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Parameters of infiltration models affected by the infiltration measurement technique and land-use

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ABSTRACT: The measurement method (MM) and the land-use (LU) are two soil structure-related attributes that are available in infiltration experiments. This study aims to hypothesize that measurement technique and land-use might be good predictors of the performance of infiltration parameter values and models. The Soil Water Infiltration Global (SWIG), which includes about 5000 experiments worldwide and assembled in the Institute of Agrosphere in Jülich, Germany, was used. Except for the known properties such as texture, measurement method, and land-use, changes were observed in organic carbon content, saturated hydraulic conductivity, bulk density, pH, initial water content, and the electrical conductivity of saturated paste. Horton and Mezencev models outperformed from Green and Amp and Two-term Philip models, hence it has been seen that Horton and Mezencev models could be preferred according to the measurement method. To determine the most influential predictors of these two models' parameters, the machine learning method "regression trees" was applied. In 80 % of cases for both models, the textural class, the MM (40 % of cases), and the LU were found as the most influential predictors. The accuracy of parameter estimates increased when a subset of measurements was used with the same method to estimate infiltration parameters. Textural class, LU, bulk density, and K_{sat} were determined as the most influential predictors for the parameters of the Horton. However, textural class, LU, and organic carbon content became most important in the case of the Mezencev model. Overall, estimates of the infiltration equation parameters can be more accurate if they have been developed for the same MM as in the task at hand. The MM and the LU provide useful surrogate information about the effect of soil structure on infiltration.

Keywords: water infiltration, soil structure, modeling, regression trees, measurement method.

INTRODUCTION

Infiltration is one of the major processes that control soil water flow and storage in soil-plant-atmosphere systems and runoff and groundwater recharge (Hillel, 1980; Brutsaert, 2005). Infiltration depends on soil properties, wetting rates, rainfall and irrigation characteristics, soil and crop management, and vegetation cover and type (Vereecken et al., 2019). Infiltration rate is highly dependent on texture of soils (Rawls, 1992; Mohammadi and Refahi, 2006); and soil texture and structure affect the water holding capacity of the soil that controls the water accessibility in the soil (Al-Azawi, 1985; Mirzaee et al., 2014). The contribution of macropores associated with the soil surface to the infiltration rate is determined by their origin, shape, structure, and twistiness (Edwards, 1982). Therefore, the high infiltration rate in uncultivated soils is due to the macro-pore networks extending up to the surface, subjecting the macropore networks' continuity in these soils (Erşahin, 2001). Soil organic carbon and soil bulk density are often highly related, and an increase in total soil organic carbon content reduces soil bulk density and improves water infiltration (Franzluebbers, 2002). Modeling infiltration dynamics has a long history (Green and Ampt, 1911; Kostiakov, 1932; Horton, 1939; Philip, 1957a,b; Mein and Larson, 1973; Kao and Hunt, 1996; Argyrokastritis and Kerkides, 2003; Dashtaki et al., 2009). Two groups of empirical infiltration equations were developed. One of the equation groups originated from the formulation of Horton (1941), and another group was based on the Kostiakov (1932) approach (Vereecken et al., 2019). Later, these equations were modified and extended to be suitable for various initial and boundary conditions (Lewis, 1937; Mezencev, 1948; Smith, 1972; Furman et al., 2006; Parhi et al., 2007).

Physics-based infiltration equations were developed along with empirical ones. The Green-Ampt model originally occurred to measure the ponded infiltration into uniform soil columns (Green and Ampt, 1911) and is the earliest physically based conceptual infiltration model (Mirzaee et al., 2014). This model calculates many variables that indicate in-situ conditions and captures the water movement's macroscale behavior in soils during infiltration (Assouline, 2013; Putte et al., 2013). Philip (1957a) solved the one-dimensional Richards equation by assuming that the soil's hydraulic conductivity and diffusivity are soil water content functions (Jhaa et al., 2019). This solution applies to the first infiltration stages into a relatively dry soil profile where gravity plays only a minor role (Assouline, 2013).

Many researchers have analyzed the accuracy of infiltration models by comparing the computed and observed infiltration rates or cumulative infiltration volumes for various soil textures, infiltration MMs, and region-specific soil properties (Shukla et al., 2003b; Chahinian et al., 2005; Dashtaki et al., 2009; Haghighi et al., 2010; Mirzaee et al., 2014; Philip et al., 2018; Bayabil et al., 2019; Wang and Chu, 2020). Substantial differences in model performance were reported (Sihag et al., 2017). For example, the Horton model has been the best predictor for the infiltration under different tillage and rotations in a soil clay-loam in north-west Iran (Mohammed, 2006). Sihag et al. (2017) reported that Philip's model provided the best fit in a wasteland in India (Machiwal et al., 2006). Dashtaki et al. (2009) evaluated Kostiakov, Mezencev, Horton, and Philip's performance by the double-ring method under 123 different soil moisture, temperature regimes, and land-use in Iran. They concluded that the Mezencev model could provide the best site-independent performance. Haghighi et al. (2010) used a double-ring infiltrometer at 48 sample points in Iran. They found that the Horton model overperformed the Mezencev and Philip models, and attributed that to differences in soil conditions such as soil particle size distribution. They noted that infiltration rate had a high dependency on the soil texture (Rawls, 1992; Mohammadi and Refahi, 2006). Shiraki et al. (2019) evaluated five infiltration models (Philip, Swartzendruber, Brutsaert, Mezencev, and Horton). They noted that the Mezencev model exhibited the highest fitting performance, but fitted parameters sometimes had non-physical values. These authors reported that the Horton model was the most effective. Shukla et al. (2003a) analyzed ten infiltration models, and assessed the time dependence of infiltration parameters and the model accuracy precision using infiltration data from double-ring infiltrometer tests. The conclusion of this study stated that overall the three-parameter Horton model gave the best fit of infiltration data for most land-use types, including forest.

