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Model calibration using hydropedological insights to improve the simulation of internal hydrological processes using SWAT+

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Abstract

Soils affect the distribution of hydrological processes by partitioning precipitation into different components of the water balance. Therefore, understanding soil-water dynamics at a catchment scale remains imperative to future water resource management. In this study, the value of hydropedological insights was examined to calibrate a processes-based model. Soil morphology was used as soft data to assist in the calibration of the Soil Water Assessment Tool (SWAT+) model at five different catchment scales (48, 56, 174, 674, and 2421 km²) in the Sabie River catchment, South Africa. The aim of this study was to calibrate the SWAT+ model to accurately simulate long-term monthly streamflow predictions as well as to reflect internal soil hydrological processes using a procedure focusing on hydropedology as a calibration tool in a multigauge system. Results indicated that calibration improved streamflow predictions where R^2 improved by 2%–8%. Nash-Sutcliffe Efficiency (NSE) improved from negative correlations to values exceeding 0.5 at four of the five catchment scales compared to the uncalibrated model. Results confirm that soil mapping units can be calibrated individually within SWAT+ to improve the representation of hydrological processes. Particularly, the spatial linkage between hydropedology and hydrological processes, which is captured within the soil map of the catchment, can be adequately reflected within the model simulations after calibration. This research will lead to an improved understanding of hydro-pedology as soft data to improve hydrological modelling accuracy.

KEYWORDS

hydrological soil types, hydropedology, soft calibration, SWAT+

1 | INTRODUCTION

Soils are a primary control mechanism in determining hydrological processes within a landscape by partitioning precipitation into the different components of the water balance. This is the result of soil's ability to absorb, store, and transmit water at different spatial and temporal scales (Smit & Van Tol, 2022). These hydrological processes largely determine the volume, variability, and residence times of water resources within a landscape, which in turn determines the

agricultural potential, functionality of ecosystems and economic opportunities within different catchments (Mengistu et al., 2019). However, the logistical impracticality of measuring these hydrological processes at landscape-scale has resulted that these processes remain most practically quantified using hydrological models, which simplify and represent real-world hydrological systems (Devia et al., 2015).

Soil and water are inextricably linked (Bouma et al., 2022). Soils provide valuable ecosystem services such as food production, carbon, and nutrient cycling, flood mitigation and water filtration and purification

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(Lal et al., 2021). These services are intimately linked to the spatio-temporal variation of hydrological flowpaths such as surface runoff, infiltration, lateral flow, evaporation, and percolation. Water, on the other hand, plays a fundamental role in soil formation and results in soil properties such as soil colour, the formation and distribution of mottles as well as soil texture and structure (Van Tol & Le Roux, 2019). These identifiable soil properties are a direct product of the dominant hydrological processes present during their formation and may be linked to different hydrological processes based on selected soil properties. This interactive relationship between soil and water is the foundation of the multi-disciplinary field called *hydropedology* (Lin, 2003), which has enabled the conceptualization of different hydrological processes in areas with none or limited hydrometric measurements. *Hydropedology* has been defined as the study of the interconnected relationship between soils and water, specifically how soils affect different hydrological processes and how these processes in turn affect soil formation and soil function (Smit & Van Tol, 2022).

However, one of the primary issues with modern hydrological models is their reliance on a calibration period, where results are primarily focused on accurately simulating a specific point observation, such as streamflow gauges (Arnold et al., 2015). Modern hydrological models contain a level of complexity within their structure, which allows a high level of parameterization and adaptability. This often leads to where different model configurations all result in similar outputs, which has become known as *equifinality* (Arnold et al., 2015; Van Tol et al., 2021), and although these models and corresponding modelling approaches might provide statistically accurate model simulations in terms of point observations, it remains questionable if these models accurately reflect the relevant internal hydrological processes or if these models are capable of accurately simulating land use or climate change scenarios beyond the current environmental conditions, for which they were calibrated (Van Tol et al., 2020).

Although researchers agree that internal catchment processes should be adequately reflected through the model structure and parameters, even if it is at the expense of model performance metrics (Arnold et al., 2015). However, different approaches to improve internal catchment process representation remains limited. The inclusion of *soft data*, defined as information, which may not necessarily be measured directly but can be related to a hydrological process or processes, has been put forth to resolve this issue and improve internal hydrological processes accuracy (Yen et al., 2019).

The use of *soft data* in SWAT+ has been growing rapidly as can be seen in Chawanda, Arnold, et al. (2020); Chawanda, George, et al. (2020) and Chawanda et al. (2024) which used *soft data* for hydrological mass balance calibration for an Africa SWAT+ model as well as using *soft calibration* procedures to assess land use and climate change scenarios. Also, the development of the SWATDoctR (Plunge et al., 2024) aids in the identification of parameterization errors. However, these *soft calibration* routines do not specifically focus on hydrological processes at the soil level.

Hydropedology combined with digital soil mapping has provided an intriguing source of *soft data* in hydrological modelling as it allows the spatial capture of different soil hydrological processes observable at the pedon level and enables the accurate extrapolation of these

processes to hillslope and catchment level (Lin, 2003). Therefore, enabling the capture and transfer of information related to different hydrological processes within different soil mapping units for hydrological modelling purposes. Several researchers have assessed *hydropedological* insights as input to process based hydrological modelling, illustrating the improved accuracy that hydrological soil information achieves (Smit et al., 2023a; Smit & Van Tol, 2022; Van Tol et al., 2020).

The aim of this paper was to improve hydrological modelling accuracy by reflecting internal hydrological processes more accurately by incorporating a novel calibration using *hydropedological* insights as *soft data*. The first objective was to determine appropriate and sensitive model parameters to include in the calibration procedure. Secondly, to apply a manual calibration approach where selected model parameters were calibrated to reflect an accurate prediction of long-term measured streamflow as well as dominant soil hydrological process for each hydrological soil type. The objective of using *hydropedological* insight in the calibration process was achieved by applying a novel expert knowledge procedure to link measurable soil morphology to different hydrological processes. This approach was evaluated by statistical comparison with measured long-term streamflow prior to and after calibration as well as an interpretation of water balance components and their linkage to *hydropedological* insights.

2 | MATERIALS AND METHODS

2.1 | Study area

The 2421 km² Sabie catchment is in the Mpumalanga province of South Africa (Figure 1) and forms part of the larger transboundary Incomati River basin in the east of the country. The catchment stretches from the Drakensberg Escarpment in the west at an altitude of 2218 meters above sea level (m.a.s.l.) and gradually flattens towards the east with an altitude of 250 m.a.s.l. as the Sabie River is later joined by the Sand River before continuing to flow eastward into Mozambique. The catchment consists of a wide range of geology complexes but is predominantly crystalline in nature (igneous and metamorphic) and comprises various ranges of bedrock lithologies, consisting of quartzites, granites, andesites and gneiss formations (Council for Geosciences, 2007).

