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Comprehensive Evaluation of Soil Substrate Improvement Based on the Minimum Data Set Method

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Abstract: Long-term transitional grazing on the northern slopes of the Tianshan Mountains in Xinjiang has led to severe vegetation degradation, loss of self-renewal capacity and regional ecological degradation in the region. This study was conducted to improve the soil quality and vegetation restoration efficiency in the foreland zone of the northern slope of the Tianshan Mountains (Xiangyataizi slope) using xanthic acid, bentonite, a green plant growth regulator (GGR) and high amounts of mulch as improvement materials, and eight sets of experiments were conducted. Fifteen physical and chemical indicators were selected as the total data set (TDS), and the minimum data set (MDS) was constructed using principal component analysis (PCA) combined with norm values to evaluate the soils in the study area by nonlinear (NL) and linear (L) evaluation methods. The results showed that the soil quality evaluation indexes of the MDS included effective phosphorus, organic matter, percentage of powder, total potassium and total salt for the Xiangyataizi slope of the Tianshan Mountains. The SQI was ($p < 0.05$). The VI treatment significantly improved soil quality; that is, plastic mulch applied to soil with 250 g of fulvic acid, 1000 g of bentonite and 15 g of GGR (mixed with 100 kg of water) was the best treatment. Additionally, since the nonlinear soil quality evaluation method (SQI-NL) had a smaller variation interval and coefficient of variation of the soil quality index compared with linear soil quality evaluation method (SQI-L), the coefficient of determination between the MDS and TDS was 0.873 and 0.811 under the SQI-NL and SQI-L evaluation methods, respectively. The nonlinear soil quality evaluation method had better applicability in this region, and the minimum data set was more accurate for soil quality evaluation.

Keywords: the northern slope of the Tianshan Mountains; vegetation; soil quality evaluation methods; principal component analysis; minimum data set

Citation: Tang, D.; Yang, J.; Cheng, P. Comprehensive Evaluation of Soil Substrate Improvement Based on the Minimum Data Set Method. *Sustainability* **2022**, *14*, 3939. https://doi.org/10.3390/su14073939

Academic Editors: Giancarlo Pagnani, Marika Pellegrini, Debasis Mitra and Periyasamy Panneerselvam

Received: 7 February 2022
Accepted: 23 March 2022
Published: 26 March 2022

1. Introduction

The front mountain belt of the northern slope of the Tianshan Mountains is a territorial system of relatively low mountains and intermountain depressions located in front of the main mountain range [1]. As a unique geomorphic landscape, the frontal belt of the northern slope of the Tianshan Mountains has relatively few forest resources, simple species and poor soil, which, coupled with extensive human activities in recent years, has led to serious damage to the water and soil conservation functions in the area [2]. In arid and semiarid ecologically fragile regions in particular, anthropogenic-induced changes in the soil structure and soil properties have reduced the stability of desert grassland ecosystems and have led to the rapid development of soil desertification and salinization, leading to vegetation degradation and frequent droughts [3]. Therefore, improving soil quality is conducive to increasing vegetation cover in these regions and plays an important role in maintaining ecosystem stability in the foreland zone of the northern slopes of the Tianshan.

Currently, the main methods of improving soil are the guest soil method [4] and the soil substrate improvement method [5]. L.C. Ram et al. [6] added an appropriate amount of coal ash to the topsoil of a drainage field during the ecological restoration of open-pit coal mines, and this method effectively improved the soil and increased the vegetation cover. Sena et al. [7] effectively improved the soil quality through natural recovery by adding water retention agents and grey sandstone to the soil. Ruilian et al. [8] used ground cover and straw mulch and applied chemical substances such as rare earth, grass ash and rooting powder to treat the rooted soil, which significantly improved the soil quality and vegetation cover on the Loess Plateau. Soil is the basis for plant growth, and the quality of the soil determines vegetation growth [9]. However, since soil quality itself is difficult to quantify directly, the evaluation of soil quality is usually achieved by a comprehensive assessment of the soil physical and chemical properties [10]. Accurate evaluation results depend on appropriate analytical methods, and the main methods of soil quality evaluation at this stage are mathematical and statistical methods, including grey system theory [11], fuzzy mathematics [12], principal component analysis (PCA) [13], and artificial neural networks [14]. These evaluation methods make it more difficult to carry out experimental analysis on a large number of soil quality indicators, and the evaluation results are slightly insufficient in terms of precision and credibility [15]. As soils vary from place to place and are complex and variable, it is particularly important to choose an appropriate evaluation method to assess the soil quality of a particular soil or region. Adding the right amount of soil conditioner will significantly improve the quality of the soil. At present, most studies on soil quality evaluation focus on soil physicochemical and biological property indexes under different vegetation types, forest stand structures and different land-use types, while there are fewer studies on improving soil quality in the region through the addition of soil amendments. In particular, there are few reports on soil quality evaluation under specific environmental influences in the front mountain belt of the northern slope of the Tianshan.

Therefore, this study takes the Xiangyataizi slope of the Tianshan North Slope Front Range as the research object, takes the physical and chemical properties of soil as the basis, determines the index weights and verifies the applicability of different evaluation methods through the screening of a minimum data set to reveal the changes in soil quality in the study area under the conditions of adding different improvement substances. The choice of soil evaluation methods may tend to be more toward nonlinear evaluation methods. This research provides the most suitable soil evaluation methods and a scientific basis for protecting and improving the soil quality for vegetation restoration of the Tianshan North Slope Front Range.

2. Materials and Methods

2.1. Overview of the Study Area

The present study was conducted in the foreland area of the northern slope of the Tianshan Mountains under the jurisdiction of the Eastern Tianshan State Forestry Administration, Xinjiang Uygur Autonomous Region, which is geographically located on the Xiangyataizi slope, (86°06′08.74″~86°06′14.61″ E, 43°53′31.48″~43°53′40.61″ N). The area is arid and water-scarce, with poor soil and fragile ecology, belonging to the typical temperate continental arid climate. The average annual precipitation is 324.62 mm, mainly concentrated in May~July, accounting for approximately 50~60% of the total precipitation. The annual evaporation is 1691 mm. Strongest winds up to 16 m/s occur in May. The soil type is chestnut calcium soil and desert soil, and the soil is compact and alkaline with poor fertility.

The zonal vegetation in the study area belongs to the desert steppe zone, with sparse vegetation and low coverage. Macrophanerophytes include *Populus euphratica*, *Populus alba*, *Prunus sibirica*, *Ulmus pumila* and *Prunus cerasifera*. Shrubs include *Rosa acicularis*, *Caragana roborovskyi*, *Hippophae rhamnoides*, *Xanthoceras sorbifolium* and *Haloxylon ammodendron*. Herbs include *Astragalus laxmannii*, *Salsola collina*, *Cuscuta chinensis*, *Achnatherum splendens*, *Agropyron cristatum* and *Setaria viridis*.

