Effects of spatial soil moisture variability in forests plots on model parametrization and simulated groundwater recharge estimates

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Abstract.

Soil-Vegetation-Atmosphere Transfer (SVAT) models are essential tools for simulating and underploting the dynamic interactions governing water balance components within forest ecosystems. These models are widely employed to predict hydrological responses to environmental change, including the impacts of shifting meteorological conditions on forested landscapes. Despite their usefulness, the reliability of SVAT models is frequently compromised by uncertainties arising from incomplete or imprecise input data. These limitations often result in model assumptions that may lead to over- or underestimation of critical water balance components such as groundwater recharge. In order to improve the accuracy of SVAT models, observed soil moisture data are integrated to enhance parameterization processes by aligning simulated outputs with measured values. However, uncertainties remain regarding the selection of representative soil moisture profiles for calibration and the extent of measurements necessary to robustly characterize a forest plot. To address these challenges, the present study explores the spatial variability of soil moisture across two forested plots with contrasting soil and vegetation conditions by the deployment of an extensive network of soil moisture probes in 11 profiles per plot. The influence of soil moisture variability on the adjustment of model input parameters during the calibration process and its subsequent impact on the computation of groundwater recharge is evaluated. The findings reveal that soil moisture variability at the plot characterized by a heterogeneous soil was greater, both horizontally and in depth, throughout the study period. These patterns of variability are also mirrored in the different parameter sets obtained from the calibration of the LWF Brook90 model, based on the recorded soil moisture time series in each of the 11 profiles per plot. The most significant variation is observed in the infiltration and hydraulic soil parameters, whereby this is more pronounced at the plot with heterogeneous soil structure. Nevertheless, when examining the groundwater recharge rates calculated using the 30 best-performing parameter sets for each of the 11 profiles, both plots exhibited comparable temporal patterns and in particular similar variations in total volumes of groundwater recharge. These results suggest that model-inherent uncertainties, including parameter interactions, equifinality and dimensional simplifications, have a stronger impact on model outputs than uncertainties arising from variability in soil moisture caused by spatial heterogeneity of soil texture and hydraulic properties within the plot. Taking into account both sources of uncertainty,

the application of ~~bootstrapping techniques~~Monte Carlo based subsampling demonstrated that groundwater recharge could be reliably estimated using data from only ~~6~~2 to ~~7~~3 soil profiles at the investigated 20 × 20 m plot~~per plot~~, providing a representative picture of its spatial variability. ~~In general, the results indicate that using data from only a few soil profiles is not sufficient to capture the full range of groundwater recharge dynamics.~~ These numbers are indicative rather than universal thresholds, as the required sampling density is strongly site-specific and depends on local soil structure and model related uncertainties.

Keywords: Soil moisture variability, Soil-Vegetation-Atmosphere Transfer model, groundwater recharge

1 Introduction

Forests are vital contributors to the hydrological cycle, playing a pivotal role in aquifer recharge while safeguarding the quality and availability of freshwater resources (Chang, 2012). Acting as natural filtration systems, they regulate the movement of water from the topsoil into groundwater reservoirs. The vegetation in forests, especially trees, intercepts rainfall, consuming water by root water uptake as well as transpiration and allowing it to infiltrate slowly into the soil (Hewlett, 2003). Protecting and managing these forested areas is essential for maintaining sustainable groundwater replenishment in both quantity and quality. Furthermore, the availability of water is a critical determinant for the ecological functionality and long-term viability of forest ecosystems. Forests exhibit a pronounced sensitivity to variability in water supply, with significant implications for their growth dynamics, resilience to environmental stressors, and overall productivity (Williams et al., 2013). One of the greatest challenges facing forest ecosystems is the alteration of meteorological conditions due to climate change. Shifts in precipitation patterns, including reduced rainfall during the growing season and an increase in extreme weather events such as droughts and heavy precipitation fundamentally alter soil water dynamics.~~leading to excessive surface runoff, represent critical challenges.~~ ~~These changes constrain water availability for trees and inhibit water fluxes from the unsaturated soil zone to underlying groundwater reserves~~ While drought periods directly limit plant water availability, intense precipitation events may enhance rapid surface runoff or preferential flow, thereby modifying the partitioning between evapotranspiration, runoff and groundwater recharge (Meusburger et al., 2022). Hereby, groundwater recharge represents a key interface between terrestrial ecosystems and long-term water resources, as it determines the replenishment of aquifers that sustain baseflow in streams, buffer drought impacts, and provide drinking water supplies. In forested catchments, recharge processes are strongly controlled by vegetation structure, root distribution, and soil hydraulic properties, making them highly sensitive to climate-induced changes in water balance. In case of alterations in groundwater recharge ~~Consequently,~~ significant effects on forest structure and species distribution arise, including stress reactions such as widespread tree mortality, reduced canopy cover and increased susceptibility to pests and diseases (Gebeyehu and Hirpo, 2019; Klesse et al., 2023; Senf et al., 2020). Given these challenges, quantifying the magnitude and variability of soil water fluxes contributing to groundwater recharge is thus essential for understanding forest hydrology under changing climatic conditions and for evaluating the sustainability of water resources in forested landscapes. ~~it is essential to underplot and quantify the processes governing forest water balance and to estimate~~

~~accurately the volume of water percolating into the ground eventually reaching the groundwater table to become recharge. Hereby, soil water fluxes leading to groundwater recharge are of particular interest due to their critical role in the hydrological cycle and their influence on subsurface dynamics and long-term water resource sustainability in forested areas.~~

However, precise estimation of groundwater recharge remains inherently complex as it demands detailed insights into the multifaceted interactions among soil properties, vegetation characteristics, and atmospheric dynamics within forest ecosystems (Schmidt-Walter et al., 2020). In general, key components influencing groundwater recharge in forested landscapes include precipitation, interception, evaporation, surface runoff, transpiration, percolation, and soil storage capacity. The interplay of these components is regulated by an various site-specific factors, such as climatic conditions (e.g., temperature and precipitation patterns), forest characteristics (e.g., species composition, structural age, plot density, canopy architecture, root system development, and overall tree health), understory vegetation, and soil attributes (e.g., texture, type, and permeability) (Chang, 2006). To address these complexities, environmental monitoring in forest ecosystems seeks to quantify water fluxes with precision as a basis for determining water availability for transpiration across different tree species and its contribution to groundwater recharge.

Using Soil-Vegetation-Atmosphere Transfer (SVAT) models has been established as indispensable tools for simulating hydrological processes within forest ecosystems as they can effectively capture the temporal dynamics of soil moisture and estimate water fluxes in forest environments (Speich et al. 2020; van der Salm et al. 2007). However, their predictive accuracy is often constrained by limitations in the quality and availability of input data as well as by the challenges of defining appropriate initial and boundary conditions. A large number of parameters related to canopy structure, vegetation characteristics, root distribution patterns, and soil hydraulic properties must be defined for effective model implementation (Meusburger et al., 2022). Yet, many of these parameters cannot be directly derived from field observations, resulting in significant uncertainties in parameter estimation (Franks et al., 1997). Such uncertainties frequently can lead to over- or underestimations of critical hydrological components, including water available for transpiration and percolation to the groundwater, thereby reducing the SVAT model's predictive capability (Kirchner, 2006; Kuppel et al., 2018). To address this issue, various strategies have been developed to reduce parameter uncertainty and improve model robustness. These include sensitivity analyses, ensemble simulations, Bayesian calibration frameworks and the use of expert knowledge or literature-based parameter ranges. In this study, automatic calibration techniques leveraging observed site-specific soil moisture measurements, are employed, which represent one effective approach among many (~~(~~Beven, 2006a; Saltelli et al., 2007; Vrugt et al., 2008~~)~~)). ~~Incorporating these site-specific observations enables refinement of input parameters, effectively reducing mismatches and potentially enhancing the reliability of water balance predictions.~~ Incorporating site-specific observations can support the refinement of input parameters, which may reduce mismatches between simulated and observed values and improve the representation of water balance components. However, the reliability of such improvements depends on the calibration strategy and the inclusion of independent validation data to avoid overfitting. When carefully implemented, improved parameterization can contribute to a more robust understanding of hydrological dynamics and water fluxes within forested landscapes. ~~This improved parameterization facilitates a more accurate representation of hydrological dynamics, contributing to a better understanding of water fluxes and their interrelations within forested landscapes.~~

However, soil moisture exhibits high spatial and temporal variability even within forest plots, driven by factors such as heterogeneities in soil texture, hydraulic properties, topographic gradients, and dynamic interactions with surface water systems, precipitation, and vegetation distribution (Vereecken et al., 2016; Western et al., 2004). Numerous studies have investigated spatial soil moisture variability (Choi et al. 2007; Fatichi et al. 2015; Mohanty et al. 2000; Ojha et al. 2014; Teuling and Troch 2005; Vereecken et al. 2008; Western et al. 1999), consistently demonstrating that that variability tends to increase across larger spatial scales (Famiglietti et al. 2008; Western et al. 1999). This variability poses a challenge for model calibration, as a parameter set calibrated to a single location often fails to capture the full range of observed soil moisture conditions within a study area (Beven 2006). Recognizing spatial variability in soil moisture is crucial for improving the predictive performance of hydrological models, particularly in the context of water balance components such as evapotranspiration and infiltration (Famiglietti and Wood 1994). Research has shown that spatial differences in soil hydraulic properties can lead to substantial variations in simulated water balance components, such as transpiration, runoff, and deep percolation (Montzka et al., 2017). However, uncertainty remains regarding the optimal quantity and selection of soil moisture observations necessary to adequately represent a plot for model calibration and estimation of groundwater recharge. In the context of forest environmental monitoring, the installation of soil moisture observation profiles is often restricted to a limited number of locations (Vorobevskii et al., 2024). This limitation is primarily attributed to the significant financial investment required for advanced measurement technologies, compounded by a general underestimation of the critical role of representative soil moisture data in deriving reliable estimations of forest water balance components.

Recognizing these challenges, this present study seeks to evaluate the gains of installing a larger number of soil moisture sensors to obtain data for model calibration. To address this, an expanded monitoring network comprising multiple soil moisture probes was established across two forest plots at different sites in Germany, each characterized by contrasting environmental and boundary conditions. The collected data were analysed to identify and underplot spatial and temporal soil moisture variability across the study areas, including differences at distinct depths and locations. The observations were further used for the calibration of the SVAT model LWF-BROOK90.jl to assess their influence on estimated model parameters and model outputs, especially on ground water recharge. The focus on plot-scale instead of multi-site or gridded estimations allows for a mechanistic evaluation of model performance under well-controlled conditions, using high-resolution soil moisture data. This level of detail is crucial for understanding site-specific processes such as root-zone dynamics, canopy interception, and soil hydraulic behaviour - factors that are often averaged out or parameterized in large-scale models. By addressing uncertainties associated with soil moisture variability and model parameterization, this our analysis contributes to the ongoing discourse on the spatial resolution required for hydrological model calibration. The findings should emphasize the importance of balancing single versus multiple parameterizations to ensure representativeness in heterogeneous forest landscapes, ultimately enhancing the accuracy of groundwater recharge estimations in forest landscapes.

2 Methods

2.1 Study sites & data

The research concentrated on two sites within the ICOS (Integrated Carbon Observation System) monitoring network, which are also part of the IPCC Network (Intergovernmental Panel on Climate Change), selected for contrasting soil characteristics and their well-established infrastructure and suitability for comprehensive data collection (Table 1).

Table 1 Characterisation of the two sites instrumented as part of the study

	Kienhorst	**Tharandt**
Coordinates (-)	52°58' N / 13°39' E	50°57'N, 13°34' E
Elevation (m)	66	385
Slope (°)	0	~~7~~4
Median Temperature (°C)	8.5	8.1~~2~~
Annual Precipitation (mm)	422 (2022), ~~5~~6~~77~~81 (2023), 580 (2024), 523 (2025)	~~843~~657 (2022), 864 (2023), 745 (2024), 551 (2025)
Vegetation	Pinus / Vaccinium myrtillus / Bryophyta	Picea / Larix/ Bryophyta
Soil type *, soil texture class, stone content	Haplic Podzol, S~~s~~and, ~~no stones~~0%	~~Haplic~~Cambric Podzol, ~~s~~Silt loam, ~~10 – 20~~40-60%, partially perching properties
Geology	Glacial sediments including their periglacial overprints	Periglacial sediments consisting of debris from rhyolite and loess
Hydrogeology	Water level upper aquifer -17 m b.g. on average	Water level upper aquifer -13 m b.g. on average

(Kallweit and Engel, 2016), (Anchorstation Tharandter Wald - Ökomessfeld), *(IUSS Working Group (WRB), 2022)

2.1.1 Study site Kienhorst

The study area is situated in the heart of the Schorfheide, the largest continuous forested region in the state of Brandenburg, Germany (Fig. 1A). This plot consists of a 115-year-old pines, with ground vegetation primarily composed of dwarf shrubs, blueberry herbs and branch mosses (Kallweit and Engel, 2016). Humus form is raw humus with an Of/Oh ratio of 6 (IUSS Working Group (WRB), 2022). The mineral soil consists of fine sand, and roots seem to grow deeper than 1.5 m (Fig. 1B).

2.2.2 Study site Tharandt

The study site is situated in the heart of Tharandter Wald, a dense forest covering approximately 6000 hectares on the lower reaches of the northern slopes of the Ore Mountains (Fig. 1C). The forest is characterized by a 129-year-old spruce plot, with ground vegetation primarily composed of grasses and mosses (Anchorstation Tharandter Wald - Ökomessfeld). Humus form is raw humus overlaying a loamy mineral soil with up to 60% stone content throughout the profile (Fig. 1D). Roots seem to grow not deeper than 0.8 m. At different locations on the plot (approx. 35%), the subsoil > 0.5 m depth exhibits redoximorphic patterns indicating perching properties, which means extremely low permeability. This results in the accumulation of stagnant water during periods of heavy rainfall, as the infiltrating precipitation encounters significant resistance, hindering its downward movement through the soil layers (Braeutigam, 2012).

