Sensitivity analysis of point and parametric pedotransfer functions for estimating water retention of soils in Algeria

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 prediction uncertainty can be apportioned to different sources of uncertainty in inputs. In this study, the question addressed was: Which variable input is the main or best complementary predictor of water retention, and at which water potential? Two approaches were adopted to generate PTFs: multiple linear regressions (MLR) for point PTFs; and multiple non-linear regressions (MNLR) for parametric PTFs. Reliability tests showed that point PTFs provided better estimates than parametric PTFs (RMSE: 0.0414; 0.0444 cm^3 cm^{-3} and 0.0613; 0.0605 cm^3 cm^{-3} at -33 kPa and -1500 kPa, respectively). The local parametric PTFs provided better estimates than Rosetta PTFs at -33 kPa. No significant difference in accuracy, however, was found between the parametric PTFs and Rosetta H2 at -1500 kPa, with RMSE values of 0.0605 cm^3 cm^{-3} and 0.0636 cm^3 cm^{-3}, respectively. The results of global sensitivity analyses (GSAs) showed that the mathematical formalism of PTFs and their input variables reacted differently in terms of point pressure and texture. The point and parametric PTFs were sensitive mainly to the sand fraction in the fine and medium textural classes. The use of clay percentage (C %) and bulk density (BD) as inputs in the medium textural class improved the estimation of PTFs at -33 kPa.

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

I. Introduction

Predictive information on the spatial distribution of soil water and its availability for plants enables producers to take effective decisions (e.g., on nutrient management and plant cover) to maximize profitability. The soil-water balance is central to many processes that influence plant growth and the degradation of soil and water resources.

Hydrologists face the situation where soil hydraulic data such as water retention or hydraulic conductivity are often missing. Therefore, pedotransfer functions (PTFs) are used as an alternative to estimate these properties. The extrapolation of PTFs in different agropedoclimatic context limits their performance (Touil et al., 2016). The development of local PTFs could be useful in meeting the agricultural requirements for modelling with reasonable accuracy.

Soil-water retention (SWR) curves can usually be estimated using two approaches: point PTFs and parameter PTFs. With point PTFs, SWR is estimated at defined pressure points (Pachepsky et

al., 1996; Minasny et al., 1999). One of the most commonly used SWR curves is the Van Genuchten model (1980). With parameter PTFs, the parameters of SWR models, such as θs, θr, α and n, are estimated by fitting them to the data and then relating then 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). Schaap et al. (2001) developed the Rosetta package based on the artificial neural network (ANN) method, which uses five hierarchical models to predict the van Genuchten (VG) parameters (θs, θr, α and n) with soil texture classes only and the input data (texture, bulk density [BD], and one or two water content values at -33 and -1500 kPa).

PTFs for point and parametric estimation of SWR from basic soil properties can be developed using multiple regression methods (Lin et al., 1999; Mayr and Jarvis, 1999; Tomasella et al., 2000). Some 97% of PTFs are based on multiple linear and polynomial regressions of nth order techniques (Botula et al. 2014).

Using PTFs in environments that differ from those from which they were derived can lead to an under- or overestimation of SWR. Several studies have shown that SWR is a complex function of soil structure and composition (Rawls et al., 1991; Wösten et al., 2001; Rawls et al., 2003; Mirus et al., 2015). Applying PTFs to different textural or structural classes could also be a source of uncertainty (Bruand et al., 2002; Pachepsky et al., 2003). SWR and hydraulic conductivity vary widely and non-linearly with soil-water potential. Soil texture is the main determinant of the water-holding characteristics of most agricultural soils (Saxton et al., 1986). The relationship between the SWR curve and particle size distribution (PSD) has been 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). SWR depends mainly on texture, with other factors such as BD, structure, organic matter (OM), clay type and hysteresis having a secondary impact (Williams et al., 1983, Saxton et al., 1986, Vereecken et al., 1989, Winfield et al., 2006).

The variability in PTF response depends on the variability and uncertainty of one or more of the input variables. Uncertainty analysis in the variety of available PTF approaches is necessary to minimize error in estimation and identify its source. Recently, sensitivity analysis techniques and uncertainty analysis have begun to receive considerable attention in PTF studies (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 main or best complementary predictor of SWR, and at which potential? Global sensitivity analysis (GSA) enables us to study how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model inputs (Saltelli et al., 2000). Generally, GSA is useful for identifying which variables make the main contribution to output variables (Jaques et al., 2004).

The objectives of this study were to:

- Develop and validate two PTF approaches using regression methods: point PTFs for estimating SWR in Algerian soils at -33 kPa and -1500 kPa; and parametric PTFs for estimating the VG parameters
- Study the impact of each input on the PTF responses

II.   Materials and methods

1.   The database

The soil dataset used for this study was collected from various regions in Algeria, mainly in the north, which has a Mediterranean climate. It contained 242 samples, with basic soil properties: texture fractions (based on the USDA system; clay and silty-clayey for most of the soils, Fig. 3a), BD, OM content and water content at -33 kPa and -1500kPa. Descriptive statistics of the development and validation datasets are presented in Table 1. The available database was split into two datasets. Subset 1, which was used to develop the PTFs, contained 78.1% of the samples. Used as the calibration set, they were collected from the coastal plain of Annaba in north-eastern Algeria (13 samples), the Beni Slimane plain of Media (42 samples), the Kherba El Abadia plain of Ain Defla (54 samples) and the Lower Cheliff plain in north-western Algeria (80 samples). Subset 2 contained the remaining 21.9% of the samples. Used to verify the PTFs, they were collected from Benziane valley in the lower south-western Cheliff plain. The depth of the two upper horizons varied from site to site, with a maximum of 30 cm for surface horizons and more than 30 cm for subsurface horizons.

PSD analysis was conducted using the international Robinson's pipette method (Robinson, 1922). Undisturbed soil samples obtained with 500-1,000 cm^3 cylinders were used to determine BD. The SWR values at -33 kPa and -1500 kPa were obtained using Richards's apparatus (Richards et al., 1943). Undisturbed soil samples were collected near field capacity with 100 cm^3 cylinders. Water content was measured using the gravimetric method at 105°C (24 h). Organic carbon content was determined using the wet oxidation method (Walkley and Black, 1934). Variation in soil texture in the dataset is displayed using the textural triangle proposed by FAO (1990) in Figure 3b.

