https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

Calibrating on Downscaled Satellite Soil Moisture Data Can Improve Watershed Model Performance in Predicting Soil Moisture Variability

Binyam Workeye Asfaw[1], Siam Maksud[1], Daniel R. Fuka[1], Amy S. Collick[2], Robin R. White[3], Zachary M. Easton[1]

[1]Department of Biological Systems Engineering, Virginia Tech, Blacksburg, VA

[2]Department of Agricultural Science, Morehead State University, Morehead, KY

[3]School of Animal Sciences, Virginia Tech, Blacksburg, VA

Correspondence to: Zachary M. Easton (zeaston@vt.edu)

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

Abstract

Watershed streamflow is often the focus of hydrological model calibration and evaluation, despite other potential objectives, including water quality management, flood protection, and 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 the performance of downscaled and bias corrected soil moisture calibrated models against streamflow calibrated models both under single and multi-objective scenarios on field scale soil moisture estimation performance. Downscaled satellite soil moisture data and streamflow data are used to calibrate a Soil and Water Assessment Tool – Variable Source Area model initialized using topographic index classes to create hydrologic response units. In-situ soil moisture measurements at 25 locations across a 4-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 performance in estimating streamflow. The multi-objective calibration using streamflow and satellite soil moisture improved overall model performance both in estimating streamflow and soil moisture. A three-class topographic index hydrologic response unit definition allowed for adequate representation of saturation excess runoff process. Downscaling enabled calibration in a small 14 km^2 watershed using coarse satellite soil moisture data.

1 INTRODUCTION

Many parameters used in process-based hydrological models are difficult to determine or measure. Hence, parameter estimation and model calibration are used to ensure that a model

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

suitably represents a hydrologic system (Pechlivanidis et al., 2011). Watershed streamflow response is often the focus of hydrological model calibration and evaluation, despite many other potential objectives including water quality management, flood protection, agricultural management. Streamflow data is often used to calibrate a model because it is relatively easy to acquire and is a good integrator of the hydrological mass balance, as well as various processes occurring in the watershed, such as runoff generation, soil moisture redistribution, and evapotranspiration. However, calibrating a model on streamflow, when other processes are (also) of interest, may inadequately represent these other processes.

Calibrating models on hydrologic processes, such as soil moisture, requires sufficient information on these variables. However, at a watershed scale, direct and accurate soil moisture observation is time consuming and expensive (Vereecken et al., 2015). While methods exist to facilitate direct measurement of soil moisture, including time domain reflectometry (TDR), frequency domain reflectometry, and physical methods, such as the traditional gravimetric sampling, using these or similar point measurement techniques to monitor soil moisture variability in heterogenous watersheds requires an extensive network of measurement points (Brocca et al., 2010).

Distributed and continuous remotely sensed soil moisture data are becoming increasingly available, opening new avenues for incorporating and estimating soil moisture variability in hydrologic modelling (Brocca et al., 2017). Satellites dedicated to estimating the average surface moisture condition at several km resolution have become more common. The European Space Agency (ESA) Soil Moisture and Ocean Salinity (SMOS), the first mission dedicated to soil moisture (Mascaro et al., 2011, https://earth.esa.int/eogateway/ missions/smos), is one example. The European Space Agency Climate Change Initiative soil moisture product has

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

daily temporal and 0.25^0 (~25 km) spatial resolutions (Han et al., 2020; Kundu et al., 2017). The NASA Soil Moisture Active Passive (SMAP) satellite mission is another example designed to collect surface soil moisture at 36 km spatial resolution at a daily temporal resolution (O'Neill et al., 2018). The Advanced Scatterometer (ASCAT) (H SAF, 2021) and Advanced Microwave Scanning Radiometer 2 (AMSR2) (Cho et al., 2015) are additional examples that provide soil moisture products, ranging in resolution from 10-25 km.

Previous studies have attempted to improve hydrological model performance by incorporating satellite soil moisture data into hydrological modelling frameworks. For instance, Nanda et al., (2023) used Enhanced SMAP L3 9 km resolution product (SPL3SMP_E) to calibrate the Variable Infiltration Capacity model reporting significant improvement in streamflow and drought estimation. Rajib et al., (2016) using AMSR ~1 cm soil moisture to calibrate a Soil and Water Assessment Tool (SWAT) model reported improved surface soil moisture estimation (~1cm) with no improvement in streamflow estimation and on soil moisture for deeper soil layers, which they attributed to SWAT's structural deficiency in its evapotranspiration mechanism. They showed soil moisture estimates for deep layers improved when in-situ observed (0-600mm) data from a single sensor is used together with streamflow to calibrate SWAT at the hydrologic response unit (HRU) level. However, their overall reported goodness of fit values for soil moisture remained low (Kling Gupta Efficiency = 0.14 - 0.35, R^2 = 0.11 - 0.25) for all scenarios tested. This overall poor performance can also be due to the direct use of point scale measurement of soil moisture as a representative estimate for HRU scale average soil moisture conditions. López López et al. (2017) showed that using several products (evapotranspiration, soil moisture, and streamflow) together to calibrate SWAT resulted in improved streamflow predictions than using soil moisture alone when

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

compared to estimates from a streamflow-calibrated model. In contrast, Dangol et al. (2023) calibrated SWAT using satellite soil moisture alone and improved soil moisture performance but reduced streamflow estimation performance. In addition, multi-objective calibration showed no improvement compared to calibration solely on streamflow. Reported improvements in soil moisture performance were not evaluated against in-situ soil moisture measurements, which is important given the uncertainty surrounding satellite soil moisture products. Others incorporated satellite soil moisture data using data assimilation techniques for updating model state instead of direct adjustment of model parameter values (Azimi et al., 2020; De Santis et al., 2021; Patil & Ramsankaran, 2017; Sun, 2016; Wakigari & Leconte, 2023) and reported improved model simulation performance for streamflow. Fewer 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). For instance, Rajib et al. (2016) compared model estimated soil moisture against in-situ observations for both streamflow only and multi-objective model calibration; however, they reported low fitness values likely due to the scale of comparison, point measurements up to ~ 2 km^2 average model estimate. And 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 (> 2km^2), and additional effort is required to inform field-scale management applications.

There are several challenges to incorporating remotely sensed satellite soil moisture products into hydrological model calibration. The resolution of satellite soil moisture products presents a challenge for use in small watersheds of size less than the soil moisture product resolution. Studies that use satellite soil moisture data for model calibration occur primarily in watersheds

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

larger than ~ 700 km^2 (Dangol et al., 2023; Eini et al., 2023; López López et al., 2017; Rajib et al., 2016). Downscaling satellite soil moisture data to capture finer resolution variabilities may extend the use of satellite soil moisture data for constraining watershed model parameters in watersheds < 100 km^2.

In this work, a machine learning based downscaling technique is applied to generate high resolution (500 m) soil moisture data. In addition, while satellite soil moisture may represent average soil moisture condition at a watershed scale adequately, at a finer scale bias correction may be needed to ensure the range of soil moisture variability observed in in-situ measurements id suitable captured. The overall objective of this work was to evaluate the use of soil moisture data to calibrate a watershed model in a small saturation excess runoff dominated watershed. Specifically, to incorporate downscaled satellite soil moisture data into a high-resolution Soil and Water Assessment Tool (SWAT) - Variable Source Area (VSA) model (Easton et al., 2008) to improve soil moisture and streamflow estimates, and to quantify model parameter uncertainty under single and multi-objective calibrations. As illustrated in previous studies, SWAT-VSA can capture fine scale variabilities in runoff generation adequately by informing model structure using the topographic index (TI) in watersheds where saturation excess controls runoff generation (Beven et al., 2021). We compare the accuracy of soil moisture estimates from models calibrated against streamflow (SF), downscaled soil moisture (DSM), and a multi-objective (MO) streamflow/soil moisture model against in-situ soil moisture measurements at a fine spatial scale. An added benefit of the method is that it opens model application to areas without streamflow gaging stations.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

2 MATERIAL AND METHODS

2.1 Soil Moisture Data

2.1.1 SMAP Soil Moisture and Downscaling

The NASA Soil Moisture Active Passive (SMAP) is a global surface soil moisture acquisition mission (Entekhabi et al., 2014; O'Neill et al., 2023). The mission uses an L-band radiometer and L-band radar. The two instruments together meet the mission requirements of 0.04 m^3 m^{-3} accuracy at 9 km resolution (Entekhabi et al., 2014). However, the radar failed three months into the mission limiting data resolution to the radiometer sensor, currently 36 km. To overcome this gap in producing finer resolution products several methods have been applied. Interpolation techniques were used to generate a product at 9 km resolution (Chan et al., 2018); a data assimilation procedure and radar data from Sentinel-1 were used to generate a product at 3km resolution (Das et al., 2018); machine learning algorithms produced data at 1 km resolution (Abbaszadeh et al., 2021); and incorporating Kalman Filter into the Modified Palmer Two-Layer soil moisture model produced the National Aeronautics and Space Administration (NASA) and the United States Department of Agriculture (USDA) Enhanced SMAP at 10 km resolution.

