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A soil quality index for evaluation of degradation under land use and soil erosion categories in a small mountainous catchment, Iran

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Abstract: Soil erosion and land use type have long been viewed as being particularly important drivers of soil degradation. The objectives of this study, therefore, were to select a new soil quality index (SQI) which varies significantly with land use/soil erosion, and to evaluate the new SQI using expert opinion. In total, 18 soil physical, chemical, and biochemical properties (indicators) were measured on 56 soil samples collected from four land use/soil erosion categories (rangeland/surface erosion, rangeland/ subsurface erosion, cultivated land/surface erosion and dry-farming land/surface erosion). Principal component and classification analysis (PCCA) identified five PCs that explained 77.7% of the variation in soil properties with the biochemical PC varying significantly with land use/soil erosion. General discriminant analysis (GDA) selected urease and clay as the most sensitive properties distinguishing the land use/soil erosion categories. The GDA canonical scores for the new SQI were significantly correlated with expert opinion soil surface summed scores (for soil movement, surface litter, pedestalling, rills and flow pattern) derived using the U.S. Department of the Interior Bureau of Land Management (BLM) method. A forward stepwise general regression model revealed that the new SQI values were explained by soil movement, surface litter, and the summed values of the soil surface factors. Overall, this study confirmed that soil quality in the study area in Iran is controlled by land use and corresponding soil erosion.

Keywords: Soil quality index; Land use; Erosion status; Soil enzyme activities; Multivariate statistical techniques

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Introduction

Soils deliver multiple services to humankind but are under threat from a range of competing uses and intensification of management practices (Drobnik et al. 2018; Godfray et al. 2010; Muñoz-Rojas 2018; Stolte et al. 2016). Here, it is vitally important to acknowledge that soil is essentially a non-renewable resource at timescales relevant to agricultural production and economic development since its regeneration, post degradation, can be extremely slow (Lal 2015). Expansive soil degradation has, nevertheless, been reported by numerous studies (Akhtar-Schuster et al. 2017; Keesstra et al. 2016; Stavi and Lal 2015). In particular, accelerated soil erosion is a serious global problem (Van Oost et al. 2007). Soil erosion leads to on-site soil degradation as result of the loss of soil organic matter and nutrients. Soil degradation can also manifest in other ways including, for example, compaction, sealing, salinization, acidification, alkalinization, chemical or heavy metal contamination, biodiversity decline and increased incidence of floods or landslides (Ayoubi et al. 2014; Bindraban et al. 2012; Emadi et al. 2009; European Commission 2006; Jónsson et al. 2016; Nabiollahi et al. 2018a; Nabiollahi et al. 2017; Nosrati 2013; Pham et al. 2018; Yu et al. 2018a). Such widespread issues are important in the context of the United Nations' 17 Sustainable Development Goals (SDGs, Keesstra et al. 2016), since sustainable soil management has direct relevance to at least half of them (Jónsson et al. 2016).

In broad terms, soil quality can be defined as "the capacity of a soil to function, within ecosystem and land use boundaries, to sustain productivity, maintain environmental quality, and promote plant and animal health" (Dilly et al. 2018; Doran and Parkin 1994; Karlen et al. 1997). Soil quality is thereby a critical aspect of ecosystem functioning and agricultural sustainability and reflects the abiotic and biotic interaction of processes that sustain plant and animal productivity. In contrast, soil health refers to the capacity of soil to sustain critical functions (Bünemann et al. 2018; de Paul Obade 2019).

The capacity of soil to function can be reflected by measured soil physical, chemical and biological properties, also known as soil quality indicators. Soil quality therefore integrates physical, chemical and biological components and processes and the interactions among them (Andrews et al. 2004; Dexter 2004; Karlen et al. 2001; Thoumazeau et al. 2019). As a result, comprehensive characterisation of soil quality should be based on such multiple attributes and functions (O'Sullivan et al. 2015). Here, identification of indices has been called for as a means of assessing soil quality and progress towards improved sustainability (Easdale 2016). Such indices combine and integrate critical indicators and thereby simplify complex information by quantifying and communicating salient features of soil quality to multiple stakeholders for providing improved transparency on the basis for decision-making for soil management (Arshad and Martin 2002; Burger and Kelting 1999; Doran and Parkin 1994; Jesinghaus 1999; Jónsson et al. 2016). Soil quality indices (SQIs) should be selected according to the soil functions of interest and the defined management goals including both on-farm and broader environmental outcomes (Drobnik et al. 2018; Karlen et al. 2006; Rapport et al. 1998).

A wide range of soil properties have been used as soil quality indicators. An effective property or indicator should be able to differentiate between potential land units (e.g. land use types, soil erosion) and should be sensitive to both natural processes or conditions and anthropogenic management. Soil enzyme activities provide a means of assessing the degree of soil degradation because they act as early and sensitive indicators of soil ecological stress (Chaer et al. 2009; Nosrati 2013) due to microbial activities being closely related to enzyme activities in many soil functions (Zornoza et al. 2007). It is therefore not surprising that changes in soil enzyme activities have been suggested as indicators of changes to, or disturbances of, the soil ecosystem (de Andrade Barbosa et al. 2019; Naseby and Lynch 2002). Soil enzymes are inherently more sensitive to environmental conditions than other soil properties and therefore reflect the interaction between natural biochemical processes and anthropogenic management practices within a catchment.

The fundamental steps for developing a SQI comprise the pre-selection of potential indicators, indicator scoring and indicator integration into the final SQI. Two categories of SQI exist; those describing the current condition of soil on the basis of detailed field measurements (Arshad and Martin 2002) and those that monitor change in response to management systems (Oberholzer et al. 2012). Selection of variables (indicators) for inclusion in a SQI may be simplified by statistical methods. Several multivariate statistical techniques and modelling approaches have been widely applied to evaluate soil quality for different soils under different management regimes (Biswas et al. 2017; Brejda et al. 2000; de Paul Obade and Lal 2016;

Nabiollahi et al. 2018a,b; Nosrati 2013; Raiesi 2017; Sánchez-Navarro et al. 2015; Yu et al. 2018b; Zuber et al. 2017). While the number and diversity of soil quality studies has increased, there remains a need to explore the scope for developing new SQIs.

Soil quality degradation in Iran is widespread (Ayoubi et al. 2014; Emadi et al. 2009; Nosrati 2013; Raiesi 2017; Rezapour 2014). Current socio-economic pressures in Iran pose a serious threat to soil quality and thereby both food security and environmental protection. In this context, the objectives of this study, therefore, were: (1) to determine soil quality principal components (PCs) which vary significantly with land use/soil erosion categories; (2) to select a SQI from these PCs that can be used for soil quality monitoring, and; (3) to examine whether a relationship exists between the resulting SQI and expert opinion based on the soil surface factors (SSF) scoring form of the U.S. Department of the Interior Bureau of Land Management (BLM).

1 Materials and Methods

1.1 Study area

The study was conducted in the Zidasht catchment (36° 05′35″ to 36°11′46″N and 50°37′46″ to 50°44′56″E), which is part of the Taleghan Drainage Basin, in the Southern Alborz Mountains, 90 km Northwest of Tehran, Iran (Figure 1). The drainage area of the Zidasht study catchment is 62.3 km², including 11.26 km² (18.1% of total area) of crop fields (irrigated and dry-farming lands), 0.19 ha (0.3% of total area) of residential use, and 5085 km² (81.6% of total area) of natural rangelands (grass, forbs and shrubs e.g. *Astragalus gossypinus, Agropyron intermedium, Bromus tomentellus*). The Zidasht catchment has a mountainous topography, with a minimum and maximum elevation of 1690 m and 3038 m above sea level, respectively. The average slope gradient is 20%. The soil map of Iran provided by the Iran Forests, Range and Watershed Management Organization (IFRWMO) shows that the soils within the catchment are mainly Typic Xerorthents, Lithic Xerorthents, Typic Haploxerepts, and Typic Calcixerepts. Based on the data provided by the Iran Meteorological Organization, long-term (1975-2015) mean annual precipitation in the study area is about 456 mm. Mean annual and mean monthly minimum/maximum temperatures are reported as 9.7°C, 2.4°C and 17°C, respectively.

