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SELECTING PARAMETERS FOR AN SOIL QUALITY INDEX

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During the last decades, soil quality evaluation emerged as a very important field of study, especially with the «new» reconnaissance of the multiple soil functions in the environment. Up to the present moment there are no standard methods of soil quality evaluation, as it is defined taking into account only the soil and not the whole complex of «land» elements as did previous evaluating systems. In this respect, Principal Component Analysis emerged as the main method of reaching a minimum data set, in order to create indices of soil quality.

Keywords: soil quality index, parameter selection, minimum data set, principal component analysis.

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ВИБІР ПАРАМЕТРІВ ДЛЯ ПОКАЗНИКА ЯКОСТІ ҐРУНТУ

Протягом останніх десятиріч, оцінка якості ґрунту стала дуже важливою областю дослідження, особливо з «новою» рекогносцировкою різних функцій ґрунту в навколишньому середовищі. В теперішній час відсутні стандартні методи оцінки якості ґрунту, оскільки вона визначається з врахуванням тільки одного ґрунту, а не всього комплексу елементів «землі», як це було в попередніх оціночних системах. В цьому відношенні аналіз головних компонентів є основним методом досягнення мінімального набору даних для створення показників якості ґрунту.

Ключові слова: показник якості ґрунту, вибір параметрів, мінімальний ряд даних, аналіз головних компонентів.

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ВЫБОР ПАРАМЕТРОВ ДЛЯ ПОКАЗАТЕЛЯ КАЧЕСТВА ПОЧВЫ

В течение последних десятилетий, оценка качества почвы стала очень важной областью исследования, особенно с «новой» рекогносцировкой различных функций почвы в окружающей среде. В настоящее время отсутствуют стандартные методы оценки качества почвы, так как она определяется с учетом только одной почвы, а не всего комплекса элементов «земли», как это было в предыдущих оценочных системах. В этом отношении анализ главных компонентов явился основным методом достижения минимального набора данных для создания показателей качества почвы.

Ключевые слова: показатель качества почвы, выбор параметров, минимальный набор данных, анализ главных компонентов.

Soil quality and its protection are some of the main contemporaneous preoccupations, rivaled only by climatic changes and their impact or by biodiversity protection. In the last decades, more and more studies accentuate the need of solving problems such as alimentary security and the corresponding quality of environmental components. In this context evolved the discussions regarding soil quality. As Cârstea (2001) remarks, these preoccupations have their roots in the harmful effects of increased soil resources' exploitation.

Soil quality evaluation is necessary for monitoring the long term effects of the agricultural practice son soil; appreciating the economic impact of the politics that desire to improve soil quality; appreciating the politics that address the factors that affect soil quality. One of the objectives of soil quality evaluation is the prognosis of its susceptibility to different risk phenomena, so as to support the specific functions regarding its quality.

MATERIALS AND METHODS

In order to exemplify the application of Principal Component Analysis in the reduction of the number of parameters used in soil quality evaluation, we have chosen the basin of Horoiata from Tutova Hills. The soil database included over 130 profiles. The number of parameters we arrived at in the end, after using and pedotransfer functions for determining some properties not analyzed in the field or laboratory, was of 33.

Parameter selection – the minimum data set

The appreciations regarding soil degradation, as well as the necessity of remedies, imply the use of soil quality indicators. Their use depends mainly on the potential of the respective indicator to assure correct and useful information. After collecting the data, usually occurs the dilemma of how many and what parameters should be included in the evaluation.

The selection criteria for soil quality indicators need to include a series of aspects (sensibility, significance, measurement efficiency, scientific validity). Although there were some attempts to integrate these criteria in an unique formula, up to the present date we do not have a systematic procedure that would assure an objective selection of the parameters to be used in soil quality evaluation.

The necessities of the indicator selection process are according to Breckenridge et al. (2000) the following: applicability and interpretability in different regions; correlation with changes in ecosystem processes, spatial and temporal variability, ability to be quantified through a synoptic or automatic monitoring, the costs of equipment and analytical data; the quantity and quality of data; sensibility to changes; warning potential; the state of the method (standardized or experimental); costs.

Doran and Zeiss (2000) have established as selection criteria of the indicators the following: sensibility to variations in utilization; correlation with soil functions; use in elucidating ecosystem processes; utility for farmers; easiness to use and the costs of indicators' analysis.

