

1 **DEVELOPMENT OF TERNARY DIAGRAMS FOR ESTIMATING WATER**
2 **RETENTION PROPERTIES USING A GEOSTATISTICAL APPROACH**

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14 **Abstract**

15 Most pedotransfer functions (PTFs) have adopted soil texture information as the main
16 predictor to estimate soil hydraulic properties, whether inputs are defined in terms of the
17 relative proportion of different grain size particles or texture-based classifications. The
18 objective of this study was to develop ternary diagrams for estimating soil water retention at -
19 33 and -1500 kPa matric potentials, corresponding to the field capacity and wilting point,
20 respectively, from particle size distribution using a geostatistical approach. The texture
21 triangle was divided into a 1% grid of soil texture composition resulting in 4332 different soil
22 textures. Measured soil water retention values determined in 742 soil horizons/layers located
23 in Portugal were then used to develop and validate the ternary diagrams. The development
24 subset included two-thirds of the data, and the validation subset the remaining samples. The
25 soil water content values were displayed in the ternary diagram according to the coordinates
26 given by the particles size distribution determined in the same soil samples. The measured

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27 volumetric water content values were then interpolated to the remaining areas of the ternary
28 diagrams using ordinary kriging. Uncertainty analysis resulted in a root mean square error of
29 0.040 and 0.033 $\text{cm}^3 \text{cm}^{-3}$ obtained when comparing the interpolated water contents at -33 and
30 -1500 kPa matric potentials values, respectively, with the measured ones included in the
31 validation dataset. The estimation variance was also considered to assess the uncertainty of
32 the estimations. The available water content of Portuguese soils was then derived from both
33 ternary diagrams. The ternary diagrams may thus serve as simplified tools for estimating
34 water retention properties from particle size distribution and eventually serve as an alternative
35 to the traditional statistical regression and data mining techniques used to derive PTFs.

36

37 **Keywords:** Field capacity; Ordinary kriging; Soil Texture; Uncertainty; Wilting point.

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40 **1. Introduction**

41 Modern hydrologic modeling studies require a quantitative and precise understanding of soil
42 hydraulic properties. That information is essential for a wide range of applications, such as
43 research on soil and water conservation, irrigation scheduling, solute transport, virus and
44 bacterial migration, plant growth, and plant stress. However, classical methods for direct
45 measurement of soil hydraulic properties (Dane and Topp, 2002) are known to be costly, time
46 consuming, and impractical for large-scale applications in which many samples are required
47 to quantify the spatial and temporal variability of those properties. Hence, pedotransfer
48 functions (PTFs) have been developed as an alternative to classical methods to indirectly
49 estimate soil hydraulic properties from basic soil physical and chemical properties (Bouma,
50 1989; Vereecken et al., 1989; McBratney et al., 2002; Pachepsky and Rawls, 2004), thus

51 overcoming some of the limitations mentioned earlier, especially when the objective is to
52 characterise soil hydraulic properties at large scales.

53 Most of the available PTFs use soil-texture-based information as the main predictor to
54 estimate the hydraulic behaviour of soils. This popular option is justified by the fact that soil
55 texture characteristics are among the most easily measured soil properties, and also by the
56 assumption that soil texture is the dominant soil variable in determining hydraulic properties,
57 while other soil variables, such as bulk density or organic matter content, have a secondary
58 effect (Twarakavi et al., 2010). The simplest texture based PTFs were developed to provide
59 estimates of average soil water retention properties or hydraulic parameters for different
60 texture classes (e.g., Wösten et al., 1995; Schaap and Leij, 1998; Bruand et al., 2003; Al
61 Majou et al., 2008; Ramos et al., 2013a). More complex functions have also been developed
62 by relating the particle size limits of the soil constituents to soil hydraulics using multiple
63 regression analysis or data mining tools (e.g., Gupta and Larson, 1979; Saxton et al., 1986;
64 Schaap et al., 2001; Nemes et al., 2006; Haghverdi et al., 2012). Although the hierarchical
65 approaches followed in many of those studies showed that the accuracy of PTFs improved
66 considerably when other variables (usually bulk density), rather than soil texture information
67 alone, were used also as predictors, texture based PTFs have been considered to also provide
68 reasonably accurate estimates of soil hydraulic properties for many research and technical
69 applications (Vereecken et al., 2010).

70 Soil texture is normally represented in a ternary diagram, function of sand, silt and clay
71 percentages, where the limits of the texture classes vary according to the texture classification
72 system used. However, the soil texture triangle has also had more applications than simply
73 grouping texture information data, namely it has also been used as a tool to estimate soil
74 hydraulic properties. Saxton et al. (1986) divided the soil texture triangle into grids of 10%
75 sand and 10% clay content increments to develop texture based PTFs for generalized

76 predictions of soil hydraulic properties in each grid cell. Later, Saxton and Rawls (2006)
77 updated the previous work to further include the effect of organic matter, bulk density, gravel,
78 and salinity in their model and provide a broadly applicable predictive system. The developed
79 model has been successfully applied to a wide variety of analysis, particularly those related to
80 agricultural hydrology and water management, since estimates do not involve complex
81 mathematical methods, and the texture triangle serves as a familiar tool to users for estimating
82 the soil water characteristics. Twarakavi et al. (2010) also focused on the relations between
83 the texture triangle and soil hydraulic properties. Those authors estimated soil hydraulic
84 properties throughout the entire soil texture triangle as a function of sand, silt, and clay
85 contents using the ROSETTA PTFs (Schaap et al., 2001) such that the various soil texture
86 possibilities (i.e., combinations of sand, silt, and clay percentages) were considered. They
87 then concluded that although the soil texture triangle was qualitatively very similar to the soil
88 hydraulic triangle, differences existed especially for soils where capillary forces dominate the
89 flow throughout the soils. Bormann (2007) took those studies one step forward and performed
90 water balance calculations for the entire space of the soil texture triangle, after dividing it into
91 1% grid cells and applying Rawls and Brakensiek (1985) PTFs for obtaining the soil
92 hydraulic properties.

93 In this study, a geostatistical approach was used to spatially interpolate water retention
94 values (the field capacity and wilting point) available in a soil database (Gonçalves et al.,
95 2011) throughout the entire soil texture triangle. Kriging is generally considered to be the best
96 method for spatial interpolation that also includes information on uncertainty (Goovaerts,
97 1999, 2001). Although there are countless applications to its application in soil science, as far
98 as we know the kriging estimator has never been used as a PTF to actually derive soil
99 hydraulic properties from basic soil data. To proceed with this study, three very basic
100 assumptions had to be validated:

101 (i) Soil texture and soil water retention properties available in the database were
102 assumed as being determined in the same sample. This is usually not the case in most PTFs
103 where the predictors used in their development, although measured in the same soil horizon,
104 are not always determined directly on the soil samples used for measuring the hydraulic
105 properties. As referred by Vereecken et al. (2010), this becomes more important as the spatial
106 and temporal variability of additional soils information increase and the information content is
107 not related anymore to the samples on which the hydraulic properties were determined. Thus,
108 taking into account the size of the database used in this study, the error resulting from this
109 assumption was not considered to be relevant.

110 (ii) Soil texture was assumed as the main predictor to estimate soil hydraulic properties.
111 As mentioned earlier, this is the main assumption sustaining all texture based PTFs, since
112 these two soil properties normally exhibit a high correlation.

113 (iii) The spatial continuity of soil hydraulic properties along the soil texture triangle
114 could be described by means of a variogram. Taking into account that soil texture is the main
115 soil property considered when grouping soils having similar water retention curves (Wösten et
116 al., 1995; Bruand et al., 2003; Ramos et al., 2013a), and that the soil texture triangle and the
117 soil hydraulic triangle can be relatively similar (Twarakavi et al., 2010), we assumed that
118 there could be a spatial dependence of soil hydraulic properties, at least within the limits of
119 each soil texture class. The percentage units that define the texture triangle were thus
120 converted into metric units to allow the application of geostatistics.

121 The objective of this study is thus to develop ternary diagrams for estimating point
122 specific water retention values (the field capacity and wilting point) of Portuguese soils using
123 a geostatistical approach. The available water capacity was later computed from both ternary
124 diagrams.

