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Predicting of soil water characteristics curve with modified Van Genuchten model by particle size distribution data

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Abstract

Direct measurement of soil moisture characteristics curve (SMC) due to spatial and temporal variation is labor and expensive. So, prediction of SMC from basic soil properties which can be measured easily would be satisfactory. In this study, we use a dataset containing 18 UNSODA soil samples to evaluate the performance of modified Van Genuchten (VG) model. We make a comparison between the results obtained from modified VG model and ROSETTA software showing that the modification of VG model increases the accuracy of SMC. The model bias was related to particles size and particles surface energy. We concluded that modified VG model improve predictions of SMC more accurate for large scale hydrological management.

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Introduction

Many researchers intended to estimate SMC indirectly by means of soil basic properties. Estimation of hydraulic conductivity curve (HCC) significantly correlates with soil water retention curve which indicate the relation of water content and matric potential. Unsaturated zone plays important role in soil, water and plant relationship which links surface water to underground water (Harter and Hopmans 2004). Water movement has key role in quality and quantity of underground water. Nowadays, researchers paid special attention to model water behavior in soil. Thus, accessing to quantitative information of soil accelerate the numerical modeling of soil moisture characteristic curve (SMC). Moreover, direct measurement of SMC is difficult and inaccurate (Schaap and Leij, 1998; Christiaens and Feyen, 2001; Islam et al., 2006; Abbasi et al 2011) therefore many researchers intended to estimate SMC indirectly by means of soil basic properties (Antinoro et al., 2014). Estimation of hydraulic conductivity curve (HCC) significantly correlates with soil water retention curve which indicate the relation of water content and matric potential (Hunt et al., 2013).

In recent years, researchers paid considerable attention to predict SMC in terms of pore size distribution (PoSD) with using soil basic physical properties (Nimmo et al., 2007; Mohammadi and Meskini-Vishkaee, 2013). These approaches which called transfer functions can be classified in three groups: 1)The statistical techniques (pedo-transfer functions) or neural network models which determine the correlation of basic soil properties (e.g, sand, silt, clay percentages, organic matter content) and SMC points or parameters (Dashtaki et al., 2010; Vereecken et al., 2010; Abbasi et al., 2011), Available and reliable databases provide variety of inputs for statistical models therefore, these models were widely used(Hwang and Choi, 2006). Van Genuchten (VG) model is the most popular parametric model which is still attracting special attention of soil scientist and hydrologist.

VG model assumed that SMC has different unknown parameters which are empirical and database dependent. Therefore evaluation of soil water retention curve is difficult and in accurate. Many researchers used VG model to predict water retention curve (Ghanbarian-Alavijeh *et al.*, 2010, Mohammadi and Meskini-Vishkaee, 2013). 2) Physico-empirical models which express the relation of particle size distribution (PSD) with PoSD. 3) Conceptual models which predict the soil hydraulic properties based on some conceptual assumptions without using any emperical coefficient.

Recently, Mohammadi and Vanclooster (2011) developed a robust, conceptual transfer function to estimate the SMC from the PSD (MV model). In many researches the VG model is fitted to experimental water retention curve which is not available in continuous range we decided to develop a new method to predict SMC of VG model through PSD data. Therefore, the objectives of this study are 1) to predict continuous SMC by PSD using the UNSODA database to compare the performance of new method with obtained results of ROSETTA software.

Material and method

UNSODA database18 soil samples of UNSODA database with at least 4 PSD data were selected to estimate SMC. The selected codes according to the soil texture are presented in table 1. UNSODA database contains unsaturated hydraulic characteristics of 790 soil samples of all over the world specially Europe and America which are used to develop the estimations of water flow and solute transport management.

Table 1. Distribution of textural classes of UNSODAcodes used to evaluate and compare of models.

Textural class	Loamy sand		Sand	Sandy loam
	1011	1051	2203	1101
UNSODA codes	1013		4520	1130
	3131		4132	1210
	4062			2111
	2101			3292
	2105			4172
	1031			1131

The Eq. (2) was used to fit on the full range of PSD data with at least 4 measured points. To evaluate the unknown coefficients of Eq. (2), the trust region algorithm of Matlab8.3 software (Matlab 8.3, The Math works Inc., Natick, MA, USA) was used. The parameter of ξ was calculated easily using available bulk and particle densities. In most UNSODA soil samples, Θ_s is available, for those with no access to Θ_s , we used Chan and Govindaraju (2004) suggestion where they assumed saturation moisture content to be equal to corresponding moisture content of the lowest matric potential.

ROSETTA software is also used to estimate SMC parameters of VG model with using SSCBD model option (sand, silt and clay percentages and bulk density are model predictors).

