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Effect of soil organic carbon on soil water retention

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Abstract

Reports about the relationship between soil water retention and organic carbon content are contradictory. We hypothesized that this relationship is affected by both proportions of textural components and amount of organic carbon. To test the hypothesis, we used the U.S. National Soil Characterization database and the database from pilot studies on soil quality as affected by long-term management. Regression trees and group method of data handling (GMDH) revealed a complex joint effect of texture and taxonomic order on water retention at -33 kPa. Adding information on taxonomic order and on taxonomic order and organic carbon content to the textural class brought 10% and 20% improvement in water retention estimation, respectively, as compared with estimation from the textural class alone. Using total clay, sand and silt along with organic carbon content and taxonomic order resulted in 25% improvement in accuracy over using textural classes. Similar but lower trends in accuracy were found for water retention at -1500 kPa and the slope of the water retention curve. At low organic carbon contents, the sensitivity of the water retention to changes in organic matter content was highest in sandy soils. Increase in organic matter content led to increase of water retention in sandy soils, and to a decrease in fine-textured soils. At high organic carbon values, all soils showed an increase in water retention. The largest increase was in sandy and silty soils. Results are expressed as equations that can be used to evaluate effect of the carbon sequestration and management practices on soil hydraulic properties.

Keywords: Organic carbon; Water retention; Pedotransfer function; Regression tree; Soil quality

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1. Introduction

Soil water retention is a major soil hydraulic property that governs soil functioning in ecosystems and greatly affects soil management. Data on soil water retention are used in research and applications in hydrology, agronomy, meteorology, ecology, environmental protection, and many other soil-related fields. Soil water retention is measured in some soil survey programs. However, these measurements are impractical at the design stage of some projects, as well as in large-scale applications, and water retention needs to be estimated from other soil properties available from soil survey. Regression equations for such estimation are often called pedotransfer functions (PTF). Extensive research has shown that water retention is a complex function of soil structure and composition (Rawls et al., 1991; Wösten et al., 2001). Soil organic matter content and composition affect both soil structure and adsorption properties; therefore, water retention may be affected by changes in soil organic matter that occur because of both climate change and modifications of management practices. Thus, effects of organic matter on soil water retention should be understood and quantified.

Reports on the effect of changes in soil organic matter on soil water retention are contradictory. Table 1 summarizes findings of different authors. Rawls and Brakensiek (1982) and Rawls et al. (1983) found useful to include the organic carbon content in the list of PTF inputs for both − 33 and − 1500 kPa. Bell and van Keulen (1995) saw the need to use both organic carbon content and pH in estimating water content at wilting point. Beke and McCormick (1985) and Petersen et al. (1968) found it useful to employ data on organic matter content to estimate water content at − 1500 kPa, but not at − 33 kPa. In contrast, the use of organic matter content improved PTFs at − 33 kPa, but not at − 1500 kPa, in the work of Calhoun et al. (1973). Viville et al. (1986) indicated that the differences in water retention within soil profiles correlated with profiles of the organic matter content. Hollis et al. (1977) found the organic matter content to be the most influential soil variable to estimate water content at −5 kPa. Lal (1979) and Danalatos et al. (1994) did not find any effect of organic matter content on water retention; the latter

Table 1
Observed effect of organic matter content on soil water retention at two water potentials

Authors	− 33 kPa	− 1500 kPa
Bauer and Black (1981)	Yes	Yes
Bell and van Keulen (1995)	No	Yes
Beke and McCormick (1985)	No	Yes
Petersen et al. (1968)	No	Yes
Calhoun et al. (1973)	Yes	No
Lal (1979)	No	No
Danalatos et al. (1994)	No	No
De Jong (1983)	Yes	Yes
Jamison and Kroth (1958)	Yes	Yes
Riley (1979)	Yes	Yes
McBride and MacIntosh (1984)	ND	Yes
Salter and Haworth (1961)	No	No

attributed that to the generally low organic matter content in their samples. Similarly, Puckett et al. (1985) did not use organic matter in PTFs because of its low level in samples. Bauer and Black (1981) found that the effect of organic carbon on water retention in disturbed samples was substantial in sandy soil and marginal in medium- and fine-textured soils. De Jong (1983) experimented with disturbed soil samples and found that the increase in organic matter content meant higher water content at all suctions. Similar observations were made by several other authors (Jamison and Kroth, 1958; Petersen et al., 1968; Riley, 1979; Ambroise et al., 1992; Kern, 1995). Salter and Haworth (1961) argued that organic matter might not be an important predictor to estimate water content at specific suctions, but it is an important factor if water contents at field capacity and wilting point are measured directly. McBride and MacIntosh (1984) found that organic matter content affected water retention at -1500 kPa only when this content was larger than 5%. Most of the cited authors worked with small number of soils from a specific region. Kay et al. (1997) compared relative effects of organic matter on water retention using PTFs developed in different regions and found large regional differences.

