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Determining the impacts of deforestation and corn cultivation on soil quality in tropical acidic red soils using a soil quality index

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ABSTRACT

Forests around the globe have been converted to agricultural land to meet human demands. The investigation of soil quality index (SQI) as affected by land use change is essential to prevent and control soil degradation mainly in rapidly developing nations. Research on the effects of land-use change on soil quality, especially within deep soil layers, remains lacking despite the prevalence of forest conversion. Here, we selected six paired plots in an intact forest and an adjacent corn field and collected soil samples from 11 layers at depths of 0–140 cm. We then evaluated 16 soil variables for inclusion in a minimum data set and built a SQI from this dataset. Our results indicate that soil organic carbon, total nitrogen, potassium, and free iron are the most important indicators of soil quality in tropical acidic red soils. Deforestation and corn cultivation related to significant decreases in SQI. Of note, SQI decreased to a differing extent among different soil layers, implying that degradation was not constant among layers, despite the fact that tilling typically affects only the top 0–20 cm of soil. The effect of agricultural conversion on soil quality was more pronounced in topsoil soil layers than in the deep layer. The main driver of soil degradation in corn fields was found to be reduced total nitrogen, followed by reduced potassium. Therefore, mitigating or reducing the loss of these nutrients is recommended, possibly through fertilization. We also note that active iron plays an important role in maintaining soil organic carbon concentrations, and thus is critical for maintaining soil quality.

1. Introduction

Inappropriate land use changes usually cause land and soil degradation (Bruun et al., 2013; Davaria et al., 2020). Deforestation is the most important factor to land degradation, because it's changes soil environment, nutrition and carbon cycle (Rezapour and Alipour, 2017). In the 1980s, in order to develop the economy, a large amount of deforestation in southwest China was converted into cultivated land (Min et al., 2019). As a main crop type, corn is planted in large numbers, replacing forests. Due to dominated environment restrictions, this conversion is not sustainable (Jafarnejadi et al., 2013). There are even reports that a large number of dry farming lands were abandoned because of the soil quality degradation (Davaria et al., 2020). Soil degradation endangers sustainable agricultural development. The current demand for agricultural products, which is driven by economic and population growth, is promoting ongoing forest conversion to agricultural land (Bakhshandeh et al., 2019). Careless land-use change can lead to the destruction of natural ecosystems, soil erosion, and soil degradation (Bruun et al., 2013), all of which negatively affect soil properties, quality, and health (Saviozzi et al., 2001; Raiesi and Beheshti, 2014; Davaria et al., 2020).

Specifically, land-use changes affect soil organic matter inputs (Guo et al., 2017), canopy structure (Finzi et al., 1998), and soil moisture and nutrient migration (Sakin, 2014; Six and Paustian, 2014), which in turn alter the intensity, extent, and pathways of soil nutrient cycling, ultimately affecting soil properties and quality (Hu et al., 2018).

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Agricultural management practices and land-use changes can alter the physical, chemical, and biological properties of soil (Qi et al., 2018), which are determinants of soil quality (Marzaioli et al., 2010). Management and land-use changes are also related to increased carbon emissions; forest conversion to agricultural land has reduced global soil organic carbon (SOC) storage by 31–52% (Wang et al., 2017).

Deforestation, specifically in terms of conversion to high-production agriculture, greatly affects soil quality (Davaria et al., 2020). Reduced biomass inputs lead to reduced SOC and total nitrogen (TN) (Bakhshandeh et al., 2019). Moreover, tilling affects the physical and chemical characteristics of soil (Zuber et al., 2017; Barbosa et al., 2019), including bulk density (BD) (Korkanç, 2014) and electrical conductivity (EC), and has been shown to relate to increased pH (Davaria et al., 2020), reduced TN (Wang et al., 2016a) and increased soil microbial respiration (Bayranvand et al., 2017). Tilling also promotes the loss of SOC; the surface soil layer can lose up to half of its organic carbon through tilling (Gelaw et al., 2014; Soleimani et al., 2019). Relative to forest soils, cultivated lands typically have reduced microbial activity and nutrient concentrations as well as higher heavy metal concentrations (Marzaioli et al., 2010). Although a considerable amount of research has focused on soil quality impacts following forest conversion to agriculture, the majority has focused on the surface layers, i.e., depths < 60 cm. Thus, the impact of land conversion on deep soil layers remains unclear.

Soil quality is an umbrella term incorporating physical, chemical, and biological parameters. These soil aspects are interdependent and may respond differently to land-use changes, thus, individual parameters may be poor indicators of soil quality (Mukherjee and Lal, 2014; Davaria et al., 2020). Instead, a more holistic methodological approach should be used to assess changes (Granatstein and Bezdicek, 1992; Raiesi, 2017). Currently, comprehensive methods for evaluating soil quality include qualitative (e.g., visual), semi-quantitative (Doran and Parkin, 1994), and quantitative methods (Andrews et al., 2002; Davaria et al., 2020). The difference between semi-quantitative and quantitative is the way to obtain the minimum data set. The semi-quantitative method is to select the minimum data set from the total data set through expert opinions, and the quantitative method is to extract the minimum data set through statistical methods, for example, principal component analysis, multiple correlation, factor analysis (Andrews et al., 2002). Quantitative assessments of soil quality are usually achieved through laboratory analyses of physical, chemical, and biological parameters, in combination with soil quality indices (SQIs) (Marzaioli et al., 2010). SQIs can be determined via the standard scoring function, nonlinear scoring function, or linear scoring function methods (Li et al., 2020), where the SQI value represents soil quality. Generally, SQIs are easy to use and offer flexibility (Leite Chaves et al., 2017). Previous studies have tended to focus on individual soil properties when assessing the impacts of land-use change, and comprehensive evaluation methods have rarely been applied, particularly for deep soil layers.

Over the past several decades, Xishuangbanna, an area in southwestern China, has undergone severe deforestation (Min et al., 2019). Forest conversion to agricultural land has occurred on a large scale, typically for corn, tea, and coffee cultivation (Min et al., 2019). Understanding how these activities affect soil quality and determining the causes of those changes are the foundational steps toward reasonable agricultural management policies, which are vital to sustainable development and maintaining soil quality in cultivated land. Here, using forest sites as controls, we assessed deforested land under long-term corn cultivation. We determined 19 physical, chemical, and environmental factors from 11 soil layers 0–140 cm in depth and used a minimum data set (MDS) approach to assess changes in soil quality. Compared to previous work, our objectives were to quantify the impact of deforestation and corn cultivation on soil quality at different depths in tropical area, especially deep soil, and to determine causal mechanisms that promote soil degradation at different soil depths.

2. Materials and methods

2.1. Study area

This study was located in the Dadugang Forest in Xishuangbanna, Yunnan Province, southwestern China (22°30′ N, 100°27′–101°12′ E, Fig. 1). The area is located south of the Tropic of Cancer and receives approximately 2000 h of sunshine annually. The climate is typical northern tropical humid monsoon, with a rainy season from May–October and a dry season from November–April (Hemati et al., 2020). The geomorphologic type is dominated by tectonic denudation, low and middle mountains. Elevation at the study site ranges from 1330 to 1360 m, with an average annual temperature of 18 °C and average annual precipitation of 1200–1700 mm. The soil is classified as Ferralsols according to the Food and Agricultural Organization of the United Nations classification. Parent rock is Cretaceous sandstone. In acidic red soils, especially in tropical regions, the effects of weathering and leaching are strong, with low nutrient content and high iron content. Intact forest areas are dominated by *Castanopsis fleuryi*, *Lithocarpus truncatus*, *Homalium hainanense*, *Pinus yunnanensis*, *Millettia leptobotrya* and *Bambusa blumeana* (Wang et al., 2016b). Agricultural conversion happened in 1984, when parts of the native broad-leaved evergreen forest were deforested for the establishment of corn fields. Since then, corn cultivation has been continuous in the study area and has been planted continuously for 34 years. The corn cultivation is a conventional farming system. Tilling is completed once annually in March to a depth of 20 cm and corn is planted in April. In October, corn is harvested and the stalks are left in place. The corn planting is terraced, the row spacing is 60 cm, and the plant spacing is 50 cm. During the growth season, weeds were manually weeded once in June. The weeding method was to turn the soil and bury the weeds in the soil to a depth of about 15–20 cm. In agricultural practices, we did not fertilize, use pesticides and irrigate. Study sites were selected based on soil texture, parent material, aspect, location, and site history, with selected plots sharing soil formation factors. Thus, the differences in soil properties between forested sites and adjacent corn fields were attributed solely to changes in land use and vegetation cover (Raiesi, 2017). We used artificially reclaimed cornfield soil in comparison with un-reclaimed virgin forest soil to determine the potential influence of agriculture on soil quality.

