

Impact of Soil Data Representation on Streamflow Modelling: A Contiguous-Object Connectivity Approach Case Study in Switzerland

Joana Eichenberger^{1,3}, Bettina Schaeffli^{2,3}, Tatenda Lemann¹

¹ Centre for Development and Environment (CDE), University of Bern, Mittelstrasse 32, 3012 Bern, Switzerland

² Institute of Geography (GIUB), University of Bern, Hallerstrasse 12, 3012 Bern, Switzerland

³ Oeschger Centre for Climate Change Research (OCCR), University of Bern, Hallerstrasse 12, 3012 Bern, Switzerland

Preprint status. This manuscript is a non-peer-reviewed preprint submitted to EarthArXiv. It has also been submitted to the *Journal of Hydrology: Regional Studies* for peer review and possible publication. Subsequent versions of this manuscript may differ from the present version. If accepted, the final peer-reviewed publication will be linked to the EarthArXiv record via the peer-reviewed publication DOI. The authors welcome feedback; please contact the corresponding author.

Corresponding author: Joana Eichenberger

Email: joana.eichenberger@unibe.ch

Impact of Soil Data Representation on Streamflow Modelling: A Contiguous-Object Connectivity Approach SWAT+ Case Study in Switzerland

Joana Eichenberger^{a,c,*}, Bettina Schaeffli^{b,c}, Tatenda Lemann^a

^aCentre for Development and Environment (CDE), University of Bern, Mittelstrasse 32, Bern, 3012, Switzerland

^bInstitute of Geography (GIUB), University of Bern, Hallerstrasse 12, Bern, 3012, Switzerland

^cOeschger Center for Climate Change Research (OCCR), University of Bern, Hallerstrasse 12, Bern, 3012, Switzerland

Abstract

Study Region: The study focuses on the 100 km² Petite Glâne catchment in the western Swiss Plateau, a predominantly agricultural basin where hydrological modelling is constrained by limited detailed soil information.

Study Focus: We investigate how alternative soil datasets influence streamflow performance, parameter sensitivity, and internal hydrological processes in a Contiguous-Object Connectivity Approach (COCOA) Soil and Water Assessment Tool Plus (SWAT+) model. Three otherwise identical model setups use a global low-resolution dataset (World-Soil), a national medium-resolution dataset (Swiss-Soil), and a high-resolution local dataset (Local-Soil). COCOA SWAT+ maintains identical spatial modelling units across all three soil scenarios, separating soil-data effects from changes in model discretisation.

New Hydrological Insights for the Region: Before calibration, soil representation strongly affects water partitioning: World-Soil produces the greatest surface runoff, Swiss-Soil the greatest subsurface-flow contributions, and Local-Soil the highest evapotranspiration. After calibration, outlet-streamflow performance converges, with comparable relative Nash–Sutcliffe efficiency and slightly higher Kling–Gupta efficiency for Swiss-Soil, while contrasting internal water partitioning, soil-water storage, and groundwater-release behaviour persist. Differences are most apparent under median- and low-flow conditions. These results show that similar outlet-streamflow performance can mask substantial differences in simulated catchment functioning. For this Swiss catchment, higher soil detail does not systematically improve calibrated outlet-streamflow performance. Soil datasets should therefore be selected according to the intended modelling objective, and internal hydrological diagnostics should complement conventional streamflow-performance metrics.

Keywords: Soil Data Representation, Streamflow Modeling, SWAT+, Water Balance, Parameter Sensitivity, Catchment

1. Introduction

Many hydrological models rely on soil property input data to parameterize the three fundamental hydrological functions of a catchment, which are water partitioning, storage and release (Dunne, 1978; Wagener et al., 2007). The use of soil data in these hydrological models depends on the model type: models that are based on hydrological response units (HRUs) can use soil data in combination with land use data to identify HRUs, e.g., the PREVAH model (Viviroli et al., 2007) or the SWAT model (Arnold et al., 2012).

*Corresponding author

Email address: joana.eichenberger@unibe.ch (Joana Eichenberger)

Fully distributed models (i.e., grid-based models) use soil data to distribute the model parameters in space. Examples are the MIKE-SHE model (DHI, 2011), the mHM model (Heinz et al., 2026), or the VIC model (Liang et al., 1994). Within distributed models, soil data are typically used for process parameterization in combination with pedotransfer functions (e.g., MIKE SHE, VIC, SWAT) or for the delineation of HRUs (e.g., PREVAH, SWAT).

Some hydrological models provide default soil databases; however, their usefulness depends on the study’s geographic scope. VIC, for instance, is equipped with default soil databases based on the U.S. State Soil Geographic Database (STATSGO) (USDA, 1995b) and SWAT with STATSGO and the U.S. Soil Survey Geographic Database (SSURGO) (USDA, 1995a). To use these models outside of the USA, modelers can adapt local soil datasets as input data.

Various studies showed that local soil input data explicitly restricted to a study area can better represent soil-water dynamics due to the high spatial variability of soil properties caused by small changes in topography compared to global soil property maps (Huang et al., 2022; Krpec et al., 2020; Bayabil and Dile, 2020; Horta et al., 2024; Bouslihim et al., 2025). Yet, in many regions of the world, reliable local soil data are sparse and producing local soil maps is costly (Zeraatpisheh et al., 2017; Escamilla-Rivera et al., 2022; Diek et al., 2014; Zhang et al., 2017). Therefore, when local soil data are lacking or creating a new soil database from existing soil datasets is challenging, modelers rely on global soil texture maps, which are readily available with model-specific look-up tables, such as the Digital Soil Map of the World (DSMW) (FAO-UNESCO, 2003) or the Harmonized World Soil Database (HWSD) (JRC, 2012; FAO and IIASA, 2023). These "ready to use" low-resolution global digital soil maps may limit the applicability of hydrological models (Escamilla-Rivera et al., 2022; Shrestha et al., 2006; Quinn et al., 2005; Bouslihim et al., 2025).

For calibrated models (such as VIC or SWAT), poor data resolution can generally be compensated by parameter calibration; this holds in particular for input data like precipitation (Huang et al., 2019; Kleidorfer et al., 2009), digital elevation model (DEM) (Lin et al., 2013), as well as soil data (Bhandari et al., 2018). This implies, however, that the calibrated parameters strongly depend on the used input data, including input variables (e.g., precipitation) and data used for model parameterization (e.g., soil data); hence, changes in input data require recalibration. This makes it difficult to isolate the impact of input-data-driven uncertainties on total modeling uncertainty (Lin et al., 2013), and input-data-driven uncertainty remains poorly understood. Therefore, the impacts of input data on model uncertainties are often assessed without prior calibration via sensitivity analysis (Zhang et al., 2014; Tan et al., 2015; Moges et al., 2023), or the model’s sensitivity to data uncertainty is compared before and after calibration (Kim et al., 2024; Busico et al., 2020; Yang et al., 2019). For (semi-)distributed precipitation-streamflow models, a special focus is hereby typically on the question of how soil data resolution influences the model outputs. For fully distributed models (in contrast to HRU-based models), we might expect that higher-resolution input data, which better captures the spatial variability of the underlying processes, necessarily leads to better model performance. But given the averaging effect of catchments, the impact of finer resolution data is often not visible in overall model performance, e.g., in terms of streamflow simulation at the catchment outlet (Bormann, 2006; Sciuto and Diekkrüger, 2010; Li et al., 2013; Baroni et al., 2017).

Analyses of the link between physiographic input data resolution and hydrological model performance are complicated by the model structure: in HRU-based models (such as PREVAH or SWAT), the soil

data or DEM resolution directly influences the number and size of the HRUs, the reference unit for which the water balance is calculated (Romanowicz et al., 2005; Viviroli et al., 2007; Moges et al., 2023; Fernando et al., 2025). The higher the spatial variability of the physiographic input data, the more and the smaller the resulting HRUs are. This, in turn, increases the computational time and, more importantly, modifies how the model represents dominant hydrological processes. Although López-Ballesteros et al. (2023) and Bhandari et al. (2018) conclude that finer-resolution soil input data performed better before and after calibration, the influence of catchment subdivision and soil data resolution is off-set by the calibration, leading to relatively consistent model outputs across different watershed configurations (Kumar and Merwade, 2009).

Recently, a new type of semi-distributed models emerged with the development of SWAT+ (Bieger et al., 2017), a new and completely revised version of the SWAT model. There are two ways of setting up the SWAT+ model; the primary tool is the QGIS interface for SWAT+ (QSWAT+), while an alternative tool is the contiguous-object connectivity approach (COCOA) SWAT+ model builder SWATbuildR (Schürz et al., 2022; Schürz, 2022; Piniewski et al., 2024). The former still uses the concepts established for SWAT2012 model setups with i) traditional HRUs (lumped areas with similar land uses, soils, and slopes) without a spatial reference and ii) routing units (RTU), the smallest spatial units with spatial reference, usually formed by multiple HRUs. The COCOA workflow, however, enables a model setup where a catchment is split into "Land Objects", the new reference unit for which the water balance is calculated, replacing traditional HRUs. Land Objects are defined solely by the land use/land cover, and soil and DEM data resolution have no influence on the number and size of Land Objects. This opens new opportunities to simulate the hydrological effect of small-scale landscape units (such as buffer stripes, irrigation ponds) (Magnier et al., 2024; Marval et al., 2022), which is essential to assess the effect of small-scale water management measures on the partition, storage and release of water. However, this new model structure type also calls for new analyses of the effect of soil input data resolution on hydrological model performance.

Therefore, this study aims to assess how the choice of soil input data impacts the COCOA SWAT+ model outputs. The analysis is based on a case study from Switzerland, a country with surprisingly poor soil data: soil property maps of Switzerland are scarce and the few existing have a relatively coarse resolution because of a limited dataset (Gupta et al., 2024). For instance, SoilGrids 2.0 (Poggio et al., 2021) offers global soil property maps at 250m resolution, yet for Switzerland, the map is based on only 14 samples. Since Switzerland is not part of the European Union, using soil property maps for the European continent is not an alternative. Switzerland is excluded from many European maps, often called the "Swiss white lake phenomenon" (de Brogniez et al., 2015; Právělie et al., 2024).

To analyze the impact of soil data resolution for this case study, we set up three COCOA SWAT+ models in the exact same way but with three different soil input datasets: a) the Digital Soil Map of the World (FAO-UNESCO, 2003) (low-resolution dataset), b) the Swiss Soil Suitability Map FSO (2000) (medium-resolution dataset) and c) a high-resolution local soil property map especially created for this study (Nussbaum and Burgos, 2023). The model performance of the three model setups regarding stream-flow simulation is compared before and after calibration. Understanding how soil property data affect the hydrological catchment functions (water partition, storage, and release) can support modelers in choosing the input data as well as decision-makers in environmental planning regarding resource allocation for data collection efforts. Moreover, it is crucial for improving the accuracy and efficiency of catchment management strategies.

2. Study Area and Data

2.1. Petite Glâne catchment

The study area is the catchment of the Petite Glâne stream in the western Swiss plateau (46°43'-46°56' N to 6°45'-7°01'E) (Fig. 1a). The catchment's area is 100 km², with elevations ranging from 429 to 810 m asl, and a mean elevation of 556 m asl (Fig. 1b). The study area is largely dominated by agricultural land use: about 75% of the area is arable land, pasture or meadow and 12% is covered by forest (Fig. 1d).

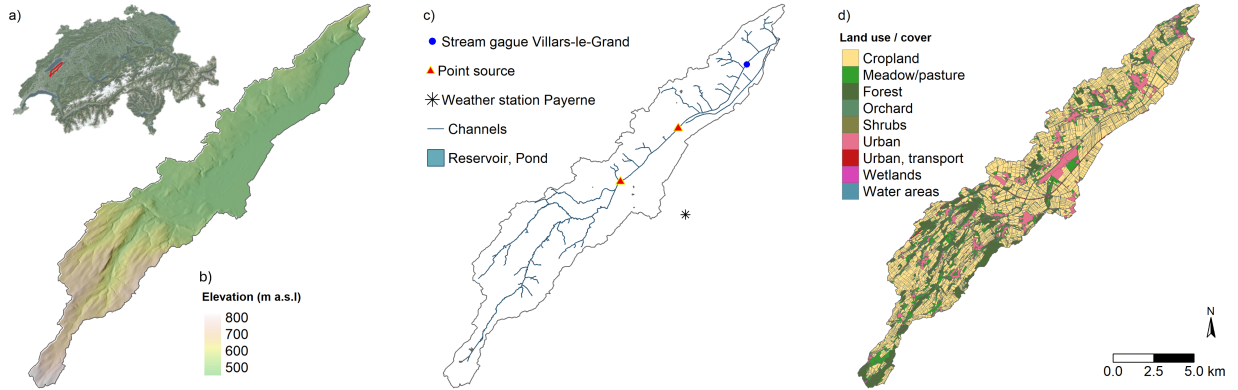


Figure 1: Study area: location of the Petite Glâne catchment in western Swiss plateau (a); elevation distribution (b); channel network with ponds, stream gauging station at Villars-le-Grand, weather station at Payerne, point sources/ wastewater treatment plant inlets at Bussy and Grandcour (c); land use and land cover map (d).

The nearest weather station is located in Payerne, 1.5 km outside the catchment, where temperature, precipitation, relative humidity, solar radiation and wind have been measured since 1981 (Fig. 1c). The average annual precipitation between 1993 and 2020 in Payerne ranged from 581 mm/yr (2011) to 1132 mm/yr (2001), with an average of 852 mm/yr.

At the catchment outlet, the gauging station Villars-le-Grand has been operated from 1993 to 2021 (Fig. 1c). The mean streamflow during this time period was 0.9 m³/s. The streamflow regime is characterized by a higher flow in winter and spring (highest mean monthly flow in January with 1.48 m³/s) and lower flow in summer and autumn (lowest mean monthly flow in August with 0.53 m³/s). The maximum (hourly) streamflow measured was 30.2 m³/s (12.03.2001), which corresponds to a statistical annual return period of 20 years (DGE-DRINA-EAU, 2022). Based on the observed mean daily streamflow of 0.9 m³/s, the corresponding annual runoff depth is approximately 278 mm/yr. Given the mean annual precipitation of 852 mm/yr, this results in an annual runoff ratio (streamflow divided by precipitation) of approximately 0.33.

2.2. Data

The data used for this study are listed with relevant detail in Table A1 and are not described further except for the soil data.

2.2.1. Soil data

In this study, we compare the performance of three different soil datasets for streamflow modeling with SWAT+. To date, Switzerland has no nation-wide detailed soil map, accordingly, hydrological model

Table 1: Overview of scenarios with different soil datasets

Soil Scenario	World-Soil	Swiss-Soil	Local-Soil
Soil Dataset	Digital Soil Map of the World FAO-UNESCO (2003)	Swiss Soil Suitability Map (FSO, 2000)	soil property map modeled by Nussbaum and Burgos (2023) based on soil profile data from different sources Burgos and Nussbaum (2020a,b); NABODAT (2018)
Data type	vector	vector	raster
Scale / resolution	1:5,000,000	1:200,000	10 m x 10 m
Effective spatial detail	~ 2–5 km	~ 100-200 m	10 m
Spatial variability for study area	2 soil texture classes	4 soil texture classes	10 soil texture classes

applications in Switzerland mostly use the national, medium-resolution soil suitability map (available at the scale of 1:200,000 - corresponding to an effective spatial detail of approximately 100 - 200 m, (Zarrineh et al., 2018; Abbaspour et al., 2007; Rahman et al., 2015, 2014, 2013; Andrianaki et al., 2019; Lehmann et al., 2019)). Alternatively, modelers can use freely available global digital soil maps, which are either low-resolution (typically 1-5 km) (e.g., FAO-UNESCO, 2003; FAO and IIASA, 2023) or medium-resolution but poorly representative (low number of samples) (e.g., Poggio et al., 2021). A more costly option is to create a high-resolution soil dataset specifically for the study area (e.g., Gupta et al., 2024; Nussbaum et al., 2018; Baltensweiler et al., 2021).

To explore the influence of different soil data resolution, we define three soil scenarios that use different resolution data for model parameterization: "*World-Soil*" for global data, "*Swiss-Soil*" for national data, and "*Local-Soil*" for a site-specific dataset, developed by Nussbaum and Burgos (2023) (Tab. 1).

For the World-Soil scenario, we use the Digital Soil Map of the World (DSMW, 1:5,000,000) (FAO-UNESCO, 2003), a freely available global digital soil property map available in a format readily compatible with SWAT. The DSMW has a very low resolution and subdivides the study area into two soil types: loam in the catchment's upper area and clay loam in the plain (Fig. 2). The maximal soil depth is similar for both classes: 0.97 m for the loamy and 1 m for the clay loam soil. Moreover, the DSMW divides the soil into two layers: an upper soil (0 - 0.3 m) and a lower soil (0.3 - 1 m).

For the Swiss-Soil scenario, we used the Swiss Soil Suitability Map (SSSM, 1:200,000) (FSO, 2000). It is an improvement to the low-resolution global maps; nevertheless, the SSSM is not a classical soil property map but a representation of areas with equivalent utilization possibilities. In the absence of better soil property maps, former SWAT studies in Switzerland have mostly used the SSSM (e.g., Abbaspour et al., 2007; Rahman et al., 2014, 2015; Andrianaki et al., 2019; Zarrineh et al., 2018, 2020). The SSSM has a more sandy texture with mainly sandy loam in the upper zone and loamy sand in the plain (Fig. 2). The soil is subdivided into 3 layers (topsoil 0 - 0.01 m, upper soil 0.01 - 0.2 m and lower soil 0.2 - 0.9 m), yet the maximal soil depth for all soil classes is 2.5 m.

For the Local-Soil scenario, a 10 m resolution soil map specifically for this study was generated by Nussbaum and Burgos (2023) based on existing local soil profile data. This local soil map shows similar soil texture patterns as the DSMW - yet with more spatial variations: loamy and sandy loam soil in the upper

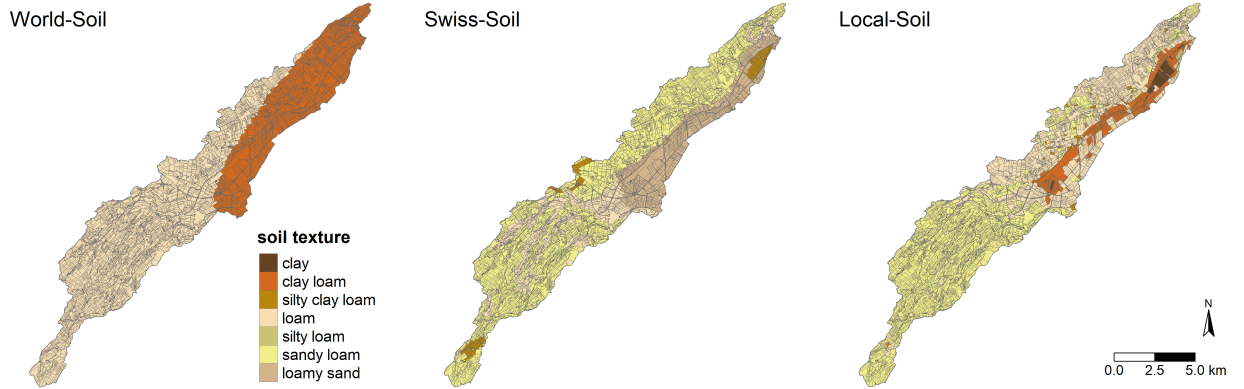


Figure 2: Land objects with texture of dominant soil classes for scenarios World-Soil, Swiss-Soil, and Local-Soil.

zone and clay loam and clay soil in the plain. In this high-resolution soil property map, the soil profile is subdivided into eight layers with 0.15 m intervals starting with 0 - 0.15 m and ending with 1.05 m - 1.2 m. Maximum soil depth varies greatly, ranging from 0.43 m to 1.19 m, with a mean depth of 0.94 m. The majority of grid cells (P10-P90) have soil depths between 0.80 m and 1.08 m.

3. Methods

3.1. Soil dataset preprocessing for SWAT+

To analyze the impact of soil data representation, we set up three SWAT+ soil scenarios with the Contiguous-Object Connectivity Approach (COCOA) methodology: a) World-Soil, b) Swiss-Soil and c) Local-Soil. The models are set up in the exact same way, maintaining the same spatial Land Objects, climate data, land use and general model structure but use different soil datasets. Each scenario is calibrated independently but using the same calibration parameter sets, and the resulting streamflow and internal hydrological behaviour are compared (Fig. 3).

The three soil datasets differ in their spatial and vertical detail. The World-Soil dataset provides only two soil types and distinguishes between an upper and a lower soil layer. The Swiss-Soil dataset offers medium-resolution information with four types and includes a topsoil layer in addition to the upper and lower layers. Finally, the Local-Soil dataset includes ten soil types at 10 m resolution and subdivides the soil profile into layers with 0.15 m intervals.

The global and Swiss soil datasets are available in a "ready-to-use" format compatible with SWAT+. In contrast, the high-resolution soil dataset requires additional preprocessing, which is achieved with the SWAT+ model input data preparation tool SWATprepR (Plunge, 2023). This preprocessing step extracts the information of the available high-resolution raster maps (10 m x 10 m) per soil layer (15 cm intervals) and soil attribute (clay, silt, sand, humus, and skeleton content (%), as well as depth to the high water table and upper limit of the C horizon) and combines it into the input format required by SWAT+: one single soil raster map (here 10 m x 10 m), which defines the spatial distribution of soil units, a *usersoil* table containing layer-wise soil properties, and a *soil lookup* table that links raster soil identifiers to the corresponding soil profiles.

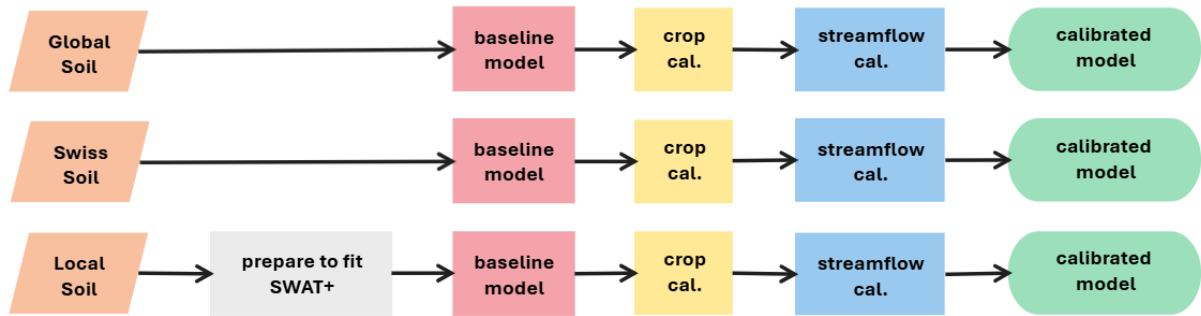


Figure 3: Workflow from alternative soil input datasets to calibrated SWAT+ model configurations for the World-Soil, Swiss-Soil, and Local-Soil scenarios.

For all three soil datasets, soil physical properties (bulk density, moist soil albedo of the top layer, USLE soil erodibility (K) factor, saturated hydraulic conductivity, hydrologic soil group, and available water capacity) are estimated using pedotransfer functions for each soil unit as proposed by Schürz et al. (2022).