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126

127 **2. Material and Methods**

128 **2.1. The data set**

129 The ternary diagrams were developed for estimating the field capacity and wilting point of
130 Portuguese soils from particle size distribution. The field capacity and wilting point were here
131 assumed to correspond to the water retention values at -33 and -1500 kPa, respectively. The
132 data was extracted from the PROPSOLO soil database (Gonçalves et al., 2011), which gathers
133 all information on soil hydraulic and pedological properties from soil profiles obtained from
134 research projects and academic studies performed at the Portuguese National Institute of
135 Agronomic and Veterinarian Research (former Estação Agronómica Nacional). This database
136 contains practically all of the existing knowledge on the soil hydraulic properties of
137 Portuguese soils (with the exception of a few specific retention points found in soil survey
138 studies).

139 The data included information on soil texture and water retention properties of 742
140 horizons/layers studied in 346 soil profiles located in Portugal between 1977 and 2012 (Fig.
141 1). The soil reference groups (FAO, 2006) represented were Fluvisols (36.4%), Luvisols
142 (29.5%), Vertisols (9.8%), Cambisols (8.7%), Calcisols (6.6%), Anthrosols (4.0%), Arenosols
143 (1.4%), Podzols (0.9%), Regosols (0.9%), Ferralsols (0.6%), Leptosols (0.6%), and Planosols
144 (0.6%).

145 The data was randomly divided in two subsets, a development set composed of two-
146 thirds of the data (495 horizons/layers), and a validation set with the remaining one-third of
147 the data (247 horizons/layers). Table 1 presents the main physical and chemical properties of
148 the two datasets. The particle size distribution was obtained using the pipette method for
149 particles having diameters $<2 \mu\text{m}$ (clay) and between $20\text{--}2 \mu\text{m}$ (silt), and by sieving for
150 particles between $200\text{--}20 \mu\text{m}$ (fine sand) and between $200\text{--}2000 \mu\text{m}$ (coarse sand). These

151 textural classes follow the Portuguese classification system (Gomes and Silva, 1962) and are
152 based on the International Soil Science Society (ISSS) particle limits (Atterberg scale). The
153 organic carbon (OC) content was determined by the Walkley–Black method (Nelson and
154 Sommers, 1982). The dry bulk density (ρ_b) was obtained by drying volumetric soil samples
155 (100 cm^3) at $105 \text{ }^\circ\text{C}$ for 48 h. The gravimetric water content at -33 kPa matric potential was
156 determined on undisturbed soil samples (100 cm^3) using suction tables (Romano et al., 2002;
157 used in 494 horizons/layers) or the pressure plate apparatus (Dane and Hopmans, 2002; used
158 in 212 horizons/layers). The gravimetric water content at -1500 kPa matric potential was also
159 determined on undisturbed soil samples (100 cm^3) using the pressure plate apparatus. Then,
160 the volumetric water content for each horizon/layer and each matric potential was computed
161 from the gravimetric water contents and the bulk density of the corresponding horizon/layer.

162 In the case of 36 soil horizons/layers where the volumetric water content at -33 kPa
163 matric potential was not readily available, the missing values were estimated by introducing
164 values derived from the fitted van Genuchten model (1980) to each individual water retention
165 curve, also available in the soil database for all soil horizons/layers. The van Genuchten
166 model describes the volumetric soil water content, $\theta \text{ (L}^3 \text{ L}^{-3}\text{)}$, as a function of matric potential,
167 $\psi \text{ (L)}$, in the following form:

$$168 \quad S_e(\psi) = \frac{\theta(\psi) - \theta_r}{\theta_s - \theta_r} = \frac{1}{\left(1 + |\alpha \psi|^\eta\right)^{1-1/\eta}} \quad (1)$$

169 in which S_e is the effective saturation, θ_r and θ_s denote the residual and saturated water
170 contents ($\text{L}^3 \text{ L}^{-3}$), respectively, $\alpha \text{ (L}^{-1}\text{)}$ and $\eta \text{ (-)}$ are empirical shape parameters. This
171 procedure introduced an error to the subsequent calculations and model evaluations resulting
172 from the non-perfect fit of the fitted model to the experimental data ($\text{RMSE} = 0.012 \text{ cm}^3 \text{ cm}^{-3}$),
173 in line with published results (e.g., Nemes and Rawls, 2006; Ramos et al., 2013a). The

174 errors were thus relatively small compared with the errors usually obtained using PTFs, and
175 therefore, the fitted values were assumed as if they were measured.

176

177 **2.2. Development of the ternary diagrams**

178 The soil texture triangle was divided into a 1% grid of soil texture composition resulting in
179 4332 different soil textures (i.e., different combinations of sand, silt, and clay percentages).
180 Figure 2 shows the textural distribution of the datasets used for the development of the ternary
181 diagrams and for their validation. The soil texture triangle was converted into ternary
182 diagrams by replacing the percentage units by metric units (cm were used for convenience),
183 and by including the soil water retention values at -33 and -1500 kPa matric potentials in the
184 coordinates given by the particles size distribution determined in the same soil samples.
185 Measured $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ within the same location (i.e., same particle size distribution)
186 were averaged. The measured volumetric water content values $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ were then
187 interpolated to the remaining areas of the ternary diagrams using ordinary kriging.

188 The spatial pattern of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ in each ternary diagram was first described
189 from the semi-variance of the differences between measured values included in the
190 development set using the experimental semivariogram (Goovaerts, 1997; Yates and Warrick,
191 2002), as follows:

$$192 \quad \gamma_e(\mathbf{h}) = \frac{1}{2n(\mathbf{h})} \sum_{i=1}^{n(\mathbf{h})} [Z(\mathbf{x}_i) - Z(\mathbf{x}_{i+\mathbf{h}})]^2 \quad (2)$$

193 where $n(\mathbf{h})$ is the total number of pairs of observation points (\mathbf{x}_i and $\mathbf{x}_{i+\mathbf{h}}$; $i = 1, \dots, n$) of the
194 variable Z (i.e., $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$) that are separated by a distance \mathbf{h} . The omnidirectional
195 semivariogram was computed, and hence the spatial variability was assumed to be identical in
196 all directions. The variogram was defined by assigning pairs of measured values of $\theta_{-33 \text{ kPa}}$ and
197 $\theta_{-1500 \text{ kPa}}$ to a lag interval of 5 cm ($\mathbf{h}_i = i \text{ 5 cm}$), since data was irregularly distributed in the
198 texture triangle (Fig. 2). A theoretical variogram was then fitted to the experimental

199 semivariogram using a Gaussian model with nugget effect (Goovaerts, 1997; Yates and
 200 Warrick, 2002):

$$201 \quad \gamma_t(h) = \begin{cases} C_0 + C_1 \left[1 - \exp\left(\frac{-3h^2}{a^2}\right) \right] & \text{for } h \leq a \\ C_0 + C_1 & \text{for } h > a \end{cases} \quad (3)$$

202 where C_0 is the nugget (-), C_1 is the sill (-), and a is the range (L). The nugget, C_0 , is a
 203 measure of discontinuity at the origin of the semivariogram which mainly arises from various
 204 sources of unexplained errors, such as measurement errors or the existence of spatial
 205 variations at distances smaller than the shortest sampling interval. The sill, C_1 , should be
 206 approximately equal to the variance of the data. Finally, the range, a , corresponds to the
 207 distance at which the semivariance approaches the sill, and represents the separation distance
 208 beyond which two values of the variable can be considered statistically independent.

209 Ordinary kriging was the geostatistical interpolation method selected (Goovaerts, 1997;
 210 Yates and Warrick, 2002). The kriging estimator, $Z^*(x)$, provided an estimate of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$
 211 at a location x_0 of the ternary diagram that contained no information. The estimator is
 212 written as a linear combination of the measured values, $Z(x_i)$, that is,

$$213 \quad Z^*(x_0) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (4)$$

214 where the observation at each location was weighted by λ_i . The value of λ_i depended on its
 215 proximity and orientation to x_0 and to the other sample locations, x_i . Since by definition,

$$216 \quad E[Z^*(x_0)] = \sum_{i=1}^n \lambda_i E[Z(x_i)] \quad (5)$$

217 and

$$218 \quad E[Z(x)] = m \quad (6)$$

219 the estimates will be unbiased (i.e., $E[Z(x) - Z^*(x_0)] = 0$). The following ordinary kriging
 220 system was solved in order to minimize the prediction variance:

$$\begin{cases} \sum_{i=1}^n \lambda_i \gamma(x_k - x_i) + \mu = \gamma(x_k - x_0) \\ \sum_{i=1}^n \lambda_i = 1 \end{cases} \quad (7)$$

where $E[]$ is the expected value, m is the mean value of $Z(x)$, γ is the semivariance between data pairs, μ is the Lagrange parameter accounting for the constraint on the weights, and $k = 1, \dots, n$.