2.2. Test Setup and Sample Collection

The experiment was conducted in October 2020, and the required amendment materials were placed in the soil at a depth of 20–40 cm in different ratios (Table 1). Bare-root seedlings of *Rosa acicularis* grade I were planted in horizontal trenches (trench width 80 cm, depth 40 cm) and watered with freezing water after planting. Eight treatments were selected in the study area in September 2021 (Figure 1 and Table 2). Treatment I was the control type. Sampling was performed by serpentine sampling, and four sample sites were chosen for each treatment. Each sample site was replicated three times for a total of 96 soil samples, and the inter-root soil of rows in each of the eight treatments was collected and mixed uniformly. Then, 1 kg of soil sample was retained using the quadrat method. The soil samples were transported to the laboratory and dried by natural air, and the plant residues and debris were removed and sieved through a 2 mm sieve before being used for the determination of indoor indexes.

Table 1. Soil amendment material gradient setting.

Soil Improvement Materials	Gradient Settings			
	1	2	3	4
Fulvic acid/g	0	250	500	1000
Bentonite/g	0	500	1000	1500
GGR/g (Green plant growth regulator) (Mixed with 100 kg of water)	0	5	10	15
Plastic mulching (0: NO; 1: YES)	-	-	-	-

Figure 1. Distribution of 8 processing configurations (red boxes represent sampling points).

Table 2. Experimental design.

Treatment	Fulvic Acid/A	Bentonite/B	GGR /C	Plastic Mulching/D
I ($A_1B_1C_1D_0$)	1	1	1	0
II ($A_2B_3C_4D_0$)	2	3	4	0
III ($A_3B_2C_3D_0$)	3	2	3	0
IV ($A_4B_4C_2D_0$)	4	4	2	0
V ($A_1B_1C_1D_1$)	1	1	1	1
VI ($A_2B_3C_4D_1$)	2	3	4	1
VII ($A_3B_2C_3D_1$)	3	2	3	1
VIII ($A_4B_4C_2D_1$)	4	4	2	1

2.3. Sample Determination Method

Based on a summary of relevant research results, a total of 15 soil physical and chemical indicators were measured in this study, and the measurement methods were as follows: percentages of clay, silt and sand were analysed using a Microtrac particle analyser (UPA model 9340 manufactured by Microtrac Inc., Montgomeryville, PA, USA). Soil particle size classification is based on the American system of classification; the grading is based on the following Table 3. The pH was determined by the water–soil ratio 1:1 potentiometric method [16]. Electrical conductivity was measured using a Raytheon conductivity meter [17]. The total salt amount was determined by the mass method [18]. The soil bulk density was determined by the ring knife method [19]. Organic matter and organic carbon were determined by the potassium dichromate volumetric method–dilution heat method [20]. Total nitrogen was determined by the semimicro Kjeldahl distillation method [21]. Total phosphorus was determined by the concentrated sulfuric acid and perchloric acid decoction–molybdenum antimony anticolorimetric method [22]. Total potassium and available potassium were determined by the flame photometric method [23]. Available nitrogen was determined by the alkali diffusion method [24]. Available phosphorus was determined by the sodium bicarbonate method [25].

Table 3. Soil particle size classification criteria.

Classification	Particle Size
Sand	2~0.05 mm
Silt	0.05~0.002 mm
Clay	<0.002 mm

2.4. Soil Quality Evaluation Methods

2.4.1. Construction of the Minimum Data Set of Evaluation Indexes Based on PCA

Soil quality evaluation requires the selection of appropriate soil quality indicators that should have a significant impact on soil function and final evaluation results [26]; these indicators were selected as the MDS. PCA, as a data simplification tool, was used for the construction of the MDS by transforming multiple indicators into a few indicators through dimensionality reduction [27]. The general idea is that principal components with eigenvalues ≥ 1 are extracted, and those with indicator loadings greater than 0.5 are divided into a group. If the loadings of an indicator for different principal components are greater than 0.5, they will be merged into a group with a lower correlation with other indicators. The norm values of each indicator were calculated separately, and the indicators in each group with norm values within 10% of the maximum norm value in the group were selected. When multiple indicators were retained in a group, the Pearson correlation coefficient was used to determine whether each indicator needed to be retained. If the correlation coefficient between indicators was less than 0.5, all indicators were retained, and if the indicators were significantly correlated within the principal components ($r \geq 0.5$), the indicator with the highest norm value was selected to enter the MDS [28].

Because a larger norm value indicates a greater combined loading of the indicator on all principal components, a larger norm value contains more information on soil quality. The norm value is calculated as follows:

$$N_{ij} = \sqrt{\sum_{n=1}^{j} \left(r_{ij}^2 \delta_j \right)} \tag{1}$$

where N_{ij} denotes the norm value of the ith indicator for the first jth principal component with eigenvalues greater than 1; r_{ij} denotes the loading of the ith indicator for the jth principal component; and δ_j is the eigenvalue of the jth principal component.

2.4.2. Soil Quality Scoring Model Development

(1) Nonlinear scoring model for soil quality

The measured values of the soil indicators were converted into suitable scores between 0 and 1 by a nonlinear evaluation model with the following model:

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

where S_{NL} is the score of soil indicators between 0 and 1, a is the maximum score of 1, x denotes the measured value of soil indicators, x_0 denotes the mean value of the corresponding indicator and b is the slope of the equation; the "more is better" type indicator was determined as −2.5, and the "less is better" type indicator was determined as 2.5 [29].

(2) Linear scoring model for soil quality

The linear scoring model was used to transform each indicator into a dimensionless score between 0 and 1. In this study, the "more is better" and "less is better" equations were selected and modelled as follows.

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

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

where S_L represents the linear score (0~1), x represents the measured value of the indicator, L represents the minimum value of the indicator and H represents the maximum value of the indicator. Equation (3) is the "more is better" type indicator score function, and Equation (4) is the "less is better" type indicator score function [30].

2.4.3. Weighting of Evaluation Indicators

The common factor variance obtained from PCA reflects the degree of the contribution of an indicator to the overall variance, and the larger its value, the greater its contribution to the overall variance [31]. This study used PCA to calculate the weight value of each indicator. The weights are equal to the ratio of the value of the common factor variance of each indicator to the sum of the common factor variance of all indicators [32].

2.4.4. Calculation of the Soil Quality Index

The scores and weights of each index were obtained, and then the soil quality index (*SQI*) was calculated according to Equation (5):

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

where S_i represents the indicator score, n represents the number of indicators, and W_i represents the indicator weight value; the higher the *SQI* value, the better the soil quality.

2.5. Data Processing

Excel 2016 was used for data processing; SPSS 24.0 was used for correlation analysis, ANOVA and PCA; and Origin 2018 was used for correlation analysis and graphing. Statistical tests were performed using one-way ANOVA and multiple comparisons. Using the Least Significant Difference (LSD) method to test for differences in soil physicochemical indicators under different treatments (significance level α = 0.05). Correlations between soil indicators were analysed using Pearson correlations.