Modeling infiltration is an essential component of hydrological modeling in a wide range of applications. Therefore, predicting which infiltration model will perform better in site-specific conditions presents substantial interest. Developing such predictions belongs to the field of pedotransfer function development (Van Looy et al., 2017). We note that both measurement method and land-use are categorical variables that serve as predictors in the pedotransfer development for infiltration parameters. The ample examples show that the accuracy of pedotransfer functions (PTFs) relying on the categorical input variables (class PTFs) can be high, especially when they are developed for large regional or interregional databases. Rawls and Pachepsky (2002) developed accurate PTFs for the soil water content at -33kPa matric potential using mostly categorical variables such as textural class and hillslope position along with slope value. Lilly (2000) presented class pedotransfer functions for saturated hydraulic conductivity where soil structural class served as one of the inputs. Nguyen et al. (2014) were successful in using the categorical soil structure information to improve the water retention estimation. This type of pedotransfer function has the advantage of direct inputs from soil maps that contain the class rather than continuous information about soil basic properties. Developing PTF for infiltration parameters with all or the majority of inputs as categorical variables appears to be an exciting research avenue to explore. The main objective of this study was to determine which attributes may serve as predictors of the performance of different infiltration models and the parameter values in those models.

MATERIALS AND METHODS

Database

The database SWIG has been assembled in the Institute of Agrosphere in Yülich, Germany (Rahmati et al., 2018). Site-measurements (n = 5023) were obtained from more than 90 sources. Each dataset includes some soil properties from the following list: texture, organic carbon content, bulk density, particle density, saturated hydraulic conductivity (K_{sat}), saturated volumetric soil water content (WC_s), initial volumetric soil water content (WC_i), wet-aggregate stability (WAS), the electrical conductivity (EC), and pH. Most datasets include the infiltration measurement method (95 %) and land-use (76 %). Textural distributions of soils are given in figures 1a and 1b, and land-use types in figures 2c and 2d, and table 1. Methods used for infiltration measurement of soils are presented in table 1.

Infiltration equations and their comparison and parameterization

Four selected infiltration models differ by their mathematical structure and the number of fitting parameters (Table 2). The database analysis was exploratory and aimed to find the subdivision of the database into the most homogeneous groups of datasets with simultaneous determination of factors controlling the separation of those groups. Classification and Regression Trees (CART) algorithms are very efficient for that purpose as they create grips that are not only most homogeneous but also separated as far as possible from each other. Also, these algorithms provide very transparent results that are easy to interpret. In this study, we used the CART algorithm implemented in the R package ‘rpart’ with default control parameters, i.e., without setting the ‘control’ list in the call to the ‘rpart’ routine (R Development Core Team, 2019). This facilitated the exploration of the database structure. This algorithm splits datasets into two groups that are the most homogeneous internally and most dissimilar to each other with respect to the target variable (De’ath and Fabricius, 2000). The whole dataset is split into two

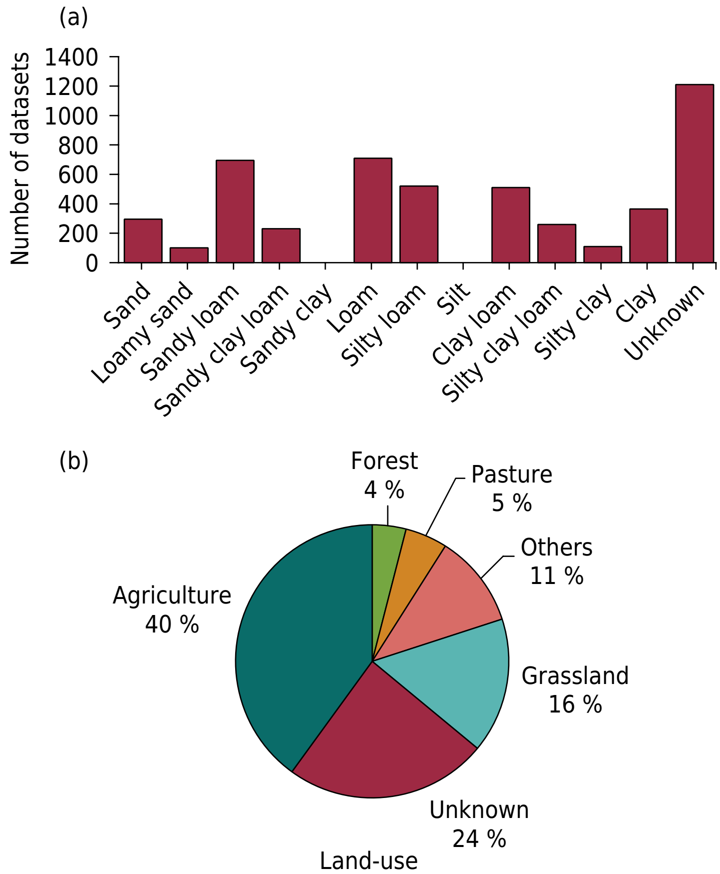

Figure 1. Histogram of textural distribution (a) and land-uses of the soils (b) (Rahmati et al., 2018).

