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1 **Transferability of continuous- and class-pedotransfer functions to predict water**
2 **retention properties of semiarid Syrian soils**

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15

16 **Running title:** Water retention properties of semiarid Syrian soil

17

18 **Abstract**

19 Hydraulic properties of soils, particularly water retention, are key for appropriate management
20 of semiarid soils. Very few pedotransfer functions (PTFs) have been developed to predict
21 these properties for soils of Mediterranean regions, where data are particularly scarce. We
22 investigated the transferability of PTFs to semiarid soils. The quality of the prediction was
23 compared to that for soils originating from temperate regions for which most PTFs were
24 developed. We used two soil datasets, one from the Paris basin (French dataset, $n = 30$), and a
25 Syrian dataset ($n = 30$). Soil samples were collected in winter when the water content was
26 near field capacity. Composition and water content of the samples were determined at seven
27 water potentials. Continuous- and class-PTFs developed using different predictors were tested
28 using the two datasets and their performance compared to those developed using artificial
29 neural networks (ANN). The best performance and transferability of the PTFs for both
30 datasets used soil water content at field capacity as predictor after stratification by texture.
31 The quality of prediction was similar to that for ANN-PTFs. Continuous- and class-PTFs may
32 be transferable to other countries with performances that vary according to their ability to
33 account for variation in soil composition and structure. Taking into account predictors of
34 composition (particle size distribution, texture, organic carbon content) and structure (bulk
35 density, porosity, field capacity) did not lead to a better performance and best transferability
36 potential.

37 **Keywords:** Pedotransfer functions, Soil water retention, Syrian soils, Field capacity, Texture,
38 Bulk density.

39

40 **Introduction**

41 The hydraulic properties of soils, particularly soil water retention properties, are key data for
42 the appropriate management of soils. These properties, which are generally unavailable and

43 expensive to measure, can be predicted from other more easily measured properties using
44 prediction tools called “pedotransfer functions (PTFs)” (Bouma, 1989). PTFs have been
45 applied in a large number of studies in recent decades (e.g. Cornelis *et al.*, 2001; Wösten *et*
46 *al.*, 2001; Al Majou *et al.*, 2007; Nasta *et al.*, 2009; Haghverdi *et al.*, 2015; Nemes, 2015;
47 Khlosi *et al.*, 2016; Nguyen *et al.*, 2017).

48 PTFs can be grouped into two categories, continuous-PTFs and class-PTFs (Wösten *et al.*,
49 1999). Continuous-PTFs enable the continuous prediction of the water retention curve (WRC)
50 over the whole soil water content range, i.e. from water saturation to residual water content
51 (e.g. Vereecken *et al.*, 1989; Wösten *et al.*, 1999; Hodnett & Tomasella, 2002; Al Majou *et*
52 *al.*, 2008a; Ghorbani *et al.*, 2010; Haghverdi *et al.*, 2012; Medrado & Lima, 2014) (Table 1).
53 The class-PTFs predict the water retention curve discontinuously by grouping the data
54 according to the functional behaviour of different horizons but may also be grouped according
55 to some other criteria, such as texture or bulk density (Wösten *et al.*, 1990; Baker, 2008).
56 Thus, a single mean value or several mean values of the hydraulic properties are selected to
57 represent each class (Wösten *et al.*, 1999; Schaap *et al.*, 2001; Hodnett & Tomasella, 2002;
58 Nemes, 2002; Bruand *et al.*, 2003; Pachepsky *et al.*, 2006; Al Majou *et al.*, 2007). Class-PTFs
59 are often easy to use because they usually require little information about the soil compared
60 with most continuous-PTFs that are more demanding of soil characteristics (Lilly *et al.*, 1999;
61 Nemes *et al.*, 2003). However, they are often regarded as leading to poorer quality predictions
62 than continuous-PTFs (Wösten *et al.*, 1995). The issue of whether WRC prediction is best
63 carried out with continuous-PTFs or with class-PTFs is still debated (Wösten *et al.*, 1999;
64 Medeiros *et al.*, 2014) as is the issue of their transferability to other regions than those from
65 which the soils originated to establish the PTFs considered (Cresswell *et al.*, 2006; Touil *et*
66 *al.*, 2016). Few studies relate to the prediction of the WRC of soils in the Mediterranean basin
67 (Dridi & Dilmi, 2011; Mohawesh, 2013; Wösten *et al.*, 2013). Thus, in Syria and in other

68 countries of the Mediterranean basin, there is still little information available on hydraulic
69 properties of soils and establishment of national soil databases is only just beginning
70 (Sommer *et al.*, 2012; Khlosi *et al.*, 2013).

71 Other approaches, such as artificial neural networks (ANN) (Haykin, 1994; Schaap *et al.*,
72 2001), support vector machines (SVM) (Twarakavi *et al.*, 2009) or the k-nearest neighbor
73 technique (k-NN) (Nemes *et al.*, 2006a) have also been developed in recent decades to predict
74 the water retention properties of soils. The approach using artificial neural networks (ANN)
75 use one or more hidden layers or hidden units and are based on a self-learning process by
76 using a set of soils for which the water retention properties and the basic properties are known
77 (Table 1). Artificial neural network-based PTFs were introduced by Pachepsky *et al.* (1996)
78 and Schaap and Bouten (1996). Unlike continuous- and class-PTFs, they do not require an a
79 priori model (e.g. linear or exponential functions) (Nemes *et al.*, 2002). During the last two
80 decades, ANNs have been used extensively to predict soil water retention and their
81 performance has been compared with PTFs based on other approaches (Minasny *et al.*, 2004;
82 Twarakavi *et al.*, 2009; Nguyen *et al.*, 2017).

83 The objective of the present study was to select continuous- and class-PTFs from the literature
84 and to analyze the quality of prediction when used for a set of French soils and a set of Syrian
85 soils originating from temperate and Mediterranean regions, respectively. Prediction
86 performance results for the selected continuous- and class-PTFs were also compared with
87 those for ANN-PTFs. Additionally, their transferability to soil in France and Syria were
88 assessed, given that the compared PTFs were established with soil samples from different
89 origins.

90

91 **Materials and methods**

92 *Soil data sets*

93 A first set of soil samples was collected in France. Thus, 30 horizons (12 horizons A or Ap
94 and 18 horizons E, B or C) originating from soils developed on sedimentary rocks in the Paris
95 basin were sampled in winter. The climate of the Paris basin is temperate and influenced by
96 the Atlantic Ocean, according to the distance from the coast. The soils were Cambisols,
97 Luvisols and Fluvisols (ISSS Working Group R.B., 1998) (Bruand & Tessier, 2000).

98 Another set of soil samples was collected in Syria. The soil samples were also collected in
99 winter between latitudes 32 and 37° N and longitudes 35 to 42° E, an area with a
100 Mediterranean or degraded Mediterranean climate (Rigot, 2006). Along the coast, the climate
101 is Mediterranean but continental influences and aridity contribute to a rapid degradation of the
102 Mediterranean climate as the distance from the coast increases. A set of 30 horizons (16
103 horizons A or Ap and 14 horizons E, B or C) resulting from four sites were chosen as being
104 representative of the main soil types. They were developed on calcareous and volcano-
105 sedimentary (basaltic) parent materials and collected in Aridisols, Inceptisols and Vertisols
106 (Ilaiwi, 1980; Yuksel, 1982; Land Classification and Soil Survey of the Syrian Arab Republic,
107 1982) or Calcisols, Gypsisols, Inceptisols and Vertisols (van Liere, 1995).

108 For each horizon, the particle size distribution without decarbonation (Robert & Tessier,
109 1974), the bulk density of clods and horizons (Bruand & Tessier, 2000), the organic carbon
110 content by oxidation using an excess amount of potassium dichromate in a sulphuric acid
111 controlled at 135°C (Baize, 2000), the CaCO₃ content (Dupuis, 1969) and cation exchange
112 capacity (CEC) (Ciesielski & Sterckeman, 1997) were determined. The volumetric water
113 content was determined for the 60 soil samples from the two datasets at the water potential
114 values -10 hPa ($\theta_{1,0}$), -33 hPa ($\theta_{1,5}$), -100 hPa ($\theta_{2,0}$), -330 hPa ($\theta_{2,5}$), -1000 hPa ($\theta_{3,0}$), -3300
115 hPa ($\theta_{3,5}$), -15000 hPa ($\theta_{4,2}$) using the pressure plate extractor method (Bruand & Tessier,
116 2000).