3. Results and Analysis

3.1. Soil Quality Evaluation Index Statistics

The physical and chemical properties of the soil under different treatments are shown in Table 4. The highest percentage of clay and silt particles and the lowest percentage of sand particles were measured in the VI treatment. The percentages of powder and sand particles did not differ significantly ($p > 0.05$) among treatments, while the lowest content of powder particles and the highest content of sand particles were found in the IV treatment. The highest conductivity was 556.71 ms/cm in the V treatment, which was significantly different from the other treatments ($p < 0.05$). The pH was significantly lower in the IV treatment than in the other treatments ($p < 0.05$). Both the soil bulk density and total salt contents were highest in VI, with values of 1.33 g/cm^3 and 1.53 g/kg, respectively. The total salt content was lowest in I, and the difference between the other treatments was not significant ($p > 0.05$). The mean values of organic matter and organic carbon were significantly highest in the V treatment and lowest in the IV treatment ($p < 0.05$). Total phosphorus, total nitrogen, effective phosphorus and alkaline-digested nitrogen all reached their maximum values in the VII treatment, with values of 0.77 g/kg, 24.9 mg/kg, 0.87 g/kg and 54.66 mg/kg, respectively, and were significantly different from the other treatments ($p < 0.05$); the treatments with the lowest values were IV and III. Total potassium reached its maximum value (19.80 g/kg) in VI and minimum value (14.93 g/kg) in the V treatment, which were significantly different from the other treatments ($p < 0.05$). Fast-acting potassium was significantly higher ($p < 0.05$) in the III treatment and significantly lower ($p < 0.05$) in the IV treatment, but the difference between the other treatments was not significant ($p > 0.05$).

3.2. MDS of Soil Quality Evaluation Indicators

The loading matrix of each indicator is shown in Table 5 and Figure 2, and the results of the PCA showed that only five principal components had eigenvalues greater than 1. The cumulative explanation percentage reached 74.602%, indicating that these five principal components had strong explanatory power and could explain 74.602% of the total variance.

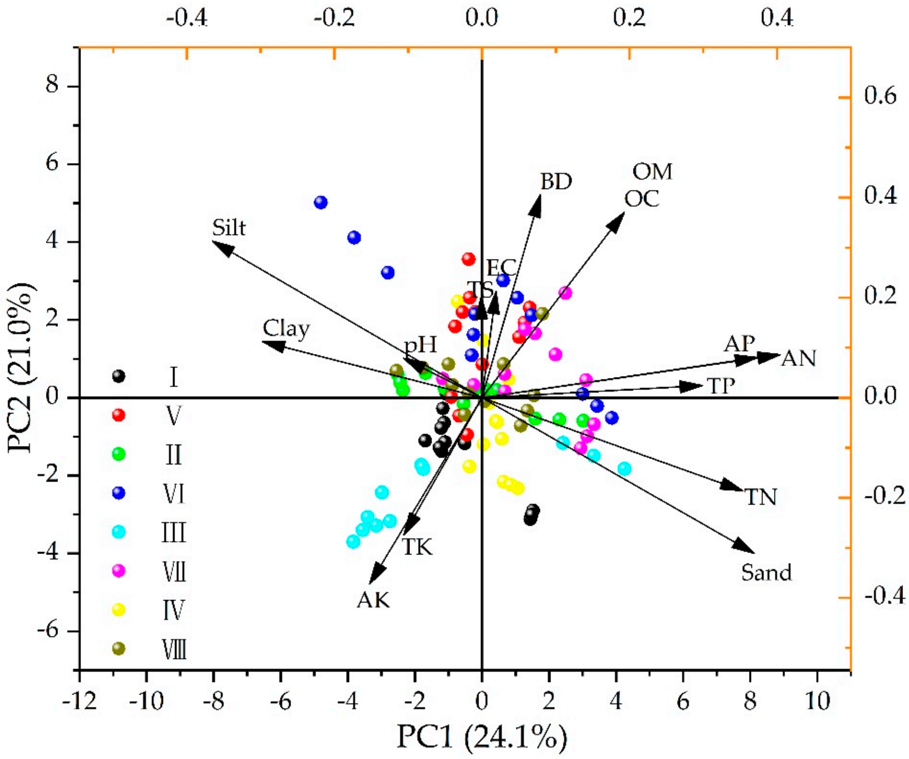

Figure 2. PCA plots of each soil evaluation index under different treatments.

Table 4. Statistics of soil quality evaluation indicators under different treatments.

Indicators	I	II	III	IV	V	VI	VII	VIII
Clay/%	0.21 ± 0.03 ab	0.14 ± 0.04 ab	0.28 ± 0.08 a	0.21 ± 0.02 ab	0.17 ± 0.02 ab	0.39 ± 0.18 a	0.13 ± 0.02 ab	0.15 ± 0.02 ab
Silt/%	28.87 ± 1.49 a	32.42 ± 2.28 a	30.40 ± 1.86 a	28.10 ± 1.82 ab	32.97 ± 1.51 a	34.44 ± 2.99 a	30.37 ± 1.66 a	31.23 ± 2.22 a
Sand/%	70.92 ± 1.5 a	67.45 ± 2.31 a	69.32 ± 1.89 a	71.69 ± 1.82 a	66.87 ± 1.51 a	65.17 ± 3.16 ab	69.49 ± 1.68 a	68.62 ± 2.23 a
EC (ms/cm)	179.79 ± 12.5 b	282.63 ± 47.91 ab	177.98 ± 15.02 b	489.06 ± 147.99 ab	556.71 ± 127.24 a	379.78 ± 127.20 ab	518.13 ± 87.14 ab	404.31 ± 118.44 ab
pH	7.93 ± 0.12 a	8.02 ± 0.07 a	7.98 ± 0.03 a	7.45 ± 0.04 b	7.86 ± 0.11 a	7.97 ± 0.04 a	8.06 ± 0.05 a	7.88 ± 0.08 a
TS (g/kg)	0.98 ± 0.05 b	1.41 ± 0.12 a	1.20 ± 0.07 ab	1.47 ± 0.17 a	1.15 ± 0.05 ab	1.53 ± 0.15 a	1.47 ± 0.19 a	1.21 ± 0.08 ab
BD (g/cm^{-3})	1.22 ± 0.02 b	1.33 ± 0.03 b	1.21 ± 0.01 b	1.25 ± 0.02 ab	1.32 ± 0.02 a	1.18 ± 0.02 a	1.30 ± 0.04 a	1.31 ± 0.02 a
OC (g/kg)	5.05 ± 0.19 c	7.33 ± 0.31 ab	5.13 ± 0.93 bc	4.86 ± 0.41 c	7.37 ± 0.68 a	7.45 ± 0.38 a	6.40 ± 0.58 abc	6.77 ± 1.06 abc
OM (g/kg)	8.70 ± 0.33 c	12.64 ± 0.54 ab	8.84 ± 1.61 bc	8.37 ± 0.71 c	12.71 ± 0.65 a	12.84 ± 1.17 a	11.04 ± 1.00 abc	11.67 ± 1.82 abc
TP (g/kg)	0.57 ± 0.04 ab	0.59 ± 0.06 b	0.49 ± 0.08 b	0.43 ± 0.02 b	0.54 ± 0.04 b	0.60 ± 0.10 ab	0.77 ± 0.05 a	0.53 ± 0.05 b
AP (mg/kg)	17.23 ± 1.08 cd	19.10 ± 2.05 bcd	16.53 ± 1.57 d	21.74 ± 0.43 abc	19.04 ± 0.87 bcd	22.39 ± 1.67 ab	24.90 ± 0.81 a	18.08 ± 1.00 bcd
TN (g/kg)	0.72 ± 0.10 b	0.67 ± 0.05 c	0.77 ± 0.06 b	0.72 ± 0.06 b	0.64 ± 0.04 c	0.69 ± 0.09 bc	0.87 ± 0.05 a	0.78 ± 0.09 b
AN (mg/kg)	31.64 ± 3.34 b	44.01 ± 5.37 ab	37.91 ± 8.37 ab	40.52 ± 1.75 ab	35.86 ± 4.86 ab	45.33 ± 6.40 ab	54.66 ± 5.57 a	34.11 ± 2.52 b
TK (g/kg)	18.27 ± 0.56 bc	19.80 ± 0.62 b	22.74 ± 0.82 a	17.17 ± 0.56 cd	14.93 ± 0.76 d	17.40 ± 0.83 bcd	18.19 ± 0.85 bc	17.20 ± 0.77 bcd
AK (mg/kg)	255.13 ± 12.58 b	263.38 ± 12.79 b	399.13 ± 18.41 a	157.00 ± 9.42 c	214.63 ± 21.31 b	204.38 ± 12.67 b	244.00 ± 11.77 b	246.50 ± 12.69 b