2.2. Soil sampling and analysis

Soil samples were collected in December 2018. Six pairs of plots were selected for sampling, with one plot in each pair located in intact forest and the other in an adjacent cornfield (Fig. 1). The distance between each sample is about two hundred meters. The size of the study area is about 60 ha. A total number of 132 soil mixed samples were taken from the two land use types. Within each plot we also measured slope, as determined using a compass, aspect, and collected GPS coordinates. We dug soil pits in all plots by first removing surface litter and then digging a pit 150 cm deep × 60 cm wide × 100 cm long. We then scraped multiple samples of thin layers of soil from the exposed soil profile at depths relating to 11 layers from 0 – 140 cm in depth (i.e., 0–10 cm, 10–20 cm, 20–30 cm, 30–40 cm, 40–50 cm, 50–60 cm, 60–70 cm, 70–80 cm, 80–100 cm, 100–120 cm, and 120–140 cm, A-K). We mixed the replicate samples taken from each layer were placed in a labeled sample bag. The soil samples were used to determine physical and chemical soil properties. The soil samples were air-dried in the laboratory and the stones and plant roots are removed, and then passed through a 2 mm sieve for further analysis. To measure BD and water content, we collected a soil sample from the middle of each soil layer using a ring cutter with a volume of 100 cm^3. Take another 20 g of soil near the sampling bottom of the ring knife, put it into a covered aluminum box with a known weight, labeled, weighed fresh, and brought back to the laboratory for further analysis. To determine the moisture content. Soil samples were air-dried and passed through a 2 mm mesh sieve prior to any analysis

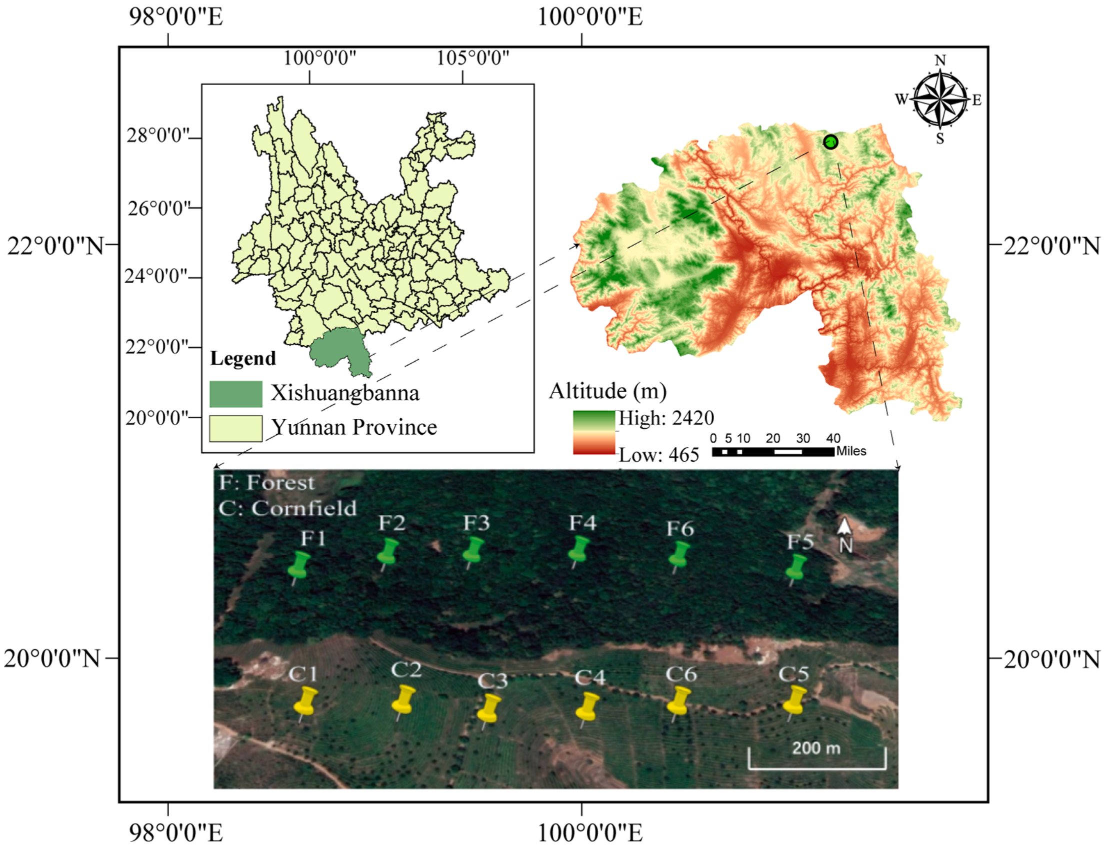

Fig. 1. Map displaying the study area with six pairs of sample plots (n = 12 plots in total). Forest sites as denoted by "F"; corn field sites are denoted by "C".

(Rezapour and Alipour, 2017).

water content was calculated using the equation ((soil fresh weight – soil dry weight)/soil dry weight) × 100 (Zhang and Shangguan, 2016). Prior to calculating BD, soil samples were dried in an oven at 103 °C for 24 h. Dry weight was then measured, and BD was calculated as the ratio of the soil core dry weight to the metallic core internal volume. Soil particle-size analysis (Xiao et al., 2018) was conducted using a laser particle-size analyzer (LPSA, Mastersizer 3000, Malvern Panalytical, Malvern, United Kingdom); soil particles were divided into silt, sand, and clay. Soil pH was determined by potentiometry (water:soil ratio = 2.5:1) after equilibration for 30 min (FE28, Mettle, Zurich, Switzerland; Ou et al., 2017). TN was determined using the Kjeldahl method (Bremner and Mulvaney, 1982). SOC was determined using the Walkley–Black method (Walkley and Black, 1934) and EC was measured using a conductivity meter (S30, Mettler Toledo, Columbus, Ohio, USA) (Yin et al., 2019). The determination of phosphorus (P), potassium (K), aluminum (Al), calcium (Ca), sodium (Na), magnesium (Mg), and sulfur (S) elements concentration adopted X-Ray fluorescence spectrometry (Zhang et al., 2018). Take about 3 g of a sample with a particle size of <74 μm (100Φ) after grinding in an agate bowl and place it in a mold. Use low-pressure polyethylene powder to border and embed the bottom, and the soil samples were set on a tablet press (ZHY-401B, Beijing ZhongHeChuangYe Science & Technology Development Co., Ltd, China) to press into a disc with a diameter of 32 mm and tested by an X-ray fluorescence spectrometer (AXiOSMAX minerals, PANalytical B.V., Netherlands). During the test, the ambient temperature was 23 °C and the relative humidity was 56%. Active iron (Fe_o) was determined using acid ammonium oxalate extraction (Schwertmann, 1964). Iron extracted with citrate–bicarbonate–dithionate was described as free iron (Fe_d) (Mehra and Jackson, 1960). Total iron (Fe_t) in the soil was determined following the method of Torrent et al. (2010) and was calculated as crystalline iron.

2.3. SQI development

The SQI was developed using three steps. First, a MDS was selected using the load and eigenvalues obtained from a principal component analysis (PCA), wherein a MDS is a non-redundant set of parameters that reflect soil quality (Lou et al., 2019). Second, we normalized the variables in the MDS using a standard scoring function, and finally we obtained the SQI according to these scores and variable weights (Raiesi, 2017).

2.3.1. Determining the minimum data set

Soil quality should be assessed by sensitive indicators of changes in soil processes and their related functions (Guo et al., 2017). In this context, the total data set (TDS) method contained 16 soil properties (BD, TP, water content, pH, Fe_t, TN, K, Fe_o, Fe_d, Al, Ca, Mg, Na, S, EC, SOC), including soil parameters that affect nutrient cycling and soil structure and function. The TDS can provide a comprehensive result in evaluating soil quality (Li et al., 2019a; Jahany and Rezapour, 2020). When the evaluated samples are extended to a larger area, it will be inevitably expensive and laborious, and many soil properties are highly correlated in TDS (Jahany and Rezapour, 2020). Therefore, we introduced MDS, reduced the number of indicators used to evaluate SQI, and selected key indicators that contain sufficient information for SQI evaluation (Li et al., 2020). Evaluating the results of PCA constructed by TDS is an important step in determining MDS and reducing data redundancy. PCA is widely accepted as a data reduction tool (Shao et al., 2020).

