

Retraction

Retracted: Evaluation of Soil Quality for Different Types of Land Use Based on Minimum Dataset in the Typical Desert Steppe in Ningxia, China

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Tian, Z. Xu, J. Wang, and Z. Wang, "Evaluation of Soil Quality for Different Types of Land Use Based on Minimum Dataset in the Typical Desert Steppe in Ningxia, China," *Journal of Advanced Transportation*, vol. 2022, Article ID 7506189, 14 pages, 2022.

Research Article

Evaluation of Soil Quality for Different Types of Land Use Based on Minimum Dataset in the Typical Desert Steppe in Ningxia, China

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When the grassland ecosystem is under investigation, soil quality indexes (SQIs) are constructed to evaluate soil quality substantially, especially in desert grasslands and other ecologically fragile areas. This research used the total dataset (TDS), minimum dataset (MDS), approaches dealing with selecting better indexes, and scoring methods utilizing linear and nonlinear expressions to assess the typical desert grasslands in Yanchi County, Ningxia, China. The utilization of four different lands such as forestland (FL), shrubland (SL), natural restoration grassland (GL), and abandoned farmland (AL) in the study area were researched. Physical, chemical, and biological indicators, a total number of twenty, were measured. Principal component analysis and norm values were used to select indicators based on the MDS. The results suggested that nine soil indicators, namely, soil water content (WC), total soil porosity (TP), percentage of soil sand (sand), percentage of soil clay (clay); soil organic carbon (SOC), total nitrogen (TN), available nitrogen (AN), urease activity (UA), and catalase activity (CA) were selected for the MDS. The distribution of the SQI in the types of land use was similar concerning the two evaluation methods. The nonlinear scoring method utilizing the MDS was found the most proper to compute the SQI since the maximum F statistics, coefficient of variation (CV), and correlation results are obtained. The SQI outcomes that were ranked concerning the types of land use were found to be shrubland (SL) > natural restoration grassland (GL) > abandoned farmland (AL) > forestland (FL). In the four types of soil, shrub afforestation can be used as a beneficial ecological measure to restore the soil quality of typical desert grasslands in the research area.

1. Introduction

A vital resource of the ecosystem, soil, is assessed as the significant and nonrenewable pillar and plays a key role to regulate nutrient absorption, utilizing water and increasing productivity. The decrease in soil quality has been a global environmental crisis [1, 2]. The desert grassland in Yanchi County of Ningxia is an ecologically fragile area with severe soil erosion, desertification, salinization, and uneven spatial distribution. Due to its location between the agricultural and pastoral transition zones, various land management measures such as farmland, forestland, grassland, and artificial vegetation restoration are of particular importance. A few studies that have dealt with the assessment of soil quality in different types of land use have been of great significance to

maintaining soil productivity, protecting the soil environment, and promoting the development of desert grassland in this area. Measuring the quality of soil could not be conducted directly, and derivations can be conducted based on indicators. Moreover, evaluation indicators of soil quality are complex and contain physical, chemical, and biological features of the soil. Their processes are further determined by soil functions that meet the key management objectives [3, 4]. These indicators are sensitive to dynamic alterations occurring in the conditions of soil causing the computed indicators more sensitive. Moreover, indicators could change based on different types of land use and plant restoration measures [5]. There exist several methods to assess soil quality. Soil quality indexes (SQIs) are an efficient instrument to evaluate soil quality [6]. Also, it helps reduce the

dimensionality problem when the dataset composes of several variables. Hence, the evaluation process becomes simpler and more accurate. However, choosing appropriate indicators remains a difficult problem to be solved when using SQIs for soil quality. The indicators are expected to have an important effect on soil function and evaluation results [7]. Therefore, the scientific way of selecting quantitative and qualitative indicators and establishing a suitable minimum dataset (MDS) is the key step towards the assessment of SQIs. Former research just included both physical and chemical features and ignored the biological features, even though biological indicators could have the potentials to provide more insights. Besides, when all three types of indicators are combined to construct the evaluation of SQIs, the soil quality could be measured as accurately as possible [8, 9]. Therefore, the physical, chemical, and biological properties must be considered concurrently when selecting indicators to accurately analyze soil quality.

The calculation of SQIs requires the best representative indicators to be selected concerning soil functions. Linear and nonlinear approaches are utilized to obtain scores that are integrated into indicators of soil quality [10, 11]. The PCA method has been extensively employed to eliminate dimensionality issues in data analysis [12]. Pang et al. [13] used the PCA method and correlation measure with the combination of sensitivity calculation comprehensively to study the soil quality of various models used for vegetation restoration in rocky desertification areas. Li et al. [14] used both the PCA method and norm values to construct an MDS to assess indicators of soil quality under the various methods of vegetation restoration in the open-pit coal mine reclamation area of Zhungeer Banner in the Inner Mongolia Autonomous Region. Several experts suggest the establishment of an MDS to use a linear scoring model to evaluate soil quality and to lower the cost of the process [12, 15]. A precise assessment of soil quality depends on the utilization of appropriate analysis methods. If no linearity exists between the quality score and the index value, a nonlinear model is preferred to be used over the linear. Additionally, due to soil complexity and variability, suitable soil evaluation methods must be further verified [16]. Besides, it should be kept in mind that multiple methods with both advantages and disadvantages to evaluate soil quality are available [17–19]. Researchers globally have conducted abundant research on the adaptability of evaluation methods of soil quality such as in the Kurdistan province of Iran, the Loess Plateau of China, and the rocky desertification control area in Guizhou, China [6, 20, 21].

However, a limited number of research studies evaluating soil quality under the anthropogenic disturbance of the typical desert steppe in northwest China are found. Prior research just contained the features' physical and chemical properties and ignored the biological features, even though biological indicators could have the potentials to provide more insights. This study combines physical, chemical, and biological features of the soil by employing the MDS generated by the PCA method and then two scoring approaches, linear and nonlinear, to generate the most appropriate SQI indicators utilized. By doing so, the investigation leads to

finding the impact of the attributes on soil quality when a change of land use occurs in the research field.

The rest of the study is organized as follows: Section 2 contains some fundamental aspects of the research. The study area, sample collection, and physical analysis are described and explained in detail. Then, the evaluation method, construction of scoring models, derivation of weights for the indexes, and SQI calculation are explained concerning total and minimum datasets. The results of the analysis are presented in Section 3. Section 4 is allocated for the findings. Discussion is given in Section 5. Section 6 concludes the research with prospective future research directions.

