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Multivariate and Spatial Analysis of Soil Quality in Kafr El-Sheikh Governorate, Egypt

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ABSTRACT

A precise evaluation of soil quality (SQ) is important for sustainable land-use planning. An assessment of SQ was done in 674.13 km^2 (67413 ha) of the agricultural lands in west of Kafr El-Sheikh Governorate, Egypt. Thirty soil profiles were dug and samples were collected and analyzed for different physicochemical properties. A score was assigned for each SQ indicator using linear scoring function. The soil quality index (SQI) was computed using three indices; additive index, weighted additive index and Nemoro index. Each SQI was calculated using two methods of indicator selection; total dataset (TDS) and minimum dataset (MDS) extracted by principal component analysis (PCA). Results showed that electrical conductivity, calcium carbonate, silt, bulk density and water holding capacity were included in the MDS that accounted for 84.37% of the total variance of the TDS. High significant correlations occurred between SQIs calculated using TDS and MDS under the three models, indicating high efficiency of the PCA to establish a MDS for the study area. The highest correlation and most prediction occurred when applying the weighted additive index. Further investigations are recommended to appraise indicators included in the MDS.

Keywords: Factor analysis, Minimum dataset, Soil quality index, Spatial analysis, Kafr El-Sheikh

INTRODUCTION

Soil quality (SQ) is defined as "the capacity of a soil to have a biological function, to sustain plant and animal production, to maintain or enhance water and air quality and support human health and habitation" (Vincent *et al.*, 2018). The process of predicting the capacity of a soil for performing a certain function is known as SQ evaluation (de La Rosa, 2005). This is a valuable decision-making tool to grade croplands, adopt suitable management and conserve resources and to establish an early alarming system for the potential decline in soil multi-functionality (Schloter *et al.*, 2018).

Quantitative assessment of SQ includes three steps: (i) selecting soil properties known as indicators, (ii) scoring, and (iii) integrating the scores into a single index (Guo *et al.*, 2017). The total data set (TDS) and minimum data set (MDS) are used for indicator selection; the former is a variety of indicators based on specific properties of soil, while the latter is a collection of a minimum number of indicators based on correlations among indicators (Rahmanipour *et al.*, 2014). Scores are assigned to each indicator using linear and/or none linear scoring functions (Raiesi, 2017). The scores are finally combined into an index using various models including additive quality (AQI), weighted quality (WQI), and Nemoro quality indices (NQI) (Nabiollahi *et al.*, 2017).

A high number of soil physicochemical properties are included in quality indexing. However, as measurements of indicators are time-consuming, developing simple and effective indices based on the most informative and reliable indicators is of great importance (Pascazioa *et al.*, 2018). Multivariate analysis such as principal component analysis (PCA) is a data reduction tool used for reducing indicator loads and avoiding data redundancy (Armenise *et al.*, 2013). It uses TDS of indicator to extract the appropriate ones in the form of MDS to be included in SQ indexing. The MDS is a site-specific of which the applicability to certain soil type, region, and land use should be appraised before recommendations (Biswas *et al.*, 2017).

The spatial analysis or spatial statics in the geographic information system (GIS) includes the analytical techniques that study entities in conjunction with their dimensions and associated attributes (ElBaroudy, 2015). Interpolation predicts unknown values of any geographic point using a limited number of known points. It depends on the assumption that things that are close to one another are more alike than those that are farther apart (Xie *et al.*, 2011). One of the most common interpolation methods is the inverse distance weighted (IDW) that is widely used in agricultural practices (Moghanm, 2015). The IDW estimates cell values by averaging the values of sample data points in the neighborhood of each processing cell. The closer a point is to the center of the cell being estimated, the more influence, or weight; it has in the averaging process (ESRI, 2014).

Surface soil samples are used for assessing SQ; however, soil-environment functionality is affected by inherent as well as anthropic aspects (Karlen *et al.*, 2013). Thus, assessing SQ using surface soil solely gives an incomplete vision, since crop yield is affected by surface and subsurface soil properties (Vasu *et al.*, 2016). Using data reduction techniques allows increasing the intensity of soil sampling, providing a better evaluation of SQ from a spatial analysis point of view (Rahmanipour *et al.*, 2014). In this respect, the goal of the current work was to use physicochemical properties of soil profiles in some agricultural lands in Kafr El-Sheikh Governorate, Egypt for evaluating soil quality in the study area using selection methods of TDS and MDS and three indexing models to select the most appropriate model.

