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

Hassan Al Majou, B Hassani, Ary Bruand

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H. Al Majou[a b*], B. Hassani[c], A. Bruand[a]

[a]*Institut des Sciences de la Terre d'Orléans (ISTO), Université d'Orléans, CNRS/INSU, BRGM, 1A Rue de la Férollerie, 45071 Orléans Cedex 2, France.*

[b]*Department of Soil Science, Faculty of Agronomy, University of Damascus, PO Box 30621, Damascus, Syria.*

[c]*Department of Soil & Land Reclamation, Faculty of Agriculture, Aleppo University, Aleppo, Syria.*

***Corresponding author:** email Hassan.Almajou@univ-orleans.fr

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Abstract

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

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

Introduction

The hydraulic properties of soils, particularly soil water retention properties, are key data for the appropriate management of soils. These properties, which are generally unavailable and expensive to measure, can be predicted from other more easily measured properties using prediction tools called "pedotransfer functions (PTFs)" (Bouma, 1989). PTFs have been applied in a large number of studies in recent decades (e.g. Cornelis *et al*., 2001; Wösten *et al*., 2001; Al Majou *et al*., 2007; Nasta *et al.*, 2009; Haghverdi *et al*., 2015; Nemes, 2015; Khlosi *et al*., 2016; Nguyen *et al*., 2017).

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

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

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

Materials and methods

Soil data sets

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

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

For each horizon, the particle size distribution without decarbonation (Robert & Tessier, 1974), the bulk density of clods and horizons (Bruand & Tessier, 2000), the organic carbon content by oxidation using an excess amount of potassium dichromate in a sulphuric acid controlled at 135°C (Baize, 2000), the $CaCO_3$ content (Dupuis, 1969) and cation exchange capacity (CEC) (Ciesielski & Sterckeman, 1997) were determined. The volumetric water content was determined for the 60 soil samples from the two datasets at the water potential 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 hPa ($\theta_{3.5}$), –15000 hPa ($\theta_{4.2}$) using the pressure plate extractor method (Bruand & Tessier, 2000).

The continuous- and class-PTFs selected

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

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

On the other hand, some of the class-PTFs directly predict the parameters of a WRC model after stratification according to soil characteristics such as texture, bulk density, the type of horizon or type of soil, as input data (Table 1, Fig. 1c). Among this group of class-PTFs, those established after stratification by texture alone, and by both the type of horizon and texture with soils originating from North America (Schaap-class-PTFs, see Table 1 in Schaap *et al*., 2001), Europe (Wösten-class-PTFs, see Table 4 in Wösten *et al*., 1999) and France (T-H-VG-class-PTFs, see Table 3 in Al Majou *et al*., 2008a), respectively, were selected for this study (Table 1).

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

The Artificial Neural Networks-PTFs

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Results and discussion

Characteristics of the studied soils

The studied horizons showed Fine, Very Fine or Medium texture in the European triangle of texture (Commission of the European Communities, 1985) and no coarse elements (Table 2, Fig. 2a). Particle size distribution mean values for the datasets from France and Syria were close (Fig. 2b−c). However, the Syrian dataset showed a smaller mean OC content because of the higher temperatures, limited precipitation and tillage systems that rapidly oxidize organic matter (Mrabet, 2011). As for the smaller mean bulk density of the Syrian soils, it can be attributed to a larger macroporosity in most horizons as observed in the field (data not shown). The mean $CaCO_3$ content and CEC were greater in the Syrian dataset.

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

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

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

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

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

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

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

Results recorded with the French dataset show that there was no PTF that performed best for all four criteria (Table 4). The smallest estimation bias was recorded with the Wösten-continuous-PTFs (MEP = –0.002 cm^3/cm^3), the best precision with the Vereecken-continuous-PTFs (SDP = 0.040 cm^3/cm^3), the smallest root mean square error with the Ghanbarian-continuous-PTFs (RMSE = 0.046 cm^3/cm^3) and the greatest correlation coefficient with the Wösten-class-PTFs (R^2 = 0.83 cm^3/cm^3) (Fig. 5a, b, d, g). However, the performance of the Ghanbarian-continuous-PTFs is among the best except for the correlation coefficient (R^2 = 0.26 cm^3/cm^3) (Table 4) (Fig. 5d).

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

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

Evaluation of the performance of the Artificial Neural Networks

The ANN-PTFs developed with the French national database (Fig. 7a) led to a prediction quality for the French dataset used in this study (Table 5) that was close to the prediction quality recorded with the best PTFs tested (T-FC-class-PTFs, Table 3) (Fig. 7c). The RMSE which varies inversely with the overall prediction quality was slightly greater with the ANN than the one recorded with the T-FC-class-PTFs (0.030 and 0.023 cm^3/cm^3, respectively) (Tables 3 and 5). The correlation coefficient, which measures the strength of the linear relation between the predicted and measured water content, was slightly greater with the ANN-PTFs than with the T-FC-class-PTFs (0.85 and 0.81, respectively). It should also be mentioned that the prediction quality recorded with the T-FC-class-PTFs was not so far from the one observed with the ANN-PTFs when applied to the test dataset (20% of the original data, i.e. 91 samples belonging to the French national database) since the RMSE were 0.023 and 0.029 cm^3/cm^3, respectively, and the R^2, 0.81 and 0.89, respectively (Tables 3 and 5).

