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Suitability of Soil Water Retention Characteristic Models (SWRC) in Regions and Soil Depth

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Abstract

Soil Water Retention Characteristics (SWRC) models have been widely used in many applications. Presently, there are many models in the literature and many more still being developed so much so that it is confusing which model to prefer. The current choice of the appropriate model to use has not been well guided by any incisive research on the predictive performance of these models. Consequently, SWRC model applications have been largely moved by convenience. This study used a global dataset to evaluate 12 commonly used SWRC models. The measured data onto which the models were evaluated was grouped into different soil depths and different regions of the world. The evaluation used correlation, Nash-Sutcliffe efficiency, and residual standard error statistics to choose the best overall performing model and models for each category. It gives an indication of the type of SWRC models to use in different regions of the world and depths of sampling. The suitability of the models to regions showed that the Fredlund and Xing model had the best performance in subsoils in Africa; Omuto in Southern Asia; and van Genuchten in subsoils of the other regions. It is recommended that many more models be tested using the procedures in this study so that benchmarks can be established on SWRC model selection suitable for various regions.

Keywords

Soil Water Retention Characteristic, Soil Properties, Retention Models

1. Introduction

Water is held in the soil by gravity, matric suction, and osmotic forces. The models describing different levels of these forces and the corresponding amount of water held in the soil are known as soil water retention characteristics

(SWRC) models. There are two major categories of these models in the literature: pedotransfer functions (PTFs) which relate easily measurable soil properties to SWRC [1] and mathematical functions that can be fitted to experimental SWRC [2]. Predictive models under these two categories have been widely used in the literature in areas such as irrigation water management, crop-yield estimation, global circulation modeling, land degradation assessment, geotechnical engineering, etc. [3] [4] [5] [6] [7]. The major difference between these two model categories is that the mathematical functions contain fitting parameters which can be related to soil physical properties while PTFs do not necessarily have this relationship. Consequently, the mathematical functions have been used as a fundamental input in the various applications using SWRC. PTFs have been used largely as an alternate method to derive the parameters of the mathematical functions. This explains why there is still an active research to produce better user-friendly and accurate mathematical models for SWRC than the existing models [8] [9] [10].

There are many documented mathematical models for SWRC. Reviews of literature on these models show that the popular ones are those that contain three-, four- and five-parameters [11] [12]. For example, a review by Leong and Rahardjo [11] showed that the popular models are Brooks-Corey, Farrel-Larson, Fredlund-Xing, Gardner, McKee-Bumb, van Genuchten, and Williams SWRC models. Another review by Bullied *et al.* [13] portrayed Campbell, Russo and Tani models as popular in addition to some of the models contained in the review by Leong and Rhardjo [11]. Another aspect of these reviews shows that the popular models mostly have high success rates in areas where they were developed. It is important to note that they were developed and tested in different regions of the world. Consequently, some of them have been successful in those areas, others have been modified to extend their applications in independent areas, while some have been used in different places without regard to whether they are successful or not. Still, many more are being developed in an attempt to improve on the existing models. However, there is no exhaustive study to compare their performance in different regions of the world. There is a need to determine the relative performance of these models in order to guide their application or encourage further development of new models.

Since the advent of digital soil mapping (DSM) and digital soil assessment (DSA) paradigms, there has been an upsurge of development of soil inference models and the need to increase accurate application of soil mapping products [14]. Soil hydraulic parameters and hydrologic functions cannot be left behind in this regard. There is a need to improve accuracy of their assessment and application within the realms of DSM and DSA. This present study contributed towards this goal by testing the performance of commonly used SWRC models on a global dataset. The focus on the use of a global dataset was to establish regions where these models can register the best performance and consequently inform users of these models where they can guarantee a high level of certainty.

2. Materials and Methods

2.1. SWRC Models Analyzed

The SWRC models analyzed in this study and their curve-fitting parameters are given in Table 1. The models were also placed into three groups: five-parameter, four-parameter, and three-parameter SWRC models. This grouping was necessary because models with many parameters may tend to perform better than those with few parameters and lead to biased performance comparison.

The five-parameter models were those proposed by Fredlund and Xing [2], Omuto [15] and van Genutchen [16]. The van Genuchten [16] model is that in which n and m parameters are independent. The four-parameter models were those proposed by Kosugi [8], Dexter *et al.* [9], van Genuchten [16] (in which the parameter $m = 1 - 1/n$), Gardner [17], Brooks and Corey [18], and Russo [19]. The three-parameter models were those proposed by Campbell [20], Tani [21], and McKee and Bumb [22].