The machine learning tool, 'mlhrsm' package in R (Peng et al., 2024) was used to further downscale the NASA-USDA Enhanced SMAP to 500 m resolution data for use in model calibration. The mlhrsm package in R uses a pretrained quantile random forest model for downscaling. The random forest model is trained using Sentinel-1 backscatter, MODIS land surface temperature, Landsat 8 (surface reflectance, NDVI and NDWI), United States Geological Survey (USGS) 10 m Digital Elevation Model (DEM), POLARIS (clay, sand and

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

bulk density), and NLCD land cover. The downscaling algorithm returns soil moisture data as volumetric water content (VWC) for a target region at the selected 500 m resolution. The data covers the period from April 2015 to August 2022.

2.1.2 In-situ Soil Moisture

In-situ soil moisture was collected on 20 dates from 25 randomly selected points in a 4.2 ha pasture in the 1-3 days following precipitation events for the period from March 2023 to January 2024. 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). The daily average field scale soil moisture was estimated from the 25-point measurements by using TI class distribution in the field as an estimator for spatial moisture distribution. Calculated field scale average soil moisture was used for model performance evaluation against model estimates across the same domain, Fig. A1. Additional details on this dataset are reported in Asfaw et al., (2025).

2.2 Study Area

Stroubles Creek is a 19.5 km long perennial stream draining a 57 km^2 watershed in the New River Valley, VA, Fig. A2. In this study, the watershed outlet, 80^0 26’ 47’’ W and 37^0 12’ 10’’ N, is selected about 1 km downstream of the flow monitoring station where the stream drains a 17.1 km^2 area. At this stream reach, the Stroubles Creek is a third order headwater stream (Hofmeister et al., 2015) formed when two tributaries, the Central Branch and the Webb Branch come together after draining the urban section of Blacksburg Town. Stroubles Creek watershed is located in Montgomery County, Virginia. It is within the Valley and Ridge physiographic region. Geologically the area is dominated by dolomite and limestone formations; springs and

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

sink holes are also present (Ketabchy, 2018; Parece et al., 2010). The area receives 1200 mm annual precipitation of which 760 mm is subject to evapotranspiration (Asfaw et al., 2025).

The Virginia Tech StREAM Lab monitoring station, located at 80°26’ 42’’ W and 37°12’ 37’’ N, is the stream flow data source; at this monitoring station the creak drains the upper 14.5 km^2 watershed. Most of the measurements have been active since 2012. A particular interest in this study is the stage/discharge data. The watershed has 67% pervious and 32% impervious land cover (Nayeb Yazdi et al., 2019).

2.3 SWAT-VSA model

SWAT is a semi distributed watershed scale hydrologic and water quality model. To simulate surface and subsurface runoff and various chemical and sediment export, SWAT requires landuse, soil, agricultural management, weather and topographic data. SWAT-VSA is a modification to SWAT to simulate variable source area hydrology VSA (Easton et al., 2008). To accomplish this, the curve number (CN) model of runoff generation is modified to continuously redistribute the average watershed soil moisture storage, S, based on terrain properties (Easton et al., 2008; Fuka et al., 2016). SWAT-VSA in addition to soil and land use uses TI values to build hydrologic response units (HRUs) (Easton et al., 2008).

SWAT computes the soil water content for each layer individually. Infiltration to the top layer is estimated after subtracting evaporative demand and surface runoff estimates from precipitation at a daily time step. SWAT directly handles saturated gravity flows in the vertical direction as percolation. Moisture depletion during unsaturated conditions is indirectly compensated through plant uptake and transpiration and soil water evaporation in the soil layers. These unsaturated moisture depletion mechanisms in the soil layers are often optimized

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

during model calibration by using the plant evapotranspiration compensation factor (EPCO) and soil evaporation compensation factor (ESCO) parameters.

SWAT assumes homogeneous moisture distribution in each soil layer. When the individual soil layer's depth in the model is very large, the uniform soil water distribution per soil layer assumption poses a problem by averaging moisture over large vertical depths. An adjustment is required before a direct comparison can be made between SWAT computed soil moisture, the downscaled surface soil moisture, and in-situ TDR measurements, where the latter two are for the top 50 mm and 120 mm soil depths, respectively. To ensure meaningful comparison, the SWAT output is modified to write out 0-50mm layer and a 50-120 mm layer in addition to standard layers in SWAT. Consequently, adding more layers can have an added benefit of accurately simulating moisture variability in the top layers during wetting and drying. In addition, since SWAT soil moisture output only reports the available water content in depth units, it is first converted to a volumetric basis and adjusted by the water content at a permanent wilting point for the dominant soil in the watershed.

2.3.1 Model Initialization

The SWAT model initialization was developed using ArcSWAT version 2012.10_8.26 in ArcGIS Desktop 10.8.2. The 2019 landuse 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 three TI classes. Using Natural

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

Breaks from Spatial Analyst in Arc GIS, TI values were sliced 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. 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). Soils data were collected from the FAO-UNESCO Digital Soil Map (FAO, 2007). 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. To calculate daily average flow from the instantaneous stage records: first, stage was converted to flow using a rating curve developed for the location; second, a time series between the start and end dates was enumerated for each corresponding flow value including missing data using the zoo package in R (Zeileis et al., 2025); and third, mean daily flow values were calculated excluding dates with missing values for at least consecutive 12 hrs. The resulting data extended from 2011 to 2024, a total of 14 years. The data for years 2011 and 2012 were excluded due to extended periods of missing values. The first 10 years period (Jan 2013 – Dec 2021) was used for model calibration and the last two years and five months (Jan 2022 - May 2024) period was used for model evaluation.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

2.4.2 Soil Moisture

The SWAT VSA model was initialized using the USGS 3DEP 1m resolution DEM, and areas of similar landuse, soil, and TI classes were intersected to form HRUs. Enhanced SMAP grid resolution is 100 km^2, close to an order of magnitude larger than the watershed area (~14 km^2). Therefore, the downscaled soil moisture data were averaged to the watershed scale and calibration at watershed level was assumed to be adequate. After initial downscaling, we compared the mean and range in the in-situ soil moisture data of the pasture against the downscaled satellite soil moisture data. This comparison revealed the downscaled satellite data had a narrower range and less variability than measured soil moisture, with the average satellite estimated maximum soil saturated moisture content of 32%, while the in situ saturated soil moisture reached 45%. To ensure comparable results, the downscaled soil moisture data was bias corrected for those days with significant precipitation input, Eq. (1). A three-day rolling mean was applied for smoothing after bias correction:

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

Where $\theta_{s,cor}$ is the bias corrected soil moisture, 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 soil moisture, k is a scaling factor, and d is a threshold effective precipitation depth in mm calculated as equivalent value to bring the top 120 mm soil from field capacity to saturation. The bias correction procedure resulted in satellite and in-situ soil moisture data with similar mean and range.

