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Examining the value of hydropedological information on hydrological modeling at different scales in the Sabie catchment, South Africa

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Abstract

Detailed soil information is increasingly sought after for watershed-scale hydrological modeling to better understand the soil–water interactions at a landscape level. In South Africa, 8% of the surface area is responsible for 50% of the mean annual runoff. Thus, understanding the soil–water dynamics in these catchments remains imperative to future water resource management. In this study, the value of hydropedological information is tested by comparing a detailed hydropedological map based on infield soil information to the best readily available soil information at five different catchment sizes (48, 56, 174, 674, and 2421 km²) using the soil and water assessment tool (SWAT)+ model in the Sabie catchment, South Africa. The aim was to determine the value of hydropedological information at different scales as well as illustrate the value of hydropedology as soft data to improve hydrological process representation. Improved hydropedological information significantly improved long-term streamflow simulations at all catchment sizes, except for the largest catchment (2421 km²). It is assumed that the resulting improved streamflow simulations are a direct result of the improved hydrological process representation achieved by the hydropedological information. Here, we argue that hydropedological information should form an important soft data tool to better understand and simulate different hydrological processes.

1 | INTRODUCTION

One of the modern challenges related to water resource management is understanding and representing soil–water interactions within a landscape-scale context (Kahmen et al., 2005; Smith, 2014; Wei et al., 2016; Zhang et al., 2015).

Abbreviations: AWC, available water capacity; Bd, bulk density; DSM, digital soil mapping; HRU, hydrological response unit; KGE, Kling–Gupta efficiency; Ksat, saturated hydraulic conductivity; NSE, Nash–Sutcliffe efficiency; PBIAS, percentage bias; SWAT, soil and water assessment tool.

With both soil and water being fundamental components of the hydrological processes within a catchment, understanding these processes remains imperative to understanding how a catchment responds to different land use management and climate change regimes (Bouma, 2016). Therefore, accurate soil information, especially soil hydraulic properties, is an important input parameter for physically based hydrological models (Worqlul et al., 2018). The interdisciplinary field of hydropedology which was first conceptualized by Lin (2003) includes the fields of hydrology, pedology, and soil physics and enables the study of soil–water dynamics at various scales

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(Lin et al., 2005). Hydrogeology has especially been particularly applicable in hydrological modeling as it provides a more detailed spatial understanding of soil–water interactions by improving the accuracy of internal catchment hydrological processes such as infiltration, runoff, lateral flow, percolation, return flow, and evapotranspiration at different scales within greatly varying catchments (Bryant et al., 2006; Me et al., 2015).

By combining modern digital soil mapping (DSM) techniques (McBratney et al., 2003) with hydrogeological insight (Van Tol et al., 2021), soil scientists can now produce detailed large-scale hydrological soil datasets for modeling purposes (Julich et al., 2012; Van Tol et al., 2015; Van Zijl et al., 2020; Van Tol & Van Zijl, 2022; Wahren et al., 2016). This practice has also been underpinned by several studies, which have indicated that improved soil information does indeed improve hydrological modeling efficiency (Bossa et al., 2012; Diek et al., 2014; Romanowicz et al., 2005; Smit & Van Tol, 2022). Examples of these also include where the Soil Land Inference Model (SoLIM) was used to create a more detailed soil map in a data-scarce catchment in north-central Portugal. The more detailed soil map led to a 7% increase in prediction accuracy compared to legacy soil data and coincided with a reduction in parameter uncertainty. Detailed hydrogeological information has also been applied widely in South Africa which saw hydrological soil information being applied to three different catchment sizes (640 km², 550 km², and 54 km²) in an urbanized catchment in South Africa, where hydrogeological soil information improved modeling accuracy at all three catchment sizes when compared to readily available soil information (Van Tol et al., 2021). Smit and Van Tol (2022) illustrated that although long-term streamflow simulations were similar using hydrogeological information compared to readily available soil information, hydrogeological information substantially improved the simulation of soil hydrological processes. These results also indicated that accurate streamflow simulations do not necessarily mean accurate internal hydrological processes. Harrison et al. (2022) used hydrogeological insight and measured hydraulic properties to substantially improve lateral flow simulations using hydrogeological insight in a mountainous catchment of South Africa. However, others maintain that the statistically small modeling improvements do not necessarily justify the cost and time to gather the improved soil information, or that improved soil information does not necessarily lead to more accurate hydrological modeling (Chen et al., 2016; Geza & McCray, 2008).

The value of hydrogeological information may also extend beyond the ability to accurately model long-term streamflow predictions. The argument is that hydrogeological information may serve as an effective “soft data” tool, especially in ungauged basins where streamflow data were absent or unre-

Core Ideas

- Improved soil information affects hydrological modeling accuracy.
- Catchment size affects the importance of soil information in modeling accuracy.
- Soil input resolution affects soil and water assessment tool (SWAT)+ hydrological response unit (HRU) structure and functionality.
- Hydrogeology improves soil hydrological process representation.

liable (Seibert & McDonnell, 2002). The use of “soft data” in hydrological modeling is defined as information that may not necessarily be measured directly but can be related to a hydrological process or processes (Van Tol et al., 2021; Winsemius et al., 2009).

In this study, the primary objective was to evaluate the impact of hydrogeological information on process-based hydrological modeling. This was achieved by statistically comparing long-term streamflow modeling accuracy using two levels of soil information, namely, hydrogeological information and South Africa’s most readily available soil information. Our focus was on the direct contribution of soil information on modeling efficiency and therefore we did not calibrate the model through extensive automated calibration techniques to favor one model but rather kept all inputs constant except for the soil information between modeling simulations and essentially treating the catchment as ungauged.

2 | MATERIALS AND METHODS

2.1 | Study area

The 2421 km² Sabie catchment is located in the Mpumalanga province of South Africa (Figure 1) and forms part of the larger transboundary Incomati river basin. 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 toward the east with an altitude of 250 m.a.s.l. as the Sabie River continues to flow eastward into Mozambique. The ambient geology is predominantly crystalline (igneous and metamorphic) and comprises various ranges of bedrock lithologies, primarily consisting of quartzites, granites, andesites, and gneiss formations (Council for Geosciences, 2007).