We determined the loads and eigenvalues resulting from the PCA, and selected principle components (PCs) with eigenvalues ≥1 to construct a soil quality index evaluation system. Variables with factor load values ≥0.5 in the same PC were grouped together. If the same soil variable had a factor load value ≥0.5 on multiple PCs, that variable was incorporated into the PC in which it had a higher value. Following grouping, we calculated norm values for each parameter (Lou et al., 2019) according to Eq. (1). We then selected the variables within 10% of the highest scores from each group. According to the principle of representativeness and relative independence of soil quality evaluation indicators, correlation analysis was then used to determine whether some variables with high norm values within groups were redundant and the MDS could be further reduced (Armenise et al., 2013). The geometric meaning of norm is the length of the vector norm of the variable in the multidimensional space composed of principal components. The longer the length is, the greater the comprehensive load of the variable on all principal components is. Corresponding, the more soil quality information the variable contains. Norm values were calculated as:

$$Norm_{ik} = \sqrt{\sum_{i=1}^{k} (\mu_{ik}^2 \lambda_k)} \tag{1}$$

where $Norm_{ik}$ is the comprehensive load of the *i*-th variable on the first *k* principal component with an eigenvalue ≥ 1; μ_{ik} is the load of the *i*-th variable on the *k*-th principal component, and λ_k is the *k*-th principal component eigenvalue.

2.3.2. Variable scoring

Given that different variables had different numerical scales, we used a scoring function to normalize the data (Marzaioli et al., 2010; Nabiollahi et al., 2017). The standard scoring function has been widely used in soil functional indices because of its accuracy (Liu et al., 2014, 2018; Sun et al., 2020a). The standard scoring function converts the range of values of each variable included in the MDS into dimensionless values that range between 0 and 1. These scores represent the explanatory contribution of each parameter to soil quality. Scoring algorithms indicate whether a variable should be retained in the MDS; retained variables should increase in score (ascending membership function), and variables with decreasing scores should be removed (descending membership function) (Guo et al., 2017). Variables with ascending membership functions (including SOC, TN, and K) have a positive effect on soil quality, and those with descending functions indicate a negative effect (such as BD and EC).

The ascending membership function equation was as follows:

$$F(X) = \begin{cases} 0.1 & x \leqslant x_1 \\ 0.9\dfrac{x - x_1}{x_2 - x_1} + 0.1 & x_1 < x < x_2 \\ 1.0 & x \geqslant x_2 \end{cases} \tag{2}$$

The falling membership function equation was as follows:

$$F(X) = \begin{cases} 0.1 & x \geqslant x_2 \\ 0.9\dfrac{x_2 - x}{x_2 - x_1} + 0.1 & x_1 < x < x_2 \\ 1.0 & x \leqslant x_1 \end{cases} \tag{3}$$

F(X) is the index score between 0.1 –1, X is the actual measured value of each MDS index and X_1 and X_2 are the minimum and maximum values of the index, respectively.

2.3.3. Assigning variable weights

Each soil variable explained a certain amount of variation in the TDS (Raiesi, 2017). Weights for the MDS and TDS were determined from the PCA results (Yu et al., 2018). The commonality of each indicator ranged from 0 to 1, where the value indicated the contribution of each variable to the overall variance; the higher the commonality value, the greater the contribution (Li et al., 2019a). Weights for the MDS were calculated as:

$$W_i = C_i / \sum_{i=1}^{n} C_i \tag{4}$$

where $W_i$is the variable weight, $C_i$is the commonality value of the variable, and n is the number of variables included in the MDS (Shao et al., 2020).

2.3.4. Developing the soil quality index

A SQI can be used to quantify changes in soil quality caused by land-use change. SQI scores generally reflect key soil parameters, wherein a high SQI value indicates high soil quality. We used Eq. (5) to calculate a comprehensive soil quality score, and we specifically focused on soil quality under different land-use types. SQI values of 1–0.8 are considered very high, 0.8–0.6 high, 0.6–0.4 medium, 0.4–0.2 low, and 0.2–0 very low (Levi et al., 2020). We calculated the SQI as:

$$SQI = \sum_{i=1}^{n} W_i N_i \tag{5}$$

where SQI is the soil quality index (0–1), W_i is the weight assigned to each variable, N_i is the variable score, and n is the number of variables in the MDS. The test of the validity of PCA was carried out by the Kaiser-Meyer-Olkin measure (KMO) of sampling adequacy and Bartlett's test of sphericity. In this context, both KMO (KMO = 0.681) and Bartlett's test of sphericity (p = 0.000) indicated the validity of using PCA. According to the classification criteria, SQI was divided into five grades as follows: very high (grade I, SQI $\geq$ 0.85), high (grade II, 0.85 $\geq$ SQI $\geq$ 0.7); moderate (grade III, 0.7 $\geq$ SQI $\geq$ 0.55), low (Grade IV, 0.55 $\geq$ SQI $\geq$ 0.4); Grade V, (SQI < 0.4). In these criteria, it is considered that grade I is the most suitable for plant growth, Grade II is suitable for plant growth, Grade III is suitable for plant growth, but there are some limitations, grade IV is more serious than grade III, grade V soil has the most severe restrictions on plant growth (Qi et al., 2009; Jahany and Rezapour, 2020).

2.4. Statistical analyses

The median absolute deviation method was used to remove outliers. Prior to statistical analyses, we tested the data for normality and equal variance, and transformed variables as needed to meet the assumptions of the *t*-test. Soil variables, standardized variable scores, and SQI values were all analyzed using paired *t*-tests. A one-way analysis of variance (ANOVA) was used to assess SQI values within land-use types at different soil depths. All analyses were performed using Microsoft Excel 2019 and SPSS version 20.0 software.

3. Results

3.1. Soil variables in forest and agricultural plots

Relative to the soils in the forest plots, the soil that have undergone deforestation and 34 years of continuous corn cultivation have showed some significantly changes ($P < 0.05$) in different soil depths (Table A.1). In the 0–10 cm soil layer, pH, Fe_d and Fe_o were significantly increased relative to forest soils ($P < 0.05$), whereas water content, K and TN were significantly reduced ($P < 0.05$, Table A.1). In the 10–20 cm soil layer pH, TP, Fe_d and Fe_o were significantly higher, and TN, K and EC were significantly lower ($P < 0.05$, Table A.1). In the 20–30 cm layer, pH, Fe_d, Fe_o and S were significantly higher and TN, K was significantly lower ($P < 0.05$, Table A.1). In the 30–40 cm layer, Fe_d and Fe_o were significantly higher and TN and BD were significantly lower ($P < 0.05$, Table A.1). In the 40–50 cm layer, Fe_d was significantly higher and BD was significantly lower ($P < 0.05$, Table A.1), and in the 50–70 cm layer, BD and EC were significantly lower ($P < 0.05$, Table A.1). In the 70–100 cm soil layer, BD was again significantly lower ($P < 0.05$,

Table A.1), and in the 100–140 cm layer, pH was significantly lower ($P < 0.05$, Table A.1). There were no significant differences among the remaining soil variables between the land-use types in each soil layer ($P > 0.05$, Table A.1).

3.2. Differences in soil quality between land-use types

3.2.1. Minimum data set

PCA was applied to analyze 16 soil quality indicators and there were four PCs with eigenvalues > 1, values ranging from 1.301 to 4.642. They contributed 78.2% cumulatively, explaining the variability of most soil variables. In the PCA, BD, SOC, TP, Fe_o, Ca, and S formed the first group, accounted for 29.013% of the total variance. SOC had the highest norm value (1.996) and SOC and TP were highly correlated (0.825) (Tables 1 and 2). Therefore, SOC was chosen to represent PC-1 due to the high-loading value. Water content, Fe_t, Fe_d, and Al formed the second group, accounted for 21.850% of the total variance. had the highest norm value (1.827) among the variables in the second group and was correlated with Fe_t, water content, and Al (0.958, 0.553, and 0.932, respectively), so we only chosen Fe_d represent PC-2. K, Mg, and Na formed the third group, accounted for 19.179% of the total variance, there is a significant correlation between the two high load indicators K and Mg (0.954). Therefore, K with the highest loading value (1.662) was retained to represent PC-3. EC, pH, and TN formed the fourth group, accounted for 8.132% of the total variance, EC was excluded from the third group based on its norm value. Finally, the highest norm value within the fourth group was observed for TN (1.252), which was related to pH (0.533) (Table 1). Therefore, the final MDS included SOC, Fe_d, K, and TN.

3.2.2. Soil quality index

The concentrations of TN and K were lower in all soil layers in the corn field relative to the forest soil (0–140 cm, Fig. 2). In terms of vertical distribution, the TN concentrations in both corn-field and forest soil decreased sharply with increasing soil depth between 0 – 50 cm ($P < 0.05$), but there were no significant increases or decreases below 50 cm ($P > 0.05$, Fig. 2A). K concentrations did not vary significantly among soil layers in either land-use type ($P > 0.05$, Fig. 2B). SOC concentrations did not differ between the corn field and forest soils in any soil layer ($P > 0.05$, Fig. 2C). However, within both land-use types, SOC decreased with increasing soil depth to 70 cm, after which there were no significant differences among layers (Fig. 2C). Fe_d concentrations were significantly higher in the 0–50-cm soil layer in the corn field than in the forest soil ($P < 0.05$), but there was no difference between the land-use types at soil depths > 50 cm ($P < 0.05$, Fig. 2D). In terms of vertical distribution, Fe_d concentrations in both land-use types gradually increased with increasing depth, but there were no significant differences among layers in the corn field ($P > 0.05$, Fig. 2D).