The variograms calculation and fitting, and the implementation of the kriging method were carried out with the geoMS software package (CMRP, 2000).

227

2.3. Uncertainty analyses

The uncertainty of the ordinary kriging interpolation estimates was considered to be the estimation variance in each grid cell of the ternary diagrams. The estimation variance σ^2 gives an indication of the quality of the estimates and was computed as follows (Goovaerts, 1997; Yates and Warrick, 2002),

$$\sigma_k^2(x_0) = \sum_{i=1}^n \lambda_i \gamma(x_i - x_0) + \mu \quad (8)$$

The ternary diagrams were also validated by comparing measured $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ values included in the validation dataset with ordinary kriging estimates using various quantitative measures of the uncertainty, such as the determination coefficient (R^2), the mean error (ME), and the root mean square error (RMSE), given by:

$$R^2 = \left[\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{i=1}^n (O_i - \bar{O})^2 \right]^{0.5} \left[\sum_{i=1}^n (P_i - \bar{P})^2 \right]^{0.5}} \right]^2 \quad (9)$$

$$ME = \frac{1}{n} \sum_{i=1}^n (P_i - O_i) \quad (10)$$

$$240 \quad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n-1}} \quad (11)$$

241 where n is the number of observations, O_i are the measured values, P_i are the interpolation
 242 predictions, \bar{O} is the average of the measured values, and \bar{P} is the average of the
 243 interpolation predictions.

244

245

246 **3. Results and Discussion**

247 **3.1. Spatial patterns of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$**

248 Figure 3 presents the experimental and theoretical semivariograms obtained for $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$.
 249 The fitted parameters of the Gaussian model are given in Table 2. The nugget value
 250 found for $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ corresponded to 15.4 and 6.1% of the total variance (C),
 251 respectively. As referred above, these values can be explained by sampling or measurement
 252 errors, and by variability that occurs at scales too small to characterize, which in this case
 253 correspond to variability that cannot be explained only by variations in soil texture. This
 254 unexplained variability is surely attributed to the effect of bulk density, organic matter, soil
 255 structure, soil mineralogy, soil chemical composition, and land use and management on water
 256 retention properties. Like in the development of traditional PTFs, grouping data by
 257 considering the effect of those soil properties (Wösten et al., 2001) would likely be
 258 advantageous in order to reduce the unexplained variability found in the development of the
 259 ternary diagrams. However, that approach would require a much larger database than the one
 260 currently available. The larger nugget value found for the semivariogram of $\theta_{-33 \text{ kPa}}$ may be
 261 further related to the different methodologies used for measuring water retention at -33 kPa
 262 matric potential (Schaap and Leij, 1998).

263 The spatial continuity of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ reached a range of 39.7 and 24.6 cm in the
264 ternary diagrams, respectively. Water retention values were thus correlated with samples
265 located in neighbor texture classes, but more distanced areas of the texture triangle showed no
266 correlation with those measured values. These findings seem to be very useful to understand
267 the limitations of the simplest texture based PTFs, the class-PTFs (Wösten et al., 2001), when
268 estimating water retention properties for different texture classes. These class-PTFs estimate
269 average soil water retention properties for different texture classes based on the arithmetic
270 (e.g., Bruand et al., 2003; Al Majou et al., 2008; Ramos et al., 2013a) or geometric mean
271 (e.g., Wösten et al., 1995, 1999) of the datasets. However, for most regions of the texture
272 triangle water retention values are sometimes better correlated with data included in their
273 vicinity which may well be included in a neighbor texture class.

274

275 **3.2. Ternary diagrams**

276 Figure 4 presents the ternary diagram developed by ordinary kriging for estimating $\theta_{-33 \text{ kPa}}$
277 from particle size distribution. The resulting estimation variance is also shown in the same
278 figure. Soil water retention values at -33 kPa matric potential were lower in the coarser
279 texture classes and increased gradually with the increment of clay and silt contents. Basically,
280 the ordinary kriging method calculated $\theta_{-33 \text{ kPa}}$ for all 4332 grid cells of the ternary diagram as
281 a kind of weighted average of the measured values in the vicinity of each grid cell. The
282 neighboring sample point values were weighted according to the semivariance as a function
283 of distance to the prediction location. The kriging method also compensated for the effects of
284 data clustering, by assigning individual points within a cluster less weight than isolated data
285 points. This showed to be particularly useful when interpolating water content values to
286 regions of the texture triangle where the information available in the development set was
287 scarcer.

288 The mean and standard deviation values of the interpolated $\theta_{-33 \text{ kPa}}$ ternary diagram were
289 0.365 and 0.086 $\text{cm}^3 \text{cm}^{-3}$, respectively. The mean value was thus higher than the one
290 registered in the development dataset (0.287 $\text{cm}^3 \text{cm}^{-3}$; Table 1). The difference found resulted
291 from the fact that the interpolated ternary diagram estimated $\theta_{-33 \text{ kPa}}$ for all 4332 soil textures,
292 including regions of the texture triangle where the development dataset had no information
293 (e.g., the silty texture class, and the region of the texture triangle with clay content higher than
294 65%), thus producing significant differences in the classes of the interpolated histogram with
295 higher water contents (not shown). The estimation variance was very high in those regions,
296 and thus local estimates of $\theta_{-33 \text{ kPa}}$ were not realistic (Fig. 4). For the remaining regions of the
297 ternary diagram, the estimation variance was low and estimates were considered to be
298 accurate. In these regions, the mean value given by the kriging estimator ($m = 0.338 \text{ cm}^3 \text{ cm}^{-3}$
299 where, for example, $\sigma^2 \leq 0.002$) and the mean value of the development dataset tended to be
300 closer.

301 Figure 5 presents the interpolated $\theta_{-1500 \text{ kPa}}$ ternary diagram and the respective estimation
302 variance. Soil water retention values at -1500 kPa matric potential were also lower in the
303 coarser texture classes and increased progressively with the increase of clay content.
304 However, soil water retention did not increase as gradually as registered for the $\theta_{-33 \text{ kPa}}$ ternary
305 diagram, since there are a few regions of the texture triangle (e.g., the area in the vicinity of
306 the soil texture with 50% clay, 32% silt, and 18% sand) that clearly needed more information
307 when estimating $\theta_{-1500 \text{ kPa}}$. The mean and standard deviation values of the interpolated $\theta_{-1500 \text{ kPa}}$
308 ternary diagram were 0.216 and 0.101 $\text{cm}^3 \text{cm}^{-3}$, respectively. The mean value was once again
309 higher than the one in the development dataset (0.162 $\text{cm}^3 \text{cm}^{-3}$; Table 1), but it was slightly
310 lower where $\sigma^2 \leq 0.002$ ($m = 0.204 \text{ cm}^3 \text{ cm}^{-3}$).

311 The results of the goodness-of-fit tests between measured and estimated water retention
312 values at both matric potentials are presented in Table 3. Figure 6 shows the corresponding

313 scatter plots between measured and estimated values. The kriging method produced an
314 acceptable estimation of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$, with ME values being very close to zero. RMSE
315 values also showed that estimates were relatively accurate. RMSE were 0.040 and 0.033 cm^3
316 cm^{-3} for the estimates of $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$, respectively. The R^2 values were considerably
317 high and identical for both water contents ($R^2 > 0.78$), indicating also a good agreement
318 between measurements and predictions. However, data in the $\theta_{-1500 \text{ kPa}}$ scatter plot was found
319 to be slightly more dispersing than for $\theta_{-33 \text{ kPa}}$.