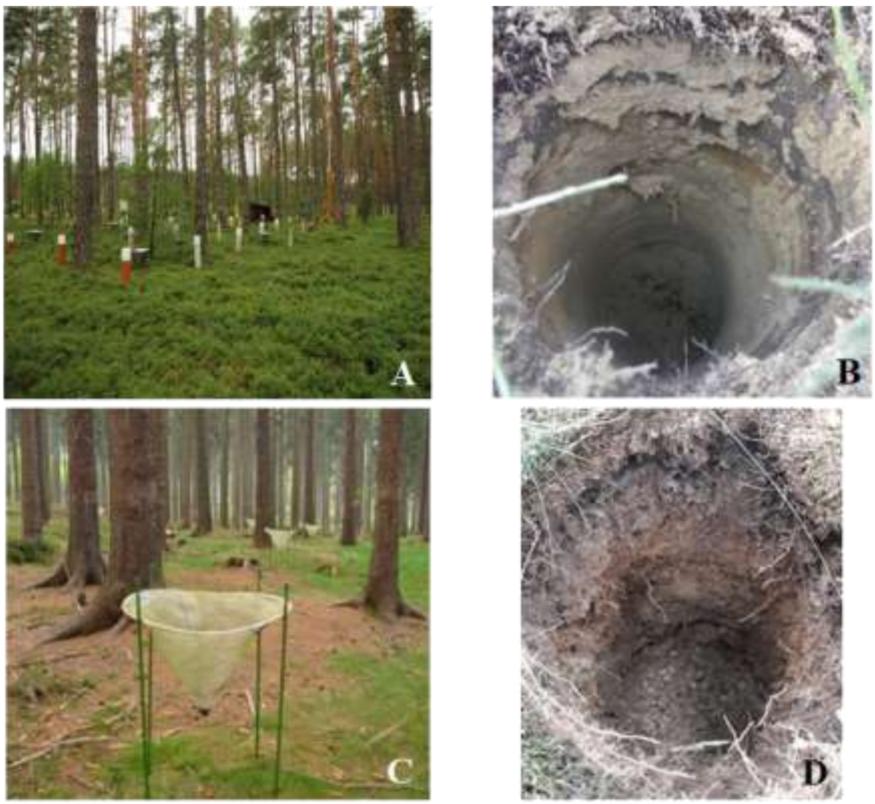

Figure 1 View of Kienhorst plot (A), soil characteristics of Kienhorst plot (B), view of Tharandt plot (C), soil characteristics of Tharandt plot (D) (photograph by Fichtner, 2023)

2.2 Soil moisture measurements

2.2.1 Set up soil moisture monitoring network

At the two study sites located in distinct climatic regions of Germany, extensive networks of 44 soil moisture probes were deployed. Each of the 11 soil profiles was equipped with four probes placed at depths of 10, 30, 50, and 80 cm (Fig. 2C). The study utilized SMT100 soil moisture probes (Truebner Company 2025), with integrated temperature measurement, operating based on the Time Domain Transmission (TDT) principle (Fig. 2A) (Qu et al., 2013). The specified accuracy for absolute measurements is ±3 vol. % for soil moisture (without site-specific calibration) and between 0.2°C and 0.4°C for soil temperature. The sensor provides average measurement values across its full length of 10 cm. In this study, the manufacturer's calibration (multi-point laboratory calibration against gravimetrically determined volumetric water contents in standard mineral soils) was applied instead of site-specific calibration, as the focus was on the soil moisture dynamics rather than absolute values (Sprenger et al. 2015; Demand et al. 2019). To prevent water accumulation on the probes and ensure minimal interference with vertical vapor fluxes, the probes were installed horizontally with their narrow edge oriented vertically (Fig. 2C).

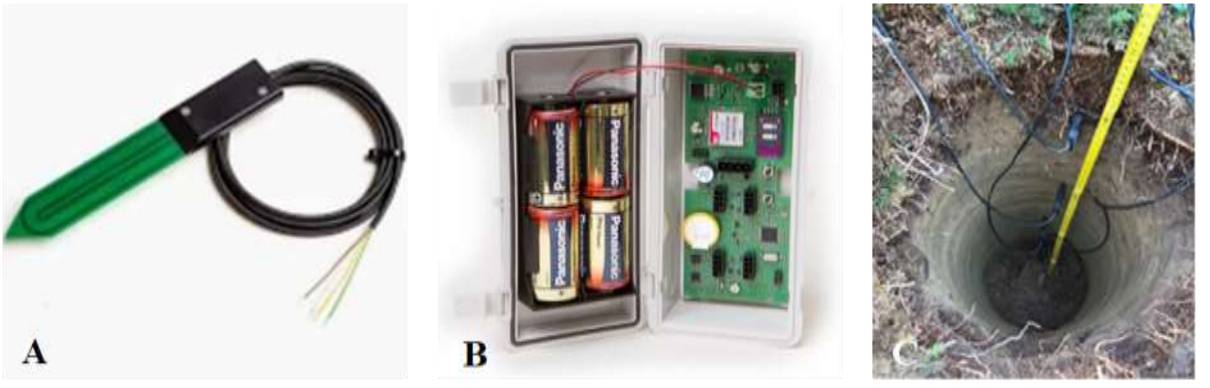

Figure 2 SMT100 Sensor (Truebner Company)(A), Datalogger TrueLog200 (Truebner Company)(B), soil profile with installed sensors (photograph by Fichtner, 2023) (C)

Data was collected every 10 minutes using the battery-powered TrueLog200 data logger (Fig. 2B). The data loggers are configured and accessed via the accompanying logger software. Equipped with a GSM modem, the loggers can transmit recorded data through the mobile phone network.

2.2.2 Selection of positioning soil moisture measurements

To identify soil moisture variability at the study plot, the location of the 11 soil profiles per plot were installed at randomized locations within an area of 20 x 20 meters (Fig. 3A+B). Previous research has demonstrated that installing soil moisture sensors in a minimum of 10 profiles is sufficient to capture plot-specific variability effectively (Berthelin et al., 2020). The random sampling approach was employed to determine the soil profile coordinates, ensuring that each location was selected with equal probability. This method was chosen to maintain the independence of data points, facilitating robust statistical analysis. Additionally, randomized placement across the study area helps to avoid potential systematic errors caused by unrecognized gradients in soil moisture distribution. This strategy ensures comprehensive coverage of the variability present in the field.

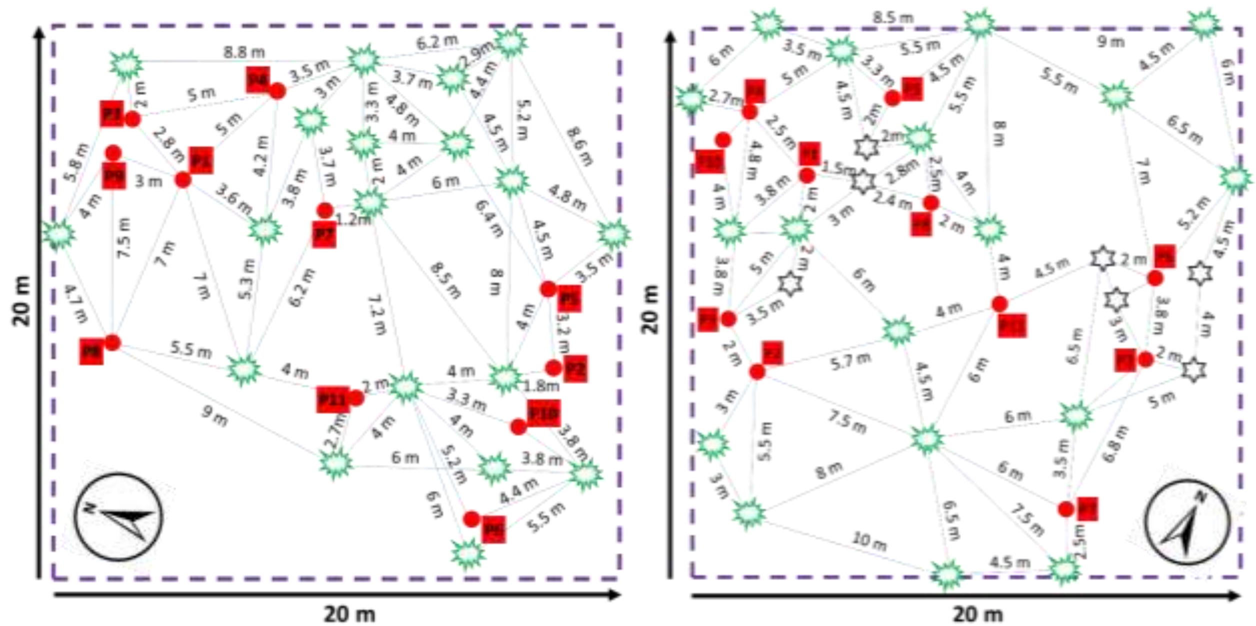

Figure 3 Randomly distributed soil profiles (red) in the 20 x 20 m plot at Kienhorst site (A) and at Tharandt site (B), living trees = green, tree stumps = black

2.3 Water balance model LWF BROOK90.jl

Water balance models or Soil–vegetation–atmosphere transfer (SVAT) models are valuable tools for estimating detailed atmosphere–plant–soil water exchange as well as waterfluxes within terrestrial ecosystems using a 1D simplification representing of evatransp~~o~~iration and vertical soil water movement processes (Olioso et al., 2005). ~~he model LWF-BROOK90.jl, a process-based, one-dimensional SVAT model,~~ LWF-BROOK90.jl, a process-based, one-dimensional SVAT model, developed to simulate daily vertical water fluxes within soil–plant–atmosphere systems at the point scale, was applied in this study. In addition to simulating water fluxes and storage dynamics, LWF-BROOK90.jl also includes an isotope module for modelling stable water isotopes; however, isotope simulations were beyond the scope of the present study. Owing to its vertical structure, the model is particularly suited for forest hydrology studies and ecohydrological process analysis, rather than fully distributed catchment-scale simulations.~~was utilized for the analyses presented in this study.~~ LWF-BROOK90.jl~~It~~ represents a complete reimplementation of the LWF-BROOK90 model in the Julia programming language (Bernhard et al., 2020). It ~~,~~ build~~ing~~s upon ~~on the code from~~ the R package LWF-BROOK90R, its underlying Fortran source code~~,~~ and the original BROOK90 (v4.8) implementation (Federer et al., 2003; Schmidt-Walter et al., 2020)~~.~~, while preserving the conceptual structure and process formulations of its predecessors. Water movement is represented as a vertically coupled soil–plant–atmosphere continuum consisting of a single-layer (“big-leaf”) canopy, a snowpack when present, a multi-layer soil column with user-defined thickness and hydraulic properties and a conceptual groundwater store. The modeled storage compartments comprise interception (separately for liquid precipitation and snow), snowpack, vertically discretized soil water, plant water storage and groundwater. A more detailed model description including the underlying processes and fluxes is provided in the Supplement, Section Model description.

~~The water flux is computed by numerically solving the Richards equations using the Mualem–van Genuchten hydraulic parameters and preferential flow (van Genuchten, 1980; Mualem, 1976) governs unsaturated and saturated water movement in soil. The model dynamically adjusts percolation rates depending on soil hydraulic conductivity and water potential gradients.~~

2.3.1 Model input ~~and vertical discretization~~

In general, the LWF-BROOK90.jl model is driven by daily meteorological forcing data and physically based parameter sets describing ~~requires as input~~ soil hydraulic (Mualem-van Genuchten parameters, hydraulic conductivity), canopy as well as ~~and~~ vegetation characteristics~~properties~~. ~~(e.g., leaf area index, root depth, and stomatal resistance),~~ All input data are provided as structured csv-files.

Meteorological forcing

Time series of meteorological variables (precipitation, min. and max. air temperature, relative humidity, wind speed and solar radiation) were obtained from the locally operating meteorological stations at both ICOS sites (ICOS Ecosystem Station Kienhorst (DE-Kie), 2025; ICOS Ecosystem Station Tharandt (DE-Tha), 2025) located in grassland areas near the sites. Observations at 30-minute resolution were aggregated to daily values representative of the study sites. The average duration of precipitation events was fixed at 4 hours for all months, following the recommendation in the original BROOK90 documentation as a satisfactory approximation. Although the use of daily forcing combined with a constant storm duration may smooth short-term rainfall extremes and slightly affect infiltration and percolation dynamics, this simplification is considered appropriate for the temporal and spatial scales addressed in this study.

Soil hydraulic parameterization and vertical discretization

At both sites, the modeled soil profiles extended to a depth of 3 m and were subdivided into three main soil horizons with distinct hydraulic properties. The lower layer was extended to 3 m to determine a uniform lower boundary and assure the infiltration process in the model. Initial estimates of soil hydraulic properties down to a depth of 0.8 m were derived from site-specific measurements, including sieve analyses and subsequent determination of Mualem–van Genuchten parameters by using the pedotransfer functions of (Wösten et al., 1999).

For numerical simulation, the profile was discretized into computational layers with a vertical resolution of 5 cm in the upper 30 cm and 10 cm in deeper sections. Layer thicknesses were chosen to reflect expected gradients in soil hydraulic properties and rooting density. This discretization enables a realistic representation of vertical variability in soil water retention, percolation as well as root water uptake. Additional parameters used to describe soil and infiltration processes (e.g., infiltration exponent that determines distribution of infiltration water with depth, soil depth until which infiltration is distributed, quickflow fraction of infiltrating water at field capacity) were specified based on provided information by ICOS site managers or relevant literature (Supplement, Tables S1–S2).

~~For an adequate representation of the vertical variability of soil water dynamics, the soil profiles were discretized into layers with a vertical resolution of 5 cm in the upper soil horizons (up to 30 cm) and 10 cm for deeper horizons (soil horizons.csv). The layer thickness was adjusted depending on expected gradients in soil hydraulic properties and rooting depth. This stratification allows for a more accurate simulation of water retention, percolation, and root water uptake across the profile. Furthermore, it ensures that soil moisture dynamics are realistically captured at the defined observation depths, allowing for a consistent comparison between simulated and observed soil moisture values.~~*Vegetation and canopy parameterization*

Parameters describing canopy characteristics (e.g., average leaf width, interception capacity per unit LAI or SAI), vegetation hydraulics (e.g., maximum leaf vapour conductance under fully open stomata, vapor pressure deficit at which stomatal conductance is halved) and root system characteristics (e.g., maximum and initial root depth, average radius of the fine or water-absorbing roots) were also defined based on data provided by the managers of the ICOS sites or relevant literature (Supplement, Tables S1 and 2).