The review of the existing studies of the effect of organic carbon on soil water retention begets a hypothesis that this effect may depend on proportions of textural components and amount of organic carbon. The objective of this work was to test the hypothesis using the massive U.S. National Soil Characterization Database and the database from pilot studies on soil quality as affected by long-term management.

2. Materials and methods

2.1. Soil data sets

A subset of about 12,000 samples was extracted from the National Soil Characterization database (Soil Survey Staff, 1995). The samples had data on soil texture, organic matter content, water retention at -33 kPa and -1500 kPa, bulk density at -33 kPa, and a taxonomic characterization. An overview of properties of the subset is presented in Fig. 1. Sandy loams, loams, and silt loams were represented best and together constituted more than 60% of all samples. Silts, sands, sandy clay loams, and sands were represented each with less than 300 samples. Mollisols and Alfisols were represented better than other taxonomic orders, whereas Spodosols, Oxysols, and Histosols were represented relatively poorly. The organic carbon content in the samples encompassed a range from 0.1% to 20% representative for mineral soils. Methods of soil analysis were the same for all the samples (Soil Survey Laboratory Methods Manual, 1996).

The database from pilot studies on soil quality as affected by long-term management includes 111 samples from A horizon taken at sites in Colorado (4 samples), Iowa (11), Minnesota (27), Missouri (9), Montana (6), Nebraska (23), North Dakota (14), Texas (17), where properties of the same soil are compared under native vegetation, under conventional cropping system, and under soil conservation practice. There were five Udolfs, five Ustols, two Aqualfs, one Ustalf, and one Aquoll among the soils. Silty clay loams were represented with 26% of all samples, loams, and silt loams constituted 19% each, loamy sands, sandy loams, and clay loams were represented with 9% of samples

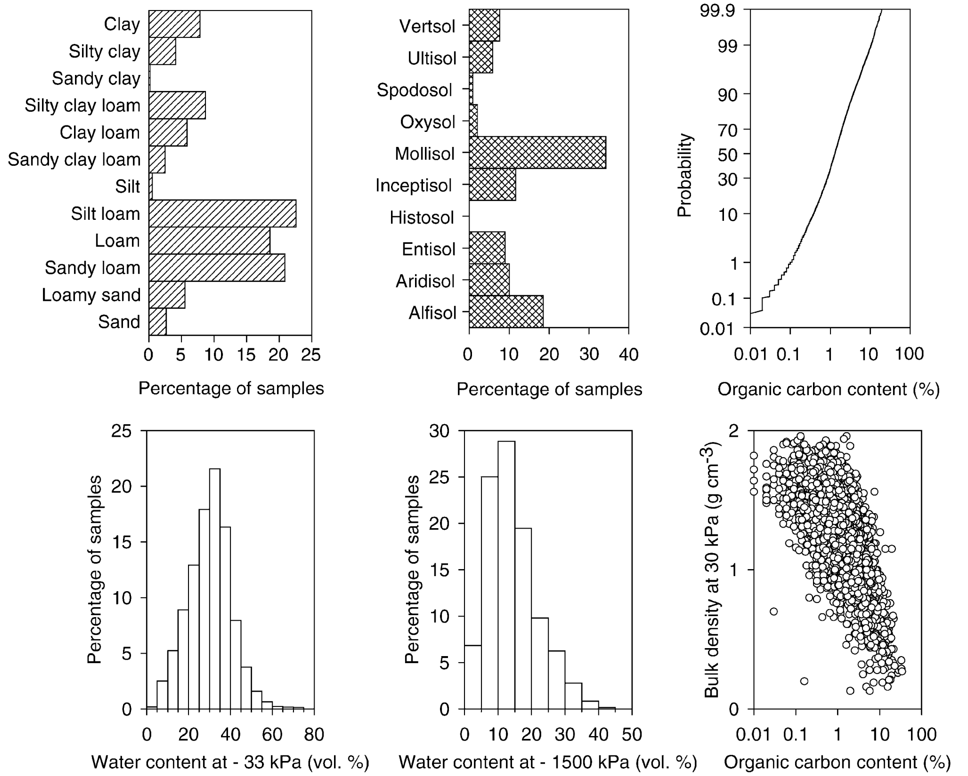

Fig. 1. Overview of the subset from the US National Soil Characterization database used in this work.

each, 5% of all samples were sands, and clays and sandy clay loams were about 2.5% each.

2.2. Methods to quantify the effect of organic carbon on water retention

The regression tree modeling and the group method of data handling (GMDH) were applied to relate the water retention at −33 and −1500 kPa to organic carbon content and texture. Regression tree modeling is an exploratory technique for uncovering structure in data (Clark and Pregibon, 1992). The resulting model partitions data first into two groups, then into four groups, etc., providing groups as homogeneous as possible at each level of partitioning. Each partitioning can be viewed as a branching, and the final fit of model to data looks as a tree with two branches originating in each node. Regression trees were used in studies on land quality assessment and soil properties estimation (Van Lanen et al., 1992; McKenzie and Jacqier, 1997; McKenzie and Ryan, 1999). The SPLUS software (Mathsoft, 1999) has been used in this work.