Community analysis results provided MDS weights as follows: SOC = 0.285, TN = 0.303, K = 0.258, Fe_d = 0.154 (Table 3). Thus, the SQI was calculated from the MDS using these weights and the standard scoring function method. The SQI of the corn-field soil was lower than that of the forest soil at all depths (0–140 cm) and significantly lower at depths of 0–100 cm ($P < 0.05$, Fig. 3). SQI values gradually decreased from the surface to deeper layers in both soil types, with significant decreases in layers 0–70 cm in depth in the cornfield soil and between the surface and 50 cm layer in the forest soil. After deforestation and planting corn, the MDS-SQI of each layer of soil decreased by 20.15%–33.08%. The soil quality is classified by SQI, and only 0–30 cm of forest is classified as Class III; 30–60 cm of forest soil and 0–20 cm of cornfield are classified as Class IV; the rest of soil layers are all Class V, indicating the research the acid red soil in the area is relatively barren. We also assessed the linear fit between the SQI derived from the MDS and the SQI derived from the TDS, MDS-SQI = 2.0052TDS-MDS–0.6305, $R^2 = 0.721$ ($P < 0.05$, Fig. 4).

Soil variables had differing contributions to the SQI in both land-use types (Fig. 5). The contributions of SOC and TN to the SQI decreased with increasing soil depth, but the contributions of K and Fe_d increased with increasing depth (Fig. 5). After transformation of the forest into corn field, in top soil (0–10 cm), the contribution of SOC to SQI increased from 33.93% to 41.24%, the contribution of TN decreased from 40.66% to 27.73%, and K decreased from 17.90% to 14.21%, and Fe_d's contribution to SQI increased from 7.51% to 16.82% (Fig. 5). In the deepest layer (120–140 cm), the contribution of SOC to SQI increased from 11.38% to 13.00%, and the contribution of TN increased from 15.79% to 20.97%, K decreased from 42.05% to 28.36%, and the contribution of Fe_d to SQI increased from 30.79% to 37.66% (Fig. 5).

4. Discussion

4.1. Effects of deforestation and planting corn on soil properties

Changes in land use and vegetation cover can lead to changes in soil properties (Davaria et al., 2020). N is one of the most important

Table 1
Soil attributes principal component factor load and Norm value.

Soil attribute	Grouping	PC				Commonality	Norm value
		1	2	3	4		
BD	1	−0.652	−0.317	0.509	−0.087	0.791	1.768
SOC	1	0.908	−0.179	−0.019	0.181	0.890	1.996
TP	1	0.868	−0.003	−0.140	0.019	0.774	1.887
Fe_o	1	0.643	−0.122	0.529	0.057	0.711	1.683
Ca	1	0.790	0.077	−0.271	−0.236	0.759	1.793
S	1	0.718	−0.028	−0.299	0.276	0.682	1.664
WC	2	0.435	0.715	0.150	0.093	0.733	1.658
Fe_t	2	−0.065	0.948	0.140	0.007	0.922	1.794
Fe_d	2	−0.121	0.966	−0.016	−0.076	0.954	1.827
Al	2	−0.092	0.953	−0.059	−0.044	0.922	1.796
K	3	−0.128	0.187	0.904	0.205	0.911	1.662
Mg	3	−0.190	−0.008	0.880	0.210	0.855	1.613
Na	3	−0.158	0.116	0.753	−0.090	0.613	1.383
pH	4	0.135	0.172	−0.491	−0.592	0.639	1.176
TN	4	0.147	0.137	0.458	0.764	0.682	1.252
EC	4	0.220	0.036	−0.166	0.770	0.670	1.042
Eigenvalues		4.642	3.496	3.069	1.301		
Variance (%)		29.013	21.850	19.179	8.132		
Cumulative variance (%)		29.013	50.863	70.042	78.174		

Notes: BD, bulk density; SOC, soil organic carbon; TP, total phosphorus; Fe_o, active iron; Ca, calcium; S, sulfur; WC, water content; Fe_t, total iron; Fe_d, free iron; Al, aluminum; K, potassium; Mg, magnesium; Na, sodium; TN, total nitrogen; EC, electrical conductivity. The same as below.

Table 2
Correlations matrix for measured soil attributes across the study depths (0–140 cm layer) and sites (n = 12). The abbreviations are described in Table 1.

Soil attribute	WC	pH	SOC	Fe_t	TN	TP	K	Fe_d	Al	Mg
WC	1									
pH	0.069	1								
SOC	0.241	−0.085	1							
Fe_t	0.579	0.043	−0.188	1						
TN	0.058	−0.533	0.130	0.087	1					
TP	0.229	0.151	0.825	−0.031	0.057	1				
K	0.208	−0.506	−0.134	0.318	0.407	−0.1739	1			
Fe_d	0.553	0.156	−0.268	0.958	−0.058	−0.0624	0.171	1		
Al	0.580	0.180	−0.270	0.884	−0.019	−0.0559	0.114	0.932	1	
Mg	0.038	−0.507	−0.180	0.133	0.426	−0.2099	0.954	−0.0225	−0.0621	1

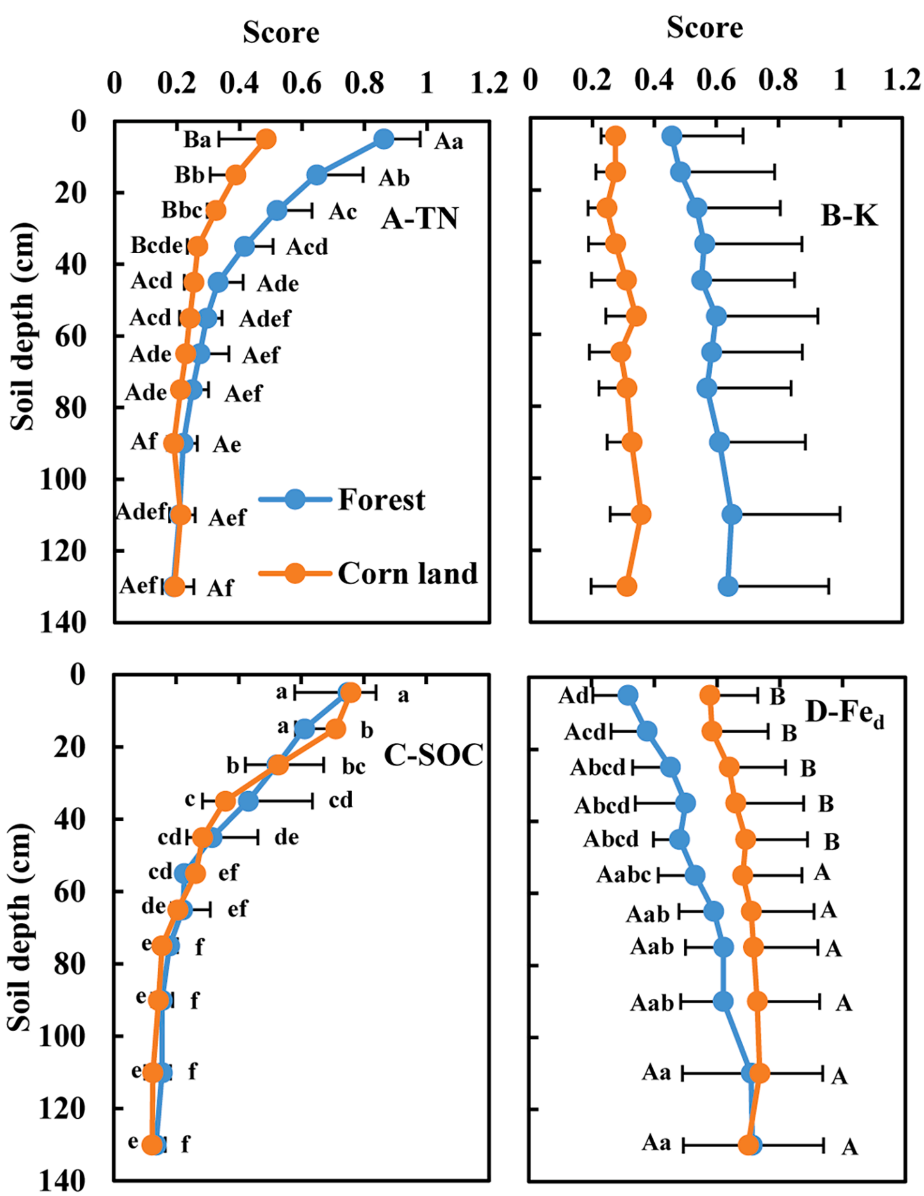

Fig. 2. Standard function scores of A) total nitrogen (TN), B) potassium (K), C) soil organic carbon (SOC), and D) free Iron (Fe_d) in 11 soil layers from 0 to 140 cm in depth. Independent sample *T*-test and one-way ANOVA were used to compare the mean differences of the two land use methods and eleven soil layers. Different lowercase letters denote significant differences among soil layers in the same land use, and uppercase letters indicate significant differences among the different land uses in the same layer ($p < 0.05$; Tukey post-hoc test). Forest sites as denoted by "F", corn field sites are denoted by "C". Values represented as means (n = 6) ± standard deviation.