2. Materials and Methods

In this research, we propose a new approach that combines statistical methods with scoring approaches utilizing linear and nonlinear expressions to determine SQIs. Thus, the objective of this research has three folds: an area featuring a transitional zone varying from arid to semiarid with continental monsoon climate has been researched limitedly and investigated, a comprehensive implementation of statistical analysis such as ANOVA, PCA method, and correlation measure is concurrently utilized to decrease the number of attributes related to soil quality, finding weights of indexes. Then, linear and nonlinear approaches that use the extracted attributes generate indexes of soil quality concerning various types of land use. Moreover, the scoring approach based on nonlinear function outperforms the linear one. Even though physical and chemical attributes have been widely used in the calculation of SQIs, biological attributes have rarely been utilized. This research combines all.

2.1. Depiction and Features of the Study Area. The research field is located in the desert steppe region of eastern Yanchi County, Ningxia Hui Autonomous Region in China. The region has a fragile environment, which has a continental monsoon climate that is characterized by regions changing between arid through semiarid. The yearly mean temperature is 8°C. There is a significant climate difference between winter and summer with an average temperature difference of approximately 18°C. The difference in the temperature between day and night in autumn and winter can fluctuate 20°C. Flora is characterized with transitional properties, for example, Gaoshawo Town in the Eurasian steppe area, which is a transitional zone of the central China steppe area. The altitude varies from 1300 m to 1500 m. The average annual rainfall is less than 200 mm and is concentrated between July and September, accounting for approximately 70% of yearly precipitation. The annual evaporation is above 2000 mm, the yearly mean wind speed is 3 m/s, and strong winds (wind speed >17 m/s) mainly occur in spring. The structure of the soil primarily consists of lime calcium. The study site is northeast of Fanjiquan Village in Gaoshawo Town (106°84.204'E, 38°02.754'N). The surface layer composes of barren soil whose composition is mainly sandy soil. The plants are sparse covering less than 30% [22, 23]. Various

artificial shrubs have been planted since the 1970s for ecological restoration. The types of major plants are called *Caragana korshinskii*, *Leymus secalinus*, *Artemisia scoparia*, *Lespedeza potaninii*, *Glycyrrhiza uralensis*, *Lespedeza bicolor*, *Heteropappus altaicus*, *Setaria viridis*, and *Agriophyllum squarrosum*.

2.2. Collection of Soil Sample and Physical Analysis. The four different types of land use that had similar slopes and aspects were set up in this study, as given in Table 1. The composition of the area is as follows: naturally restored grassland (GL), shrubland (SL), forestland (FL), and abandoned farmland (AL). GL has naturally restored desert grassland. While SL was artificially planted *Cerasus humilis* for five years, FL was artificially planted *Caragana korshinskii* for fifteen years. AL used to be arable land for corn has been abandoned for five years and was a bare wasteland with sparse weeds. *Caragana korshinskii* was planted in strips, while *Cerasus humilis* was planted uniformly with row spacing and both were single vegetation types.

The soil samples were collected from July to August in 2019 at depths of 0–20 and 20–40 cm, and each sampling point used a five-point method to constitute a mixed sample. Each type of land use consists of soil data changing between 20 and 30 samples, which reached a total of 104 collected soil samples. Afterward, plastic bags were used to store the soil examples that were kept in an ice bucket at 4°C and quickly delivered to the laboratory. After removing all types of impurities such as plant litter, roots, and stones, each sample went through a 2 mm sieve and was divided in half. While soil enzyme is determined utilizing one portion kept at 4°C, the other placed outside to be dried, and then analyzed concerning physical and chemical properties. Table 1 provides information regarding the different types of land use.

The total number of physical, chemical, and biological indicators was twenty and determined based on the measurement of various attributes available in “Soil Agrochemical Analysis” [24]. The implemented indicators are presented as follows: soil pH was found by the 1 : 1 electrode approach for the water-soil ratio. Soil bulk density (BD), total porosity (TP), and water content (WC) were found utilizing the method called the cutting ring water immersion. We used the electrode method for soil electrical conductivity (EC) and the Malvern laser particle size analysis method to determine the sand, clay, and silt percentages of soil. The $K_2Cr_2O_7$ volumetric method was utilized for soil organic carbon (SOC). Total nitrogen (TN) was found using the Kjeldahl method and available nitrogen (AN) by the $KMnO_4$ oxidation method [25]. Total phosphorus (TPP) was determined by the NaOH alkali solution-molybdenum-antimony colorimetric method. Total potassium (TK) was found using the NaOH melting method, and available phosphorus (AP) was extracted by the $NaHCO_3$ -molybdenum-antimony colorimetry method. Available potassium (AK) was determined by ammonium acetate extract-flame photometry. Soil enzyme activities (UA, urease; SA, sucrase; CEA, cellulase; PPA, phosphatase; CA, catalase) were determined using the micromethod kit by ELISA detection,

which refers to the manual for specific methods of soil urease (sucrase, cellulase, phosphatase, and catalase) using the ELISA Kit (Shanghai, China: Shanghai Hengyuan Biotechnology Co., Ltd., <http://www.hyswsh.com>).

2.3. The Evaluation Method of Soil Quality

2.3.1. Datasets: Total and Minimum. The physical, chemical, and biological characteristics of the soil, a total of twenty, were selected and thoroughly considered. First, ANOVA was conducted for each soil indicator. The indicators found statistically significant concerning the four types of land use were selected as attributes of the TDS [6, 26]. Second, after standardizing the data, the PCA method was conducted to determine the indicators that will be entered into the MDS. The principal components are determined with the criteria of eigenvalue ≥ 1 , and those with index loadings greater than 0.5 are grouped. If the loading of a particular index in different principal components was greater than 0.5, it was merged into a group with a lower correlation to other indexes. The norm value of the indicators of each group was calculated, and the norm value of the index in each group within the largest 10% was chosen. When several indicators were grouped under the same principal component, the correlation measure was utilized to find the redundant indicators. If the correlation coefficient between the indicators was less than 0.5, all indicators could be retained. If significant correlations are found between the indicators within the principal component, $r > 0.5$, the indicator with the maximum norm value was chosen to enter into the MDS [20].

The formula of the norm value is defined by

$$N_{ik} = \sqrt{\sum_{i=1}^k (u_{ik}^2 e_k)}, \quad (1)$$

where N_{ik} represents the norm value of the first k principal components of the i^{th} index whose eigenvalue is greater than 1; u_{ik} represents the loading of the i^{th} index on the k^{th} principal component, and e_k is the eigenvalue of the k^{th} principal component.

2.3.2. Construction of a Scoring Model for the Soil Quality. After determining the indicators of the TDS and MDS, we used scoring approaches based on linear and nonlinear functions to map each soil indicator into [0, 1] interval [27, 28]. Sensitivity of soil quality is used to determine the indicators represented by two different types. The improvement of soil quality led each index to increase. Thus, it was suitable for the “more is better” scoring model; otherwise, it was suitable for the “less is better” scoring model.

