Calibrating on Downscaled Satellite Soil Moisture Data Can Improve Watershed Model Performance in Predicting 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~~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 calibrations~~scenarios~~ on field scale soil moisture estimation performance. In this work, ~~D~~downscaled satellite soil moisture ~~data~~ and streamflow data are used to calibrate a Soil and Water Assessment Tool – Variable Source Area model initialized using a terrain informed process~~topographic index classes~~ 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~~ in estimating streamflow~~. The multi-objective calibration using streamflow and satellite soil moisture improved overall model performance for 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.~~ 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

~~Many parameters used in process-based h~~Hydrological model calibration~~s~~ is~~are~~ most commonly performed using streamflow observations because they are widely available and integrate catchment-scale water balance behavior ~~difficult to determine or measure. Hence, parameter estimation and model calibration are used to ensure that a model suitably represents a hydrologic system~~ (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. ~~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).~~ 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) (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 ~~metrics~~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 López et al. 2017). These trade-offs reflect differences in watershed scale, dominant runoff mechanisms, satellite sensing depth, preprocessing approaches, and model structure.

~~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 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.~~

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 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~~er~~ 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). ~~And~~ W~~w~~hile 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.

~~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 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.~~

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.

~~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 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.~~

In this study, we evaluate whether downscaled and bias- corrected satellite soil moisture data can improve internal hydrologic state estimation in a small (~14.5 km²), 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, ~~but also~~as well as through independent 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 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, receiving1200 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.

~~2.1~~2.2 Soil Moisture Data

~~2.1.1~~2.2.1 SMAP Soil Moisture and Downscaling

~~The NASA Soil Moisture Active Passive (~~SMAP~~)~~ is a global surface soil moisture acquisition mission at 36 km resolution (Entekhabi et al., 2014; O'Neill et al., 2023), using~~. The mission uses~~ an L-band radiometer and L-band radar. Several approaches~~techniques~~ were used -to post-process and increase SMAP product resolution for different applications ~~to generate a product at 9 km~~ (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)~~ produced the National Aeronautics and Space Administration (NASA) and the United States Department of Agriculture (USDA) Enhanced SMAP at 10 km resolution~~.

~~The~~In this study, satellite soil moisture derived from the Enhanced SMAP product and downscaled to 500 m resolution using ~~the~~a machine learning tool, the 'mlhrsm' package in R (Peng et al., 2024), was used~~, was used in this study 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~~downscaling applies a pretrained quantile random forest model ~~for downscaling. The random forest model is trained using~~that uses multi-sensor predictors including Sentinel-1 backscatter, MODIS land surface temperature, Landsat-derived vegetation indices ~~8~~ (surface reflectance, NDVI and NDWI), ~~United States Geological Survey (USGS)~~ a 10 m USGS ~~D~~digital e~~E~~levation m~~M~~odel (DEM), POLARIS soil properties (clay, sand and bulk density), and NLCD land~~-~~cover classes.

The downscaling ~~downscaling algorithm returns~~model outputs daily volumetric soil moisture estimates (m^3 m^{-3}) ~~data as volumetric water content (VWC) for a target region at the selected~~for each 500 m cell intersecting the watershed for ~~resolution. The data covers~~ the period ~~from~~ April 2015 to August 2022. The downscaled soil moisture ~~fields~~ ~~were~~was spatially averaged across the watershed to generate a daily watershed mean soil moisture time series used for model calibration.

~~2.1.2~~2.2.2 In-situ Soil Moisture

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

Mean f~~F~~ield- scale ~~mean~~ 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 ~~T~~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.,~~al. (2025).

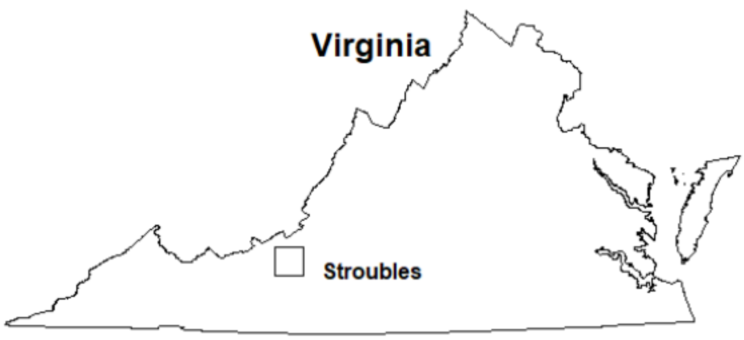
~~2.2 Study Area~~

~~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 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 km² 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.~~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~~-~~of~~to~~ SWAT ~~simulate~~ designed to represent ~~variable source area hydrology~~ VSA hydrology which is characteristic of saturation- excess- dominated landscapes (Easton et al., 2008).



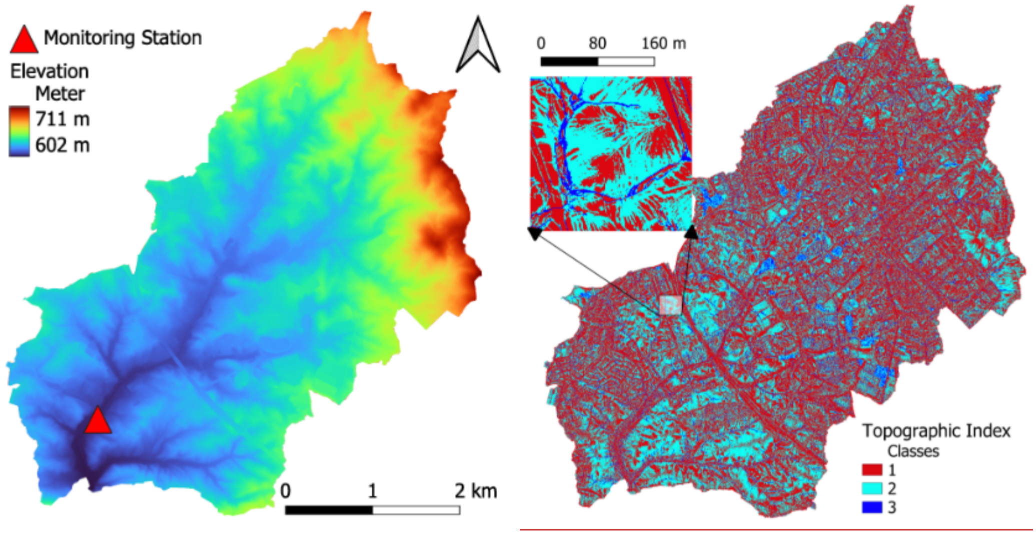
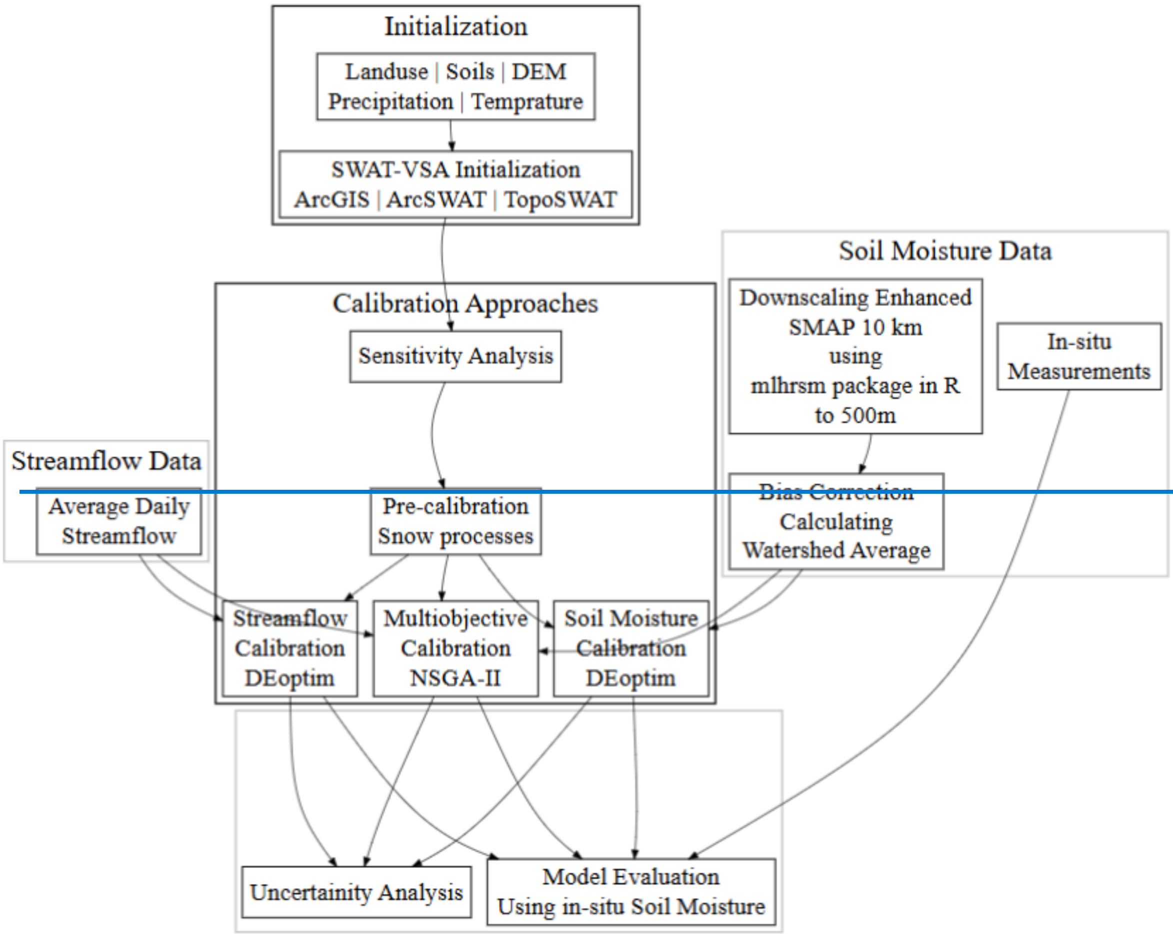