Regression trees partition data in a recursive fashion. Suppose that a database is organized as a table with columns x_1, x_2, x_3, . . ., x_N, representing predictor variables and the column y representing the response variable. First, the database table is sorted by column x_1, and all possible splits of this column into two parts are used to compute the measure of inhomoneity among the values y in these two parts. Then the database table is sorted by column x_2, and all possible splits are used to compute a measure of inhomoneity among y, etc. Finally, all splits in all columns are compared and the predictor variable is found to provide the split with the smallest inhomogeneity in two parts of database. This variable provides the first branching of the tree: the part of the database table with values of the branching variable above (below) the split constitutes the left (right) branch. The first node is formed by the split, and the first binary partitioning is accomplished. The branch tables are further partitioned in the same way.

The important advantage of regression trees is that predictor variables appropriate for tree-based models can be both numeric and categorical, the latter are called factors in the literature (Breiman et al., 1993) and SPLUS software manuals (Mathsoft, 1999). If x is a factor, with say k levels, in general, there are $2^{k-1}-1$ possibilities to make a split. All of them are tested for inhomogeneity in the response variable. For example, if x has three levels (a,b,c), the possible splits consist of $a\,|\,bc$, $ab\,|\,c$, and $b\,|\,ac$. If x is numeric with k distinct values, then there are $k-1$ ways to divide the levels/values into two contiguous, nonoverlapping sets.

The inhomogeneity after a split is measured by computing deviances which for an observation y are defined as

$$D(\mu y) = \sum (y_i - \mu)^2.$$

Here, μ is the mean value across all observations. Each possible split generates left $\sum_L D(\hat{\mu}_L, y)$ and right $\sum_R D(\hat{\mu}_R, y)$ deviance values, and the split deviance which is the sum of right and left deviances:

$$D_{\text{split}}(\hat{\mu}_L, \hat{\mu}_R, y) = \sum_L D(\hat{\mu}_L, y_i) + \sum_R D(\hat{\mu}_R, y_i).$$

The split that maximizes the change in deviance

$$\Delta D = \sum D(\mu, y_i) - D_{\text{split}}(\hat{\mu}_L, \hat{\mu}_R, y)$$

is the split chosen at a given node. The number of terminal nodes can be an input in the algorithm.

The group method of data handling (GMDH) was used to develop the equations to relate water retention to contents of textural components and organic carbon. Group method of data handling (GMDH) combines advantages of regression analysis and artificial neural networks (Hecht-Nielsen, 1990). The GMDH constructs a flexible equation of neural network type to relate the inputs to outputs; at the same time, it has a built-in algorithm to retain only essential input variables (Farlow, 1984). The GMDH has been recently used to develop pedotransfer functions (Pachepsky and Rawls, 1999; Gimènez et al., 2001).

The general functioning of the GMDH algorithm can be understood from the following example. Let the original data contain one column of observed values of y, and N columns containing observed values of the independent variables x_1, x_2,..., x_N. The algorithm works by iterations consisting of three steps. In the original version of the algorithm, step 1 consists of obtaining preliminary estimates of y using quadratic regressions:

$$z = A + Bu + Cv + Du^2 + Euv + Fv^2$$

where A, B, C, D, E, and F are regression coefficients. All independent variables $x_1, x_2, \ldots, x_N$ are taken two at a time to become u and v in this equation, and regressions are found so that values of z best fit the dependent variable y. The resulting columns of z_m values, $m = 1, 2, N(N-1)/2$, contain estimates of y from each polynomial and are interpreted as new variables that may have better predictive capability than the original $x_1, x_2, \ldots, x_N$. Step 2 consists of screening out the least effective new variables based on the fit quality. The list of input variables is modified at the end of step 2. Step 3 consists of testing whether the set of equations can be further improved. The smallest value of the selection criterion obtained from this iteration is compared with the smallest value obtained from the previous iteration. If an improvement is achieved, steps 1 and 2 are repeated; otherwise, the iterations stop and the network is built.

The version of the GMDH algorithm used in this study is coded in the commercial software ModelQuest (AbTech Corp., 1992–1996). This software uses three input variables at a time to obtain preliminary estimates from either linear combinations of input variables or cubic polynomials of two or three independent variables. The number of variables to retain in the input list is limited. Both original input variables and the output variable are normalized to have zero mean and unit variance, and the normalized variables participate in network building.

Both the regression trees and the GMDH are iteratively building models of progressively increasing complexity. The processes have to be stopped to prevent overtfitting; otherwise, the predictive capability of the resulting models with respect to new data will be deplorable. The jackknife cross-validation method (Good, 1999) was applied with both algorithms in this work. The database was randomly divided 10 times into development and testing subsets in 9:1 proportion, and the average accuracy of estimating water retention was expressed by root-mean-square error (RMSE) for both development and testing subsets. The number of terminal nodes and the number of iteration in the GMDH algorithm were varied to provide the minimum average RMSE in the validation data sets.