The scoring model based on nonlinear expression is described by

$$S_{NL} = \frac{a}{1 + (x/x_0)^b}. \quad (2)$$

In equation (2), S_{NL} is the score of the soil index taking values in [0, 1] interval, the highest score is denoted by an

TABLE 1: Information of different types of land use in the research field.

Type of land use	Vegetation type	Longitude/ latitude	Altitude (m)	Gradient (°)	Aspect	Main plant species
GL	Natural restoration land	106°84.442'E, 38°02.935'N	1397	5	NW	<i>Artemisia scoparia</i> , <i>Glycyrrhiza uralensis</i> , <i>Lespedeza bicolor</i> , <i>Heteropappus altaicus</i> , <i>Setaria viridis</i> , <i>Agriophyllum squarrosum</i>
SL	Artificial shrub land of <i>Cerasus humilis</i> > five years	106°84.256'E, 38°02.976'N	1400	10	NW	<i>Glycyrrhiza uralensis</i> , <i>Heteropappus</i> <i>altaicus</i> , <i>Setaria viridis</i> , <i>Agriophyllum</i> <i>squarrosum</i> , <i>Convolvulus arvensis</i>
FL	Artificial forestland of <i>Caragana korshinskii</i> > fifteen years	106°84.248'E, 38°02.827'N	1400	10	NW	<i>Leymus secalinus</i> , <i>Setaria viridis</i> , <i>Lespedeza</i> <i>davurica</i> , <i>Heteropappus altaicus</i> , Puncturevine Caltrop Fruit
AL	Abandoned land > five years	106°84.182'E, 38°02.901'N	1399	5	NW	<i>Artemisia scoparia</i> , <i>Setaria viridis</i> , <i>Agriophyllum squarrosum</i>

FL, forestland; SL, shrubland; GL, natural restoration grassland; AL, abandoned farmland.

($a = 1$), the measured soil index value is denoted by x , x_0 is the corresponding average of the index, and the slope of the equation is denoted by b . While the type of index called “more is better” is denoted by -2.5 , the type of index called “less is better” is denoted by 2.5 [29, 30].

The linear scoring model is defined by

$$S_L = \frac{x - L}{H - L}, \quad (3)$$

$$S_L = 1 - \frac{x - L}{H - L}. \quad (4)$$

In equations (3) and (4), S_L is the linear score (0-1), x is the measured value of the index, and L and H are the lowest and highest values of the index, respectively. While equation (3) is called the “more is better” function type of the index scoring, equation (4) is called the “less is better” function type of the index scoring.

2.3.3. Evaluation of Index Weight and SQI Calculation. The PCA method was used to calculate the weight of each indicator. The weight was computed as a division of two quantities, which are the variance of the common factor of each indicator to the sum of the variance of the common factor of all indicators. After obtaining the score and weight of each index, the calculation of the SQI was defined by

$$SQI = \sum_{i=1}^n W_i \times S_i. \quad (5)$$

In equation (5), S_i , n , and W_i is called the score of the index, the number of indicators, and weight of each index, respectively. The higher the SQI value is, the higher the soil quality is [31].

2.4. Software Used for the Data Analysis. SPSS 22.0 version and Microsoft Excel 2010 were utilized to analyze the data. While SPSS 22.0 was used for correlation and regression, ANOVA analysis, and PCA method, Microsoft Excel 2010 was used plot results.

3. Analysis of Results

This section contains a detailed account of the research. How statistical analysis such as ANOVA, PCA, and correlation analysis is used to determine the MDS is explained, which contains nine of them. Then, scoring methods applied to find the SQIs containing physical, chemical, and biological features pertinent to the quality of soil are provided concerning the significant outcomes. The SQIs that represent the different types of land use are finally determined.

3.1. Statistical Results of the Evaluation Indicators for Soil Quality. The physical, chemical, and biological indicators of different types of land use are given in Table 2. Substantial distinctions were determined concerning 19 soil features, except for the percentage of soil silt. Hence, these 19 indicators were selected as the TDS and analyzed for PCA. Grassland had the highest values for WC, pH, BD, EC, and TP (water content, soil pH, soil bulk density, soil electrical conductivity, and total phosphorus). When other types of land use are a concern, while both pH and BD (soil pH and soil bulk density) were the highest values in the forestland, pH and BD (soil pH and soil bulk density) were the lowest in abandoned land. Forestland, shrubland, and abandoned land had the highest TP scores (total phosphorus). Besides, concerning soil particle composition, forestland had the highest sand value, which is significantly higher than that of grassland ($P < 0.05$). On the other hand, the lowest was in the clay, which is significantly lower than those of both grassland and shrubland ($P < 0.05$). Shrubland had higher SOC, TN, and AN (soil organic carbon, total nitrogen, and available nitrogen). Forestland had lower soil chemical indexes, except for TK (total potassium), followed by abandoned land. Grassland had the highest TN and AK (total nitrogen and available potassium) and had, however, the lowest AN (available nitrogen). Shrubland had the highest soil biological indicators of UA, SA, CEA, PPA, and CA (urease, sucrase, cellulase, phosphatase, and catalase). Table 2 provides the mean and standard deviation values of each indicator concerning four different types of land use. Besides, statistically significant indicators are denoted by bold values.

TABLE 2: Mean \pm SD values of soil quality evaluation indicators based on different sites and ANOVA results with significant ones ($P < 0.05$).