nutrients in agricultural land and is a limiting element to corn growth (Li et al., 2019a; Zheng et al., 2019). Here, we found that TN and K concentrations were lower in corn-field soils relative to forest soils. This may be because harvesting corn removes N from the system annually. In addition, the farming disturbance itself leads to a loss of both N and K (Shi et al., 2018; Bakhshandeh et al., 2019). We did not observe significant differences in soil P concentrations between forest and corn-field soils, which may be due to low movement of P in the soil (Lou et al., 2019). Furthermore, we did not observe a significant reduction in SOC in corn-field vs. forest soils. This may be due to current agricultural practices in the study area, which ensure that soil is not left bare and exposed throughout the year. In addition, corn-field soils had greater Fe_o concentrations at depths of 0–60 cm, and Fe_o can promote SOC storage (Sun et al., 2020b; Bai et al., 2020; Zong et al., 2020). Fe_d significantly

Table 3
Weight of soil quality indicators assigned by principal component analysis in the minimum data set (MDS). The abbreviations are described in Table 1.

Soil property	principle component analysis	
	Communality	Weight
Fe_d	0.484	0.154
SOC	0.899	0.285
TN	0.957	0.303
K	0.814	0.258

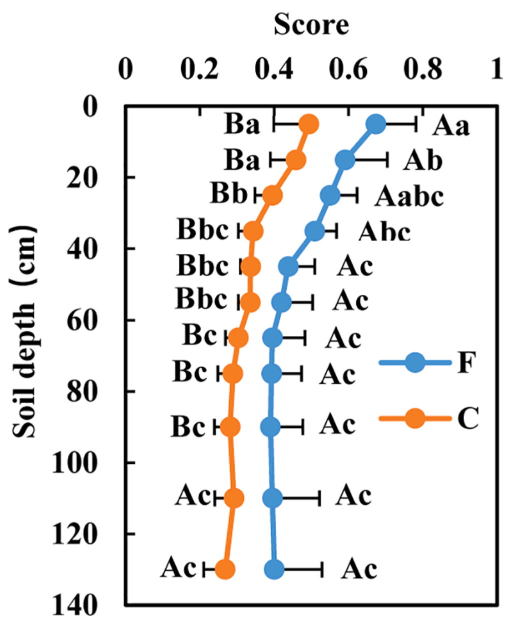

Fig. 3. Standard function scores of the SQI for both forest (blue) and corn-field (red) soils between 0 and 140 cm in depth. Different lowercase letters denote significant differences among soil layers in the same land use, and uppercase letters indicate significant differences among the different land uses in the same layer ($p < 0.05$; Tukey post-hoc test). Values represent means ($n = 6$) ± standard deviation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

rises in the 0–50 cm soil layer, the reason for the increase in Fe_d can be attributed to the rise in Fe_o. Human cultivation promotes soil development, which destroys the lattice structure of natural aluminosilicate minerals in soil and releases Fe (Chang et al., 1999; Takahashi et al., 1999). Meanwhile, Fe combines with water to form Fe_o, an important indicator of soil development (Chang et al., 1999; Takahashi et al., 1999). This may be the reason for the increase in the proportion of Fe_o (Bai et al., 2020, Zong et al., 2020).

BD is an important physical soil indicator that reflects soil quality, it is closely related to soil attributes such as erosion, pore structure, and permeability (Lou et al., 2019). BD was significantly lower in the corn-field soils relative to the forest soils, possibly because of soil disturbance caused by agricultural activities. However, BD was also lower in the corn field at depths 30–100 cm, the reasons for which are unclear. We found no significant differences in soil particle size among soil layers between the two land-use types, which implies that deforestation and conversion to agriculture did not affect soil texture. water content was significantly lower in the surface soil layer (0–10 cm) of the corn field relative to the forest soil, but there were no differences at greater depths. Surely, the forest canopy shades the soil surface which can:(a) lead to enhance more infiltration of rainfall water into the soil and (b) serves as a vapor barrier and suppresses evaporation against moisture losses from the soil (Khresat et al., 2008; Rezapour and Alipour, 2017). Soil pH was significantly higher in the cornfield at depths of 0–30 cm than in the forest

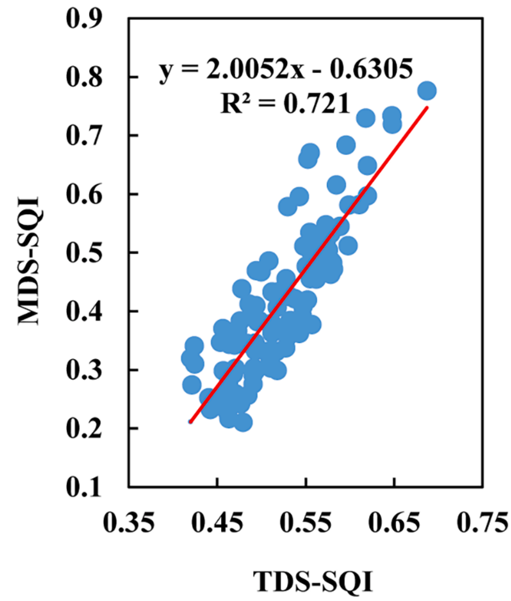

Fig. 4. Linear regression between the SQI derived from the MDS (y-axis) and that derived from the TDS (x-axis).

soil, and the pH of the deep soil layers (100–140 cm) was significantly lower. The reasons for this phenomenon may be that cultivation accelerates leaching of H^+ ions in surface soil (Li et al., 2016) and typically mixes lower, carbonate-bearing soil layers with the surface soil, which leads to an increase in pH (Davaria et al., 2020). Higher pH reduces the bioavailability of the heavy metal cadmium, which reduces cadmium, and also arsenic, absorption by crops and thereby suppresses heavy-metal damage and promotes crop growth (Wang et al., 2015).

EC, Na, Mg, and Ca reflect soil salinity, and soils with high EC values and high concentrations of these elements may be in the process of salinization, which relates to poor soil quality and function (Levi et al., 2020). We observed lower EC and Na and Mg concentrations in corn-field soil relative to forest soil, but higher Ca, Al, and S concentrations. This may be because the return rate of alkaline elements is higher in forest soil by the recycling of basic compounds (e.g., Na and K) through tree-root uptake, translocation into plant shoots and re-entry into the soil with litter fall and decomposition, which results in a higher EC (Rezapour and Alipour, 2017; Bakhshandeh et al., 2019). In addition, the perennial or seasonal cover of forest soil changes the water-heat balance under natural conditions (e.g., high temperatures, low leaching due to rain, and strong evaporation), which leads to soils that are not fully leached by rain and thus salt may accumulate on the soil surface (Bakhshandeh et al., 2019). Furthermore, agricultural practices can result in increased soil permeability, which promotes leaching, and thus reduces surface cations and anions (Bakhshandeh et al., 2019). We note that the EC values we observed in both land-use types are within the salinity tolerance range for most plants (<1 dS m^{-1}), and thus not likely to affect plant growth or soil microorganisms (Davaria et al., 2020).