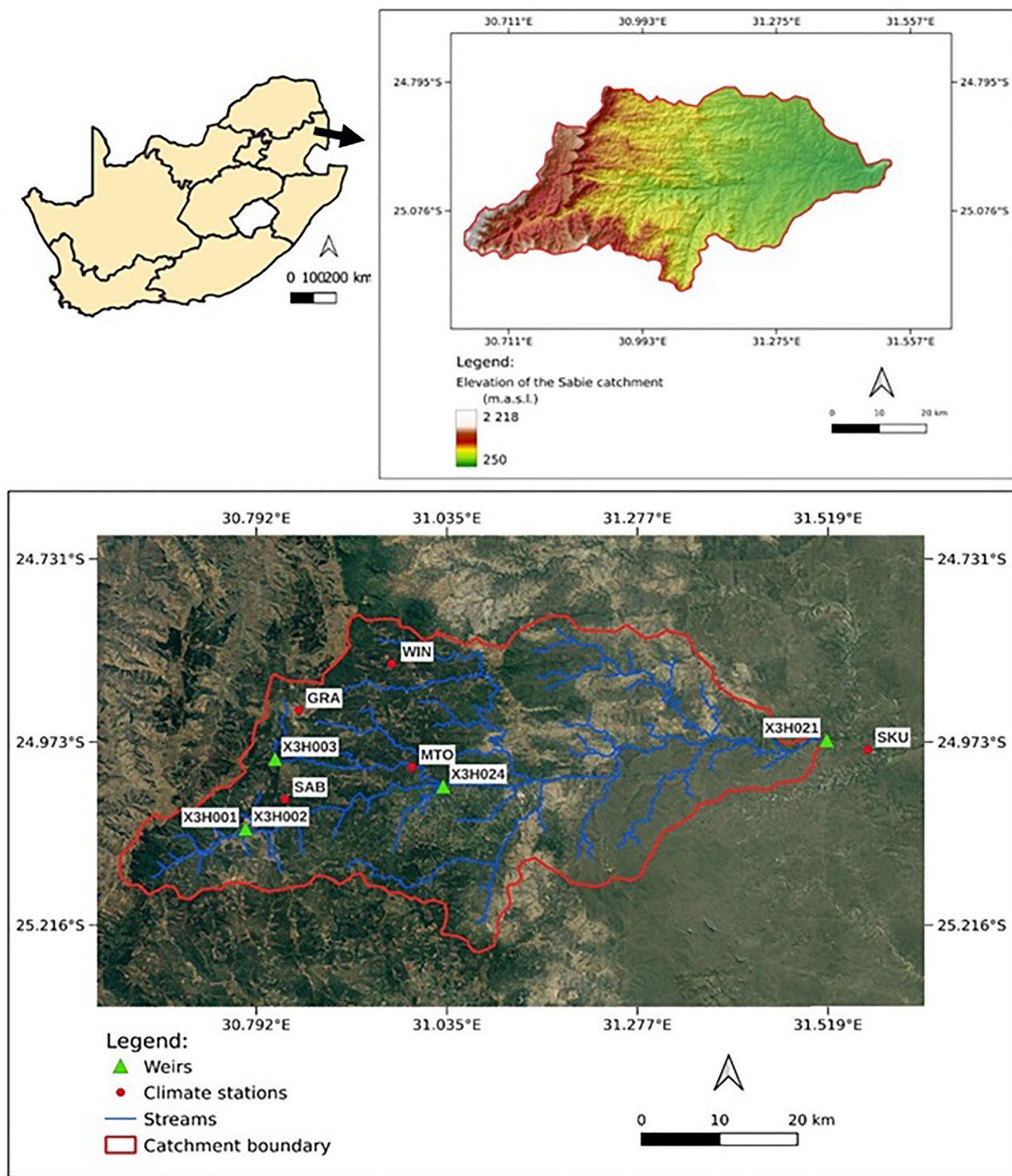


FIGURE 1 The Sabie River catchment, including elevation, weirs and climate stations.

With a semi-arid warm and hot climate in the east of the catchment and a temperate warm climate in the west of the catchment, a strong rainfall gradient ranging from 1600 mm in the west to 550 mm in the east exists within the catchment. Rainfall occurs mainly in the austral summer and normally results from convective thunderstorms, although periodic high-intensity rainfall events do occur from cyclones that

form over the Indian Ocean and track inland, where the orographic effect of the Drakensberg Escarpment creates severe localized flooding (Kruger et al., 2002). The main bioregions of the catchment consist of savanna at lower altitudes and montane grasslands and montane forests in the mountainous regions, which have been heavily altered by commercial forestry applications (Mucina & Rutherford, 2006).

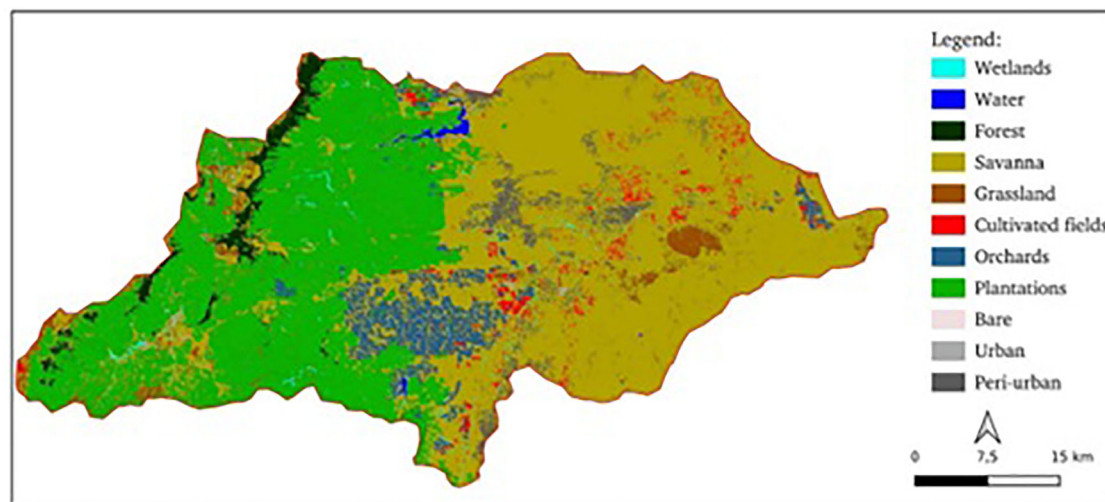


FIGURE 2 The land uses within the study area as demarcated from the 2013–2014 National Land Cover Map.

2.2 | Model, inputs, and setup

The soil and water assessment tool (SWAT) model is a process-based semi-distributed catchment model, which is widely used to simulate water quality and quantity predictions and assess the impacts of physical changes such as land use and climate changes in catchments across the globe with SWAT+ being an enhanced iteration of the renowned (Arnold et al., 1998). The QSWAT+ (v. 2.3) plugin was used to set up the watershed. As one of the first steps, the model divides the catchment into hydrological response units (HRUs). An HRU is a homogenous area in terms of soil, land use, and slope. The model calculates various components of the water balance, such as overland flow, infiltration, lateral flow, percolation, return flow, evapotranspiration, and discharge to the stream from each individual HRU. For a more complete description of the SWAT model, see Neitsch et al. (2011), and for changes in the SWAT+ version, see Bieger et al. (2017). The model was run from the start of January 2000 until the end of December 2019. The model warm-up period lasted for the first 4 years, followed by a 16-year validation period.

Daily rainfall data were obtained from four climate stations, namely, Sabie (SAB), Dunnottar at MTO Forestry (MTO), Rietspruit near God's Window (WIN), and Skukuza (SKU). Minimum and maximum temperatures were obtained from two climate stations, namely, Skukuza (SKU) and Graskop (GRA). All data were received courtesy of the South African Weather Service. 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 m × 30 m Shuttle Radar Topography Mission DEM (USGS, 2022). Land cover data (Figure 2) was obtained from the 2013/2014 South African National Land-Cover Map

(GeoterraImage, 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.

Both model runs were left uncalibrated to ensure that differences between model runs were only as a result of differences in soil input information, and therefore ensure that direct comparisons between soil datasets could be made. This was done due to the fact that any form of manual calibration would benefit either one or the other in predicting streamflow accuracy because of differences in how each model simulated different hydrological processes. This in essence meant that the catchment was treated as ungauged for the duration of the study.

2.3 | Soil information

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 as well as physical properties for each individual soil horizon with the unit, such as depth to bottom of soil layer, bulk density (Bd), available water capacity (AWC), saturated hydraulic conductivity (Ksat), organic carbon content, clay, silt, sand, and rock fragment contents, as well as moist soil albedo and the soil erodibility factor.

