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Evaluation of European hydraulic pedotransfer functions for boreal agricultural soils against Finnish data

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Soil hydraulic properties are essential information for sustainable agriculture and environmental management, yet their measurement is time-consuming and costly. Pedotransfer functions (PTFs) are widely used to estimate these properties from basic soil data, but few have been developed or validated for boreal conditions. This study evaluated two sets of European PTFs for boreal arable soils using a Finnish dataset of 800 water retention curves (5530 measurements) and 293 saturated hydraulic conductivity (K_{sat}) measurements. To assess PTF performance in modelling context, a functional evaluation with HYDRUS-1D was conducted for clayey fields, comparing simulations using measured and PTF-predicted water retention data. Performance of PTFs was reasonable in terms of water retention (RMSE 0.07–0.09 $cm^3\ cm^{-3}$ and R^2 0.63–0.79) and functional evaluation (R^2 0.56–0.97). These results were comparable to previous studies, indicating suitability for boreal arable soils. A hierarchy of PTF performance is provided to guide their selection, while highlighting the importance of considering soil texture in their application. K_{sat} PTFs performed poorly and systematically underestimated measured values (R^2 -2.17 – -0.86), which highlights the demand for further development before reliable application to boreal soils.

Key words: Soil hydraulic properties, Pedotransfer functions, Water retention, Saturated hydraulic conductivity, Functional evaluation, Hydrus-1D

Introduction

Soil hydraulic properties are important information for sustainable agricultural and environmental management, as they regulate key processes such as soil-water balance, plant growth, nutrient availability, erosion, and contaminant leaching (Rabot et al. 2018, Fatichi et al. 2020). Reliable soil property information is becoming increasingly important for maintaining soil health and productivity under changing climate conditions (Lehmann et al. 2020, Blanchy et al. 2023). An important use of such information is computational modelling, which requires representative soil parameterisation to simulate and assess, for example, water and solute dynamics, plant growth, and carbon sequestration across spatial and temporal scales (e.g., Pinheiro et al. 2019, Defterdarović et al. 2021, Hao et al. 2025). However, soil hydraulic property information is often spatially limited, and direct measurements are costly and laborious, making them impractical for large-scale applications.

Pedotransfer functions (PTF) provide a solution by estimating complex soil characteristics, such as hydraulic properties, based on commonly available or easily measurable soil properties (Bouma 1989). Over the years, various PTFs have been developed employing different methodologies, predictor variables, and calibration data (e.g., Schaap et al. 2001, Wösten et al. 2001, Vereecken et al. 2010, Patil and Singh 2016). Two comprehensive PTF sets have been developed for European soils; (1) euptfv1 by Tóth et al. (2015) using linear regression or regression tree, and (2) euptfv2 by Szabó et al. (2021) using random forest. These PTF sets have been evaluated in several studies; for example, Darmann et al. (2024) assessed them using Austrian soil data, while Nasta et al. (2021) based their evaluation on datasets from Europe and the USA, with a few case studies from Italy. Furthermore, euptfv1 has been applied in various hydrological studies, such as Ganot et al. (2017), Tóth et al. (2017), and Zare et al. (2024).

PTFs have only rarely been developed or validated specifically for agricultural soils of boreal climatic zone (Rajkai et al. 1996, Riley et al. 1996), despite previous studies have emphasised that PTFs should be used with caution outside their area of development (Patil and Singh 2016). Thus, it is crucial to test the applicability of the European PTFs for boreal soils. This need is underlined by the EU directive on soil monitoring EC 2025), which proposes using PTFs for estimating soil water retention capacity and saturated hydraulic conductivity. The PTFs by Tóth et al. (2015) and Szabó et al. (2021) were developed with EU-HYDI dataset (Weynants et al. 2013), which primarily included data from temperate, continental, or mediterranean climatic zones of Europe, but only limited amount of data for the boreal climate zone from Sweden and Norway and no data from Finland (Weynants et al. 2013). The distinct climatic conditions of the boreal zone—such as seasonal snow cover, freezing and thawing cycles of the soil, and short growing season—modify soil structure and thus also affect its hydraulic properties (Klöffel et al. 2024).

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Weber et al. (2024) reviewed the current state of PTF development and use with the aim of systematising PTF research and providing a roadmap for future development. A key research gap they identified is the discrepancy between the scale of PTF derivation (from laboratory-measured parameters) and application (at field, catchment, or regional level). PTFs are typically calibrated and validated by directly comparing PTF-predicted hydraulic properties to measured values. To shift the evaluation closer to the scale of PTF application, Weber et al. (2024) recommended applying a functional evaluation. According to the definition of Vereecken et al. (1992), functional evaluation refers to "the statistical examination of the variability in the outcome of a simulation model for a specific application when the variability arises solely from uncertainty in the PTFs". Examples of functional evaluation applied to PTFs can be found in studies by Kalumba et al. (2021), Nasta et al. (2021), Ramos et al. (2023), and Weihermüller et al. (2021).

The objectives of this study were to evaluate the performance of European PTFs by Tóth et al. (2015) and Szabó et al. (2021) for boreal agricultural soils against Finnish data and to provide recommendations for their use and development in these northern conditions. The evaluation consisted of parametric and functional evaluations. The parametric evaluation assessed the performance of PTFs in predicting saturated hydraulic conductivity, van Genuchten (1980) model parameters for water retention, and water content at key suctions (saturation, field capacity, and wilting point) against measured soil hydraulic properties. The functional evaluation compared the results of parameterising HYDRUS-1D (Šimůnek et al. 2013) with both measured and PTF-predicted water retention properties to simulate water table depth and subsurface drainage. The functional evaluation aimed to explore and demonstrate the effects of parameterising water retention properties in a hydrological model with different PTFs. The evaluations covered different soil textures but emphasised clayey soils, which dominate major agricultural areas in southern Finland (Heikkinen et al. 2013). Structured clay soils have complex hydraulic properties (Jarvis 2007), and they have significant water quality impacts due to their high capacity to transport particle-bound phosphorus to surface waters (Uusitalo et al. 2003, Jarvis 2007).

Altogether, this study provides the first comprehensive evaluation of European PTFs for Finnish boreal soils. By testing two widely used PTF sets with data from boreal soils, especially clayey soils common in northern agricultural areas, the study addresses a clear gap in their geographic validation. The two-stage evaluation, combining parametric and functional assessments, supports understanding of PTF suitability, informed application and further development for boreal soils.

Materials and methods

Soil data

The soil data for PTF evaluation was compiled from research conducted between 1982 and 2022 (Alakukku et al. 2010, Vakkilainen et al. 2010, Hakojärvi et al. 2013, Tammeorg et al. 2014, Honkanen et al. 2021, Fayos et al. 2022, Rasa et al. 2023, Soinne et al. 2023, Räty et al. 2024, Suojala-Ahlfors 2024). Soil data from 20 different fields were used, with most samples collected from fields in Jokioinen, south-west Finland (Fig. 1). The dataset comprised 800 water retention curves (WRC; with a total of 5530 water content measurements) from 19 different sites and 293 saturated hydraulic conductivity (K_{sat}) measurements from five sites (Table S1).