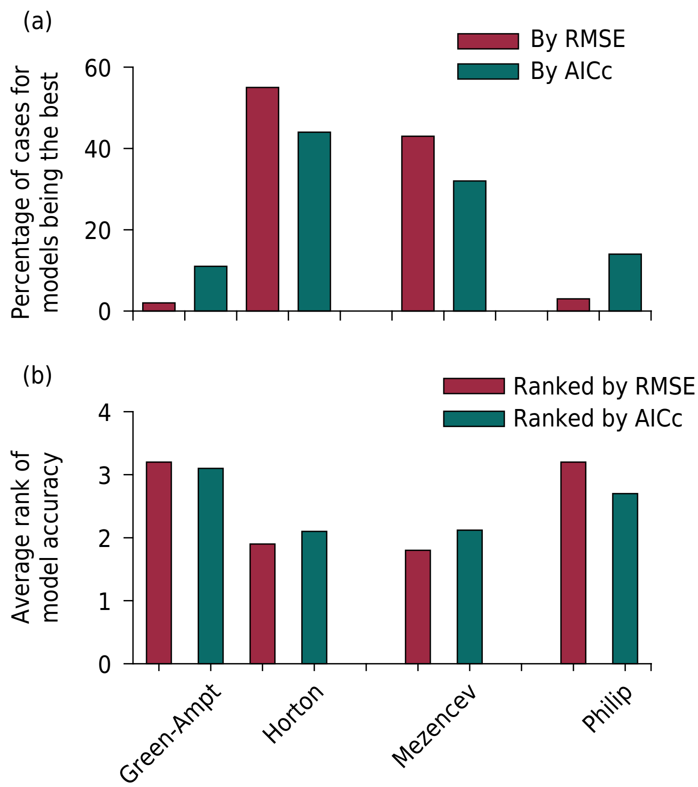

Figure 2. Percentage of cases for the model being the best (a), and the average rank of models (one is the highest and four is the lowest) (b). RMSE: Root Mean Square Error; AICc: Akaike information criterion.

Table 1. Methods used in measurement and land-use types of soils (Rahmati et al., 2018)

Methods	N	Methods	N	Land-use	N
Mini infiltrometer	1141	Guelph permeameter	181	Agriculture	2018
The double ring infiltrometer	828	Aardvark permeameter	50	Grass	821
Tension infiltrometer	753	Micro infiltrometer	37	Urban	405
Disc infiltrometer	607	Hood infiltrometer	23	Pasture	229
The single ring infiltrometer	570	The linear source method	10	Forest	204
Rainfall simulator	374	The point source method	4	Garden	152
The Beerkan (BEST)	197				

N: number of uses.

Table 2. Infiltration equations that were used in this study

Authors	Original Infiltration Equations	Used Forms of Infiltration Equation
Green and Ampt (1911)	$F(t) = Kt + \psi\Delta\theta\ ln\left[1 + \frac{F(t)}{\psi\Delta\theta}\right]$	$F(t) = b_1t + b_2\ ln\left[1 + \frac{F(t)}{b_2}\right]$
Horton (1939)	$F(t) = f_ct + \frac{f_0 - f_c}{k}(1 - e^{-kt})$	$F(t) = b_3t + b_1(1 - e^{-b_2t})$
Mezencev (1948)	$F(t) = kt^a + f_0t$	$F(t) = b_1t^{b_2} + b_3t$
Two-term Philip (1957a)	$F(t) = St^{0.5} + ct$	$F(t) = b_1t^{0.5} + b_2t$

F(t) is the cumulative infiltration capacity at time t (mm h^{-1}). In the Green and Amp equation, K is unsaturated hydraulic conductivity; ψ is the wetting front soil suction head; and θ is the water content. In the Horton equation, f_c is the final or equilibrium infiltration rate (mm h^{-1}); f_0 is the initial infiltration rate (mm h^{-1}); k is the a constant representing the rate of decrease in f capacity. In the Mezencev equation, *k* and *a* are empirical constants (unitless) ($k > 0$ and $0 < a < 1$). In the Two-term Philip equation, S is the sorptivity (cm $min^{0.5}$); c is the constant. b_1, b_2, and b_3 are the fitting parameters.

subgroups, which, in turn, are divided into two subgroups each, etc., until groups become small and the algorithm ends. The predicted value of the target variable is the average within each of the final small groups when the algorithm is used as a regression tool. The algorithm works as a classifier if the target variables are categorical. In such a case, the target variable for the final small groups is found by voting among the datasets in these groups.