Figure 1: Location map of the Stroubles Creek (top), digital elevation model (left) and Topographic Index Class (right; magnified view of 4.2 ha pasture field inset).


Initialization
Landuse | Soils | DEM
Precipitation | Temprature
SWAT-VSA Initialization
ArcGIS | ArcSWAT | TopoSWAT
Soil Moisture Data
Downscaling Enhanced
SMAP 10 km
using
mlhrsm package in R
to 500m
In-situ
Measurements
Calibration Approaches
Sensitivity Analysis
Streamflow Data
Average Daily
Streamflow
Pre-calibration
Snow processes
Bias Correction
Calculating
Watershed Average
Streamflow
Calibration
DEoptim
Multiobjective
Calibration
NSGA-II
Soil Moisture
Calibration
DEoptim
Uncertainity Analysis
Model Evaluation
Using in-situ Soil Moisture

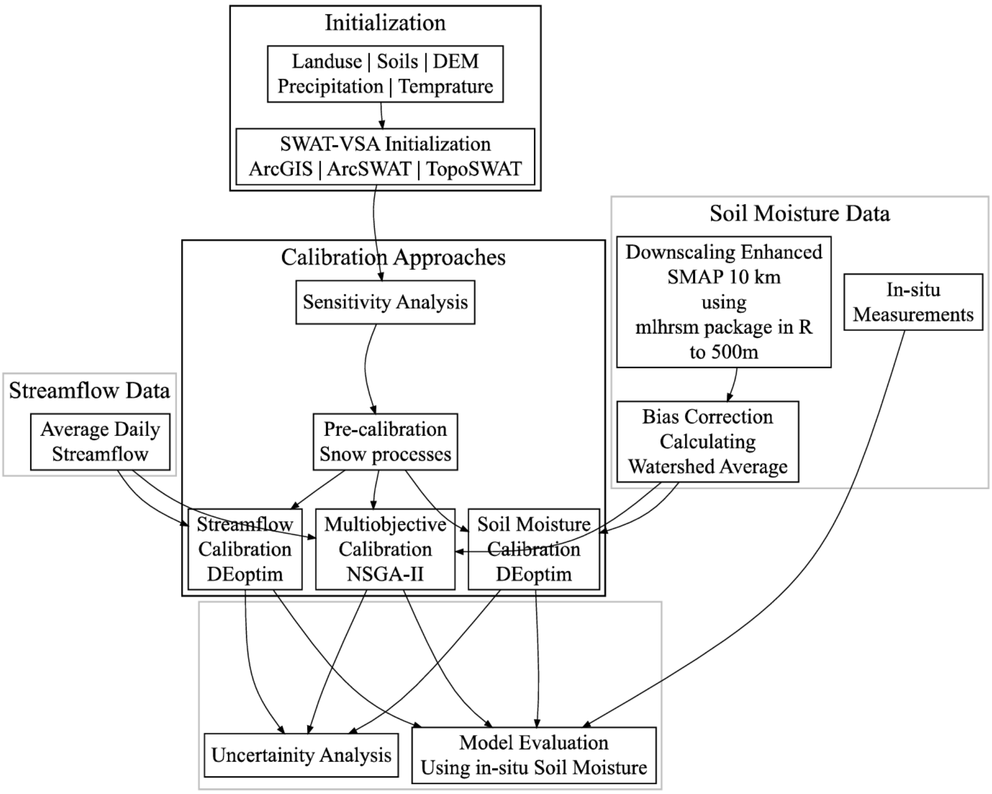


Figure 2: Workflow of data processing, model calibration, and model-performance evaluation.

~~To accomplish this~~In SWAT-VSA, the curve number (CN) based ~~model of~~ runoff formulation~~generation is modified to continuously redistribute the average watershed soil moisture storage, S, based on terrain properties~~ 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). ~~SWAT-VSA in addition to soil and land use uses~~ TI values together with soil and land use ~~information,~~information are used to define ~~build hydrologic response units (~~HRUs, which consequently ~~that~~ represent spatial variability in runoff ~~propensity~~generation and soil moisture state.~~) (Easton et al., 2008).~~

SWAT computes the soil water content for each layer individually at a daily time step. Infiltration to the surface~~top~~ layer is calculated~~estimated~~ after subtracting evaporative demand and surface runoff ~~estimates~~ from precipitation at a daily time step. ~~SWAT directly handles saturated gravity flows in the v~~Vertical drainage of excess soil water is simulated as percolation, while soil moisture depletion under unsaturated conditions occur ~~is indirectly compensated~~ through plant uptake and transpiration and soil water evaporation from~~in~~ the soil layers. These unsaturated zone processes ~~moisture depletion mechanisms in the soil layers are often optimized during model calibration by using the~~ 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.

~~SWAT assumes homogeneous moisture distribution~~With~~-~~in each soil layer. ~~When the individual soil layer's depth in the model is very large,~~ SWAT assumes ~~the~~ homogeneous ~~uniform soil water~~moisture distribution, When the model ~~per~~ soil layer are thick this assumption ~~poses a problem by~~can dampen simulated moisture variability in surface soil layers and complicate comparison with surface- sensitive satellite products and shallow in-situ measurements. ~~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 enable~~ensure~~ ~~meaningful~~depth consistent comparison among modeled, satellite- derived, and in-situ soil moisture, the SWAT soil profile was modified to explicitly simulate the ~~output is modified to write out~~ 0-50 mm ~~layer~~ and ~~a~~ 50-120 mm layers in addition to standard ~~layers in SWAT~~profile. Reported soil water content was converted from depth units to volumetric water content ~~in depth units, it is first converted to a volumetric basis and~~ adjusted relative to the~~by the water content at a~~ permanent wilting point for the dominant soil in the watershed. This modification improves 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 ~~developed~~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 three TI class generation~~es~~ from Asfaw et al. (2025). Using Natural Breaks from Spatial Analyst in Arc GIS, TI values were grouped~~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. 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 ~~a were~~ missing. ~~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 streamflow record~~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 ~~(~~January 2013 – December 2021~~)~~ was used for model calibration, and ~~the last two years and five months (~~January 2022 - May 2024~~)~~ ~~period~~ were~~was~~ reserved~~used~~ for model evaluation. The streamflow data also provides ~~for~~ an independent data source for model evaluation when ~~calibrating on~~calibrating soil moisture.

