

Calibration Using Downscaled and Bias-Corrected Satellite Soil-Moisture Data Can Improve
Watershed Model Representation of Soil-Moisture Variability

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Abstract

Watershed streamflow is often the focus of hydrological model calibration and evaluation, despite other potential objectives, including water quality management, flood protection, or agricultural management. When hydrological models are calibrated on streamflow, intermediate processes such as those affecting soil-moisture are not necessarily well represented. This research evaluated whether calibration using downscaled and bias-corrected satellite soil-moisture improves prediction of field-scale soil-moisture relative to conventional streamflow-based calibration. In this work, downscaled satellite soil-moisture and streamflow data are used to calibrate a Soil and Water Assessment Tool – Variable Source Area model initialized using a terrain informed process to create hydrologic response units. In-situ soil-moisture measurements at 25 locations across a 4.2-ha mixed-grass pasture located in southwestern Virginia were used to estimate field-scale average soil-moisture variability for model evaluation. Leveraging downscaled satellite soil-moisture data substantially improved estimation of temporal soil-moisture variability without affecting the model streamflow performance. The multi-objective calibration using streamflow and satellite soil-moisture improved soil-moisture performance while maintaining streamflow performance comparable to streamflow-only calibration. These results demonstrate the potential for satellite soil-moisture-informed calibration to improve internal hydrologic state estimation in small, saturation excess watersheds. Furthermore, these results highlight the importance of coupling statistical performance gains with evaluation of hydrologic realism when extending such approaches to broader modeling applications.

1. INTRODUCTION

Hydrological model calibration is most commonly performed using streamflow observations because they are widely available and integrate catchment-scale water balance behavior

(Pechlivanidis et al., 2011). However, calibration based solely on streamflow can leave internal states and fluxes, particularly soil-moisture, poorly constrained, despite their central role in governing evapotranspiration, runoff generation, and hydrologic connectivity (Brocca et al., 2017). Inadequate representation of soil-moisture therefore limits model usefulness for applications such as agricultural management, water quality assessment, and interpretation of vadoze zone process-level behavior.

Direct characterization of watershed-scale soil-moisture is challenging due to strong spatial heterogeneity and the cost of dense monitoring networks (Brocca et al., 2010; Vereecken et al., 2015). Satellite-based soil-moisture products therefore provide an attractive alternative, offering spatially continuous observations that can complement traditional calibration targets. Products derived from missions such as Soil Moisture Active Passive (SMAP) (Colliander et al., 2017; O'Neill et al., 2018), Soil Moisture and Ocean Salinity (SMOS) (Kundu et al., 2017), Advanced Scatterometer (ASCAT) (H SAF, 2021), and Advanced Microwave Scanning Radiometer 2 (AMSR2) (Cho et al., 2015) have been increasingly incorporated into hydrological model calibration and data assimilation frameworks (Brocca et al., 2017). Reported outcomes, however, are mixed. Some studies show improved model streamflow or drought estimation performance (Azimi et al., 2020; De Santis et al., 2021; Nanda et al., 2023; Patil & Ramsankaran, 2017; Sun, 2016; Wakigari & Leconte, 2023), while others report improved soil-moisture simulation with little or no degradation streamflow performance (Rajib et al., 2016; Dangol et al., 2023; Duethmann et al., 2022; López et al., 2017). These trade-offs reflect differences in watershed-scale, dominant runoff mechanisms, satellite sensing depth, preprocessing approaches, and model structure.

Uncertainty in soil-moisture observation/estimation is particularly pronounced in small, saturation-excess-dominated watersheds, where runoff generation depends strongly on antecedent root zone soil-moisture storage, topographic convergence, and hydrologic

connectivity (Beven et al. 2021; Easton et al., 2008; Lyon et al., 2004). In such settings, coarse-resolution satellite soil-moisture products, both native and downscaled, may capture large scale temporal dynamics but fail to represent event-scale wetness organization critical for runoff initiation (Gomis-Cebolla et al., 2022; Duethmann et al., 2022). Moreover, many previous studies are conducted in large basins ($>700 \text{ km}^2$), with comparatively few demonstrations in smaller basins (Duethmann et al., 2022; Dangol et al., 2023) and most lack independent evaluation of internal state estimates against field observations, limiting insight into whether calibration improvements reflect physical realism or compensatory parameter behavior. In addition, few studies report the effect of incorporating satellite soil-moisture products for model calibration on both soil-moisture and streamflow estimation performance (Dangol et al., 2023; Eini et al., 2023; Rajib et al., 2016). While there is agreement that remotely sensed soil-moisture can be used to calibrate a watershed model for improved soil-moisture estimation, the scale of soil-moisture outputs is still coarse ($> 2 \text{ km}^2$), and additional effort is required to inform field-scale management applications (Mascaro et al., 2011).

Watershed models play a critical role in translating spatially continuous, remotely sensed observations into field-scale predictions of hydrologic states and processes. Their utility depends not only on the availability of satellite data, but on whether model structure can realistically map those observations onto the dominant controls governing runoff generation and soil-moisture variability. The Soil and Water Assessment Tool (SWAT) Variable Source Area (VSA) model (SWAT-VSA) provides a targeted framework for evaluating satellite-informed calibration in saturation-excess environments. By redistributing soil and hydrologic properties according to topographic index (TI) classes, SWAT-VSA improves representation of spatial saturation patterns and runoff source areas relative to conventional hydrologic response unit (HRU) definitions (Easton et al., 2008; Fuka et al., 2016). This structure also supports scale-consistent evaluation of modeled soil-moisture using TI-weighted aggregation

of field measurements, helping bridge the gap between point observations, satellite products, and model states.

In this study, we evaluate whether downscaled and empirically bias corrected satellite soil-moisture product can improve internal hydrologic state estimation in a small ($\sim 14.5 \text{ km}^2$), saturation excess dominated watershed using SWAT-VSA. We contrast three calibration strategies: (i) streamflow only, (ii) soil-moisture only, and (iii) multi-objective calibration using both streamflow and satellite soil-moisture. Model performance is evaluated using both conventional goodness of fit statistics, as well as through comparison against field-scale soil-moisture measurements collected across a 4.2 ha monitoring field and aggregated using TI-based weighting consistent with the model structure (Easton et al., 2008; Asfaw et al., 2025).

The objectives were to test whether satellite soil-moisture informed calibration improves temporal soil-moisture variability without degrading streamflow performance, and whether multi-objective calibration can balance predictive accuracy with hydrologic realism. By combining downscaled satellite soil-moisture, terrain informed model structure, and independent field evaluation, this work advances understanding of when and how satellite soil-moisture can meaningfully constrain watershed model parameters in small, terrain-controlled catchments.

2. MATERIAL AND METHODS

2.1. Study Area

The study was conducted in the upper Stroubles Creek watershed, Montgomery County, Virginia, USA. Streamflow was measured at the Virginia Tech StREAM (Stream Research, Education and Management) Lab monitoring station (Hofmeister et al., 2015), which drains a

14.5 km² headwater watershed within the Valley and Ridge physiographic region. The watershed is characterized by dolomite and limestone geology with springs and sink holes (Ketabchy, 2018; Parece et al., 2010). The climate is humid, temperate, receiving 1200 mm annual precipitation of which 760 mm is subject to evapotranspiration (Ketabchy, 2018; Asfaw et al., 2025). The watershed has 67% pervious and 32% impervious land cover (Nayeb Yazdi et al., 2019).

The watershed is strongly saturation excess dominated (Asfaw et al., 2025), with runoff generation controlled by topography and shallow soil storage, making it well suited for evaluation of VSA hydrology and satellite soil-moisture informed calibration.

2.2 Soil-Moisture Data

2.2.1 Soil Moisture Active Passive (SMAP) Soil-Moisture and Downscaling

SMAP is a global surface soil-moisture acquisition mission at 36 km resolution (Entekhabi et al., 2014; O'Neill et al., 2023), using an L-band radiometer and L-band radar. Several approaches were used to post-process and increase SMAP product resolution for different applications (Abbaszadeh et al., 2021, Chan et al., 2018; Das et al., 2018;). Among such efforts was the National Aeronautics and Space Administration (NASA) and the United States Department of Agriculture (USDA) Enhanced SMAP 10 km resolution product, generated by incorporating SMAP data using Kalman Filter into the Modified Palmer Two-Layer soil-moisture model (Mladenova et al., 2020).

In this study, satellite soil-moisture derived from the Enhanced SMAP product and downscaled to 500 m resolution using a machine learning tool, the 'mlhrsm' package in R (Peng et al., 2024), was used. The downscaling applies a pretrained quantile random forest model that uses multi-sensor predictors including Sentinel-1 backscatter, MODIS land surface temperature, Landsat-derived vegetation indices (surface reflectance, NDVI and

NDWI), a 10 m USGS digital elevation model (DEM), POLARIS soil properties (clay, sand and bulk density), and NLCD land-cover classes.

The downscaling model outputs daily volumetric soil-moisture estimates ($\text{m}^3 \text{m}^{-3}$) for each 500 m cell intersecting the watershed for the period April 2015 to August 2022. The downscaled soil-moisture was spatially averaged across the watershed to generate a daily watershed mean soil-moisture time series used for model calibration.

2.2.2 In-Situ Soil-Moisture

In-situ soil-moisture measurements were collected on 20 sampling dates between March 2023 and January 2024 at 25 locations within a 4.2 ha mixed-grass pasture located inside the watershed. Sampling locations were distributed across the field covering the full range of terrain classes present. Measurements were collected 1–3 days following precipitation events to capture soil-moisture conditions ranging from near wilting point to near saturation ($0.15\text{--}0.45 \text{ m}^3 \text{m}^{-3}$).

Mean field-scale soil-moisture was calculated using TI class weighted aggregation, consistent with the SWAT-VSA HRU structure. Point measurements were first grouped by TI class and then aggregated to a field-scale mean using the relative areal coverage of each TI class within the monitoring field. Although the monitored field represents a small fraction of the watershed, previous studies in similar saturation excess system show that spatial soil-moisture variability is primarily governed by topographic controls rather than localized soil heterogeneity (Easton et al., 2008; Lyon et al., 2004; Asfaw et al., 2025). While land use and soil variability contribute to watershed-scale moisture patterns, the small size of the watershed supports the assumption of near uniform precipitation and evapotranspiration inputs, reducing the likelihood that climatic gradients confound field to watershed comparisons. Furthermore, previous work in the study area shows that spatial soil-moisture

differences are dominated by topographic effects rather than local soil variation effects (Asfaw et al., 2025).

The temporal variability of soil-moisture was well represented in the data with observations occurring on days near to the soil permanent wilting point and saturated soil-moisture conditions (0.15 – 0.45 volumetric water content). Calculated field-scale average soil-moisture was used for model performance evaluation across the same domain. Additional details on this dataset are reported in Asfaw et al. (2025).

2.3 SWAT-VSA model

The SWAT model is a semi distributed, watershed-scale hydrologic and water quality model that simulates the water balance, surface runoff, subsurface flow, and associated sediment and nutrient transport using land use, soil, management, weather, and topographic inputs (Neitsch et al., 2009). SWAT-VSA is a modification to SWAT designed to represent VSA hydrology which is characteristic of saturation excess dominated landscapes (Easton et al., 2008).

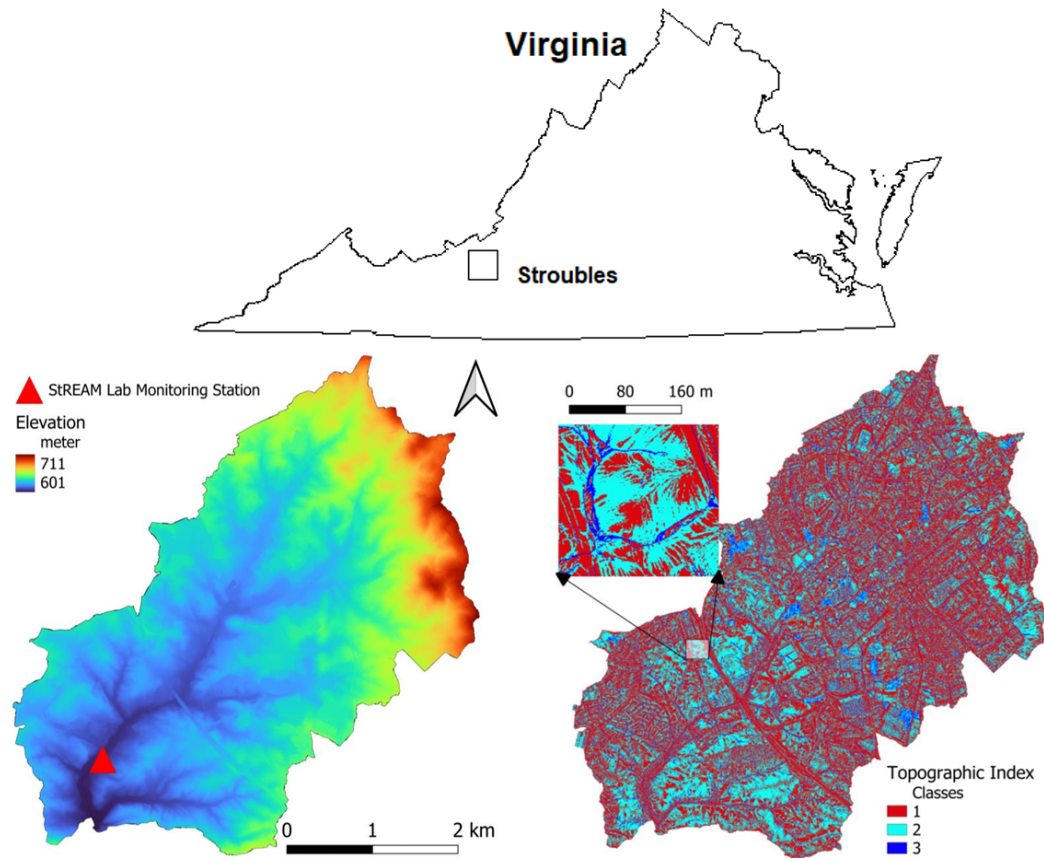


Figure 1: Location map of the Stroubles Creek watershed (top), digital elevation model (left) and Topographic Index Class (right; magnified view of 4.2 ha pasture field inset).