117 ***The continuous- and class-PTFs selected***

118 Among continuous-PTFs, some enable the direct prediction of the parameters of a WRC
119 model (Table 1). In most studies, these continuous-PTFs are multiple linear regressions or
120 non linear regressions providing the parameters of the van Genuchten model (1980) as output
121 variables by using the particle size distribution, the organic carbon content and the bulk
122 density as input soil properties (e.g. Tomasella *et al.*, 2003; Schaap *et al.*, 2001) (Fig. 1a).
123 Among this group of continuous-PTFs, those established with a large number of European
124 soils (Wösten-continuous-PTFs, see Table 5 in Wösten *et al.* 1999), with Belgian soils
125 (Vereecken-continuous-PTFs, see Table 7 in Vereecken *et al.*, 1989), and with French soils
126 (VG-continuous-PTFs, see Table 6 in Al Majou *et al.*, 2008a) were selected for this study
127 (Table 1). They all estimate the parameters of the van Genuchten model (1980).

128 Other continuous-PTFs do not directly predict the parameters of a WRC model but rather the
129 water content at several matric potentials as output variables, generally by using the particle
130 size distribution, the organic carbon content and the bulk density as input data (e.g. Pachepsky
131 & Rawls, 1999; Reichert *et al.*, 2009; Ghanbarian & Millán, 2010; Minasny & Hartemink,
132 2011) (Fig. 1b). Then, knowing the water content at different water potentials, a WRC model
133 is adjusted to the predicted water contents. Among this group of continuous-PTFs, those
134 established with Brazilian soils (Reichert-continuous-PTFs, see Table 4 in Reichert *et al.*,
135 2009), with French soils (PSD-continuous-PTFs and FC-continuous-PTFs, see Table 4 & 5 in
136 Al Majou *et al.*, 2008a), with soils originating from the USA (Ghanbarian-continuous-PTFs,
137 see Table 5 model 1 in Ghanbarian & Millán, 2010) and with soils originating from tropical
138 regions (Minasny-continuous-PTFs, see section 5.1 in Minasny & Hartemink., 2011) were
139 selected for this study (Table 1). They estimate water contents at three to seven values of
140 water potential and concern a large range of soil types.

141 On the other hand, some of the class-PTFs directly predict the parameters of a WRC model
142 after stratification according to soil characteristics such as texture, bulk density, the type of

143 horizon or type of soil, as input data (Table 1, Fig. 1c). Among this group of class-PTFs, those
144 established after stratification by texture alone, and by both the type of horizon and texture
145 with soils originating from North America (Schaap-class-PTFs, see Table 1 in Schaap *et al.*,
146 2001), Europe (Wösten-class-PTFs, see Table 4 in Wösten *et al.*, 1999) and France (T-H-VG-
147 class-PTFs, see Table 3 in Al Majou *et al.*, 2008a), respectively, were selected for this study
148 (Table 1).

149 Finally, other class-PTFs are sets of water contents at different values of water potential, these
150 water contents being related also to classes of soil characteristics such as texture, bulk density,
151 the type of horizon or type of soil, as input data (Table 1, Fig. 1d). Among this group of class-
152 PTFs, those established with French soils after stratification by either texture alone, by both
153 texture and bulk density or by all the three predictors texture, bulk density and type of horizon
154 (T-FC-class-PTFs, see Tables 5 Al Majou *et al.*, 2008a; T-class-PTFs, T-BD-class-PTFs, T-
155 BD-H-class-PTFs, see Tables 2, 4 and 5 in Al Majou *et al.*, 2008b) and providing sets of
156 water content at seven values of water potential were selected for this study.

157 ***The Artificial Neural Networks-PTFs***

158 The type of ANN selected was the one most commonly used to predict the hydraulic
159 properties of soils (Børgesen & Schaap, 2005; Fashi, 2014). It usually consists of a three-layer
160 feed forward back propagation network using, for each model, input layers (basic soil
161 properties), hidden layers, and output layers (soil hydraulic properties), (Fig. 1e). Each neuron
162 of the hidden layer calculates the sum s , of a weighted combination w_i , of its input signals x_i ,
163 and a bias term w_0 , and passes the result through the activation functions that were tangent
164 hyperbolic and linear in the hidden and output layers, respectively.

$$165 \quad s = \sum_{i=1}^n w_i x_i + w_0 \quad (1)$$

166 The Levenberg-Marquardt algorithm (Demuth & Beale, 2000) was implemented to speed up
 167 the training of the multi-layer feed-forward neural network. The number of neurons in the
 168 hidden layer has to be found through trial and error; the number tested here varied from 1 to
 169 10 neurons. The feed-forward process stops once the output is predicted. Back-propagation
 170 algorithms try to minimize the error (minimize the sum of squares of the residuals between
 171 the measured and predicted outputs) of the mathematical system represented by the neural
 172 network's weights. The error is estimated as the difference between the actual and computed
 173 outputs.

174 The French national database used by Al Majou *et al.* (2008b) to develop continuous- and
 175 class-PTFs, including those discussed in this study, and which consists of 456 samples was
 176 used to train and evaluate the predictive performance of the ANN developed (Table 2). To
 177 continue to test the ANN method, the ANN developed was then applied to the French and
 178 Syrian datasets. The ANN simulations were performed by using the neural network toolbox
 179 provided by Matlab (R2014b).

180 ***Criteria used to evaluate the performance of the continuous- and class-PTFs***

181 To assess the continuous and class-PTFs performance, we used the mean error of prediction
 182 (MEP) and the standard deviation of prediction (SDP) which provide information on the
 183 estimation bias and precision, respectively, as follows:

184
$$MEP = \frac{1}{l' \cdot l} \sum_{j=1}^{l'} \sum_{i=1}^l (\theta_{p,j,i} - \theta_{m,j,i}) \quad (2)$$

185
$$SDP = \left\{ \frac{1}{l' \cdot l} \sum_{j=1}^{l'} \sum_{i=1}^l [(\theta_{p,j,i} - \theta_{m,j,i}) - MEP]^2 \right\}^{1/2} \quad (3)$$

186

187 where $\theta_{p,j,i}$ is the predicted water content at matric potential i for the horizon j , $\theta_{m,i,j}$ is the
 188 measured water content at matric potential i for the horizon j , and l is the number of matric
 189 potentials for each horizon ($l=7$ in this study) and l' is the number of horizons studied.

190 The root mean square error (*RMSE*) which is commonly used to test PTFs (e.g. Wösten *et al.*,
 191 2001; Schaap, 2004; Lamorski *et al.*, 2008) and which varies according to both the overall
 192 prediction bias and the overall prediction precision was also computed:

193

$$194 \quad RMSE = \left\{ \frac{1}{l' \cdot l} \sum_{j=1}^{l'} \sum_{i=1}^l (\theta_{p,j,i} - \theta_{m,j,i})^2 \right\}^{1/2} \quad (4)$$

195 Beside these three statistical criteria, the coefficient of determination (R^2) was computed:

$$196 \quad R^2 = 1 - \frac{\sum_{j=1}^{l'} \sum_{i=1}^l (\theta_{p,j,i} - \theta_{m,j,i})^2}{\sum_{j=1}^{l'} \sum_{i=1}^l (\theta_{m,j,i} - \bar{\theta}_{m,i})^2} \quad (5)$$

197 where $\bar{\theta}_{m,i}$ represents the average of the measured water content at the matric potential i . The
 198 value of the coefficient of determination (R^2) measures the strength of the linear relation
 199 between the predicted and measured values.

200 **Results and discussion**

201 ***Characteristics of the studied soils***

202 The studied horizons showed Fine, Very Fine or Medium texture in the European triangle of
 203 texture (Commission of the European Communities, 1985) and no coarse elements (Table 2,
 204 Fig. 2a). Particle size distribution mean values for the datasets from France and Syria were
 205 close (Fig. 2b–c). However, the Syrian dataset showed a smaller mean OC content because of
 206 the higher temperatures, limited precipitation and tillage systems that rapidly oxidize organic
 207 matter (Mrabet, 2011). As for the smaller mean bulk density of the Syrian soils, it can be

208 attributed to a larger macroporosity in most horizons as observed in the field (data not
209 shown). The mean CaCO_3 content and CEC were greater in the Syrian dataset.

210 Results also showed a greater water content for matric potential ranging from -10 hPa ($\theta_{1.0}$) to
211 -330 hPa ($\theta_{2.5}$) for the Syrian dataset. These greater water contents are consistent with the
212 smaller mean bulk density recorded for the Syrian dataset and a greater proportion of swelling
213 clays in the Syrian dataset as indicated by the greater mean CEC (36.5 cmol_c/kg), the OC
214 content being smaller in Syrian soils and the clay content similar in the two data sets.