320 Table 4 shows the accuracy of published PTFs that are available for estimating soil
321 hydraulic properties of Portuguese soils, and which estimates can be compared with those
322 obtained with the ternary diagrams. We limited our comparison to PTFs that used partially or
323 the entire dataset used in this study. The class-PTFs developed by Ramos et al. (2013a)
324 produced RMSE values that varied between 0.042 and 0.055 $\text{cm}^3 \text{ cm}^{-3}$ when estimating θ_{-33}
325 kPa , and between 0.037 and 0.048 $\text{cm}^3 \text{ cm}^{-3}$ when predicting $\theta_{-1500 \text{ kPa}}$. The best estimates,
326 achieved with the class-PTFs developed after grouping data by ISSS texture classes and bulk
327 density, can be comparable with the estimates given by the ternary diagrams. The point PTFs
328 developed by Ramos et al. (2013b) yielded RMSE values of 0.040 and 0.036 $\text{cm}^3 \text{ cm}^{-3}$ also
329 when predicting $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$, respectively, thus producing very similar predictions to
330 those given by the kriging method. On the other hand, the parametric PTFs developed by
331 Gonçalves et al. (1997), Wösten et al. (1999), and Ramos et al. (2013b) resulted in slightly
332 higher RMSE values ($\geq 0.046 \text{ cm}^3 \text{ cm}^{-3}$) than those calculated with estimates given by the
333 ternary diagrams. Hence, Table 4 shows that similar or even better predictions of $\theta_{-33 \text{ kPa}}$ and
334 $\theta_{-1500 \text{ kPa}}$ can be obtained with the ternary diagrams. The only predictor needed is the particle
335 size distribution, while the other comparable PTFs require relatively more predictors than the
336 needs of those diagrams. In terms of number of predictors, the ternary diagrams seem to be
337 quite useful as they are the only PTFs that do not require bulk density, despite results are

338 given in terms of volumetric water contents. Although this soil property is simple to measure,
339 sampling undisturbed samples in different soil horizons/layers distributed over large areas in
340 order to measure bulk density may be a very laborious task.

341

342 **3.3. Available water capacity**

343 Figure 7 shows estimates of the available water capacity (AWC), calculated as the difference
344 between $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$, and setting soil depth to 1 m as reference for comparison
345 between estimates. AWC was only calculated for areas of the ternary diagrams where the
346 estimation variance of either $\theta_{-33 \text{ kPa}}$ or $\theta_{-1500 \text{ kPa}}$ was lower than 0.002. This value was chosen
347 arbitrarily, but is much lower than the dataset total variance (Table 2). Therefore, we only
348 considered estimates that may be considered reliable and avoided extrapolations produced by
349 the kriging estimator.

350 The largest AWC estimates were obtained for the medium fine texture classes. The
351 coarser texture classes and the soils with 65% clay content seem to present lower AWC.
352 However, the low estimates found for these latter soils are produced in a region of the ternary
353 diagram where the estimation variance increases rapidly with the increase of the clay content,
354 i.e., those predictions are near the limits of a region where the kriging estimator starts to
355 extrapolate information instead of interpolating it, and thus care should be taken when using
356 that information. Nevertheless, the histogram presented in Fig. 8 shows that estimates of the
357 AWC have an average value of 134.1 mm/m, a variance of 3150.7, and kurtosis (0.45) and
358 skewness (0.83) close to zero. However, the Chi-Square and Kolmogorov-Smirnov (p value =
359 $0.00 < 0.01$) goodness-of-fit tests rejected the hypothesis that AWC is normally distributed at
360 a level of 99% confidence since soil water content information in the very fine and medium
361 fine texture classes is missing.

362 The ternary diagrams developed in this study ($\theta_{-33 \text{ kPa}}$, $\theta_{-1500 \text{ kPa}}$, and AWC) may
363 potentially be useful for many scientific and technical domains, but they seem more relevant
364 to agricultural water management, particularly irrigation management and scheduling.
365 Various water balance models require the type of information provided by the ternary
366 diagrams here developed at point scale (Liu et al., 1998; George et al., 2000; Chopart et al.,
367 2007; Steduto et al., 2009; Khaledian et al., 2009; Rosa et al., 2012). Those that are associated
368 to a geographical information system and are applied at field scale (Troch et al, 1993; Fortes
369 et al., 2005; Ojeda-Bustamante et al., 2007) can make even further use of the ternary diagrams
370 here developed for estimating soil water retention properties of Portuguese soils.

371

372

373 **4. Conclusions**

374 The geostatistical approach was able to provide reliable estimates of soil water retention at -
375 33 and -1500 kPa matric potentials using only the relative proportion of different grain size
376 particles (sand, silt, and clay) as input data. The ordinary kriging method was helpful to
377 understand which estimates of the soil water retention were valid based on the values of the
378 estimation variance, and thus extrapolations were avoided.

379 The RMSE values were 0.040 and 0.033 $\text{cm}^3 \text{ cm}^{-3}$ when comparing the estimates
380 provided by the $\theta_{-33 \text{ kPa}}$ and $\theta_{-1500 \text{ kPa}}$ ternary diagrams, respectively, and the measured values
381 included in the validation dataset. Those values are comparable to the estimates provided by
382 most of the available PTFs for estimating soil water retention properties of Portuguese soils.
383 The ternary diagrams may thus serve as simplified tools for estimating those properties from
384 particle size distribution and eventually serve as an alternative to the traditional statistical
385 regression and data mining techniques used to derive PTFs.

386

387

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394 **References**

395 Al Majou, H., Bruand, A., Duval, O., Le Bas, C., Vautier, A., 2008. Prediction of soil water
396 retention properties after stratification by combining texture, bulk density and the type
397 of horizon. *Soil Use and Management* 24, 383-391, doi:10.1111/j.1475-
398 2743.2008.00180.x.

399 Bormann, H., 2007. Analysis of the suitability of the German soil texture classification for the
400 regional scale application of physical based hydrological model. *Advances in*
401 *Geoscience* 11, 7-13, doi:10.5194/adgeo-11-7-2007.

402 Bouma, J., 1989. Using soil survey data for quantitative land evaluation. *Advances in Soil*
403 *Science* 9, 177-213.

404 Bruand, A., Pérez Fernandez, P., Duval, O., 2003. Use of class pedotransfer functions based
405 on texture and bulk density of clods to generate water retention curves. *Soil Use and*
406 *Management* 19, 232-242, doi:10.1111/j.1475-2743.2003.tb00309.x.

407 Chopart, J.L., Mézino, M., Aure, F., Le Mézo, L., Mété, M., Vauclin, M., 2007. OSIRI: A
408 simple decision-making tool for monitoring irrigation of small farms in heterogeneous
409 environments. *Agricultural Water Management* 87, 128-138,
410 doi:10.1016/j.agwat.2006.06.023.

411 CMRP (Centro de Modelização de Reservatórios Petrolíferos), 2000. Manual do geoMS v1.0.
412 Instituto Superior Técnico, Lisboa, Portugal.

413 Dane, J.H., Hopmans, J.W., 2002. Pressure plate extractor. In: Dane, J.H., Topp, G.C. (Eds.),
414 Methods of Soil Analysis, Part 4, Physical Methods. Soil Science Society of America
415 book Series, Madison, Wisconsin, pp. 688-690.

416 Dane, J.H., Topp, G.C., 2002. Methods of soil analysis. Part 4, Physical methods. Soil
417 Science Society of America book Series, Madison, Wisconsin.

418 FAO, 2006. World reference base for soil resources. A framework for international
419 classification, correlation and communication. World Soil Resources Report 103, Food
420 and Agriculture Organization of the United Nations, Rome, Italy.

421 Fortes, P.S., Platonov, A.E., Pereira, L.S., 2005. GISAREG – A GIS based irrigation
422 scheduling simulation model to support improved water use. Agricultural Water
423 Management 77, 159-179, doi:10.1016/j.agwat.2004.09.042.

424 George, B.A., Shende, S.A., Raghuwanshi, N.S., 2000. Development and testing of an
425 irrigation scheduling model. Agricultural Water Management 46, 121–136,
426 doi:10.1016/S0378-3774(00)00083-4.

427 Gomes, M.P., Silva, A.A., 1962. Um novo diagrama triangular para a classificação básica da
428 textura do solo. Garcia da Orta 10, 171–179.

429 Gonçalves, M.C., Pereira, L.S., Leij, F.J., 1997. Pedo-transfer functions for estimating
430 unsaturated hydraulic properties of Portuguese soils. European Journal of Soil Science
431 48, 387-400, doi:10.1111/j.1365-2389.1997.tb00205.x.

432 Gonçalves, M.C., Ramos, T.B., Pires, F.P., 2011. Base de dados georreferenciada das
433 propriedades do solo. In: Coelho, P.S., Reis, P. (Eds.), Agrorural. Contributos
434 Científicos. Instituto Nacional dos Recursos Biológicos, Oeiras, Portugal, pp. 564-574.