The Akaike information criterion AIC_c (Burnham and Anderson, 2002) was applied to select the best infiltration equation for each dataset (Equation 1). This criterion was used in past pedotransfer studies of soil water retention curves and the comparison models of particle-size distribution data (Minasny et al., 1999; Hwang et al., 2002; Hadzick et al., 2011). This statistic was computed as:

$$AIC_c = 2p + n\left[ln\left(2\pi\frac{RSS}{n}\right) + 1\right] + \frac{2p(p+1)}{n-p-1} \qquad \text{Eq. 1}$$

in which: p is the total number of the model parameters; n is the total number of observation times in the dataset; and RSS is the residual sum of squares for the cumulative infiltration. The determination coefficient (Equation 2) and the root-mean-squared error (Equation 3) were also computed.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad \text{Eq. 2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x - y)^2} \qquad \text{Eq. 3}$$

In equation 2, x_i and y_i represent the actual and predicted values of the observed cumulative infiltration, respectively, and n is the number of observations.

RESULTS

The exploratory statistics of soil properties (Rahmati et al., 2018) are given in table 3. The K_{sat}, SAR (sodium adsorption ratio), EC, and OC values showed the highest coefficient of variation (CV%) compared with other soil variables. Soils in the database contain, on average, a relatively high percentage of OC (3.1 %), and sand and silt with 38.5 and 35.8 %, respectively (Table 3).

Comparing the four infiltration models' performance showed that Horton and Mezencev models outperformed the two others (Figure 2), and Horton or Mezencev models could be preferred according to the measurement method.

The regression tree algorithm showed that the measurement method, the textural class, and the land-use were the most influential predictors in 80 % of cases for both Horton and Mezencev models (Figure 3), and clay, silt, and sand contents were used instead of the texture class (Figure 4). Cumulative probability functions of the Horton and Mezencev models parameters across all datasets and across the datasets where Horton and Mezencev models were the best are given in figures 5 and 6, respectively. According to the probability functions of the Horton and Mezencev models parameters, b_2 for Horton and b_1 for the Mezencev model (Table 2) are found to be better than other parameters (Figures 5 and 6).

The accuracy of regression trees relating to infiltration parameters to the site-specific data is characterized in figure 7 and table 4. The best explanatory variables for Horton and Mezencev models are given in table 5. The most influential variables to build the trees given missing data command imputation for Horton and Mezencev models are shown in table 6.

Table 3. Exploratory statistics of some properties in SWIG database (N = 5023)

Soil properties	N	Fr	Max.	Min.	Mean	SD	CV
		%					%
Sand (%)	3842	76	100.0	1.0	38.5	23.8	61
Clay (%)	3842	76	80.0	0.0	23.6	15.1	64
OC (%)	3102	62	87.9	0.0	3.1	6.2	200
D_b (g cm^{-3})	3295	66	2.8	0.1	1.3	0.8	21
K_{sat} (cm h^{-1})	1895	38	3004.3	0.0	41.0	174.9	426
WC_s (cm^3 cm^{-3})	1400	28	0.9	0.0	0.4	0.1	24
WC_i (cm^3 cm^{-3})	1569	31	0.6	0.0	0.2	0.2	67
WC_r (cm^3 cm^{-3})	263	5	0.4	0.0	0.1	0.1	85
FC (cm^3 cm^{-3})	74	1	0.5	0.1	0.3	0.1	33
pH	1081	22	8.6	4.7	7.4	0.1	12
CEC (cmol$_c$ kg^{-1})	357	7	26.0	3.0	17.0	3.5	21

N: Number of samples; Fr: frequency (%); SD: standard deviation; CV: coefficient of variation; OC: organic carbon content; D_b: bulk density; K_{sat}: saturated hydraulic conductivity; WC_s: saturated volumetric soil water content; WC_i: initial volumetric soil water content; WC_r: residual volumetric soil water content; FC: water content at field capacity; CEC: cation exchange capacity.

