SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

Sensitivity analysis of point and parametric pedotransfer functions for estimating soil water retention

Sami Touil [a,b,c], Aurore Degre [b], Mohamed Nacer Chabaca [a]

[a] *Superior National School of Agronomy, El Harrach, Algiers, Algeria*
[b] *Gembloux Agro-Bio Tech, Biosystem Engineering (BIOSE), Soil—Water—Plant Exchanges, University of Liège, Passage des Déportés 2,Gembloux 5030, Belgium*
[c] *Laboratory of Crop Production and Sustainable Valorization of Natural Resources, University of Djilali Bounaama Khemis Miliana, Ain Defla, Algeria.*

Correspondence to: Sami Touil (touil_sy@hotmail.fr)

Abstract

Improving the accuracy of pedotransfer functions (PTFs) requires studying how the uncertainty in prediction can be apportioned to different sources of uncertainty in inputs. In this study, the question is, which variable input is the principal one or the better complimentary predictor of water retention, and at which water potential? Two approaches were adopted to generate PTF—multiple linear regressions (MLR) for point PTF and the multiple non-linear regressions (MNLR) for parametric PTFs. Reliability tests show that the point PTF provides better estimates than the parametric model (RMSE: 0.0414; 0.0444 and 0.0613; 0.0605 at -33 kPa and-1500 kPa, respectively). The local parametric PTFs provided better estimates than Rosetta PTFs at – 33 kPa. However, no significant difference in accuracy was found between the parametric PTFs and Rosetta-H2 at -1500 kPa with RMSE values (0.0605 $cm^3\ cm^{-3}$ and 0.0636 $cm^3\ cm^{-3}$). The results of the global sensitivity analyses show that the mathematical formalism of PTF and its input variables react differently in terms of point pressure and texture. The point and parametric PTFs are sensitive primarily to the sand fraction in fine and medium textural classes. A favourable impact of bulk density and clay content is recorded with accuracy in the estimation of PTFs at -33 kPa in the medium class.

Keywords: soil water retention, multiple regressions, pedotransfer function, sensitivity

I. Introduction

The predictive information on the spatial distribution of soil water and its availability for plants will allow producers to take effective decisions to maximise profitability (e.g. nutrient management and plant cover). The soil-water balance is in the centre of many processes that influence plant growth and the degradation of soil and water resources. However, due to high temporal and spatial variability in the hydraulic characteristics, a large number of samples are generally required to accurately characterise field conditions (Khodaverdiloo et al., 2011).

Hydrologists are often faced with the situation where one or more of the pedotransfer functions (PTFs) inputs are not available. Reports on the evaluation of PTFs outside the area of development are rare, and the results reveal that extrapolation of PTF in different agropedoclimatic context is limited (Touil et al., 2016). The development of local PTF could be useful to meet the agricultural requirements for modelling with reasonable accuracy.

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

Soil water retention curves can usually be constructed by two approaches: the point and parameter PTFs. In the point PTFs, the soil water retention is estimated at defined pressure points (Pachepsky et al., 1996; Minasny et al., 1999). The parameterisation method estimates the parameters of soil water retention models such as θs, θr, α and n, by fitting it to the data and then relating by empirical correlation to basic soil properties (Vereecken et al., 1992; Wösten et al., 1995; Schaap et al., 1998; Minasny and McBratney, 2002; Rawls and Brakensiek, 1985; Van Genuchten et al., 1992; Wösten et al., 2001; Vereecken et al., 2010). One of the most commonly used water retention curves is the Van Genuchten model (1980). Schaap et al. (2001) developed the Rosetta package based on the artificial neural network method (ANN), which implements five hierarchical models to predict these parameters with well-defined limits (the soil texture classes only) and the most widespread input data (texture, density, and one or two points of water retention).

PTFs for point and parametric estimation of water retention curves from basic soil properties can be developed by using multiple regression methods (Lin et al., 1999; Mayr and Jarvis, 1999; Tomasella et al., 2000). An advantage of regression techniques is that most fundamental input parameters can be determined using stepwise regression.

Moreover, using pedotransfer functions in different environments either underestimate or overestimate the water retention. Several studies have shown that water retention is a complex function of soil structure and composition (Rawls et al., 1991; Wösten et al., 2001; Rawls et al., 2003). Applications of PTFs on different textural or structure classes may also be a source of uncertainty. Soil-water potential and hydraulic conductivity vary widely and non-linearly with water content for different soil textures. Experience has shown that soil texture predominantly determines the water-holding characteristics of most agricultural soils (Saxton et al., 1986). The relationship between the soil water retention curve (SWRC) and particle size distribution, was investigated in many studies (Jonasson et al., 1992; Minasny et al., 2006; Ghanbarian et al., 2009; Xu Yang et al., 2013; Tae-Kyu Lee et al., 2014). Williams et al. (1983) and Saxton et al. (1986) report that the PTFs depend mostly on texture, and other factors such as bulk density, structure, organic matter, clay type, and hysteresis may all have a secondary impact.

The variability of PTF response depends on variability and uncertainty of one or more input variables. The uncertainty analysis in the variety of pedotransfer (PTF) available approaches is a necessity to minimise the error in estimation and identify its source. Recently, sensitivity analysis techniques and uncertainty analysis have received considerable attention in the study of PTF (Nemes et al., 2006b; Kay et al., 1997; Grunwald et al., 2001; Deng et al., 2009; Moeys et al., 2012; Loosvelt et al., 2013). The question is, which variable input is the principal one or the better complimentary predictor of water retention, and at which potential? The global sensitivity analysis (GSA) allows us to study how the uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input (Saltelli et al., 2000). Generally, the GSA is very useful to know which variables mostly contribute to output variables (Jaques et al., 2004).

The objective of this study is:

1. Deriving and validating two approaches of PTFs from basic soil properties, using regression methods:
   - Point PTFs for estimation of soil water retention at -33 kPa and at -1500 kPa;
   - Parametric PTFs for estimating the Van Genuchten curve parameters and comparing the predictive performance with the Rosetta models;
2. Studying the impact of each input perturbation on the PTFs output.

II. Materials & methods

1. The database

The PTFs are developed by using a database collected from some Algerian regions. Subset 1 containing 70 % of the samples (n = 189) from the coastal plain of Annaba located in the north-eastern part of Algeria (n=13), the plain of Beni Slimane of Media (n=42), the Kherba El Abadia plain of Ain defla (n=54) and samples randomly selected from Lower Cheliff plain in northwestern of Algeria (n= 80), soil series was used as the calibration set. Subset 2 with the remaining 21% (n = 53) from Benziane valley in the south west lower Cheliff plain, soil series was selected to verify the PTFs (Table 1). The depth of the two upper horizons varies from site to site with maximum of 30 cm for surface horizons and upper than 30 cm for subsurface horizons.

