{-3} and -0.021 m^3m^{-3}, respectively. There is no clear trend or pattern in the bias values of watersheds following their elevation range. However, watersheds with higher relative relief, greater than 500m, show higher variability marked by long whiskers than other watersheds. Further watersheds with low variation in bias are more commonly found in regions with smaller elevation ranges. Although exceptions exist in both cases, a possible reason is that some of these watersheds (e.g., 22, 27, 29, and 31) have a significant portion of their area urban or waterbodies, causing fewer SMAP L3 pixels with recommended quality to represent the watershed.

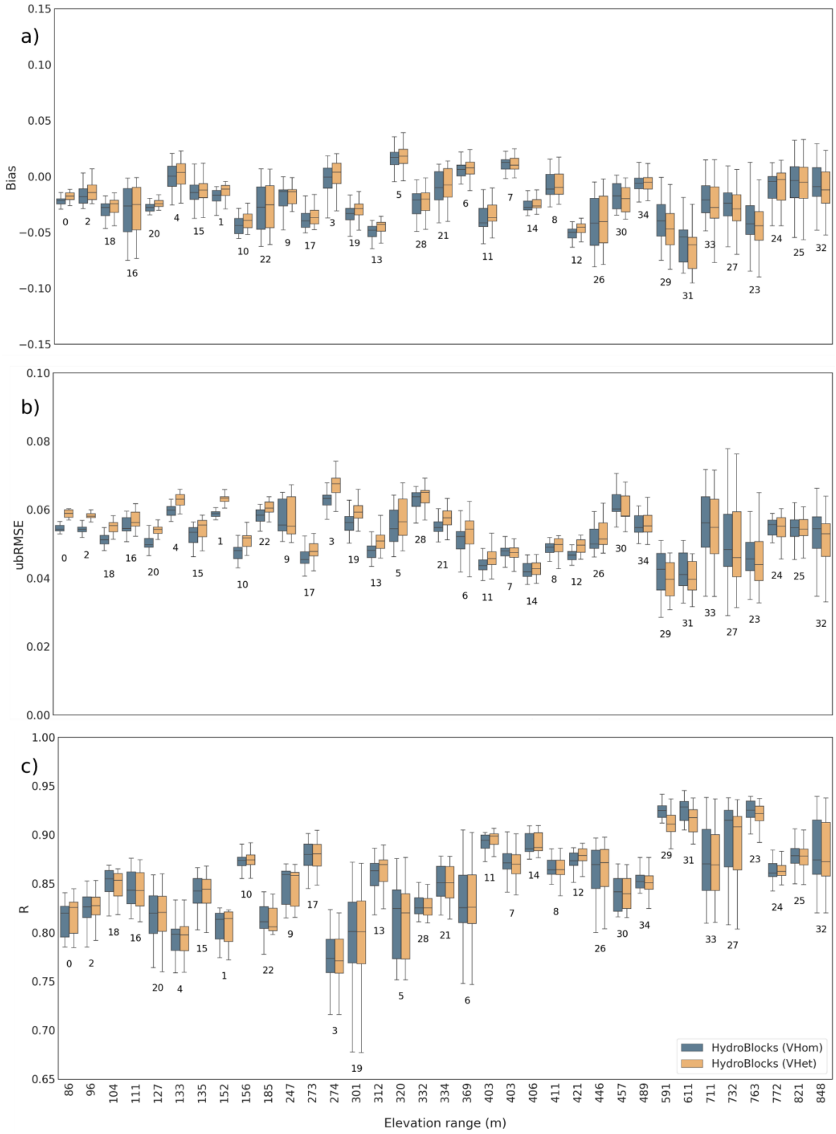

Figure 8: Box plot showing the performance of HydroBlocks (VHom) and HydroBlocks (VHet) model in simulating surface soil moisture to SMAP L3 observations in terms of (a) bias, (b) ubRMSE, (c) R. Watersheds

are arranged in terms of their elevation range (representing topographic variations) along the x-axis. Each boxplot corresponds to a watershed identified by their number provided in Fig.1.

The ubRMSE median values of HydroBlocks (both configurations) simulated surface soil moisture measurements vary between 0.04 m^3m^{-3} and 0.06 m^3m^{-3} across 35 watersheds. The median ubRMSE values for HydroBlocks surface soil moisture simulations are generally higher in the VHet configuration, with a basin-wide average of 0.053 m^3/m^3 compared to 0.052 m^3/m^3 for VHom simulations. Further, surface soil moisture simulations from both model configurations of HydroBlocks also show a strong correlation with SMAP L3 observations, as shown in Fig.8. Both HydroBlocks configurations have similar median values of Pearson correlation in all watersheds,with their values lying between 0.78 and 0.95. When upscaled to 9kmx9km, both versions of HydroBlocks performed well with low bias and high correlation with respect to SMAP L3 observations. Since both HydroBlocks use the same soil properties at the surface, the difference between their simulation for the surface layer is minimal. Besides, the influence of soil properties is significant in soil moisture simulations at a finer scale than at a coarser resolution (Crow et al., 2012).