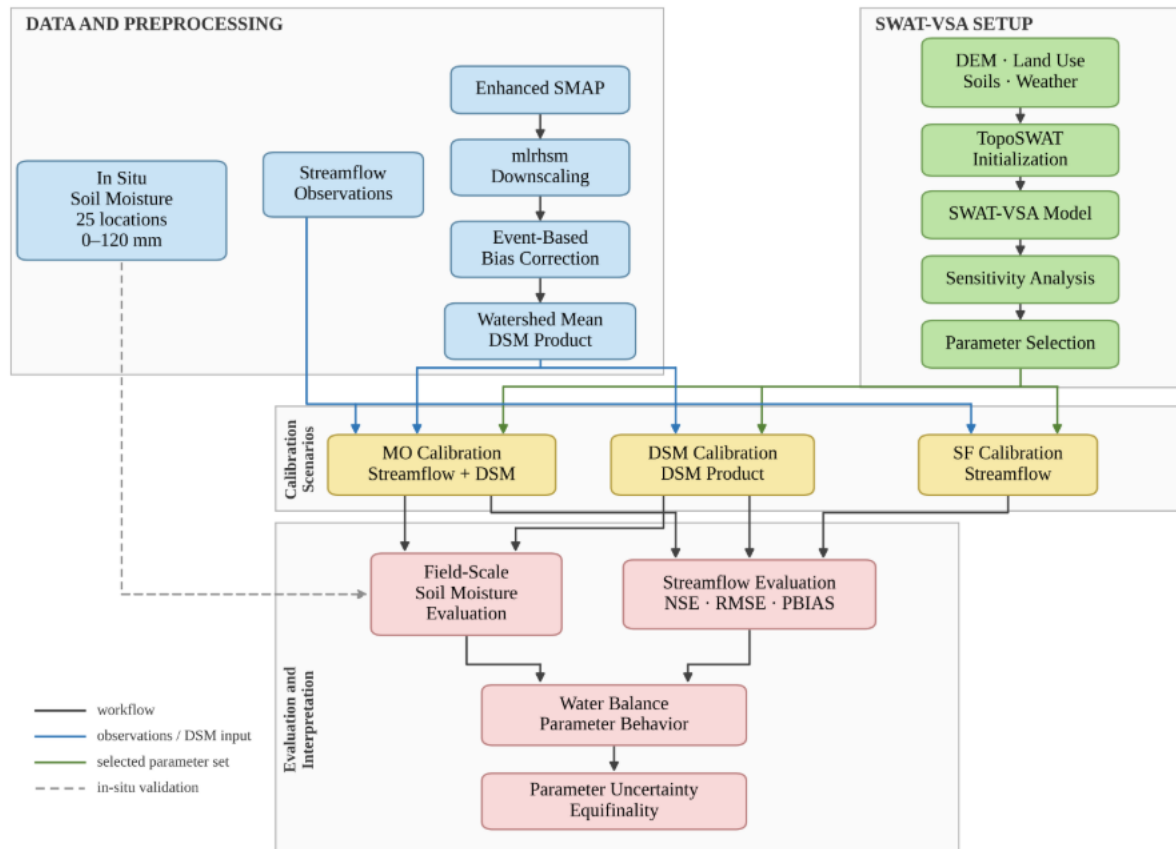


Figure 2: Study workflow showing generation of the downscaled and bias-corrected soil-moisture product (DSM), SWAT-VSA setup, calibration, evaluation, and uncertainty analysis. Three calibration approaches were compared: streamflow-only (SF), soil-moisture-only (DSM), and multi-objective (MO). Streamflow and field-scale in-situ soil-moisture observations were used to assess model performance and interpret parameter behavior and equifinality.

In SWAT-VSA, the curve number (CN) based runoff formulation is adapted to continuously redistribute watershed average soil-moisture storage as a function of topographic index (TI), thereby linking runoff generation to terrain-controlled wetness patterns (Easton et al., 2008; Fuka et al., 2016). TI values together with soil and land use information are used to define HRUs, which consequently represent spatial variability in runoff generation and soil-moisture

state. SWAT computes the soil water content for each layer individually at a daily time step. Infiltration to the surface layer is calculated after subtracting evaporative demand and surface runoff from precipitation at a daily time step. Vertical drainage of excess soil water is simulated as percolation, while soil-moisture depletion under unsaturated conditions occurs through plant uptake and transpiration and soil water evaporation from the soil layers. These unsaturated zone processes are influenced by the plant evapotranspiration compensation factor (EPCO) and soil evaporation compensation factor (ESCO) parameters, which are commonly adjusted during calibration to regulate vertical moisture redistribution. Within each soil layer, SWAT assumes homogeneous moisture distribution. When the model soil layer is thick, this assumption can dampen simulated moisture variability in surface soil layers and complicate comparison with surface sensitive satellite products and shallow in-situ measurements. To enable depth-consistent comparison among modeled, satellite derived, and in-situ soil-moisture, the SWAT soil profile was modified to explicitly simulate the 0-50 mm and 50-120 mm layers in addition to standard profile. Reported soil water content was converted from depth units to volumetric water content adjusted relative to the permanent wilting point for the dominant soil in the watershed. This modification improves the representation of near surface wetting and drying cycles and facilitates direct comparison across data sources.

2.3.1 Model Initialization

The SWAT-VSA model initialization was performed using ArcSWAT version 2012.10_8.26 in ArcGIS Desktop 10.8.2. The 2019 land use data were retrieved from the US Geologic Survey (USGS) National Land Cover Data (NLDC) website using the ‘get_nlcd’ function from ‘FedData’ package in R (Bocinsky et al., 2025; Jin et al., 2023). The USGS 3DEP program 1m resolution elevation data were used for watershed delineation, estimation of slope, and calculation of TI.

The VSA initialization was executed using TopoSWAT (Fuka & Easton, 2016), an ArcGIS plugin. The plugin was modified to enable generation of three TI classes from Asfaw et al. (2025). Using Natural Breaks from Spatial Analyst in Arc GIS, TI values were grouped into each class minimizing variance within class and maximizing variance among classes. The three TI classes from class 3 to 1 cover 6%, 38%, and 56% of the watershed area, respectively. Soils data were collected from the FAO-UNESCO Digital Soil Map (FAO, 2007). TopoSWAT downscales soil texture, soil depth, available water capacity, and hydraulic conductivity across TI classes. This was demonstrated to improve spatial representation of soil properties in VSA dominated watersheds (Fuka et al., 2016; Collick et al., 2015). Weather data from the Global Historical Climatology Network (GHCN) were used for model forcing. The data were acquired using the ‘FillMissWX’ function in R (Garna et al., 2023).

2.4 Data for Model Calibration and Evaluation

2.4.1 Streamflow Data

The StREAM lab monitoring station collects stage readings at a frequency of 10-15 minutes. Model calibration and evaluation were performed at a daily timestep. Stage was converted to discharge using a site-specific rating curve and aggregated to daily mean streamflow values using the zoo package in R (Zeileis et al., 2025). Daily values were excluded if more than 12 hours or more of data were missing. The resulting streamflow record extended from 2011 to 2024. The data for years 2011 and 2012 were excluded due to extended periods of missing values. The period January 2013 – December 2021 was used for model calibration, and January 2022 - May 2024 were reserved for model evaluation. The streamflow data also provides an independent data source for model evaluation when calibrating soilmoisture.

2.4.2 Soil-Moisture

The downscaled, 500 m resolution soil-moisture product was spatially averaged across the watershed to generate a daily watershed-mean soil-moisture time series for calibration. Downscaling was required because the native 10 km Enhanced SMAP resolution is far larger than the 14.5 km² watershed. The 500 m downscaled product constrains the satellite signal to the watershed boundary and improves temporal representativeness at the scale of interest. These spatio-temporal improvements are needed to constrain soil-moisture-related model parameters at the watershed-scale. The choice of 500 m resolution was also constrained by the available pretrained models in the mlhrsm downscaling package, which does not currently provide alternative target resolutions. Importantly, spatial averaging of the downscaled soil-moisture fields does not undermine the value of using the SWAT-VSA model. SWAT-VSA relies on TI-based HRUs to represent spatial patterns of saturation and runoff generation. While calibration uses a watershed-scale soil-moisture time series, the model internally maintains spatially explicit hydrologic processes using TI classes. HRU weighted aggregation ensures that model predicted soilmoisture is scaled to the watershed or field boundary in a manner consistent with the model's internal hydrologic structure. Following initial comparison with in-situ measurements, the downscaled satellite soil moisture exhibited a narrower dynamic range and attenuated peak wetness relative to observed soil moisture in the monitoring field (maximum ~32% versus ~45% volumetric water content) To address this limitation, a simple event-based bias-correction was applied at the watershed scale for days with substantial effective precipitation, Eq. 1. The corrected soil moisture, $\theta_{s,cor}$, was calculated as:

$$\theta_{s,cor} = \begin{cases} \theta_s + k\sigma & \text{if } dP \geq d \\ \theta_s & \text{if } dP < d \end{cases} \quad (\text{Eq. 1})$$

where $\theta_{s,cor}$ is the watershed mean downscaled and bias corrected soilmoisture, σ is average standard deviation of the uncertainty bound around the downscaled mean soil-moisture estimates from the mlhrsm, θ_s is the average downscaled watershed soilmoisture, k is a scaling factor, and d is a threshold effective precipitation depth in mm calculated as equivalent value to bring the 0-50-mm soil layer from field capacity to saturation. This depth corresponds to the soil layer represented by the satellite soil-moisture product and used in model calibration. A second derived soil layer was also calculated: the 0–120 mm composite soil-moisture layer was used only for independent evaluation against field observations.

A three-day rolling mean was applied following bias-correction. In-situ soil-moisture observations were not used in the derivation of the bias-correction parameters. However, they were considered when selecting among Pareto-equivalent solutions and therefore should be viewed as an auxiliary model-selection criterion rather than a fully independent validation dataset (Table A1).

Although calibration uses the downscaled and bias-corrected satellite soil-moisture data, model evaluation is performed using independent observations not involved in preprocessing or calibration. In particular, in-situ soil-moisture measurements collected at 25 locations within the 4.2-ha field (0–120 mm depth) were used exclusively for model evaluation, not for calibration, providing an independent benchmark for field-scale soil-moisture dynamics. All calibration analyses hereafter refer to the watershed average bias-corrected soil-moisture time series unless otherwise noted.

2.4.3 Bias-Correction Rationale and Procedure

An event-based bias-correction was applied to the watershed average downscaled soil-moisture series to enhance short term wetting responses while preserving the long-term temporal structure. The correction (Eq. 1), is triggered when daily effective precipitation exceeds a threshold of 5 mm, representing the depth, d , required to fill the soil layer from field capacity to saturation over the top 0–50 mm. When triggered, the downscaled soil-moisture estimate is increased by a multiple (k) of the model reported uncertainty (σ), where σ is the standard deviation around the downscaled mean returned by the mlhrsm quantile random forest model.

This approach selectively expands peak soil-moisture responses during hydrologically important events, addressing the observed attenuation of wetness extremes in the uncorrected downscaled product while leaving dry period behavior and long term means unchanged. The precipitation threshold reflects the shallow storage deficit that must be overcome before saturation excess runoff responses emerge in topographically organized landscapes.

In situ soil-moisture observations were not used to derive or calibrate the bias-correction parameters (σ , k , or d). Instead, σ is provided directly by the downscaling model, d is estimated from soil hydraulic properties and target depth, and k is set a priori for parsimony. In-situ measurements are used only for independent model evaluation and to qualitatively confirm that the corrected soil-moisture series exhibits a physically realistic range of wetness.

2.5 Model Calibration

2.5.1 Model Sensitivity

To identify the most influential parameters for calibration of the SWAT-VSA model, a sensitivity analysis was performed. A total of 20 parameters relevant to streamflow generation and soil-moisture dynamics were evaluated using relative sensitivity based on changes in Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) from January 1, 2015,

through December 31, 2019. Table 1 provides the tested parameters, and their rank based on relative sensitivity values. Because the sensitivity analysis was based on streamflow NSE, parameters that primarily influence soil-moisture dynamics may be underrepresented in the resulting rankings. However, all parameters with known relevance to soil-water storage and redistribution were retained for calibration.

2.5.2 Calibration Strategy

Model calibration targeted daily streamflow and watershed average soil-moisture in the top 0-50 mm soil layer. Three calibration approaches were included: 1) streamflow only, 2) soil moisture only, and 3) a multi-objective calibration using both streamflow and soil-moisture data. Prior to calibrations, baseflow and snow processes were pre-calibrated following a stepwise calibration approach to constrain parameter ranges. Snow parameters were subsequently held constant as initial analysis indicated the values provide adequate representation of snow processes. Baseflow separation was performed using the 'baseflowseparation' function from EcoHydRology package (Fuka et al., 2013; Nathan & McMahon, 1990). Table 1 provides the calibrated parameters and their ranges for each method.