Each soil sample included information on sample depth, clay content (CL; mass-% of particles 0–2 µm), silt content (SI; mass-% of particles 2–50/60/63 µm), sand content (SA; mass-% of particles 50/60/63–2000 µm), organic carbon content (OC; mass-%), bulk density (BD; g cm^{-3}), cation exchange capacity (CEC; cmol kg^{-1}), and pH. According to summary statistics (Table 1), the ranges of soil properties in our data fall within those of the EU-HYDI dataset (Weynants et al. 2013), which was used to develop the PTFs evaluated here (Tóth et al. 2015, Szabó et al. 2021). Detailed measurement methods are reported in the original research where the data were collected from (Alakukku et al. 2010, Vakkilainen et al. 2010, Hakojärvi et al. 2013, Tammeorg et al. 2014, Honkanen et al. 2021, Fayos et al. 2022, Rasa et al. 2023, Soinne et al. 2023, Räty et al. 2024, Suojala-Ahlfors 2024). The hydraulic properties were mainly measured using laboratory methods rather than field methods. All relevant data supporting the PTF evaluation were included in the current study, despite the use of varying measurement methods and sample sizes, following an approach similar to the compilation of the EU-HYDI dataset. Since the classification of particle size distribution to soil classes varies on a logarithmic scale, the above-mentioned differences in the upper end of the silt ranges (50/60/63 µm) were considered minor.

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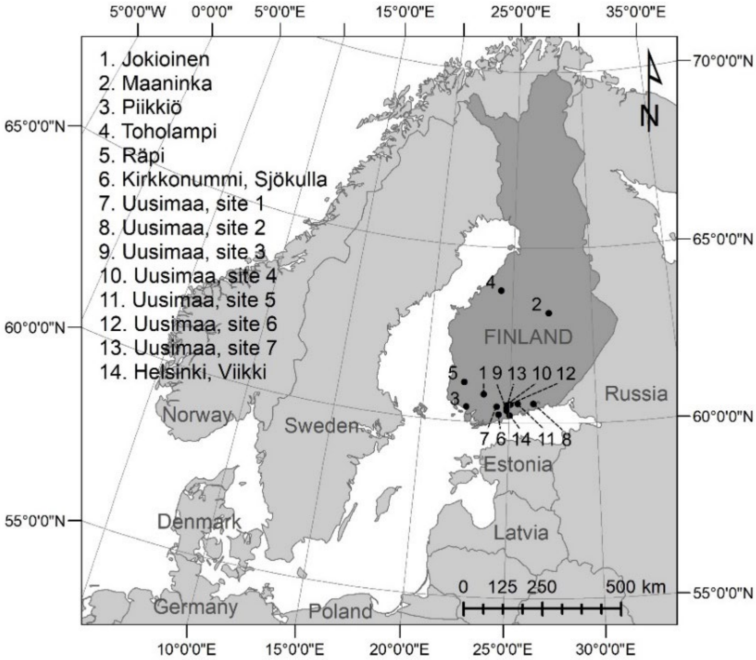

Fig. 1. Locations of the soil data used in this study. The Jokioinen site contains four separate fields, and each of the Uusimaa sites 3, 4, and 5 contains two separate fields (Table S1).

To evaluate the PTF performance across different soil types, the data were divided into four soil texture groups according to the USDA classification of general soil texture groups: clayey, loamy, silty, and sandy soils (Soil Science Division Staff 2017). The distributions of WRC and K_{sat} measurements by these soil texture groups are shown in Table S1.

Table 1. Descriptive statistics of the physicochemical properties of the soil samples used for evaluating the pedotransfer functions (PTFs)

		Sand	Silt	Clay	Bulk density	Organic carbon	Cation exchange capacity	pH
		(%)	(%)	(%)	(g cm^{-3})	(%)	(cmol kg^{-1})	(-)
WRC	Min	1.24	6.00	3.00	0.69	0.30	8.42	5.40
	Max	90.00	67.00	90.10	1.60	7.65	35.75	7.51
	Mean	29.91	36.90	33.19	1.17	2.27	18.11	6.46
	SD	25.98	18.12	22.62	0.21	1.09	5.97	0.43
	Median	17.00	41.02	20.00	1.23	2.11	19.00	6.40
K_{sat}	Min	1.80	6.80	8.32	0.87	0.30	12.60	5.49
	Max	43.47	53.20	90.10	1.64	6.84	35.75	7.51
	Mean	18.79	35.10	46.61	1.27	2.23	21.55	6.33
	SD	12.55	12.93	23.68	0.14	1.33	6.38	0.38
	Median	14.55	34.50	52.00	1.25	1.90	22.65	6.28

Pedotransfer functions

The evaluated European PTFs included those by Tóth et al. (2015; euptfv1) and Szabó et al. (2021; euptfv2), both derived using the EU-HYDI dataset (Weynants et al. 2013). Euptfv1 were derived using linear regression and/or regression trees, while euptf2 were developed using random forest machine learning method. According to Szabó et al. (2021), the euptfv2 improved prediction accuracy, included additional information about prediction uncertainty, and provided functions for more predictor variable combinations in comparison to euptfv1.

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The soil hydraulic properties predicted in this study were water retention and hydraulic conductivity. The focus was on parametric PTFs (Table 2) for deriving the water retention curve, as these parameters are commonly required in modelling applications. Both euptfv1 and euptfv2 used the van Genuchten model (van Genuchten, 1980; VG) to parameterise WRC. The VG model describes soil water retention at a given suction as:

$$\theta_h = \theta_r + \frac{\theta_s - \theta_r}{[1 + (\alpha h)^n]^m} \quad (1)$$

where θ_h is water content at suction *h* [cm^3 cm^{-3}], θ_r and θ_s are residual and saturated water contents [cm^3 cm^{-3}], *h* is suction [cm] (i.e., the absolute value of matric potential or pressure head), and *α* [cm^{-1}], *n* [-] and *m* [-] are shape parameters, with *m* calculated as *m* = 1 – 1/*n*.

In addition to parametric PTFs, an evaluation was conducted for point PTFs (Table S2), which estimate water contents directly at specific suctions: (1) saturation (THS: *h* = 0 cm), (2) field capacity (FC2: *h* = 100 cm; FC: *h* = 330 cm), and (3) wilting point (WP: *h* = 15000 cm). For hydraulic conductivity, the evaluation focused on predictions at saturation (*h* = 0 cm; i.e., K_{sat}).

Table 2 and Table S2 summarise the European PTFs (Tóth et al. 2015, Szabó et al. 2021) evaluated in our study. These PTFs predict the studied hydraulic properties using predictor variables available in our data.

Table 2. Parametric PTFs evaluated in this study

Name of PTF*	Predicted hydraulic property	Predictor variables	Source
PTF20_v1	VG parameters for WRC	CL, SI, SA, OC, pH, CEC	Tóth et al. (2015)
PTF22_v1	VG parameters for WRC	CL, SI, SA, top/subsoil, OC, BD, pH	
PTF21_v1	VG parameters for WRC	CL, SI, SA, top/subsoil, OC, BD	
PTF01_v2	VG parameters for WRC	CL, SI, SA, depth	Szabó et al. (2021)
PTF02_v2	VG parameters for WRC	CL, SI, SA, depth, OC	
PTF03_v2	VG parameters for WRC	CL, SI, SA, depth, BD	
PTF05_v2	VG parameters for WRC	CL, SI, SA, depth, pH	
PTF06_v2	VG parameters for WRC	CL, SI, SA, depth, CEC	
PTF07_v2	VG parameters for WRC	CL, SI, SA, depth, OC, BD	
PTF09_v2	VG parameters for WRC	CL, SI, SA, depth, OC, pH	
PTF10_v2	VG parameters for WRC	CL, SI, SA, depth, OC, CEC	
PTF12_v2	VG parameters for WRC	CL, SI, SA, depth, BD, pH	
PTF13_v2	VG parameters for WRC	CL, SI, SA, depth, BD, CEC	
PTF16_v2	VG parameters for WRC	CL, SI, SA, depth, pH, CEC	
PTF22_v2	VG parameters for WRC	CL, SI, SA, depth, OC, pH, CEC	
PTF25_v2	VG parameters for WRC	CL, SI, SA, depth, BD, pH, CEC	
PTF29_v2	VG parameters for WRC	CL, SI, SA, depth, OC, BD, pH, CEC	
PTF16_v1	K_{sat}	CL, SI, SA, top/subsoil, OC	Tóth et al. (2015)
PTF17_v1	K_{sat}	CL, SI, top/subsoil, pH, CEC	
PTF01_v2	K_{sat}	CL, SI, SA, depth	Szabó et al. (2021)
PTF02_v2	K_{sat}	CL, SI, SA, depth, OC	
PTF05_v2	K_{sat}	CL, SI, SA, depth, pH	

* _v1: PTFs from euptfv1 (Tóth et al. 2015), _v2: PTFs from euptfv2 (Szabó et al. 2021); WRC: water retention curve; K_{sat}: saturated hydraulic conductivity; CL: clay 0–2 µm, SI: silt 2–50/60/63 µm and SA: sand 50/60/63–2000 µm (mass-%); OC: organic carbon (mass-%); BD: bulk density (g cm^{-3}); CEC: cation exchange capacity (cmol kg^{-1}); pH (in water).