2.3.1 | Land Type dataset

The Land Type database was developed between 1972 and 2002 and covers the entire country of South Africa at a 1:250,000 scale. A Land Type polygon is defined as

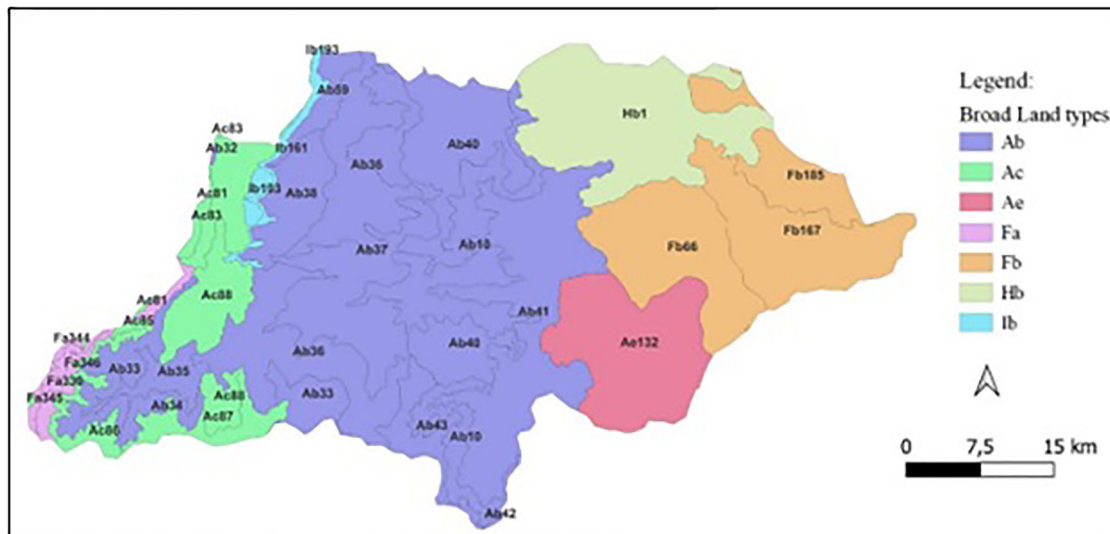


FIGURE 3 The Land Types present within the study area (Land Type Survey Staff, 1972–2002).

“a homogeneous, unique combination of terrain type, soil pattern, and macroclimate zone.” The Land Type survey identified 7070 unique Land Type polygons based on some 400,000 soil observations (approximately 1 observation per 300 h) (Paterson et al., 2015). Figure 3 highlights the broad Land Types within the Sabie catchment.

The Land Type database has also already been converted to a readily available spatial soil database specifically for use within the SWAT model. In the Sabie catchment, there are seven broad Land Type groups that could be divided into 42 different individual Land Types each with their own set of hydraulic properties (Table 1).

2.3.2 | Hydrosol dataset

The second soil dataset was the hydropedological dataset (Hydrosol) developed by using modern DSM techniques, an infield hydropedological soil survey, and legacy soil information. Details on the DSM approach are described in Smit et al. (2023) but briefly, we develop an extensive environmental covariate dataset which included geology, terrain variables such as planform curvature and profile curvature, climate variables such as mean annual minimum temperature and mean annual maximum temperature, and lastly, spectral covariates such as brightness index, coloration index, redness index, saturation index, and NDVI values for both the wet and dry seasons. A massive number of legacy soil observations ($n = 12,875$) were obtained from various legacy soil datasets, which were reclassified in accordance with the hydropedological groupings of South African soils (Table 2; Van Tol & Le Roux, 2019). A further 108 soil observations were made by hand auger during an infield hydropedological survey, which underwent the same reclassification.

The hydropedological database was divided into training (75%) and evaluation (25%) datasets. We used the well-known k-means clustering algorithm to overcome the imbalance of training data. The final soil map was then created in the R environment by running the multinomial logistic regression algorithm on the training data and using the validation data to test the accuracy of the hydropedological map, which had an evaluation point accuracy of 62% and a Cohen's kappa statistic value of 0.46. These results indicated that the hydropedological map obtained moderate agreement with reality and was therefore deemed to be acceptable for use in the modeling exercise (Figure 4).

Undisturbed core samples were collected from 78 representative diagnostic horizons within the study area during the field survey. These core samples were used to determine B_d , particle size distribution, and water retention characteristics. These results were combined with the already existing Land Type modal profile data, and then the required SWAT+ hydraulic parameters were obtained by averaging these properties for each hydropedological soil type (Table 3).

2.3.3 | Differences between datasets

Two model runs were set up for the two levels of soil information. Only the soil information differed between setups as all other factors were constant for both simulation runs. However, the Hydrosol and Land Type soil datasets differed both spatially (Figures 3 and 4) and in their hydraulic properties (Tables 1 and 3).

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

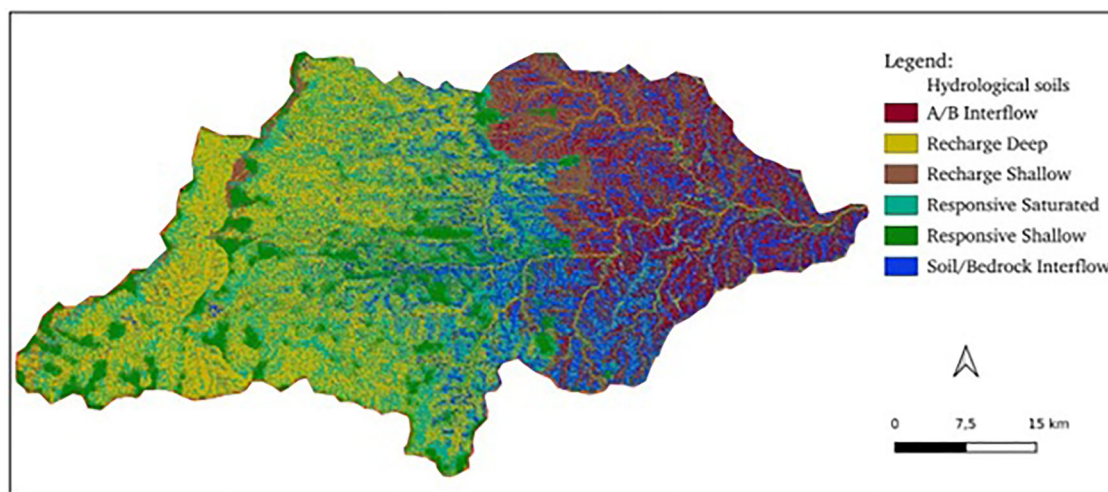


FIGURE 4 The hydrogeological map of the study area.

where Q_{surf} is the overland runoff or rainfall excess (mm H_2O), P_i is the precipitation depth for the day (mm H_2O), and I_a is the initial abstraction lost from canopy interception, surface storage, and infiltration prior to runoff. The water retention parameter (S) (mm H_2O) is estimated using the following equation:

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

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, with the soil hydrologic group and land use being the most important variables within the equation. In addition, the CN value of each HRU is updated according to the antecedent soil moisture content for each daily timestep (Neitsch et al., 2011; Zhang et al., 2019).

SWAT divides soil 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; and (D) soils with a high runoff potential, with very slow infiltration rates with very slow rates of water transmission (Neitsch et al., 2011). These hydrologic groups largely determine the surface runoff potential of different soils as they directly affect the SCS curve designation given by the model. As these hydrologic groups differ spatially between datasets, the curve numbers and asso-

ciated runoff characteristics will differ greatly between model runs.

Lateral flow is calculated by SWAT using a kinematic storage model, which simulates the movement of water in a two-dimensional cross-section of a hillslope (Neitsch et al., 2011). 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 (Equation 3).

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

where $\text{SW}_{\text{excess}}$ is 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. The increased spatial resolution of the Hydrosol map should result in an increased number of HRUs, which would result in a more complex model structure compared to the Land Type dataset. More HRUs and differences in porosity between soil datasets will affect how the model simulates lateral flow values.

The differences in hydraulic properties between the two levels of soil information should also affect modeling accuracy. The increased soil depth, AWCs, and clay content and decreased Ksat values of the Hydrosol map should result in more water being stored within the soil profile for longer periods, leading to more available water for root uptake, plant growth, and evapotranspiration. More antecedent moisture within the soil should also lower CN2 values, which remains

TABLE 1 The main hydraulic properties of the Land Type mapping units (means are followed by minimum and maximum values in brackets).