215 *Evaluation of the continuous- and class-PTFs developed with the French national database*

216 The performance of the continuous- and class-PTFs developed with the French national
217 database showed that the best prediction was recorded for the French dataset with the class-
218 PTFs using the water content at field capacity as predictor after stratification by texture (T-
219 FC-class-PTFs). These class-PTFs are the only ones that perform best for three statistical
220 criteria (Table 3): the root mean square error (RMSE = 0.023 cm³/cm³) was the smallest and
221 the precision (SDP = 0.023 cm³/cm³) and coefficient of determination ($R^2 = 0.81$), the greatest
222 (Table 3) (Fig. 3d). The worst prediction was recorded with the class-PTFs after successive
223 stratification by texture and bulk density (T-BD-class-PTFs) with the smallest precision (SDP
224 = 0.036 cm³/cm³) and coefficient of correlation ($R^2 = 0.52$) and the largest root mean square
225 error (RMSE = 0.036 cm³/cm³) (Table 3) (Fig. 3f). The continuous-PTFs developed for the
226 parameters of the van Genuchten model (1980) (VG-continuous-PTFs) led to similar results
227 to those obtained with the T-BD-class-PTFs, with small precision (SDP = 0.036 cm³/cm³) and
228 high root mean square error (RMSE = 0.036 cm³/cm³) (Table 3) (Fig. 3a).

229 With the Syrian dataset, the best performance was also recorded with the class-PTFs using
230 water content at field capacity as predictor after stratification by texture (T-FC-class-PTFs)
231 (Table 3). The estimation bias (MEP = -0.001 cm³/cm³) and the root mean square error

232 (RMSE = 0.029 cm³/cm³) were the smallest and the precision (SDP = 0.029 cm³/cm³) the
233 greatest, the coefficient of determination ($R^2 = 0.75$) being the second largest with the T-FC-
234 class-PTFs (Table 3) (Fig. 4d). The worst prediction was recorded with the continuous-PTFs
235 developed for the parameters of the van Genuchten model (1980) (VG-continuous-PTFs) with
236 the smallest precision (SDP = 0.046 cm³/cm³), a high estimation bias (MEP = 0.022 cm³/cm³)
237 and the highest root mean square error (RMSE = 0.048 cm³/cm³) (Table 3) (Fig. 4a). The
238 class-PTFs after successive stratification by texture and bulk density (T-BD-class-PTFs) gave
239 results that had rather poor precision and root mean square error, though the estimation bias
240 was very small (MEP = 0.001 cm³/cm³) and the coefficient of determination was much
241 smaller ($R^2 = 0.51$) (Fig. 4f) than with the VG-continuous-PTFs.

242 In accordance with the results published by Cresswell *et al.* (2006), the rather good results
243 recorded with the class-PTFs that used the water content at field capacity as predictor are
244 likely related to the fact that the field capacity corresponds to a point on the water retention
245 curve corresponding to a water potential close to -100 hPa (Al Majou *et al.*, 2008a).
246 Preliminary stratification by texture increases the prediction quality (Table 3) since the shape
247 of the WRC and the relative location of the water content corresponding to field capacity on
248 that curve vary according to texture. Comparison of the performance recorded with the French
249 and Syrian datasets using the averaged criteria show that the continuous- and class-PTFs
250 perform better when used for the French dataset (Table 3) which can be considered to be
251 related to the origin of the soils used to develop the tested PTFs.

252 ***Evaluation of the selected continuous- and class-PTFs from the literature and not using***
253 ***French soils exclusively***

254 Results recorded with the French dataset show that there was no PTF that performed best for
255 all four criteria (Table 4). The smallest estimation bias was recorded with the Wösten-

256 continuous-PTFs (MEP = $-0.002 \text{ cm}^3/\text{cm}^3$), the best precision with the Vereecken-
257 continuous-PTFs (SDP = $0.040 \text{ cm}^3/\text{cm}^3$), the smallest root mean square error with the
258 Ghanbarian-continuous-PTFs (RMSE = $0.046 \text{ cm}^3/\text{cm}^3$) and the greatest correlation
259 coefficient with the Wösten-class-PTFs ($R^2 = 0.83 \text{ cm}^3/\text{cm}^3$) (Fig. 5a, b, d, g). However, the
260 performance of the Ghanbarian-continuous-PTFs is among the best except for the correlation
261 coefficient ($R^2 = 0.26 \text{ cm}^3/\text{cm}^3$) (Table 4) (Fig. 5d).

262 On the other hand, results recorded with the Syrian dataset show that the Wösten-class-PTFs
263 led to the best results for precision (SDP = $0.045 \text{ cm}^3/\text{cm}^3$), the smallest root mean squared
264 error (RMSE = $0.047 \text{ cm}^3/\text{cm}^3$), the greatest correlation coefficient ($R^2 = 0.83$) but a rather
265 intermediate prediction bias (MEP = $0.019 \text{ cm}^3/\text{cm}^3$) (Table 4) (Fig. 6g).

266 Comparison of the results recorded with the French and Syrian datasets using the averaged
267 criteria show similar performances but much smaller than those recorded with the continuous-
268 and class-PTFs derived from the French national database (Tables 3 and 4).

269 *Evaluation of the performance of the Artificial Neural Networks*

270 The ANN-PTFs developed with the French national database (Fig. 7a) led to a prediction
271 quality for the French dataset used in this study (Table 5) that was close to the prediction
272 quality recorded with the best PTFs tested (T-FC-class-PTFs, Table 3) (Fig. 7c). The RMSE
273 which varies inversely with the overall prediction quality was slightly greater with the ANN
274 than the one recorded with the T-FC-class-PTFs (0.030 and $0.023 \text{ cm}^3/\text{cm}^3$, respectively)
275 (Tables 3 and 5). The correlation coefficient, which measures the strength of the linear
276 relation between the predicted and measured water content, was slightly greater with the
277 ANN-PTFs than with the T-FC-class-PTFs (0.85 and 0.81 , respectively). It should also be
278 mentioned that the prediction quality recorded with the T-FC-class-PTFs was not so far from
279 the one observed with the ANN-PTFs when applied to the test dataset (20% of the original

280 data, i.e. 91 samples belonging to the French national database) since the RMSE were 0.023
281 and $0.029 \text{ cm}^3/\text{cm}^3$, respectively, and the R^2 , 0.81 and 0.89, respectively (Tables 3 and 5).
282 On the other hand, the ANN-PTFs developed with the French national database led to a
283 smaller prediction quality for the Syrian dataset than with the T-FC-class-PTFs developed by
284 Al Majou *et al.* (2008a). The RMSE recorded with the ANN-PTFs and the T-FC-class-PTFs
285 was much greater (0.049 and $0.029 \text{ cm}^3/\text{cm}^3$, respectively) (Tables 3 and 5) and the
286 correlation coefficients recorded with the ANN-PTFs slightly greater than with the T-FC-
287 class-PTFs (0.78 and 0.75, respectively) (Fig. 7b).
288 The analysis of the results also showed that the PTFs selected in the literature and not using
289 French soils performed less well than the ANN-PTFs, as already reported in the literature
290 (Nguyen *et al.*, 2017) (Tables 4 and 5). The RMSE and R^2 were respectively greater and
291 smaller than with the ANN-PTFs, using the PTFs selected in the literature and not using
292 French soils. The Wösten-class-PTFs had however a much higher correlation coefficient (R^2
293 = 0.83 for the French and Syrian datasets) than that recorded for the other PTFs selected in the
294 literature and fairly similar to the correlation coefficient recorded with the ANN (Tables 4 and
295 5).

296

297 **Conclusion**

298 Our results show that PTFs developed for French soils are transferable to the Syrian soils
299 selected for this study of semiarid Mediterranean soils. With the class-PTFs which use the soil
300 water content at field capacity as predictor after stratification by texture, the quality of
301 prediction is similar to that recorded with ANNs which are nowadays recognized as leading to
302 a quality of prediction better or similar to those recorded with the PTFs published in the
303 literature. The performance of these PTFs can be explained by the fact that a point on the
304 water retention curve is actually used as a predictor even if the attribution of an accurate water

305 potential value to the field capacity state is not possible. Stratification by texture prior to the
306 development of these PTFs then increases their ability to predict the water retention properties
307 properly, as the shape of the water retention curve is closely related to the soil texture. In
308 other words, the performance of the class-PTFs which use the field water content as predictor
309 after stratification by texture is likely related to using information about both the elementary
310 particle size distribution (texture) and their assemblage (structure and related porosity) which
311 are known to be major basic soil properties responsible for variability in water retention
312 properties. When the soil water content at field capacity is not available, the best performance
313 recorded remains less clear. If the coefficient of determination recorded with continuous-PTFs
314 is large when using texture information as predictor, the bias is large when applied to Syrian
315 soils. With a lower coefficient of determination but the other statistical criteria close to those
316 recorded when using water content at field capacity as predictor, our results show that worthy
317 results in terms of transferability potential were recorded with class-PTFs using bulk density
318 as predictor after stratification by texture.