1.2 Soil sampling

Based on land use and soil erosion types, the study catchment was divided into four land units (categories) for sampling; rangeland/surface erosion, rangeland/subsurface erosion, cultivated (irrigated) land /surface erosion and dry-farming (rain-fed) land/surface erosion. A total of 56 representative soil samples were collected from different locations within the catchment in uniform topographic units characteristic of the four groups, thereby yielding 15, 15, 15 and 11 samples from rangeland/surface erosion, rangeland/subsurface erosion, cultivated land/ surface erosion and dry-farming land/surface erosion, respectively (Figure 1). All samples were collected manually with a trowel from the upper 5 cm of the soil layer since visual evidence suggested this was representative of the active depth of surface soil erosion. In order to ensure that the surface erosion samples were representative of the potential heterogeneity of the individual land use in question, composite samples, comprising five sub-samples, were collected over an area of approximately 100 m². This composite sampling technique, by collecting replicate independent equal mass sub-samples (~100 g), was used to address the micro-spatial variability of the soil properties. To collect sub-samples from transects of the characteristic surface erosion, a zigzag strategy was used. In this manner, individual sub-samples were typically collected using a zigzag (a 'W' shaped pattern) sampling pattern at the individual locations that were distributed across the portion of the study area represented by this land use category (Figure 1). The subsurface erosion samples were collected by scraping soil from the full vertical extent of actively eroding bank faces. At each bank sampling site, five equal mass sub-samples were collected within 20 m reaches and composited.

Following collection, the soil samples were gently air-dried and dry sieved (<2 mm). For enzyme activity analysis, however, a portion of each soil sample was temporarily conserved in a sealed plastic bag and stored in a cool box on ice

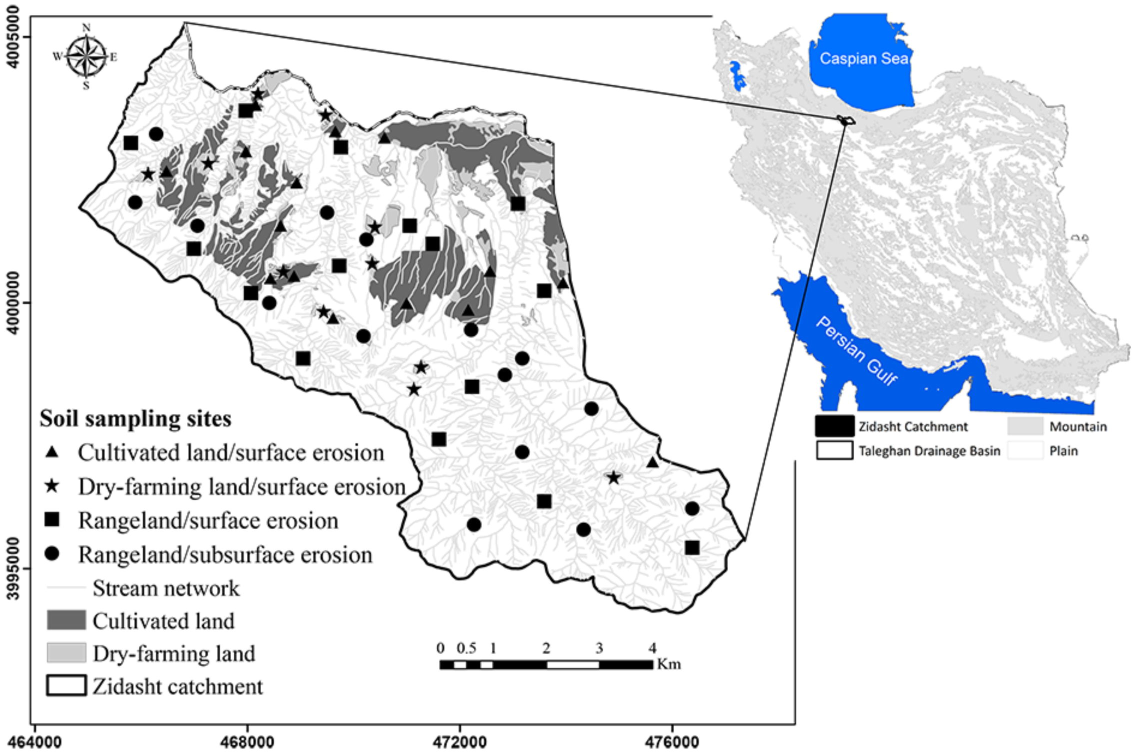

Figure 1 Study area location map and soil sampling sites.

for transportation to the laboratory. This kept the sub-samples for enzyme activity analysis field moist and cool until analysis.

The U.S. Department of the Interior Bureau of Land Management (BLM) soil surface factors (SSF) reconnaissance procedure (Sadeghi 2005), based on six visible soil surface features, was selected as to provide soil functions for the qualitative assessment of the SQI. Here, values for the six soil surface indices (soil movement, surface litter, surface rock, pedestalling, rills and flow pattern) were estimated. In essence, each feature is assigned a numerical value representing the degree of soil degradation as a result of erosion processes. The first five factors are scored from zero to fourteen, whereas the last one is scored up to fifteen. Scores assigned to each individual factor were summed (sum of SSF) to represent soil erosion intensity from 'very little' to 'very active' erosion.

1.3 Soil sample laboratory analyses

A representative range of soil physical, chemical and biological properties were analysed. These included particle size distribution (clay, silt and sand), soil organic carbon (SOC), total nitrogen (TN), electrical conductivity (EC), pH, available water capacity (AWC), water holding capacity (WHC), bulk density (BD), enzyme activities (urease, alkaline phosphatase, β-glucosidase and dehydrogenase), calcium (Ca), potassium (K), magnesium (Mg), sodium (Na) and phosphorous (P) were measured on the soil samples (<2 mm fraction) as potential indicators for inclusion in the final SQI. Following dispersion with sodium hexametaphosphate, particle size distribution (clay, silt and sand) was measured using the hydrometer method (Kroetsch and Wang 2008). SOC content was measured by the Walkley-Black method (Skjemstad and Baldock 2008) and TN was determined by the Kjeldahl method (Rutherford et al. 2008). Acid dissolution of carbonate and subsequent titration of CO_2 with NaOH was used as a basis for calcium carbonate determination (Nelson 1982). A pH and EC meter (Mettler Toledo) was used to measure electrical conductivity (EC) and pH in a 1:1 soil:water suspension. Soil available water capacity (AWC) was measured based on difference between the volumetric water content at field capacity (FC) and permanent wilting point (PWP). The water contents at a potential of 10 kPa and 1500 kPa represent the FC and PWP, respectively. The soil water content at FC and PWP was determined using a pressure plate extractor (Cassel and Nielsen 1986; Townend and Reeve 2001). Soil water holding capacity (WHC) was determined as water contents at field capacity. Soil bulk density (BD) was assayed using Forster (1995). One gram of the sieved oven-dried soil samples was analyzed for calcium (Ca), potassium (K), magnesium (Mg), sodium (Na) and phosphorous (P) following aqua regia ($HCl–HNO_3$; 3:1; for 2 h) digestion in a Velp Thermo-reactor using atomic absorption spectroscopy (AAS; Varian SpectrAA-20 Plus) and a standard solution (Merck KGaA, Frankfurter, Germany). The accuracy of the AAS analysis was >94.5%, while the corresponding precision was >95% for all elements.

The four enzyme activities (urease, alkaline phosphatase, β-glucosidase and dehydrogenase) were measured by absorption on a spectrophotometer (DR6000™ UV VIS Spectrophotometer). Using urea as a substrate, urease activity (UA) was assessed on the basis of the ammonium released after the incubation of soil samples with a borate buffer for 2 h at 37°C (Alef and Nannipieri 1995). Alkaline phosphatase (APA) and β-glucosidase (βGA) activities were respectively determined using p-nitrophenylphosphate and p-nitrophenyl-β-D-glucopyranoside as substrates and the release and detection of p-nitrophenol (Tabatabai 1994). Dehydrogenase activity (DHA) was assessed by incubating the soil with 2,3,5-triphenyltetrazolium chloride for 24 h at 37°C and measuring the triphenyl formazan (Tabatabai 1994). All enzyme activities were reported on an oven dry-weight basis, determined by drying the soils for 24 h at 105°C.