Further, rootzone soil moisture simulated by HydroBlocks (both model configurations) is compared with SMAP L4 data for the year 2020 across all SMAP pixels in terms of bias, ubRMSE, and Person correlation, and the results are shown in Fig.9. Contrary to surface soil moisture plots, there is significant wet bias in many watersheds when compared to SMAP L4 analysis product. The median bias values range between -0.01 m^3m^{-3} to 0.15 m^3m^{-3} in both HydroBlocks configurations, as shown in Fig.9(a). Most watersheds show minimal variability in ubRMSE values, ranging from 0.03 to 0.055 m^3/m^3, with a few exceptions (watersheds 9, 25, 28, 30 and 33). However, the median ubRMSE values across all watersheds remain below 0.055 m^3/m^3 (see Fig. 9(b)) and have a higher correlation with SMAP L4 data, with their median Pearson correlation values ranging between 0.76 and 0.93, as shown in Fig 8(c). The median correlation values for VHom simulations are marginally higher, with an average of 0.85, while VHet simulations have an average median correlation value of 0.83. The higher correlation of VHom simulations to SMAP L4 data can also be due to vertically homogeneous soil parameters considered in the CLM while generating SMAP L4 rootzone soil moisture data.However, in either configurations, performance metrics reveal higher consistency between model simulated rootzone soil moisture and SMAP L4 data.

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Preprint. Discussion started: 6 December 2024

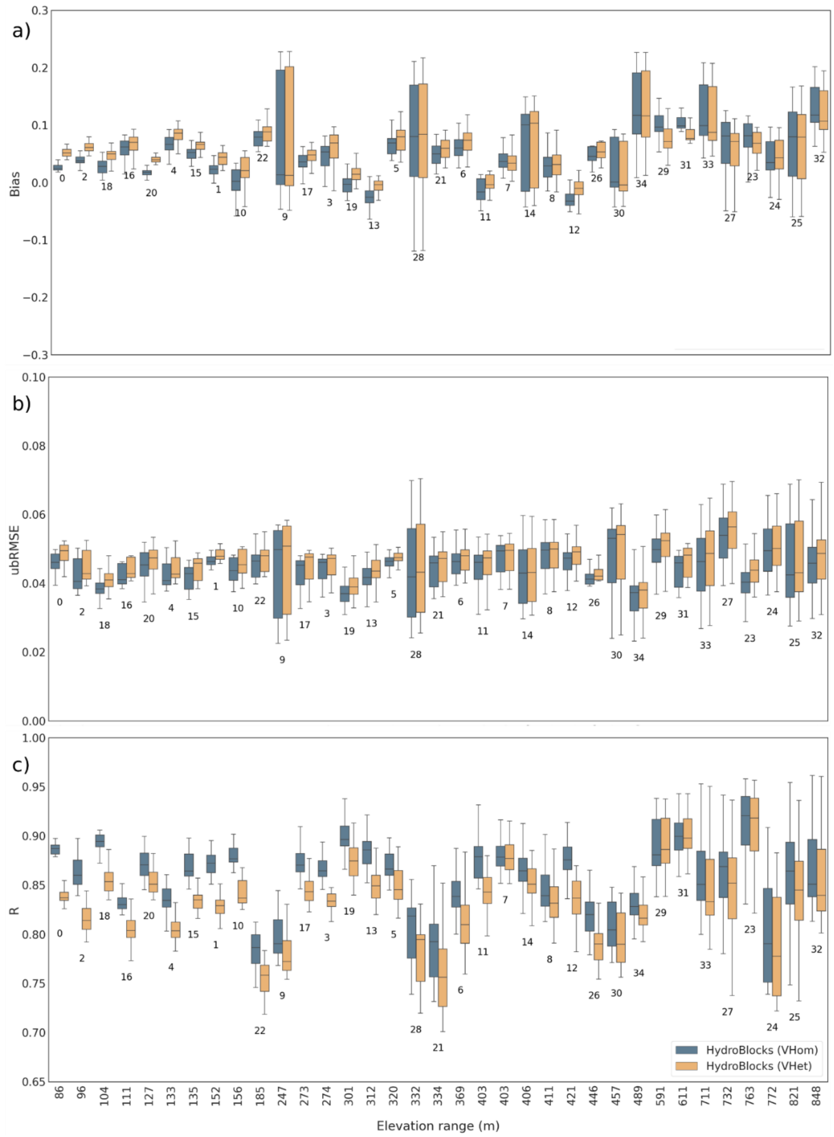

Figure 9: Box plot showing the performance of HydroBlocks VHom and VHet configurations in simulating rootzone soil moisture to SMAP L4 observations in terms of (a) bias, (b) ubRMSE, (c) R. Watersheds are arranged according to their elevation range (representing topographic variations) along the x-axis. Each boxplot corresponds to a watershed identified by their number near the whiskers, matching those provided in Fig 1.