The advantage of regression trees is the transparency of results, and the relative importance of inputs can be easily assessed. The GMDH algorithm provides equations that can be used both for predictions and for the sensitivity analysis. We used regression trees first to explore data, and then GMDH to build regression equations.

3. Results

3.1. Regression trees

The regression tree for the soil water content at − 33 kPa is shown in Fig. 2. Soil textural class and organic carbon content are predictor variables. The first split divides soils by their textural class. Sands, loamy sands, and sandy loams form one large group,

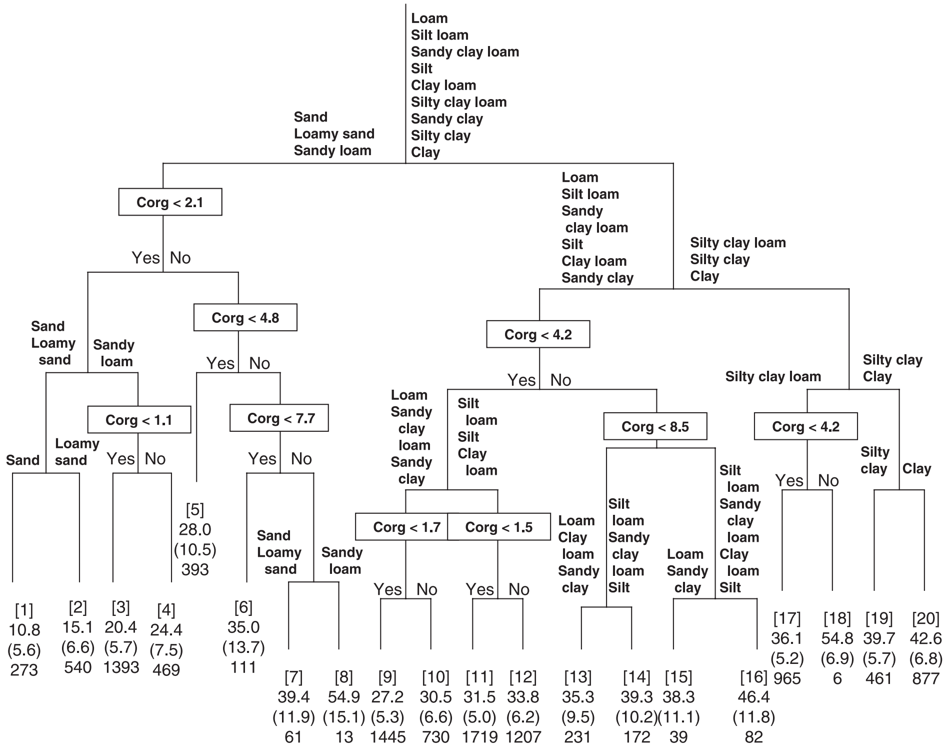

Fig. 2. Regression tree for soil water retention at −33 kPa with textural class and organic carbon content (C_{org}) used as predictors. The group or the node number is shown in brackets, the average volumetric water content in the group is shown below the node number, the standard deviation within the group is shown in parentheses, and the bottom number is the count of samples in the group.

and soils with finer texture form another one. The organic carbon content (C_{org}) is the most important splitting variable in coarse-textured soils, the critical value is 2.1%. Finer soils are further split in the group with fine texture (loam, silt loam, sandy clay loam, silt, clay loam, and sandy clay) and another group with the very fine texture (silty clay loam, silty clay, and clay). The organic carbon content is the next important split variable in soil with fine texture, whereas soils with the very fine texture continue to be partitioned by the textural class. Only silty clay and clay soils do not show a need in using C_{org} to make the soil sample groups more homogeneous by their water retention at −33 kPa.

Partitions by organic carbon contents result in forming groups with larger average water contents for larger C_{org} (see node pairs [3] and [4], [9] and [10], [11] and [12], [17] and [18], and the group of nodes [1]–[4] vs. the group [5]–[8]). Although a general trend of increase in water retention at −33 kPa with the increase in clay content can be seen in Fig. 2, samples of coarse soils with high organic carbon content may have average water retention higher than samples of fine-textured soils with low organic carbon content (see pairs of nodes [7] and [11] or [5] and [9]). Several small groups of samples have very high average water retention which is caused by the low bulk density in those samples (nodes [7], [8], and [18]).

Regression tree for the water retention at − 1500 kPa is shown in Fig. 3. Predictors here were clay, sand, and organic carbon content. The tree shows organic carbon plays a substantial role in defining water retention at − 1500 kPa in soils with clay content less than 19%, i.e., in sands, loamy sands, sandy loams, and coarse-textured loams and silt loams. In coarse soils, an increase in organic carbon increases the water retention (see pairs of nodes [1] and [2], [6] and [7], and triplet of nodes [8], [9], and [10]). Organic carbon becomes not important in sandy soils with low organic matter content (node [3]). In soils with clay content greater than 19%, the average group water retention grows as the clay content increases.