The downscaled, watershed average, and bias-corrected data were used for model calibration. From here forward, these data are referred to simply as soil moisture data for brevity.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

2.5 Model Calibration

2.5.1 Model Sensitivity

To identify the most influential parameters for calibration of a SWAT-VSA model a sensitivity analysis was performed. A total of 20 parameters to which streamflow predictions are sensitive and which have theoretical significance for soil moisture estimation were included in the sensitivity analysis. The analysis was executed using the relative sensitivity calculated based on successively evaluated Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) values and corresponding value changes in parameters. The relative sensitivity values were calculated for model simulation from January 1, 2015, through December 31, 2019. Table 1 provides the tested parameters, and their rank based on relative sensitivity values.

2.5.2 Calibration Strategy

Calibration was performed by adjusting values of model parameters found to be influential on model outputs to maximize the agreement between observed and simulated values. The target model outputs were streamflow and average watershed soil moisture in the top 50 mm soil layer. Three model calibration approaches included calibration on streamflow, calibration on soil moisture data, and a multi-objective calibration on both streamflow and soil moisture data (multi-objective). Before the three separate calibrations were executed, parameters related to baseflow and snow processes were pre-calibrated following a stepwise calibration approach. The purpose of the baseflow and snow calibration was to find a suitable range for baseflow-related model parameters during the calibration. The snow parameters were set constant at pre-calibrated values because initial analysis indicated the values provide adequate estimation of snow fall component of the observed total precipitation. Baseflow separation was performed

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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.

The two single-objective model calibrations were performed using a differential evolutionary algorithm, an exhaustive parameter space searching algorithm using mutations, crossover, and selection minimizing the model objective function defined on model efficiency measures. The algorithm was implemented using the 'DEoptim' R package (Mullen et al., 2011). The multi-objective calibration was performed using non-dominated sorting genetic algorithm (NSGAII), a multi-objective optimization algorithm using non-dominated sorting, crowding distance calculation, selection, crossover and mutation solving for the pareto front solution for the two objectives (Bekele & Nicklow, 2007; Deb et al., 2000). The NSGA-II algorithm identified a set of pareto solutions from which a solution is selected given the modeling objective. To select the best solution from the multi-objective pareto front solutions, in addition to maximizing the objective function on streamflow and satellite soil moisture data, the model accuracy in estimating the field scale soil moisture was evaluated using the in-situ soil moisture measurements. The algorithm was implemented using the Python library 'pymoo' (Blank & Deb, 2020).

To implement the CN based VSA implementation, a three TI class initialization was used. The TI classes divided the watershed into three zones, each with assumed uniform runoff generation and incrementally lesser propensity to generate runoff from TI class 3 (wet) to 1 (dry). These class identifications were incorporated into HRU delineation. The parameter CN2 (curve number for the average soil moisture conditions), was used to estimate the watershed average storage deficit S; and was updated after each calibration iteration in the management files

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

(*.mgt) for each corresponding HRU. To distribute the value of average CN2 to class 1 (CN2-1), class 2 (CN2-2) and class 3 (CN2-3), as estimates of local storage deficit, the distribution relationship proposed in Easton et al. (2008) was used. Adjustment factors derived from this distribution were updated during each iteration based on the new estimate of the watershed average CN2. HRUs on low lying and converging landform were assigned to TI class 3 and the largest CN2 value corresponding to the smallest storage deficit, and consequently the greatest runoff. Initial estimates for CN2 were based on a simple water balance calculation using the method described in Lyon et al. (2004), while subsequent values were estimated by the optimization algorithm, but still maintaining the distribution of relative CN2 values.

2.5.3 Goodness of Fit Measures

Four complimentary goodness of fit measures, the coefficient of determination (R^2), the root mean squared error (RMSE), the percent bias (PBIAS), and the Nash-Sutcliffe efficiency (NSE) were used to evaluate model performance (Krause et al., 2005; Moriasi et al., 2007). Calibration on streamflow was performed to maximize the NSE value as this is the most widely used approach. Compared to streamflow, soil moisture typically has smaller variances, but also a longer memory (i.e., soil moisture takes longer to recede than streamflow in humid climates). Soil moisture also has upper and lower bounds limited by the soil porosity and textural properties. The NSE normalizes the variance in observed data (Krause et al., 2005) and therefore may be overly sensitive to small errors in data with small variance. The RMSE is sensitive to the magnitude of error and can be a suitable objective function to reduce absolute error when estimating data with high frequency fluctuation. It is also a commonly used metric in satellite soil moisture validation studies (Entekhabi et al., 2010).

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

2.5.4 Parameter Uncertainty

During calibration, DEoptim was set up to evaluate 13 parameter vectors in each iteration for a total of 50 iterations, over 650 parameter vectors in total. Parameter uncertainty was quantified using the parameter vectors, which yielded streamflow estimation performance of NSE ≥ 0.5, soil moisture estimation performance of RMSE ≤ 0.05 $m^3\ m^{-3}$, 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):

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

Where, Po is parameter value from parameters vectors which fulfilled the selection criteria, and $R_{min/max}$ are initial parameter ranges.

3 RESULTS

Table 1 presents the model sensitivity and calibration results. As described previously, the soil depth parameter is not calibrated but rather was adjusted during the model initialization; this ensured equivalent comparison between observed and simulated soil moisture (Table 1). As explained in section 2.5.2, the CN2 parameter adjustment factors were updated in each iteration based on the watershed average CN2 estimate, and the method presented in Easton et.al. (2008). The adjustment factors distributed the watershed level storage deficit to local storage deficit following TI classification of HRUs. Parameters controlling runoff processes and soil properties (CN2, Bulk Density, Available Water Content (AWC), ESCO, Saturated Hydraulic

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

Conductivity (Ksat), EPCO) in Table 1, were found to be influential across calibration approaches, while parameters controlling baseflow process were less influential. Calibration of the CN2 and Bulk Density parameters resulted in similar values across calibration approaches, while AWC, ESCO, Ksat and EPCO were substantially different.

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	2.7
‡ 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	5.3
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
¶ Calibration on streamflow (SF); Calibration on soil moisture (DSM); Calibration multi-objective (MO)

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

3.1 Streamflow Calibration

The streamflow model calibration was carried out to maximize NSE value and resulted in good agreement between daily modelled and observed streamflow. After the final calibration, NSE, RMSE, and PBIAS values were 0.58, 0.32, -4.1%, respectively. As shown in Figure 1, the streamflow calibrated model captured baseflow well, and while the timing of high flows was well captured, the model occasionally underestimated peak flows with an overall prediction bias of -4.1 %. The streamflow calibrated model soil moisture estimates when compared to the soil moisture data have RMSE, R^2 and NSE values of 0.07, 0.50 and -0.64. The model explained 50% of the soil moisture variability in the soil moisture data with an RMSE of 0.07. However, as shown in Fig. 2 and Fig. A3, the timing of the estimated soil moisture peaks was mismatched as indicated by the poor NSE value.