Broad Land Types	Horizon	Hydro-group	Depth (mm)	Bd (g/cm ³)	AWC (mm/mm)	Ksat (mm/h)	OC (%)	Clay (%)	Silt (%)	Sand (%)
Ae	A	A	270 (230,300)	1.45 (1.40,1.50)	0.085 (0.08,0.094)	145 (13,210)	0.7	8.3	13.3	78.3
	B		550 (450–670)	1.45 (1.40,1.50)	0.086 (0.68,0.09)	85 (13,210)	0.1	9.3	13.3	77.3
Ac	A	A	270 (230,300)	1.45 (1.40,1.50)	0.087 (0.085,0.089)	146 (13,210)	0.5	6.2	12.5	81.3
	B		500 (400–700)	1.45 (1.40,1.50)	0.097 (0.74,0.11)	135 (13,210)	0.1	6.6	12.5	80.9
Ab	A	A	290 (240,300)	1.45 (1.40,1.50)	0.089 (0.086,0.094)	147 (13,210)	0.8	9.2	13.3	77.5
	B		500 (450–650)	1.45 (1.40,1.50)	0.093 (0.68,0.10)	85 (13,210)	0.1	9.4	13.3	77.3
Fb	A	C	270 (270,270)	1.50 (1.40,1.60)	0.074 (0.068,0.080)	9 (4,3,13)	1.0	19.3	17.5	63.2
	B		550 (450–670)	1.45 (1.40,1.50)	0.056 (0.48,0.09)	9 (4,3,13)	0.2	19.3	17.5	63.2
Fa	A	C	280 (270,290)	1.50 (1.4,1.60)	0.08 (0.074,0.090)	35 (13,210)	0.9	15.3	16.3	68.5
	B		300 (300,300)	1.45 (1.40,1.50)	0.07 (0.68,0.09)	35 (13,61)	0.1	15.3	16.3	68.5
Hb	A	B	250 (210,300)	1.45 (1.40,1.50)	0.076 (0.068,0.090)	145 (13,210)	0.5	11.5	14.7	73.7
	B		300 (300–300)	1.45 (1.40,1.50)	0.076 (0.68,0.094)	50 (13,210)	0.1	11.5	14.7	73.7
Ib	A	D	290 (290,290)	1.45 (1.40,1.50)	0.088 (0.086,0.090)	110 (13,210)	0.4	11.0	15.0	74.0
	B		375 (300–450)	1.45 (1.40,1.50)	0.085 (0.68,0.09)	40 (13,61)	0.1	11.0	15.0	74.0

Abbreviations: AWC, available water capacity; Bd, bulk density; Ksat, saturated hydraulic conductivity; OC, organic carbon.

one of the most sensitive parameters within the SWAT model (Mengistu et al., 2019; Wahren et al., 2016). CN2 is the runoff curve number for Moisture Condition II, calculated by the soil conservation service (SCS) runoff equation and adjusted soil moisture before a precipitation event. The CN2 value is therefore also directly affected by the initial soil hydrologic group of each soil mapping unit and will differ between model runs.

2.4 | Validation data and statistical comparison

Five weirs were used to validate long-term streamflow simulations, which is managed by the Department of Water and Sanitation. These gauges, (from smallest drainage area to largest), were X3H003 which drains 48 km², X3H002 which drains 56 km², X3H001 which drains 174 km², X3H024 which drains 674 km², and X3H021 which drains the entire study area at 2421 km². Daily streamflow was converted to monthly average values for comparison purposes.

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). PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, while negative values indicate model overestimation (Moriassi et al., 2007; Equation 4).

$$PBIAS = \frac{\sum_{i=1}^n V_o - \sum_{i=1}^n V_e}{\sum_{i=1}^n V_o} \% \quad (4)$$

where V_o and V_e are, respectively, the observed and simulated volumes of water for day i .

NSE is a normalized statistic that determines the relative magnitude of the residual variance (“noise”) compared to the measured data variance (“information”). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line (Nash & Sutcliffe, 1970; Equation 5).

$$NSE = \frac{\sum_{i=1}^{12} (Q_{oi} - Q_{ei})^2}{\sum_{i=1}^{12} (Q_{oi} - \bar{Q}_o)^2} \quad (5)$$

where Q_{oi} and Q_{ei} are, respectively, observed and estimated discharge of day i and $\bar{Q}_o$ is the mean of the observed discharges. The optimum value is 1.0, with higher values indicating better model performance.

KGE incorporates correlation, variability bias, and mean bias (Gupta et al., 2009) and is increasingly used for model

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

Hydrological mapping unit	Soil form	WRB reference groups	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.

calibration and evaluation (Equation 6).

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_e}{\sigma_o} - 1\right)^2 + \left(\frac{\bar{Q}_e}{\bar{Q}_o} - 1\right)^2} \quad (6)$$

where r is the correlation coefficient between the observed and simulated flows, σ_o and σ_e are standard deviations of observed and simulated flows respectively. $\bar{Q}_e$ and $\bar{Q}_o$ represent the mean of the simulated and observed discharges, respectively.

3 | RESULTS AND DISCUSSION

3.1 | Streamflow simulations

The two model set-ups for the two levels of soil information had an identical number of sub-basins (119) and landscape units (616), because the same DEM was used to delineate these. The number of HRUs differed significantly where the hydrosol model contained 11,883 HRUs compared to the 3332 HRUs contained within the Land Type model. The large discrepancy between model HRUs is purely a result of the spatial differences between the soil input information. Even though the Hydrosol soil dataset contained fewer individual mapping units, the far greater level of detail (30 m × 30 m) of these mapping units still resulted in a significantly increased number of HRUs.

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. 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 model at X3H003, X3H001, and X3H024 all yielded satisfactory results, with R^2 values of 0.66, 0.67, and 0.71, respectively. On the other hand, the Land Type model simulations provided satisfactory results at X3H001 and X3H024, with R^2 values of 0.61 and 0.62, respectively. All Hydrosol simulations achieved satisfactory KGE values, in accordance with Knoben et al. (2019) with values above the -0.41 threshold. However, the Land Type model did not meet the minimum KGE threshold at X3H003 and X3H002 with values of -0.43 and -0.55 , respectively.

Both models produced disappointing PBIAS values, where only the Land Type model achieved PBIAS values below the 15% threshold set by Moriasi et al. (2015) at X3H024 and X3H021. However, the Hydrosol model provided more accurate PBIAS values at X3H003, X3H002, and X3H001, although they did not meet the 15% criteria. Analyzing NSE values, the Hydrosol model outperformed the Land Type model at each catchment scale, with only the Hydrosol model achieving an acceptable NSE value of 0.54 at X3H024.

Peak flows were overestimated by both models, however, the Hydrosol dataset yielded far lower peak flows than the Land Type dataset (Figure 5), which improved modeling accuracy at smaller scales (X3H001, X3H002, and X3H003) but resulted in the underestimation of peak flows at the largest catchment scale (X3H021). Baseflow simulations were also substantially underestimated by both models at all catchment