On the other hand, the ANN-PTFs developed with the French national database led to a smaller prediction quality for the Syrian dataset than with the T-FC-class-PTFs developed by Al Majou *et al.* (2008a). The RMSE recorded with the ANN-PTFs and the T-FC-class-PTFs was much greater (0.049 and 0.029 cm^3/cm^3, respectively) (Tables 3 and 5) and the correlation coefficients recorded with the ANN-PTFs slightly greater than with the T-FC-class-PTFs (0.78 and 0.75, respectively) (Fig. 7b).

The analysis of the results also showed that the PTFs selected in the literature and not using French soils performed less well than the ANN-PTFs, as already reported in the literature (Nguyen *et al*., 2017) (Tables 4 and 5). The RMSE and R^2 were respectively greater and smaller than with the ANN-PTFs, using the PTFs selected in the literature and not using French soils. The Wösten-class-PTFs had however a much higher correlation coefficient (R^2 = 0.83 for the French and Syrian datasets) than that recorded for the other PTFs selected in the literature and fairly similar to the correlation coefficient recorded with the ANN (Tables 4 and 5).

Conclusion

Our results show that PTFs developed for French soils are transferable to the Syrian soils selected for this study of semiarid Mediterranean soils. With the class-PTFs which use the soil water content at field capacity as predictor after stratification by texture, the quality of prediction is similar to that recorded with ANNs which are nowadays recognized as leading to a quality of prediction better or similar to those recorded with the PTFs published in the literature. The performance of these PTFs can be explained by the fact that a point on the water retention curve is actually used as a predictor even if the attribution of an accurate water potential value to the field capacity state is not possible. Stratification by texture prior to the development of these PTFs then increases their ability to predict the water retention properties properly, as the shape of the water retention curve is closely related to the soil texture. In other words, the performance of the class-PTFs which use the field water content as predictor after stratification by texture is likely related to using information about both the elementary particle size distribution (texture) and their assemblage (structure and related porosity) which are known to be major basic soil properties responsible for variability in water retention properties. When the soil water content at field capacity is not available, the best performance recorded remains less clear. If the coefficient of determination recorded with continuous-PTFs is large when using texture information as predictor, the bias is large when applied to Syrian soils. With a lower coefficient of determination but the other statistical criteria close to those recorded when using water content at field capacity as predictor, our results show that worthy results in terms of transferability potential were recorded with class-PTFs using bulk density as predictor after stratification by texture.

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

Finally, our results show that continuous- or class-PTFs could be considered as transferable with satisfactory performance to other countries where database of hydraulic soil properties are not available to establish their own PTFs. The expected prediction quality of the PTFs transferred appeared to be mainly related to their ability to take into account predictors related to the characteristics of the elementary particles and their assemblage, since the best results were recorded with PTFs which combine predictors related to both soil composition and structure. Our results also showed that taking into account several predictors related to soil composition together (particle size distribution, texture, organic carbon content) and soil structure together (bulk density, porosity, field capacity) does not lead to a better performance and subsequently to the best transferability potential. It is noteworthy that the best performance were recorded by the class-PTFs that use texture as stratification criteria and then the water content at field capacity as structure information.

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Table 1
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 *et al.* (1989)
		PSD, BD, OM	Europe	Wösten *et al.* (1999)
		PSD, BD, OC, pH, CEC	Tropics	Hodnett & Tomasella (2002)
		PSD, BD, Me	Brazil	Tomasella *et al.* (2003)
		PSD	India	Adhikary *et al.* (2008)
		PSD, BD, OC	France	Al Majou *et al.* (2008a)
		PSD, OC, pH	India	Santra & Das (2008)
		PSD, BD, d_g, σ_g	Iran	Ghorbani *et al.* (2010)
		PSD, BD, OC	India	Patil *et al.* (2012)
		PSD, BD, OM	Brazil	Medrado & Lima, (2014)
	ANN	PSD, BD, θ_{33}, θ_{1500}	North America, Europe	Schaap *et al.* (2001)
		PSD, BD, OM, θ_{1}, θ_{10}, θ_{100}, θ_{1500}	Denmark	Børgesen & Schaap (2005)
		PSD, BD, OC, log(h)	Iran, Australia	Haghverdi *et al.* (2012)
	SVM	PSD, BD, log(h)	USA	Twarakavi *et al.* (2009)
Set of θ at different water potentials	MLR and LR	PSD, BD, Me	Brazil	Tomasella *et al.* (2003)
		θ_{FC}	France	Al Majou *et al.* (2008a)
		PSD, BD, OM	Brazil	Reichert *et al.* (2009)
		PSD, BD, d_g, σ_g, $\theta(h)$	USA, France	Ghanbarian & Millán (2010)
		PSD, BD, d_g, σ_g	Iran	Ghorbani *et al.* (2010)
		PSD, BD, OC	Tropics, USA	Minasny & Hartemink (2011)
		PSD, BD, OM, PL	Syria	Khlosi *et al.* (2016)
		PSD, BD, OC, log(h)	Vietnam	Nguyen *et al.* (2017)
	ANN	PSD, BD, OM, θ_{1}, θ_{10}, θ_{100}, θ_{1500}	Denmark	Børgesen & Schaap (2005)
		PSD, BD	Poland	Lamorski *et al.* (2008)
		PSD, BD, OC, log(h)	Iran, Australia	Haghverdi *et al.* (2012)
		PSD, BD, OC	India	Patil *et al.* (2012)
		PSD, BD, OM, PL	Syria	Khlosi *et al.* (2016)
		PSD, BD, OC, log(h)	Vietnamese	Nguyen *et al.* (2017)
	SVM	PSD, BD	Poland	Lamorski *et al.* (2008)

