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A scaling approach, predicting the continuous form of soil moisture characteristics curve, from soil particle size distribution and bulk density data

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Abstract

A substantial number of models, predicting the Soil Moisture Characteristic Curve (SMC) from Particle Size Distribution (PSD) data, underestimate the dry range of the SMC especially in soils with high clay and organic matter contents. In this study, we applied a continuous form of the PSD model to predict the SMC and subsequently, we developed a physically based scaling approach to reduce the model's bias at the dry range of the SMC. The soil particles packing parameter, obtained from the porosity was considered as a characteristic length. The model was tested by using eighty-two soil samples, selected from the UNSODA database. The result showed that the scaling approach properly estimate the SMC for all soil samples. In comparison to the formerly used physically based SMC model, the proposed approach improved the model estimations by an average of 30 % for all soil samples. However, the advantage of this new approach was larger for the fine and medium textured soils than that for the coarse textured soil. In view that in this approach there is no further need for empirical parameters, we conclude that this approach could become applicable for estimating SMC at the larger field scale.

1 Introduction

Increasing contamination of the groundwater resources, have profoundly accentuated the need for accurate predictions of subsurface flow and chemical transport. Water flow and subsequent chemical transport are largely determined by the soil hydraulic properties, such as the Soil Moisture Characteristics curve (SMC) (Wang et al., 2002; Mohammadi et al., 2009). Measuring the soil hydraulic properties is still difficult, labor intensive, and expensive. Therefore, many researchers have made an attempt to develop an indirect method as an alternative to the direct measurement of hydraulic properties. For the SMC, indirect methods are classified into conceptual methods (Nimmo et al., 2007; Mohammadi and Vanclooster, 2011), semiphysical methods (e.g. Arya and

Paris, 1981; Haverkamp and Parlange, 1982; Wu et al., 1990; Smetten and Gregory, 1996) and empirical methods (e.g. Saxton et al., 1986; Schaap et al., 1998).

The semiphysical methods are mainly based on shape similarity between the SMC and the Particle Size Distribution (PSD) curve (Zhung et al., 2001; Schaap, 2005; Haverkamp et al., 2005; Hwang and Choi, 2006), implying that the pore size distribution (PoSD) is closely related to PSD (Arya et al., 2008). Arya and Paris (1981) did a pioneering work (AP model) for developing semiphysical models. They showed that, the pore size which is associated with a pore volume, is determined by scaling the pore length, using a scaling factor, α. They demonstrated that, an average value of 1.38 for α, scales the pore lengths based on spherical particles to natural pore lengths properly. However, later investigations by Arya et al. (1982), Tyler and Wheatcraft (1989), Basile and D'Urso (1997) and Vaz et al. (2005) revealed that α value varies between 1.02–2.97 for fine and coarse textured soils, respectively. A slight error in the estimation of α may result in considerable error in predicting the SMC (Shuh et al., 1988). Schuh et al. (1988) found that the value of α varies with soil texture and suction head, especially in the wet range of sandy soils. Using three formulations of α, Arya et al. (1999) modeled the parameter α as a function of particle sizes and showed that α was not constant and therefore it decreased with increasing particle size, especially for the coarse fractions. Tyler and Wheatcraft (1989) showed that the parameter α is equivalent to the fractal dimension of a tortuous fractal pore.

Although, the empirical methods have been developed extensively (e.g. Puhlmann and von Wilpert, 2012), the performance of an empirical method will depend on the databases, being used for the model calibration and testing (Tietje and Tapkenhinrichs, 1993; Kern, 1995; Schaap and Leij, 1998; Schaap et al., 2004; Haverkamp et al., 2005; Hwang and Choi, 2006). Therefore, hitherto, all the attempts have so far been made to reduce the sensitivity of the indirect methods to empirical and database-dependent parameters. For instance, Mohammadi and Vanclooster (2011), proposed a conceptual robust model (MV) that, does not included empirical parameter and is independent of the databases that are being used. The disadvantages of the most semi-physical or conceptual models such as the AP and MV models are, the use of "bundle of cylindrical capillaries" (BCC) concept to represent the pore space geometry and the lack of consideration of surface forces (Or and Tuller, 1999; Tuller et al., 1999) which leads to the underestimation of the dry range of the SMC (Arya et al., 1999; Hwang and Choi, 2006; Mohammadi and Vanclooster, 2011). Such underestimations would result in large error in modeling of mechanical properties of unsaturated soil (Gras et al., 2010) and biological processes including plant water uptake (Ryel et al., 2002) and microbial activity (Jamieson et al., 2002; Santamaría and Toranzos, 2003) especially in arid environments.