MATERIALS AND METHODS

Site description

The area is located in west of Kafr El-Sheikh Governorate, Egypt between 30° 27′ 48″ - 30° 29′ 27″ E and 31° 03′ 43″ - 31° 22′ 53″ N (Fig. 1) with a total area of 674.13 km^2 (67413 ha). According to Said (1993), the area is covered with deposits of neonile which accumulated during the late Pleistocene era. Abuzaid *et al.* (2018) showed that the main landscape in the area is floodplain that includes five geomorphic units, *i.e.* levee, overflow mantle, recent terraces, middle terraces, and old terraces. Based on EMA (2011) and Soil Survey Staff (2014), the soil temperature regime is "Thermic" and the moisture regime is "Torric".

Soil sampling and analysis

Thirty soil profiles were geo-referenced (Fig. 2) using the GPS and dug to 150 cm depth. They were described according to FAO (2006). A number of 90 soil samples (disturbed and undisturbed) were collected from the horizons. Samples were air dried, grounded and sieved through a 2-mm mesh. Soil chemical analysis, including pH in 1 : 2.5 soil-water suspension, electrical conductivity (EC) in soil paste extract, cation exchange capacity (CEC), exchangeable sodium percentage (ESP), organic matter (OM) and calcium carbonate were determined according to standard methods of Sparks *et al.* (1996). Soil physical analyses, including particle size distribution using the pipette method, bulk density (BD) using core method, total porosity (TP), water holding capacity (WHC) infiltration rate (IR) and penetration resistance (PR) were performed according to Flint and Flint (2002).

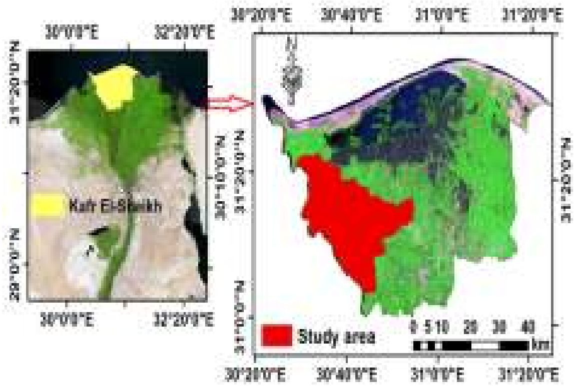

Fig. 1. Location map of the study area

Assessment of soil quality (SQ)

1. Indicator selection

Total data set (TDS)

Fourteen parameters were selected in TDS for their sensitivity in SQ appraising (Table 1). Obtaining a unique value for the whole soil profile, weighted mean value (WMV) for each indicator (property) was calculated by multiplying value of the property by the thickness of soil horizon and dividing the resultant by the depth of soil profile. Before calculations, soil pH data were converted to hydrogen ion concentrations and were then transformed back into pH.

Minimum dataset (MDS)

The MDS was established through the PCA. Only the factors with eigenvalues of > 1 and those that explained at least 5% of the variation in the data set were chosen. For each PC, only highly loaded variables (having absolute values within 10% of the highest factor loading) were retained for the MDS since they are the most representative of SQ (Biswas *et al.*, 2017). If more than one variable was retained under a PC, a multi-variate correlation was used to decide which was included. Well-correlated variables were considered redundant, and thus highest loaded was only included in the MDS. When the highly weighted variables were not correlated, each was considered important and was selected in the MDS (Guo *et al.*, 2017).

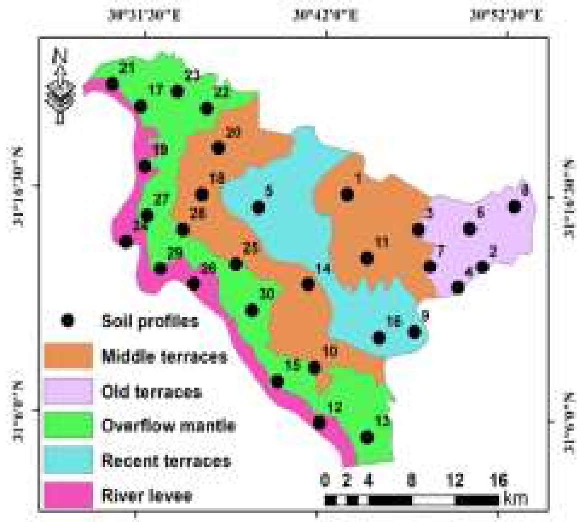

Fig. 2. Geomorphic map (After Abuzaid, *et al.*, 2018) and locations of soil profiles

2. Indicator scoring

A score ranging from 0 to 1 was assigned to each indicator through the linear scoring function (Raiesi, 2017) using three standard scoring functions; low is better (Eq. 1), more is better (Eq. 2) and optimal range (Table 1).

$$\mathbf{LS} = \frac{\mathbf{X_{min}}}{\mathbf{X}} \quad (1)$$

$$\mathbf{LS} = \frac{\mathbf{X}}{\mathbf{X_{max}}} \quad (2)$$

Where LS is the linear score, X is the indicator value and X_{min} and X_{max} are the minimum and maximum value respectively of each indicator.