The SWR model devised by Van Genuchten (1980) is defined as:

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

Where θ_r and θ_s are residual and saturated soil-water content ($cm^3 \ cm^{-3}$), respectively, and α (cm^{-1}) and n are the shape factors of the SWR function. The VG parameters were indirectly estimated for each soil sample from four levels of measured data inputs: sand, silt and clay percentages, and BD using the Rosetta model H3 (Schaap et al., 2001). The 'm' parameter was calculated as follows:

m = 1 -1 / n.

2.   PTF development

Two approaches were used in this study to develop the PTFs: point PTFs for estimating SWR for particular points of pressure (h); and parametric PTFs for predicting the VG parameters. Each

121 water content level at selected water potentials of -33 kPa and -1500 kPa and estimated VG
122 parameters were related to basic soil properties (i.e., sand, silt, clay content, OM content and BD)
123 using multiple regression techniques (Table 2). The most significant input variables were determined
124 using the Pearson correlation (α =5%). T For the multiple-linear regression (MLR) models, the general
125 form of the resulting equations was expressed thus:

126 $Y = a_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4$ (2)

127

128 For the multiple-non-linear regression (MNLR) models, it was expressed thus:

129 $Y = a_0 + b_1 X_1 + b_2 X_2 + b_3 X_1{}^2 + b_4 X_2{}^2 + b_5 X_1{}^3 + b_6 X_2{}^3 + b_7 X_1 {}^* X_2 + b_8 X_1{}^2{}^* X_2 + b_9 X_1{}^* X_2{}^2$

130 (3)

131 Where Y represents the dependent variable, a_0 is the intercept; b_1..., b_n are the regression
132 coefficients, and X_1 to X_4 refer to the independent variables representing the basic soil properties.

133 The prediction quality of the point and parametric PTFs developed from Algerian soils were
134 then compared with three Rosetta PTFs (H1, H2 and H3). We chose the Rosetta model because it
135 gives the user flexibility in inputting the data required (Stumpp et al., 2009), with the option of five
136 levels based on input data (Schaap et al. 2002):
137 • H1: Textural classes (USDA system)
138 • H2 : Clay+Silt+Sand
139 • H3: Clay+Silt+Sand+ BD
140 • H4: Clay+Silt+Sand+ BD +Volumic water at -33 kPa
141 • H5: Clay+Silt+Sand+ BD +Volumic water at -33 kPa + Volumic water at -1500 kPa

142

143 The Rosetta model was also chosen because it has given reasonable predictions in several evaluation
144 studies (Frederick et al., 2004, Nemes et al., 2003). In our study, the three Rosetta model levels (H1,
145 H2, and H3) were selected to compare their performance in the Algerian soils because they require
146 only texture data and BD as inputs, as well as the locally developed PTFs.
147   3. Evaluation criteria

148 PTFs are regularly assessed by comparing the values that they predict with the measured values
149 (Pachepsky and Rawls, 1999). In order to assess the validity of the PTFs developed, we used the
150 following criteria: mean prediction error (ME) to indicate the bias of the estimate; root mean square
151 error (RMSE) to assess the quality of the prediction (it is frequently used in studies on PTFs); and the
152 index of agreement (d) developed by Willmott and Wicks (1980) and Willmott (1981) as a standardized
153 measure of the degree of model prediction error. They were calculated using the following equations,
154 respectively:

155 $$ME = \frac{1}{N} \sum_{i=1}^{n} (\theta_p - \theta_m)$$ (4)

156 Where N is number of horizons, and θ_p, θ_m, predicted and measured volumetric water content,
157 respectively. The estimate was better when ME was close to 0'. Negative ME values indicated an
158 average underestimation of θ_m, whereas positive values indicated overestimation.

159    $$RMSE = \left\{ \frac{1}{n} \sum_{i=1}^{n} (\theta_{\mathrm{p}} - \theta_{\mathrm{m}})^2 \right\}^{\frac{1}{2}} \tag{5}$$

160   Thus, the lower the RMSE, the better the estimate.

161    $$d = 1 - \frac{\frac{1}{n} \sum_{i=1}^{n} (\theta_{\mathrm{p}} - \theta_{\mathrm{m}})^2}{\sum_{i=1}^{n} \left[|(\theta_{\mathrm{p}} - \bar{\theta}_{\mathrm{m}})| + |(\theta_{\mathrm{m}} - \bar{\theta}_{\mathrm{m}})| \right]^2} \tag{6}$$

162
163   The index of agreement varied from 0 to 1, with higher index values indicating that the modeled values

164   θ_{p} were in better agreement with the observations θ_{m}.

165

166   4.   Global sensitivity analysis (GSA)

167

168   GSA involves determining which part of the variance in model response is due to variance in which

169   input variable or group of inputs. The impact of the parameters is quantified by calculating the global

170   sensitivity indices.

171   The Sobol method (Sobol, 1990) is an independent GSA method based on decomposition of

172   the variance. When the model is non-linear and non-monotonic, the decomposition of the output

173   variance is still defined and can be used. The Sobol model is represented by the following function:

174

175    $$Y = f(X_1, X_2, X_3, \ldots, X_p) \tag{7}$$

176   Where Y is the model output (or objective function) and $X = (X_1, \ldots, X_p)$ is the input variable set.

177    $$V(Y) = V(E(Y|X)) + E(Var(Y|X)) \tag{8}$$

178

179   Where V(Y) is the total variance in the model, V (E(Y|X)) and E (Var(Y|X)) signify variance in the

180   conditional expected value and expected value of the conditional variance, respectively. When the

181   input variables X_i are independent, the variance decomposition of the model is:

182    $$V(Y) = \sum_{i=1}^{p} V_i + \sum_i \sum_j V_{ij} + + \sum_i \sum_j \sum_p V_{ijp} + \ldots \ldots + V_{1,2,3,\ldots p} \tag{9}$$

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

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

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

186
187   Where V_i is the proportion of variance due to variable X_i. Dividing V_i by V(Y) produces the expression

188   of the first-order sensitivity index (S_i), such that:

189

190    $$S_i = \frac{V_i}{V(Y)} = \frac{V[E(Y/X_i)]}{V(Y)} \tag{10}$$

191   The term S_i is the measure that guarantees an informed choice in cases where the factors are

192   correlated and interact (Saltelli and Tarantola, 2002). This index is always between 0 and 1, and

193   represents a proper measurement of the sensitivity used to classify the input variables in order of

194   importance (Saltelli and Tarantola, 2001).