435 Goovaerts, P., 1997. Geostatistics for natural resources evaluation. Oxford University Press,
436 New York.

437 Goovaerts, P., 1999. Geostatistics in soil science: state-of-the-art and perspectives. *Geoderma*
438 89, 1-45, doi:10.1016/S0016-7061(98)00078-0.

439 Goovaerts, P., 2001. Geostatistical modeling of uncertainty in soil science. *Geoderma* 103, 3-
440 26, doi:10.1016/S0016-7061(01)00067-2.

441 Gupta, S.C., Larson, W.E., 1979. Estimating soil water retention characteristics from particle
442 size distribution, organic matter content, and bulk density. *Water Resources Research*
443 15, 1633-1635, doi:10.1029/WR015i006p01633.

444 Haghverdi, A., Cornelis, W.M., Ghahraman, B., 2012. A pseudo-continuous neural network
445 approach for developing water retention pedotransfer functions with limited data.
446 *Journal of Hydrology* 442-443, 46-54, doi:10.1016/j.jhydrol.2012.03.036.

447 Khaledian, M.R., Mailhol, J.C., Ruelle, P., Rosique, P., 2009. Adapting PILOTE model for
448 water and yield management under direct seeding system: The case of corn and durum
449 wheat in a Mediterranean context. *Agricultural Water Management* 96, 757-770,
450 doi:10.1016/j.agwat.2008.10.011.

451 Liu, Y., Teixeira, J.L., Zhang, H.J., Pereira, L.S., 1998. Model validation and crop
452 coefficients for irrigation scheduling in the North China Plain. *Agricultural Water*
453 *Management* 36: 233-246, doi:10.1016/S0378-3774(97)00051-6.

454 McBratney, A.B., Minasny, B., Cattle, S.R., Vervoort, R.W., 2002. From pedotransfer
455 functions to soil inference systems. *Geoderma* 109, 41-73, doi:10.1016/S0016-
456 7061(02)00139-8.

457 Nelson, D.W., Sommers, L.E., 1982. Total carbon, organic carbon, and organic matter. In:
458 Page, A.L., et al. (Eds.), *Methods of soil analysis, Part 2, Chemical and microbiological*
459 *properties*. ASA and SSSA, Madison, WI, pp. 539-579.

460 Nemes, A., Rawls, W.J., 2006. Evaluation of different representations of the particle-size
461 distribution to predict soil water retention. *Geoderma* 132, 47-58,
462 doi:10.1016/j.geoderma.2005.04.018.

463 Nemes, A., Rawls, W.J., Pachepsky, Y.A., 2006. Use of a nonparametric nearest-neighbor
464 technique to estimate soil water retention. *Soil Science Society of America Journal* 70,
465 327–336, doi:10.2136/sssaj2005.0128.

466 Pachepsky, Y.A., Rawls, W.J., 2004. Development of pedotransfer functions in soil
467 hydrology. Elsevier, Amsterdam, The Netherlands.

468 Ojeda-Bustamante, W., González-Camacho, J.M., Sifuentes-Ibarra, E., Isidro, E., Rendón-
469 Pimentel, L., 2007. Using spatial information systems to improve water management in
470 México. *Agricultural Water Management* 89, 81-88, doi:10.1016/j.agwat.2006.11.002.

471 Ramos, T.B., Gonçalves, M.C., Brito, D., Martins, J.C., Pereira, L.S., 2013a. Development of
472 class pedotransfer functions for integrating water retention properties into Portuguese
473 soil maps. *Soil Research* 51, doi:10.1071/SR12347.

474 Ramos, T.B., Gonçalves, M.C., Martins, J.C., Pereira, L.S., 2013b. Comparação de diferentes
475 funções de pedotransferência para estimar as propriedades hidráulicas em Portugal. In:
476 Gonçalves, M.C., Martins, J.C. (Eds.), *Proceedings do Encontro Anual de Ciência do*
477 *Solo*, 26-28 Julho, Instituto Nacional de Investigação Agrária e Veterinária, Oeiras,
478 Portugal.

479 Rawls, W.J., Brakensiek, D.L., 1985. Prediction of soil water properties for hydrologic
480 modelling. In: Jones, E., Ward, T.J. (Eds.), *Watershed management in the Eighties*
481 (Proceedings). ASCE, Denver, Colorado, pp. 293-299.

482 Romano, N., Hopmans, J.W., Dane, J.H., 2002. Suction table. In: Dane, J.H., Topp, G.C.,
483 (Eds.), *Methods of Soil Analysis, Part 4, Physical Methods*. Soil Science Society of
484 America Book Series, Madison, Wisconsin, pp. 692-698.

485 Rosa, R., Paredes, P., Rodrigues, G.C., Alves, I., Fernando, R.M., Pereira, L.S., Allen, R.G.,
486 2012. Implementing the dual crop coefficient approach in interactive software. 1.
487 Background and computational strategy. *Agricultural Water Management* 103, 8-24,
488 doi:10.1016/j.agwat.2011.10.013

489 Saxton, K.E., Rawls, W.J., Romberger, J.S., Papendick, R.I., 1986. Estimating generalized
490 soil water characteristics from texture. *Soil Science Society of America Journal* 50,
491 1031–1036, doi:10.2136/sssaj1986.03615995005000040039x.

492 Saxton, K.E., Rawls, W.J., 2006. Soil water characteristics estimates by texture and organic
493 matter for hydrologic solutions. *Soil Science Society of America Journal* 70, 1569–
494 1578, doi:10.2136/sssaj2005.0117.

495 Schaap, M.G., Leij, F.J., 1998. Database-related accuracy and uncertainty of pedotransfer
496 functions. *Soil Science* 163, 765-779, doi:10.1097/00010694-199810000-00001.

497 Schaap, M.G., Leij, F.J., van Genuchten, M.Th., 2001. ROSETTA: a computer program for
498 estimating soil hydraulic parameters with hierarchical pedotransfer functions. *Journal of*
499 *Hydrology* 251, 163-176, doi:10.1016/S0022-1694(01)00466-8.

500 Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop — The FAO Crop Model to
501 Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agronomy*
502 *Journal* 101, 426-437, doi:10.2134/agronj2008.0139s.

503 Troch, P.A., Mancini, M., Paniconi, C., Wood, E.F., 1993. Evaluation of a distributed
504 catchment scale water balance model. *Water Resources Research* 29, 1805–1817,
505 doi:10.1029/93WR00398.

506 Twarakavi, N.K.C., Šimůnek, J, Schaap, M.G., 2010. Can texture-based classification
507 optimally classify soils with respect to soil hydraulics? *Water Resources Research* 46,
508 W01501, doi:10.1029/2009WR007939.

509 van Genuchten, M.Th., 1980. A closed form equation for predicting the hydraulic
510 conductivity of unsaturated soils. *Soil Science Society of America Journal* 44, 892-898,
511 doi:10.2136/sssaj1980.03615995004400050002x.

512 Vereecken, H., Maes, J., Feyen, J., Darius, P., 1989. Estimating the soil moisture retention
513 characteristics from texture, bulk density, and carbon content. *Soil Science* 148, 389-
514 403.

515 Vereecken, H., Weynants, M., Javaux, M., Pachepsky, Y., Schaap, M.G., van Genuchten,
516 M.Th., 2010. Using pedotransfer functions to estimate the van Genuchten-Mualem soil
517 hydraulic properties: a review. *Vadose Zone Journal* 9, 795-820,
518 doi:10.2136/vzj2010.0045.

519 Wösten, J.H.M., Finke, P.A., Jansen, M.J.W., 1995. Comparison of class and continuous
520 pedotransfer functions to generate soil hydraulic characteristics. *Geoderma* 66, 227-237,
521 doi:10.1016/0016-7061(94)00079-P.

522 Wösten, J.H.M., Lilly, A., Nemes, A., Le Bas, C., 1999. Development and use of a database
523 of hydraulic properties of European soils. *Geoderma* 90, 169-185, doi:10.1016/S0016-
524 7061(98)00132-3.

525 Wösten, J.H.M., Pachepsky, Y.A., Rawls, W.J., 2001. Pedotransfer functions: bridging the
526 gap between available basic soil data and missing soil hydraulic characteristics. *Journal*
527 *of Hydrology* 251, 123-150, doi:10.1016/S0022-1694(01)00464-4.

