

A NEW APPROACH FOR COMPARISON OF SOIL CHARACTERISTICS USING GREY RELATIONAL ANALYSIS AND PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Multivariate statistical analysis are important tools to assess soil quality. In this study, grey relational analysis and principal component analysis methods were implemented in order to identify the most influential variables affecting soil quality. For this aim, soil characteristics such as organic matter (SOM), mean weight diameter (MWD), aggregate stability (AS), dispersion ratio (DR), penetration resistance (PR), bulk density (ρ_b), total porosity (TP), air permeability (AP), permeability coefficient (PC), liquid limit (LL), plastic limit (PL), plasticity index (PI), shrinkage limit (SL), friability index (FI), optimum moisture content (OMC), and maximum dry bulk density (ρ_{b-max}) of soil specimens obtained from 45 different soil samples were measured. The PC (0.67), PI (0.65), MWD (0.65), PR (0.59), ρ_{b-max} (0.56), AP (0.55), ρ_b (0.54), TP (0.53), FI (0.53), DR (0.53), PL (0.53), LL (0.52), OMC (0.50), AS (0.50), SL (0.50) and SOM (0.47) were found to be the most significant variables associated with soil quality based on the mean values of grey relational coefficients. Grey relational grades calculated using three values obtained from principal component analysis displayed that Soil III 4% (0.98) had the highest quality, whereas Soil I control (0.34) had the lowest quality. Nearly a similar ranking occurred in two statistical calculation cases (GRA and GRA-PCA). Results obtained have shown that these two methods are suitable for solving complicated relationships between multiple factors and variables in soil research.

Keywords: Soil quality, Physical and mechanical characteristics, Principal component analysis (PCA), Grey relational analysis (GRA)

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INTRODUCTION

Improvement of physical, chemical, biological, and mechanical properties of soil by adding organic and inorganic amendments has been increasingly identified as an important issue not only for the improvement of soil quality, fertility, and productivity but also for the minimization of land degradation. Sustainable agriculture, closely related to the improvement of soil physical, chemical, biological and mechanical characteristics, is dependent on the capacity of soil to function at present and in the future for an indefinite period of time (Tittarelli and Canaly, 2003). Soil organic amendment is one of the economically viable and environmentally compatible component of management practices to improve soil quality and maintain its continuity, thus agricultural sustainability. The positive effects of organic waste addition on soil properties have been reported by several authors (Lindsay and Logan, 1998; Doran and Zeiss, 2000; Tejada *et al.* 2006; Asghari *et al.* 2009; Aksakal *et al.* 2016; Sari *et al.* 2017), and

data sets of these studies are commonly evaluated by classical statistical methods such as ANOVA, t-test, regression, and correlation, etc. The incomplete or limited formation of data makes it difficult to model and control complex systems using classical statistical methods, which means that more sophisticated methods are still required.

Proper use of statistical methods and probability theories involves working with a clear dataset in which complexities have been excluded. However, because of the dynamic environmental structure, it is difficult to achieve this. It is inevitable to work with uncertainty in order to enhance our awareness and draw conclusions from environmental processes. In environmental studies, such as agriculture, many factors or properties simultaneously influence the system. It is important to ascertain the crucial relationships among the factors and to decide the relevant ones significantly influencing certain objectives (Juan *et al.* 2013). A rational approach to express the results of agricultural studies could be done using statistical methods that can evaluate the entire data

set instead of individual elements and take into account many variables at the same time.

Concepts of uncertainty and modeling principles of them have been studied extensively for many years. The grey system theory developed by Deng in the year 1982 is an effective statistical method to solve problems having poor, insufficient, and uncertain information (Deng, 1982; Lu *et al.* 2009). It not only defines the relationships between the factors but also aims to reveal the influential factors significantly affecting the system. A system containing knowns (white) and unknowns (black) is named as “grey system” and it is described as the bridge between an uncertain and known state. Therefore, grey system can be used to clarify which of the available factors are important and to rank and classify among these factors using a limited number of data (Deng, 1982; Lu *et al.* 2009). Grey relational analysis (GRA) is appropriate for solving complicated relationships between multiple factors and variables and has been successfully applied to many fields, such as plant-soil system (Xu *et al.* 2018), soil infiltration (Juan *et al.* 2013) and estimation of leaf water content (Jin *et al.* 2013) in agriculture, industry (Pan *et al.* 2007; Lu *et al.* 2009; Wang and Wang, 2013), and environment (Deepanraj *et al.* 2017).

Principal component analysis (PCA) is a multivariate data reduction technique aimed at explaining data across several inter-correlated quantitative dependent variables (Borvka *et al.* 2005; Abdi and Williams, 2010; Primpas *et al.* 2010). PCA method is highly applicable to agricultural and environmental science studies in which high correlation is observed among the variables. Moreover, PCA compresses the size, simplify the description of the data set, and does not impose requirements for normality and homoscedasticity, and therefore, there is no need for data transformations that strongly distort the original information (Karydis, 1992; Henderson and Seaby, 2008). PCA technique has been applied successfully to environmental (Davis *et al.* 2009; Mihailovi *et al.* 2015; Fernández *et al.* 2018) and agricultural (Fox and Metla, 2005; Kooch *et al.* 2008; Khan *et al.*, 2014) data sets.

Statistical methods that can evaluate the whole data set rather than individual elements better correspond to the real situation in soil because variations in soil properties are high and they relate to several variables. Proper use of these methods can provide not only a concise summary of the complex information but also describes the relationships more precisely than univariate statistics. Therefore, the application of statistical techniques such as GRA and PCA methods are much more conceivable in comparison with classical methods. This study was undertaken to evaluate and verify which relationships and factors can provide a good way of characterizing vermicompost application on soil properties using GRA and PCA.

MATERIALS AND METHODS

Materials: A pot experiment evaluating the effects of vermicompost on soil aggregation, certain physical properties, consistency limits, and compactibility was conducted under laboratory condition, where mean air temperature and relative humidity were set to 25 ± 2 °C and $60 \pm 5\%$, respectively. Soil samples were collected from the 0 to 20 cm depth of commonly distributed soil great groups under similar tillage and crop management practices in the agricultural fields of Erzurum, Turkey. Soils were classified as Ustorthent (sandy loam-Soil I), Fluvaquent (loam-Soil II), and Haplustert (clay-Soil III) according to Soil Survey Staff (2014).

Field moist soil samples were air-dried and crumbled to pass through an 8-mm sieve. The commercial animal waste vermicomposts processed by earthworms *Eisenia fetida* (Savigny 1826) (Lumbricidae, Oligochaeta) passed through a 4-mm sieve was applied within the rates of 0 (control), 0.5, 1, 2, and 4%, respectively on a weight/weight (w/w) basis. Soil and vermicompost with defined amounts were mixed and added to the experimental pots. Amount of soils used in each pot were 17, 16 and 14 kg for Soil I, II, and III, respectively. The pots were arranged in a factorial combination of 3 soils \times 5 vermicompost rates with 3 replications for each treatment combination using a completely randomized design. Soils were incubated for 90 days at near field capacity by adding water with 3 days intervals under constant laboratory conditions. General characteristics of soils and vermicompost used in the study were given in Table 1.