195 In order to quantify variation in the sensitivity index (V $_{Si}$) of an input factor X_i, we fixed it at $Xi = Xi *$

196 ($Xi *$: the average when the variable follows the normal distribution, the median when the variable

197 follows the lognormal distribution). In order to calculate how much this assumption changed the

198 variance of Y, we used this formula:

199 $$V_{Si} = \left(\frac{V[E(Y/X)]}{V(Y)} - \frac{V[E(Y/Xi=Xi*)]}{V(Y)} \right) * 100 \tag{11}$$

200 $V_{Si} > 0$ and S_i close to 1 indicate increasing accuracy of PTFs;

201 $V_{Si} < 0$ and S_i close to 1 indicate increasing accuracy of PTFs;

202 $V_{Si} > 0$ and S_i close to 0 indicate decreasing accuracy of PTFs;

203 $V_{Si} < 0$ and S_i close to 0 indicate decreasing accuracy of PTFs.

204 In addition, combining the RMSE and S_i enabled us to detect the contribution of each variable to

205 improvement in the quality of prediction of the PTFs.

206

III. Results and discussion
207
208

209 In Table 3, most of the PTFs underestimated SWR except for the point PTF at the two

210 pressure points (-33 kPa and -1500 kPa). The Rosetta H2 model, which considers only texture as an

211 input, gave a smaller ME value than the H1 and H3 models (- 0.0728; -0.0436 $cm^3 cm^{-3}$ at -33 kPa and

212 -1500 kPa, respectively$^)$.

213 The poor ME values indicated better estimates of PTFs. They were produced after the

214 application of point PTFs followed by parametric PTFs.

215 Among the five tested models in the Lower Cheliff soils, the point PTFs (MLR) derived from a

216 database taken from some Algerian soils had the lowest RMSE values (0.041 and 0.044 $cm^3 cm^{-3}$ at -

217 33 kPa and -1500 kPa, respectively). Performances equivalent or superior to PTFs derived by multiple

218 regression methods have been reported in some studies (Minasny et al., 1999; Nemes et al., 2003).

219 The non-linear models (parametric PTFs), however, gave a better estimation than the Rosetta models

220 based on ANN (RMSE: 0.0613 and 0.0605 $cm^3 cm^{-3}$ at -33 kPa and -1500 kPa, respectively). The

221 RMSE and ME values of the three Rosetta models also showed that H2 was better than H1 or H3

222 (Table 3).

223 The index of agreement results showed that point PTFs were more suitable for Lower Cheliff

224 soils than parametric PTFs (Figure 6), with values of 0.9975 and 0.9911 $cm^3 cm^{-3}$). Similar

225 comparisons in different regions were undertaken by Minasny et al. (1999), Tomasella et al. (2003)

226 and Ghorbani Dashtaki et al. (2010), who all reported similar differences between these two PTF

227 approaches.

228 As Table 3 shows, there was no significant difference in RMSE values between the parametric

229 PTFs and Rosetta H2 at -1500 kPa (RMSE: 0.0605 $cm^3 cm^{-3}$ and 0.0636 $cm^3 cm^{-3}$, respectively).

230
231 1. Sensitivity index before textural grouping
232

233   In the development of PTFs, using PSD as an input is the usual approach (texture as an
234 overall expression of PSD, clay, silt and sand content) and its contribution is fundamental to
235 understanding the process of retaining water at different pressure points, although various physical
236 and chemical characteristics are used to describe the SWR curve, such as BD and OM.
237   The importance of each input variable was assessed by the first order S_i. It was clear for the
238 PTFs developed that OM% and clay percentages (C%) were the variables with the greatest impact
239 (Figure 2). For the point PTFs (MLR), the most sensitive estimations were at two pressure points (S_i:
240 0.821; 0.782 at -33 kPa and 0.630; 0.585 at -1500 kPa for OM% and C%, respectively). The
241 percentage of silt (S_i%) was second in importance in parametric PTFs (0.576 at -33 kPa) after OM,
242 followed by BD and C (Fig. 2). The S_i values placed sand content in third place in the MLR
243 (0.262; 0.162), indicating that its impact on the parametric model was almost insignificant, with very
244 low values (S_i: 0.077; 0.017) at -33 kPa and -1500 kPa, respectively).
245   The prediction quality of point PTFs (MLR) can be explained, first, by taking into account the
246 basic characteristics of soil as an input from the textural and structural information given by the BD.
247 Second, point PTFs (MLR) are based mainly on these input variables, unlike parameter PTFs
248 (MNLR), which have inputs other than texture and BD, as well as other parameters (VG parameters:
249 θ_r, θ_s, α, n).
250
251   2.   Sensitivity and uncertainty analysis after the textural grouping
252
253   The sensitivity of the multiple regression methods (linear and non-linear) used to develop PTFs
254 from basic soil characteristics for estimating SWR for different textural classes was analyzed. We
255 grouped the samples into three classes of particles (Figure 3) in line with FAO guidelines (FAO,
256 1990): very fine (12 samples); fine (31 samples); and medium (10 samples).

257   The results showed that after the textural grouping, there was an improvement in the quality
258 estimation of PTFs only in the medium class (Figure 4). A better prediction at -1500 kPa was provided
259 by point PTFs (RMSE = 0.027 cm^3 cm^{-3}) and parametric PTFs (RMSE = 0.038 cm^3 cm^{-3}) at -1500 kPa.

261 **1. Texture:** After textural grouping, the MLR and MNLR PTFs developed were always sensitive
262 mainly to the sand fraction in the fine and medium classes (Table 4). The variation in the first S_i in
263 the point PTFs was significantly greater in the medium texture class at the two pressure points (-33
264 kPa and -1500 kPa). In the MNLR, sand had the most influence, particularly with regard to the fine
265 class (-40.9%, 18.9% at -33 kPa and 1500 kPa) and the medium class (-16.7% at -1500 kPa).
266 The S_i of a variable quantifies the influence of its uncertainty on the output. This is the part of the
267 variability output explained by the variability input. What was confirmed after calculating the variation
268 in the first order S_i was that the PTFs developed were still more influenced by the variability in sand at
269 -33 kPa than at -1500 kPa. This impact could be explained by the irregularity of the dispersion of sand
270 content in the validation database, with a coefficient of variation (CV) of about 119% compared with
271 the other input variables (33%, 18%, 9% and 57% for clay, silt, BD and OM, respectively). This
272 heterogeneity in the sand data series clearly influenced the uncertainty of the PTF response.