The Sabie catchment has a semi-arid warm and hot climate in the east of the catchment and a temperate warm climate in the west of the catchment (Schulze, 2007). Average minimum temperatures range from 2 to 10°C and average maximum temperatures range from 21 to 32°C. Actual evapotranspiration rates vary between 750 to 1100 mm annually (Riddell et al., 2020; Van Eekelen et al., 2015). Rainfall ranges from 1600 mm per year in the west to 550 mm per year in the east, where rainfall occurs mainly in the austral summer and normally results from convective thunderstorms, although periodic high-intensity rainfall events do occur from cyclones where the orographic effect of the Drakensberg Escarpment creates severe localized flooding (Kruger et al., 2002). Most of the catchment consists of the savanna, montane grasslands, and montane forest biomes, where

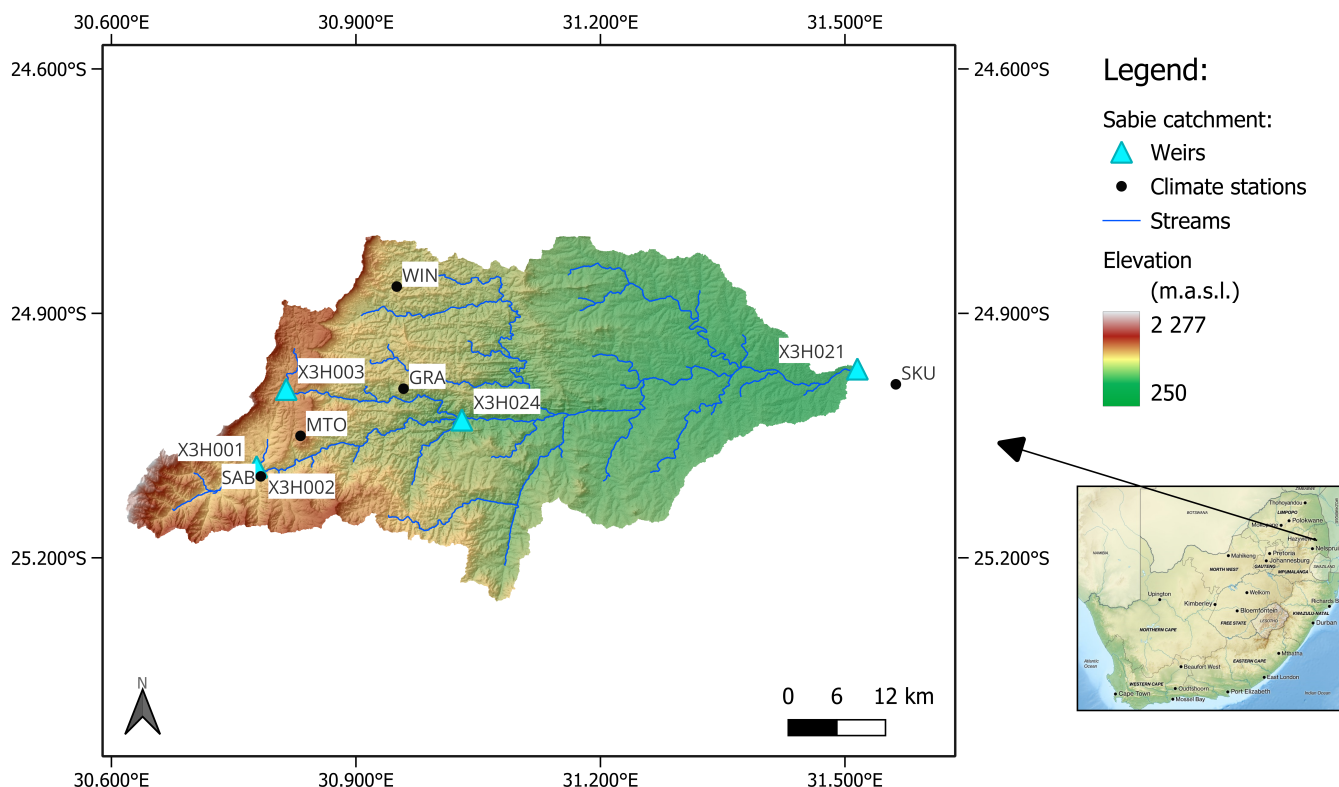


FIGURE 1 The Sabie River catchment, including elevation, weirs and climate stations.

anthropogenic changes have resulted in much of the afro-montane forest being replaced for commercial forestry applications (Mucina & Rutherford, 2006).

The mountainous soils of the Sabie catchment are characterized by well-weathered soils being either deep apedal soils (Acrisols and Nitisols) or shallow apedal soils (Leptosols), where apedal refers to weakly-structured well-aerated soils, on midslope and hillcrest positions depending on the parent material. Alluvial (Fluvisols) or saturated high clay (Gleysols) soils are also prominent of footslope and valley bottom terrain positions depending on upslope environmental covariates. The lowland soils are shallower and gravelly as they are less weathered and primarily controlled by differences in parent material. These soils show a more distinct toposequence with apedal soils (Acrisols and Nitisols) on hillcrest, albic soils (Arenosols) on midslope and footslope terrain positions. A small number of duplex soils (Solonetz) are also present on footslope and valley bottom terrain positions. Apedal soils (Nitisols and Fluvisols) are also present on valley bottom terrain positions as floodplains form on the major river networks (IUSS Working Group WRB, 2015).

2.2 | Model setup and inputs

The SWAT model or Soil and Water Assessment Tool (Arnold et al., 1998) is a process-based semi-distributed catchment model, which is widely used to simulate water quality and quantity. The model is also used to simulate the impact of physical changes to

TABLE 1 The characteristics of the hydrological mapping units of the Sabie catchment.

Run type	Warmup	Main simulation
Calibration	1999–2003	2004–2009
Validation	-	2010–2019

catchments such as land use and climate changes in catchments across the globe with SWAT+ being an enhanced iteration of the model. The SWAT+ model divides the catchment into hydrological response units (HRUs), where an HRU represents a homogenous area in terms of soil, land use and slope. The model calculates various components of the water balance, such as surface runoff, infiltration, lateral flow, percolation, return flow, evapotranspiration, and discharge to the stream from each individual HRUs at a daily timestep. For the theoretical manual of the SWAT model see Neitsch et al. (2011). Bieger et al. (2017) also describes the changes between the SWAT and SWAT+ versions, which is a more flexible version of SWAT. The QSWAT+ (v.2.3) plugin was used to set up the watershed, where SWAT+ Editor (v.2.3.3) was used to edit and run the model. The model was run from the start of January 1999 until the end of December 2019, where the model warm-up period lasted for the first 5 years, followed by a 5-year calibration period from the start of 2004 to the end of 2009 and a 10-year validation period from the start of 2010 to the end of 2019 as can be seen in Table 1.

The South African Weather Service provided daily rainfall data for four climate stations, namely, Sabie (SAB), Dunnotar at MTO

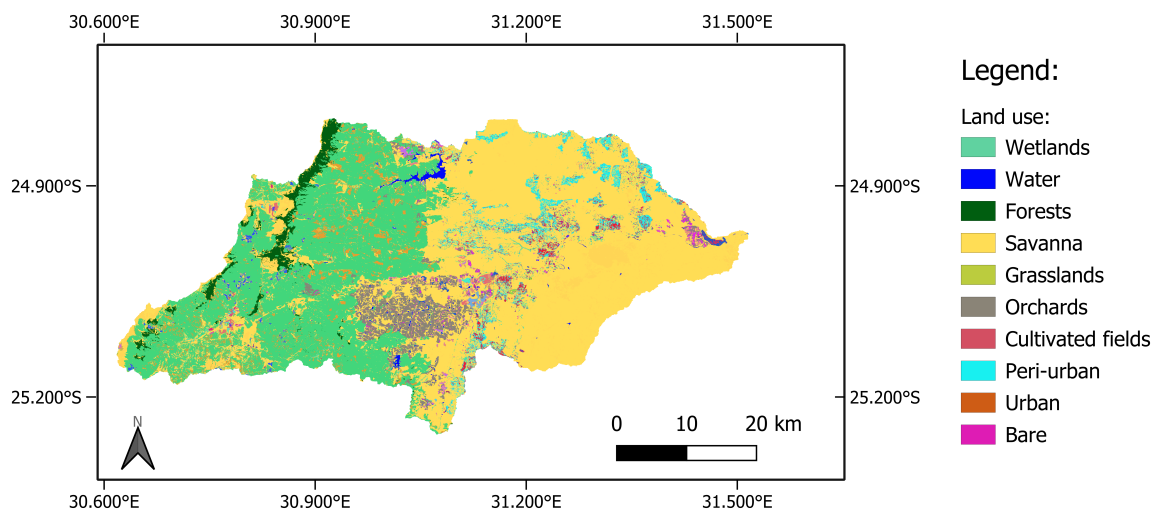


FIGURE 2 The land uses within the study area as demarcated from the 2013/2014 National Land Cover Map.