To predict continuous SMC, Naveed et al. (2012) parameterized the van Genuchten model based on the SMC data points predicted by their proposed model using organic matter, clay, silt and fine and coarse sands. Mohammadi and Meskini-Vishkaee (2013) integrated the MV model with the van Genuchten (VG) model (van Genuchten, 1980) to predict the continuous SMC curve (MV-VG model) from PSD data and found that ignoring the residual moisture content (θ_r) is the main source of systematic error resulted from the MV model. They further tested and compared four approaches to predict the θ_r, and showed that the incorporation of the safely estimated value of the θ_r, will improve the MV-VG prediction results. However, the estimation of $\theta_r$has some limitations, due to the lack of a conceptual underpinning and the poor predictability of θ_r (Leij et al., 2002). Tuller and Or (2005) suggested that, the introduction of θ_r as a fitting parameter in most SMC models often makes the physical representation of key processes in the dry soils vague. Moreover, they pointed out that, the dry range of the SMC shows remarkable scaling behavior. In recent years, the scaling theory has been widely used as an effective tool to describe the variation of the soil hydraulic properties (Sharma and Luxmoore, 1979; Ahuja et al., 1984; Eching et al., 1994; Kosugi and Hopmans, 1998; Oliveira et al., 2006; Nasta et al., 2009). The concept of geometric similitude and similar media was used to develop scaling theory in soil physics (Miller and Miller, 1956). Scaling methods provide a means to relate hydraulic properties of different soils to those of a reference soil, using scaling factors (Nasta et al., 2009). On the other hand, some attempts have been made to modify the original scaling method (Warrick et al., 1977; Vogel et al., 1991; Deurer and Duijnisveld, 2000; Das et al., 2005). Arya et al. (2008) developed a procedure to scale natural pore lengths, directly from straight pore lengths. They exhibited that, scaling approach is less sensitive to uncertainties in model parameters and provides better predictions of the SMC, compared with the AP model.

Kosugi (1996) showed that the SMC can be expressed by a lognormal pore-size distribution function, while Kosugi and Hopmans (1998) found that the set of scaling factors is lognormally distributed when PoSD curve is lognormal. Hayashi et al. (2007) used the Kosugi model (Kosugi, 1996) to evaluate the effectiveness of three kinds of scaling factors obtained by the microscopic characteristic length, standard deviation of pore-size distribution and the porosity. They indicated that in the natural forested hillslope soils, the variability in the SMC is characterized by variability in the effective soil pore volume. Nasta et al. (2009) concluded that the scaling of the PSD curves provides for adequate characterization of the mean and variance of SMCs, which allows for characterization of the soil spatial variability. Many researchers developed empirical models for expressing the SMC; since the parameters of these models do not address the physical significance of the medium. Hence the spatial variability in the pore structure of soils is not fully understood (Hayashi et al., 2007). Likewise, the conventional scaling approaches are based on empirical curve fitting, without considering the physical meaning of the scaling factor (Perfect, 2005; Millán and González-Posada, 2005). To apply these models, one needs to determine the scaling factor, where the complexity of measurements of the pore–size and pore–volume distributions easily nullifies the estimation of the scaling factors. Nevertheless, some efforts have been made to relate the scaling factor to the soil texture (Tuli et al., 2001; Millán et al., 2003).

From this brief review, we conclude that although the scaling approaches improves the modeling and prediction of the SMC, most scaling approaches imply empirical parameters and a robust fully conceptual approach for the estimation of the SMC from easily measurable properties still lacks. The MV model, underestimated the moisture content in the dry range of the SMC, because of the simplified pore geometric concepts, in particular the packing parameter which does not effectively reflect the pore geometry. The general aim of our current work on this subject is to augment and improve the accuracy of the model proposed by Mohammadi and Meskini-Vishkaee (2013) using a scaling approach.

Therefore the objectives of this study were (i) to formulate a robust and physically-based model to scale the SMC from the PSD and porosity, and (ii) to compare the model performance with the results from the existing MV-VG model, using soils documented in the UNSODA data base (Nemes et al., 2000).