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, t~~The downscaled, 500 m resolution, soil moisture product~~data~~ ~~were~~was spatially averaged across~~to~~ the watershed to generate a daily~~scale and calibration at~~ watershed-mean soil moisture timeseries for calibration~~ level was assumed to be adequate~~. 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 essential for constraining 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 ~~topographic-index~~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 soil moisture is scaled to the watershed or field boundary in a manner consistent with the model's internal hydrologic structure.

~~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%.~~ 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 ~~ensure comparable results~~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:

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

~~W~~where $\theta_{s,cor}$ is the watershed mean downscaled and 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. 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.~~The bias correction procedure resulted in satellite and in-situ soil moisture data with similar mean and range.~~

Although calibration uses the downscaled and bias corrected satellite soil moisture data, all 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, providing an independent benchmark for field scale soil moisture dynamics.

To ensure consistent comparison across data sources, soil moisture depths were aligned between satellite estimates, model outputs, and in-situ measurements. The 0–50 mm SWAT soil layer was used for calibration against the satellite soil -moisture series, while a 0–120 mm composite layer was reserved for evaluation against field measurements (Table A1). All calibration analyses hereafter refer to the watershed- average, bias -corrected soil -moisture time series unless otherwise noted.

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.

Bias-Correction Rationale, Procedure, and Non-circularity

A parsimonious 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 ~~upper~~ soil ~~storage~~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~~plausible~~ 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 ~~tune~~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 ~~a~~the SWAT-VSA ~~model~~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~~ relevant to streamflow generation and soil-moisture dynamics were evaluated using ~~in the sensitivity analysis. The analysis was executed using the~~ relative sensitivity ~~calculated~~ based on ~~successively evaluated~~changes in Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) from~~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

Model ~~C~~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~~ targeted ~~model outputs were~~daily streamflow and ~~average~~ watershed average soil moisture in the top 0-50 mm soil layer. Three ~~model~~ calibration approaches were included: 1) ~~calibration on~~ streamflow only, ~~calibration on~~ 2) soil moisture only~~data~~, and 3) a multi-objective calibration ~~on~~using both streamflow and soil moisture data ~~(multi-objective)~~. ~~Before the three separate~~Prior to calibrations, ~~were executed, parameters related to~~ baseflow and snow processes were pre-calibrated following a stepwise calibration approach to constrain parameter ranges. ~~The purpose of the baseflow and snow calibration was to find a suitable range for baseflow-related model parameters during the calibration. The s~~Snow parameters were subsequently held~~et~~ constant ~~at pre-calibrated values because~~as initial analysis indicated the values provide adequate ~~estimation of snow fall component of the observed total~~

~~precipitation~~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.

~~The two s~~Single-objective model calibrations were performed using a differential evolutionary algorithm, an exhaustive parameter space search~~ing 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). Thirteen parameter vectors were evaluated per generation over 50 generations, for a total of 650 parameter vectors. Fifty generations was deemed sufficient after monitoring the successive diminishing returns in objective function minimization. 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) implemented using the Python library 'pymoo' (Blank & Deb, 2020). ~~The NSGA-II algorithm identified a set of~~Among pareto-optimal solutions, f~~rom 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,~~inal model selection additionally considered ~~the model accuracy in estimating~~skill in reproducing~~ the~~ field-~~-~~scale in-situ soil moisture ~~was evaluated using the in-situ soil moisture measurements~~observations. ~~The algorithm was implemented using the Python library 'pymoo' (Blank & Deb, 2020).~~

T~~o implement the CN based ~~he VSA implementation employed, ~~a ~~three TI classes ~~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)~~representing progressively wetter landscape positions.~~ These class identifications~~

~~were incorporated into HRU delineation.~~ The ~~parameter~~ CN2 parameter ~~–~~(curve number for the average soil moisture conditions), was used to estimate the watershed average moisture storage deficit S, ~~;~~ and ~~was updated after each calibration iteration in the management files (*.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~~redistributed across TI classes following the relationship ~~proposed~~developed in Easton et al. (2008)~~ was used~~. CN2 values for individual HRUs were updated at each calibration iteration based on the optimized watershed-average CN2~~ and the relationship~~. Initial ~~estimates for~~ CN2 estimates were ~~based on a simple~~derived using a water-~~-~~balance approach~~calculation using the method described in~~ (Lyon et al. ~~(~~2004), with~~hile~~ subsequent adjustment ~~values were estimated by the~~governed 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,~~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). ~~Calibration on s~~Streamflow calibration sought ~~was performed~~ 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

~~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~~sets developed during model calibration that satisfied performance thresholds of NSE ≥ 0.5 for streamflow, ~~soil moisture estimation performance of~~ RMSE ≤ 0.05 $m^3\ m^{-3}$~~,~~ 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):

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

w~~W~~here, 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 ~~presents the model sensitivity and calibration results~~summarizes parameter sensitivity and calibrated values across the three calibration approaches. ~~As described previously, t~~The soil depth parameter ~~is~~was not calibrated but rather was adjusted during the model initialization to~~;~~ ~~this~~ ensure~~d~~ 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.~~ 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~~processes~~ and soil ~~properties~~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 ~~process~~ were less influential. Calibrat~~ion of the~~ed CN2 and b~~B~~ulk d~~D~~ensity parameters were~~resulted in~~ similar ~~values~~ across calibration approaches, while AWC, ESCO, Ksat and EPCO ~~were~~differed substantially, reflecting contrasting calibration targets~~ 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	replace	500	1000	17	996	813	649

	aquifer for "revap" initiation (mm)							
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~~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. Following bias correction, the soil moisture product exhibits increased peak responses immediately following precipitation events, and improved temporal agreement with in-situ measurements (Fig. 3). 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.

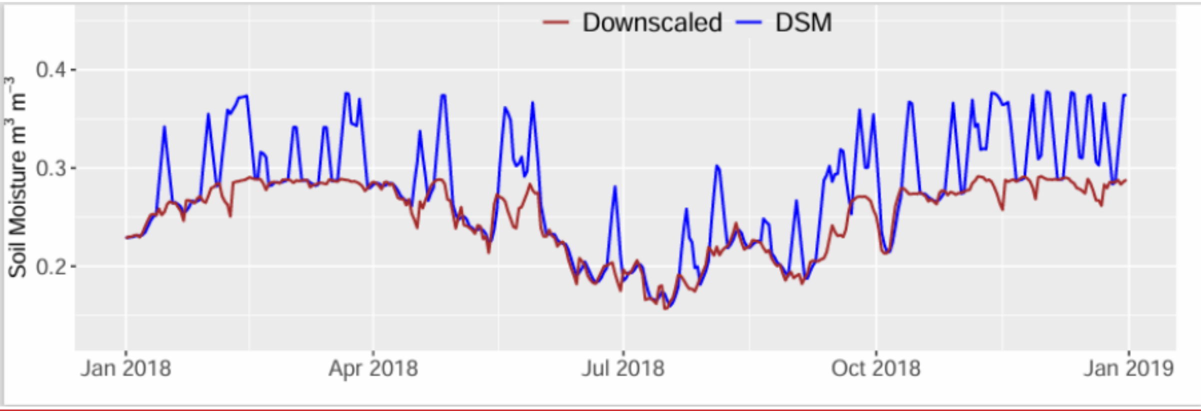


Figure 3: Time series of downscaled (mlrhsm product) and downscaled-bias-corrected soil moisture (DSM) at the watershed scale. Only data from one year are shown for brevity and clarity.