3.3 Importance of Soil Vertical Heterogeneity in HydroBlocks

We compared layer-wise soil moisture from HydroBlocks VHet and VHom experiments in terms of mean bias and unbiased Root Mean Square Difference (ubRMSD). Such a comparison is done to understand the changes in the model simulations after incorporating soil vertical heterogeneity in the model. Surface soil moisture from both

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

configurations is compared at each HRU for each watershed, as shown in Fig.10. Watersheds are sorted in terms of their elevation range to check for topographic influence. A low wet bias, with median values close to zero, was attributed to the same soil properties in the surface soil layer for both configurations. Consequently, no substantial evidence exists that soil moisture simulations in the surface layer differ according to topographical variations. The ubRMSD between the two configurations has median values in all watersheds around 0.01 m^3m^{-3} and no greater than 0.02 m^3m^{-3}. However, in some watersheds, the ubRMSD can reach up to 0.03 m^3m^{-3}. This indicates that the influence of soil properties is more random at the surface layer (evident from high ubRMSD values) than having a systematic influence (evident from low bias). It may be noted that Noah-MP follows Richards equation, which also depends on soil hydraulic properties of adjacent soil layers. Besides, soil parameters in Noah-MP influence the runoff and infiltration and, eventually, soil moisture (Cuntz et al., 2016; Kishné et al., 2017). In HydroBlocks (VHet), these soil parameters are heterogeneous along the soil column, and their influence is also considered in determining the infiltrated water (Niu et al., 2005, 2011).

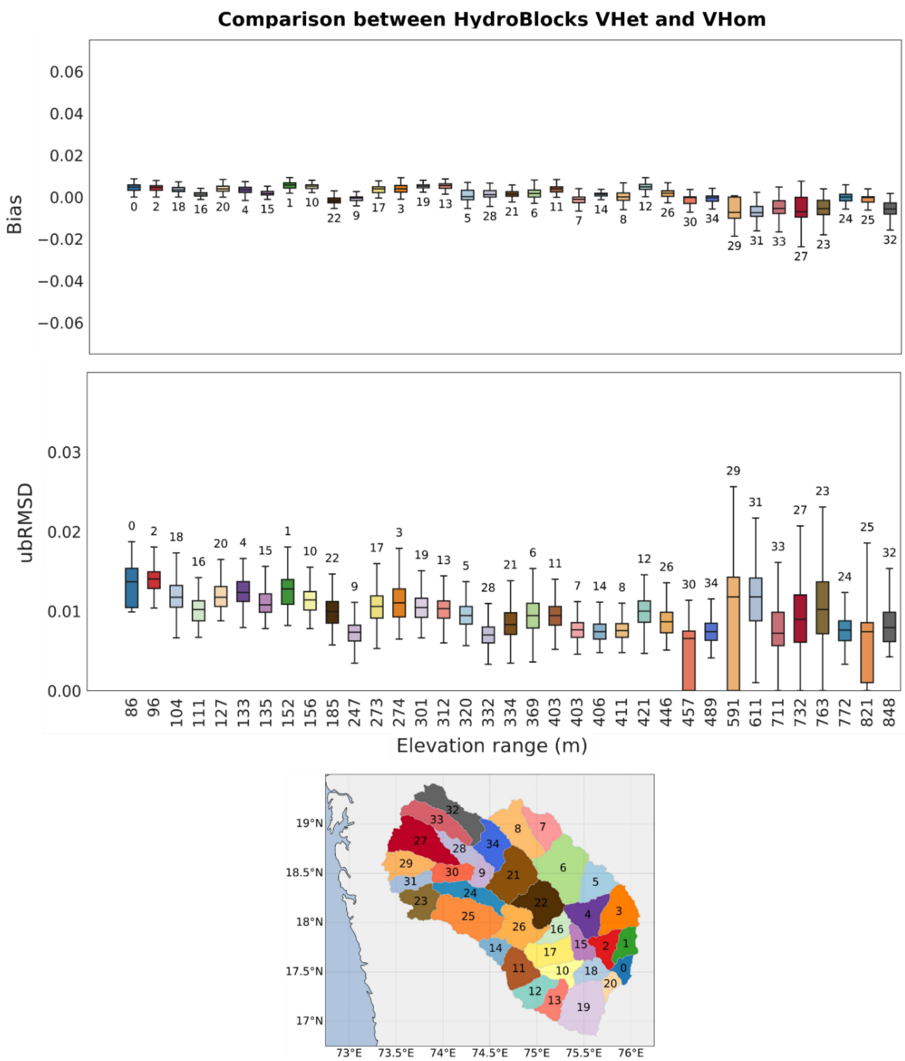

Figure 10: Box plot showing the comparison between HydroBlocks VHet and VHom configurations in simulating surface soil moisture in terms of bias and ubRMSD. These two metrics are calculated for VHet simulations with respect to VHom. Watersheds are arranged according to their elevation range (representing topographic variations) along the x-axis. Watersheds are identified by their number and colour, as shown in the spatial plot.

Figure 11 shows the difference in rootzone soil moisture simulations between HydroBlocks VHet and VHom configurations. In the case of rootzone soil moisture, watersheds with less variation in topography (elevation range < 300 m) show positive bias with their median values around 0.02 m^3m^{-3}, and watersheds having high topographical variations tend more to be negatively biased, albeit their median values are close to zero. The ubRMSD values between rootzone soil moisture simulations from two model configurations are low, with median values less than 0.01 m^3m^{-3}. Exceptions are observed in those watersheds having significant topographic variations. However, the ubRMSD values for rootzone soil moisture are lower than surface soil moisture. Indeed,

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

soil moisture simulation variations become more systematic (high bias) in the deeper layers (Fig.S2-S5 in the Supplementary Material).