Note: The numbers in the table indicate mean ± standard error. Duncan's multiple comparison method was used to analyse the variability of the same index between treatments ($p < 0.05$), and different letters indicate significant differences. EC: electrical conductivity; TS: total salt; BD: bulk density; OC: organic carbon; OM: organic matter; TP: total phosphorus; TN: total nitrogen; TK: total potassium; AP: available phosphorus; AN: available nitrogen; AK: available potassium.

Table 5. Loading matrix and norm values for each indicator.

Indicators	PC1	PC2	PC3	PC4	PC5	Grouping	Norm
AN	0.760	0.165	0.137	0.418	0.209	1	1.569
Silt	0.698	−0.557	−0.035	−0.317	−0.008	1	1.676
Sand	−0.692	0.560	0.035	0.313	−0.011	1	1.669
pH	0.691	0.135	−0.323	0.444	0.067	1	1.493
TN	0.654	−0.297	0.187	0.106	0.228	1	1.388
Clay	−0.565	0.206	0.032	0.280	0.508	1	1.300
TP	0.558	0.051	0.041	0.469	−0.349	1	1.256
BD	0.154	0.692	−0.203	0.061	−0.243	2	1.304
OM	0.368	0.659	0.543	−0.260	0.049	2	1.572
OC	0.368	0.659	0.503	−0.235	0.049	2	1.540
AK	−0.281	−0.642	0.401	0.177	−0.043	2	1.376
EC	0.029	0.363	−0.647	0.162	−0.269	3	1.159
AP	−0.196	0.144	0.617	0.161	−0.591	3	1.187
TK	−0.184	−0.448	0.412	0.557	−0.015	4	1.227
TS	0.008	0.360	0.114	0.143	0.529	5	0.894
Eigenvalue	3.526	3.046	1.937	1.434	1.247		
percent	23.507	20.304	12.915	9.561	8.315		
Cumulative percent	23.507	43.811	56.726	66.287	74.602		

The indicators with absolute loading values greater than 0.5 for the principal components were grouped, and the norm values of each indicator were calculated. Subsequently, the following indicators were initially selected according to the principle of selecting norm values within 10% of the maximum value in each group: AN, silt, sand, OM, OC, AP, TK and TS. Through correlation analysis between indicators and comparing the correlation coefficients between two indicators in the same group (Figure 3), the final MDS of the soil quality evaluation indicators in this study was determined to be silt, OM, AP, TK and TS.

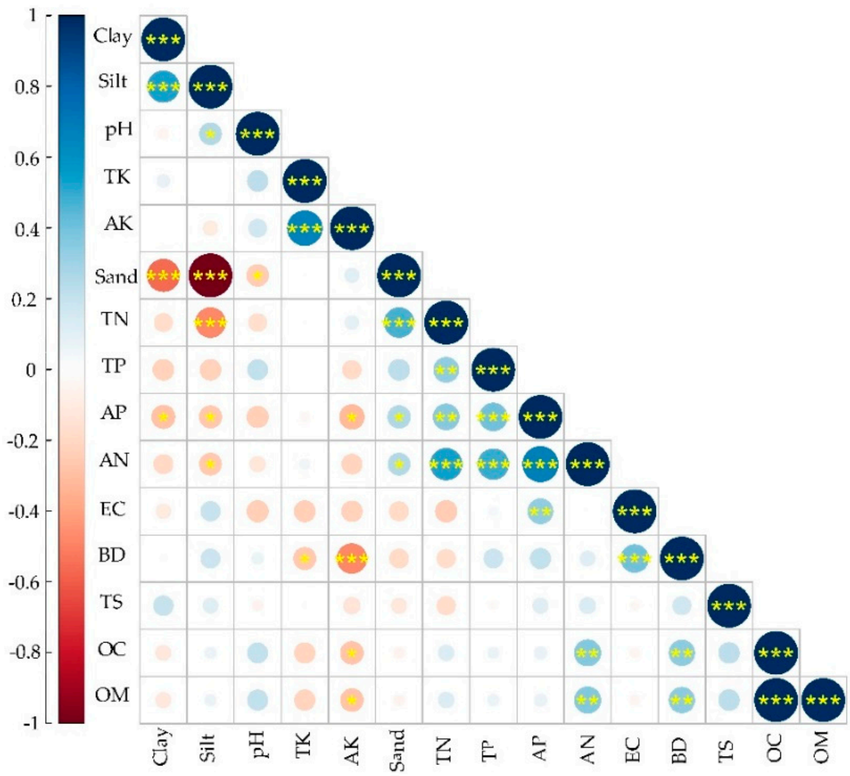

Figure 3. Soil quality evaluation index correlation coefficient matrix. "*" denotes significant difference at 0.05 level; "**" denotes significant difference at 0.01 level; "***" denotes highly significant difference at the 0.001 level.

3.3. Soil Quality Evaluation Based on Two Scoring Models

After the MDS indicators were determined, PCA was performed to obtain the common factor variance of each indicator, and then the weights of each indicator were calculated. As shown in Table 6, the values of the silt, TS, OM, AP and TK weights in the minimum data set were 0.194, 0.173, 0.214, 0.225 and 0.194, respectively, indicating that effective phosphorus contributed the most to soil quality in the study area, followed by organic matter, total salinity and total potassium. The MDS indicators were transformed into scores between 0 and 1 by Equations (2)–(4). In this study, TS was considered a "less is better" function because excessive salinity in the soil can affect plant growth and eventually lead to a decrease in soil quality. Silt, OM, AP and TK are specific representations of soil structure and nutrients and are applicable to the "more is better" type function.

Table 6. Common factor variances and weights of the MDS and TDS for soil quality evaluation.