Single-objective model calibrations were performed using a differential evolutionary algorithm, an exhaustive parameter space search using the 'DEoptim' R package (Mullen et al., 2011). Thirteen parameter vectors were evaluated per generation over 50 generations, for a total of 650 parameter vectors. Fifty generations were deemed sufficient after monitoring the successive diminishing returns in objective function minimization. The multi-objective calibration was performed using non-dominated sorting genetic algorithm (NSGAI) for the pareto front solution (Bekele & Nicklow, 2007; Deb et al., 2000) implemented using the Python library 'pymoo' (Blank & Deb, 2020). Among pareto-optimal solutions, final model selection additionally considered skill in reproducing field-scale in-situ soil-moisture

observations. The VSA implementation employed three TI classes representing progressively wetter landscape positions. The CN2 parameter (curve number for average soil-moisture conditions) was used to estimate the watershed average moisture storage deficit S and redistributed across TI classes following the relationship developed in Easton et al. (2008). CN2 values for individual HRUs were updated at each calibration iteration based on the optimized watershed-average CN2. Initial CN2 estimates were derived using a water-balance approach (Lyon et al. 2004), with subsequent adjustment governed by the optimization algorithm.

2.5.3 Goodness of Fit Measures

Model performance was evaluated using the coefficient of determination (R^2), the root mean squared error (RMSE), the percent bias (PBIAS), and the Nash-Sutcliffe efficiency (NSE) (Krause et al., 2005; Moriasi et al., 2007). Streamflow calibration sought to maximize the NSE value as this is the most widely used approach. For soil-moisture, the RMSE was used due to the bounded range, lower variance, and longer memory of soil-moisture time series, for which NSE can be overly sensitive to small errors (Entekhabi et al., 2010; Krause et al., 2005).

2.5.4 Parameter Uncertainty

Parameter uncertainty was quantified using the parameter sets developed during model calibration that satisfied performance thresholds of $NSE \geq 0.5$ for streamflow, $RMSE \leq 0.05 \text{ m}^3 \text{ m}^{-3}$ for soil moisture, or both. The extent of parameter uncertainty associated with each parameter was then scaled from 0-100 using the initial parameter range and the equation given below. Normalized parameter uncertainty (P_n) provides an equal scale for comparison across parameters (Kumar & Merwade, (2009) and Rajib & Merwade, (2016):

$$P_n = \left(\frac{P_o - R_{min}}{R_{max} - R_{min}} \right) * 100 \quad (2)$$

where, P_n is the normalized parameter uncertainty, P_o is parameter value from parameters vectors which fulfilled the selection criteria, and $R_{min/max}$ are initial parameter ranges.

3. RESULTS

Table 1 summarizes parameter sensitivity and calibrated values across the three calibration approaches. The soil depth parameter was not calibrated but rather was adjusted during the model initialization to ensure equivalent comparison between observed and simulated soil moisture (Table 1). During calibration, the curve number parameter (CN2) was updated at each iteration by redistributing the watershed-average storage deficit across hydrologic response units according to TI classes following Easton et al. (2008).

Parameters controlling runoff generation and soil-moisture dynamics (CN2, Bulk Density, Available Water Content (AWC), ESCO, Saturated Hydraulic Conductivity (Ksat), EPCO) in Table 1, were found to be influential across calibration approaches, while parameters controlling baseflow were less influential. Calibrated CN2 and bulk density parameters were similar across calibration approaches, while AWC, ESCO, Ksat and EPCO differed substantially, reflecting contrasting calibration targets.

Table 1: Model parameter sensitivity rank, initial range, and calibrated values.

Parameter	Description	Method	Range		§ SR	¶ Calibrated value		
			min	max		SF	DSM	MO
CN2	Runoff curve number of moisture condition II	replace	40	70	1	42.0	46.7	41.4
Depth	Soil depth	multiply	0.3	3	2	† NC	† NC	† NC
Bulk Density	Soil bulk density	multiply	0.5	1.5	3	0.93	1.22	1.13
‡ SMFMN	Snow melt factor minimum	replace	0	5	4	4.50	4.50	4.50
AWC	Available water content	multiply	0.3	3	5	2.55	1.5	2.70
‡ SMFMX	Snow melt factor maximum	replace	0	5	6	4.50	4.50	4.50

ESCO	Soil evaporation compensation factor	replace	0.1	1	7	0.11	0.69	0.34
Ksat	Saturated hydraulic conductivity	multiply	0.3	3	8	2.36	1.55	2.92
EPCO	Plant evaporation compensation factor	replace	0	1	9	0.94	0.77	0.85
‡ TIMP	Snowpack temperature lag factor	replace	0.01	1	10	0.01	0.01	0.01
‡ SFTMP	Snow fall temperature	replace	-5	5	11	4.00	4.00	4.00
‡ SMTMP	Snow melt temperature	replace	-5	5	12	2.00	2.00	2.00
GW_DELAY	Ground water delay (days)	replace	1	7	13	5.85	3.59	5.30
ALPHA_BF	Baseflow alpha factor (days)	replace	0.12	0.30	14	0.25	0.18	0.26
GWQMN	Threshold depth of water in the shallow aquifer required for return flow initiation (mm)	replace	10	500	15	417	213	494
GW_REVAP	Groundwater “revap” coefficient	replace	0.01	0.05	16	0.04	0.03	0.05
REVAPMN	Threshold depth of water in the shallow aquifer for “revap” initiation (mm)	replace	500	1000	17	996	813	649
RCHRG_DP	Recharges to deep aquifer (fraction)	replace	0.25	0.35	18	0.34	0.33	0.32
SURLAG	Surface runoff lag coefficient	replace	0	15	19	5.15	3.3	4.5

† Not Calibrated

‡ Pre-calibrated snow processes parameter values are underlined

§ Sensitivity Ranking (SR), using streamflow as the target variable

¶ Calibration on streamflow (SF); Calibration on soil-moisture (DSM); Calibration multi-objective (MO)

3.1 Comparison of Downscaled and Bias-Corrected Soil-Moisture Products

To evaluate how bias-correction alters the soil-moisture signal used for calibration, two

products were compared at the watershed-scale: (1) the 500-m downscaled soil-moisture

series generated using the mlhrsm pretrained quantile random forest model, and (2) the bias corrected downscaled product used in model calibration. The uncorrected downscaled soil-moisture product exhibits a reduced dynamic range and underrepresents peak wetness relative to in-situ observations, as indicated by comparison with field observations presented in Section 3.3.2. Following bias-correction, the soil-moisture product exhibits increased peak responses immediately following precipitation events, and a greater dynamic range (Fig. 3). Comparison statistics against the independent field observations are presented in Fig. 6

The bias-correction primarily affects wet-period responses while the lower envelope of the soil-moisture signal remains unchanged, confirming that the procedure enhances event responsiveness without artificially shifting long-term trends.

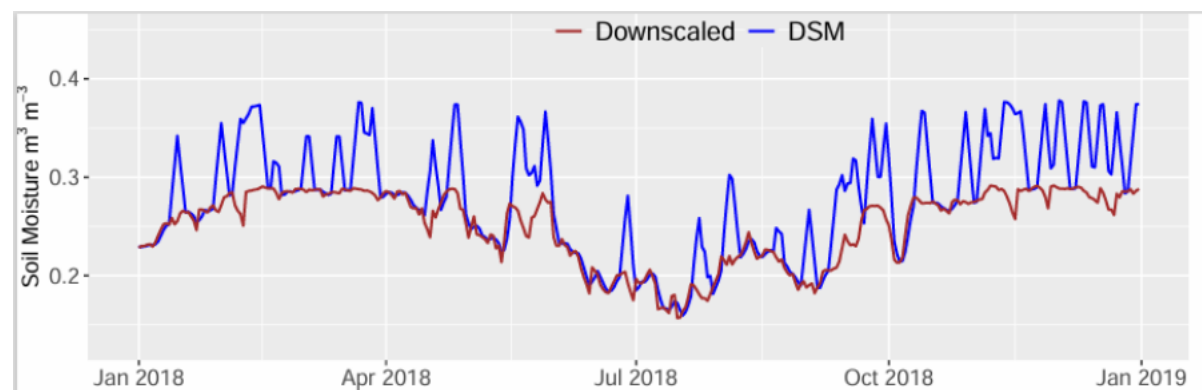


Figure 3: Time series of downscaled (mlhrsm product) and downscaled-bias-corrected soil-moisture (DSM) at the watershed-scale. Data from only one year are shown for clarity.

Streamflow Estimation Performance

The three calibration approaches produced comparable streamflow estimation performance during the calibration period, with slightly lower performance for the soil-moisture calibrated model. Calibration targeting streamflow resulted in NSE, RMSE, and PBIAS values of 0.58, 0.32, -4.1%, respectively (Fig. 4). The multi-objective calibration, optimizing both streamflow and soil-moisture, achieved identical NSE and RMSE values (0.58 and 0.32 $\text{m}^3 \text{s}^{-1}$), with a more negative PBIAS (-10.7%), indicating increased underestimation bias. The

soil-moisture calibration was not optimized for streamflow but nonetheless reproduced daily streamflow dynamics with an NSE of 0.54, RMSE of $0.33 \text{ m}^3 \text{ s}^{-1}$, and PBIAS of 28.7% (Fig. 4), reflecting a consistent overestimation bias. Both the streamflow and multi-objective calibrated models reproduced baseflow magnitude and the timing of high-flow events, although peak flows were occasionally underestimated, particularly for the multi-objective calibration. In contrast, the soil-moisture calibrated model exhibited systematic overestimation of low flows (Fig. A1), reflected in the positive streamflow bias.

3.3 Soil-Moisture Estimation Performance

3.3.1 Calibration-Scale Soil-Moisture (Satellite)

When evaluated against the bias corrected downscaled soil-moisture calibration target, the streamflow-calibrated model resulted in RMSE, R^2 , and NSE values of $0.07 \text{ m}^3 \text{ m}^{-3}$, 0.50, and -0.64, respectively. Calibration directly targeting soil-moisture reduced RMSE to $0.05 \text{ m}^3 \text{ m}^{-3}$ and improved NSE to 0.12, while explaining approximately 50% of observed variability, Fig. 5. The multi-objective calibration produced similar RMSE ($0.05 \text{ m}^3 \text{ m}^{-3}$) and R^2 (0.48), with improved alignment along the 1:1 line relative to the streamflow only model (Fig. 5; A2).

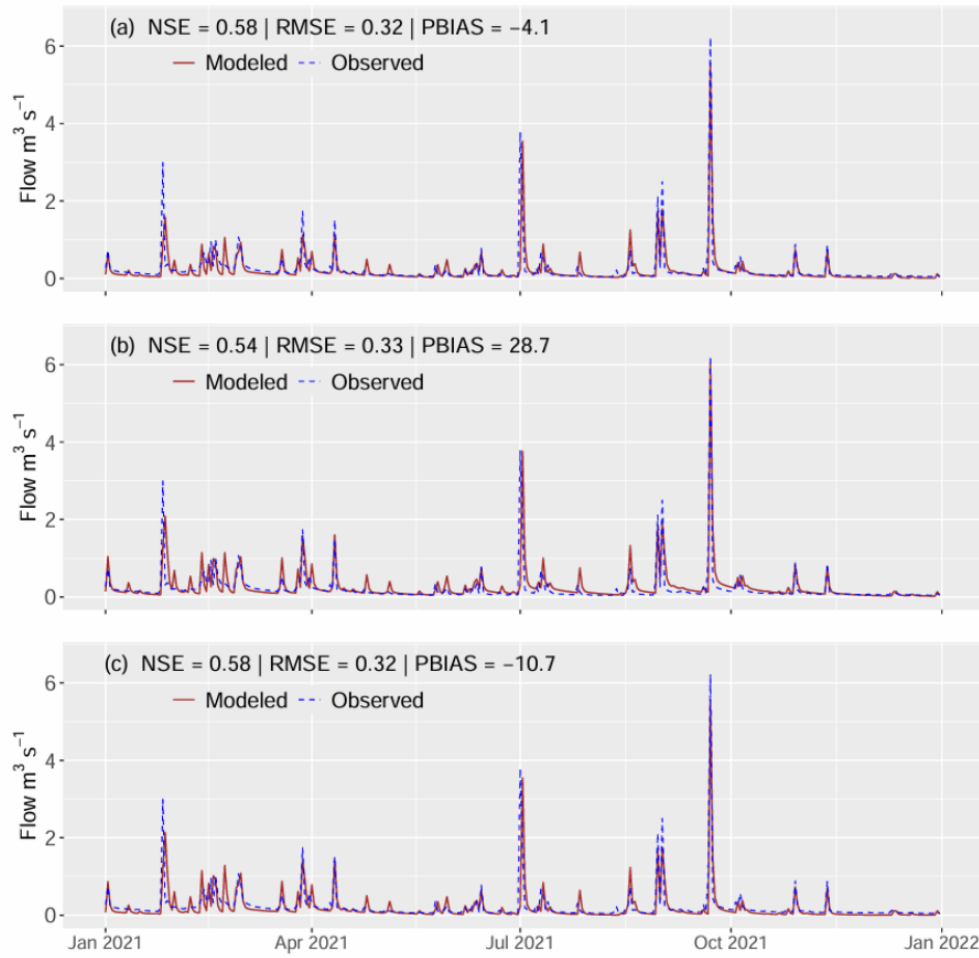


Figure 4: Model streamflow prediction performance calibration period a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration (see Fig. A3 for the complete time series).