~~3.1~~3.2 Streamflow Estimation Performance~~Calibration~~

The three calibration approaches produced comparable streamflow estimation performance during ~~model~~the calibration period, with slightly lower performance for the soil moisture calibrated model. ~~was carried out to maximize NSE value and resulted in good agreement between daily modelled and observed streamflow. After the final calibration,~~Calibration targeting streamflow resulted in NSE, RMSE, and PBIAS values of ~~were~~ 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 m^3 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 m^3 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.

~~As shown in~~ **Error! Reference source not found.**~~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, R² 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.~~

3.3 Soil Moisture Estimation Performance~~Calibration~~

~~3.2~~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 m^3 m^{-3}, 0.50, and -0.64, respectively. C~~c~~alibration directly targeting soil moisture reduced~~resulted in a~~ RMSE to~~value of~~ 0.05 m^3 m^{-3}~~.~~ and improved ~~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~~to 0.12, while explaining approximately 50% of observed variability, -1~~Figure 2~~Fig. 5. ~~The model underestimated soil moisture, as illustrated by proportion of data above~~The multi-objective calibration produced similar RMSE (0.05 m^3 m^{-3}) and R^2 (0.48), with improved alignment along the 1:1 line ~~in Fig. 2 and the temporal variability in~~relative to the streamflow-only model~~s~~ (Fig. 5; ~~Fig.~~ A2~~3~~). ~~The model's daily stream flow estimation performance was satisfactory with NSE, RMSE, and PBIAS values of 0.54, 0.03 m³/s, and 28.7 %, respectively (~~**Error! Reference source not found.**~~Figure 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.~~

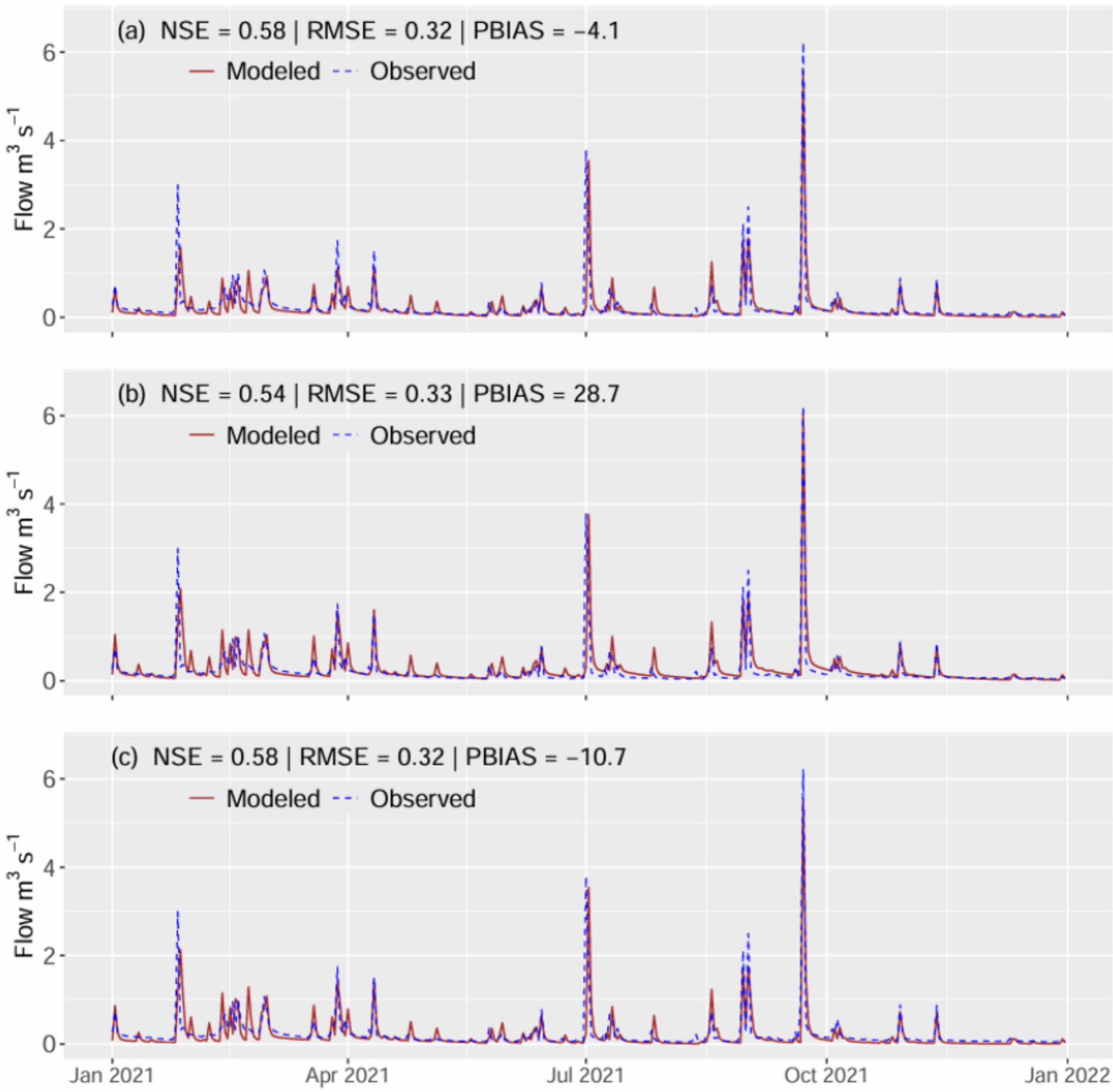


Figure 4: Model streamflow prediction performance calibration period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration (see also Fig. A3 for full time series).

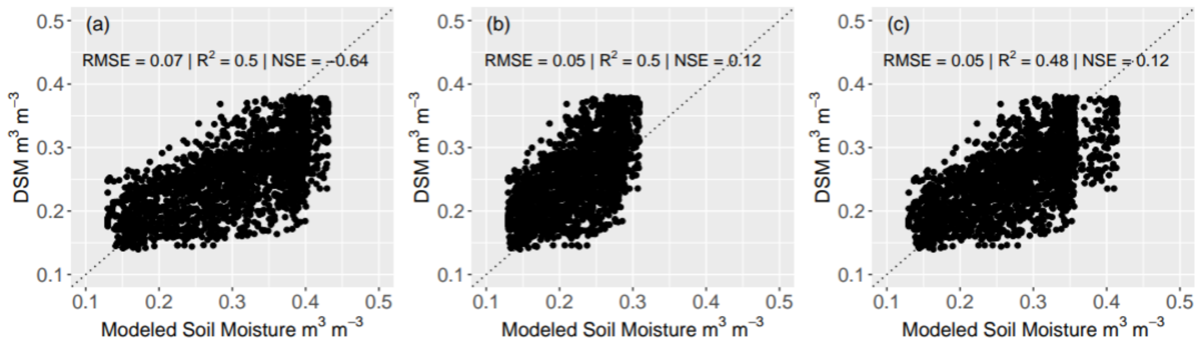


Figure 5: Model soil moisture estimation performance during the calibration period compared against downscaled and bias corrected soil moisture data calibrated on a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

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 m^3 m^{-3} in the streamflow calibration to 0.03 m^3 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).