		PSD, BD, OC	Vietnam	Nguyen *et al.* (2015)
		PSD, BD, OM, PL	Syria	Khlosi *et al.* (2016)
		PSD, BD, OC, log(h)	Vietnam	Nguyen *et al.* (2017)
	k-NN	PSD, BD, OM	USA	Nemes *et al.* (2006a)
		PSD, BD, OC	India	Patil *et al.* (2012)
		PSD, BD	USA, Belgium	Haghverdi *et al.* (2015)
		PSD, BD, OC	Vietnam	Nguyen *et al.* (2015)
		PSD, BD, OC, log(h)	Vietnam	Nguyen *et al.* (2017)
		Class-PTF		
Parameters of a water retention curve model	Multiple parameters class distribution	T, Hor.	Europe	Wösten *et al.* (1999)
		T, Hor.	Tropics	Hodnett & Tomasella (2002)
		T, Hor.	France	Al Majou *et al.* (2007)
		T, Hor.	France	Al Majou *et al.* (2008a)
	Mono parameter class distribution	T	North America, Europe	Schaap *et al.* (2001)
Set of θ at different water potentials	Multiple parameter class distribution	T, BD	France	Bruand *et al.* (2003)
		T, BD, Hor.	France	Al Majou *et al.* (2008b)
		Statistical distribution of dataset (texture, horizon)	Europe	Baker (2008)
		T, BD, Hor.	Portugal	Ramos *et al.* (2013)
	Mono parameter class distribution	T, FC	France	Al Majou *et al.* (2008a)
		T	France	Al Majou *et al.* (2008b)

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: 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: 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: texture class, Hor: type of horizon (topsoil or subsoil).

Table 2

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

	Coarse elements (%)	Particle size distribution (%)			OC g/kg	$CaCO_3$ g/kg	CEC $Cmol_c$/kg	D_b g/cm^3	Volumetric water content (cm^3/cm^3) at matric potential h (θ_h) in hPa						
	>2000 µm	<2 µm	2-50 µm	50-2000 µm					θ_{10}	θ_{33}	θ_{100}	θ_{330}	θ_{1000}	θ_{3300}	θ_{15000}
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.

Table 3

Validation criteria of the continuous-PTFs and class-PTFs developed with the French national 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

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

Table 4

Criteria enabling assessment of the prediction quality for the continuous- and class-PTFs 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