1.4 Statistical tests

Previous studies to identify new SQIs use either total datasets (TDS) or minimum datasets (MDS). The latter can be selected by expert opinion (Andrews et al. 2004; Lima et al. 2013) or statistical analyses (Andrews et al. 2004; Rojas et al. 2016). The use of MDS recognises that no single property can provide a comprehensive measurement of soil quality (Garrigues et al. 2012; Masto et al. 2008; Wienhold et al. 2004; Yu et al. 2018b). Many studies use normalisation of indicator scores on the basis of linear or non-linear scoring functions (D'Hose et al. 2014; Sharma et al. 2005) and integrate the normalised indicators into SQIs using additive or multiplicative techniques (D'Hose et al. 2014; De Laurentiis et al. 2019; Lima et al. 2013; Masto et al. 2008; Sharma et al. 2005). The statistical tests for confirming MDS include, amongst others, PCA and varimax rotation followed by simple linear regression (Juhos et al. 2016), cluster analysis (Dilly et al. 2018) and correlation, PCA and discriminant function analysis (DFA) (Juhos et al. 2019). For SQI evaluation, some previous work has used either ANOVA or MANOVA to test associations between SQIs and soil management groups (de Andrade Barbosa et al. 2019; de Paul Obade and Lal 2016; Kiani et al. 2017; Molaeinasab et al. 2018; Nakajima et al. 2015).

The statistical procedure for identifying the new SQI is summarised in Figure 2. The Kolmogorov-Smirnov statistic was used to test the goodness-of-fit (GOF) of the laboratory data to a normal distribution. The Leven test was performed to assess the homogeneity of variance. One-way analysis of variance (ANOVA; F-test) was used for the different soil properties individually to examine for significant influences of the land use and soil erosion categories. Correlation analysis was also performed between the soil properties to determine if identification of underlying principal components (PC) patterns would be possible.

To identify a SQI from the list of indicators, first principal component & classification analysis (PCCA) was used to group the soil properties into statistical principal components (PCs) based on their correlation structure. PCCA was performed on standardized variables to eliminate the effect of different measurement units on the determination of factor loading. PCCA can be used as a classification technique in addition to reducing the dimensions of the original variable space so that the relations among variables and cases can be highlighted. PCCA therefore offers users with advantages over the more widely used factor analysis (FA) or PCA, by providing a basis for classification as well as variable reduction for the MDS. To do this, the variables and the cases are plotted in the space generated by the factor axes. This technique works in very much the same way as principal component analysis (PCA) but with one crucial difference; the individuals must be

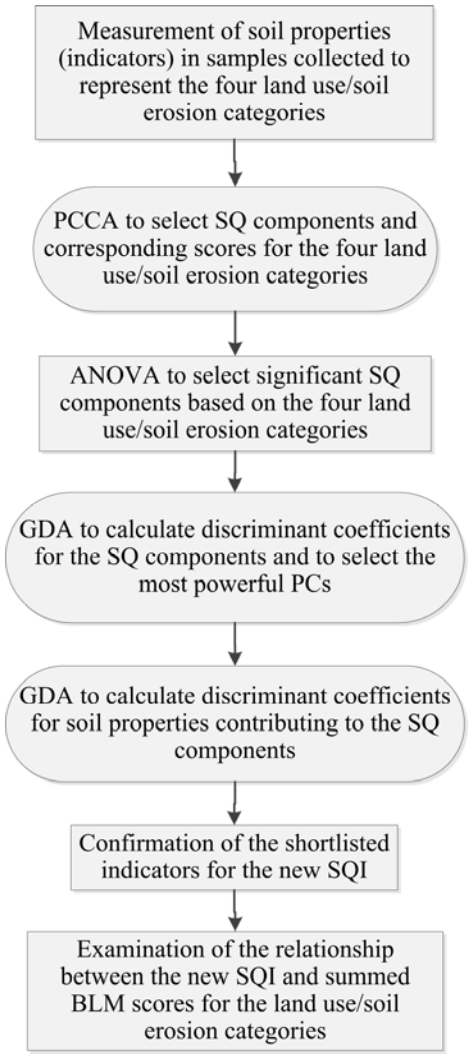

Figure 2 Flow diagram summarising the key steps in this study for soil quality index (SQI) creation.

assigned to groups before the analysis. The test then calculates the variable weightings that will maximize the differences between groups rather than individuals as is the case with PCA. The PCCA produces weightings that will allow you to identify those variables that are the most different between groups (land use and soil erosion categories in this study) and discard those that are the same.

PCs with eigenvalues >1 were retained and subjected to a varimax rotation to minimize the number of soil properties (indicators) that have high loadings on each PC. Under a particular PC, each property is given a weight or factor loading that represents the contribution of that property to the composition of the PC. Only the highly-weighted properties were retained from each PC. Highly weighted property loadings were defined as having absolute values within 10% of the highest property loading. In addition, communalities of every single soil property for each PC model were calculated to estimate the portion of variance in each of the soil properties explained by the rotated PCs. Less importance should be ascribed to soil properties with low communalities when interpreting variable associations represented by each PC.

In the next step, PCs scores for each sample point were calculated and analyzed using a ANOVA Tukey HSD post-hoc tests ($p<0.05$) using the four land use/soil erosion categories as the independent variables, to determine which PCs varied significantly with those land use/soil erosion categories. General discriminant analysis (GDA) was then used to select the statistical PCs that were most discriminating between the four land use/soil erosion categories. Following selection of the most discriminating PCs, soil properties that comprised these PCs were also subjected to GDA to select soil quality indicators for inclusion in the final SQI.

Correlation analysis was performed between the canonical score values of the selected discriminant functions resulting from GDA and the summed score values of the six soil surface factors derived from the BLM method to evaluate the new SQI. Additionally, the most significant soil properties included in the new SQI data set resulting from GDA were used as independent variables to fit a linear stepwise multiple regression with soil surface indices (comprising the six BLM method soil surface factors as well as the summed values of the SSF) as dependent variables to assess how well the new SQI represented the soil sampling sites in the study area. STATISTICA V. 8.0 (StatSoft 2008) was used for all statistical tests.

2 Results and Discussion

2.1 Identification of the new SQI

Assessment of changes in soil quality status is essential for evaluating the impacts of different land management practices, but this requires selection of key indicators for inclusion in a SQI (Arshad and Martin 2002). The basic statistics for the soil properties (indicators) within each different land use/soil erosion category are summarized in Table 1. The results of one-way ANOVA with the soil properties as dependent variables and the land use/soil erosion categories as independent variables are also presented in Table 1. The ANOVA results confirmed that SOC, soil TN and the soil enzyme activities showed significant contrasts between the land use/soil erosion categories at the 95% level of statistical confidence (Table 1). These results also demonstrated that the β-Glucosidase and urease soil enzyme activities showed higher significant contrasts between the land use/soil erosion categories (Table 1) and thereby appear to be promising as diagnostic biological properties (indicators) for soil quality assessment in the study area.

If there were no correlation between soil attributes, identification of underlying factor patterns would not be possible (Brejda et al. 2000). However, in the case of the samples retrieved from the study area, the 2-tailed correlation matrix for the soil properties showed several correlations among the variables with significant relationships (p < 0.05) being identified among 56 of 171 possible soil property pairs (Table 2). In general soil texture attributes correlated with soil organic attributes (including SOC, TN and enzyme activities). In addition, SOC and TN were positively correlated with soil enzyme activities. In contrast, percentage sand was negatively correlated with silt, clay, AWC, WHC, SOC, TN, and UA. The strongest negative correlations were between percentage sand and percentage silt (r=-0.92) or percentage clay (r=-0.90). The strongest positive correlations were between percentage AWC and WHC (r=-0.92), SOC and TN (r=-0.94), K and Mg (r=-0.98). The results revealed strong positive correlations between enzyme activity pairs (r>0.78). BD and Ca were not correlated with other soil properties (Table 2). The large amount of correlation present among the soil properties indicated that they can be grouped into homogenous sets of variables based on their correlation patterns and thereby used as indicators of soil quality in conjunction with the land use and soil erosion categories identified in the study area.