The particle size analysis, conducted using the international Robinson's pipette method. Soil samples taken by cylinders of 500-1000 cm3 (According to the case) were used to determine soil bulk density (BD).The water retention values at -33 kPa and -1500 kPa were obtained by Richards's apparatus for samples were collected in moisture nearby to field capacity, by cylinders with a volume of 100 cm3. The water content measurements were conducted by gravimetric method at 105 C° (24h). The organic carbon content was determined by wet oxidation method

The soil water retention model of Van Genuchten (1980) is defended as:

$$\theta(h) = \theta_r + \frac{\theta_s - \theta_r}{(1+|\alpha h|^n)^m} \quad (1)$$

Where θ_r and θ_s are the residual and saturated soil water contents ($cm^3\ cm^{-3}$), respectively, and α (cm^{-1}) and n are the shape factors of the water retention function. The Van Genuchten parameters will be calculated for each soil sample using the RETC code (Schaap et al., 2001). The "m" parameter was calculated as follows: m = 1 -1 / n

2. Evaluation criteria

The PTF are regularly assessed by the comparison of the values that they predicted and the measured values (Pachepsky and Rawls, 1999). To discuss the validity of PTF developed, we used the following: the mean prediction error (ME) to inform the bias of the estimate; the mean square error (RMSE) as an estimator of quality prediction that was frequently used in the literature on the pedotransfer functions; and the index of agreement (d) developed by Willmott and Wicks (1980), and Willmott (1981) as a standardised module in order to measure the model prediction error. They are calculated using the following equation, respectively:

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

$$\boldsymbol{ME} = \frac{1}{n}\sum_{i=1}^{n}(\theta_{\mathrm{p}} - \theta_{\mathrm{m}}) \quad (2)$$

with n, number of horizons, θ_p, and the predicted volumetric water content and θ_m the measured volumetric water content. The estimate is even less skewed than ME and is close to 0. When ME is positive, PTF tested overestimated θ_m and when it is negative PTF tested underestimated θ.

$$\boldsymbol{RMSE} = \left\{\frac{1}{n}\sum_{i=1}^{n}(\theta_{\mathrm{p}} - \theta_{\mathrm{m}})^2\right\}^{\frac{1}{2}} \quad (3)$$

Thus, when the mean square error (RMSE) is low, the better the estimate.

$$\boldsymbol{d} = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(\theta_{\mathrm{p}} - \theta_{\mathrm{m}})^2}{\sum_{i=1}^{n}\left[\left|(\theta_{\mathrm{p}} - \overline{\theta}_{\mathrm{m}})\right| + \left|(\theta_{\mathrm{m}} - \overline{\theta}_{\mathrm{m}})\right|\right]^2} \quad (4)$$

The index of agreement (d) Varies between 0 and 1. Close to of 1 indicates a better matching between measured and predicted values (Willmott and Wicks, 1980; Willmott, 1981).

3. Global sensitivity analysis (GSA)

The global sensitivity analysis consists of determining which part of the variance of model response is due to the variance of which input variable or group of inputs**.** These methods quantify the impact of the parameters by the calculation of global sensitivity indices.

The Sobol method (Sobol, 1990) is an independent global sensitivity analysis that is based on decomposition of the variance or may manage the functions and non-linear and non-monotonic models. The Sobol model is represented by the following function:

$$Y = f\,(X_1, X2, X3, \ldots\ldots, X_p) \quad (5)$$

Where Y is the model output (or objective function) and X=(X1,…,Xp) is the variable set.

a. Sobol decomposition of variance

The total variance of Y is defined; then:

$$V(Y) = V\,(E\,(Y\,|X)) + E\,(Var\,(Y\,|X)) \quad (6)$$

When the input variables *X*i are independent, the variance decomposition of the model is:

$$V(Y) = \sum_{i=1}^{p} V_i + \sum_i\sum_j V_{ij} + + \sum_i\sum_j\sum_p V_{ijp} + \ldots\ldots\ldots + V_{1,2,3,\ldots,p} \quad (7)$$

$$V_i = V\,[\,E(Y|X_i)]$$

$$V_{ij} = V\,[\,E(Y|X_i\,,\,X_j)]\,-V_i\text{-}V_j$$

$$V_{ijp} = V\,[\,E(Y|X_i\,,\,X_j,\,X_p)]\,-\,V_{ij}\,-\,V_{ip}\,-\,V_{jp}\,-\,V_i\,-\,V_j\,-\,V_p$$

Dividing V_i by V(Y) we obtain the expression of the first-order sensitivity index noted S_i such that:

$$S_i = \frac{V_i}{V(Y)} = \frac{V[E(Y/X_i)]}{V(Y)} \quad (8)$$

The term S_i is the measure that guarantees an informed choice in the cases where the factors are correlated and interact (Saltelli and Tarantola, 2002). This index is always between [0.1], and represents a proper measure of the sensitivity used to classify the input variables in order of importance (Saltelli and Tarantola, 2001).

To calculate the variation of sensitivity index (V_{Si}) we propose:

$$V_{Si} = \left(\frac{V[E(Y/X)]}{V(Y)} - \frac{V[E(Y/\,Xi{=}\mathrm{X}i*)]}{V(Y)} \right) * 100 \qquad (9)$$

$$\begin{cases} V_{Si} > 0 \text{ and } S_i \text{ close to 1 indicate increasing accuracy of PTFs (+: favourable impact);} \\ V_{Si} < 0 \text{ and } S_i \text{ close to 1 indicate increasing accuracy of PTFs (+: favourable impact);} \\ V_{Si} > 0 \text{ and } S_i \text{ close to 0 indicate decreasing accuracy of PTFs (- : adverse impact);} \\ V_{Si} < 0 \text{ and } S_i \text{ close to 0 indicate decreasing accuracy of PTFs (- : adverse impact).} \end{cases}$$

Moreover, coupling the RMSE and sensitivity index S_i allowed us to detect the contribution of each variable for the improvement of the quality of prediction of PTFs.