Table 1. Dataset for soil quality assessment

Indicator	Associated soil function	SSF	Optimal range	Limits reference
Sand	Fertility, structure, erosion & water retention	LB		
Silt		MB		
Clay		OR	25%	Armenise *et al.* (2013)
OM				
WHC	Water storage and availability	MB		
IR		OR	0.3 cm hr^{-1}	FAO (1985)
BD	Soil structure	LB		
TP	Water and air movement	OR	50%	Expert opinion
EC	Microbial activity and plant growth	OR	0.2 – 2 dS m^{-1}	Rahmanipour *et al.* (2014)
pH	Nutrients and rooting relations	OR	7	Nabiollahi *et al.* (2017)
CEC	Nutrient retention	MB		
ESP	Water infiltration and movement	LB		
$CaCO_3$	Root penetration and water relations	LB		
PR		LB		

OM, organic matter; WHC, water holding capacity; IR, infiltration rate; BD, bulk density; TP, total porosity; EC, electrical conductivity; CEC, cation exchange capacity; ESP, exchangeable sodium percentage, PR; penetration resistance, SSF, standard scoring function; MB, more is better; LB, less is better; OR, optimum range.

More is better function was applied to indicators being preferred when in high values, while less is better function was applied to indicators restrict good soil functionality when in high values. For optimum range function, indicators were scored as more is better up to a threshold value then scored as less is better above this threshold.

3. Developing soil quality indices (SQIs)

1. Additive quality index (AQI)

This index was calculated according to Nabiollahi *et al.* (2017) using the following equation:

$$\mathbf{AQI} = \sum_{i=0}^{n} \frac{S}{n} \quad (3)$$

Where S is the score of the indicator and n is the number of indicators used in the index.

2. Weighted additive quality index (WQI)

Each indicator was assigned a weight value by means of PCA. For the TDS, weights were calculated as the quotient of the communality of indicator divided by the sum of the communality of all indicators (Guo *et al.*, 2017). Weights of MDS were calculated based on variation of the PCA (Mukherjee and Lal, 2014). The variation of each respective PC (%) was divided by the total percentage of variation of all PCs with eigenvectors > 1. The WQI was calculated according to Raiesi (2017) as follows:

$$\mathbf{WQI} = \sum_{i=0}^{n} W_i \times S_i \quad (4)$$

Where W is the weight value of the indicator and S is the score of indicator

3. Nemoro quality index (NQI)

This index evaluates soil quality based on the minimum and average scores of indicator (Guo *et al.*, 2017; Nabiollahi *et al.*, 2017) as follows:

$$\mathbf{NQI} = \sqrt{\frac{P_{aver}^2 + P_{min}^2}{2}} \times \frac{n-1}{n} \quad (5)$$

Where P_{aver} and P_{min} are the average and minimum of indicator scores, and n is the number of indicators included in calculations.

Statistical and spatial analysis

The statistical analysis was carried out using IBM SPSS 19.0 software and Microsoft Excel. The correlation and regression between SQIs computed from TDS and MDS was analyzed to verify how well the MDS represented the TDS. Spatial analysis of SQIs was executed using ArcGIS 10.2.2. The interpolation was performed using the inverse distance weighting (IDW). The raster layers were reclassified into five equal intervals to identify SQ grades, *i.e.* I, II III, IV and V (very high, high, moderate, low and very low, respectively). The raster to polygon tool was used to extract area of each grade.

RESULTS AND DISCUSSION

Soil physicochemical properties

The soils were very deep (depth > 150 cm) and flat to gently sloping (slope < 2%). According to Soil Science Division Staff (2017), the soils were slightly to moderately alkaline (pH 7.36-7.99), and none to moderately saline (EC 1.35-8.36 dS m^{-1}) as shown in Table 2. The ESP ranged from 6.15 to 37.45, indicating none to high sodicity (alkalinity) hazards (FAO, 1988). In north Nile Delta, salinization and sodifiction result from Mediterranean seawater intrusion besides poor soil and water management practices (Mohamed, 2017). Particle size distribution (PSD) indicated ranges of 13.01 to 35.82% for sand, 16.30 to 43.44% for silt, and 25.92 to 65.80% for clay. Soil textural classes included clay, clay loam and loam, with clay being the most predominant class. The soils showed variation in $CaCO_3$ ranging from 21.21 to 39.10 g kg^{-1}.