4.2. MDS method for soil evaluation

The 16 variables included in the TDS were reduced to 4 in the MDS using a PCA. Certainly, some important soil-quality information may be lost through the PCA reduction process (Yu et al., 2018), but the MDS method reduces the number of variables, avoids redundancy, reduces cost and time, and improves overall efficiency. Therefore, the MDS method has been widely used in determining SQIs (Nabiollahi et al., 2017). Here, SOC, K, TN, and Fe_d were retained in the MDS. Thus, our MDS reflected comprehensive soil indicators, representing both physical

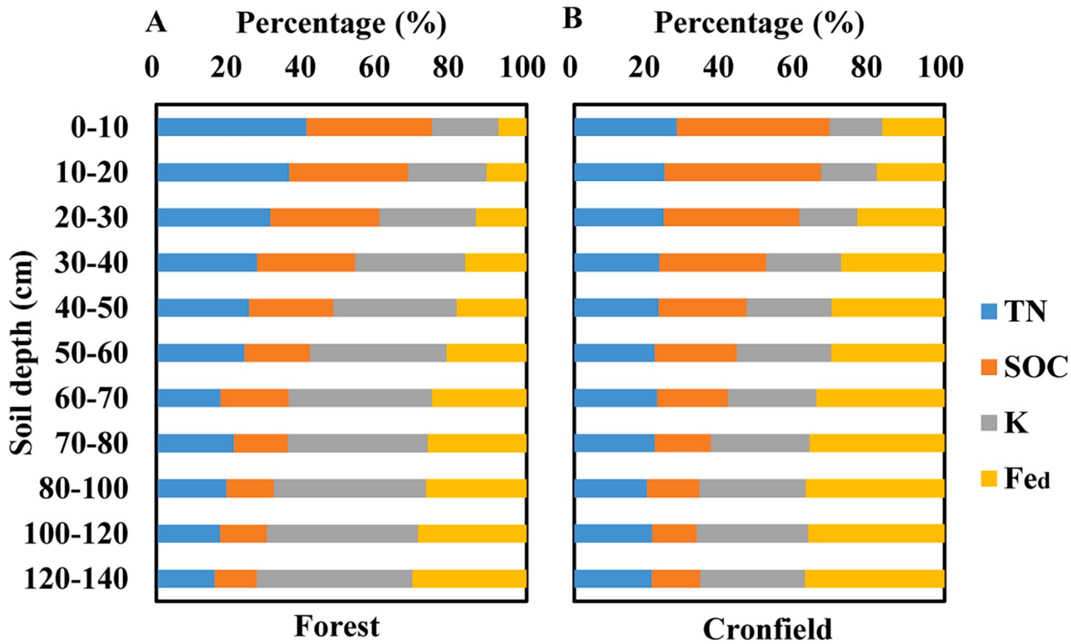

Fig. 5. The contributions of the minimum data set (MDS) variables [scored and weighted TN, SOC, K, and Fe_d] to the soil quality index (SQI) across 11 soil layers from depths of 0–140 cm, estimated using the standard scoring function method.

and chemical attributes, for determining soil quality (Li et al., 2013, 2020). SOC plays an important role in soil processes such as nutrient cycling and storage and is used worldwide as a soil quality indicator (Raiesi, 2017). N and K concentrations are also widely used as indicators (Li et al., 2013; Liu et al., 2018) because they are important nutrients for plant growth and crop production (Li et al., 2020). Indicators such as BD and EC were excluded from our SQI, likely because we assessed collinearity to avoid redundancy (Li et al., 2019b). Fe is essential for plant growth and development, and is an essential co-factor for many cellular processes. Our findings imply that Fe_d is an important indicator for evaluating soil quality in acidic red soils. Fe_d contains both crystalline iron and Fe_o, and Fe_o can promote SOC storage (Sun et al., 2020b; Bai et al., 2020).

When comparing the SQIs developed from the MDS and TDS, we observed a significant, positive correlation (MDS-SQI = 2.0052TDS-MDS–0.6305, $R^2 = 0.721$ ($P < 0.05$, Fig. 4)), which indicated that the SQI developed from the MDS was effective in evaluating soil quality (Shao et al., 2020). Thus, the MDS that we selected provided sufficient information to assess changes in quality in the acidic red soils of our study region, and represented major factors that affect soil quality in tropical red soils.

4.3. Effects of deforestation and planting corn on soil quality

As in previous research, we found that forest conversion to cultivated had a negative impact on soil quality (Toohey et al., 2018; Davaria et al., 2020). In our study area, 34 years after deforestation and conversion, soil layers between 0 – 100 cm showed a significant decrease in quality, despite the fact that tilling typically affects only the top 0–20 cm of soil. The effect of agricultural conversion on soil quality was more significant in topsoil soil layers than in the deep layer. Soil quality was highest in the surface layers of the forest soil, due to relatively high SOC, TN, and K concentrations. As has been observed in other research findings (Wang et al., 2018; Bakhshandeh et al., 2019), long-term agricultural cultivation leads to reduced concentrations of TN and K, which relate to declines in soil quality. Of note, although farming typically results in SOC loss (Guo et al., 2009; Raiesi and Beheshti, 2014), we observed equivalent SOC concentrations in corn-field and forest soils, but significantly higher Fe_d and Fe_o concentrations in corn-field soils, and Fe_o, which is the main component of Fe_d, promotes SOC storage (Sun et al., 2020b; Bai et al., 2020). Therefore, because of its role in maintaining SOC concentrations, Fe_o plays a vital role in maintaining soil quality in tropical red soils.

5. Conclusion

We used MDS determined by PCA to build SQI for tropical red soils, and evaluated the impact of deforestation and 34 years of continuous corn cultivation on soil quality. Our results indicate that forest conversion to agricultural land and corn planting led to degradation of soil quality. After deforestation and planting corn, the SQI of each layer of soil decreased by 20.15%–33.08%. Although soil disturbance due to farming typically occurs only in the arable layer, the soil has been significantly degraded in the 0–100 cm soil layers. On the one hand, the loss of TN and K is the main factor of soil degradation, which is greatly affected by land use change, which promotes the deterioration of soil quality. On the other hand, we note that Fe_o is vital to maintain SOC concentrations and thus soil quality in acidic red soils. Thus, soil degradation in deep soil layers deserves further research. Overall, the inclusion of land-use change soils in the SQI evaluation helps to establish a useful relationship between the SQI and management strategies. Nevertheless, the data may be site-specific, and its applicability to other areas and land uses must be assessed.

CRediT authorship contribution statement

Wuping Huang: Data curation, Methodology, Software, Writing - original draft. **Mingming Zong:** Conceptualization, Visualization, Methodology. **Zexin Fan:** Formal analysis, Resources. **Yuan Feng:** Data curation, Investigation. **Shiyu Li:** Supervision, Writing - review & editing. **Changqun Duan:** Funding acquisition, Project administration. **Haixia Li:** Formal analysis, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.107580.

References

Andrews, S.S., Karlen, D.L., Mitchell, J.P., 2002. A comparison of soil quality indexing methods for vegetable production systems in Northern California. Agric. Ecosyst. Environ. 90 (1), 25–45. https://doi.org/10.1016/S0167-8809(01)00174-8.

Armenise, E., Redmile-Gordon, M.A., Stellacci, A.M., Ciccarese, A., Rubino, P., 2013. Developing a soil quality index to compare soil fitness for agricultural use under different managements in the Mediterranean environment. Soil Tillage Res. 130, 91–98. https://doi.org/10.1016/j.still.2013.02.013.

Bai, J.Y., Zong, M.M., Li, S.Y., Li, H.X., Duan, C.Q., Feng, Y., Peng, C.H., Zhang, X.L., Sun, D., Lin, C., Shi, Y.C., Zheng, G.Y., Wang, H.D., Liu, D.X., Li, F.R., Huang, W.P., 2020. Nitrogen, water content, phosphorus and active iron jointly regulate soil organic carbon in tropical acid red soil forest. J. Soil Sci. Eur. https://doi.org/10.1111/ejss.12966.

Bakhshandeh, E., Hossieni, M., Zeraatpisheh, M., Francaviglia, R., 2019. Land use change effects on soil quality and biological fertility: a case study in northern Iran. Eur. J. Soil Sci. 95, 103119 https://doi.org/10.1016/j.ejsobi.2019.103119.

Barbosa, L.C., Magalhães, P.S.G., Bordonal, R.O., Cherubin, M.R., Castioni, G.A.F., Tenelli, S., Franco, H.C.J., Carvalho, J.L.N., 2019. Soil physical quality associated with tillage practices during sugarcane planting in south-central Brazil. Soil Tillage Res. 195, 104383 https://doi.org/10.1016/j.still.2019.104383.

Bayranvand, M., Kooch, Y., Rey, A., 2017. Earthworm population and microbial activity temporal dynamics in a Caspian Hyrcanian mixed forest. Eur. J. For. Res. 136, 447–456. https://doi.org/10.1007/s10342-017-1044-5.

Bremner, J.M., Mulvaney, C.S., 1982. Nitrogen-Total. In: Page, A.L. (Ed.), Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties. American Society of Agronomy, Soil Science Society of America. E-Publish Inc., New York, pp. 595–624.

Bruun, T.B., Elberling, B., De Neergaard, A., Magid, J., 2013. Organic carbon dynamics in different soil types after conversion of forest to agriculture. Land Degrad. Dev. 26, 272–283. https://doi.org/10.1002/ldr.2205.

Chang, Q.R., Feng, L.X., Nian, X., 1999. Study on soil iron oxide in Hanzhong, Shaanxi and its genetic significance (in Chinese). Chin. J. Soil Sci. 30, 14–16.

Davaria, M., Gholamia, L., Nabiollahia, K., Homaeeb, M., Jafaric, H.J., 2020. Deforestation and cultivation of sparse forest impacts on soil quality (case study: West Iran, Baneh). Soil Tillage Res. 198, 104504 https://doi.org/10.1016/j.still.2019.104504.