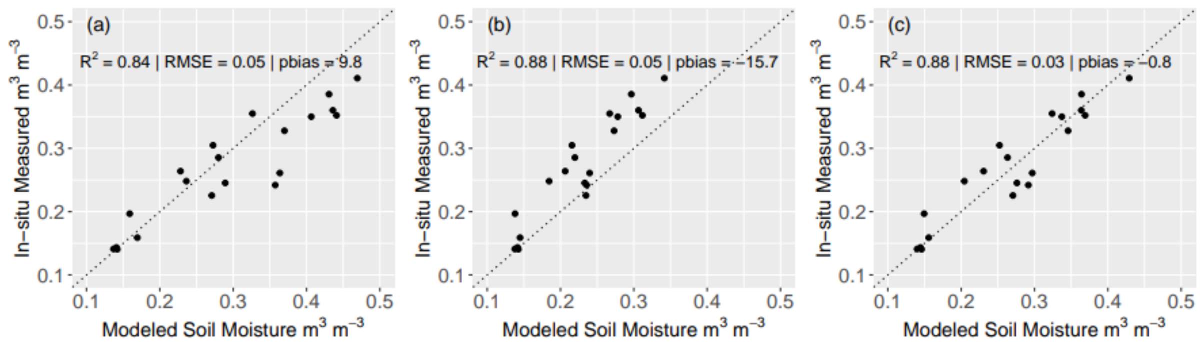


Figure 6: Soil moisture estimation performance of the three models in the evaluation period at field scale against field scale average soil moisture estimate from in-situ measurements; a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

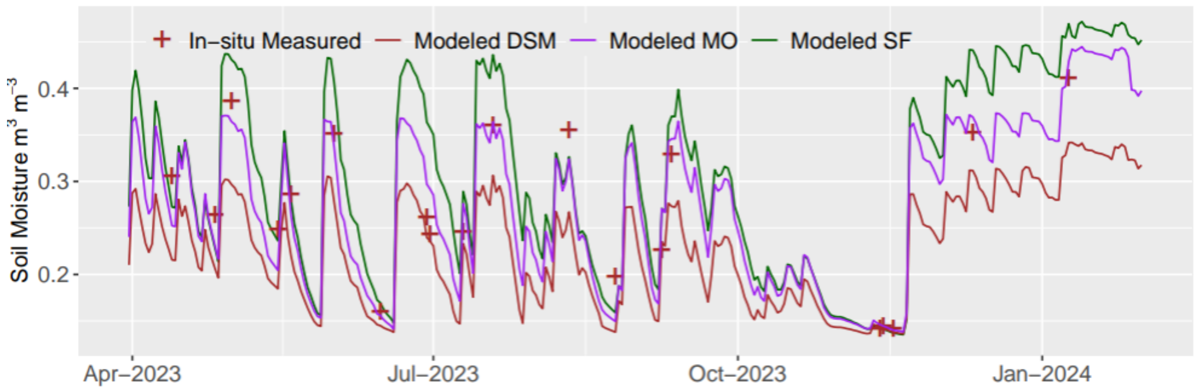


Figure 7: Temporal variability of modeled and measured soil moisture for the three calibration approaches average over the top 120mm soil layer; streamflow only (SF), soil moisture only (DSM), and Multi-objective (MO).

~~Figure~~ 1~~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.~~

~~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, ~~**Error! Reference source not found.**~~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, ~~1~~Figure 2.~~

3.4 ~~Parameter Estimation and ~~Water Balance and Parameter Behavior~~Evaluation~~

~~The CN2 values did not differ substantially between the three models.~~~~Water balance components differed among the three calibration approaches (Fig. 6).~~ 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). ~~This is also evident from the surface runoff component in the water balance values, which range between 19.3% and 23.7%, ~~Figure 82~~Figure 3. Among the three calibration approaches ~~T~~t~~he soil moisture-calibrated~~ only calibration~~ model produced~~resulted~~ 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).

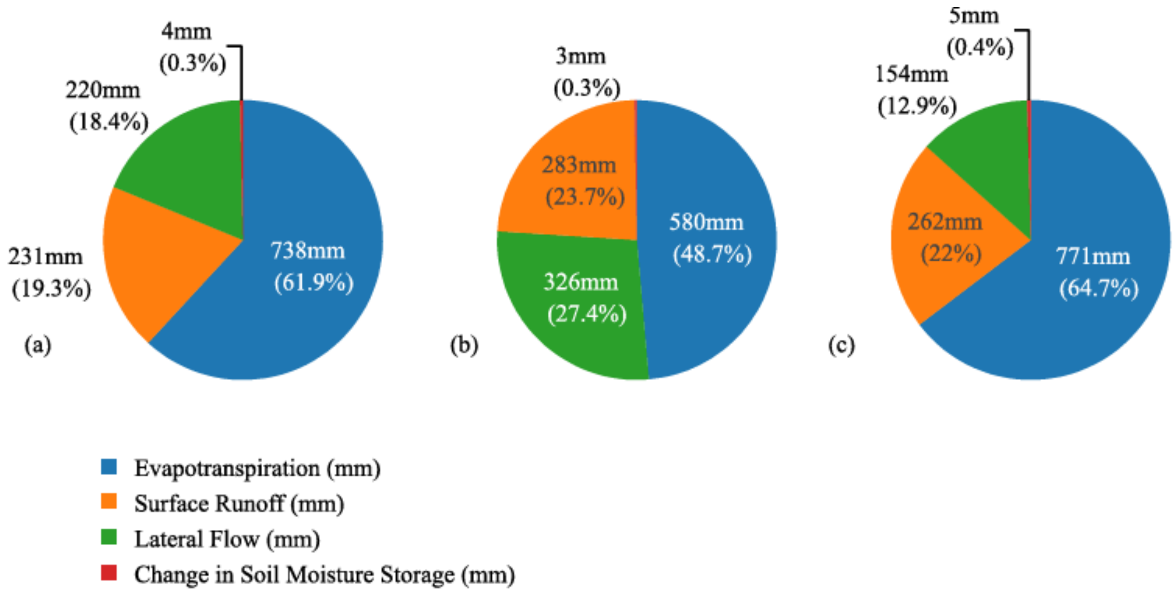


Figure 82~~3~~: Model water balance estimation a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

The difference in ET and lateral flow components ~~in~~between the soil moisture only calibrated model ~~as compared to~~and the other two ~~models~~calibration approaches may be due to the reduced soil moisture variability and reduced AWC in the soil moisture only calibration~~, which had~~. This calibration produces a lower mean and coefficient of variation (CV), compared to ~~soil moisture estimate from the streamflow and multi-objective calibrated models~~the other approaches~~,~~ (Table 2)~~. 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.~~ While these 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~~, only the algorithm allows for 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.~~ 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**	**Standard Deviation**	**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 comparative~~showed satisfactory~~ streamflow estimation performance with NSE values ranging from~~of~~ 0.55 to~~–~~ 0.56 and RMSE 0.25 m^3 m^{-3}~~,~~ (Fig. 9)Figure 93~~Figure 4~~. The soil moisture-calibrated model ~~showed an over-estimation~~exhibited positive bias i~~o~~n daily streamflow estimation ~~average over the simulation period of~~ (18.6 %), primarily during low flow conditions.~~; while~~ In contrast, the streamflow and multi-objective calibrated models showed an under-estimation bias of -11.9 and -21.7%, respectively~~,~~ (Fig. 9)Figure 93~~Figure 4~~.

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.~~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. 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.~~