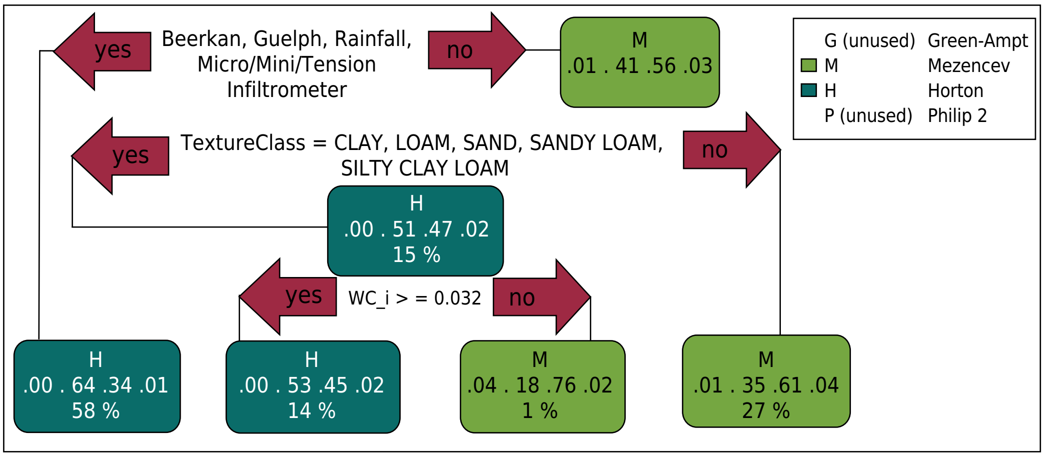

Figure 3. Application of the classification and regression tree algorithm. Letters H and M denote cases of Horton and Mezencev model being the best. The string of four fractions gives the proportions of Green-Ampt, Horton, Mezencev, and Philip models being the best in the group of datasets. The percentages show the fraction of datasets from this group in the entire database. $WC_{\_i}$: Initial volume of soil water content.

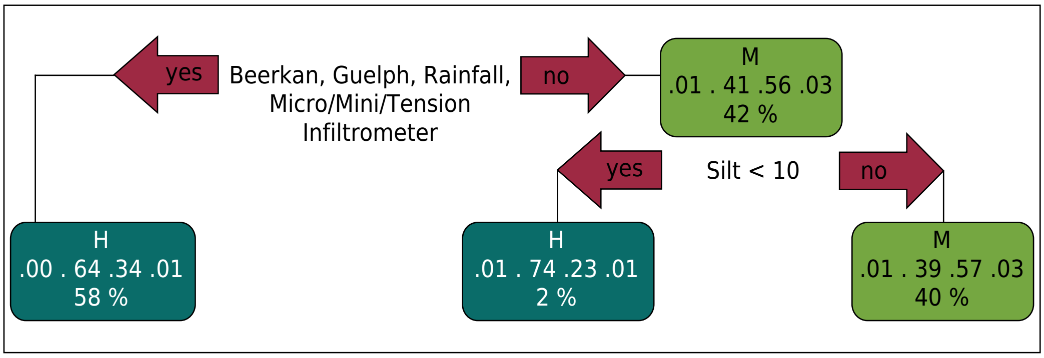

Figure 4. Use of clay, silt, and sand contents as soil texture characteristics in regression trees. Explanations are in the caption of figure 4. M: Mezencev model; H: Horton model.

DISCUSSION

According to the evaluation of selected four infiltration models by AICc (Akaike information criterion) and regression trees, Horton and Mezencev models were found to be the best predictors and could be preferred according to the measurement method (Figure 2). The MM and the LU, which are two soil structure-related attributes, were good predictors of the performance of selected infiltration models and of the parameter values in those models.

Many studies conducted under different soil conditions with double-ring and mini-disc infiltrometers are compatible with our results. Lei et al. (2020) reported that Ahuja et al. (2007), Mirzaee et al. (2014), Nie et al. (2017), and Jhaa et al. (2019) compared infiltration models using data obtained from different regions (Iran, China, India, etc.) with various soil's textures and bulk density. Their results showed that the Mezencev model gave high prediction accuracy for the cumulative infiltration. Li et al. (2020) evaluated four models' accuracy (Horton, Kostiakov, Mezencev, and Philip) in simulating the infiltration process. They reported that the Horton model, which considers the initial infiltration rate, had higher accuracy. Hajabbasi (2006) evaluated the Kostiakov, Horton, and Philip's infiltration models under different tillage and rotations in a clay loam in Northwest Iran and reported that the Horton model gave the best prediction of infiltration rate in that region.

The reason why the measurement method is the best predictor may be the differences in the contact area of the instrument used in the measurement. Studies report that the