Data used in this study were obtained from our previous studies (Aksakal *et al.* 2016; Sari *et al.* 2017) to evaluate and verify which relationships and factors can provide an appropriate way to characterize the effects of vermicompost amendments on soil properties using GRA and PCA. Data presented in Part I (Aksakal *et al.*, 2016) evaluated the effects of vermicompost amendments on mean weight diameter (MWD), aggregate stability (AS), dispersion ratio (DR), organic matter (SOM), bulk density (ρ_b), total porosity (TP), permeability coefficient (PC), air permeability (AP), and penetration resistance (PR). Effects of vermicompost on liquid limit (LL), plastic limit (PL), plasticity index (PI), shrinkage limit (SL), friability index (FI), optimum moisture content (OMC), and maximum dry bulk density (ρ_{b-max}) were presented in Part II (Sari *et al.*, 2017). For more information about the experimental design and results, we refer the interested readers to read Part I and II.

METHODS

Grey relational analysis (GRA): A system containing knowns (white) and unknowns (black) is named as “grey

system” and it is the bridge between an uncertain and known state. In other words, the grey system is based on the rule that some information is known and some are unknown. GRA determines the degree of relationship between each factor in a grey system and the factor (reference series) series compared. Each factor is defined as an array (row or column). The degree of influence between the factors is called the grey relational degree (Deng, 1982; Lu *et al.* 2009).

The steps of the grey relational analysis method are as follows;

1. Formation of Reference and Comparison Series.: Generating reference data series ($o(k)$) and comparison of data series ($i(k)$)

$$o(k) = (o(1), o(2), \dots, o(n)) \quad k=1, 2, \dots, n$$

where n is the number of respondents.

$$i(k) = (i(1), i(2), \dots, i(n)) \quad k=1, 2, \dots, n; \quad i=1, 2, \dots, m$$

Table 1. General characteristics of soils and vermicompost used in the study (Mean±Std).

Properties	Soils and Material				
	Soil I	Soil II	Soil III	Vermicompost (VC)	
Clay (%)	16.59±1.21	25.85±1.09	64.24±0.04	-	Particle size distribution (%)
Silt (%)	24.54±0.16	40.67±2.52	19.14±0.07	-	4000-3000 μ 1.12
Sand (%)	58.87±1.20	33.48±1.44	16.62±0.07	-	3000-2000 μ 1.38
Textural class	Sandy loam	Loam	Clay	-	2000-1000 μ 5.54
Great soil group	Ustorthent	Fluvaquent	Haplustert	-	1000-500 μ 10.79
CEC (cmol kg ⁻¹)	22.54±1.28	40.67±1.34	47.01±1.48	-	500-420 μ 2.72
CaCO ₃ (%)	0.46±0.02	0.51±0.03	0.85±0.04	-	420-297 μ 10.59
Organic matter (%)	1.93±0.07	1.24±0.09	1.12±0.03	34.91±1.12	297-250 μ 0.70
pH	6.57±0.08 [§]	7.75±0.02 [§]	7.26±0.04 [§]	8.17±0.04	250-100 μ 4.93
EC (mS cm ⁻¹)	0.54±0.09 [§]	0.85±0.05 [§]	1.06±0.08 [§]	5.69±0.11	100-74 μ 13.32
Particle density (g cm ⁻³)	2.66±0.02	2.63±0.02	2.67±0.02	2.23±0.02	74-53 μ 1.63
Bulk density (g cm ⁻³)	1.32±0.02	1.21±0.02	1.07±0.03	0.58±0.01	<53 μ 47.28
Field capacity (%P _v)	19.12±0.93	25.83±1.15	44.12±1.21		
XRF analysis (Concentration, %)	O	47.29	46.96	47.71	47.55
	Ca	3.85	4.88	2.10	17.19
	Si	31.67	30.25	32.51	14.22
	Mg	1.44	1.51	1.77	5.13
	K	2.09	1.75	1.93	3.20
	Al	8.43	8.32	8.90	2.67
	P	0.17	0.16	0.05	1.49
	S	0.04	0.05	0.07	0.74
	Fe	1.82	2.42	2.18	0.56
	Na	1.75	1.42	0.48	0.54
	Mn	0.04	0.06	0.05	0.04
Sr	0.01	0.01	0.01	0.03	

Soil Survey Staff (2014)

[§] Determined in 1:2.5 (soil:water) extract.

Determined in saturation extract.

the comparison data series consists of n values and m is number of values.

2. Normalization of Data (when necessary)

If the analyzed factor has different measurement units, they should be converted to the same measurement unit before performing GRA. Furthermore, normalization should be conducted if the range of data set is high or absolute standard values are too high. There are three types of normalization;

The maximum approach is suitable for the larger the better expectancy. The maximum approach;

$$x_i(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad 1)$$

where $x_i(k)$ and $x_i^0(k)$ denote the normalized and original values of the i^{th} data series, respectively. The $\min x_i^0(k)$ is $\max x_i^0(k)$ represent the minimum and maximum values of the i^{th} data series, respectively.

The minimum approach is suitable for the lower the better expectancy. The minimum approach;

$$x_i(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (2)$$

The objective approach is between the range of the minimum and maximum expectancy. The objective approach;

$$x_i(k) = 1 - \frac{|x_i^0(k) - x^0|}{\max x_i^0(k) - x^0} \quad (3)$$

where x^0 is objective value of the data series.

After normalization, values vary between 0 and 1. If the values in the series are desired to take small values, "the minimum" normalization method is employed and the points that take small values in linear normalization take values close to "1", while those taking great values take values close to "0".

3. Coefficient matrix is formed by taking the difference values between comparison data set and reference data set.

$$o_{ij}(k) = |x_0(k) - x_j(k)| \quad (4)$$

4. The minimum and the maximum values are determined in coefficient matrix.

$$\begin{aligned} \min &= \min_i \min_k |x_0(k) - x_j(k)| \\ \max &= \max_i \max_k |x_0(k) - x_j(k)| \end{aligned} \quad (5)$$

5. The Grey Relational Coefficient (GRC) of each observation can be calculated as follows;

$$\varepsilon(x_0(k), x_j(k)) = \frac{\min_i \min_k + \xi \max_i \max_k}{o_{ij}(k) + \xi \max_i \max_k} \quad (6)$$

where $k=1, 2, \dots, n$, $i=1, 2, \dots, m$, $j=1, 2, \dots, m$, $\xi \in (0,1)$. ξ is the distinguishing coefficients that adjusts the difference between $\min_i \min_k$ and $\max_i \max_k$ and is suggested as 0.5. ξ , takes a value between 0 and 1 and is the distinguishing coefficient that adjusts the difference between $\min_i \min_k$ and $\max_i \max_k$. It is generally taken as 0.5.

6. Grey relational coefficient is determined by taking the averages of Grey relation coefficients. The Grey Relational Grade (GRG) is obtained by

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \varepsilon(x_0(k), x_j(k)) \quad (7)$$

The magnitude of grey relational degree γ_i reflects general degree of standard deviation of original data set from the reference data series (Wu, 2007).

7. The effect of each factor or variable is definitely not the same in real practice. Thus, equation 7 can be changed as follows:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n w_k \varepsilon(x_0(k), x_j(k)) \quad (8)$$

where, w_k is weight value. When weight values are the same, GRG values obtained according to equation 7 and 8 are the same. Grey relational analysis is used to determine the relationship between the series in GRG. If the two series are same, GRG becomes equal. Weight values (w_k) used in this study were obtained from principal component analysis (PCA).