3.2. Baseline model setup and parametrization

The three COCOA SWAT+ models are set up identically with respect to model structure, parameterization approach, and non-soil input data. Differences between the scenarios arise solely from the soil datasets used, which provide soil physical properties at different spatial resolutions. The workflow of the model setup is presented in Figure 4 and is based on Schürz et al. (2022). The baseline models are built using the COCOA SWAT+ model builder SWATbuildR (Schürz, 2022). As mentioned before, the COCOA SWAT+ model setup approach splits the catchment into "Land Objects", the new reference unit for which the water balance is calculated, replacing traditional HRUs. The required input data are catchment boundary, land use (including multi-year field-level crop sequences and tile drainage data), DEM, soil data, channel network, point source locations and weather data (see used sources in Tab. A1). In our case study, each model setup contains 8,056 Land Objects. This number is very high compared to the number of HRUs in other SWAT studies (e.g., López-Ballesteros et al. (2023); Moges et al. (2023)). However, Land Objects are based on the land-use input layer and represent field-scale structures. Given the mosaic character of land use in the study area, this high number is reasonable.

During this initial set-up, some model parameters are either undefined or set to default numbers. For instance, the Curve Number (CN) and Manning's roughness coefficient for overland flow (OVN) require further manual parameterization; we assign the most representative CN and OVN values to each land use and management classes.

Since the model also simulates nutrient cycling (not further assessed here), nitrogen (NH_4 and NO_3) atmospheric deposition is added as an input, extracted from European Monitoring and Evaluation Programme (EMEP) (Plunge and Rets, 2024). Finally, agricultural management schedules, including tillage, sowing, fertilisation, and harvesting operations, are developed based on official crop rotation recommendations (Jeangros and Courvoisier, 2019), crop factsheets published by Swiss agricultural extension services, and consultations with local farmers. These management schedules are implemented in SWAT+ using the

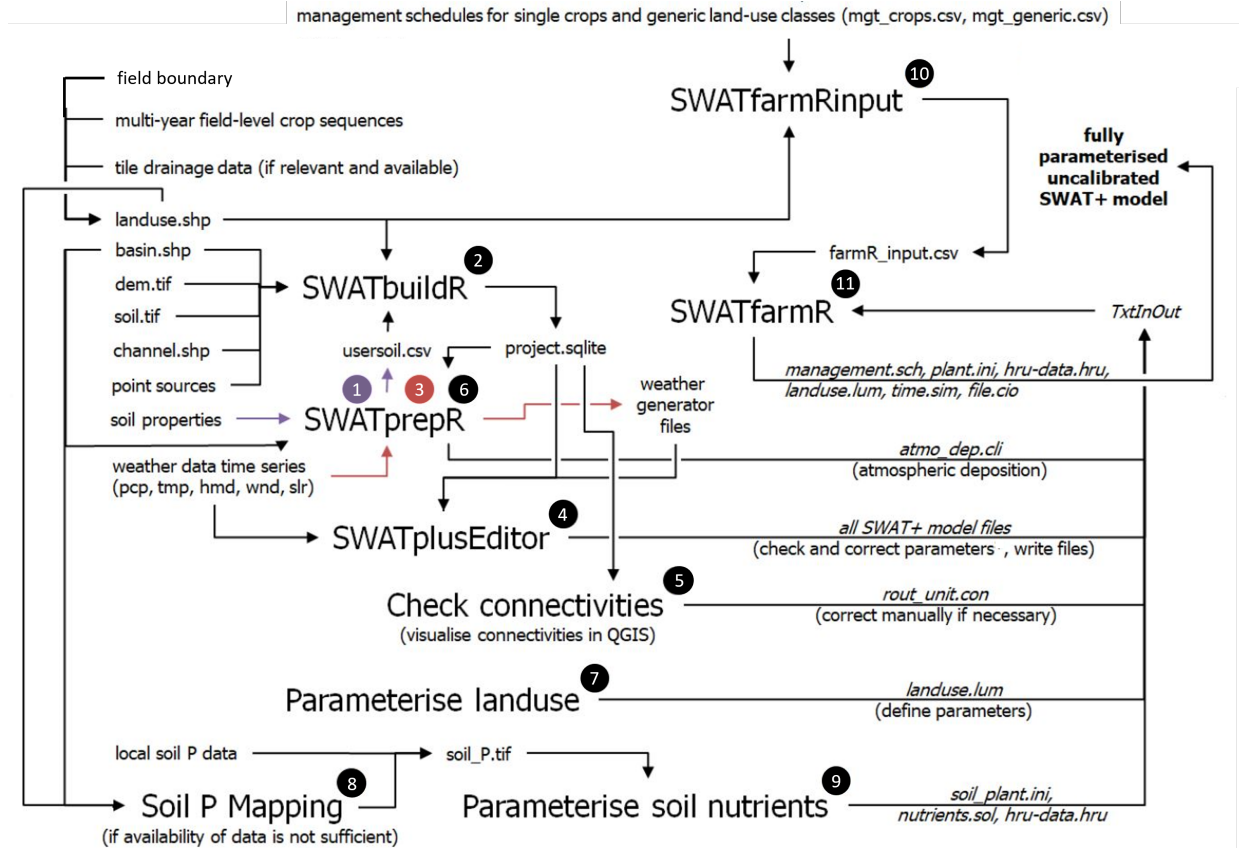


Figure 4: Workflow for a fully parameterized, uncalibrated SWAT+ model setup in 11 steps, based on Piniewski et al. (2024)

SWATfarmR package (Schuerz, 2022) for each cropland Land Object.

3.2.1. Assessment of soil data resolution effect on Land-Object properties

In the model set-up, the properties of the terrain (from DEM) and soil (from soil data) are aggregated at the Land Object level by retaining the dominant soil and terrain characteristics within each object. The aggregation of the soil raster input to the dominant soil is shown in Figure 5.

This aggregation procedure may cause the loss of information, as certain soil texture classes may always be replaced by more dominant classes. To assess the impact of aggregation on average domain-wide properties, the soil texture distributions from the original input datasets are compared to the soil texture distributions obtained after aggregation. In addition, Shannon entropy is used to quantify changes in soil texture diversity induced by the aggregation procedure. Shannon entropy is a commonly used metric of diversity that captures both the number of classes and the evenness of their distribution, with higher values indicating greater diversity and more uniform distributions. It is calculated as $H = -\sum p_i \log(p_i)$, where p_i represents the proportion of each texture class. The difference between the distributions before and after aggregation gives an indication on how the aggregation process interacts with the original datasets. However, it cannot be used to gain behavior (since the model never sees the original data). In exchange, differences in the aggregated soil texture distributions between datasets, as quantified by Shannon entropy, might give hints on how the soil datasets affect the model behavior at catchment-scale.

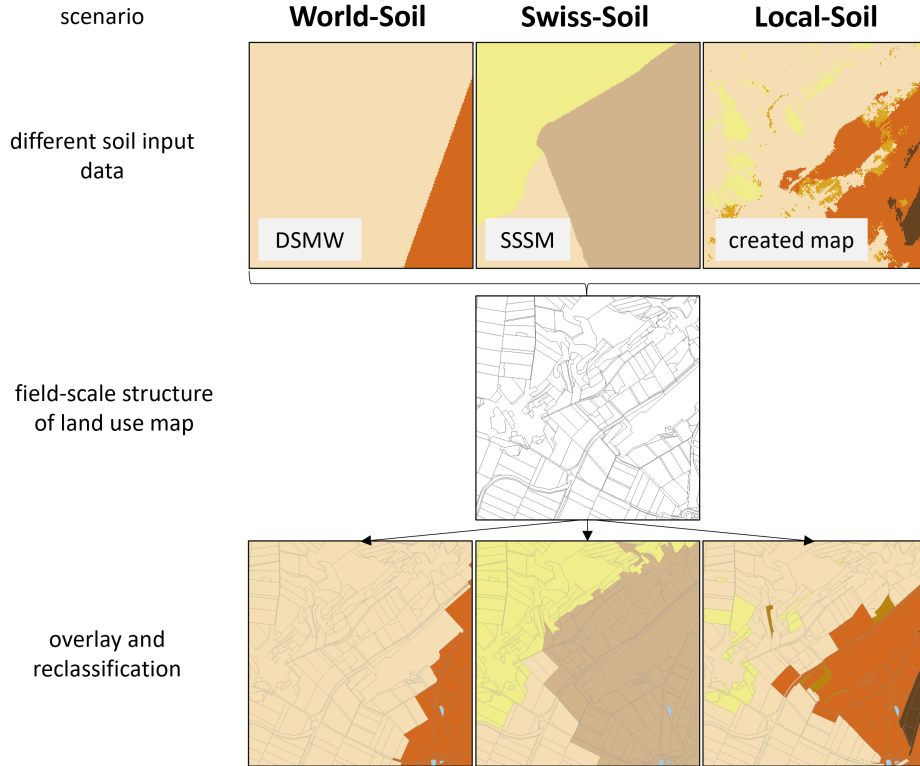


Figure 5: Dominant soil aggregation in three SWAT+ model setups, each with different soil raster inputs.

3.2.2. Verification of model setup and input data

Given the computational expense of model parameter calibration, the model comes with a tool to check the initial setup (before calibration), SWATdoctR (Schürz and Plunge, 2022). SWATdoctR enables the assessment of whether i) the weather input data are correctly interpreted by the model and produce plausible climate variables (PET, ET, precipitation, snow fall), ii) agricultural management operations are correctly triggered, iii) plant growth is simulated reasonably, and iv) point source and the tile drainage inputs are properly parametrized in terms of units, magnitude and process activation. For that purpose, we run the model from 2008 to 2020, which provides 3 years of model warm-up (to initialize state variables) and 10 years of simulated data for model evaluation. The latter ensures that the entire crop rotation cycle can be thoroughly examined. The model setup verification is an iterative process: identified problems have to be fixed in all three soil scenarios (World-Soil, Swiss-Soil, and Local-Soil) before the verification is repeated.

Crop-growth parameters are initially adjusted to obtain plausible crop development and yields and are subsequently held constant across the three soil scenarios. This preliminary adjustment is not part of the soil-aggregation or streamflow-calibration analysis and is therefore not included in the comparison among soil scenarios. For transparency, the resulting crop-parameter adjustments are documented in Appendix A2, and crop-specific distributions of potential heat units, yield, and biomass are provided in Figures S4-S6.

3.3. Model calibration and evaluation

Model calibration of parameters influencing streamflow simulation in this study is achieved in two steps with the SWATtunR R package (Plunge et al., 2024): first, a parameter sensitivity analysis (see Sec. 3.3.1)

and second, a streamflow calibration and evaluation (see Section 3.3.2).

3.3.1. Sensitivity analysis for parameters influencing streamflow simulation

Calibrating the selected model to reproduce streamflow with different soil data representation scenarios is challenging due to its high number of potential parameters to calibrate (i.e., more than 185 calibration parameters). To reduce the number of parameters we first carry out a global sensitivity analysis (GSA) using a multiple regression approach to identify the most relevant parameters affecting streamflow simulation for each of the three scenarios with different soil datasets. Changing the resolution of input data (soil data) requires recalibration of the model for each dataset, which is a major challenge in any model sensitivity analysis that assesses the effect of data resolution (e.g., Brath et al., 2004). For this initial sensitivity analysis, we retain the same set-up as for model calibration, which is done separately for each of the three soil scenarios (each with a different soil data representation scenario) based on observed streamflow data from the Villars-le-Grand gauging station at catchment outlet. The three scenarios are run from 1990 to 2020, split into a warm-up period for state variable initialisation (1990-1992) and simulation period (1993–2020). The basic principle of this GSA is to i) first generate a large ensemble of proposal parameter sets that spans the prior parameter range, ii) select one or several model performance metrics, iii) simulate daily streamflow corresponding to all parameter sets and compute the selected performance metrics on the corresponding simulated streamflow, iv) build a multiple regression model that takes as explanatory variables the parameter ensembles (i.e., each parameter is one variable) and as predictor the model performance metric (build several models if we have several predictors), v) derive the regression coefficients and assess the statistical significance of each parameter, vi) decide which model parameters to retain for further calibration based on the significance of each parameter. Given the high number of parameters to calibrate, we need to perform an a priori selection of which ones to include in the GSA. For this study, the initial selection includes 25 parameters covering processes such as evapotranspiration, surface runoff, lateral subsurface flow, base flow, tile drainage, percolation and groundwater flow (see Tab. A4).

The prior parameter range for step i) above are selected based on literature to constrain the sampled parameter values to plausible ranges (Arnold et al., 2012; Llanos-Paez et al., 2023; Nkiaka et al., 2018; Schürz et al., 2022; Zarrineh et al., 2018). Where relative parameter changes could produce values outside the absolute limits defined in the SWAT+ parameter database (cal_parms.cal), SWAT+ constrains the resulting values to these limits. For the sampling method for step i), we use the Latin Hypercube Sampling (LHS) because, compared to the Monte Carlo simulation, it ensures full interval coverage with a smaller sample standard deviation (Abyani and Bahaari, 2020), making it a more efficient choice for GSA and model calibration. The size of the parameter ensemble is set to 1000, which is a compromise between spanning well the parameter space and the computational cost (one model run takes approximately 35 min, 1000 model runs in parallel on a computer with 26 cores takes about 2 days).

For the GSA performance metric, we select the Nash–Sutcliffe model efficiency coefficient (NSE) and the Kling–Gupta efficiency (KGE) to analyze which parameters most influence model performance. NSE is a popular objective function in hydrological modeling studies and is defined as:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (Q_{\text{obs},i} - Q_{\text{sim},i})^2}{\sum_{i=1}^n (Q_{\text{obs},i} - \bar{Q}_{\text{obs}})^2}, \quad (1)$$

where $Q_{\text{obs},i}$ and $Q_{\text{sim},i}$ are the observed and simulated streamflow values at time i , respectively, and

$\overline{Q}_{\text{obs}}$ is mean observed streamflow.

As studies have shown that NSE is oversensitive to peak flows and underestimates the variability in streamflow (Gupta et al., 2009; Althoff and Rodrigues, 2021), we also use KGE, which evaluates model performance through its correlation, variability, and mean-bias components. It is balanced for bias under both low- and peak-flow conditions (Althoff and Rodrigues, 2021).

$$\text{KGE} = 1 - \sqrt{\left(\frac{\sigma_{\text{sim}}}{\sigma_{\text{obs}}} - 1\right)^2 + \left(\frac{\mu_{\text{sim}}}{\mu_{\text{obs}}} - 1\right)^2 + (r - 1)^2} \quad (2)$$

where:

- σ_{obs} and σ_{sim} are the standard deviation of observed and simulated streamflow values,
- μ_{obs} and μ_{sim} are their respective means, and
- r is the correlation coefficient according to Pearson.

KGE and NSE both range from $-\infty$ to 1. Nevertheless, they should not be interpreted the same way; if the mean observed value is used as benchmark, NSE is equal to 0 while KGE is -0.41 (Althoff and Rodrigues, 2021; Knoben et al., 2019). Therefore, for this study, we will consider $0 < \text{NSE} \leq 1$ and $-0.41 < \text{KGE} \leq 1$ as reasonable performance and values closer to 1, indicating better model performance.

We aim to retain the same set of parameters across all three setups. To determine which parameter should be included in the calibration, we quantify for each soil scenario and performance metric their statistical significance in the GSA using a t-test derived from the multiple regression framework. Larger absolute t -statistics and smaller p -values provide stronger statistical evidence that a parameter is associated with model performance. We define significance using a threshold of $p < 0.05$. A parameter is retained for calibration if it is statistically significant in at least two of the three soil scenarios for both performance metrics (KGE and NSE), or if it is significant across all three soil scenarios for at least one of the metrics.

As a robustness check, we repeat the sensitivity analysis using calibration-period NSE and using NSE_{rel} over both the calibration and entire simulation periods. These additional analyses use the same existing 1,000 simulations and do not alter the parameter set used in the subsequent 2,000-run ensembles.

3.3.2. Streamflow calibration and evaluation

Based on the outputs of the GSA, we then calibrate the model using the subset of retained parameters. A new LHS set is generated for the defined parameter boundaries, and the scenarios are each rerun 2,000 times. Performance within these final ensembles is evaluated using NSE_{rel} and KGE. Ordinary NSE is not used for selecting the final parameter sets because it gives greater weight to errors during high-flow conditions. NSE_{rel} has been developed as an alternative to NSE to counteract drawbacks of NSE (Krause et al., 2005); it is less sensitive to peak flows and more sensitive to low-flow conditions (Althoff and Rodrigues, 2021; Krause et al., 2005). Like NSE, NSE_{rel} ranges from $-\infty$ to 1, with values closer to 1 indicating better agreement between observed and simulated streamflow. It is defined as:

$$\text{NSE}_{\text{rel}} = 1 - \frac{\sum_{i=1}^n \left(\frac{Q_{\text{obs},i} - Q_{\text{sim},i}}{Q_{\text{obs},i}} \right)^2}{\sum_{i=1}^n \left(\frac{Q_{\text{obs},i} - \overline{Q}_{\text{obs}}}{\overline{Q}_{\text{obs}}} \right)^2} \quad (3)$$

where:

- $Q_{obs,i}$ and $Q_{sim,i}$ are the observed and simulated values at time i and
- $\overline{Q_{obs}}$ is the mean of observed values,

To assess the goodness of fit, simulations are ranked separately according to KGE and NSE_{rel} , with rank 1 assigned to the best-performing simulation for each metric. The two ranks are then summed for each simulation, and the best 1% simulations with the lowest combined rank are retained ($n = 20$ of 2000). This approach gives equal importance to both objective functions while avoiding direct aggregation of metrics with different statistical properties. The selected parameter-set IDs are retained for the evaluation and entire simulation periods; parameter sets are not reselected using evaluation-period performance.

Streamflow performance is evaluated using daily NSE_{rel} and KGE for the calibration period (1993–2010), evaluation period (2011–2020), and entire simulation period (1993–2020). For each period, the distributions of both metrics are summarized by their mean, minimum, and maximum for the 20 calibration-selected parameter sets and all 2,000 simulations. To assess temporal consistency, calibration-period performance is compared with evaluation-period performance for the same parameter sets. Pearson correlation coefficients quantify the linear association between calibration and evaluation performance. The mean signed difference, mean absolute difference, and root mean square deviation from the 1:1 line are additionally calculated. The mean signed difference indicates systematic improvement or deterioration during evaluation, whereas smaller mean absolute differences and root mean square deviations indicate greater consistency in absolute performance between the two periods. The calibration-selected best-performing 1% ($n = 20$) is highlighted separately in this comparison.

Parameter-related predictive uncertainty is characterized using an empirical 95% parameter-ensemble interval. At each time step, this interval is defined by the 2.5th and 97.5th percentiles of streamflow simulated by the best 1% calibration-selected parameter sets and is hereafter referred to as the 95% prediction uncertainty band (95PPU). The P -factor represents the proportion of the observed streamflow values enclosed by the 95PPU band, whereas the R -factor represents the mean width of the 95PPU band divided by the standard deviation of the observed streamflow values. A larger P -factor indicates higher observational coverage, while a smaller R -factor indicates a narrower ensemble interval. Following commonly used guidance (Abbaspour et al., 2015, 2007; Carlos Mendoza et al., 2021), P -factor values above 0.7 and R -factor values below 1.5 are used as contextual reference values rather than strict acceptance thresholds. One P -factor and one R -factor are calculated for each soil scenario and analysis period. The primary assessment is based on the best 1% calibration-selected parameter sets. The corresponding metrics are also calculated for the full 2,000 simulation ensemble to show how parameter screening affects ensemble coverage and spread. This analysis quantifies uncertainty arising from variability among the retained parameter sets, conditional on the SWAT+ model structure, forcing data, observations, and calibration procedure. It does not account for uncertainty in the forcing data, observations, or model structure and should therefore not be interpreted as a comprehensive probabilistic uncertainty assessment.

Streamflow performance and parameter-related predictive uncertainty are assessed at the daily time step. NSE_{rel} and KGE are calculated from daily observed and simulated streamflow, and the daily 95PPU, P -factor, and R -factor are calculated separately for the calibration, evaluation, and entire simulation periods. For graphical presentation only, we aggregate the daily observed and simulated streamflow series to monthly

mean streamflow. We subsequently calculate the monthly ensemble medians and 95PPU bounds from the aggregated streamflow series of the same best 1% calibration-selected parameter sets. Thus, parameter-set selection and all reported performance and parameter-related predictive uncertainty metrics remain based on daily streamflow; monthly aggregation is used only to improve the readability of Figure 7.

Because the preliminary GSA uses observations from the entire 1993–2020 period, the evaluation period is not fully independent of model development. However, selection of the best-performing parameter sets from the final 2,000-run ensembles uses calibration-period performance only. The evaluation period therefore assesses the temporal transferability of the selected parameter sets rather than providing a fully independent model validation.

3.4. *Water balance dynamics and flow-regime signatures*

In addition to performance metrics, we assess the average annual water balance components of the three model setups to characterize their internal hydrological behaviour. The water balance is evaluated before and after calibration. Before-calibration values are obtained from one initial uncalibrated simulation for each soil scenario, whereas after-calibration values are summarized across the best 1% calibration-selected parameter sets. The water balance components assessed are evapotranspiration, surface runoff, lateral flow, baseflow, and percolation. Average soil-water storage is additionally included as a storage diagnostic. They are calculated over the entire simulation period (1993–2020) and for the calibrated models, we use the ensemble median as the central estimate and the minimum–maximum range to describe the spread among the selected parameter sets. This water balance assessment allows us to evaluate both the effects of soil map resolution, implemented within the COCOA SWAT+ framework, and how subsequent calibration influences water balance partitioning. Because independent observations of internal fluxes and stores are unavailable, this analysis compares simulated process partitioning among the model configurations but does not validate the internal fluxes or storages.

To examine temporal behaviour beyond the average annual water balance, we calculate annual and seasonal streamflow and evapotranspiration for the same best 1% calibration-selected parameter sets. Daily streamflow is aggregated to annual and July–August mean streamflow for each parameter set and year. Simulated streamflow distributions are compared with the corresponding observed distributions during the calibration and evaluation periods. July–August is analysed separately to characterize model behaviour during the principal summer low-flow period. Monthly simulated evapotranspiration is aggregated to annual, July–August, and April–September totals for each parameter set and year and is compared among the three soil scenarios. July–August evapotranspiration represents water loss during the summer low-flow period, whereas the April–September total characterizes cumulative evapotranspiration over the main growing season.

In addition, flow-duration curves are calculated from daily streamflow separately for the calibration and evaluation periods. For each soil scenario, the median flow-duration curve and the 2.5th–97.5th percentile range of the 20 calibration-selected parameter sets are compared with the observed curve. We also calculate the Q05, Q50, and Q347. Q05 and Q50 denote streamflow exceeded 5% and 50% of the time, respectively, while Q347 denotes the streamflow exceeded on 347 days per year - a critical low-flow statistic defined by the Federal Office for the Environment (FOEN) under Article 4 of the Waters Protection Act. These diagnostics indicate whether differences among the soil scenarios are concentrated in high-, median-, or low-flow conditions.

To further characterize the delayed-flow contribution, we estimate the baseflow index (BFI) from daily observed and simulated streamflow using the UKIH-f smoothed-minima method (UKIH, 1980; Mao et al., 2024). The daily streamflow series is divided into consecutive five-day blocks, and the minimum streamflow in each block is identified. Turning points are selected using a factor of $f = 0.9$, and baseflow between consecutive turning points is estimated by linear interpolation. BFI is calculated as the ratio of summed estimated baseflow to summed total streamflow. The same procedure is applied to the observed record and each of the 1% best calibration-selected simulations for the calibration, evaluation, and entire simulation periods. Because hydrograph separation is method-dependent, BFI is treated as a comparative indicator of delayed-flow behaviour rather than a direct measurement of groundwater contribution.