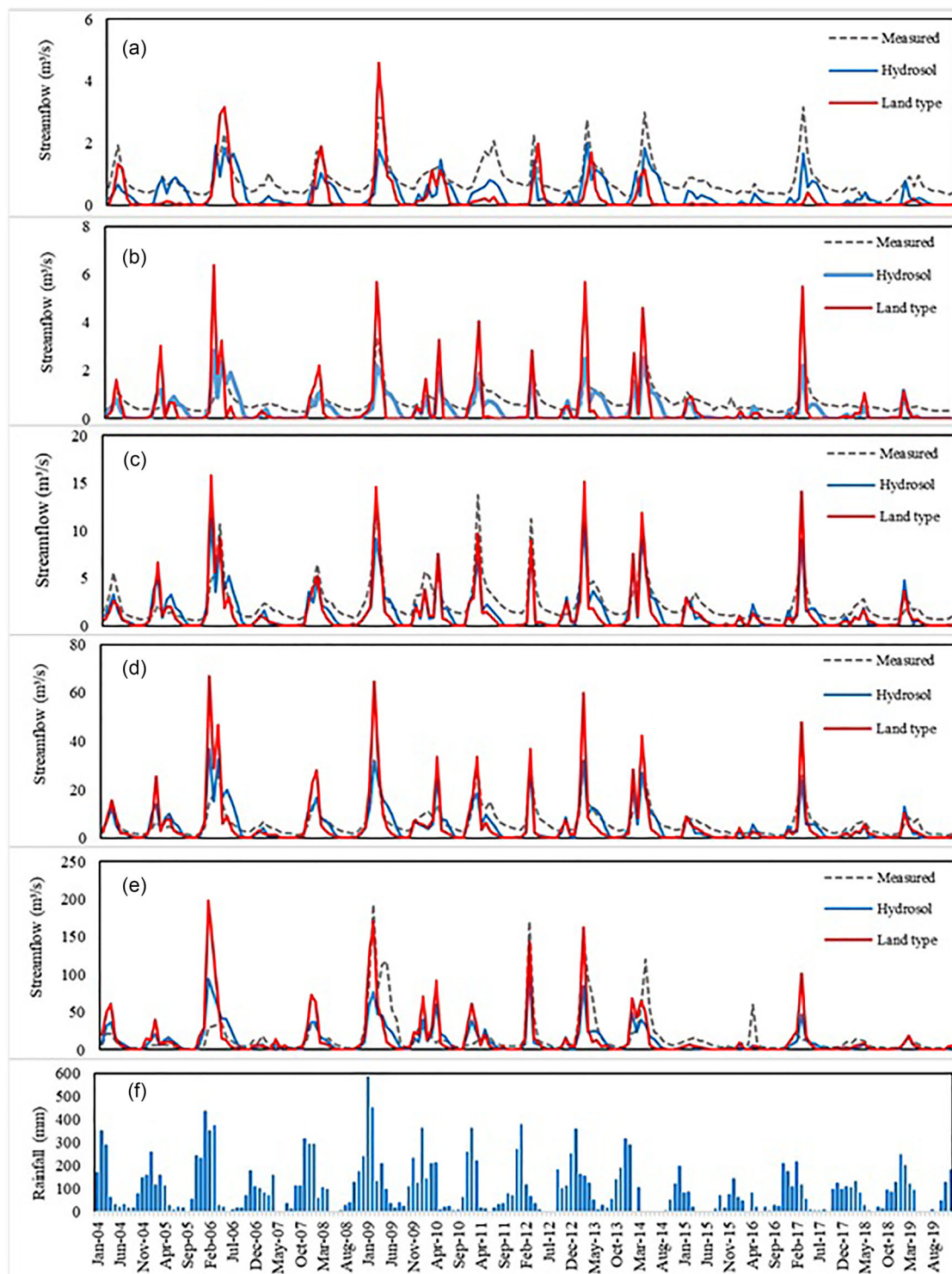


FIGURE 5 Monthly simulated streamflow for the Landtype and Hydrosol model runs compared to observed streamflow at (a) X3H003, (b) X3H002, (c) X3H001, (d) X3H024, (e) X3H021 together with (f) the average monthly rainfall during the validation period.

levels but particularly at smaller catchment sizes (48 km², 56 km², and 174 km²) where considerable baseflow contributions exist (Figure 5). The positive PBIAS values across all model simulations also equate to the general underestimation of total streamflow values which can also be attributed to the

underestimation of baseflow values across all catchment levels. SWAT+ allows users to adjust groundwater parameters to mitigate or correct baseflow values.

Statistical comparison between the two models over the 16-year simulation period indicated a substantial difference

TABLE 3 The main hydraulic properties of the Hydrosol mapping units.

Hydrological soil types	Horizon	Hydro-group	Depth (mm)	Bd (g/cm ³)	AWC (mm/mm)	Ksat (mm/h)	OC (%)	Clay (%)	Silt (%)	Sand (%)
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

Abbreviations: AWC, available water capacity; Bd, bulk density; Ksat, saturated hydraulic conductivity; OC, organic carbon.

TABLE 4 Statistical indicators of monthly streamflow simulations at five catchment levels.

Catchment	Soil data	R ²	PBIAS	NSE	KGE
X3H003	Land Type	0.46	68.27	−0.76	−0.43
	Hydrosol	0.66	53.92	0.03	0.41
X3H002	Land Type	0.42	37.34	−3.24	−0.55
	Hydrosol	0.57	43.67	−0.22	0.41
X3H001	Land Type	0.68	41.04	0.3	0.48
	Hydrosol	0.67	37.27	0.48	0.58
X3H024	Land Type	0.7	11.6	−0.41	0.09
	Hydrosol	0.71	20.85	0.54	0.67
X3H021	Land Type	0.44	13.29	0.28	0.63
	Hydrosol	0.54	33.5	0.49	0.42

Abbreviations: KGE, Kling–Gupta efficiency; R², coefficient of determination; NSE, Nash–Sutcliffe efficiency; PBIAS, percentage bias.

between the two levels of soil information. It could be inferred that the Hydrosol model outperformed the Land Type model, at four of the five catchment scales (48 km², 56 km², 174 km², and 674 km²) when comparing monthly observed streamflow values (Figure 5 and Table 4), where the higher R², NSE, and KGE values indicated improved model performance. The improved modeling accuracy is presumed to be a direct result of the improved simulation of real-world hydrological processes by improving the accuracy of soil information in the model. However, it does seem as if the importance of soil information decreases as the catchment size increases, which could be a result of the increased variability of soil properties, such as texture, organic matter content, and hydraulic conductivity, which may vary widely across catchments. The ineffectiveness of improved soil information at our largest catchment scale (2421 km²) is in accordance with both Chen et al. (2016) which found soil resolution was relatively insignificant when modeling streamflow and sediment yield in a 2421 km² catchment and Ayana et al. (2019) who concluded that improved soil data resolution only marginally improved streamflow simulations with an improved NSE of only 1% in a 16,000 km² catchment in Ethiopia. Both studies were conducted in large-scale catchments, and therefore these results suggest that improved soil information does not necessarily improve modeling accuracy in large-scale catchments.

3.2 | Hydrological processes

These differences in streamflow simulations and hydrological processes are a direct result of the differences between soil data input datasets and how soil input data affects the simulation of these different hydrological processes.

TABLE 5 Average annual hydrological processes at each catchment scale.

Catchment	Soil data	Precipitation (mm year ⁻¹)	Overland flow (mm year ⁻¹)	Lateral flow (mm year ⁻¹)	Perco (mm year ⁻¹)	ET (mm year ⁻¹)
X3H003	Hydrosol	1375	105	5	165	1006
	Land Type		232	8	126	949
X3H002	Hydrosol	1374	135	5	152	1034
	Land Type		323	24	63	964
X3H001	Hydrosol	1374	173	10	150	960
	Land Type		346	76	97	936
X3H024	Hydrosol	1285	136	7	138	958
	Land Type		296	37	74	932
X3H021	Hydrosol	1109	106	4	99	842
	Land Type		239	17	43	813

Abbreviations: Perco, percolation; ET, evapotranspiration.

The major hydrological processes differed substantially between model simulations (Table 5) at each of the five catchments. The Hydrosol simulations resulted in far lower average annual overland flow values than its Land Type counterpart, with values of 105, 135, 173, 136, and 106 compared to 232, 323, 346, 296, and 239 mm, respectively. As surface runoff directly impacts the permeability of soils, land use, and antecedent soil water conditions within each HRU and land use values remained constant between simulations, the difference in soil hydrological group and accompanying soil physical properties severely impact how surface runoff is simulated within the model (Neitsch et al., 2011; Zhang et al., 2019). Recharge deep soils that are the dominant hydrogeological soil within each of the five catchments contain the hydrologic soil group A designation, where low SCS curve numbers prohibit large overland flow values from being simulated, resulting in more infiltration within the soil profile.