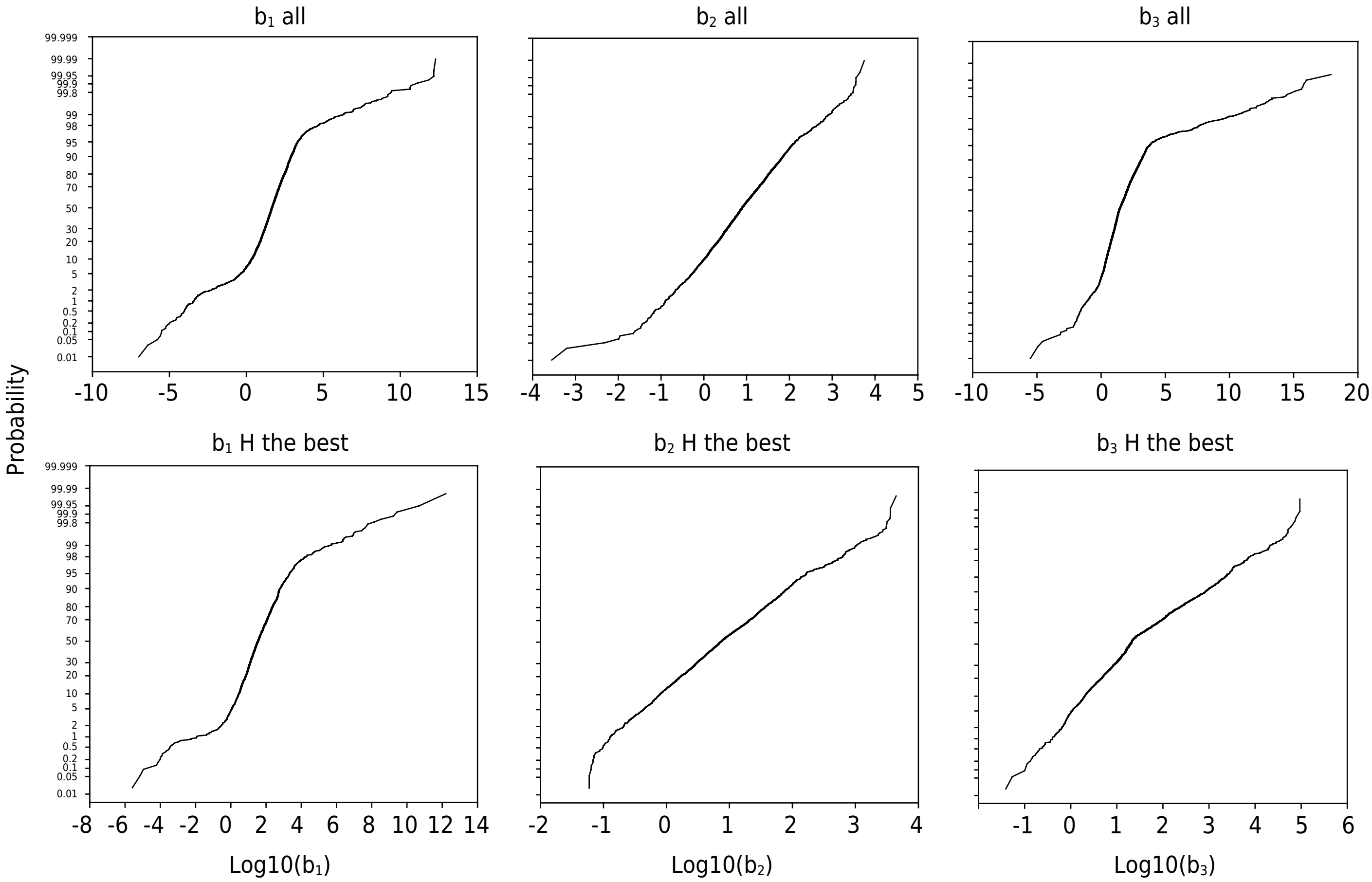

Figure 5. Parameters of the Horton (H) model across all datasets and across the datasets where Horton model was the best.