There is a transition from wet bias to dry bias in rootzone soil moisture simulations with an increase in topographic variations, as shown in Fig. 11. Such a transition is not observed when the simulations are compared with SMAP L4 product at coarse resolution (9 km; Fig. 9). Topography and soil textural properties affect soil moisture simulations at higher resolution as they are crucial in determining the saturated soil fraction, hence the runoff and infiltration (Singh et al., 2015). However, in the present study, the difference in both model configurations is only due to the vertical heterogeneity of soil properties. Hence, any association between rootzone soil moisture and topographical variation is attributed to soil heterogeneity at subsurface layers and their relationship with topography. Both soil properties and topographic information influence the subsurface lateral flows. Therefore, it is crucial to understand the significance of each soil property in simulating soil moisture at each layer. For this purpose, we performed a sensitivity analysis of Noah-MP soil parameters, which are presented in the next section.

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Preprint. Discussion started: 6 December 2024

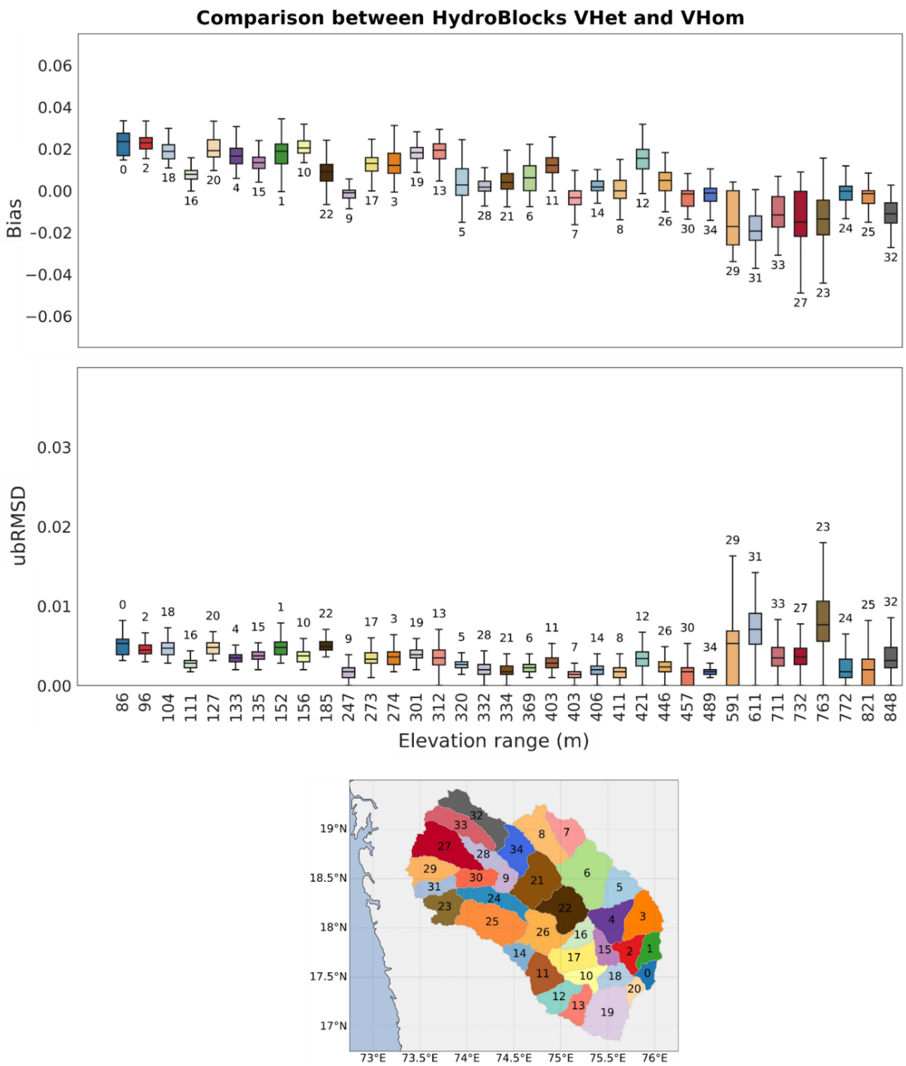

Figure 11: Box plot showing the comparison between HydroBlocks VHet and VHom configurations in simulating rootzone soil moisture in terms of bias and ubRMSD. Watersheds are arranged according to their elevation range (representing topographic variations) along the x-axis. Watersheds are identified by their number and colour, as shown in the spatial plot.