Finally, monthly average soil-water storage, aquifer storage, and aquifer flow are inspected through time for the calibration and evaluation periods. For each scenario and month, the ensemble median and 2.5th–97.5th percentile range of the best 1% selected parameter sets are calculated. These state and release variables are used to assess whether the soil scenarios exhibit different seasonal storage and groundwater-release dynamics.

4. Results

4.1. Parameter sensitivity, streamflow performance, and predictive uncertainty

The GSA performed using the multiple-regression approach identifies 13 parameters that meet the pre-defined selection criteria for statistically significant sensitivity across soil scenarios and performance metrics and are therefore retained for subsequent steam flow calibration. Specifically, a parameter is retained if it significantly influences model performance ($p < 0.05$) in at least two soil scenarios for both KGE and NSE, or in all three soil scenarios for at least one of the two metrics.

As shown in Table A4, the KGE-based regressions show a relatively consistent sensitivity pattern across the three soil scenarios. Ten parameters have statistically significant effects on KGE in all three scenarios: soil evaporation compensation factor (ESCO), AWC, soil water factor for CN3 (CN3_SWF), surface runoff lag coefficient (SURLAG), soil bulk density (BD), depth from soil surface to bottom of layer (Z), percolation coefficient (PERCO), threshold depth from surface to water table for groundwater flow to occur (FLO_MIN), threshold depth of water in the shallow aquifer for revaporation to occur (REVAP_MIN), and baseflow alpha factor (ALPHA) are significant for all three soil datasets. In contrast, five parameters have statistically significant effects on NSE in all three scenarios: SURLAG, average slope length for lateral subsurface flow (LAT_len), lateral flow coefficient (LAT_CO), BD, and REVAP_MIN. Under NSE, the GSA detects significant relationships between model parameters and performance across the broadest range of hydrological processes for Local-Soil, with eleven parameters showing significant effects, compared with seven in both World-Soil and Swiss-Soil. Beyond these differences in the number of significant parameters, the sensitivity of individual parameters - and, in some cases, the sign of their regression coefficients - also varies among the soil scenarios. For example, CN2 is significant for NSE in World-Soil and Local-Soil but not in Swiss-Soil, while PERCO is significant for NSE in Swiss-Soil and Local-Soil but not in World-Soil.

The regression coefficients of CN3_SWF and SURLAG also change sign among scenarios, indicating that their relationships with model performance depend on the soil representation. SURLAG, BD, and REVAP_MIN are statistically significant for both performance metrics in all three scenarios and show the most consistent statistical relevance to streamflow performance, although the direction of the SURLAG

relationship is not consistent. Overall, the results indicate that changing the soil dataset modifies not only which parameters control model performance but also how individual parameters relate to the selected performance metrics. The 13 retained parameters are subsequently used to generate 2,000 parameter sets for each model setup. The parameter values of the best 1% calibration-selected sets are summarized in Table A5.

To assess whether parameter retention was sensitive to the choice of NSE formulation and analysis period, we compared four GSA variants combining either NSE or NSE_{rel} with either the calibration period or the entire simulation period (Table A3). The resulting parameter sets were broadly consistent: ten parameters were retained in all four variants, whereas the retention of available water capacity (AWC), the SCS runoff curve number for antecedent moisture condition II (CN2), and the lateral-flow coefficient (LATQ_CO) depended on the metric–period combination. Thus, the core parameter set was robust to these methodological choices, although the selection of these three parameters was not.

A scatter plot the performamnce metric values for the calibration period against those for the evaluation period shows that parameter sets with higher calibration-period NSE_{rel} and KGE values generally also achieved higher values during evaluation (Fig. 6). However, for NSE_{rel} , most simulations lie below the 1:1 line, indicating generally lower performance during evaluation. This difference becomes larger and more variable among parameter sets with lower calibration-period NSE_{rel} values, particularly for World-Soil.

The best 1% parameter sets are selected using the combined ranking of daily calibration-period NSE_{rel} and KGE; the same parameter-set IDs are retained for the evaluation and entire simulation periods. In contrast, the best 1% parameter sets (selected using the combined ranking of daily calibration-period NSE_{rel} and KGE; the same parameter-set IDs are retained for the evaluation and entire simulation periods) form compact clusters near the upper-right end of the 1:1 line, indicating good temporal consistency between the calibration and the evaluation period (Fig. 6). Among these selected parameter sets, mean NSE_{rel} is similar across scenarios during calibration (0.84–0.85), evaluation (0.75–0.76), and the entire simulation period (0.82–0.83). These values are so close, that they cannot be further interpreted. In other words, based on streamflow metrics alone, the different scenarios cannot be further differentiated. Furthermore, the absolute difference between KGE and NSE values should not be interpreted: the two metrics do not have the same scale.

Table 2: Mean relative Nash–Sutcliffe efficiency (NSE_{rel}) and Kling–Gupta efficiency (KGE), with minimum–maximum ranges in parentheses, for for the best 1% parameter sets and all 2,000 simulations. The best 1% parameter sets are selected using the combined ranking of daily calibration-period NSE_{rel} and KGE; the same parameter-set IDs are retained for the evaluation and entire simulation periods.

Period	Scenario	Best 1% ($n = 20$)		All simulations ($n = 2,000$)	
		NSE_{rel}	KGE	NSE_{rel}	KGE
Calibration	World-Soil	0.836 (0.813–0.867)	0.687 (0.635–0.727)	0.715 (–0.217–0.887)	0.535 (0.148–0.773)
	Swiss-Soil	0.848 (0.828–0.883)	0.689 (0.631–0.766)	0.746 (0.050–0.891)	0.562 (0.224–0.803)
	Local-Soil	0.846 (0.828–0.861)	0.624 (0.584–0.726)	0.761 (0.295–0.872)	0.485 (0.184–0.783)
Evaluation	World-Soil	0.747 (0.725–0.781)	0.710 (0.664–0.758)	0.552 (–1.233–0.842)	0.514 (0.065–0.771)
	Swiss-Soil	0.752 (0.708–0.801)	0.722 (0.643–0.775)	0.640 (–0.406–0.826)	0.566 (0.196–0.778)
	Local-Soil	0.749 (0.702–0.794)	0.669 (0.598–0.769)	0.690 (–0.071–0.824)	0.507 (0.113–0.774)
Entire simulation	World-Soil	0.816 (0.797–0.841)	0.698 (0.651–0.735)	0.677 (–0.471–0.863)	0.534 (0.134–0.782)
	Swiss-Soil	0.825 (0.803–0.863)	0.703 (0.637–0.779)	0.724 (–0.049–0.871)	0.569 (0.227–0.800)
	Local-Soil	0.823 (0.806–0.846)	0.639 (0.599–0.745)	0.749 (0.233–0.848)	0.494 (0.181–0.769)

Across all three soil scenarios, the selected best 1% parameter sets reproduce the main seasonal and

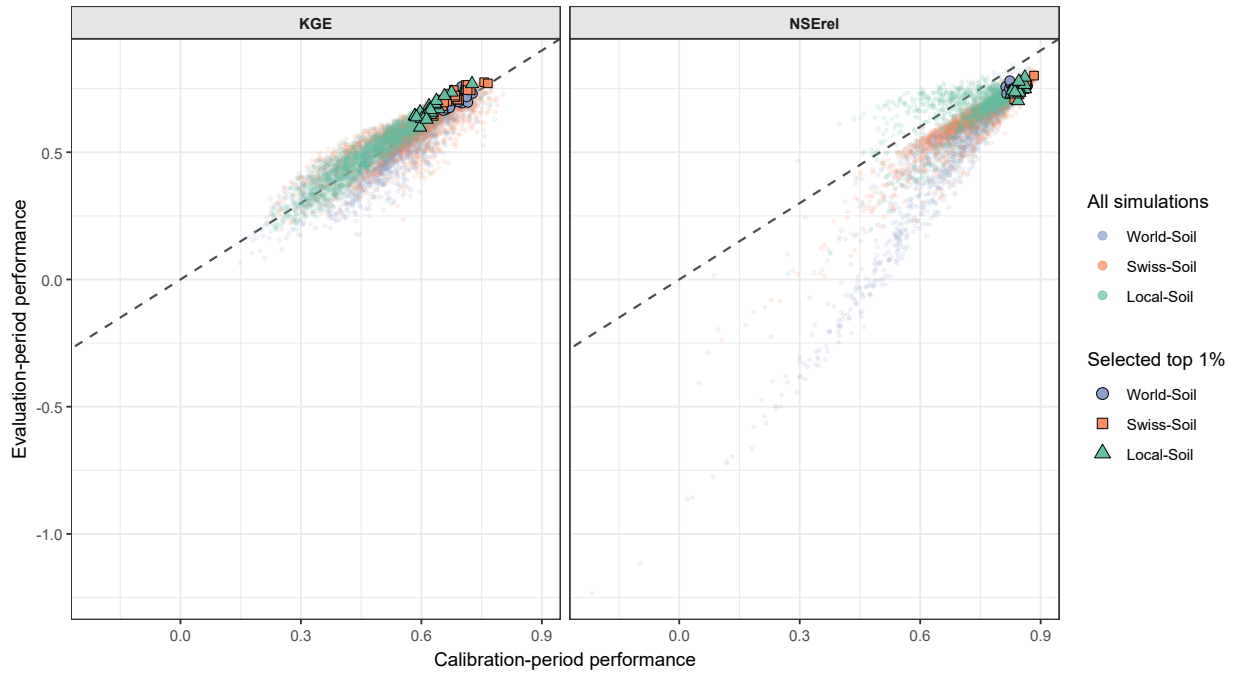


Figure 6: Relationship between calibration- and evaluation-period performance across 2,000 simulations for each soil scenario. Each point represents the performance of the same parameter set during calibration and evaluation for KGE and NSErel. Large symbols with black outlines indicate the calibration-selected best 1% ($n=20$) for each scenario. These parameter sets were selected by ranking all 2,000 sets separately according to calibration-period KGE and NSErel, assigning equal weight to the two rankings, and retaining the 20 sets with the lowest summed ranks. The dashed 1:1 line indicates equal performance during the two periods.

interannual patterns in observed streamflow during both the calibration and evaluation periods (Figure 7). This underlines that these patterns are mostly climate-input driven and are reproduced even with default parameter values. However, the observed flow is generally underestimated by the simulations, also when looking at the full range of the 2000 simulations (see Figure S6). This points towards input data uncertainty, which is not further addressed here (see the work of Heinz et al. (2026) for further details on precipitation input uncertainty in this area).

The daily coverage and spread of the parameter ensemble are summarized in Table S1. For the selected best 1% parameter sets, the daily P-factors range from 0.36 to 0.46 during calibration and from 0.41 to 0.50 during evaluation, whereas the daily R-factors range from 0.31 to 0.39 and from 0.38 to 0.47, respectively. Thus, the selected best 1% parameter sets produce narrow bands around the daily streamflow simulations but do not contain most observed daily streamflow values (Figure 7). This is to be expected (Beven and Binley, 2014) since parameter uncertainty only accounts for a small amount of total model uncertainty, which is composed of data uncertainty (input and output uncertainty) and model structural uncertainty (Kavetski et al., 2006).

4.2. Water balance before and after streamflow calibration

Before calibration, the three soil scenarios show distinctly different water-balance partitioning (Fig. 8; see also Tab.S2). World-Soil is characterized by the largest surface runoff contribution and comparatively small percolation and baseflow contributions. In contrast, Swiss-Soil produces the highest lateral flow, baseflow and percolation contributions, while Local-Soil produces the highest actual evapotranspiration (ET) and lowest average soil-water storage.

Calibration substantially modifies water-balance partitioning, particularly in the World-Soil and Swiss-Soil scenarios. In World-Soil, median surface runoff decreases from 145 to 103 mm yr⁻¹, while percolation increases from 20 to 91 mm yr⁻¹ and baseflow increases from 19 to 85 mm yr⁻¹. Lateral flow decreases from 16 to 8 mm yr⁻¹, whereas actual ET changes only slightly, from 469 to 479 mm yr⁻¹. In Swiss-Soil, calibration increases surface runoff from 39 to 74 mm yr⁻¹, lateral flow from 48 to 87 mm yr⁻¹, while actual ET decreases from 510 to 465 mm yr⁻¹, percolation from 227 to 156 mm yr⁻¹, and baseflow from 212 to 148 mm yr⁻¹. In Local-Soil, calibration shows small calibration-induced changes in lateral flow (31 to 35 mm yr⁻¹) and ET (557 to 543 mm yr⁻¹). Its baseflow and percolation values drop by almost half with 101 to 55 mm yr⁻¹ and 108 to 58 mm yr⁻¹, respectively, while surface runoff increases from 39 to 63 mm yr⁻¹.

Despite these calibration-induced changes, the scenarios retain distinct water-balance partitioning. After calibration, World-Soil continues to produce the highest median surface-runoff contribution, whereas Swiss-Soil produces the highest subsurface flows (lateral flow, baseflow and percolation) and Local-Soil continues with highest actual ET and lowest average soil-water storage. In particular baseflow contributions are markedly different, with 85 mm/yr (World-Soil), 148 mm/yr (Swiss-Soil) and 55 mm/yr (Local-Soil), which is further discussed in the next subsection.

For regional comparison, the Hydrologic Atlas of Switzerland (HADES) indicates a mean annual actual ET of approximately 550-600 mm yr⁻¹ for the catchment during 1973-1992 (Menzel et al., 1999). In addition, the available reference simulations from CAMELS-CH Höge et al. (2023), based on the PREVAH (Viviroli et al., 2007) model, yield a value of 590 mm/yr for 1993-2020. The initial and calibrated Local-Soil values (557 and 543 mm yr⁻¹, respectively), are closer to these regional estimates than the corresponding

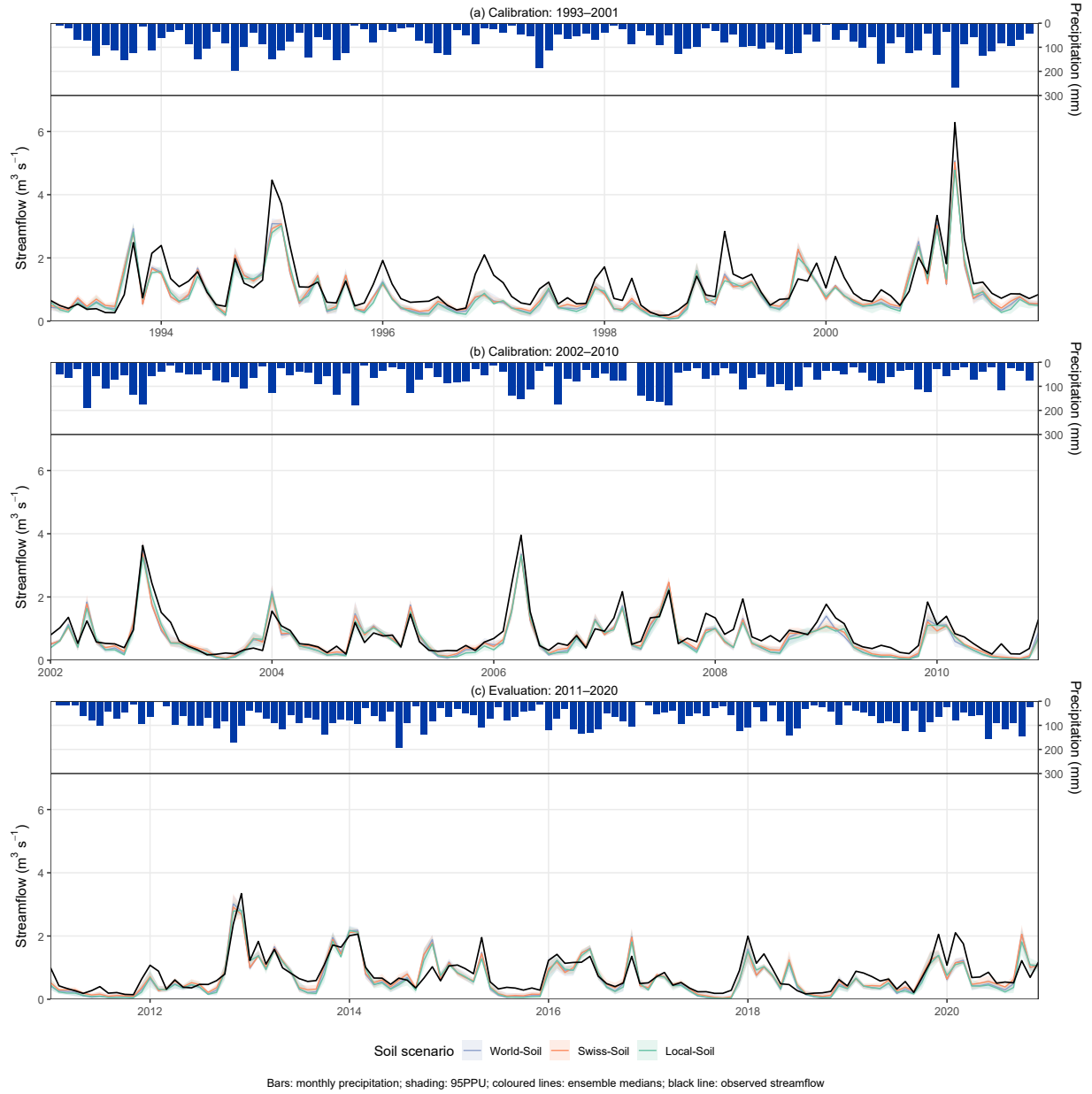


Figure 7: Monthly observed and simulated streamflow during the calibration (a and b) and evaluation (c) periods for the World-Soil, Swiss-Soil, and Local-Soil scenarios. Coloured lines represent the median streamflow of the best 1% calibration-selected parameter sets; shaded areas indicate the corresponding 95% prediction uncertainty (95PPU), and the black line shows observed streamflow. Daily simulated and observed streamflow values were aggregated to monthly means before calculating the ensemble median and 95PPU. The bars from above show monthly precipitation.

World-Soil and Swiss-Soil values. Because both references are spatially derived or model-based estimates rather than direct catchment observations, they provide contextual benchmarks rather than independent validation of simulated ET.

The broad and partly overlapping ranges of the best 1% calibration-selected parameter sets, particularly for subsurface-flow components, show that calibration on streamflow alone cannot further reduce model parameter uncertainty for these fluxes and that the model parameters compensate the differences among the soil scenarios differently for the different scenarios. Nevertheless, the ensemble medians of the 20 best sets preserve contrasting internal hydrological responses between the three model configurations.

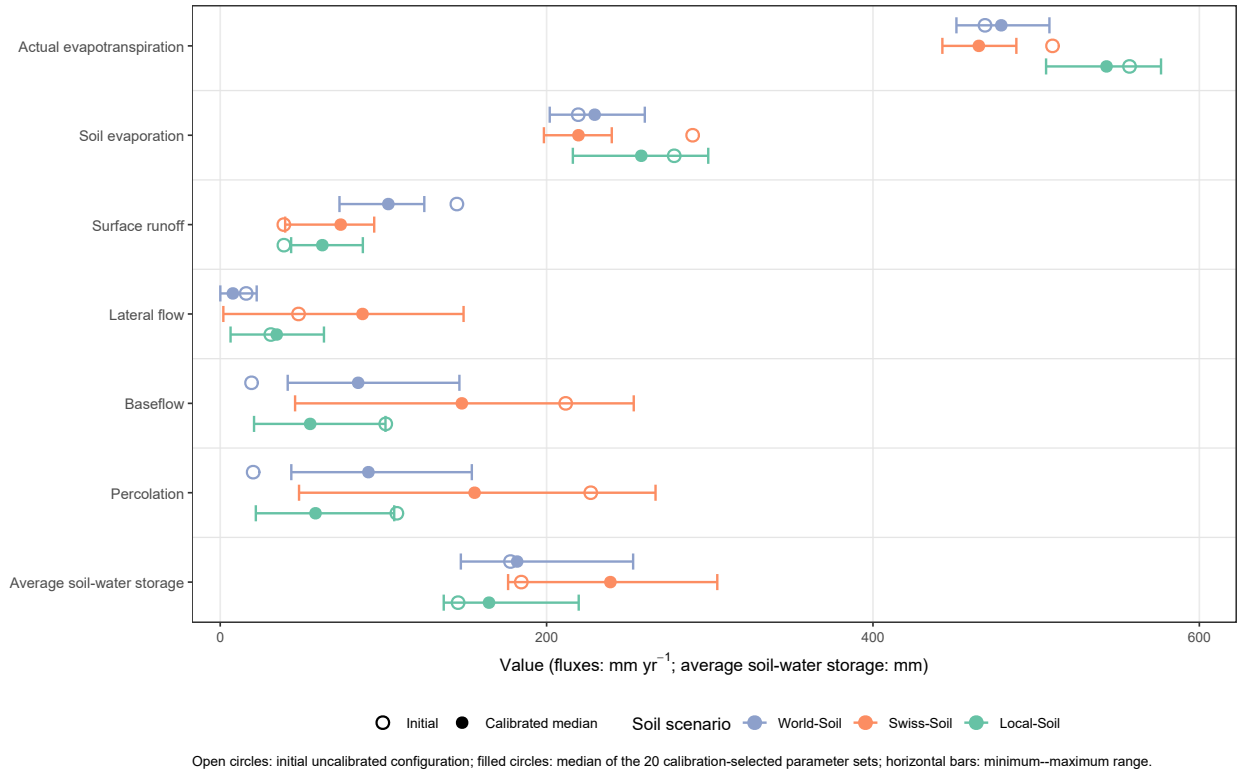


Figure 8: Average annual water balance components before and after streamflow calibration for the World-Soil, Swiss-Soil, and Local-Soil scenarios. Open circles show values from the initial uncalibrated configurations. Filled circles show the median across the best 1% calibration-selected parameter sets, and horizontal bars show their minimum–maximum range. Values summarize the 1993–2020 simulation period following a 1990–1992 warm-up period. For context, mean annual precipitation and potential ET over this period are 849 and 731 mm yr⁻¹, respectively.

4.3. Flow-regime and seasonal behaviour

Annual mean streamflow distributions for the best 1% calibration-selected parameter sets are broadly similar among the three soil scenarios and generally overlap during both calibration and evaluation (Fig. 9). Nevertheless, their medians are generally lower than the observed median, particularly during evaluation. Differences are more apparent for low-flow season July–August. All three scenarios underestimate the observed summer-flow distribution, with World-Soil producing the lowest median summer streamflow and Swiss-Soil generally producing the highest summer-flow and is therefore closest to the observations. Local-Soil exhibits intermediate summer streamflow but remains below the observed distribution. This underlines

that simulated ET (which is lowest for World-Soil producing the least summer-flow) is less important for summer-flow simulations than the simulated baseflow, which is markedly different for the three scenarios.

The simulated distributions also include several high summer-flow values, especially during calibration, showing that the disagreement is concentrated primarily in the central and lower parts of the summer-flow distribution rather than in all individual years. Numerical summaries of the annual and July–August distributions, including medians and 2.5th–97.5th percentile intervals, are reported in Table S3.