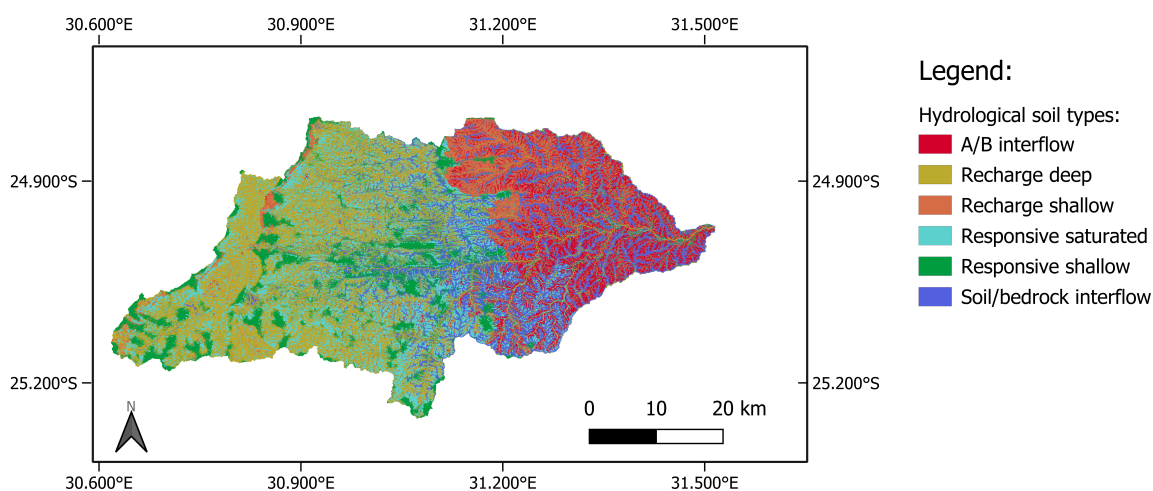


FIGURE 3 The hydropedological map of the study area (Smit et al., 2023a).

Forestry (MTO), Rietspruit near God's Window (WIN) and Skukuza (SKU) (Figure 1). Minimum and maximum temperatures were also obtained for two climate stations, SKU and Graskop (GRA). Daily solar radiation, relative humidity and wind speed were obtained from the Climate Forecast System Reanalysis, which was done by the National Center for Environmental Prediction (Saha et al., 2015).

The Digital Elevation Model (DEM) was obtained from a 30×30 m Shuttle Radar Topography Mission Digital Elevation Model (USGS, 2022). Land cover data (Figure 2) was obtained from the 2013/14 South African National Land-Cover Map (Geoterralmage, 2015). Predefined SWAT values for different land use classes were used as input data for the land cover. Dams were identified from the land cover and included in the model set-up as 'reservoirs' with default values.

Soil properties govern the movement of water and air through the soil profile and have a major impact on the cycling of water, sediment, and nutrients within each HRU. SWAT+ requires both the spatial soil mapping unit and physical properties for each individual soil horizon within the unit, such as depth to bottom of soil layer, bulk

density, available water capacity, saturated hydraulic conductivity, organic carbon content, clay, silt, sand, and rock fragment contents, as well as moist soil albedo and the soil erodibility factor.

As described in Smit et al. (2023b), a hydropedological dataset (Hydrosol) was developed for the Sabie River catchment by using modern digital soil mapping techniques, an infield hydropedological soil survey and legacy soil information (Figure 3). The soils of the catchment were grouped based on their hydropedological characteristics (Table 2) as defined by Van Tol and Le Roux (2019).

Therefore, the Hydrosol map captured the spatial distribution of dominant hydrological processes within the Sabie catchment, where each mapping unit is an additional data source for modelling purposes. Details on the DSM approach is described in Smit et al. (2023a), where the resultant hydrological soil map achieved a spatial evaluation point accuracy of 62% and a Cohen's Kappa statistic value of 0.46 at a 30×30 m grid and was populated by infield measured hydraulic soil properties (Table 3). The Hydrosol dataset was therefore deemed to be acceptable for use in the modelling exercise.

TABLE 2 The characteristics of the hydrological mapping units of the Sabie catchment.

Hydrological mapping unit ^a	Soil form ^b	WRB reference groups ^c	Defining hydrological characteristic
Recharge deep	Hutton, Longtom, Kranskop	Acrisols, Nitisols, Fluvisols	Deep soils without any morphological indication of saturation. Vertical flow through and out of the profile into the underlying bedrock is the dominant flow direction.
Recharge shallow	Glenrosa, Nomanci	Leptosols	Shallow soils without any morphological indication of saturation. Vertical flow through and out of the profile into the underlying fractured bedrock is the dominant flow direction.
Responsive saturated	Katspruit, Champagne	Gleysols	Soils with morphological evidence of long periods of saturation promoting the generation of overland flow due to saturation excess.
Responsive shallow	Mispah, Graskop	Leptosols	Shallow soils overlying relatively impermeable bedrock. Limited storage capacity results in the generation of overland flow after rainfall events.
A/B interflow	Estcourt, Sterkspruit	Solonetz	Duplex soils where the textural discontinuity facilitates build-up of water in the topsoil, with discharge in a predominantly lateral direction.
Soil/bedrock interflow	Fernwood, Cartref	Arenosols	Soils overlying relatively impermeable bedrock. Hydromorphic properties signify temporal build of water on the soil/bedrock interface and slow discharge in a predominantly lateral direction.

^aVan Tol & Le Roux, 2019.^bSoil Classification Working Group, 2018.^cIUSS Working Group, WRB, 2020.**TABLE 3** The main hydraulic properties of the hydrosol mapping units.

Hydrological soil types	Horizon	Soil hydraulic group	Depth	Bd ^a	AWC ^b	Ksat ^c	OC ^d	Clay	Silt	Sand
			Mm	g/cm ³	Mm/mm	Mm/h	%	%	%	%
A/B Interflow	A	C	150	1.38	0.101	40.1	1.1	18	21	61
	B		1400	1.58	0.122	8.54	0.2	40	13	47
Recharge Deep	A	A	200	1.41	0.107	11.58	5.2	31	27	42
	B		2400	1.46	0.119	7.8	1.5	34	29	37
	C		3000	1.51	0.119	5.7	0.2	33	32	35
Recharge Shallow	A	D	400	1.4	0.107	27.27	5.5	32	12	56
Responsive Saturated	A	C	200	1.36	0.104	32.01	4	25	18	57
	B		1800	1.51	0.121	11.74	1.8	38	14	48
Responsive Shallow	A	D	300	1.34	0.104	40.5	5	25	15	60
Soil/bedrock Interflow	A	A	200	1.4	0.100	40	1.5	17	20	62
	B		1600	1.38	0.113	78	0.4	19	5	76

^aBd–Bulk Density.^bAWC–Available Water Capacity.^cKsat–Saturated Hydraulic Conductivity.^dOC–Organic Carbon.

2.3 | Hydropedological approach to calibration

The reproducibility of different catchment modelling calibration and validation procedures has long been an issue for the hydrological modelling community. Chawanda, Arnold, et al. (2020); Chawanda, George, et al. (2020) developed user-friendly workflows to address

this issue, specifically for SWAT+. The calibration process was therefore conducted along the standards set forth by Chawanda, Arnold, et al. (2020); Chawanda, George, et al. (2020) to ensure reproducibility of the calibration procedure. Practical calibration guidelines have been well established and can be found in the SWAT manual (Arnold et al., 2011) where calibration is either automated or conducted

manually by selecting the most sensitive parameters and adjusting them accordingly (Arnold et al., 2011; Mengistu et al., 2019; Tuppad et al., 2011).