3.4 Sensitivity Analysis of Soil Parameters

We analyzed the results from the Sobol sensitivity test across all the HRUs in watershed 20 to understand the most sensitive parameters and their seasonal variation at different layers. Figure 12 presents the sensitivity analysis result in one of the HRUs of the watershed within their respective SMAP grid cell (same grid of the time series in Fig.3 and Fig.4). Through the Sobol analysis, the role of different parameters and their interactions with each other in simulating soil moisture at every layer across the season is studied. The light colour bar represents the

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

Hydrology and Earth System Sciences
Discussions

first-order Sobol index (S_i) value for a parameter indicating the proportion of total variance in soil moisture output, and it is driven by variance corresponding to only that parameter. The darker colour bar is the total-order Sobol index (S_T), depicting the contribution of that parameter, including its interaction with other parameters, to the total variance in soil moisture output. Hence, the difference between these two indicates the significance of parameter interaction.

Fig.12 shows that parameter interactions become prominent during the monsoon (June-September), followed by post-monsoon (October-December), and minimal during the summer months (January-May) at the surface layer. Although parameter interactions in deeper layers are less than in the surface layer, as expected, these interactions remain more significant during the monsoon than in other months. This also implies the importance of precipitation in driving soil hydraulic properties and thus influencing soil moisture dynamics. During the monsoon (June-September) till layer 3, soil moisture at the wilting point (WLTSMC), soil porosity (MAXSMC), and the Brooks-Corey parameter (BB) are the significant parameters, while other soil parameters (SATPSI, SATDW, SATDK, REFSMC, DRYSMC) have equal significance (approximately S_T =0.6 at the surface layer to S_T = 0.3 at layer 3) as shown in Fig.12. Within the deeper layers (layer 4 and layer 5), the order of parameter significance is consistent, with MAXSMC as the most significant parameter across all seasons, followed by BB, and the remaining parameters have equal but less significance. All other parameters have minimal direct significance from January to May. During the post-monsoon season, interactions increase; however, MAXSMC and BB remain the only parameters with significant first-order Sobol index values in all layers. The significance of MAXSMC in deeper layers is also evident in Fig 12, which shows the number of HRUs where a specific soil parameter is the most sensitive across three seasons at every soil layer. Soil porosity (MAXSMC) plays a crucial role in determining the water-holding capacity of the soil, the movement of water within the soil and ultimately runoff and evaporation, thus exerting a dominant control over soil moisture. (Arsenault et al., 2018; Cuntz et al., 2016). For the same reason, the dominance of MAXSMC increases in the deeper layers, even in the dry months (October to May). Further, the difference in the Sobol index values of parameters is minimal in deeper layers. This could be a reason for the systematic influence (high bias of VHet simulations compared to VHom) on rootzone soil moisture (Fig.11).

WLTSMC is another parameter that has significance on soil moisture till layer 3. During monsoon and at the surface layer, WLTSMC has S_T = 0.8 and is equally significant parameter as MAXSMC across the watershed. During January-May, interactions between the parameters are limited across the layers, with minimal interaction at the surface. In these months, WLTSMC has some significance till layer 3, with the first-order Sobol index value greater than 0.1. WLTSMC controls stomatal resistance and, subsequently, the water availability for transpiration (Arsenault et al., 2018). Consequently, WLTSMC becomes significant only during the monsoon and afterward, as in Fig.12 and Fig.13, when sufficient water is available for plants, or LAI is prominent. In deeper layers below 60 cm from the surface, the importance of WLTSMC is reduced significantly because the model simulations are parameterized to have root depth NROOT up to the third layer. Beyond this, the transpiration process is not considered; hence, its dominance was reduced. This also emphasizes the importance of the parameter root depth and the necessity of introducing a dynamic root depth when the focus is on hyper-resolution soil moisture simulation, especially in regions of fragmented agricultural systems (Gayler et al., 2014; Liu et al., 2020; Niu et al., 2020).

https://doi.org/10.5194/hess-2024-339
Preprint. Discussion started: 6 December 2024

BB is another significant soil parameter for soil moisture simulation, particularly in the surface layer. During January -May, BB shows high sensitivity ($S_T = 0.7$) at the surface with minimal interactions, as shown in Fig.13 and Fig.13. During this season, transpiration loss in most months is zero as LAI used in the period accounts for zero, and runoff is minimal with limited precipitation events. Hence, any isolated precipitation events can induce evaporation, causing some variability in surface soil moisture, as shown in Fig.3. The parameter BB indicates the pore size distribution, which defines a relationship between soil moisture and matric potential, and in defining saturated hydraulic conductivity (SATDK), and diffusivity of soil water at saturation (SATDW). Hence, the parameter BB is also significant in deciding the loss of water from the surface layer, either percolating to the sub-surface layers and contributing to sub-surface runoff or evaporation (Cuntz et al., 2016) and is thus crucial in simulating surface layer soil moisture. During monsoon, with more precipitation events and vegetation, this exponential parameter (BB) interacts with other parameters, including MAXSMC, SATDK, and SATDK, causing it to be a sensitive soil parameter in terms of total-order Sobol index rather than first-order (Fig.12). Its influence on soil moisture dynamics is also evident during the post-monsoon season, October to December, where it interacts with other soil parameters, although less than that during monsoon.