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Evaluation criteria

PTFs were evaluated against the measurements in terms of root mean square error (RMSE), R-squared (R^2), and mean error (ME), which are commonly used metrics for PTF evaluation (Vereecken et al. 2010, Patil and Singh 2016, Nasta et al. 2021). They were calculated in the same way as in Szabó et al. (2021) and Tóth et al. (2015) to allow comparison:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(M_i - P_i)^2}{N}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(M_i - P_i)^2}{\sum_{i=1}^{N}(M_i - \bar{M}_i)^2} \tag{3}$$

$$ME = \frac{1}{N}\sum_{i=1}^{N}(M_i - P_i) \tag{4}$$

where *P* is the predicted value, *M* is the measured value, and *N* is the number of data points. *RMSE* quantifies the deviation between predicted and measured values, with *RMSE* closer to 0 indicating a better fit. R^2 quantifies the proportion of variance in the measured data explained by the predictions: values close to 1 indicate a good fit, values near 0 indicate that the model performs no better than using the mean of measured values as a predictor, whereas negative values occur when the residual variance exceeds the variance of the measurements around their mean, meaning predictions perform worse than this mean-based reference. *ME* assesses whether predicted values systematically under- or overestimate measured values

For further analysis, 95% confidence intervals of each R^2 of PTFs were calculated via nonparametric bootstrapping (1000 resamples per PTF). For each resample, measured and predicted water retention values were paired, sampled with replacement, and R^2 was recalculated. The 2.5th and 97.5th percentiles of the bootstrap R^2 distribution were set as the bounds of the 95% confidence interval.

Functional evaluation

The functional evaluation used HYDRUS-1D (Šimůnek et al. 2013) to compare the effects of water retention curve parameterization on simulation outcomes. In the comparison, the parameterization was conducted based on measurements versus PTFs. This simplified numerical experiment served as a controlled test to explore and demonstrate these effects in a subsurface-drained clay soil where water flow is dominated by preferential pathways. Drained structured soils with preferential flow are typical in the study region.

HYDRUS-1D is a software package that numerically solves the Richards equation to simulate one-dimensional water, heat, and solute transport in variably-saturated media (Šimůnek et al. 2013). Soil water flow was modelled using the dual-porosity module, in which all water flow occurs in inter-aggregate pore space (e.g., macropores, fractures). The pore space within the soil aggregates (soil matrix) does not convey water in the module (Šimůnek et al. 2013). Thus, the model is suitable for soils where preferential flowpaths dominate the water flow. The equations describing soil water flow are provided in Supplementary materials (Eqs. S1, S2 and S3) and water retention characteristics were described using the VG model (Eq. 1).

The functional evaluation used an existing HYDRUS-1D application as a controlled numerical experiment. This application was initially set up, calibrated, and validated for the Nummela experimental field in Jokioinen (Fig. 1) by Turunen et al. (2020). The Nummela field is heavy clay (mean clay content 66%) with a slope of <1% and artificial subsurface drainage at 1 m depth. Water flow is dominated by preferential flow paths providing relatively rapid drainage to the subsurface drains. The field is typically cultivated with oats and barley. The field was simulated as a 2 m deep one-dimensional soil profile with five horizons (0–20, 20–40, 40–60, 60–100, and 100–200 cm). More detailed information on the field and model setup can be found in Turunen et al. (2020).

The functional evaluation focused on water retention properties of the immobile pore region and their effects on simulated water table depth and subsurface drainage. Two approaches were used to parameterise the VG model of the immobile pore zone: a) fitting the VG model to measured soil water content and suction data using the least squares method, and b) estimating VG model parameters using PTFs with soil properties from the corresponding sample as predictors.

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As comprehensive water retention measurements were not available for the Nummela field, two nearby clayey experimental fields in Jokioinen (Lintupaju and Kotkanoja, Fig. 1) were used to parameterise the VG model in both approaches. These fields were selected for their similarity to Nummela in terms of soil type, clay content, and PTF predictor variables, and they were also cultivated with barley. Two sampling sites were included per field (Soil 1A and 1B from Lintupaju; Soil 2A and 2B from Kotkanoja, Table S3). Water retention and soil property measurements were available from three layers (0–20, 20–35, and 35–60 cm); deeper HYDRUS-1D horizons were parameterised according to the deepest measured layer. Measured water retention data and fitted VG models are shown in Figure S1 and Figure S2, and soil properties in Table S3. Further details on the Lintupaju and Kotkanoja fields and measurement methods are provided in Hakojärvi et al. (2013).

For each soil parameterisation, a 100-day simulation was run with HYDRUS-1D. The simulation started from a fully saturated soil profile, representing conditions after a major rainfall or snowmelt event typical of late autumn or early spring in Finnish clay fields. The profile was then allowed to drain to the drainage depth of 1 m, followed by two rainfall events: 15 mm in total on days 35–37 and 5 mm on day 70. To isolate the effects of soil hydraulic parameterisation and simplify the setup, potential evaporation and transpiration were set to zero. This represents conditions of minimal evapotranspiration, typical of cold and wet periods outside the growing season when most runoff occurs. The evaluated variables were drainage via artificial subsurface drains (cumulative and daily) and groundwater table depth (daily). Drainage outflow is the dominant outflow component and groundwater levels provide a simple indicator on changes in soil profile water content dynamics. Differences between simulation outcomes were quantified using RMSE (Eq. S1) and R^2 (Eq. S2), with calculations starting from day 5 to minimise the impact of initial conditions, which were identical for all simulations.

Results

Estimation of water retention

The comparison of measured against predicted water retention showed that the random forest PTFs (euptfv2) slightly outperformed the regression-based PTFs (euptfv1; Table 3).

Table 3. Performance of PTFs in predicting VG parameters to describe WRC. PTFs are listed from the best- to the worst-performing, based on RMSE and R^2 calculated between the measured and predicted water contents (N = 5530).