Indicators	TDS		MDS	
	Communality	Weight	Communality	Weight
Clay	0.699	0.062		
Silt	0.899	0.080	0.707	0.194
Sand	0.891	0.080		
EC	0.649	0.058		
pH	0.802	0.072		
TS	0.443	0.040	0.632	0.173
BD	0.607	0.054		
OC	0.935	0.084		
OM	0.935	0.084	0.779	0.214
TP	0.657	0.059		
AP	0.815	0.073	0.821	0.225
TN	0.614	0.055		
AN	0.842	0.075		
TK	0.716	0.064	0.705	0.193
AK	0.685	0.061		

As shown in Figure 4a, the average nonlinear soil quality evaluation index based on the MDS under different soil treatments was VI (0.564) > V (0.532) > II (0.521) > VII (0.517) > VIII (0.498) > III (0.480) > I (0.472) > IV (0.411). As shown in Figure 4b, VI (0.548) > V (0.516) > II (0.489) > VII (0.477) > VIII (0.453) > III (0.434) > I (0.417) > IV (0.386). The distribution of the SQI under different soil amendment treatments was completely consistent in both evaluation methods, mainly showing that plastic mulch significantly increased the SQI ($p < 0.05$), and the addition of appropriate amounts of fulvic acid, bentonite and GGR also increased the SQI ($p < 0.05$). The SQI was significantly higher in the VI treatment than in the other treatments, while IV had a significantly lower value than that in the other treatments ($p < 0.05$). In the nonlinear soil quality evaluation model, there was no significant difference between treatments II, V, VII ($p > 0.05$) and the other treatments ($p < 0.05$). There was no significant difference between I, III, VIII ($p > 0.05$) and the other treatments ($p < 0.05$). The average SQI was 0.124 times higher with plastic mulch than without mulch. In the linear soil quality evaluation model, there were no significant differences between treatments II, VII and VIII ($p > 0.05$), but there were significant differences with other treatments ($p < 0.05$). There was also no significant difference ($p > 0.05$) between the I and III treatments, and there was a significant difference ($p < 0.05$) with other treatments; the SQI was 1.157 times higher with plastic mulch than without mulch.

3.4. Validation of the Applicability of the Soil Quality Evaluation Method Based on the MDS

High accuracy is often obtained when evaluating soil quality through a total data set of soil quality evaluation indicators, but the large number of indicators leads to complicated and time-consuming experimental analysis. The simplification of indicator data sets through a range of statistical methods, however, leads to a decrease in assessment accuracy.

Therefore, there is a need to validate the applicability of the MDS of evaluation indicators for a region or a specific soil type.

The total data set and the common factor variance of each indicator were obtained by PCA, the weights of each indicator in the total data set were calculated (Table 6) and the soil quality based on the total data set of soil quality evaluation indicators was analysed by the above method. As shown in Figure 5, the correlation between the MDS of the indicators and the total data set under the two soil quality evaluation methods was high. The regression equation for the nonlinear scoring model (Figure 5a) was $y = 0.834x + 0.025$ ($n = 96$, $R^2 = 0.873$, $p < 0.001$). The regression equation for the linear scoring model (Figure 5b) was $y = 0.651x + 0.103$ ($n = 96$, $R^2 = 0.811$, $p < 0.001$), where y denotes the TDS and x denotes the MDS.

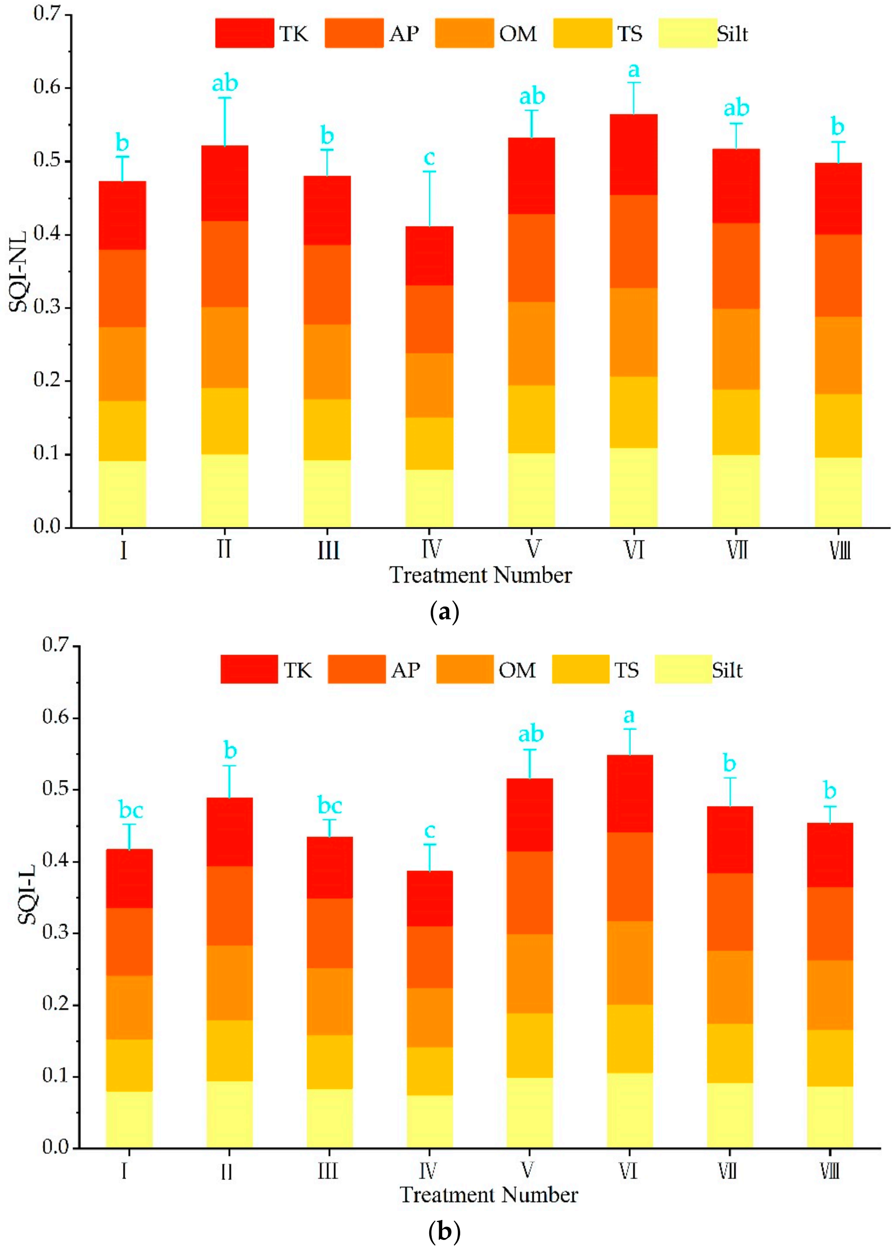

Figure 4. (**a**) Soil quality index of the nonlinear scoring model (SQI-NL). (**b**) Soil quality index of the linear scoring model (SQI-L). Same lowercase letters indicate no significant difference at the 0.05 level, different lowercase letters indicate xian-zhuchayi at the 0.05 level.