Soil indicator	Soil use types				ANOVA F	P
	Grassland (GL)	Shrub land (SL)	Forest land (FL)	Abandoned land (AL)		
WC (%)	9.87 \pm 0.15 ^a	7.39 \pm 0.39 ^b	5.20 \pm 0.42 ^c	4.36 \pm 0.29 ^c	33.594	0.000
pH	9.22 \pm 0.13 ^a	8.98 \pm 0.09 ^{ab}	9.18 \pm 0.01 ^a	8.85 \pm 0.06 ^b	3.107	0.044
BD (%)	1.58 \pm 0.04 ^a	1.51 \pm 0.02 ^{ab}	1.58 \pm 0.03 ^a	1.49 \pm 0.02 ^b	2.531	0.039
EC (ms·cm ⁻³)	117.07 \pm 15.32 ^a	81.42 \pm 1.94 ^b	80.94 \pm 1.99 ^b	90.79 \pm 5.10 ^b	5.930	0.003
TP (%)	40.41 \pm 1.52 ^b	42.97 \pm 0.83 ^{ab}	40.32 \pm 1.18 ^b	43.96 \pm 0.92 ^a	2.511	0.021
Sand (%)	76.29 \pm 1.17 ^b	73.40 \pm 2.32 ^{ab}	80.42 \pm 1.13 ^a	77.75 \pm 0.83 ^{ab}	2.301	0.031
Silt (%)	8.76 \pm 0.46 ^a	9.17 \pm 1.43 ^a	10.10 \pm 0.35 ^a	9.73 \pm 0.34 ^a	0.205	0.892
Clay (%)	14.96 \pm 1.10 ^a	17.44 \pm 1.73 ^a	9.49 \pm 1.40 ^b	12.53 \pm 0.78 ^{ab}	4.734	0.009
SOC (g·kg ⁻¹)	10.93 \pm 0.74 ^b	14.02 \pm 0.38 ^a	6.24 \pm 0.26 ^c	12.67 \pm 0.69 ^a	41.906	0.000
TN (g·kg ⁻¹)	0.32 \pm 0.02 ^a	0.30 \pm 0.02 ^a	0.12 \pm 0.02 ^b	0.32 \pm 0.04 ^a	15.156	0.000
TPP (g·kg ⁻¹)	0.36 \pm 0.04 ^b	0.34 \pm 0.02 ^b	0.39 \pm 0.02 ^b	0.48 \pm 0.03 ^a	6.764	0.002
TK (g·kg ⁻¹)	0.19 \pm 0.01 ^{ab}	0.18 \pm 0.00 ^b	0.21 \pm 0.01 ^a	0.14 \pm 0.01 ^c	9.325	0.000
AN (mg·kg ⁻¹)	11.66 \pm 0.24 ^c	15.11 \pm 0.19 ^a	12.45 \pm 0.27 ^{bc}	13.09 \pm 0.34 ^b	36.341	0.000
AP (mg·kg ⁻¹)	5.72 \pm 0.21 ^b	5.46 \pm 0.09 ^b	3.46 \pm 0.36 ^c	7.28 \pm 0.85 ^a	13.622	0.000
AK (mg·kg ⁻¹)	700.77 \pm 42.45 ^a	433.59 \pm 66.89 ^b	73.24 \pm 9.23 ^c	240.51 \pm 36.88 ^c	16.787	0.000
UA (IU/L)	1907.06 \pm 188.44 ^b	2563.92 \pm 155.18 ^a	2185.98 \pm 234.40 ^{ab}	1037.03 \pm 190.00 ^c	11.878	0.000
SA (U/L)	838.86 \pm 69.54 ^b	1091.27 \pm 84.83 ^a	893.90 \pm 20.94 ^{ab}	729.70 \pm 56.51 ^b	4.394	0.013
CEA (U/L)	147.80 \pm 12.64 ^a	162.09 \pm 7.42 ^a	120.65 \pm 1.38 ^b	103.86 \pm 8.81 ^b	9.774	0.000
PPA (IU/L)	52.17 \pm 3.12 ^c	79.14 \pm 1.27 ^a	59.22 \pm 1.82 ^{bc}	63.23 \pm 6.43 ^b	16.607	0.000
CA (U/ML)	12.22 \pm 0.22 ^b	13.97 \pm 0.16 ^a	11.82 \pm 0.48 ^b	10.85 \pm 0.33 ^c	26.294	0.000

WC, soil water content; BD, bulk density; EC, soil electric conductivity; TP, total soil porosity; sand, percentage of soil sand; silt, percentage of soil silt; clay, percentage of soil clay; SOC, soil organic carbon; TN, total nitrogen; TPP, total phosphorus; TK, total potassium; AN, available nitrogen; AP, available phosphorus; AK, available potassium; UA, urease; SA, sucrase; CEA, cellulase; PPA, phosphatase; CA, catalase.

3.2. Selection of the MDS. Table 3 provides the results of the PCA method. The first six principal components had eigenvalues greater than 1, and the cumulatively total explained variance was found to be 80.54%. The first six principal components had strong explanatory power which was reached. A group of indexes was formed whose absolute values of the loadings in each principal component were greater than 0.5, and the norm value of each index in each group was also calculated. Applying a selection principle to the norm value of each group was based on the largest 10% of the highest values. The generated primary indexes were called CA, AN, CEA, clay, PPA, UA, SOC, AK, WC, TN, BD, TP, and sand (catalase, available nitrogen, cellulase, clay, phosphatase, urease, soil organic carbon, available potassium, water content, total nitrogen, soil bulk density, total porosity, and sand), which are given in Table 4. To determine which indicators remained in the same group, Pearson correlations between indicators were calculated. If the correlations between indicators were insignificant, all indicators could be kept in the MDS. The indicator having the maximum weighted coefficient was, otherwise, chosen for the MDS. Therefore, the further screened MDS indicators were found to be SOC, TN, AN, WC, TP, sand, clay, UA, and CA (soil organic carbon, total nitrogen, available nitrogen, water content, total porosity, sand, clay, urease, and catalase), and utilize correlation analysis given in Table 5. Table 3 through 5 present eigenvalues and variance contributions of PCA, loading scores and norm values of each indicator, and correlations between indicators, respectively.

3.3. Evaluation of Soil Quality. PCA was performed on the TDS and MDS, and the weight of each dataset index was

calculated according to the ratio of the total variance of the common factor. Table 6 provides the estimated parameters of linear and nonlinear expressions and the weights of two sets, which are the TDS and MDS. The scoring method that utilizes linear and nonlinear expressions was utilized to convert the TDS and MDS indicators to scores between 0 and 1 by utilizing equations (2)–(4). In the MDS, the larger the percentage of clay grows, the worse the water permeability of the soil and the higher the CA becomes, which indicates that this soil type contained more harmful hydrogen peroxide. Therefore, appropriate clay and CA (catalase) were of the “less is better” function type. UA, TN, AN, SOC, sand, WC, and TP (urease, total nitrogen, available nitrogen, soil organic carbon, sand, water content, and total soil porosity) characterize the structure and nutrient status of the soil, which were appropriate for the “more is better” function type. In the TDS that is the same as those in the MDS, the higher the EC (soil electric conductivity) grows, the higher the total soil salinity becomes, which was prone to soil acidification and secondary salinization in addition to the above indicators. Therefore, EC (soil electric conductivity) was appropriate for the “less is better” function type. The SQIs derived for the TDS and MDS are denoted as follows.

$$\text{SQI-LT or SQI-NLT} = \text{WC} \times 0.05 + \text{pH} \times 0.046 + \text{BD} \times 0.064 + \text{EC} \times 0.049 + \text{TP} \times 0.064 + \text{sand} \times 0.064 + \text{clay} \times 0.059 + \text{SOC} \times 0.056 + \text{TN} \times 0.047 + \text{TPP} \times 0.049 + \text{TK} \times 0.049 + \text{TN} \times 0.057 + \text{AP} \times 0.047 + \text{AK} \times 0.055 + \text{UA} \times 0.056 + \text{SA} \times 0.037 + \text{CEA} \times 0.046 + \text{PPA} \times 0.052 + \text{CA} \times 0.053$$

$$\text{SQI-LM or SQI-NLM} = \text{WC} \times 0.1 + \text{TP} \times 0.099 + \text{sand} \times 0.107 + \text{clay} \times 0.121 + \text{SOC} \times 0.112 + \text{TN} \times 0.073 + \text{TN} \times 0.119 + \text{UA} \times 0.144 + \text{CA} \times 0.127$$

TABLE 3: Eigenvalues and variance contribution rates of the PCA method.