Maximum LAI (4 for Kienhorst / 5 for Tharandt) for the tree layer was set according to site-specific measurements provided by the ICOS site management (Supplement, Tables S1–S2). Seasonal LAI dynamics were derived from site-specific phenological observations, thereby providing a realistic representation of temporal canopy development and its influence on evapotranspiration. Understory leaf area index (LAI), including contributions from dwarf shrubs and bryophytes, can constitute a non-negligible component of total vegetation cover in temperate and boreal forests. Remote sensing and field studies indicate that understory LAI can reach values of approximately 2–3 $m^2\ m^{-2}$ during the growing season in forest types where low shrubs and mosses are abundant (Liu et al., 2017). At the Kienhorst site, understory vegetation (mosses and blueberry shrubs) was therefore represented by adding an additional LAI of 2 to the tree LAI, as the model does not allow the simultaneous representation of multiple canopy layers. This adjustment accounts for evapotranspiration from ground vegetation and prevents an overestimation of simulated percolation.

Definition of vertical and lateral flow components

Throughfall and snowmelt reaching the soil surface were partitioned into vertical and lateral flow components according to site-specific parameterization. At Kienhorst site, characterized by highly permeable sandy soils, unrestricted vertical drainage was assumed by setting the drainage multiplier drain to 1. This configuration allows free percolation from the deepest soil layer to the conceptual groundwater store. Preferential macropore bypass flow (bypar) was deactivated, as structured preferential flow is not expected in the homogeneous sandy substrate. A small fraction of near-surface runoff was permitted (Maximum 5%). In contrast, at Tharandt site, vertical drainage from the lowest soil layer was restricted (drain < 1) to account for poorly permeable subsoil horizons that limit downward percolation. Preferential bypass flow (bypar) was activated to represent rapid flow pathways associated with the stony and structurally heterogeneous soil matrix. Surface runoff was not permitted at this site. At both locations, the parameter controlling slow lateral subsurface flow (dsfl), which represents gradual downslope water release from all soil layers, was effectively disabled by defining the slope parameter (dslope) as zero. Furthermore, the groundwater table option (GWAT) was deactivated at both sites, implying that no dynamic shallow groundwater table was simulated and that recharge was represented solely as percolation to the conceptual groundwater store.

2.3.2 Modell calibration

First of all, reference simulations were conducted to obtain an initial, uncalibrated assessment of evapotranspiration and soil water dynamics under observed meteorological conditions. This allowed early identification of structural model limitations and provided a physically based benchmark for subsequent calibration. To avoid artefacts from uncertain initial states, simulations were preceded by a 15 months warm-up period and the resulting model states served as initial conditions for the subsequent 24-month evaluation period.

Model calibration itself focused on identifying the key soil hydraulic and vegetation-related parameters controlling system dynamics, using soil moisture time series at four depths across 11 profiles. The number of calibrated parameters was limited to a process-relevant subset, with all others fixed within physically plausible ranges. To reduce computational complexity and minimize the risk of overfitting, which is primarily related to the number of calibrated variables, only the most influential inputs were retained. These were selected based on literature knowledge, expert judgment and the physical characteristics of the study area. Parameters expected to have negligible impact on model outcomes were fixed at default or literature-based values, allowing the calibration to focus on the key variables controlling system dynamics (Supplement, Tables S1 and S2). ~~The objective of the calibration process was to identify inversely key soil hydraulic and vegetation-related input parameters of the model by using soil moisture time series recorded from March 2023 to October 2024 in the four different depths within the 11 soil profiles each. The input parameter values and ranges were derived from three main sources – in situ field measurements, data provided by ICOS site operators and relevant literature (Supplement, Table S1). To optimize the calibration process, a preselection of input parameters was conducted based on the results of a sensitivity analyses (Aguilar Avila, 2024). Parameters that exhibited negligible influence on model outcomes were fixed to reduce computational complexity (Supplement, Table S1).~~ Finally, 1~~7~~0 (Kienhorst) / 14 (Tharandt) ~~critical input~~ parameters ~~on model performance~~ were chosen for calibration within their predefined ranges. These parameters encompassed variables related to canopy structure, vegetation hydraulics, root distribution, soil physical processes and hydraulic properties; ~~11~~5 (Kienhorst) / 8 (Tharandt) of valid for the entire subsurface, 5 (Kienhorst) / ~~six~~6 (Tharandt) of them with individual variations respecting the defined discretization scheme. ~~-~~A total of 100,000 sets of these selected parameters were generated using Latin Hypercube Sampling (LHS) to ensure broad and unbiased coverage of the parameter space as well as to capture potential variability in model responses within a feasible range of computational costs. Although known parameter correlations, typically determined by soil texture and structure, were not explicitly considered, this approach allows exploration of model sensitivity across a wide range of plausible values. Incorporating correlations could refine sampling, but independent random sampling has been shown to be a valid method for assessing uncertainty in hydrological model calibration, particularly when the goal is to capture the overall range of system responses (Beven, 2006a; Vrugt et al., 2008). ~~For calibration, 100,000 random combinations of these 17 parameters were generated using the Latin Hypercube Sampling (LHS) strategy ensuring a well-distributed exploration of the parameter space within a feasible range of computational costs. (Beven, 2006a; Vrugt et al., 2008)~~Model calibration was conducted over a 24-month period (march 2023 to march 2025) to capture a wide range of hydro-meteorological conditions, particularly contrasting different soil moisture states, ensuring a robust representation of system behaviour under both wet and dry conditions as well as reducing the likelihood that parameter optimization is biased toward specific short-term patterns or individual events. A 15-month warm-up period was also applied as a precursor to the calibration phase to minimize the influence of initial conditions and allow model states to approach dynamic equilibrium. ~~The LWF-BROOK90.jl model was then executed for each of the 100,000 parameter sets. An initialization (spin-up) period of approximately three months was implemented to minimize the influence of initial condition uncertainties on the simulation of soil moisture and water fluxes.~~ Remaining predictive uncertainty was evaluated using a split-sample approach to assess model robustness and minimize overfitting. The full simulation period was divided into a calibration (70%, 24 months) and an independent validation phase (30%, 9 months), ensuring that model performance was tested under hydrological conditions not used for parameter estimation. The validation period covered both wet and dry states, providing a stringent test of the model's ability to reproduce soil moisture dynamics, evapotranspiration, and drainage responses under contrasting conditions. Although longer validation periods would further increase confidence in long-term transferability, the applied split-sample strategy, combined with reduced parameter freedom, suggests that overfitting effects are limited.

Model performance was evaluated using the Kling-Gupta Efficiency (KGE) score (Supplement, Section Statistics), as it provides a balanced assessment of correlation, bias~~,~~ and variability between simulated and observed soil moisture dynamics across multiple depths (Gupta et al., 2009). For further analysis of water balance components, the 30 best-performing simulations according to KGE for each of the 11 individual profiles per plot were selected. This selection represents a compromise between model accuracy and the exploration of plausible model behaviour, allowing for a robust and nuanced evaluation of model uncertainty.

2.3.3 Model output and evaluation

In addition to the various variables relevant to water dynamics and recharge processes calculated by the model, such as ~~evapotranspiration~~ evapotranspiration~~(ET) and root water uptake (RWU)~~, the primary focus of the evaluation was on groundwater recharge generated at daily resolution. While the other variables provided important insights into the water balance and plant–soil interactions, groundwater recharge was of particular interest due to its critical role in sustaining long-term water availability and its sensitivity to both model-inherent factors and the spatial variability of soil moisture used for calibration. To investigate this in detail, the 30 best-performing simulations for individual soil profiles, each based on its respective calibrated parameter set, were analysed to determine whether uncertainties in groundwater recharge rates arising from site characteristic or model structure, such as parameter interactions, equifinality or~~, and~~ dimensional simplifications.~~,~~ ~~have a greater influence on model outputs than those related to spatial heterogeneity in soil texture and hydraulic properties within the plot.~~

The simulated water balance was derived from model outputs and used to quantify the dominant hydrological fluxes and storage components at the study sites. Temporal dynamics were evaluated at daily resolution and subsequently aggregated to annual scales to capture variability under contrasting hydro-meteorological conditions. Water balance closure was assessed to verify the internal consistency of the simulations and to ensure that fluxes and storage changes were represented coherently.

~~In addition, a bootstrapping procedure was performed using a two-sample Kolmogorov–Smirnov (KS) test (Supplement, Section Statistics) to determine the minimum number of soil profiles necessary for a representative estimation of groundwater recharge across the studied 20 × 20 m plots. The analysis was based on simulated groundwater recharge values produced by the LWFBrook90 model for 11 soil profiles, each yielding 30 values derived from calibration with observed soil moisture measurements, resulting in a total of 330 values. For varying numbers of profiles (n = 1 to 11), random subsets of n profiles were repeatedly drawn (1000 iterations per subset size), and their aggregated value distributions were statistically compared to the full dataset (all 11 profiles). The KS test was employed to assess whether the distribution of the subsample significantly differed from that of the complete set.~~ To determine the number of soil profiles required for a representative estimation of groundwater recharge within 20 × 20 m plots, a Monte Carlo–based subsampling approach was applied, aiming to quantify how groundwater recharge estimates change with varying numbers of included soil profiles. From the 11 available soil profiles, each providing 30 groundwater recharge estimates (n = 330), random subsets of increasing size (n = 1–11) were repeatedly drawn. For each subset, aggregated groundwater recharge was calculated and the procedure was iterated multiple times to capture variability across combinations. Representativeness was assessed based on the stability of distribution metrics: subsets were considered adequate when their mean deviated by less than ±10 % from the full dataset and their 95 % confidence intervals substantially overlapped. This approach enables a robust evaluation of the minimum number of profiles required to capture groundwater recharge variability without relying on strict assumptions about sample independence.

3 Results

3.1 Observed soil moisture dynamics

Initially, the visual examination of soil moisture time series across the 11 soil profiles each, measured at four depths (10, 30, 50, and 80 cm) at the Kienhorst (Fig. 4) and Tharandt (Fig. 5) plot, revealed distinct patterns of variability. Seasonal effects were evident at both study locations across nearly all soil depths due to the fluctuating intensity and timing of precipitation events and the changing consumption of water by vegetation.

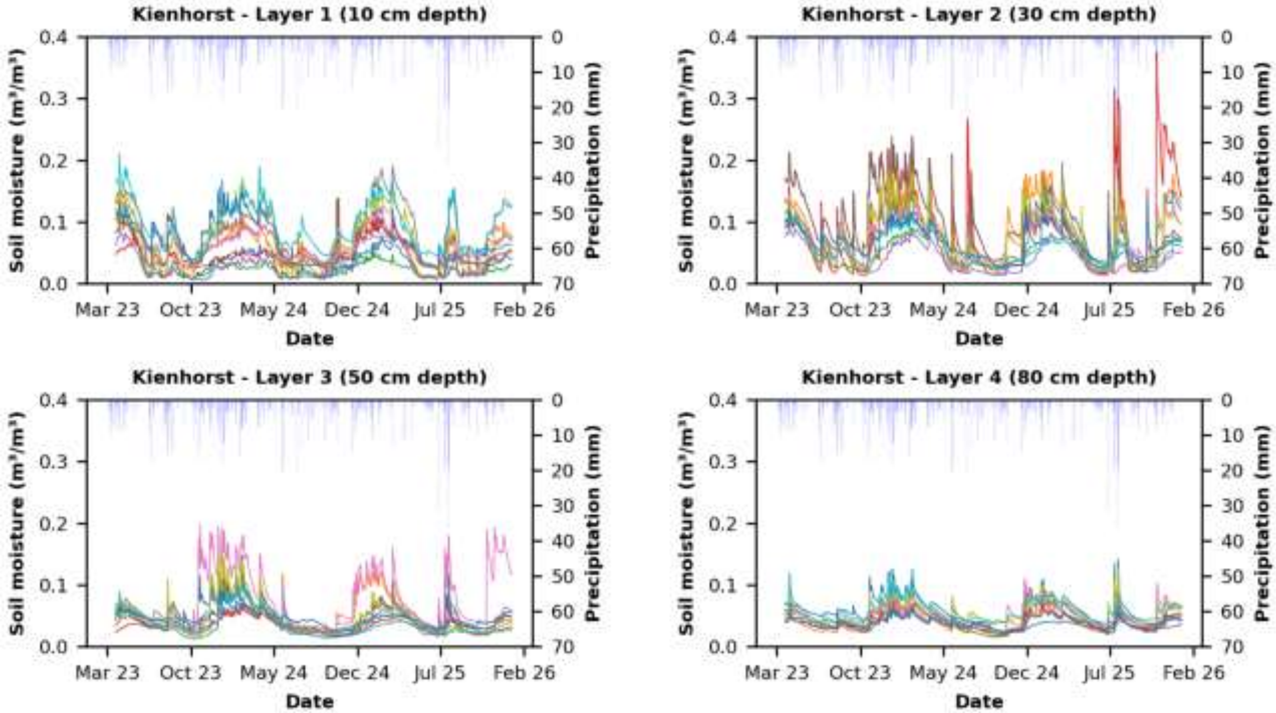

Figure 4 Observed soil moisture at Kienhorst plot – Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm, each line represents the soil moisture of one of the 11 profiles, soil moisture raw measurements; no correction for potential sensor spikes or artefacts was performed.

However, the redistribution and consumption of precipitation water on its way through the unsaturated soil zone resulted in a diminished manifestation of seasonal patterns in the lower soil horizons. Notably, certain soil profiles at the Tharandt plot exhibited an almost uniform low moisture level throughout the year in the lower horizons, indicating limited seasonal variability in these depths. Additionally, rapid and pronounced increases in soil moisture following heavy rainfall events were observed in several, but not all, soil profiles at the Tharandt plot due to waterlogging following heavy rainfall events caused by poorly permeable soil layers. These conditions are consistent with field observations, where it was possible to observe this phenomenon. At the Kienhorst plot, the range of observed soil moisture values and the variability between individual profiles were consistently low both in dry and wet periods with evident uniformity of soil moisture across all depths. Soil moisture exhibited a consistent pattern across all depths, with a range of approximately 15 vol. % between minimum and maximum values. Conversely, the Tharandt plot was characterized by significant fluctuations in soil moisture content, coupled with considerable variability between individual profiles, particularly during and following heavy precipitation events occurring here more often. At this plot, the range between minimum and maximum moisture content reached nearly 50 vol. %, highlighting the pronounced heterogeneity of soil water dynamics.