The results of PCCA showed that the first five principal components (PCs) with eigenvalues >1 (Figure 3a) accounted for >77% of the variability among the soil properties for the four land use/ soil erosion categories (Table 3). Considering the communality estimates for individual soil

Table 1 Means and standard deviations (S.D.) of the soil properties and results of the one-way ANOVA comparing the soil properties within the different land use/soil erosion categories. (S= surface erosion; SS= subsurface erosion)

Soil properties	Rangeland/S		Rangeland/SS		Cultivated land/S		Dry-farming land/S		ANOVA statistics	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Multiple R^2	F
Sand (g kg^{-1})	545.3	196.0	503.6	212.1	535.3	190.9	568.0	199.3	0.11	0.2
Silt (g kg^{-1})	244.6	113.2	246.1	125.4	221.4	113.7	209.0	103.0	0.14	0.4
Clay (g kg^{-1})	210.1	104.7	250.2	101.4	243.3	105.9	223.0	103.3	0.15	0.4
Available Water Capacity (%)	9.4	1.6	9.1	2.9	9.2	1.7	8.6	2.0	0.14	0.4
Water holding capacity (%)	21.8	4.6	19.5	6.3	19.9	4.5	18.8	5.3	0.22	0.9
Bulk density (Mg m^{-3})	1.2	0.1	1.2	0.2	1.3	0.3	1.2	0.1	0.20	0.8
EC (dS m^{-1})	0.5	0.1	0.3	0.1	0.3	0.1	0.6	0.9	0.20	0.7
pH	7.3	0.1	7.2	0.1	7.2	0.2	7.1	0.3	0.21	0.8
Soil Organic C (g kg^{-1})	17.9	9.4	10.0	5.2	9.5	4.2	9.6	5.5	0.50	5.9*
Total N (g kg^{-1})	3.2	2.2	1.8	0.9	1.7	0.7	1.7	1.0	0.46	4.6*
Ca (g kg^{-1})	92.9	43.2	73.6	42.1	68.9	39.2	69.8	42.2	0.24	1.1
K (g kg^{-1})	31.7	12.7	29.8	5.7	33.0	14.3	28.3	5.1	0.18	0.6
Mg (g kg^{-1})	31.9	12.6	29.2	5.3	32.4	13.3	28.8	5.7	0.16	0.5
Na (g kg^{-1})	1.1	1.2	1.1	1.1	1.7	2.5	0.9	1.3	0.18	0.6
P (g kg^{-1})	0.4	0.1	0.5	0.1	0.4	0.1	0.5	0.1	0.16	0.4
Urease (µg NH_4^+–N g^{-1} h^{-1} dry soil)	98.5	41.9	27.7	16.5	14.5	7.4	56.8	31.4	0.77	25.0*
Alkaline phosphatase (µg PNP g^{-1} h^{-1} dry soil)	686.9	369.1	243.9	131.7	135.3	62.1	363.5	151.9	0.71	17.7*
β-Glucosidase (µg PNP g^{-1} h^{-1} dry soil)	1005.8	480.3	253.3	232.9	104.6	43.7	410.7	219.5	0.78	26.6*
Dehydrogenase (µg TPF g^{-1} h^{-1} dry soil)	18.5	9.3	5.3	3.6	2.7	0.8	7.8	3.7	0.76	23.8*

Table 2 Correlation coefficients among the measured soil properties (Soil-p)

Soil-p	Sand	Silt	Clay	AWC	WHC	BD	EC	pH	SOC	TN	Ca	K	Mg	Na	P	UA	APA	βGA
Silt	-0.92*	1.00																
Clay	-0.90*	0.66*	1.00															
AWC	-0.64*	0.55*	0.62*	1.00														
WHC	-0.66*	0.57*	0.64*	0.90*	1.00													
BD	0.02	-0.07	0.05	0.04	-0.05	1.00												
EC	0.06	-0.04	-0.08	-0.06	-0.03	-0.02	1.00											
pH	0.03	-0.08	0.02	-0.13	-0.10	-0.01	-0.06	1.00										
SOC	-0.30*	0.34*	0.20	0.34*	0.59*	-0.09	0.02	-0.18	1.00									
TN	-0.29*	0.34*	0.18	0.36*	0.59*	-0.11	-0.05	-0.27*	0.94*	1.00								
Ca	-0.03	-0.07	0.14	0.00	-0.05	-0.03	0.08	0.70*	-0.14	-0.25	1.00							
K	0.00	0.07	-0.09	-0.11	-0.07	-0.10	0.06	-0.09	-0.14	-0.17	-0.08	1.00						
Mg	0.01	0.09	-0.12	-0.12	-0.09	-0.12	0.05	-0.08	-0.11	-0.16	-0.10	0.98*	1.00					
Na	0.32*	-0.24	-0.35*	-0.33*	-0.33*	-0.04	0.30*	-0.08	-0.23	-0.26	-0.04	0.64*	0.57*	1.00				
P	0.30*	-0.24	-0.31*	-0.31*	-0.35*	0.06	-0.08	-0.13	-0.31*	-0.17	-0.19	0.06	-0.04	0.39*	1.00			
UA	-0.31*	0.35*	0.21	0.32*	0.46*	-0.14	-0.01	-0.14	0.60*	0.63*	0.05	0.10	0.13	-0.21	-0.08	1.00		
APA	-0.10	0.16	0.01	0.22	0.32*	-0.24	0.03	-0.10	0.60*	0.60*	0.18	0.01	0.04	-0.19	-0.13	0.79*	1.00	
βGA	-0.10	0.18	0.00	0.16	0.31*	-0.14	0.00	-0.08	0.65*	0.67*	0.13	0.04	0.07	-0.20	-0.14	0.85*	0.89*	1.00
DA	-0.16	0.22	0.07	0.20	0.35*	-0.13	0.01	-0.05	0.68*	0.65*	0.18	0.06	0.08	-0.17	-0.18	0.87*	0.88*	0.96*

Note: AWC, available water capacity; WHC, water holding capacity; BD, bulk density; EC, electrical conductivity; SOC, soil organic C; TN, total N; UA, urease activity; APA, alkaline phosphatase activity; βGA, β-glucosidase; DA, dehydrogenase activity. * Correlation is significant at the 0.05 level (2-tailed).

attributes, these five PCs explained >75% of variance for 15 soil attributes with the exception being for AWC, BD, Na and P. Thus, those four properties were the least important attributes due to their lowest communality estimates (Table 3). The PC corresponding to the largest eigenvalue (6.1) accounted for approximately 32% of the total variance. The second PC corresponding to the second eigenvalue (3.2) accounted for approximately 16% of the total variance. The third PC corresponding to the third eigenvalue (2.4) accounted for approximately 13% of the total variance. The forth PC corresponding to the forth eigenvalue (1.9) accounted for 10% of the total variance. The fifth PC corresponding to the fifth eigenvalue (1.1) accounted for approximately 5% of the total variance (Table 3).

The highly-weighted soil properties under PC1 with absolute values within 10% of the highest soil property (0.97 for βGA) loading (the loading of selected soil properties should be greater than 0.87) were UA, APA and DA. The first PC was termed the soil biochemical component. Under PC2, the highly-weighted soil properties with absolute values within 10% of the highest soil property (0.95 for sand) loading (the loading of selected soil properties should be greater than 0.85) were represented by clay. The second PC was therefore termed the soil texture component. The highly-weighted soil properties under PC3 with absolute values within 10% of the highest soil property (0.98 for K) loading (the loading of selected soil properties should be greater than 0.88) were represented by Mg. The third PC was thereby termed the soil geochemical component. Under PC4, the highly-weighted soil properties with absolute values within 10% of the highest soil property (0.92 for Ca) loading (the loading of selected soil properties should be greater than 0.83) were represented by pH and accordingly, the fourth PC was termed the soil acidity component. Under PC5, no highly-weighted soil properties with absolute values within 10% of the highest soil property (0.93 for EC) loading (the loading of selected soil properties should be greater than 0.84) were identified (Table 3). Accordingly, the fifth PC was termed the soil salinity component.

The plot of factor coordinates of the soil properties for the first two PCs showed that the selected soil properties were represented by the current coordinate system (the range of correlation coefficients; -1 to +1) (Figure 3b). Because the PCCA was based on correlations, the closer a soil property in this plot is to the unit circle; the better is its representation by the current coordinate system. These results illustrated that PCCA can be used as a tool for identifying important dimensions in a set of soil properties and to identify those land use and soil erosion categories with similar or dissimilar characteristics.