Different parameters within SWAT have different levels of sensitivity within the model, which allows modellers the opportunity to calibrate different hydrological processes such as surface runoff, lateral flow, return flow, and evapotranspiration rates (Wagner et al., 2022). The most sensitive parameters for calibration within the Sabie catchment was determined using Latin Hypercube Sampling approach with 2000 iterations within R-SWAT (Nguyen et al., 2022) with Kling-Gupta Efficiency as objective function.

Researchers have shown that the soil conservation service curve number II (CN2) the most sensitive parameter in SWAT streamflow simulations (Mengistu et al., 2019) as it reflects the characteristics of the watershed prior to a rainfall event largely determines surface runoff and is dependent to the initial CN value assigned to the HRU by the model. Surface runoff is calculated using the following equations:

$$Q_{\text{surf}} = \frac{(Pi - Ia)^2}{(Pi - Ia + S)} \quad (1)$$

where Q_{surf} is the overland runoff or rainfall excess (mm H₂O), Pi is the precipitation depth for the day (mm H₂O), Ia is the initial abstraction lost from canopy interception, surface storage, and infiltration prior to runoff. The water retention parameter (S) (mm H₂O) is estimated by:

$$S = 25.4 \left(\frac{1000}{\text{CN}} - 10 \right), \quad (2)$$

where CN is the curve number at a daily timestep, which is a function of soil permeability, land use, and antecedent soil moisture content. The CN values are based on the soil hydrologic group of the soil mapping unit, land use, and initial hydrologic condition, the soil hydrologic group and land use being the most important variables within the equation. (Neitsch et al., 2011; Zhang et al., 2019).

SWAT divides soils into four distinct soil hydrologic groups based on the infiltration characteristics of the soil, namely, A, soils with a low runoff potential, containing high infiltration rates and being well drained with a high rate of water transmission. B, soils with moderate infiltration rates with moderate rates of water transmission and being moderately well drained. C, soils with low infiltration rates often contain a layer that impedes the downward movement of water with low rates of water transmission. D, soils with a high runoff potential, with very slow infiltration rates with very slow rates of water transmission (Neitsch et al., 2011). Each soil mapping unit is assigned a specific soil hydrologic group that dictates, which CN values are assigned. Therefore, differences in runoff values between different soils on similar land uses are largely determined by the soil hydrologic group assigned and corresponding CN values.

Lateral flow therefore occurs when soil water exceeds field capacity with the underlying layer being impermeable or semi-permeable. The kinematic approximation method assumes that the

flowpaths are parallel to the bedrock and that the hydraulic gradient equals the slope of the hill (Neitsch et al., 2011).

$$SW_{\text{excess}} = \frac{1000 \cdot H_0 \cdot \theta_d \cdot L_{\text{hill}}}{2} \quad (3)$$

where SW_{excess} equals the drainable water volume within the saturated zone of the soil per unit area (mm), H_0 equals the saturated thickness of the hillslope outlet as a fraction of the total thickness (mm/mm), θ_d equals the drainable porosity of the soil (mm/mm), and L_{hill} equals the length of the hillslope (m) (Neitsch et al., 2011). The drainage porosity of the soil equals the total porosity of the soil minus the soil porosity when the soil horizon is at field capacity.

$$Q_{\text{lat}} = 24 \cdot H_0 \cdot K_{\text{sat}} \cdot \text{slp}, \quad (4)$$

where Q_{lat} is the water discharge from the hillslope outlet, H_0 equals the saturated thickness of the hillslope outlet as a fraction of the total thickness (mm/mm), K_{sat} is the saturated hydraulic conductivity for the specific soil layer and slp is the slope value as the increase in elevation per distance unit for the specific hillslope.

SWAT+ calculates percolation using a storage routing methodology, where water percolates if the soil water content exceeds the field capacity of the specific soil layer, and the layer below is not yet saturated. The equation used to calculate the amount of percolation that occurs is:

$$w_{\text{perc}} = SW_{\text{excess}} \cdot \left(1 - \exp \left[\frac{-\Delta t}{TT_{\text{perc}}} \right] \right), \quad (5)$$

where w_{perc} is the amount of water percolating from the specific soil layer, SW_{excess} is the drainable soil water available, Δt is the time step (hours) and TT_{perc} is the travel time for percolation (hours). The travel time for percolation is defined in the model using:

$$TT_{\text{perc}} = \frac{\text{SAT} - \text{FC}}{K_{\text{sat}}}, \quad (6)$$

where TT_{perc} is the travel time for percolation (hours), SAT is the amount of water within the specific soil layer when completely saturated, FC is the soil water content at field capacity, and K_{sat} is the saturated hydraulic conductivity for the specific soil layer.

Therefore, K_{sat} largely determines if lateral flow or percolation is simulated by the model, where the lower the K_{sat} value within the soil layer, the lower the lateral flow value and higher the percolation ratio simulated.

Manipulating and calibrating major hydrological processes such as surface runoff, lateral flow and percolation remains imperative to accurately modelling water resources throughout a landscape. The uncalibrated SWAT+ model (Smit et al., 2023a) illustrated that the hydrological soil types within the catchment did not necessarily accurately reflect the dominant hydrological process associated with each soil mapping unit, such as *Interflow* soils not simulating sufficient

lateral flow volumes and *Recharge Shallow* soils primarily contributing surface runoff volumes, with limited percolation contributions.

SWAT+ incorporates parameters that allows the calibration of these processes, where PERCO and LATQ_CO parameters are linear coefficients that can be applied to the hillslope storage equation to limit lateral flow and percolation values (Wagner et al., 2022). Therefore, these parameters could potentially be manually calibrated to link soil morphology to dominant hydrological processes and accurately reflect these processes for each mapping unit as the current soil hydraulic properties fail to correctly simulate these processes.

The DEM, soil, land use, evapotranspiration, and weather input data were described within this paper as well as (Smit et al., 2023b). Sub-basin, reservoirs, management operations and HRU delineation have also been described (Smit et al., 2023b). Both models used the variable storage method as routing option.

Multi-gauge automatic calibration is often time-consuming, data-intensive and computationally demanding even for small watersheds (Chawanda, Arnold, et al. (2020); Chawanda, George, et al., 2020). Practically, calibration was performed through manual calibration of the most sensitive parameters identified by the sensitivity analysis and literature, performing several final iterations to fine tune results based on streamflow accuracy and hydrological process representation at the soil level. The calibration procedure needed to accomplish two goals. Firstly, the model needed to be calibrated to reflect accurate streamflow values by more accurately representing baseflow and peakflow volumes and secondly, each hydrological soil type needed to reflect their dominant hydrological response identified by their inherent hydrological soil mapping unit. Therefore, CN2, PERCO, and LATQ_CO were calibrated for each mapping unit to ensure lateral flow is simulated in *Interflow soils* (A/B and Soil/bedrock), percolation dominates in *Recharge soils* (Deep and Shallow), and surface runoff dominates in *Responsive soils* (Saturated and Shallow). Hydrogeological insight is therefore applied as a source of soft data informing the calibration procedure to better represent hydrological processes spatially.

2.4 | Calibration and validation

Five weirs were used to validate long-term streamflow simulations, which are managed by the Department of Water and Sanitation (DWS). These gauges, from smallest drainage area to largest were X3H003 that drains 48 km², X3H002 that drains 56 km², X3H001 that drains 174 km², X3H024 that drains 674 km², and X3H021 that drains the entire study area at 2421 km². Monthly streamflow averages were used for statistical analysis.

For statistical comparison, four widely used statistical indicators were employed, namely coefficient of determination (R^2), percentage bias (PBIAS), Nash-Sutcliffe efficiency (NSE) and Kling-Gupta efficiency (KGE). Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts.