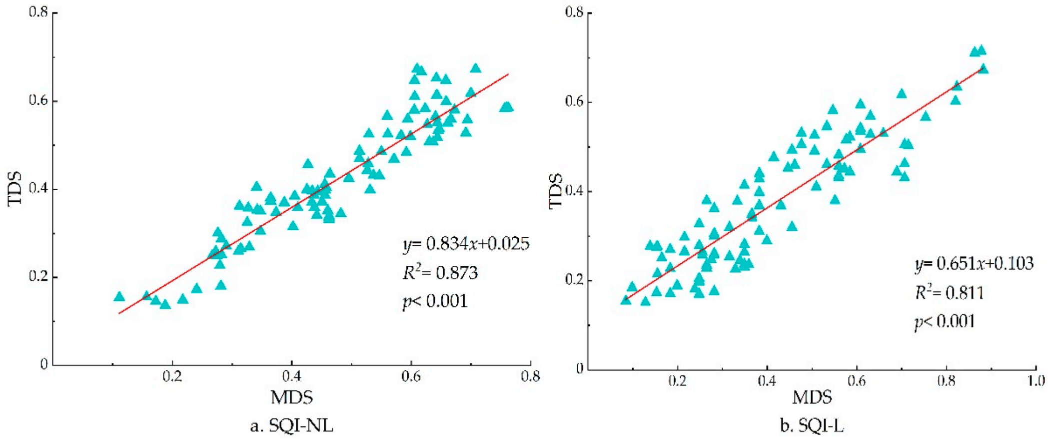

Figure 5. (**a**) Relationship between MDS and TDS under two evaluation methods (the range of variation in the SQI-NL) (**b**) Relationship between MDS and TDS under two evaluation methods (the range of variation in the SQI-L).

The range of variation in the SQI-NL based on the MDS was 0.111–0.762 with a coefficient of variation of 32.32%, while the range of variation in the SQI-L based on the MDS was 0.085–0.882 with a coefficient of variation of 47.18%. The interval of variation and coefficient of variation of the SQI obtained by the MDS-based SQI-NL method were smaller than those obtained by the SQI-L method, indicating that the method is more sensitive to the variability of the SQI. In addition, from the fitting effect (Figure 5), the TDS and MDS were significantly and positively correlated under both the SQI-NL and the SQI-L evaluation methods, but the R^2 was 0.873 and 0.811, respectively, and the fitting effect obtained by the SQI-NL method was better and therefore had higher accuracy and could replace the TDS for soil quality evaluation.

4. Discussion

4.1. Variability of Soil Physicochemical Properties under Different Treatments

Soil conditioners can effectively improve the soil structure; balance the relationship between soil water, fertilizer, air, heat and biology; increase the number of soil microorganisms; and improve enzyme activity, thus enhancing soil quality [33]. The addition of appropriate amounts of xanthic acid, bentonite and GGR at the time of vegetation restoration had a significant effect on soil quality, and increasing topsoil cover significantly improved the soil quality coefficient. A study by Wan, Shao, et al. [34] in southern Henan Province found that the use of ground cover, the use of chemicals such as GGR rooting agents and SSAP drought and water-retention agents optimized the soil and improved plant survival. Liu Yan, et al. [35] concluded that edible mushroom waste, water-retention agents and fly ash had relatively significant effects on soil substrate improvement. Zheng, Yi, et al. [36] concluded that the application of bentonite–humic acid-based amendments to sandy soils could reduce the transpiration rate of crops; reduce the gaseous losses of soil nitrogen; and improve the nitrogen fertilizer utilization, seed yield and quality of maize. Salman, M., et al. [37] added bentonite and biochar to the conditions and basis of maize cultivation in a river loop irrigation area to significantly improve soil quality and crop yield. EI-Nagar, D. A., et al. [38] showed through field and pot experiment data that the addition of bentonite significantly improved soil water holding capacity and could significantly increase crop yield. Haider et al. [39] used biochar and humic acid soil amendments to improve plant performance under water-limited conditions. When added to the soil biochar (1.5 and 3%; *w*/*w*), humic acid (8 kg/ha) significantly increased the biomass yield and the water and N use efficiency of plants. Bentonite is a natural soil amendment that can reduce soil water loss and increase crop yield. Jma, B., et al. [40] use treatments including six rates of bentonite amendments (0, 6, 12, 18, 24 and 30 Mg/ha) applied to crop. The results show that application of bentonite significantly increased soil microbial biomass parameters, soil organic C, total N and total P over the experimental period. The application rate of 18 Mg/ha had the greatest effect in the first year, whereas 30 Mg/ha bentonite had the greatest effect in the fifth year. In the current study, eight treatments were established, and the results showed that the SQI was highest under the VI treatment. That is, adding 250 g of fulvic acid, 1000 g of bentonite and 15 g of GGR (each mixed with 100 kg of water) to the soil under mulching conditions significantly enhanced the soil quality factor and increased the vegetation cover. In this study, the smallest amount of xanthic acid significantly improved the soil quality, and the lowest soil quality coefficient was achieved when xanthic acid and bentonite were added in the maximum amount set in this study. It has been shown that mulching significantly reduces soil bulk density and pH; increases soil cumulative temperature, enzyme activity, organic matter content and plant uptake of ammonium nitrogen; and contributes to yield improvement and metabolite accumulation [41]. In this study, plastic mulching significantly improved soil quality because the soil silt, clay, organic matter and organic carbon were significantly higher under mulched conditions compared with the treatments without mulch, while the soil bulk density was significantly lower than that in the other treatments. Therefore, when revegetating the area, adding appropriate amounts of soil amendments such as bentonite and fulvic acid to the soil will significantly improve the soil quality, and increasing the soil surface cover will also improve the soil quality indicators.

4.2. Variability of the SQI under Different Treatments

This study was conducted using PCA combined with norm values for the selection of the MDS, introducing norm values to analyse the loadings of indicators for all principal components and avoiding the loss of indicators for other principal components [42]. The results of some scholars' studies on MDSs for soil quality evaluation showed that soil bulk density, pH, percent powder, organic matter, effective phosphorus and water content had a high frequency of use [43], and the inclusion of percent silt, organic matter and available phosphorus in the MDS in this study was consistent with the results of most studies [44–48]. Furthermore, total potassium and total salinity were selected as the MDS for this study area, indicating that the main influential factors of soil quality in this study area, in addition to effective phosphorus, organic matter and percentage of powder particles, included the weathering of soil minerals and soil salinization, which had a more significant effect on soil quality. Because the soils in the study area are gravelly gobies, long-term exposure to air will lead to physical and chemical weathering, resulting in a greater impact on soil quality due to the total potassium content in the region. Moreover, the low annual precipitation and high evaporation in the study area led to the upward transport of deep soil salts with water evaporation, which intensified soil salinization. Among the five indicators selected by PCA, effective phosphorus and organic matter contributed the most to the soil quality evaluation (with the largest weights of 0.225 and 0.214, respectively), which is consistent with the findings of Qi et al. [49] and Li et al. [50]. Therefore, the five MDS indicators selected in this study have practical significance for the evaluation of soil quality in the vegetation restoration of the frontal zone of the northern slope of the Tianshan.