Principal Component Analysis (PCA): The PCA is a method of explaining the variance structure explained by variables with correlations with new variables, which are linear components of the original variables with no correlation between them. The number of base components is as many as or less than the number of

original variables. In the presence of the principal components, the variance-covariance matrix of the original variables or the correlation matrix is used. Variables are the variance-covariance matrix in the same measure and the correlation matrix is used in the variable measure. The basic components are employed to analyze the dimension and to deduce. The basic components are calculated on the basis of the following equation (Kuo *et al.*, 2008; Mehat *et al.*, 2014).

$$Y_m = \sum_{i=1}^n X_m(i) \cdot V_{i1} \quad (9)$$

The square of the eigenvalue vectors indicates the contribution of the physical and mechanical characteristics factor corresponding to the base components. The average of the contributions of the physical and mechanical characteristics factors obtained by squaring each eigenvalue vector gives the weight values (w_k) of the physical and mechanical characteristics variables (Mehat *et al.*, 2014). According to the analysis of the basic components, the grey correlation values of each sample are calculated using the weight values (w_k) obtained for each variable.

Xuerui *et al.* (2007) and Xiaojun *et al.* (2010) formulized the standard deviation of the grey correlation grades in the presence of the upper and lower bounds of grey correlation grades as follows.

$$S_{\gamma_i} = \sqrt{\frac{\sum_{i=1}^n (\varepsilon_i - \gamma_i)^2}{(n-1)}} \quad (10)$$

where γ_i : Grey relationship grades are calculated according to arithmetic mean equations (Xuerui *et al.* 2007).

Correlation matrix was used to find principal components in this study. To obtain correlation matrix, first, grey relational coefficients for each physical and mechanical characteristics in forty-five specimens and correlation coefficient matrix between physical and mechanical characteristics were calculated using coefficient matrix according to equation 6. Using this correlation, coefficient matrix (**R**) eigenvalues (λ) and eigenvectors (**V**) were calculated according to the following equations (Kuo *et al.* 2008; Mehat *et al.* 2014).

$$(\mathbf{R} - \lambda \mathbf{I}_m) \mathbf{V}_i = 0 \quad (11)$$

$$\sum_{k=1}^n \lambda_k = n \quad (12)$$

where λ_k is an eigenvalue, **R** is correlation matrix, **I** is unit vector, n is number of physical and mechanical characteristic, and V_{ik} is the eigenvector;

$\mathbf{V}_{i1} = [a_{k1}, a_{k2}, \dots, a_{kn}]^T$ corresponds to eigenvalue λ_k (13)

The principal components are calculated by the following equation:

$$Y_m = \sum_{i=1}^n X_m(i) \cdot V_{i1} \quad (14)$$

where Y is the principal component, X is the grey relational coefficient, and V is the eigenvector corresponding to X .

Square of eigenvectors show the contribution of physical and mechanical characteristics that corresponds to principal components. Average of contribution shares

of physical and mechanical characteristics obtained by taking the squares of each eigenvector gives weight values of physical and mechanical characteristics variables (Mehat *et al.* 2014). (S1 ,..., S45) GRG values of each specimen were calculated using weight values obtained for each variables (w_k) according to principal component analysis. All the statistical evaluations were performed using SPSS v.20.0 (IBM, 2011) and Excel package program.

RESULTS AND DISCUSSION

Minimum, maximum and mean values of investigated physical and mechanical characteristics and raw data obtained from forty-five specimens are presented in Table 2. As the units of physical and mechanical characteristics in data set are different, measurement units of evaluated characteristics should be converted to the same unit and normalization should be performed before conducting GRA. Normalized values for physical and mechanical characteristics were calculated using equations 1, 2 and 3 and the difference value between comparability sequence and reference sequence were calculated using equation 4 and the normalized data are presented in Table 3. Normalization decreases the variation in sequence and the obtained new values vary between 0-1 after normalization. "The minimum approach" normalization method is used if the values in the series are desired to take small values. In linear normalization, points that take small values take values close to "1", while great values take values close to "0". If the values in the series are desired to take great values, "the maximum" normalization method is used. The points with great values take values close to "1", while those having small values take values close to "0". Grey relational coefficients were calculated for each physical and mechanical characteristics using equation 6 and grey relational coefficients of each physical and mechanical characteristics are presented in Table 4.

Considering mean grey relation coefficients (Table 4), the most significant criteria were found as PC (0.671), PI (0.649), MWD (0.647), PR (0.590), b_{-max} (0.558), AP (0.552), b (0.536), TP (0.532), FI (0.532), DR (0.531), PL (0.525), LL (0.518), OMC (0.503), AS (0.503), SL (0.500) and SOM (0.466) for the data set. Grey relation grades (GRG) were determined using the application of PCA to grey relational coefficients presented in Table 5. Null hypothesis correlation matrix is formed as unit matrix to test the applicability of PCA to data set. Bartlett's sphericity test was employed to test the applicability of PCA on data set, in other words, to test whether the correlation coefficients matrix was a unit matrix. Bartlett's sphericity test value was found to be 258.710 ($p < 0.001$). It can be stated that correlation matrix was not unit matrix, in other words, correlations between some variables in the correlation matrix were significant

and thus PCA can be applied to data set. PCA results of GRC obtained for physical and mechanical characteristics in forty-five soil specimens are presented in Table 5. The components with an eigenvalue greater than 1 were considered as significant. The total variation in the data set is described by 85.96% in the first six factors.

Eigenvalues of principal components are presented in Table 5. The components with an eigenvalue greater than 1 were considered as significant. Eigenvalues of principal components were found to be 3.93, 3.037, 2.114, 1.607, 1.179, 1.025, 0.862, 0.438, 0.421, 0.195, 0.084, 0.063, 0.042, 0.001 and 0.000 respectively. 86.47% of total variation in data set was explained by first three factors (b_{-max} , LL, and PL). White 56.21% of total variance was explained by the b_{-max} (1st factor); 18.79% of total variance was explained by the LL (2nd factor); and 11.47% was explained by the PL (3rd factor). Other thirteen components were found to explain 13.53% of total variation. These components were not considered as significant (Figure 1).

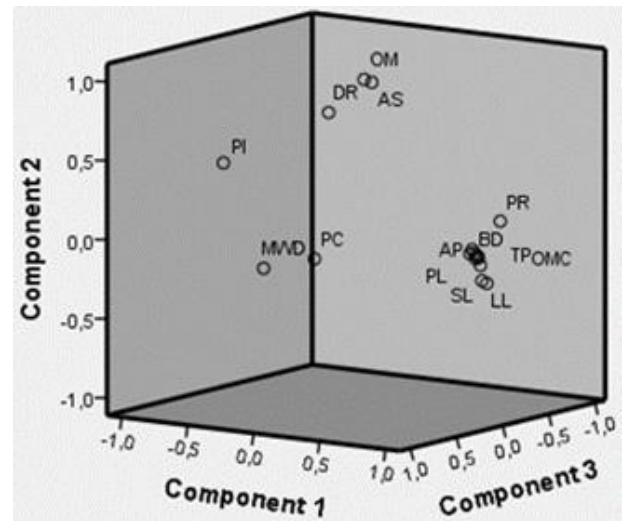


Figure 1. Component plot in rotated space

When comparisons were made according to GRG, the specimens with a GRG value that is close to 1 is expressed to have the highest physical and mechanical characteristics. GRG values closer to 1 showed that there was a high relation between real values and reference values, while GRG values close to 0 showed a low relation. For each variable, the reference values are taken as the highest physical and mechanical characteristics value. Accordingly, it could be stated as the higher the physical and mechanical characteristics of the soil the higher the GRG values, and the lower the physical and mechanical characteristics of soil the lower the GRG values. As seen from Table 6, GRG reflected that the highest physical and mechanical characteristics were seen on specimens numbered S45 (0.812), S43 (0.792), S44 (0.787), S40 (0.725), S42 (0.716), S41 (0.708),

Table 2. Raw data of each physical and mechanical characteristics for forty-five comparability sequences and their descriptive statistics values.