Table 2. Weighted mean average of soil properties

Profile	pH	EC, dS m^{-1}	OM, g kg^{-1}	CEC, cmolc kg^{-1}	ESP	$CaCO_3$, g kg^{-1}	Sand, %	Silt, %	Clay, %	Textural class	BD, Mg m^{-3}	TP, %	WHC, %	IR, cm h^{-1}	PR, MPa
1	7.48	1.81	12.06	28.21	24.16	29.19	27.48	40.10	32.42	CL	1.80	31.96	36.15	0.34	3.38
2	7.81	5.43	12.83	24.25	8.25	24.04	28.68	43.44	27.88	CL	1.69	36.23	36.98	0.48	3.08
3	7.73	5.12	16.73	33.03	11.87	21.21	24.80	37.24	37.96	CL	1.91	27.81	39.01	0.26	4.00
4	7.76	5.29	12.47	37.27	8.07	23.15	26.51	30.66	42.83	C	1.67	36.83	36.55	0.20	3.00
5	7.55	1.93	12.36	35.62	23.62	29.65	26.95	32.11	40.94	C	1.78	32.83	37.15	0.22	3.35
6	7.79	4.94	13.41	24.12	8.32	26.79	30.94	26.75	42.31	C	1.71	35.51	37.12	0.20	3.16
7	7.85	4.92	18.60	31.99	10.82	22.06	21.79	34.68	43.53	C	1.90	28.45	37.08	0.23	3.68
8	7.75	6.03	13.90	34.27	12.79	24.29	19.99	33.59	46.42	C	1.91	28.08	37.94	0.21	3.93
9	7.49	8.46	18.14	41.03	18.38	33.33	23.10	29.74	47.16	C	1.89	28.53	37.30	0.19	3.88
10	7.57	1.55	12.41	25.55	9.90	27.84	27.78	42.85	29.37	CL	1.88	29.13	37.15	0.41	3.76
11	7.68	5.78	12.50	33.61	11.89	29.13	24.52	36.86	38.63	CL	1.84	30.57	36.13	0.25	3.63
12	7.70	1.59	12.78	37.51	9.15	26.29	27.45	29.44	43.12	C	1.84	30.42	37.65	0.19	3.66
13	7.53	7.56	17.43	43.16	16.96	33.04	21.99	28.40	49.61	C	1.88	29.06	37.75	0.18	3.85
14	7.63	5.62	14.55	35.02	12.26	31.61	24.36	35.70	39.94	CL	1.83	31.09	36.55	0.24	3.47
15	7.56	7.55	18.38	39.53	11.50	34.83	21.05	31.56	47.39	C	1.89	28.79	39.23	0.20	3.91
16	7.68	6.82	17.46	39.09	15.36	33.56	15.44	36.39	48.17	C	1.91	27.92	39.12	0.22	4.07
17	7.89	1.71	17.13	34.12	16.64	32.47	35.82	24.96	39.22	CL	1.99	24.78	35.81	0.21	4.53
18	7.76	7.11	18.01	51.89	37.28	25.11	21.57	18.79	59.65	C	1.92	27.70	40.38	0.18	4.00
19	7.45	1.35	10.76	57.25	34.00	35.07	17.90	16.30	65.80	C	1.87	29.55	39.73	0.22	3.70
20	7.80	6.13	21.60	51.51	37.45	24.27	16.20	24.59	59.21	C	1.90	28.34	39.30	0.21	3.93
21	7.99	1.91	16.98	35.67	15.84	29.24	32.68	26.32	41.00	C	1.90	28.19	36.90	0.19	3.84
22	7.83	7.62	20.52	44.81	36.93	23.39	16.24	24.38	59.38	C	1.94	26.98	43.11	0.21	4.16
23	7.41	2.44	12.92	55.12	30.77	32.20	13.01	22.66	64.34	C	1.89	28.68	43.36	0.24	3.85
24	7.74	7.13	16.85	32.53	13.03	32.30	32.21	30.40	37.39	CL	1.82	31.40	36.50	0.23	3.67
25	7.71	3.72	9.87	22.55	6.15	29.74	33.83	40.26	25.92	L	1.63	38.49	38.00	0.58	2.95
26	7.36	7.43	15.69	35.36	10.89	36.74	30.68	28.68	40.65	C	1.91	28.08	37.50	0.20	4.33
27	7.75	5.43	12.92	33.34	12.72	35.75	31.18	30.50	38.33	CL	1.85	30.15	36.60	0.23	3.71
28	7.74	3.65	8.83	36.23	6.78	29.23	21.23	37.13	41.64	C	1.70	36.04	37.25	0.24	3.19
29	7.78	3.96	9.78	25.18	7.37	30.78	24.58	34.62	40.79	C	1.71	35.36	36.72	0.23	3.25
30	7.49	8.86	18.11	37.45	11.87	39.10	19.45	34.92	45.63	C	1.92	27.70	37.62	0.21	4.17