The overall distribution patterns of soil quality derived from the nonlinear and linear quality evaluation methods were consistent, but the applicability of the two methods in the region was different. The results of the study found that the range of variation (0.111–0.762) and coefficient of variation (32.32%) of the MDS-based SQI-NL method SQI were smaller than the range of variation (0.085–0.882) and coefficient of variation (47.18%) of the SQI-L soil quality index. Larger intervals of variation in soil quality coefficients make the identification and classification of soil quality more difficult [51], while smaller coefficients of variation indicate higher sensitivity in response to changes in environmental conditions and reflect the factors influencing the changes in soil quality. Additionally, the goodness of fit of the TDS and MDS under the SQI-NL method (0.873) was higher than that of the SQI-L (0.811). Andrews et al. [52] concluded that the SQI-NL method was more realistic in reflecting the function of soil, and the correlation between the MDS and TDS was higher for the SQI-NL method than for the SQI-L method, indicating that the SQI-NL evaluation method has better accuracy and practicality and can better reflect the soil quality. Therefore, the MDS-based SQI-NL evaluation method has good applicability within this study area and can be used and applied in the future under the same soil conditions.

5. Conclusions

1) The MDSs and weights of the indicators applicable to the evaluation of soil quality during the vegetation restoration in the front range of the northern slope of the Tianshan were as follows: available phosphorus > organic matter > percentage of silt particles > total potassium > total salt content.
2) Nonlinear and linear evaluation methods based on the MDS SQI ranking were as follows: VI > V > III > VII > VIII > III > I > IV. The VI treatment significantly improved soil quality; that is, plastic mulch applied to soil with 250 g of fulvic acid, 1000 g of bentonite and 15 g of GGR (mixed with 100 kg of water) was the best treatment.
3) Compared with the linear soil quality evaluation method, the nonlinear soil quality evaluation method had better applicability to the evaluation of soil quality in this region.
4) The coefficients of determination between the MDS and the TDS under the nonlinear soil quality evaluation method and the linear soil quality evaluation method were 0.873 and 0.811, respectively, indicating that the MDS could accurately replace the TDS for soil quality evaluation in this study area.

Author Contributions: D.T.: Conceptualization, methodology, software, writing—review and editing. J.Y.: Conceptualization, supervision, writing—review and editing, resources. P.C.: Project administration, resources. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Special Financial Fund for Natural Forest Protection Project "Research and demonstration of vegetation restoration technology in the front mountain belt of the North slope of Tianshan Mountains, Xinjiang, China". P.C.(XJTB2020-03).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: First: I would like to express my deepest gratitude to my mentor, He is a respected, responsible and resourceful scholar who provided me with valuable guidance at every stage of writing this article paper. Without his enlightening teaching, impressive kindness and patience, I would be unable to complete my thesis. He has inspired me, not only in this thesis, but also in my future studies. I want to thank my little friend. The insightful and valuable suggestions from editors and reviewers have greatly improved the quality of this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Liu, C.; Yan, X.; Jiang, F. Influence of precipitation ditrilution on desert vegetation of Northem Piedmont Tianshan Mountains—Analyis based on daily NDVI and precipitation data. *Acta Ecol. Sin.* **2020**, *40*, 7790–7804. [CrossRef]
2. Tang, D.; Song, L.L.; Jacobs, D.F.; Mei, L.; Peng, L.; Song, H.J.; Wu, J.S. Physiological responses of plants to drought stress in the Northern Piedmont, Tianshan Mountains. *Arid Zone Res.* **2021**, *38*, 1683–1694. [CrossRef]
3. Fernandez, R.D.; Castro-Díez, P.; Aragón, R.; Pérez-Harguindeguy, N. Changes in community functional structure and ecosystem properties along an invasion gradient of *Ligustrum lucidum*. *J. Veg. Sci.* **2021**, *32*, e13098. [CrossRef]
4. Bouzouidja, R.; Bechet, B.; Hanzlikova, J.; Snekota, M.; Le Guern, C.; Capiaux, H.; Jean-Soro, L.; Claverie, R.; Joimel, S.; Schwartz, C.; et al. Simplified performance assessment methodology for addressing soil quality of nature-based solutions. *J. Soils Sediments* **2021**, *21*, 1909–1927. [CrossRef]
5. Esra, G.; Yeliz, Y.A. Improvement of thermally durable soil material with perlite additive. *Environ. Earth Sci.* **2022**, *81*, 1–13. [CrossRef]