528 Yates, S.R., Warrick, A.W., 2002. Geostatistics. In: Dane, J.H., Topp, G.C. (Eds.), *Methods*
529 *of Soil Analysis, Part 4, Physical Methods*. Soil Science Society of America book
530 Series, Madison, Wisconsin, pp. 81-118.

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Table 1

Main physical and chemical properties of the datasets used in the development and validation of the ternary diagrams.

Statistics	Particle size distribution				Organic carbon (g kg ⁻¹)	Bulk density (g cm ⁻³)	Volumetric water contents	
	2000-200 μm	200-20 μm	20-2 μm	<2 μm			θ _{.33 kPa}	θ _{.1500 kPa}
	(%)						(cm ³ cm ⁻³)	
Development set (n = 495)								
Mean	20.7	34.5	21.6	23.2	0.74	1.50	0.287	0.162
Std. Deviation	17.7	15.2	11.8	14.7	0.54	0.18	0.089	0.081
Minimum	0.1	0.7	1.1	0.6	0.00	0.91	0.029	0.007
Maximum	94.4	70.7	68.1	63.3	2.51	1.90	0.536	0.407
Validation set (n = 247)								
Mean	21.4	34.7	20.5	23.4	0.72	1.52	0.282	0.158
Std. Deviation	17.1	15.4	12.4	14.3	0.52	0.18	0.086	0.073
Minimum	0.1	0.8	0.9	0.1	0.00	0.92	0.029	0.006
Maximum	94.6	73.6	60.2	62.2	2.21	1.87	0.535	0.359

Table 2

Parameters of the Gaussian model fitted to the experimental semivariograms.

Volumetric water contents	Nugget C₀ (-)	Sill C₁ (-)	Total variance C (-)	Range a (cm)
$\theta_{-33 \text{ kPa}}$	0.0012	0.0078	0.009	39.745
$\theta_{-1500 \text{ kPa}}$	0.0004	0.0066	0.007	24.604

Table 3

Results of the statistical analysis between measured water retention values at -33 and -1500 kPa and ordinary kriging estimates.

Statistics	Volumetric water contents	
	$\theta_{-33 \text{ kPa}}$	$\theta_{-1500 \text{ kPa}}$
R^2 (-)	0.788	0.802
ME ($\text{cm}^3 \text{ cm}^{-3}$)	-0.001	0.001
RMSE ($\text{cm}^3 \text{ cm}^{-3}$)	0.040	0.033

Table 4

Accuracy of published pedotransfer functions in the estimation of water retention values at -33 and -1500 kPa included in the database.

PTFs	Predictors	RMSE ($\text{cm}^3 \text{cm}^{-3}$)	
		$\theta_{-33 \text{ kPa}}$	$\theta_{-1500 \text{ kPa}}$
1. Class-PTFs			
Ramos et al. (2013a)	FAO texture classes	0.055	0.048
	FAO texture classes + depth	0.054	0.047
	FAO texture classes + ρ_b	0.049	0.047
	FAO texture classes + depth + ρ_b	0.047	0.046
	ISSS texture classes	0.049	0.039
	ISSS texture classes + depth	0.047	0.038
	ISSS texture classes + ρ_b	0.042	0.037
Wösten et al. (1999)	FAO texture classes + depth	0.063	0.051
2. Continuous PTFs			
2.1. Point PTFs			
Ramos et al. (2013b)	$\text{Si}_{20 \mu\text{m}}$, C, ρ_b , Z	0.040	0.036
2.2. Parametric PTFs			
Gonçalves et al. (1997)	CS, FS, $\text{Si}_{20 \mu\text{m}}$, C, ρ_b , Z, OM, pH	0.046	0.053
Wösten et al. (1999)	$\text{Si}_{50 \mu\text{m}}$, C, ρ_b , OM, depth	0.049	0.045
Ramos et al. (2013b)	CS, FS, $\text{Si}_{20 \mu\text{m}}$, C, ρ_b , Z	0.084	0.051

CS, coarse sand; FS, fine sand; $\text{Si}_{20 \mu\text{m}}$, silt fraction at 20 μm ; $\text{Si}_{50 \mu\text{m}}$, silt fraction at 50 μm ; C, clay; ρ_b , bulk density; Z, mean depth; OM, organic matter; depth, qualitative variable having the values 1 (topsoils) and 0 (subsoils).

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Fig. 4. Ternary diagrams soil water content values at -33 kPa matric potential estimated with ordinary kriging (top) and estimation variance (bottom) of those estimates (figures on the left show the ISSS texture classes; figures on the right show the contour plots of the estimates).

Fig. 5. Ternary diagrams soil water content values at -1500 kPa matric potential estimated with ordinary kriging (top) and estimation variance (bottom) of those estimates (figures on the left show the ISSS texture classes; figures on the right show the contour plots of the estimates).

Fig. 6. Scatter plot of prediction of soil water content at -33 and -1500 kPa matric potentials with ordinary kriging versus measured values included in the validation dataset.

Fig. 7. Ternary diagram with estimates of the available water capacity (AWC).

Fig. 8. Histogram with estimates of the available water capacity (AWC).

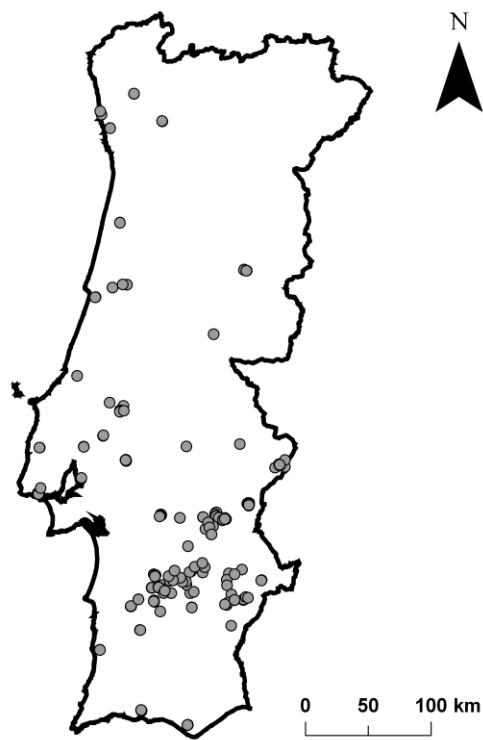


Fig 1. Location of the soil profiles.

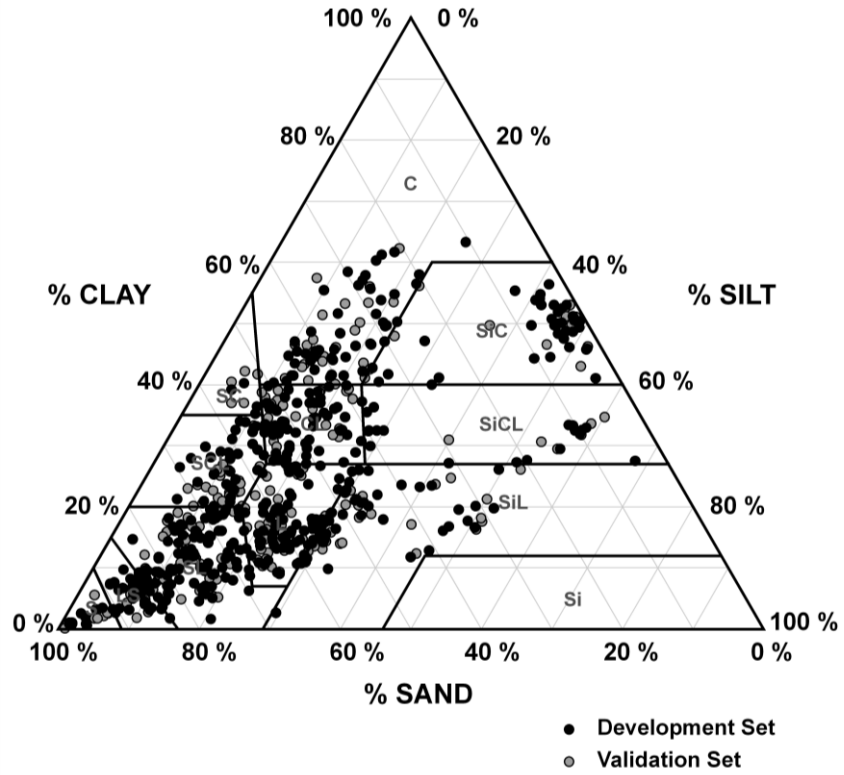


Fig. 2. Textural distribution of the datasets used in the development and validation of the ternary diagrams.