Name of PTF*	RMSE (cm^3 cm^{-3})	R^2 (-)	R^2 95% CI (-)	Predictors
PTF05_v2	0.066	0.791	0.777–0.803	CL, SI, SA, depth, pH
PTF10_v2	0.066	0.788	0.776–0.800	CL, SI, SA, depth, OC, CEC
PTF09_v2	0.067	0.787	0.774–0.798	CL, SI, SA, depth, OC, pH
PTF01_v2	0.067	0.783	0.767–0.797	CL, SI, SA, depth
PTF20_v1	0.068	0.777	0.766–0.788	CL, SI, SA, OC, pH, CEC
PTF02_v2	0.068	0.777	0.762–0.789	CL, SI, SA, depth, OC
PTF06_v2	0.069	0.773	0.759–0.786	CL, SI, SA, depth, CEC
PTF22_v2	0.070	0.762	0.748–0.775	CL, SI, SA, depth, OC, pH, CEC
PTF13_v2	0.071	0.755	0.740–0.769	CL, SI, SA, depth, BD, CEC
PTF16_v2	0.071	0.754	0.738–0.769	CL, SI, SA, depth, pH, CEC
PTF22_v1	0.072	0.749	0.733–0.763	CL, SI, SA, top/subsoil, OC, BD, pH
PTF12_v2	0.073	0.743	0.728–0.757	CL, SI, SA, depth, BD, pH
PTF03_v2	0.075	0.731	0.713–0.746	CL, SI, SA, depth, BD
PTF07_v2	0.076	0.721	0.704–0.737	CL, SI, SA, depth, OC, BD
PTF29_v2	0.078	0.709	0.691–0.726	CL, SI, SA, depth, OC, BD, pH, CEC
PTF25_v2	0.078	0.705	0.687–0.722	CL, SI, SA, depth, BD, pH, CEC
PTF21_v1	0.087	0.633	0.608–0.654	CL, SI, SA, top/subsoil, OC, BD

*_v1: PTFs from euptfv1 (Tóth et al. 2015), _v2: PTFs from euptfv2 (Szabó et al. 2021); CL: clay 0–2 µm, SI: silt 2–50/60/63 µm, and SA: sand 50/60/63–2000 µm (mass-%); OC: organic carbon (mass-%); BD: bulk density (g cm^{-3}); CEC: cation exchange capacity (cmol kg^{-1}); pH (in water)

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Random forest PTF05_v2 (Fig. 2) using soil texture (CL, SI, SA) depth, and pH as predictors, had the best performance with RMSE of 0.07 cm^3 cm^{-3} and R^2 of 0.79. For the best-performing regression PTF20_v1, using soil texture, OC, CEC, and pH as predictors, the corresponding values were 0.07 cm^3 cm^{-3} and 0.78, respectively. Even the random forest PTF01_v2, based only on soil texture and depth, outperformed the regression PTFs. However, the small differences in the 95% confidence intervals for R^2 among many PTFs suggest similar performance. In general, PTFs including BD had weaker performance.

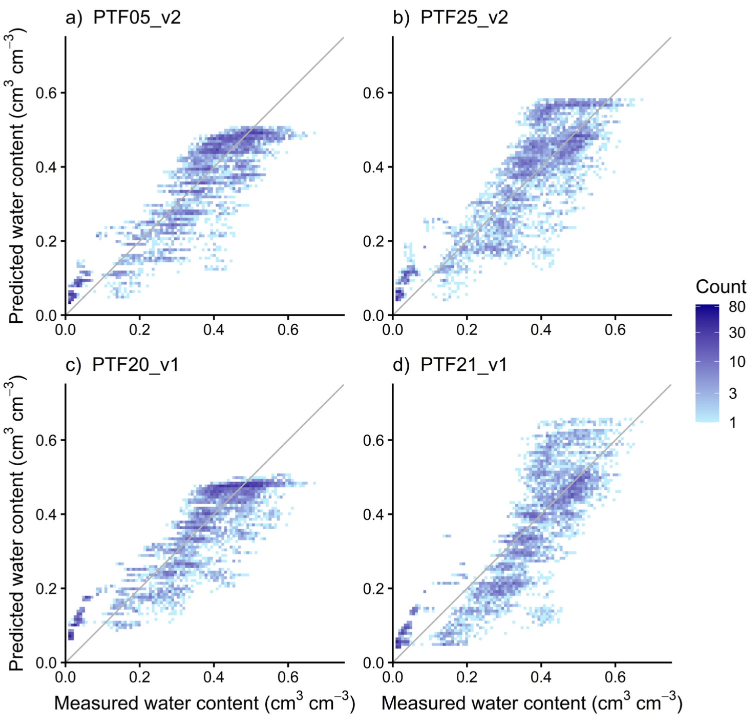

Fig. 2. The measured versus the PTF-predicted water content computed with the VG model: the a) best- and the b) worst-performing random forest PTFs (_v2; euptfv2; Szabó et al. 2021), and the c) best- and the d) worst-performing regression PTFs (_v1; euptfv1; Tóth et al. 2015)

The mean errors indicated that PTFs mostly underestimated water content, although slight overestimation occurred between 5–250 cm and above 15 000 cm suction (Fig. 2 and Fig. 3). The largest errors appeared at high suctions (1000–15000 cm) for most models. An exception was regression PTF22_v1, which performed best at these higher suctions (mean error < 0.05 cm^3 cm^{-3}) but showed larger errors by underestimation at low suctions (20–50 cm; Fig. S3).

The performance of parametric PTFs was approximately at the same level compared to point PTFs that directly predicted water content at saturation, field capacity, and wilting point (Tables S4, S5, S6, S7). In general, PTFs were the most successful in predicting water content at field capacity (FC2, h = 100 cm) and wilting point (WP). At FC2, the best performer was a point PTF FC2_PTF01_v2, with RMSE of 0.04 cm^3 cm^{-3} and R^2 of 0.74, while at WP, the best results were obtained with a parametric PTF05_v2 (RMSE 0.07 cm^3 cm^{-3} and R^2 0.68). Although R^2 values were lowest for all PTFs at saturation, the RMSE values remained moderate (0.04–0.07 cm^3 cm^{-3}).

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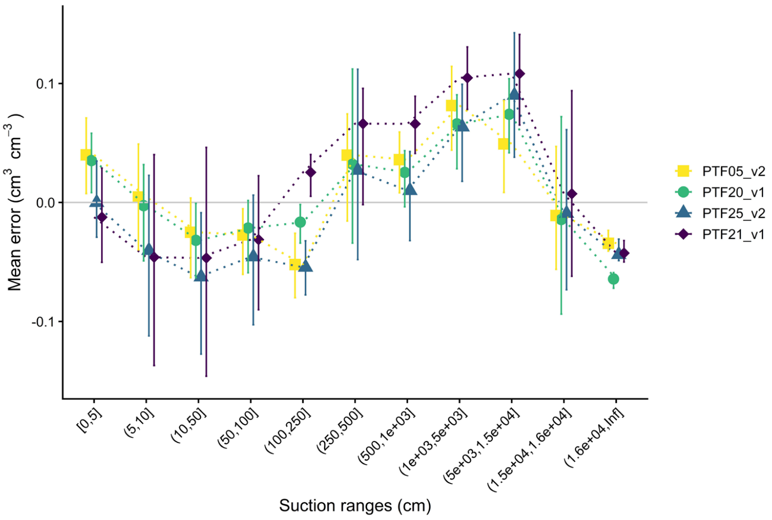

Fig. 3. Mean and interquartile range of errors by suction for the best-performing (PTF05_v2 and PTF20_v1) and worst-performing (PTF25_v2 and PTF21_v1) random forest and regression PTFs. The symbols and error ranges were given a slight offset along the horizontal axis to facilitate clearer visualisation by avoiding overlapping.

Across soil texture groups (Fig. 4), PTFs performed best in loamy soils (RMSE 0.05–0.07 cm^3 cm^{-3}; R^2 0.82–0.90; Table S9), followed by silty soils (RMSE 0.05–0.07 cm^3 cm^{-3}; R^2 0.80–0.87; Table S10). In sandy and clayey soils, the overall PTF performance was lower; even the best models showed only moderate accuracy, whereas the weakest performed poorly (sandy: RMSE 0.08–0.12 cm^3 cm^{-3}; R^2 0.42–0.77; Table S11, and clayey: RMSE 0.06–0.10 cm^3 cm^{-3}; R^2 -0.02–0.61; Table S8). The best- and worst-performing PTFs varied by soil texture group, and comprehensive ranked lists of PTFs by texture group are presented in the supplementary materials (Tables S8, S9, S10, S11).