The use of quality indicators depends mainly on the capacity or ability of the indicator to assure a certain and useful information. The utility differs from situation to situation according to a series of aspects that characterize the complexity of the respective case. This gives the so called acceptance degree or the potential of the respective indicator for a certain purpose. Cameron et al. (1996) have proposed an equation of the: **A** = **X**(**SUMIR)** type, in which the acceptance degree of the respective indicator (A) represents the sum of some characteristics or parameters which receive a score from 1 to 5. This sum is made of the sensibility of the indicator to the respective process (S), the usefulness in understanding the value significance (U), measurements efficiency (M), the predictable influence of the property on soil, plant and animal health and on productivity (I), the relation with ecosystem processes implied in environmental quality and sustainability (R). To each equation parameter is given a score (1-5) on the basis of the evaluator's knowledge and experience. The sum of individual scores gives the acceptance level A, which may be compared to that of other potential indicators. For example bulk density may receive a SUMIR = 44532, giving a value of 18 from the maximum of 25 (72%), while particle size may receive 13222, meaning 10/25.

Another problem is that some indicators do not take into consideration simultaneously and objectively both the positive and negative potential of the factors implied. Typically are recognized only the positive or negative factors.

The first step in developing a soil quality model is the qualitative description of a good quality soil's attributes. If the soil function is for example to promote soil productivity, the soil should be allowed a easy rooting, to accept, retain and regulate water and air circulation; to stock, offer and recycle nutrients, to facilitate biological activity.

The second step is to replace quantitative measurements for the qualitative attributes of the soil and their combination into a model that would assure a soil quality index.

In this way occurred the notion of the **minimum data set (MDS)** – a set of measurements considered basin in soil evaluation. The realization of the minimum data set is an absolutely necessary instrument in the evaluation of soil quality. This minimum data set should include physical, chemical and biological properties that allow soil quality evaluation.

In 1994, Larson and Pierce have described (but not applied) the use of mathematic functions that involved minimum data sets and pedotransfer functions. Doran and Jones (1996) have proposed for the MDS's physical, chemical and biological indicators 4 parameters each, while Gomez et al. (1996) defined 6 indicators. Govaers et al. (2006) have tried to establish an MDS for a corn and maize crop system. There are many such studies that defined according to the specific of the study area a smaller or larger number of indicators. Even if there are papers that present 20 or even more indicators, it is suggested that such studies are research ones and not practical monitoring programs. A simple set of well established properties may offer much useful information, with higher chances of being accepted. Andrews et al. (2002) consider that a smaller number of indicators carefully chosen may offer adequate information for qualitative evaluations.

A relatively recent approach, yet more and more frequently used in establishing the MDS is the principal component analysis (PCA). PCA and factorial analysis are mainly used to identify groups of related variables that define the so-called latent dimensions (principal components or factors) of a complex of variables. The methods may be used to reduce the number of studied variables. PCA is a way of identifying trends in the data, and to express the data in such a way so as to underline associations and differentiations. The advantage is that once discovered these patterns, the data set may be compressed by reducing the number of dimensions without loosing too much information. PCA was named one of the most remarkable results of applied linear algebra, being used in a multitude of domains. It is a simple method, which with reduced efforts assures a way of reducing a complex data set to a smaller dimension, so as to show the simplified, hidden dimension of that set (Dodge, 2008).

Combining indicators in quantitative descriptions of soil quality

Indices are decisional tools used to make complex information more accessible. The soil quality index is created to help farmers in determining soil health tendencies as a result of management practices, and thus to see if there is a need in changing these practices. Though, indices may be used to compare different agricultural practices (Andrews et al., 2003).

These indices begin by specifying soil functions, then the processes important for each function, and then one or several strata of soil characteristics, which are indicators for processes. The advantages of such a hierarchic structure are that it approaches the multiple functions of the soil, and the fact that a single characterization may have a different importance for each function. The same measurements may get a different significance in interpretation when each aspect of soil quality is computed. For example, a coarse texture has a positive effect on water infiltration, but not on its retention.

Soil quality indicators and indices should be selected according to soil functions we are interested in. These purposes may frequently be individual, being mainly focused on the farm scale, but can also be social, including larger environmental effects (soil erosion, water and air pollution etc). Once the managerial purposes have been identified, indexing soil quality implies three steps: choosing the appropriate indicators in a MDS, transforming the indicator values and combining then in an index (Andrews et al. 2005).

Andrews et al. (2004) describe the steps involved in the creation of an index. After selecting and measuring the indicators in the MDS, the second step (indicator interpretation) implies transforming each indicator value using non-linear functions. The measured values are transformed into values from 0 to 1, so that the scores might be combined to form a single value. Each scoring function is made up of an algorithm or logical affirmation. Each indicator measurement is transformed into a non-unitary value (0-1) that represents the level associated to the function in the system. A score of 1 represents the higher function possible for that system, meaning that the indicator does not limit soil functions and processes.