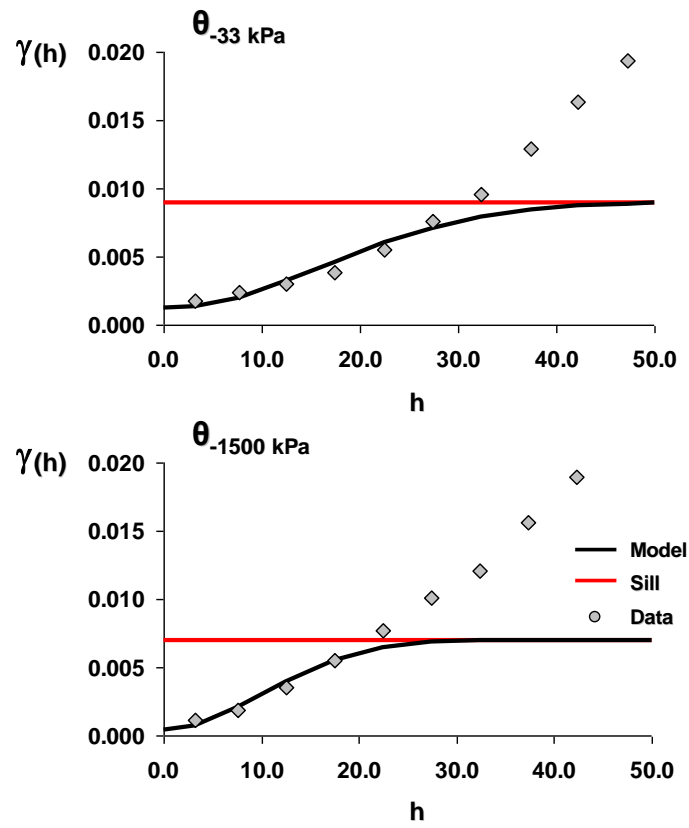


Fig. 3. Experimental semivariogram of $\theta_{-33 \text{ kPa}}$ (top) and $\theta_{-1500 \text{ kPa}}$ (bottom) with the Gaussian model fitted.

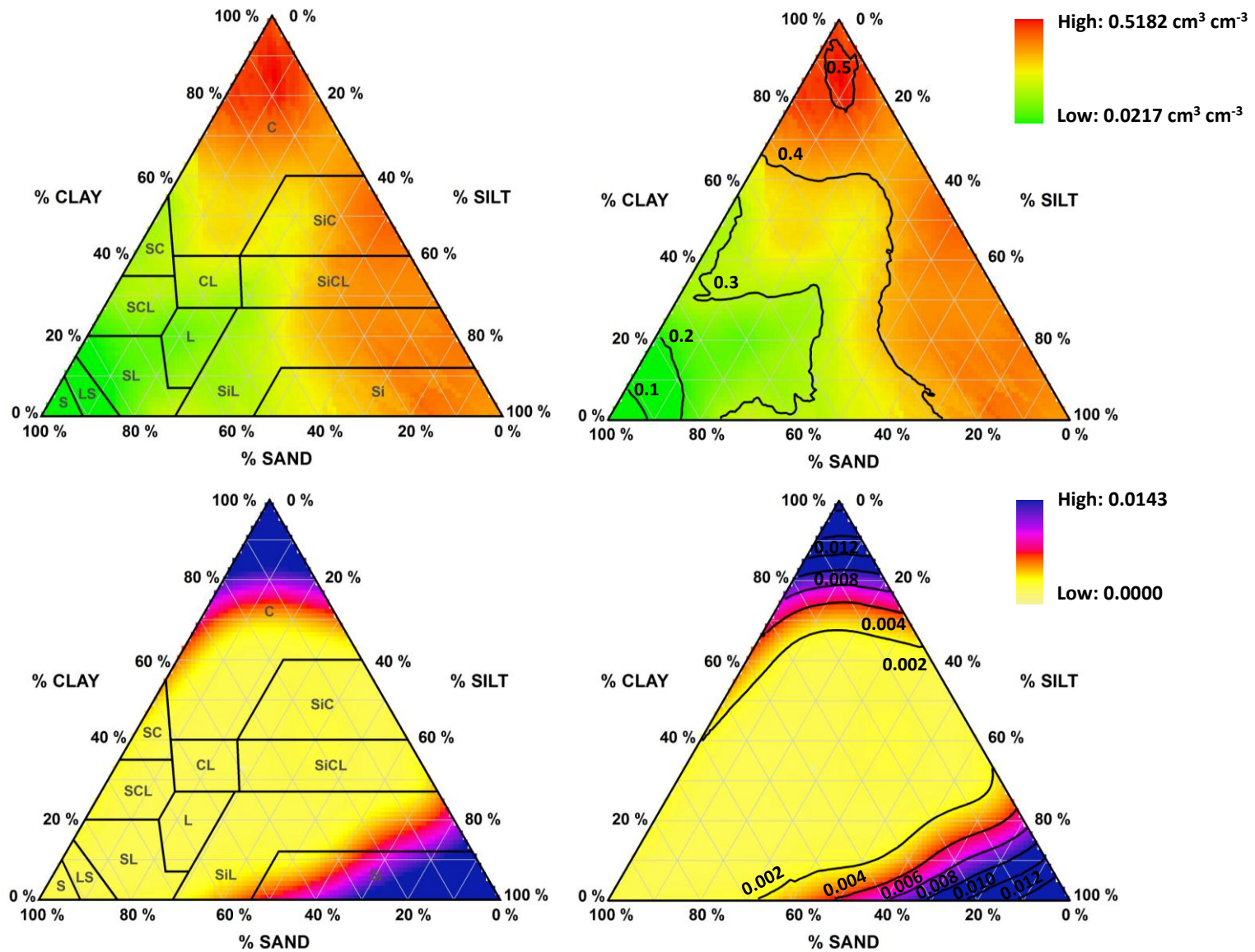


Fig. 4. Ternary diagrams soil water content values at -33 kPa matric potential estimated with ordinary kriging (top) and estimation variance (bottom) of those estimates (figures on the left show the ISSS texture classes; figures on the right show the contour plots of the estimates).