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Preprint. Discussion started: 6 December 2024

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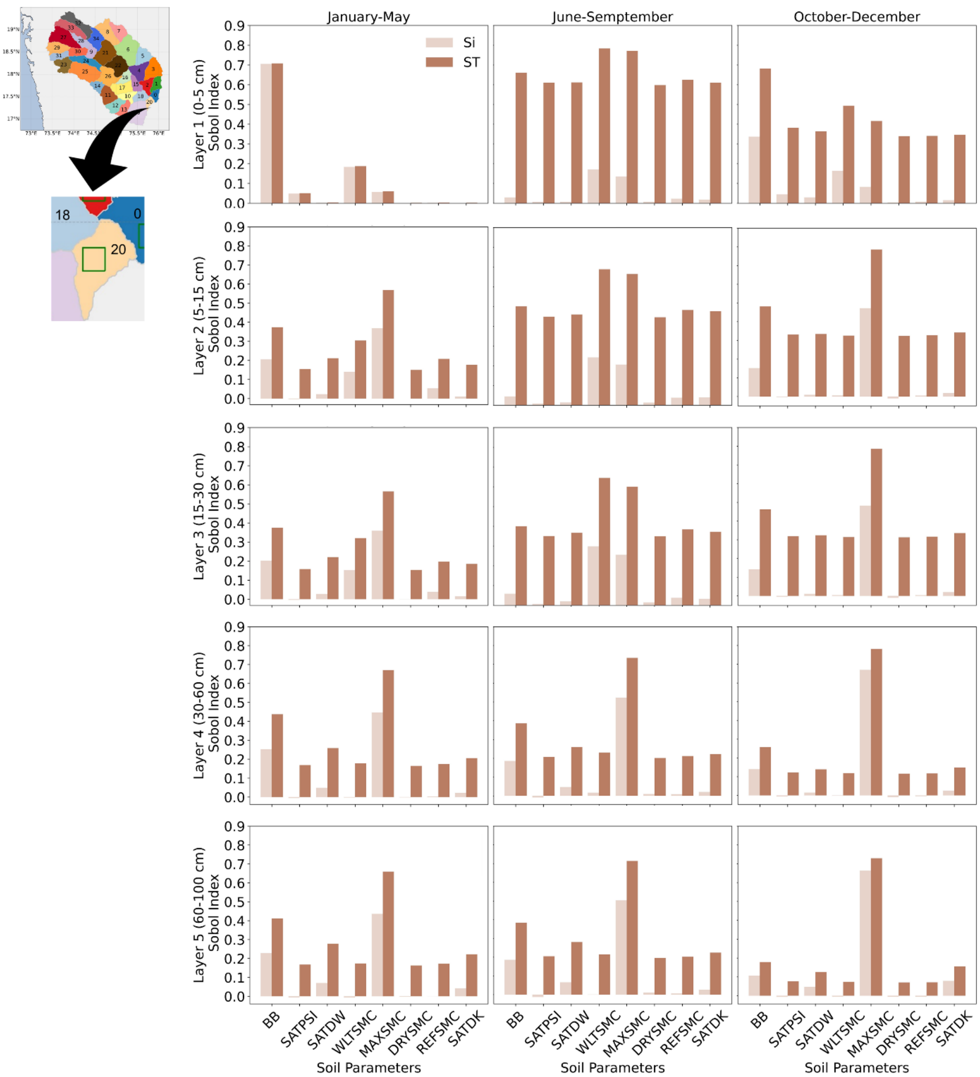

Figure 12: Sensitivity of the Noah-MP soil parameters on an HRU within the SMAP pixel (green box in the watershed map), used in the time series plots of watershed 20, to identify the influence of soil parameters across different seasons at every layer. The first-order Sobol index, S_i, (light colour bar), indicates the parameter contribution (no interaction with other parameters) to the total variance in soil moisture output. The total-order Sobol index, S_T (darker colour bar), indicates the parameter contribution, including its interaction with other parameters with respect to the total variance in soil moisture output.