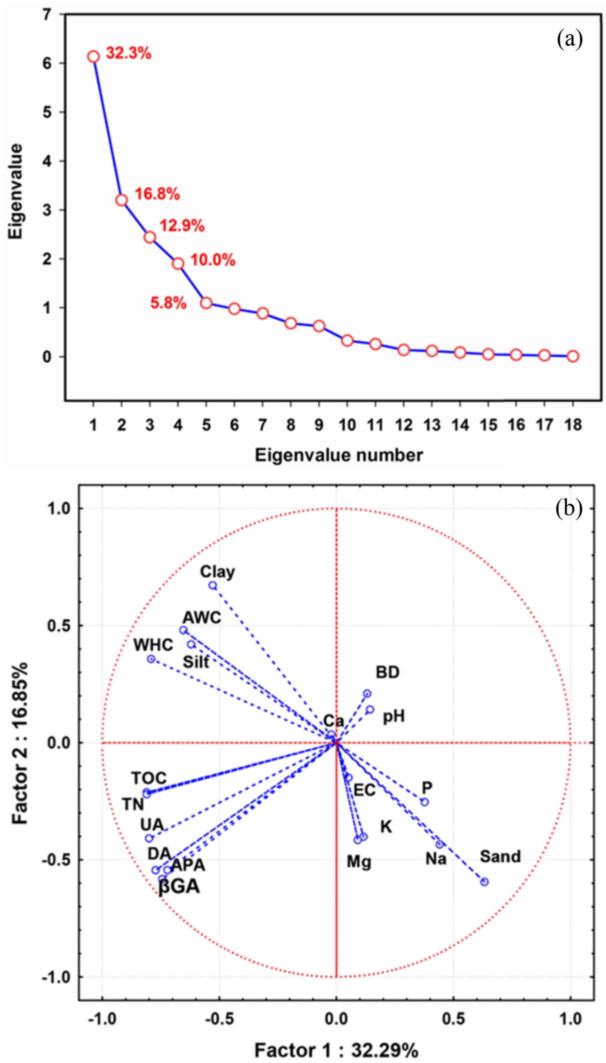

Figure 3 (a) Scree plot output from the principal component & classification analysis (PCCA), (b) Projection of the soil properties on the PC-plane using PCCA.

PCs scores were calculated using the resulting component score coefficient matrix and tested for significant differences between the land use/ soil erosion categories using one-way ANOVA (Table 3). PC scores for only the soil biochemical component and soil texture component varied significantly with the land use/ soil erosion categories (Table 3). Average soil biochemical component scores were negative for cultivated land/surface erosion but positive for rangeland/surface erosion, rangeland/ subsurface erosion, and dry-farming land/surface erosion (Table 3). Average soil texture component scores were negative for cultivated land/surface erosion and rangeland/surface erosion but the magnitude of the scores for rangeland/surface erosion was not as large as that for cultivated land/surface erosion (Table 3). This pattern is consistent with the effects of land use and erosion on soil enzyme activities and soil particle size as sensitive attributes.

GDA was performed with the four land use/ soil erosion categories as the grouping variable and the five PCs as independent variables to remove redundant components. The standardized canonical discriminant function coefficients present the weightings given to each of the PCs to maximize the differences between the groups. The results of GDA of the five PCs for soil properties (indicators) (Y1) showed that the discriminant coefficients (Eq.1) explained >97% of the variance ($p < 0.0001$):

$$Y1 = -0.95PC2 - 0.93PC1 + 0.44PC4 - 0.41PC3 - 0.05PC5 \quad (1)$$

Based upon the value of the discriminant coefficient in Eq.1, soil texture (PC2) and soil biochemical (PC1) had approximately equal coefficients and were dominant. The discriminant coefficients for the soil texture and soil biochemical components were about twofold larger than the corresponding coefficients for soil geochemical (PC3) and soil acidity (PC4) and were about twentyfold larger than the coefficient for soil salinity (PC5) (Eq.1). Thus, the soil texture and soil biochemical components were most powerful in discriminating between the four land use/ erosion categories and were taken as the most useful indicators for assessing the SQI. These results also indicated that soil acidity, soil geochemistry and soil salinity were not useful indicators for monitoring changes in soil quality under the different land use and erosion categories in the study area.

Measured soil properties comprising the soil biochemical (PC1) and soil texture (PC2) (urease, alkaline phosphatase, β-glucosidase, dehydrogenase, sand and clay) components were subjected to GDA to determine the soil quality equation. The standardized canonical discriminant function coefficients of the soil properties comprising PC1 and PC2 indicated that urease followed by % clay, β-glucosidase, % sand, alkaline phosphatase and dehydrogenase were the most powerful soil attributes in discriminating among the four land use/ erosion categories (Eq.2).

Table 3 Principle components (PCs) loadings from the PCCA and ANOVA results for the PCs.

Variables	PC1	PC2	PC3	PC4	PC5	Communality estimates
Sand	-0.06	-0.95	0.02	0.02	0.08	0.91
Silt	0.14	0.84	-0.12	0.07	-0.09	0.75
Clay	-0.05	0.89	0.08	-0.11	-0.07	0.82
AWC	0.16	0.80	0.15	0.09	0.05	0.70
WHC	0.34	0.80	0.13	0.13	0.10	0.80
BD	-0.23	0.01	0.17	0.08	0.01	0.09
EC	-0.01	-0.06	-0.11	-0.01	0.93	0.88
pH	-0.09	-0.03	0.06	-0.86	-0.06	0.76
SOC	0.74	0.31	0.21	0.26	0.17	0.79
TN	0.75	0.28	0.24	0.37	0.06	0.84
Ca	0.10	0.01	0.04	-0.92	0.10	0.87
K	0.03	0.01	-0.98	0.04	-0.02	0.95
Mg	0.06	0.01	-0.96	0.03	-0.02	0.92
Na	-0.17	-0.34	-0.71	0.12	0.27	0.74
P	-0.14	-0.43	-0.12	0.28	-0.31	0.40
UA	0.87	0.25	-0.09	0.02	-0.08	0.83
APA	0.92	0.04	0.00	-0.08	0.02	0.86
βGA	0.97	0.03	-0.01	-0.05	-0.02	0.94
DA	0.96	0.09	-0.04	-0.09	0.01	0.94
Eigenvalue	6.1	3.2	2.4	1.9	1.1	
% Total variance	32.3	16.8	12.9	10.0	5.8	
Cumulative % variance	32.3	49.1	62.0	72.0	77.8	
ANOVA results						
F	6.57	7.36	1.12	1.05	0.15	
p	0.0008	0.0003	0.35	0.38	0.93	
Mean scores of the four land use/soil erosion categories						
Rangeland/surface erosion	0.16 b	-0.05 ab	-0.17 a	-0.19 a	-0.10 a	
Rangeland/subsurface erosion	0.49 b	0.52 b	0.37 a	-0.17 a	-0.01 a	
Cultivated land/surface erosion	-0.83 a*	-0.81 a	-0.24 a	0.38 a	-0.02 a	
Dry-farming land/surface erosion	0.25 b	0.46 b	0.05 a	-0.03 a	0.18 a	

Note: AWC, available water capacity; WHC, water holding capacity; BD, bulk density; EC, electrical conductivity; SOC, soil organic C; TN, total N; UA, urease activity; APA, alkaline phosphatase activity; βGA, β-glucosidase; DA, dehydrogenase activity. * Different small letters indicate that the scores are significantly different at the 0.05 level based on the Tukey unequal N HSD Post Hoc test.

SQI = 0.91(urease) – 0.42(clay) + 0.30(β-glucosidase) + 0.21(sand) + 0.03(alkaline phosphatase) – 0.02 (dehydrogenase) (2)

For Eq.2, the most dominant and sensitive measured soil properties were urease and % clay (Eq.2). The urease was not significantly correlated to clay (r=0.21; Table 2). Therefore, both urease and clay appear to offer the greatest potential for monitoring and assessing changes in soil quality with changes in land use and erosion in the study area.

2.2 SQI evaluation

To assess soil quality, the canonical scores of discriminant functions were calculated with the four land use/erosion categories as the grouping variable and the six retained soil properties comprising PC1 and PC2 as independent variables. The Chi-square test results for the successive functions showed that only discriminant function 1 (DF1) (Eigen-value=2.4, canonical R=0.83, Wilk's Lambda=0.25, Chi-square=69, p<0.0001) accounted for 75% of the total variance represented by differences between the groups. Thus, the canonical scores of this function (DF1) were used to evaluate soil quality by investigating the correlation between DF1 and the expert opinion soil surface indices (soil movement, surface litter, pedestalling, rills and flow pattern) derived using the BLM method.

DF1 was shown to have a strong significantly positive correlation (r>0.84; p<0.01) with urease, alkaline phosphatase, β-glucosidase and dehydrogenase but no significant correlation with % clay and sand (r<0.16; p>0.05).