III. Results and discussion

1. The PTF derived

We chose to use the Rosetta PTFs in this study because it is one of the latest PTFs and gave reasonable predictions in several evaluation studies (Nemes et al., 2003). The quality prediction of point and parametric PTF developed in this study will be compared with the three Rosetta PTFs (H1, H2, and H3). Three Rosetta models (H1, H2, and H3) were selected because they require the texture and bulk density as inputs.

In Table 3, the majority of PTFs evaluated underestimate the soil water retentions except the point model at the two pressure points (-33 kPa and -1500 kPa). The hierarchy Rosetta model H2, which considers only texture as input, gave a smaller ME value compared with both H1 and H3 hierarchies models (- 0.0728; -0.0436 $cm^3\,cm^{-3}$ at -33 kPa and -1500 kPa, respectively).

The poor ME values indicate better estimates of PTFs; they were produced after the application of PTF points followed by the PTF parameters.

Among the five tested models in the Lower Cheliff soils, the PTF points (MLR) derived from a database taken from some Algerian soils had the lowest values of RMSE (0,041 and 0,044 $cm^3\,cm^{-3}$ at -33 kPa and -1500 kPa, respectively). Performances equivalent or superior to PTFs derived by multiple regression methods have been reported (Minasny et al., 1999; Nemes et al., 2003). However, the non-linear models (parametric PTF) adapt better than the Rosetta models based on the artificial neurons network (RMSE: 0.0613; 0.0605 cm 3 cm^{-3} at -33 kPa and -1500 kPa, respectively). Furthermore, the RMSE and the ME values of three Rosetta models show that H2 is better than H1 and H3 (Table 3).

In term of predictors, the results show that the OM improves the quality of adjustment.

Other evaluation criteria noted that the index of agreement also shows that the point PTF is more suitable for Lower Cheliff soils than the parametric PTF (Fig. 6) with values *of **(d)*** (0.9975, 0.9911 $cm^3\,cm^{-3}$). A similar comparison in different regions was made by Minasny et al. (1999), Tomasella et al. (2003) and Ghorbani Dashtaki et al. (2010). All have reported similar differences between these two types of PTFs.

While no significant difference in accuracy was found between the parametric PTFs and Rosetta-H2 at -1500 kPa with RMSE value (0.0605 cm^3 cm^{-3} and 0.0636 cm^3 cm^{-3}). The poor accuracy of Rosetta PTFs can depend on several factors such as the similarity between the application region and the database region source, geology, and bioclimatic context (Wagner et al., 2001; Wösten et al., 2001; Ghorbani et al., 2011; Touil et al., 2016).

2. Sensitivity index before the textural classification

In the development of pedotransfer functions, using the particle-size distribution (PSD) as input is generally the common approach (texture as a global expression of the particle size distribution, clay, silt and sand content), and its contribution is fundamental to understanding the process of retaining water at different pressure points, although various physical and chemical characteristics are used to describe the water retention curve such as the bulk density and organic matter.

In this section, the importance of each input variable is assessed by the first order sensitivity index (S_i). It is clear for the PTFs developed, the organic matter (OM %) and the clay percentages (C %) are the variables that have the most impact particularly on point PTF (MLR) estimation in two pressure points with S_i in order to (OM: 0.821; 0.630) and (C %: 0.782; 0.585) at -33 kPa and -1500 kPa, respectively (Fig. 2). The percentage of silt (Si %) is in a second range of importance in parametric PTF (0.576 at -33 kPa) after OM, followed by the bulk density and clay (Fig. 2). The S_i values class the sand content in third order in MLR (0.262; 0.162), thus its impact on the parametric model is almost insignificant with very low values index (S_i: 0.077; 0.017) at -33 kPa and -1500 kPa, respectively.

The prediction quality of point PTF developed by linear multiple regression (MLR) can be explained first by taking into account the basic characteristics of soil as an input through the texture and structure information given by the bulk density. Secondly, the MLR formation is mainly based on these input variables compared to parametric PTF using the non-linear multiple regression (MNLR), which has as input more than texture and the bulk density, but also other parameters (parameters of the Van Genuchten curve: Θ_r, Θ_s, α, n, m).

3. Sensitivity and uncertainty analysis after the textural classification

This section will analyse the sensitivity of multiple regression methods (linear and non-linear) developed for the basic soil characteristics on estimating water retention in different textural classes. Water retention and conductivity are directly related to the geometry of the pore network, depending on the size and assemblage of the elementary soil particles. In this order we have grouped the samples into three classes of particles according to textural classes of the FOA guidelines (FOA, 1990), which give a very fine class (N = 12), fine (N = 31) and medium (N = 10).

The results show the improvement of the quality estimation of PTFs after textural stratification, particularly in medium class (Fig. 4). Indeed, a better prediction was recorded by point PTF (RMSE = 0.027 cm^3 cm^{-3}) and parametric PTF (RMSE = 0.038 cm^3 cm^{-3}) at -1500 kPa. The stability in estimation of PTF before and after classification is noted in the very fine class (Fig. 4). This can be explained by the difficulties there are for linking the water retention properties of the samples with their size distribution as their structural state may be variable.

1. Sand content: After textural classification, PTFs developed (MLR and MNLR) are always sensitive primarily to the sand fraction in fine and medium classes (Table 5). The variation of the first sensitivity index in point PTF is significantly greater in the medium texture class at the two pressure points (-33 kPa and -1500 kPa). Into the MNLR, sand has the most influence particularly when it is applied to the fine class (-40.9%, 18.9% at -33 kPa and 1500 kPa) and medium class (-16.7% at -1500 kPa).

The sensitivity index of a variable quantifies the influence of its uncertainty on the output. This is the part of the variability output explained by the variability input. What has been confirmed after calculating the variation of the first order sensitivity index (V_{Si}), is that the PTFs developed are still very influenced by the variability of sand at -33 kPa more than at -1500 kPa. This impact can be explained by the irregularity of the dispersion of sand content in the validation database with a coefficient of variation (CV) approximately 119% compared to the other input variables (33%; 18%; 9%; 57% for clay, silt, bulk density, organic matter, respectively). This heterogeneity of the sand data series clearly influences the uncertainty of pedotransfer functions response.

Moreover, looking at the matrix correlation (Table 6), the clay and silt fraction are significantly correlated with the sand content. Saltelli and Tarantola (2002) observe that when X_1 and X_2 are correlated with a third factor X_3, the sensitivity index calculated depends on the force of this correlation as well as the distribution of X_3. In this case, the index power may be influenced by this statistical association, as we can explain the higher value difference of index variation of sand percentage compared with the other variables (Fig. 2).