3.2 Soil Moisture Calibration

Soil moisture model calibration was performed to minimize the RMSE between measured and modeled soil moisture in the 0 - 50 mm soil layer. The calibration resulted in a RMSE value of 0.05 $m^3 m^{-3}$. The model explained 50% of the soil moisture variability in the soil moisture data and improved estimation of the soil moisture peaks with an NSE of 0.12, Figure 2. The model underestimated soil moisture, as illustrated by proportion of data above the 1:1 line in Fig. 2 and the temporal variability in Fig. A3. The model's daily stream flow estimation performance was satisfactory with NSE, RMSE, and PBIAS values of 0.54, 0.03 m^3/s, and 28.7 %, respectively (Figure 1Figure 1), with moderately overestimated low flows, and well predicted peak flows. The overall bias of the soil moisture only calibration was 28.7%, attributable to poor low flow prediction.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

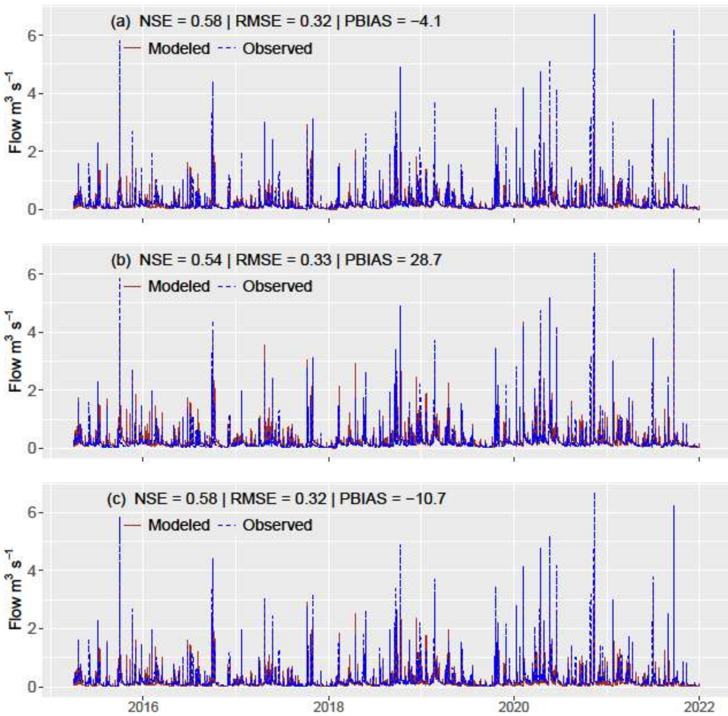

Figure 1: Model streamflow prediction performance calibration period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

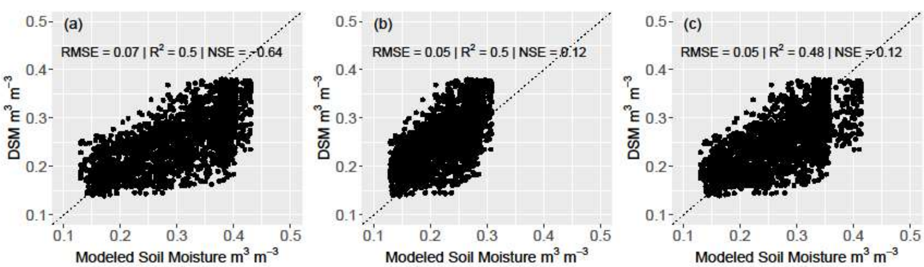

Figure 2: Model soil moisture estimation performance during the calibration period compared against downscaled and bias corrected soil moisture data calibrated on a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

3.3 Multi-objective Calibration

The multi-objective model calibration optimized soil moisture and streamflow simultaneously. The algorithm returned 14 candidate solutions on a pareto front. Among the candidate models, the best model was selected based on the performance against in-situ soil moisture measurements. The parameter values of the multi-objective calibrated model are presented in Table 1. The model showed satisfactory performance in streamflow estimation with NSE, RMSE, and PBIAS values of 0.58, 0.32 $m^3 m^{-3}$, and -10.7 %, respectively, Figure 1.

The RMSE, R^2, and NSE values for soil moisture estimation were 0.05 $m^3 m^{-3}$, 0.48, and 0.12, respectively. The performance shows that the model was able to explain 48% of the soil moisture variability in the observed soil moisture data. Model soil moisture estimates also showed better correspondence with measured soil moisture data with improved alignment on the one-to-one line when compared to the streamflow model, Figure 2.

3.4 Parameter Estimation and Water Balance Evaluation

The CN2 values did not differ substantially between the three models. The average CN2 values were 42, 41.4, and 46.7 for the streamflow, multi-objective and soil moisture models respectively, Table 1. This is also evident from the surface runoff component in the water balance values, which range between 19.3% and 23.7%, Figure 3. Among the three calibration approaches the soil moisture only calibration resulted in substantially different ET and lateral flow. The majority of the incoming precipitation returns to the atmosphere in the form of ET with the remaining water balance eventually contributing to streamflow with little to no deep percolation.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

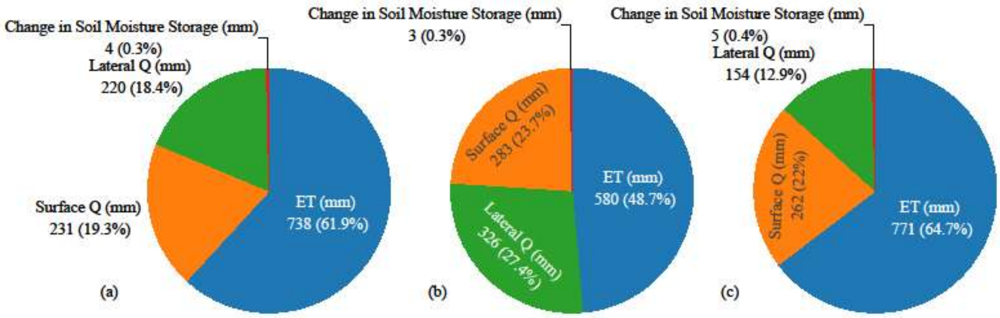

Figure 3: Model water balance estimation a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

3.5 Model Evaluation and Comparison

During the model evaluation period (01 Jan 2022 – 31 May 2024) all three models showed satisfactory streamflow estimation performance with NSE values of 0.55 – 0.56 and RMSE 0.25 $m^3\ m^{-3}$, Figure 4. The soil moisture calibrated model showed an over-estimation bias on daily streamflow estimation average over the simulation period of 18.6 %, primarily during low flows; while streamflow and multi-objective calibrated models showed an under-estimation bias of -11.9 and -21.7%, respectively, Figure 4.

The soil moisture measurements are used as the primary data for model performance evaluation of soil moisture estimates from each of the models. At the field scale, the performance of the three models in estimating soil moisture in the topsoil layer (50mm) is evaluated using RMSE, R^2, and PBIAS. The streamflow calibrated model explained 84% of the variability ($R^2 = 0.84$), while soil moisture and multi-objective calibrated models explained 88% of the soil moisture variability ($R^2 = 0.88$), Fig. 5. The streamflow calibrated model over-predicted moderate to high soil moisture conditions while the soil moisture calibrated model under predicted, Fig. 6.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

The multi-objective calibration reduced RMSE of model estimated soil moisture compared to the stream flow only and soil moisture only calibrated models from 0.05 $m^3 m^{-3}$ to 0.03 $m^3 m^{-3}$ and PBIAS from 9.8 and -15.7 to -0.8, Fig. 5. The time series plot, Fig. 6, also shows that the streamflow calibrated model performs better for low soil moisture conditions compared to high soil moisture conditions.

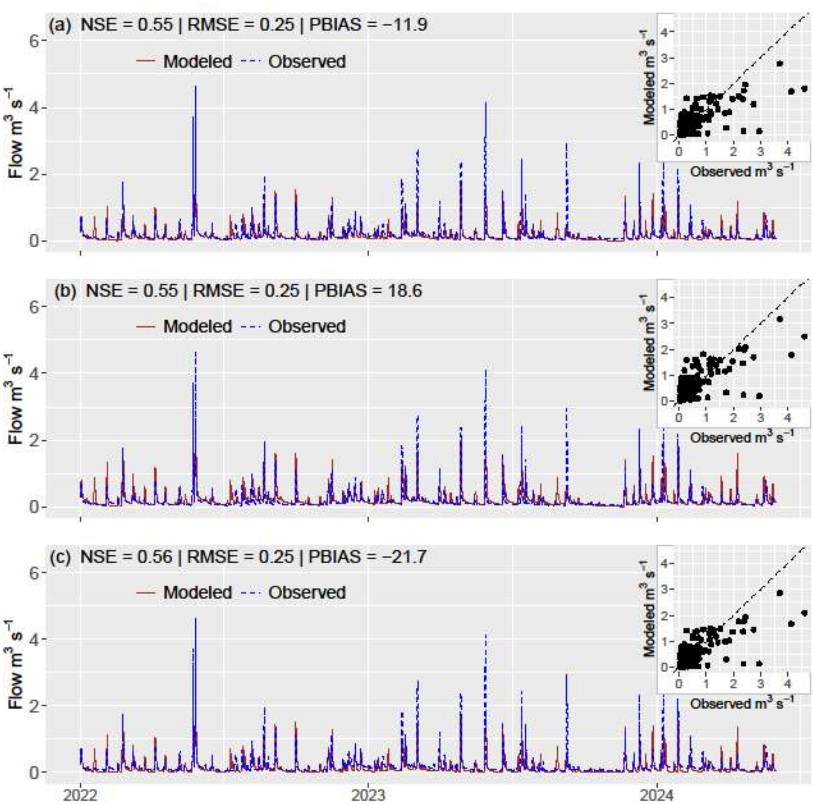

Figure 4: Model streamflow estimation performance evaluation period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