273 Looking at the matrix correlation (Table 5), the clay and silt fractions were significantly correlated with
274 sand content. Saltelli and Tarantola (2002) observed that when X_1 and X_2 were correlated with a third
275 factor, X_3, the S_i calculated depended on the force of this correlation as well as the distribution of X_3. In
276 this case, the index power could be influenced by this statistical association, as it explains the higher
277 value difference of index variation in the sand percentage compared with the other variables (Fig. 2).
278 We observed that point PTF (MLR) produced a lower error of estimation when the variation of the first
279 order S_i for sand was the most important (MLR in the medium class: RMSE 0.030; 0.027 cm^3 cm^{-3} with
280 V_{Si} -103% and 86.4% at -33 kPa and -1500 kPa, respectively]. A negative S_i variation in sand content
281 when the latter was fixed was apparent in all texture classes (Table 4). This could be explained by the
282 proportional relationship between sand and clay content, particularly in the validation dataset with a
283 dominant clay texture. Insignificant sensitivity of sand was recorded for the very fine texture. Rawls et
284 al. (2003) observed that 10% of sand provides an increase in SWR at low clay content and a decrease
285 in SWR at high clay content of more than 50%.

286 The relationship between VG's SWR curve parameters (especially n and α) and PSD has been
287 examined in many studies (e.g., Minasny et al., 2007; Benson et al., 2014) in order to explain why the
288 sand impact increases in the fine texture class in parametric PTFs. It could be explained by the
289 predominant presence of sand and clay content as inputs in parametric PTFs. For soils with clay
290 content between 35% and 70%, water content is greatly influenced by the percentage of sand in the
291 soil (Loosvelt et al., 2013).

292 In addition, when the sand content of a sample increased to 60%, the drying rate was faster and water
293 absorbing ability was weaker than with the low sand content. When sand content falls to 20%, the
294 small pores occupy a large part of the pore structure, making the soil compact (Hao et al., 2015).
295 In the medium texture class, there was increasing accuracy in PTFs after fixing the clay content at -33
296 kPa. This could be explained by the reduced clay percentage in the medium class (mean of clay [%] =
297 23%), which produced fewer errors at -33 kPa. The greatest impact of clay (%) was observed at -1500
298 kPa in the point and parametric PTFs in different textural classes (Figure 4). The clay content of soils
299 is a major predictor for modelling the permanent wilting point of soils (Minasny et al., 1999).
300 The accuracy of the PTFs decreased when they were applied to some soil samples with a clay content
301 (%) > 60% (Figure 4). In the very fine class, insignificant sensitivity was recorded at all pressures
302 defined in this study. In this class, the variation in clay was much lower because it is only the dominant
303 solid fraction, which could explain the smaller variation in S_i after fixing the clay percentage. SWR was
304 higher in the very fine and fine classes than in the medium class, because they quickly drained water
305 initially retained.
306 The silt percentage was introduced as an explanatory variable only in parametric PTFs (MNLR). This
307 fraction is known for its ability to retain water at high and medium soil water potentials. The GSA
308 showed that the silt percentage had a stronger impact on the estimation of parametric PTFs at -1500
309 kPa than at -33 kPa with the MNLR model. After textural grouping, an important variation in the first
310 order S_i was observed in the medium class (-36.7% to -1500 kPa). The lowest values were recorded
311 in the very fine class. It was clear that the silt percentage has an important role in estimating VG's

312 parameters (α, n), and that its use as an input influences the estimate in the medium and fine classes.
313 There was an increasing accuracy, however, in the PTFs recorded in the fine class at -1500 kPa. With
314 silt and clay as inputs, there was a better estimation. Plant-available water content variation is more
315 related to sand and silt than to clay content (Reichert et al., 2009).

316 **2. Bulk density**: this is the second most influential variable on the point PTF (MLR) response is by
317 variation of sensitivity index on all textural class, mainly in the very fine textural class with elevated
318 values at -33 kPa (V_{Si} = -50, 5%). In parametric PTFs, BD influenced the medium class at -33 kPa.
319 The results showed the accuracy of quality estimation in the medium class when fixing the BD at -33
320 kPa for the two PTF approaches (Table 4). The very fine textural class represented 16 surface
321 samples (0–30 cm) with a dominance of clay texture. In a similar study on clay soils, volumetric water
322 content (VWC) was highly related to the inverse of BD at field capacity (Bruand et al., 1996)**.** This
323 might also explain the fact that many soils with high clay content in the database are Vertisols in which
324 BD and VWC are lower (Rawls et al., 2003). The inclusion of BD as an input provides information on
325 pore volume, which can influence the performance of PTFs when applied to soil with high clay content.
326 In addition, the soil structural information characterized by BD measurements is an indirect
327 measurement of pore space and is affected mainly by texture and structure. For structureless soils,
328 primarily coarse and medium textured soils, the capillary pore-size distribution can be satisfactorily
329 described by PSD. The medium texture is related in general to pore-size distribution, as large particles
330 give rise to large pores between them, and therefore have a major influence on the SWR curve (Arya
331 and Paris, 1981; Nimmo, 2004)**.** With BD and texture as inputs in point PTF (MLR), predicted values
332 very close to the experimental results are obtained. This study showed that the effect of using soil
333 structural information in estimating SWR depended on the type of regression technique (Nguyen et al.,
334 2015).

335 **3. Organic matter content:** The most insignificant variation in the S_i after textural grouping related to
336 OM content. This could be explained, first, by the poor OM content in the Algerian soil samples. Lal
337 (1979) did not find any effect of OM content on SWR. Danalatos et al. (1994) attributed this to the
338 generally low OM content in their samples. Second, homogeneity of the data for OM content in every
339 textural class reduced the variation in PTF response. The increasing accuracy of parametric PTFs,
340 however, was apparent for medium-textured soils at -33 kPa, where OM was used as an input to
341 predict θ_s. SWR at -33 kPa is affected more strongly by organic carbon than at -1500 kPa (Rawls et
342 al., 2003). The sensitivity analysis conducted by Rawls et al. (2003) to study the role of OM content as
343 a predictor showed that the SWR of coarse-textured soils is much more sensitive to changes in
344 organic carbon than is the case with fine-textured soils. Bauer and Black (1981) found that the effect
345 of organic carbon on SWR in disturbed samples was substantial in sandy soil and marginal in medium
346 and fine textured soils.