Figure 4 shows the mean error of the best- and worst-performing regression and random forest PTFs by suction across texture groups. The smallest errors generally occurred at the lowest suctions, except in clayey soils, where weaker PTFs overestimated water content at 10–50 cm suction. Otherwise, the largest errors in clayey, loamy, and silty soils occurred when PTFs underestimated water content at 1000–5000 cm suction. Sandy soils showed a different pattern in the mean error distribution: the best PTF performed well at 1000–5000 cm suction, while the largest mean error appeared at suctions of 250–500 cm. Measurement coverage across the suction range varied by texture group, being highest for clayey and lowest for sandy soils (Fig. S5).

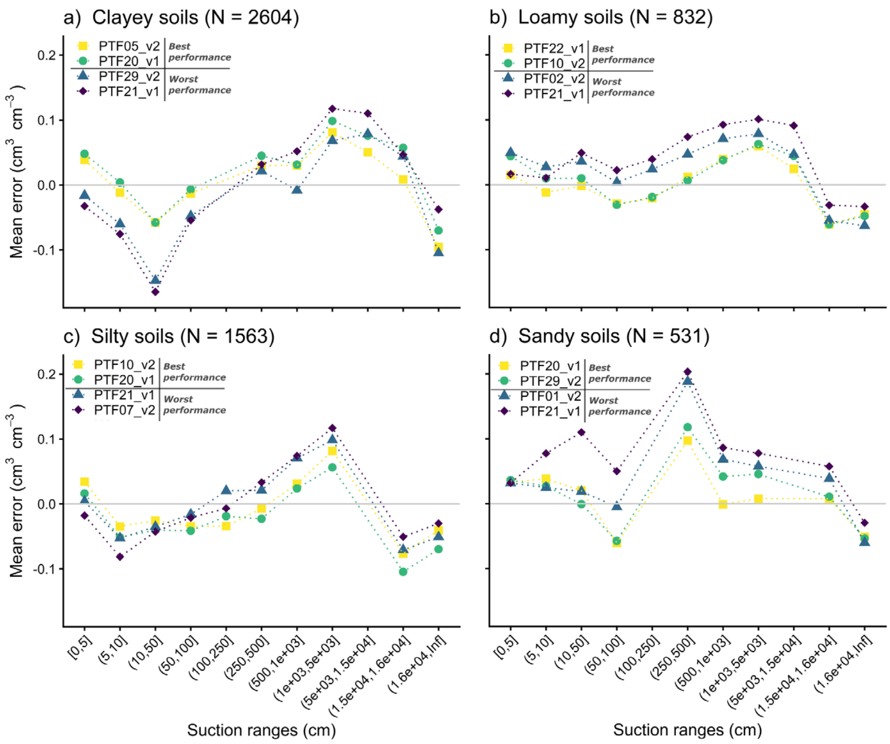

Fig. 4. Mean error by suction for the best- and worst-performing PTFs across the soil texture groups: a) clayey, b) loamy, c) silty, and d) sandy soils. Random forest and refression PTFs are denoted by v2 and v1, respectively, in the legends

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Estimation of saturated hydraulic conductivity

Evaluation of PTFs predicting K_{sat} showed low performance overall (Table 4). The best-performing random forest PTF05_v2 slightly outperformed the best-performing regression PTF17_v1, though both produced negative R^2 values. Measured K_{sat} values varied widely, with most PTFs underestimating them (Fig. S6). The random forest PTFs provided prediction intervals to assess uncertainty; however, the 90% prediction interval of the best-performing PTF05_v2 did not cover the upper end of the measured K_{sat} values. Analysis by soil texture group was omitted because of the generally poor model performance.

Table 4. Performance of PTFs in predicting K_{sat}. PTFs are listed from the best- to the worst-performing, based on RMSE and R^2 calculated between the measured and predicted K_{sat} (N = 293).

Name of PTF*	RMSE (log10 [cm d^{-1}])	R^2 (-)	R^2 95% CI (-)	Predictors
PTF05_v2	1.672	-0.856	-1.334 – -0.530	CL, SI, SA, depth, pH
PTF17_v1	2.025	-1.722	-2.496 – -1.216	CL, SI, top/subsoil, pH, CEC
PTF01_v2	2.044	-1.774	-2.648 – -1.211	CL, SI, SA, depth
PTF16_v1	2.113	-1.963	-2.916 – -1.405	CL, SI, SA, top/subsoil, OC
PTF02_v2	2.186	-2.171	-3.118 – -1.565	CL, SI, SA, depth, OC

*_v1: PTFs from euptfv1 (Tóth et al. 2015), _v2: PTFs from euptfv2 (Szabó et al. 2021); CL: clay 0–2 µm, SI: silt 2–50/60/63 µm, and SA: sand 50/60/63–2000 µm (mass-%); OC: organic carbon (mass-%); CEC: cation exchange capacity (cmol kg^{-1}); pH (in water).

Functional evaluation

HYDRUS-1D simulations parameterised with PTFs often corresponded approximately to measurement-based simulations, but in Soils 1A and 2B, the PTF-based simulations tended to overestimate drainage and underestimate water table depth (Fig. 5 and Fig. 6). Different PTFs produced varying ranges of simulated drainage and water table depth, with larger variability in Soils 2 than Soils 1.

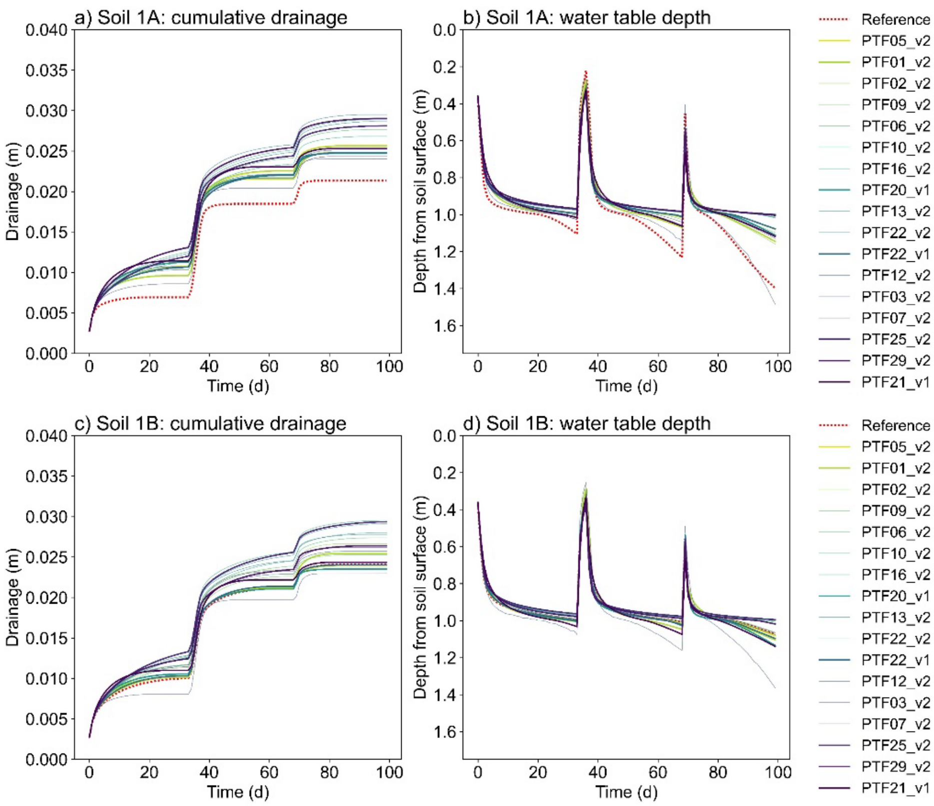

Fig. 5. Drainage (a, c) and water table depth (b, d) simulated with HYDRUS-1D for soil profiles 1A and 1B. Both the reference (red dotted line) and PTF-based simulations are shown. PTF-based simulations are coloured from yellow-green to blue-purple according to their performance in Section 3.1. (Table S7). The best and worst random forest and regression curves are bolded, based on both parametric and functional evaluations.