The third step implies the integration in an index that would be the final evaluation of soil quality. Andrews et al. (2002) have discovered small differences between additive, weighted and max-min methods in the case that we use indicator values calibrated non-linearly. Thus they have chosen the simplest method – the additive one – summing the scores of each indicator, dividing to the number of indicators and then multiplying by 10.

Karlen and Stott (1994) have also used Standard Scoring Functions to define the relations between soil indicators and its functions. Thus they separated four function types: SSF1 – if the value of the indicator increases, the function increases; SSF2 – there is an optimum interval outside of which the function decreases; SSF3 – indicator decreases, the function increases; SSF4 – the function is optimum with the exception of a certain interval of indicator values).

In what regards examples of indices, Andrews et al. (2002) for example defined a weighted additive index of soil quality:

SQI = $\sum_{i=1}^{n} W_i \times S_i$, where W_i is the weighting factor of the principal component, and S_i is the score of the indicator (0 to 1). The MDS in this case included organic matter, electroconductivity, soil reaction, bulk density and aggregate stability. In this case,

$$SQI=\sum_{i=1}^{n} 0{,}61 \times S_{SOM} + 0{,}61 \times S_{ECI} + 0{,}16 \times S_{pHi} + 0{,}16 \times S_{WSA} \times S_{ZNi} + 0{,}09 \times S_{BDi}$$

S being the score for the respective variable and the (i) coefficients the weighting factors resulted from PCA.

The domain literature accentuates the need of indexing the diversity of soil functions, yet all the indices are narrow, taking into account only the factors related to crop growth and productivity. Even with reference to productivity, quality is indefinable in the case of systems so complex such as soils.

Sojka and Upchurch (1999) and Letey et al. (2003) affirm that probably soil quality cannot be at the moment evaluated, but only estimated. They suggest that evaluation shouldn't be based on a specific determination of a single intended use, but should be based on very dynamic properties.

RESULTS AND DISCUSSIONS

Soil parameters are in a very large number. More, the present systems of soil quality evaluation from our country are in fact terrain / land evaluation systems that take into account besides the intrinsic soil parameters also terrain or climatic parameters, external to our object of study. Although performing, these systems also imply quite complicated calculations.

Following the approach *indicators – selecting an MDS – combining indicators in a final index*, we had to initially find a method of reducing the number of indicators, more exactly to select the most important. For this we used the PCA method recommended by several authors (Andrews et a. 2002, 2003, 2005; Brejda and Moormans, 2001; Chen, 1999; Govaerts et al., 2006; Gregorich et al., 1994; Guilin et al., 2007; Hussain et al., 1999; Karlen and Stott, 1994; Murage et al., 2000; Wander et al., 2002).

The main applications of the factorial techniques are the reduction of the variables number and detecting the structure of the relations between them. Thus, if we have a strong correlation between two variables, we may conclude that they are redundant. If we represent the correlation between the two variables in a graphic, we may draw a regression line that will represent the linear relation between them. If we may define a variable that would approximate the regression line, then it would capture the essence of the first two variables. The scores of the variables linked to the new factor, represented by the regression line, may be used later to represent the essence of the new variable. In a way we have reduced the two variables to a single factor – the linear combination of the two variables. If we extend this example to multiple variables, the computations will be more difficult, but the basic principle remains the same (Statistica manual).

Simpler, the extraction of the principal components is reduced to a maximization rotation of the original space of the variable. For example, in a graphic we may think at the regression line as being the original X axis, rotated in such a way so as to approximate the regression line. This type of rotation is named variance maximization, because the criterion is to maximize the variance of the new factor, minimizing the variance around him.

When we have more than two variables, they define a space exactly as two define a plane. Thus, we realize a three-dimensional graphic and may draw a plane between the data. With more than three variables it becomes impossible to graphically illustrate the method, yet the logic of the variance maximization rotation remains the same.

After we have found the line on which the variance is maximum, a part of the variation remains around this line. In PCA, after the first factor has been extracted, we continue to define another line that would maximize the variability remaining, and so on, extracting consecutive factors. Because each consecutive factor is defined to maximize the variability not captured by the previous one, they are independent one from another (table 1). As we extract consecutive factors, they explain less and less variation. The decision to stop extracting factors depends on the place where very small variability remains.