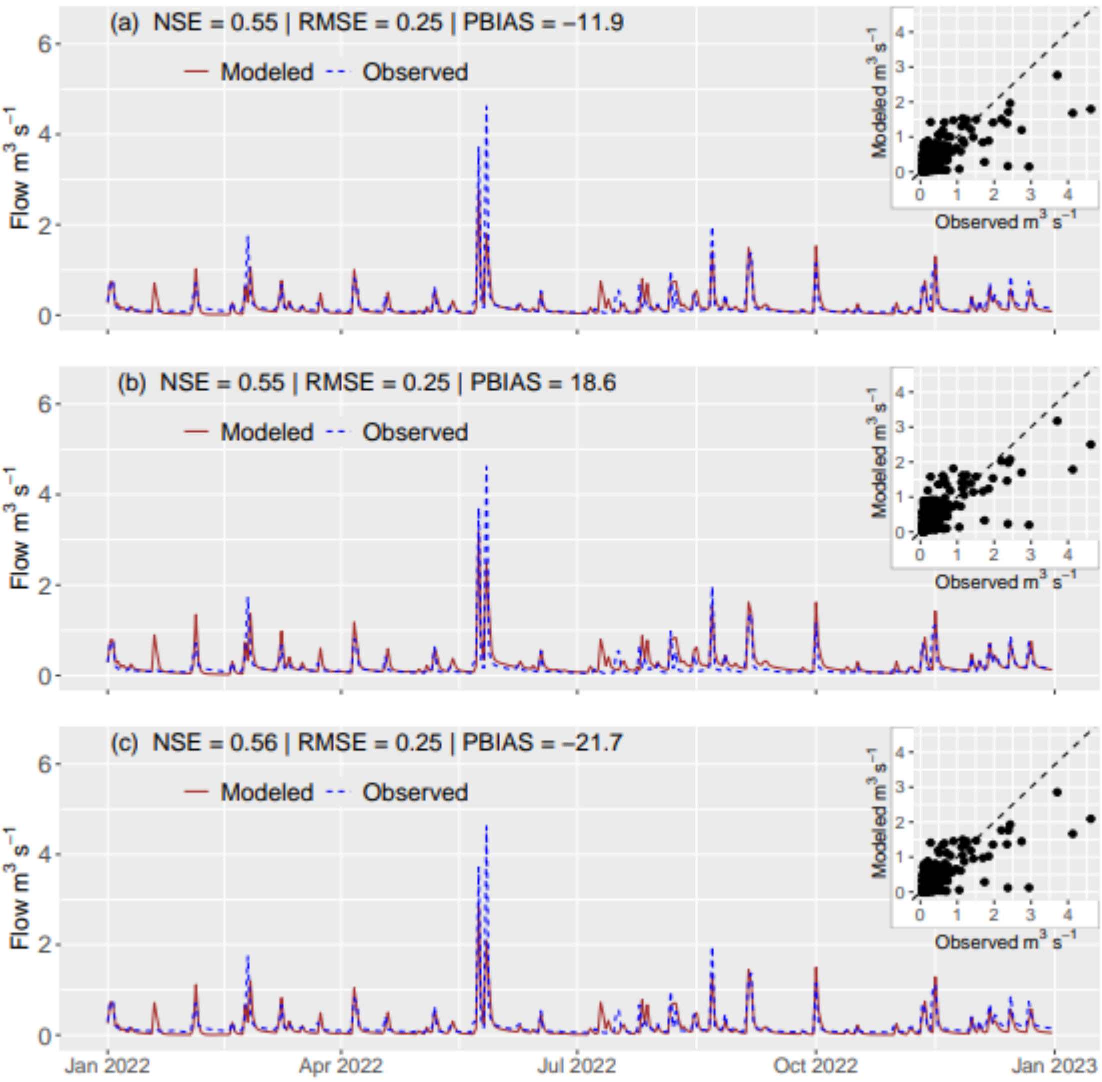


Figure 934: Model streamflow estimation performance evaluation period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration (see also Fig. A4).~~Figure~~ 45~~: Soil moisture estimation performance of the three models in the evaluation period at 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~~ 56~~: 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 ~~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~~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 ~~parsimonious~~ event-based bias-correction approach applied here selectively enhanced soil ~~-~~moisture responses during precipitation events while preserving ~~dry-period~~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 and avoids~~ing~~ circularity.

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~~The parsimonious event-based bias-correction approach applied here 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 and avoiding circularity.~~

~~4.1~~4.2 Impact of Calibration Strategy on Streamflow Soil Moisture Dynamics~~Calibration~~

Across calibration strategies, streamflow estimation performance remained broadly comparable, indicating that inclusion of satellite soil moisture did not substantially degrade streamflow skill. This ~~outcome~~ contrasts with studies reporting pronounced reductions in streamflow performance when models are calibrated solely on soil moisture ~~remote-sensing~~remote sensing products (Dangol et al., 2023; Kofidou & Gemitzi, 2023) or under certain multi-objective ~~with streamflow~~ calibration frameworks (Duethmann et al., 2022 and Mei et al., 2023) ~~and~~. The results here suggests that the combination of the SWAT-VSA model structure and ~~bias-corrected~~bias corrected satellite soil moisture calibration target helped limit~~ted~~ trade-offs between contrasting internal soil mois~~osi~~ture state ~~estimation~~ 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) ~~highlighted~~ showed that streamflow underestimation w~~ere highe~~as more~~r~~ 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 ~~deeper~~ model structur~~ee related~~, ~~like~~ for instance potential ~~deficiencey~~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 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 record.~~ ~~The streamflow-only calibration~~The calibration strategies yielded satisfactory streamflow performance (NSE = 0~~0~~.54-0.58). Although ~~better~~increased levels of streamflow skill (NSE = 0.6) have been reported for this same~~e~~ study watershed~~elsewhere~~ using SWAT (e.g., Thilakarathne et al., 2018), direct comparison of NSE values ~~across different watersheds is of limited interpretive value given differences in watershed characteristics, runoff mechanisms, and calibration data length. More relevant here is~~could be misleading as ~~that~~ 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.

~~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.~~ 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.

~~4.2~~4.3 ~~Soil Moisture Calibration~~Statistical Improvements verses 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.

~~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~~vary~~. Kofidou & Gemitzi, (2023) reported a reduction in NSE from 0.58 to 0.51. In contrast,~~, while ~~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.~~

~~4.3~~4.4 ~~Multi-objective Calibration~~Parameter Behavior, Compensation, and Structural Model Constraints

~~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 ~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. 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.~~

~~Differences in calibrated parameter values across strategies highlight the role of compensation in achieving statistical fit. Soil-moisture-only calibration favored lower available water content and shifts in evapotranspiration-related parameters, leading to reduced evapotranspiration and increased streamflow.~~

~~These behaviors are partly attributable to structural constraints within SWAT-VSA and SWAT more generally (Rajib et al., 2016). SWAT represents unsaturated flow using vertically lumped soil layers and does not explicitly simulate lateral redistribution of soil moisture among HRUs. In saturation-excess systems, where downslope redistribution and hydrologic connectivity strongly influence wetness patterns, these simplifications can 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).~~

~~The multi-objective calibration mitigated some of these limitations by constraining parameters across multiple objectives, reducing extreme parameter combinations, and dampening compensation effects. 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. This finding is consistent with studies showing that multi-objective frameworks can improve internal consistency even when model structure remains unchanged (Bekele & Nicklow, 2007; Rajib et al., 2016).~~ 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).

~~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~~4.5 Parameter Uncertainty and Equifinality~~Estimation and Water Balance Evaluation~~

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 (Fig. 10) was lowest under multi-objective calibration, particularly for soil water and evapotranspiration related parameters. ~~In Figure 10,~~ A wider range or spread in parameter values indicates higher uncertainty, reflecting a greater number of equally acceptable solutions and increased equifinality (Beven, 1993). Simultaneously constraining streamflow and soil-moisture objectives reduced the range of acceptable parameter combinations, thereby limiting equifinality. ~~—i.e. as the iterative search space for the optimum parameter value widens the possibility of the optimization algorithm arriving at several equally performing solutions increases. Constraining parameters simultaneously with streamflow and soil-moisture objectives reduced the range of acceptable parameter combinations, thereby limiting equifinality (Beven, 1993).~~ Reduced uncertainty in parameters such as AWC, Ksat, ESCO, and EPCO indicates that multi-objective calibration more effectively constrains processes governing soil -water storage and vertical redistribution.