Calculate the accuracy of each prediction

To calculate the accuracy of each prediction, the root mean square error (RMSE) between observed and predicted moisture content was computed. Determination of coefficient (R²) is also presented to evaluate the correlation of observed moisture content and predicted one. The relative improvement (RI) was calculated to compare the prediction methods (McBrantney, 2002):

$$RI = \frac{RMSE_{VG} - RMSE_{R}}{RMSE_{VG}}$$
(3)

which $RMSE_{VG}$, $RMSE_R$ are RMSE of proposed equation (as the reference model) or ROSETTA (as the comparative approaches)respectively. A positive RI (-) indicates that the accuracy of predicted moisture contents are improved with using new method or ROSETTA approach.

Theory

Van Genuchten (1980) proposed parametric model to predict water retention curve is defined as

$$= \frac{z^{-r}}{(1+(\alpha h)^{n})^{m}} + r$$
(1)

where $\Theta(L^{3}L^{-3})$ is the soil moisture content, Θ_{s} and Θ_{r} (L³L⁻³)are the saturated soil moisture content and

residual water content, h (L) is the matric suction, n, m and α are fitting coefficients. Mohammadi and Vanclooster (2011) developed a model (MV model) to predict the soil matric suction from particle size. Meskini- Vishkaee*et al.* (2014) presented new model (MM model) using scaling method to predict the water characteristic curve by particle size. According the MV model and MM model prediction of water retention curve is accessible accurately. Combination of MV and MM model is defined as:

$$\sum_{1}^{i} wi = \frac{1}{\left(1 + \left(\alpha \frac{\cos 4\pi \xi}{r_{1}}\right)^{n_{*}}\right)^{n_{*}}}$$
(2)

Eq. (2) is fitted to the PSD data to estimate VG model parameters (m, n and α) as a SMC prediction model.

Result and discussion

The selected codes according to the soil texture are presented in table UNSODA database contains unsaturated hydraulic characteristics of 790 soil samples of all over the world specially Europe and America which are used to develop the estimations of water flow and solute transport management. The Eq. (2) was used to fit on the full range of PSD data with at least 4 measured points. To evaluate the unknown coefficients of Eq.(2), the trust region algorithm of Matlab 8.3 software (Matlab 8.3, The Mathworks Inc., Natick, MA, USA)was used. The parameter of ξ was calculated easily using available bulk and particle densities. In most UNSODA soil samples, Θ_s is available, for those with no access to Θ_s , we used Chan and Govindaraju (2004) suggestion where they assumed saturation moisture content to be equal to corresponding moisture content of the lowest matric potential. ROSETTA software is also used to estimate SMC parameters of VG model with using SSCBD model option (sand, silt and clay percentages and bulk density are model predictors). To calculate the accuracy of each prediction, the root mean square error (RMSE) between observed and predicted moisture content was computed. Determination of coefficient (R²) is also presented to evaluate the correlation of observed moisture content and predicted one.

The relative improvement (RI) was calculated to compare the prediction methods, which $RMSE_{VG}$, $RMSE_R$ are RMSE of proposed equation (as the reference model) or ROSETTA (as the comparative approaches) respectively. A positive RI (-) indicates that the accuracy of predicted moisture contents are improved with using new method or ROSETTA approach.

Fig. 1 (A-C) represents the experimental and estimated SMC for loamy sand (code: 4062), sand (code: 4132) and sandy loam (code: 2111), soils with using proposed method and ROSETTA software. The overall view of fig. 1 (A-C) shows that the modified VG

model estimates continuous SMC for all selected soils. In loamy sand, VG model under predicts in dry range of SMC. Water retention curve of ROSETTA software under predicts smoothly in wide range of moisture content. SMC of sand soils is predicted more accurately in full range while ROSETTA software under predicts negligibly. In sandy loam soil experimental measured points were not available in dry range. The proposed method and ROSETTA software noticeably under predicts in dry range while in wet range of SMC Eq. (2) and ROSETTA software over predicts. This model assumes that all soil particles are spherical and the soil structure can influence only the soil bulk density.



Fig. 1. Examples of measured and predicted water retention curve of proposed method (equation 2) and ROSETTA software for: (A) loamy sand soil, (B) sand soil and (C) sandy loam.

Mohammadi and Vanclooster (2011), Mohammadi and Meskini- Vishkaee (2013) ignore the effects of soil organic matter content, particle surface energy, lens and film water volume.

So, the under prediction of modified VG model can be partially related to MV model assumption. The results of Eq. (2) and ROSETTA software are presented in table 2.