*: Computed using the absolute value of every MEP

Table 5

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

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

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

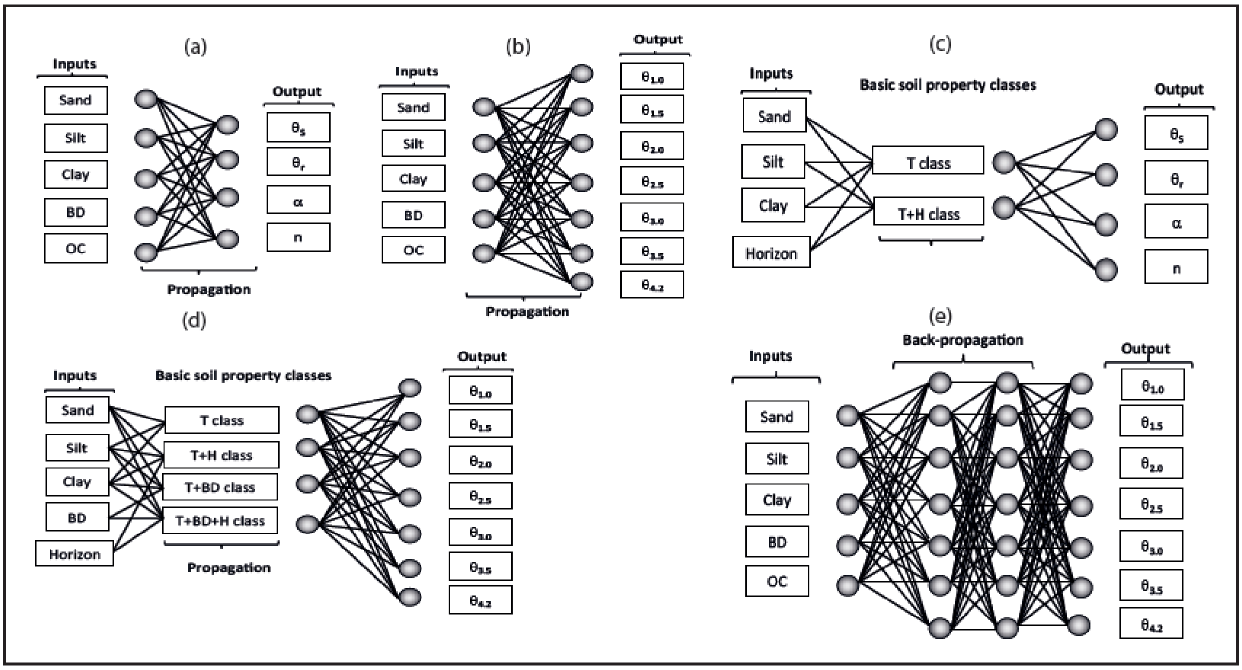

Figure 1: The typical topologies of the continuous and class-PTFs used in this study. (a): continuous-PTFs providing the parameters of the van Genuchten model (1980), (b): continuous-PTFs providing the water content at several matric potentials, (c): class-PTFs providing the parameters of the van Genuchten model (1980), (d): class-PTFs providing the water content at several matric potentials, and (e): artificial neural networks (ANN)-PTFs. θ_1, $\theta_{1.5}$..., $\theta_{4.2}$: volumetric water content in cm^3 cm^{-3} at seven different matric potentials, θ_r, θ_s, α 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).