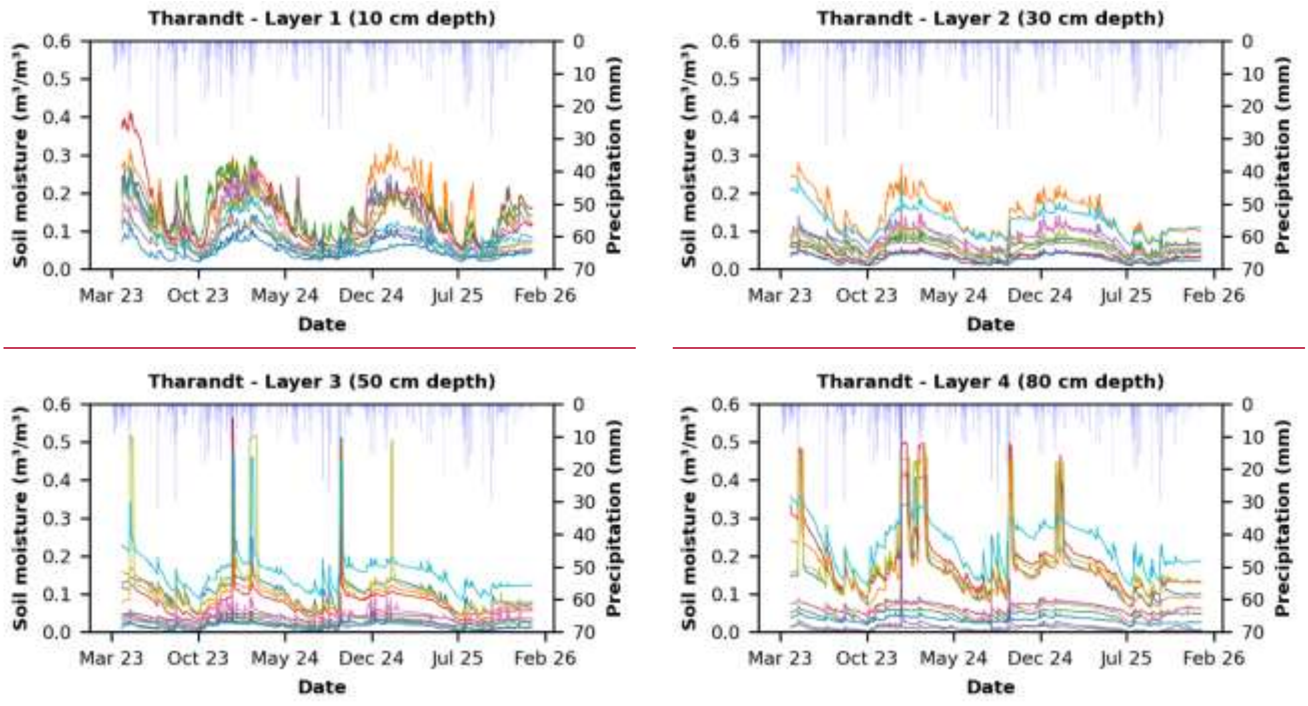

Figure 5 Observed soil moisture at Tharandt plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm, each line represents the soil moisture of one of the 11 profiles, soil moisture raw measurements; no correction for potential sensor spikes or artefacts was performed.

3.2 Model calibration

3.2.1 Simulated soil moisture dynamics and their performance

The uncalibrated reference simulation shows an overall insufficient agreement with the observed soil moisture dynamics at both plots and across all investigated depths (Figures 6 and 7). While the temporal evolution is generally well represented, including both the seasonal patterns and short-term responses to precipitation events, this is primarily reflected in acceptable values of the KGE correlation component (Supplement Table S6 and S10). Despite this qualitative agreement in temporal dynamics, the overall KGE values indicate clear limitations in the model's quantitative performance. In particular, systematic discrepancies exist in terms of the magnitude and variability of soil moisture. The simulation tends to overestimate soil moisture, especially during wetter periods, while exhibiting a reduced sensitivity under dry conditions compared to observations. These biases are further supported by elevated values of the KGE components for variability bias and mean bias (Supplement Table S7, S8, S11 and S12). Overall, these results suggest that the model is capable of reproducing the general system behavior and temporal patterns, but fails to accurately capture the observed soil moisture levels. This highlights the need for model calibration to improve both the magnitude and variability of the simulations, and thereby enhance overall model performance.

Comparison with reference simulations demonstrated that calibration markedly improved the representation of soil moisture, resulting in strong agreement between simulated and observed values in both temporal dynamics and magnitude across most profiles at both study plots over depth.
~~The calibration outcomes demonstrate strong correspondence between the temporal dynamics and magnitude of soil moisture changes in the simulated compared to the observed soil moisture across most profiles at both study locations over depth, which are reflected by constantly high KGE values (Fig. 6 and 7, for complete results of calibration see Supplement, Fig. S1 and S2).~~

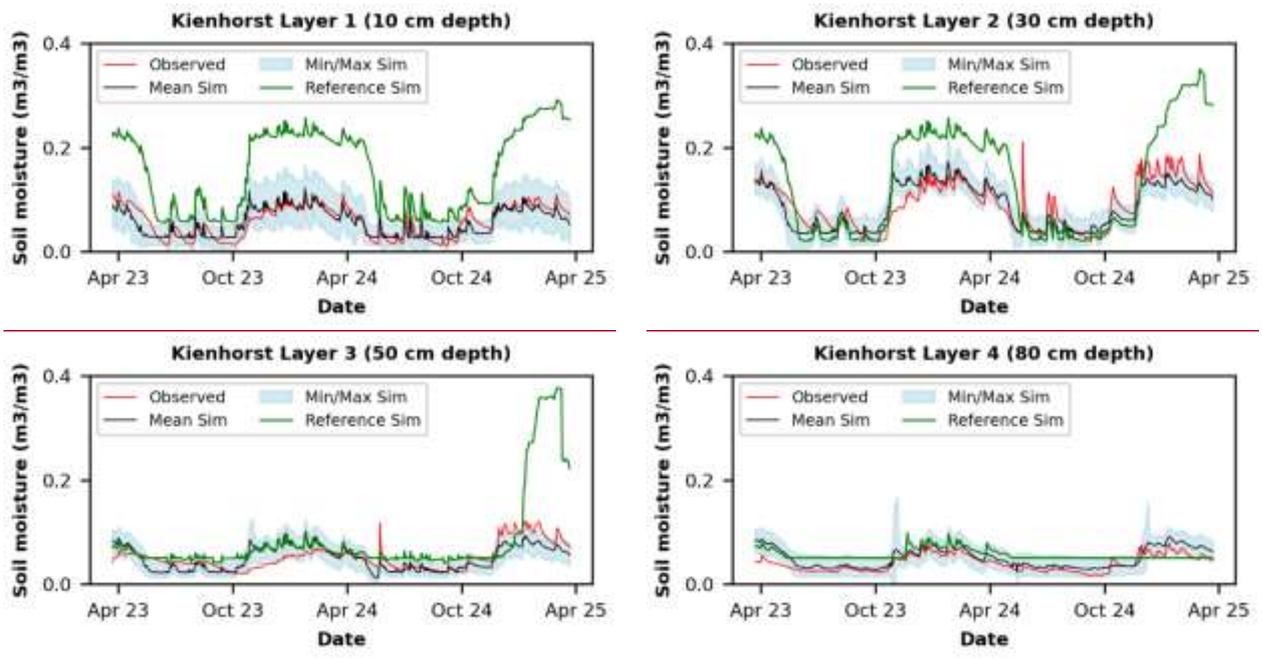

Figure 6 ~~Observed and simulated soil moisture exemplary for soil profile 9 at Kienhorst plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm~~ Soil moisture - Observed (red) versus reference simulation (green) as well as average of the 30 best calibrated simulations (black) and their uncertainty bandwidth (blue) exemplary for soil profile 2 at Kienhorst plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm

This improved performance is also reflected in consistently higher KGE values. (Fig. 6 and 7, Supplement, Fig. S1 and S2 and Tab. S5 and S9). The model calibration effectively reproduced seasonal variations evident in the measured soil moisture values, including the response to prolonged dry periods and the rapid recovery following significant precipitation events. Minor discrepancies in the absolute values, timing of peaks and magnitudes were detected in the profiles over the depth. Significant deviations were observed here during periods of extreme wet conditions, especially at the Tharandt plot.~~represented by lower KGE values~~ Specifically, while the timing of sharp increases in soil moisture following heavy rainfall events closely aligns with the observed data, the model underestimates the magnitude and the duration of these rises (Fig. 7, depth 50 and 80 cm).

Despite the existing deviations, the model performance demonstrates a high level of precision in replicating absolute soil moisture values across the 11 soil profiles and four measured depths (10, 30, 50, and 80 cm), what can be proven by consistently high KGE scores across most profiles (Supplement, Table ~~S2~~S5 and ~~S3~~S9). Even for profiles with greater variability or complex conditions, the model maintains acceptable accuracy, with KGE values not falling below ~~0.01~~0.11 (Gupta et al., 2009). A more detailed analysis of the individual KGE components (Supplement Tables 6–8 and 10–12) reveals that the values for correlation, variability bias and mean bias are generally within ranges indicative of a satisfactory reproduction of the observed soil moisture dynamics (Gupta et al., 2009).

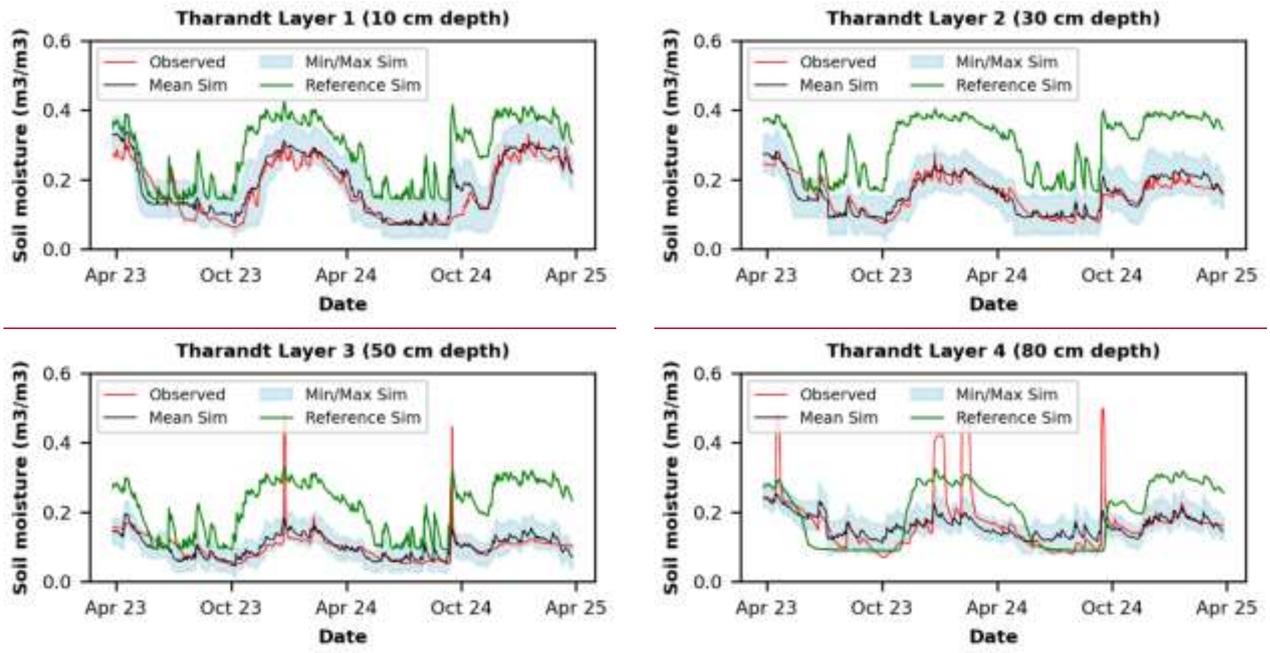

Figure 7 ~~Observed and simulated soil moisture exemplary for profile 1 at Tharandt plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm~~Soil moisture - Observed (red) versus reference simulation (green) as well as average of the 30 best calibrated simulations (black) and their uncertainty bandwidth (blue) exemplary for soil profile 2 at Kienhorst plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm

The correlation component, in particular, confirms the model's ability to capture the temporal structure of the observations. Slight overestimations of soil moisture variability are reflected in the variability bias values, pointing to a tendency of the model to simulate somewhat stronger fluctuations than observed. Similarly, minor deviations in mean bias indicate small systematic offsets in the simulated moisture levels.

The validation results show a mixed performance overall. At the Kienhorst plot, the model demonstrates an acceptable performance during the validation period. Both the seasonal dynamics and the transitions between wet and dry phases are reproduced reasonably well (Figure 8). Some overestimation of soil moisture variability is evident, as reflected in elevated values of the KGE variability bias component, while the correlation and mean bias remain within acceptable ranges (Supplement Table 6 to 8). In contrast, model performance at the Tharandt plot during the validation period is less satisfactory (Figure 9). The model shows clear limitations in reproducing changes between wet and dry phases, as well as in capturing the variability and correlation of simulated versus observed soil moisture, which is also reflected in the respective KGE components (Supplement Table 10 to 12). However, it should be noted that the hydrological conditions in 2025 differed substantially from those during the calibration period (2023–2024).