A summary of the regression tree accuracy with various predictors is shown in Table 2. Using the taxonomic order as a predictor improves predictions as compared with using only textural class for the − 33 kPa matrix potential. However, using organic carbon with textural class makes predictions substantially better and a further addition of the taxonomic order does not bring much improvement. Using proportions of textural components make predictions slightly better than just using the textural class. The bulk density value makes better predictor than the organic carbon content at this matrix potential. For the matrix potential − 1500 kPa, using organic carbon and taxonomic order along with the textural class result in small improvement of predictions. Bringing proportions of textural components as the predictors gives a substantial improvement as compared with using just textural class, and organic carbon content adds to accuracy if used with sand and clay.

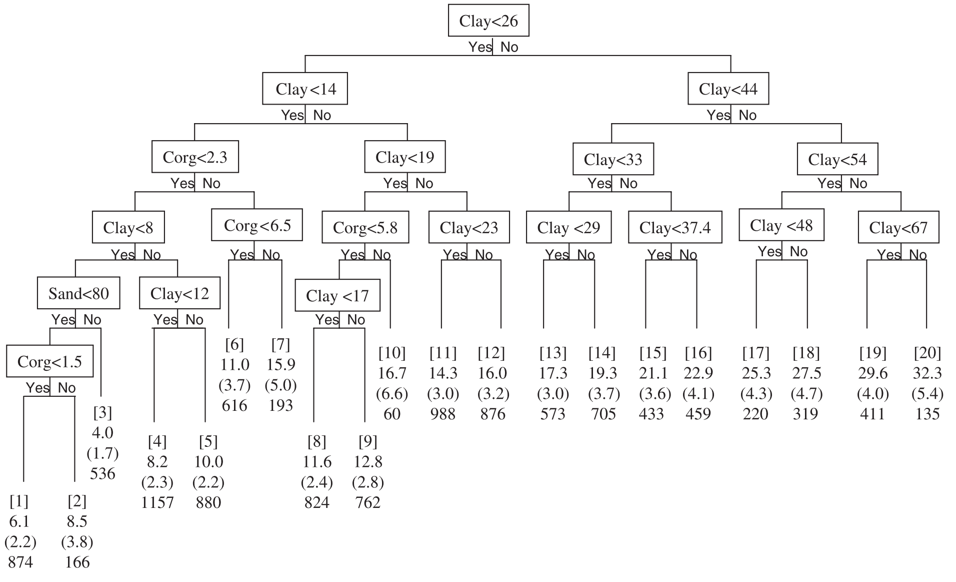

Fig. 3. Regression tree for the soil water retention at − 1500 kPa with proportions of textural fractions and organic carbon content (C_{org}) used as predictors. The group or the node number is shown in brackets, the average volumetric water content in the group is shown below the node number, the standard deviation within the group is shown in parentheses, and the bottom number is the count of samples in the group.

Table 2
Root-mean-square error of the water retention predictions with regression trees

Predictors	Volumetric water content at − 33 kPa, θ_{33} (%)	Volumetric water content at − 1500 kPa, θ_{1500} (%)	$\theta_{33}-\theta_{1500}$	Slope
No textural information				
Organic carbon	9.0	6.9	6.6	0.092
Textural class				
Textural class	7.4	3.9	6.6	0.077
Textural class + taxonomic order	6.9	3.8	6.3	0.076
Textural class + organic carbon	6.4	3.7	6.1	0.076
Textural class + organic carbon + taxonomic order	6.3	3.6	5.9	0.074
Textural composition				
Clay + silt + sand	7.0	3.4	6.2	0.069
Clay + silt + sand + organic carbon	6.2	3.1	5.8	0.069
Clay + silt + sand + organic carbon + taxonomic order	5.9	3.1	5.8	0.067
Texture + bulk density				
Clay + silt + sand + bulk density	5.6	3.1	5.6	0.067

3.2. Group method of data handling

Application of the GMDH resulted in the following equations to estimate water retention at − 33 kPa (θ_{33}) and − 1500 kPa (θ_{1500}), both in vol.%:

$$\begin{aligned}\theta_{33} = {} & 29.7528 + 10.3544(0.0461615 + 0.290955x - 0.0496845x^2 \\ & + 0.00704802x^3 + 0.269101y - 0.176528xy + 0.0543138x^2y + 0.1982y^2 \\ & - 0.060699y^3 - 0.320249z - 0.0111693x^2z + 0.14104yz + 0.0657345xyz \\ & - 0.102026y^2z - 0.04012z^2 + 0.160838xz^2 - 0.121392yz^2 - 0.0616676z^3);\end{aligned}$$