Principal components	Initial eigenvalues		Sum of squared of initial loading factors	
	Eigenvalue	Contribution (%)	Eigenvalue	Contribution (%)
1	5.076	25.379	5.076	25.379
2	3.436	17.182	3.436	17.182
3	2.671	13.356	2.671	13.356
4	2.387	11.933	2.387	11.933
5	1.528	7.639	1.528	7.639
6	1.010	5.051	1.010	5.051
7-20		19.460		
			Cumulative contribution (%)	Cumulative contribution (%)
			25.379	25.379
			42.560	42.560
			55.916	55.916
			67.850	67.850
			75.488	75.488
			80.540	80.540
			100.000	100.000

TABLE 4: Loading matrix and norm values for each indicator.

Indicator	PC1	PC2	PC3	PC4	PC5	PC6	Groups	Norm
CA	0.801	0.222	-0.199	0.245	0.104	-0.078	1	1.923
AN	0.737	-0.272	-0.457	0.082	0.09	0.166	1	1.904
CEA	0.705	0.373	0.066	-0.152	0.148	-0.122	1	1.765
PPA	0.596	-0.312	-0.461	0.327	0.151	0.091	1	1.733
TPP	-0.594	-0.475	-0.016	0.198	0.206	0.308	1	1.680
SA	0.53	0.218	-0.369	0.11	0.289	0.041	1	1.453
TK	-0.014	0.758	-0.155	0.186	-0.225	-0.249	2	1.504
AP	0.117	-0.666	0.37	-0.183	0.271	0.137	2	1.473
pH	0.051	0.593	0.235	-0.217	-0.34	0.354	2	1.336
UA	0.565	0.564	-0.307	-0.211	0.238	0.142	2	1.783
SOC	0.688	-0.545	0.166	-0.044	0.062	-0.239	2	1.888
EC	0.007	0.259	0.734	-0.308	0.1	0.188	3	1.395
AK	0.427	0.043	0.67	0.189	-0.061	-0.419	3	1.549
WC	0.522	0.434	0.535	-0.022	0.147	0.037	3	1.682
TN	0.398	-0.45	0.502	0.059	0.3	-0.112	3	1.527
BD	-0.349	0.378	0.21	0.682	0.44	0.116	4	1.627
TP	0.351	-0.378	-0.208	-0.68	-0.442	-0.124	4	1.628
Sand	-0.499	0.186	-0.226	-0.568	0.51	-0.25	5	1.658
Clay	0.677	-0.113	0.26	0.197	-0.359	0.509	6	1.761

WC, soil water content; BD, bulk density; EC, soil electric conductivity; TP, total soil porosity; sand, percentage of soil sand; clay, percentage of soil clay; SOC, soil organic carbon; TN, total nitrogen; TPP, total phosphorus; TK, total potassium; AN, available nitrogen; AP, available phosphorus; AK, available potassium; UA, urease; SA, sucrose; CEA, cellulase; PPA, phosphatase; CA, catalase.

TABLE 5: Correlation measures of the soil features.

	WC	pH	BD	EC	TP	Sand	Clay	SOC	TN	TPP	TK	AN	AP	AK	UA	SA	CEA	PPA	CA
WC	1																		
pH	0.262	1																	
BD	0.133	-0.004	1																
EC	0.411*	0.455*	0.093	1															
TP	-0.132	0.007	-0.999**	-0.092	1														
Sand	-0.237	-0.050	0.000	0.067	-0.001	1													
Clay	0.452*	0.132	-0.189	0.064	0.185	-0.847**	1												
SOC	0.194	-0.306	-0.419*	-0.039	0.423*	-0.371*	0.427*	1											
TN	0.257	-0.260	-0.061	0.193	0.062	-0.239	0.350	0.576**	1										
TPP	-0.504**	-0.283	0.246	-0.099	-0.252	0.144	-0.260	-0.191	0.035	1									
TK	0.148	0.371*	0.237	-0.048	-0.239	0.032	-0.095	-0.377*	-0.382*	-0.286	1								
AN	-0.043	-0.180	-0.344	-0.293	0.347	-0.345	0.417*	0.510**	0.230	-0.173	-0.203	1							
AP	0.001	-0.205	-0.196	0.213	0.196	-0.051	0.106	0.535**	0.441*	0.277	-0.625**	0.095	1						
AK	0.522**	0.147	0.044	0.375*	-0.036	-0.353	0.286	0.411*	0.544**	-0.339	0.065	-0.014	0.164	1					
UA	0.384*	0.299	-0.067	0.038	0.064	0.098	0.161	0.002	-0.113	-0.568**	0.332	0.455*	-0.266	-0.029	1				
SA	0.209	0.114	-0.001	-0.176	0.004	-0.069	0.109	0.206	0.011	-0.316	0.108	0.521**	-0.133	0.015	0.462*	1			
CEA	0.535**	0.181	-0.126	0.249	0.127	-0.135	0.313	0.419*	0.076	-0.566**	0.256	0.404*	-0.051	0.298	0.545**	0.490**	1		
PPA	-0.068	-0.255	-0.133	-0.421*	0.134	-0.341	0.313	0.454*	0.162	-0.089	-0.135	0.767**	0.166	0.017	0.258	0.501**	0.171	1	
CA	0.424*	-0.043	-0.041	-0.157	0.041	-0.367*	0.454*	0.386*	0.190	-0.496**	0.255	0.635**	-0.165	0.286	0.669**	0.394*	0.537**	0.586**	1

** $P < 0.01$. * $P < 0.05$. WC, soil water content; BD, bulk density; EC, soil electric conductivity; TP, total soil porosity; sand, percentage of soil sand; clay, percentage of soil clay; SOC, soil organic carbon; TN, total nitrogen; TPP, total phosphorus; TK, total potassium; AN, available nitrogen; AP, available phosphorus; AK, available potassium; UA, urease; SA, sucrose; CEA, cellulase; PPA, phosphatase; CA, catalase.

TABLE 6: Commonality and weight of the TDS and MDS: parameters of linear and nonlinear equations.