Soil	Specimen Number	Dose (w/w, %)	SOM	MWD	AS	DR	PR	b	TP	AP	PC	LL	PL	PI	SL	FI	OMC	b-max
Soil I (Ustorthent)	S1	0 (Control)	1.90	3.92	28.91	44.63	2.96	1.31	50.64	92.36	10.54	25.86	18.22	7.64	6.41	11.81	13.92	1.89
	S2	0 (Control)	1.88	4.52	31.94	48.63	2.78	1.33	50.01	100.62	14.44	27.38	19.13	8.25	6.75	12.38	14.01	1.92
	S3	0 (Control)	2.01	4.02	30.69	45.98	2.89	1.31	50.64	78.98	13.29	28.02	20.33	7.69	7.05	13.28	15.37	1.91
	S4	0.5	2.15	3.93	41.69	43.93	2.38	1.28	51.88	104.88	16.08	29.25	21.10	8.15	7.25	13.85	16.12	1.81
	S5	0.5	2.18	4.07	38.78	48.22	2.58	1.24	53.38	112.75	19.67	29.78	22.71	7.07	7.60	15.11	16.13	1.83
	S6	0.5	2.17	3.34	39.85	41.73	2.69	1.25	52.88	101.37	22.85	28.42	20.61	7.81	7.06	13.55	15.77	1.85
	S7	1	2.27	3.55	43.98	41.48	2.03	1.24	53.38	123.26	22.29	34.26	24.29	9.97	8.47	15.82	16.83	1.81
	S8	1	2.22	3.59	44.00	42.97	2.00	1.24	53.38	107.23	39.64	32.16	22.15	10.01	7.84	14.31	18.85	1.80
	S9	1	2.35	3.01	46.61	42.60	1.93	1.23	53.76	104.76	41.86	31.44	21.07	10.37	7.56	13.51	18.64	1.78
	S10	2	2.44	2.89	54.49	40.76	1.86	1.2	54.77	122.86	42.06	36.83	25.08	11.75	8.62	16.46	21.59	1.78
	S11	2	2.61	3.39	56.51	38.51	1.47	1.19	55.36	131.61	40.65	36.50	24.65	11.85	8.51	16.14	19.50	1.79
	S12	2	2.49	2.49	57.89	37.36	1.58	1.18	55.54	115.95	26.48	37.38	27.49	9.89	9.07	18.42	21.06	1.75
	S13	4	3.44	2.86	66.49	30.95	1.22	1.15	56.79	136.33	34.25	39.35	29.51	9.84	10.47	19.04	23.93	1.74
	S14	4	2.91	2.89	66.89	31.84	1.08	1.15	56.73	129.93	22.32	42.89	32.73	10.16	11.51	21.22	22.90	1.75
	S15	4	3.34	2.39	67.13	27.54	1.23	1.14	57.09	134.35	31.18	41.70	31.56	10.14	11.15	20.41	24.25	1.72
	S16	0 (Control)	1.14	5.71	27.05	42.29	4.23	1.20	54.37	70.55	3.71	38.17	26.93	11.24	9.47	17.47	19.91	1.75
S17	0 (Control)	1.30	5.11	28.90	40.15	3.95	1.23	53.31	67.88	1.98	39.34	28.14	11.20	9.83	18.31	19.89	1.73	
S18	0 (Control)	1.29	5.18	25.82	45.99	4.07	1.21	53.99	48.05	2.63	36.92	26.28	10.64	9.20	17.09	19.59	1.73	
Soil II (Fluvaquent)	S19	0.5	1.44	4.72	31.28	41.10	3.90	1.15	56.27	121.57	8.13	40.32	28.98	11.34	9.98	19.01	21.96	1.68
	S20	0.5	1.38	5.03	31.18	38.47	3.80	1.18	55.28	131.67	2.39	41.06	29.18	11.88	10.10	19.08	21.85	1.70
	S21	0.5	1.49	5.22	32.06	35.18	3.96	1.20	54.47	100.62	4.61	39.92	27.22	12.70	9.62	17.60	22.41	1.69
	S22	1	1.43	4.24	32.71	28.03	3.46	1.18	55.14	103.46	5.57	41.06	30.79	10.27	10.45	20.34	23.15	1.65
	S23	1	1.57	4.30	37.15	28.13	4.13	1.15	56.16	95.70	9.19	42.91	31.89	11.02	10.87	21.02	22.14	1.66
	S24	1	1.66	4.62	36.29	36.44	3.57	1.13	57.10	141.53	6.15	43.16	32.94	10.22	11.08	21.86	24.90	1.67
	S25	2	1.81	4.09	41.19	33.92	2.64	1.11	57.81	187.04	13.34	44.59	32.99	11.60	10.85	22.14	26.89	1.61
	S26	2	2.32	4.04	41.40	28.69	2.85	1.10	58.20	200.65	12.98	45.61	34.12	11.49	11.16	22.97	25.50	1.58
	S27	2	1.71	3.01	39.26	28.96	2.26	1.08	58.94	157.00	8.19	47.16	36.18	10.98	11.67	24.50	27.01	1.60
	S28	4	3.04	3.32	52.68	27.64	1.52	1.01	61.63	226.33	10.57	48.84	38.87	9.97	13.40	25.48	27.63	1.51
	S29	4	2.95	2.70	50.05	30.29	1.90	1.04	60.46	186.07	11.98	50.89	41.91	8.98	14.21	27.70	28.77	1.58
	S30	4	2.47	2.86	50.55	30.12	1.79	1.05	60.08	188.59	6.99	51.92	42.96	8.96	14.53	28.43	28.18	1.57
Soil III (Haplustert)	S31	0 (Control)	1.14	7.63	24.97	48.37	1.62	1.07	59.82	181.19	0.79	68.41	39.19	29.22	15.29	23.90	29.48	1.41
	S32	0 (Control)	1.09	8.32	27.85	48.82	1.44	1.04	61.17	176.87	0.66	69.69	41.67	28.02	15.90	25.77	26.91	1.47
	S33	0 (Control)	1.12	7.69	16.31	43.91	1.17	1.10	58.89	196.62	0.81	71.19	42.11	29.08	16.16	25.95	30.31	1.45
	S34	0.5	1.22	7.25	30.01	43.83	0.83	1.02	61.86	204.85	3.08	71.77	43.25	28.52	16.31	26.94	33.95	1.37
	S35	0.5	1.36	6.19	32.49	44.14	0.82	1.03	61.24	208.16	2.35	72.35	43.04	29.31	16.34	26.70	30.34	1.37
	S36	0.5	1.32	7.55	22.74	45.79	1.17	0.99	62.97	213.14	3.41	70.03	42.17	27.86	15.91	26.26	33.84	1.38
	S37	1	1.44	6.30	32.29	40.40	1.02	0.97	63.75	223.66	10.39	73.56	45.38	28.18	17.02	28.37	31.52	1.36
	S38	1	1.48	6.66	35.62	43.62	0.86	1.00	62.44	217.11	8.32	74.77	46.59	28.18	17.38	29.21	32.01	1.35