EC, electrical conductivity; OM, organic matter; CEC, cation exchange capacity; ESP, exchangeable sodium percentage; C, clay; CL, clay loam; L, Loam; BD, bulk density; WHC; water holding capacity; IR, infiltration rate; PR, penetration resistance

Little variations in PDS and $CaCO_3$ among the soils could be attributed to homogenous parent materials of fluvial origin (Embabi, 2018). The soil OM was very low to moderate (Hazelton and Murphy, 2016) with a range of 8.83 to 21.60 g kg^{-1} due to high temperature (Jafari *et al.*, 2018). The CEC varied from moderate to very high (Hazelton and Murphy, 2016), as it ranged from 22.55 to 57.25 cmolc kg^{-1}. Soil WHC was high (Pulido *et al.*, 2017) with a range of 35.81 to 43.36%. The soils had low to medium water infiltration rate (FAO, 1985), since it ranged from 0.18 to 0.58 cm hr^{-1}. The BD varied from moderate to very high (Hazelton and Murphy, 2016), as it ranged from 1.63 to 1.99 Mg m^{-3}. Total porosity (TP) ranged from 24.78 to 3849%. The PR ranged from 2.95 to 4.53 MPa, indicating compact to very compact soils (Medvedev, 2009).

Correlations among soil properties

The CEC and WHC showed a high positive significant correlation ($P < 0.01$) with clay, but high negative significant ones with sand and silt (Table 3). The BD had a high significant positive correlation with clay, but a high significant negative correlation with slit and a significant negative one ($P < 0.05$) with sand. On the other hand, the TP and BD had a high significant negative correlation with clay, but a high significant positive correlation with slit and a significant positive one ($P < 0.05$) with sand. The IR showed high negative correlations ($P < 0.01$) with clay and BD, but a high positive one with silt. The PR had high negative correlations ($P < 0.01$) with clay and BD, but high positive ones with silt and TP. It has been reported that soil PSD is a key factor for controlling soil physicochemical properties (Khaledian *et al.*, 2017). The fine particles of clay and silt, unlike coarse ones of sand, have a higher specific surface area, thereby increasing soil sorption capacity (Blume *et al.*, 2016b) and water retention (Blume *et al.*, 2016a). In addition, fine particles have higher pore space, and thus increase soil porosity (Blume *et al.*, 2016a). The fine fractions also induce decreases in water movement by blocking the effective pores due to their small sizes, and bulk density for their relatively lower density of 1.0-1.6 Mg m^{-3} compared with 1.4-1.8 Mg m^{-3} for sands (McCarty *et al.*, 2016). Increase in bulk density causes soil compaction due to the reduction in soil porosity, and thus restrict root penetration (Shah *et al.*, 2017)

The principal component analysis (PCA)

The PCA (Table 4) show that the first five PCs had eigenvalues ≥1 and explained 84.37% of the variance for TDS. The eigenvectors after VARIMAX rotation indicated that WHC had the highest loading value, and sand and clay had values within 10% of this value. As the three parameters were significantly correlated with each other, the WHC was considered for PC1. In the same manner, BD, TP and PR were highly weighted and well correlated, thus the BD was selected for PC2. On the other hand, silt, EC and $CaCO_3$ had the highest loading under PC3, PC4, and PC5, respectively. Hence they remained in the MDS.