Indicators	TDS		MDS		Linear		Nonlinear	
	Communality	Weight	Communality	Weight	X_{max}	X_{min}	Mean	Slope (b)
WC	0.770	0.050	0.658	0.100	10.25	3.54	6.84	-2.5
pH	0.698	0.046			9.70	8.45	9.04	2.5
BD	0.981	0.064			1.72	1.33	1.53	2.5
EC	0.745	0.049			170.50	72.8	90.33	2.5
TP	0.982	0.064	0.651	0.099	49.64	35.09	42.13	-2.5
Sand	0.980	0.064	0.705	0.107	83.1	56.83	75.25	-2.5
Clay	0.899	0.059	0.797	0.121	27.54	6.66	14.37	2.5
SOC	0.860	0.056	0.740	0.112	16.10	5.42	11.58	-2.5
TN	0.719	0.047	0.481	0.073	0.46	0.07	0.27	-2.5
TPP	0.754	0.049			0.56	0.21	0.38	-2.5
TK	0.746	0.049			0.24	0.12	0.18	-2.5
AN	0.869	0.057	0.787	0.119	16.74	10.04	13.49	-2.5
AP	0.720	0.047			10.32	2.43	5.48	-2.5
AK	0.848	0.055			850.03	49.50	376.34	-2.5
UA	0.853	0.056	0.951	0.144	3121.76	417.65	2051.58	-2.5
SA	0.561	0.037			1681.84	606.16	929.00	-2.5
CEA	0.701	0.046			195.13	72.45	139.30	-2.5
PPA	0.803	0.052			83.88	41.53	66.58	-2.5
CA	0.807	0.053	0.839	0.127	14.46	10.04	12.56	2.5

WC, soil water content; BD, bulk density; EC, soil electric conductivity; TP, total soil porosity; sand, percentage of soil sand; clay, percentage of soil clay; SOC, soil organic carbon; TN, total nitrogen; TPP, total phosphorus; TK, total potassium; AN, available nitrogen; AP, available phosphorus; AK, available potassium; UA, urease; SA, sucrase; CEA, cellulase; PPA, phosphatase; CA, catalase.

Table 6 provides the commonality and weight of the TDS and MDS based on nonlinear and linear equations.

As shown in Figure 1, the values of the SQIs based on the four types of land use were 0.471–0.534, 0.512–0.587, 0.453–0.5328, and 0.502–0.603 concerning SQI-NLT, SQI-LT, SQI-NLM, and SQI-LM, and the computed SQI for SL was bigger than that for others. Based on the two evaluation methods, the changes in the SQI in the types of land use were similar. The order of SQI values was found to be $SL > GL > AL > FL$, and the computed SQI for SL was substantially bigger than that for FL. Both AL and FL had lower SQI values, and the SQI value of FL was the lowest. This result showed that artificial vegetation restoration improved the soil quality index when compared with the natural restoration of grassland and abandoned farmland. Due to the higher F and CV values, the sensitivity of SQI values generated based on the nonlinear approach was higher than the SQI values based on the linear approach. Figure 1 shows statistical results of SQI-NLT, SQI-LT, SQI-NLM, and SQI-LM.

3.4. Comparison and Validation of Indexes and Methods. We used regression analysis to verify the applicability of the evaluation indexes to determine the soil quality and methods. The computed SQIs employing both the TDS and MDS were found to be strongly correlated whose R^2 statistics alter between 0.6384 and 0.7598, as shown in Figures 2(a) and 2(b). The correlation measures suggested that all SQIs were substantially and positively correlated. The correlation of the SQI between the TDS and MDS is found higher when linear and nonlinear approaches are a concern. Moreover, the result of the MDS is larger than that of the TDS. Compared with the SQI-L method, the SQI-NL method

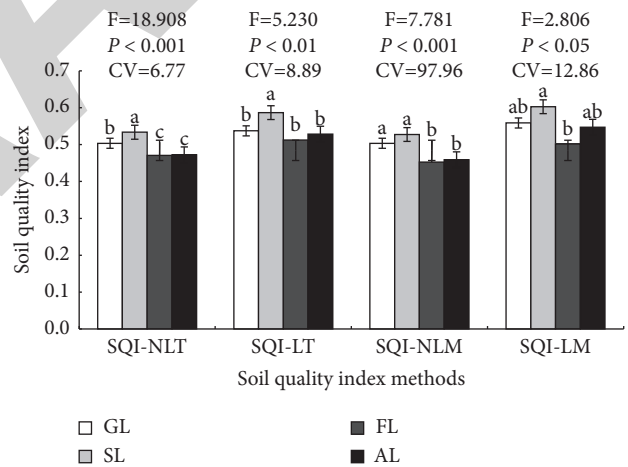


FIGURE 1: The indexes of soil quality constructed among different types of land use are compared. The different lowercase letters denote substantially important types of land use at $P < 0.05$. Standard errors are denoted by the bar graphs. GL, grassland; SL, shrubland; FL, forestland; AL, abandoned land; SQI-LT, linear scoring-TDS; SQI-LM, linear scoring-MDS; SQI-NLT, nonlinear scoring-TDS; SQI-NLM, nonlinear scoring-MDS.

based on the MDS obtained a larger SQI variation interval and coefficient of variation, indicating that the method was more sensitive to SQI changes. Figure 2 shows that the fitting effect computed by the SQI-NL approach was better, as it was more accurate and could replace the TDS for soil quality evaluation. Figure 2 shows the fitting results of the linear model and nonlinear models concerning SQI-L and SQI-NL.

Table 7 provides the correlation values between four indicators, which are called SQI-LT, SQI-NLT, SQI-LM, and SQI-NLM.

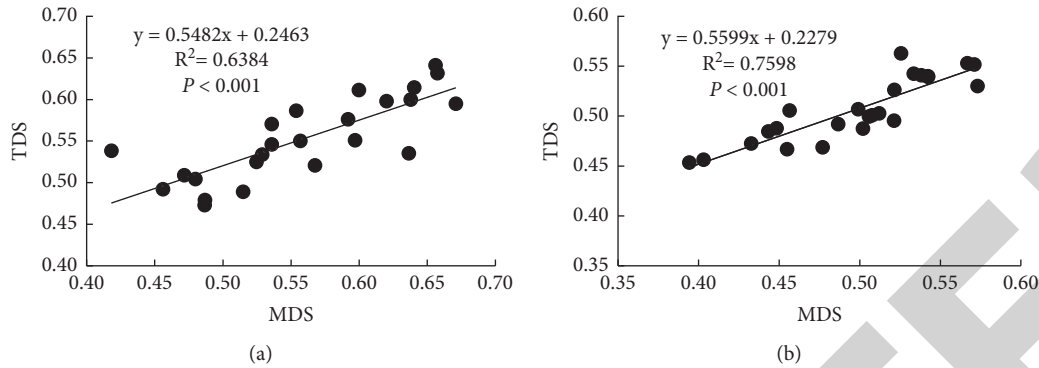


FIGURE 2: TDS and MDS' linear scoring (a) and nonlinear scoring (b) approaches utilized to compute the relationships between the indexes of soil quality.