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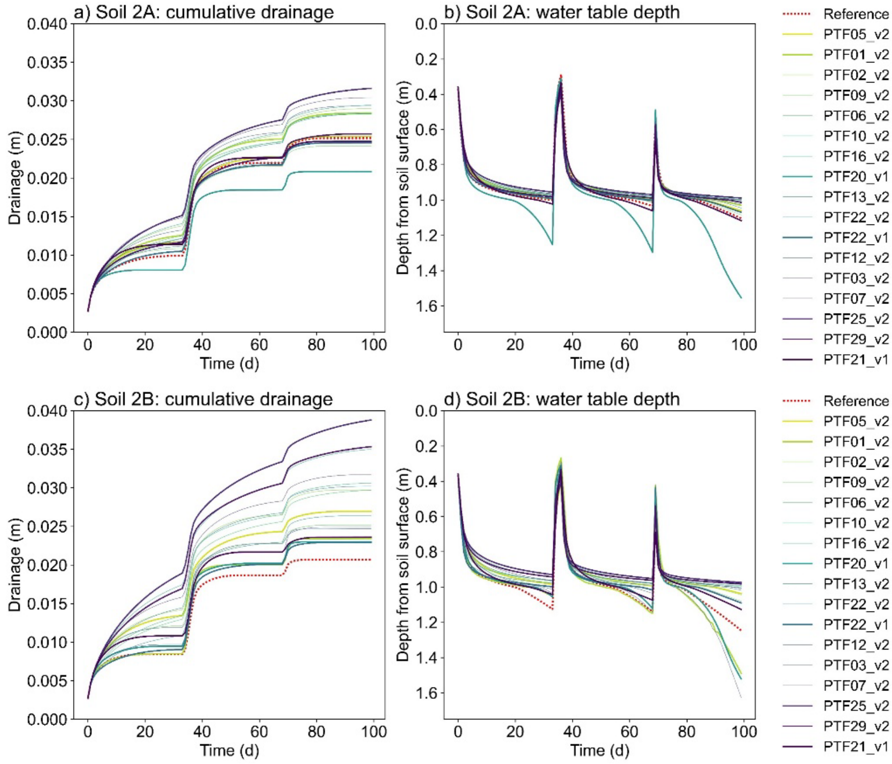

Fig. 6. Drainage (a, c) and water table depth (b, d) simulated with HYDRUS-1D for soil profiles 2A and 2B. Both the reference (red dotted line) and PTF-based simulations are shown. PTF-based simulations are coloured from yellow-green to blue-purple according to their performance in Section 3.1. (Table S7). The best and worst random forest and regression curves are bolded, based on both parametric and functional evaluations.

The best-performing random forest PTF was PTF01_v2, with R^2 of 0.96 in daily drainage simulations (Table 5) and R^2 of 0.83 in water table depth simulations (Table 6).

Table 5. Performance of PTFs in HYDRUS-1D simulations for daily drainage compared to measurement-based simulation. PTFs are listed from the best- to the worst-performing, based on RMSE and R^2.

Name of PTF*	RMSE (mm)	R^2 (-)	R^2 95% CI (-)	Predictors
PTF22_v1	0.081	0.967	0.949–0.979	CL, SI, SA, top/subsoil, OC, BD, pH
PTF01_v2	0.092	0.957	0.931–0.971	CL, SI, SA, depth
PTF12_v2	0.092	0.957	0.938–0.968	CL, SI, SA, depth, BD, pH
PTF20_v1	0.092	0.957	0.930–0.974	CL, SI, SA, OC, pH, CEC
PTF09_v2	0.094	0.955	0.935–0.966	CL, SI, SA, depth, OC, pH
PTF03_v2	0.101	0.948	0.919–0.965	CL, SI, SA, depth, BD
PTF05_v2	0.102	0.947	0.921–0.961	CL, SI, SA, depth, pH
PTF13_v2	0.102	0.946	0.916–0.963	CL, SI, SA, depth, BD, CEC
PTF21_v1	0.105	0.943	0.911–0.961	CL, SI, SA, top/subsoil, OC, BD
PTF02_v2	0.109	0.939	0.906–0.957	CL, SI, SA, depth, OC
PTF10_v2	0.109	0.939	0.902–0.959	CL, SI, SA, depth, OC, CEC
PTF06_v2	0.113	0.935	0.901–0.954	CL, SI, SA, depth, CEC
PTF22_v2	0.114	0.933	0.895–0.952	CL, SI, SA, depth, OC, pH, CEC
PTF07_v2	0.136	0.906	0.860–0.930	CL, SI, SA, depth, OC, BD
PTF29_v2	0.142	0.897	0.843–0.926	CL, SI, SA, depth, OC, BD, pH, CEC
PTF16_v2	0.149	0.886	0.831–0.916	CL, SI, SA, depth, pH, CEC
PTF25_v2	0.165	0.860	0.786–0.901	CL, SI, SA, depth, BD, pH, CEC

*_v1: PTFs from euptfv1 (Tóth et al. 2015), _v2: PTFs from euptfv2 (Szabó et al. 2021); CL: clay 0–2 µm, SI: silt 2–50/60/63 µm, and SA: sand 50/60/63–2000 µm (mass-%); OC: organic carbon (mass-%); BD: bulk density (g cm^{-3}); CEC: cation exchange capacity (cmol kg^{-1}); pH (in water)

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Table 6. Performance of PTFs in HYDRUS-1D simulations for water table depth compared to measurement-based simulation. PTFs are listed from the best- to the worst-performing, based on the RMSE and R^2.

Name of PTF*	RMSE (m)	R^2 (-)	R^2 95% CI (-)	Predictors
PTF01_v2	0.064	0.832	0.767–0.877	CL, SI, SA, depth
PTF21_v1	0.065	0.829	0.765–0.876	CL, SI, SA, top/subsoil, OC, BD
PTF12_v2	0.067	0.815	0.741–0.868	CL, SI, SA, depth, BD, pH
PTF02_v2	0.070	0.802	0.732–0.853	CL, SI, SA, depth, OC
PTF09_v2	0.071	0.795	0.716–0.854	CL, SI, SA, depth, OC, pH
PTF22_v1	0.072	0.788	0.702–0.852	CL, SI, SA, top/subsoil, OC, BD, pH
PTF03_v2	0.074	0.779	0.671–0.850	CL, SI, SA, depth, BD
PTF05_v2	0.078	0.753	0.661–0.823	CL, SI, SA, depth, pH
PTF07_v2	0.079	0.745	0.655–0.811	CL, SI, SA, depth, OC, BD
PTF22_v2	0.090	0.672	0.543–0.767	CL, SI, SA, depth, OC, pH, CEC
PTF13_v2	0.090	0.669	0.537–0.766	CL, SI, SA, depth, BD, CEC
PTF06_v2	0.092	0.658	0.525–0.755	CL, SI, SA, depth, CEC
PTF10_v2	0.092	0.654	0.516–0.755	CL, SI, SA, depth, OC, CEC
PTF16_v2	0.097	0.619	0.478–0.722	CL, SI, SA, depth, pH, CEC
PTF29_v2	0.097	0.619	0.474–0.726	CL, SI, SA, depth, OC, BD, pH, CEC
PTF20_v1	0.102	0.577	0.389–0.702	CL, SI, SA, OC, pH, CEC
PTF25_v2	0.102	0.575	0.418–0.689	CL, SI, SA, depth, BD, pH, CEC

*_v1: PTFs from euptfv1 (Tóth et al. 2015), _v2: PTFs from euptfv2 (Szabó et al. 2021); CL: clay 0–2 µm, SI: silt 2–50/60/63 µm, and SA: sand 50/60/63–2000 µm (mass-%); OC: organic carbon (mass-%); BD: bulk density (g cm^{-3}); CEC: cation exchange capacity (cmol kg^{-1}); pH (in water).