319 Analysis of the performance recorded with the continuous- and class-PTFs selected in the
320 literature shows a poorer quality of prediction than PTFs developed with French soils. This
321 probably has nothing to do with the origin of the soils but with a more appropriate
322 consideration of soil characteristics related to soil composition and structure. The high
323 correlation coefficients recorded with the class-PTFs developed by Wösten *et al.* (1999) and
324 Shaap *et al.* (2001) are therefore likely related to their use of stratification by texture, thus
325 leading to a high consistency of the water content variation according to water potential even
326 if the prediction bias and prediction accuracy are high and low, as shown by the MEP and
327 SDP, respectively.

328 Finally, our results show that continuous- or class-PTFs could be considered as transferable
329 with satisfactory performance to other countries where database of hydraulic soil properties

330 are not available to establish their own PTFs. The expected prediction quality of the PTFs
331 transferred appeared to be mainly related to their ability to take into account predictors related
332 to the characteristics of the elementary particles and their assemblage, since the best results
333 were recorded with PTFs which combine predictors related to both soil composition and
334 structure. Our results also showed that taking into account several predictors related to soil
335 composition together (particle size distribution, texture, organic carbon content) and soil
336 structure together (bulk density, porosity, field capacity) does not lead to a better performance
337 and subsequently to the best transferability potential. It is noteworthy that the best
338 performance were recorded by the class-PTFs that use texture as stratification criteria and
339 then the water content at field capacity as structure information.

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345

346 **References**

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537 Table 1
 538 List of continuous- and class-PTFs according to the output variables and relationship between input and output variables.

Output variables	Relationship between input and output variables (continuous-PTFs) and stratification type (class-PTFs)	Input variables	Geographical domain or country	Reference	
Continuous-PTF					
Parameters of a water retention curve model	MLR	PSD, BD, OC	Belgium	Vereecken <i>et al.</i> (1989)	
		PSD, BD, OM	Europe	Wösten <i>et al.</i> (1999)	
		PSD, BD, OC, pH, CEC	Tropics	Hodnett & Tomasella (2002)	
		PSD, BD, Me	Brazil	Tomasella <i>et al.</i> (2003)	
		PSD	India	Adhikary <i>et al.</i> (2008)	
		PSD, BD, OC	France	Al Majou <i>et al.</i> (2008a)	
		PSD, OC, pH	India	Santra & Das (2008)	
		PSD, BD, d_g , σ_g	Iran	Ghorbani <i>et al.</i> (2010)	
		PSD, BD, OC	India	Patil <i>et al.</i> (2012)	
		PSD, BD, OM	Brazil	Medrado & Lima, (2014)	
		ANN	PSD, BD, θ_{33} , θ_{1500}	North America, Europe	Schaap <i>et al.</i> (2001)
			PSD, BD, OM, θ_1 , θ_{10} , θ_{100} , θ_{1500}	Denmark	Børgesen & Schaap (2005)
			PSD, BD, OC, $\log(h)$	Iran, Australia	Haghverdi <i>et al.</i> (2012)
	SVM	PSD, BD, $\log(h)$	USA	Twarakavi <i>et al.</i> (2009)	
Set of θ at different water potentials	MLR and LR	PSD, BD, Me	Brazil	Tomasella <i>et al.</i> (2003)	
		θ_{FC}	France	Al Majou <i>et al.</i> (2008a)	
		PSD, BD, OM	Brazil	Reichert <i>et al.</i> (2009)	
		PSD, BD, d_g , σ_g , $\theta(h)$	USA, France	Ghanbarian & Millán (2010)	
		PSD, BD, d_g , σ_g	Iran	Ghorbani <i>et al.</i> (2010)	
		PSD, BD, OC	Tropics, USA	Minasny & Hartemink (2011)	
		PSD, BD, OM, PL	Syria	Khlosi <i>et al.</i> (2016)	
		PSD, BD, OC, $\log(h)$	Vietnam	Nguyen <i>et al.</i> (2017)	
		ANN	PSD, BD, OM, θ_1 , θ_{10} , θ_{100} , θ_{1500}	Denmark	Børgesen & Schaap (2005)
			PSD, BD	Poland	Lamorski <i>et al.</i> (2008)
			PSD, BD, OC, $\log(h)$	Iran, Australia	Haghverdi <i>et al.</i> (2012)
			PSD, BD, OC	India	Patil <i>et al.</i> (2012)
			PSD, BD, OM, PL	Syria	Khlosi <i>et al.</i> (2016)
	PSD, BD, OC, $\log(h)$	Vietnamese	Nguyen <i>et al.</i> (2017)		
	SVM	PSD, BD	Poland	Lamorski <i>et al.</i> (2008)	

k-NN	PSD, BD, OC	Vietnam	Nguyen <i>et al.</i> (2015)
	PSD, BD, OM, PL	Syria	Khlosi <i>et al.</i> (2016)
	PSD, BD, OC, $\log(h)$	Vietnam	Nguyen <i>et al.</i> (2017)
	PSD, BD, OM	USA	Nemes <i>et al.</i> (2006a)
	PSD, BD, OC	India	Patil <i>et al.</i> (2012)
	PSD, BD	USA, Belgium	Haghverdi <i>et al.</i> (2015)
	PSD, BD, OC	Vietnam	Nguyen <i>et al.</i> (2015)
PSD, BD, OC, $\log(h)$	Vietnam	Nguyen <i>et al.</i> (2017)	

Class-PTF

Parameters of a water retention curve model	Multiple parameters class distribution	T, Hor.	Europe	Wösten <i>et al.</i> (1999)
		T, Hor.	Tropics	Hodnett & Tomasella (2002)
		T, Hor.	France	Al Majou <i>et al.</i> (2007)
		T, Hor.	France	Al Majou <i>et al.</i> (2008a)
	Mono parameter class distribution	T	North America, Europe	Schaap <i>et al.</i> (2001)
Set of θ at different water potentials	Multiple parameter class distribution	T, BD	France	Bruand <i>et al.</i> (2003)
		T, BD, Hor.	France	Al Majou <i>et al.</i> (2008b)
		Statistical distribution of dataset (texture, horizon)	Europe	Baker (2008)
	Mono parameter class distribution	T, BD, Hor.	Portugal	Ramos <i>et al.</i> (2013)
		T, FC	France	Al Majou <i>et al.</i> (2008a)
		T	France	Al Majou <i>et al.</i> (2008b)

539 MLR : multiple linear regression, LR: linear regression, ANN: artificial neural networks, SVM: support vector machine, k-NN: k nearest neighbor technique, PSD: particle size distribution, BD:
540 bulk density, OC: organic carbon, OM: organic matter, CEC: cation exchange capacity, Me: moisture equivalent, d_g : geometric mean particle size diameter, σ_g : geometric standard deviation, PL:
541 plastic limit, θ_{FC} : volumetric water content at field capacity, $\theta_{(1, 10, 33, 100, 1500)}$ volumetric water content at matric potential (kPa), $\log(h)$: logarithm of the absolute value of matric head in cm water, T:
542 texture class, Hor: type of horizon (topsoil or subsoil).
543