Table 3. Correlation matrix among soil physicochemical properties

Indicator	pH	EC	OM	CEC	ESP	$CaCO_3$	Sand	Silt	Clay	BD	TP	WHC	IR	PR
pH	1.00													
EC	0.101	1.00												
OM	0.516^{**}	0.485^{**}	1.00											
CEC	-0.212^{*}	0.03	0.056	1.00										
ESP	-0.280^{**}	-0.08	-0.224^{*}	0.665^{**}	1.00									
$CaCO_3$	-0.266^{*}	0.05	-0.275^{**}	0.143	0.085	1.00								
Sand	0.267^{*}	-0.217^{*}	-0.108	-0.642^{**}	-0.399^{**}	0.065	1.00							
Silt	0.021	0.07	-0.009	-0.711^{**}	-0.585^{**}	-0.143	0.095	1.00						
Clay	-0.188	0.09	0.076	0.915^{**}	0.669^{**}	0.058	-0.716^{**}	-0.763^{**}	1.00					
BD	-0.108	0.03	0.110	0.454^{**}	0.367^{**}	0.176	-0.251^{*}	$-.354^{**}$	0.411^{**}	1.00				
TP	0.108	-0.03	-0.110	-0.454^{**}	-0.367^{**}	-0.176	0.251^{*}	0.354^{**}	-0.411^{**}	-1.000^{**}	1.00			
WHC	-0.099	-0.12	-0.109	0.134	0.122	-0.144	-0.046	-0.102	0.101	-0.204	0.204	1.00		
IR	-0.121	-0.12	-0.211^{*}	-0.420^{**}	-0.119	-0.128	0.201	0.537^{**}	-0.507^{**}	-0.405^{**}	0.405^{**}	-0.100	1.00	
PR	-0.152	0.04	0.036	0.370^{**}	0.331^{**}	0.224^{*}	-0.178	-0.332^{**}	0.348^{**}	0.921^{**}	-0.921^{**}	-0.201	-0.365^{**}	1.00

Table 4. Results of the PCA of soil properties in the study area

PCA parameter	PC1	PC2	PC3	PC4	PC5		
Eigenvalue	5.367	2.160	1.960	1.260	1.060		
Variance (%)	38.330	15.420	13.990	9.030	7.590		
Cumulative (%)	38.330	53.760	67.740	76.770	84.370		
Weighting factor	0.454	0.183	0.166	0.107	0.090		
Indicator		Eigenvectors				Communality	Weight
pH	-0.365	-0.089	0.320	0.189	0.677	0.738	0.063
EC	0.084	-0.005	-0.006	0.891	-0.055	0.803	0.068
OM	-0.051	0.100	0.178	0.671	0.572	0.823	0.070
CEC	0.783	0.237	0.451	0.009	-0.082	0.879	0.074
ESP	0.715	0.215	0.209	-0.304	-0.114	0.706	0.060
CaCO3	-0.133	0.124	0.274	0.100	-0.839	0.823	0.070
Sand	-0.819	-0.118	0.117	-0.322	0.021	0.802	0.068
Silt	-0.433	-0.155	-0.796	0.212	0.017	0.891	0.075
Clay	0.836	0.186	0.482	0.060	-0.025	0.969	0.082
BD	0.183	0.961	0.163	0.022	-0.030	0.984	0.083
TP	-0.183	-0.961	-0.162	-0.022	0.030	0.984	0.083
WHC	0.874	0.060	0.009	-0.004	0.028	0.769	0.065
IR	-0.068	-0.288	-0.762	-0.211	0.003	0.713	0.060
PR	0.128	0.939	0.132	0.003	-0.110	0.928	0.079

*** Bold face factor loading are considered high weighted** **** Underlined and italic face factor loading are selected as MDS**

Assessment of SQ

1. According to TDS

The spatial distributions of SQ grades under two indicator methods and three indices (Table 5 and Fig 3) reveal that moderate quality (Grade III) was predominated when applying the three indices, and occupied around half of the total area, while very low quality (Grade V) represented the lowest portion. According to AQI, soils of Grade III occupied 48.01% of the total area, while the remaining area was occupied by soils of Grades I, II, IV, and V, representing 2.88, 16.08, 29.22 and 3.81%, respectively. Using WQI model, 47.82% of the area belonged to Grade III, while 2.61, 20.04, 26.20 and 3.33% of the area belonged to Grades I, II, IV and V, respectively. The distribution of SQ grades when applying NQI model was as follows: 1.85% for Grade I, 25.67% for Grade II, 48.69% for Grade III, 20.64% for Grade IV, and 3.15% for Grade V.