For PTF01_v2, cumulative drainages across Soils 1A–2B was on average 11.9% higher than the reference. Regression PTFs showed varying performance depending on the simulation type: PTF21_v1 was most accurate for water table depth (R^2 0.83), whereas PTF22_v1 performed best for drainage (R^2 0.97; on average 6.1% overestimation of cumulative drainage).

On average, cumulative drainage in PTF-based simulations exceeded the measurement-based reference by 19.1%, with the largest overestimations at Soil 1A (23.5%; Soil 1A in Fig. 5) and Soil 2B (37.0%; Soil 2B in Fig. 6). At Soil 2B, where the functional evaluation yielded the weakest results, this was already apparent in the PTF-predicted water retention curves, which consistently underestimated water content at nearly all sampling depths and suctions (Fig. S2).

Discussion

Estimation of water retention

The regression-based euptfv1 and random forest euptfv2 performed relatively well in the evaluation with Finnish data compared to other studies evaluating PTFs predicting VG parameters with datasets independent of their development. For example, Weynants et al. (2009) tested HYPRES (Wösten et al. 1999), Rosetta (Schaap et al. 2001), and PTFs of Vereecken et al. (1989) with a dataset by Cornelis et al. (2005), reporting RMSE range of 0.09 to 0.14 cm^3 cm^{-3} and R^2 range of 0.58 to 0.84. In our study, RMSEs ranged from 0.07 to 0.09 cm^3 cm^{-3} and R^2 from 0.63 to 0.79. A comprehensive review of PTFs predicting VG parameters by Vereecken et al. (2010) reported validation RMSEs ranging from 0.04 to 0.14 cm^3 cm^{-3}. However, the lowest RMSEs (0.04–0.05 cm^3 cm^{-3}) were achieved by PTFS where measured water content at one or more suctions were included as predictor (Børgesen et al. 2008, Børgesen and Schaap 2005). Without this predictor, RMSEs increased to 0.05–0.06 cm^3 cm^{-3}. Although water content measurements improve accuracy, such PTFs have limited applicability since water content measurements are rarely available. Furthermore, the RMSEs reported by Børgesen et al. (2008) and Børgesen and Schaap (2005) resulted from cross-validation of PTFs with the same dataset used to develop them. Vereecken et al. (2010) thus concluded that PTF validation should rely on completely independent datasets, as applied in this study.

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The performance of euptfv1 and euptfv2 in predicting water retention of Finnish agricultural soils was weaker than in the original publications where the PTFs were cross-validated on a European scale. In Tóth et al. (2015), regression PTFs achieved RMSE of 0.05 $cm^3 cm^{-3}$, while in Szabó et al. (2021), RMSEs of random forest PTFs ranged from 0.04 to 0.07 $cm^3 cm^{-3}$. When evaluating PTFs with Finnish data, these values increased by 48% and 42%, respectively, and R^2-values, only provided for random forest PTFs by Szabó et al. (2021), decreased by 12%. This trend was expected, as previous studies have shown prediction accuracy decreasing when PTFs are applied outside their development region (Vereecken et al. 2010, Patil and Singh 2016).

Comparison of the performance of different PTFs revealed that some simpler PTFs performed surprisingly well: PTF01_v2 even achieved better RMSE and R^2 values than reported by Szabó et al. (2021). In contrast to Tóth et al. (2015) and Szabó et al. (2021), in our study PTFs with more predictors did not necessarily improve accuracy. In particular, PTFs including BD as a predictor showed modest performance. However, this effect was mainly present in clayey soils (Table S8) and not in other soil texture groups (Tables S9, S10, S11), but was reflected in the overall results (Table 3) as the clayey soils formed a large proportion of the measurements. In the clayey soils, the largest mean errors in PTF predictions occurred at low suctions (10–50 cm), where PTFs using BD as a predictor overestimated water content. The contribution of BD is in contrast to Tóth et al. (2015) and Szabó et al. (2021), who both identified BD as one of the most important predictors for water retention, especially near saturation. According to the analysis of Szabó et al. (2021), BD was clearly the single most important predictor for both VG parameters (relative importance of BD > 70%) and (relative importance of BD > 20%). The importance of bulk density as a predictor of water content near saturation has also been noted in other studies as well (e.g., Schaap et al. 2001, Børgesen and Schaap 2005).

Differences between our dataset and the EU-HYDI database used to develop euptfv1 and euptfv2 likely explain these discrepancies in performance. Although the range of predictor variables in our dataset fell within that of the EU-HYDI dataset, the mean and median values of the variables varied; for instance, soil data in this study emphasized clayey soils (mean CL 33.2% vs. 21.9%, Tóth et al. 2015). Loamy and silty soils, where both regression and random forest PTFs performed better, were more represented in the original training data.

Fuentes-Guevara et al. (2022) argued that PTF performance depends less on geographic or climatic similarity of the PTF source area and application location but rather the similarity in correlation structures of PTF development and application datasets. In their study, the strongest correlations between PTF input variables and prediction residuals were observed for bulk density (BD) in the Wösten (1999) and Rosetta (Schaap et al. 2001) PTFs; the relationship between BD and water retention in their evaluation data and in the data used to develop those PTFs was different. Although BD is often a key variable for estimating water retention, its effect on water retention appears to vary. While correlation analysis could not be conducted here due to restricted EU-HYDI access, our results suggest that in clayey Finnish soils, the BD–water retention relationship differs from that of the EU-HYDI dataset. While the reasons are not clear, it can be speculated that it could be related to factors such as compaction, macroporosity and differences in fine-particle characteristics (e.g. Keskinen et al. 2022, Peters et al. 2025).

The shape of the mean error by suction range curves (Fig. 3 and Fig. 4) resembled those reported by Tóth et al. (2015) and Szabó et al. (2021). Although the use of random forest method improved prediction accuracy from Tóth et al. (2015) to Szabó et al. (2021), the mean error distribution along the suction range remained largely consistent, suggesting that some discrepancies may stem from the VG model itself.

Recently, Norouzi et al. (2025) reported promising results in estimating water retention curve using physics-informed neural networks without relying on a specific model, such as VG, to parameterise the curve. Despite its reported weaknesses (e.g., Schaap and Leij 2000, Ippisch et al. 2006), the VG model remains widely used (Vereecken et al. 2010), embedded in various models for flow and transport in porous media, such as HYDRUS and FLUSH (Warsta et al. 2013). To facilitate compatibility to common modelling applications, this study focused on PTFs predicting water retention via VG parameters.

However, a brief evaluation was also conducted for point PTFs predicting water retention at key suctions along the water retention curve (saturation, field capacity at h = 100 cm and 330 cm, and wilting point). Tóth et al. (2015) and Szabó et al. (2021) recommended point PTFs when the entire water retention curve or VG parameters are not required, as according to them, the performance of point PTFs was either equal or better than parametric PTFs. In this study, no clear outperformance of point PTFs was observed. The performance of point and parametric PTFs varied according to the predictor variables used.