$$\begin{aligned}\theta_{1500} = {} & 14.2568 + 7.36318(0.06865 + 0.108713x - 0.0157225x^2 + 0.00102805x^3 \\ & + 0.886569y - 0.223581xy + 0.0126379x^2y - 0.017059y^2 \\ & + 0.0135266xy^2 - 0.0334434y^3 - 0.0535182z - 0.0354271xz \\ & - 0.00261313x^2z - 0.154563yz - 0.0160219xyz - 0.0400606y^2z \\ & - 0.104875z^2 + 0.0159857xz^2 - 0.0671656yz^2 - 0.0260699z^3)\end{aligned}$$

where $x = -0.837531 + 0.430183\mathrm{C_{org}}$; $y = -1.40744 + 0.0661969\mathrm{Clay}$; $z = -1.51866 + 0.0393284\mathrm{Sand}$; $0.02 < \mathrm{C_{org}} < 28.44$; $0.0 < \mathrm{Clay} < 90$; and $0.7 < \mathrm{Sand} < 95$. The RMSE of those equations is 6.3 vol.% for − 33 kPa and 3.1 vol.% for − 33 and − 1500 kPa, respectively. The RMSE were higher, 6.8 and 3.4 vol.%, respectively, when only clay and sand content were used.

The GMDH equations were used to generate isolines of water content at − 33 kPa for various values of organic matter content as shown in Fig. 4. It can be seen that for the same proportion of clay and sand, the water retention mostly increases as the organic carbon content increases. However, a decrease in water retention with the increase in C_{org} value can be seen for fine-textured soils with high clay content. Where water retention increases in parallel with C_{org}, the largest increment in water contents occurs in coarse-textured soils. Isolines of water contents at − 1500 kPa for various C_{org} are shown in Fig. 5. A substantial increase in water retention with the increase of C_{org} can be observed in samples with low clay contents. An opposite trend can be seen in soils with very large clay contents.

The GMDH equations allow one to estimate the sensitivity of water retention to changes in organic carbon content for different levels of the initial carbon content in soil. An example of such estimation is shown in Fig. 6, where changes in water content at − 33 kPa per 1% increase in organic carbon content are shown for three levels of the organic carbon content before the change. At low carbon content of 1%, the sensitivity is the highest. Water retention dramatically increases (decreases) in soils with low (high) clay content. An intermediate value of the initial organic carbon content of 3% makes the changes less dramatic, but clay contents of about 50% continue to separate regions of the textural triangle in which changes in water retention occur in the same or in opposite

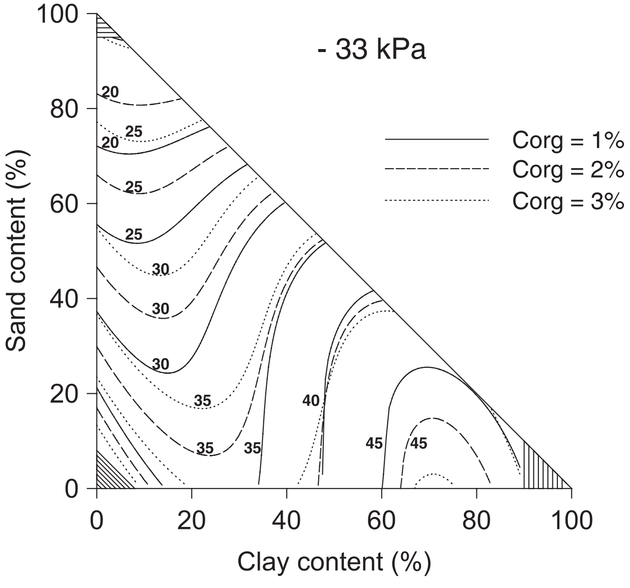

Fig. 4. Isolines of soil water content at − 33 kPa in the textural triangle at different organic carbon contents. No data were available for excluded corner areas of the triangle.

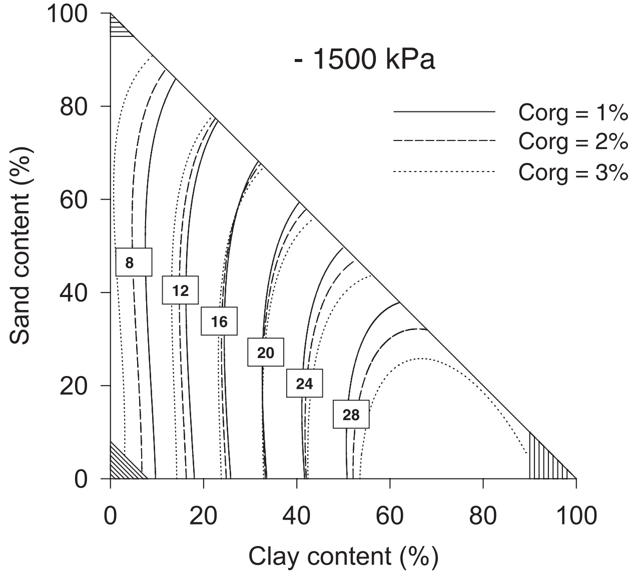

Fig. 5. Isolines of soil water content at − 1500 kPa in the textural triangle at different organic carbon contents. No data were available for excluded corner areas of the triangle.