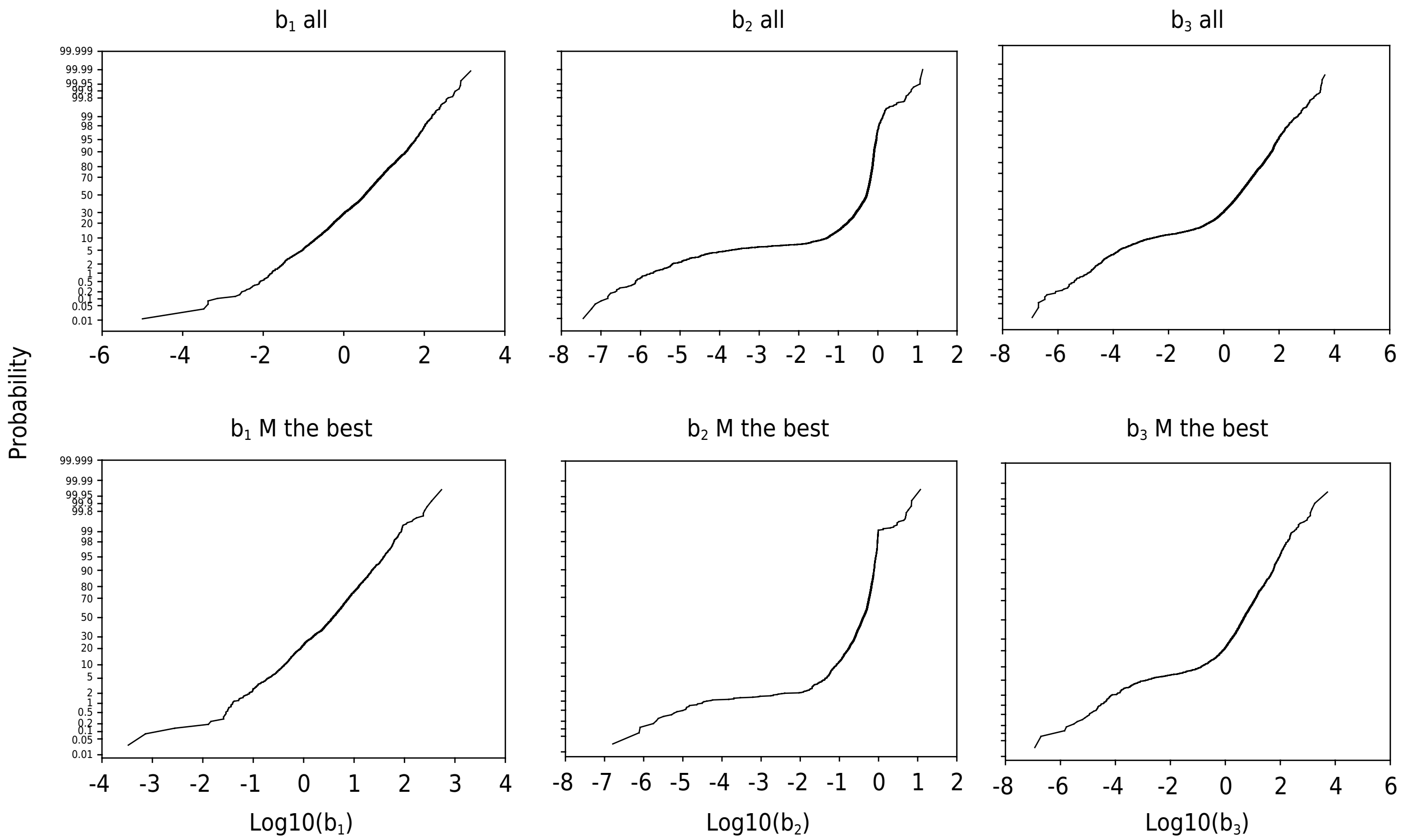

Figure 6. Parameters of the Mezencev (M) model across all datasets and across the datasets where the Mezencev model was the best.

contact areas of the infiltrometers have substantial effects on hydraulic conductivity and infiltration measurements (Ciollaro and Romano, 1995; Lai and Ren, 2007; Pachepsky et al., 2014).

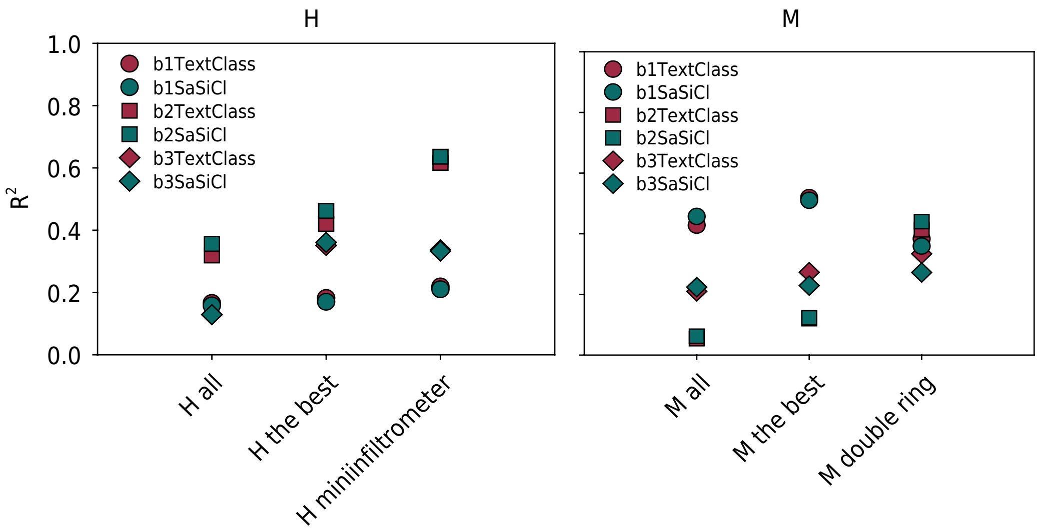

Figure 7. Performance of regression tree models relating to infiltration parameters for Horton (H) and Mezencev (M) models.

Table 4. Performance of regression tree models relating to infiltration parameters for Horton and Mezencev models

Dataset	RMSE			r		
	Horton equation $F(t) = b_3t + b_1(1 - e^{-b2t})$					
	b_1	b_2	b_3	b_1	b_2	b_3
H all (958)[(1)]	0.49	0.43	0.28	0.64	0.71	0.70
H the best (504)	0.48	0.42	0.27	0.65	0.72	0.72
H MDI (142)	0.08	0.07	0.05	0.45	0.54	0.70
	Mezencev equation $F(t) = b_1t^{b_2} + b_3t$					
M-all (728)	0.48	0.35	0.21	0.63	0.86	0.93
M-best (378)	0.22	0.29	0.26	0.44	0.46	0.51
M-DRI (45)	0.64	0.49	0.31	0.56	0.77	0.82

[(1)] Total number of measurements in the dataset; RMSE: Root Mean Square Error; H: Horton model; M: Mezencev model; MDI: Minidisc infiltrometer; DRI: Double Ring Infiltrometer.