347 **IV.   Conclusion**

348   The objective of this study was to analyze the sensitivity of estimating the SWR properties of
349 Algerian soil using PTFs. We developed and validated point and parametric PTFs from basic soil
350 properties using regression techniques and compared their predictive capabilities with the Rosetta

models (H1, H2, and H3). The reliability tests showed that point PTFs produce more accurate estimations than parametric PTFs. The derived parametric PTFs, however, provided better estimates than the Rosetta models originally developed from a large intercontinental database.

The GSA showed that the mathematical formalism of the PTF models and their input variables reacted differently in terms of point pressure and textural class:

- After textural grouping, the two PTF approaches developed (MLR and MNLR) were always sensitive primarily to the sand fraction in the fine and medium classes at -33 kPa, rather than at -1500 kPa.
- The results illustrated the accuracy of quality estimation in the medium class for the two PTF approaches when fixing the clay percentage (C %) and BD at -33 kPa.
- The accuracy of PTFs decreased when they were applied to soil samples with a clay content > 60%.
- The most insignificant variation in the S_i after textural grouping was related to the OM content in Algerian soils.

References

Arya, L.M., 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.

Aubert, G.: Méthodes d'analyses des sols, Edit.C.R.D.P. Marseille, 189, 1978.

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

Benson, C., Chiang, I., Chalermyanont, T., 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.

Botula, Y. D., Van Ranst, E., Cornelis, W.M.: Pedotransfer functions to predict water retention of soils from the humid tropics: a review, Brazilian Journal of Soil Science, 38, 679-698, 2014.

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.

BRUAND, A., PEREZ-FERNANDEZ, P., DUVAL, O., QUETIN, P., NICOULLAUD, B., GAILLARD, H., RAISON, L., PESSAUD, J.F. and PRUD'HOMME, L.: Estimation des propriétés de rétention en eau des sols: utilisation de classe de pédotransfert après stratifications texturale et texturo-structurale. Etud. Gest. Sols, 9:105-125, 2002.

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.

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.

388 Deng, H.L., Ye, M., Schaap, M.G., Khaleel, R.: Quantification of uncertainty in pedotransfer function-
389 based parameter estimation for unsaturated flow modeling. Water Resour. Res., 45, W04409, 2009.
390 Ghanbarian- Alavijeh, B., Liaghat, A.M.: Evaluation of soil texture data for estimating soil water
391 retention curve, Can. J. Soil Sci, 89, 461–471, 2009.

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

394 Ghorbani Dashtaki, S., Homaee, M., Khodaverdiloo, H.: Derivation and validation of pedotransfer
395 functions for estimating soil water retention curve using a variety of soil data. Soil Use Manage, 26,
396 68-74, 2010.
397 GRUNWALD, S.; McSWEENEY, K.; ROONEY, D.J. & LOWERY, B.: Soil layer models created with
398 profile cone penetrometer data. Geoderma, (103), 181-201, 2001.
399 Hao, D.R., Liao, H.J., Ning, C.M., and Shan, X.P.: The microstructure and soil water characteristic of
400 unsaturated loess. Unsaturated Soil Mechanics - from Theory to Practice, Proceedings of the 6th Asia
401 Pacific Conference on Unsaturated Soils (Guilin, China, 23-26 October 2015), Edited by Zhenghan
402 Chen, Changfu Wei, De ´an Sun, and Xongfu Xu, 163–167, DOI: 10.1201/b19248-22, 2015.
403 Jacques, J., Lavergne, C., Devictor, N.: Sensitivity analysis in presence of model uncertainty and
404 correlated inputs. In Proceedings of SAMO2004, 2004.
405 Jacques, J., Lavergne, C., Devictor, N.: Sensitivity analysis in presence of model uncertainty and
406 correlated inputs. Reliability Engineering & System Safety, 91, 1126–1134, 2006.
407 Jonasson, S.A.: Estimation of the Van Genuchten parameters from grain-size distribution. p. 443-451.
408 In M. Th. Van Genuchten et al. (ed.) Proc. of the Int. Workshop Indirect Methods for Estimating the
409 Hydraulic Properties of Unsaturated Soils, Riverside, CA. 11-13 Oct. 1989, Univ. of California,
410 Riverside, 1992.

411 Kay, B.D., da Silva, A.P., Baldock, J.A.: Sensitivity of soil structure to changes in organic carbon
412 content: predictions using pedotransfer functions. Can. J. Soil Sci., 77, 655–667, 1997.
413 Khodaverdiloo, H., Homaee, M., van Genuchten, M.Th., Dashtaki, S.G.: Deriving and validating
414 pedotransfer functions for some calcareous soils. J. Hydrol, 399, 93–99, 2011.

415 Loosvelt, L., Vernieuwe, H., Pauwels, V.R.N., De Baets, B., Verhoest, N.E.C.: Local sensitivity
416 analysis for compositional data with application to soil texture in hydrologic modelling, Hydrol. Earth
417 Syst. Sci., 17, 461–478, 2013.
418 Lal, R.: Physical properties and moisture retention characteristics of some Nigerian soils. Geoderma
419 21, 209 – 223, 1979.
420 Lin H.S., McInnes K.J., Wilding L.P., Hallmark C.T.: Effects of soil morphology on hydraulic
421 properties: II. Hydraulic pedotransfer functions. Soil Sci. Soc. Am. J., 63, 955–961, 1999.

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

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

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

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

430   Mirus, B.B.: Evaluating the importance of characterizing soil structure and horizons in parameterizing
431   a hydrologic process model. Hydrological Processes, 29(21), 4611-4623, 2015.

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

435   Nemes, A., Rawls, W.J., Pachepsky, Y.A., van Genuchten, M.T.: Sensitivity analysis of the
436   nonparametric nearest neighbor technique to estimate soil water retention. Vadose Zone J. 5 (4),
437   1222–1235, 2006b.

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

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

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

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

446   Pachepsky, Y.A., Rawls, W.J., Timlin, D.J.: The current status of pedotransfer functions: Their
447   accuracy, reliability, and utility in field and regional-scale modeling. In Assessment of Non-point
448   Source Pollution in the Vadose Zone, Geophys. Monogr, Ser., vol. 108, edited by D. L. Corwin, K.
449   Loague, and T. R. Ellsworth, 223-234, AGU, Washington, D. C, 1999.