Table 1

The variance explained by the first two 12 factors extracted by PCA

	Eigenvalues	**Total variance**	**Cumulative eigenvalues**	**Cumulative variance**
I	**16.79**	**50.88**	**16.79**	**50.88**
II	**6.30**	**19.11**	**23.09**	**69.99**
III	**2.33**	**7.07**	**25.43**	**77.06**
IV	**1.57**	**4.77**	**27.01**	**81.84**
V	**1.49**	**4.53**	**28.50**	**86.38**
VI	**1.19**	**3.62**	**29.70**	**90.00**
VII	0.70	2.13	30.40	92.14
VIII	0.56	1.70	30.97	93.84
IX	0.51	1.55	31.48	95.40
X	0.40	1.23	31.89	96.64
XI	0.31	0.95	32.20	97.60
XII	0.28	0.85	32.49	98.45

We applied PCA to the 33 parameters taken into account. In table 1 we find the variances on the new factors, in the third column being expressed as percentage of the total variance. The variances extracted by the factors are named eigenvalues.

After we measured how much variance is extracted by each factor, we may decide how many to retain. Although the decision is arbitrary, there are some general lines used in practice. The **Kaiser criterion** says that first we retain the factors with eigenvalues higher than 1. In essence, it is as if a factor does not extract at least the equivalent of an original variable, we do not take it into account. This criterion was proposed by (1960) and is probably the most used. The **scree test** is a graphic method proposed by Cattell (1966) (fig. 1). We may represent the eigenvalues on a simple line.

Cattell suggests we should to find the breaking point where the easy decrease of the Eigenvalues tends to become uniform towards the right part of the graphic. At the right of this point we find only factorial debris. According to this criterion, we should retain quite few factors (three) (Rogerson, 2001).

It is possible to know the significance of the factors, to interpret them in an easily understandable manner. If we analyze the correlations between the variables, we will see that some of them are higher and other smaller, situation that reflects the independent factors in the correlation matrix. In this case will be analyzed the correlations between the variables and the new factors, named factor loadings (table 2).

It is visible that the first factor is stronger correlated with the variables than the second. We see that at least in the case of the first factor the number of variables determining it is very large. If we would retain all the 6 factors with eigenvalues larger than 1, we will have to retain almost all the variables taken into analysis.

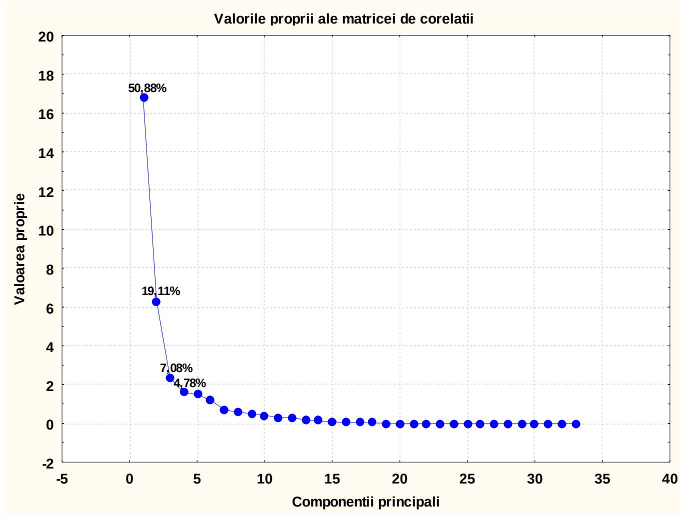
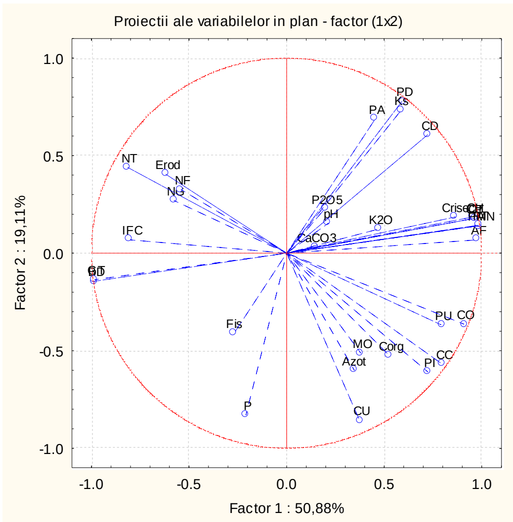