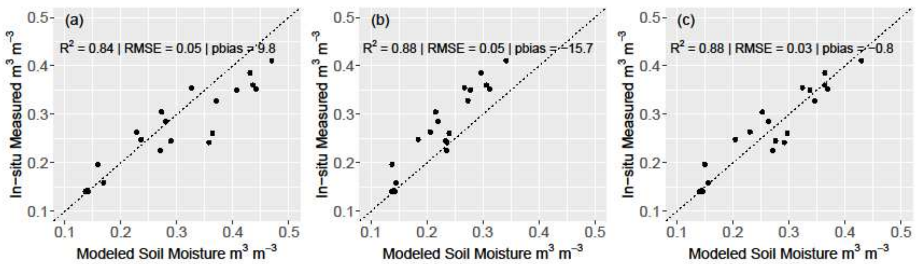

Figure 5: Soil moisture estimation performance of the three models in the evaluation period at field scale against field scale average soil moisture estimate from in-situ measurements.

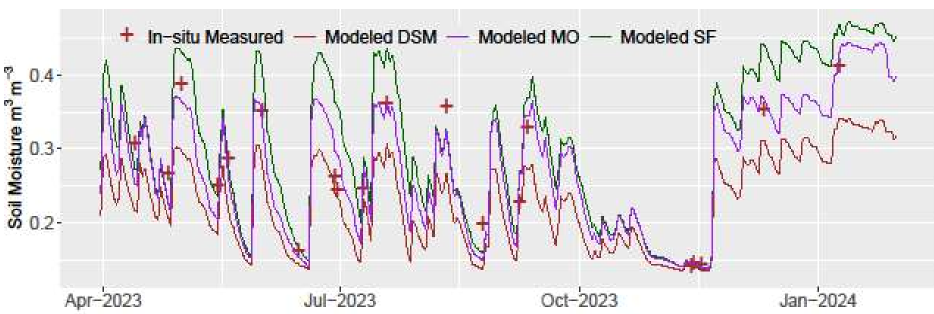

Figure 6: Temporal variability of modeled and measured soil moisture for the three calibration approaches average over the top 120mm soil layer; streamflow only (SF), soil moisture only (DSM), and Multi-objective (MO).

4 DISCUSSION

4.1 Streamflow Calibration

The streamflow only calibration yielded a satisfactory NSE of 0.58. A slightly better NSE value of 0.60 was reported for streamflow by Thilakarathne et al., (2018) although they used only a 2- year stream flow record for model calibration and perhaps their model may not have seen a wide range of variability in streamflow compared to our calibration using ~10- year flow

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

record. Streamflow calibrated parameter values are presented in Table 1. Parameters describing soil properties - Bulk Density, AWC, and Ksat - increased from values in the soils database by -7%, 155% and 136%, respectively. Indeed, Buell, (2022) and Fuka et al. (2016) showed that large scale soil databases may not be representative of local soil properties such as texture, horizon thickness, and organic matter content. Therefore, allowing more variation in soil properties parameters during calibration is justified.

4.2 Soil Moisture Calibration

Calibrating the model on soil moisture improved the model's soil moisture performance but slightly reduced streamflow performance for the calibration period, Fig. 1. Reductions in streamflow performance when calibrating soil moisture are reported in several studies (Dangol et al., 2023; Kofidou & Gemitzi, 2023). However, the scales of the reductions are different. Kofidou & Gemitzi, (2023) reported a reduction in NSE from 0.58 to 0.51. In contrast, Dangol et al. (2023) reported a decline in the model streamflow performance with the NSE declining from 0.56 to -0.22. These inconsistencies in reported model performance can emanate from the type and resolution of satellite data used in the study, the data preprocessing steps such as bias correction, model structure and resolution, or from the runoff generation mechanism in the watershed, and soil moisture variability. Dangol et al. (2023) attributed poor model performance to the quality of remotely sensed products and suggested careful assessment. Here, we note that preprocessing bias using effective precipitation as described in the methods improved the performance of the downscaled soil moisture data for model calibration.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

4.3 Multi-objective Calibration

The multi-objective calibrated model showed satisfactory performance for both streamflow and soil moisture estimation. The multi-objective model also showed greater temporal variability compared to the soil moisture only model, Fig. A3. This may be related to improved parameter estimation, as multi-objective calibration constrains parameters controlling both soil moisture and streamflow processes simultaneously. Overall, the multi-objective calibrated model was able to match the performance of the streamflow only calibrated model for streamflow estimation and the performance of soil moisture only calibrated model for soil moisture estimation.

Investigating the utility of multi-objective calibration in hydrological modeling using soil moisture, evapotranspiration, and surface runoff products on 20 watersheds in the lake Michigan watershed, Mei et al. (2023) found that multi-objective calibration improved model performance for evapotranspiration, soil moisture, or surface runoff but with a reduction in streamflow performance compared to model calibrated on streamflow only. Duethmann et al. (2022) also reported improvement in soil moisture estimation with a concurrent reduction in streamflow performance as compared to a streamflow only calibrated model. Mei et al. (2023) noted the reduction in streamflow estimation performance was the least when using soil moisture compared to when using ET or runoff products in addition to streamflow. In addition both Duethmann et al. (2022) and Mei et al. (2023) reported model calibration on streamflow and soil moisture improved ET simulation as well, which Mei et al. (2023) attributed to improved representation of soil moisture variability in the multi-objective model while Duethmann et al. (2022) attributed it simply to difference in parameter values. Their findings are in line with our results except streamflow performance of the multi-objective model is equivalent to the streamflow model with a slight increase in bias. Other studies have also reported similar findings using multi-objective calibration with varying degrees of success on soil moisture estimation performance and corresponding reduction in streamflow estimation performance as compared to model calibrated on streamflow only (Kofidou & Gemitzi, 2023; Rajib et al., 2016). Comparing results across studies requires caution, as satellite soil moisture products differ in sensing depth, resolution, and post-processing. Additionally, most studies use distinct scaling and smoothing methods, such as the soil water index (Wagner et al., 1999), to align satellite data with reference soil depths or in-situ measurements.

In the multi-objective calibration, model parameters were selected based on model performance defined on objective functions optimizing both streamflow and soil moisture. Theoretically, given adequate temporal and spatial resolution, model structure, and the calibration approach, the measured soil moisture data could be expected to complement the streamflow data by constraining the antecedent moisture conditions (Brocca et al., 2017; Wagner et al., 2007). This leads to improved prediction of both soil moisture and streamflow. In this regard, the bias correction approach, based on effective precipitation, used to enhance the temporal fluctuation of the soil moisture data may have aided in improved model estimation of both streamflow and soil moisture.