Table 5. Parameters of the Horton and Mezencev model across the Horton and Mezencev model-specific datasets

Horton Dataset	b_1			b_2			b_3		
	Topsplit	Second split		Topsplit	Second split		Topsplit	Second split	
H all	Method	K_{sat}	D_b	Method	OC	K_{sat}	Method	Method	
H the best	Method	Method	K_{sat}	Method	WC_i	K_{sat}	Method	Method	TClas
H MDI	D_b	K_{sat}	TClas	K_{sat}	TClas	OC	D_b	D_b	OC
Mezencev Dataset	b_1			b_2			b_3		
	Topsplit	Second split		Topsplit	Second split		Topsplit	Second split	
M all	Method	TClas	K_{sat}	Method	TClas		Method	Method	K_{sat}
M the best	Method	Method	Method	Method	TClas	D_b	Method	TClas	K_{sat}
M MDI	Landuse	WC_i		WC_i	OC	D_b	Landuse	TClas	TClas

H: Horton model; M: Mezencev model; OC: organic carbon content; D_b: soil bulk density; K_{sat}: soil saturated hydraulic conductivity; WC_i: initial volumetric soil water content; TClas: texture clas; MDI: minidisc infiltrometer; b_1, b_2 and b_3 are empirical parameters of the models.

Table 6. Most important variables to build the trees given missing data command imputation for Horton and Mezencev models

Horton Dataset		**b_1**			**b_2**			**b_3**	
H all	Method	Landuse	K_{sat}	Method	TClas	Landuse	Method	Landuse	TClas
	54	18	11	32	21	19	90	5	5
H the best	Method	TClas	Landuse	Method	TClas	Landuse	Method	TClas	Landuse
	43	25	18	29	22	17	59	19	11
H MDI	TClas	Landuse	K_{sat}	TClas	K_{sat}	D_b	TClas	OC	D_b
	26	20	20	27	24	20	36	30	19
Mezencev Dataset		**b_1**			**b_2**			**b_3**	
M all	Method	TClas	Landuse	Method	TClas	Landuse	Method	Landuse	TClas
	50	22	20	51	42	7	45	23	19
M the best	Method	Landuse	TClas	TClas	Method	Landuse	TClas	Method	D_b
	62	17	16	48	26	14	34	28	12
M MDI	Landuse	TClas	OC	Landuse	TClas	OC	TClas	Landuse	OC
	42	21	20	36	23	21	38	33	24

H: Horton model; M: Mezencev model; OC: organic carbon content; D_b: soil bulk density; TClas: texture clas; MDI: Minidisc infiltrometer; b_1, b_2, and b_3 are empirical parameters of the models.

Both meta-analysis and site-specific studies in different regions demonstrated substantial changes in the infiltration process as land-use changed. Sun et al. (2018) summarized a large number of studies in China and showed that initial and steady infiltration rates increased after land-use changes from grassland to the forest (+41 %), shrubland to the forest (+43 %), and cropland to agroforestry (+70 %, +84 %). Soil infiltration rates declined after land-use changed from grassland to cropland (-45 %), shrubland to cropland (-64 %), and forest to cropland (54 %, 42 %). Yimer et al. (2008), in a study in Ethiopia, found that in cultivated and grazed land compared with forest, infiltration capacities were 70 and 45 % smaller, respectively. In the study in Indonesia, Har et al. (2021) demonstrated that the land-use change caused a substantial change in the infiltration capacity.

Besides measurement methods and land-use, soil properties have considerable effects on the infiltration process (Angelaki et al., 2013). The soil textural class was found to be the most influential predictor, with measurement method and land-use in 80 % of cases for Horton and Mezencev infiltration models (Figures 3 and 4). It may be concluded that differences in model performance under the same infiltration measurement technique could be attributed to differences in soil conditions. Robin and Bora (2019) reported that the Horton model's better performance compared with the Modified Kostiakov model with data from the cultivated lands on hillslope and plain surface in Meghalaya, India. Dexter (2004) stated that soil cultivation affects the soil's physical properties and increases the pore structure and porosity, influencing the passage of water through the soil surface and changing the soil's ability to hold water. On the other hand, Zhang and Fang (2007) stated that soil infiltration increased as soil bulk density decreased with deep plowing.

Soil structure and soil structure-related attributes such as soil organic carbon, bulk density, and initial water content affect infiltration (Figure 3, Tables 5 and 6). Estimates of the infiltration equation parameters can be more accurate if they have been developed for the same MM. The measurement method was the most influential predictor due to infiltrometers having different contact areas. An increase in the infiltrometer diameter increases the infiltration rate and the cumulative infiltration (Wu and Pan, 1997). Li et al. (2019a) performed a series of double-ring infiltration tests with different diameters. In this work, the scale effect was observed in the experimental data and caused scale dependence in infiltration models' parameters.

CONCLUSIONS

This study compared the effect of some soil properties and related attributes on selected infiltration models' performance. The database SWIG encompasses approximately 5000 data across the world. The Horton and the Mezencev models performed the best. Measurement method, land-use, and soil texture were the most influential independent variables controlling the models' performance. Lack of knowledge of the model parameters for different soils and conditions makes the use of these models difficult. Different models may be preferred for different measurement techniques and land-use.

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AUTHOR CONTRIBUTIONS

Conceptualization: Yakov Pachepsky (lead).

Data curation: Gülay Karahan (lead).

Methodology: Yakov Pachepsky (lead).

Validation: Gülay Karahan (supporting) and Yakov Pachepsky (lead).

Writing – original draft: Gülay Karahan (lead).

Writing – review & editing: Gülay Karahan (supporting) and Yakov Pachepsky (lead).

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