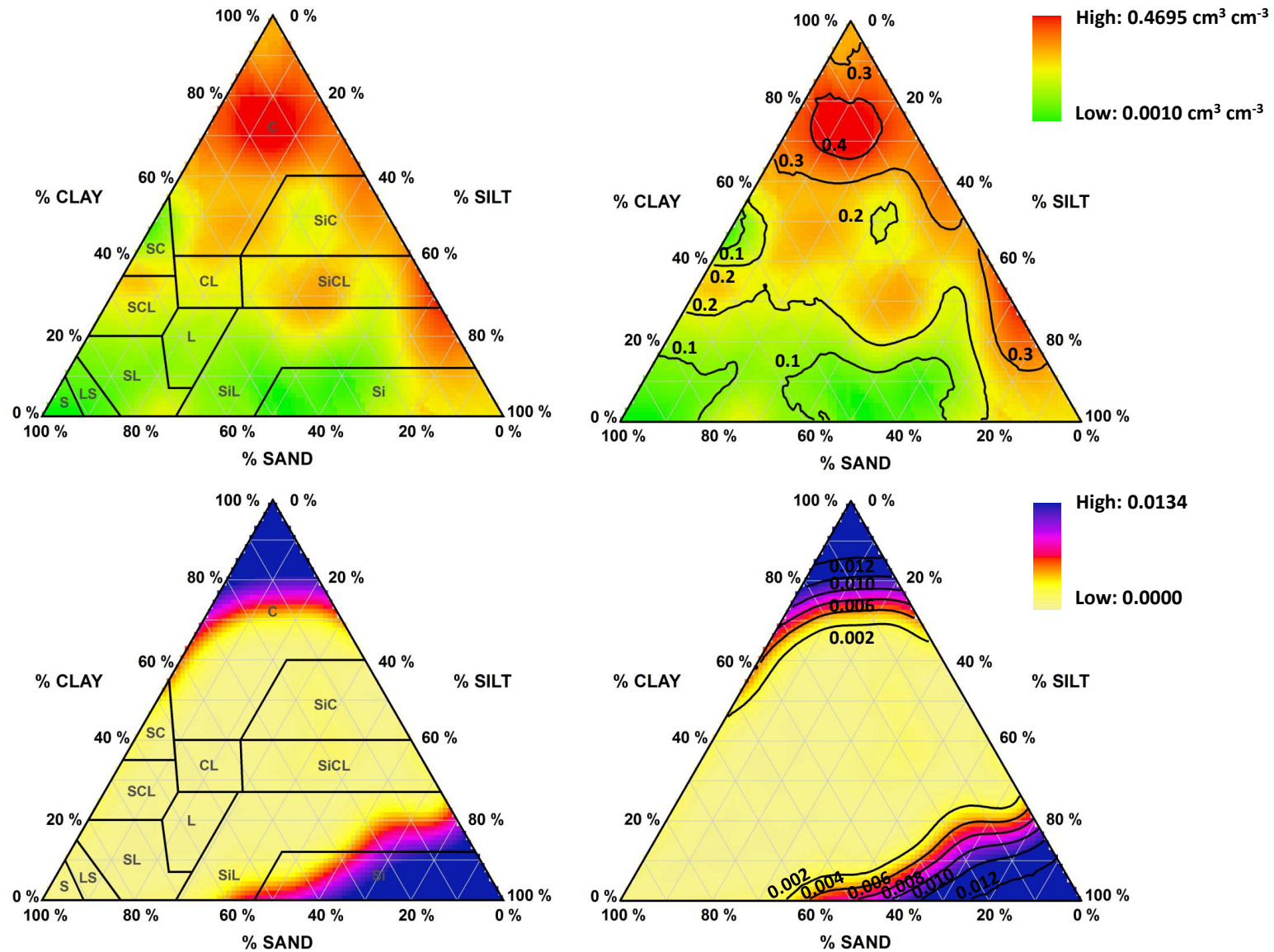


Fig. 5. Ternary diagrams soil water content values at -1500 kPa matric potential estimated with ordinary kriging (top) and estimation variance (bottom) of those estimates (figures on the left show the ISSS texture classes; figures on the right show the contour plots of the estimates).

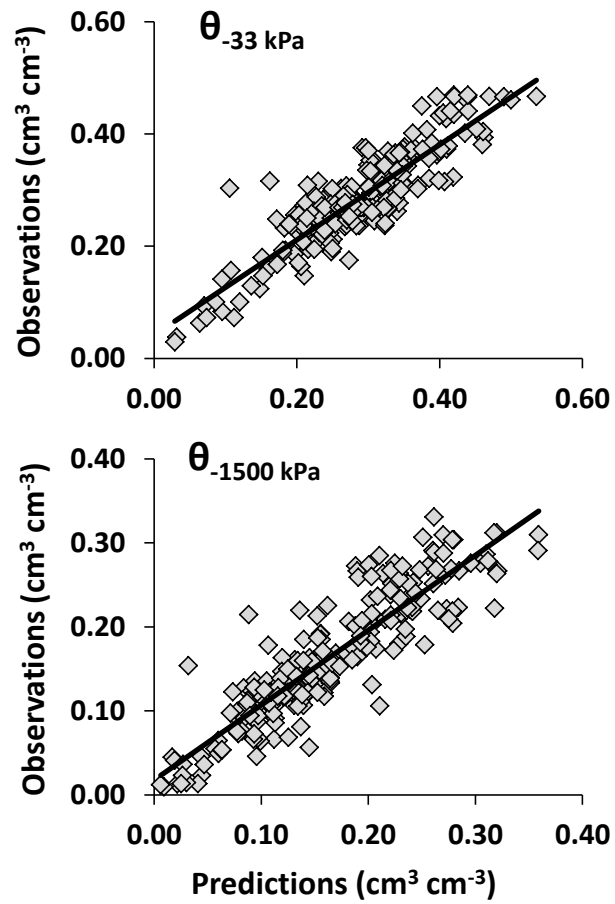


Fig. 6. Scatter plot of prediction of soil water content at -33 and -1500 kPa matric potentials with ordinary kriging versus measured values included in the validation dataset.

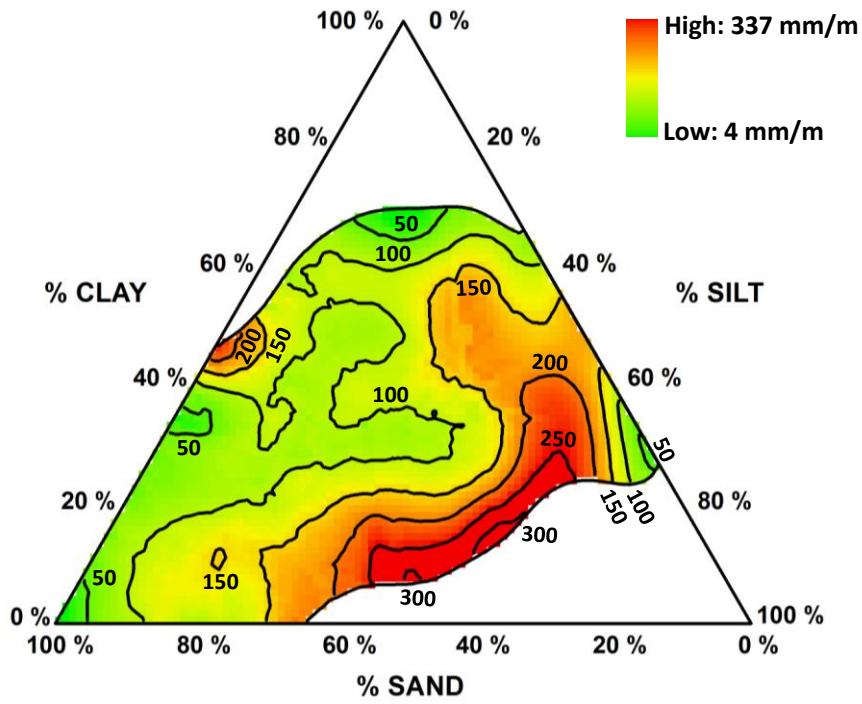


Fig. 7. Ternary diagram with estimates of the available water capacity (AWC).

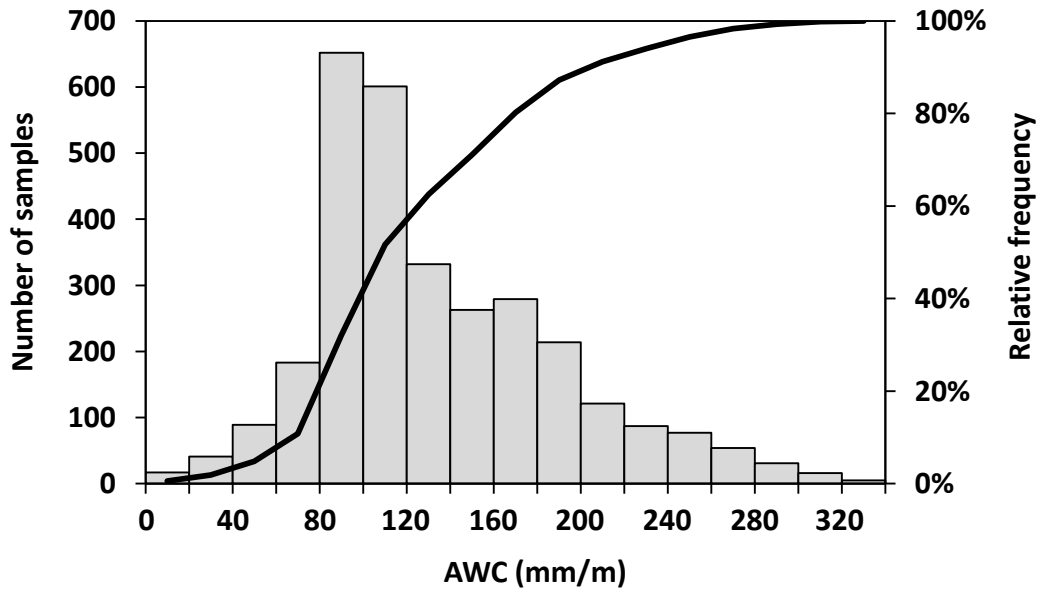


Fig. 8. Histogram with estimates of the available water capacity (AWC).