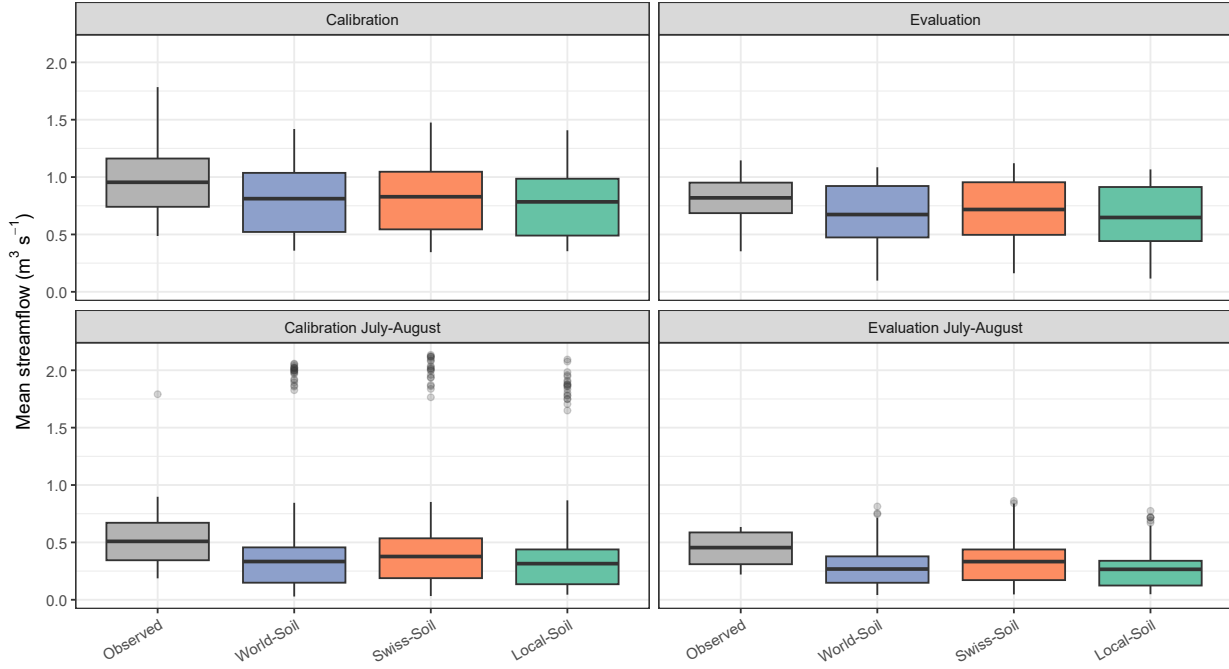


Figure 9: Distributions of annual and July–August mean streamflow during the calibration and evaluation periods. Simulated distributions include annual or seasonal values from the best 1% parameter sets selected using the combined ranking of daily calibration-period NSErel and KGE, while observed distributions represent the corresponding annual or seasonal observed values. The boxplots therefore summarize interannual variability and, for the simulations, variability among the selected parameter sets.

Differences among the flow regimes become clearer along the flow-duration curves (Fig. 10). The three simulated curves are similar at low exceedance probabilities, indicating limited differences under high-flow conditions. Their separation increases toward median- and low-flow conditions, which are more influenced by soil-induced partitioning than rainfall-dominated high flows, where simulation quality mainly depends on the input quality. Swiss-Soil generally maintains the highest streamflow in the lower part of the flow-duration curve, whereas World-Soil produces the lowest median and low flows, particularly during evaluation. The observed curve lies above the simulated ensemble medians over most median- and low-flow exceedance probabilities, indicating that all three scenarios underestimate flow persistence. This is also reflected in Q_{50} and Q_{347} , which are consistently lower than the corresponding observed values during calibration and evaluation. Swiss-Soil produces the Q_{50} and Q_{347} values closest to the observations, while World-Soil shows the greatest low-flow underestimation. By contrast, evaluation-period Q_{05} is slightly overestimated by the simulated ensembles, showing that the evaluation bias changes across the flow regime. Uncertainty increases toward Q_{347} , and the overlap among the scenario intervals indicates that these differences represent

systematic tendencies rather than complete separation among the soil scenarios. Median and 2.5th–97.5th percentile values of Q_{05} , Q_{50} , and Q_{347} are given in Table S4.

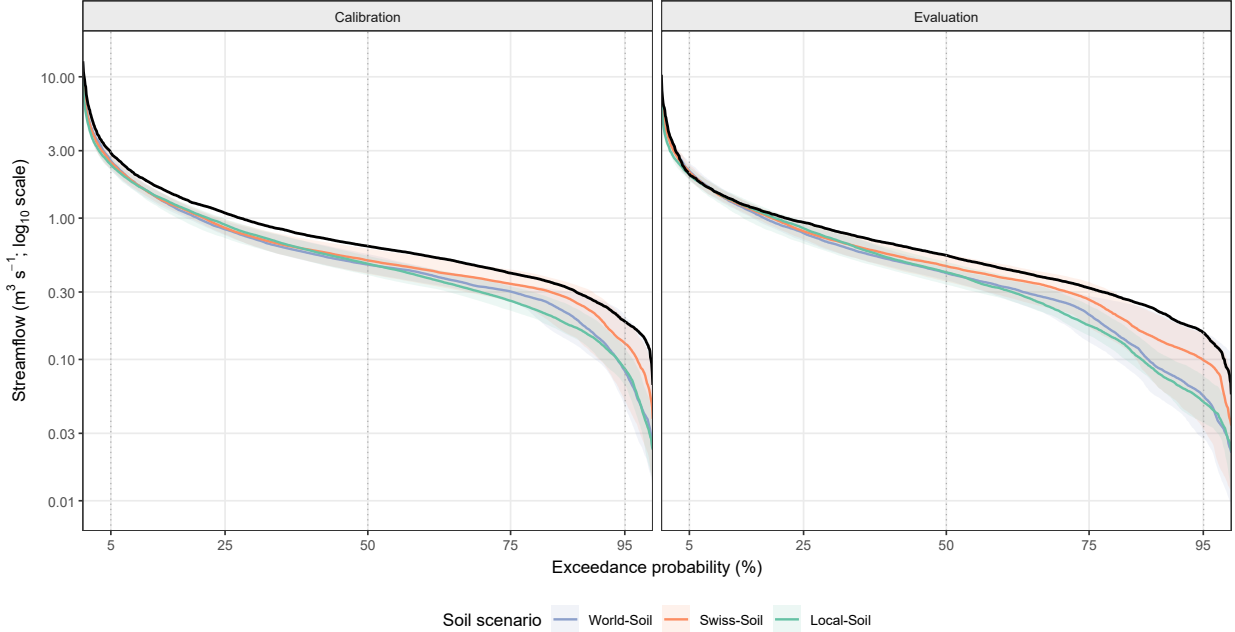


Figure 10: Observed and simulated flow-duration curves during the calibration and evaluation periods. Streamflow is shown on a logarithmic y-axis. Coloured lines show the median flow-duration curves of the best 1% calibration-selected parameter sets, and shaded areas show the corresponding 2.5th–97.5th percentile ranges. The black line represents observed streamflow. Vertical dotted lines indicate Q_{05} and Q_{50} , corresponding to exceedance probabilities of 5% and 50%, respectively, and Q_{347} , the Swiss critical low-flow statistic.

The ET distributions show a more consistent separation among soil scenarios than the streamflow distributions (Fig. 11). Local-Soil produces the highest annual, July–August, and April–September ET during both calibration and evaluation. World-Soil and Swiss-Soil have more similar median ET, although Swiss-Soil displays greater variability, particularly during evaluation. The persistence of the Local-Soil response across annual, peak-summer, and growing-season aggregations indicates that its higher ET is not restricted to a small number of months. The numerical distributions, including their medians and range for the 1% best parameter sets, are reported in Table S5.

Hydrograph separation indicates an observed baseflow index of 0.57 during calibration and 0.60 during evaluation (Fig. 12). Median simulated BFI is consistently highest for Local-Soil and lowest for World-Soil. Over the entire simulation period: median BFI amounts to 0.59, 0.55, and 0.54 for Local-Soil, Swiss-Soil, and World-Soil, respectively, compared with an observed value of 0.58. Nevertheless, the simulated BFI distributions encompass the observed value in all three soil scenarios and periods. The systematic underestimation of median and low streamflow therefore cannot be explained solely by differences in the overall fraction of streamflow classified as baseflow. Differences in the timing and persistence of groundwater release may also contribute to the low-flow bias.

The monthly state and flux variables further demonstrate that similar streamflow performance does not imply equivalent internal hydrological behaviour (Fig. 13). Soil-water storage follows a comparable

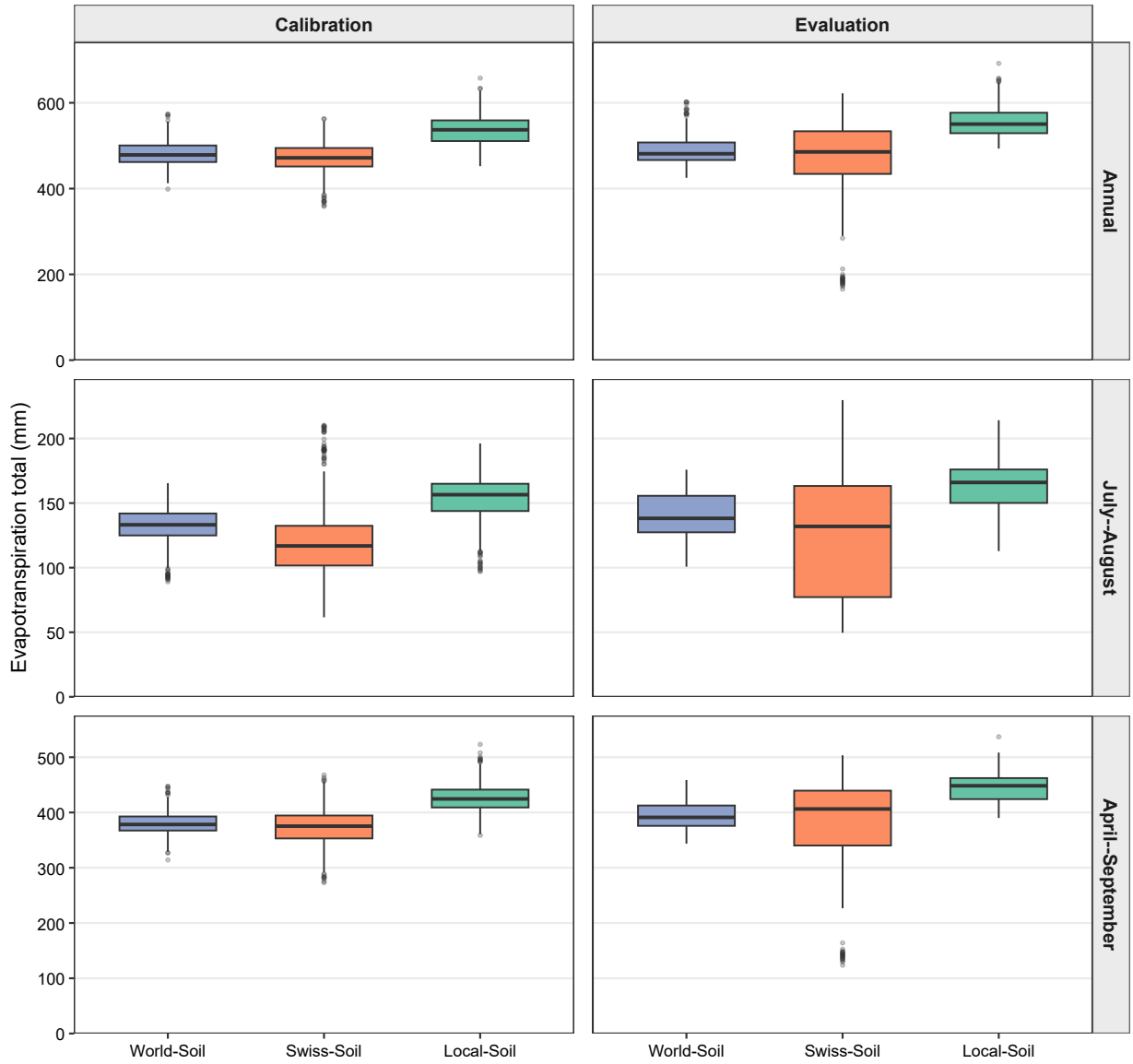


Figure 11: Distributions of annual, July–August, and April–September ET totals during the calibration and evaluation periods for the World-Soil, Swiss-Soil, and Local-Soil scenarios. Simulated distributions include values from the best 1% calibration-selected parameter sets. The boxplots therefore represent both interannual variability and variability among the selected parameter sets. July–August represents the principal summer low-flow period, whereas April–September represents cumulative ET over the main growing season.

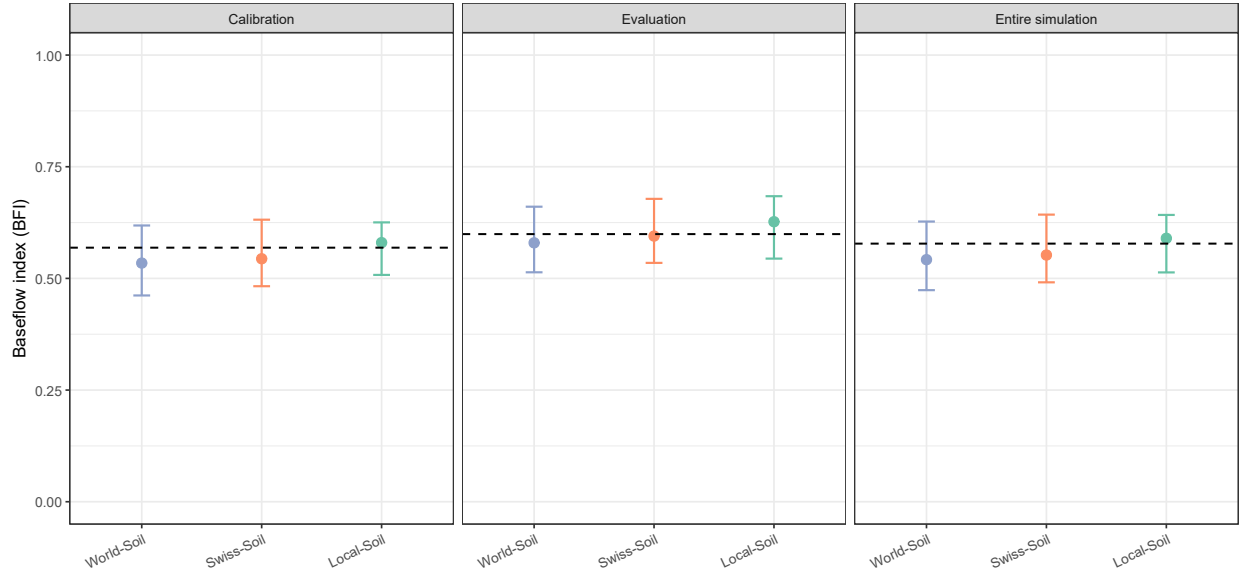


Figure 12: Baseflow index (BFI) calculated from daily observed and simulated streamflow using the UKIH-f smoothed-minima method during the calibration, evaluation, and entire simulation periods. Points and vertical bars represent the median and minimum–maximum range, respectively, across the 1% best calibration-selected parameter sets. The black dashed lines indicate the corresponding observed BFI. BFI is interpreted as a streamflow-derived indicator of delayed flow rather than as a direct measurement of groundwater contribution.

seasonal pattern in all three configurations, reflecting their common meteorological forcing, but Swiss-Soil generally maintains higher storage than World- and Local-Soil. Differences in median aquifer storage are smaller, although Swiss-Soil exhibits a substantially wider parameter range for the 20 best sets. Swiss-Soil also produces higher median baseflow and markedly higher ensemble spread, whereas World- and Local-Soil show lower and more constrained baseflow release. These differences persist through both calibration and evaluation. Thus, the three setups reproduce broadly similar streamflow dynamics (conditioned on the observed streamflow) while representing the storage and release of water differently.

4.4. COCOA SWAT+ model and dominant soil aggregation

The dominant soil aggregation process has no notable impact on the soil texture composition of the two coarser soil datasets, World-Soil and Swiss-Soil (see Figure S2). The main texture classes in Local-Soil also remain close to the original, with more notable changes for silty loam and sandy clay loam. However, the five less frequent Local-Soil texture classes (silty clay, sandy clay, silty clay loam, loamy sand and sand) disappear entirely with the dominant soil aggregation process. These five soil classes together cover about 11 ha or 0.1% of the study area. Therefore, although their disappearance might have some effect on the water balance of single Land Objects, this can be neglected regarding catchment-scale results.

The limited effect of dominant soil aggregation is also reflected in Shannon entropy. Soil texture entropy decreases from 1.09 to 1.04 for Local-Soil and from 1.04 to 1.03 for Swiss-Soil, corresponding to reductions of 4.0% and 0.8%, respectively. For World-Soil, entropy remains unchanged at 0.64. Thus, aggregation results in a small loss of soil-texture diversity for Local-Soil but has little or no effect on the diversity represented by the two coarser soil datasets.

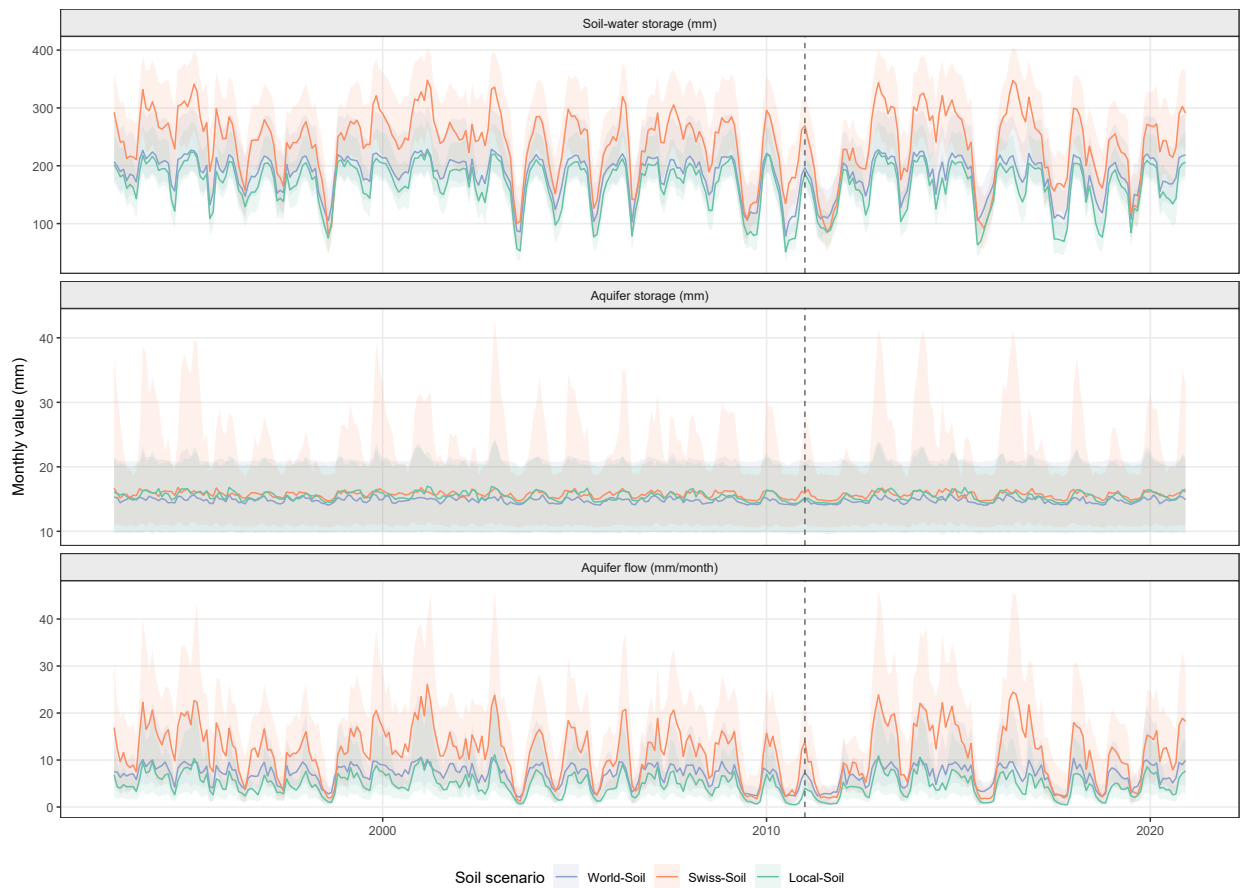


Figure 13: Monthly soil-water storage, aquifer storage, and aquifer flow for the World-Soil, Swiss-Soil, and Local-Soil scenarios during 1993–2020. Coloured lines represent ensemble medians of the best 1% calibration-selected parameter sets, and shaded areas show the corresponding 2.5th–97.5th percentile ranges. The vertical dashed line separates the calibration period (1993–2010) from the evaluation period (2011–2020).

5. Discussion

To our knowledge, this study is the first to explicitly assess alternative soil representations within the COCOA SWAT+ framework. In conventional SWAT applications, increasing soil resolution generally also changes the number and size of HRUs, thereby increasing computational costs and confounding the effects of the soil data with changes in spatial discretisation (Romanowicz et al., 2005; Viviroli et al., 2007; Moges et al., 2023; Fernando et al., 2025). By decoupling soil input data from the spatial units used for water-balance calculations, the COCOA setup allows the three soil representations to be compared while maintaining the same number and spatial configuration of Land Objects. The observed differences can therefore be attributed more directly to differences among the soil datasets (including their spatial resolution, soil properties, and vertical layering) rather than to changes in model spatial structure.

High-resolution soil input data with high spatial and vertical variability are often expected to improve the representation of soil–water dynamics in hydrological models, in particular if higher spatial variability increases the degree-of-freedom of the model or the number of model parameters, which is not the case here (Huang et al., 2022; Krpec et al., 2020; Bayabil and Dile, 2020; Horta et al., 2024). Our results show that increasing the spatial and vertical detail of the soil information does not systematically improve catchment-scale streamflow performance. Among the best 1% calibration-selected parameter sets, the three soil scenarios achieve similar NSE_{rel} values, while Swiss-Soil generally produces the highest KGE (Tab. 2; Fig. 6). Differences among the soil scenarios become, however, evident in the analysis of water flux partitioning, evapotranspiration, soil-water storage, and groundwater release (Figs. 8, 11, and 13).

These findings agree with previous studies showing that calibration can compensate for limitations in the resolution of precipitation, DEM, and soil inputs (Huang et al., 2019; Kleidorfer et al., 2009; Lin et al., 2013; Bhandari et al., 2018). They also support the expectation formulated in the Introduction that spatial differences in model inputs can be attenuated by catchment-scale averaging and may therefore not be apparent in streamflow at the catchment outlet (Bormann, 2006; Sciuto and Diekkrüger, 2010; Li et al., 2013; Baroni et al., 2017). Although some studies report better performance with finer-resolution soil data (López-Ballesteros et al., 2023; Bhandari et al., 2018), our results are more consistent with the work of Kumar and Merwade (2009), who show that calibration can offset the influence of catchment subdivision and input-data resolution and produce relatively similar aggregated model outputs.

The GSA shows that parameter influence depends not only on the model performance metrics but also on the soil dataset. The statistical significance and, in some cases, the direction of parameter effects vary among the three scenarios, particularly for parameters associated with surface-runoff generation, lateral flow, percolation, and groundwater processes (Tab. A4). This demonstrates that the effect of a calibration parameter cannot be considered independently of the soil representation to which it is applied. Nevertheless, several parameters remain influential across all three scenarios.