544 Table 2

545 Descriptive statistics of main characteristics of the soil dataset used in this study.

	Coarse elements	Particle size distribution			OC	CaCO ₃	CEC	D _b	Volumetric water content (cm ³ /cm ³) at matric potential h (θ_h) in						
	(%)	(%)							g/kg	g/kg	Cmol _c /kg	g/cm ³	hPa		
	>2000	<2	2-50	50-2000					θ_{10}	θ_{33}	θ_{100}	θ_{330}	θ_{1000}	θ_{3300}	θ_{15000}
	μm	μm	μm	μm											
French National database used to train and test the PTFs (n = 456)															
mean	<1	29.3	43.8	26.9	6.0	54.2	14.8	1.52	0.354	0.335	0.315	0.289	0.259	0.221	0.187
s.d.	–	15.4	21.8	25.6	5.1	171.3	9.0	0.15	0.068	0.070	0.075	0.076	0.079	0.076	0.073
min.	–	1.9	1.6	0.1	0.0	0.0	0.6	0.95	0.134	0.100	0.080	0.056	0.045	0.033	0.013
max.	–	92.9	82.1	95.4	28.8	982	52.8	1.98	0.605	0.596	0.586	0.557	0.510	0.462	0.370
French soil samples used to test the PTFs (n = 30)															
mean	<1	42.1	32.0	25.9	8.58	34.30	22.03	1.45	0.387	0.365	0.347	0.326	0.307	0.274	0.244
s.d.	–	14.4	13.7	15.1	6.8	98.5	10.1	0.16	0.049	0.050	0.051	0.054	0.055	0.050	0.058
min.	–	20.1	10.5	3.1	0.0	0.0	5.30	1.10	0.310	0.295	0.275	0.242	0.203	0.167	0.142
max.	–	68.9	53.5	59.8	28.8	424	45.90	1.77	0.496	0.489	0.469	0.446	0.415	0.366	0.363
Syrian soil samples used to test the PTFs (n = 30)															
mean	<1	41.4	32.8	27.8	1.18	63.7	36.5	1.22	0.436	0.417	0.388	0.344	0.307	0.277	0.239
s.d.	–	16.0	9.8	11.7	0.96	77.9	7.3	0.10	0.061	0.058	0.055	0.050	0.051	0.062	0.067
min.	–	12.2	11.6	8.0	0.36	7.2	23.7	1.04	0.352	0.341	0.324	0.285	0.242	0.198	0.149
max.	–	69.1	53.3	53.0	3.9	310	49.2	1.41	0.577	0.559	0.507	0.474	0.444	0.435	0.404

s.d., min, max are the standard deviation, minimum and maximum of soil variables.

546
547
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549
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551
552

553 Table 3
 554 Validation criteria of the continuous-PTFs and class-PTFs developed with the French national
 555 database when applied to the French and Syrian datasets.

PTFs type	Descriptive statistics of the relationship between measured and predicted water content			
	MEP (cm ³ /cm ³)	SDP (cm ³ /cm ³)	RMSE (cm ³ /cm ³)	R ²
French dataset (n=30)				
VG-continuous-PTFs	-3*10 ⁻⁴	0.036	0.036	0.77
PSD-continuous-PTFs	-0.003	0.033	0.033	0.81
FC-continuous-PTFs	-0.012	0.028	0.031	0.66
T-FC-class-PTFs	-0.001	0.023	0.023	0.81
T-class-PTFs	-0.002	0.028	0.028	0.71
T-BD-class-PTFs	0.003	0.036	0.036	0.52
T-BD-H-class-PTFs	-0.002	0.029	0.029	0.69
T-H-VG-class-PTFs	-0.003	0.030	0.030	0.68
Average	0.003*	0.030	0.031	0.71
Syrian dataset (n=30)				
VG-continuous-PTFs	0.022	0.046	0.048	0.74
PSD-continuous-PTFs	-0.021	0.033	0.035	0.85
FC-continuous-PTFs	-0.005	0.033	0.034	0.66
T-FC-class-PTFs	-0.001	0.029	0.029	0.75
T-class-PTFs	-0.025	0.039	0.047	0.36
T-BD-class-PTFs	0.001	0.041	0.041	0.51
T-BD-H-class-PTFs	0.002	0.039	0.039	0.56
T-H-VG-class-PTFs	-0.024	0.037	0.044	0.43
Average	0.013*	0.037	0.040	0.61

556 *: Computed using the absolute value of every MEP. VG-continuous-PTFs are the continuous pedotransfer functions developed for the
 557 parameters of the van Genuchten model using multiple regression equations, PSD-continuous-PTFs are the continuous pedotransfer
 558 functions developed by multiple regression equations using particle-size distribution (PSD), organic carbon and bulk density, FC-continuous-
 559 PTFs are the continuous pedotransfer functions developed by using the water content at field capacity, T-FC-class-PTFs are the class
 560 pedotransfer functions developed by using the water content at field capacity as predictor after stratification by texture., T-class-PTFs are the
 561 pedotransfer functions developed after stratification by texture, T-BD-class-PTFs are the pedotransfer functions developed after stratification
 562 by texture and bulk density, T-BD-H-class-PTFs are the pedotransfer functions developed for texture and bulk density classes according to
 563 the type of horizon, T-H-VG-class-PTFs are the pedotransfer functions developed after stratification by texture and type of horizon (topsoil
 564 and subsoil) for the parameters of the van Genuchten model (1980).

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575 Table 4
 576 Criteria enabling assessment of the prediction quality for the continuous- and class-PTFs
 577 selected in the literature and not using the French national database.

PTFs type	Descriptive statistics of the relationship between measured and predicted water content			
	MEP (cm ³ /cm ³)	SDP (cm ³ /cm ³)	RMSE (cm ³ /cm ³)	R ²
		French dataset (n=30)		
Wösten-continuous-PTFs	-0.002	0.051	0.051	0.30
Vereecken-continuous-PTFs	0.038	0.040	0.055	0.21
Reichert-continuous-PTFs	0.031	0.042	0.052	0.12
Ghanbarian-continuous-PTFs	0.005	0.045	0.046	0.26
Minasny-continuous-PTFs	0.016	0.051	0.054	0.20
Schaap-class-PTFs	-0.019	0.072	0.075	0.60
Wösten-class-PTFs	0.040	0.050	0.064	0.83
Average	0.022*	0.050	0.057	0.36
		Syrian dataset (n=30)		
Wösten-continuous-PTFs	0.005	0.059	0.059	0.43
Vereecken-continuous-PTFs	0.022	0.052	0.052	0.20
Reichert-continuous-PTFs	-0.020	0.044	0.048	0.42
Ghanbarian-continuous-PTFs	-0.006	0.051	0.051	0.21
Minasny-continuous-PTFs	0.003	0.050	0.050	0.30
Schaap-class-PTFs	-0.048	0.056	0.074	0.76
Wösten-class-PTFs	0.019	0.043	0.047	0.83
Average	0.018*	0.051	0.054	0.45

578 *: Computed using the absolute value of every MEP

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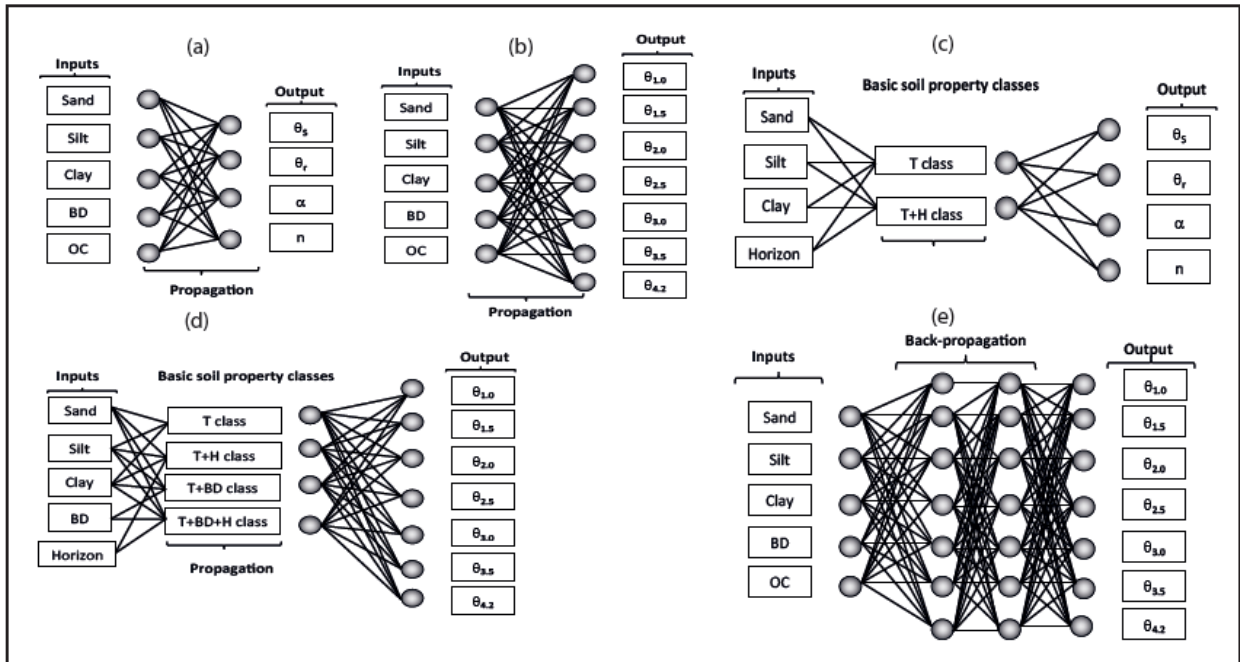
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591 Table 5
 592 Descriptive statistics of the relationship between measured and predicted water content
 593 developed by artificial neural networks (ANN).