Table 5. Soil quality classification in the study area

Indicator	Index		Grades				
			Very high I	High II	Moderate III	Low IV	Very low V
TDS	AQI	Score	< 0.67	0.67 - 0.69	0.69 - 0.71	0.71 - 0.73	> 0.73
		Area, km^2	19.43	108.39	323.66	197.00	25.66
		Area, %	2.88	16.08	48.01	29.22	3.81
	WQI	Score	< 0.67	0.67 - 0.69	0.69 - 0.71	0.71 - 0.73	> 0.73
		Area, km^2	17.60	135.10	322.36	176.63	22.45
		Area, %	2.61	20.04	47.82	26.20	3.33
	NQI	Score	< 0.47	0.47 - 0.49	0.49 - 0.52	0.52 - 0.54	>0.54
		Area, km^2	12.48	173.04	328.26	139.15	21.20
		Area, %	1.85	25.67	48.69	20.64	3.15
MDS	AQI	Score	< 0.70	0.70 - 0.75	75 - 0.79	0.79 - 0.84	> 0.84
		Area, km^2	50.72	253.64	276.85	78.30	14.63
		Area, %	7.52	37.62	41.07	11.61	2.17
	WQI	Score	< 0.77	0.77 - 0.80	0.80 - 0.83	0.83 - 0.86	> 0.86
		Area, km^2	42.12	232.92	295.39	91.93	11.77
		Area, %	6.25	34.55	43.82	13.64	1.75
	NQI	Score	< 0.45	0.45 - 0.50	0.50 - 0.56	0.56 - 0.61	> 0.61
		Area, km^2	88.89	347.93	162.57	60.69	14.05
		Area, %	13.19	51.61	24.12	9.00	2.08

TDS, total dataset; MDS, minimum dataset; AQI, assertive quality index; WQI, weighted quality index; NQI, Nemoro quality index.

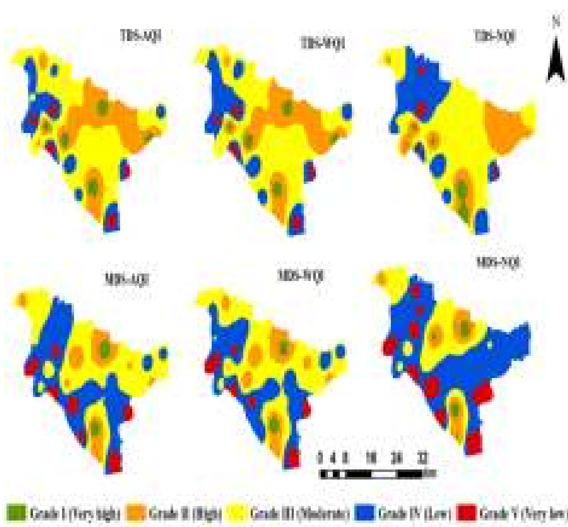

Fig. 3. Soil quality maps in the studied area

2. According to MDS

Soils of Grade III dominated the area when applying AQI and WQI and those of Grade II were predominant under NQI, while soils of Grade V occupied the smallest areas under the three models (Table 6 and Fig. 3). For the AQI, 41.07% of the area was represented by soils of Grade III, while the remaining area was occupied by soils of Grade I (7.52%), Grade II (37.62%), Grade IV (11.61%) and Grade V (2.17%). Under WQI model, 43.82% of the area belonged to Grade III, while the remaining area belonged to Grades I, II, IV and V, repressing 6.25, 34.55, 13.64 and 1.75%, respectively. In contrast to the other models, results of NQI model showed that Grade II accounted for half of the area (51.61%), while 13.19% for Grade I, 24.12% for Grade III, 9.00% for Grade IV and 2.08% for Grade V.

Comparison of indices

The linear relationships (Fig. 4) showed high significant correlations ($P < 0.01$) between SQIs calculated using MDS and TDS with different models. This result indicates that MDS well represented the TDS in the study area, and could be used to track temporal changes in SQ (Qi *et al.*, 2009; Guo *et al.*, 2017). The PCA is a powerful tool to assess MDS for different soil types (Armenise *et al.*, 2013; Biswas *et al.*, 2017). Values of R^2 between TDS and MDS were 0.71, 0.80 and 0.49 for AQI, WQI and NQI, respectively. Consequently, the most suitable model for the area was WQI. This is similar to studies of other agricultural lands in arid and semi-arid regions. Rahmanipour *et al.* (2014) obtained a high correlation between MDS and TDS when applying WQI compared with NQI. Moreover, Nabiollahi *et al.* (2017) reported that WQI and MDS approach can adequately represent the TDS rather than AQI or NQI. This trend could be attributed to using weights of indicators that discriminates the importance of each soil property independently. For the WQI, all selected indicators are considered but directed by their relative importance, with highly weighted parameters being key factors. For NQI model, in contrast, indicator with the lowest score is added to the scores average, assigning it preferential importance. In other words, NQI gives more importance to the lowest score parameter, without considering its weight (Qi *et al.*, 2009; Guo *et al.*, 2017). Similar to NQI, the AQI is determined without considering the relative weights of indicators. In addition, it is subjective and relies mainly on researcher's opinion; however it is easier to implement rather than others models (Mukherjee and Lal, 2014; Nabiollahi *et al.*, 2017).