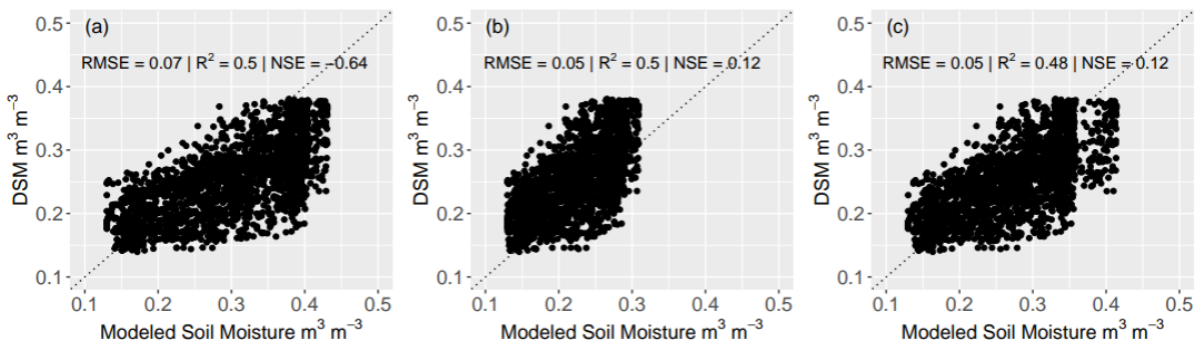


Figure 5: Model soil-moisture estimation performance during the calibration period compared against downscaled and bias corrected soil-moisture data calibrated on a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration.

3.3.2 Field-Scale Soil-Moisture-In-Situ Evaluation

Independent field-scale evaluation using in-situ soil- moisture measurements (0–120 mm) showed improved model performance when soil-moisture was included in the calibration. The streamflow calibrated model explained 50% of the observed soil-moisture variability ($R^2 = 0.5$), whereas the soil-moisture and multi-objective calibrations explained 88% of the observed soil-moisture variability ($R^2 = 0.88$) (Fig. 6). The multi-objective calibrated model reduced RMSE from $0.05 \text{ m}^3 \text{ m}^{-3}$ in the streamflow calibration to $0.03 \text{ m}^3 \text{ m}^{-3}$ and reduced PBIAS to -0.8% . Time-series comparison indicates reduced bias across a broader range of soil-moisture conditions for the multi-objective calibration approach (Fig. 7).

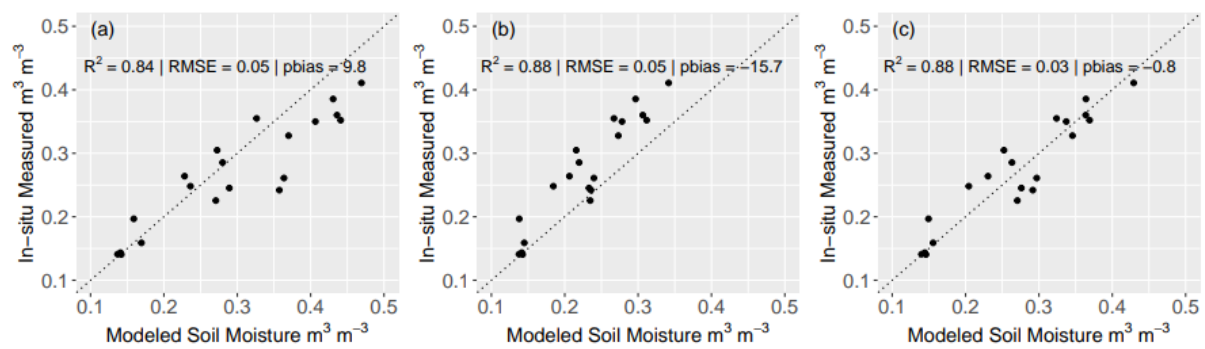


Figure 6: Soil-moisture estimation performance of the three models in the evaluation period at field-scale against field-scale average soil-moisture estimate from in-situ measurements; a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration.

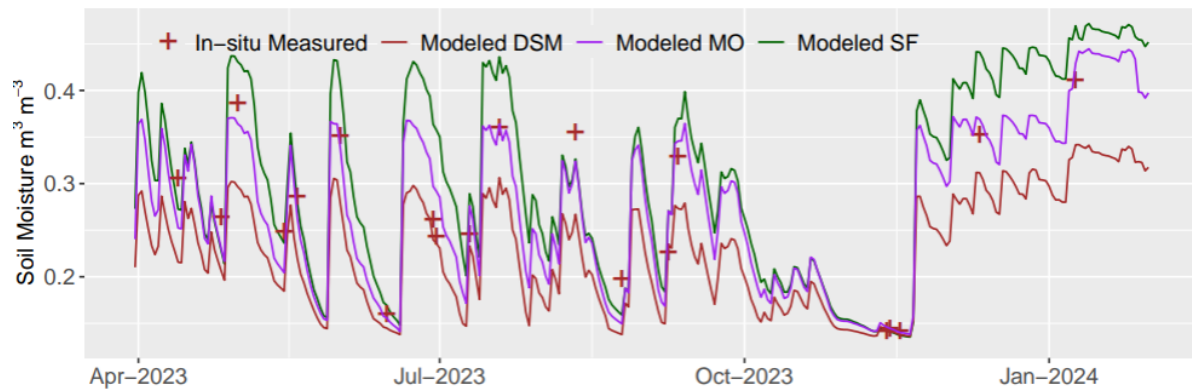


Figure 7: Temporal variability of modeled and measured soil-moisture for the three calibration approaches average over the top 120 mm soil layer; streamflow only (SF), soil-moisture only (DSM), and Multi-objective (MO).

3.4 Water Balance and Parameter Behavior

This section examines whether improvements in model performance metrics correspond to physically realistic hydrologic behavior or arise primarily from compensatory parameter adjustments. Surface runoff fractions were similar across models, reflecting comparable calibrated CN2 values. The average CN2 values were 42, 41.4, and 46.7 for the streamflow, multi-objective and soil-moisture calibrated models, respectively (Table 1), resulting in surface runoff values between 19.3% and 23.7% of the water balance (Fig. 8). The soil-moisture calibrated model produced lower ET and higher total streamflow relative to the other two approaches, whereas the streamflow and multi-objective calibrated models yielded similar partitioning among ET, lateral flow, and surface runoff components (Fig. 8).

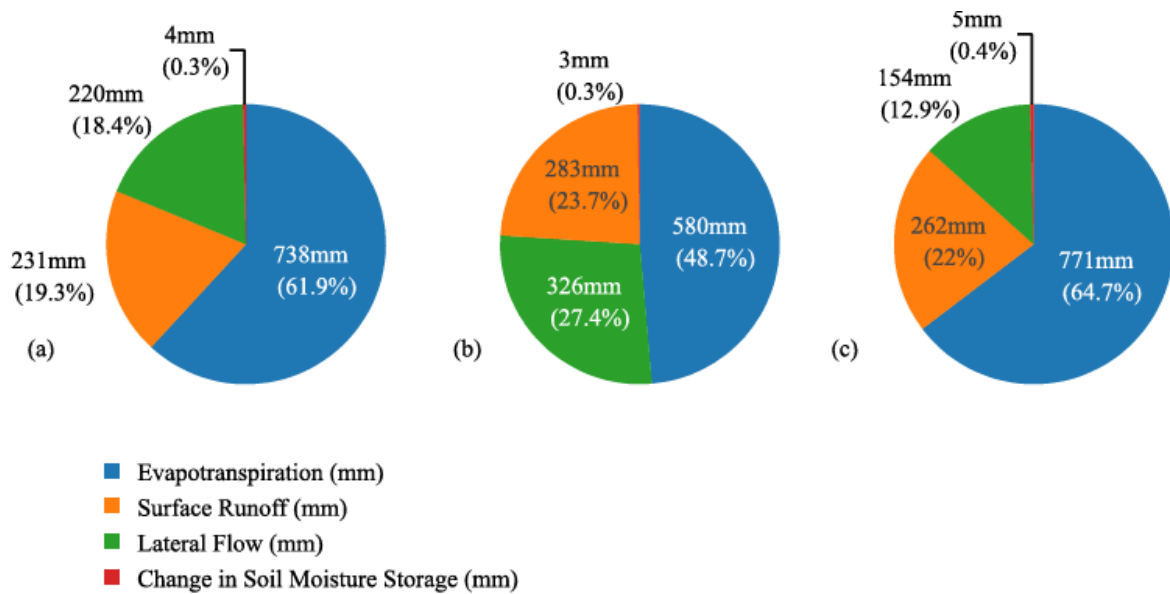


Figure 8: Model water balance estimation a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration.

The difference in ET and lateral flow components between the soil-moisture only calibrated model and the other two calibration approaches may be due to the reduced soil-moisture variability and reduced AWC in the soil-moisture only calibration. This calibration produces a lower mean and coefficient of variation (CV), compared to the other approaches (Table 2). While the values were comparable to the measured soil-moisture data, they diverged from the higher mean and variability simulated by the streamflow- and multi-objective calibrated models. When calibrating on streamflow, the optimization algorithm permits greater variability in soil-moisture related parameters because streamflow exhibits higher temporal variability (CV) than soil-moisture. In contrast, calibration against soil-moisture directly minimizes errors in the soil-moisture time series, constraining parameter variability, and favoring parameter sets that reproduce the lower variance structure of the soil-moisture observations. As a result, the soil-moisture-only calibration converges on lower AWC and dampened soil-moisture dynamics, with corresponding implications for ET and lateral flow partitioning.

Table 2: Soil-moisture variability during the calibration period (observed and modeled).

Soil-moisture	Mean (cm ³ cm ⁻³)	Standard Deviation (cm ³ cm ⁻³)	Coefficient of Variation (%)
Soil-moisture data (measured)	0.26	0.06	22.4
From streamflow model	0.31	0.08	26.9
From soil-moisture model	0.23	0.05	21.8
From multi-objective model	0.28	0.07	24.8

3.5 Model Evaluation and Comparison

During the model evaluation period (01 Jan 2022 – 31 May 2024) all three models produced comparable streamflow estimation performance with NSE values ranging from 0.55 to 0.56 and RMSE 0.25 m³ m^{-s} (Fig. 9). The soil-moisture-calibrated model exhibited positive bias in daily streamflow estimation (18.6%), primarily during low flow conditions. In contrast, the streamflow and multi-objective calibrated models showed an under-estimation bias of -11.9 and -21.7%, respectively (Fig. 9).

Overall, streamflow performance during the evaluation period was consistent with relative differences observed during calibration, confirming comparable predictive skill across calibration strategies under independent conditions.

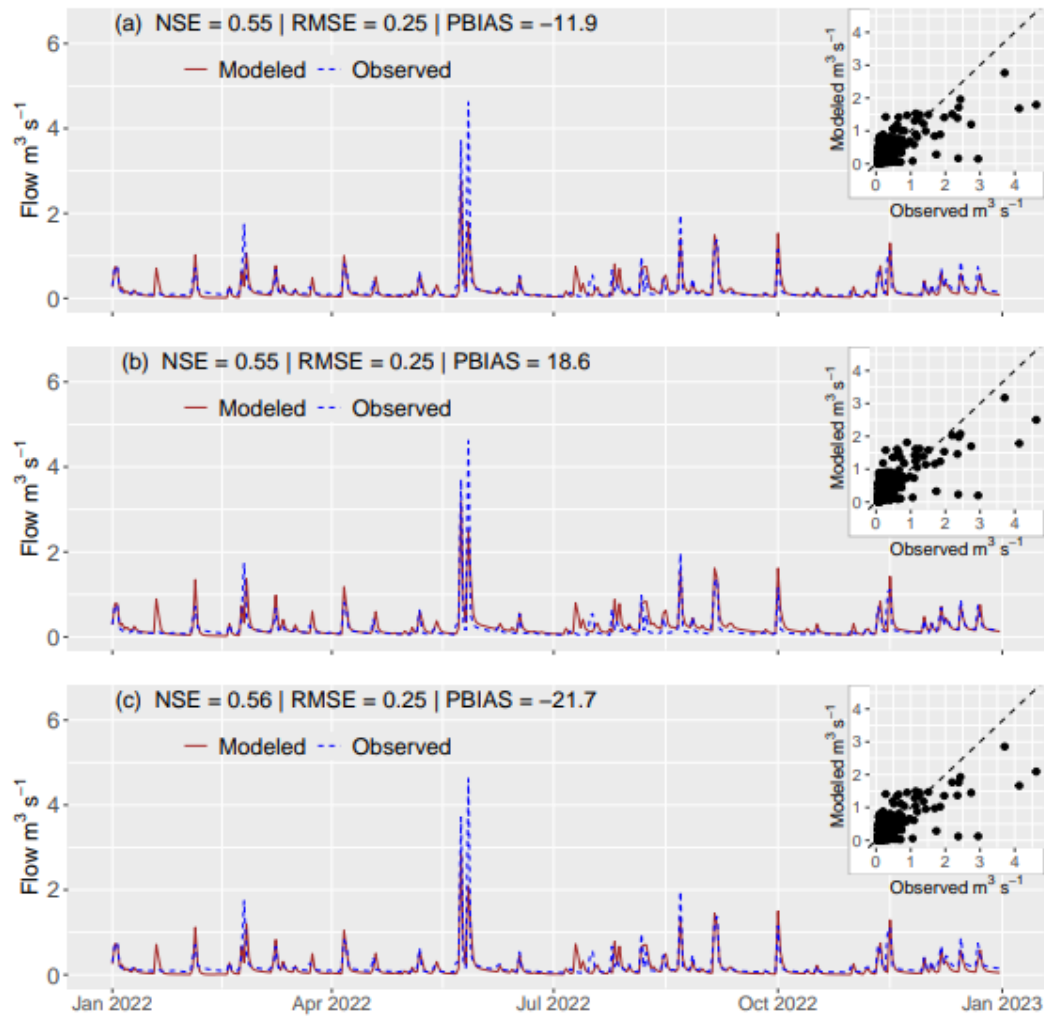


Figure 9: Model streamflow estimation performance evaluation period a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration (see also Fig. A4).