2 Theory

Because of the close similarity between the shapes of the PSD and SMC curves, many researchers expressed a SMC model in terms of a PSD model (Haverkamp and Parlange, 1982; Fredlund et al., 2000; Zhuang et al., 2001). The SMC model developed by van Genuchten (1980) is very flexible, widely used and given by:

$$S_e = \left[\frac{1}{1+(\alpha h)^n}\right]^m \tag{1}$$

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} \tag{2}$$

where θ ($L^3 L^{-3}$) is the soil moisture content, S_e (–) is effective saturation degree and θ_s ($L^3 L^{-3}$) and θ_r ($L^3 L^{-3}$) are saturated and residual soil moisture contents, respectively. The parameters n, m and α (L^{-1}) are fitting coefficients, and h (L) is the suction head.

The suction head, h_i (L), corresponding to the particle radius of the ith fraction R_i (L) is given by (Mohammadi and Vanclooster, 2011):

$$h_i = \frac{0.543 \times 10^{-4}}{R_i}\zeta \tag{3}$$

where ζ (–) is a coefficient depending on the state of soilparticles packing and is defined as:

$$\zeta = \frac{1.9099}{1+e} \tag{4}$$

where e (–) is the void ratio given by

$$e = \frac{\rho_s - \rho_b}{\rho_s} \tag{5}$$

where the ρ_s ($\mathrm{M\,L^{-3}}$) and ρ_b ($\mathrm{M\,L^{-3}}$) are soil particle and bulk densities respectively.

Arya and Paris (1981) suggested that the moisture content, θ_i ($\mathrm{L^3\,L^{-3}}$), can be obtained from PSD and θ_s ($\mathrm{L^3\,L^{-3}}$), as:

$$\theta_i = \theta_s \sum_{j=1}^{j=i} w_j; \quad i = 1, 2, 3, \ldots, k \tag{6}$$

where w_j is the mass fraction of particles (–) in the jth particle-size fraction. Considering that the

$$P_i = \sum_{j=1}^{j=i} w_j \tag{7}$$

would result in:

$$\theta_i/\theta_s = S \tag{8}$$

where S (–) is the saturation degree and P_i (–) is cumulative mass fraction of soil particles. It is obvious, that if $\theta_r = 0$ then, $S_e = S$ and subsequently $S = P_i$. Arya and Paris (1981) however, ignored the residual moisture content, while it may be a considerable value for many types of soil and clayey soils in particular. Combining Eqs. (1) and (3) with Eq. (7) yields:

$$P_i = \left[\frac{1}{1 + \left(\alpha \frac{0.543 \times 10^{-4}}{R_i} \zeta \right)^n} \right]^m \tag{9}$$

In Eq. (9), the cumulative mass fraction, P_i, is substituted with the S_e in Eq. (1). Hence, fitting of the Eq. (9) to the PSD data, enables one to directly predict the SMC parameters (n, m and α). Moreover, these coefficients allow expression of the continuous form of predicted SMC. Since, assuming that $\theta_\mathrm{r} = 0$ would result in model underestimation in dry range of the SMC (Mohammadi and Meskini-Vishkaee, 2013), we developed a conceptual scaling approach to reduce the model bias.

2.1 Scaling approach

Following the Miller and Miller (1956) scaling theory, we assume that, the geometrically-identical soils are characterized by the similarity of PoSD and PSD, but differ in their microscopic length scale, which is defined as follows (Nasta et al., 2009):

$$\beta = \frac{\overline{\gamma}}{\gamma} \tag{10}$$

where β is a scaling factor, $\overline{\gamma}$ and γ represent the microscopic characteristic lengths of the reference soil and actual soil respectively. For instance, Kosugi and Hopmans (1998) proposed the median suction head, as the macroscopic characteristic length to scale SMC.

Following Hayashi et al. (2007), we suggest that the porosity is an appropriate property for inferring a characteristic length. Since, the soil porosity is linked to the packing parameter, ζ, in the MV model (Eq. 4), we hypothesize that ζ is the characteristic length of the soil.