The pronounced differences in water-balance components before calibration demonstrate that the soil representation strongly affects runoff partitioning in SWAT+. Unlike DEM resolution, which can have a relatively limited direct effect on outputs such as streamflow, surface runoff and groundwater recharge (Moges et al., 2023), soil hydraulic properties directly regulate the assignment of hydrologic soil groups within the SCS curve-number framework and therefore impact water partitioning, storage and release. As our simulations show, the default partitioning (i.e. if the model is run with default parameter value ranges) with the World-Soil scenario favours a surface-runoff-dominated response; the Swiss-soil scenario favours a

subsurface-flow-oriented response. This reflects differences in how the scenarios represent infiltration, vertical fluxes, and storage capacities with default parameter values (Fig. 8; see also Tab.S2).

Calibration substantially modifies this default water-balance partitioning. However, the calibrated scenarios retain contrasting water flux partitioning. World-Soil produces the largest median surface-runoff contribution, Swiss-Soil produces the highest lateral flow, baseflow, percolation, and soil-water storage, and Local-Soil produces the highest evapotranspiration and lowest soil water storage (Fig. 8; see also Tab.S2). This behaviour underlines the classical equifinality challenge in hydrological modelling, whereby different parameter sets and model configurations can produce similar streamflow at the catchment outlet (Beven and Freer, 2001; Beven, 2012). Calibration can therefore reduce differences in aggregated streamflow while masking distinct internal process representations. As highlighted by Kirchner (2006), models may obtain the "right answers for the wrong reasons" when evaluation is based exclusively on outlet-streamflow metrics.

The observed long-term mean annual streamflow of approximately 278 mm yr^{-1} corresponds to a runoff ratio of about 0.33 for the period 1993-2020 (the full simulation period), indicating that approximately one-third of annual precipitation leaves the catchment as streamflow at the gauging station. The calibrated actual-evapotranspiration medians of $465\text{--}543 \text{ mm yr}^{-1}$ correspond to approximately 55–64% of the mean annual precipitation of 849 mm yr^{-1} (Fig. 8; see also Tab.S2). Relatively moderate differences in evapotranspiration and subsurface storage can therefore have an appreciable effect on streamflow generation. In particular, the consistently higher annual and seasonal evapotranspiration in Local-Soil may reduce the water available for storage and streamflow generation and thereby contribute to its lower simulated summer and low-flow values (Fig. 11; see also Tab.S5). However, the overlap among the parameter-ensemble ranges and the absence of direct catchment-scale observations of evapotranspiration, internal fluxes, and water storage prevent this relationship from being established causally. Consequently, the contrasting water-partitioning and storage dynamics are hydrologically important, but they do not establish which soil scenario provides the most realistic or "better" representation of catchment processes.

The averaging effect of the catchment is particularly apparent in the annual streamflow distributions, which overlap substantially among the three scenarios (Fig. 9; see also Tab.S3). Differences become clearer during the summer months, July–August, and toward the median- and low-flow parts of the flow-duration curves. All three scenarios underestimate summer streamflow, Q_{50} , and Q_{347} , whereas their high-flow responses are more similar to one another and to the observations (Figs. 10, see also Fig.S7 and Tab.S4). Soil representation therefore has a higher influence on sustained median and low flows than on the highest streamflow conditions.

Swiss-Soil generally produces the highest Q_{50} and Q_{347} and lies closest to the observed values. This is consistent with its higher simulated percolation, baseflow, soil-water storage, and aquifer flow (Figs. 8 and 13, see also Fig.S7) and suggests that its representation of soil and groundwater processes supports a more sustained release of stored water during recession and low-flow periods. World-Soil and Local-Soil produce lower Q_{347} values despite their contrasting internal water-balance partitioning, illustrating that similar low-flow deficiencies can result from different simulated water partitioning. The relative ensemble spread increases toward Q_{347} , indicating that very low streamflow is particularly variable among the selected parameter sets. However, because the scenario ranges overlap, these results indicate systematic ensemble tendencies rather than a complete separation of the three soil scenarios (see Tab.S4).

The observed baseflow index ranges from 0.57 to 0.60 across the analysis periods, indicating that delayed

subsurface-flow pathways contribute substantially to streamflow in the Petite Glâne (Fig. 12). Subsurface storage and delayed water release, including groundwater contributions, are therefore likely to be particularly important for maintaining summer and other low flows. This interpretation is consistent with Heinz et al. (2026), who show that changes in soil-water retention and groundwater recharge affect summer streamflow and low-flow occurrence in the same catchment. The systematic underestimation of Q_{50} and Q_{347} across all three soil scenarios may indicate that groundwater storage is depleted too rapidly, that groundwater release during dry periods is insufficient, or that relevant groundwater exchanges are not fully represented. The persistence of the bias despite the use of NSE_{rel} , which gives higher weight to low-flow errors than ordinary NSE, further suggests a common structural or input-related limitation rather than a problem that can be resolved solely through soil-data representation.

The systematic underestimation of summer streamflow and Q_{347} suggests that the model configurations do not fully reproduce the observed persistence of low flow (Figs. 9 and 10, see also Fig. S7). The observed BFI of 0.57 during calibration and 0.60 during evaluation indicates that approximately 57–60% of streamflow is classified as delayed flow by the UKIH-f method. The simulated ensemble ranges encompass these values in all three soil scenarios (Fig. 12), suggesting that the low-flow underestimation is not caused solely by an insufficient overall delayed-flow fraction. Instead, the models may inadequately represent the seasonal timing and persistence of groundwater release. Because BFI is derived statistically from streamflow, it does not provide a direct measurement of groundwater contribution.

This interpretation is supported by the contrasting simulated state variables. Although all scenarios follow similar seasonal patterns under the same meteorological forcing, Swiss-Soil maintains higher soil-water storage and produces higher aquifer flow and substantially wider groundwater-related uncertainty ranges than World-Soil and Local-Soil (Fig. 13). Nevertheless, even Swiss-Soil underestimates observed low streamflow. The state-variable results consequently show that the scenarios represent groundwater storage and release differently, but they do not establish which representation is most realistic because groundwater-level, soil-moisture, and baseflow observations are unavailable.

The results have implications for both hydrological modelling and the allocation of resources for soil-data collection. If model evaluation is based only on catchment-outlet streamflow, the additional spatial information in a high-resolution soil dataset may appear to provide limited benefit because calibration and catchment-scale averaging reduce the differences in associated streamflow simulations. However, the water flux partitioning, the seasonal analysis and analysis of flow-duration curves and state-variable demonstrate that the selected soil dataset affects how the model partitions, stores, and releases water. These differences are relevant when models are used to assess drought, groundwater recharge, evapotranspiration, agricultural water availability, land-use change, or management interventions, even if outlet-streamflow metrics differ only slightly.

The COCOA SWAT+ framework is useful in this context because it maintains a consistent spatial discretisation across the soil scenarios. This avoids the simultaneous change in HRU number that complicates soil-resolution comparisons in conventional SWAT applications. Nevertheless, the scenarios differ not only in nominal spatial resolution but also in soil properties, number of soil types, and vertical layering. The observed responses should therefore be attributed to alternative soil representations rather than to spatial resolution alone. Dominant soil aggregation also removes some rare Local-Soil texture classes, although these account for only approximately 0.1% of the catchment and are unlikely to dominate the catchment-scale

results (see Figure S2).

Several additional limitations affect the strength of the conclusions. First, only streamflow is evaluated against direct catchment observations. Evapotranspiration, soil-water storage, aquifer storage, percolation, and groundwater release are compared among model configurations but cannot be directly validated. Independent process observations could include spatially representative eddy-covariance measurements of evapotranspiration (Zink et al., 2017), in situ soil-moisture (Duethmann et al., 2022), and hydrochemical or isotopic tracers to quantify groundwater recharge (Schilling et al., 2021). Such observations would help determine whether differences among the scenarios represent plausible catchment processes rather than alternative ways of reproducing outlet streamflow.

Second, the best 1% calibration-selected parameter sets represent only part of the total uncertainty. Input and output data uncertainty, uncertainty in the soil-property data, model structural uncertainty, and uncertainty introduced by spatial aggregation are not comprehensively quantified.

Third, the GSA is performed over the entire 1993–2020 simulation period to identify the sensitive parameters subsequently included in the calibration. Consequently, evaluation-period observations contribute to the selection of the calibrated parameter subset. However, the parameter values and the best 1% ensemble are selected using calibration-period performance only. The evaluation period is therefore not fully independent of model development and is interpreted as an assessment of temporal transferability rather than a fully independent model validation. Nevertheless, the robustness analysis shows that restricting the GSA to the calibration period results in a broadly similar parameter subset (Tab. A3).

Future work should evaluate the model configurations against additional process-related observations, particularly remotely sensed or field-based evapotranspiration, soil moisture, groundwater levels, and independently estimated baseflow. Such observations would help determine whether the contrasting internal responses represent realistic hydrological differences or compensating model errors. The Swiss Soil Property Map published in 2024 (Gupta et al., 2024) also provides an opportunity to test whether a more recent national dataset offers a useful compromise between readily available regional information and costly high-resolution local mapping.

6. Conclusion

This study assesses how three soil datasets of increasing spatial and vertical detail influence a Contiguous-Object Connectivity Approach (COCOA) SWAT+ model: the low-resolution global World-Soil dataset, the medium-resolution national Swiss-Soil dataset, and the high-resolution Local-Soil dataset developed specifically for the study area. By maintaining identical spatial modelling units and non-soil inputs across the three scenarios, the study isolates differences associated with soil representation from changes in model spatial structure. The three soil scenarios show clearly different parameter sensitivities and water partitioning, demonstrating that soil representation affects model behaviour beyond catchment-outlet streamflow performance. After calibration, the best-performing parameter sets achieve very similar NSE_{rel} values across all scenarios, while Swiss-Soil consistently achieves the highest KGE. Increasing the spatial detail of the soil data therefore does not lead to a systematic improvement in streamflow performance.

Differences among the scenarios remain evident in the associated internal hydrological model behaviour. Differences are more apparent during median- and low-flow conditions than during high flows. Calibration therefore reduces differences in outlet-streamflow performance without eliminating differences in simulated

737 water partitioning, storage, and release. Because these internal fluxes and stores cannot be independently
738 validated in the framework of this study, the results do not identify one soil representation as physically
739 superior.

740 Overall, the findings show that the value of higher-resolution soil information depends on the modelling
741 objective and understanding how soil-property data affect water partitioning, storage, and release can sup-
742 port modelers in selecting input data that are appropriate for the intended application. If the primary aim
743 is calibrated catchment-outlet streamflow, a medium-resolution dataset such as the Swiss-Soil may be suffi-
744 cient. However, the Local-Soil dataset provides greater spatial and vertical soil detail, which is reflected in
745 distinct simulated internal hydrological behavior. For catchment management and environmental planning,
746 investment in higher-quality soil information is therefore most valuable when decisions depend on internal
747 processes such as groundwater recharge, evapotranspiration, soil-water availability, or low-flow dynamics.
748 The appropriate soil dataset should therefore be selected according to the processes and management ques-
749 tions the model is intended to represent, rather than on spatial resolution alone.

Supplementary information

Funding

This study has received funding from the European Union’s Horizon 2020 research and innovation program under grant agreement No. 862756.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used OpenAI’s ChatGPT and Codex to assist with language editing, R-code development and debugging, and the formatting of figures and tables. After using these tools, the authors reviewed, verified, and edited the resulting content as needed and take full responsibility for the content of the published article.

Data availability

Data sources are provided in Table A1.

Code availability

The R scripts used to assess soil texture before and after dominant soil aggregation, conduct the sensitivity analysis, calibrate and evaluate the models, and generate the figures and tables are available at: <https://github.com/JoanaEichenberger/Impact-of-Soil-Data-Representation-on-Streamflow-Modeling-with-CO2-SWAT-Workflow>. The repository includes documentation of the required software packages and workflow. The SWAT+ executable and associated tools are available from their respective developers. The complete outputs of the individual SWAT+ simulations are not included but are available from the corresponding author upon request.

CRediT authorship contribution statement

Joana Eichenberger: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing - Original Draft, Writing - Review & Editing. **Bettina Schaepli:** Supervision, Writing - Review & Editing. **Tatenda Lemann:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

References

- Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology* 524, 733–752. doi:10.1016/j.jhydrol.2015.03.027.
- Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., Srinivasan, R., 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology* 333, 413–430. doi:10.1016/j.jhydrol.2006.09.014.
- Abyani, M., Bahaari, M.R., 2020. A comparative reliability study of corroded pipelines based on Monte Carlo Simulation and Latin Hypercube Sampling methods. *International Journal of Pressure Vessels and Piping* 181, 104079. doi:10.1016/j.ijpvp.2020.104079.
- Althoff, D., Rodrigues, L.N., 2021. Goodness-of-fit criteria for hydrological models: Model calibration and performance assessment. *Journal of Hydrology* 600, 126674. doi:10.1016/j.jhydrol.2021.126674.
- Andrianaki, M., Shrestha, J., Kobierska, F., Nikolaidis, N.P., Bernasconi, S.M., 2019. Assessment of SWAT spatial and temporal transferability for a high-altitude glacierized catchment. *Hydrology and Earth System Sciences* 23, 3219–3232. doi:10.5194/hess-23-3219-2019.
- Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., 2012. SWAT: Model use, calibration, and validation. *Transactions of the ASABE* 55, 1491–1580. doi:10.13031/2013.42256.
- Baltensweiler, A., Walthert, L., Hanewinkel, M., Zimmermann, S., Nussbaum, M., 2021. Machine learning based soil maps for a wide range of soil properties for the forested area of Switzerland. *Geoderma Regional* 27, e00437. doi:10.1016/j.geodrs.2021.e00437.
- Baroni, G., Zink, M., Kumar, R., Samaniego, L., Attinger, S., 2017. Effects of uncertainty in soil properties on simulated hydrological states and fluxes at different spatio-temporal scales. *Hydrology and Earth System Sciences* 21, 2301–2320. doi:10.5194/hess-21-2301-2017.
- Bayabil, H.K., Dile, Y.T., 2020. Improving Hydrologic Simulations of a Small Watershed through Soil Data Integration. *Water* 12, 2763. doi:10.3390/w12102763.
- Beven, K., Binley, A., 2014. GLUE: 20 years on. *Hydrological Processes* 28, 5897–5918. URL: <https://onlinelibrary.wiley.com/doi/10.1002/hyp.10082>, doi:10.1002/hyp.10082.
- Beven, K., Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology* 249, 11–29. doi:10.1016/S0022-1694(01)00421-8.
- Beven, K.J., 2012. *Rainfall-runoff modelling: the primer*. 2nd ed ed., Wiley-Blackwell, Chichester, West Sussex ; Hoboken, NJ.
- Bhandari, R., Thakali, R., Kandissounon, A., Kalra, A., Ahmad, S., 2018. Effects of Soil Data Resolution on the Simulated Stream Flow and Water Quality: Application of Watershed-Based SWAT Model. *World Environmental and Water Resources Congress 2018*, American Society of Civil Engineers, Minneapolis, Minnesota. doi:10.1061/9780784481400.035.

814 Bieger, K., Arnold, J.G., Rathjens, H., White, M.J., Bosch, D.D., Allen, P.M., Volk, M., Srinivasan, R.,
815 2017. Introduction to SWAT+, A Completely Restructured Version of the Soil and Water Assessment
816 Tool. *JAWRA Journal of the American Water Resources Association* 53, 115–130. doi:10.1111/1752-1
817 688.12482.

818 Bormann, H., 2006. Impact of spatial data resolution on simulated catchment water balances and model
819 performance of the multi-scale TOPLATS model. *Hydrology and Earth System Sciences* 10, 165–179.
820 doi:10.5194/hess-10-165-2006.

821 Bouslihim, Y., Ouarani, M., Taia, S., El Khalki, E.M., Hadri, A., Kharrou, M.H., Chehbouni, A., 2025. The
822 impact of soil data on SWAT modeling: Effects, requirements, and future directions. *Scientific African*
823 28, e02694. doi:10.1016/j.sciaf.2025.e02694.

824 Brath, A., Montanari, A., Toth, E., 2004. Analysis of the effects of different scenarios of historical data
825 availability on the calibration of a spatially-distributed hydrological model. *Journal of Hydrology* 291,
826 232–253. doi:10.1016/j.jhydro1.2003.12.044.

827 de Brogniez, D., Ballabio, C., Stevens, A., Jones, R.J.A., Montanarella, L., van Wesemael, B., 2015. A map
828 of the topsoil organic carbon content of Europe generated by a generalized additive model. *European*
829 *Journal of Soil Science* 66, 121–134. doi:10.1111/ejss.12193.

830 Burgos, S., Nussbaum, M., 2020a. Analyse et mise valeur des données pédologiques du canton de Vaud,
831 résultats du Workpackage II. Technical Report. Bern University of Applied Sciences.

832 Burgos, S., Nussbaum, M., 2020b. Stratégie pour une cartographie du canton de Vaud: inventaire et analyses
833 des données existantes, proposition d'un set de données de vérification. Workpackage I. Technical Report.
834 Bern University of Applied Sciences.

835 Busico, G., Colombani, N., Fronzi, D., Pellegrini, M., Tazioli, A., Mastrocicco, M., 2020. Evaluating
836 SWAT model performance, considering different soils data input, to quantify actual and future runoff
837 susceptibility in a highly urbanized basin. *Journal of Environmental Management* 266, 110625. doi:10.1
838 016/j.jenvman.2020.110625.

839 Carlos Mendoza, J.A., Chavez Alcazar, T.A., Zuñiga Medina, S.A., 2021. Calibration and Uncertainty
840 Analysis for Modelling Runoff in the Tambo River Basin, Peru, Using Sequential Uncertainty Fitting
841 Ver-2 (SUFI-2) Algorithm. *Air, Soil and Water Research* 14, 1178622120988707. doi:10.1177/11786221
842 20988707.

843 DGE-DIRNA-EAU, . Veille Hydro-météorologique du Canton de Vaud - Petite-Glâne, Villars-le-Grand /
844 Période 1993 - 2020. URL: [https://www.vhv.ch/xt_vh_718536/station_view.php?cfg=display_VH_](https://www.vhv.ch/xt_vh_718536/station_view.php?cfg=display_VH_ARCHIVES&measurement_set_id=77)
845 [ARCHIVES&measurement_set_id=77](https://www.vhv.ch/xt_vh_718536/station_view.php?cfg=display_VH_ARCHIVES&measurement_set_id=77).

846 DGE-DRINA-EAU, 2022. Station limnimétrique: Petite-Glâne. Technical Report. Direction Générale de
847 l'Environnement DRINA-EAU. URL: [https://www.vhv.ch/shared/file_db_get.php?document_id=](https://www.vhv.ch/shared/file_db_get.php?document_id=280&site=xt_vh)
848 [280&site=xt_vh](https://www.vhv.ch/shared/file_db_get.php?document_id=280&site=xt_vh).

849 DHI, 2011. MIKE SHE - User Guide and Reference Manual. Technical Report. DHI A/S. Aarhus, Denmark.
850 URL: https://manuals.mikepoweredbydhi.help/latest/Water_Resources/MIKE_SHE_Print.pdf.

851 Diek, S., Temme, A.J.A.M., Teuling, A.J., 2014. The effect of spatial soil variation on the hydrology of a semi-
852 arid Rocky Mountains catchment. *Geoderma* 235-236, 113–126. doi:10.1016/j.geoderma.2014.06.028.

853 Duethmann, D., Smith, A., Soulsby, C., Kleine, L., Wagner, W., Hahn, S., Tetzlaff, D., 2022. Evaluating
854 satellite-derived soil moisture data for improving the internal consistency of process-based ecohydrological
855 modelling. *Journal of Hydrology* 614, 128462. URL: [https://www.sciencedirect.com/science/arti](https://www.sciencedirect.com/science/article/pii/S0022169422010320)
856 [cle/pii/S0022169422010320](https://www.sciencedirect.com/science/article/pii/S0022169422010320), doi:10.1016/j.jhydrol.2022.128462.

857 Dunne, T., 1978. Field Studies of Hillslope Flow Processes, in: Kirkby, M.J. (Ed.), *Hillslope Hydrology*.
858 John Wiley and Sons, Chirchester, UK, pp. 227–293.

859 Escamilla-Rivera, V., Cortina-Villar, S., Vaca, R.A., Golicher, D., Arellano-Monterrosas, J., Honey-Rosés,
860 J., 2022. Effects of Finer Scale Soil Survey and Land-Use Classification on SWAT Hydrological Modelling
861 Accuracy in Data-Poor Study Areas. *Journal of Water Resource and Protection* 14, 100–125. doi:10.423
862 6/jwarp.2022.142007.

863 FAO, IIASA, 2023. Harmonized World Soil Database version 2.0. Technical Report. FAO, Rome, Italy and
864 IIASA, Laxenburg, Austria. URL: [https://www.fao.org/soils-portal/data-hub/soil-maps-and-d](https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/)
865 [atabases/harmonized-world-soil-database-v20/en/](https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/).

866 FAO-UNESCO, 2003. Digital Soil Map of the World, version 3.6. URL: [https://data.apps.fao.org/ma](https://data.apps.fao.org/map/catalog/srv/eng/catalog.search?uuid=71a5fe65-fc6a-4605-8a35-d1627afeb71b&layers=GEO)
867 [p/catalog/srv/eng/catalog.search?uuid=71a5fe65-fc6a-4605-8a35-d1627afeb71b&layers=GEO](https://data.apps.fao.org/map/catalog/srv/eng/catalog.search?uuid=71a5fe65-fc6a-4605-8a35-d1627afeb71b&layers=GEO)
868 [NETWORK:sd-1c_agg_38183#/metadata/446ed430-8383-11db-b9b2-000d939bc5d8](https://data.apps.fao.org/map/catalog/srv/eng/catalog.search?uuid=71a5fe65-fc6a-4605-8a35-d1627afeb71b&layers=GEO).

869 Fernando, S.M., Zhang, L., Feger, K.H., 2025. Assessing the impact of soil data resolution on streamflow
870 prediction with SWAT in a mesoscale headwater basin of Sri Lanka. *Journal of Hydrology: Regional*
871 *Studies* 61, 102683. doi:10.1016/j.ejrh.2025.102683.

872 FOEN, 2010. Topographical catchment areas of Swiss waterbodies 2 km². URL: [https://opendata.swiss/e](https://opendata.swiss/en/dataset/topographische-einzugsgebiete-der-schweizer-gewasser-teileinzugsgebiete-2km2)
873 [n/dataset/topographische-einzugsgebiete-der-schweizer-gewasser-teileinzugsgebiete-2km2](https://opendata.swiss/en/dataset/topographische-einzugsgebiete-der-schweizer-gewasser-teileinzugsgebiete-2km2).

874 FSO, 2000. Swiss soil suitability map (1:200,000). URL: [https://www.bfs.admin.ch/bfs/en/home/ser](https://www.bfs.admin.ch/bfs/en/home/services/geostat/swiss-federal-statistics-geodata/land-use-cover-suitability/derivative-complementary-data/swiss-soil-suitability-map.html)
875 [vices/geostat/swiss-federal-statistics-geodata/land-use-cover-suitability/derivative-c](https://www.bfs.admin.ch/bfs/en/home/services/geostat/swiss-federal-statistics-geodata/land-use-cover-suitability/derivative-complementary-data/swiss-soil-suitability-map.html)
876 [omplementary-data/swiss-soil-suitability-map.html](https://www.bfs.admin.ch/bfs/en/home/services/geostat/swiss-federal-statistics-geodata/land-use-cover-suitability/derivative-complementary-data/swiss-soil-suitability-map.html).