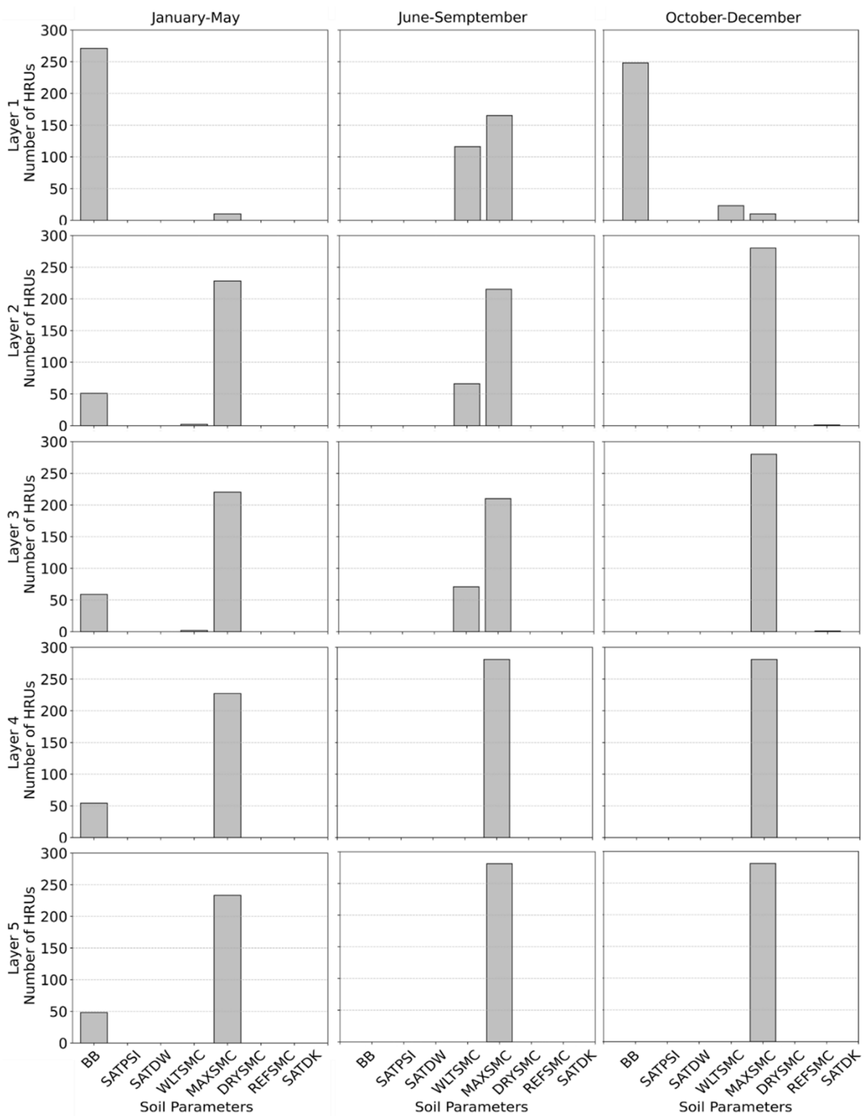

Figure 13: Distribution of HRUs where a particular soil parameter exhibits the highest sensitivity (total-order Sobol index) across three distinct seasons, as determined by sensitivity testing on watershed 20 at HRU scale conducted at various soil layers with all the HRUs within the watershed.

3.5 The added value of hyper-resolution modeling and vertical soil properties for small-sized farms

HydroBlocks simulations have improved spatial heterogeneity of soil moisture at the surface (σ_θ, of VHet = 0.088 m^3m^{-3} and VHom =0.084 m^3m^{-3}) and rootzone (σ_θ, of VHet = 0.093 m^3m^{-3} and VHom =0.09 m^3m^{-3}) while maintaining temporal consistency to macroscale products. As previously mentioned, the fragmented agricultural system in India leads to significant diversity in agricultural practices. Consequently, there is substantial sub-grid heterogeneity in irrigation requirements as well (Gumma et al., 2024). With improved subgrid heterogeneity of

Hydrology and Earth System Sciences
Discussions

soil moisture simulations (Fig. 5(b) and Fig.6(b)), HydroBlocks, as a hyper-resolution LSM, can cater to the demands of field-scale agricultural applications. The climatological conditions of the present study area, characterized by arid conditions and limited precipitation events, demand effective water management practices, which have global relevance. Hyper-resolution soil moisture with sub-grid heterogeneity can provide information regarding crop water deficiency, and with precision agriculture, water management practices can be improved (Peng et al., 2021).

HydroBlocks VHet simulations reveal that the deeper layer soil properties have a systematic influence (evident from high bias in Fig.10) at the rootzone and random influence at the surface layer (evident from high ubRMSD in Fig.11). At field scale soil properties are crucial in determining the spatial heterogeneity of soil moisture (Crow et al., 2012; Vergopolan et al., 2022). Incorporating vertical soil properties in the model better represents the ground reality, and the results reveal that VHet of soil can improve the rootzone soil moisture simulations. HydroBlocks VHet has higher spatial and subgrid variability than VHom at rootzone soil moisture (Fig.5(b) and Fig.6(b)). Developing a hyper-resolution LSM for farm scale soil moisture requires key improvement in several aspects including improved representation of surface and subsurface interactions (Wood et al., 2011). The HydroBlocks configurations used in the current study are limited by a lack of surface water routing, subsurface lateral connectivity during unsaturated conditions, dynamic representation of LAI and root depth, as well as improved topographical representation. Incorporating vertical soil properties in the model is one of the critical steps to achieve improved rootzone soil moisture simulations. Accurate estimates of rootzone soil moisture are critical for understanding and forecasting droughts (Ochsner et al., 2013). With their coarse resolution, traditional dynamic models have limited capability to capture field-scale variation in drought events (Abolafia-Rosenzweig et al., 2023). High-quality soil moisture data at the field scale can provide improved spatial heterogeneity, benefiting small-holding farmers (Peng et al., 2021; Vergopolan et al., 2021) through early warning of extreme events and thus reducing the crop loss risk.