2.2. Input Data

The global data used for analysis of the SWRC models was downloaded on 6th May 2013. The data contained soil water content (θ in $cm^3 \cdot cm^{-3}$) at various levels

Table 1. SWRC models tested.

Model name	Abbreviation	Equation	Fitting parameters
		Five parameter models	
Van Genuchten	VG1	$\theta(h)=\theta_r+(\theta_s-\theta_r)\Big/\left[1+(\alpha h)^n\right]^m$	θ_r, θ_s, α, n, m
Fredlund-Xing	FX	$\theta(h)=\theta_r+(\theta_s-\theta_r)\Big/\left[\ln\left[2.7183+(\alpha h)^n\right]\right]^m$	θ_r, θ_s, α, n, m
Omuto	Omuto	$\theta(h)=\theta_r+\theta_{s1}*\exp(-\alpha_1 h)+\theta_{s2}*\exp(-\alpha_2 h)$	θ_r, θ_{s1}, θ_{s2}, α_1, α_2
		Four-parameter models	
Gardner	Gard	$\theta(h)=\theta_r+(\theta_s-\theta_r)/\left[1+\alpha h^n\right]$	θ_r, θ_s, α, n
Brooks-Corey	BC	$\theta(h)=\theta_r+(\theta_s-\theta_r)/(\alpha h)^n$	θ_r, θ_s, α, n
Kosugi	Kosugi	$\theta(h)=\theta_r+(\theta_s-\theta_r)Q\left[\ln(\alpha h)/n\right]$, Q is complimentary normal distribution function define as $Q(h)=1-\int_h^\infty\left(\left(\exp(-0.5h^2)\right)/\sqrt{2\pi}\right)\mathrm{d}h$	θ_r, θ_s, α, n
Double exponential	Dexpo	$\theta(h)=\theta_{s1}*\exp(-\alpha_1 h)+\theta_{s2}*\exp(-\alpha_2 h)$	θ_{s1}, θ_{s2}, α_1, α_2
Van Genuchten	VG2	$\theta(h)=\theta_r+(\theta_s-\theta_r)\Big/\left[1+(\alpha h)^n\right]^{1-1/n}$	θ_r, θ_s, α, n
Russo	Ruso	$\theta(h)=\theta_r+(\theta_s-\theta_r)\Big/\left[\left(1+0.5*(\alpha h)^n\right)*\exp\left(-0.5*(\alpha h)\right)\right]^{2/(n+2)}$	θ_r, θ_s, α, n
		Three-parameter models	
McKee-Bumb	MB	$\theta(h)=\theta_r+(\theta_s-\theta_r)*\exp(-\alpha h)$	θ_r, θ_s, α
Campbell	Camp	$\theta(h)=\theta_s*(\alpha h)^n$	θ_s, α, n
Tani	Tani	$\theta(h)=\theta_r+(\theta_s-\theta_r)*\left[1+(\alpha h)\right]*\exp(-\alpha h)$	θ_r, θ_s, α

of suction potential (h in cm). Only samples with at least eight (8) levels of suction potential and water contents were considered. The samples were grouped into topsoil (at depths between 0 cm and 50 cm from the soil surface) and subsoil (at depths greater than 50 cm from the soil surface). This grouping of samples into various depths was mainly to provide suitability of the models to various uses like irrigation modeling, watershed management and geotechnical investigations since soil depths are considered. These two groups were further split into samples from Central America, South America, Africa, Europe, Middle East, North Asia, and South Asia (**Figure 1**).

Data description and associated measurement methods have been given in Batjes [23]. There were at least nine (9) samples with complete SWRC data (*i.e.* with eight suction potential levels) for topsoil and at least six (6) samples with complete SWRC data for subsoils in each region. Preliminary analysis of the data showed that the samples had at least one measurement around saturation (*i.e.* when the suction potential is very low), at least one inflection point, and at least one measurement around the dry end (*i.e.* when the suction potential is very high). In addition, the majority of the samples had an inflection point around −1.0 m suction potential.