direction with changes in C_{org}. The high initial value of the initial organic carbon content of 5% results in a different sensitivity pattern. An increase in organic matter content leads to the increase in water retention practically for all textures although high clay content leads to the comparatively smaller increases. The tendency of silty soils to respond to the changes in C_{org} with changes in their water retention similarly to sandy soils having the same clay contents can be clearly seen at 5% initial C_{org} value. The same tendency can be traced at lower initial C_{org} values.

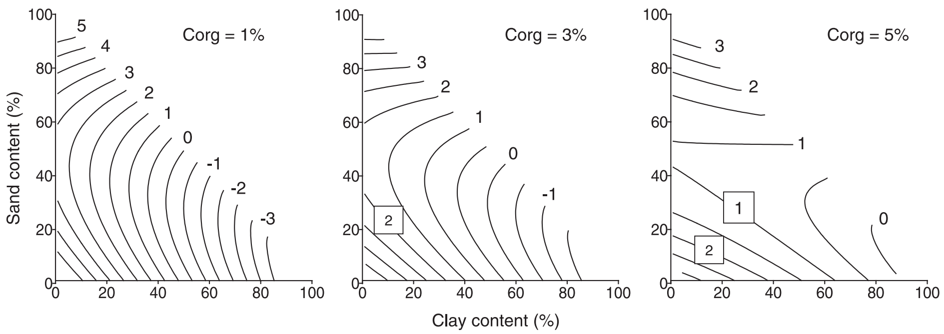

Fig. 6. Changes in soil water content at − 33 kPa (vol.%) per 1% change in organic carbon content with various initial carbon contents C_{org} shown in the graph.

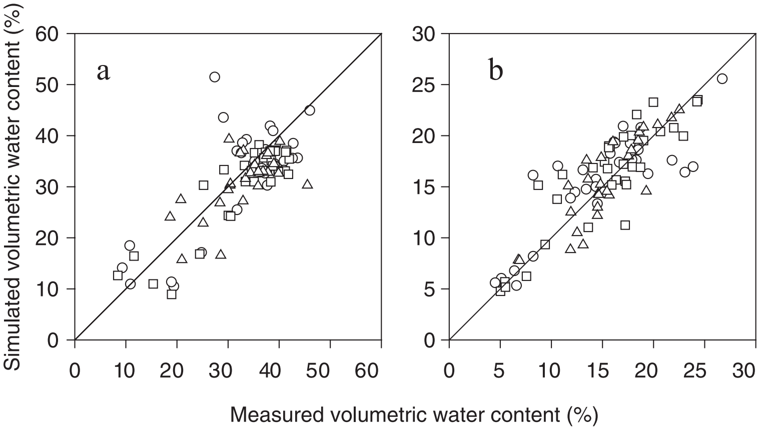

Fig. 7. Results of applying the GMDH equations to the data set from NRCS soil quality studies. ○, native vegetation; □, conventional practice; △, soil conservation practice. (a) − 33 kPa, (b) − 1500 kPa.

3.3. Testing the GMDH equations with data from pilot studies of soil quality

Results of estimating water retention with the data from the independent data set from the NRCS pilot study of soil quality are shown in Fig. 7. The root mean square of estimates is 5.9% and 2.6% for water retention at − 33 and at − 1500 kPa, respectively. This accuracy is even better than across the whole database. Slopes of regressions of measured vs. simulated values did not differ significantly for native, conventional and conservation subsets at the 0.05 significance level.

4. Discussion

Organic carbon content appeared to be an important soil property to improve estimation of soil water retention from soil texture. Including C_{org} in regressions improved accuracy of regression tree (Table 1) and GMDH predictions. The 15% and 10% decrease in RMSE were achieved at − 33 and − 1500 kPa, respectively. This may be related to the fact that the structure-forming effect of organic matter is affecting the water retention at water content close to field capacity to larger extent than water retention close to the wilting point. The water retention of organic matter itself is a probable reason of the effect of C_{org} on water retention at − 1500 kPa although the organic matter is known to modify the availability of adsorption sites of clay minerals to water (Cristensen, 1996). Using sand, silt, and clay contents resulted in slight improvement over using just textural class (Table 2). Such improvement was more pronounced for water retention at − 1500 kPa than at − 33 kPa.