4. DISCUSSION

4.1 Effect of Downscaling and Bias-Correction on the Soil-Moisture Signal

The downscaled satellite soil-moisture product captured the broad temporal patterns of wetting and drying at the watershed-scale but exhibited a reduced dynamic range and attenuated peak wetness relative to in-situ observations. This behavior is consistent with previous evaluations of satellite and downscaled soil-moisture products, which often

reproduce large-scale temporal variability but smooth event and fine-scale extremes, particularly in topographically complex catchments (Brocca et al., 2017; Duethmann et al., 2022).

The event-based bias-correction selectively enhanced soil-moisture responses during precipitation events while preserving dry period behavior and long-term seasonal structure. By conditioning the adjustment on effective precipitation, the correction addressed the commonly reported attenuation of peak wetness in pretrained downscaling products without altering the lower envelope of the soil-moisture signal (Duethmann et al., 2022; Xu et al., 2025). Importantly, the correction parameters were not derived from in-situ soil-moisture measurements, ensuring that the adjusted product remained independent of the evaluation data. The experimental design was intended to evaluate the utility of the final downscaled and bias-corrected soil-moisture product for calibration and was not designed to isolate the relative contributions of the native satellite retrieval, downscaling procedure, and bias-correction method. Consequently, the reported performance improvements should be interpreted as the combined effect of the preprocessing and calibration framework.

4.2 Impact of Calibration Strategy on Streamflow Soil-moisture Dynamics

Across calibration strategies, streamflow estimation performance remained broadly comparable, indicating that inclusion of satellite soil-moisture did not substantially degrade streamflow skill. This contrasts with studies reporting pronounced reductions in streamflow performance when models are calibrated solely on soil-moisture remote sensing products (Dangol et al., 2023; Kofidou & Gemitzi, 2023) or under certain multi-objective calibration frameworks (Duethmann et al., 2022; Mei et al., 2023). The results here suggest that the combination of the SWAT-VSA model structure and bias corrected satellite soil-moisture calibration target helped limit tradeoffs between contrasting internal soil-moisture state and preserving integrated streamflow fluxes.

Nevertheless, the calibration strategy influenced bias patterns. The soil-moisture only calibrated model consistently overestimated low flows, whereas the streamflow- and multi-objective calibrated models exhibited underestimation bias (Fig. A1). Duethmann et al. (2022) showed that streamflow underestimation was more pronounced when soil-moisture was included in the calibration. Such differences among calibration strategies may not be simple parameter trade-off issue but rather could be related to model structure, for instance potential deficiencies in the evapotranspiration mechanism (Rajib et al. 2016), potentially leading to inadequate handling of water balance partitioning and over-compensation of related parameters.

In contrast, soil-moisture estimation, particularly at the field-scale, was more sensitive to calibration strategy. Both soil-moisture only and multi-objective calibration improved agreement with observed soil-moisture dynamics relative to streamflow-only calibration, consistent with studies demonstrating the value of soil-moisture data for constraining internal model states (Rajib & Merwade, 2016; Mei et al., 2023).

The calibration strategies yielded satisfactory streamflow performance ($NSE = 0.54-0.58$). Although increased levels of streamflow skill ($NSE = 0.6$) have been reported for this same study watershed using SWAT (e.g., Thilakarathne et al., 2018), direct comparison of NSE values could be misleading as streamflow performance here was achieved over a long calibration period (~10 years) encompassing substantial hydrologic variability. This indicates that the calibrated parameter set maintains reasonable process behavior across a broad range of flow regimes and antecedent moisture conditions, rather than being tuned to short-term or event specific dynamics.

Parameters describing soil physical properties, including bulk density, available water capacity, and saturated hydraulic conductivity, deviated from baseline values in the soil database by -7% , $+155\%$, and $+136\%$, respectively. Such adjustments are consistent with

previous findings showing that regional or large-scale soil datasets often fail to represent local soil characteristics, including texture, horizon thickness, and organic matter content (Buell, 2022; Fuka et al., 2016). Accordingly, allowing substantial flexibility in soil property parameters during calibration is justified for improving hydrologic performance in small, topographically complex watersheds.

4.3 Statistical Improvements versus Hydrologic Realism

Although soil-moisture only calibration produced measurable improvements in statistical agreement with soil-moisture observations, these gains did not uniformly translate into improved behavior across all hydrologic processes. The soil-moisture calibrated model better reproduced soil surface wetting dynamics but exhibited biased low flow behavior and altered water-balance partitioning. This pattern illustrates a central concern raised in recent multi-objective calibration studies: improvements in fit to a particular variable may reflect parameter compensation rather than improved process representation (Gupta et al., 2009; Duethmann et al., 2022; Mei et al., 2023).

The multi-objective calibration provided more balanced results by simultaneously constraining streamflow and soil-moisture responses. Independent field-scale evaluation showed that this approach reduced both RMSE and bias across a wider range of soil-moisture conditions while preserving streamflow performance comparable to streamflow only calibration. These findings align with previous work showing that multi-objective approaches can reduce equifinality and improve internal consistency, even if individual hydrologic performance metrics do not increase dramatically (Rajib et al., 2016; Silvestro et al., 2015).

Crucially, this study reinforces the distinction between improved statistical fit and improved hydrologic realism. Gains in soil-moisture metrics alone should not be interpreted as

evidence of improved system representation unless supported by independent evaluation and water balance diagnostics.

4.4 Parameter Behavior, Compensation, and Structural Model Constraints

Calibrated curve number (CN2) values distributed across topographic index (TI) classes reveal strongly heterogeneous runoff contributions consistent with saturation excess hydrology. TI class 1, which covers 56% of the watershed, contributes only ~9% of total surface runoff on a per area basis, while TI class 3, representing just 6% of the watershed, generates approximately 30%. Such disproportional contributions are characteristic of saturation excess systems, where runoff is concentrated in low lying, convergent landscape positions receiving sustained subsurface moisture inputs from upslope areas (Dahlke et al., 2009; Easton et al., 2008; Lyon et al., 2004). In SWAT-VSA, this behavior is indirectly represented by redistributing CN2 values according to local storage deficit, linking runoff generation to terrain-controlled wetness patterns.

The surface runoff lag coefficient (SURLAG) was higher in the streamflow only calibration than in the other approaches; however, this had a negligible impact on runoff timing because the watershed time of concentration is less than 1.5 hr. Differences among calibration strategies were more pronounced for evapotranspiration related parameters. The multi-objective calibration favored ESCO and EPCO values that increased water extraction from deeper soil layers, resulting in higher ET and reduced excess runoff. In contrast, the soil-moisture only calibration produced ESCO and EPCO values near unity that effectively compensated for one another, dampening vertical moisture redistribution and contributing to reduced ET.

Groundwater and baseflow parameters had little influence across all calibrations, with near zero percolation estimated, consistent with shallow soils and limited vertical drainage in

saturation excess landscapes. Differences in calibrated parameter values highlight compensatory behavior: soil-moisture only calibration favored lower available water content (AWC) and ET, increasing simulated streamflow while improving surface soil-moisture fit but altering internal water balance partitioning.

These outcomes reflect structural constraints within SWAT-VSA and SWAT more broadly, which represent unsaturated flow using vertically lumped soil layers and do not explicitly simulate lateral redistribution of soil-moisture among HRUs (Rajib et al., 2016). In saturation excess systems, where downslope redistribution and hydrologic connectivity dominate wetness evolution, these simplifications limit the model's ability to translate improved surface soil-moisture fit into realistic subsurface fluxes and recession behavior (Easton et al., 2008; Lyon et al., 2004).

Multi-objective calibration mitigated these limitations by jointly constraining streamflow and soil-moisture, reducing extreme parameter combinations and dampening compensation effects. When combined with physically informed preprocessing, soil-moisture observations can complement streamflow data by constraining antecedent moisture conditions that govern runoff generation (Brocca et al., 2017; Wagner et al., 2007). Here, the event-based bias-correction approach likely improved the hydrologic relevance of the satellite soil-moisture signal, contributing to improved consistency in both soil-moisture and streamflow simulation (Bekele & Nicklow, 2007; Rajib et al., 2016).

4.5 Parameter Uncertainty and Equifinality

While the previous section focused on how different calibration strategies alter parameter values and process behavior, this section examines how those strategies affect parameter uncertainty and equifinality.

Consistent with previous studies (Rajib & Merwade, 2016; Silvestro et al., 2015), parameter uncertainty was lowest under multi-objective calibration (Fig. 10), particularly for soil-water- and evapotranspiration-related parameters. Figure 10 shows that the range of acceptable values for AWC, Ksat, ESCO, and EPCO was substantially narrower under multi-objective calibration than under either streamflow-only or soil-moisture-only calibration. This reduced parameter spread indicates fewer equally acceptable parameter combinations and therefore reduced equifinality (Beven, 1993). By simultaneously constraining streamflow and soil-moisture dynamics, the multi-objective calibration more effectively restricted the feasible parameter space and improved confidence in parameters governing soil-water storage and vertical moisture redistribution. Together with the water-balance analysis, these results suggest that multi-objective calibration not only improved model performance but also reduced compensatory parameter behavior.

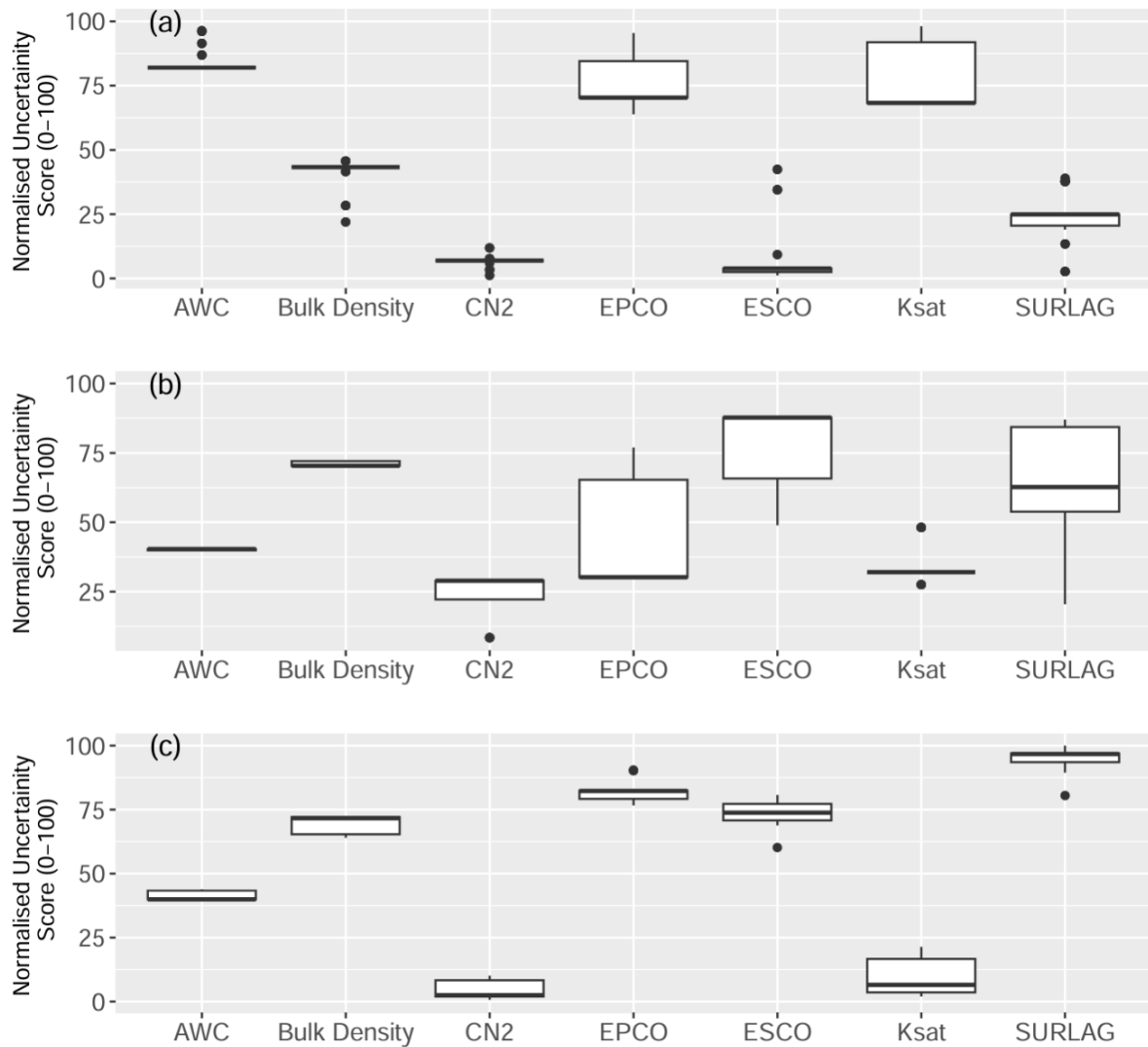


Figure 10: Parameter uncertainty estimate derived from DEoptim calibration iterations for a) streamflow only, b) soil-moisture only and, c) multi-objective calibration. The height of the boxplot demonstrates the range of different values the parameters took while yielding acceptable model performance. The values are calculated using the normalized uncertainty score from Kumar & Merwade (2009), where 0 and 100 represent the minimum and maximum parameter value as defined by the normalized calibration range.

4.6 Implications for Small Saturation-Excess Watersheds

The results demonstrate that downscaled, empirically bias corrected satellite soil-moisture data can improve internal hydrologic state estimation in small, saturation excess dominated

watersheds when combined with a terrain-informed model structure. The SWAT-VSA framework, using TI based HRUs and TI-weighted field-scale evaluation, enables direct assessment of whether calibration improvements extend to management relevant scales (Easton et al., 2008; Asfaw et al., 2025).