2.3. Data Analysis

The models in **Table 1** were fitted to measured SWRC data using nonlinear curve fitting method. The analysis of these models in predicting measured SWRC for various regions and depths were analyzed using the following popular statistics:

1) Residual standard error, RSE

$$\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2\Big/\left(n-2\right) \tag{1}$$

2) Nash-Sutcliffe model efficiency, EF

$$1-\left[\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2\Big/\sum_{i=1}^{n}\left(y_i-\overline{y}_i\right)^2\right] \tag{2}$$

3) Correlation, r^2

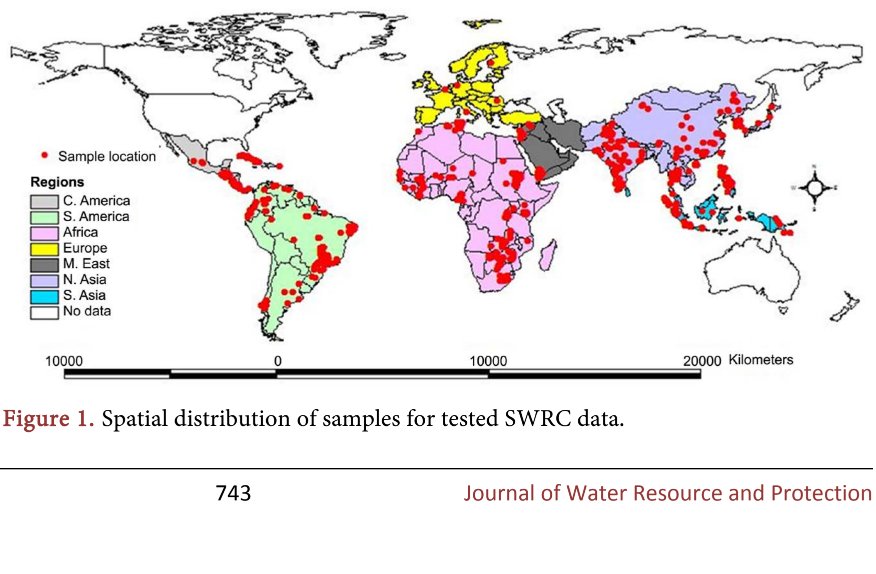

Figure 1. Spatial distribution of samples for tested SWRC data.

$$\left(n\sum_{i=1}^{n} y_i \hat{y}_i - \left(\sum y_i\right)\left(\sum \hat{y}_i\right)\right)^2 \Big/ \left[\left(n\left(\sum y_i^2\right) - \left(\sum y\right)^2\right) - \left(n\left(\sum \hat{y}_i^2\right) - \left(\sum \hat{y}_i\right)^2\right)\right] \quad (3)$$

where y_i is the measured soil water contents, $\hat{y}_i$ are the fitted soil water content, $\bar{y}_i$ is the mean measured soil water contents, and n are the number of data points (*i.e.* soil moisture levels for each soil sample). In analysis, values of EF and r^2 close to unity and low RSE are preferred for a good model.

3. SWRC Models Suitability in Various Regions and Depths

The suitability of SWRC models in various regions was done by comparing their performance with data from different regions of the world and depths of soil sample below the soil surface. Using correlation statistics, the performance of the five-parameter models using the subsoils data showed that the Fredlund and Xing model had the best performance (R^2 = 0.9964) in Africa; Omuto in Southern Asia (R^2 = 0.9987) and van Genuchten in Central America, South America, Europe and Northern Asiaregions (Table 2). In the four-parameter category, The van Genuchten, four-parameter model, did well among the other four-parameter models in subsoil Africa, America, Europe, Asia, M. East regions with R^2 of 0.9931, 0.9973, 0.9922, 0.9935, 0.9899, 0.9903 and 0.9977 respectively.

Using topsoil samples, in the five-parameter category, Omutomodel performed well in North and South Asiaregions with R^2 of 0.9991 and 0.9986 respectively, Fredlund and Xing model did well in Africa and south America regions with R^2 of 0.9960 and 0.9976 respectively. The five-parameter van Genuchtenmodel performed well in Central America and Europe with R^2 of 0.9948 and 0.9971 while the four-parameter van Genuchtenmodel was found to perform well in all the other regions except in Central America and Europe on the topsoil samples. The three-parameter exponential model proposed by McKee and Bumb outperformed the other models in the three-parameter category in all regions and soil depths. This performance pattern was also portrayed by the other statistical indices (*i.e.* RSE and EF).