~~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 ~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 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 32: 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, 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 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.~~

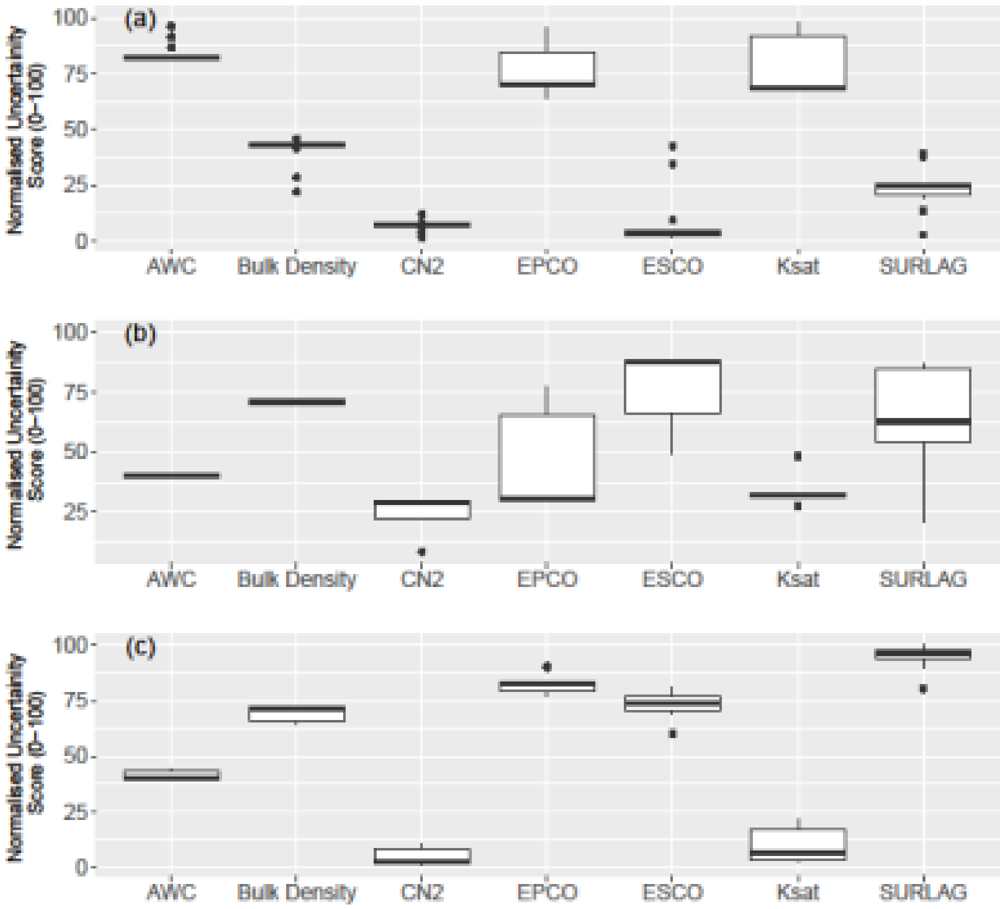

Figure 6~~7~~10: Parameter uncertainty estimate derived from DEoptim calibration iterations for a) streamflow only, b) soil moisture only and, c) multi-objective calibration. The height of the boxplot demonstrates the range of different values the parameters took while yielding acceptable model performance. 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.

~~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.~~

4.6 Implications for Small Saturation-Excess Watersheds

The results demonstrate that downscaled~~ and~~, empirically bias-corrected satellite soil -moisture data can improve internal hydr~~r~~ologic state estimation in small, saturation-excess-dominated watersheds when ~~paired~~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 ~~way by balancing~~balance between surface wetness dynamics ~~with~~ and integrated flow behavior, ~~but~~although its effectiveness remains ~~contingent~~ 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 ~~single,~~ small (14.5 km²), saturation-excess-dominated watershed. While appropriate for evaluating soil-moisture -driven calibration in ~~terrain-controlled~~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~~event based ~~bias-correction~~bias correction approach applied here relies on ~~watershed-average~~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 ~~dominate~~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~~ in the same way~~. Nonetheless, saturation-excess processes are widespread in humid~~ and wet~~ 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~~of headwater catchments.

The downscaled soil moisture product underestimates peak wetness during high-moisture periods. Although the ~~applied bias-corrected~~bias correction~~ product~~ 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.

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~~ed~~ leveraging downscaled satellite soil moisture data substantially improves~~d~~ estimation of temporal variability of soil moisture without deteriorating the model accuracy in streamflow estimation. ~~In comparison, multi-objective calibration using 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.~~ Multi-objective calibration using both streamflow and soil moisture data outperformed single-objective approaches by improving estimation of both variables while reducing parameter uncertainty. Calibration based solely on soil moisture led to improved soil-moisture performance with only 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 ~~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.~~, 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.

~~While~~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.

APPENDIX

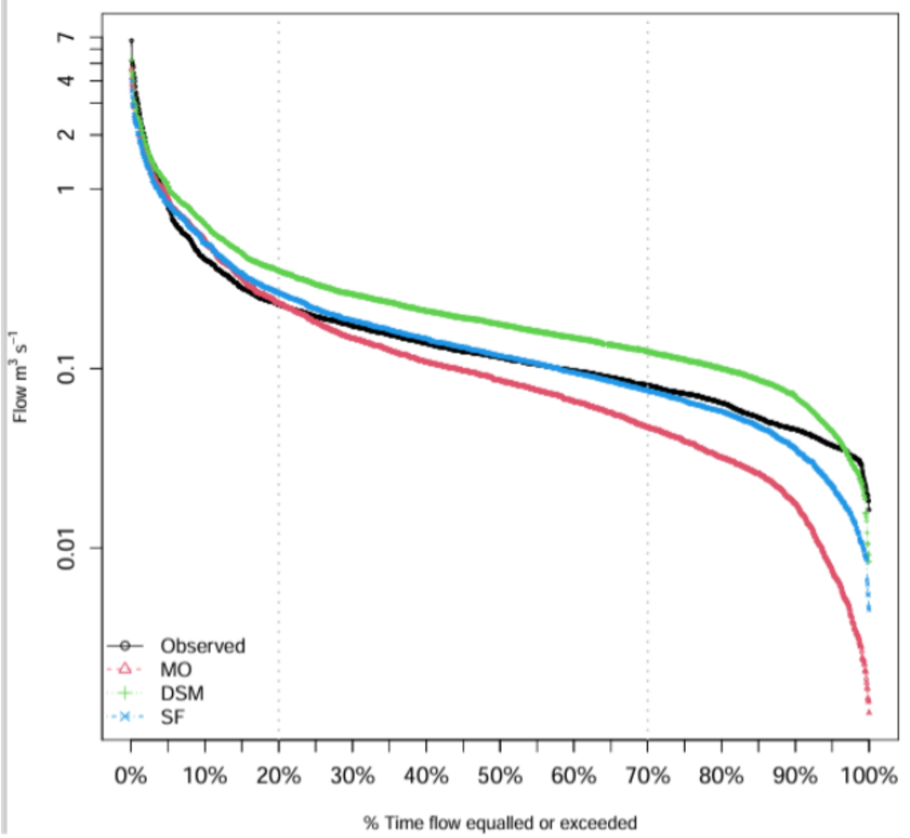

Figure A1: Flow-duration curves comparing observed daily streamflow with simulations from the soil-moisture-only (DSM), streamflow-only (SF), and multi-objective (MO) calibration strategies. Differences among curves illustrate how calibration targets influence hydrologic realism: DSM captures surface 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.

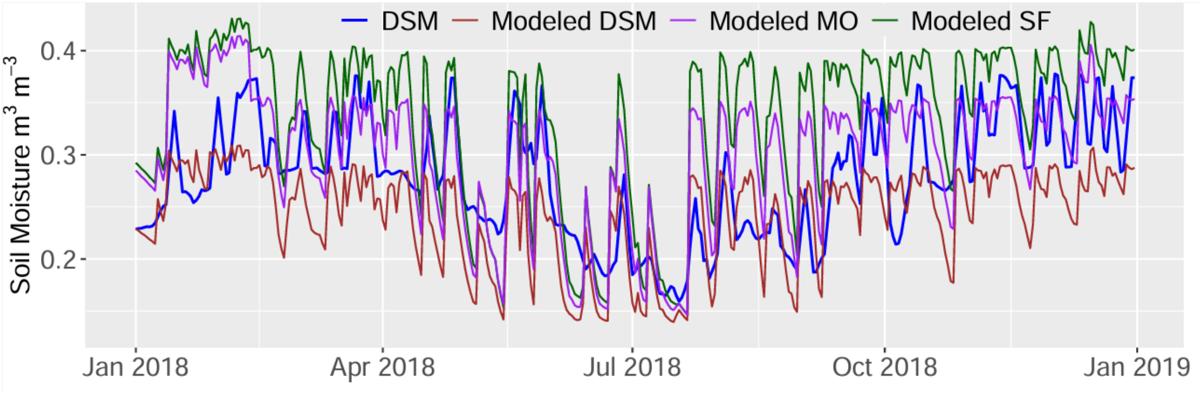

Fig. A2~~3~~: Time series of modeled surface soil moisture (50 mm) from the three calibration approaches and DSM data; calibrated on DSM data (Modeled DSM), Multi-objective calibration using DSM data and streamflow (Modeled MO), calibrated on streamflow (Modeled SF).