Fig. 1. **Eigenvalues of the correlation matrix – the Cattell test**



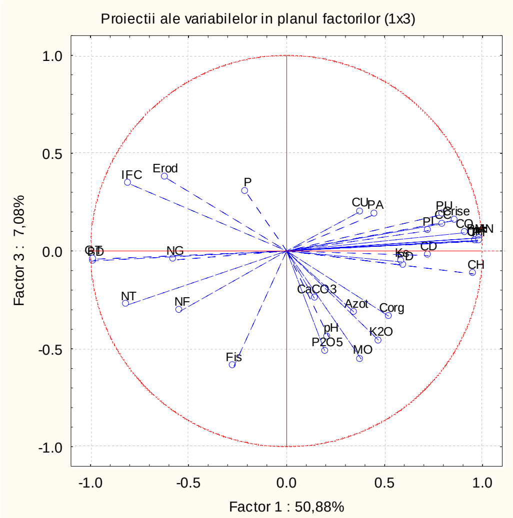


Fig. 2. **Plane rotations of factor I in relation to factors II and III**

Table 2

Factor loadings

	I	II	III	IV	V	VI
pH	0.21	0.15	-0.44	-0.08	-0.73	-0.04
$CaCO_3$	0.14	0.03	-0.24	-0.27	-0.81	0.02
Total carbon	0.52	**-0.52**	-0.34	0.31	0.11	0.20
Organic matter	0.38	**-0.51**	**-0.55**	0.01	0.17	0.21
Nitrogen	0.35	**-0.60**	-0.32	0.35	0.03	0.29
P_2O_5	0.19	0.23	**-0.51**	0.26	0.06	-0.55
K_2O	0.47	0.12	-0.46	0.36	-0.13	-0.31
Coarse sand	**-0.58**	0.27	-0.05	0.61	-0.02	-0.07
Fine sand	-0.54	0.33	-0.31	-0.58	0.17	0.15
Silt	-0.21	**-0.83**	0.30	0.15	-0.20	-0.09
Clay	**0.99**	0.14	0.07	-0.04	0.02	-0.02
Fine clay	**0.98**	0.07	0.06	-0.01	0.02	-0.03
Total sand	**-0.81**	0.44	-0.28	-0.06	0.12	0.08
Bulk density	**-0.99**	-0.14	-0.05	0.05	-0.01	0.00
Crust formation index	**-0.80**	0.07	0.34	0.11	-0.22	0.20
Hygroscopicity coefficient	**0.95**	0.19	-0.12	0.02	0.10	0.07
Pore cipher	**0.96**	0.18	0.05	0.07	-0.03	0.15
Drainage porosity	**0.59**	**0.78**	-0.07	0.04	0.02	0.13
Available porosity	**0.79**	-0.37	0.19	0.09	-0.14	0.28
Inactive porosity	**0.72**	-0.61	0.10	-0.11	0.03	-0.22
Field capacity	**0.80**	**-0.57**	0.14	-0.05	-0.03	-0.07
Total water capacity	**0.96**	0.18	0.05	0.07	-0.03	0.15
Wilting point	**0.91**	-0.36	0.09	-0.04	0.00	-0.08
Available water	0.37	**-0.86**	0.20	-0.08	-0.06	-0.03
Drainage capacity	**0.72**	**0.61**	-0.02	0.12	-0.02	0.24
Air porosity	0.45	**0.69**	0.19	0.33	-0.10	0.27
Minimum needed porosity	**0.99**	0.14	0.07	-0.04	0.02	-0.02
Compaction degree	**-0.98**	-0.14	-0.04	0.08	-0.02	0.03
Total porosity	**0.99**	0.14	0.05	-0.05	0.01	0.00
Capillary rise	**0.86**	0.19	0.16	-0.22	0.00	-0.08
Cracking	-0.27	-0.41	**-0.59**	-0.14	0.05	0.41
Erodability	**-0.62**	0.41	0.38	0.22	-0.21	0.14
Hydraulic conductivity	**0.59**	**0.73**	-0.06	-0.16	0.13	-0.11

We could represent factor loadings in a graphic, in which each variable would be represented by a point. In this graphic we can rotate the axes in any direction, without modifying the relative location of points one to another. Still, the coordinates of the points (factor loadings) will change. There are several rotation strategies, whose purpose is to obtain a clearer pattern of the loadings, thus making interpretation easier.

Applying a varimax rotation, the pattern becomes clearer (table 3). The first factor is marked by high loadings for some attributes, while the following on others. Only factor IV is not clearer explained by any variable, only coarse sand and erodability contributing to its explanation. If we look at the first two factors, we see that they are explained by factors depending on soil texture, so we decided to renounce factor IV. In conclusion, soil quality in this case may be defined on the basis of the analysis of five factors. If we initially wanted to retain three factors according to Casell principle, after the varimax rotation we will retain 5 of the initial 6 factors with Eigenvalues higher than 1, that together explain 83% of the variation. The advantage of the varimax rotation is clear in the classification of the factors. Thus the first factor is determined by clay and fine clay content, bulk density, hygroscopicity coefficient, drainage porosity, total water capacity, drainage capacity, air porosity, compaction degree, total porosity, capillary rise and hydraulic conductivity. The second factor is determined by fine and total sand, silt content, inactive porosity, field capacity for water and available water capacity. The third factor is determined by total carbon, organic matter, nitrogen content and cracking susceptibility. The last two factors are determined by soil reaction and carbonates content on one side and phosphorous on the other (fig. 3).