Correlation analysis of DF1 with the six soil surface indices derived from the BLM method showed that DF1 was negatively correlated to soil movement (r=-0.49; p<0.05), surface litter (r=-0.43; p<0.05), surface rock (r=-0.39; p<0.05), surface rills (r=-0.44; p<0.05), flow pattern (r=-0.51; p<0.05) and the sum of SSF score values (r=-0.62; p<0.01), while the pedestalling (r=-0.24; p>0.05) was not significantly correlated to DF1.

The results of multiple regression models for the soil surface indices (comprising the six BLM method soil surface factors as well as the summed values of the SSF) as dependent variables and, the most dominant and sensitive soil properties included in the new SQI data set as independent variables, showed that: soil movement (R^2=0.52, F=5.9, p = 0.005), surface rills (R^2=0.56, F=6.0, p=0.005), and the sum of SSF (R^2=0.67, F=8.9, p=0.001), included urease activity and clay variables in regression models. While the pedestalling (R^2=0.42, F=3.0, p=0.04) only included clay within the SQI dataset.

The above results of correlations and multiple regression models demonstrated that the SQI is sensitive to soil surface factor changes resulting from soil erosion in different land use categories in the study area. Therefore, enzyme activities and soil texture can be used as optimum components of the new SQI for assessing the degree of soil degradation resulting from erosive processes.

Since soil physical, chemical and biological properties or processes vary spatio-temporally, the corresponding indicators included in SQIs inevitably varies among environmental settings and agricultural systems (Bai et al. 2018; Doran 2002; Spiegel et al. 2015). SQIs therefore need to be designed and interpreted as setting-specific (Biswas et al. 2017; Juhos et al. 2019; Raiesi and Kabiri 2016). But even in a given setting or agricultural system, it is important to characterise the heterogeneity of the relationships between physical, chemical and biological parameters (Dilly et al. 2018). Abiotic properties such as bulk density or soil texture are typically less variable than biological properties (Dilly et al. 2003). Recent advances in data collection, including remote sensing and analytical techniques such as molecular methods permit enormous opportunities to develop and improve SQIs and to assess their relevance over greater spatial areas (Muñoz-Rojas 2018). It is also important to test SQIs using as many categories of soil degradation as possible to assess the degree of sensitivity. Testing SQIs versus a limited set of a priori degrees of soil degradation runs the risk of failing to confirm index sensitivity. For comparative purposes, it is also useful to examine SQI scores for reference sites, although the identification of true reference sites with no degradation is becoming challenging in many settings. As the development and uptake of new SQIs continues to expand, however, data standardization across scales will be important, and here, current initiatives aiming towards global harmonisation of soil data such as the Global Soil Partnership (Montanarella 2015) will be important. Since different erosion processes have the potential to remove soil and associated constituents including organic matter, micro-organisms and enzymes associated with soil horizons, it is important to sample different erosion depth categories in developing and testing SQIs.

In accordance with the study reported herein, much work on SQIs continues to adopt a reductionist approach focused on the application of statistical tests to identify a MDS. Nevertheless, it remains important to consider the integrative basis of the constituent indicators in any SQI, since soil quality ultimately reflects complex interactions between physico-chemical processes and biological assemblages (Thoumazeau et al. 2019; Vogel et al. 2018). On this basis, a combination of physico-chemical and biological indicators is preferable and the new SQI reported in this study satisfies that generic requirement. Any index must inevitably take some degree of reductionist approach to ensure that data requirements are pragmatic and affordable; otherwise, it is rendered useless in terms of stakeholder uptake.

Farmers frequently have the best knowledge of which soil properties are most relevant to their specific circumstances and, on this basis, it is beneficial to accommodate the experience and knowledge of farmers in testing and refining SQIs with a participatory approach (Bai et al. 2018; Lima et al. 2013; Palm et al. 2014). Farmers typically rely on a combination of observations and chemical analyses to assess the state of their soils (Wood and Litterick 2017) and the testing of SQIs using easily assembled soil observational scores can support their credibility. For SQIs to be most useful in supporting multi-objective decision-making, however, they need to incorporate properties or components recognised by multiple stakeholders as a means of fostering dialogue and consensus-based decisions which are deemed credible (Drobnik et al. 2018; Jónsson et al. 2016; Sébastien and Bauler 2013; Turnhout et al. 2007; Yu et al. 2018b). Uptake of SQIs is often hindered by their inherent complexity and the costs of data collection and interpretation (Herrick 2000). Future research is therefore needed to test the new SQI reported here with both farmers and additional stakeholders. Ultimately, the uptake of SQIs is strongly influenced by any initial investment costs, effort required for sample collection and ease of data interpretation (Doran and Zeiss 2000; Krüger et al. 2018; Muñoz-Rojas 2018). Some of the variables included in the work reported herein might preclude wide uptake of the new SQI, but farmer testing is required to assess this.

3 Conclusions

Soil quality, as a generic concept, has attained increasing importance to help address growing concerns about soil sustainability and the need to monitor the impacts of environmental and management change. In response, many previous studies have undertaken work to identify SQIs to facilitate both scientific and land management assessments for policy evaluation. Development of SQIs acknowledges the multi-dimensionality of the soil system. It remains critical for SQIs to be sensitive to land management change and either predictive or anticipatory of the impacts of policy change and for the sensitivity to be confirmed using bespoke studies in specific geoclimatic settings. Development, validation and sustained application of SQIs will be vitally important in relation to achieving the UN SDGs, since they provide one means of monitoring progress. Further research beyond the study reported in this paper is needed to investigate the sensitivity of the new SQI identified herein for the assessment of soil quality in other regions of Iran. The data processing methodology applied in this study is more generic and could be tested by other studies aiming to identify robust SQIs.

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References

Akhtar-Schuster M, Stringer LC, Erlewein A, et al. (2017) Unpacking the concept of land degradation neutrality and addressing its operation through the Rio Conventions. Journal of Environmental Management 195:4-15.
Alef K, Nannipieri P (1995) Urease activity. In: Alef K, Nannipieri P (eds.), Methods in Applied Soil Microbiology and Biochemistry. Academic Press Inc, San Diego, CA. pp 316-320.
Andrews SS, Karlen DL, Cambardella CA (2004) The soil management assessment framework. Soil Science Society of America Journal 68:1945-1962.
Arshad MA, Martin S (2002) Identifying critical limits for soil quality indicators in agro-ecosystems. Agriculture, Ecosystems & Environment 88:153-160.
Ayoubi S, Emami N, Ghaffari N, et al. (2014) Pasture degradation effects on soil quality indicators at different hillslope positions in a semiarid region of western Iran. Environmental Earth Sciences 71:375-381.
Bai Z, Caspari T, Gonzalez MR, et al. (2018) Effects of agricultural management practices on soil quality: A review of long-term experiments for Europe and China. Agriculture, Ecosystems & Environment 265:1-7.
Bindraban PS, van der Velde M, Ye L, et al. (2012) Assessing the impact of soil degradation on food production. Current Opinion in Environmental Sustainability 4:478-488.
Biswas S, Hazra GC, Purakayastha TJ, et al. (2017) Establishment of critical limits of indicators and indices of soil quality in rice-rice cropping systems under different soil orders. Geoderma 292:34-48. https://doi.org/10.1016/j.geoderma.2017.01.003
Brejda JJ, Karlen DL, Smith JL, Allan DL (2000) Identification of regional soil quality factors and indicators II. Northern Mississippi Loess Hills and Palouse Prairie. Soil Science Society of America Journal 64:2125-2135.
Bünemann EK, Bongiorno G, Bai Z, et al. (2018) Soil quality – A critical review. Soil Biology and Biochemistry 120:105-125. https://doi.org/10.1016/j.soilbio.2018.01.030
Burger JA, Kelting DL (1999) Using soil quality indicators to assess forest stand management. Forest Ecology and Management 122:155-166.
Cassel DK, Nielsen DR (1986) Field capacity and available water capacity. In: Klute A (ed.), Methods of Soil Analysis part 1. Soil Physical Properties. Agron. Monogr. 9. ASA and SSSA, Madison, WI. pp 901-924.
Chaer GM, Myrold DD, Bottomley PJ (2009) A soil quality index based on the equilibrium between soil organic matter and biochemical properties of undisturbed coniferous forest soils of the Pacific Northwest. Soil Biology and Biochemistry