We can see that point PTF (MLR) produces a lower error of estimation when the variation sensitivity index calculated for sand is the leading [MLR in the medium class: RMSE (0.030; 0.027 cm^3 cm^{-3}) with V_{Si} = (-103%. 86.4%) at -33 kPa and -1500 kPa, respectively]. A negative V_{Si} of sand content when the latter is fixed is noticed on all texture classes (Table 5). This can be explained by the proportional relationship between the sand and clay content, particularly in the dataset of validation with dominant clay texture. Insignificant sensitivity of sand was recorded in very fine texture. Rawls et al. (2003) observed that 10% of sand provides an increase in water retention at low clay content and a decrease in water retention at high clay content of more than 50%.

It is important to note the relationship of the Van Genuchten water retention curve parameters (especially n and α) and particle size distribution were conducted recently in many studies (e.g. Minasny et al., 2007; Benson et al., 2014) in order to explain why the sand impact increase in fine texture class in parametric PTF. It can be explained by the majority presence of sand and clay content as input on parametric PTFs. For soils with clay content between 35% and 70%, water content is highly influenced by the percentage of sand in the soil (Loosvelt et al., 2013).

Moreover, when the sand content of the sample increases to 60%, the drying rate is quicker and water absorbing ability is weaker compared with the small sand content. When the sand content

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

decreases to 20% the small pores occupy a large part of the pore structure, making the soil compact (Hao et al., 2015).

2. Bulk density: the second most influential variable on the point PTF (MLR) response is by variation of sensitivity index on all textural class, mainly in the very fine textural class with elevated values at -33 kPa ($V_{S}i$ = -50, 5%). In the parametric PTF, the bulk density influences the medium class at -33 kPa. The result shows that the favourable impact of BD is according to the accuracy of quality estimation at -33 kPa in the medium class on two developed approaches of PTFs (Table 5). The very fine textural class represents 16 surface samples (0–30 cm) with a dominance of clay texture. In a similar study on clay soils, the volumetric water content is hugely related to the inverse of bulk density at field capacity (Bruand et al., 1996). It may also explain the fact that many soils with high clay content in the database are vertisols in which they increase in organic matter, decrease bulk density and decrease the volumetric water content (Rawls et al., 2003). The inclusion of the bulk density in the development PTFs leads to a pore volume that cannot retain water for the potential range studied (-33 kPa and -1500 kPa).

In addition, the soil structural information characterised by measurements of bulk density is an indirect measurement of pore space and is affected primarily by texture and structure. For structure-less soils, primarily coarse and medium textured soils, the capillary pore-size distribution can be satisfactorily described by particle size distribution. The medium texture relates in a general way to the pore-size distribution, as large particles give rise to large pores between them, and therefore, is a major influence on the soil water retention curve (Arya and Paris, 1981; Nimmo, 2004)**.** With this variable, and the texture used as inputs in point PTF (MLR), the nearest experimental results are obtained. The results of this study can confirm that the effect of the use of the soil structural information on the estimation of the soil water retention depends on the use of regression techniques (Nguyen et al., 2015).

3. Clay content: For medium texture the favourable sensitivity is determined by clay content at -33 kPa. This can be explained by the reduction of clay percentage in the medium class (mean of clay (%) = 23%), which produces fewer errors at -33 kPa. The highest impact of clay (%) was observed at -1500 kPa on the point and parametric PTF in different textural classes (Fig. 4). The clay content of soils is a major predictor for modelling the permanent wilting point of soils (Minasny et al., 1999).

Moreover, in this study, the accuracy of PTFs decrease when they were applied to some soil samples with the Clay (%) > 60% (Fig. 4). In the very fine class, insignificant sensitivity is recorded at all pressures defined in this study. In this class, the variation of clay is much lower, for the reason that the latter is only the dominant solid fraction, and this can explain the smaller variation of sensitivity index after fixing the clay percentage. The very fine and fine classes have advanced water retention t more those of the medium class, because it quickly drains water initially retained. In other words, the use of clay as PTF input in medium textured soils leads to results that are more or less erroneous.

4. Silt content: In this study silt was introduced as an explanatory variable only in MNLR parametric PTFs. This fraction is known for its ability to retain water to high and medium potential. The analysis results show that the global sensitivity class and the silt as the second input were the most disturbing estimates of water retention at -1500 kPa more than at -33 kPa on MNLR model. After textural stratification, the main values of V_{Si} have been found in medium class (-36.7% to -1500 kPa). The lowest were recorded in the very fine class, or the texture is pure clay. It is clear that the percentage of silt has a very important role in estimating of the Van Genuchten parameters (α, n), and consequently, its use as input in MNLR influences the estimate in the medium and fine class. Nevertheless, there is a favourable impact recorded in fine class at -1500 kPa. Its presence with the clay content in the fine class has led to a better pedological interpretation of the soil water retention in silty-clay texture. The plant-available water content variation is more related to sand and silt than to clay content (Reichert et al., 2009).

5. Organic matter content: The most insignificant variation of sensitivity index (V_Si) after textural stratification is attributed to the organic matter content. This can be explained firstly by the poor OM on the Algerian soils. Lal (1979) and Danalatos et al. (1994) did not find any effect of organic matter content on water retention; the latter attributed it to the generally low organic matter content in their samples. Secondly, homogeneity of the data for OM content in every textural class decreases the variation of PTFs response, as the latter is always considered the better predictor of soil water retention particularly in clayey soils. However, positive sensitivity impact is observed on parametric PTF in medium-textured soils at -33 kPa where the OM is used as input to predict saturated soil water contents. Soil water retention at -33 kPa is affected more strongly by the organic carbon than at -1500 kPa (Rawls et al., 2003). The sensitivity analysis made by Rawls et al. (2003), in order to study the role of organic matter content as predictor, shows that water retention of coarse-textured soils is much more sensitive to changes in organic carbon as compared with fine-textured soils. Bauer and Black (1981) found that the effect of organic carbon on water retention in disturbed samples was substantial in sandy soil and marginal in medium and fine textured soils.

IV. Conclusion

The present study suggests that the soil water retention is controlled by different variables such as organic matter, clay content and sand content at different points of soil water potential, and not directly related to the parameters of the water retention curve such as the van Genuchten model. The reliability tests show that the point PTF predicts more accuracy than the parametric models. Indeed, the derived parametric PTFs provide better estimates than the Rosetta models that were originally developed from a large intercontinental database.