	Training data		Test data	
	RMSE (cm ³ /cm ³)	<i>R</i> ²	RMSE (cm ³ /cm ³)	<i>R</i> ²
French National database	0.030	0.90	0.029	0.89
Syrian dataset	-	-	0.049	0.78
French dataset	-	-	0.030	0.85

594 Soil properties used in predictive procedures are the sand, silt, clay and organic carbon contents, and the bulk density.
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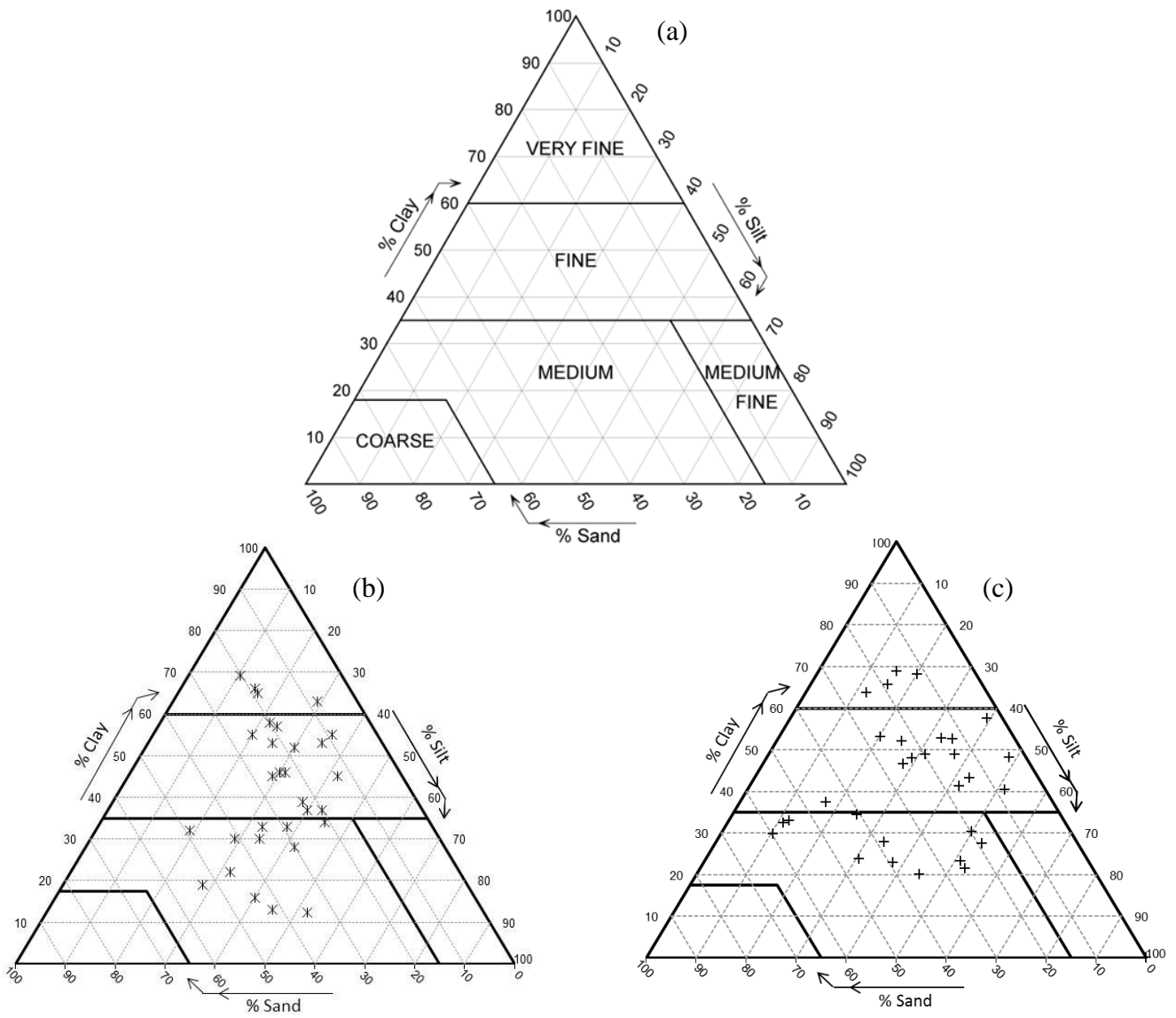


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Figure 1: The typical topologies of the continuous and class-PTFs used in this study. (a): continuous-PTFs providing the parameters of the van Genuchten model (1980), (b): continuous-PTFs providing the water content at several matric potentials, (c): class-PTFs providing the parameters of the van Genuchten model (1980), (d): class-PTFs providing the water content at several matric potentials, and (e): artificial neural networks (ANN)-PTFs. $\theta_1, \theta_{1.5}, \dots, \theta_{4.2}$: volumetric water content in $\text{cm}^3 \text{cm}^{-3}$ at seven different matric potentials, $\theta_r, \theta_s, \alpha$ and n are the parameters of the van Genuchten equation, T: texture, BD: bulk density, OC: organic carbon, H: type of horizon (topsoil or subsoil).