4.4 Parameter Estimation and Water Balance Evaluation

The CN2 values for TI class 1 (18.3 to 22.3), when distributed using the adjustment factors discussed in the methods, indicate that areas under TI class 1 contribute very little to surface runoff, TI class 1 covers 56% of the watershed area but generates only 9% of watershed runoff per unit area. At the calibrated CN2 values, TI class 3, 6% of the watershed area generates

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

~30% of total surface runoff. This is not unusual for saturation excess dominated watersheds, where surface runoff occurs on low lying and converging planform areas of limited spatial extent that receive subsurface moisture flux from upslope areas (Dahlke et al., 2009; Easton et al., 2008; Lyon et al., 2004). Soil moisture variability due to surface and subsurface flux exchange in the watershed is indirectly estimated by distributing CN2 values according to the local storage deficit (Dahlke et al., 2009; Easton et al., 2008). The SURLAG (surface runoff lag time) coefficient for the streamflow only calibrated model is higher than the values for the soil moisture and multi-objective calibrated models, yet this difference has a small effect in delaying surface runoff from reaching the stream outlet as the time of concentration in these watersheds is less than 1.5 hrs.

The difference in ET and lateral flow components in the soil moisture only calibrated model as compared to the other two models may be due to the reduced soil moisture variability and reduced AWC in the soil moisture only calibration, which had a lower mean and coefficient of variation (CV), compared to soil moisture estimate from the streamflow and multi-objective calibrated models, Table 2. Although the soil bulk density was high for soil moisture calibration, Table 1, which compensated for reduced AWC via reductions in soil porosity; looking at Fig. A3 and Fig. 6 it was clear that soil moisture remained mostly under 0.40 m^3 m^{-3} for all models. This indicates that higher porosity values in the streamflow only and multi-objective calibrated models were less frequently activated for moisture storage. Mean, standard deviation, and CV values for soil moisture estimates of the three models are presented in Table 2. The lowest mean and CV values were for the soil moisture only calibrated model, which was comparable to the measured soil moisture data but less similar to the estimates from the streamflow calibrated model. When calibrating on streamflow, only the algorithm allows for

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

greater variability in soil moisture related parameters because streamflow has higher CV compared to soil moisture. In contrast, the soil moisture model calculates objective function changes directly on soil moisture estimates and is thereby influenced by the characteristics of the soil moisture data.

Other parameters that affect ET such as ESCO and EPCO had more effect on the multi-objective calibrated model where both parameters force more ET from lower soil layers, Table 1. Unsaturated moisture flux between soil layers is indirectly modeled in SWAT using two equations controlled by the ESCO and EPCO parameters (Neitsch et al., 2009). The soil moisture model has both ESCO and EPCO close to 1 compensating each other – that is EPCO allows for more ET to be accessed from lower soil layers and ESCO allows for less, while for streamflow and multi-objective calibrated models both parameters allow more ET to come from lower soil layers, Table 1. Groundwater and baseflow parameters have little effect on the results with close to zero percolation estimated across all three models.

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

Soil Moisture	**Mean**	**Standard Deviation**	**Coefficient of Variation**
Soil moisture data	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

4.5 Model Evaluation and Comparison

Similar to findings in other studies incorporating soil moisture in model calibration improved soil moisture estimation, for example, Duethmann et al. (2022), Kofidou & Gemitzi, (2023), and Rajib et al. (2016) showed multi-objective calibration improved model soil moisture estimation performance when compared to streamflow only calibrated models. In contrast,

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

Dangol et al. (2023) reported that the use of multi-objective calibration (streamflow with satellite products) did not necessarily improve overall model performance. Our result suggests that multi-objective calibration improved soil moisture predictions substantially without deteriorating streamflow estimates.

The original SMAP mission objectives were to achieve a RMSE of 0.04 $m^3 m^{-3}$ or less at original mission resolution (Colliander et al., 2017; Entekhabi et al., 2014). The product used in this study is reported to meet an RMSE of 0.08 $m^3 m^{-3}$ against in-situ measurement at the downscaled resolution (Peng et al., 2024). Although, the in-situ measurements used in this study do not overlap in time with the mlhrsm downscaled SMAP mission data affording no direct evaluation – the multi-objective calibration of SWAT-VSA model using soil moisture data improved the modeled soil moisture estimates at the field scale, Fig. 5 and Fig. 6. All three models underestimated peak flows during the evaluation period. This may be due to the quality of the precipitation data used or due to the presence of substantial urban/impervious surfaces in the watershed, which are typically less well simulated by SWAT.

4.6 Parameter uncertainty

Among the advantages of multi-objective calibration reported in previous studies was the reduction of parameter uncertainty (Kundu et al., 2017; Rajib et al., 2016; Silvestro et al., 2015). Equifinality is a well-known problem in model calibration where combinations of different parameter values may result in equally plausible objective function solutions (Beven, 1993). To evaluate parameter uncertainty across the calibration approaches a normalized uncertainty score was calculated using Eq. (2), Fig. 7. Using this approach, a wider range or spread in parameter values indicates higher uncertainty – i.e. as the iterative search space for

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

the optimum parameter value widens the possibility of the optimization algorithm arriving at several equally performing solutions increases, Fig. 7. In other words, the algorithm required a wider range of parameter values to find a satisfactory solution.

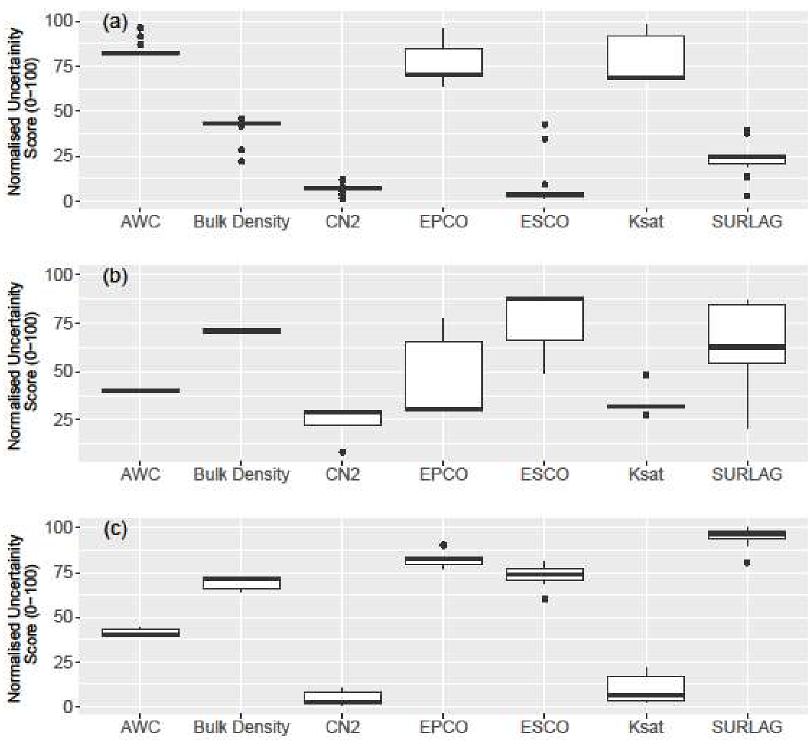

Figure 7: Parameter uncertainty estimate derived from DEoptim calibration iterations for the models calibrated on a) streamflow only, b) soil moisture only and, c) multi-objective calibration. The height of the boxplot demonstrates the range of different values the parameters took while yielding acceptable model performance. The values are calculated using normalized uncertainty score (Kumar & Merwade, 2009). Where 0 and 100 represent the minimum and maximum parameter value as defined by the normalized calibration range.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

The AWC, Bulk Density, and Ksat parameters show lower relative uncertainty when soil moisture is part of the calibration objective. This is not surprising as these parameters directly impact the soil moisture state, Fig. 7b and Fig. 7c. Moreover, the values the parameter take within the calibration range are different than when calibrating on streamflow only, for example, Ksat takes high values for streamflow only calibration and low values for the other two within the calibration range – hence the extent to which the parameters affect model behavior is different for soil moisture and streamflow calibration. CN2 and SURLAG have the lowest uncertainty, demonstrated by the height of the boxplot, when streamflow is part of the calibration objective, Fig. 7a and Fig. 7c. This is not unexpected, as AWC, Bulk Density, and Ksat have a stronger influence on soil moisture, while CN2 and SURLAG influence streamflow to a greater extent. Overall, parameter estimation uncertainty is reduced when using the multi-objective calibration approach similar to findings in Rajib & Merwade, (2016) and Silvestro et al. (2015) – this was likely because the parameters were constrained on multiple objectives, which limited the possibility for inter-parameter compensation. Other parameters, such as EPCO and ESCO, although not physically based, also display substantially reduced uncertainty under multi-objective calibration.