450   Pachepsky. Y.A., Rawls, W.J.: Soil structure and pedotransfer function. Eur,J,Soil Sci, (54), 443-452,
451   2003.

452   Rawls, W., Pachepsky, Y., Ritchie, J.: Effect of soil organic carbon on soil water retention. Geoderma,
453   116, 61–76, 2003.

454   Rawls, W.J., Brakensiek, D.L.: Prediction of soil water properties for hydrologic modeling. p. 293–299.
455   In E.B. Jones and T.J.Ward (ed.) Proc. Symp.Water shed Management in the Eighties, Denver, CO.
456   30 Apr.–1 May 1985, Am. Soc. Civil Eng., New York, 1985.

457   Rawls, W.J., Pachepsky Y.A., Shen, M.H.: Testing soil water retention estimation with the MUUF
458   pedotransfer model using data from the southern United States. Journal of Hydrology, 251, 177-185,
459   2001.

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

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

465 Richards, L.A., Fireman, M.: Pressure-plate apparatus for measuring moisture sorption and
466 transmission by soils. Soil Sci. 56: 395–404, 1943.

467 Robinson, G.W.: A new method for the mechanical analysis of soils and other dispersions. J. Agric.
468 Sci., 12, 1922.

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

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

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

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

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

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

481 Sobol, I.M.: On sensitivity estimation for nonlinear mathematical models. Matematicheskoe
482 Modelirovanie (In Russian). Translated in: Mathematical Modeling & Computational Experiment, 2(1),
483 112-118, 1990.

484 Stumpp, C., Engelhardt, S., Hofmann, M., Huwe, B.: Evaluation of Pedotransfer Functions for
485 Estimating Soil Hydraulic Properties of Prevalent Soils in a Catchment of the Bavarian Alps. European
486 Journal of Forest Research, 128(6), 609-620, 2009.

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

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

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

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

495 Van Genuchten, M.Th., Leij, F.J., and Yates, S.R..: The RETC code for quantifying the hydraulic
496 functions of unsaturated soils. Report No. EPA/600/2-91/065. R. S. Kerr Environmental Research
497 Laboratory, U. S. Environmental Protection Agency, Ada, OK, 85, 1991.
498 Van Genuchten, M.Th., Leij, F.J., Lund, L.J. (ed.).: Indirect methods for estimating the hydraulic
499 proprieties of unsaturated soils. U.S. Salinity Lab., Riverside, CA, 1992.
500 Van Genuchten, M.Th.: A closed-form equation for predicting the hydraulic conductivity of unsaturated
501 soils. Soil Sci. Soc. Am. J., 44, 892-898, 1980.

502 Vereecken, H., Feyen, J., Maes, J., Darius, P.: Estimating the soil moisture retention characteristic
503 from texture, bulk density, and carbon content. Soil Sci, 148,389-403, 1989.
504 Vereecken, H., Diels, J., Vanorshoven, J., Feyen, J., Bouma, J.: Functional evaluation of pedotransfer
505 functions for the estimation on of soil hydraulic properties. Soil Sci. Soc. Am. J, 56, 1371–1378, 1992.

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

509 Walkley, A., Black, I.A.: An examination of the Degtjareff method for determining organic carbon in
510 soils: Effect of variations in digestion conditions and of inorganic soil constituent. Soil Sci, 63, 251-263,
511 1934.
512 Willmott, C.J.: On the validation of models. Physical Geography, 2, 184–194, 1981.
513 Willmott, C.J, Wicks, D.E.: An empirical method for the spatial interpolation of monthly precipitation
514 within California. Physical Geography,1, 59–73, 1980.
515 Winfield, K.A., Nimmo, J.R., Izbicki, J.A., MartinResolving, P.M.: Structural Influences on Water-
516 Retention Properties of Alluvial Deposits. Vadose Zone Journal, (5), 706-719, 2006.
517 Wosten, J.H.M., Lilly, A., Nemes, A., Le Bas, C.: Development and use of a database of hydraulic
518 properties of European soils. Geoderma, 90, 169–185, 1999.

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

521 Wösten, J.H.M., Y.A. Pachepsky, W.J. Rawls.: Pedotransfer functions: Bridging the gap between
522 available basic soil data and missing soil hydraulic characteristics. J. Hydrol, 251, 123–150, 2001.
523 Xu Yang and Xueyi You: Estimating Parameters of Van Genuchten Model for Soil Water Retention
524 Curve by Intelligent Algorithms. Appl. Math. Inf. Sci, 7 (5), 1977-1983, 2013.
525
526
527
528
529
530
531

532 **Tables:**

533
534
535
536
537 **Table 1**. Soil characteristics of the developed and validated datasets.
538

	PSD					VWC (cm^3 cm^{-3})	
	S (%)	Si (%)	C (%)	BD (g/cm^3)	OM (%)	- 33 kPa	-1500 kPa
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 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

539 *(*) S: sand, C: clay, Si: silt, BD: bulk density, OM: organic matter, PSD: particle size distribution, VWC: volumetric*
540 *water content*
541
542 **Table 2**. Multiple regression coefficient R^2 and regression coefficients of models developed.

543
544

		Point PTFs		Parametric PTFs			
		-33 kPa	-1500 kPa	θ**s**(cm^3 cm^3)	θ**r**(cm^3 cm^3)	α	n
	Regression technique	MLR		MLR	MNLR		
	Inputs (*)	S%, C%, BD, OM	S%, C%, BD,	S%, C%, BD, OM	C%,S%	Si%, S%	C%, Si%
	Multiple R^2	0.74	0.66	0.62	0.67	0.60	0.66
	a_0	0.0246	-0.0627	0.4136	9.00×10^{-02}	3.00×10^{-03}	2.90
	b_1	-0.0040	-0.0029	-0.0013	7.78×10^{-04}	-1.00×10^{-04}	-2.77×10^{-03}
	b_2	0.0012	0.00165	0.0002	3.20×10^{-04}	8.90×10^{-05}	-9.48×10^{-02}
Regression coefficients	b_3	0.2554	0.1837	0.0177	-6.36×10^{-05}	5.40×10^{-06}	-3.66×10^{-04}
	b_4	0.0067		- 0.0018	1.20×10^{-05}	-4.50×10^{-06}	2.03×10^{-03}
	b_5	-	-	-	9.30×10^{-07}	-7.30×10^{-08}	2.49×10^{-06}
	b_6	-	-	-	-1.00×10^{-07}	4.50×10^{-08}	-1.50×10^{-05}
	b_7	-	-	-	9.00×10^{-02}	7.70×10^{-06}	2.84×10^{-04}
	b_8	-	-	-	7.78×10^{-04}	-3.10×10^{-08}	4.91×10^{-06}
	b_9	-	--	-	3.20×10^{-04}	-3.10×10^{-08}	-5.32×10^{-06}