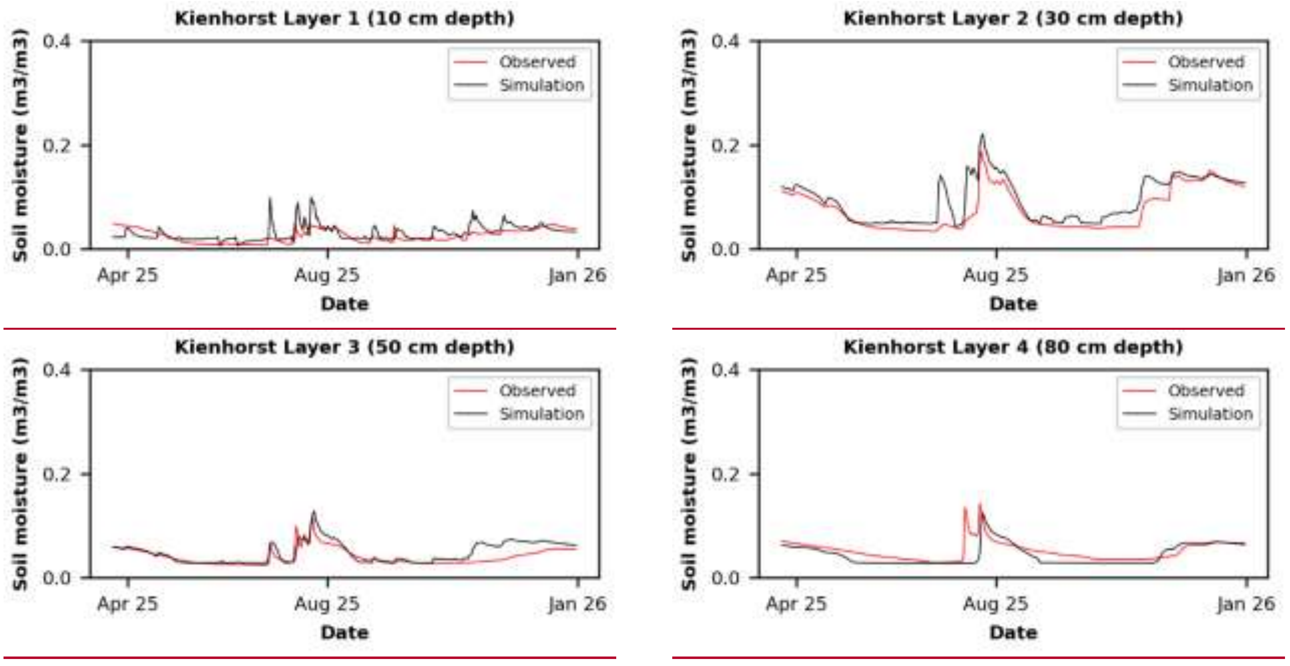

Figure 8 Soil moisture - Observed (red) versus simulated (black) based on the best parameter set of the 30 best simulatins during validation period exemplary for profile 1 at Kienhorst plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm

In particular, precipitation amounts were lower, and periods of waterlogging observed during calibration did not occur in 2025. Against this background, the reduced model performance at the Tharandt plot appears plausible, as the model is applied outside the range of conditions it was calibrated for.

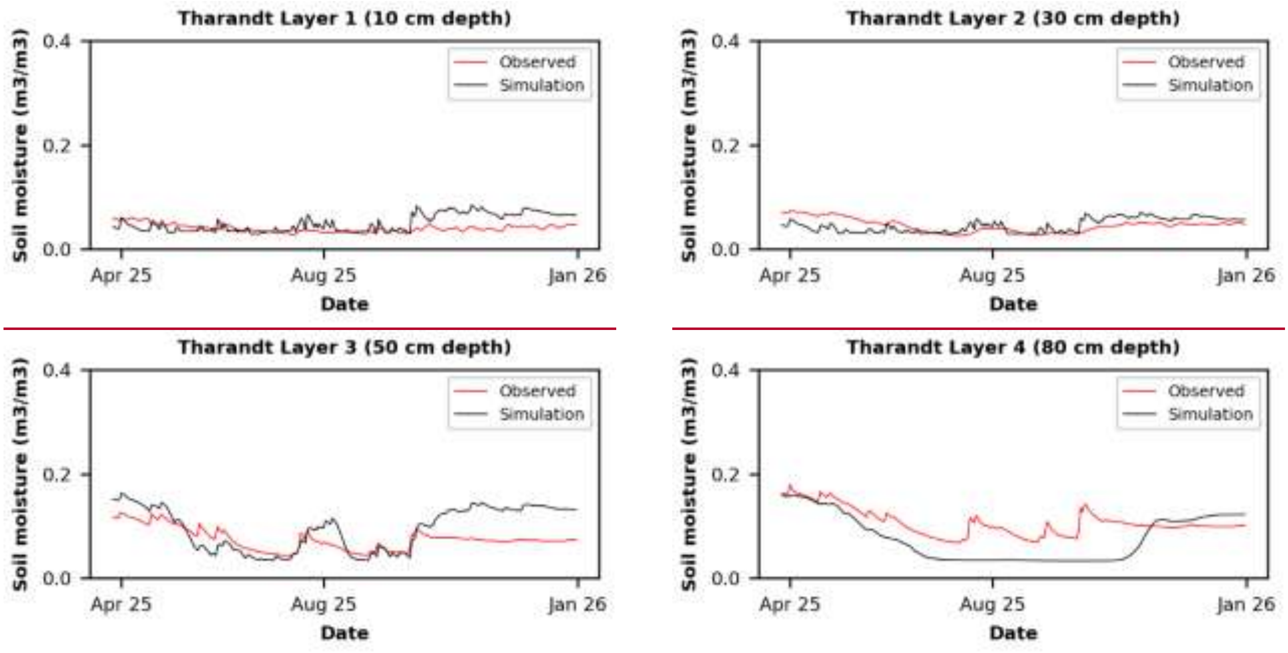

Figure 9 Soil moisture - Observed (red) versus simulated (black) based on the best parameter set of the 30 best simulatins during validation period exemplary for profile 1 at Kienhorst plot - Layer 1, 10 cm, Layer 2, 30 cm, Layer 3, 50 cm and Layer 4, 80 cm

3.2.2 Calibrated parameter combinations

The analysis of the variation of the individual calibrated input parameters in the 11 soil profiles each based on the 30 best simulations derived from calibration highlights significantly greater variation in the calibrated parameters at the Tharandt plot compared to the Kienhorst plot (Supplement, Fig. S~~3~~5 and S~~4~~6). Notably, the highest variation was observed in soil hydraulic and soil process parameters, such as ths (saturated volumetric water content), thr (residual volumetric water content), npar (width of the soil's pore-size distribution), ksat (saturated hydraulic conductivity), idepth (soil depth until which infiltration is distributed) and~~,~~ qfpar~~fc~~ (quickflow shape parameter~~fraction of infiltrating water at field capacity~~)~~,~~. ~~drain (multiplier to partially activate drainage) and length slope (slope length for downslope flow).~~ Especially at the Tharandt plot, also a strong variation in these parameters can be observed across the discretized soil layers, whereas the variation over depth is less pronounced at the Kienhorst ~~plot~~plot. Increased variation of the calibrated soil hydraulic parameters at the Tharandt plot can be attributed to the heterogeneous soil composition, which is characterised by alternating, poorly permeable layers, stones and underlying layers with low permeability. This heterogeneity increased the sensitivity of the site to precipitation events, which is reflected in pronounced differences in soil moisture dynamics between the profiles and consequently also in the calibrated parameter sets. For the parameters that characterize the vegetation and root system, there was greater variation for the parameters ~~ksnvp (reduction factor to reduce snow evaporation),~~ cvpd (vapor pressure deficit at which stomatal conductance is halved) and maxrootdepth (maximum root depth), although these were similarly strong at both the Kienhorst and Tharandt plot.

For further interpretation and to assess the uncertainty associated with the differing characteristics of the 11 soil profiles at both plots, the coefficient of variation (CV) was calculated based on the mean value of the individual calibrated parameters in the 11 profiles (Fig. ~~8~~10, upper part)~~, reflecting the uncertainty arising from the different characteristics of the 11 soil profiles at the two plots as well as based on the individual parameters of the 30 best simulations for the single profiles, reflecting model uncertainty~~. The higher CV values observed at the Tharandt plot ~~when comparing the individual parameters across the 11 soil profiles~~ highlight the greater variability in calibrated soil hydraulic and process parameters ~~at the Tharandt site~~ (maximum CV ~~0.6~~0.42 for Tharandt versus CV ~~0.21~~0.12 for Kienhorst).~~ This increased variation reflects the higher heterogeneity in soil characteristics at Tharandt compared to the more homogeneous conditions at Kienhorst.~~ While these differences are consistent with the known variability of site conditions, they represent variability in parameter estimates derived from model calibration rather than direct measurements of soil physical properties.

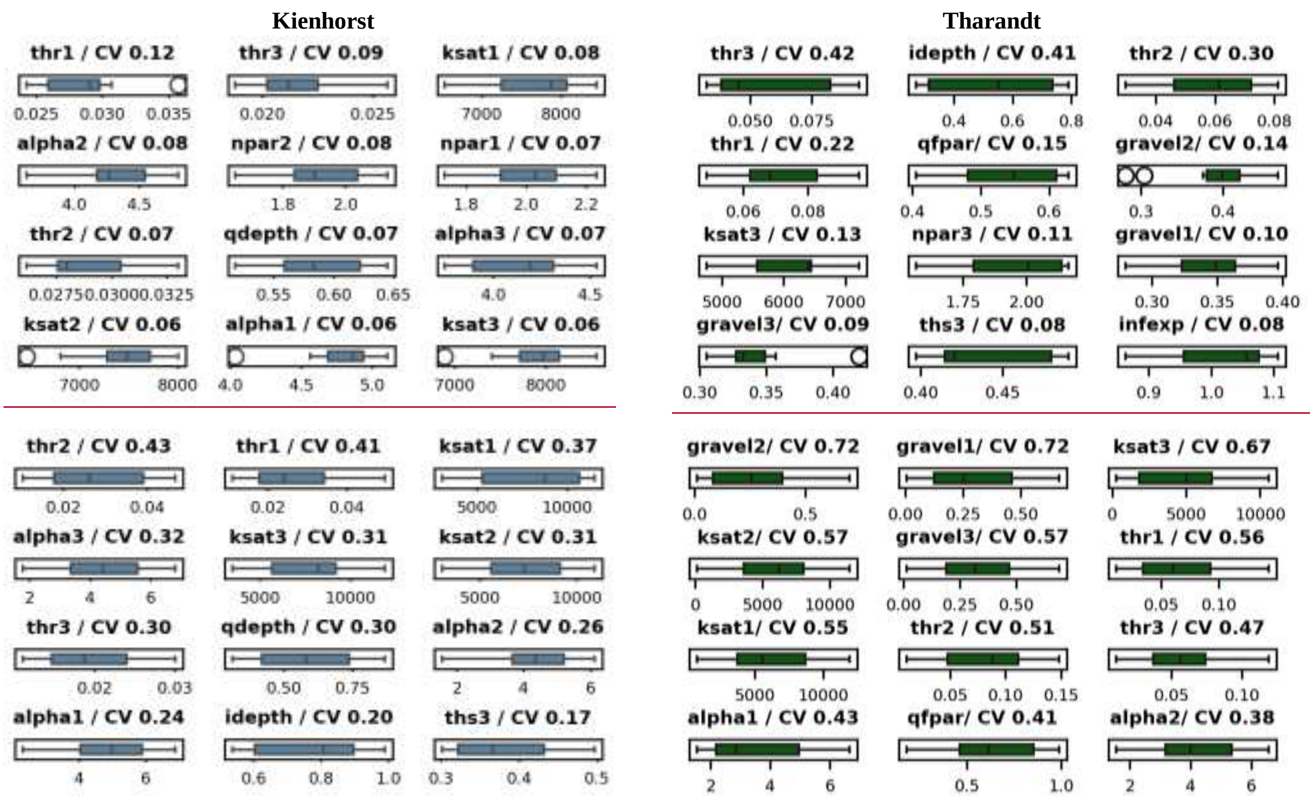

Figure ~~8~~10 Parameter variation for the 12 parameters with the highest coefficient of variation for the Kienhorst and Tharandt ~~plot~~plot – based on the ~~mean~~average of calibrated parameter values derived from the 30 best simulations ~~of the 11 profiles~~ (upper figures) and based on the individual parameters of the 30 best simulations for soil profile 1 (lower figures)

Further, ~~the comparison of the two types of calculated CV~~ the CV was calculated based on the individual parameters of the 30 best simulations for the single profiles, reflecting model uncertainty and allows ~~determining~~assessment of whether variability in model outcomes is driven more by differences in soil profile characteristics or by the uncertainties inherent in the model structure and parameterization (Fig. 10, lower part). The results show that the variation within the 30 best simulations for the individual soil profiles exceeds the variability observed between the 11 soil profiles for most of the parameters ~~This effect is particularly pronounced~~ at the Kienhorst and Tharandt plot. This indicates a relatively wide range of parameter sets yielding similarly good model performance. Such behaviour is commonly referred to as equifinality, meaning that different parameter combinations can lead to comparable simulation results. At both plots, this model related uncertainty, expressed as the variation among parameter sets, exceeds the variation attributable to differences between soil profiles.

3.3~~.~~ Influence of spatial variability and model parameter uncertainty on simulated groundwater recharge

~~Besides certain similarities, clear differences in the time series of daily groundwater recharge estimates at the two plots can be observed (Fig. 9).~~ The daily groundwater recharge time series revealed pronounced fluctuations throughout the study periods, with seasonal and vegetation-period effects distinctly evident (Fig. 11). At both the Kienhorst and Tharandt plots, groundwater recharge predominantly occurs outside the vegetation period, between November and April, when the consumption of precipitation water by processes such as evaporation, root water uptake and transpiration is reduced to a minimum. Conversely, between April and October, these processes utilize nearly all available precipitation water, effectively limiting groundwater recharge during the vegetation period. Despite these shared temporal patterns, the magnitude, variability and temporal distribution of recharge events differed substantially between the two contrasting soil environments.

At Kienhorst plot, characterized by a homogeneous sandy soil, groundwater recharge exhibited sharp, high-amplitude peaks that occurred shortly after major precipitation events. The high hydraulic conductivity and low water-holding capacity of the sand, facilitated rapid infiltration and percolation. Consequently, recharge responded almost immediately to rainfall inputs, resulting in short but intense recharge pulses. This rapid response produced a high degree of short term variability throughout the year, with frequent fluctuations in recharge rates even during transitional seasons. The results displayed relatively small differences in the magnitude and timing of recharge events between the 11 soil profiles, reflecting the overall homogeneity of the site. Variability among profiles was primarily expressed in the height of individual peaks, while the temporal structure remained largely consistent across simulations.