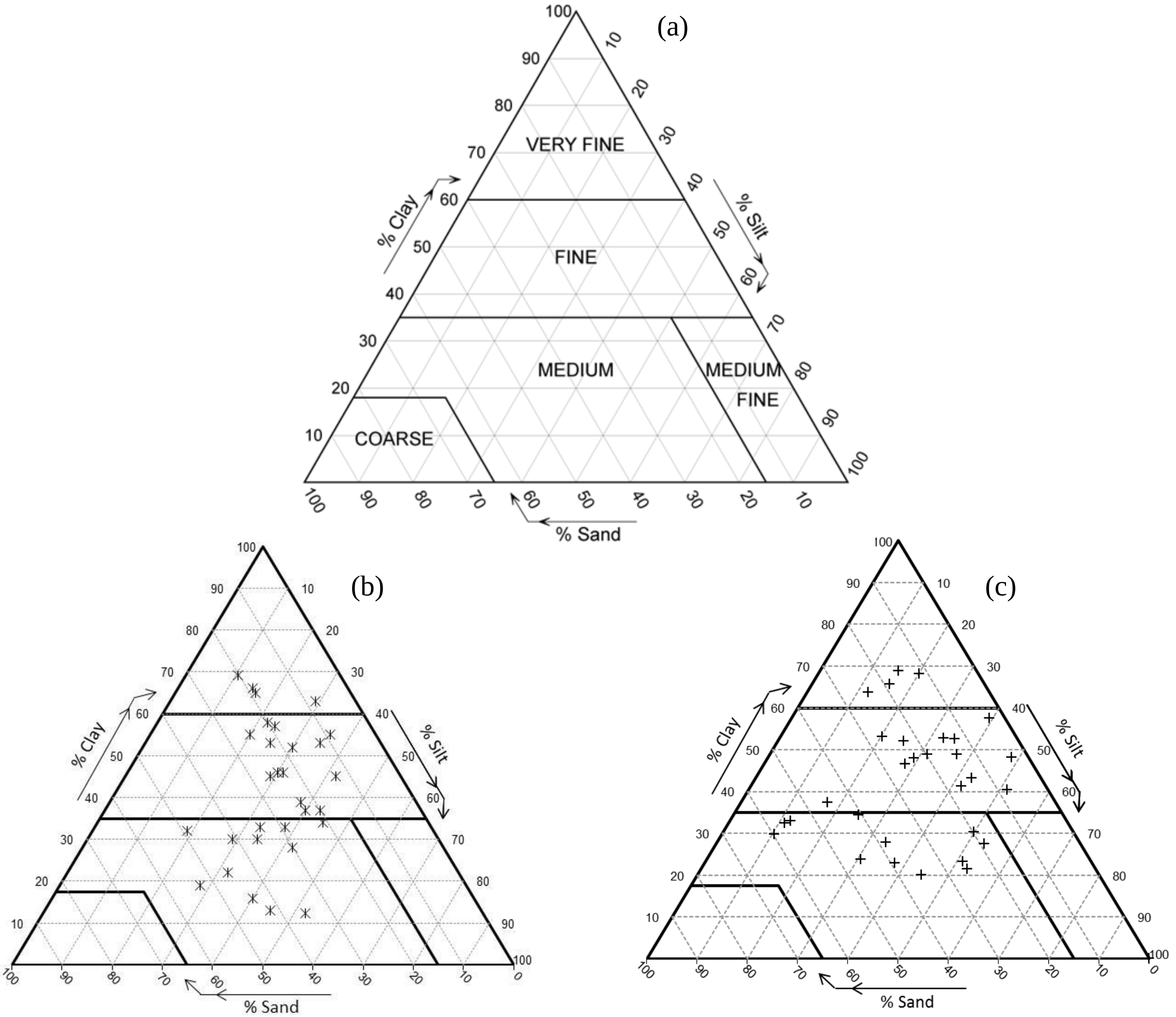

Figure 2: FAO triangle (FAO, 1990) of texture used (a), distribution of soil texture from samples used in this study to test the validity of the continuous- and class-PTFs selected, Syrian soil samples (b) and French soil samples (c).

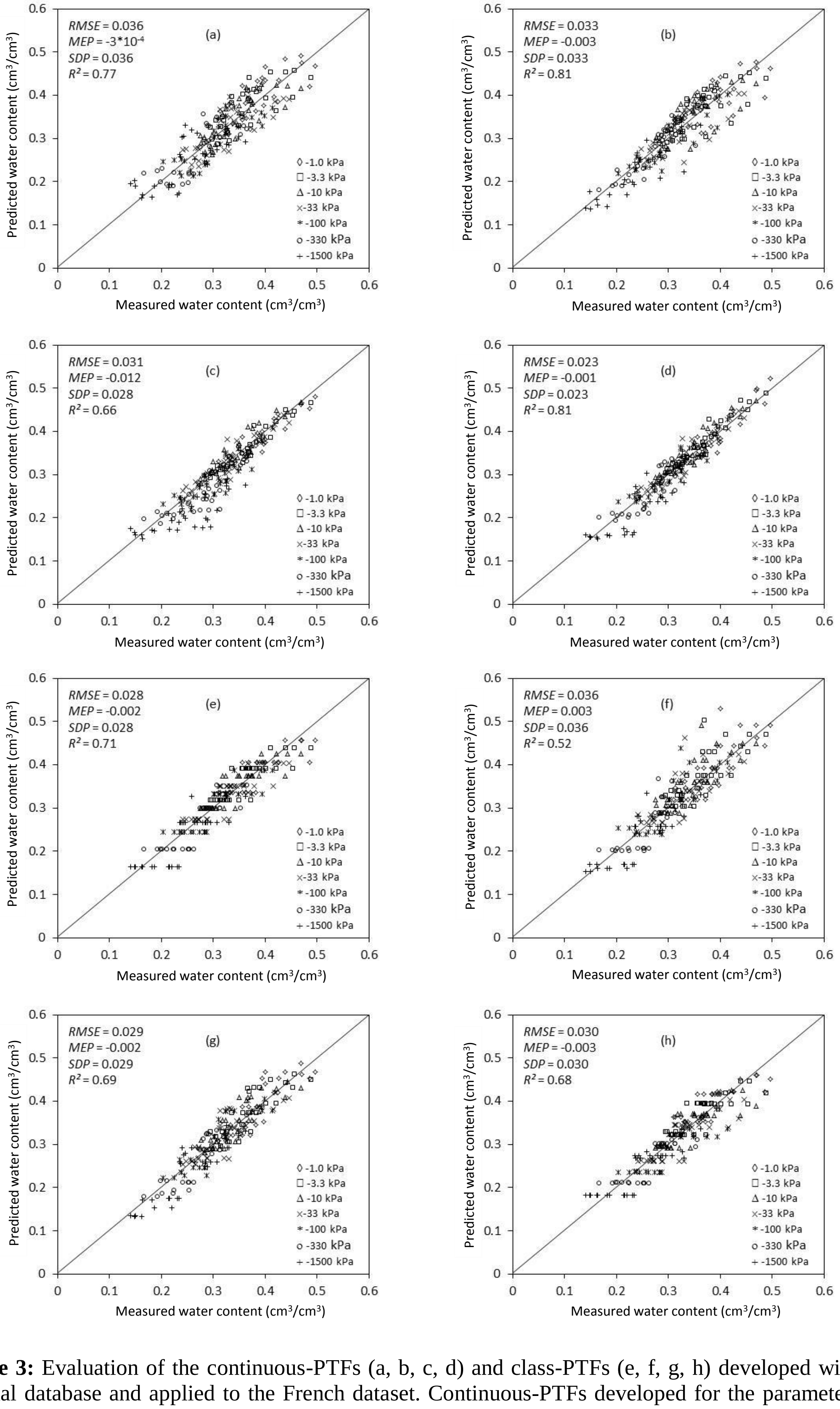

Figure 3: Evaluation of the continuous-PTFs (a, b, c, d) and class-PTFs (e, f, g, h) developed with the French national database and applied to the French dataset. Continuous-PTFs developed for the parameters of the van Genuchten model (1980) (a), continuous-PTFs developed by multiple regression equations (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).