545 *(*) S: sand, C: clay, Si: silt, BD: bulk density, OM: organic matter, MLR: Multiple Linear Regression, MNLR:*
546 *Multiple Non-linear Regression.*
547
548
549
550
551
552
553
554
555
556
557
558

559 **Table 3.** Evaluation criteria of water retention pedotransfer functions (PTFs) at -33 kPa and -1500 kPa.

560

			-33 kPa	*-1500 kPa*
ME (cm^3 cm^{-3})	*Point PTF*	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})	*Point PTF*	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})	*Point PTF*	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

561

562

563 **Table 4.** Variation of first order sensitivity index (S_i) in the different 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	

564 Abs: absent in the model, V $_{Si}$: variation first sensitivity index;   A.E.: improving estimation.

565

566 **Table 5.** Pearson correlation matrix between basic soil characteristics in the validation dataset of 53
567 soil samples.

Variables	S$_i$%	S %	C (%)	BD (g/cm^3)	OM (%)
Si%	**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 in bold differ from 0 to a level of significance α = 0.05

579 *Si: silt, S: sand, C: clay, BD: bulk density, OM: organic matter*
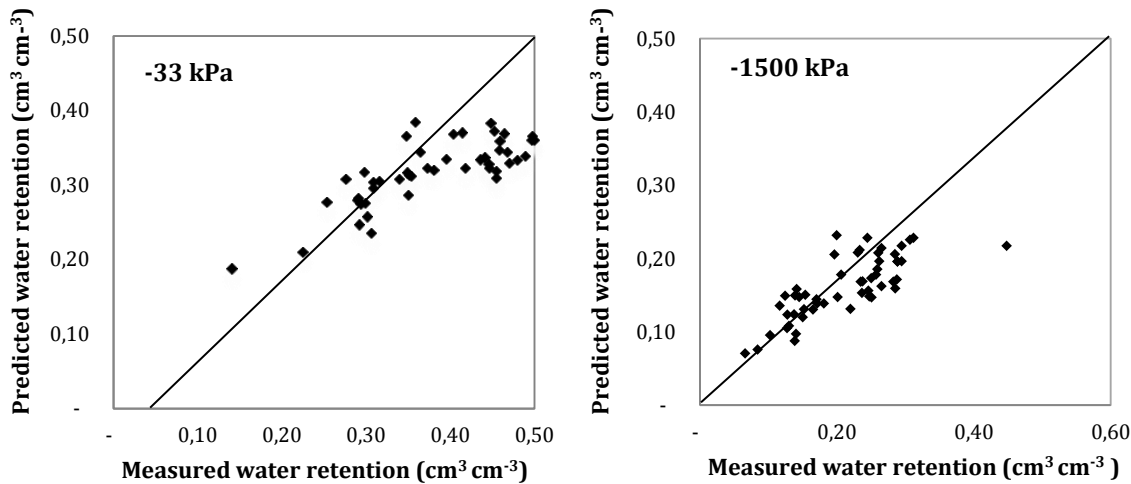
Figures:

589
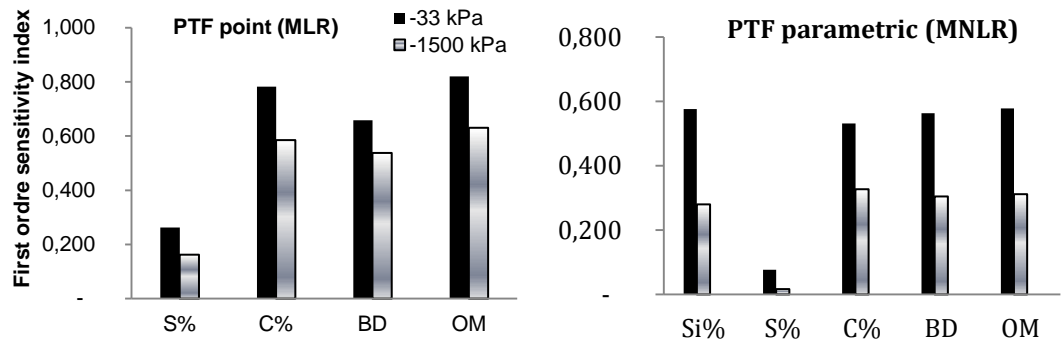590 **Figure 1**. Scatter plots of measured versus predicted soil water retention by Rosetta H2.

591
592 **Figure 2.** First order sensitivity index
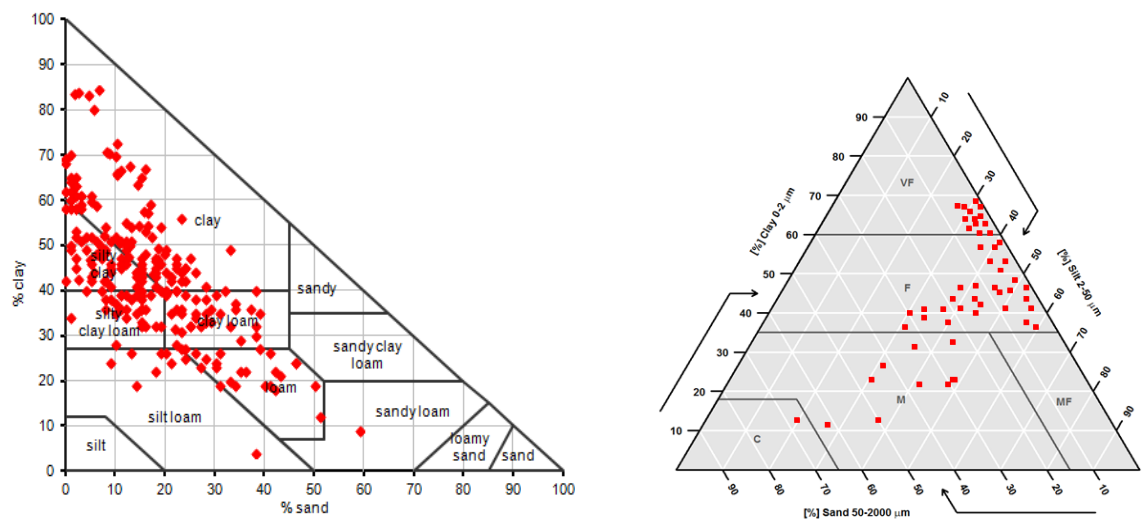