41:822-830.
D'Hose T, Cougnon M, De Vliegher A, et al. (2014) The positive relationship between soil quality and crop production: A case study on the effect of farm compost application. Applied Soil Ecology 75:189-198. https://doi.org/10.1016/j.apsoil.2013.11.013
de Andrade Barbosa M, de Sousa Ferraz RL, Coutinho ELM, et al. (2019) Multivariate analysis and modeling of soil quality indicators in long-term management systems. Science of the Total Environment 657:457-465. https://doi.org/10.1016/j.scitotenv.2018.11.441
De Laurentiis V, Secchi M, Bos U, et al. (2019) Soil quality index: Exploring options for a comprehensive assessment of land use impacts in LCA. Journal of Cleaner Production 215:63-74.
de Paul Obade V (2019) Integrating management information with soil quality dynamics to monitor agricultural productivity. Science of The Total Environment 651:2036-2043.
de Paul Obade V, Lal R (2016) Towards a standard technique for soil quality assessment. Geoderma 265:96-102. https://doi.org/10.1016/j.geoderma.2015.11.023
Dexter AR (2004) Soil physical quality: Part I. Theory, effects of soil texture, density, and organic matter, and effects on root growth. Geoderma 120:201-214.
Dilly O, Blume HP, Munch JC (2003) Soil microbial activities in Luvisols and Anthrosols during 9 years of region-typical tillage and fertilisation practices in northern Germany. Biogeochemistry 65:319-339. https://doi.org/10.1023/a:1026271006634
Dilly O, Pompili L, Benedetti A (2018) Soil micro-biological indicators separated land use practices in contrast to abiotic soil properties at the 50km scale under summer warm Mediterranean climate in northern Italy. Ecological indicators 84: 298-303. https://doi.org/10.1016/j.ecolind.2017.08.013
Doran JW (2002) Soil health and global sustainability: translating science into practice. Agriculture, Ecosystems & Environment 88:119-127. https://doi.org/10.1016/S0167-8809(01)00246-8
Doran JW, Parkin TB (1994) Defining and assessing soil quality. In: Doran JW, Coleman DC, Bezdicek DF, Stewart BA (eds.), Defining Soil Quality for a Sustainable Environment. vol definingsoilqua. SSSA Spec. Publ. 35. ASA, Madison, WI. pp 3-21.
Doran JW, Zeiss MR (2000) Soil health and sustainability: managing the biotic component of soil quality. Applied Soil Ecology 15:3-11. https://doi.org/10.1016/S0929-1393(00)00067-6
Drobnik T, Greiner L, Keller A, Grêt-Regamey A (2018) Soil quality indicators – From soil functions to ecosystem services. Ecological Indicators 94:151-169. https://doi.org/10.1016/j.ecolind.2018.06.052
Easdale MH (2016) Zero net livelihood degradation – the quest for a multidimensional protocol to combat desertification. Soil 2:129-134. https://doi.org/10.5194/soil-2-129-2016
Emadi M, Baghernejad M, Memarian HR (2009) Effect of land-use change on soil fertility characteristics within water-stable aggregates of two cultivated soils in northern Iran. Land Use Policy 26:452-457.
European Commission (2006) Thematic Strategy for Soil Protection. COM(2006)231 final, Brussels. p 12.
Forster JC (1995) Soil physical analysis. In: Alef K, Nannipieri P (eds.), Methods in Applied Soil Microbiology and Biochemistry. Academic Press Inc, San Diego, CA. pp 105-106.
Garrigues E, Corson MS, Angers DA, et al. (2012) Soil quality in Life Cycle Assessment: Towards development of an indicator. Ecological Indicators 18:434-442. https://doi.org/10.1016/j.ecolind.2011.12.014
Godfray HCJ, Beddington JR, Crute IR, et al. (2010) Food Security: The Challenge of Feeding 9 Billion People. Science 327:812-818. https://doi.org/10.1126/science.1185383
Herrick JE (2000) Soil quality: an indicator of sustainable land management? Applied Soil Ecology 15:75-83. https://doi.org/10.1016/S0929-1393(00)00073-1
Jesinghaus J (1999) The Indicators. Part I: Introduction to the political and theoretical background. A European system of environmental pressure indices. In: First Volume of the Environmental Pressure Indices Handbook. European Commission, Joint Research Centre, Institute for Systems, Informatics and Safety (ISIS), Luxembourg.
Jónsson JÖG, Davíðsdóttir B, Jónsdóttir EM, et al. (2016) Soil indicators for sustainable development: A transdisciplinary approach for indicator development using expert stakeholders. Agriculture, Ecosystems & Environment 232:179-189. https://doi.org/10.1016/j.agee.2016.08.009
Juhos K, Czigány S, Madarász B, Ladányi M (2019) Interpretation of soil quality indicators for land suitability assessment – A multivariate approach for Central European arable soils. Ecological Indicators 99:261-272. https://doi.org/10.1016/j.ecolind.2018.11.063
Juhos K, Szabó S, Ladányi M (2016) Explore the influence of soil quality on crop yield using statistically-derived pedological indicators. Ecological Indicators 63: 366-373. https://doi.org/10.1016/j.ecolind.2015.12.029
Karlen DL, Andrews SS, Doran JW (2001) Soil quality: Current concepts and applications. Advances in Agronomy, Academic Press. pp 1-40.
Karlen DL, Hurley EG, Andrews SS, et al. (2006) Crop rotation effects on soil quality at three northern corn/soybean belt locations. Agronomy journal 98:484-495.
Karlen DL, Mausbach MJ, Doran JW, et al. (1997) Soil quality: a concept, definition, and framework for evaluation. Soil Science Society of America Journal 61: 4-10. https://doi.org/10.2136/sssaj1997.03615995006100010001x
Keesstra SD, Bouma J, Wallinga J, et al. (2016) The significance of soils and soil science towards realization of the United Nations Sustainable Development Goals. SOIL 2:111-128. https://doi.org/10.5194/soil-2-111-2016
Kiani M, Hernandez-Ramirez G, Quideau S, et al. (2017) Quantifying sensitive soil quality indicators across contrasting long-term land management systems: Crop rotations and nutrient regimes. Agriculture, Ecosystems & Environment 248:123-135. https://doi.org/10.1016/j.agee.2017.07.018
Kroetsch D, Wang C (2008) Particle size distribution. In: Carter MR, Gregorich EG (eds) Soil Sampling and Methods of Analysis. 2 edn. CRC Press, Taylor & Francis Group, Boca Raton. pp 713-725.
Krüger I, Chartin C, van Wesemael B, Carnol M (2018) Defining a reference system for biological indicators of agricultural soil quality in Wallonia, Belgium. Ecological Indicators 95:568-578. https://doi.org/10.1016/j.ecolind.2018.08.010
Lal R (2015) Restoring Soil Quality to Mitigate Soil Degradation. Sustainability 7:5875.
Lima ACR, Brussaard L, Totola MR, et al. (2013) A functional evaluation of three indicator sets for assessing soil quality. Applied Soil Ecology 64:194-200. https://doi.org/10.1016/j.apsoil.2012.12.009
Masto RE, Chhonkar PK, Singh D, Patra AK (2008) Alternative soil quality indices for evaluating the effect of intensive cropping, fertilisation and manuring for 31 years in the semi-arid soils of India. Environ Monit Assess 136:419-435. https://doi.org/10.1007/s10661-007-9697-z
Molaeinasab A, Bashari H, Tarkesh Esfahani M, Mosaddeghi MR (2018) Soil surface quality assessment in rangeland ecosystems with different protection levels, central Iran. Catena 171:72-82. https://doi.org/10.1016/j.catena.2018.07.004
Montanarella L (2015) The global soil partnership. Paper presented at the IOP Conf. Series: Earth and Environmental Science 25 (2015) 012001.
Muñoz-Rojas M (2018) Soil quality indicators: critical tools in ecosystem restoration. Current Opinion in Environmental Science & Health 5:47-52. https://doi.org/10.1016/j.coesh.2018.04.007
Nabiollahi K, Golmohamadi F, Taghizadeh-Mehrjardi R, et al. (2018a) Assessing the effects of slope gradient and land use change on soil quality degradation through digital mapping of soil quality indices and soil loss rate. Geoderma 318:16-28. https://doi.org/10.1016/j.geoderma.2017.12.024
Nabiollahi K, Taghizadeh-Mehrjardi R, Eskandari S (2018b) Assessing and monitoring the soil quality of forested and agricultural areas using soil-quality indices and digital soil-