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Estimation of saturated hydraulic conductivity

Although extensive, the K_{sat} dataset used for PTF evaluation mainly represented clayey soils. Previous studies have found challenges in predicting K_{sat}, especially in fine-textured soils (e.g., Weynants et al. 2009, Zhang et al. 2019). In this study, the performance of PTFs (both euptfv1 and euptfv2) for Finnish soils was poor (RMSE 1.67–2.19 $\log_{10}$ [cm d^{-1}]). In comparison, Tóth et al. (2015) and Szabó et al. (2021) reported RMSEs between 0.90 and 1.09 $\log_{10}$ [cm d^{-1}] and 0.94 and 1.18 $\log_{10}$ [cm d^{-1}], respectively. Zhang and Schaap (2019) also reviewed several K_{sat} PTFs, with RMSEs ranging from 0.53 $\log_{10}$ [cm d^{-1}] (Li et al. 2007) to 1.39 $\log_{10}$ [cm d^{-1}] (Tóth et al. 2015, PTF15 not evaluated here). Overall, the RMSEs in this study exceed those previously reported, indicating that these PTFs are unsuitable for predicting K_{sat} in boreal clayey soils. Our dataset was too limited to draw conclusions on the PTF performance in coarser soils under boreal climate.

Previous research has highlighted lack of information on soil structure, particularly macroporosity, as a major constraint in predicting K_{sat} (Weynants et al. 2009, Zhang et al. 2019). Macropores contribute substantially to soil water flow; they have been reported to contribute 78–94% of the total water flow in clayey soils and 49–74% in coarser soils (Lin et al. 1997, Keskinen et al. 2019). As noted by Jokinen (2024), the presumed high macroporosity in the soils of this study most likely affects K_{sat} values, meaning that including soil structural information is essential for improving the performance of K_{sat} PTFs.

Functional evaluation

The results of the parametric and functional evaluations had similarities. The best (PTF01_v2) and worst (PTF25_v2) PTFs in the functional evaluation showed similar performance as in the parametric one (Table S7 for clayey soils), where these two PTFs ranked second best and second worst, respectively. Otherwise, PTF performance differed somewhat between the two evaluations. In particular, the regression PTF rankings varied in simulating water table depth and drainage, and were inconsistent with the parametric evaluation. While PTF20_v1 was the most accurate regression PTF in the parametric evaluation (Table S7), in the functional evaluation PTF22_v1 outperformed it in drainage simulations (Table 5), and both PTF21_v1 and PTF22_v1 in water table depth simulations (Table 6).

Nasta et al. (2021) and Ramos et al. (2023) also conducted functional evaluations for PTFs using HYDRUS-1D. Nasta et al. (2021) applied several PTFs (Wösten et al. 1999, Schaap et al. 2001, Weynants et al. 2009, Szabó et al. 2021) with HYDRUS-1D to simulate soil water balance components of a southern Italian peach orchard over a 13-year period. Their R^2 in predicting daily water storage varied between 0.86 and 0.88. In our evaluation, PTFs performed slightly better for daily drainage (R^2 0.86–0.97) but weaker for water table depth (R^2 0.58–0.83). Ramos et al. (2023) used their own set of PTFs and HYDRUS-1D to predict soil moisture of southern Portuguese fields at depths of 0.1, 0.3, 0.5, and 0.7, reporting lower R^2 values between 0.000 and 0.58.

In this study, the functional evaluation focused on clayey soils, which were best represented in our dataset. However, in the parametric evaluation, PTFs yielded the weakest results in clayey soils in comparison to other soil texture groups (Fig. 4). Functional evaluation in coarser soils might therefore yield better results, though this remains uncertain without further research.

Based on the functional evaluation, PTFs performed best in Soils 1B and 2A and worst in Soils 1A and 2B (Fig. 5 and Fig. 6). The variability in PTF performance even within a single field demonstrates the strong heterogeneity of soil properties, which is a widely recognised challenge (e.g., Gülser et al. 2016, Moradi et al. 2016). In field-scale modelling, if only a few predictor samples are available for PTFs, the impact of the sample representativeness on model outcomes can be challenging to estimate. An interesting further development step would be to functionally evaluate also how differences between water retention curves measured in situ (field) and laboratory (e.g. Weber et al. 2024) can affect modeling outcomes. While functional evaluation has been relatively rarely conducted, our evaluation provided information on how the uncertainties in PTFs can propagate to field scale hydrology. The approach was based on simulations, and further development of the approach could include for example using independent hydrological data for model validation purposes.

Ways forward

The evaluation of PTFs against boreal agricultural soil data from Finland provides a hierarchy of PTF performance to guide the choice of the most suitable PTFs. While the evaluation was rather comprehensive for clayey soils, the main shortcoming was the limited availability soil data; water retention data originated from 19 sites and hydraulic

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conductivity from five sites, representing unevenly different soil texture classes. A more thorough evaluation would require new extensive measurement campaigns, which would take into account the spatial variation of the predictors in the sampling design. Comprehensive soil data would support the development of PTFs tailored to boreal conditions—which is especially crucial for applicable K_{sat} PTFs— and contribute to potential future needs for soil monitoring, as outlined in the EU Soil Monitoring Law (EC 2025).

Conclusions

The performance of the PTFs in euptfv1 (Tóth et al. 2015) and euptfv2 (Szabó et al. 2021) was evaluated through parametric and functional approaches for boreal agricultural soils using Finnish measurement data, addressing a key gap in geographic validation of PTFs. The evaluation provided insights into the performance of different PTFs across soil textures and moisture conditions, and highlighted the uncertainties associated with their application in practical modelling, supporting informed selection and use of PTFs and contributing to their future development. The relevance of our results is underlined by the EU Soil Monitoring Law, which lists water retention and K_{sat} among the soil health indicators to be monitored, with PTFs identified as an alternative to direct measurement (EC 2025).

PTFs predicting water retention capacity performed moderately well in Finnish soils; RMSE and R^2 were comparable to previous studies evaluating PTFs with independent data. Functional evaluation results were also in line with other related studies, suggesting that these PTFs can be applied for modelling in boreal agricultural soils, while considering their uncertainties.

No single water retention PTF proved unambiguously best for boreal agricultural soils. PTF05_v2 was most accurate in the parametric evaluation with the entire Finnish dataset and when limiting the evaluation to clayey soils, while PTF22_v1, PTF10_v2, and PTF20_v1 performed best for loamy, silty, and sandy soils, respectively. In the functional evaluation, PTF01_v2 achieved the best results. Furthermore, in clayey soils, PTFs not including bulk density as a predictor consistently outperformed those including it. Therefore, when choosing the PTF for boreal agricultural areas, users should consider available predictors, soil texture of the target area (if the use is limited to certain soil textures), and whether the full water retention curve and/or VG parameters are needed or only the water retention at certain suctions. Uncertainties discussed in this study should be considered. If possible, applying multiple PTFs is useful to obtain an estimated range of water retention. However, the results of the functional evaluation showed that even with this approach, PTFs may in some cases systematically over- or underestimate water retention capacity.

PTFs predicting K_{sat} performed poorly, systematically underestimating measured values. Previous studies have found similar challenges in predicting K_{sat}, particularly in clay-rich soils, where most of the data of this study originated. One of the main reasons behind the poor performance of K_{sat} PTFs is probably the impact of macropores, which is even more pronounced in clayey soils. Consequently, K_{sat} PTFs require refinement before application to boreal soils.

Future research and development of PTFs for boreal soils require more comprehensive data on soil properties, and performance differences across soil textures should be systematically considered to ensure robust and generalizable PTF applications.To achieve even moderate performance, PTFs predicting K_{sat} will likely need to include structural information, such as macroporosity estimates, as an input variable. More representative dataset across all soil texture classes would enable extending the functional evaluation of water retention PTFs to coarser soils as well.

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