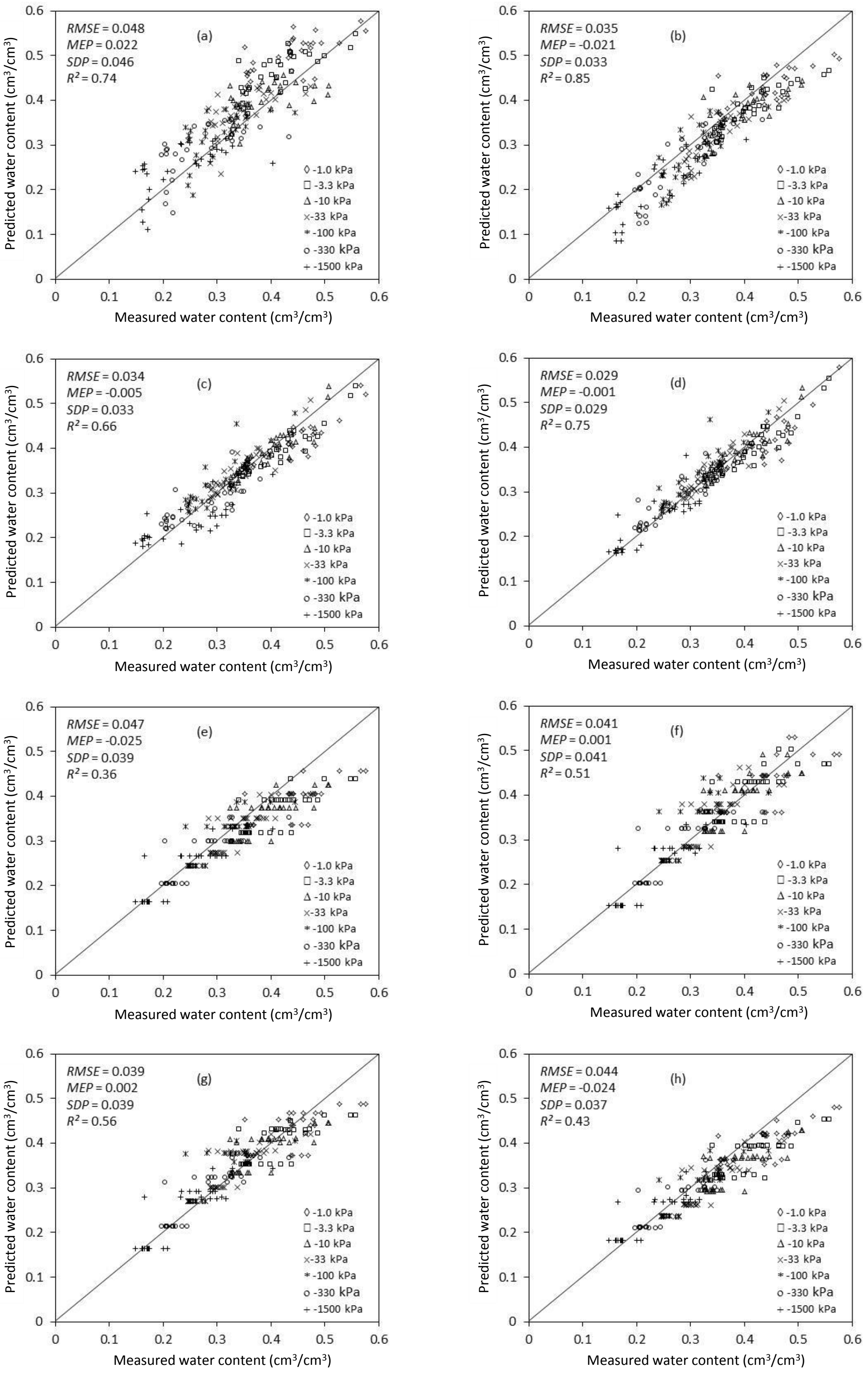

Figure 4: Evaluation of the continuous-PTFs (a, b, c, d) and class-PTFs (e, f, g, h) developed with the French national database and applied to the Syrian dataset. Continuous-PTFs developed for the parameters of the van Genuchten model (1980) (a), continuous-PTFs developed by multiple regression equations (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).