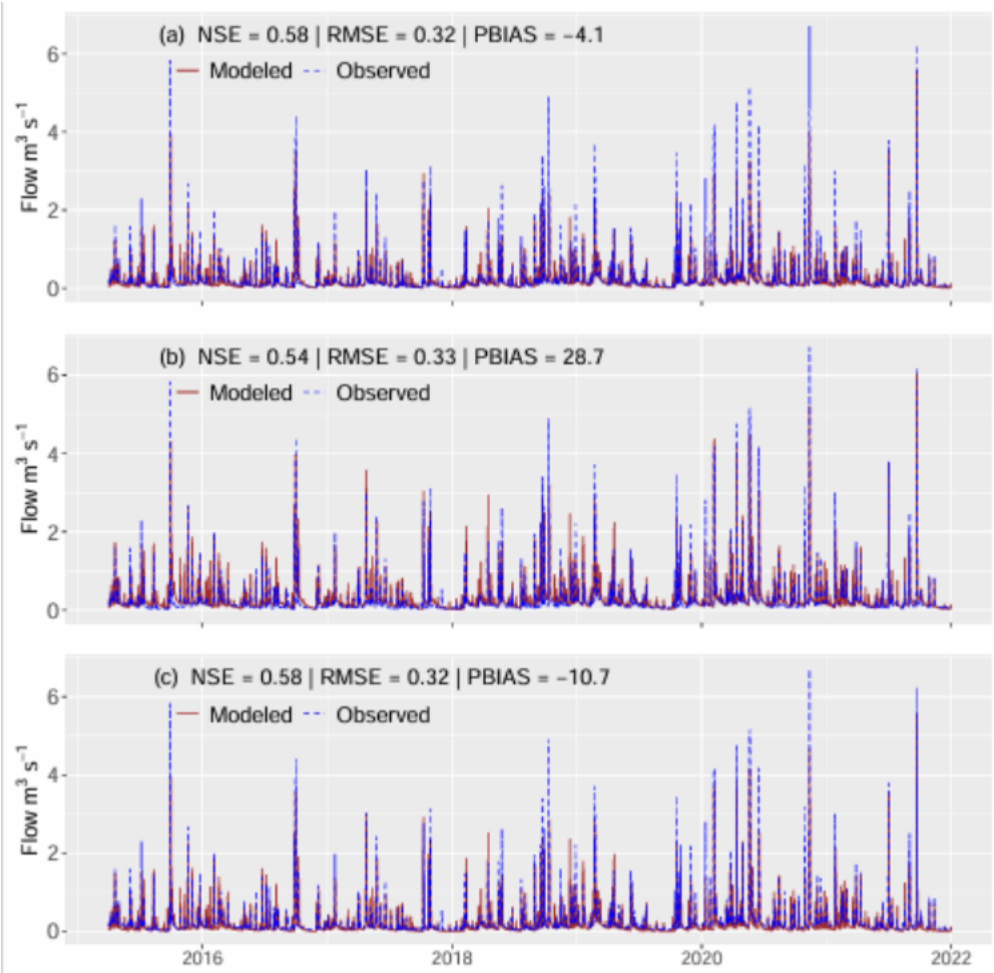

Figure A3: Full time series of model streamflow prediction performance calibration period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

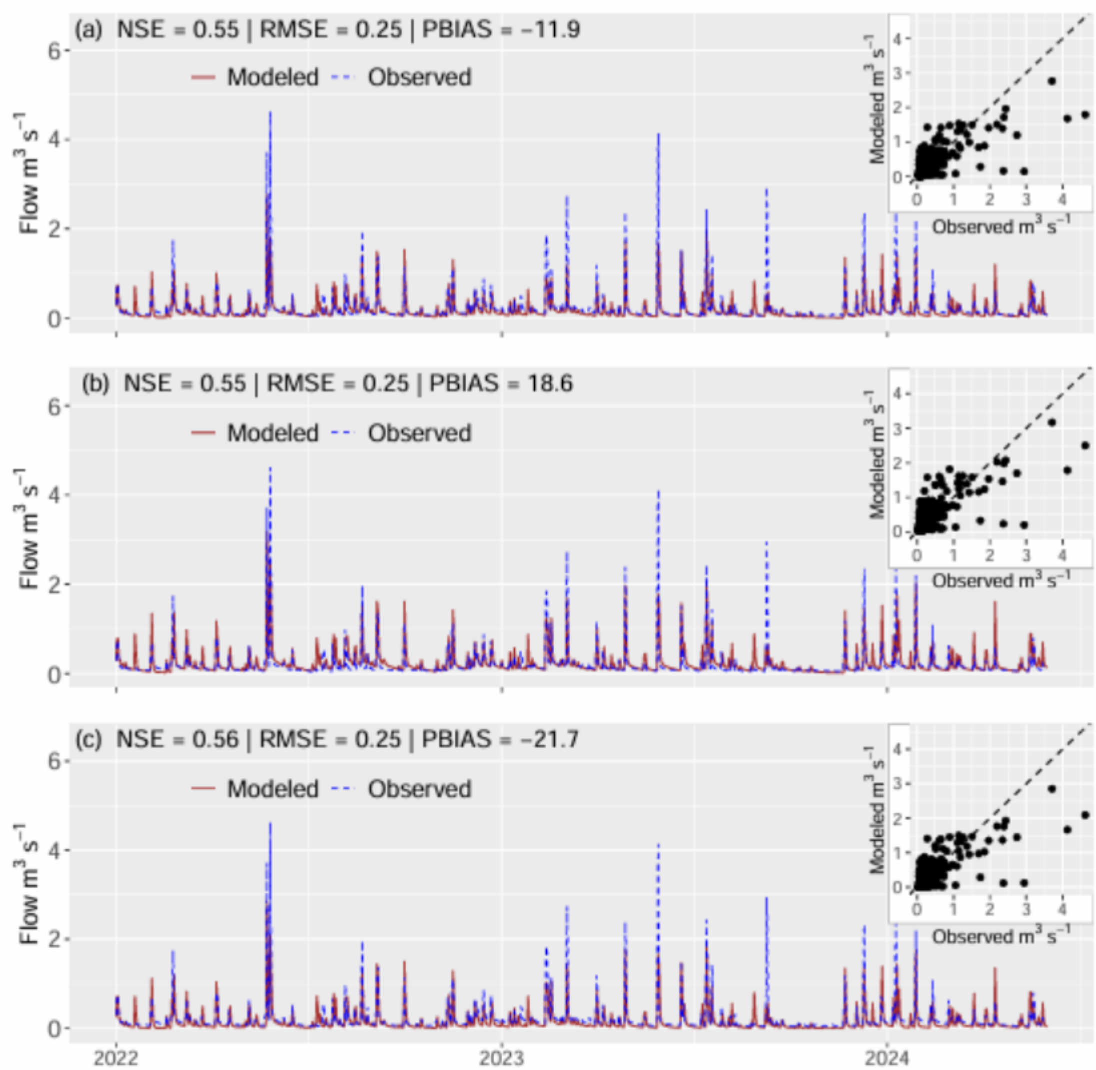

Figure A4: Model streamflow prediction performance evaluation period a) streamflow only (SF) calibration b) soil moisture only (DSM) calibration c) multi-objective (MO) calibration.

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 evaluation only

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

CODE AVAILABILITY

~~The code used to run the simulations is available in a GitHub repository.~~

~~https://github.com/saizanaandezana/Stroubles_Creek_SWAT_VSA_model~~

Available upon request

DATA AVAILABILITY

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

TEAM LIST

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AUTHOR CONTRIBUTION

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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.

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