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We assume that the reference soil is the one, which consists of uniform-size spherical particles that are arranged in random close packing state, leading to minimum porosity (known as the Kepler conjecture in literature of crystallography). Literature suggests that the porosity of this packing state is 0.259 (Hopkins and Stillinger, 2009). Subsequently, the maximum value of packing parameter, $\zeta_{\max}$, would equal to 1.41432 for reference soil. Hence the scaling factor, λ, for each soil sample can be defined by:

$$\lambda = \frac{\zeta}{\zeta_{\max}} \tag{11}$$

In general, the values of the pore size distribution index, n, (Eqs. 1 and 9) and ζ are large for the coarse-textured soils and small for the fine-textured soils. We suggest that the λ can scale the parameter "n", obtained from fitting Eq. (9) to the PSD data, to the index manifested by "n" in the SMC model (Eq. 1) (hereafter n^*) as follows:

$$n^* = \lambda \times n \tag{12}$$

where n^* is scaled to the PoSD index in VG model. Hence, the modified model is

$$\frac{\theta}{\theta_s} = \left[\frac{1}{1+(\alpha h)^{n^*}}\right]^m \tag{13}$$

In summary, given a known θ_s we can calculate ζ and subsequently λ using Eq. (11). The soil parameter "α" and "m" are obtained from fitting Eq. (9) to the PSD data and, n^*, is estimated by Eq. (12), and consequently the SMC is predicted directly by Eq. (13).

3 Material and methods

Eighty-two soil samples, with a wide range of physical properties that contained at least five PSD data, were selected from the UNSODA hydraulic properties database (Nemes et al., 2000). UNSODA is a database of basic soil and hydraulic properties from 790 samples, gathered from all over the world, and compiled by the US Department of Agriculture. All soils are summarized in Table 1. The PSD curves for the selected soils were divided into k fractions according to the method proposed by Arya and Paris (1981) and Arya et al. (1999). In this procedure, volumetric moisture contents corresponding to the ith fraction were computed, using Eq. (6) and suction heads were predicted, using Eq. (3), in which the parameter ζ was calculated with Eq. (4). In this study, we assumed that, the porosity is equivalent to θ_s. For soils, that neither provide a porosity nor a θ_s, the first point of the SMC data that corresponds to the lowest suction head were used as θ_s (Chan and Govindaraju, 2004).

We fitted Eq. (9) to the PSD data. We used nonlinear regression analysis to fit Eq. (9) to the PSD, using Matlab7.1 software (Matlab 7.1, The Mathworks Inc., Natick, MA) and the Marquardt–Levenberg algorithm (Marquardt, 1963). We calculated for each soil the scaling factor, using either the bulk density or the available saturated soil moisture content, and predicted the SMC.

For each prediction, the agreement between the predicted moisture content $\theta_{i(\mathrm{p})}$ and measured moisture content $\theta_{i(\mathrm{m})}$ was expressed in terms of the root mean square errors (RMSEs), given by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\theta_{i(\mathrm{p})} - \theta_{i(\mathrm{m})})} \tag{14}$$

in which n is the number of observed data points. The relative improvement (RI) resulted from the scaling approach rather than MV-VG model was calculated as follows (Minasny and McBartney, 2002):

$$\mathrm{RI}\ (\%) = \frac{\mathrm{RMSE_M} - \mathrm{RMSE_S}}{\mathrm{RMSE_M}} \times 100 \tag{15}$$

where, RI is the Relative Improvement, $\mathrm{RMSE_M}$ and $\mathrm{RMSE_S}$ are RMSE values of the MV-VG model and the current scaled model. Obviously, the negative RI values indicate that the scaling approach would diminish the accuracy level of prediction of the SMC in comparison with the MV-VG model.

We also fitted a cubic polynomial function to overall predicted data and, calculated the area between the fitted polynomial and the 1 : 1 line from the difference of the numerical integrals of these two functions (do Carmo, 1976).

4 Results and discussion

To analyze the performance of the proposed scaling approach, the RMSE was used as an index, to compare models for each soil and textural class. Table 2 depicts this comparison and demonstrates the improved accuracy of the presented scaled approach. The RMSEs of the predicted and measured moisture contents, ranged from 0.0223 to 0.1502 for the original MV-VG model (average 0.0852), and from 0.0169 to 0.1122 (average 0.0601) for the scaled approach. The improvement is also reflected by RI in Table 2. Except for soils no. 3033 (Clay loam) and 3090 (Silt loam), the scaling approach resulted in more accurate predictions for all soils. Table 2 also indicates that the scaling approach can improve the model estimations on average by 30 %.