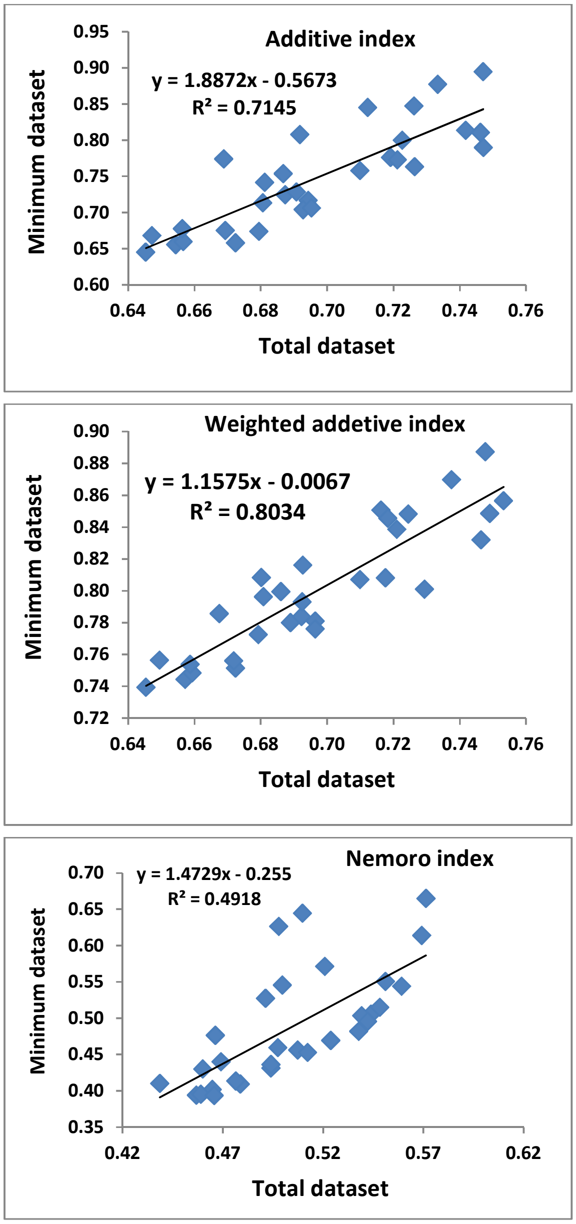

Fig. 4. Linear relationship between soil quality indices calculated total dataset and minimum dataset

CONCLUSION

The PCA provides an effective tool to establish a MDS in the study area to reduce time and cost of sampling an analysis. Among various soil physicochemical properties, EC, $CaCO_3$, silt, bulk density and water holding capacity were considered in the MDS. For the TDS, Grade III occupied nearly half of the area under AQI, WQI and NQI models, while Grade II was predominant when applying MDS under WQI and NQI. The highest correlation and most prediction occurred when applying the WQI. This model would be to track temporal changes in SQ in the study area in response to management practices and environmental risks. However, indicators included in the MDS should be assessed over time.

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التحليل المتعدد المتغيرات والمكاني لجودة التربة في محافظة كفر الشيخ - مصر

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تهدف هذه الدراسة إلى تقييم جودة التربة في بعض الأراضي الواقعة غرب محافظة كفر الشيخ – مصر بإستخدام التحليل المتعدد المتغيرات والمكاني لخواص التربة. ولتحقيق ذلك تم عمل 30 قطاع أرضي في منطقة الدراسة وجمعت منها عينات التربة من مختلف الآفاق. أوضحت النتائج أن التوصيل الكهربي، كربونات الكالسيوم، السلت، الكثافة الظاهرية، و السعة الحقلية هي العوامل الرئيسية الدالة على خصائص التربة بالمنطقة. كما وجد إرتباط معنوي قوي بين دلائل جودة التربة المحسوبة على أساس هذه الخصائص الأربعة وتلك المحسوبة على أساس كل البيانات، مما يؤكد دقة طريقة إستخلاص هذه البيانات الممثلة. سجلت أعلى قيمة لمعامل الإرتباط عند إستخدام الطريقة الوزنية، مما يدل على ملاءمة هذه الطريقة في تتبع التغيرات الزمنية لجودة التربة في منطقة الدراسة تحت تأثير عمليات الخدمة والظروف البيئية المحيطة.