TABLE 7: Correlations between the indexes of the four soil qualities.

	SQI-LT	SQI-NLT	SQI-LM	SQI-NLM
SQI-LT	1			
SQI-NLT	0.719**	1		
SQI-LM	0.787**	0.523**	1	
SQI-NLM	0.579**	0.869**	0.542**	1

**Significant at $P < 0.01$. SQI-LT, linear scoring-TDS; SQI-LM, linear scoring-MDS; SQI-NLT, nonlinear scoring-TDS; SQI-NLM, nonlinear scoring-MDS.

4. Findings

Based on a set of statistical analysis, the most favorable set of indicators, namely, SOC, TN, AN, WC, TP, sand, clay, UA, and CA (soil organic carbon, total nitrogen, available nitrogen, water content, total porosity, sand, clay, urease, and catalase) was determined. According to four types of land use, grassland had the highest values for WC, TN, and TP (water content, total nitrogen, and total phosphorus) and had, however, the lowest AN (available nitrogen). Forestland, shrubland, and abandoned land had the highest TP (total phosphorus). Besides, concerning soil particle composition, forestland had the biggest sand, which is substantially larger than that of grassland. On the other hand, it is the lowest in the clay, which is significantly lower than that of both grassland and shrubland. Shrubland had higher SOC, TN, and AN (soil organic carbon, total nitrogen, and available nitrogen). Shrubland had the highest soil biological indicators UA and CA (urease and catalase).

When SQIs are a concern, SL having SQI values was larger than those of other types of land use. Based on the two evaluation methods, the changes in the SQI in the types of land use were similar. The order of SQI values was found to be $SL > GL > AL > FL$, and SL having the SQI value was substantially larger than that of FL. Both AL and FL had lower SQI values, and the FL having the SQI value had the lowest. This result suggested that artificial vegetation restoration improved the soil quality index when compared with the natural restoration of grassland and abandoned farmland. The outcome of the SQI computed based on the nonlinear approach was more accurate than the outcome of the SQI calculated based on the linear approach. Figure 1

shows the statistical results of SQI-NLT, SQI-LT, SQI-NLM, and SQI-LM.

5. Discussion

5.1. Differences in Soil Characteristics under Different Types of Land Utilizations. The twenty soil indicators were inconsistent. Soil moisture and structure are called the first factors that need to be considered in arid and semiarid regions to improve land use [32]. In this research, the surface soil moisture content of the land use (0–40 cm) varied considerably since the surface soil was directly affected by precipitation, ground wind, and radiation, and the changes were found more obvious. This finding is coherent with former research studies [33, 34]. *Caragana korshinskii* is generally believed to have a large root system and causes surface water to be lost since the root system develops and extends through the soil [35]. Wang and Gao [36] conducted long-term positioning observations in the semiarid Loess hilly area located at Guyuan, Ningxia, and found that the soil water content of the *Caragana korshinskii* forest at various depths was lower than those of abandoned farmland. The dynamic changes in soil moisture in shrubland are relatively small, while the soil moisture content of enclosed grassland and grazing grassland changes significantly [37]. The soil moisture of FL and SL in this study plot was substantially less than that of GL.

Substantial divergences were found in soil structure indicators in the types of land use. While BD (bulk density) in GL and FL was the largest, it was the smallest in AL. On the other hand, TP (total soil porosity) showed the opposite pattern. While it was the largest in AL, it was the smallest in GL, which was coherent with the results of Liang et al. [38]. There was a sheep farm close to the study area, causing GL and FL to have higher BD (bulk density) due to grazing trampling, while SL and AL had relatively lower BD (bulk density) due to manual management. This outcome verified the results presented in studies by Wheeler et al. [39] and Zhou et al. [30]. Some other studies suggest that the reduction of soil BD (bulk density) effectively improves the structure of aeolian sandy soil, making the soil looseness, aeration, and more coordinated water availability [40]. No substantial divergence was found in the percentage of soil silt

under the types of land use. While the percentage of sand in SL was the smallest, and the percentage of clay was the largest. This result was due to the large growth of the *Cercaria humilis* shrub caused by the developed and shallower root system and the higher coverage. This finding was consistent with the research results of *Artemisia ordosica* shrubs done by Xia Jiangbao et al. [41]. The vegetation restoration of desert grassland is an important ecological management measure, and vegetation restoration is a long process. Michaelides et al. [42] pointed out that vegetation restoration had no significant impact on the composition of soil particles in the short term, which also indicated that once soil desertification occurred, it would be difficult to reverse. The clay content of *Cercaria humilis* shrub land increased significantly, which may be associated with a large number of withered litters. These physical clay particles will be deposited in semidecomposed or decomposed litter, forming a layer of crust in the later stage, which will play a positive role in sand fixation and soil improvement [43].

Soil chemistry is an important indicator affecting soil quality. Reducing human disturbance and increasing organic carbon can lead to improved soil structure [44]. The soil investigated in the research field was poor consisting of generally low contents of nitrogen (N), phosphorus (P), and potassium (K). In arid regions, soil nutrients primarily come from litter and rhizosphere exudates on the soil surface [45]. In this study, SL had high SOC and N (soil organic carbon and nitrogen), and FL had lower soil chemical indicators. While GL had the highest TN, TK, and AK (total nitrogen, total potassium, and available potassium), it had the lowest AN (available nitrogen), which indicates that soil nutrients in the different soil types were significantly different. Besides, the nutrient contents of SL and GL were significantly higher than those of FL and AL due to the relatively rich vegetation of SL and GL caused by the short growth cycle and strong ability to enrich soil nutrients. Researchers have found that SOC (soil organic carbon) increases after planting shrubs and forests due to the relatively rich vegetation of shrubland, short growth cycle, and strong ability to enrich soil nutrients [46]. Vegetation restoration can change soil compactness through the extension of roots [47]. Besides, both canopy interception of fine grains and organic debris also contribute to improving both the physical and chemical features of soil [48]. Additionally, since GL was located in a village, there was no enforced grazing prohibition, causing grazing interference, and the exposed sand layer continuously deepened and led to land desertification [49]. SL was maintained by artificially planting, cultivating, and managing stubble, pruning, harvesting during fruit maturity, and returning branches to the field, which also promoted the element cycle of the soil-plant ecosystem [30].