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 showed leveraging downscaled satellite soil moisture data substantially improved estimation of temporal variability of soil moisture without deteriorating the model accuracy in streamflow estimation. In comparison, multi-objective calibration using

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

streamflow and satellite soil moisture improved overall model performance both in estimating streamflow and soil moisture more than calibration individually for streamflow and soil moisture. The model calibrated on soil moisture only showed minimal decline in streamflow estimation performance for the calibration and evaluation period compared to the model calibrated on streamflow only. It also resulted in improved soil moisture estimation performance. Machine learning based satellite soil moisture downscaling, using the 'mlrhsm' package in R, provided adequate data to calibrate a high-resolution SWAT-VSA model in a small watershed. Parameter uncertainty varied with calibration data and the calibration approach, soil parameters were better constrained with soil moisture data, and streamflow parameters with streamflow data. Multi-objective calibration reduced parameter uncertainty. Additional investigation is required to replicate this approach in diverse watersheds as well as evaluating both surface and deep layer soil moisture performance. Long-term water balance estimates varied widely across the three calibration approaches. Further investigation, for example using in-situ ET measurement, is needed to assess how soil moisture data influences watershed water balance components. The findings in this study have implications for use of watershed models in ungauged basins for both streamflow and soil moisture estimation. This is particularly significant as remotely sensed satellite soil moisture products have global coverage.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

APPENDICES

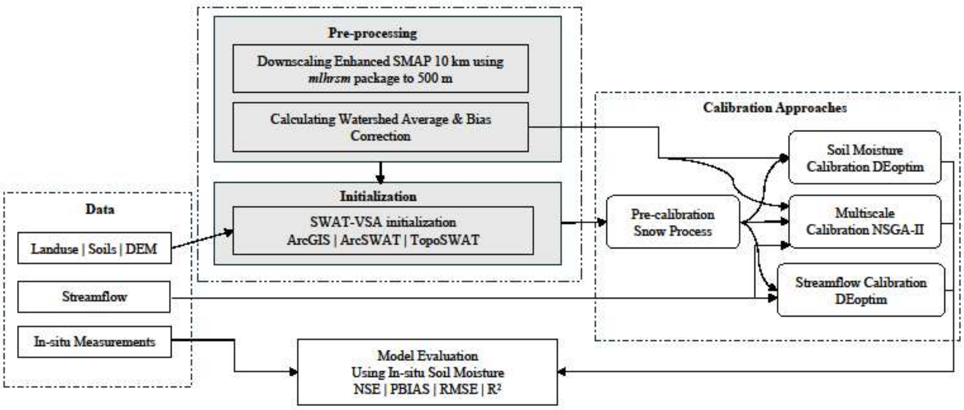

Fig. A1: General workflow of the data pre-processing, model calibration and model performance evaluation.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

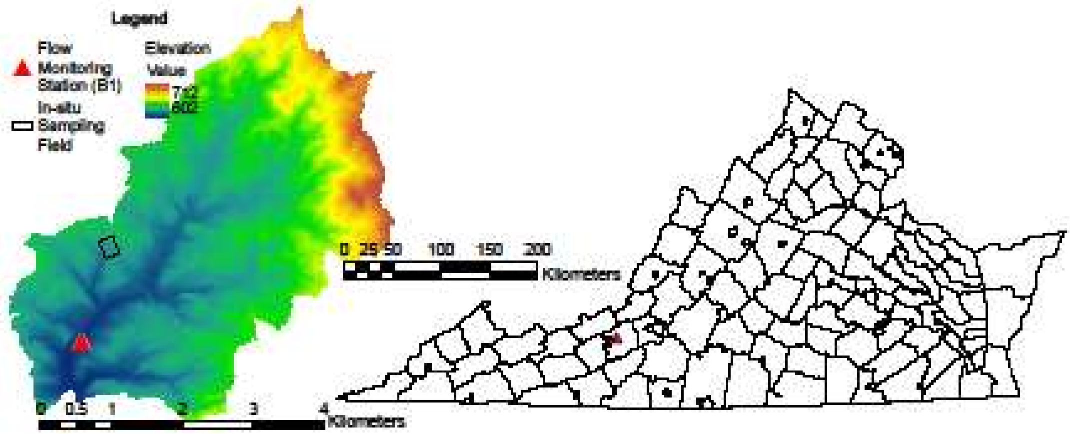

Fig. A2: Location map of the Stroubles Creek

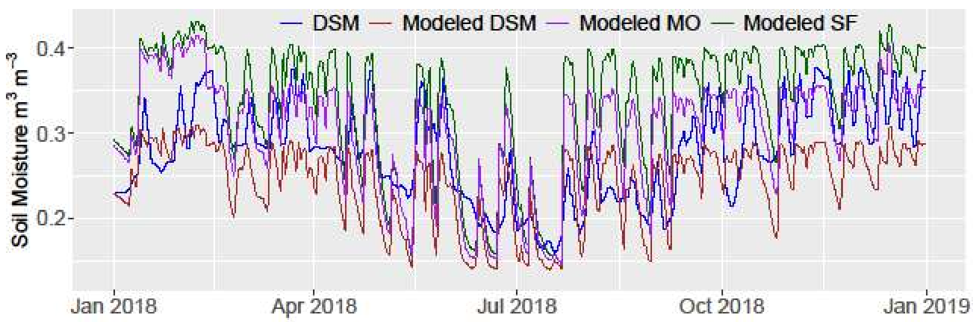

Fig. A3: Time series of modeled surface soil moisture (50 mm) from the three calibration approaches and DSM data; calibrated on DSM data (Modeled DSM), Multi-objective calibration using DSM data and streamflow (Modeled MO), calibrated on streamflow (Modeled SF).

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

CODE AVAILABILITY

The code used to run the simulations is available in a GitHub repository. https://github.com/saizanaandezana/Stroubles_Creek_SWAT_VSA_model

DATA AVAILABILITY

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

TEAM LIST

Binyam Workeye Asfaw; Siam Maksud; Daniel R. Fuka; Amy S. Collick; Robin R. White; Zachary M. Easton

AUTHOR CONTRIBUTION

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

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

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

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

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

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

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

COMPETING INTERESTS

Authors declare that they have no competing interest.

ACKNOWLEDGEMENTS

We acknowledge USDA CPS for the financial support.

FINANCIAL SUPPORT

This research was funded by USDA CPS award number 2021-67021-34769.