At the same time, the findings underscore the need for caution. Soil-moisture only calibration can yield misleading improvements if evaluated solely on statistical metrics, particularly in models with simplified representations of unsaturated and lateral soil-moisture processes. Multi-objective calibration offers a more robust balance between surface wetness dynamics and integrated flow behavior, although its effectiveness remains dependent on watershed characteristics and model structure (Duethmann et al., 2022; Mei et al., 2023). While the added complexity of downscaling and multi-objective calibration is warranted in this small, saturation excess watershed, caution is needed in generalizing these findings to other settings or assuming that improved satellite soil-moisture fit automatically implies improved hydrologic realism.

4.7 Limitations

This study was conducted in a small (14.5 km²), saturation excess dominated watershed. While appropriate for evaluating soil-moisture driven calibration in terrain controlled hydrologic systems, this limits the generalizability of the findings. In larger or more heterogeneous watersheds, greater spatial variability in precipitation, land use, soils, and hydrologic connectivity may influence both the downscaled soil-moisture behavior and the calibration performance. In particular, the event-based bias-correction approach applied here relies on watershed average effective precipitation and may not capture spatially variable wetting responses in more complex basins.

The applicability of the SWAT-VSA model is restricted to saturation excess runoff environments, where shallow soil storage deficits and topographic convergence largely control runoff generation. Watersheds dominated by infiltration excess processes, weak terrain control, or arid and semi-arid conditions may not benefit from the TI-based structure. Nonetheless, saturation excess processes are widespread in humid temperate regions of the United States (Buchanan et al., 2018) as well as globally, suggesting that this approach remains relevant to a broad class of headwater catchments.

The downscaled soil-moisture product underestimates peak wetness during high moisture periods. Although the bias-correction improves event scale responsiveness while preserving long-term temporal structure, it does not resolve underlying spatial or physical limitations of the satellite product. Consequently, the performance improvements should be interpreted as enhanced temporal constraint rather than complete correction of soil-moisture uncertainty. Furthermore, the relative contributions of the Enhanced SMAP product, machine-learning downscaling, and event-based bias-correction were not evaluated independently. Future work should compare calibration performance across these intermediate products to better quantify their individual contributions.

Overall, the findings should be interpreted within these constraints. Application of this framework beyond small, saturation excess watersheds will require careful consideration of watershed characteristics and evaluation across additional sites before broader inferences are made.

5. CONCLUSIONS

This study evaluated the utility of downscaled satellite soil-moisture data for calibrating a SWAT-VSA model in a small watershed for enhanced estimation of field-scale soil-moisture variability. The results show that leveraging downscaled satellite soil-moisture data

substantially improves estimation of temporal variability of soil-moisture without deteriorating the model accuracy in streamflow estimation. Multi-objective calibration using both streamflow and soil-moisture data improved soil-moisture performance and maintained streamflow performance comparable to streamflow-only calibration. Calibration based solely on soil-moisture led to improved soil-moisture performance with minimal declines in streamflow skill relative to streamflow only calibration.

Machine learning based satellite soil-moisture downscaling, using the ‘mlrhsm’ package in R, provided soil-moisture data of sufficient resolution and temporal fidelity to calibrate a high-resolution SWAT-VSA model in this watershed. Parameter uncertainty varied with calibration approach; soil parameters were better constrained with soil-moisture data, and streamflow parameters with streamflow data. Multi-objective calibration reduced parameter uncertainty. Long-term water balance estimates varied widely across the three calibration approaches, indicating the need for further evaluation, particularly using independent evapotranspiration measurements, to assess how soil-moisture constraints influence internal flux partitioning.

Overall, these findings highlight the potential of remotely sensed soil-moisture products to improve hydrologic model calibration, particularly in data-limited and ungauged basins. However, further evaluation is required in ungauged watersheds where no local soil-moisture or streamflow data are available for validation or qualitative assessment. Given their global coverage, satellite soil-moisture datasets offer a promising pathway for enhancing both streamflow and soil-moisture estimation when combined with terrain informed model structures and multi-objective calibration frameworks.

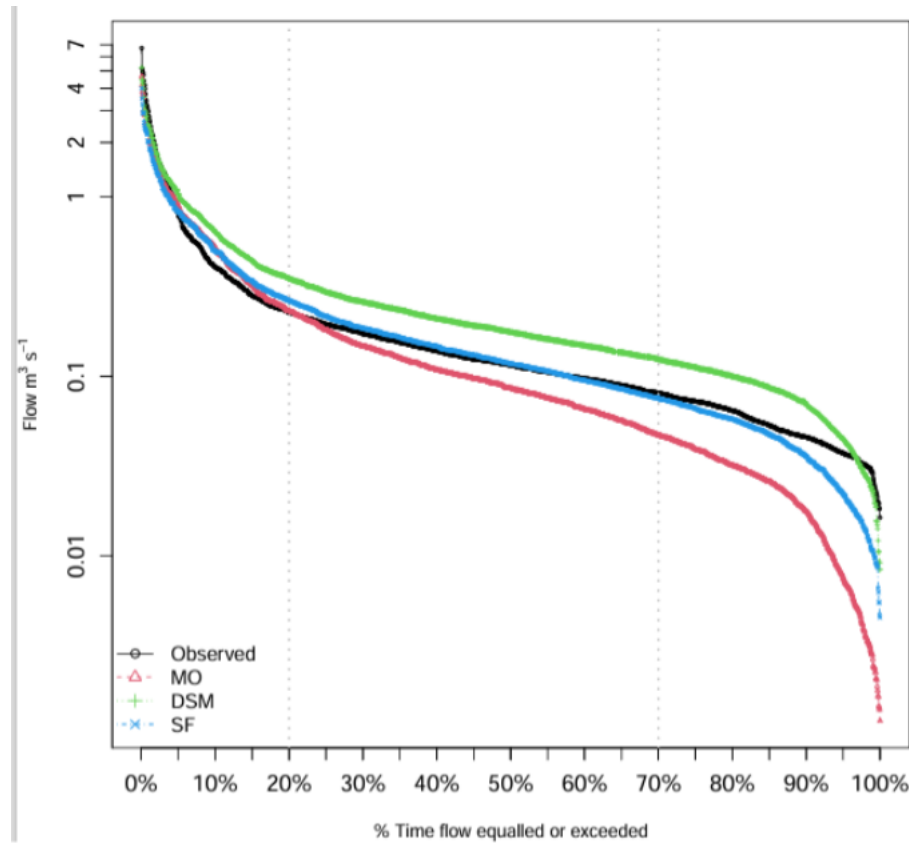


Figure A1: Flow duration curves comparing observed daily streamflow with simulations from the soil-moisture only (DSM), streamflow only (SF), and multi-objective (MO) calibration strategies. Differences among curves illustrate how calibration targets influence hydrologic realism: DSM captures surface wetting dynamics, but underestimates recession flows and high-flow peaks, whereas MO and SF better reproduce the observed distribution across both high-frequency (low flows) and low-frequency (peak flow) events.

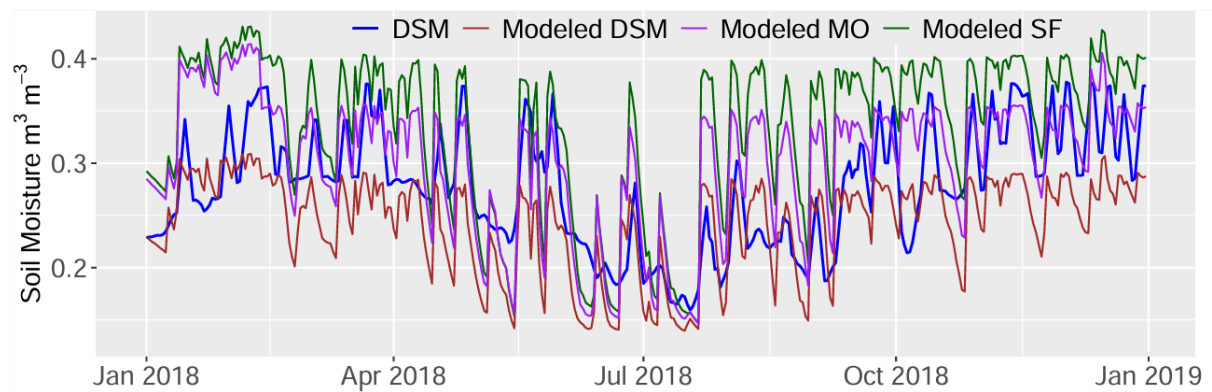


Fig. A2: Time series of modeled surface soil-moisture (50 mm) from the three calibration approaches and DSM data; calibrated on DSM data (Modeled DSM), Multi-objective calibration using DSM data and streamflow (Modeled MO), calibrated on streamflow (Modeled SF).

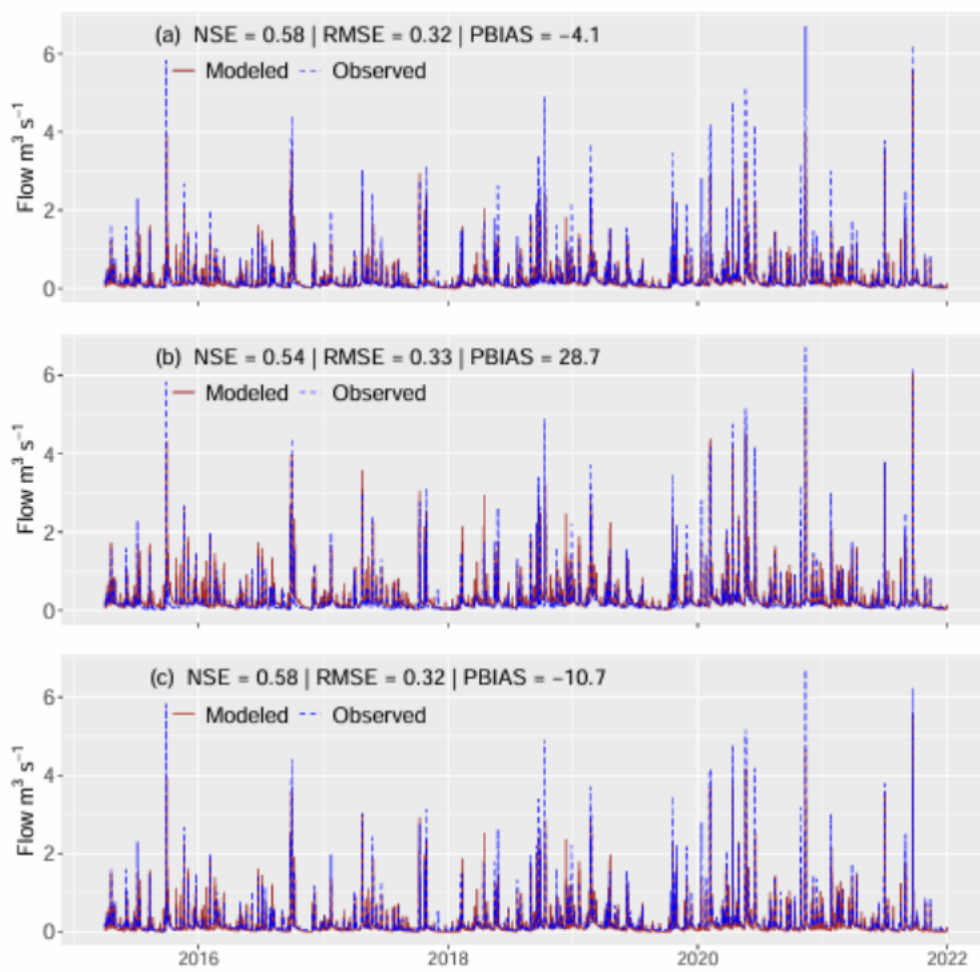


Figure- A3: Full time series of model streamflow prediction performance calibration period a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration.

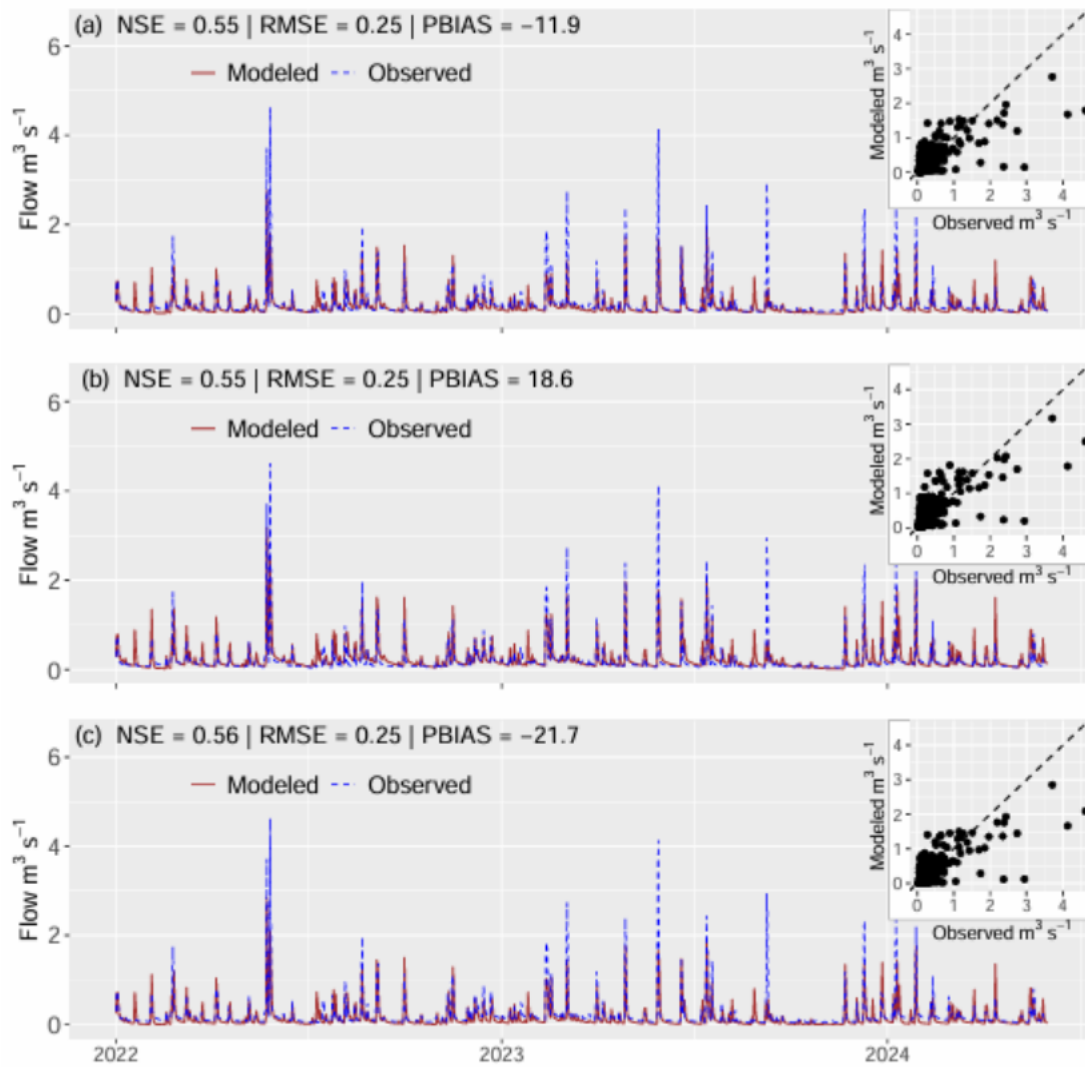


Figure A4: Model streamflow prediction performance evaluation period a) streamflow only (SF) calibration b) soil-moisture only (DSM) calibration c) multi-objective (MO) calibration.