For the fine and medium textured soils, the values of RI are larger than for the coarse textured soil. This result was expected, because the MV and MV-VG models underestimate the dry range moisture content for the fine texture soils (Mohammadi and Vanclooster, 2011; Mohammadi and Meskini, 2013) and subsequently the scaling approach was more effective for these soils.

We examined the possible relations between the RI and soil physical properties. Among all parameters, the saturated moisture content and scaling factor show strong relations with the RI. Figure 1a shows that the RI values increase significantly with the saturated moisture content of the soils, i.e. the scaling approach would more effectively improve the model accuracy for the fine texture soils with higher θ_s. This result can be confirmed with Fig. 1b, which exhibits that the scaling factor is inversely correlated with the IR factor (Fig. 1b). Indeed, the soils with high porosity commonly have abundant amount of clay materials and organic matter, characterized with high surface energy. These attributes are the main sources of errors of the MV and MV-VG models. Typical examples of measured vs. predicted SMCs with the MV-VG model and the scaling approach for clay, sandy loam, loam, and silt loam textures are presented in Fig. 2a–f. For the clay (codes: 2340 and 4681), sandy loam (code: 3180 and 3200), loam (code: 3191) and silt loam (code: 3090) soils, the scaling approach fits the data well and outperforms the MV-VG model at entire range of the SMC. For the silt loam soil (code: 3090), the scaling approach slightly overestimates the moisture content through the entire range of suction heads and the MV-VG model underestimates the moisture content at low suction heads. Overall, the scaling approach performs better than MV-VG model for all soil samples (Table 2 and Fig. 3) but, the performance of scaling approach did not suitably respond for two soil samples (codes: 3033, 3090). The model error may be related to simplified representation of the total porosity which is considered equal to the saturated volumetric moisture content. The swelling properties and high organic carbon content of these soils (> 4 %, 3.85 % respectively) may partially be a source of these errors. We further suspect that the complexity of the relationship between PSD, PoSD and pore connectivity can be effective in the model performance (Zhang et al., 2001). The assumption of the similarity between PSD and PoSD does not perform equally well to all soils.

We tentatively conclude that the scaling of the PSD curves using the parameter ζ generally performs better in predicting the SMC as compared to the original MV-VG model. The un-scaled MV-VG model underestimates the moisture content at high suction heads.

Figure 3 compares all estimated moisture contents, using MV-VG model and scaling approach, respectively, with the measured soil moisture content for all the 82 soil samples. The overall predictability of the two methods is evaluated by comparing the experimental data and the predicted soil moisture content on a 1 : 1 plot. Linear regression of the measured and estimated moisture contents, using the two methods for all the soil samples showed that, the slope values were 0.7675 and 0.8484 and the coefficients of determination (R^2) between the estimated results and measured data for all soils were 0.765 and 0.8565 for MV-VG model and scaling approach, respectively. Hence, the MV-VG model and the scaling approach, underestimate the moisture content by about 23 % and 15 % respectively, while the bias of the scaling approach is less than MV-VG model. Regarding the R^2, the scaling method still remains the most preferable method. Comparing the overall predictability of the two methods, the correlation coefficient of linear regression, as a statistical summary, cannot exclusively replace visual examination of the data. We therefore, use the cubic polynomial function to adequately express the data variations. The fitted polynomial functions are drawn as shadowed red curves in Fig. 3a and b. We further suggest that the area between the fitted curve and the 1 : 1 line (AE), is an expression of the systematic error. The values of AE were 0.0369 and 0.0250 for the MV-VG model and the scaling approach respectively. It confirms that the level of systematic errors of the scaling approach is about 33 % less than that of MV-VG model. This result can be confirmed by the comparison of the R^2 values obtained when predicting the SMC for each soil with two methods (Table 2 columns 5 and 6).

We conclude that the scaled PSD curve will result in a more accurate prediction of the SMC as compared to the un-scaled PSD data. Moreover, the physically based scaling approach allows the upscaling of the physically based parameters which is essential for the parameterization of the soil hydraulic properties for large study areas from individual soil samples (Kosugi and Hopmans, 1998). To scale the SMC, Tuller and Or (2005) used the soil specific surface area (SA) and the thickness of water film to express the moisture content in dry range of the SMC. Despite, their reasonable model performance, the application of their procedure was limited, due to difficulty in the measurement or the estimation of SA.