Table 3

Factor loadings after the Varimax rotation

Parameter	I	II	III	IV	V	VI
pH	0.16	-0.05	0.08	-0.03	**0.84**	0.23
$CaCO_3$	0.06	0.04	-0.02	0.07	**0.90**	-0.03
Total carbon	0.22	0.45	**0.73**	0.00	-0.05	0.16
Organic matter	0.10	0.19	**0.80**	0.28	0.02	0.14
Nitrogen	0.04	0.45	**0.76**	-0.09	-0.01	0.07
P_2O_5	0.13	-0.12	0.03	0.03	0.05	**0.83**
K_2O	0.35	0.10	0.20	-0.10	0.21	**0.68**
Coarse sand	-0.40	-0.26	-0.13	**-0.68**	-0.13	0.26
Fine sand	-0.28	**-0.80**	-0.04	0.33	0.06	-0.21
Silt	-0.58	**0.72**	0.08	0.00	0.00	-0.18
Clay	**0.92**	0.32	0.06	0.18	0.05	0.12
Fine clay	**0.87**	0.37	0.10	0.18	0.03	0.14
Total sand	-0.49	**-0.82**	-0.11	-0.18	-0.04	0.01
Bulk density	**-0.92**	-0.31	-0.07	-0.19	-0.06	-0.11
Crust formation index	**-0.61**	-0.19	-0.31	-0.44	0.02	-0.40
Hygroscopicity coefficient	**0.92**	0.18	0.22	0.14	0.02	0.19
Pore cipher	**0.94**	0.28	0.14	0.02	0.08	0.05
Drainage porosity	**0.89**	-0.35	-0.12	-0.17	0.08	0.14
Available porosity	0.56	**0.65**	0.33	0.03	0.10	-0.21
Inactive porosity	0.31	**0.78**	0.21	0.47	-0.02	0.10
Field capacity	0.42	**0.79**	0.26	0.35	0.02	0.00
Total water capacity	**0.94**	0.28	0.14	0.02	0.08	0.05
Wilting point	0.60	**0.67**	0.22	0.32	0.02	0.08
Available water	-0.07	**0.83**	0.29	0.34	-0.01	-0.17
Drainage capacity	**0.94**	-0.15	0.01	-0.21	0.09	0.07
Air porosity	**0.76**	-0.16	-0.17	-0.52	0.04	-0.02
Minimum needed porosity	**0.92**	0.32	0.06	0.18	0.05	0.12
Compaction degree	**-0.91**	-0.31	-0.06	-0.22	-0.06	-0.13
Total porosity	**0.92**	0.31	0.07	0.19	0.06	0.11
Capillary rise	**0.83**	0.25	-0.11	0.30	0.07	0.04
Cracking	-0.39	-0.21	**0.72**	0.16	0.15	-0.13
Erodability	-0.31	-0.30	-0.47	**-0.57**	0.01	-0.27
Hydraulic conductivity	**0.83**	-0.34	-0.25	0.12	0.01	0.24
Eigenvalue	**13.80**	**6.52**	**3.26**	**2.49**	**1.67**	**1.96**
Explained variance	**0.42**	**0.20**	**0.10**	**0.08**	**0.05**	**0.06**