4. Conclusions

Recent studies proved the necessity of understanding horizontal and vertical soil heterogeneity in simulating hyper-resolution surface soil moisture (Vergopolan et al., 2022; Xu et al., 2023). Considering the importance of rootzone soil moisture in agriculture and India's fragmented agricultural system, this study implemented soil vertical heterogeneity in the hyper-resolution LSM to simulate surface and rootzone soil moisture in a predominantly cropland area in India for the first time. Since a field observation network for soil moisture in this study area was in progress, we assessed the performance of HydroBlocks against an available in situ station data, as well as SMAP L3 observations and SMAP L4 data for surface and rootzone soil moisture, respectively. The results from our study point out the following:

- At the field scale, HydroBlocks simulations with vertically homogeneous and vertically heterogeneous soil properties show improved spatial heterogeneity (for surface, σ_θ, of VHet = 0.088 m^3m^{-3} and VHom =0.084 m^3m^{-3}; for the rootzone, σ_θ, of VHet = 0.093 m^3m^{-3} and VHom = 0.09 m^3m^{-3}) compared to the macroscale products dataset. This is accomplished by considering various interactions between different physical controls, including topography, precipitation, land cover, and soil properties at the finer scale (Vergopolan et al., 2022)

- Evaluation against in situ data revealed that both VHet and VHom simulations performed similarly toward surface soil moisture simulation. However, VHet systematically improves soil moisture simulation than VHom by reducing the bias at all sub-surface layers. In the deeper layer (0-60 cm), VHet simulations show low bias (0.059 m^3m^{-3}) similar ubRMSE (0.066 m^3m^{-3}) and higher Pearson's correlation (0.60) than VHom with performance metrics of 0.067 m^3m^{-3}, 0.066 m^3m^{-3} and 0.59 respectively.
- The 30m resolution HydroBlocks (VHet and VHom) simulations upscaled to ~10 km resolution showed a temporal pattern consistent with SMAP data. When evaluated against SMAP L3 observations and SMAP L4 data, both model configurations performed well in terms of bias (0.02 m^3m^{-3}, 0.021 m^3m^{-3}), ubRMSE (0.053 m^3m^{-3}, 0.052 m^3m^{-3}), and Pearson's correlation (0.85, 0.85) for surface soil moisture and bias (0.056 m^3m^{-3}, 0.049 m^3m^{-3}), ubRMSE (0.046 m^3m^{-3}, 0.045 m^3m^{-3}), and Pearson's correlation (0.83, 0.85) for rootzone soil moisture.
- Comparison between HydroBlocks vertically homogeneous and vertically heterogeneous simulations reveal that deeper layer soil properties have a random influence on surface soil moisture and have a systematic influence on deeper layer soil moisture. Results also indicated that the influence of soil properties on rootzone soil moisture follows a topographical variation.
- Soil porosity (MAXSMC), the wilting point (WLTSMC), and Brooks-Corey parameter (BB) are crucial parameters influencing soil moisture at every layer and season. However, there is a season-wise variation in the interaction between soil parameters, which is more significant during monsoon than in other seasons.
- Sensitivity analysis across soil layers indicates a transition in the significance of soil parameters between the surface and deeper layers, with the order of significance remaining consistent between the deeper layers (below 30 cm from the surface). However, the exactness of such an influence requires an in-depth analysis in the future. Hence, incorporating soil vertical heterogeneity in LSMs is critical to the reliability of rootzone soil moisture simulations at a farm scale.

Although this study is limited by the lack of network of in situ observations to validate the simulations, comparison with the only in-situ observation available yielded promising results on the quality of simulations. Acknowledging this limitation, pertaining to in situ validation, we assessed the importance of hyper-resolution LSM in soil moisture simulation for farm-scale studies by comparing the simulations with available satellite-based soil moisture products, and analyzed the sensitivity of different model configurations and the importance of soil properties in simulating multi-layer soil moisture at farm scales. The current study uses lookup table of LAI values, which depicts variability during and post monsoon seasons. Incorporating dynamic LAI and dynamic root depth can improve soil moisture simulations (Liu et al., 2020; Niu et al., 2020). Future studies will focus on bringing LAI at the HRU scale and adopting a dynamic LAI scheme in the model. Further understanding the influence of topography and improving its parametrization to suit hyper-resolution is also necessary for improving soil moisture simulations.

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Hydrology and Earth System Sciences
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Discussions

Code and Data availability

IMD in situ observations are available on request from https://dsp.imdpune.gov.in/, ERA5-Land soil moisture: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land/ (Muñoz-Sabater et al., 2021), SMAP L3 enhanced surface soil moisture: https://doi.org/10.5067/4DQ54OUIJ9DL (O'Neill et al., 2021), SMAP L4 rootzone soil moisture: https://doi.org/10.5067/60HB8VIP2T8W (Reichle et al., 2014), GLEAM v3.6 surface and rootzone soil moisture: https://www.gleam.eu/ (Martens et al., 2017), SoilGrids soil data: https://soilgrids.org/ (Hengl et al., 2017), HydroBlocks source code: https://github.com/chaneyn/HydroBlocks/tree/dev_noemi, (Chaney et al., 2016).

Author contributions

VK was responsible for the conceptualization, methodology, data processing and analysis, model development, prepared the manuscript-original draft including all figures, and led the writing of the paper with contributions from all the co-authors. KL, and JI were responsible for the conceptualization, supervision, and methodology of the study and writing -review and editing of the manuscript. NV was responsible for the supervision, software, writing -review, and editing of the manuscript. BBS provided in situ data for validation and writing -review and editing of the manuscript.

Competing Interests

None of the authors have competing interests.

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