~~A detailed examination of the simulated time series reveals that the greatest discrepancies between profiles, reflecting the uncertainty arising from the different characteristics of the 11 soil profiles at the sites, emerge following precipitation events occurring outside the vegetation period. During the growing season, when soil water fluxes are generally low due to high evapotranspiration, the time series exhibit notably similar patterns across profiles, indicating limited vertical percolation and groundwater recharge. Substantial differences, however, are observed in the magnitude and timing of groundwater recharge between the two plots. At Kienhorst, recharge is characterized by relatively uniform and moderate values during the non-vegetation period. Conversely, the Tharandt plot exhibits episodic and significantly more intense recharge events, predominantly following stronger precipitation.~~

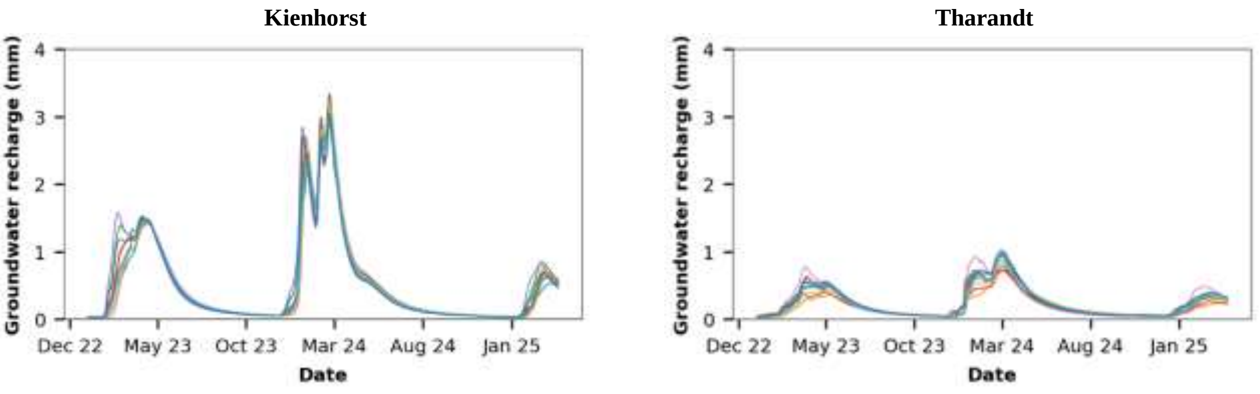

Figure ~~9~~11 Simulated time series of daily groundwater recharge based on model parameterisation of the individual 11 profiles for Kienhorst and Tharandt plot - mean of the 30 best simulations per soil profile ~~(upper figures), simulated time series of daily groundwater recharge – mean as well as minimum and maximum values of the 30 best simulations exemplary for soil profile 1 (lower figures)~~

In contrast, at Tharandt plot, underlain by a heterogeneous loamy soil with a substantial stone content, exhibited a markedly attenuated recharge signal. Peak magnitudes were consistently lower and recharge events were broader and more prolonged. The reduced hydraulic conductivity and higher field capacity of the loamy matrix delayed percolation, causing water to be retained in the upper soil layers before contributing to recharge. As a result, the temporal variability was considerably dampened, and recharge patterns appeared smoother and more regulated. Sensitivity to precipitation events was also lower, recharge increases occurred only after sustained wet periods or when soil moisture approached saturation, leading to a delayed and buffered hydrological response. Moreover, heterogeneity of soil matrix including bypass flow contributed substantially to the variability among the 11 soil profiles, which is slightly more pronounced at the Tharandt plot than at the Kienhorst plot. This variability was expressed both in the magnitude and timing of recharge events.

Considering the range of the 30 simulated time series of groundwater recharge per profile, reflecting model uncertainty, it becomes evident that the largest discrepancies between the individual simulations occur predominantly during periods outside the growing season and following heavy precipitation events (Fig. ~~9~~12).

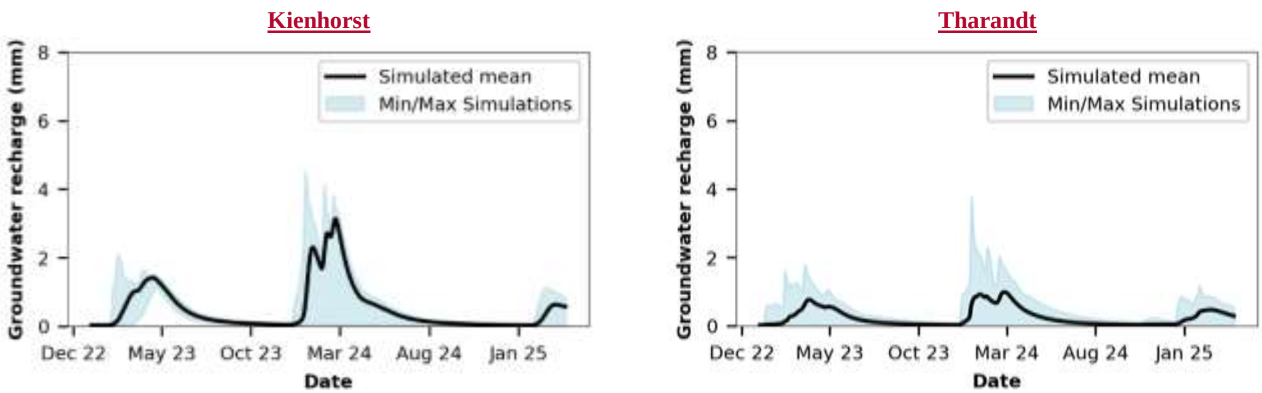

Figure 12 Simulated time series of daily groundwater recharge based on model parameterisation of the individual 11 profiles for Kienhorst and Tharandt plot - mean as well as minimum and maximum values of the 30 best simulations exemplary for soil profile 1

The uncertainty band is particularly wide during periods of high recharge, indicating that peak events are more sensitive to parameter choices than low-flow periods. During periods of low recharge, the uncertainty band narrows considerably, indicating that the model is more constrained under dry conditions. Moreover, the spread between the simulations is slightly more pronounced at the Tharandt plot compared to the Kienhorst plot. This indicates that groundwater recharge at Tharandt site is more sensitive to parameter variability and structural assumptions within the model.

An analysis of cumulative groundwater recharge highlights substantial spatial variability across the 11 soil profiles at both plots separated for the years 2023 and 2024 (Fig. 1~~0~~3). At the Kienhorst plot, ~~mean~~ annual recharge among the 11 profiles ranged from ~~60~~139 to ~~126~~178 mm in 2023 and from ~~115~~226 to ~~194~~254 mm in 2024~~, while the groundwater recharge calculated using the model parameterisation based on the mean value of the 11 soil moisture time series was~~ In contrast, the ~~At~~Tharandt plot showed markedly lower recharge rates, with values ~~varied~~ between ~~80~~51 and ~~134~~77 mm in 2023 and ~~between 34~~85 to ~~123~~114 mm in 2024, ~~the corresponding mean values amount to 119 mm for 2023 and 103 mm for 2024~~while exhibiting a similarly degree of profile-to-profile variability. These differences primarily reflect the contrasting soil hydraulic environments: the sandy, homogeneous substrate at the Kienhorst plot promotes efficient percolation and thus higher recharge amounts, whereas the stone-rich, loamy soil at the Tharandt plot restricts percolation and reduces overall recharge, even though its structural heterogeneity does not translate into substantially greater spatial variability among profiles.

Kienhorst **Tharandt**

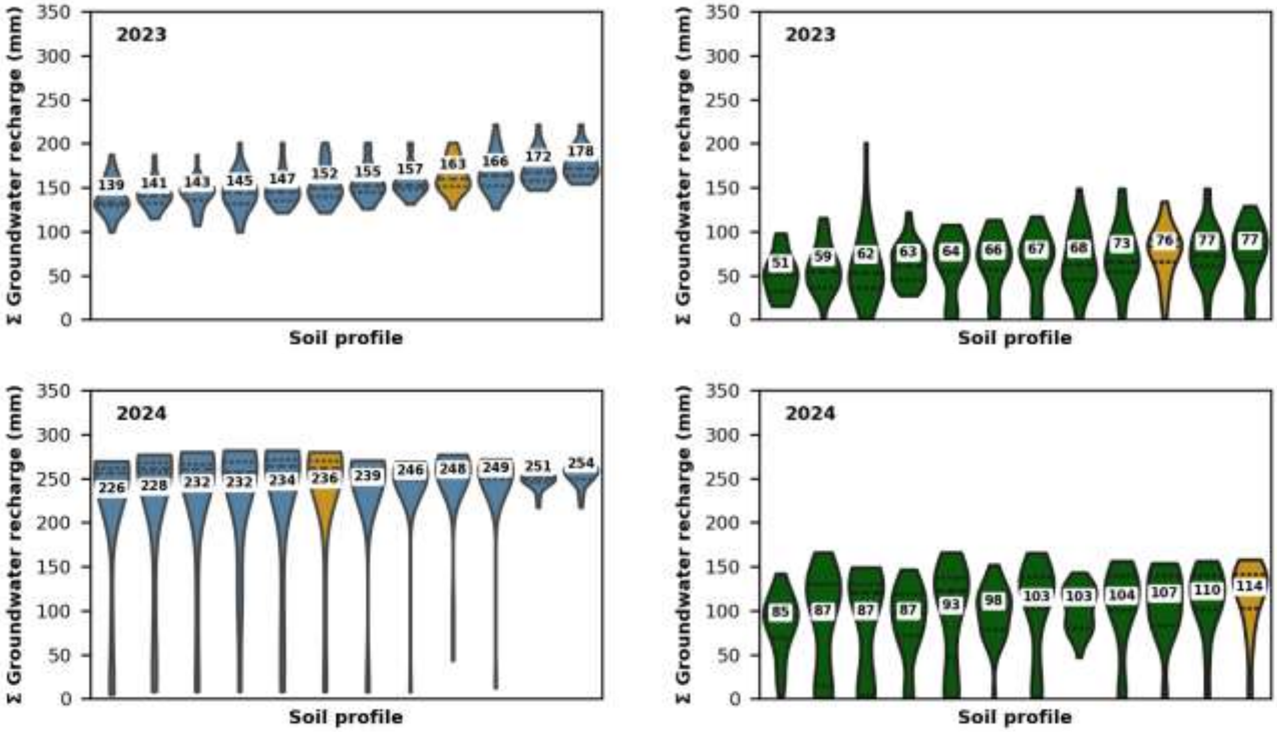

Figure 1~~0~~3 Calculated cumulative groundwater recharge volume ranges based on the parameter sets of the 30 best simulations for the individual 11 soil profiles (blue/green) as well the average value given as a number for each profile - separated for 2023 (upper figures) and 2024 (lower figures) at Kienhorst and Tharandt plot, furthermore the calculated cumulative groundwater recharge volume ranges based on the parameter sets of the 30 best simulations for the mean value of the 11 soil profiles (orange), the violins display the upper bound as the third quartile (75th percentile), the lower bound as the first quartile (25th percentile) as well as the median, the outer edges of the violin extend to the actual minimum and maximum values of the data.

At Kienhorst site, the groundwater recharge calculated using the model parameterisation based on the mean value of the 11 soil moisture time series lies close to the centre of the ensemble (163 mm in 2023 and 236 mm in 2024), suggesting that the spatially averaged soil moisture signal provides a representative estimate of annual recharge for this relatively homogeneous site. At the Tharandt plot, the mean-based values also fall within the ensemble range (76 mm in 2023 and 114 mm in 2024), although the 2024 value lies at the upper boundary of that range and therefore does not necessarily represent the central tendency of the profile-specific simulations. This reflects the nonlinear relationship between soil moisture dynamics and percolation processes in heterogeneous soils: averaging soil moisture does not fully capture the variability introduced by preferential flow and spatially variable hydraulic properties.

To further analyse the recharge dynamics and to check the plausibility of calculated values, annual groundwater recharge was expressed as a percentage of annual precipitation. At Kienhorst plot, recharge amounted to 20 to 26 % of precipitation in 2023 and 39 to 44 % in 2024. At Tharandt plot, the corresponding values were 6 to 9 % in 2023 and 12 to 15 % in 2024. These percentages highlight the strong influence of soil hydraulic properties on the partitioning of precipitation: despite receiving substantially more rainfall, Tharandt plot exhibits markedly lower recharge efficiency due to higher water retention, the buffering effects of the loamy matrix and preferential pathways promoting localized bypass flow. In contrast, the sandy soil at Kienhorst plot promotes rapid drainage and limited water storage, resulting in a much larger fraction of precipitation contributing to groundwater recharge.

To assess the plausibility of the simulated groundwater recharge and to ensure that the simulated amounts are physically realistic in relation to the available water input and the site-specific evaporative demand, full annual water balance evaluation for the years 2023 and 2024 was carried out based on the mean model parameterisation of the individual 11 profiles (Figure 14, Supplement Table 15 and 16).