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

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

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

Brocca, L., Ciabatta, L., Massari, C., Camici, S., & Tarpanelli, A. (2017). Soil Moisture for Hydrological Applications: Open Questions and New Opportunities. *Water*, *9*(2), 2. https://doi.org/10.3390/w9020140

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

Buell, E. N. (2022). *Improved Environmental Characterization to Support Natural Resource Decision Making: (1) Distributed Soil Characterization, and (2) Treatment of Legacy Nutrients*. http://hdl.handle.net/10919/112013

Chan, S. K., Bindlish, R., O'Neill, P., Jackson, T., Njoku, E., Dunbar, S., Chaubell, J., Piepmeier, J., Yueh, S., Entekhabi, D., Colliander, A., Chen, F., Cosh, M. H., Caldwell, T., Walker, J., Berg, A., McNairn, H., Thibeault, M., Martínez-Fernández, J., Uldall, F., Seyfried, M., Bosch, D., Starks, P., Holifield Collins, C., Prueger, J., Van Der Velde, R., Asanuma, J., Palecki, M., Small, E. E., Zreda, M., Calvet, J., Crow, W. T., & Kerr, Y. (2018). Development and assessment of the SMAP enhanced passive soil moisture product. *Remote Sensing of Environment*, *204*, 931–941. https://doi.org/10.1016/j.rse.2017.08.025

Cho, E., Moon, H., & Choi, M. (2015). First Assessment of the Advanced Microwave Scanning Radiometer 2 (AMSR2) Soil Moisture Contents in Northeast Asia. *Journal of Meteorology. Series 2*, *93*(1), 117–129. https://doi.org/10.2151/jmsj.2015-008

Colliander, A., T.J. Jackson, R. Bindlish, S. Chan, N. Das, S.B. Kim, M.H. Cosh, R.S. Dunbar, L. Dang, L. Pashaian, J. Asanuma, K. Aida, A. Berg, T. Rowlandson, D. Bosch, T. Caldwell, K. Caylor, D. Goodrich, H. al Jassar, E. Lopez-Baeza, J. Martínez-Fernández, A. González-Zamora, S. Livingston, H. McNairn, A. Pacheco, M. Moghaddam, C. Montzka, C. Notarnicola, G. Niedrist, T. Pellarin, J. Prueger, J. Pulliainen, K. Rautiainen, J. Ramos, M. Seyfried, P. Starks, Z. Su, Y. Zeng, R. van der Velde, M. Thibeault, W. Dorigo, M. Vreugdenhil, J.P. Walker, X. Wu, A. Monerris, P.E. O'Neill, D. Entekhabi, E.G. Njoku, & S. Yueh. (2017). Validation of SMAP surface soil

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

moisture products with core validation sites. *Remote Sensing of Environment*, *191*, 215–231. https://doi.org/10.1016/j.rse.2017.01.021

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

Dangol, S., Zhang, X., Liang, X.-Z., Anderson, M., Crow, W., Lee, S., Moglen, G. E., & Mccarty, G. W. (2023). Multivariate Calibration of the SWAT Model Using Remotely Sensed Datasets. *Remote Sensing*, 2417 (22 pp.). https://doi.org/10.3390/rs15092417

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

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

Deb, K., Agrawal, S., Pratap, A., & Meyarivan, T. (2000). A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II. In M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, & H.-P. Schwefel

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

(Eds.), *Parallel Problem Solving from Nature PPSN VI* (pp. 849–858). Springer. https://doi.org/10.1007/3-540-45356-3_83

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

Easton, Z. M., Fuka, D. R., Walter, M. T., Cowan, D. M., Schneiderman, E. M., & Steenhuis, T. S. (2008). Re-conceptualizing the soil and water assessment tool (SWAT) model to predict runoff from variable source areas. *Journal of Hydrology*, *348*(3), 279–291. https://doi.org/10.1016/j.jhydrol.2007.10.008

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

Entekhabi, D., Reichle, R. H., Koster, R. D., & Crow, W. T. (2010). *Performance Metrics for Soil Moisture Retrievals and Application Requirements*. https://doi.org/10.1175/2010JHM1223.1

Entekhabi, D., Yueh, Si., & De Lannoy, G. (2014). *SMAP handbook*.

Food and Agriculture Organization of the United Nations (FAO). (2007). *FAO Digital Soil Map of the World (DSMW)*. https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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

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

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

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

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

Han, L., Wang, C., Liu, Q., Wang, G., Yu, T., Gu, X., & Zhang, Y. (2020). Soil Moisture Mapping Based on Multi-Source Fusion of Optical, Near-Infrared, Thermal Infrared, and Digital Elevation Model Data via the Bayesian Maximum Entropy Framework. *Remote Sensing*, *12*(23). https://doi.org/10.3390/rs12233916

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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

Jin, S., Dewitz, J., Danielson, P., Granneman, B., Costello, C., Smith, K., & Zhu, Z. (2023). National Land Cover Database 2019: A New Strategy for Creating Clean Leaf-On and Leaf-Off Landsat Composite Images. *Journal of Remote Sensing*, *3*, 0022. https://doi.org/10.34133/remotesensing.0022

Ketabchy, M. (2018). *Thermal Evaluation of an Urbanized Watershed using SWMM and MINUHET: A Case Study of Stroubles Creek Watershed, Blacksburg, VA* [Thesis, Virginia Tech]. https://vtechworks.lib.vt.edu/handle/10919/81977

Kofidou, M., & Gemitzi, A. (2023). Assimilating Soil Moisture Information to Improve the Performance of SWAT Hydrological Model. *Hydrology*, *10*(8), 8. https://doi.org/10.3390/hydrology10080176

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

Kumar, S., & Merwade, V. (2009). Impact of Watershed Subdivision and Soil Data Resolution on SWAT Model Calibration and Parameter Uncertainty. *JAWRA Journal of the American Water Resources Association*, *45*(5), 1179–1196. https://doi.org/10.1111/j.1752-1688.2009.00353.x

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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

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

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

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

Moore, C., & Doherty, J. (2005). Role of the calibration process in reducing model predictive error. *Water Resources Research*, *41*(5). https://doi.org/10.1029/2004WR003501

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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., & Andreadis, K. (2023). *Optimizing Hydrologic Model Soil Physical Properties with Smap Soil Moisture: A Pathway for Skillful Assessment of Streamflow and Drought*. https://doi.org/10.2139/ssrn.4635449

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Nathan, R. J., & McMahon, T. A. (1990). Evaluation of automated techniques for base flow and recession analyses. *Water Resources Research*, *26*(7), 1465–1473. https://doi.org/10.1029/WR026i007p01465

Nayeb Yazdi, M., Ketabchy, M., Sample, D. J., Scott, D., & Liao, H. (2019). An evaluation of HSPF and SWMM for simulating streamflow regimes in an urban watershed. *Environmental Modelling & Software*, *118*, 211–225. https://doi.org/10.1016/j.envsoft.2019.05.008

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2009). *Soil and water assessment tool theoretical documentation*. version 2009.

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

O'Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., & Chaubell, J. (2018). SMAP L3 radiometer global daily 36 km EASE-grid soil moisture, Version 5. *Natl. Snow Ice Data Cent*, 1–82.

O'Neill, P. E., Chan, S., Njoku, E. G., Jackson, T., Bindlish, R., Chaubell, J., & Colliander, A. (2023). SMAP Enhanced L3 Radiometer Global and Polar Grid Daily 9 km EASE-Grid Soil Moisture. *Boulder, Colorado, USA: NASA Nafional Snow and Ice Data Center Distributed Acfive Archive Center*.

Parece, T., Dibetitto, S., Sprague, T., & Younos, T. (2010). *The Stroubles Creek Watershed: History of Development and Chronicles of Research*.

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

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

Peng, Y., Yang, Z., Zhang, Z., & Huang, J. (2024). A Machine Learning-Based High-Resolution Soil Moisture Mapping and Spatial–Temporal Analysis: The mlhrsm Package. *Agronomy*, *14*(3), 3. https://doi.org/10.3390/agronomy14030421

https://doi.org/10.5194/egusphere-2025-5813
Preprint. Discussion started: 4 December 2025

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

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

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

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

Sun, L. (2016). *Streamflow and Soil Moisture Assimilation in the SWAT model Using the Extended Kalman Filter*. https://doi.org/10.20381/RUOR-4934

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

Vereecken, H., Huisman, J. A., Hendricks Franssen, H. J., Brüggemann, N., Bogena, H. R., Kollet, S., Javaux, M., van der Kruk, J., & Vanderborght, J. (2015). Soil hydrology:

Recent methodological advances, challenges, and perspectives. *Water Resources Research*, *51*(4), 2616–2633. https://doi.org/10.1002/2014WR016852

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

Wagner, W., Lemoine, G., & Rott, H. (1999). A Method for Estimating Soil Moisture from ERS Scatterometer and Soil Data. *Remote Sensing of Environment*, *70*(2), 191–207. https://doi.org/10.1016/S0034-4257(99)00036-X

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

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