Soil enzymes reflect the transformation capacity of soil carbon (SC), nitrogen (N), and phosphorus (P) and have a vital status in the cycling of soil nutrients [50]. When types of land use are a concern, SL had higher activities, such as UA, SA, CEA, PPA, and CA (urease, sucrase, cellulase, phosphate, and catalase). The soil had a higher clay content and could absorb more soil organic matter, which could provide sufficient nutrients for enzymes [51, 52]. When compared

with GL and AL, SL had a more developed root system, rich litter, and a larger number of microorganisms, which was indicative of the formation of better conditions of soil environment, promoted the accumulation and cyclic metabolism of nutrients and enhanced soil enzyme activity [53]. This result was in contrast with one presented in Tian et al. [54] in the karst region of Guizhou, China, whereas the finding was consistent with the research results in the northwest region [20]. When restoring vegetation is underway, the human disturbance will affect soil quality to a certain extent, and shrubland has an impact on maintaining water and soil and improving soil enzyme activity.

5.2. Soil Quality Evaluation of Different Types of Land Utilizations.

The comparative evaluation of soil quality is a parallel comparison between the differences in soil quality in various regions caused by different methods of land use [55]. The properties and complexity of the soil determining the assessment indicators of soil quality must be complex, representing the physical, chemical, and biological features and their processes. Thus, a substantial effect on the soil function and the final evaluation results are expected [3, 7]. Many soil quality evaluations tend to select more than 20 soil properties for the soil quality evaluation index system [56, 57]. The TDS is highly accurate to evaluate soil quality. However, utilization of the TDS requires much time, more human power, and brings more complications when the analysis is conducted. In this research, the combination of norm values with the PCA led to finding the MDS, and 9 indicators of them were selected from 19 indicators related to the TDS. These indicators included important chemical indicators such as SOC, TN, and AN (soil organic carbon, total nitrogen, and available nitrogen) and physical indicators that reflect soil structure such as WC, sand, clay, and TP (water content, sand, clay, and total soil porosity) and were significantly related to the number of soil microorganisms and organic matter content. Biological indicators such as UA and CA (urease and cellulase) were comprehensive and representative. Some scholars have summarized the research results of soil quality evaluation pertinent to the MDS globally [58–60] and also covered a majority of the physical, chemical, and biological characteristics of soil such as BD, SOC, silt, sand, and WC (bulk density, soil organic carbon, silt, sand, and water content), which have a higher frequency utilization. The indicators of SOC, WC, sand, and clay (soil organic carbon, water content, sand, and clay) in this study were consistent with the results of most research. Therefore, the MDS indicators selected in this study have a practical significance to assess soil quality in various types of land use and restoring fields of vegetation in both the study area and similar areas of the Ningxia desert grassland.

The soil quality index and correlation analysis for the types of land use showed that the four computed SQIs employing scoring approaches based on linear and non-linear expressions utilized the TDS and the MDS that were consistent and could reflect the soil quality significantly. The magnitude of the CV denotes the sensitivity of the SQI to alterations of conditions occurring in the environment. The

larger the sensitivity to alterations of conditions in the environment becomes, the more evident the influencing factors representing changes in soil quality found. Thus, providing more effective guidance for improving soil quality for scientific management is suggested [16]. The larger CV and F statistics leading to the SQI generated by a scoring method utilizing a nonlinear approach suggested that it was more sensitive than the SQI based on the linear scoring approach. Thus, the SQI computed by scoring approach utilizing nonlinear expression was more precise and is found in this study. On the other hand, both linear and nonlinear scoring models have advantages and disadvantages. The scoring approach utilizing linear expression provides better ease of use than the scoring approach utilizing nonlinear expression since it is the most adapted approach available in the literature [61, 62]. However, it is suggested that while the result of the linear scoring method only represents the relative soil quality of the test area, the nonlinear scoring method can better reflect the soil function and is not restricted by region. Therefore, many soil quality evaluation results indicate that the nonlinear scoring method has a better representation in the calculation of soil quality [6, 11, 14]. Based on comprehensive analysis, the SQI-NLM in this study better reflects soil conditions and can be implemented as an effective model to assess the soil quality for different types of land use in Ningxia desert grassland.

The four different types of land use have different effects on soil quality in the Ningxia desert steppe. The SQI values for the types of land use selected were ranked as SL > GL > AL > FL in this study. Since the biomass of shrubs has increased significantly and the coverage is strong, artificially planted *Cercasus humilis* has a higher colonization density, shallower root system, wider distribution, and no grazing interference; thereby, it results in improving soil quality. This result is consistent with previous studies [63–65]. The desert grasslands in Ningxia, the northwest, and the Loess Plateau are severely degraded. The extensive use of *Caragana korshinskii* for afforestation caused groundwater depletion and sparse understory herbaceous plants. More appropriate tree species for vegetation restoration needs to be introduced. As a result, the SQI of FL was lower than that of GL and AL and lower than that of SL, which implies that shrub afforestation in this area has an effect on land quality improvement and can be used as a benchmark for the regeneration of tree species and restoration of artificial vegetation in this area.

6. Conclusion

This research evaluated the soil quality of different types of land use in a typical desert steppe in Yanchi County, Ningxia, China. Two different index selection and scoring approaches were utilized to calculate the SQI. While the PCA method and norm value screening are used to determine which MDS indicators are chosen, the two scoring methods are employed to construct SQIs.

Thus, the MDS indicators, namely, TN, AN, SOC, WC, TP, sand, clay, UA, and CA (total nitrogen, available

nitrogen, soil organic carbon, water content, total soil porosity, sand, clay, urease, and catalase) were found to be employed in the construction of SQI indexes. The alterations in the four constructed SQIs with two distinct scoring approaches were consistent and strongly correlated. SQI-NL with the maximum CV and correlation measure is useful as an indicator of soil quality in this area. SL had the highest SQI, and the SQI values of the types of land use were ranked as SL > GL > AL > FL. The results showed that shrub afforestation as an ecologically viable measure is found to restore the soil quality of typical desert grasslands in Ningxia and has importance for the guidance of ecological construction of the research field.

The advantages of this research have two folds. The first comes from the implementation of biological indicators, which have been largely overlooked in the previous studies, and this research focuses on the area that has been studied in just a few cases. The second is pertinent to proposing a new method that finds SQIs. Comparing the results of this research with the studies just using physical and chemical attributes could provide better insights concerning SQIs, which is the limitation of this research.

Additional research related to the same area and soil conditions is further needed for future studies. Besides, the currently utilized nine indicators are still relatively large and should be reduced to a smaller set. Thus, optimization-based methods should be employed to find better indexes that represent the soil condition.

Data Availability

The data used to support the findings of this study are included within the article and are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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