S39	1	1.51	6.33	25.54	43.57	0.82	0.98	63.31	223.25	11.52	72.65	43.87	28.78	16.64	27.23	33.31	1.35
S40	2	1.53	5.89	32.64	43.53	0.83	0.88	66.99	224.99	9.53	78.62	52.19	26.43	18.19	34.00	34.75	1.31
S41	2	1.58	5.94	31.00	40.09	0.55	0.93	65.18	239.64	12.86	76.82	50.17	26.65	17.65	32.52	35.01	1.33
S42	2	1.74	5.05	29.75	43.39	0.72	0.92	65.49	242.13	15.31	75.16	49.90	25.26	17.39	32.51	33.78	1.30
S43	4	2.15	4.92	38.68	38.27	0.56	0.90	66.35	253.02	8.56	81.15	53.74	27.41	20.33	33.41	37.93	1.30
S44	4	2.04	5.04	37.42	36.73	0.54	0.88	66.92	243.58	7.04	79.57	52.17	27.40	19.84	32.33	40.42	1.29
S45	4	2.10	4.59	39.42	38.15	0.35	0.92	65.37	260.14	9.68	83.93	54.11	29.82	20.77	33.34	37.78	1.28
Minimum		1.09	2.39	16.31	27.54	0.35	0.88	50.01	48.05	0.66	25.86	18.22	7.07	6.41	11.81	13.92	1.28
Maximum		3.44	8.32	67.13	48.82	4.23	1.33	66.99	260.14	42.06	83.93	54.11	29.82	20.77	34.00	40.42	1.92
Mean		1.92	4.67	38.45	39.23	2.04	1.11	58.03	156.27	13.56	50.51	34.43	16.07	12.29	22.15	25.33	1.60

SOM: soil organic matter, MWD: mean weight diameter, AS: aggregate stability, DR: dispersion ratio, PR: penetration resistance, ρ_b : bulk density, TP: total porosity, AP: air permeability, PC: permeability coefficient, LL: liquid limit, PL: plastic limit, PI: plasticity index, SL: shrinkage limit, FI: friability index, OMC: optimum moisture content, ρ_{b-max} : maximum dry bulk density

Table 3. Normalized values of the responses and the difference values between the comparability sequence and reference sequence (μ_0).

Soil	Specimen Number	Dose (w/w,%)	SOM	MWD	AS	DR	PR	ρ_b	TP	AP	PC	LL	PL	PI	SL	FI	OMC	ρ_{b-max}
Soil I (Ustorthent)	S1	0	0.345	0.991	0.248	0.197	0.327	0.044	0.037	0.209	0.894	0.000	0.000	0.975	0.000	0.000	0.000	0.047
	S2	0	0.336	0.959	0.308	0.009	0.374	0.000	0.000	0.248	0.969	0.026	0.025	0.948	0.024	0.026	0.003	0.000
	S3	0	0.391	0.822	0.283	0.133	0.345	0.044	0.037	0.146	0.991	0.037	0.059	0.973	0.045	0.066	0.055	0.016
	S4	0.5	0.451	0.797	0.499	0.230	0.477	0.111	0.110	0.268	0.912	0.058	0.080	0.953	0.058	0.092	0.083	0.172
	S5	0.5	0.464	0.836	0.442	0.028	0.425	0.200	0.198	0.305	0.786	0.068	0.125	1.000	0.083	0.149	0.083	0.141
	S6	0.5	0.460	0.636	0.463	0.333	0.397	0.178	0.169	0.251	0.674	0.044	0.067	0.967	0.045	0.078	0.070	0.109
	S7	1	0.502	0.693	0.544	0.345	0.567	0.200	0.198	0.355	0.694	0.145	0.169	0.873	0.143	0.181	0.110	0.172
	S8	1	0.481	0.704	0.545	0.275	0.575	0.200	0.198	0.279	0.085	0.108	0.110	0.871	0.100	0.113	0.186	0.188
	S9	1	0.536	0.545	0.596	0.292	0.593	0.222	0.221	0.267	0.007	0.096	0.079	0.855	0.080	0.077	0.178	0.219
	S10	2	0.574	0.512	0.751	0.379	0.611	0.289	0.280	0.353	0.000	0.189	0.191	0.794	0.154	0.210	0.289	0.219
	S11	2	0.647	0.649	0.791	0.484	0.711	0.311	0.315	0.394	0.049	0.183	0.179	0.790	0.146	0.195	0.211	0.203
	S12	2	0.596	0.403	0.818	0.539	0.683	0.333	0.326	0.320	0.547	0.198	0.258	0.876	0.185	0.298	0.269	0.266
	S13	4	1.000	0.504	0.987	0.840	0.776	0.400	0.399	0.416	0.274	0.232	0.315	0.878	0.283	0.326	0.378	0.281
	S14	4	0.774	0.512	0.995	0.798	0.812	0.400	0.396	0.386	0.693	0.293	0.404	0.864	0.355	0.424	0.339	0.266
S15	4	0.957	0.375	1.000	1.000	0.773	0.422	0.417	0.407	0.382	0.273	0.372	0.865	0.330	0.388	0.390	0.313	
Soil II (Fluvaquent)	S16	0	0.021	0.715	0.211	0.307	0.000	0.289	0.257	0.106	0.654	0.212	0.243	0.817	0.213	0.255	0.226	0.266
	S17	0	0.089	0.879	0.248	0.407	0.072	0.222	0.194	0.093	0.594	0.232	0.276	0.818	0.238	0.293	0.225	0.297
	S18	0	0.085	0.860	0.187	0.133	0.041	0.267	0.234	0.000	0.616	0.190	0.225	0.843	0.194	0.238	0.214	0.297
	S19	0.5	0.149	0.986	0.295	0.363	0.085	0.400	0.369	0.347	0.809	0.249	0.300	0.812	0.249	0.324	0.303	0.375
	S20	0.5	0.123	0.901	0.293	0.486	0.111	0.333	0.310	0.394	0.608	0.262	0.305	0.789	0.257	0.328	0.299	0.344
	S21	0.5	0.170	0.849	0.310	0.641	0.070	0.289	0.263	0.248	0.686	0.242	0.251	0.753	0.224	0.261	0.320	0.359
	S22	1	0.145	0.882	0.323	0.977	0.198	0.333	0.302	0.261	0.720	0.262	0.350	0.859	0.281	0.384	0.348	0.422
	S23	1	0.204	0.899	0.410	0.972	0.026	0.400	0.362	0.225	0.847	0.294	0.381	0.826	0.311	0.415	0.310	0.406
	S24	1	0.243	0.986	0.393	0.582	0.170	0.444	0.418	0.441	0.740	0.298	0.410	0.862	0.325	0.453	0.414	0.391