The group-results shown in Table 2 may be used to guide models selection in case available SWRC data has limited suction potential levels. For example in Africa, if SWRC data has four measured suction potential levels then the exponential model by McBee and Bumb would give reliable results; in the case of SWRC data having five measured suction levels then the four-parameter van Genuchten model should be preferred; and in the case of SWRC data having at least six measured suction potential levels then Fredlund and Xing model should be preferred. It should be noted that, in order to guarantee best predictive results with these models, the minimum data-points for the SWRC data should contain at least three important points: at least a point around the saturation, at least a point at any of the inflection points (e.g. at air-entry potential), and a point around the dry end. These are anchoring points which are important in SWRC model fitting.

Table 2. Summary statistics of SWRC models performance.

	Five parameter models			Four parameter models						Three parameter models		
						Overall statistics						
Model	VG1	FX	Omuto	VG2	Gard	D.expo	Ruso	BC	Kosugi	MB	Tani	Campbel
RSE	0.0106	0.0166	0.0099	0.0123	0.0134	0.0200	0.0287	0.0535	0.0375	0.0241	0.0292	0.1112
r^2	0.9956	0.9891	0.9958	0.9940	0.9929	0.9844	0.9677	0.8869	0.9448	0.9785	0.9688	0.4899
EF	0.9955	0.9891	0.9958	0.9940	0.9929	0.9844	0.9675	0.8868	0.9448	0.9785	0.9688	0.4736
						Correlation (r^2) for Subsoil						
Model	VG1	FX	Omuto	VG2	Gard	D.expo	Ruso	BC	Kosugi	MB	Tani	Campbel
Africa	0.9932	0.9964	0.9947	0.9931	0.9896	0.9824	0.9719	0.8678	0.9649	0.9764	0.9722	0.3736
C. America	0.9982	0.9564	0.9955	0.9973	0.9952	0.9776		0.9005	0.9998	0.9110	0.8610	0.2614
S. America	0.9945	0.9923	0.9936	0.9922	0.9921	0.9847	0.9523	0.8397	0.8296	0.9800	0.9761	0.3031
Europe	0.9954	0.9573	0.9948	0.9935	0.9929	0.9806	0.9548	0.7879	0.9330	0.9732	0.9553	0.0015
N. Asia	0.9926	0.9910	0.9923	0.9899	0.9898	0.9825	0.9868	0.9134	0.9598	0.9749	0.9604	0.9515
S. Asia	0.9953	0.9896	0.9987	0.9903	0.9884	0.9585	0.7872	0.8745	0.8340	0.9396	0.8990	0.3563
M. East	0.9989	0.9979	0.9978	0.9977	0.9927	0.9779	0.9615	0.8075	0.8090	0.9481	0.9067	0.5617
						Correlation (r^2) for Topsoil						
Model	VG1	FX	Omuto	VG2	Gard	D.expo	Ruso	BC	Kosugi	MB	Tani	Campbel
Africa	0.9955	0.9960	0.9929	0.9919	0.9908	0.9844	0.9711	0.8580	0.9369	0.9706	0.9596	0.6117
C. America	0.9948	0.9920	0.9835	0.9888	0.9924	0.9342	0.8353	0.9454	0.9760	0.9722	0.9487	0.7219
S. America	0.9973	0.9976	0.9950	0.9935	0.9857	0.9801	0.9463	0.8166	0.8975	0.9624	0.9395	0.8226
Europe	0.9971	0.8734	0.9961	0.9942	0.9955	0.9644	0.8693	0.7890	0.8711	0.9579	0.9275	0.4374
N. Asia	0.9972	0.9969	0.9991	0.9968	0.9947	0.9863	0.9688	0.8927	0.8708	0.9736	0.9550	0.5899
S. Asia	0.9943	0.9875	0.9986	0.9883	0.9872	0.9486	0.7800	0.8362	0.8344	0.9307	0.8754	0.7562
M. East	0.9962	0.9941	0.9977	0.9731	0.9716	0.9571	0.8018	0.8613	0.8434	0.9210	0.8915	0.7763

Best performing model in the category.

4. Conclusion

This study used a global measured dataset of SWRC to evaluate popular models for fitting SWRC. The analysis serves as a guide for selecting the models to be preferred for fitting SWRC models to use in different regions of the world and depths of sampling. Van Genuchten model (both the four and five parameter models) had the best performance in most of the regions and soil depth. This was notable in Africa, Central America, South America, Europe and Northern Asia regions. The three-parameter McKee and Bumb model also performed well in all regions and soil depths. Owing to the good performance of exponential-based models, the analysis also floated a suggestion for future models to develop models based on exponential pore-size distribution. It is recommended that many more models be tested using the procedures used in this study so that benchmarks can be established on SWRC model selection for different applications.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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