Furthermore, the global sensitivity analyses show that the mathematical formalism of PTF models and their input variables react differently in terms of point pressure and textural class:

- It is clear that the soil water retention is highly related to the OM and clay content.
- After textural classification, the two approaches of PTFs developed (MLR and MNLR) are always sensitive primarily to the sand fraction in fine and medium class at -33 kPa more than at -1500 kPa.
- The results show that the favourable impact of BD is according to the accuracy of quality estimation of the two approaches of PTFs developed at -33 kPa in the medium class.

- The accuracy of PTFs decrease when they were applied to some soil samples with the Clay (%) > 60%.
- The most insignificant variation of sensitivity index V_{Si} after textural stratification is attributed to the organic matter content in Algerian soils.

Reference

Benson, C., Chiang, I., Chalermyanont, T., and Sawangsuriya, A.: Estimating van Genuchten Parameters α and n for Clean Sands from Particle Size Distribution Data, From Soil Behavior Fundamentals to Innovations in Geotechnical Engineering, 410-427, 2014.

Nimmo, J.R.: Porosity and Pore Size Distribution, in Hillel, D., ed. Encyclopedia of Soils in the Environment, London, Elsevier, 3, 295-303, 2004.

Ghanbarian-Alavijeh, B., Liaghat, A., Huang, G. H. and van Genuchten, M. Th.: Estimation of the van Genuchten soil water retention properties from soil textural data, Pedosphere, 20(4), 456–465, 2010.

Wosten, J. H. M., Lilly, A., Nemes, A., and Le Bas, C.: Development and use of a database of hydraulic properties of European soils, Geoderma, 90, 169–185, 1999.

Minasny, B. and McBratney, A. B.: Estimating the water retention shape parameter from sand and clay content, Soil Sci. Soc. Am. J, 71, 1105–1110, 2007.

Saxton, K.E., W.J. Rawls, J.S. Romberger,and R.I. Papendick.: Estimating generalized soil-water characteristics from texture, Soil Sci. Soc. Am. J. 50, 1031-1036, 1986.

Khodaverdiloo, H., Homaee, M., van Genuchten, M.Th., Dashtaki, S.G.: Deriving and validating pedotransfer functions for some calcareous soils, J. Hydrol, 399, 93–99, 2011.

Touil S., Degré A., Chabaca M.N.: Transposability of pedotransfer functions for estimating water retention of Algerian soils, Desalination and Water Treatment, 57(12), 5232-5240, 2016,

Pachepsky, Y. A., D. Timmlin, and G. Varallyay: 1996, Artificial neural networks to estimate soil water retention from easily measurable data, Soil Sci. Soc. Am. J., 60(3), 727 – 733, 1996.

Minasny, B., A. B. McBratney, and K. Bristow: Comparison of different approaches to the development of pedotransfer function for water-retention curves, Geoderma, 93(3–4), 225–253, 1999.

Vereecken, H., J. Diels, J. Vanorshoven, J. Feyen, and J. Bouma.: Functional evaluation of pedotransfer functions for the estimation on of soil hydraulic properties. Soil Sci. Soc. Am. J, 56, 1371–1378, 1992.

Wösten, J.H.M., Finke, P.A., Jansen, M.J.W.: Comparison of class and continuous pedotransfer functions to generate soil hydraulic characteristics, Geoderma, 66, 227–237, 1995.

Schaap, M.G., and F.J. Leij.: Using neural networks to predict soil water retention and soil hydraulic conductivity, Soil Tillage Res, 47, 37–42, 1998b.

B. Minasny, A.B. McBratney: Uncertainty analysis for pedotransfer functions, Eur. J. Soil Sci, 53, 417–429, 2002.

Rawls, W.J., and D.L. Brakensiek. : Prediction of soil water properties for hydrologic modeling. p. 293–299. In E.B. Jones and T.J.Ward (ed.) Proc. Symp.Water shed Management in the Eighties, Denver, CO. 30 Apr.–1 May 1985, Am. Soc. Civil Eng., New York, 1985.

Van Genuchten, M.Th., F.J. Leij, and L.J. Lund (ed.).: Indirect methods for estimating the hydraulic proprieties of unsaturated soils, U.S. Salinity Lab., Riverside, CA, 1992.

Wösten, J.H.M., Y.A. Pachepsky, and W.J. Rawls.: Pedotransfer functions: Bridging the gap between available basic soil data and missing soil hydraulic characteristics, J. Hydrol, 251, 123–150, 2001.

Vereecken, H., M. Weynants, M. Javaux, Y. Pachepsky, M. G. Schaap and M. Th. van Genuchten: Using pedotransfer functions to estimate the van Genuchten–Mualem soil hydraulic properties: A review, Vadose Zone J, 9, 795-820, 2010.

Van GENUCHTEN, M.Th.: A closed-form equation for predicting the hydraulic conductivity of unsaturated soils, Soil Sci. Soc. Am. J., 44, 892-898, 1980.

M.G. Schaap, F.J. Leij, M.Th van Genuchten,: Rosetta: A computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions, J. Hydrol, 251, 163–176, 2001.

Lin H.S., McInnes K.J., Wilding L.P., Hallmark C.T.: Effects of soil morphology on hydraulic properties: II. Hydraulic pedotransfer functions, Soil Sci. Soc. Am. J., 63, 955–961, 1999.

Mayr, T., and N.J. Jarvis.: Pedotransfer functions to estimate soil water retention parameters for a modified Brooks-Corey type model, Geoderma, 91, 1–9, 1999.

TOMASELLA, J.; HODNETT, M.G. & ROSSATO, L.: Pedotransfer functions for the estimation of soil water retention in Brazilian soils. Soil Sci. Soc. Am. J., 64:327- 338, 2000 TOMASELLA, J.; HODNETT, M.G. & ROSSATO, L. Pedotransfer functions for the estimation of soil water retention in Brazilian soils, Soil Sci. Soc. Am. J., 64, 327- 338, 2000.

Rawls, W.J.; gish, T.J. & brakensiek, D.L.: Estimating soil water retention from soil physical properties and characteristics, Adv. Soil Sci., 16, 213-234, 1991.

Rawls, W., Pachepsky, Y. & Ritchie, J.: Effect of soil organic carbon on soil water retention, Geoderma, 116, 61–76, 2003.

Saxton, K. E., W. L. Rawls, J. S. Rosenberger, and R. I. Papendick: Estimating generalized soil-water characteristics from texture, Soil Sci. Soc. Am. J., 50, 1031-1036, 1986.