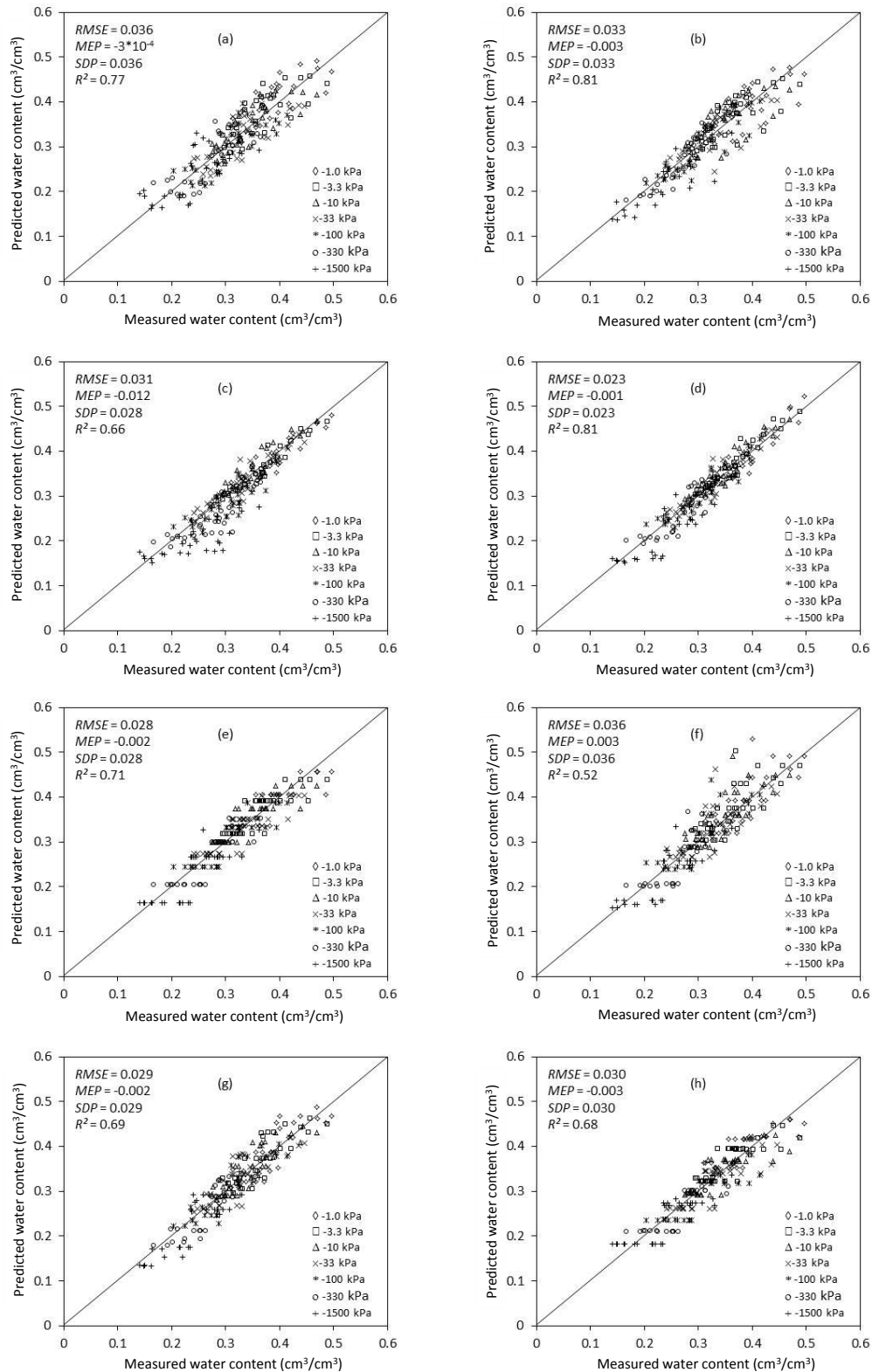
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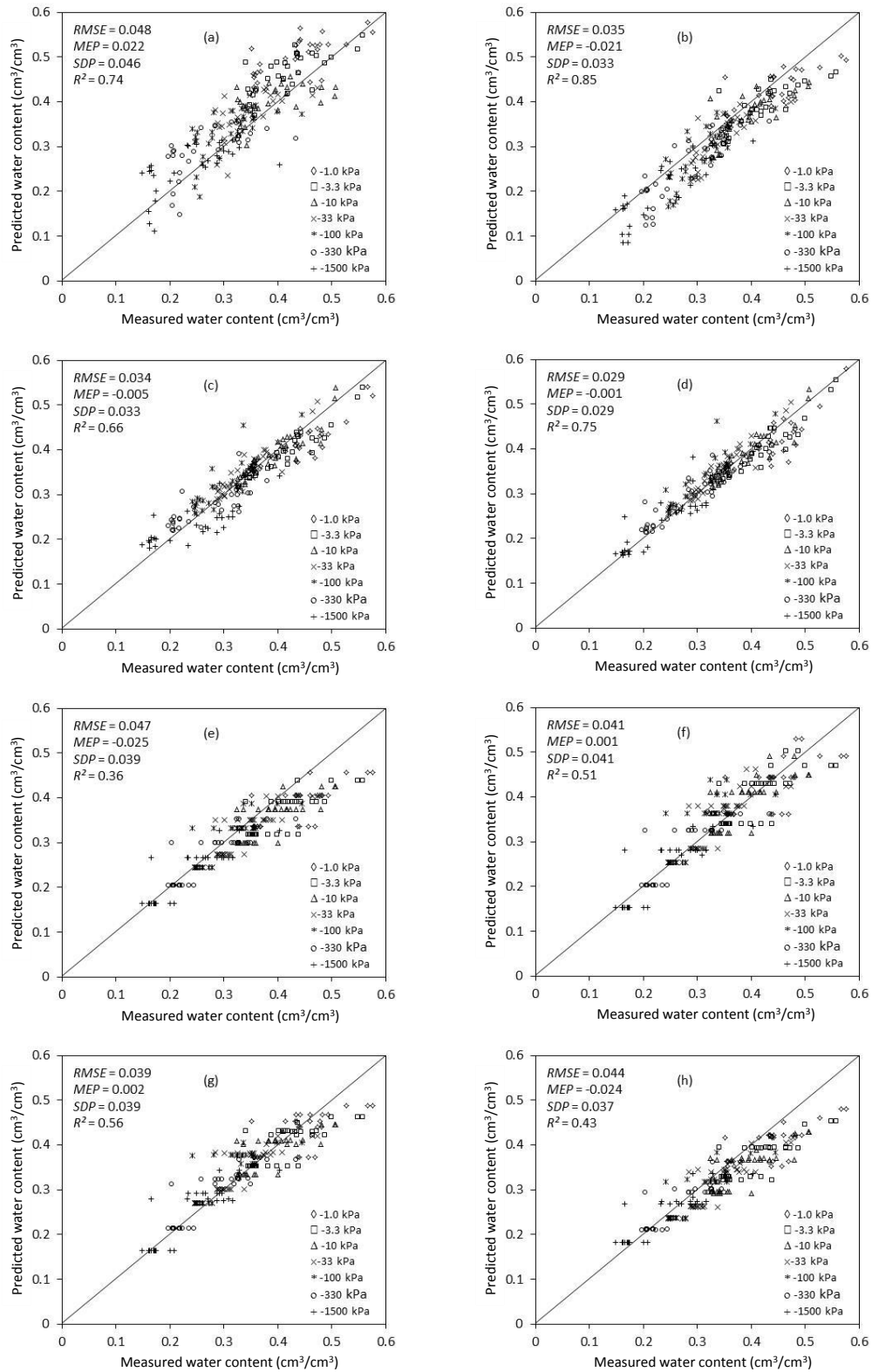
625 **Figure 2:** FAO triangle (FAO, 1990) of texture used (a), distribution of soil texture from samples used in this
626 study to test the validity of the continuous- and class-PTFs selected, Syrian soil samples (b) and French soil
627 samples (c).
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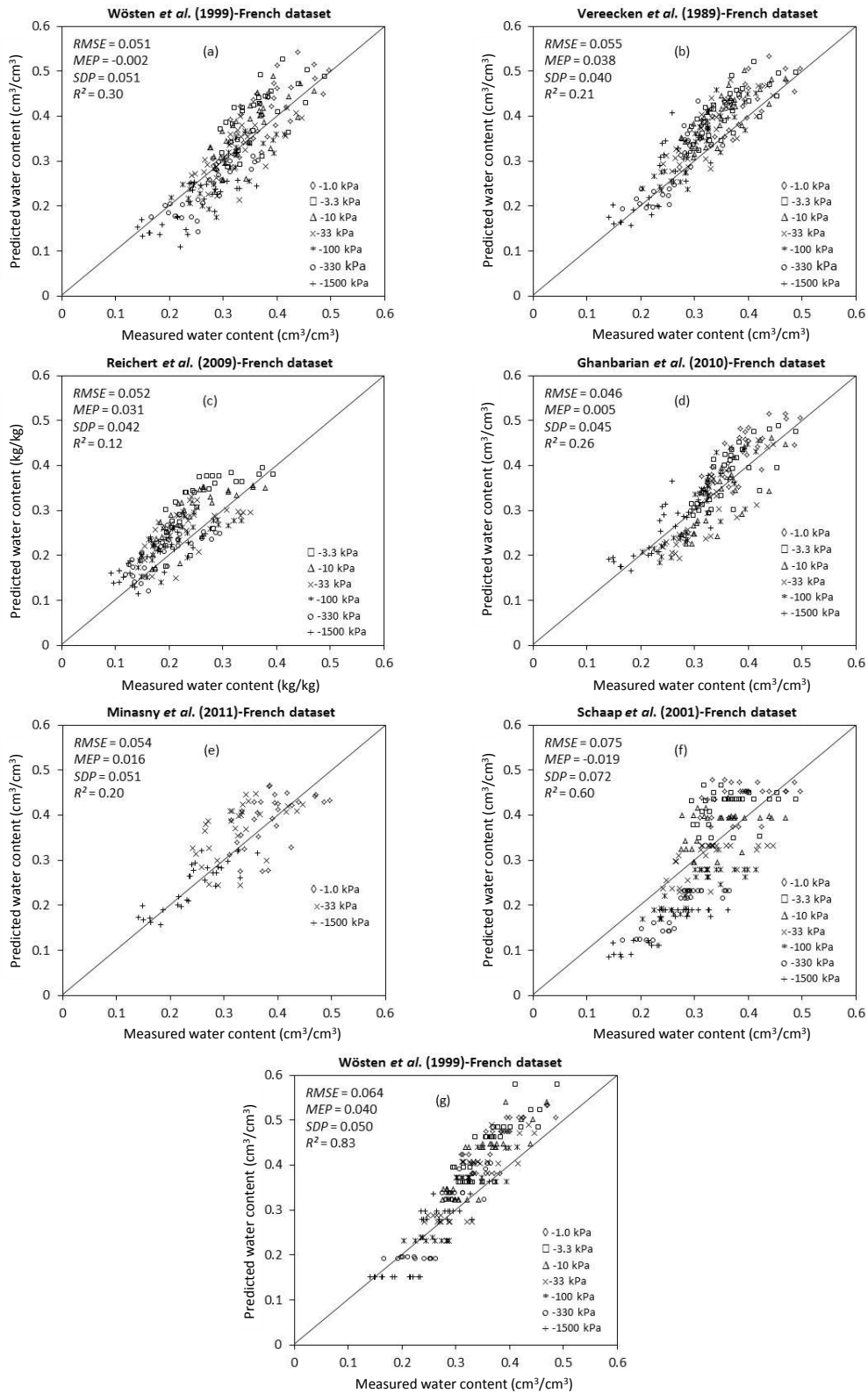
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Figure 3: Evaluation of the continuous-PTFs (a, b, c, d) and class-PTFs (e, f, g, h) developed with the French national database and applied to the French dataset. Continuous-PTFs developed for the parameters of the van Genuchten model (1980) (a), continuous-PTFs developed by multiple regression equations (b), continuous-PTFs with the volumetric water content at field capacity (c), class-PTFs with the volumetric water content at field capacity after stratification by class of texture (d), class-PFTs by class of texture (e), by class of texture and bulk density (f), by class of texture and bulk density after grouping according to the type of horizon (g) and finally by class of texture for the parameters of the van Genuchten model (1980) (h).