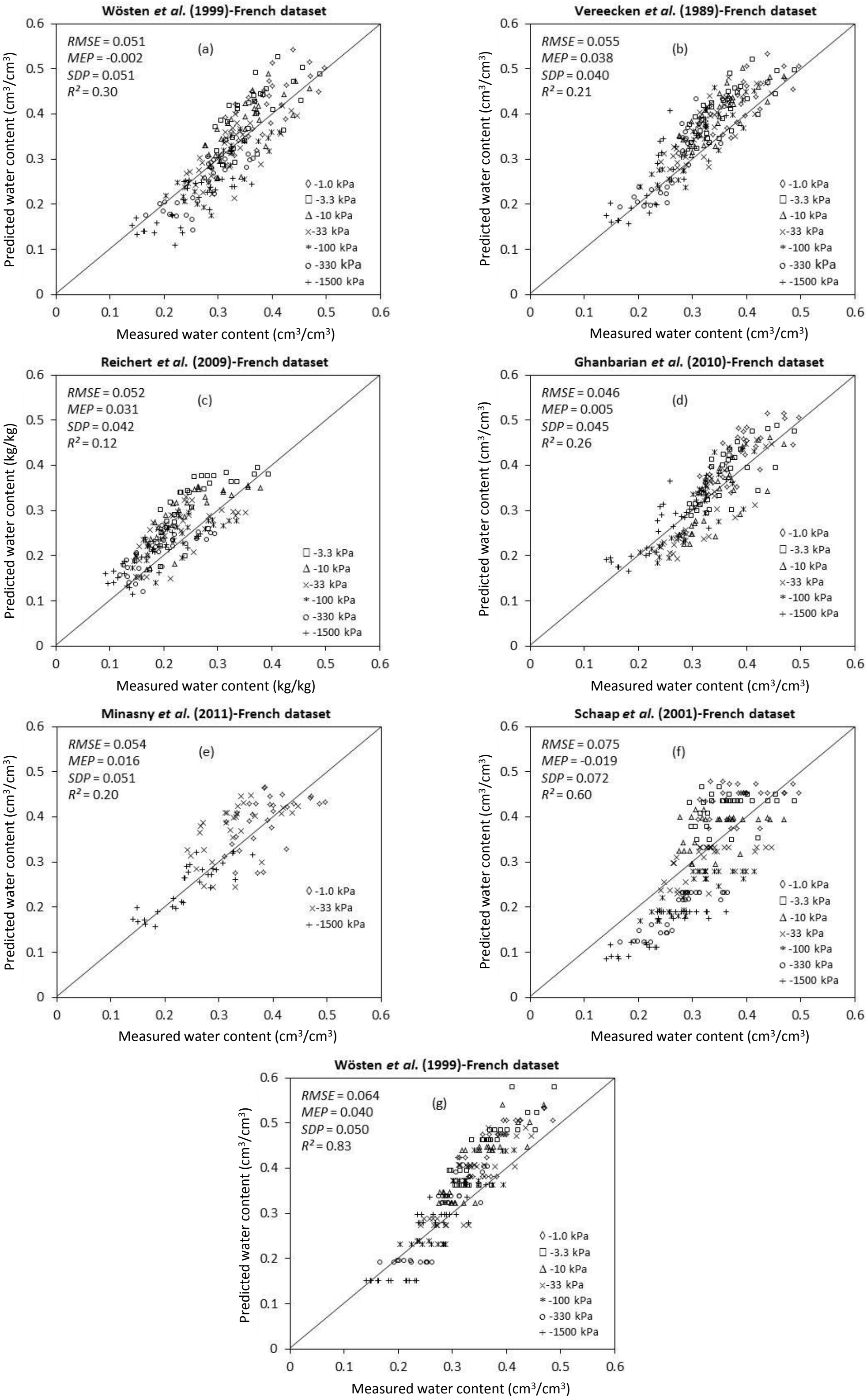

Figure 5: Evaluation of the continuous-PTFs (a, b, c, d, e), and class-PTFs (f, g) selected in the literature when applied to the French dataset. R^2 were computed for all matric potential values together.