The Hydrosol dataset resulted in consistently lower lateral flow simulation at all five catchment levels, with values of 5, 5, 10, 7, and 4 compared to 8, 24, 76, 37, and 17 mm, respectively. The same factors that affect the soil runoff process affect lateral flow, where lower AWCs and shallower soil profiles of the Land Type dataset allow for more lateral flow to occur because less water is needed to reach field capacity due to shallower profiles and lower AWCs. These results are also in accordance with the hydrological soil types within the catchments. Lateral flow or interflow soils (A/B and soil/bedrock) are the least prevalent hydrological soil types within the Sabie River system, where X3H021 contains the only substantial amount of interflow soils at 25.5%.

Far higher percolation values were simulated by the Hydrosol model than the Land Type model at all five levels, decreasing as the catchment size increased from 165 mm per year at X3H003 to 99 mm per year at X3H021, which is presumably a result of differences in soil hydraulic properties but also in the decreased amount of precipitation within

larger catchments. The SWAT model allows water to percolate if the soil water content exceeds field capacity for the specific soil layer and the underneath soil layer is still unsaturated. This is therefore a function of the amount of soil water available to percolate, the field capacity of soil layers as well as their Ksat. The variability of percolation is therefore largely affected by the spatial variability of various soil properties such as the depth of the soil profile, Bd, Ksat, and AWC of the soils, but also a product of SCS curve numbers where low curve numbers yield higher infiltration rates, allowing more water to enter the soil profile and potentially be available for percolation.

The Hydrosol dataset also simulated high evapotranspiration value compared to the Land Type dataset with values of at all five catchment scales, with values of 1006, 1034, 960, 958, and 842 compared to 949, 964, 936, and 932 mm per year, respectively. These results are comparable to other studies in the region such as Van Eekelen et al. (2015) with values of 1143 mm for plantations, 1087 mm for forest and woodlands, and 690 mm per year for savanna and shrublands. Riddell et al. (2020) also found riparian savanna vegetation would record evapotranspiration values between 765 and 806 mm for one hydrological year within the region. Therefore, both models simulated reasonably accurate evapotranspiration values with high values where plantations and forests are the dominant land use, such as X3H003, X3H002, and X3H001, with decreasing values at the larger catchments that subsequently include more savanna and shrubland vegetation, such as X3H024 and X3H021. However, differences between evapotranspiration values are a direct result of differences in soil properties, where more water stored within the soil profile, due to deeper soils with large AWCs, results in more water being available for root uptake and evapotranspiration, as can be seen by the higher evapotranspiration values of the Hydrosol model compared to the Land Type model.

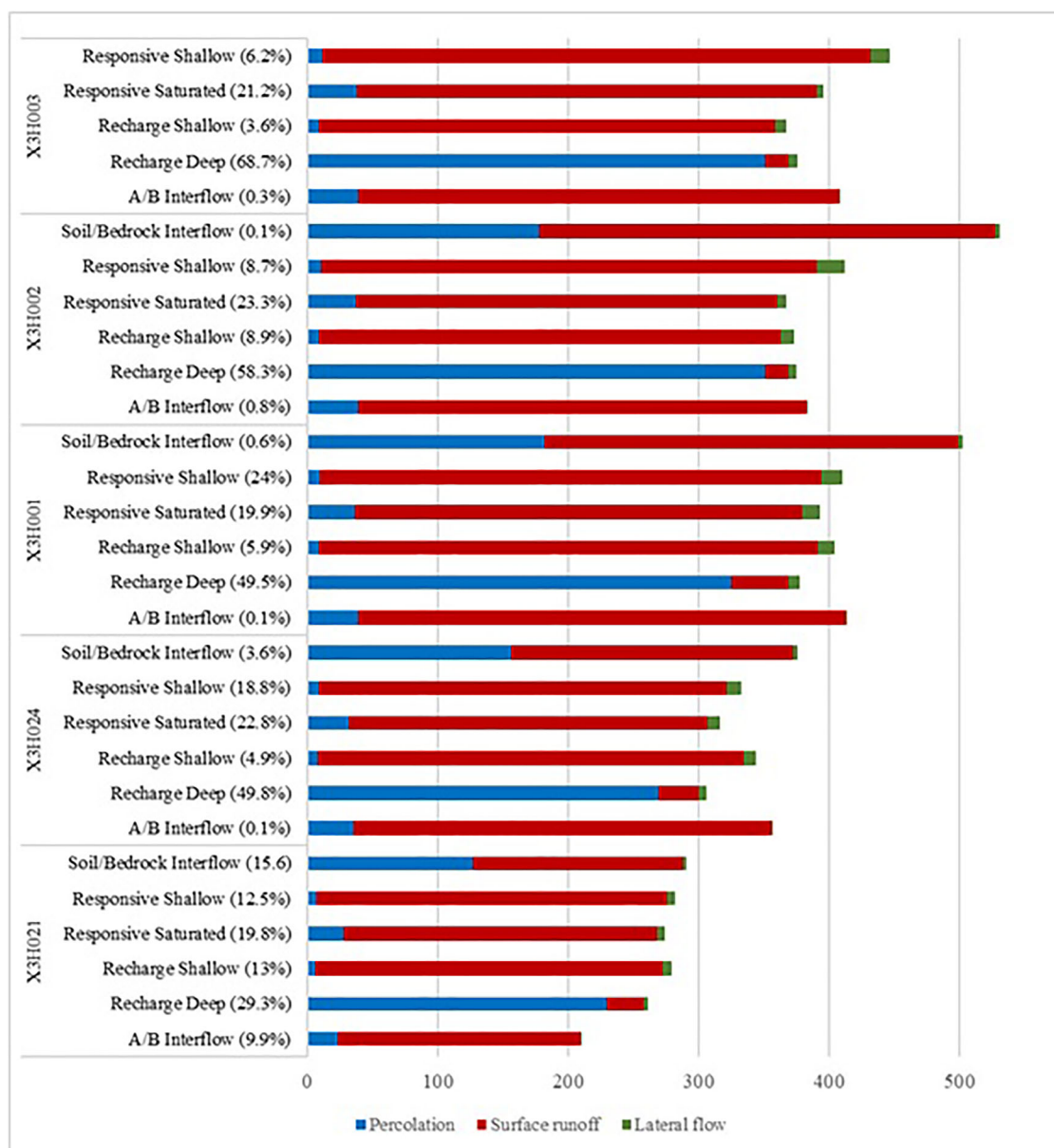


FIGURE 6 Average annual percolation, surface runoff and lateral flow values (mm) for the Hydrosol dataset as well as percentage of each mapping unit.

Figures 6 and 7 illustrate the average annual surface runoff, lateral flow, and percolation differences between each soil mapping unit between the two model simulations as well as the percentage spatial coverage of each mapping unit within each catchment. On average the Hydrosol soils simulated far lower average annual lateral flow, lower percolation rates, and higher surface runoff values than their Land Type counterparts, except for recharge deep soils. Recharge deep soils are the dominant hydrological soil types within the Hydrosol map and are prevalent at all five catchment scales; the average annual surface runoff and lateral flow values at each catchment outlet therefore remained lower than the simulated values of the Land Type model.

Recharge deep soils contain the hydrological soil group A designation, where low SCS curve numbers would prohibit large overland flow values to be simulated but rather result in higher infiltration rates. Recharge deep soils contained deeper soil profiles, with higher AWCs than the Land Type dataset, which means more water can infiltrate and be stored within the soil profile, without the profile reaching field capacity, affecting the simulation of different hydrological processes. These results are in accordance with other studies focusing on soil information in hydrological modeling (Bouslihim et al., 2019; Wang & Melesse, 2006).