Doran, J.W., Parkin, T.B., 1994. Defining and assessing soil quality. In: Doran, J.W., Coleman, D.C., Bezdicek, D.F., Stewart, B.A. (Eds.). Defining Soil Quality for a Sustainable Environment. SSSA Special Publication No. 35, ASA and SSSA, Madison, WI, pp. 3–21.

Finzi, A.C., Breemen, N.V., Canham, C.D., 1998. Canopy tree-soil interactions within temperate forests: species effects on soil carbon and nitrogen. Ecol. Appl. 8 (2), 440–446. https://doi.org/10.1890/1051-0761(1998)008[0440:CTSIWT]2.0.CO;2.

Gelaw, A.M., Singh, B.R., Lal, R., 2014. Soil organic carbon and total nitrogen stocks under different land uses in a semi-arid watershed in Tigray, Northern Ethiopia. Agric Ecosyst. Environ. 188, 256–263. https://doi.org/10.1016/j.agee.2014.02.035.

Granatstein, D., Bezdicek, D.F., 1992. The need for a soil quality index: local and regional perspectives. Am. J. Altern. Agric. 7 (1–2), 12–16. https://doi.org/10.1017/S0889189300004380.

Guo, L.L., Sun, Z., Zhu, O., Han, D.R., Li, F.D., 2017. A comparison of soil quality evaluation methods for Fluvisol along the lower Yellow River. Catena 152, 135–143. https://doi.org/10.1016/j.catena.2017.01.015.

Guo, Y.J., Ni, Y., Han, J.G., 2009. The influence of land use change on chemical and biological properties of steppe soils in northern China. Arid Land Res. Manage. 23 (3), 197–212. https://doi.org/10.1080/15324980903028553.

Hemati, Z., Selvalakshmi, S., Xia, S.W., Yang, X.D., 2020. Identification of indicators: Monitoring the impacts of rubber plantations on soil quality in Xishuangbanna, Southwest China. Ecol. Indic. 116, 106491 https://doi.org/10.1016/j.ecolind.2020.106491.

Hu, Y., Li, Y., Hou, Y.L., 2018. The variation of soil organic carbon fractions and soil enzyme activity of different land use types in Minjiang River valley. Ecol. Environ. Sci. 27 (9), 1617–1624. https://doi.org/10.16258/j.cnki.1674-5906.2018.09.005.

Jafarnejadi, A.R., Sayyad, G.H., Homaee, M., Davamei, A.H., 2013. Spatial variability of soil total and DTPA-extractable cadmium caused by long-term application of phosphate fertilizers, crop rotation, and soil characteristics. Environ. Monit. Assess. 185, 4087–4096. https://doi.org/10.1007/s10661-012-2851-2.

Jahany, M., Rezapour, S., 2020. Assessment of the quality indices of soils irrigated with treated wastewater in a calcareous semi-arid environment. Ecol. Ind. 109, 105800 https://doi.org/10.1016/j.ecolind.2019.105800.

Khresat, S., Al-Bakri, J., Al-Tahhan, R., 2008. Impacts of land use/cover change on soil properties in the Mediterranean region of northwestern Jordan. Land Degrad. Dev. 19 (4), 397–407. https://doi.org/10.1002/ldr.847.

Korkanç, S.Y., 2014. Effects of afforestation on soil organic carbon and other soil properties. Catena 123, 62–69. https://doi.org/10.1016/j.catena.2014.07.009.

Leite Chaves, H.M., Concha Lozada, C.M., Gaspar, R.O., 2017. Soil quality index of an Oxisol under different land uses in the Brazilian savannah. Geoderma Reg. 10, 183–190. https://doi.org/10.1016/j.geodrs.2017.07.007.

Levi, N., Karnieli, A., Paz-Kagan, T., 2020. Using reflectance spectroscopy for detecting land-use effects on soil quality in drylands. Soil Tillage Res. 199, 104571 https://doi.org/10.1016/j.still.2020.104571.

Li, P., Shi, K., Wang, Y.Y., Kong, D.N., Liu, T., Jiao, J.G., Liu, M.Q., Li, H.X., Hu, F., 2019a. Soil quality assessment of wheat-maize cropping system with different productivities in China: establishing a minimum data set. Soil Tillage Res. 190, 31–40. https://doi.org/10.1016/j.still.2019.02.019.

Li, P., Wu, M.C., Kang, G.D., Zhu, B.J., Li, H.X., Hu, F., Jiao, J.G., 2020. Soil quality response to organic amendments on dryland red soil in subtropical China. Geoderma 373, 114416. https://doi.org/10.1016/j.geoderma.2020.114416.

Li, P., Zhang, T.L., Wang, X.X., Yu, D.S., 2013. Development of biological soil quality indicator system for subtropical China. Soil Tillage Res. 126, 112–118. https://doi.org/10.1016/j.still.2012.07.011.

Li, S.Y., Li, H.X., Yang, C.L., Wang, Y.D., Xue, H., Niu, Y.F., 2016. Rates of soil acidification in tea plantations and possible causes. Agric. Ecosyst. Environ. 233, 60–66. https://doi.org/10.1016/j.agee.2016.08.036.

Li, X.Y., Wang, D.Y., Ren, Y.X., Wang, Z.M., Zhou, Y.H., 2019b. Soil quality assessment of croplands in the black soil zone of Jilin Province, China: establishing a minimum data set model. Ecol. Ind. 107, 105251 https://doi.org/10.1016/j.ecolind.2019.03.028.

Liu, J., Wu, L.C., Chen, D., Yu, Z.G., Wei, C.J., 2018. Development of a soil quality index for Camellia oleifera forestland yield under three different parent materials in Southern China. Soil Tillage Res. 176, 45–50. https://doi.org/10.1016/j.still.2017.09.013. Get rights and content.

Liu, Z.J., Zhou, W., Shen, J.B., Li, S.T., Liang, G.Q., Wang, X.B., Sun, J.W., Ai, C., 2014. Soil quality assessment of acid sulfate paddy soils with different productivities in Guangdong Province, China. J. Integr. Agric. 13 (1), 177–186. https://doi.org/10.1016/S2095-3119(13)60594-8.

Lou, Y.B., Shi, D.M., Jiang, G.Y., Jin, H.F., Chen, Z.F., Lin, Z., 2019. Soil quality evaluation of sloping farmland surface in Purple Hilly region based on minimum data set. Sci. Soil Water Conserv. 17 (5), 75–85. https://doi.org/10.16843/j.sswc.2019.05.009.

Marzaioli, R., D'Ascoli, R., De Pascale, R.A., Rutigliano, F.A., 2010. Soil quality in a Mediterranean area of Southern Italy as related to different land use types. Appl. Soil Ecol. 44 (3), 205–212. https://doi.org/10.1016/j.apsoil.2009.12.007.

Mehra, O.P., Jackson, M.L., 1960. Iron oxide removal from soils and clays by a dithionite-citrate system buffered with sodium bicarbonate. Clays Clay Miner. 7, 317–327. https://doi.org/10.1016/B978-0-08-009235-5.50026-7.

Min, S., Huang, J.K., Waibel, H., Yang, X.Q., Cadisch, G., 2019. Rubber Boom, Land Use Change and the Implications for Carbon Balances in Xishuangbanna, Southwest China. Ecol. Econ. 156, 57–67. https://doi.org/10.1016/j.ecolecon.2018.09.009.

Mukherjee, A., Lal, R., 2014. Comparison of soil quality index using three methods. PLoS ONE 9, e105981. https://doi.org/10.1371/journal.pone.0105981.

Nabiollahi, K., Taghizadeh-Mehrjardi, R., Kerry, R., Moradian, S., 2017. Assessment of soil quality indices for salt-affected agricultural land in Kurdistan province, Iran. Ecol. Indic. 83, 482–494. https://doi.org/10.1016/j.ecolind.2017.08.001.

Ou, Y., Rousseau, A.N., Wang, L.X., Yan, B.X., 2017. Spatio-temporal patterns of soil organic carbon and pH in relation to environmental factors—a case study of the Black Soil Region of Northeastern China. Agric. Ecosyst. Environ. 245, 22–31. https://doi.org/10.1016/j.agee.2017.05.003.

Qi, Y., Darilek, J.L., Huang, B., Zhao, Y., Sun, W., Gu, Z., 2009. Evaluating soil quality indices in an agricultural region of Jiangsu Province, China. Geoderma 149, 325–333. https://doi.org/10.1016/j.geoderma.2008.12.015.

Qi, Y.B., Chen, T., Pu, J., Yang, F.Q., Shukla, M.K., Chang, Q.R., 2018. Response of soil physical, chemical and microbial biomass properties to land use changes in fixed desertified land. Catena 160, 339–344. https://doi.org/10.1016/j.catena.2017.10.007.