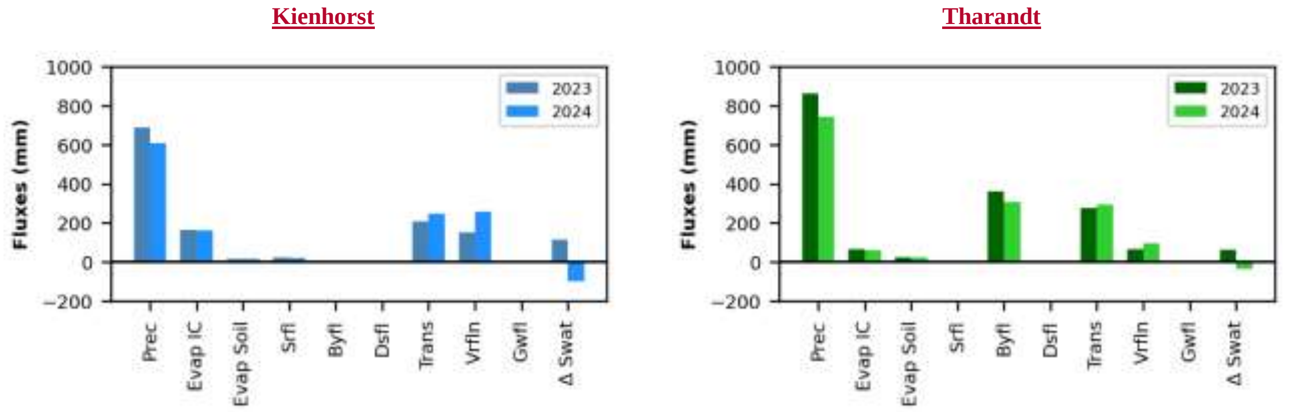

Figure 14 Calculated water balance components based on the mean model parameterisation of the individual 11 profiles for Kienhorst and Tharandt plot – Prec = precipitation, Evap IC = interception evaporation, Evap soil = soil evaporation, Srfl = surface runoff, Byfl = bypass flow, Dsfl = lateral or downslope movement of matric water to streamflow, Trans = transpiration, Vrfln = vertical drainage to groundwater, Gwfl = discharge of groundwater to streamflow, Δ Swat = change of soil water storage

The results of the water balance indicate that the dominant processes consuming precipitation input differ between the two sites, reflecting both their contrasting soil hydraulic properties and the structure of the model. At the Kienhorst plot, precipitation is primarily partitioned into interception, transpiration and substantial vertical drainage to groundwater, consistent with the rapid percolation and limited storage capacity of the sandy substrate. At the Tharandt plot, in contrast, precipitation is consumed mainly by interception, transpiration and bypass flow, with groundwater recharge remaining comparatively small due to the strong retention and reduced matrix conductivity of the loamy, stone-rich soil as well as the stone induced preferential pathways. The negative change of soil water storage at both plots in 2024 indicate a net depletion of soil water storage, which is plausible given the dry conditions in 2024 and the stronger evapotranspirative demand during the growing season. Overall, the balance closes well and the relative magnitudes of the fluxes align with the expected soil hydraulic behaviour at both sites.

3.5 Minimum number of measurements

The results of the performed bootstrappingMonte Carlo–based subsampling procedure ~~by using a two-sample Kolmogorov–Smirnov (KS) test indicate that when using a low number of soil profiles, specifically fewer than 5 profiles for the Kienhorst and Tharandt plot (Fig. 11), significant differences from the full dataset frequently occur. In these cases, the proportion of tests showing non-significant differences remains on a lower level, indicating that such small subsets do not adequately represent the overall groundwater recharge distribution. Conversely, with more than 6 profiles at both plots, over 95% of tests indicate non-significant differences, meeting the typical criterion for statistical significance.~~ show that groundwater recharge estimates vary substantially when only a small number of soil profiles is used and they become statistically stable only once a sufficient sample size is reached (Figure 15). A comparison of the two study sites highlights slight pronounced differences in the sampling effort required to achieve the level of statistical reliability. At Kienhorst plot, only two soil profiles are sufficient for 95% of all subset means to remain within ±10% of the overall mean, indicating a relatively homogeneous system with low spatial variability. In contrast, the Tharandt plot requires approximately three profiles to reach the same accuracy threshold, reflecting a higher degree of spatial heterogeneity. These findings demonstrate that the number of profiles needed to obtain robust groundwater recharge estimates is strongly site-dependent.

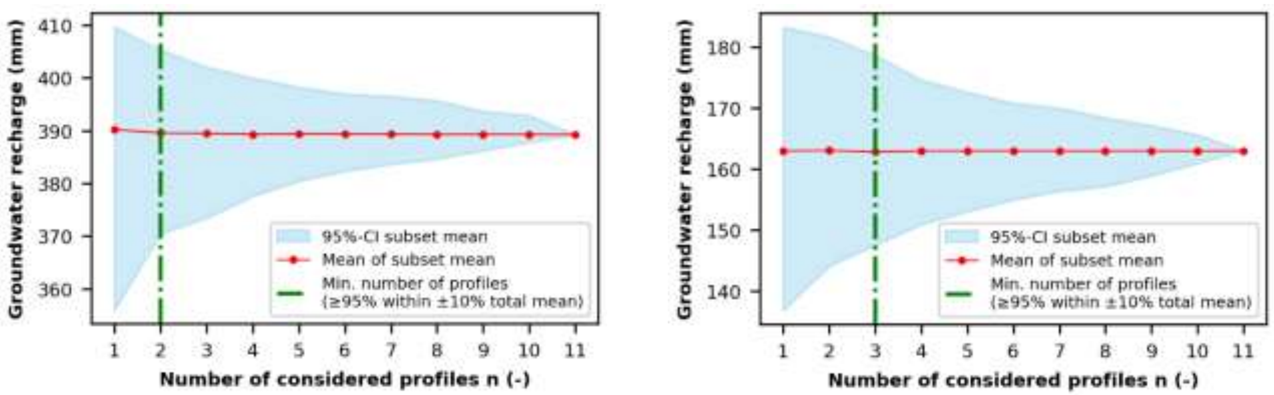

Figure 1~~1~~5 Results of the Monte-Carlo subsampling based on 330 the randomly drawn groundwater recharge subsets for Kienhorst and Tharandt plot - the blue band shows the 95% confidence interval of the subset means, the red line represents the average subset mean for each sample size and the green vertical line marks the minimum number of soil profiles required for 95% of all subset means to fall within ±10% of the overall mean.

~~Percentage of tests with not significant differences between the aggregated groundwater recharge value distributions of the chosen profiles (30 * n profiles) and the full dataset of groundwater recharge values (11 profiles * 30 = 330) for varying numbers of profiles assuming under the null hypothesis that the sample originates from the same distribution as the overall dataset.~~

4 Discussion

4.1 Observed soil moisture variability

Observed soil moisture at the investigated forest plots revealed pronounced differences, both laterally across the investigated area and vertically with soil depth with larger fluctuations and absolute values at the Tharandt plot. These differences are primarily driven by site-specific factors like rainfall/throughfall patterns, soil hydraulics as well as subordinated by vegetation properties. The relatively uniform temporal and absolute progression of soil moisture observed at the Kienhorst plot reflects the homogeneous characteristics of its soil matrix. The sandy soil, characterized by evenly distributed pore spaces and low water-holding capacity over the entire soil profile, contributes to the consistent distribution of soil moisture with moderate volumetric content across all depths. In contrast, likewise to the soil moisture patterns found by Berthelin et al. (2023) the soil moisture dynamics at the Tharandt plot exhibit significant variability, attributable to its heterogeneous soil characteristics. This includes alternating layers of silty soil with variable permeability, higher stone content, and underlying geological features such as impermeable layers of clayey material beneath the upper soil horizons. The observations align with the findings of Vereecken et al. (2016), who highlighted the influence of soil texture and hydraulic properties on spatial variability in soil moisture. At Tharandt plot, accumulation of stagnant water during periods of heavy rainfall at some locations underscores the site's sensitivity to rainfall. This phenomenon is consistent with prior studies by Famiglietti and Wood (1994), which emphasize the role of reduced soil permeability and hydraulic conductivity in limiting infiltration rates and enhancing water retention within heterogeneous soil profiles.

4.2 Model calibration

Although the uncalibrated model reproduces the general temporal patterns of soil-moisture dynamics, it systematically overestimates moisture levels and fails to capture the observed variability reflected in the poor variability and mean bias components of KGE. This is indicating structural and parametric deficiencies in the representation of soil hydraulic and root properties. For example, overestimated saturated hydraulic conductivity (Ksat) or mis-scaled van Genuchten parameters may lead to overly rapid drainage and exaggerated soil moisture variability. Likewise, an underestimation of soil water storage capacity due to low porosity or limited rooting depth can further contribute to the observed biases. Such shortcomings may lead to unrealistic percolation fluxes and potentially inflated groundwater recharge estimates, underscoring the need for targeted model calibration at the two sites of investigation.

Following the identified performance limitations of the uncalibrated model, the subsequent calibration substantially improved the simulation of soil moisture dynamics and emphasises the need for site-specific calibration. Despite the spatial heterogeneities in soil characteristics, the SVAT model, when calibrated with site-specific soil moisture observations, was capable of capturing the observed dynamics and variability for most profiles at both plots with acceptable precision. ~~This indicates the model's capacity in general to represent key hydrological processes such as infiltration, evapotranspiration, root water uptake, water retention and soil water redistribution under diverse conditions, what can be proven by sufficient KGE values for most of the observation points.~~ The applied calibration substantially enhances confidence in the model's representation of subsurface water storage dynamics.

Nevertheless, discrepancies between observed and simulated soil moisture remain, particularly slight mean bias and variability bias tendencies that point to residual structural or parametric deficiencies. ~~particularly in response to high-intensity precipitation events followed by rapid and strong increase in soil moisture.~~ The model results tended to underestimate the rapid rise ~~increase~~in soil moisture and struggles to replicate the absolute magnitude of the observed response during high-intensity precipitation events. ~~of soil moisture values.~~ Consequently, short-term peak dynamics and associated rapid percolation pulses may be underrepresented. Because groundwater recharge estimates are directly derived from the simulated percolation response, the inability to represent these rapid transitions implies that recharge may be underestimated during such conditions. These discrepancies suggest limitations in the parameterization of the model for heterogeneous soil profiles and highlight inherent simplifications in the 1D modeling approach when preferential or fast flow processes dominate. Processes that have been identified as important drivers of focused recharge in heterogeneous soils (Berthelin et al., 2023; Ries et al., 2015) are not explicitly resolved in the model. ~~. This may restrict the model's capacity to fully capture the complexities of plot-specific conditions and processes such as spatial soil heterogeneity and the lateral water flux between neighbouring soil compartments~~This may restrict the model's capacity to fully capture the complexities of plot-specific conditions and processes such as spatial soil heterogeneity and the lateral water flux between neighbouring soil compartments (McDonnell, 1990). ~~, The importance of focussed recharge processes due to soil heterogeneities was also pointed out by Ries et al. (2015) and Berthelin et al. (2023). Yet, the generally high KGE performances indicate that the weaknesses of the model in representing this behaviour well did not substantially affect the overall realism of the simulations.~~ Part of the discrepancy between simulated and observed soil moisture ~~In addition, we must account that the observed differences in absolute soil moisture values~~ may partly stem from the measurement uncertainty that originates from the accuracy of the soil moisture sensors used in this study, which is ± 3 % of soil moisture (Truebner Company, 2025) and the effective uncertainty of field soil moisture measurements inherent to all soil moisture measurements (Jackisch et al., 2020). ~~This inherent variability introduces additional uncertainty into the observed data, which should be taken into account when interpreting deviations between simulated and observed values, particularly in profiles where differences fall within this error range.~~ This uncertainty becomes particularly relevant during the substantial fraction of the observation period characterized by very dry conditions (<5 vol.-%), where the relative influence of the sensor error is large and the numerical dominance of dry states in the calibration dataset may influence parameter optimization. Although groundwater recharge predominantly occurs under wetter conditions, where percolation is active and sensor uncertainty is comparatively less critical, indirect calibration effects cannot be fully excluded. There is a risk that the calibration procedure, applied to the full time series, may favour parameter sets that reproduce the prolonged dry states well, while comparatively underrepresenting the wetter periods that are more relevant for groundwater-recharge generation. To assess the potential influence of this bias more systematically, future work should compare calibrations based on the full time series with calibrations restricted to periods exceeding $\theta > 10$ vol.-%, allowing an evaluation of how strongly the representation of dry conditions affects recharge estimates.

Further, ~~On the other site,~~ the analysis showed that incorporating multi-depth soil moisture observations significantly improves the representativeness of the simulated soil water distribution, especially in heterogeneous soil systems as at ~~in~~ Tharandt plot. Multiple observation points along the soil profile allow for a more nuanced assessment of the sensitivity of individual model parameters at different depths by calibrating the model against a higher density of data that captures both surface and subsurface processes. This was also observed by Houska et al. (2014), who demonstrated that the inclusion of soil moisture data at different depths increases the representativeness of the simulated soil water distribution and thus increases the identifiability of model parameters.

Building on the calibration results, the subsequent validation using the calibrated parameter sets revealed a mixed model performance, with acceptable temporal robustness at the Kienhorst plot but clear limitations at Tharandt plot, where the calibrated model struggled to reproduce wet-dry changes and soil moisture variability. These shortcomings are plausible given that the hydrological conditions for the validation period differed substantially from the calibration period. Consequently, the application of the Tharandt parameter set for estimating groundwater recharge in 2025 is associated with increased uncertainty and a site- and period specific recalibration would likely improve model reliability under such altered conditions. In general, it can be stated that the use of the calibrated parameters is unproblematic as long as hydrological conditions do not deviate substantially from those of the calibration period, whereas markedly altered conditions warrant a careful reassessment of their suitability for example through recalibration or by extending the validation period. Despite this limitations at the Tharandt plot, the calibrated parameter sets were retained because they provide a consistent and physically plausible representation of system dynamics during the calibration period and thus form a reliable basis for subsequent analyses for this period.

4.3 Variability of calibrated model parameters

An analysis calibrated model parameter sets for both plots revealed a higher degree of variation in area and depth at the Tharandt plot compared to Kienhorst plot, as indicated by the coefficient of variation (Supplement, Fig. S~~3~~5 and S~~4~~6). This reflects the greater heterogeneity in soil physical properties observed at Tharandt plot, whereas Kienhorst plot is characterized by more homogeneous plot conditions~~,~~ and is a direct result of the spatially variable observed soil moisture dynamics found within the plots. Despite this broader range of plausible parameter combinations at Tharandt plot, the overall model performance remained at an acceptable level. However, a slightly reduced agreement between observed and simulated soil moisture values was observed compared to Kienhorst plot, suggesting a more complex interplay between parameter uncertainty and model behaviour in heterogeneous environments. The analysis further reveals that key soil hydraulic parameters and soil process parameters show a greater variation compared to vegetation and root parameters. This underscores their key role in soil water dynamics and highlights their contribution to overall model uncertainty. These insights are supported by the findings of Kreye and Meon (2016), who highlighted the significant impact of sub-scale spatial variability in soil hydraulic properties on hydrological process modelling. Similarly, Scharnagl et al. (2011) pointed out the value of incorporating prior knowledge of soil hydraulic parameters to enhance parameter identifiability in inverse modelling approaches. Complementing these perspectives, Baroni et al., 2010 demonstrated that uncertainties in the determination of soil hydraulic properties can substantially affect the overall performance of hydrological models.