Hayashi et al. (2007) found that in natural forested hillslope soils, the variability in the SMC is scaled and characterized by the variability in effective porosity. Nevertheless, the determination of the effective porosity is also difficult.

The scaling factor proposed in current study is defined by using the index of packing state which can be determined easily from the bulk density of soil and particle density.

5 Conclusions

Using a new scaling approach, the current study showed that the continuous form of SMC curve can be predicted from knowledge of PSD, as modeled by the van Genuchten (1980) model and particle packing state. In this approach it was assumed that the scaling factor can be defined as the ratio of packing state of a soil sample and the packing state of a reference soil. Results showed that the proposed approach can adequately predict the SMC of 82 soil samples selected from the UNSODA database. It was found further that the scaling approach provides better predictions of the SMC than MV-VG model, especially in dry range of the SMC. For soils for which the error was important, we attributed the proposed scaling approach error to high organic carbon content and swelling properties of the soil. Indeed, in these soils the soil pore structure and porosity is changing in time, leading to uncertainty in the scaling factor based on the soil porosity.

In summary, we concluded that the main advantages of the proposed scaling approach as compared to many SMC prediction models are: (i) the applied scaling factor is determined easily from soil bulk and particle densities; (ii) the scaling factor has physical meaning, which does not depend on soil database and empirical parameters; (iii) the proposed approach predicts a continuous form of the SMC; and, (iv) this approach estimates the SMC more appropriately in comparison with many other models. Considering that, there is no further need for empirical parameters, we conclude that this approach may be useful in estimating the SMC at larger field scales.

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Table 1. Textural classes and UNSODA codes for soils used for testing and evaluating the approach.

Textural class	Clay	Clay loam	Loam	Silt loam	Silty clay	Silty clay loam	Loamy sand	Sand	Sandy clay loam	Sandy loam
UNSODA codes	1400 2340 2361 2362 4120 4680 4681 2360	3033	3221 1211 1260 1261 2530 3190 3191 3222	2000, 3090 3213, 3261 4042, 4070 4180, 4181 2464, 1341 1342, 1350 1351, 1352 2001, 2002 2010, 2011 2012,	3030 1360	3100 3101 1371	1160 2102 2103 3130 3150 3152 3160 3161 3170 3171 4251	1050, 1240, 1460 1464, 1466, 2100 3133, 3134, 3140 3141, 3144, 3155 3162, 3163, 3164 3165, 3172, 3340 4051, 4152, 4263 4272, 4282, 4441 4520, 4650, 4000	3202	1130 3180 3200 3290

Table 2. Average Root Mean Square Error (RMSE), coefficients of determination (R^2), Relative Improvement (RI) and hydraulic parameters for each soil textural group, with standard deviations in parentheses.

		RMSE		R^2			Hydraulic parameters				
Soil texture	Number of soil	MV-VG model	Scaling approach	MV-VG model	Scaling approach	RI value (%)	θ_s ($L^3 L^{-3}$)	α (L^{-1})	m (–)	n (–)	n^* (–)
Clay	8	0.088 (0.014)	0.041 (0.020)	0.973 (0.017)	0.977 (0.020)	53.87 (16.74)	0.51 (0.04)	0.043 (0.085)	0.128 (0.104)	2.457 (2.195)	1.467 (1.127)
Clay loam	1	0.027	0.017	0.725	0.872	38.15	0.58	0.002	0.248	1.634	1.040
Loam	8	0.078 (0.019)	0.045 (0.015)	0.896 (0.100)	0.913 (0.088)	41.04 (17.74)	0.45 (0.06)	0.042 (0.030)	0.157 (0.079)	3.115 (1.452)	2.187 (1.100)
Silt loam	19	0.082 (0.026)	0.059 (0.020)	0.922 (0.043)	0.950 (0.033)	25.63 (20.28)	0.44 (0.04)	0.019 (0.011)	0.233 (0.365)	4.937 (2.593)	3.637 (1.982)
Silty clay	2	0.076 (0.056)	0.061 (0.022)	0.932 (0.040)	0.941 (0.010)	3.01 (43.07)	0.51 (0.09)	0.040 (0.028)	0.195 (0.157)	1.573 (1.402)	1.091 (1.039)
Silty clay loam	1	0.129	0.093	0.887	0.924	28.15	0.43	0.020	0.116	2.548	1.870
Loamy sand	11	0.093 (0.037)	0.060 (0.022)	0.893 0.062	0.926 (0.038)	32.63 (11.64)	0.40 (0.07)	0.067 (0.038)	0.179 (0.058)	5.488 (1.357)	4.048 (1.088)
Sand	27	0.093 (0.030)	0.073 (0.024)	0.854 (0.102)	0.893 0.081	20.74 (7.51)	0.37 (0.04)	0.052 (0.033)	0.458 (0.444)	5.592 (2.018)	4.380 (1.531)
Sandy clay loam	1	0.084	0.065	0.957	0.967	23.07	0.36	0.043	0.054	8.000	6.582
Sandy loam	4	0.073 (0.014)	0.035 (0.015)	0.950 (0.028)	0.971 (0.008)	51.63 (18.12)	0.46 (0.05)	0.066 (0.020)	0.093 (0.032)	5.676 (1.526)	3.980 (1.137)
Average	82	0.086[a] (0.028)	0.060[b] (0.024)	0.898 (0.084)	0.927 (0.065)	30.14 (18.88)	0.42 (0.07)	0.044 (0.040)	0.272 (0.338)	4.726 (2.329)	3.519 (1.816)