593
594
595 **Figure 3**. (a): Texture fractions of dataset (242 samples) based on USDA system. (b): Particle size
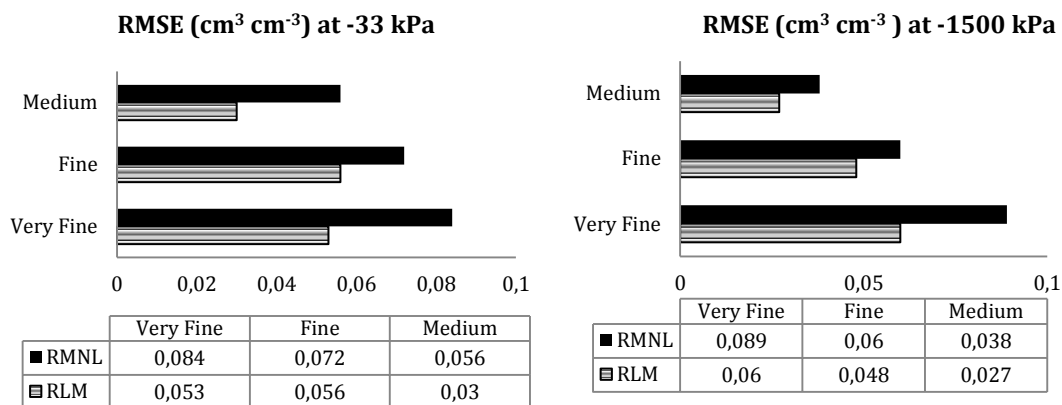596 distribution of 53 soil samples from Algeria according to FAO textural triangle.

RMSE (cm^3 cm^{-3}) at -33 kPa

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

RMSE (cm^3 cm^{-3}) at -1500 kPa

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

Figure 4. Root mean square error (RMSE) values calculated for the different textural classes.
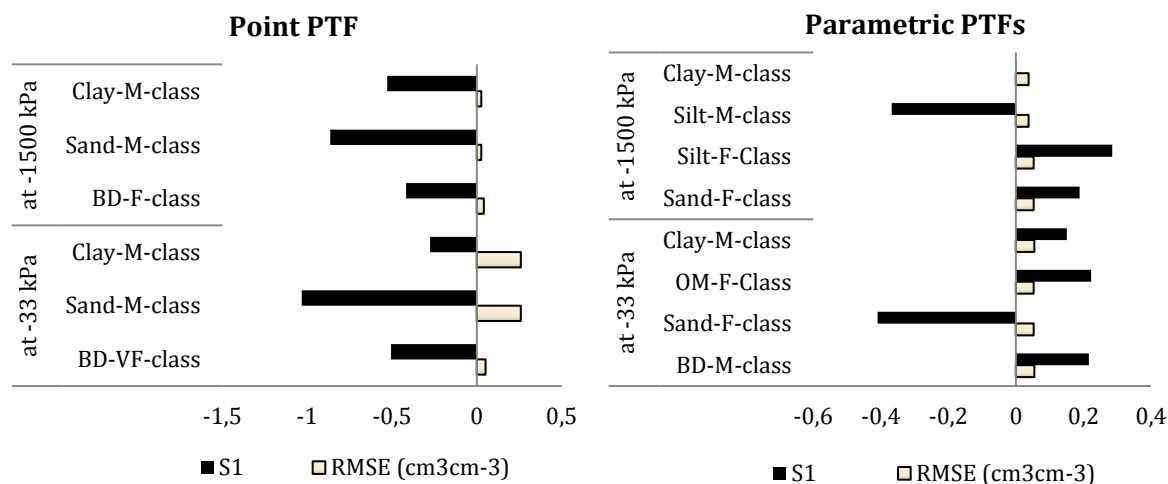
Point PTF

Parametric PTFs

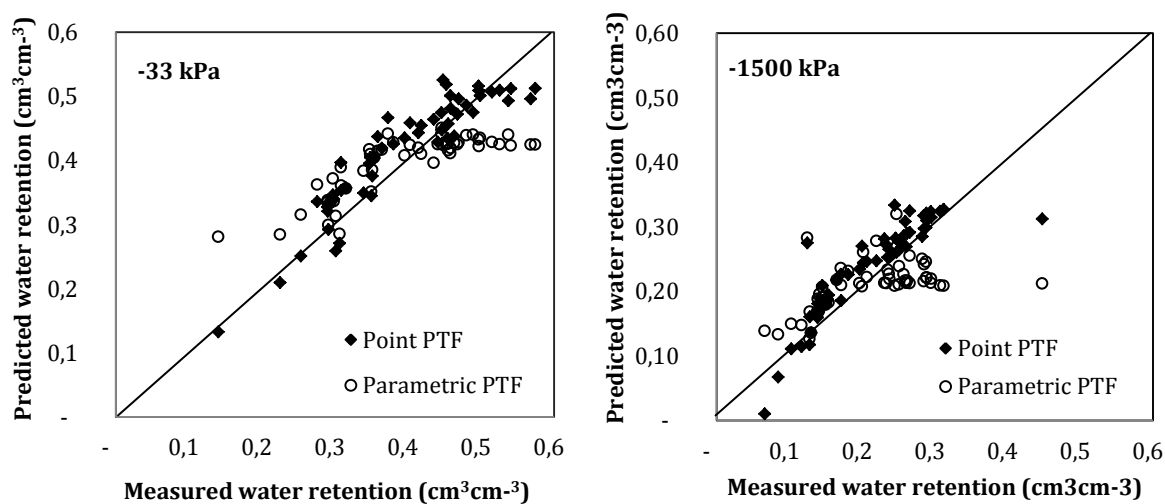**Figure 5.** Variation in first sensitivity index with RMSE after textural grouping.

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