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

Jonasson, S.A.: Estimation of the van Genuchten parameters from grain-size distribution. p. 443-451. In M. Th. van Genuchten et al. (ed.) Proc. of the Int. Workshop Indirect Methods for Estimating the Hydraulic Properties of Unsaturated Soils, Riverside, CA. 11-13 Oct. 1989, Univ. of California, Riverside, 1992.

Ghanbarian- Alavijeh, B., Liaghat, A.M.: Evaluation of soil texture data for estimating soil water retention curve, Can. J. Soil Sci, 89, 461–471, 2009.

Nguyen, P.M., J. De Pue, K.V. Le, W. Cornelis: Impact of regression methods on improved effects of soil structure on soil water retention estimates, Journal of Hydrology, (525) 598–606, 2015.

Tae-Kyu Lee, Hee-Myong Ro: Estimating soil water retention function from its particle-size distribution, Geosciences Journal, 18 (2), 219-230, 2014.

Xu Yang and Xueyi You : Estimating Parameters of Van Genuchten Model for Soil Water Retention Curve by Intelligent Algorithms, Appl. Math. Inf. Sci, 7 (5), 1977-1983, 2013.

Nemes, A., Rawls, W.J., Pachepsky, Y.A., van Genuchten, M.T.: Sensitivity analysis of the nonparametric nearest neighbor technique to estimate soil water retention, Vadose Zone J. 5 (4), 1222–1235, 2006b.

B.D. Kay, A.P. da Silva, J.A. Baldock: Sensitivity of soil structure to changes in organic carbon content: predictions using pedotransfer functions, Can. J. Soil Sci., 77, 655–667,1997.

GRUNWALD, S.; McSWEENEY, K.; ROONEY, D.J. & LOWERY, B.: Soil layer models created with profile cone penetrometer data, Geoderma, (103), 181-201, 2001.

Deng, H. L., Ye, M., Schaap, M. G., and Khaleel, R.: Quantification of uncertainty in pedotransfer function-based parameter estimation for unsaturated flow modeling, Water Resour. Res., 45, W04409, 2009.

Moeys, J., Larsbo, M., Bergström, L., Brown, C.D., Coquet, Y. and Jarvis, N.J.: Functional test of pedotransfer functions to predict water flow and solute transport with the dual-permeability model MACRO, *Hydrology and Earth System Sciences*, *16*(7), 2069-2083, 2012.

L. Loosvelt , H. Vernieuwe , V. R. N. Pauwels , B. De Baets , and N. E. C. Verhoest : Local sensitivity analysis for compositional data with application to soil texture in hydrologic modelling, Hydrol. Earth Syst. Sci., 17, 461–478, 2013.

Saltelli, A., Chan, K.: Sensitivity Analysis, Scott M. (Eds), John Wiley and Sons publishers, Probability and Statistics series, 2000.

Jacques, J., Lavergne, C. & Devictor, N.: Sensitivity analysis in presence of model uncertainty and correlated inputs, in ‘Proceedings of SAMO2004’, 2004.

Van Genuchten, M. Th., F. J. Leij, and S. R. Yates.: The RETC code for quantifying the hydraulic functions of unsaturated soils, Report No. EPA/600/2-91/065. R. S. Kerr Environmental Research Laboratory, U. S. Environmental Protection Agency, Ada, OK, 85, 1991.

Nemes, A., Schaap, M.G., Wösten, J.H.M.: Functional evaluation of pedotransfer functions derived from different scales of data collection, Soil Sci. Soc. Am. J, 67, 1093–1102, 2003.

Pachepsky, Y. A., W. J. Rawls, and D. J. Timlin: The current status of pedotransfer functions: Their accuracy, reliability, and utility in fieldand regional-scale modeling in Assessment of Non-point Source

Pollution in the Vadose Zone, Geophys. Monogr, Ser., vol. 108, edited by D. L. Corwin, K. Loague, and T. R. Ellsworth, 223 – 234, AGU, Washington, D. C, 1999.

Willmott, CJ, Wicks, DE.: An empirical method for the spatial interpolation of monthly precipitation within California, Physical Geography,1, 59–73, 1980.

Willmott, C.J.: On the validation of models. Physical Geography, 2, 184–194, 1981.

Sobol, I.M.: On sensitivity estimation for nonlinear mathematical models, Matematicheskoe Modelirovanie (In Russian), Translated in: Mathematical Modeling & Computational Experiment, 2(1), 112-118, 1990.

Saltelli, A., and Tarantola, S.: On the Relative Importance of Input Factors in Mathematical Models, Journal of the American Statistical Association, 97(459), 702-709, 2002.

Saltelli A., and Tarantola, S.: On the relative importance of input factor in mathematical models", Revised for Journal of American Statistical Association, 2001.

Chastaing, G., Gamboa, F., Prieur, C.: Generalized Hoeffding-Sobol Decomposition for Dependent Variables - Application to Sensitivity Analysis, Electronic Journal of Statistics,0 (0000), 1935-7524, DOI: 10.1214/154957804100000000,2011.

Jacques, J., Lavergne, C., Devictor, N.: Sensitivity analysis in presence of model uncertainty and correlated inputs, Reliability Engineering & System Safety, 91, 1126–1134, 2006.

Tomasella, J., Pachepsky, Y.A., Crestana, S., Rawls, W.J.: Comparison of two techniques to develop pedotransfer functions for water retention, Soil Sci. Soc. Am. J, 67 1085–1092, 2003.

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

Wagner, B., V. R. Tarnawski, V. Hennings, U. Müller, G. Wessoleke, and R. Plagge.: Evaluation of Pedotransfer functions for unsaturated soil hydraulic conductivity using an independent data set, Geoderma, 102, 275-297, 2001.

Rawls, W.J., Pachepsky Y.A., and Shen, M.H.: Testing soil water retention estimation with the MUUF pedotransfer model using data from the southern United States, Journal of Hydrology, 251, 177-185, 2001.

Arya, L. M. and Paris, J. F.: A physic empirical model to predict the soil moisture characteristic from particle-size distribution and bulk density data, Soil Sci. Soc. Am. J., 45, 1023–1030, 1981.

Minasny, B. and McBratney, A. B.: Estimating the water retention shape parameter from sand and clay content, Soil Sci. Soc. Am. J, 71: 1105–1110, 2007.