[a] Different lowercase letters indicate significant differences at $P < 0.05$.

Table 3. Symbols and abbreviations.

SMC:	Soil Moisture Characteristics curve
PSD:	Particle Size Distribution
PoSD:	Pore Size Distribution
MV:	Mohammadi and Vanclooster (2011) model
BCC:	Bundle of Cylindrical Capillaries
VG model:	van Genuchten model
MV-VG model:	integrated the MV model with the van Genuchten model
AP:	Arya and Paris (1981)
PTF:	Pedotransfer Function
RMSE:	Root Mean Square Error
θ:	the soil moisture content
S_e:	effective saturation degree
θ_s:	saturated moisture contents
θ_r:	residual moisture contents
n:	fitting coefficients
m:	fitting coefficients
α:	fitting coefficients
h:	suction head
ζ:	a coefficient depending on the state of soilparticles packing
e:	the void ratio
ρ_s:	soil particle density
ρ_b:	soil bulk density
w_j:	the mass fraction of particles in the jth particle-size fraction
S:	saturation degree
P_i:	cumulative mass fraction of soil particles
R_i:	particle radius of the ith fraction
β:	scaling factor
$\overline{\gamma}$:	microscopic characteristic lengths of the reference
γ:	microscopic characteristic lengths of the subjected soil
ζ_{max}:	maximum value of packing parameter
n:	pore size distribution index
λ:	scaling factor
n^*:	scaled the PoSD index in VG model
$\theta_{i(p)}$:	predicted moisture content
$\theta_{i(m)}$:	measured moisture content
RI:	relative improvement
$RMSE_M$:	RMSE values of MV-VG model
$RMSE_s$:	RMSE values of scaling approach
AE:	area between the fitted curve and 1 : 1 line

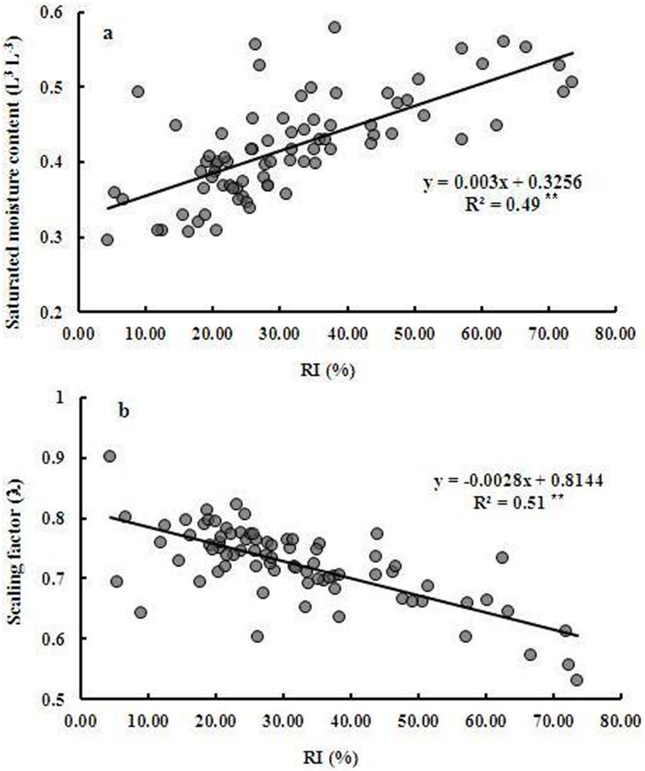

Fig. 1. The efficiency of scaling approach, % RI, defined with RMSE (Eq. 15) as function of **(a)** the saturated moisture content and **(b)** scaling factor for all soil samples. **: significant at $P = 0.01$.