Figures 6 and also illustrate how differences between individual mapping units simulate different hydrological pro-

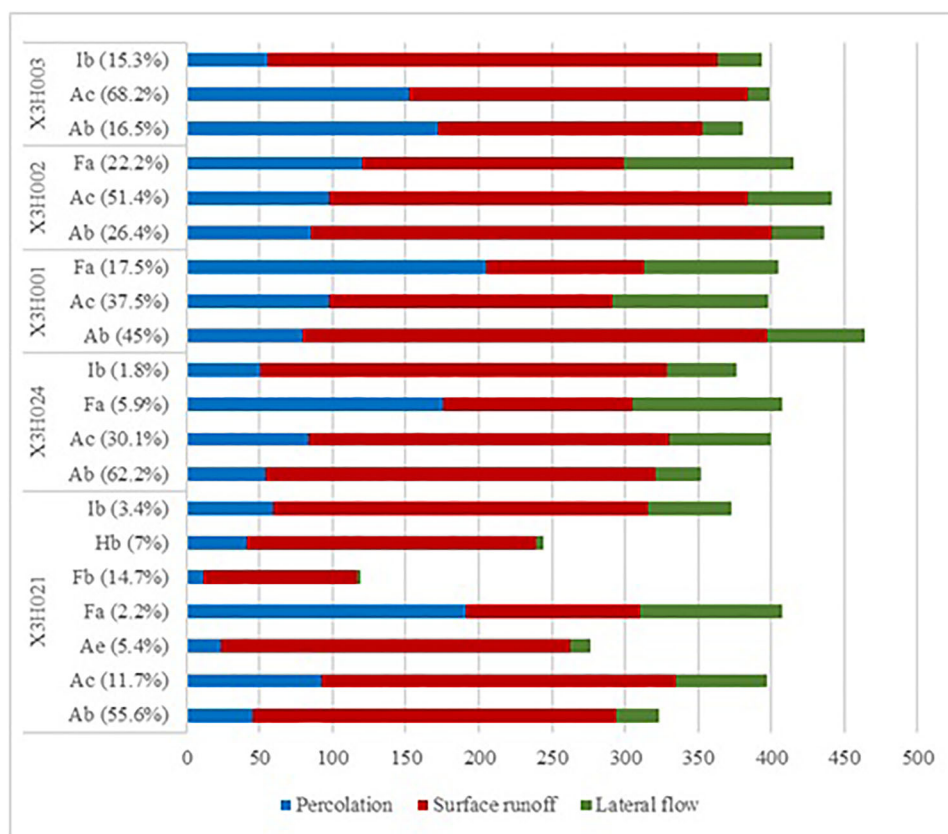


FIGURE 7 Average annual percolation, surface runoff and lateral flow values (mm) for the Land Type dataset as well as percentage of each mapping unit.

cesses under the same hydrological conditions based on soil hydraulic properties. These results suggest that even though soils are mapped according to their hydropedological characteristics, these characteristics are not necessarily reflected in the modeling outputs. For example, due to the shallow depth and comparable soil hydraulic properties, both Recharge Shallow and Responsive Shallow soils simulate similar hydrological processes at each catchment scale. The same could be said for the A/B and Soil/bedrock Interflow soils that struggle to simulate large volumes of lateral flow compared to the other mapping units within the same catchments. These results suggest that additional calibration of model parameters would be required to reflect the hydrological responses of different soils more adequately for different catchments. These results agree with Harrison et al. (2022), where the calibration of the lateral lag time coefficient parameter within the SWAT+ model was required to improve the simulation lateral flow for each hydrological soil type within a mountainous research catchment in South Africa.

Differences in average annual lateral flow and percolation rates between mapping units under the same environmental conditions highlight the importance of soil hydraulic information. In particular, these results suggest that Ksat and AWC values, which have been shown to be sensitive parameters

within the model (Mengistu et al., 2019), severely affect how these two hydrological processes are simulated. Both are calculated when soil water exceeds the field capacity of the specific soil layer. However, higher Ksat and porosity values and steep slopes encourage water to drain laterally to the nearest stream channel, whereas lower Ksat and porosity values inhibit lateral flow to the channel and encourage the percolation of excess soil water to the underlying layer (Neitsch et al., 2011). The accurate representation of these hydraulic parameters will affect whether these processes are simulated accurately.

Large percolation values also correlate extremely well with the most dominant hydrological soil type across the Sabie River catchment, Recharge soils (Deep and Shallow), as well as the large baseflow contributions seen within the measured streamflow data. The defining characteristic of these soils is the absence of any morphological indication of saturation. Vertical flow through and out of the soil profile into the underlying bedrock is the dominant flow direction (Table 2). These soils also show no indication of permanent or periodic saturation within the soil profile, no indications of major runoff events at the soil surface, and no indication of the lateral movement of water at the soil/bedrock or A/B interface (Van Tol & Le Roux, 2019). Hydropedologically

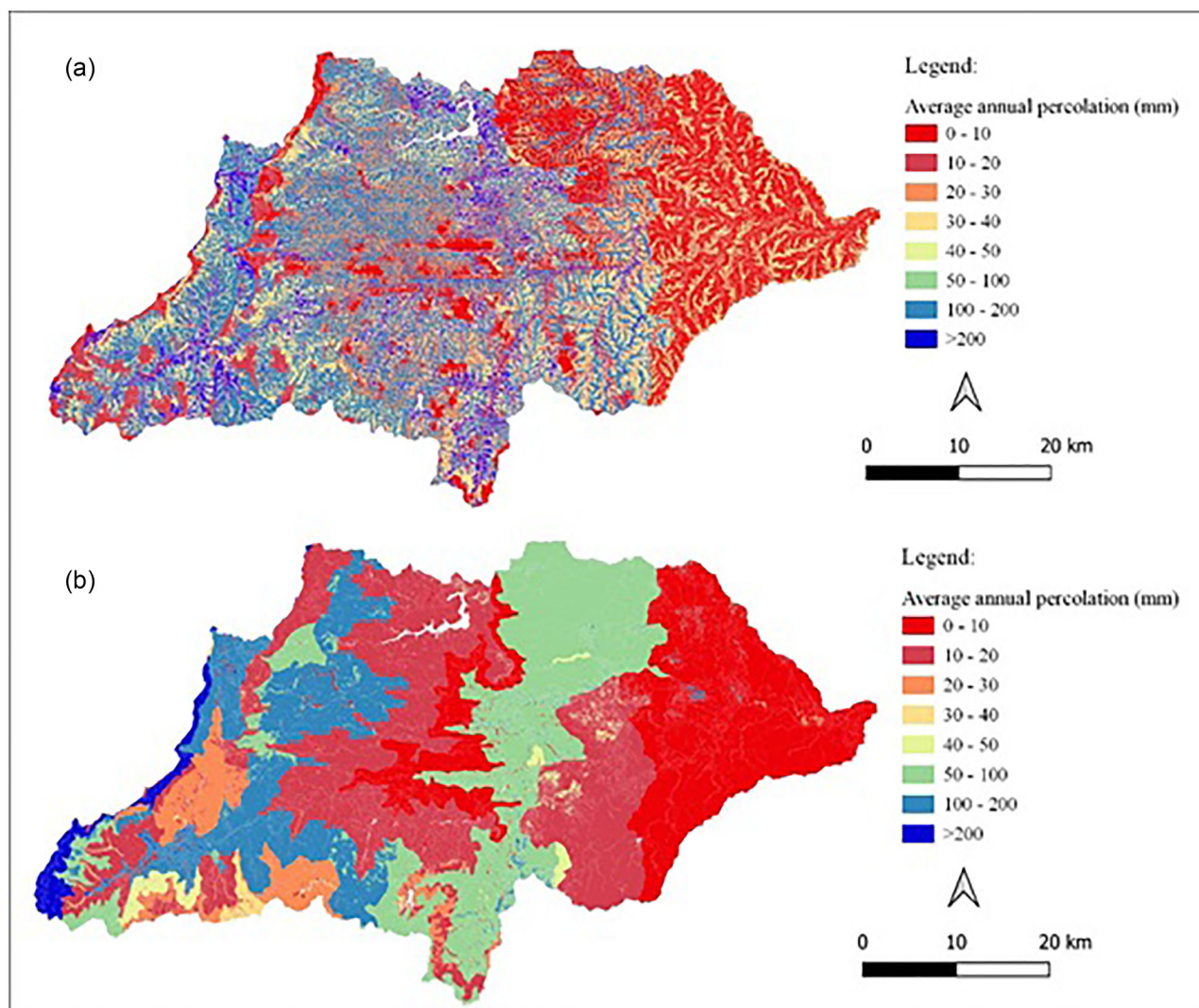


FIGURE 8 Average annual percolation values (mm) for the (a) Hydrosol and (b) Land Type dataset at the hydrological response unit (HRU) level.