3 | RESULTS

3.1 | Sensitivity analysis

Table 4 illustrates the commonly used parameters for calibration, their description and their relative sensitivity within the SWAT+ model for the Sabie River catchment. The t-stat and p-value are two statistical measurements, which assesses the sensitivity rank of each parameter. The t-stat represents a range of sensitivity, while the p-value identifies the significance of sensitivity. The higher absolute values of t-stat and low p-values (<.05) indicate a sensitive parameter. The lists of calibrated model parameters, the methods of change used, and the final calibrated values are shown in Table 5.

Firstly, ESCO, EPCO, ALPHA_BF, and RCHRG_DP were calibrated to better reflect the peakflow and baseflow characteristics of each of the five catchments, specifically by lower evapotranspiration values and increasing peakflow and baseflow values. Wagner et al. (2022) used the PERCO, CN3_SWF, and LATQ_CO parameters to calibrate different soil leaching potentials as described by Thompson et al. (2020). This approach was altered by using the CN2, PERCO, and LATQ_CO parameters to calibrate each hydrological soil type (Table 6).

In general, CN2 values were increased for all soil mapping units to improve surface runoff dynamics in the catchments and peak flow estimations. The soil hydrologic group for *Recharge Shallow* soils were altered from group D, as suggested by Arnold et al. (2011) for shallow soils, to group A, which would drastically lower the associated soil curve numbers, facilitating increased infiltration rates and therefore decreasing surface runoff values.

Due to the shallow nature of the *Recharge Shallow* soils, these soils were originally designated as soil hydrologic group D soils as recommended by the SWAT input/output documentation (Arnold et al., 2011), which suggest soils shallower than 508 mm be classified as soil hydrologic group D soils. Also, the *Interflow* soils were not simulating sufficient lateral flow as lateral flow may only occur when field capacity is exceeded and due to the high available water capacities and low saturated hydraulic conductivity values these conditions were not met (Smit et al., 2023a) (Table 6).

The PERCO parameters were also calibrated accordingly, where values were kept at default for *Recharge Deep* and *Recharge Shallow* soils but decreased for *Interflow soils* (A/B and Soil/bedrock), which would inhibit percolation and increase lateral flow for these soils. PERCO was also slightly decreased for *Responsive soils* (Saturated and Shallow) to slightly inhibit percolation, resulting in higher soil water content and potentially more surface runoff.

The LATQ_CO parameter was decreased for *Recharge soils* (Deep and Shallow) to limit lateral flow volumes, meaning more water is available to be stored within the soil profile, leading to more antecedent moisture content and potentially increased percolation values. LATQ_CO was not adjusted for *Interflow soils* (A/B and Soil/bedrock) or *Responsive Saturated* soils as these soils are major contributors to lateral flow. The adjustments of selected SWAT+ parameters should

Parameter	Description	t-stat	p-value
CN2	Initial SCS runoff curve number for moisture condition II	−5.47	0.00
ALPHA_BF	Baseflow alpha factor (l/days)	−5.16	0.00
LATQ_CO	Lateral flow coefficient	−5.26	0.00
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)	1.48	0.14
SOL_AWC	Available water capacity of the soil layer (mm H ₂ O /mm soil)	1.46	0.15
SOL_K	Soil hydraulic conductivity of the soil layer (mm H ₂ O /hour)	−1.45	0.15
SURLAG	Surface runoff lag coefficient	−1.03	0.30
EPCO	Plant uptake compensation factor	0.97	0.34
PERCO	Percolation coefficient	0.63	0.43
RCHRG_DP	Aquifer percolation coefficient for water to percolate from the shallow to the deep aquifer.	−0.34	0.64
ESCO	Soil evaporation compensation factor	−0.34	0.74
REVAP	Threshold depth of water in the shallow aquifer for “revap” to occur (mm H ₂ O)	0.65	0.83

TABLE 4 The most sensitive parameters within the SWAT+ model.

TABLE 5 Sensitive parameters applied to improve streamflow predictions.

Parameter	Catchment	Method of change	Min value	Max value	Fitted value
CN2	All	Relative	−15	15	6
ESCO	All	Replace	0	1	0.98
EPCO	All	Replace	0	1	0.45
ALPHA_BF	X3H003	Replace	0.005	0.48	0.004
	X3H002	Replace	0.005	0.48	0.0015
	X3H001	Replace	0.005	0.48	0.005
	X3H024, X3H021	Replace	0.005	0.48	0.04
RCHRG_DP	X3H003, X3H002, X3H001	Replace	0.001	0.05	0.01
	X3H021, X3H024	Replace	0.001	0.05	0.03
CH_K	All	Replace	0.5	150	34

improve the representation of internal hydrological processes by linking conceptualized hydrological processes to soil morphology.

3.2 | Streamflow predictions

The SWAT+ model had the exact same setup as used in Smit et al. (2023a). According to Knoben et al. (2019), a KGE value greater than −0.41 implies that a model prediction is a better fit than the mean observed values, where Moriasi et al. (2015) also presented improved evaluation criteria for hydrologic and water-quality models where streamflow simulations, $R^2 > 0.6$, $NSE > 0.5$ and $PBIAS \leq 15\%$ were regarded as satisfactory.

Based on these criteria presented by Moriasi et al. (2015), the simulations of the Hydrosol dataset during calibration and validation yielded satisfactory results at four of the five catchments, namely, X3H003, X3H002, X3H001, and X3H024, with R^2

values of 0.70, 0.63, 0.72, and 0.79 during the calibration period and values of 0.79, 0.62, 0.79, and 0.83 during the validation period, respectively (Table 7). These results are an improvement on the uncalibrated model, which achieved satisfactory R^2 at only three of the five catchments, namely, X3H003, X3H001, and X3H024 with values of 0.66, 0.67, and 0.71, respectively (Smit et al., 2023a).

Both during calibration and validation disappointing PBIAS values were achieved, where no catchment greater than 174 km² (X3H001) achieved PBIAS values below the 15% threshold set by Moriasi et al. (2015), however, PBIAS values were improved by 6%–8% during calibration and validation compared to the uncalibrated model (Smit et al., 2023a). In general, the negative PBIAS values during both the calibration and validation signify a general overestimation of total streamflow, which may be attributed to the overestimation of peak flows within the catchments, which could potentially be attributed to rainfall uncertainty.

TABLE 6 Manually calibrated parameters applied to improve the representation of soil hydrological processes.

Hydrological soil type	Default soil hydrologic group	Calibrated soil hydrologic group	Parameter	Default value	Calibrated value
A/B Interflow	C	C	CN2	70–85	76–89
			PERCO	1	0.5
			LATQ_CO	1	1
Recharge Deep	A	A	CN2	32–67	35–70
			PERCO	1	1
			LATQ_CO	1	0.8
Recharge Shallow	D	A	CN2	79–89	35–70
			PERCO	1	1
			LATQ_CO	1	0.8
Responsive Saturated	C	C	CN2	70–85	75–88
			PERCO	1	0.5
			LATQ_CO	1	1
Responsive Shallow	D	D	CN2	79–89	82–91
			PERCO	1	0.5
			LATQ_CO	1	1
Soil/bedrock Interflow	A	A	CN2	32–67	35–70
			PERCO	1	0.5
			LATQ_CO	1	1

TABLE 7 Statistical indicators of streamflow prediction accuracy during calibration and validation for all five catchments.