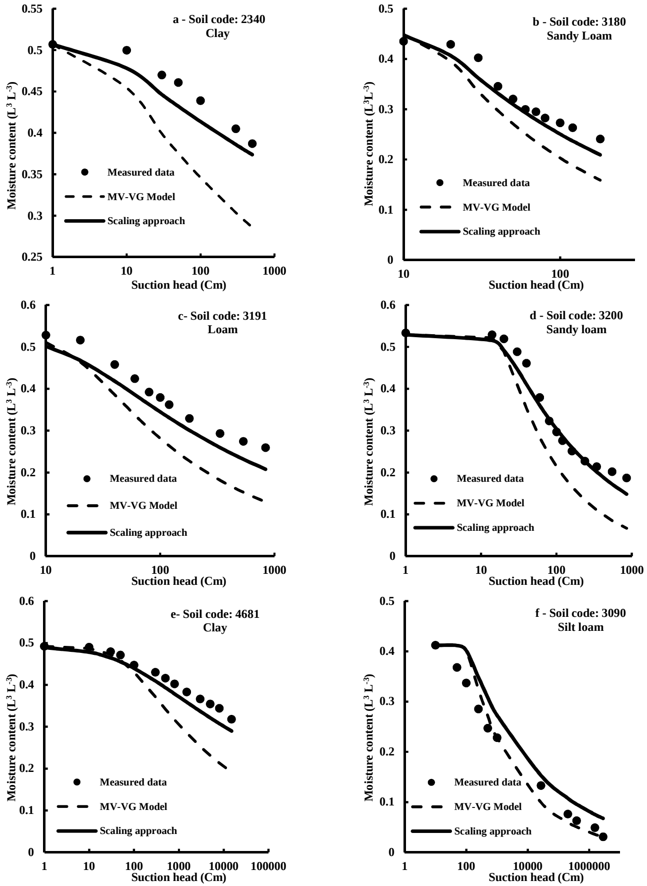

Fig. 2. Examples of measured vs. predicted soil moisture characteristics curve (SMC) for each texture using the integrated MV-VG model (Eq. 9) and scaling approach (Eq. 13): for **(a)** clay soil, **(b)** sandy loam soil, **(c)** loam soil, **(d)** sandy loam soil, **(e)** clay soil and **(f)** silt loam soil.

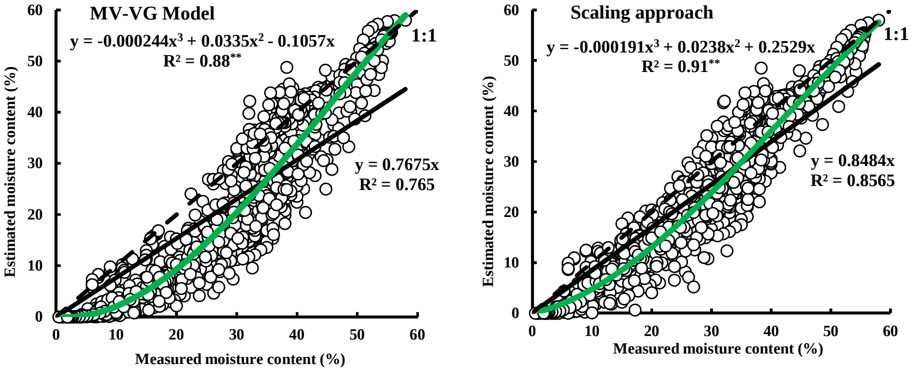

Fig. 3. Comparisons of the measured and estimated moisture contents for 82 selected soils using the MV-VG model (Eq. 9) and scaling approach (Eq. 13). Dashed lines: the 1 : 1 line. Solid lines: linear-regression line, shadowed solid red line: nonlinear-regression-line.