756 Table A1. Soil-moisture data preprocessing and model integration

Source	Nominal / effective depth represented	How we aggregate to watershed/field	Model layer used for comparison	Role in this study
Downscaled satellite SM (mlhrsm from Enhanced SMAP)	Surface layer (0–50 mm)	Average all 500 m pixels intersecting the watershed to a daily watershed mean	0–50 mm SWAT layer	Calibration target in DSM and MO scenarios
SWAT-VSA model output	Discrete layers: 0–50 mm and 50–120 mm (plus standard deeper layers)	HRU outputs aggregated to watershed or field boundaries using TI-class/HRU area weights	0–50 mm (for satellite comparison); 0–50 mm + 50–120 mm composite = 0–120 mm (for field comparison)	Calibration (0–50 mm) and Evaluation (0–120 mm)
In-situ TDR measurements (25 points)	0–120 mm (field sampling depth)	TI-class-weighted average across the 4.2 ha pasture to obtain a field-scale mean	0–120 mm model composite	Independent of model calibration, but used in Pareto solution selection

757 Note: The 0–50 mm equivalent designation for the satellite product is an operational
758 alignment for comparability; it does not imply that the satellite directly senses 50 mm
759 uniformly. The purpose is to avoid mismatched depths during calibration and to keep
760 field-scale evaluation at the measured 0–120 mm depth.

761

762 CODE AVAILABILITY

763 Available upon request

764 DATA AVAILABILITY

765 The majority of the data used in this study is publicly available.

766 TEAM LIST

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769 AUTHOR CONTRIBUTION

770 Binyam Workeye Asfaw: Conceptualization; data curation; formal analysis; investigation;
771 methodology; visualization; writing—original draft; writing—review and editing.

772 Siam Maksud: Data curation; writing—review and editing.

773 Daniel R. Fuka: Conceptualization; methodology; writing—review and editing.

774 Amy S. Collick: Methodology; writing-review and editing

775 Robin R. White: Conceptualization; funding acquisition; project administration.

776 Zachary M. Easton: Conceptualization; data curation; formal analysis; funding acquisition;
777 project administration; writing—original draft; writing—review and editing.

778 COMPETING INTERESTS

779 Authors declare that they have no competing interest.

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REFERENCES

- Abbaszadeh, P., Moradkhani, H., Gavahi, K., Kumar, S., Hain, C., Zhan, X., Duan, Q., Peters-Lidard, C., & Karimiziarani, S. (2021). High-resolution SMAP satellite soil moisture product: Exploring the opportunities. *Bulletin of the American Meteorological Society*, 102(4), 309–315.
- Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., & Van Liew, M. W. (2012). SWAT: Model use, calibration, and validation. *Transactions of the ASABE*, 55(4), 1491–1508.
- Asfaw, B. W., Fuka, D. R., Collick, A. S., White, R. R., & Easton, Z. M. (2025). Characterizing the topographic index as a tool to represent spatial soil moisture: The effect of classification approach, digital elevation model type, and resolution. *Vadose Zone Journal*, 24(4), e70031. <https://doi.org/10.1002/vzj2.70031>
- Azimi, S., Dariane, A. B., Modanesi, S., Bauer-Marschallinger, B., Bindlish, R., Wagner, W., & Massari, C. (2020). Assimilation of Sentinel 1 and SMAP – based satellite soil moisture retrievals into SWAT hydrological model: The impact of satellite revisit time and product spatial resolution on flood simulations in small basins. *Journal of Hydrology*, 581. <https://doi.org/10.1016/j.jhydrol.2019.124367>
- Bekele, E. G., & Nicklow, J. W. (2007). Multi-objective automatic calibration of SWAT using NSGA-II. *Journal of Hydrology*, 341(3), 165–176. <https://doi.org/10.1016/j.jhydrol.2007.05.014>
- Beven, K. (1993). Prophecy, reality and uncertainty in distributed hydrological modelling. *Advances in Water Resources*, 16(1), 41–51. [https://doi.org/10.1016/0309-1708\(93\)90028-E](https://doi.org/10.1016/0309-1708(93)90028-E)

808 Beven, K. J., Kirkby, M. J., Freer, J. E., & Lamb, R. (2021). A history of TOPMODEL.
809 *Hydrology and Earth System Sciences*, 25(2), 527–549. [https://doi.org/10.5194/hess-](https://doi.org/10.5194/hess-25-527-2021)
810 25-527-2021.

811 Blank, J., & Deb, K. (2020). Pymoo: Multi-Objective Optimization in Python. *IEEE Access*,
812 8, 89497–89509. IEEE Access. <https://doi.org/10.1109/ACCESS.2020.2990567>

813 Bocinsky, R. K., Beaudette, D., Chamberlain, S., Hollister, J., & Gustavsen, J. (2025).
814 *FedData: Download Geospatial Data Available from Several Federated Data*
815 *Sources* (Version 4.3.0). <https://cran.r-project.org/web/packages/FedData/index.html>

816 Brocca, L., Ciabatta, L., Massari, C., Camici, S., & Tarpanelli, A. (2017). Soil moisture for
817 hydrological applications: Open questions and new opportunities. *Water*, 9(2), 2.
818 <https://doi.org/10.3390/w9020140>

819 Brocca, L., Melone, F., Moramarco, T., & Morbidelli, R. (2010). Spatial-temporal variability
820 of soil moisture and its estimation across scales. *Water Resources Research*, 46(2).
821 <https://doi.org/10.1029/2009WR008016>

822 Buell, E. N. (2022). *Improved environmental characterization to support natural resource*
823 *decision making: (1) Distributed soil characterization, and (2) Treatment of legacy*
824 *nutrients*. <http://hdl.handle.net/10919/112013>

825 Buchanan, B., D.A. Auerbach, J. Knighton, D. Evensen, D. R. Fuka Z.M. Easton, M.
826 Wieczorek, J.A. Archibald, B. McWilliams, M.T. Walter . 2018. Estimating dominant
827 runoff modes across the conterminous United States. *Hydrological Processes*.
828 <https://doi.org/10.1002/hyp.13296>

829 Chan, S. K., Bindlish, R., O'Neill, P., Jackson, T., Njoku, E., Dunbar, S., Chaubell, J.,
830 Piepmeier, J., Yueh, S., Entekhabi, D., Colliander, A., Chen, F., Cosh, M. H.,
831 Caldwell, T., Walker, J., Berg, A., McNairn, H., Thibeault, M., Martínez-Fernández,

832 J., Uldall, F., Seyfried, M., Bosch, D., Starks, P., Holifield Collins, C., Prueger, J.,
833 Van Der Velde, R., Asanuma, J., Palecki, M., Small, E. E., Zreda, M., Calvet, J.,
834 Crow, W. T., & Kerr, Y. (2018). Development and assessment of the SMAP enhanced
835 passive soil moisture product. *Remote Sensing of Environment*, 204, 931–941.
836 <https://doi.org/10.1016/j.rse.2017.08.025>

837 Cho, E., Moon, H., & Choi, M. (2015). First assessment of the Advanced Microwave
838 Scanning Radiometer 2 (AMSR2) soil moisture contents in Northeast Asia. *Journal of*
839 *Meteorology. Series 2*, 93(1), 117–129. <https://doi.org/10.2151/jmsj.2015-008>

840 Colliander, A., T.J. Jackson, R. Bindlish, S. Chan, N. Das, S.B. Kim, M.H. Cosh, R.S.
841 Dunbar, L. Dang, L. Pashaian, J. Asanuma, K. Aida, A. Berg, T. Rowlandson, D.
842 Bosch, T. Caldwell, K. Caylor, D. Goodrich, H. al Jassar, E. Lopez-Baeza, J.
843 Martínez-Fernández, A. González-Zamora, S. Livingston, H. McNairn, A. Pacheco,
844 M. Moghaddam, C. Montzka, C. Notarnicola, G. Niedrist, T. Pellarin, J. Prueger, J.
845 Pulliainen, K. Rautiainen, J. Ramos, M. Seyfried, P. Starks, Z. Su, Y. Zeng, R. van
846 der Velde, M. Thibeault, W. Dorigo, M. Vreugdenhil, J.P. Walker, X. Wu, A.
847 Monerris, P.E. O'Neill, D. Entekhabi, E.G. Njoku, & S. Yueh. (2017). Validation of
848 SMAP surface soil moisture products with core validation sites. *Remote Sensing of*
849 *Environment*, 191, 215–231. <https://doi.org/10.1016/j.rse.2017.01.021>

850 Dahlke, H. E., Easton, Z. M., Fuka, D. R., Lyon, S. W., & Steenhuis, T. S. (2009). Modelling
851 variable source area dynamics in a CEAP watershed. *Ecohydrology*, 2(3), 337–349.
852 <https://doi.org/10.1002/eco.58>

853 Dangol, S., Zhang, X., Liang, X.-Z., Anderson, M., Crow, W., Lee, S., Moglen, G. E., &
854 Mccarty, G. W. (2023). Multivariate calibration of the SWAT model using remotely
855 sensed datasets. *Remote Sensing*, 2417 (22 pp.). <https://doi.org/10.3390/rs15092417>

856 Das, N. N., Entekhabi, D., Kim, S., Jagdhuber, T., Dunbar, S., Yueh, S., O'Neill, P. E.,
857 Colliander, A., Walker, J., & Jackson, T. J. (2018). High-resolution enhanced product
858 based on SMAP active-passive approach using sentinel 1A and 1B SAR data.
859 *International Archives of the Photogrammetry, Remote Sensing and Spatial*
860 *Information Sciences. XLII-5*, 203–205. [https://doi.org/10.5194/isprs-archives-XLII-](https://doi.org/10.5194/isprs-archives-XLII-5-203-2018)
861 [5-203-2018](https://doi.org/10.5194/isprs-archives-XLII-5-203-2018)

862 De Santis, D., Biondi, D., Crow, W. T., Camici, S., Modanesi, S., Brocca, L., & Massari, C.
863 (2021). Assimilation of satellite soil moisture products for river flow prediction: An
864 extensive experiment in over 700 catchments throughout Europe. *Water Resources*
865 *Research*, 57(6). <https://doi.org/10.1029/2021WR029643>

866 Deb, K., Agrawal, S., Pratap, A., & Meyarivan, T. (2000). A fast elitist non-dominated
867 sorting genetic algorithm for multi-objective optimization: NSGA-II. In M.
868 Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, & H.-P. Schwefel
869 (Eds.), *Parallel Problem Solving from Nature PPSN VI* (pp. 849–858). Springer.
870 https://doi.org/10.1007/3-540-45356-3_83

871 Duethmann, D., Smith, A., Soulsby, C., Kleine, L., Wagner, W., Hahn, S., & Tetzlaff, D.
872 (2022). Evaluating satellite-derived soil moisture data for improving the internal
873 consistency of process-based ecohydrological modelling. *Journal of Hydrology*, 614,
874 128462. <https://doi.org/10.1016/j.jhydrol.2022.128462>

875 Easton, Z. M., Fuka, D. R., Walter, M. T., Cowan, D. M., Schneiderman, E. M., & Steenhuis,
876 T. S. (2008). Re-conceptualizing the Soil and Water Assessment Tool (SWAT) model
877 to predict runoff from variable source areas. *Journal of Hydrology*, 348(3), 279–291.
878 <https://doi.org/10.1016/j.jhydrol.2007.10.008>

879 Eini, M. R., Massari, C., & Piniewski, M. (2023). Satellite-based soil moisture enhances the
880 reliability of agro-hydrological modeling in large transboundary river basins. *Science*
881 *of The Total Environment*, 873, 162396.
882 <https://doi.org/10.1016/j.scitotenv.2023.162396>

883 Entekhabi, D., Reichle, R. H., Koster, R. D., & Crow, W. T. (2010). Performance metrics for
884 soil moisture retrievals and application requirements. *Journal of Hydrometeorology*,
885 <https://doi.org/10.1175/2010JHM1223.1>

886 Entekhabi, D., Yueh, S., and de Lannoy, G. (2014). SMAP Handbook, Jet Propulsion
887 Laboratory, California Institute of Technology, Pasadena, CA, USA, 2014, available
888 at: <https://smap.jpl.nasa.gov/> (last access: July 2026).