Catchment	Model period	R ²	PBIAS	NSE	KGE
X3H003 (48 km ²)	Uncalibrated	0.66	53.92	0.03	0.41
	Calibration	0.70	−9.91	0.80	0.73
	Validation	0.79	2.32	0.68	0.86
X3H002 (58 km ²)	Uncalibrated	0.57	43.67	−0.22	0.41
	Calibration	0.63	−4.52	0.84	0.74
	Validation	0.62	15.34	0.67	0.65
X3H001 (174 km ²)	Uncalibrated	0.67	37.27	0.48	0.58
	Calibration	0.72	−25.45	0.36	0.53
	Validation	0.79	−20.00	0.61	0.60
X3H024 (674 km ²)	Uncalibrated	0.71	20.85	0.54	0.67
	Calibration	0.79	−21.51	0.56	0.58
	Validation	0.83	−15.87	0.76	0.74
X3H021 (2421 km ²)	Uncalibrated	0.54	33.5	0.49	0.42
	Calibration	0.42	−27.54	0.42	0.51
	Validation	0.48	−25.25	0.34	0.64

When analysing NSE values during the calibration and validation periods, only the calibration period at X3H001 and calibration and validation period at X3H021 fell outside the accepted criteria range, which lies below the 0.5 threshold. The best NSE values were obtained during calibration of both X3H003 (48 km²) and X3H002 (56 km²), with values of 0.80 and 0.84, respectively. The best NSE values during the validation period were observed at X3H003 (48 km²) and X3H024 (674 km²), with values of 0.68 and 0.76, respectively. Both calibration and validation NSE values significantly

improved from the uncalibrated hydrological model at all five scales, especially at the 48, 56, 174 km² catchment scales.

All KGE values met the satisfactory threshold values of −0.41 set by Knoben et al. (2019). The best calibration KGE values were obtained at X3H003 (48 km²) and X3H002 (56 km²) with values of 0.73, and 0.74, whereas the best validation KGE values were observed at X3H003 (48 km²) and X3H024 (674 km²) with values of 0.86 and 0.74, respectively. Both calibration and validation KGE values significantly improved from the uncalibrated hydrological

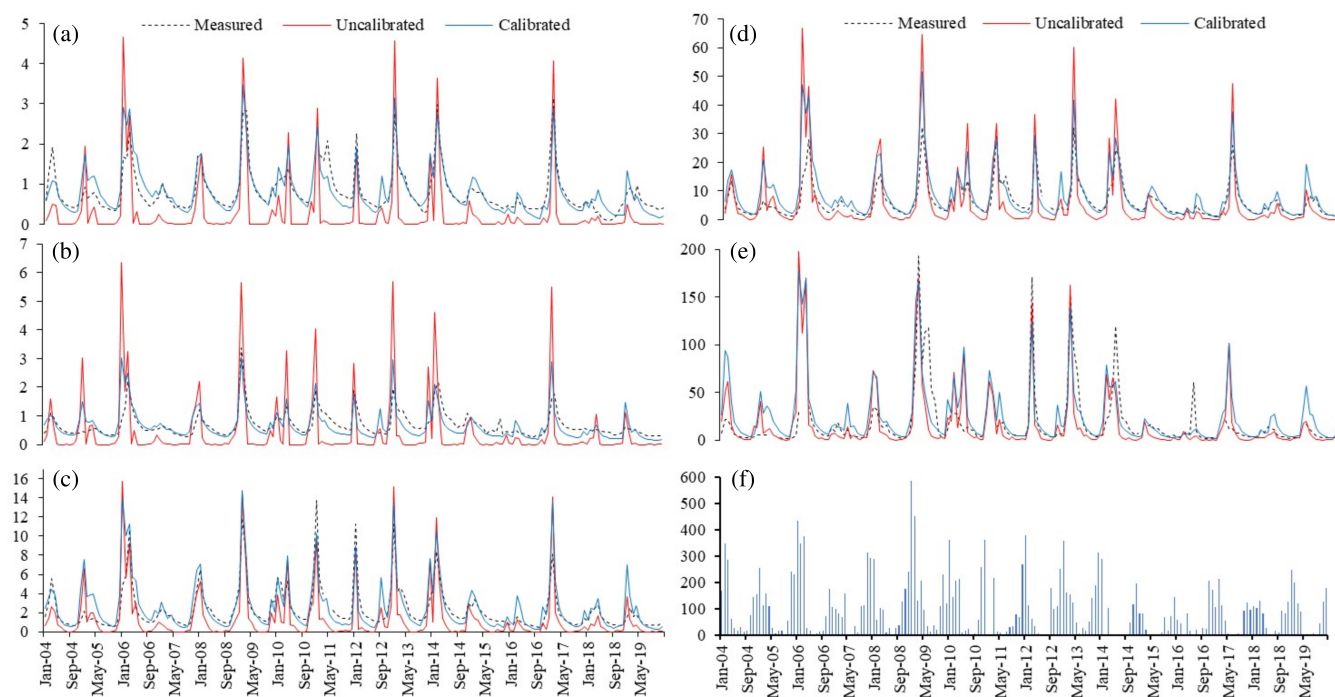


FIGURE 4 Monthly simulated streamflow for the Hydrosol model runs compared to observed streamflow at (a) X3H003, (b) X3H002, (c) X3H001, (d) X3H024, (e) X3H021 together with (f) the average monthly rainfall.

model at all five scales, especially at X3H003, X3H002, X3H001, which indicates the value of calibrated representative hydrological models at smaller scales, which is a notion supported by Smit et al. (2023a) and Van Tol et al. (2020).

The R^2 values for X3H021 decreased compared to the uncalibrated model, which could be attributed to rainfall uncertainty as well as a general overestimation of baseflow compared to the uncalibrated model. The ineffectiveness of the calibrated model at our largest catchment scales (674 and 2421 km²) is in accordance with Chen et al. (2016) and Ayana et al. (2019) where both studies were conducted in large scale catchments and the results of both studies suggested that improved soil information did not substantially improve modelling accuracy in large scale catchments. Scale and the effect thereof have been well discussed in the field of hydrological modelling, where accurately modelling small scale processes becomes increasingly difficult and time consuming as the heterogeneity of catchments increases with size (Blöschl & Sivapalan, 1995). Therefore, the reliability of conducting future scenario analyses using this model should remain questionable until modelling performance for the criteria set by Knoben et al. (2019) and Moriasi et al. (2015) are met.

Peak flows were slightly overestimated at the four smallest catchment scales (48, 56, 174, and 674 km²), with the largest overestimation of peak flow values occurring at catchment X3H024 (674 km²). Peak flows were underestimated at X3H021 (2421 km²), which is also the largest of the five catchment scales. What is readily observable is that baseflow simulations were greatly improved during calibration, where the uncalibrated model substantially underestimated baseflow

contributions, particularly at smaller catchment scales (48, 56, and 174 km²) where considerable baseflow contributions exist (Figure 4).

4 | DISCUSSION

4.1 | Calibration of streamflow

The differences in streamflow simulations are a direct product of the calibration of selected parameters, which affected how the major hydrological processes were simulated. The major hydrological processes differed between the uncalibrated and calibrated model simulations (Table 8) at each of the five catchments.

Improved streamflow predictions can primarily be a result of calibrating the selected groundwater parameters, such as ALPHA_BF, and RCHRG_DP, where both parameters were substantially decreased to improve the representation of baseflow values within the five catchments. Baseflow underestimation is still, however, prevalent at X3H003 (48 km²) and X3H002 (56 km²), which suggests that additional contributions from the deep aquifer potentially augment baseflow volumes provided by the shallow aquifer and are in accordance with other studies in the region (Saraiva Okello et al., 2018) as well as the broader region of South Africa (Van Tol et al., 2020).

In general, the calibrated model simulated far higher overland flow with values of 270, 214, 230, 209, and 170 mm compared to uncalibrated model with values of 105, 135, 173, 136, and 106 mm, respectively. The same was also true for average annual lateral flow

TABLE 8 Average annual hydrological processes at each catchment scale.