877 geodienste.ch, 2022. Landwirtschaftliche Bewirtschaftung: Nutzungsflächen 2021 (Kantone FR, VD). URL:
878 https://geodienste.ch/services/lwb_perimeter_ln_sf.

879 Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and
880 NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology* 377,
881 80–91. doi:10.1016/j.jhydrol.2009.08.003.

882 Gupta, S., Hasler, J.K., Alewell, C., 2024. Mining soil data of Switzerland: New maps for soil texture, soil
883 organic carbon, nitrogen, and phosphorus. *Geoderma Regional* 36, e00747. doi:10.1016/j.geodrs.202
884 3.e00747.

885 Heinz, M., Holzkämper, A., Kumar, R., Ledain, S., Horton, P., Schaeffli, B., 2026. From Soil to Stream:
 886 Modeling the Catchment-Scale Hydrological Effects of Increased Soil Organic Carbon. doi:[https://doi.](https://doi.org/10.5194/hess-30-2879-2026)
 887 [org/10.5194/hess-30-2879-2026](https://doi.org/10.5194/hess-30-2879-2026).

888 Horta, A., Oliveira, A.R., Azevedo, L., Ramos, T.B., 2024. Assessing the use of digital soil maps in
 889 hydrological modeling for soil-water budget simulations - implications for water management plans in
 890 southern Portugal. *Geoderma Regional* 36, e00741. doi:10.1016/j.geodrs.2023.e00741.

891 Huang, S., Eisner, S., Haddeland, I., Tadege Mengistu, Z., 2022. Evaluation of two new-generation global
 892 soil databases for macro-scale hydrological modelling in Norway. *Journal of Hydrology* 610, 127895.
 893 doi:10.1016/j.jhydro1.2022.127895.

894 Huang, Y., Bárdossy, A., Zhang, K., 2019. Sensitivity of hydrological models to temporal and spatial
 895 resolutions of rainfall data. *Hydrology and Earth System Sciences* 23, 2647–2663. doi:10.5194/hess-2
 896 3-2647-2019.

897 Höge, M., Kauzlaric, M., Siber, R., Schönenberger, U., Horton, P., Schwanbeck, J., Floriancic, M.G., Viviroli,
 898 D., Wilhelm, S., Sikorska-Senoner, A.E., Addor, N., Brunner, M., Pool, S., Zappa, M., Fenicia, F., 2023.
 899 CAMELS-CH: hydro-meteorological time series and landscape attributes for 331 catchments in hydrologic
 900 Switzerland. *Earth System Science Data* 15, 5755–5784. doi:10.5194/essd-15-5755-2023.

901 Jeangros, B., Courvoisier, N., 2019. Optimale Fruchtfolgen im Feldbau (4. Auflage). *Agrarforschung Schweiz*
 902 , 4URL: [https://www.agrarforschungschweiz.ch/wp-content/uploads/2019/12/2019_0708_2488.](https://www.agrarforschungschweiz.ch/wp-content/uploads/2019/12/2019_0708_2488.pdf)
 903 [pdf](https://www.agrarforschungschweiz.ch/wp-content/uploads/2019/12/2019_0708_2488.pdf).

904 JRC, F.I.I.C., 2012. Harmonized world soil database (version 1.2). Technical Report. FAO, Rome, Italy
 905 and IIASA, Laxenburg, Austria. URL: [https://www.fao.org/soils-portal/soil-survey/soil-map](https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/ru/)
 906 [s-and-databases/harmonized-world-soil-database-v12/ru/](https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/ru/).

907 Kavetski, D., Kuczera, G., Franks, S.W., 2006. Bayesian analysis of input uncertainty in hydrological
 908 modeling: 1. Theory. *Water Resources Research* 42. URL: [https://agupubs.onlinelibrary.wiley.co](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2005WR004368)
 909 [m/doi/10.1029/2005WR004368](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2005WR004368), doi:10.1029/2005WR004368.

910 Kim, B., Lee, G., Lee, Y., Kim, S., Noh, S.J., 2024. Assessment of the Impact of Spatial Variability
 911 on Streamflow Predictions Using High-Resolution Modeling and Parameter Estimation: Case Study of
 912 Geumho River Catchment, South Korea. *Water* 16, 591. doi:10.3390/w16040591.

913 Kirchner, J.W., 2006. Getting the right answers for the right reasons: Linking measurements, analyses, and
 914 models to advance the science of hydrology. *Water Resources Research* 42, 2005WR004362. doi:10.102
 915 9/2005WR004362.

916 Kleidorfer, M., Deletic, A., Fletcher, T., Rauch, W., 2009. Impact of input data uncertainties on urban
 917 stormwater model parameters. *Water science and technology : a journal of the International Association*
 918 *on Water Pollution Research* 60, 1545–54. doi:10.2166/wst.2009.493.

919 Knoben, W.J.M., Freer, J.E., Woods, R.A., 2019. Technical note: Inherent benchmark or not? Comparing
 920 Nash-Sutcliffe and Kling-Gupta efficiency scores. doi:10.5194/hess-2019-327.

921 Krause, P., Boyle, D.P., Bäse, F., 2005. Comparison of different efficiency criteria for hydrological model
922 assessment. *Advances in Geosciences* 5, 89–97. doi:10.5194/adgeo-5-89-2005.

923 Krpec, P., Horáček, M., Šarapatka, B., 2020. A comparison of the use of local legacy soil data and global
924 datasets for hydrological modelling a small-scale watersheds: Implications for nitrate loading estimation.
925 *Geoderma* 377, 114575. doi:10.1016/j.geoderma.2020.114575.

926 Kumar, S., Merwade, V., 2009. Impact of Watershed Subdivision and Soil Data Resolution on SWAT Model
927 Calibration and Parameter Uncertainty1. *JAWRA Journal of the American Water Resources Association*
928 45, 1179–1196. doi:10.1111/j.1752-1688.2009.00353.x.

929 Lehmann, A., Timoner, P., Fasel, M., Lacayo, M., Ashraf Vaghefi, S., Abbaspour, K.C., 2019. SWAT21:
930 A project for linking eco-hydrologic processes and services to aquatic biodiversity at river and catchment
931 levels. *Ecohydrology & Hydrobiology* 19, 182–197. doi:10.1016/j.ecohyd.2019.01.003.

932 Li, X., Zhang, Q., Ye, X., 2013. Effects of spatial information of soil physical properties on hydrological
933 modeling based on a distributed hydrological model. *Chinese Geographical Science* 23, 182–193. doi:10
934 .1007/s11769-013-0599-4.

935 Liang, X., Lettenmaier, D.P., Wood, E.F., Burges, S.J., 1994. A simple hydrologically based model of
936 land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research:*
937 *Atmospheres* 99, 14415–14428. doi:10.1029/94JD00483.

938 Liebegg, 2022a. Steckbrief Gerste. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL: <https://www.liebegg.ch/api/rm/34SNMF2VD22RPPA/gerste-steckbrief-24.pdf>.
939

940 Liebegg, 2022b. Steckbrief Kartoffeln. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL:
941 <https://www.liebegg.ch/api/rm/625BU8S73FNFR77/kartoffeln-steckbrief.pdf>.

942 Liebegg, 2022c. Steckbrief Mais. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL: <https://www.liebegg.ch/api/rm/6NF83768FM289F8/mais-steckbrief-22.pdf>.
943

944 Liebegg, 2022d. Steckbrief Sonnenblumen. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL:
945 <https://www.liebegg.ch/api/rm/7CN4MV27C3252FD/sonnenblumen-steckbrief.pdf>.

946 Liebegg, 2022e. Steckbrief Sorghum. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL:
947 <https://www.liebegg.ch/api/rm/N2G57S342V2BJ4F/sorghum-steckbrief.pdf>.

948 Liebegg, 2022f. Steckbrief Triticale. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL: <https://www.liebegg.ch/api/rm/MP664FUKXV4GPVJ/triticales-steckbrief.pdf>.
949

950 Liebegg, 2022g. Steckbrief Zuckerrüben. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL:
951 <https://www.liebegg.ch/api/rm/9Q7KT3N7W4E7QR7/zuckerrueben-steckbrief.pdf>.

952 Liebegg, 2023. Steckbrief Eiweisserbsen. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL:
953 <https://www.liebegg.ch/api/rm/75Y3S85V8TT3SGH/eiweisserbsen-steckbrief-23.pdf>.

954 Liebegg, 2024. Steckbrief Weizen. Technical Report. Landwirtschaftliches Zentrum Liebegg. URL: <https://www.liebegg.ch/api/rm/EQ5D7T3N8536TWK/weizen-steckbrief-24.pdf>.
955

- Lin, S., Jing, C., Coles, N.A., Chaplot, V., Moore, N.J., Wu, J., 2013. Evaluating DEM source and resolution uncertainties in the Soil and Water Assessment Tool. *Stochastic Environmental Research and Risk Assessment* 27, 209–221. doi:10.1007/s00477-012-0577-x.
- Llanos-Paez, O., Estrada, L., Pastén-Zapata, E., Boithias, L., Jorda-Capdevila, D., Sabater, S., Acuña, V., 2023. Spatial and temporal patterns of flow intermittency in a Mediterranean basin using the SWAT+ model. *Hydrological Sciences Journal* 68, 276–289. doi:10.1080/02626667.2022.2155523. _eprint: <https://doi.org/10.1080/02626667.2022.2155523>.
- López-Ballesteros, A., Nielsen, A., Castellanos-Osorio, G., Trolle, D., Senent-Aparicio, J., 2023. DSOLMap, a novel high-resolution global digital soil property map for the SWAT + model: Development and hydrological evaluation. *CATENA* 231, 107339. doi:10.1016/j.catena.2023.107339.
- Magnier, J., Fribourg-Blanc, B., Lemann, T., Witing, F., Critchley, W., Volk, M., 2024. Natural/Small Water Retention Measures: Their Contribution to Ecosystem-Based Concepts. *Sustainability* 16, 1308. doi:10.3390/su16031308.
- Mao, B., Wang, X., Jia, S., Liu, Z., 2024. Multi-methods to investigate the baseflow: Insight from watershed scale spatiotemporal variety perspective. *Ecological Indicators* 158, 111573. doi:10.1016/j.ecolind.2024.111573.
- Marval, S., Fučík, P., Čerkasova, N., Strauch, M., Witing, F., Plunge, S., Farkas, C., Weiland, S., Krzeminska, D., Lemann, T., 2022. SWAT+ and SWAP retention measure implementation handbook. Technical Report. EU Horizon 2020 OPTAIN Project, Grant agreement No. 862756.
- Menzel, L., Lang, H., Rohmann, M., 1999. Mean Annual Actual Evaporation 1973-1992. Technical Report. Hydrological Atlas of Switzerland (HADES). URL: <https://hydrologicalatlas.ch/products/printed-issue/evaporation/plate-4-1>.
- MeteoSwiss, . Daily weather data 1988–2020 for Payerne (PAY). Technical Report. Federal Office of Meteorology and Climatology.
- Moges, D.M., Virro, H., Kmoch, A., Cibin, R., Rohith, A.N., Martínez-Salvador, A., Conesa-García, C., Uuemaa, E., 2023. How does the choice of DEMs affect catchment hydrological modeling? *Science of The Total Environment* 892, 164627. doi:10.1016/j.scitotenv.2023.164627.
- NABODAT, 2018. Swiss Soil Dataset - Documentation Version 3. URL: <https://ccsols.ch/de/datenmanagement/bereitstellung-bodeninformationen/bodendatensatz-schweiz/>.
- Nkiaka, E., Nawaz, N.R., Lovett, J.C., 2018. Effect of single and multi-site calibration techniques on hydrological model performance, parameter estimation and predictive uncertainty: a case study in the Logone catchment, Lake Chad basin. *Stochastic Environmental Research and Risk Assessment* 32, 1665–1682. doi:10.1007/s00477-017-1466-0.
- Nussbaum, M., Burgos, S., 2023. Soil property mapping «La Broye»: Spatial predictions of basic soil properties for soil and water assessment on watershed and sub-basin level. Technical Report. Bern University of Applied Sciences.

- Nussbaum, M., Spiess, K., Baltensweiler, A., Grob, U., Keller, A., Greiner, L., Schaepman, M.E., Papritz, A., 2018. Evaluation of digital soil mapping approaches with large sets of environmental covariates. *SOIL* 4, 1–22. doi:10.5194/soil-4-1-2018.
- Piniewski, M., Strauch, M., Svajunas, P., Schürz, C., Natalja, ., Chiaradia, E., Witing, F., 2024. OPTAIN D4.4 - Assessment of NSWRM effectiveness at the catchment scale. Technical Report. EU Horizon 2020 OPTAIN Project, Grant agreement No. 862756. URL: https://www.optain.eu/sites/default/files/delivrables/OPTAIN%20D4.4%20-%20Assessment%20of%20NSWRM%20effectiveness%20at%20the%20catchment%20scale_11-04.pdf.
- Plunge, S., 2023. SWATprepR - tools for SWAT+ input data preparation, visualization and model output assessment. URL: <https://biopsichas.github.io/SWATprepR/>, doi:10.5281/zenodo.7296034. r package.
- Plunge, S., Rets, E., 2024. Atmospheric deposition - SWATprepR. URL: <https://biopsichas.github.io/SWATprepR/articles/deposition.html>.
- Plunge, S., Schuerz, C., Strauch, M., Piniewski, M., 2024. SWATtunR: Soft & Hard Calibration, Validation Package for SWAT+ models. URL: <https://github.com/biopsichas/SWATtunR>. r package version 0.0.2.
- Poggio, L., de Sousa, L.M., Batjes, N.H., Heuvelink, G.B.M., Kempen, B., Ribeiro, E., Rossiter, D., 2021. SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *SOIL* 7, 217–240. doi:10.5194/soil-7-217-2021.
- Prăvălie, R., Borrelli, P., Panagos, P., Ballabio, C., Lugato, E., Chappell, A., Miguez-Macho, G., Maggi, F., Peng, J., Niculiță, M., Roșca, B., Patriche, C., Dumitrașcu, M., Bandoc, G., Nita, I.A., Birsan, M.V., 2024. A unifying modelling of multiple land degradation pathways in Europe. *Nature Communications* 15, 3862. doi:10.1038/s41467-024-48252-x.
- Quinn, T., Zhu, A.X., Burt, J.E., 2005. Effects of detailed soil spatial information on watershed modeling across different model scales. *International Journal of Applied Earth Observation and Geoinformation* 7, 324–338. doi:10.1016/j.jag.2005.06.009.
- Rahman, K., Etienne, C., Gago-Silva, A., Maringanti, C., Beniston, M., Lehmann, A., 2014. Streamflow response to regional climate model output in the mountainous watershed: a case study from the Swiss Alps. *Environmental Earth Sciences* 17, 4357–4369. doi:<https://doi.org/10.1007/s12665-014-3336-0>.
- Rahman, K., Gago-Silva, A., Tejada, E.M., Gobiet, A., Beniston, M., Lehmann, A., 2015. An independent and combined effect analysis of land use and climate change in the upper Rhone River watershed, Switzerland. *Applied Geography* 63, 264–272. doi:10.1016/j.apgeog.2015.06.021.
- Rahman, K., Maringanti, C., Beniston, M., Widmer, F., Abbaspour, K., Lehmann, A., 2013. Streamflow Modeling in a Highly Managed Mountainous Glacier Watershed Using SWAT: The Upper Rhone River Watershed Case in Switzerland. *Water Resources Management* 27, 323–339. doi:10.1007/s11269-012-0188-9.

- Romanowicz, A.A., Vanclooster, M., Rounsevell, M., La Junesse, I., 2005. Sensitivity of the SWAT model to the soil and land use data parametrisation: a case study in the Thyle catchment, Belgium. *Ecological Modelling* 187, 27–39. doi:10.1016/j.ecolmodel.2005.01.025.
- Schilling, O.S., Parajuli, A., Otis, C.T., Müller, T.U., Quijano, W.A., Tremblay, Y., Brennwald, M.S., Nadeau, D.F., Jutras, S., Kipfer, R., Therrien, R., 2021. Quantifying Groundwater Recharge Dynamics and Unsaturated Zone Processes in Snow-Dominated Catchments via On-Site Dissolved Gas Analysis. *Water Resources Research* 57, e2020WR028479. URL: <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2020WR028479>, doi:10.1029/2020WR028479.
- Schuerz, C., 2022. SWATfarmR: Simple rule based scheduling of management operations in SWAT. URL: <https://github.com/chrissschuerz/SWATfarmR>. r package.
- Schürz, C., 2022. SWATbuildR. R Script. For access please inquire at christoph.schuerz@ufz.de.
- Schürz, C., Plunge, S., 2022. SWATdoctr. URL: <https://git.ufz.de/schuerz/swatdoctr>. r package.
- Schürz, C., Čerkasova, N., Farkas, C., Nemes, A., Plunge, S., Strauch, M., Tóth, B., Piniewski, M., 2022. SWAT+ modeling protocol for the assessment of water and nutrient retention measures in small agricultural catchments. Technical Report. EU Horizon 2020 OPTAIN Project, Grant agreement No. 862756. URL: <https://zenodo.org/records/7463395>.
- Sciuto, G., Diekkrüger, B., 2010. Influence of Soil Heterogeneity and Spatial Discretization on Catchment Water Balance Modeling. *Vadose Zone Journal* 9, 955–969. doi:10.2136/vzj2009.0166.
- Shrestha, R., Tachikawa, Y., Takara, K., 2006. Input data resolution analysis for distributed hydrological modeling. *Journal of Hydrology* 319, 36–50. doi:10.1016/j.jhydrol.2005.04.025.
- Swisstopo, 2011a. swissALTI3D. URL: <https://www.swisstopo.admin.ch/de/geodata/height/alti3d.html>.
- Swisstopo, 2011b. swissTLM3D. URL: <https://www.swisstopo.admin.ch/en/geodata/landscape/tlm3d.html#links>.
- Tan, M.L., Ficklin, D.L., Dixon, B., Ibrahim, A.L., Yusop, Z., Chaplot, V., 2015. Impacts of DEM resolution, source, and resampling technique on SWAT-simulated streamflow. *Applied Geography* 63, 357–368. doi:10.1016/j.apgeog.2015.07.014.
- Tänikon, A.F., 2022. Ergebnisse der Zentralen Auswertung von Buchhaltungsdaten (Central farm accountancy database for Switzerland). Technical Report. Agroscope. Switzerland.
- UKIH, 1980. Low Flow Studies Reports. Technical Report. UK Institute of Hydrology (UKIH).
- USDA, 1995a. Soil Survey Geographic (SSURGO) Data Base: Data Use Information. Technical Report. United States Department of Agriculture. URL: <https://www.fsl.orst.edu/pnwer/wrb/metadata/oils/ssurgo.pdf>.

- USDA, 1995b. State Soil Geographic (STATSGO) Data Base: Data use information. Technical Report. United States Department of Agriculture. URL: http://dbwww.essc.psu.edu/dbtop/doc/statsgo/statsgo_db.pdf.
- Viviroli, D., Grutz, J., Zappa, M., 2007. The Hydrological Modelling System PREVAH: Part II - Physical Model Description. Geographica Bernensia, Bern, Switzerland. URL: https://dviviroli.github.io/documents/Viviroli_et_al_2007_GB_P40_II.pdf.
- Wagener, T., Sivapalan, M., Troch, P., Woods, R., 2007. Catchment Classification and Hydrologic Similarity. Geography Compass 1, 901–931. doi:10.1111/j.1749-8198.2007.00039.x.
- Yang, Y., Pan, M., Beck, H.E., Fisher, C.K., Beighley, R.E., Kao, S.C., Hong, Y., Wood, E.F., 2019. In Quest of Calibration Density and Consistency in Hydrologic Modeling: Distributed Parameter Calibration against Streamflow Characteristics. Water Resources Research 55, 7784–7803. doi:10.1029/2018WR024178.
- Zarrineh, N., Abbaspour, K., Van Griensven, A., Jeangros, B., Holzkämper, A., 2018. Model-Based Evaluation of Land Management Strategies with Regard to Multiple Ecosystem Services. Sustainability 10, 3844. doi:10.3390/su10113844.
- Zarrineh, N., Abbaspour, K.C., Holzkämper, A., 2020. Integrated assessment of climate change impacts on multiple ecosystem services in Western Switzerland. Science of The Total Environment 708, 135212. doi:10.1016/j.scitotenv.2019.135212.
- Zeraatpisheh, M., Ayoubi, S., Jafari, A., Finke, P., 2017. Comparing the efficiency of digital and conventional soil mapping to predict soil types in a semi-arid region in Iran. Geomorphology 285, 186–204. URL: <https://www.sciencedirect.com/science/article/pii/S0169555X16307863>, doi:10.1016/j.geomorph.2017.02.015.
- Zhang, G.L., Liu, F., Song, X.d., 2017. Recent progress and future prospect of digital soil mapping: A review. Journal of Integrative Agriculture 16, 2871–2885. doi:10.1016/S2095-3119(17)61762-3.
- Zhang, P., Liu, R., Bao, Y., Wang, J., Yu, W., Shen, Z., 2014. Uncertainty of SWAT model at different DEM resolutions in a large mountainous watershed. Water Research 53, 132–144. doi:10.1016/j.watres.2014.01.018.
- Zink, M., Kumar, R., Cuntz, M., Samaniego, L., 2017. A high-resolution dataset of water fluxes and states for Germany accounting for parametric uncertainty. Hydrology and Earth System Sciences 21, 1769–1790. URL: <https://hess.copernicus.org/articles/21/1769/2017/hess-21-1769-2017.html>, doi:10.5194/hess-21-1769-2017.

Table A1: Overview of data used in model setup and parameterization

Section of Use	Dataset	Details and Sources
Model setup	Basin boundary (vector)	Catchment area number 113587, created following the instructions attached to the dataset (FOEN, 2010)
	Digital Elevation Model (raster)	swissALTI3D (Swisstopo, 2011a), 2 m resolution, available as 1 km ² tiles; pre-processing: merging tiles covering the basin boundary using “Mosaic to Raster” tool in ArcMap
	Channel network (vector)	swissTLM3 hydrography/ watercourses (Swisstopo, 2011b)
	Land use map (vector)	Created by overlaying layers of swissTLM3 (Swisstopo, 2011b) and utilised agricultural area (geodienste.ch, 2022); crop rotation for 1990-2020 based information from farmers and guidelines for optimal crop rotation (Jeangros and Courvoisier, 2019); where available, tile drainage information for each field, derived from digitalized tile drainage maps
	Soil data (raster, database, lookup table)	Soil data consists of a raster map, a soil parameter database, and a lookup table linking raster and database. The soil data used are: a) Digital Soil Map of the World (FAO-UNESCO, 2003); b) Swiss Soil Suitability Map (FSO, 2000), prepared for SWAT and used by Zarrineh et al. (2018, 2020); c) a high-resolution soil property map created for this study by Nussbaum and Burgos (2023)
	Point sources (raster and text)	Coordinates and average water, sediment, and nutrient loads emitted by the wastewater treatment plants at a) Grandcour (monthly grab samples for 2015-2022) and b) Bussy (monthly grab samples for 2015), data received from the Cantons of Vaud and Fribourg, respectively, upon request
	meteo data (text)	Daily meteorological data 1990–2020 for Payerne (PAY) available at MeteoSwiss (MeteoSwiss): precipitation [<i>mm</i>] (daily total), temperature [°C] (daily max, min and mean, 2 m above ground), wind speed [m/s] (daily mean, 2 m above ground), solar radiation [MJ/m ²] (daily mean), relative humidity (daily mean, 2 m above ground, fraction)
Model parameterization	Crop management schedule	Crop factsheets by Liebegg (2022e,b,g,f,c,d,a, 2023, 2024)
	Crop yield	Yearly average yield (dry matter) per crop, provided by Tänikon (2022)
Model evaluation	Streamflow	Streamflow [m ³ /s] at gauging station Villars-le-Grand from 1993 to 2020, 1993-2010 used for calibration and 2011-2020 for evaluation provided by the Vaud cantonal authority (DGE-DIRNA-EAU)

A2. Crop Growth Parameter Estimation

The model setup verification performed with SWATdoctR confirms that the climate inputs are processed correctly and the plant growth falls within plausible ranges, aligning with the expert knowledge of the studied watershed. Only minor adjustments to the default plant parameters are required, i.e., changing the leaf area index decline rate (*dlai_rate*) for potatoes from 10 to 5 for a more gradual decrease in leaf area compared to the default setting. During crop calibration with SWATtunR, most changes are made to the plant parameter days to maturity (*days_mat*), while keeping it realistic for the crop management schedule. Only minor changes are made to *bm_e*, *harv_idx*, *tmp_base* and *lai_pot*. The final crop-parameter adjustments are summarized in Tab. A2. Crop-specific distributions of potential heat units at harvest, yield, and biomass after parameter estimation are shown in Figures S4-S6.