889 Food and Agriculture Organization of the United Nations (FAO). (2007). FAO Digital Soil
890 Map of the World (DSMW). FAO, Rome, Italy. [https://www.fao.org/land-](https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/)
891 [water/land/land-governance/land-resources-planning-](https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/)
892 [toolbox/category/details/en/c/1026564/](https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/)

893 Fuka, D. R., Collick, A. S., Kleinman, P. J. A., Auerbach, D. A., Harmel, R. D., & Easton, Z.
894 M. (2016). Improving the spatial representation of soil properties and hydrology using
895 topographically derived initialization processes in the SWAT model. *Hydrological*
896 *Processes*. <https://doi.org/10.1002/hyp.10899>

897 Fuka, D. R., & Easton, Z. M. (2016). *TopoSWAT source*. Figshare. Dataset.
898 <https://doi.org/10.6084/m9.figshare.1342823.v4>.

899 Fuka, D. R., W, M., A, J., Garna, R. K., & Easton, Z. M. (2013). *EcoHydRology: A*
900 *community modeling foundation for EcoHydrology* (Version R package version 0.4.19
901 [software]). <https://CRAN.R-project.org/package=EcoHydRology>

902 Garna, R. K., Easton, Z. M., Faulkner, J. W., Collick, A. S., & Fuka, D. R. (2023).
 903 Employing higher density lower reliability weather data from the Global Historical
 904 Climatology Network monitors to generate serially complete weather data for
 905 watershed modelling. *Hydrological Processes*, 37(11), e15013.
 906 <https://doi.org/10.1002/hyp.15013>

907 Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the
 908 mean squared error and NSE performance criteria: Implications for improving
 909 hydrological modelling. *Journal of Hydrology*, 377(1), 80–91.
 910 <https://doi.org/10.1016/j.jhydrol.2009.08.003>

911 H SAF. (2021). *ASCAT Surface Soil Moisture Climate Data Record v7 12.5 km sampling—*
 912 *Metop, EUMETSAT SAF on Support to Operational Hydrology and Water*
 913 *Management*. https://doi.org/10.15770/EUM_SAF_H_0009

914 Hofmeister, K. L., Cianfrani, C. M., & Hession, W. C. (2015). Complexities in the stream
 915 temperature regime of a small mixed-use watershed, Blacksburg, VA. *Ecological*
 916 *Engineering*, 78, 101–111. <https://doi.org/10.1016/j.ecoleng.2014.05.019>

917 Jin, S., Dewitz, J., Danielson, P., Granneman, B., Costello, C., Smith, K., & Zhu, Z. (2023).
 918 National Land Cover Database 2019: A New strategy for creating clean leaf-on and
 919 leaf-off Landsat composite images. *Journal of Remote Sensing*, 3, 0022.
 920 <https://doi.org/10.34133/remotesensing.0022>

921 Ketabchy, M. (2018). *Thermal evaluation of an urbanized watershed using SWMM and*
 922 *MINUHET: A case study of Stroubles Creek Watershed, Blacksburg, VA* [Thesis,
 923 Virginia Tech]. <https://vtechworks.lib.vt.edu/handle/10919/81977>

924 Kofidou, M., & Gemitzi, A. (2023). Assimilating soil moisture information to improve the
 925 performance of SWAT hydrological model. *Hydrology*, 10(8), 8.
 926 <https://doi.org/10.3390/hydrology10080176>

927 Krause, P., Boyle, D. P., & Bäse, F. (2005). Comparison of different efficiency criteria for
 928 hydrological model assessment. *Advances in Geosciences*, 5, 89–97. Proceedings of
 929 the 8th Workshop for Large Scale Hydrological Modelling - Oppurg 2004 - 8th
 930 workshop for Large-scale hydrological modelling, Oppurg, Germany, 11–13
 931 November 2004. <https://doi.org/10.5194/adgeo-5-89-2005>

932 Kumar, S., & Merwade, V. (2009). Impact of watershed subdivision and soil data resolution
 933 on SWAT model calibration and parameter uncertainty. *JAWRA Journal of the*
 934 *American Water Resources Association*, 45(5), 1179–1196.
 935 <https://doi.org/10.1111/j.1752-1688.2009.00353.x>

936 Kundu, D., Vervoort, R. W., & van Ogtrop, F. F. (2017). The value of remotely sensed
 937 surface soil moisture for model calibration using SWAT. *Hydrological Processes*,
 938 31(15), 2764–2780. <https://doi.org/10.1002/hyp.11219>

939 López López, P., Sutanudjaja, E. H., Schellekens, J., Sterk, G., & Bierkens, M. F. P. (2017).
 940 Calibration of a large-scale hydrological model using satellite-based soil moisture and
 941 evapotranspiration products. *Hydrology and Earth System Sciences*, 21(6), 3125–
 942 3144. <https://doi.org/10.5194/hess-21-3125-2017>

943 Lyon, S. W., Walter, M. T., Gérard-Marchant, P., & Steenhuis, T. S. (2004). Using a
 944 topographic index to distribute variable source area runoff predicted with the SCS
 945 curve-number equation. *Hydrological Processes*, 18(15), 2757–2771.
 946 <https://doi.org/10.1002/hyp.1494>

- Mladenova, I. E., Bolten, J. D., Crow, W., Sazib, N., & Reynolds, C. (2020). Agricultural drought monitoring via the assimilation of SMAP soil moisture retrievals into a global soil water balance model. *Frontiers in Big Data*, 3, 10. <https://doi.org/10.1109/JSTARS.2019.2923555>
- Mascaro, G., Vivoni, E. R., & Deidda, R. (2011). Soil moisture downscaling across climate regions and its emergent properties. *Journal of Geophysical Research: Atmospheres*, 116(D22). <https://doi.org/10.1029/2011JD016231>
- Mei, Y., Mai, J., Do, H. X., Gronewold, A., Reeves, H., Eberts, S., Niswonger, R., Regan, R. S., & Hunt, R. J. (2023). Can hydrological models benefit from using global soil moisture, evapotranspiration, and runoff products as calibration targets? *Water Resources Research*, 59(2), e2022WR032064. <https://doi.org/10.1029/2022WR032064>
- Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, 50(3), 885–900.
- Mullen, K. M., Ardia, D., Gil, D. L., Windover, D., & Cline, J. (2011). DEoptim: An R package for global optimization by differential evolution. *Journal of Statistical Software*, 40, 1–26. <https://doi.org/10.18637/jss.v040.i06>
- Nanda, A., Jalilvand, E., Das, N. N., Bindlish, R., and Andreadis, K.: Optimizing hydrologic model soil physical properties with SMAP soil moisture: A pathway for skillful assessment of streamflow and drought, SSRN Electronic Journal [preprint], <https://doi.org/10.2139/ssrn.4635449>, 2023.

- 970 Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I
 971 — A discussion of principles. *Journal of Hydrology*, 10(3), 282–290.
 972 [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6)
- 973 Nathan, R. J., & McMahon, T. A. (1990). Evaluation of automated techniques for base flow
 974 and recession analyses. *Water Resources Research*, 26(7), 1465–1473.
 975 <https://doi.org/10.1029/WR026i007p01465>
- 976 Nayeib Yazdi, M., Ketabchy, M., Sample, D. J., Scott, D., & Liao, H. (2019). An evaluation
 977 of HSPF and SWMM for simulating streamflow regimes in an urban watershed.
 978 *Environmental Modelling & Software*, 118, 211–225.
 979 <https://doi.org/10.1016/j.envsoft.2019.05.008>
- 980 Neitsch, S. L., Arnold, J. G., Kiniry, J. R., and Williams, J. R. (2009) Soil and Water
 981 Assessment Tool theoretical documentation, Version 2009, Texas Water Resources
 982 Institute, Texas A&M University System, College Station, Texas, USA, available at:
 983 <https://swat.tamu.edu/docs/> (last access: 4 August 2026), 2009.
- 984 O’Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., & Chaubell, J. (2018).
 985 SMAP L3 radiometer global daily 36 km EASE-grid soil moisture, Version 5. *Natl.*
 986 *Snow Ice Data Cent*, 1–82.
- 987 O’Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., Chaubell, J., & Colliander,
 988 A. (2023). SMAP enhanced L3 radiometer global and polar grid daily 9 km EASE-
 989 Grid Soil Moisture. *Boulder, Colorado, USA: NASA National Snow and Ice Data*
 990 *Center Distributed Active Archive Center*.

991

992 Parece, T., Dibetitto, S., Sprague, T., and Younos, T. (2010). The Stroubles Creek
 993 Watershed: History of development and chronicles of research, Water Resources
 994 Research Center, Virginia Tech, Blacksburg, VA, USA, 2010.

995 Patil, A., & Ramsankaran, R. (2017). Improving streamflow simulations and forecasting
 996 performance of SWAT model by assimilating remotely sensed soil moisture
 997 observations. *Journal of Hydrology*, 555, 683–696.
 998 <https://doi.org/10.1016/j.jhydrol.2017.10.058>

999 Pechlivanidis, I. G., Jackson, B. M., McIntyre, N. R., & Wheeler, H. S. (2011). Catchment
 1000 scale hydrological modelling: A review of model types, calibration approaches and
 1001 uncertainty analysis methods in the context of recent developments in technology and
 1002 applications. *Global Nest Journal*, 13(3), 193–214.

1003 Peng, Y., Yang, Z., Zhang, Z., & Huang, J. (2024). A machine learning-based high-resolution
 1004 soil moisture mapping and spatial–temporal analysis: The mlhrsm package.
 1005 *Agronomy*, 14(3), 3. <https://doi.org/10.3390/agronomy14030421>

1006 Rajib, M. A., & Merwade, V. (2016). Improving soil moisture accounting and streamflow
 1007 prediction in SWAT by incorporating a modified time-dependent Curve Number
 1008 method. *Hydrological Processes*, 30(4), 603–624. <https://doi.org/10.1002/hyp.10639>

1009 Rajib, M. A., Merwade, V., & Yu, Z. (2016). Multi-objective calibration of a hydrologic
 1010 model using spatially distributed remotely sensed/in-situ soil moisture. *Journal of*
 1011 *Hydrology*, 536, 192–207. <https://doi.org/10.1016/j.jhydrol.2016.02.037>

1012 Sanford, W. E., Nelms, D. L., Pope, J. P., & Selnick, D. L. (2012). Quantifying components
 1013 of the hydrologic cycle in Virginia using chemical hydrograph separation and
 1014 multiple regression analysis. I *Scientific Investigations Report* (2011–5198). U.S.
 1015 Geological Survey. <https://doi.org/10.3133/sir20115198>

1016 Silvestro, F., Gabellani, S., Rudari, R., Delogu, F., Laiolo, P., & Boni, G. (2015). Uncertainty
 1017 reduction and parameter estimation of a distributed hydrological model with ground
 1018 and remote-sensing data. *Hydrology and Earth System Sciences*, 19(4), 1727–1751.
 1019 <https://doi.org/10.5194/hess-19-1727-2015>

1020 Sun, L.: Streamflow and Soil moisture assimilation in the SWAT model using the extended
 1021 Kalman filter, PhD dissertation, University of Regina, Regina, Saskatchewan,
 1022 Canada, <https://doi.org/10.20381/RUOR-4934>, 2016.

1023 Thilakarathne, M., Sridhar, V., & Karthikeyan, R. (2018). Spatially explicit pollutant load-
 1024 integrated in-stream *E. coli* concentration modeling in a mixed land-use catchment.
 1025 *Water Research*, 144, 87–103. <https://doi.org/10.1016/j.watres.2018.07.021>

1026 Vereecken, H., Huisman, J. A., Hendricks Franssen, H. J., Brüggemann, N., Bogaen, H. R.,
 1027 Kollet, S., Javaux, M., van der Kruk, J., & Vanderborght, J. (2015). Soil hydrology:
 1028 Recent methodological advances, challenges, and perspectives. *Water Resources*
 1029 *Research*, 51(4), 2616–2633. <https://doi.org/10.1002/2014WR016852>

1030 Wagner, W., Blöschl, G., Pampaloni, P., Calvet, J.-C., Bizzarri, B., Wigneron, J.-P., & Kerr,
 1031 Y. (2007). Operational readiness of microwave remote sensing of soil moisture for
 1032 hydrologic applications. *Hydrology Research*, 38(1), 1–20.

1033 Wagner, W., Lemoine, G., & Rott, H. (1999). A method for estimating soil moisture from
 1034 ERS scatterometer and soil data. *Remote Sensing of Environment*, 70(2), 191–207.
 1035 [https://doi.org/10.1016/S0034-4257\(99\)00036-X](https://doi.org/10.1016/S0034-4257(99)00036-X)

1036 Wakigari, S. A., & Leconte, R. (2023). Exploring the utility of the downscaled SMAP soil
 1037 moisture products in improving streamflow simulation. *Journal of Hydrology:*
 1038 *Regional Studies*, 47, 101380. <https://doi.org/10.1016/j.ejrh.2023.101380>

1039 Xu, Y., Cai, S., Huang, J., Liu, J., Shang, J., Yang, Z., & Zhang, Z. (2025). A multimodal
1040 deep learning approach for soil moisture downscaling using remote sensing and
1041 weather data. *Journal of Geophysical Research: Machine Learning and Computation*,
1042 2(3), e2025JH000639. <https://doi.org/10.1029/2025JH000639>

1043 Zeileis, A., Grothendieck, G., Ryan, J. A., Ulrich, J. M., & Andrews, F. (2025). *zoo: S3*
1044 *Infrastructure for Regular and Irregular Time Series (Z's Ordered Observations)*
1045 (Version 1.8-14). <https://cran.r-project.org/web/packages/zoo/index.html>

1046
1047
1048
1049
1050
1051
1052
1053