Catchment	Model run	Surface runoff mm.year ⁻¹	Lateral flow	Percolation	ET
X3H003	Uncalibrated	105	5	165	1006
	Calibrated	270	77	184	984
X3H002	Uncalibrated	135	5	152	1034
	Calibrated	214	93	145	955
X3H001	Uncalibrated	173	10	150	960
	Calibrated	230	130	167	944
X3H024	Uncalibrated	136	7	138	958
	Calibrated	209	121	133	932
X3H021	Uncalibrated	106	4	99	842
	Calibrated	170	75	96	802

values, where the calibrated model simulated substantially higher values at each of the five catchments, 77, 93, 130, 121, and 75 mm compared to values of 5, 5, 10, 7, and 4 mm, respectively. However, calibrated average annual percolation values only slightly increased at X3H003 and X3H001 with average annual percolation rates of 184 and 167 mm compared to the 165 and 150 mm, respectively. Whereas calibrated percolation rates slightly decreased at X3H002, X3H024, and X3H021 with values of 145, 133, and 96 mm, compared to uncalibrated values of 152, 138, and 99 mm, respectively. The calibrated model also simulated less evapotranspiration compared to the uncalibrated model with values of 984, 955, 944, 932, and 802 mm compared to 1006, 1034, 960, 958, and 842 mm, respectively.

As surface runoff is directly impacted by the permeability of soils, associated land use, and antecedent soil water conditions within each HRU, where land use values remained constant between simulations, the difference in selected calibrated parameters, especially CN2 values, affected how surface runoff was simulated within the two models (Neitsch et al., 2011; Zhang et al., 2019). On average, the CN2 value of each hydrological soil group increased after calibration, which allowed more surface runoff to be simulated.

However, ESCO also increased for the entire basin, less water was allowed to be removed by evaporation from lower levels in the soil, allowing more water to be available to either be stored within the soil, percolate, or flow laterally. However, EPCO was also decreased for the basin during calibration, which allowed less variation of the original depth distribution, from which plants could meet their transpiration demands and therefore decreased evapotranspiration values for the entire basin, further increasing the amount of water available to either be stored within the soil profile, flow laterally out of the soil profile or percolate to the underlying soil or shallow aquifer (Neitsch et al., 2011).

These changes within the model resulted in lower evapotranspiration rates after calibration, which are still in accordance with other studies in the region where evapotranspiration rates of between 690 and 1143 mm were recorded, depending on vegetation types, where savanna and shrubland vegetation types resulted in lower evapotranspiration rates than plantations and indigenous forests (Riddell et al., 2020; Van Eekelen et al., 2015). As 48.5% of the

catchment consists of savanna and only 40% consists of plantations and forest, these evapotranspiration values are reasonable (Riddell et al., 2020; Van Eekelen et al., 2015). A substantial amount of additional water was therefore made available for different hydrological processes within the Sabie River system, which were partitioned at their appropriate hydrological response at the soil level using the above-mentioned calibration approach (Figure 5).

4.2 | Calibration of hydrological soil types

Chawanda, Arnold, et al. (2020); Chawanda, George, et al. (2020) stated that automatic calibration using streamflow gauges may result in a high-performance indicator value, even with unrealistic water balance components and without internal consistency of the simulated processes. For instance, current soil water calibration procedures are primarily focused on calibrating available water capacity, bulk density, and saturated hydraulic conductivity (Wagner et al., 2022), however, calibrating these embedded parameters does not guarantee that the hydrological processes associated with each mapping type would then be reflected by the model or that their fluxes to be accurate of the real-world catchment processes. The calibration of hydrological soil types presents a method to circumnavigate these problems by providing a feasible method to improve internal hydrological process simulation in data scarce areas. Further calibration of SWAT+ parameters, in particular PERCO, LATQ_CO and CN2, allowed the linkage between hypedology and different dominant hydrological processes, which is captured within the Hydrosol dataset, to be better represented within the SWAT+ model.

After calibration *Recharge Deep* soils illustrated increases in both surface runoff and lateral flow, however, the dominant hydrological flow path remains recharge to the groundwater with *Recharge Deep* soils contributing 180 mm of recharge annually. *Recharge Shallow* soils differed substantially after calibration where far less surface runoff was simulated, slightly higher average annual lateral flow values and substantially higher percolation values were also simulated, with an average annual increase of 308 mm of recharge being simulated (Figure 5). These increases can be attributed to changing the soil

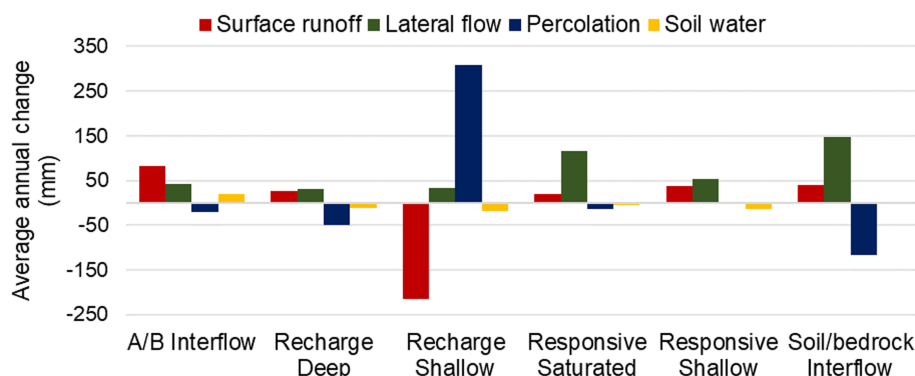


FIGURE 5 Average annual change in hydrological processes (in millimetres) at the soil level from uncalibrated to calibrated model runs for the entire catchment.

hydrologic group from D to group A, therefore drastically lowering CN values, increasing infiltration and limiting lateral flow. The dominant hydrological response of *Recharge Shallow* soils now reflects their hydropedological characteristics, which is the vertical flow through and out of the profile into the underlying fractured bedrock being the dominant flow direction, without any morphological evidence of temporary or permanent periods of saturation (Van Tol et al., 2015).

The same can be said for both *Responsive Saturated* and *Responsive Shallow* soils where surface runoff values slightly increased after calibration with values of 190 and 305 mm per annum, respectively. These soils contributed limited lateral flow and percolation volumes, primarily only contributing surface runoff, therefore, their hydropedology characteristics are accurately reflected within the model.

Soil/bedrock Interflow soils illustrated a marked increase in average annual lateral flow volumes after calibration with an increase of 132 mm, improving the hydropedological representation of these soils. The increase in lateral flow is in large part due to the PERCO parameter being adjusted, limiting percolation, therefore, increasing lateral flow volumes, indicated by the 117 mm decrease in percolation annually. Surface runoff is still the dominant hydrological process with an average annual contribution of 172 mm, which is to be expected (Van Tol et al., 2015).

A/B Interflow also illustrated improved lateral flow simulations, with decreases in percolation volumes. Surface runoff also remains the primary hydrological response with an average annual contribution of 268 mm. However, it remains uncertain if *A/B Interflow* soils are adequately reflected within the model as the SWAT+ model does not output hydrological processes for each soil horizon but rather aggregates these processes, which is a current shortcoming of the SWAT+ model.

These results are in accordance with other studies focusing on different calibration procedures in southern Africa (Chawanda, Arnold, et al. (2020); Chawanda, George, et al., 2020) as well as using hydrological soil information in hydrological modelling (Harrison et al., 2022; Sierra et al., 2018; Smit & Van Tol, 2022). These findings also emphasize the potential of calibrating hydrological models using hydropedology as an information carrier to inform improved hydrological process representation. This approach aligns with the study, by Van Tol et al. (2021) which illustrated the ability of an accurate hydrological soil map to act as data carrier for hydrological modelling

purposes. Additionally, Bouma et al. (2022) cited the need to adopt soil classification as data source and information carrier to provide solutions to the Sustainable Development Goals (SDGs) inextricably linked to soil function (Bouma et al., 2021; Lal et al., 2021).