Table A2: Crop growth parameter: Final adjusted values of crop parameters. *Absolute change, **relative change

Crop	days_mat*	lai_pot**	harv_idx**	tmp_base*	bm_e**
canp (Canola)	+20	0	0	0	0
corn (Grain Corn)	+30	0	0.1	0	0
csil (Silage Corn)	-30	0	0	0	-0.5
peas (Peas)	-10	0.5	0	-5	0
pota (Potato)	0	0	0	0	0
ryeg (Rye Grass)	-50	0	0	0	0
sgbt (Sugar Beet)	+80	0	0	0	0.1
sunf (Sunflower)	+40	0	0	0	0.4
swht (Summer Wheat)	-20	0	0	0	0
tobc (Tobacco)	-80	0	0	0	-0.5
trit (Winter Triticale)	0	0	0.05	0	0
wbar (Winter Barley)	-10	0	0	0	0
wwht (Winter Wheat)	-40	0	0.25	0	0

A3. Global sensitivity analysis

Table A3: Robustness of parameter selection to the performance metric and analysis period. Check marks indicate parameters retained according to the following selection criterion: a parameter is retained when it is statistically significant ($p < 0.05$) in at least two soil scenarios for both performance metrics, or in all three scenarios for at least one metric. The primary Global sensitivity analysis (GSA) used to select parameters for streamflow calibration combines NSE and KGE over the entire 1993–2020 simulation period. The alternative combinations of NSE or NSE_{rel} with KGE and the calibration period (1993–2010) or entire simulation period assess the robustness of parameter selection. Both analysis periods follow a 1990–1992 model warm-up period. Parameter retained across all GSA variations are highlighted in bold.

Parameter	NSE and KGE		NSE _{rel} and KGE	
	Entire period	Calibration	Entire period	Calibration
ESCO	✓	✓	✓	✓
EPCO	–	–	–	–
AWC	✓	–	✓	–
CANMX	–	–	–	–
CN2	✓	✓	–	–
CN3_SWF	✓	✓	✓	✓
OVN	–	–	–	–
SURLAG	✓	✓	✓	✓
LAT_TIME	–	–	–	–
LAT_LEN	✓	✓	✓	✓
LATQ_CO	✓	✓	–	✓
BD	✓	✓	✓	✓
K	–	–	–	–
Z	✓	✓	✓	✓
TILE_DEP	–	–	–	–
TILE_LAG	–	–	–	–
TILE_DTIME	–	–	–	–
PERCO	✓	✓	✓	✓
FLO_MIN	✓	✓	✓	✓
REVAP_CO	–	–	–	–
REVAP_MIN	✓	✓	✓	✓
ALPHA	✓	✓	✓	✓
SP_YLD	–	–	–	–
BF_MAX	–	–	–	–
CHN	–	–	–	–

Table A4: Global sensitivity analysis of selected SWAT+ parameters for the World-Soil, Swiss-Soil, and Local-Soil scenarios, based on 1,000 Latin hypercube parameter sets per scenario. Model performance is evaluated using daily streamflow over the 1993-2020 simulation period, following a 1990-1992 warm-up period. Values are multiple-regression t -statistics for the Nash-Sutcliffe efficiency (NSE) and Kling-Gupta efficiency (KGE).

Parameter	Description	Change	Range	NSE					KGE				
				World-Soil					Swiss-Soil				
				Local-Soil					World-Soil				
ESCO [†]	Soil evaporation compensation factor	absval	0.01 - 0.95	-0.25	0.30	-3.75*	-18.12*	-16.26*	-17.29*				
EPCO	Plant uptake compensation factor	absval	0.05 - 1	1.58	1.23	1.57	2.28*	1.64	0.74				
AWC [†]	Available water capacity of the soil layer	reltgh	-0.25 - 0.25	-1.00	-0.19	0.02	-2.39*	-2.53*	-2.22*				
CANMX	Maximum canopy storage	reltgh	-0.5 - 0.5	-1.17	-1.03	-1.66	-1.43	-1.36	-1.86				
CN2 [†]	Initial SCS runoff curve number for moisture condition II	reltgh	-0.15 - 0.15	-6.50*	1.04	4.68*	2.12*	1.93	4.88*				
CN3_SWF [†]	Soil water adjustment factor for CN3	absval	0 - 1	2.49*	-1.70	-6.55*	4.88*	-6.20*	-11.45*				
OVN	Overland flow Manning's N	reltgh	-0.25 - 0.25	1.29	0.60	1.32	1.30	0.66	0.27				
SURLAG [†]	Surface runoff lag coefficient	absval	0.05 - 4	-9.49*	-2.71*	12.13*	12.17*	11.66*	19.95*				
LAT_TIME	Lateral flow travel time	reltgh	-0.15 - 0.15	-0.16	-0.42	0.69	-0.15	-0.14	0.66				
LAT_LEN [†]	Average slope length for lateral subsurface flow	abschg	-30 - 30	-3.01*	-2.88*	-3.74*	-1.48	-1.68	-2.98*				
LATQ_CO [†]	Lateral flow coefficient	absval	0 - 1	-2.88*	2.61*	3.19*	0.30	-0.34	1.57				
BD [†]	Moist bulk density of the soil layer	reltgh	-0.25 - 0.25	2.61*	-4.96*	15.53*	13.75*	14.04*	36.51*				
K	Saturated hydraulic conductivity of the soil layer	reltgh	-0.5 - 2	0.06	1.41	1.73	1.54	1.43	4.58*				
Z [†]	Depth from soil surface to bottom of the soil layer	reltgh	-0.15 - 0.15	-0.82	1.88	-1.32	-5.61*	-4.44*	-6.49*				
TILE_DEP	Depth of drain tube from the soil surface	reltgh	-0.1 - 0.2	0.10	0.51	0.31	0.34	1.02	1.53				
TILE_LAG	Drain tile lag time	absval	48 - 100	-0.78	-0.50	-0.34	-0.20	-0.03	-1.56				
TILE_DTIME	Time to drain soil to field capacity	absval	48 - 100	0.14	0.13	-1.28	0.14	-0.10	-0.54				
PERCO [†]	Percolation coefficient	absval	0 - 1	1.74	-3.98*	-7.25*	8.56*	5.17*	5.73*				
FLO_MIN [†]	Threshold depth from surface to water table for groundwater flow to occur	abschg	-2 - 2	1.27	1.55	2.74*	4.63*	3.97*	5.83*				
REVAP_CO	Groundwater revaporation coefficient	absval	0.02 - 0.2	-0.84	-1.75	-0.74	-1.46	-2.25*	-1.04				
REVAP_MIN [†]	Threshold depth of water in the shallow aquifer for revaporation to occur	abschg	-2 - 2	-2.31*	-2.94*	-4.61*	-5.37*	-5.19*	-6.22*				
ALPHA [†]	Alpha factor for groundwater recession curve	absval	0.001 - 0.5	1.33	1.15	2.00*	3.18*	4.16*	4.51*				
SP_YLD	Specific yield of the shallow aquifer	absval	0.001 - 0.05	0.21	-0.24	-0.61	0.35	0.01	0.12				
BF_MAX	Max daily baseflow where all channels are contributing	absval	0.5 - 2	-1.80	-1.13	0.52	0.26	-0.13	1.86				
CHN	Manning's n value for the main channel	absval	0.02 - 0.1	-1.54	-2.10*	-1.54	-1.08	-1.40	0.03				

*: Statistically significant at $p < 0.05$.

[†]Parameter retained for calibration. Parameters are retained when they are statistically significant in at least two soil scenarios for both performance metrics or in all three scenarios for at least one performance metric.

A4. Streamflow-calibration parameters

Table A5: Calibration ranges and parameter values of the best 1% parameter sets (n=20) from the calibration period for the three soil scenarios. Values are medians with minimum–maximum ranges in parentheses. Parameter bounds are expressed as relative change (relchg), absolute change (abschg), or absolute value (absval).

Parameter	Change	Calibration range	World-Soil	Swiss-Soil	Local-Soil
ESCO	absval	0.01–0.95	0.1 (0.02–0.32)	0.13 (0.03–0.27)	0.13 (0.01–0.66)
CN3_SWF	absval	0–1	0.82 (0.32–1)	0.73 (0.32–1)	0.42 (0.04–0.91)
SURLAG	absval	0.05–4	2.15 (0.93–3.89)	2.32 (1.26–3.99)	2.36 (1.19–3.67)
LAT_LEN	abschg	-30–30	1.19 (-19.29–27.1)	8.24 (-12.31–28.57)	7.28 (-19.29–27.51)
LATQ_CO	absval	0–1	0.42 (0.01–0.8)	0.46 (0.01–0.79)	0.22 (0.04–0.61)
BD	relchg	-0.25–0.25	0.06 (-0.13–0.14)	-0.09 (-0.17–0.13)	0.02 (-0.05–0.21)
Z	relchg	-0.15–0.15	0.03 (-0.14–0.14)	0.02 (-0.12–0.12)	0.04 (-0.14–0.15)
PERCO	absval	0–1	0.61 (0.31–0.88)	0.44 (0.14–0.88)	0.61 (0.08–0.89)
FLO_MIN	abschg	-2–2	0.33 (-2–1.76)	0.11 (-1.18–1.48)	0.24 (-1.75–1.92)
REVAP_MIN	abschg	-2–2	0.86 (-1.74–1.87)	-0.53 (-1.97–2)	0.11 (-1.92–1.35)
ALPHA	absval	0–0.5	0.21 (0.02–0.49)	0.18 (0.02–0.47)	0.32 (0.03–0.46)

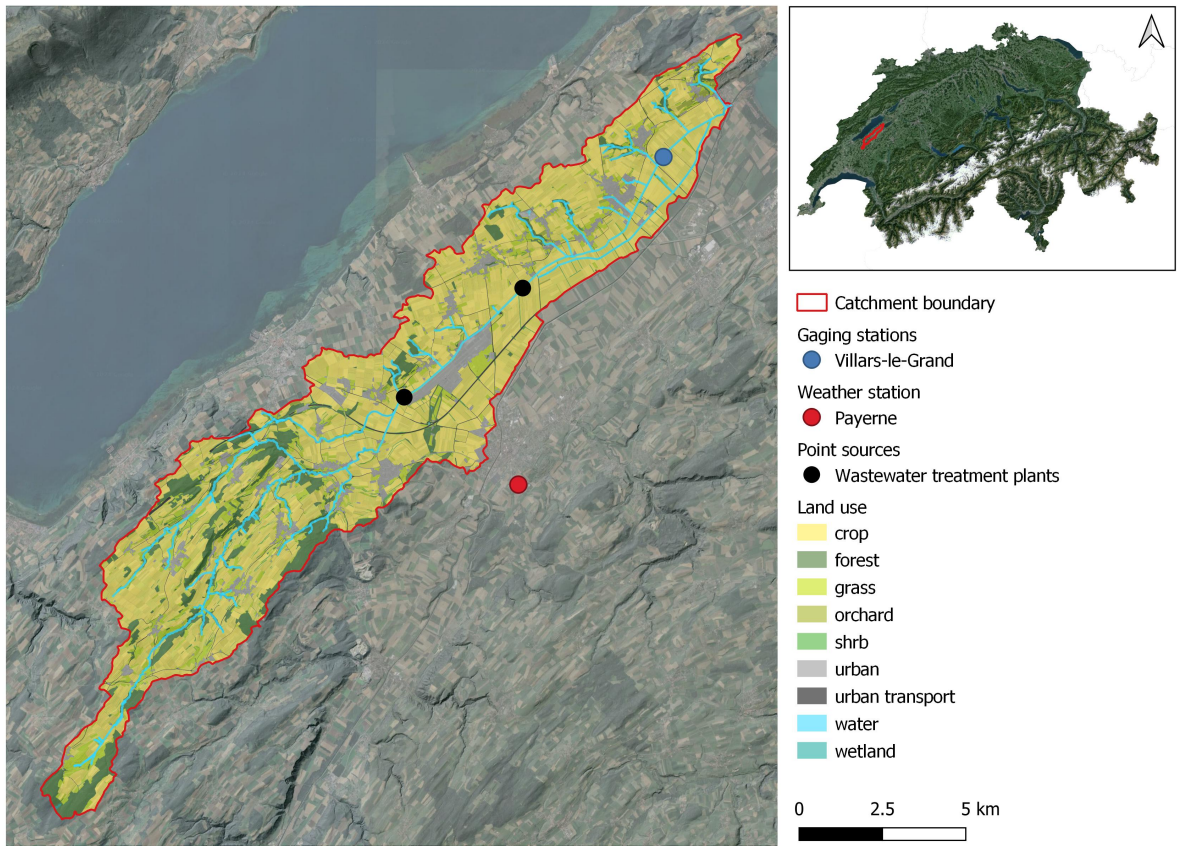


Figure S1: Location of the Petite Glâne catchment in the western Swiss Plateau.

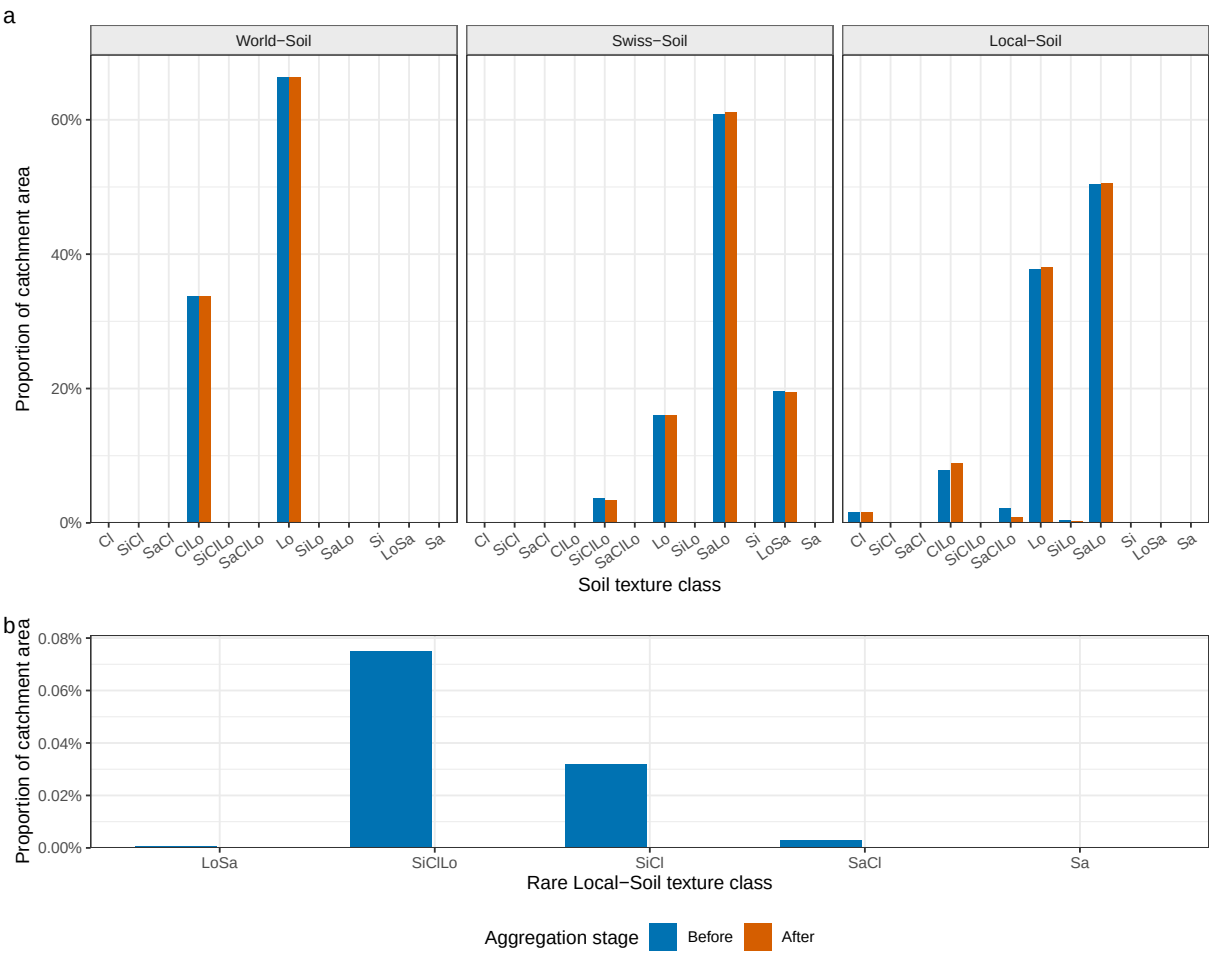


Figure S2: Soil-texture composition before and after dominant soil aggregation. (a) Proportions of catchment area represented by each soil-texture class in the World-Soil, Swiss-Soil, and Local-Soil datasets. (b) Enlarged view of five rare Local-Soil texture classes present before aggregation but absent afterward. Note the different y-axis scales. The absence of orange bars in panel (b) indicates an after-aggregation proportion of zero. Cl = clay, SiCl = silty clay, SaCl = sandy clay, ClLo = clay loam, SiClLo = silty clay loam, SaClLo = sandy clay loam, Lo = loam, SiLo = silty loam, SaLo = sandy loam, LoSa = loamy sand, Sa = sand

S3. Crop yields after crop growth parameter estimation

Distributions of simulated potential heat units (PHU) at harvest, crop yield, and biomass after crop-growth parameter estimation for the World-, Swiss- and Local-Soil scenarios. Boxplots summarize the simulated values for each crop; horizontal reference markers indicate the corresponding crop-specific target or reference values. Crop abbreviations are defined in Tab. A2.

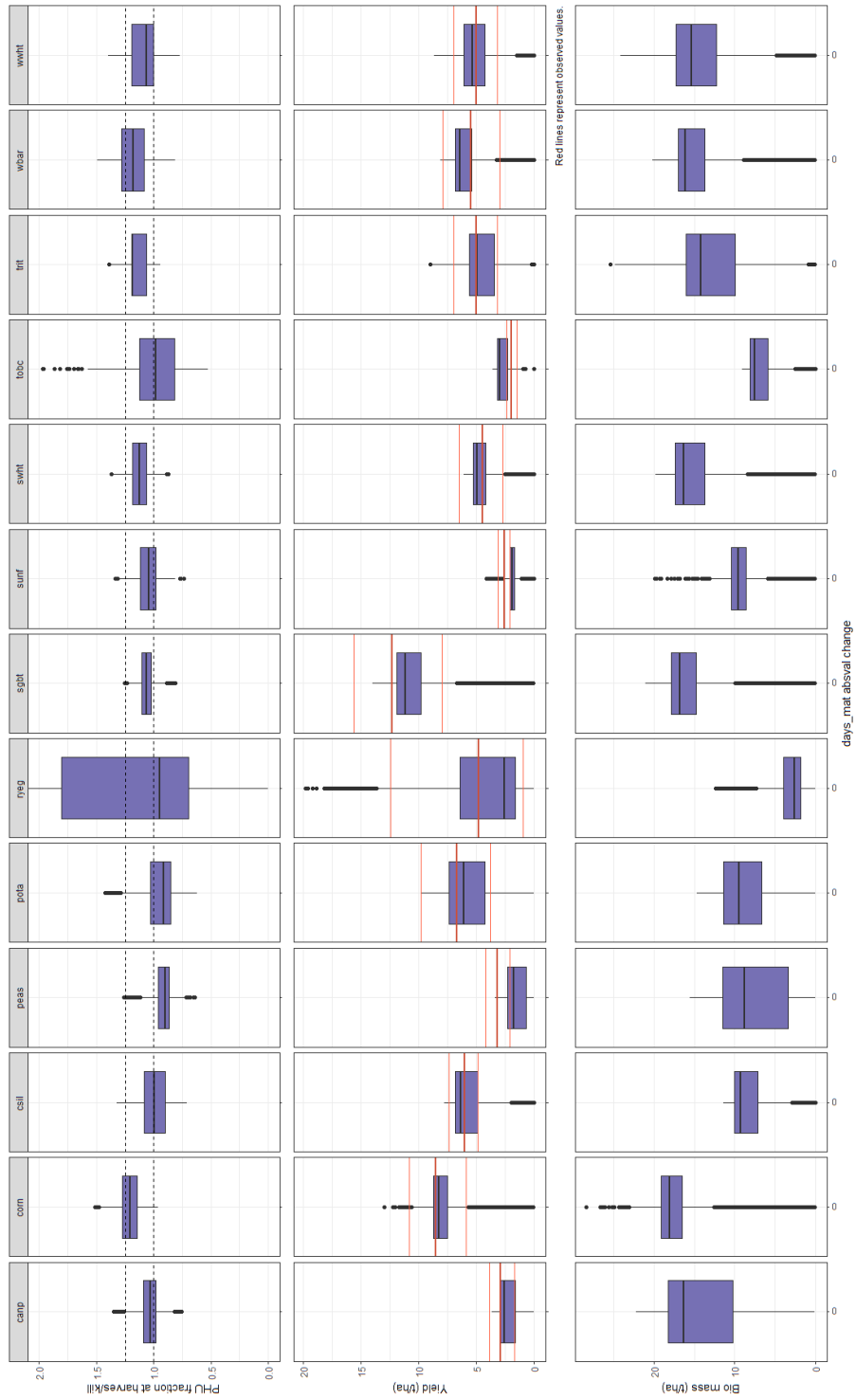


Figure S3: Distributions of simulated potential heat units (PHU) at harvest, crop yield, and biomass after crop-growth parameter estimation for the World-Soil scenario.