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		Equation (2)			ROSETTA software				
Soil texture	θs	$\Theta_{\rm r}$	n	α	m	$\Theta_{\rm r}$	n	α	m
	(L3L-3)	(L3L-3)	(-)	(L-1)	(-)	(L3L-3)	(-)	(L-1)	(-)
loamy sand	0.39	0.024	3.75	0.026	0.47	0.028	2.05	0.039	0.51
sand	0.34	0.011	3.53	0.022	3.02	0.010	2.24	0.033	0.55
sandy loam	0.32	0.032	6.89	0.029	0.23	0.041	1.47	0.046	0.32
average	0.35	0.022	4.72	0.025^{*}	1.24	0.026	1.92	0.038*	0.46

Table 2. Average values of hydraulic parameters resulted from fitting equation (2) and ROSETTA software on PSD data.

*geometric mean.

Table 2 shows that the average value of Θ_s is 0.35 for selected soils which ranges from 0.39 (loamy sand soils) to 0.32 (sandy loam soils). The average values of Θ_r for Eq. (2) and ROSETTA software are 0.022 and 0.026 respectively. Θ_r ranges from 0.011 (sand soils) to 0.032 (sandy loam soils) for Eq. (2). For ROSETTA software maximum Θ_r is also seen in sandy loam soils (0.041) while minimum Θ_r is seen in sand soils (0.01). Average value of hydraulic parameters of VG model (n and m) respectively are 4.72 and 1.24 for Eq. (2), while average value of n and m respectively are 1.92 and 0.46 for ROSETTA software. Average values of geometric means of α are 0.025 and 0.038 for Eq. (2) and ROSETTA software respectively.

The comparison of predicted SMC of Eq. (2) and ROSETTA software is presented in table 3 by statistical criteria RMSE,R² and RI. Average RMSEs of Eq. (2) and ROSETTA software are 0.0029 (ranges from 0.00075 for sand soils to 0.0051 for loamy sand soils) and 0.0157 (ranges from 0.013 for loamy sand soils to 0.018 for sandy loam soils) respectively, while the optimal value of RMSE is expected to be zero. In terms of RMSE, Eq. (2) performs significantly better than ROSETTA software by statistical analysis.

Table 3. Comparison of average of RMSE, R² and RI values of proposed method (equation (2)) and ROSETTA software in predicting the SMC.

Soil texture	Number . of soils	RMSE		R ²		RI value	
		Equation (2)	ROSETTA	Equation (2)	ROSETTA	(-)	
			software	1	software		
loamy sand	8	0.0051	0.013	0.985	0.854	0.61	
sand	3	0.00075	0.016	0.998	0.905	0.95	
sandy loam	7	0.003	0.018	0.854	0.893	0.83	
average	18	0.0029 ^b	0.0157 ^{a*}	0.9 46 ^a	0.884 ^b	0.81	
Optimal value		0		1		1	

* The different letters indicate significant differences at P<0.05

The RMSE of proposed model and ROSETTA software is substantially smaller than Meskini *et al.* (2014) which are 0.086 and 0.0.745. The least RMSE among other soil textures in sand soils (0.00075) for Eq. (2) reveals that the model performance is noticeably better in coarse texture.

Mohammadi and Vanclooster (2010) also showed that the performance of MV model decreased with fine particle content. Average values of R^2 for Eq. (2) and ROSETTA software are 0.946 and 0.884 respectively which R^2 of Eq. (2) is significantly greater than R^2 of ROSETTA software.

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In Eq. (2), maximum R^2 is 0.998 for sand soils minimum R^2 is 0.854 for sandy loam soils while the optimized value of R^2 is 1.

The maximum and minimum values of R² in ROSETTA software are 0.905 (sand soils) and 0.854 (loamy sand soils) respectively. In terms of R², the performance of modified VG model (Eq. (2)) is consistently significant in comparison with ROSETTA software. RI values draw a comparison between Eq. (2) and ROSETTA software revealing substantially accuracy rise. The average value of RI is 0.81 indicating that using modified VG model increase the accuracy of SMC predictions. RI values range from 0.95 (sand soils) to 0.61 (loamy sand soils). Decline of RI value in loamy sand soils can be attributed to fine particles and organic content. In overall view and in terms of all statistical criteria (RMSE, R² and RI), the modified VG model generally estimate SMC more accurate than ROSETTA software. Moreover, modified VG model predicts SMC of coarse textured soils markedly better.