Soil III (Haplustert)	S25	2	0.306	0.841	0.490	0.700	0.410	0.489	0.459	0.655	0.992	0.323	0.412	0.801	0.309	0.466	0.489	0.484
	S26	2	0.523	0.827	0.494	0.946	0.356	0.511	0.482	0.720	0.980	0.340	0.443	0.806	0.331	0.503	0.437	0.531
	S27	2	0.264	0.545	0.452	0.933	0.508	0.556	0.526	0.514	0.812	0.367	0.500	0.828	0.366	0.572	0.494	0.500
	S28	4	0.830	0.630	0.716	0.995	0.698	0.711	0.684	0.841	0.895	0.396	0.575	0.873	0.487	0.616	0.517	0.641
	S29	4	0.791	0.460	0.664	0.871	0.601	0.644	0.615	0.651	0.945	0.431	0.660	0.916	0.543	0.716	0.560	0.531
	S30	4	0.587	0.504	0.674	0.879	0.629	0.622	0.593	0.663	0.769	0.449	0.689	0.917	0.565	0.749	0.538	0.547
	S31	0	0.021	0.189	0.170	0.021	0.673	0.578	0.578	0.628	0.552	0.733	0.584	0.026	0.618	0.545	0.587	0.797
	S32	0	0.000	0.000	0.227	0.000	0.719	0.644	0.657	0.607	0.547	0.755	0.653	0.079	0.661	0.629	0.490	0.703
	S33	0	0.013	0.173	0.000	0.231	0.789	0.511	0.523	0.701	0.553	0.781	0.666	0.033	0.679	0.637	0.618	0.734
	S34	0.5	0.055	0.293	0.270	0.234	0.876	0.689	0.698	0.739	0.632	0.791	0.697	0.057	0.689	0.682	0.756	0.859
	S35	0.5	0.115	0.584	0.318	0.220	0.879	0.667	0.661	0.755	0.607	0.801	0.692	0.022	0.692	0.671	0.620	0.859
	S36	0.5	0.098	0.211	0.127	0.142	0.789	0.756	0.763	0.778	0.644	0.761	0.667	0.086	0.662	0.651	0.752	0.844
	S37	1	0.149	0.553	0.314	0.396	0.827	0.800	0.809	0.828	0.889	0.821	0.757	0.072	0.739	0.746	0.664	0.875
	S38	1	0.166	0.455	0.380	0.244	0.869	0.733	0.732	0.797	0.816	0.842	0.790	0.072	0.764	0.784	0.683	0.891
	S39	1	0.179	0.545	0.182	0.247	0.879	0.778	0.783	0.826	0.928	0.806	0.715	0.046	0.712	0.695	0.732	0.891
	S40	2	0.187	0.666	0.321	0.249	0.876	1.000	1.000	0.834	0.859	0.909	0.947	0.149	0.820	1.000	0.786	0.953
	S41	2	0.209	0.652	0.289	0.410	0.948	0.889	0.893	0.903	0.975	0.878	0.890	0.139	0.783	0.933	0.796	0.922
	S42	2	0.277	0.896	0.264	0.255	0.905	0.911	0.912	0.915	0.939	0.849	0.883	0.200	0.765	0.933	0.749	0.969
S43	4	0.451	0.932	0.440	0.496	0.946	0.956	0.962	0.966	0.825	0.952	0.990	0.106	0.969	0.973	0.906	0.969	
S44	4	0.404	0.899	0.415	0.568	0.951	1.000	0.996	0.922	0.771	0.925	0.946	0.106	0.935	0.925	1.000	0.984	
S45	4	0.430	0.978	0.455	0.501	1.000	0.911	0.905	1.000	0.864	1.000	1.000	0.000	1.000	0.970	0.900	1.000	

Table 4. Grey relational coefficient for forty-five comparability sequences.

Soil	Specimen Number	Dose (w/w,%)	SOM	MWD	AS	DR	PR	b	TP	AP	PC	LL	PL	PI	SL	FI	OMC	b-max	Mean GRC	
Soil I (Ustorthent)	S1	0	0.433	0.981	0.399	0.384	0.426	0.344	0.342	0.387	0.825	0.333	0.333	0.952	0.333	0.333	0.333	0.344	0.468	
	S2	0	0.430	0.924	0.419	0.335	0.444	0.333	0.333	0.399	0.942	0.339	0.339	0.906	0.339	0.339	0.334	0.333	0.468	
	S3	0	0.451	0.737	0.411	0.366	0.433	0.344	0.344	0.342	0.369	0.981	0.342	0.347	0.948	0.344	0.349	0.346	0.337	0.465
	S4	0.5	0.477	0.712	0.500	0.394	0.489	0.360	0.360	0.406	0.850	0.347	0.352	0.913	0.347	0.355	0.353	0.376	0.474	
	S5	0.5	0.483	0.753	0.473	0.340	0.465	0.385	0.384	0.418	0.700	0.349	0.364	1.000	0.353	0.370	0.353	0.368	0.472	
	S6	0.5	0.481	0.578	0.482	0.429	0.453	0.378	0.376	0.400	0.605	0.343	0.349	0.939	0.344	0.352	0.350	0.360	0.451	
	S7	1	0.501	0.620	0.523	0.433	0.536	0.385	0.384	0.437	0.620	0.369	0.376	0.797	0.369	0.379	0.360	0.376	0.466	
	S8	1	0.491	0.628	0.523	0.408	0.540	0.385	0.384	0.410	0.353	0.359	0.360	0.795	0.357	0.360	0.381	0.381	0.445	
	S9	1	0.519	0.524	0.553	0.414	0.551	0.391	0.391	0.406	0.335	0.356	0.352	0.775	0.352	0.351	0.378	0.390	0.440	
	S10	2	0.540	0.506	0.668	0.446	0.562	0.413	0.410	0.436	0.333	0.381	0.382	0.709	0.371	0.387	0.413	0.390	0.459	
	S11	2	0.586	0.588	0.705	0.492	0.634	0.421	0.422	0.452	0.345	0.380	0.379	0.704	0.369	0.383	0.388	0.386	0.477	
	S12	2	0.553	0.456	0.733	0.520	0.612	0.429	0.426	0.424	0.524	0.384	0.403	0.801	0.380	0.416	0.406	0.405	0.492	
	S13	4	1.000	0.502	0.975	0.757	0.690	0.455	0.454	0.461	0.408	0.394	0.422	0.804	0.411	0.426	0.446	0.410	0.563	
	S14	4	0.689	0.506	0.991	0.712	0.727	0.455	0.453	0.449	0.619	0.414	0.456	0.786	0.437	0.465	0.431	0.405	0.562	
	S15	4	0.922	0.445	1.000	1.000	0.688	0.464	0.462	0.457	0.447	0.407	0.443	0.787	0.427	0.449	0.450	0.421	0.579	
	S16	0	0.338	0.637	0.388	0.419	0.333	0.413	0.402	0.359	0.591	0.388	0.398	0.732	0.389	0.402	0.392	0.405	0.437	