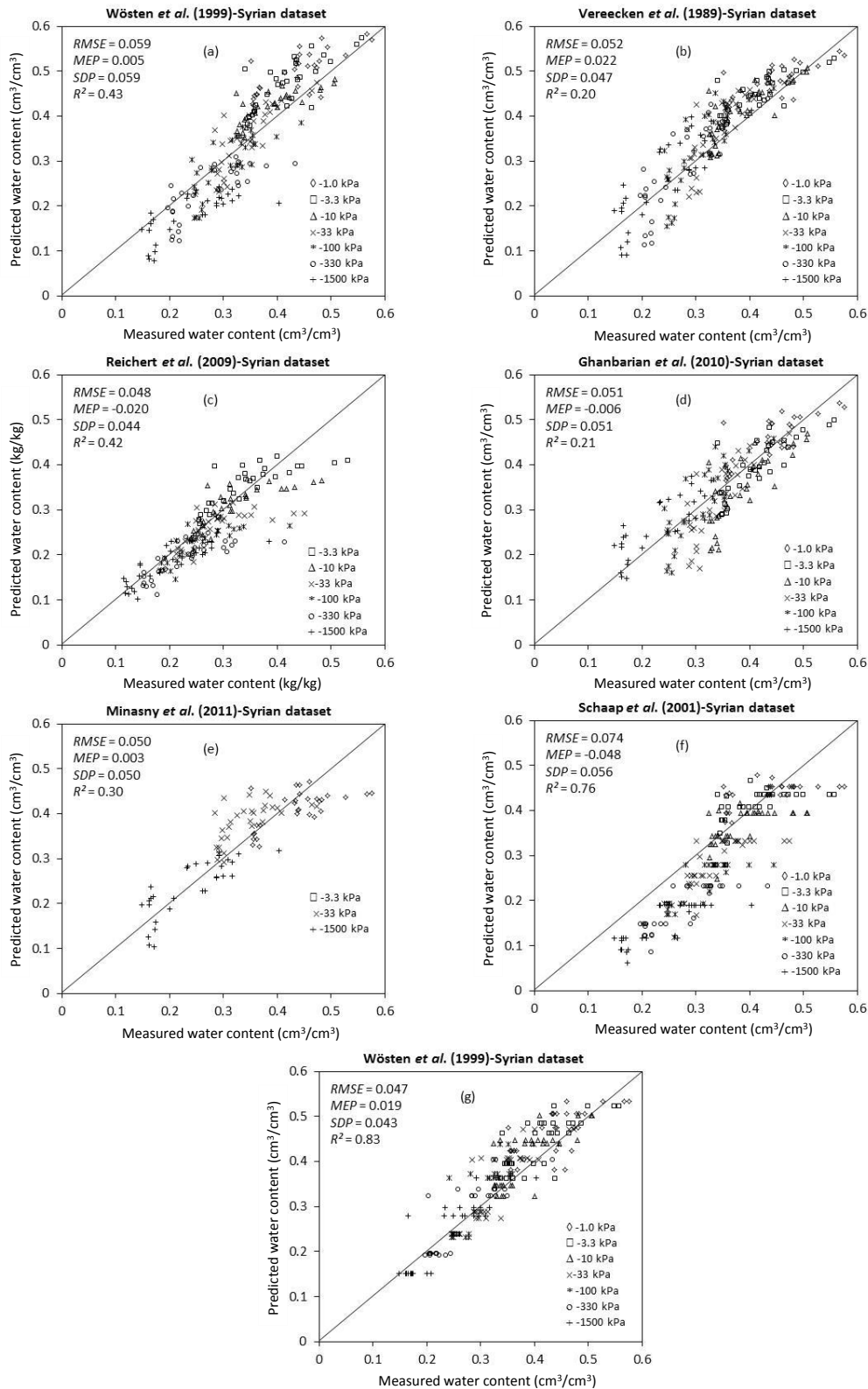
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Figure 4: Evaluation of the continuous-PTFs (a, b, c, d) and class-PTFs (e, f, g, h) developed with the French national database and applied to the Syrian dataset. Continuous-PTFs developed for the parameters of the van Genuchten model (1980) (a), continuous-PTFs developed by multiple regression equations (b), continuous-PTFs with the volumetric water content at field capacity (c), class-PTFs with the volumetric water content at field capacity after stratification by class of texture (d), class-PFTs by class of texture (e), by class of texture and bulk density (f), by class of texture and bulk density after grouping according to the type of horizon (g) and finally by class of texture for the parameters of the van Genuchten model (1980) (h).



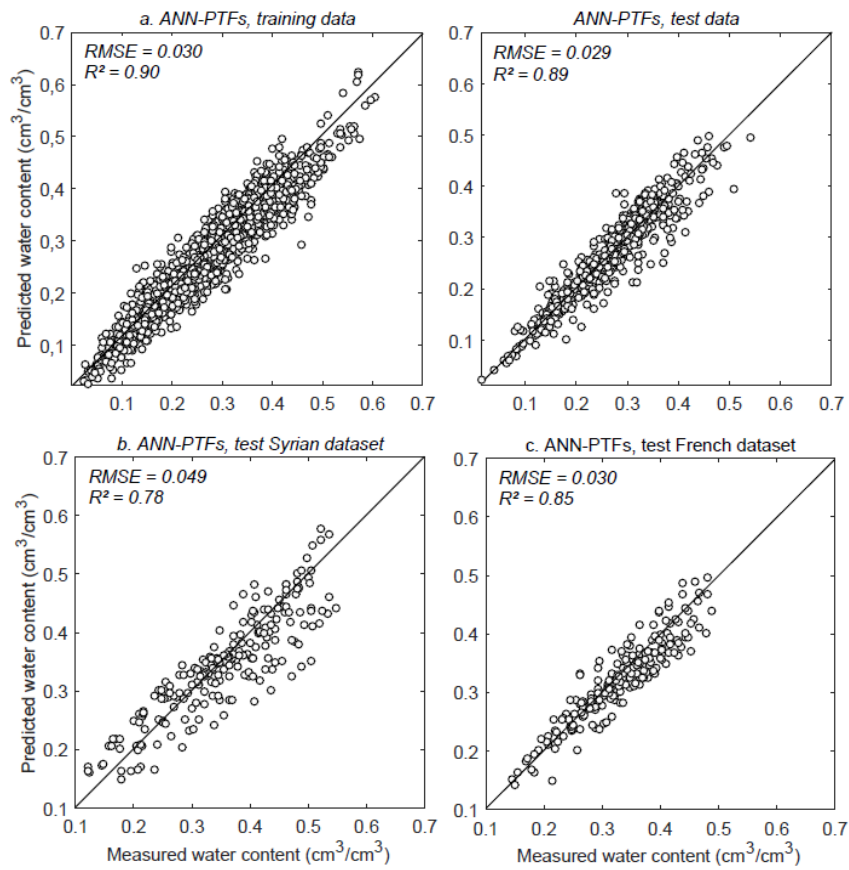
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Figure 5: Evaluation of the continuous-PTFs (a, b, c, d, e), and class-PTFs (f, g) selected in the literature when applied to the French dataset. R² were computed for all matric potential values together.



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Figure 6: Evaluation of the continuous-PTFs (a, b, c, d, e), and class-PTFs (f, g) selected in the literature when applied to the Syrian dataset. R² were computed for all matric potential values together.



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Figure 7: Measured and predicted water content (cm^3/cm^3) recorded with the artificial neural networks using soil properties (clay, silt, sand, organic carbon and bulk density) for the French national database (Al Majou *et al.*, 2008b) (a), Syrian dataset (b) and the French dataset (c).