Conclusion

In this study we used modified VG model to predict SMC using PSD data and we evaluated performance of proposed model with experimental data and obtained results of ROSETTA software. Results showed that the modified VG model consistently predicts SMC. In overall view, we concluded that using modified VG model has the convenient advantages as follow:

(i) the proposed equation can predict continuous and accurate SMC for coarse texture soils.

(ii) the modified VG model as parametric model is more accurate than ROSETTA software.

(iii) this approach provide more accurate SMC in dry range because we do not ignore the Θ_r .

Due to slight spatial and temporal variation of PSD data, the modified VG model can provide alternative hydraulic characteristics curve in large scale water and solute management.

References

Abbasi Y, Ghanbarian-Alavijeh BE, Liaghat AM, Shorafa ME. 2011. Evaluation of pedotransfer functions for estimating soil water retention curve of saline and saline-alkali soils of Iran. Pedosphere **21**, 230-237.

Antinoro C, Bagarello V, Ferro V, Giordano G, Iovino M. 2014. A simplified approach to estimate water retention for Sicilian soils by the Arya–Paris model. Geoderma **213**, 226-234.

Arya LM, Paris JF. 1981. A physicoempirical model to predict the soil moisture characteristic from particle-size distribution and bulk density data. Soil Science Society of America Journal **45**, 1023-1030.

Chan TP, Govindaraju RS. 2004. Estimating soil water retention curve from particle-size distribution data based on poly disperse sphere systems. Vadose Zone Journal **3**, 1443-1454.

Christiaens K, Feyen J. 2001. Analysis of uncertainties associated with different methods to determine soil hydraulic properties and their propagation in the distributed hydrological MIKE SHE model. Journal of Hydrology **246**, 63-81.

Dashtaki S, Homaee M, Khodaverdiloo H. 2010. Derivation and validation of pedotransfer functions for estimating soil water retention curve using a variety of soil data. Soil Use Manage **26**, 68-74.

Ghanbarian-Alavijeh B, Liaghat A, Huang Guan-Hua, Van Genuchten M Th. 2010. Estimation of the van Genuchten soil water retention properties from soil textural data **20**, 456-465.

Harter T, Hopmans J. 2004. Role of vadose zone flow processes in regional scale hydrology: Review, opportunities and challenges. Kluwer Pubp 179.

Hunt AG, Ghanbarian B, Saville KC. 2013. Unsaturated hydraulic conductivity modeling for porous media with two fractal regimes.Geoderma 207, 268-278. **Hwang SI, Choi SI**. 2006. Use of a lognormal distribution model for estimating soil water retention curves from particle-size distribution data. Journal of Hydrology **323**, 325-334.

Islam N, Wallender W, Mitchell JP, Wicks S, Howitt RE. 2006. Performance evaluation of methods for the estimation of soil hydraulic parameters and their suitability in a hydrologic model.Geoderma1 **341**, 135-151.

Mc Bratney B. 2002. The Neuro-m Method for Fitting Neural Network Parametric Pedotransfer Functions. Budiman Minasny and Alex. Soil Science Society of America Journal **66**, 352-361.

Meskini-Vishkaee F, Mohammadi MH, Vanclooster M. 2014. Predicting the soil moisture retention curve, from soil particle size distribution and bulk density data using a packing density scaling factor. Hydrology and Earth System Sciences **18**, 4053-4063.

Mohammadi MH, Meskini-Vishkaee F. 2013. Predicting soil moisture characteristic curves from continuous particle-size distribution data. Pedosphere **23**, 70-80.

Mohammadi MH, Vanclooster M. 2011. Predicting the soil moisture characteristic curve from particle size distribution with a simple conceptual model. Vadose Zone Journal **10**, 594-602. Nemes A, Schaap MG, Leij FJ, Wösten JHM. 2001. Description of the unsaturated soil hydraulic database UNSODA version 2.0. Journal of Hydrology 251, 151-162.

Nimmo JR, Herkelrath WN, Laguna Luna AM. 2007. Physically based estimation of soil water retention from textural data: General framework, new models, and streamlined existing models. Vadose Zone Journal **6**, 766-773.

Schaap MG, Leij FJ. 1998. Using neural networks to predict soil water retention and soil hydraulic conductivity. Soil and Tillage Research **47**, 37-42.

Schaap MG, Leij FJ, van Genuchten MT. 2001. ROSETTA: a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. Journal of hydrology **251**, 163-176.

Van Genuchten MT. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. Soil science society of America journal **44**, 892-898.

Vereecken H, Weynants M, Javaux M, Pachepsky Y, Schaap MG, Genuchten MT. 2010. Using pedotransfer functions to estimate the van Genuchten–Mualem soil hydraulic properties: A review. Vadose zone Journal **9**, 795-820.