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. Ecol. Ind. 75, 307–320. https://doi.org/10.1016/j.ecolind.2016.12.049.

Raiesi, F., Beheshti, A., 2014. Soil C turnover, microbial biomass and respiration, and enzymatic activities following rangeland conversion to wheat–alfalfa cropping in a semi-arid climate. Environ. Earth Sci. 72, 5073–5088. https://doi.org/10.1007/s12665-014-3376-5.

Rezapour, S., Alipour, O., 2017. Degradation of Mollisols quality after deforestation and cultivation on a transect with Mediterranean condition. Environ. Earth Sci. 76 (22), 755. https://doi.org/10.1007/s12665-017-7099-2.

Sakin, E., 2014. Organic carbon organic matter and bulk density relationships in arid-semi arid soils in Southeast Anatolia region. Afr. J. Biotechnol. 11 (6), 1373–1377. https://doi.org/10.5897/AJB11.2297.

Saviozzi, A., Levi-Minzi, R., Cardelli, R., Riffaldi, R., 2001. A comparison of soil quality in adjacent cultivated, forest and native grassland soils. Plant Soil 233, 251–259. https://doi.org/10.1023/A:1010526209076.

Schwertmann, U., 1964. Differenzierung der eisenoxide des bodens durch extraktion mit ammoniumoxalat-lösung. J. Plant Nutr. Soil Sci. 105 (3), 194–202. https://doi.org/10.1002/jpln.3591050303.
Shao, G.D., Ai, J.J., Sun, Q.W., Hou, L.Y., Dong, Y.F., 2020. Soil quality assessment under different forest types in the Mount Tai, central Eastern China. Ecol. Ind. 115, 106439 https://doi.org/10.1016/j.ecolind.2020.106439.
Shi, L.Y., Tian, X.H., Tian, X.M., Mu, C.P., Dong, F., 2018. Effects of different land use patterns on soil nutrient status in Xingkai Lake region. Hubei Agric. Sci. 57 (22), 38–40. https://doi.org/10.14088/j.cnki.issn0439-8114.2018.22.011.
Six, J., Paustian, K., 2014. Aggregate-associated soil organic matter as an ecosystem property and a measurement tool. Soil Biol. Biochem. 68, A4–A9. https://doi.org/10.1016/j.soilbio.2013.06.014.
Soleimani, A., Hosseini, S.M., Bavani, A.R.M., Jafari, M., Francaviglia, R., 2019. Influence of land use and land cover change on soil organic carbon and microbial activity in the forests of northern Iran. Catena 177, 227–237. https://doi.org/10.1016/j.catena.2019.02.018.
Sun, D., Zong, M.M., Li, S.Y., Li, H.X., Duan, C.Q., Peng, C.H., Zhao, Y.G., Bai, J.Y., Lin, C., Feng, Y., Huang, W.P., Wang, D., 2020a. The effects of the soil environment on soil organic carbon in tea plantations in Xishuangbanna, southwestern China. Agric. Ecosyst. Environ. 297, 106951 https://doi.org/10.1016/j.agee.2020.106951.
Sun, H., Jin, Q., Wang, Q.X., Shao, C., Zhang, L.L., Guan, Y.M., Tian, H.L., Li, M.H., Zhang, Y.Y., 2020b. Effects of soil quality on effective ingredients of Astragalus mongholicus from the main cultivation regions in China. Ecol. Ind. 114, 106296 https://doi.org/10.1016/j.ecolind.2020.106296.
Takahashi, T., Park, C.Y., Nakajima, H., Sekiya, H., Toriyama, K., 1999. Ferric iron transformation in soils with rotation of irrigated rice-upland crops and effect on soil tillage properties. Soil Sci. Plant Nutr. 45, 163–173. https://doi.org/10.1080/00380768.1999.10409332.
Toohey, R.C., Boll, J., Brooks, E.S., Jones, J.R., 2018. Effects of land use on soil properties and hydrological processes at the point, plot, and catchment scale in volcanic soils near Turrialba, Costa Rica. Geoderma 315, 138–148. https://doi.org/10.1016/j.geoderma.2017.11.044.
Torrent, J., Liu, Q.S., Barŕon, V, 2010. Magnetic susceptibility changes in relation to pedogenesis in a Xeralf chronosequence in northwestern Spain. Eur. J. Soil Sci. 61 (2), 161–173. https://doi.org/10.1111/j.1365-2389.2009.01216.x.
Walkley, A., Black, I.A., 1934. An examination of the degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil Sci. 37, 29–38. https://doi.org/10.1097/00010694-193401000-00003.
Wang, M.M., Chen, H.S., Zhang, W., Wang, K.L., 2018. Soil nutrients and stoichiometric ratios as affected by land use and lithology at county scale in a karst area, southwest China. Sci. Total Environ. 619–620, 1299–1307. https://doi.org/10.1016/j.scitotenv.2017.11.175.
Wang, T., Kang, F.F., Cheng, X.Q., Han, H.R., Ji, W.J., 2016a. Soil organic carbon and total nitrogen stocks under different land uses in a hilly ecological restoration area of North China. Soil Tillage Res. 163, 176–184. https://doi.org/10.1016/j.still.2016.05.015.
Wang, X.G., Zhou, M.H., Li, T., Ke, Y., Zhu, B., 2017. Land use change effects on ecosystem carbon budget in the Sichuan Basin of Southwest China: Conversion of cropland to forest ecosystem. Sci. Total Environ. 609, 556–562. https://doi.org/10.1016/j.scitotenv.2017.07.167.
Wang, X.L., Lu, L.L., Huang, X.Q., Du, R.P., He, B., Gu, M.H., 2015. Effects of Silica-calcium-Potash fertilizer on cadmium and arsenic uptake by maize in soil of compound polluted farmland. Agric. Res. Appl. 3, 8–14. https://doi.org/10.3969/j.issn.2095-0764.2015.03.002.
Wang, Y.D., Yang, C.L., Xu, G.F., Li, S.Y., Chen, G.M., Liu, B., Liu, Q.T., Yang, H.Y., 2016b. Soil organic carbon leaching characteristics of tea gardens with different planting years. J. Anhui Agric. Univ. 42, 176–181. https://doi.org/10.13610/j.cnki.1672-352x.20160311.022.
Xiao, D., Huang, Y., Feng, S., Ge, Y., Zhang, W., He, X., Wang, K., 2018. Soil organic carbon mineralization with fresh organic substrate and inorganic carbon additions in a red soil is controlled by fungal diversity along a pH gradient. Geoderma 321, 79–89. https://doi.org/10.1016/j.geoderma.2018.02.003.
Yin, S., Bai, J.H., Wang, W., Zhang, G.L., Jia, J., Cui, B.S., Liu, X.H., 2019. Effects of soil moisture on carbon mineralization in floodplain wetlands with different flooding frequencies. J. Hydrol. 574, 1074–1084. https://doi.org/10.1016/j.jhydrol.2019.05.007.
Yu, P.J., Liu, S.W., Zhang, L., Li, Q., Zhou, D.W., 2018. Selecting the minimum data set and quantitative soil quality indexing of alkaline soils under different land uses in northeastern China. Sci. Total Environ. 616–617, 564–571. https://doi.org/10.1016/j.scitotenv.2017.10.301.
Zhang, H., Wu, P.B., Fan, M.M., Zheng, S.Y., Wu, J.T., Yang, X.H., Zhang, M., Yin, A., Gao, C., 2018. Dynamics and driving factors of the organic carbon fractions in agricultural land reclaimed from coastal wetlands in eastern China. Ecol. Ind. 89, 639–647. https://doi.org/10.1016/j.ecolind.2018.01.039.
Zhang, Y.W., Shangguan, Z.P., 2016. The coupling interaction of soil water and organic carbon storage in the long vegetation restoration on the loess plateau. Ecol. Eng. 91, 574–581. https://doi.org/10.1016/j.ecoleng.2016.03.033.
Zheng, S.Y., Chen, L.S., Xie, D.J., 2019. Effects of different nitrogen fertilizer rates on soil enzyme activity and microbial biomass Carbon and Nitrogen in maize fields. Chin. Soil Water Conserv. 7, 58–60. https://doi.org/10.14123/jcnki.swcc.2019.0172.
Zong, M.M., Lin, C., Li, S.Y., Li, H.X., Duan, C.Q., Peng, C.H., Guo, Y.X., An, R.Q., 2020. Tillage activates iron to prevent soil organic carbon loss following forest conversion to cornfields in tropical acidic red soils. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2020.143253.
Zuber, S.M., Behnke, G.D., Nafziger, E.D., Villamil, M.B., 2017. Multivariate assessment of soil quality indicators for crop rotation and tillage in Illinois. Soil Tillage Res. 174, 147–155. https://doi.org/10.1016/j.still.2017.07.007.