The textural composition is a significant factor affecting the importance of organic carbon in estimating water retention. Regression trees (Figs. 2 and 3) show that the organic carbon content is a leading variable to group coarse soils by their water retention. In fine-textured soils, the organic carbon content is used as a grouping variable much later. The sensitivity analysis (Fig. 6) also shows that water retention of coarse-textured soils is much more sensitive to changes in organic carbon as compared with fine-textured soils. These results concur with data of Khaleel et al. (1981), who reviewed experiments on application of organic waste and found that the increase in gravimetric water contents at -33 kPa is larger for coarse-textured soils than those for fine-textured soils. Fig. 4 shows that either clay content alone or sand content alone is not a satisfactory predictor of the effect of the organic carbon on water retention at -33 kPa. For example, the 35% isoline with 2% C_{org} in Fig. 4 is applicable to samples with 20% of sand and 5% of clay, 10% of sand and 20% of clay, and 20% of sand and 35% of clay. Ten percent of sand provides an increase in water retention at low clay contents and a decrease in water retention at high clay contents of more than 50%. We note that the decrease in water retention in heavy clay soils with increasing organic matter content seen in Figs. 4, 5 and 6 was not previously reported in literature. This result may be database-specific because our data for high clay content soils are relatively sparse (Fig. 1a). It may also be related to the fact that many of soils with high clay contents in the database are Vertisols in which increase in organic matter decreases bulk density and decreases the volumetric water content although gravimetric water content may actually increase. A general trend of decrease in bulk density with increase of organic carbon content in the soils in the database can be traced in Fig. 1.

A detailed analysis of data on bulk density was outside of the scope of this work. We note that the bulk density value was a better complimentary predictor of water retention at -0.33 kPa as compared with organic carbon content (Table 2) and, therefore, if available, may be a preferable predictor of water retention. Bilk density values can represent the effect of organic carbon on water retention if the primary effect of organic carbon is changing bulk density. Because the correlation between organic carbon content and bulk density is relatively low (Fig. 1e), it may be interesting to try using both those properties along with texture as the water retention predictors.

The sensitivity of water retention to changes in organic matter content decreases as the initial organic carbon content increases (Fig. 6). A similar conclusion can be drawn from equations presented by Khaleel et al. (1981) for water retention of soils amended with organic waste in soils in USA, England, India, and Germany. Their equations also show that the relative increase becomes smaller as the increase in organic matter content grows. A similar pattern can be observed in Fig. 6. The reduction of the effect of increasing organic matter on water content at 5 kPa with the increase in the original value of the organic matter content was reported by Hollis et al. (1977). Water retention of peat soils will probably present a limit case for the increase of organic matter content in samples.

Satisfactory results of testing the GMDH regressions against data from NRCS studies of soil quality indicate that soil survey databases can be used to project changes in water retention caused by differences in soil management. The soil survey databases contain both data on soils in natural ecosystems and on agricultural soils, showing similar response of soil water retention to changes in organic matter content. Organic amendments caused changes in soil water retention quantitatively and qualitatively similar to those reported in this work (i.e., Gupta et al., 1977; Unger and Stewart, 1974; Kaldivko and Nelson, 1979).

The regression trees and the GMDH provided similar accuracy in estimating soil water retention. One explanation may be that the functional form of the deterministic component of relationship between water retention and soil composition is more complex than the third-degree polynomials are able to emulate. On the other hand, regression trees may have a substantial variability within the groups, but the grouping itself mimics the general pattern of relationships within the database better than the polynomials do. Example of this work indicates an opportunity of the wider use regression trees in the development of pedotransfer functions. Regression tree results (Figs. 2 and 3) provided a useful visualization of relationships in database in this work and permitted a preliminary ranking of input soil properties to estimate water retention. The differences in relative importance of organic carbon content in coarse- and fine-textured soils could be clearly seen. By design, regression trees did not allow a formal sensitivity analysis; this had to be overcome using a neural network-type regression technique of the GMDH.

Modeling of changes of carbon in soils and related changes in ecosystem productivity attract significant attention with regard to climate changes and management changes. Existing models lack the feedback effect of carbon accumulation on pore-size distributions and water retention. Results of this work can be used in those models to improve their predictive ability.

5. Conclusion

(1) Relationship of soil water retention to organic carbon content is affected by proportions of textural components.

(2) Soil water retention at -33 kPa is affected more strongly by the organic carbon than water retention at -1500 kPa.

(3) Water retention of soils with coarse texture is substantially more sensitive to the amount of organic carbon as compared with fine-textured soils.

(4) The effect of changes in organic carbon content on soil water retention depends on the proportion of textural components and the amount of organic carbon present in the soil. At low carbon contents, an increase in carbon content leads to an increase in water retention in coarse soils and to decrease in water retention in fine-textured soils. At high carbon contents, an increase in carbon contents results in an increase in water retention of all textures.

(5) A comparable accuracy in estimating water retention has been achieved with regression trees and with polynomial neural networks of the group method of data handling.

(6) Test of the predictive ability of the GMDH equations resulted in the same accuracy of estimates for the independent data from soil quality studies as for the data set from the National Soil Characterization database.

(7) The developed equations can be used to evaluate effect of the soil carbon sequestration on soil hydraulic properties.

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