Furthermore, analysis of the 30 best parameter combinations for each individual soil profile revealed that model-based uncertainty (the variation within the 30 best-performing parameter combinations) exceeds plot-based variability (differences between the 11 soil profiles).~~. This finding is particularly pronounced at the Kienhorst plot~~ Both at the Kienhorst plot, where the limited variation in measured soil properties resulted in only minor differences in profile-specific parameterisation, as well as at the Tharandt plot, where input parameters varied more strongly, parameter non identifiability emerged as a key contributor to predictive uncertainty. ~~, where the limited variation in measured soil properties resulted in relatively minor differences in input parameterization across profiles~~T~~t~~he wide range of equally well-performing parameter sets for individual profiles reflects the issue of equifinality, where multiple parameter combinations can yield similar simulation outcomes. This suggests that ~~, for Kienhorst plot,~~ model parameter ambiguity dominates the overall uncertainty. ~~This means that at plots with relatively uniform soil properties, where physical variability is limited, model-based uncertainty is the more important factor for prediction accuracy. At the Tharandt plot, by contrast, the difference between site-related and model-related parameter variation was less pronounced.~~ For several parameters, both sources of uncertainty, natural spatial heterogeneity and model-based calibration uncertainty, contributed similarly to the overall variation. At sites with pronounced heterogeneity in soil properties, such as Tharandt, this can amplify the spatial component of uncertainty and partly mask the effects of parameter equifinality. ~~This can be attributed to the more pronounced heterogeneity in soil characteristics at Tharandt, which elevates the spatial component of uncertainty and thereby partially masks the effects of equifinality.~~ In particular, these findings show that the dominant source of uncertainty can vary significantly depending on plot characteristics. At homogeneous plots, model structural uncertainty and equifinality may outweigh physical variation, while at heterogeneous sites, spatial variability in input data may dominate. Therefore, parameter selection should be guided not only by sensitivity analysis but also by an underploting of the plot-specific balance between model and data-driven uncertainty.

Based on the findings, the calibration of soil hydraulic parameters should remain plot-specific, as their variability and influence on model outcomes is both large and highly context-dependent. Conversely, parameters with consistently low variability across profiles, such as many vegetation~~-~~ related parameters, may be suitable for regionalization or transfer between plots, potentially improving scalability and reliability of water balance simulations.

4.4 Groundwater recharge estimation

Despite differences, both sites displayed a clear alignment of major recharge periods with seasonal climatic conditions, indicating that atmospheric forcing is the dominant driver of recharge dynamics. ~~The observed differences in groundwater recharge between the Kienhorst and Tharandt plots can be attributed most to variations in rainfall distribution, tree species and soil texture, what is influencing infiltration rates, water retention capacities and the timing of recharge events.~~ In addition to seasonal effects, the main differences in the time series that can be attributed to the different soil properties of both sites. Groundwater recharge at the Kienhorst plot is rapid and episodic ~~relatively uniform with moderate values~~ reflecting the sandy soil texture, associated with high permeability and low field capacity, promoting continuous infiltration and a steady recharge response to precipitation events. Limited water retention in these soils allows for minor recharge even during the vegetation period, albeit at the expense of reduced water availability for plant uptake (Hillel, 2003). ~~Similar to Ries et al. (2015) recharge occurred only in distinct pulses following heavy rainfall events.~~ In contrast, the loamy and heterogeneous soil at the Tharandt plot, ~~with higher field capacities and lower permeability, delays percolation until antecedent moisture conditions exceed the storage capacity of the upper soil layers.~~characterised by higher field capacities and lower matrix permeability, substantially delays the onset of percolation. The presence of discontinuous macropores and stone induced preferential pathways promotes rapid but spatially limited bypassing of the matrix, which reduces effective infiltration and prevents deep percolation until the upper soil layers approach their storage capacity. As a result, the recharge response is markedly damped and delayed, with lower peak magnitudes and broader, more prolonged recharge events. This restricted matrix infiltration further contributes to the low recharge efficiency despite substantial precipitation inputs. Moreover, the increased water retention at Tharandt plot enhanced soil water availability for vegetation, effectively suppressing groundwater recharge during the vegetation period (Hillel, 2003). These findings underscore the critical role of soil hydraulic properties, particularly conductivity and retention capacity, in regulating the temporal dynamics of groundwater recharge, consistent with observations by Vereecken et al. (2016) as well as the studies of Beven and Binley (1992) and Zhao et al. (2018). This is emphasizing the complexity of water fluxes in heterogeneous soil systems and their limiting effect on recharge efficiency.

The bypass flow at Tharandt plot further influenced the recharge dynamics. Because a portion of the infiltrating water bypassed the fine-textured matrix and percolated directly through preferential pathways, the matrix response remained comparatively sluggish. This process prevented full replenishment of the soil water storage before deeper percolation occurred, reinforcing the damped recharge signal.

Beyond the general attenuation of the recharge signal, Tharandt plot exhibited variability among the 11 simulated soil profiles, exceeding the profile-to-profile differences observed at Kienhorst plot. ~~,~~The combined effects of matrix heterogeneity and bypass flow contributed substantially to the variability among the 11 soil profiles, reflected in differences in both the timing and magnitude of recharge events. Profiles with stronger bypass flow exhibited earlier and occasionally sharper recharge impulses, whereas profiles with weaker bypass flow showed more delayed and smoother recharge trajectories. This divergence reflects the structural heterogeneity of the site, including differences in macroporosity, stone content and the hydraulic properties of preferential flow domains.

Regarding to groundwater recharge quantities, the results fall within the range of values reported in the literature for both plots, suggesting annual recharge rates of ~~approximately~~ 80 –~~-~~ 150 mm for Tharandt in the period from 1968 to 1999 (Goldberg and Bernhofer, 2007) and ~~around~~ ~~100~~30 - 296 mm for Kienhorst in the period 1961 to 2019~~(Birner et al., 2015)~~(Ziche and Riek, 2024), what supports the plausibility of the model outcomes. ~~Despite a more heterogeneous soil and a greater variability in parameterisation at the Tharandt plot, the variability of cumulated groundwater recharge between the different soil profiles at the more homogeneous Kienhorst plot is not substantially lower.~~ At the Tharandt plot, the heterogeneous soil conditions and the resulting greater variability in parameterisation led only to a slightly higher spread in the estimates of cumulative groundwater recharge across profiles compared with the more homogeneous Kienhorst plot. Regardless of hydrological conditions, the relative variability of mean groundwater recharge among the 11 profiles at Tharandt was roughly twice as high as at Kienhorst. This indicates that neither site heterogeneity nor the range of input parameters alone fully explains the variation in recharge estimates. Rather, other factors, such as model structure, process representation and calibration uncertainty, appear to play a decisive role in shaping recharge variability at the catchment scale. This observation is consistent with findings by Maxwell and Condon (2016), who emphasised the complex interplay between soil water fluxes, landscape features and recharge processes as well as stressed that heterogeneity does not always lead to higher variability in groundwater recharge results. It further supports the notion that model behaviour can be dominated by structural and parametric uncertainty rather than physical input variability alone. A key contributor to this phenomenon is the concept of equifinality, as extensively discussed by Beven and Freer (2001) and Beven (2006). While the model is able to reproduce the observed soil moisture dynamics with reasonable accuracy using different parameter sets, the existence of multiple parameter sets with comparable performance indicates a high degree of parameter non-uniqueness. This not only increases predictive uncertainty, but also suggests that the model structure, particularly in its one-dimensional form, may not fully capture the spatially distributed and lateral processes that influence soil water movement leading to uncertainties in groundwater recharge estimation.

The results further show that the calculated groundwater recharge based on the parameter sets of the 30 best simulations for the mean value of the 11 soil profiles at the Kienhorst plot provided a representative recharge estimate~~represents the range of groundwater recharge of the individual 11 profiles quite well~~. This averaging over serval soil moisture profiles in a forest was also proven to be useful by Berthelin et al. (2023). It suggests that, in homogeneous settings, using averaged values may provide a reasonably accurate estimate. For the Tharandt plot, this calculation did not reflect the central tendency of the profile specific simulations, the value of groundwater recharge determined in this way lies at the upper boundary of the range and therefore does not necessarily represent the central tendency of the profile-specific simulations. In this case, it would lead to an overestimation of the actual groundwater recharge. This highlights the importance of a differentiated consideration of plot-specific soil profiles and moisture distributions in modelling, in order to ensure realistic results. Solely relying on mean values cannot always adequately capture the system's heterogeneity ~~-~~and poses the risk of systematic biases in the water balance, especially in heterogeneous settings, where nonlinear percolation processes and preferential flow introduce substantial variability.

Hence, in order to cope with uncertainties in obtaining representative recharge estimates, it is advisable to define an adequate number of soil profiles equipped with soil moisture sensors that serve as critical calibration points. The performed analysis~~bootstrapping~~ (Fig. 1~~1~~4) indicated that below two (Kienhorst) or ~~6~~three (Tharandt), randomly chosen profiles, spatial variability as well as model uncertainty can still bias the representativeness of recharge estimates. ~~while selecting more than 6 profiles, the parameter uncertainty is the most prominent source of variability.~~ The results demonstrate that, regardless of site-specific characteristics and model uncertainty, the use of at least two or three soil profiles is recommended to ensure for 95% of all groundwater recharge subset means to remain within ±10% of the overall groundwater recharge mean ~~reliably capture the spatial distribution of groundwater recharge~~ at the 20 × 20 m plot scale ~~with a confidence level of 95%~~ when using the LWFBrook90 model calibrated with soil moisture data. ~~Nevertheless, the analysis also indicates that even when only a single soil profile is used, groundwater recharge can still be estimated with moderate confidence in approximately 50% of all test iterations. In other words, in half of the cases, the groundwater recharge derived from one soil profile matches the overall spatial distribution across the study area.~~ In conclusion, a targeted approach using two or three, well-instrumented soil profiles provides a robust, efficient, and practical methodology for groundwater recharge estimation using LWFBrook90, balancing model reliability with fieldwork feasibility.

4.5 Transferability and generalizability of the findings

Although the experimental setup is inherently site specific and relies on detailed soil characterization, vegetation information and profile-specific soil moisture observations, the study provides insights that extend beyond the two investigated plots. The results should therefore be interpreted as a proof of concept for high-resolution recharge modelling under realistic field conditions rather than as a universally transferable framework. Importantly, plot-scale analyses remain essential even in the context of multi-site or gridded recharge estimations. Large-scale approaches depend on upscaled parameterisations that may overlook local heterogeneities and nonlinearities in infiltration and percolation, whereas plot-scale studies provide the process understanding and high-resolution data needed to improve these models and to guide the selection of representative parameters. Focusing on plot-scale groundwater recharge allows model performance to be evaluated under well-controlled conditions using detailed soil moisture observations, thereby capturing site-specific processes—such as root-zone dynamics, canopy interception and soil hydraulic behaviour—that are often averaged out or simplified in large-scale frameworks. At the same time, the contrasting environmental conditions across the two forest plots, representing typical combinations of dominant tree species and soil types in Central European forests, suggest that the underlying process relationships are not unique to these sites but may be indicative of similarly structured and heterogeneous forest soils. Nevertheless, the generalisability of the results remains constrained, and future work should include multi-site comparisons, simplified proxy approaches and scaling strategies to more robustly assess transferability across broader environmental gradients. Bridging the gap between plot-scale understanding and landscape-scale application is therefore essential, and we see this study as a step toward that goal.

5 Conclusions

The findings of the investigation underscore the critical need for a sufficiently dense and vertically resolved network of soil moisture measurements to ensure robust model calibration and to constrain predictive uncertainty for estimating important water balance components like groundwater recharge with a SVAT model. The use of mean values derived from a limited number of measurement profiles for calibration can mask extremes in soil moisture variability, leading to systematic over- or underestimations, especially ~~both~~ in ~~homogenous and~~ heterogeneous environments. The results of this study clearly highlight the need to expand the spatial coverage of soil-moisture measurements and the associated groundwater recharge modelling, particularly at heterogeneous sites where variability in soil matrix properties is higher. Such a denser observation network would enable to cover the influence of soil moisture variability as well as model structure and equifinality on groundwater recharge estimates. Even in areas with low observed spatial variability of soil moisture, model-based uncertainty, resulting from multiple parameter combinations yielding similarly plausible outputs, can dominate simulation outcomes. This underlines the importance of explicitly addressing equifinality and parameter non-uniqueness in model calibration procedures. While the investigations provides indicative thresholds for the number of soil moisture profiles required to capture the dominant sources of uncertainty, the exact number needed to adequately represent both site heterogeneity and model-related uncertainty is highly site-specific and cannot be generalized across locations.

Multi-objective approaches that involve additional data can yield better constrained process parametrizations and give insights into which processes need a more detailed conceptual representation in the model structure. Incorporating isotopic signatures of precipitation and soil water, in addition to soil moisture data, during calibration could be an opportunity to reduce the negative impact of effects such as equifinality on the calibration process and the subsequent estimation of groundwater recharge. Several studies have demonstrated that the complementary use of stable isotope measurements ($\delta^{18}O$, $\delta^{2}H$) in precipitation, along with a comparison to the isotopic signatures in soil water, has proven to be particularly effective in narrowing down parameter uncertainty (Sprenger et al., 2015). By combining isotopic data with soil moisture information, a multidimensional calibration process is enabled, allowing for a more precise identification of parameters that govern key water transport and storage processes within the soil.

Furthermore, the results obtained for evapotranspiration and root water uptake, which significantly influence the estimation of groundwater recharge, can be validated through comparison with measured sap flow data. This validation step not only serves to verify the model's performance but also aids in further reducing the uncertainty in groundwater recharge estimates, thereby providing a promising direction for improving the overall reliability of future SVAT model applications.

Code and data availability

The source code of the LWF-BROOK90.jl model can be downloaded from https://github.com/fabern/LWFBrook90.jl

(Bernhardt, 2020). The complete model spatial input data, the meteorological data and monitoring data used in this study can be obtained upon request.

Supplemental information

The supplement related to this article is available online at …………….

Author contribution

Conceptualization: TF, AH, MM, SS, SR; Investigation (field experiments + data collection): TF; Simulation: JA, TF, KE; data analysis: JA, TF, KE; Evaluation + Visualization: TF, KE; writing (original draft preparation): TF; writing (review and editing): TF, KE, AH, MM, SS, SR.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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