4.3 | Hydrological process representation

The spatial distribution of hydrological processes also changed between uncalibrated and calibrated models as can be seen in Figure 6. More surface runoff is simulated in the drier savanna sections of the catchment after calibration because of increases in curve numbers between model simulations. The calibrated *Recharge Shallow* soils also now illustrate significantly less surface runoff, especially the most mountainous sections of the catchment.

The additional water provided after calibration for different hydrological processes significantly impacted the spatial distribution of lateral flow within the catchment, where calibration allowed significant increases in lateral flow to be simulated. Low lateral flow values in the uncalibrated model could be attributed to the low saturated hydraulic conductivity values within the Hydrosol datasets, which mostly inhibited lateral flow, allowing percolation to be the dominant hydrological process within the soil. Most of the lateral flow was simulated in the west of the catchment, where steeper slopes and significantly more rainfall occurs. Percolation also changed spatially after calibration where the spatial distribution of percolation aligns with *Recharge Deep* and *Recharge Shallow* soils.

Average annual soil water content also showed a significant spatial change after calibration, where increases in average annual soil water for *Interflow* soils (*A/B* and *Soil/bedrock*) increases soil water content in the savanna regions of the catchment in the east. Decreases in soil water content for *Recharge* (*Deep* and *Shallow*) and *Responsive Shallow* soils also affected in the spatial distribution of soil water in the mountainous regions in the west of the catchment (Figure 6), where *Recharge Deep* soils stored the most soil water due to the soils deep profile and relative position in the landscape.

This research shows that accurate hydrological soil information based on hydropedology can capture information that may serve as an effective soft data to spatially represent internal hydrological processes within a catchment, leading to improved representation of

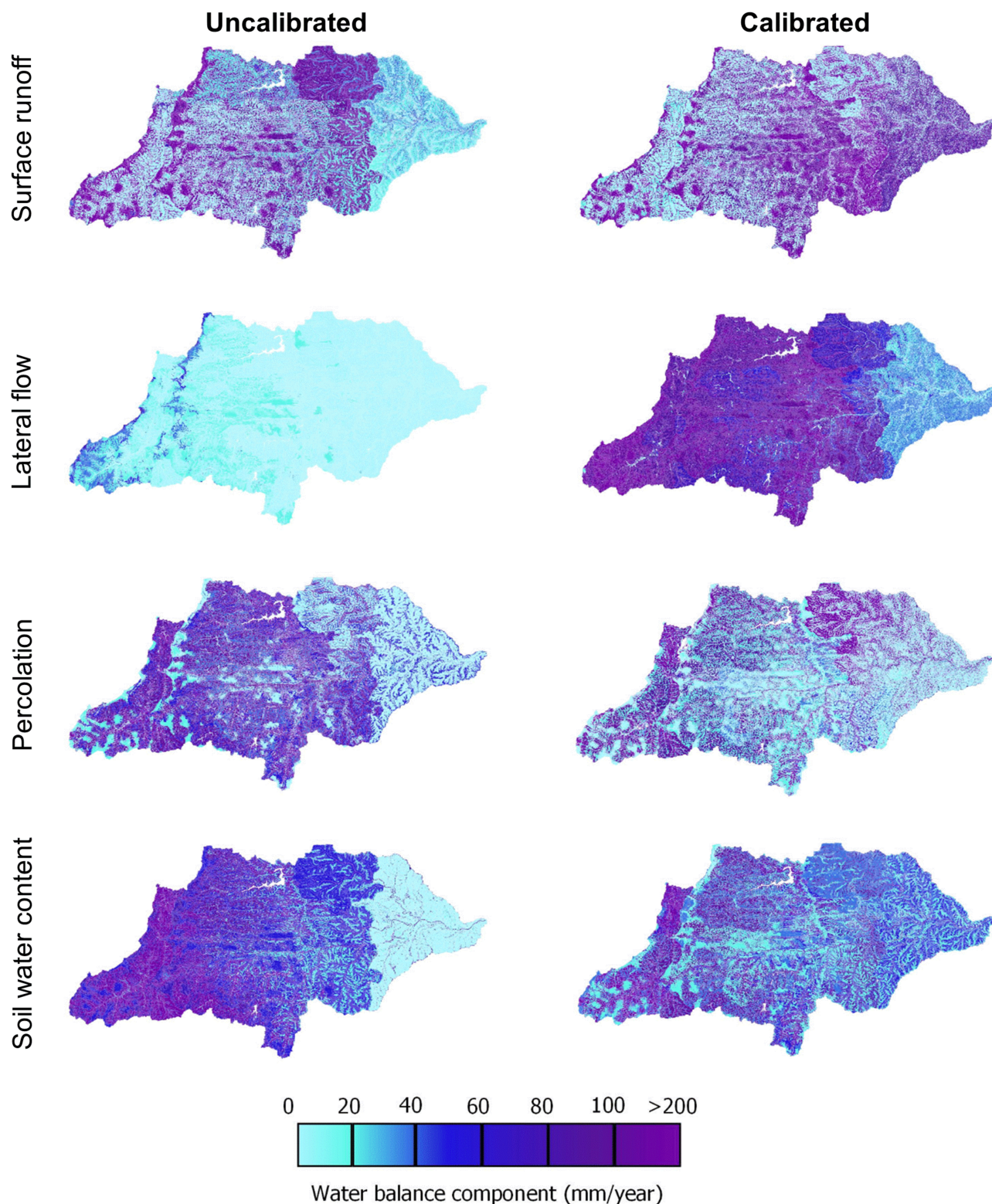


FIGURE 6 Average annual hydrological processes (in millimetres) at the HRU level for the uncalibrated and calibrated hydrological models.

internal hydrological processes (Smit & Van Tol, 2022; Van Tol et al., 2021). This research is therefore a practical application of interactions between pedologic and hydrologic processes across

spatiotemporal scales as described by Ma et al., which allows observations at the pedon level to be extrapolated to landscape scale modelling.

These results also agree with other studies focusing on the importance of process representation within the calibration procedure (Pfannerstill et al., 2017; Shafii et al., 2019). For example, Shafii et al. (2019) proposed constraining model predictions using flow pathway data to improve model calibration. Harrison et al. (2022) also suggested that lateral lag be incorporated for each hydrological soil type to improve lateral flow accuracy during calibration. Therefore, representing the spatial distribution of dominant hydrological processes remains imperative to hydrological modelling for decision-making and policy purposes (Bouslihim et al., 2019; Wahren et al., 2016). Modern water resource management plans are concerned with impacts at the local level, where the improved detail and accuracy of hydropedological information has been shown as more applicable than less detailed soil information (Harrison et al., 2022; Smit et al., 2023a).

5 | CONCLUSION

This study presented the findings of a calibration approach to improve both streamflow predictions and internal process representation using hydropedology as soft data in the Sabie River catchment, South Africa. This aim was achieved as hydropedology links each soil mapping unit to specific soil morphological features and their corresponding dominant hydrological processes.

Statistical analyses indicated substantial modelling improvement during both calibration and validation compared to the uncalibrated model. Further calibration of SWAT+ parameters, in particular PERCO, LATQ_CO, and CN2, allowed the linkage between hydropedology and different dominant hydrological processes, which implies that hydropedology could be considered as a viable source of soft data within the SWAT+ model. Accurate hydrological soil maps should form an integral part of modern process based hydrological modelling as they can act as important data sources and information carriers relating the variability of different hydrological processes across a landscape.

This is particularly promising for hydrological modelling in ungauged basins as well as the regionalization of hydrological soil information, where hydropedology could form an important soft data tool to aid different modelling approaches. Future research should focus on, firstly, testing the calibration of hydrological soil types in different hydrological conditions, determining the applications of calibrated hydrological soil information for ungauged basins as well as its impact on modelling land use and climate change scenario analyses.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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