mapping in a semi-arid environment. Archives of Agronomy and Soil Science 64:696-707.
Nabiollahi K, Taghizadeh-Mehrjardi R, Kerry R, Moradian S (2017) Assessment of soil quality indices for salt-affected agricultural land in Kurdistan Province, Iran. Ecological indicators 83:482-494.
Nakajima T, Lal R, Jiang S (2015) Soil quality index of a crosby silt loam in central Ohio. Soil and Tillage Research 146:323-328. https://doi.org/10.1016/j.still.2014.10.001
Naseby DC, Lynch JM (2002) Enzymes and microorganisms in the rhizosphere. In: Burn RG, Dick RP (eds) Enzymes in the Environment: Activity, Ecology and Applications. Marcel Dekker, New York. pp 109-123.
Nelson RE (1982) Carbonate and gypsum. In: Page AL, Miller RH, Keeney DR (eds.), Methods of Soil Analysis: Chemical and Microbiological Properties. second ed. edn. American Society of Agronomy Inc., Wisconsin. pp 181-197.
Nosrati K (2013) Assessing soil quality indicator under different land use and soil erosion using multivariate statistical techniques. Environmental Monitoring and Assessment 185:2895-2907.
O'Sullivan L, Creamer RE, Fealy R, et al. (2015) Functional Land Management for managing soil functions: A case-study of the trade-off between primary productivity and carbon storage in response to the intervention of drainage systems in Ireland. Land Use Policy 47:42-54. https://doi.org/10.1016/j.landusepol.2015.03.007
Oberholzer HR, Freiermuth Knuchel R, Weisskopf P, Gaillard G (2012) A novel method for soil quality in life cycle assessment using several soil indicators. Agronomy for Sustainable Development 32:639-649. https://doi.org/10.1007/s13593-011-0072-7
Palm C, Blanco-Canqui H, DeClerck F, et al. (2014) Conservation agriculture and ecosystem services: An overview. Agriculture, Ecosystems & Environment 187:87-105. https://doi.org/10.1016/j.agee.2013.10.010
Pham TG, Nguyen HT, Kappas M (2018) Assessment of soil quality indicators under different agricultural land uses and topographic aspects in Central Vietnam. International Soil and Water Conservation Research 6:280-288. https://doi.org/10.1016/j.iswcr.2018.08.001
Raiesi F (2017) A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. Ecological Indicators 75:307-320. https://doi.org/10.1016/j.ecolind.2016.12.049
Raiesi F, Kabiri V (2016) Identification of soil quality indicators for assessing the effect of different tillage practices through a soil quality index in a semi-arid environment. Ecological Indicators 71:198-207.
https://doi.org/10.1016/j.ecolind.2016.06.061
Rapport D et al. (1998) Evaluating landscape health: integrating societal goals and biophysical process. Journal of Environmental Management 53:1-15.
Rezapour S (2014) Response of some soil attributes to different land use types in calcareous soils with Mediterranean type climate in north-west of Iran. Environmental Earth Sciences 71:2199-2210.
Rojas JM, Prause J, Sanzano GA, et al. (2016) Soil quality indicators selection by mixed models and multivariate techniques in deforested areas for agricultural use in NW of Chaco, Argentina. Soil and Tillage Research 155:250-262. https://doi.org/10.1016/j.still.2015.08.010
Rutherford PM, McGill WB, Arocena JM, Figueiredo CT (2008) Total nitrogen. In: Carter MR, Gregorich EG (eds.), Soil Sampling and Methods of Analysis. 2 edn. CRC Press, Taylor & Francis Group, Boca Raton. pp 225-237.
Sadeghi SHR (2005) A semi-detailed technique for soil erosion mapping based on BLM and satellite image applications. Journal of Agricultural Science and Technology 7:133-142.
Sánchez-Navarro A, Gil-Vázquez JM, Delgado-Iniesta MJ, et al. (2015) Establishing an index and identification of limiting parameters for characterizing soil quality in Mediterranean ecosystems. Catena 131:35-45. https://doi.org/10.1016/j.catena.2015.02.023
Sébastien L, Bauler T (2013) Use and influence of composite indicators for sustainable development at the EU-level. Ecological Indicators 35:3-12. https://doi.org/10.1016/j.ecolind.2013.04.014
Sharma KL, Mandal UK, Srinivas K, et al. (2005) Long-term soil management effects on crop yields and soil quality in a dryland Alfisol. Soil and Tillage Research 83:246-259. https://doi.org/10.1016/j.still.2004.08.002
Skjemstad JO, Baldock JA (2008) Total and organic carbon. In: Carter MR, Gregorich EG (eds) Soil Sampling and Methods of Analysis. 2 edn. CRC Press, Taylor & Francis Group, Boca Raton. pp 225-237.
Spiegel H, Zavattaro L, Guzmán G, et al. (2015) Compatibility of Agricultural Management Practices and Mitigation and Soil Health: Impacts of Soil Management Practices on Crop Productivity, on Indicators for Climate Change Mitigation, and on the Chemical, Physical and Biological Quality of Soil. Deliverable reference number: D3.371,CATCH-C Project. www.catch-c.eu
Stavi I, Lal R (2015) Achieving zero net land degradation: challenges and opportunities. Journal of Arid Environments 112:44-51. https://doi.org/10.1016/j.jaridenv.2014.01.016
Stolte J, Tesfai M, Oygarden L, et al. (2016) Soil Threats in Europe: Status, methods, drivers and effects on ecosystem services. EUR 27607 EN. https://doi.org/10.2788/828742
Tabatabai MA (1994) Soil enzymes. In: Weaver RW, Angle JS, Bottomley PJ (eds) Methods of Soil Analysis. Part 2, Microbiological and Biochemical Properties. SSSA, Madison. pp 775-833.
Thoumazeau A, Bessou C, Renevier M-S, et al. (2019) Biofunctool®: a new framework to assess the impact of land management on soil quality. Part A: concept and validation of the set of indicators. Ecological Indicators 97:100-110. https://doi.org/10.1016/j.ecolind.2018.09.023
Townend J, Reeve MJ (2001) Water release characteristic. In: Smith KA, Mullins CE (eds.), Soil and Environmental Analysis: Physical Analysis. 2nd edn. CRC Press, New York. pp 95-140.
Turnhout E, Hisschemöller M, Eijsackers H (2007) Ecological indicators: Between the two fires of science and policy. Ecological Indicators 7:215-228. https://doi.org/10.1016/j.ecolind.2005.12.003
Van Oost K, Quine T, Govers G, et al. (2007) The impact of agricultural soil erosion on the global carbon cycle. Science 318:626-629.
Vogel HJ, Bartke S, Daedlow K, et al. (2018) A systemic approach for modeling soil functions. Soil 4:83-92. https://doi.org/10.5194/soil-4-83-2018
Wienhold BJ, Andrews SS, Karlen DL (2004) Soil quality: a review of the science and experiences in the USA. Environmental Geochemistry and Health 26:89-95. https://doi.org/10.1023/B:EGAH.0000039571.59640.3c
Wood M, Litterick AM (2017) Soil health – What should the doctor order? Soil Use and Management 33:339-345. https://doi.org/10.1111/sum.12344
Yu P, Han D, Liu S, et al. (2018a) Soil quality assessment under different land uses in an alpine grassland. Catena 171:280-287. https://doi.org/10.1016/j.catena.2018.07.021
Yu P, Liu S, Zhang L, et al. (2018b) Selecting the minimum data set and quantitative soil quality indexing of alkaline soils under different land uses in northeastern China. Science of The Total Environment 616-617:564-571. https://doi.org/10.1016/j.scitotenv.2017.10.301
Zornoza R, Mataix-Solera J, Guerrero C, et al. (2007) Evaluation of soil quality using multiple lineal regression based on physical, chemical and biochemical properties. Science of the Total Environment 378:233-237.
Zuber SM, Behnke GD, Nafziger ED, Villamil MB (2017) Multivariate assessment of soil quality indicators for crop rotation and tillage in Illinois. Soil and Tillage Research 174:147-155. https://doi.org/10.1016/j.still.2017.07.007

Suggestions:
1. Please give the full name of PCCA, GDA, SQ.
2. Redraw Figure 1 and 3. The font size should be 8 pt. Use "Times new roman" style for the words. No bold for all words. The new figure should be saved as TIFF format with a resolution of 300dpi.