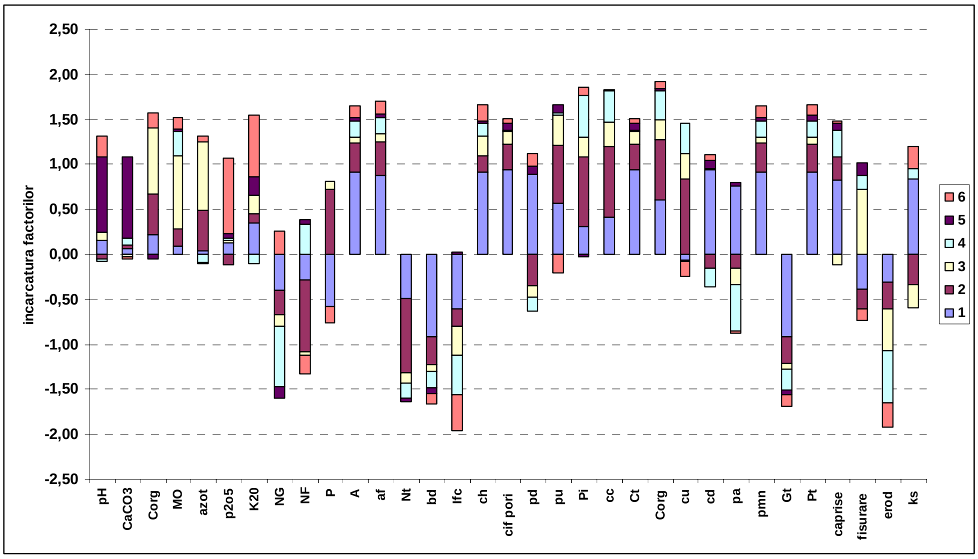


Fig. 3. **The participation of the attributes to the loadings of the 6 extracted factors (sum of variable saturation)**

Still, if we want to retain the 5 factors resulted from the analysis, we should retain a large number of indicators. Another method used by some authors (Andrews et al., 2002) is of taking into account the correlations between the indicators that condition the same factor. The logic is simple in our case, some of the indicators being obtained from pedotransfer functions. Thus we chose to retain for each principal component only one parameter, eliminating the strongly correlated ones.

The five factors are easily definable. The first factor depends mainly on the fine fraction of grain-size, the second on the medium-coarse fraction (silt-sand). The third factor is clearly conditioned by the organic carbon content, and the fourth is given by soil reaction. In the case of the last factor, it is totally determined by phosphorous content. We may affirm that the five components extracted by the factors are in fact the components of soil quality.

Proceeding at the analysis of the residual correlation matrix and of the correlation graphics, we selected one representative attribute for each factor: the clay content, fine sand content, organic carbon, soil reaction and mobile phosphorous content.

The second method used in trying to select parameters for the MDS was that of Cameron, the simplest, empiric and somehow subjective. As it can be seen from the below table, most of the properties considered being representative for an MDS are of chemical nature. This aspect is due to the fact that chemical properties are more easily affected by different interventions on soil, thus having the capacity of reflecting changes in its quality (table 4).

Table 4

Scores received by soil parameters analyzed through Cameron method

Parameter	S	U	M	I	R	SUMIR
1	2	3	4	5	6	7
Organic matter	5	5	5	5	5	25
Total nitrogen	5	5	5	5	5	25
Organic carbon	5	5	5	5	5	25
Soil pH	5	5	5	5	4	24
Potassium	4	5	5	5	4	23
Base content	4	4	5	5	4	22
Bulk density	4	5	5	5	3	22

Continuation of table 4

1	2	3	4	5	6	7
Phosphorous	4	4	5	5	4	22
Capacity of cationic exchange	4	4	5	5	3	21
Microorganisms	5	5	3	4	4	21
Soluble salts' content	3	4	5	4	4	20
Wilting point	4	4	4	4	4	20
Sodium	3	4	5	4	4	20
Depth of A horizon	2	4	5	4	4	19
Clay	2	5	5	4	3	19
Electroconductivity	3	4	5	3	3	18
Erodability	3	4	3	4	4	18
Exchangeable H (SH)	2	4	5	4	3	18
Fine sand	2	5	5	3	3	18
Fine clay	2	3	5	4	3	17
Available water capacity	3	4	3	4	3	17
Hydraulic conductivity	3	3	4	4	3	17
Useful porosity	3	4	3	4	3	17
Soil structure	3	4	4	3	3	17
Sulphates	2	3	5	4	3	17
Calcium	2	3	5	3	3	16
Compaction	3	2	5	3	3	16
Silt	2	3	5	3	3	16
Field capacity	2	4	3	3	3	15
Total water capacity	2	3	3	4	3	15
Carbonate content	2	2	5	3	3	15
Coarse sand	2	2	5	3	3	15
Water retention capacity	2	3	3	3	3	14
Air porosity	3	3	2	3	3	14
Magnesium	1	2	5	2	3	13
Manganese	1	2	5	2	3	13
Drainage porosity	3	2	2	2	3	12

Another interesting aspect in what regards this method is that it indicates with high scores at least three of the parameters selected by the PCA: organic carbon, reaction and phosphorous. Due to the fact that they enter physical properties, clay and silt contents, selected by the PCA, have lower scores, first of all due to the lack of sensibility to change. In any case, the application of Cameron's method confirms the results of the principal component analysis.