Soil III (Haplustert)	S17	0	0.354	0.806	0.399	0.458	0.350	0.391	0.383	0.355	0.552	0.394	0.409	0.734	0.396	0.414	0.392	0.416	0.450
	S18	0	0.353	0.782	0.381	0.366	0.343	0.405	0.395	0.333	0.566	0.382	0.392	0.761	0.383	0.396	0.389	0.416	0.440
	S19	0.5	0.370	0.973	0.415	0.440	0.353	0.455	0.442	0.434	0.724	0.400	0.417	0.727	0.400	0.425	0.418	0.444	0.490
	S20	0.5	0.363	0.835	0.414	0.493	0.360	0.429	0.420	0.452	0.561	0.404	0.419	0.703	0.402	0.426	0.416	0.432	0.471
	S21	0.5	0.376	0.768	0.420	0.582	0.350	0.413	0.404	0.399	0.614	0.397	0.400	0.669	0.392	0.404	0.424	0.438	0.466
	S22	1	0.369	0.809	0.425	0.956	0.384	0.429	0.417	0.404	0.641	0.404	0.435	0.780	0.410	0.448	0.434	0.464	0.513
	S23	1	0.386	0.831	0.459	0.947	0.339	0.455	0.439	0.392	0.765	0.414	0.447	0.742	0.420	0.461	0.420	0.457	0.524
	S24	1	0.398	0.973	0.452	0.545	0.376	0.474	0.462	0.472	0.658	0.416	0.459	0.783	0.426	0.478	0.461	0.451	0.518
	S25	2	0.419	0.759	0.495	0.625	0.459	0.495	0.480	0.592	0.985	0.425	0.459	0.715	0.420	0.483	0.495	0.492	0.550
	S26	2	0.512	0.743	0.497	0.902	0.437	0.506	0.491	0.641	0.961	0.431	0.473	0.720	0.428	0.501	0.470	0.516	0.577
	S27	2	0.404	0.524	0.477	0.882	0.504	0.529	0.513	0.507	0.726	0.441	0.500	0.744	0.441	0.539	0.497	0.500	0.546
	S28	4	0.746	0.575	0.637	0.991	0.624	0.634	0.613	0.758	0.827	0.453	0.541	0.797	0.493	0.566	0.509	0.582	0.647
	S29	4	0.706	0.481	0.598	0.795	0.556	0.584	0.565	0.589	0.900	0.468	0.595	0.856	0.523	0.638	0.532	0.516	0.619
	S30	4	0.548	0.502	0.605	0.805	0.574	0.570	0.551	0.597	0.684	0.476	0.617	0.858	0.535	0.666	0.520	0.525	0.602
	S31	0	0.338	0.381	0.376	0.338	0.604	0.542	0.542	0.573	0.527	0.652	0.546	0.339	0.567	0.523	0.548	0.711	0.507
	S32	0	0.333	0.333	0.393	0.333	0.640	0.584	0.593	0.560	0.525	0.671	0.591	0.352	0.596	0.574	0.495	0.627	0.513
	S33	0	0.336	0.377	0.333	0.394	0.703	0.506	0.512	0.625	0.528	0.695	0.599	0.341	0.609	0.580	0.567	0.653	0.522
	S34	0.5	0.346	0.414	0.406	0.395	0.802	0.616	0.623	0.657	0.576	0.705	0.623	0.347	0.617	0.611	0.672	0.780	0.574
	S35	0.5	0.361	0.546	0.423	0.391	0.805	0.600	0.596	0.671	0.560	0.715	0.618	0.338	0.618	0.603	0.568	0.780	0.575
	S36	0.5	0.357	0.388	0.364	0.368	0.703	0.672	0.679	0.693	0.584	0.676	0.600	0.354	0.596	0.589	0.668	0.762	0.566
	S37	1	0.370	0.528	0.422	0.453	0.743	0.714	0.724	0.744	0.818	0.737	0.673	0.350	0.657	0.663	0.598	0.800	0.625
	S38	1	0.375	0.478	0.446	0.398	0.792	0.652	0.651	0.711	0.731	0.760	0.705	0.350	0.679	0.698	0.612	0.821	0.616
	S39	1	0.378	0.524	0.379	0.399	0.805	0.692	0.698	0.742	0.875	0.720	0.637	0.344	0.635	0.621	0.651	0.821	0.620
	S40	2	0.381	0.599	0.424	0.400	0.802	1.000	1.000	0.751	0.780	0.845	0.903	0.370	0.736	1.000	0.700	0.914	0.725
	S41	2	0.387	0.590	0.413	0.459	0.907	0.818	0.824	0.838	0.953	0.803	0.820	0.367	0.697	0.882	0.710	0.865	0.708
S42	2	0.409	0.828	0.405	0.402	0.840	0.849	0.850	0.855	0.891	0.768	0.810	0.385	0.680	0.882	0.666	0.941	0.716	
S43	4	0.477	0.880	0.472	0.498	0.902	0.918	0.930	0.937	0.740	0.913	0.980	0.359	0.942	0.950	0.842	0.941	0.792	
S44	4	0.456	0.831	0.461	0.537	0.911	1.000	0.992	0.865	0.686	0.869	0.902	0.359	0.885	0.869	1.000	0.970	0.787	
S45	4	0.467	0.958	0.478	0.501	1.000	0.849	0.840	1.000	0.786	1.000	1.000	0.333	1.000	0.944	0.834	1.000	0.812	
Mean GRC		0.466	0.647	0.503	0.531	0.590	0.536	0.532	0.552	0.671	0.518	0.525	0.649	0.500	0.532	0.503	0.558	0.551	
Rank		16	3	14	10	4	7	8	6	1	12	11	2	15	9	13	5		

S28(0.647), S37 (0.625), S39 (0.620), and S29 (0.619). The presented results have displayed that while the highest physical and mechanical characteristics were obtained from S45, the lowest was recorded from S16 specimen. The higher the GRG the higher the physical and mechanical characteristics (Singh *et al.* 2014). The fact that grey relational grades (GRG) of S45 (0.812), S43 (0.792), S44 (0.787), S40 (0.725), S42 (0.716), S41 (0.708), S28 (0.647), S37 (0.625), S39 (0.620), S29 (0.619), S38 (0.616), S30 (0.602), S15 (0.579), S26 (0.577), S35 (0.575), S34 (0.574), S36 (0.566), S13 (0.563) and S14 (0.562) were greater than mean GRG (0.551) which indicates that these handled specimens had acceptable physical and mechanical characteristics. While

making comparisons between each soil specimens on the basis of GRG values, significantly high difference between GRG values shows the difference between the two soil specimens more clearly. It could be stated that the difference between GRG values of S45 and S43 soil specimens (0.812-0.792=0.020) was very low and thus S45 has higher physical and mechanical characteristics than S43.

Lower and upper units of GRG indicate whitening range of the variable. A coefficient closer to 0 means it is getting darker, in other words, there is a low relationship between real values and reference values. On the other hand, a coefficient closer

Table 5. Eigenvectors of the principal component analysis on the physical and mechanical parameters and contribution of each individual quality characteristic for the principal component.

	Component Matrix										
	Components				Components				Components		
	1	2	3		1	2	3		1	2	3
b-max	0.989	-0.048	-0.041	AP	0.955	0.104	0.128	OMC	0.963	0.075	0.045
LL	0.985	-0.049	-0.109	PI	-0.870	0.127	0.364	FI	0.963	0.074	0.149
PL	0.982	0.059	0.098	PR	0.849	0.356	-0.203	PC	0.284	-0.305	0.737
SL	0.977	0.036	0.016	AS	-0.272	0.918	0.021	MWD	-0.087	-0.453	0.682
TP	0.972	0.082	0.083	SOM	-0.232	0.908	0.171	DR	-0.143	0.611	0.535
b	0.968	0.087	0.111								

Table 6. Grey relational grade and its order for forty-five comparability sequences.