Hao, D. R., Liao, H. J., Ning, C. M., and Shan, X. P. : The microstructure and soil water characteristic of unsaturated loess, Unsaturated Soil Mechanics - from Theory to Practice, Proceedings of the 6th Asia Pacific Conference on Unsaturated Soils (Guilin, China, 23-26 October 2015), Edited by Zhenghan Chen, Changfu Wei, De ´ an Sun, and Xongfu Xu, 163–167, DOI: 10.1201/b19248-22, 2015.

Bruand, A., Duval, O., Gaillard, H., Darthout, R., Jamagne, M. : Variabilité des propriétés de rétention en eau des sols: importance de la densité apparente, Etude et Gestion des Sols, 3(1), 27-40, 1996.

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016

Reichert, J.M., Suzuki, L.E.A.S., Reinert, D.J., Horn, R., Håkansson, I.: Reference bulk density and critical degree-of-compactness for no-till crop production in subtropical highly weathered soils, Soil Tillage Res., 102, 242–254, 2009.

Lal, R.: Physical properties and moisture retention characteristics of some Nigerian soils, Geoderma 21, 209 – 223, 1979.

Danalatos, N.G., Kosmas, C.S., Driessen, P.M., Yassoglou, N.: Estimation of the draining soil moisture characteristics from standard data as recorded in soil surveys, Geoderma,64, 155 – 165, 1994.

Tables:

Table 1. Soil characteristics used for the development and validation.

	Granulometry					VWC ($cm^3\ cm^{-3}$)	
	S (%)	Si (%)	C (%)	BD (g/cm^3)	OM (%)	- 33 kPa	-1500 kP
Samples used for Deriving PTF (n = 189)							
Average	17.81	39,23	42.97	1.71	0.95	0.44	0.27
Standard Deviation	10.32	10.76	13.90	0.20	0. 93	0.09	0.08
Min	1.00	9.20	4.00	0.60	0.08	0.13	0.03
Max	50.00	67.00	84.30	2.10	8.40	0.73	0.56
Coefficient of Variation (CV)	0.58	0.27	0.32	0.12	0.98	0.21	0.31
Samples used for testing the PTF (n = 53)							
Average	12.50	41.58	45.92	1.49	0.87	0.40	0.21
Standard Deviation	14.84	7.62	14.94	0.13	0.50	0.10	0.07
Min	-	29.00	9.00	1.15	0.20	0.14	0.07
Max	59.00	58.00	70.00	1.73	2.74	0.57	0.45
Coefficient of Variation (CV)	1.19	0.18	0.33	0.09	0.57	0.24	0.35

(*) S: sand, C: clay, Si: silt, BD: bulk density, OM: organic matter, *VWC: volumetric water content*
CV: coefficient of variation.

Table 2. Multiple regression coefficient R^2 and regression coefficients of models developed.

		Points PTF (MLR)			***Parametric PTFs (MNLR : Cubic Model)***		
		-33 kPa	**-1500 kPa**	**Ѳs**($cm^3\ cm^3$)	***Ѳr***($cm^3\ cm^3$)	***α***	***n***
	Inputs (*)	*S%, C%, BD, OM*	*S%, C%, BD,*	*S%, C%, BD, OM*	C%,S%	Si%, S%	C%, Si%
	R^2 multiple	0.74	0.66	0.62	0.67	0.60	0.66
Regression Coefficients	***a***	0.0246	-0.0627	0.4136	9.00×10^{-02}	3.00×10^{-03}	2.90
	b	-0.0040	-0.0029	-0.0013	7.78×10^{-04}	-1.00×10^{-04}	-2.77×10^{-03}
	c	0.0012	0.00165	0.0002	3.20×10^{-04}	8.90×10^{-05}	-9.48×10^{-02}
	d	0.2554	0.1837	0.0177	-6.36×10^{-05}	5.40×10^{-06}	-3.66×10^{-04}
	e	0.0067		- 0.0018	1.20×10^{-05}	-4.50×10^{-06}	2.03×10^{-03}
	f	-	-	-	9.30×10^{-07}	-7.30×10^{-08}	2.49×10^{-06}
	g	-	-	-	-1.00×10^{-07}	4.50×10^{-08}	-1.50×10^{-05}
	h	-	-	-	9.00×10^{-02}	7.70×10^{-06}	2.84×10^{-04}
	i	-	-	-	7.78×10^{-04}	-3.10×10^{-08}	4.91×10^{-06}
	j	-	--	-	3.20×10^{-04}	-3.10×10^{-08}	-5.32×10^{-06}

(*) S: sand, C: clay, Si: silt, BD: bulk density, OM: organic matter (respectively)

Table 3. Evaluation criteria of PTFs at -33 kPa and -1500 kPa.

			-33 kPa	*-1500 kPa*
ME (cm^3 cm^{-3})	***PTF Point***	MLR	0.0188	0.0261
	Parametric PTF	MNLR	-0,0016	-0.0020
	Rosetta	H1	- 0.0902	-0.0458
		H2	- 0.0728	-0.0436
		H3	-0.0991	-0.0552
RMSE (cm^3 cm^{-3})	***PTF Point***	MLR	0.0414	0.0444
	Parametric PTF	MNLR	0.0613	0.0605
	Rosetta	H1	0.1170	0.0738
		H2	0.0970	0.0636
		H3	0.1280	0.0749
d (cm^3 cm^{-3})	***PTF Point***	MLR	0.9975	0.9911
	Parametric PTF	MNLR	0.9938	0.9775
	Rosetta	H1	0.9623	0.9427
		H2	0.9775	0.9597
		H3	0.9519	0.9331

Table 5. The variation of first order sensitivity index in the textural classes.

			Si (%)		**S** (%)		**C** (%)		**BD** (g/cm^3)		**OM** (%)	
		Tex-class	**V_{Si}**	**A.E**	**V_{Si}**	**A.E**	**V_{Si}**	**A.E**	**V_{Si}**	**A.E**	**V_{Si}**	**A.E**
RML	**at -33 kPa**	**VF**	*Abs*		-1.2		-0.4		-50.5	**-**	4.6	
		F	*Abs*		-43.2	**-**	-10.7	**-**	-39.9	**-**	0.2	
		M	*Abs*		-103.3	**-**	-27.5	**+**	-44.4	**+**	-5.7	
	at -1500 kPa	**VF**	*Abs*		-0.3		0.9		-27.3	**-**	1.1	
		F	*Abs*		-46.2	**-**	-20.7	**-**	-41.6	**-**	0.1	
		M	*Abs*		-86.4	**-**	-52.9	**-**	-22.9	**-**	-2.3	
MNLR	**at -33 kPa**	**VF**	0.4		-0.2		0.1		-00.1		-0.05	
		F	-1.6		-40.9	**-**	-1.1		-2.5		-0.1	
		M	15.0		-5.2		15.1	**+**	21.6	**+**	22.3	**+**
	at -1500 kPa	**VF**	- 4.6		-0.3		-1.8		-1.4		-00.5	
		F	28.6	**+**	18.9	**-**	4.6		0.4		0.1	
		M	-36.7	**-**	-16.7	**-**	-22.6	**-**	8.9		-8.4	

V_{Si}: variation first sensitivity index; A.E.: improving estimation; +: favourable impact; - : adverse impact.