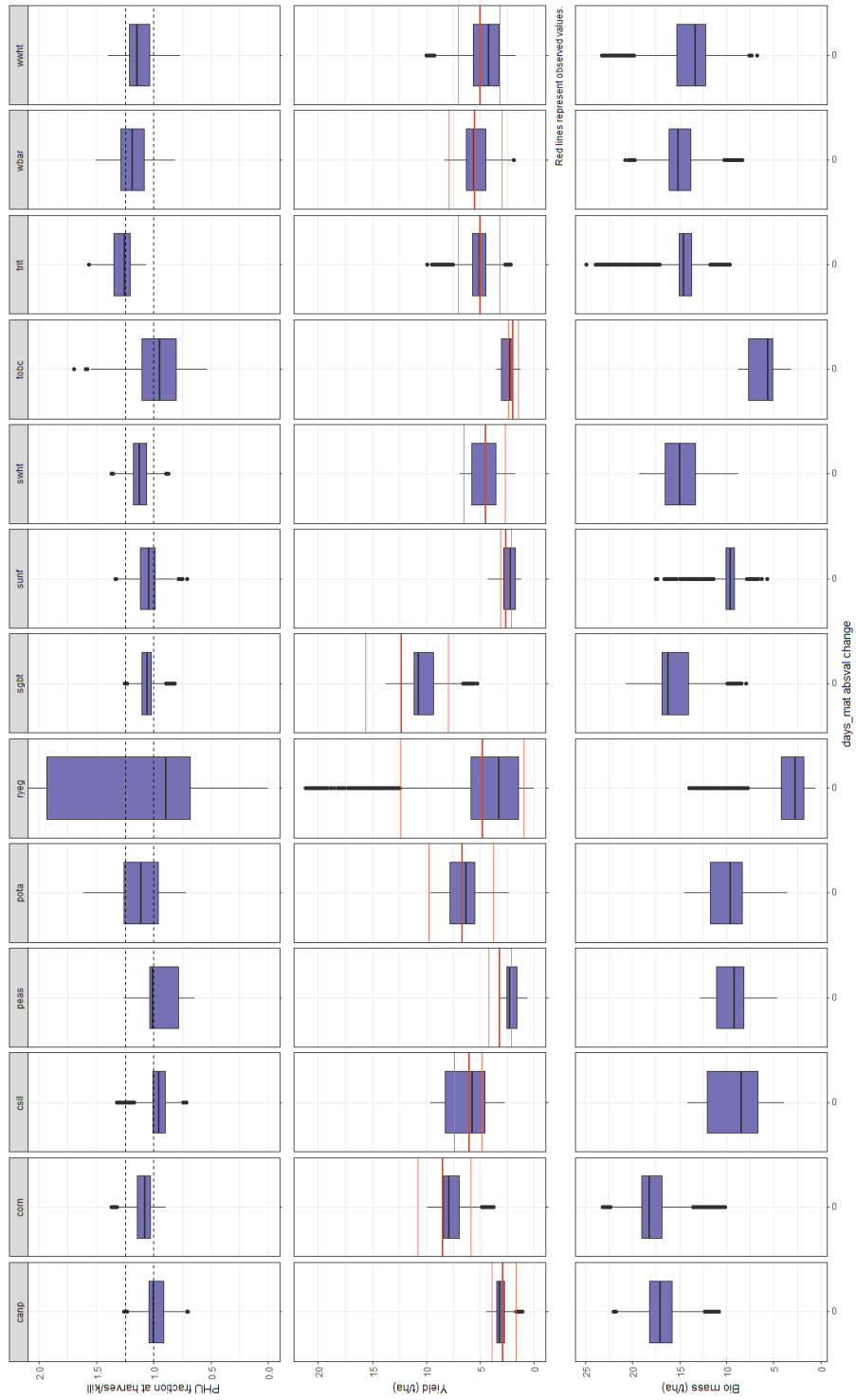


Figure S4: Distributions of simulated potential heat units (PHU) at harvest, crop yield, and biomass after crop-growth parameter estimation for the Swiss-Soil scenario.

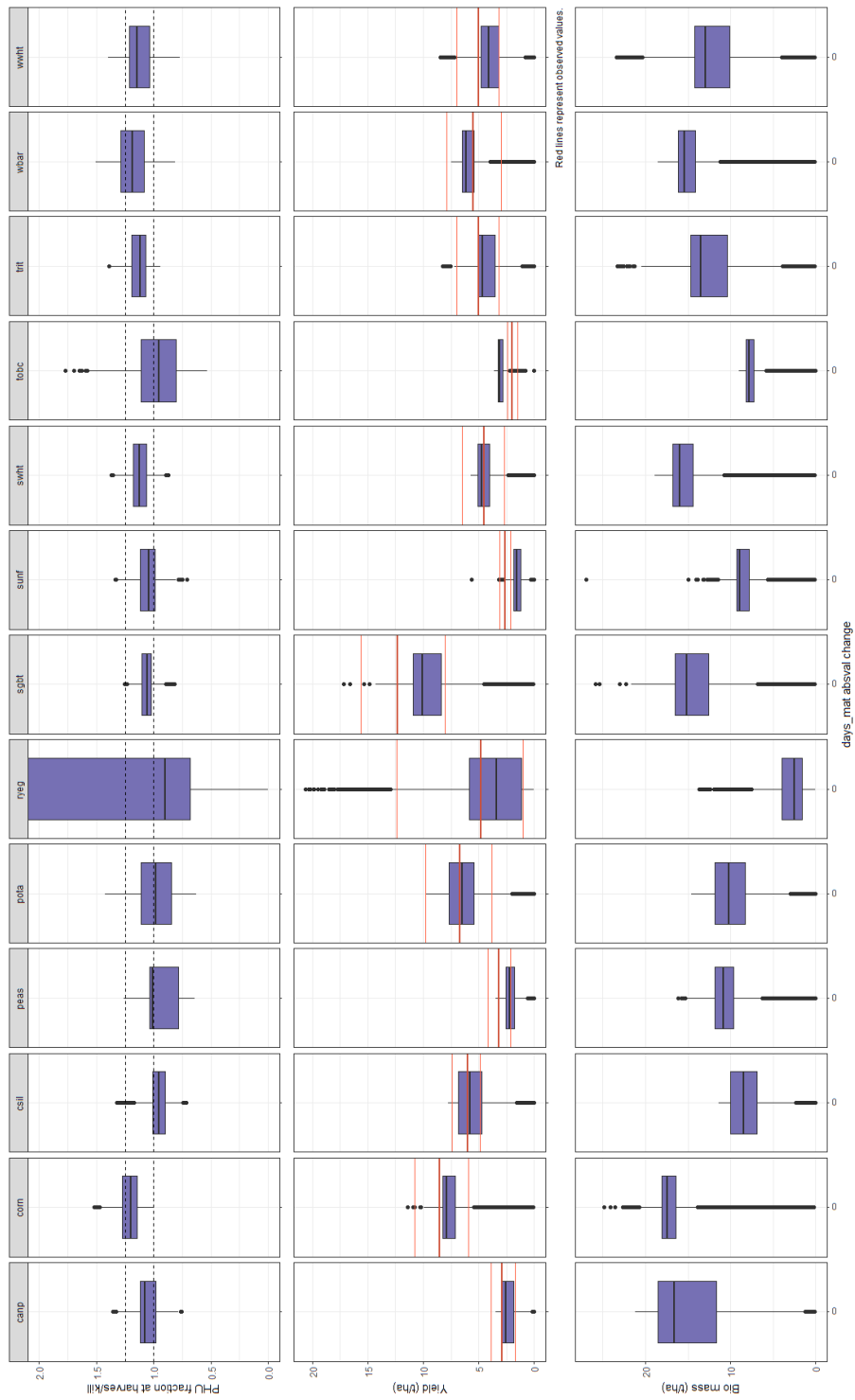


Figure S5: Distributions of simulated potential heat units (PHU) at harvest, crop yield, and biomass after crop-growth parameter estimation for the Local-Soil scenario.

S4. Predictive uncertainty

Table S1: Daily P- and R-factors for (A) the best 1% parameter sets and (B) all 2,000 simulations, calculated from the 95% prediction uncertainty (95PPU) bands. The best 1% parameter sets ($n=20$) are selected using the combined ranking of daily calibration-period NSE_{rel} and KGE. The same parameter-set IDs are retained for the evaluation and entire simulation periods. The P-factor is the proportion of observed daily streamflow values enclosed by the 95PPU band. The R-factor is the mean daily 95PPU width divided by the standard deviation of observed daily streamflow.

Period	Scenario	P-factor	R-factor
A. Best 1% ($n = 20$)			
Calibration	World-Soil	0.437	0.389
	Swiss-Soil	0.430	0.331
	Local-Soil	0.356	0.312
Evaluation	World-Soil	0.497	0.473
	Swiss-Soil	0.489	0.404
	Local-Soil	0.414	0.384
Entire simulation	World-Soil	0.458	0.406
	Swiss-Soil	0.451	0.346
	Local-Soil	0.377	0.327
B. All simulations ($n = 2,000$)			
Calibration	World-Soil	0.752	0.868
	Swiss-Soil	0.730	0.828
	Local-Soil	0.686	0.676
Evaluation	World-Soil	0.743	1.063
	Swiss-Soil	0.732	1.018
	Local-Soil	0.697	0.828
Entire simulation	World-Soil	0.749	0.909
	Swiss-Soil	0.731	0.868
	Local-Soil	0.690	0.708

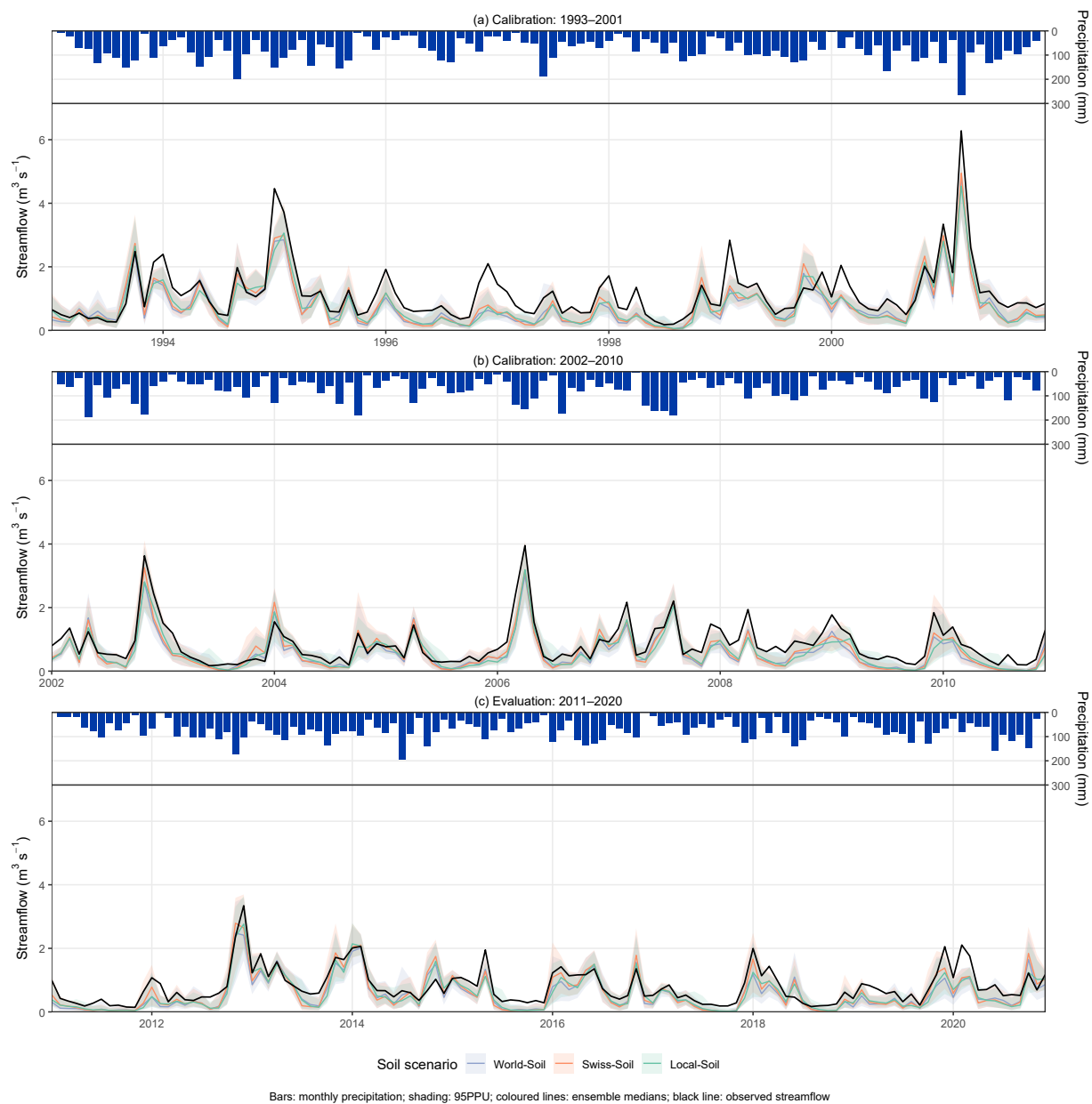


Figure S6: Monthly observed and simulated streamflow during the calibration (a and b) and evaluation (c) periods for the World-Soil, Swiss-Soil, and Local-Soil scenarios. Coloured lines represent the median streamflow of all 2000 simulations; shaded areas indicate the corresponding 95% prediction uncertainty (95PPU), and the black line shows observed streamflow. Daily simulated and observed streamflow values were aggregated to monthly means before calculating the ensemble median and 95PPU. The bars from above show monthly precipitation from the nearby weather station in Payerne (see Figure S1).

1115 **S5. Water balance components**

Table S2: Initial and calibrated average annual water balance components for the three soil scenarios. Calibrated values are medians of the best 1% calibration-selected parameter sets, with minimum–maximum ranges in parentheses. Values summarize the 1993–2020 simulation period following a 1990–1992 warm-up period. Mean annual precipitation and potential evapotranspiration over this period are 849 and 731 mm yr⁻¹, respectively. Surface runoff is `surq_cha` + `surq_res` and lateral flow is `latq_cha` + `latq_res` from `basin_wb_aa.txt` and baseflow is `flo` from `basin_aqu_aa.txt`

Component	Unit	World-Soil		Swiss-Soil		Local-Soil	
		Initial	Median (min–max)	Initial	Median (min–max)	Initial	Median (min–max)
Actual evapotranspiration	mm yr ⁻¹	468.7	478.6 (451.1–508.1)	510.0	464.9 (442.5–487.9)	557.2	543.1 (506.1–576.5)
Soil evaporation	mm yr ⁻¹	219.4	229.5 (201.9–260.2)	289.5	219.5 (198.4–239.9)	278.2	258.0 (216.1–299.1)
Surface runoff	mm yr ⁻¹	145.0	103.0 (73.1–125.1)	39.0	73.8 (39.8–94.4)	39.0	62.6 (43.4–87.4)
Lateral flow	mm yr ⁻¹	15.9	7.8 (0.1–22.3)	48.0	87.2 (1.9–149.1)	31.0	34.6 (6.3–63.6)
Baseflow	mm yr ⁻¹	19.2	84.5 (41.4–146.6)	211.7	148.1 (45.9–253.4)	101.4	55.1 (20.7–101.3)
Percolation	mm yr ⁻¹	20.2	90.8 (43.6–154.2)	227.1	155.9 (48.3–266.8)	108.2	58.4 (21.8–106.6)
Average soil-water storage	mm	177.9	182.0 (147.4–253.0)	184.5	239.1 (176.4–304.6)	145.8	164.7 (137.0–219.7)

1116 **S6. Streamflow-regime and seasonal behaviour**

Table S3: Observed and simulated annual and July–August mean streamflow distributions during calibration and evaluation. Values are medians with 2.5th–97.5th percentile intervals in parentheses. Streamflow is expressed in m³ s⁻¹. For simulated scenarios, the distributions combine interannual variability and variability among the best 1% calibration-selected parameter sets; observed distributions represent interannual variability only.

Aggregation	Scenario	Calibration		Evaluation	
		<i>n</i>	Median (2.5–97.5%)	<i>n</i>	Median (2.5–97.5%)
Annual	Observed	18	0.95 (0.51–1.68)	10	0.82 (0.38–1.11)
Annual	World-Soil	360	0.81 (0.39–1.34)	200	0.67 (0.15–1.04)
Annual	Swiss-Soil	360	0.83 (0.40–1.36)	200	0.72 (0.19–1.08)
Annual	Local-Soil	360	0.78 (0.38–1.31)	200	0.65 (0.13–1.05)
July–August	Observed	18	0.51 (0.20–1.41)	10	0.45 (0.22–0.63)
July–August	World-Soil	360	0.33 (0.05–2.00)	200	0.27 (0.05–0.68)
July–August	Swiss-Soil	360	0.38 (0.07–2.01)	200	0.33 (0.07–0.77)
July–August	Local-Soil	360	0.31 (0.06–1.87)	200	0.27 (0.07–0.67)

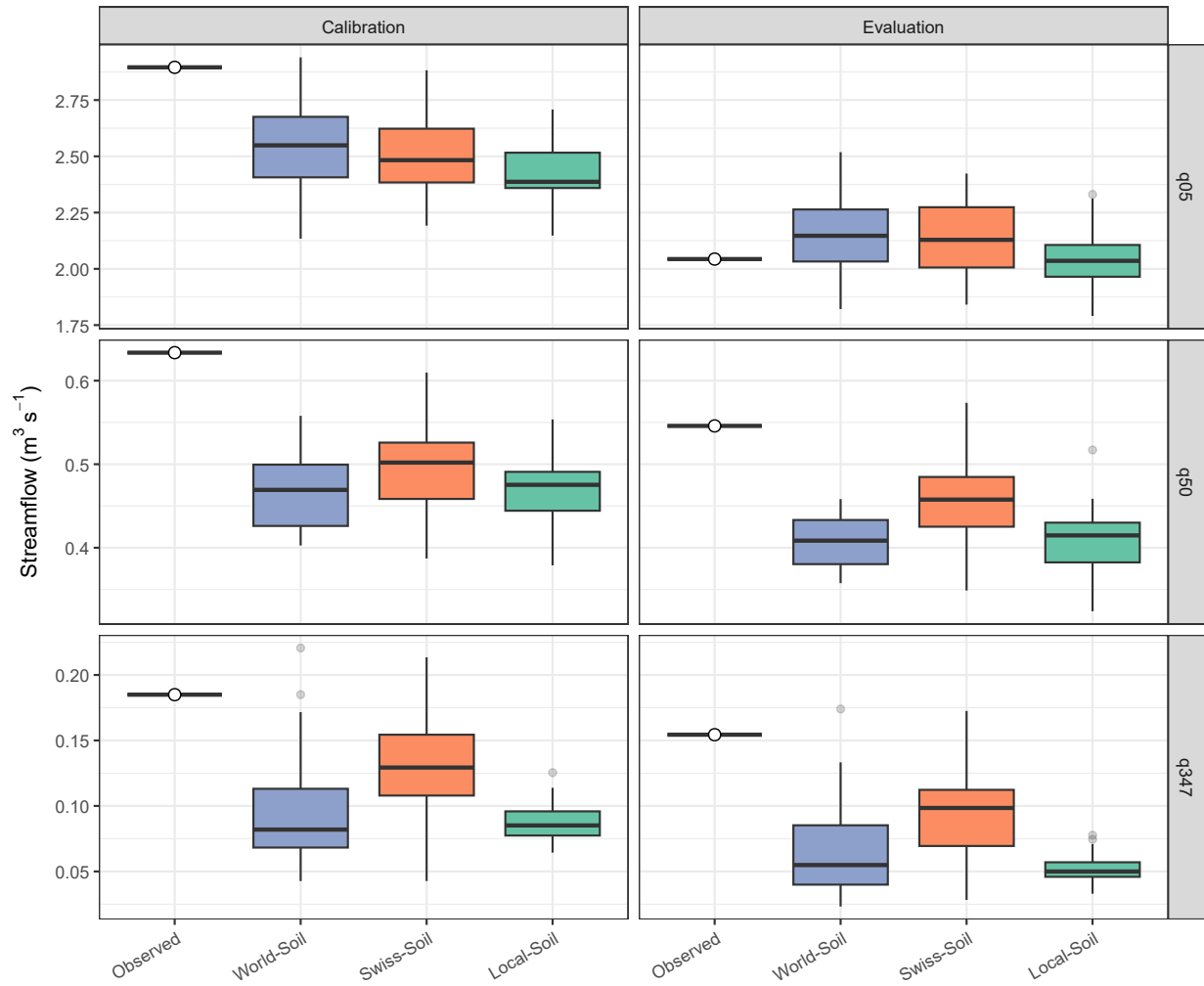


Figure S7: Observed and simulated flow-duration indicators during the calibration and evaluation periods. Boxplots show Q05, Q50, and Q347 across the best 1% calibration-selected parameter sets. Open circles represent the corresponding observed values. Q05 and Q50 denote streamflow exceeded 5% and 50% of the time, respectively, while Q347 denotes streamflow exceeded on 347 days per year.

Table S4: Observed and simulated streamflow-duration indicators during calibration and evaluation period. Simulated values are medians with 2.5th–97.5th percentile ranges of the best 1% calibration-selected parameter sets. Streamflow is expressed in m3 s⁻¹. Observed entries are single values. Q05 and Q50 denote streamflow exceeded 5% and 50% of the time; Q347 denotes streamflow exceeded on 347 days per year.

Indicator	Scenario	Streamflow during calibration period	Streamflow during evaluation period
Q_{05}	Observed	2.895	2.043
Q_{05}	World-Soil	2.549 (2.196–2.921)	2.147 (1.879–2.491)
Q_{05}	Swiss-Soil	2.483 (2.237–2.829)	2.129 (1.885–2.394)
Q_{05}	Local-Soil	2.387 (2.180–2.695)	2.035 (1.838–2.322)
Q_{50}	Observed	0.634	0.546
Q_{50}	World-Soil	0.469 (0.407–0.558)	0.408 (0.362–0.453)
Q_{50}	Swiss-Soil	0.502 (0.403–0.608)	0.458 (0.356–0.554)
Q_{50}	Local-Soil	0.475 (0.395–0.541)	0.415 (0.338–0.489)
Q_{347}	Observed	0.185	0.154
Q_{347}	World-Soil	0.082 (0.046–0.204)	0.055 (0.027–0.155)
Q_{347}	Swiss-Soil	0.129 (0.051–0.190)	0.098 (0.032–0.152)
Q_{347}	Local-Soil	0.085 (0.065–0.120)	0.050 (0.036–0.076)

Table S5: Annual, July–August, and April–September evapotranspiration distributions for the three soil scenarios during calibration and evaluation. Values are medians with 2.5th–97.5th percentile intervals in parentheses. Evapotranspiration totals are expressed in mm. The distributions combine interannual variability and variability among the best 1% calibration-selected parameter sets.

Aggregation	Scenario	Calibration		Evaluation	
		n	Median (2.5–97.5%)	n	Median (2.5–97.5%)
Annual	World-Soil	360	478.5 (425.2–548.9)	200	481.2 (444.6–585.3)
Annual	Swiss-Soil	360	471.7 (379.9–550.6)	200	485.5 (179.0–608.0)
Annual	Local-Soil	360	537.1 (469.4–615.5)	200	550.3 (500.1–649.3)
July–August	World-Soil	360	133.2 (93.9–160.0)	200	138.2 (106.1–169.4)
July–August	Swiss-Soil	360	116.8 (68.2–205.0)	200	131.9 (56.2–228.8)
July–August	Local-Soil	360	156.5 (104.0–184.8)	200	166.0 (117.0–196.9)
April–September	World-Soil	360	378.3 (337.6–428.1)	200	391.1 (359.3–450.7)
April–September	Swiss-Soil	360	375.3 (292.0–452.7)	200	406.3 (135.4–493.7)
April–September	Local-Soil	360	424.6 (374.5–491.5)	200	448.3 (400.3–501.1)