speaking, 42.3% of the entire Sabie catchment should primarily be contributing recharge (percolation) to the shallow aquifer, with this value increasing in the mountainous catchments all the way up to 72.3% of the soils in X3H003 (Figure 6).

The spatial disparity of average annual percolation values is evident in Figure 8, where the Hydrosol model simulated far higher percolation values than the Land Type model and at a far greater resolution. The Hydrosol model primarily simulated high percolation values where Recharge deep soils dominate in the mountainous sections of the catchment where high precipitation and infiltration values also exist. Low percolation values were simulated on Responsive Shallow and Recharge Shallow soils as a result of their hydrologic soil group, position on the landscape, and shallow soil profile. Percolation values in the east of the catchment showcase definite spatial variability along catenas with higher percolation rates

associated with soil/bedrock interflow and Recharge deep soils.

The Land Type model did not show the same volume generation or spatial distribution of percolation across the catchment. Rather, percolation values are haphazardly spatially distributed as a function of the soil mapping units. These results are similar to Smit and Van Tol (2022), where large spatial and temporal differences were created between model simulations with differing soil input information. Figure 9 illustrates absolute difference between the average annual percolation values of the two levels of soil information within the Sabie catchment, where the majority of the catchment differed by average annual values greater than 50 mm, especially in the headwaters of the catchment (X3H001, X3H002, X3H003, and X3H024), becoming less pronounced in the drier eastern savanna segments of the catchment. Figure 9 also highlights how differences in soil

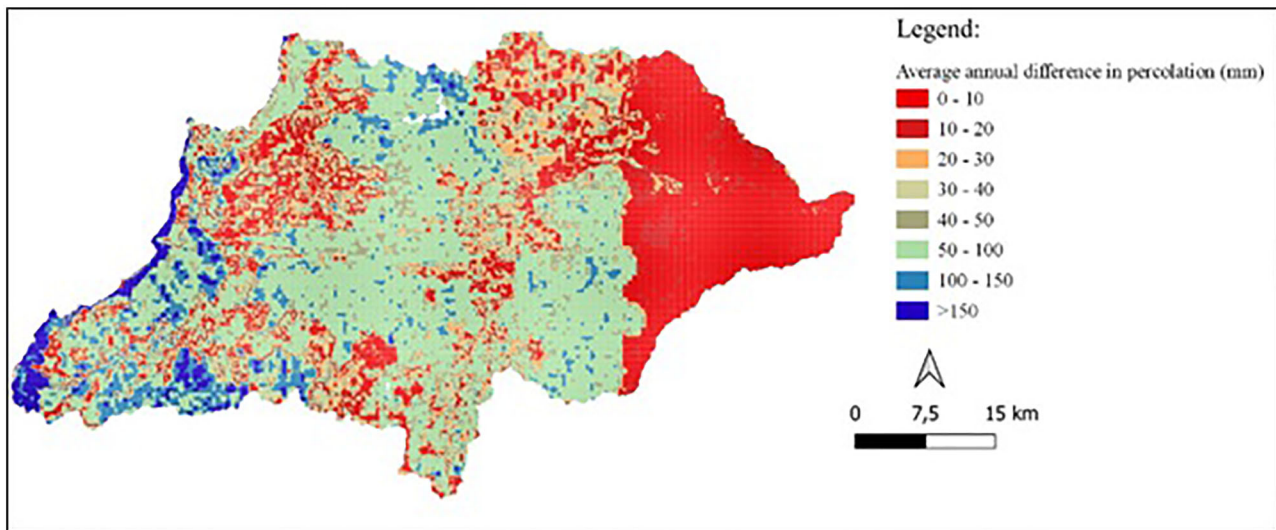


FIGURE 9 Gridded (100 m × 100 m) average annual percolation difference (mm) between the two levels of soil information.

input information translate to differences in hydrological process simulations in hydrological models.

Our assumption remains that detailed hydropedological information, based on modern DSM techniques and infield measured soil physical properties represent a more accurate representation of real-world percolation rates within the Sabie catchment. The ability of the Land Type model to therefore simulate any form of land use change or climate change scenario should be called into question as it is clear the internal hydrological process simulation as determined by the soil input data creates modeling uncertainty (Smit & Van Tol, 2022; Van Tol et al., 2021). The argument remains that hydropedological information may serve as an effective “soft data” tool to better represent internal hydrological processes within a catchment, leading to improved catchment management practices (Seibert & McDonnell, 2002; Smit & Van Tol, 2022; Van Tol et al., 2021); however, further calibration is required to achieve this goal.

The results within this study agree with other researchers that emphasize the importance of understanding the hydropedological information available within a catchment and its transferability for hydrological modeling purposes (Bouma et al., 2011; Sierra et al., 2018; Van Tol et al., 2021). Soil information plays a crucial role in refining model predictions and should be used in supporting informed decision-making in hydrological modeling and water resources management (Bouslih et al., 2019). It would be worth exploring if a multigauge calibration using the range of infield measured soil properties can continue to improve modeling accuracy, especially at large-scales where improved soil information diminishes in value. In terms of water resource management implications, this study does suggest that if large-scale applications water quantity simulations are the primary objective that the impact of hydropedological information is

negligible, especially when analyzing the modeling accuracy between the two levels of soil information at X3H021 (2421 km²). However, detailed soil information improves the hydrological process representation and improves modeling accuracy at smaller scales. Modern water resource management plans are however concerned with impacts at the local sub-catchment level, where the improved detail and accuracy of hydropedological information is more applicable than coarse soil information. The value of hydropedological information should also be further investigated for use in ungauged basins as a means of improving modeling accuracy where long-term measurements are absent.

4 | CONCLUSIONS

This study presented the findings of uncalibrated hydrological simulations using two levels of soil information in the Sabie catchment, South Africa. Detailed hydrological soil information, developed using DSM techniques, resulted in more accurate streamflow simulations at four of the five scales. The improved simulation accuracy at these scales were obtained without a calibration period, but rather by more accurately representing the internal hydrological processes of the catchment based on hydropedological insight. This is especially promising for hydrological modeling in ungauged catchments, where hydropedology could form an important soft data tool to aid modeling efforts where reliable streamflow measurements are absent.

It does seem as if the value of improved soil information decreases as the catchment size increases when analyzing mean monthly streamflow simulations, which agrees with similar research findings globally. Future research should focus on determining the ideal level of soil information for

hydrological modeling for different sized microscale and mesoscale catchments and focus on calibrating hydrological modeling using a range of infield measured soil input parameters.

AUTHOR CONTRIBUTION

Edward Smit: Data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft. **George van Zijl:** Data curation; funding acquisition; project administration; supervision. **Eddie Riddell:** Conceptualization; resources; supervision. **Johan van Tol:** Conceptualization; funding acquisition; project administration; supervision; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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