Table 6. Correlation matrix (coefficient of Pearson) of validation database (n=53).

Variables	Si%	S %	C (%)	BD (g/cm^3)	OM (%)
S%	**1**				
S %	**-0.334**	**1**			
C %	-0.159	**-0.878**	**1**		
BD (g/cm3)	0.164	-0.185	0.11	**1**	
OM (g/100g)	-0.174	-0.166	0.263	-0.19	**1**

The values which are in bold are different from 0 to a level of signification α = 0.05

Figures:

Figure 1. Scatter plots of measured versus predicted soil water retention by H2 Rosetta.

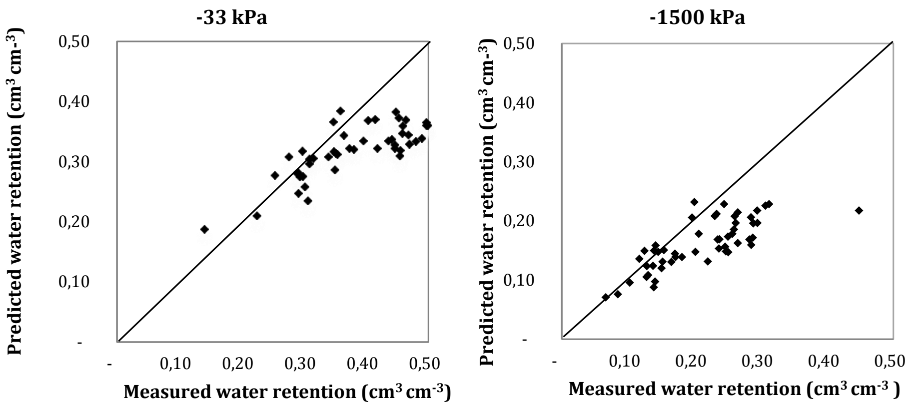


Figure 2. First order sensitivity index

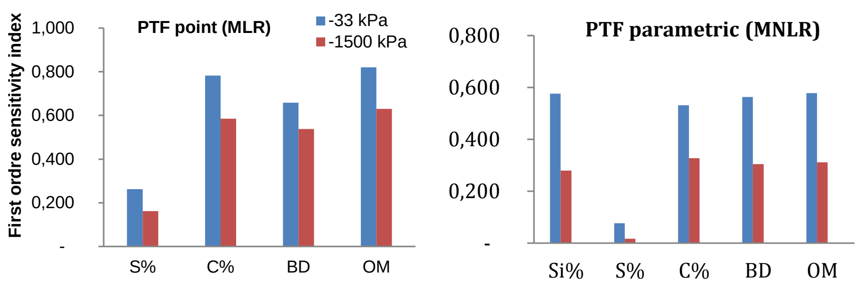


Figure 3. Textural triangle proposed by FOA (1990).

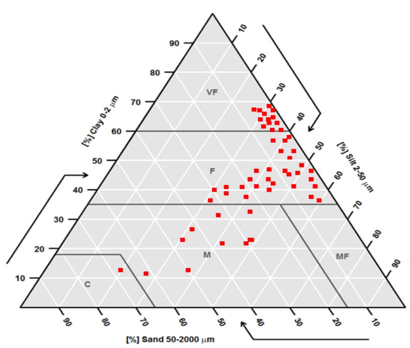
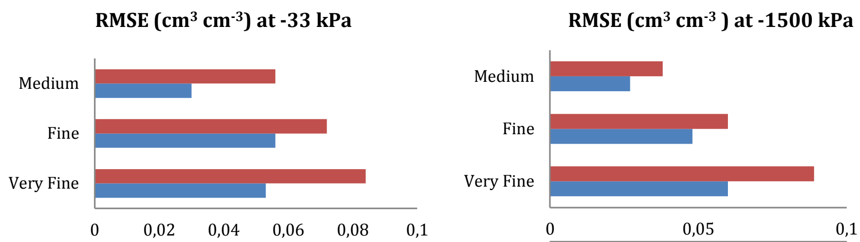


Figure 4. The RMSE criteria calculated with textural classification.

SOIL Discuss., doi:10.5194/soil-2016-18, 2016
Manuscript under review for journal SOIL
Published: 7 April 2016



	Very Fine	Fine	Medium
RMNL	0,084	0,072	0,056
RLM	0,053	0,056	0,03

	Very Fine	Fine	Medium
RMNL	0,089	0,06	0,038
RLM	0,06	0,048	0,027

Figure 5. Variation of first sensitivity index with RMSE criteria after textural classification.

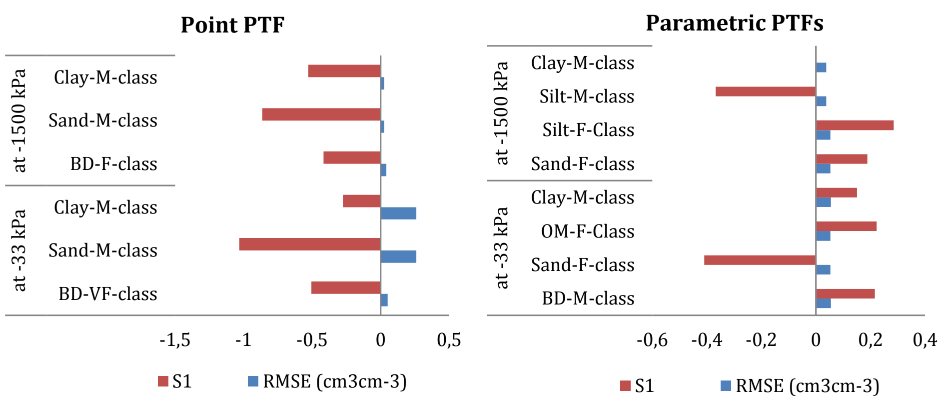


Figure 6. Scatter plots of measured soil water retention versus predicted soil water retention.