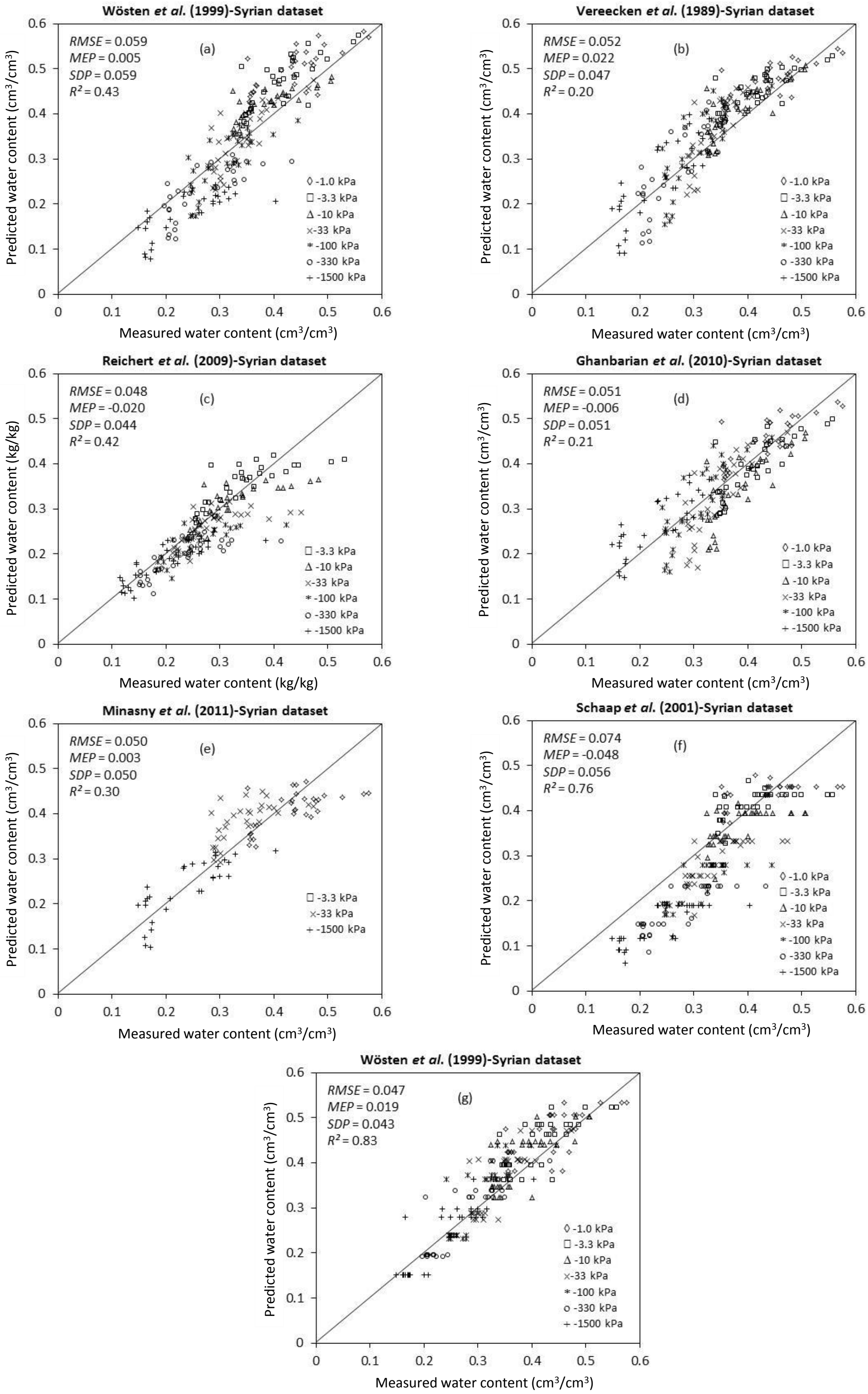

Figure 6: Evaluation of the continuous-PTFs (a, b, c, d, e), and class-PTFs (f, g) selected in the literature when applied to the Syrian dataset. R^2 were computed for all matric potential values together.

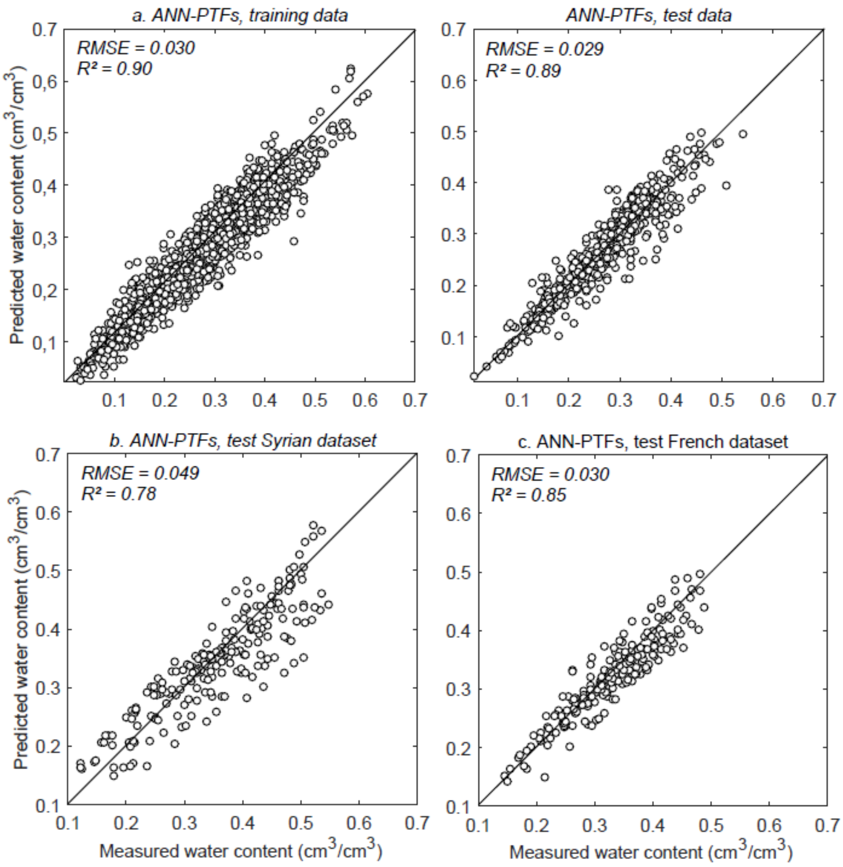

Figure 7: Measured and predicted water content (cm^3/cm^3) recorded with the artificial neural networks using soil properties (clay, silt, sand, organic carbon and bulk density) for the French national database (Al Majou *et al*., 2008b) (a), Syrian dataset (b) and the French dataset (c).