CONCLUSIONS

In conclusion, PCA is a very good method for reducing datasets including many parameters, when often some of them are redundant or closely correlated (and thus can be excluded from the analysis), and so it can be used to obtain the minimum data set needed in soil quality evaluation. More, the method brings in the light the "hidden" and sometimes not known relations between the data, easing the interpretation of the results.

REFERENCES

Andrews S. Susan, Mitchell P. Jeffrey, Mancinelli Roberta, Karlen L. Douglas, Hartz K. Timothy, Horwath R. William, Pettygrave G. Stuart, Saw M. Kate, Muck S. Daniel (2002) – On farm assessment of soil quality in California's Central Valley; Agronomy Journal, 94, 12-33.

Andrews S.S., Flora C.B., Mitchell J.P., Karlen D.L. (2003) – Growers' perceptions and acceptance of soil quality indices; Geoderma, 114, pp. 187-213.

Andrews S.S., Karlen D.L., Cambardella C.A. (2004) – The soil management assessment framework: A quantitative soil quality evaluation method; Soil Science Society of America Journal 68:1945-1962.

Andrews S.S., Karlen D.L., Mitchell J.P (2005) – A comparison of soil quality indexing methods for vegetable production systems in Northern California; Agriculture, Ecosystems and Environment, 90, pp. 25-45.

Brejda J. John, Moorman B. Thomas (2001) – Identification and interpretation of regional soil quality factors for the Central High Plains of the Midwestern USA; pp. 535-540 in D. E. Stott, R. H. Mohtar, G. C. Steinhardt (eds.) – Sustaining the global farm, selected papers from the 10th Int. Soil Conservation Organization.

Cameron K.C., Comforth I.S., McLaren R.G., Beare M.H., Basher L.R., Metherell A.K., Kerr L.E. (1996) – Soil Quality Indicators for Sustainable Agriculture in New Zealand; Lincoln Soil Quality Research Centre, Lincoln University, New Zealand.

Cârstea S. (2001) – Calitatea solului – expresie a multiplelor lui funcții; protecția şi ameliorarea ei – cerință imperativă; Lucrările celei de-a XVI-a conferințe naționale pentru ştiința solului, publicațiile SNRSS, vol. 30C, Bucureşti.

Chen Z.S. (1999) – Selecting indicators to evaluate soil quality; Exten. Bull. 473. Dept. of Agric. Chern. Nat. Taiwan Univ.

Dodge Yadolah (2008) – The Concise Encyclopedia of Statistics, Springer, 616 p.

Doran W. John, Zeiss R. Michael (2000) – Soil health and sustainability: managing the biotic component of soil quality; Applied Soil Ecology, 15, pp. 3-11.

Gomez A.A., Swete Kelly, Syers J.K., Coughlan K.J. (1996) – Measuring sustainability of agricultural systems at the farm level; In: Methods for Assessing Soil Quality. SSSA Special Publication No. 49.

Govaerts Bram, Sayre Ken, Deckers Jozef (2006) – A minimum data set for soil quality assessment of wheat and maize cropping in the highlands of Mexico; Soil and Tillage Research, 87, pp. 163-174.

Gregorich E.G., Carter M.R., Angers D.A., Monreal C.M., Ellert B.H. (1994) – Towards a minimum data set to assess soil organic matter quality in agricultural soils; Can. J. Soil Sci. 74, pp. 367-385.

Guilin Li, Jie Chen, Zhyng Sun, Manzhi Tan (2007) – Establishing a minimum dataset for soil quality assessment based on soil properties and land-use changes; Acta Ecologica Sinica, 27(7), 2715-2724.

Karlen D.L., Stott D.E. (1994) – A framework for evaluating physical and chemical indicators of soil quality; In: J.W. Doran et al. (eds.) Defining Soil Quality for a Sustainable Environment; Soil Science Society of America, Madison, WI, Special Publication 35, pp. 53-72.

Larson W.E., Pierce F.J. (1994) – The dynamics of soil quality as a measure of sustainable management; In: J.W. Doran et al. (eds.) Defining Soil Quality for a Sustainable Environment; Soil Science Society of America, Madison, WI, Special Publication 35, pp. 37-51.

Letey J., Sojka R. E., Upchurch D. R., Cassel D. K., Olson K. R., Payne W. A., Petrie S. E., Price G. H., Reginato R. J., Scott H. D., Smethurst P. J., Triplett G. B. (2003) –Deficiencies in the soil quality concept and its application; Journal of Soil and Water Conservation 58, no. 4 (Jul-Aug).

Sojka R.E., Upchurch D. R. (1999) – Reservations regarding the soil quality concept; SSSA Journal, vol. 63, no. 5, pp. 1039-1054.

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