Specimen Number	Soil	Dose (w/w, %)	GRA	Specimen Number	Soil	Dose (w/w, %)	GRA (PCA)
S45	Soil III	4	0.812	S45	Soil III	4	0.976
S43	Soil III	4	0.792	S43	Soil III	4	0.945
S44	Soil III	4	0.787	S44	Soil III	4	0.914
S40	Soil III	2	0.725	S40	Soil III	2	0.888
S42	Soil III	2	0.716	S42	Soil III	2	0.840
S41	Soil III	2	0.708	S41	Soil III	2	0.829
S28	Soil II	4	0.647	S38	Soil III	1	0.762
S37	Soil III	1	0.625	S37	Soil III	1	0.737
S39	Soil III	1	0.620	S39	Soil III	1	0.726
S29	Soil II	4	0.619	S35	Soil III	0.5	0.705
S38	Soil III	1	0.616	S34	Soil III	0.5	0.703
S30	Soil II	4	0.602	S36	Soil III	0.5	0.680
S15	Soil I	4	0.579	S33	Soil III	0 (Control)	0.649
S26	Soil II	2	0.577	S31	Soil III	0 (Control)	0.636
S35	Soil III	0.5	0.575	S32	Soil III	0 (Control)	0.630
S34	Soil III	0.5	0.574	S30	Soil II	4	0.539
S36	Soil III	0.5	0.566	S29	Soil II	4	0.526
S13	Soil I	4	0.563	S28	Soil II	4	0.525
S14	Soil I	4	0.562	S27	Soil II	2	0.480
S25	Soil II	2	0.550	S26	Soil II	2	0.473
S27	Soil II	2	0.546	S25	Soil II	2	0.459
S23	Soil II	1	0.524	S24	Soil II	1	0.442
S33	Soil III	0 (Control)	0.522	S23	Soil II	1	0.439
S24	Soil II	1	0.518	S22	Soil II	1	0.434

S22	Soil II	1	0.513	S14	Soil I	4	0.425
S32	Soil III	0 (Control)	0.513	S15	Soil I	4	0.424
S31	Soil III	0 (Control)	0.507	S19	Soil II	0.5	0.420
S12	Soil I	2	0.492	S20	Soil II	0.5	0.418
S19	Soil II	0.5	0.490	S21	Soil II	0.5	0.412
S11	Soil I	2	0.477	S13	Soil I	4	0.409
S4	Soil I	0.5	0.474	S17	Soil II	0 (Control)	0.406
S5	Soil I	0.5	0.472	S12	Soil I	2	0.397
S20	Soil II	0.5	0.471	S16	Soil II	0 (Control)	0.397
S2	Soil I	0 (Control)	0.468	S18	Soil II	0 (Control)	0.396
S1	Soil I	0 (Control)	0.468	S10	Soil I	2	0.385
S7	Soil I	1	0.466	S11	Soil I	2	0.381
S21	Soil II	4	0.466	S7	Soil I	1	0.374
S3	Soil I	0 (Control)	0.465	S8	Soil I	1	0.367
S10	Soil I	2	0.459	S9	Soil I	1	0.366
S6	Soil I	0.5	0.451	S5	Soil I	0.5	0.360
S17	Soil II	0 (Control)	0.450	S4	Soil I	0.5	0.358
S8	Soil I	1	0.445	S6	Soil I	0.5	0.351
S18	Soil II	0 (Control)	0.440	S3	Soil I	0 (Control)	0.342
S9	Soil I	1	0.440	S2	Soil I	0 (Control)	0.337
S16	Soil II	0 (Control)	0.437	S1	Soil I	0 (Control)	0.337
Mean GRA			0.551	Mean GRA (PCA)			0.533

to 1 means that it is getting whiter, in other words, there is a high relationship between the real value and the reference value. The closer the lower and upper limits of GRG are to 1, the more significant is the variable of that coefficient. Besides GRG values, lower and upper limits of GRG values should also be great to talk about certain superiority in GRG values (Xuerui *et al.* 2007).

Comparison of soil specimens according to grey relational coefficients calculated by also considering the weight values derived from PCA reflected that the specimen S45 (0.976) had the highest physical and mechanical characteristics (Table 6). While S45 has the highest physical and mechanical characteristics, whereas S1 (0.337) has the lowest. The fact that grey relational grades of S45, S43, S44, S40, S42, S41, S38, S37, S39, S35, S34, S36, S33, S31, S32 and S30 were greater than mean GRG (0.533) revealed that these soil specimens had higher physical and mechanical characteristics than the mean. However, a significantly high difference between GRG values definitely determines the difference between the two soil specimens. It can be stated that the difference between GRG values of S45 and S43 soil specimens ($0.976-0.945=0.031$) are very low and thus there was no significant physical and mechanical characteristics difference between S45, S43, S44, S40, S42, S41, S38, S37, S39 and S35. However, it could be stated that S45 had higher physical and mechanical characteristics than S17. The fact that the difference between GRG values of S45 which has the highest GRG value and S35 which has the lowest GRG value ($0.976-0.705=0.271$) shows that there is a significant physical and mechanical characteristics difference between S45 and S35.

Comparison of soil specimens according to lower and upper limits of GRGs that were calculated by also taking into account weight values revealed that physical and mechanical characteristics ranking was as S45 (0.812), S43 (0.792), S44 (0.787), S40 (0.725), S42 (0.716), S41 (0.708), S28(0.647), S37 (0.625), S39 (0.620), S29 (0.619), S38 (0.616), S30 (0.602), S15 (0.579), S26 (0.577), S35 (0.575), S34 (0.574), S36 (0.566), S13 (0.563), S14 (0.562), S25 (0.550) , S27 (0.546) and S23 (0.524) in terms of upper limits and S33 (0.522), S24 (0.518), S22 (0.513), S32 (0.513), S31 (0.507), S12 (0.492), S19 (0.490), S11 (0.477), S4 (0.474), S5 (0.472), S20 (0.471), S2 (0.468), S1 (0.468), S7 (0.466), S21 (0.466), S3 (0.465), S10 (0.459), S6 (0.451), S17 (0.450), S8 (0.445), S18 (0.440), S9 (0.440), and S16 (0.437) in terms of lower limits. The fact that also lower limits of grey relational coefficients S45, S43, S44, S40, S42, S41, S38, S37, S39, S35, S34, S36, S33, S31, S32 and S30 soil specimens were higher than mean GRG shows that these soil specimens are higher physical and mechanical characteristics than general mean among all soil specimens. Nearly a similar ranking occurred in two statistical calculation cases (GRA and GRA-PCA). This indicates that physical and mechanical characteristics grading of soil specimens is significant, in other words, there is a difference between the qualities of soil. As a result, it could be suggested that there is a significant superiority and inferiority between the qualities of soil specimens (S1 ..., S45) according to GRG values.

Conclusion: A rational approach to express the results of agricultural studies could be done using statistical methods that can evaluate the entire data set instead of

individual elements and take into account many variables at the same time. In this study, grey relational analysis and principal component analysis methods were implemented in order to identify the most influential variables affecting soil quality. Considering mean grey relation coefficients, the most significant criteria were found as PC, PI, MWD, PR, b_{-max} , AP, b_{-} , TP, FI, DR, PL, LL, OMC, AS, SL and SOM for the data set, respectively. Results obtained have displayed that while the highest physical and mechanical characteristics were obtained from S45, the lowest was recorded from S16 specimen. Nearly a similar ranking occurred in two statistical calculation cases (GRA and GRA-PCA). Results obtained have shown that these two methods are suitable for solving complicated relationships between multiple factors and variables in soil research. Therefore, the application of statistical techniques such as grey relational analysis (GRA) and principal component analysis (PCA) are much more conceivable than classical methods, for the analysis of whole data set instead of individual elements.

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