6. Ram, L.C.; Srivastava, N.K.; Tripathi, R.C.; Jha, S.K.; Sinha, A.K.; Singh, G.; Manoharan, V. Management of mine spoil for crop productivity with lignite fly ash and biological amendments. *J. Environ. Manag.* **2006**, *79*, 173–187. [CrossRef]
7. Sena, K.; Barton, C.; Hall, S.; Angel, P.; Agouridis, C.; Warner, R. Influence of Spoil type on afforestation success and natural vegetative recolonization on a surface coal mine in Appalachia, United States. *Restor. Ecol.* **2015**, *23*, 1–8. [CrossRef]
8. Han, R.; Jing, W.; Hou, Q.; Fan, H.; Qi, W. Research advance of artificial preparation and droughtresistant afforestation on Loess Plateau. *Acta Bot. Boreal.–Occident. Sin.* **2003**, *23*, 1331–1335. [CrossRef]
9. Zhang, Z.; Lv, Q.; Guo, Z.; Huang, X.; Hao, R. Soil water movement of mining waste rock and the effect on plant growth in arid, cold regions of Xinjiang, China. *Water* **2021**, *13*, 1240. [CrossRef]
10. Chen, C.; Feng, Y.; Zhao, L.-L.; Yao, H.-Y.; Wang, J.-L.; Liu, H.-L. Influences of different land use types on soil characteristics and availability in Karst area, Guizhou Province. *Acta Agrestia Sin.* **2014**, *22*, 1007–1013. [CrossRef]
11. Li, Y.; Tang, J.; Lin, N.; Yang, Y. Application of grey system theory in evaluating grassland soil quality. *J. Jilin Agric. Univ.* **2003**, *5*, 551–556. [CrossRef]
12. Hu, Y.; Wan, H.; Wu, Z.; Wu, G.; Li, H. Gis-based soil quality evaluation with fuzzy variable weight. *Acta Pedol. Sin.* **2001**, *3*, 266–274. [CrossRef]
13. Chakraborty, B.; Sambhunath, R.; Bera, A.; Adhikary, P.P.; Bera, B.; Sengupta, D.; Bhuni, G.S.; Shit, P.K. Groundwater vulnerability assessment using GIS-based DRASTIC model in the upper catchment of Dwarakeshwar river basin, West Bengal, India. *Environ. Earth Sci.* **2022**, *81*, 2. [CrossRef]
14. Katz, W.T.; Snell, J.W.; Merickel, M.B. Artificial neural networks. *Methods Enzymol.* **1992**, *21*, 610–636. [CrossRef]
15. Li, P.; Zhang, C.; Hao, M.; Zhang, Y.; Cui, Y.; Zhu, S. Soil quality evaluation for reclamation of mining area on Loess Plateau based on minimum data set. *Trans. Chin. Soc. Agric. Eng.* **2019**, *35*, 265–273. [CrossRef]
16. Volungevicius, J.; Amaleviciute, K.; Liaudanskiene, I.; Šlepetys, J. Chemical properties of Pachiterric Histosol as influenced by different land use. *Zemdirbyste* **2015**, *102*, 123–132. [CrossRef]
17. Fal, J.; Sidorowicz, A.; Żyła, G. Electrical Conductivity of Ethylene Glycol Based Nanofluids with Different Types of Thulium Oxide Nanoparticles. *Acta Phys. Pol.* **2017**, *132*, 146–148. [CrossRef]
18. Zhou, W.; Yang, K.; Bai, Z.; Cheng, H.; Liu, F. The development of topsoil properties under different reclaimed land uses in the Pingshuo opencast coalmine of Loess Plateau of China. *Ecol. Eng.* **2017**, *100*, 237–245. [CrossRef]
19. Zeng, C.; Wang, Q.; Zhang, F.; Zhang, J. Temporal changes in soil hydraulic conductivity with different soil types and irrigation methods. *Geoderma.* **2013**, *193*, 290–299. [CrossRef]
20. Andrews, S.S.; Karlen, D.L.; Cambardella, C.A. The soil management assessment framework: A quantitative soil quality evaluation method. *Soil Sci. Soc. Am. J.* **2004**, *68*, 1945–1962. [CrossRef]
21. Cao, J.; Chang, Y.; Miao, J.; Qi, S. Effect of vegetation recovery on the soil fertility quality of different slope position in semi-arid region of loess Plateau. *J. Arid Land Resour. Environ.* **2009**, *23*, 169–173. [CrossRef]
22. Borut, V.; Laura, P.; Marsan, F.A. A method for soil environmental quality evaluation for management and planning in urban areas. *Landsc. Urban Plann.* **2008**, *88*, 81–94. [CrossRef]
23. Xu, Y.; Wang, X.; Bai, J.; Wang, D.; Wang, W.; Guan, Y. Estimating the spatial distribution of soil total nitrogen and available potassium in coastal wetland soils in the Yellow River Delta by incorporating multi-source data. *Ecol. Indic.* **2020**, *111*, 106002. [CrossRef]
24. Noge, H.; Ueno, Y.; Kadir, H.A.; Yahya, W.J. Utilization of palm acid oil for a diffusion combustion burner as fuel and nitrogen oxides reduction by the thermally decomposed hydrocarbons. *Energy* **2021**, *224*, 120173. [CrossRef]
25. Ghorbanzadeh, N.; Mahsefat, M.; Farhangi, M.B.; Rad, M.K.; Proietti, P. Full research paper short-term impacts of pomace application and Pseudomonas bacteria on soil available phosphorus. *Biocatal. Agric. Biotechnol.* **2020**, *28*, 101742. [CrossRef]
26. Nakajima, T.; Lal, R.; Jiang, S. Soil quality index of a crosby silt loam in central Ohio. *Soil Tillage Res.* **2015**, *146*, 323–328. [CrossRef]
27. Rezaei, S.A.; Gilkes, R.J.; Andrews, S.S. A minimum data set for assessing soil quality in rangelands. *Geoderma* **2006**, *136*, 229–234. [CrossRef]
28. Zhang, F.; Gao, Z.; Ma, Q.; Song, Z.; Li, G.; Li, X.; Su, Y. Construction minimum data set for soil quality assessment in the Dunhuang oasis. *Chin. J. Soil Sci.* **2017**, *48*, 1047–1054. [CrossRef]
29. Zhang, C.; Xue, S.; Liu, G.; Song, Z. A comparison of soil qualities of different revegetation types in the Loess Plateau, China. *Plant Soil* **2011**, *347*, 163–178. [CrossRef]
30. Masto, R.E.; Chhonkar, P.K.; Singh, D.; Patra, A.K. Alternative soil quality indices for evaluating the effect of intensive cropping, fertilisation and manuring for 31 years in the semi-arid soils of India. *Environ. Monit. Assess.* **2008**, *136*, 419–435. [CrossRef] [PubMed]
31. Chen, Z.; Shi, D. Evaluation on cultivated-layer soil quality of sloping farmland in Yunnan based on soil management assessment framework. *Trans. Chin. Soc. Agric. Eng.* **2019**, *35*, 256–267. [CrossRef]
32. Rahmanipour, F.; Marzaioli, R.; Bahrami, H.A.; Fereidouni, Z.; Bandarabadi, S.R. Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. *Ecol. Indic.* **2014**, *40*, 19–26. [CrossRef]
33. Ishii, T.; Kadoya, K. Effects of charcoal as a soil conditioner on citrus growth and vesicular-arbuscular mycorrhizal development. *J. Jpn. Soc. Hortic. Sci.* **2008**, *63*, 529–535. [CrossRef]
34. Wan, S. Research on techniques to improve the survival rate of afforestation. *Pract. For. Technol.* **2013**, *1*, 24–25.

35. Liu, Y.; Cui, S.; Wang, C.; Sun, G. Effect evaluation of soil conditioner in the Alluvial Gold Deposit. Forest By-Product and Speciality in China. *For. By-Prod. Spec. China* **2021**, *3*, 21–24. [CrossRef]
36. Zheng, Y.; Zhou, L.; Liu, J. Effects of bentonite-humic acid on gaseous nitrogen loss, nitrogen use efficiency and maize yield on sandy soil. *Chin. J. Ecol.* **2019**, *38*, 3887–3894. [CrossRef]
37. Salman, M.; El-Eswed, B.; Khalili, F. Adsorption of humic acid on bentonite. *Appl. Clay Sci.* **2007**, *38*, 51–56. [CrossRef]
38. El-Nagar, D.A. Synthesis and characterization of nano bentonite and its effect on some properties of sandy soils. *Soil Tillage Res.* **2021**, *208*, 104872. [CrossRef]
39. Haider, K.; Azam, S.; Muller, K. Biochar but not humic acid product amendment affected maize yields via improving plant-soil moisture relations. *Plant Soil* **2015**, *395*, 141–157. [CrossRef]
40. Jma, B.; Gregorich, E.G.; Xu, S.; McLaughlin, N.B.; Ma, B.; Liu, J. Changes in soil biochemical properties following application of bentonite as a soil amendment. *Eur. J. Soil Biol.* **2021**, *102*, 103251. [CrossRef]
41. Chen, Y.; Liu, T.; Tian, X.; Wang, X.; Li, M.; Wang, S.; Wang, Z. Effects of plastic film combined with straw mulch on grain yield and water use efficiency of winter wheat in Loess Plateau. *Field Crops Res.* **2015**, *172*, 53–58. [CrossRef]
42. Wu, C.; Liu, G.; Huang, C.; Liu, Q.; Guan, X. Soil quality assessment of the Yellow River Delta based on MDS and Fuzzy Logic Model. *Resour. Sci.* **2016**, *38*, 1275–1286. [CrossRef]
43. Mohammad, S.; Nicholas, H. Quantitative soil quality indexing of temperate arable management systems. *Soil Tillage Res.* **2015**, *150*, 57–67. [CrossRef]
44. Zhi, W.; Li, Z. Assessing the soil quality of long-term reclaimed waste water-irrigated cropland. *Geoderma* **2003**, *114*, 261–278. [CrossRef]
45. Emami, H. Pore size distribution as a soil physical quality index for agricultural and pasture soils in northeastern iran. *Pedosphere* **2013**, *23*, 312–320. [CrossRef]
46. Duraisamy, V.; Surendra, K.S. Soil quality index (SQI) as a tool to evaluate crop productivity in semi-arid deccan plateau india. *Geoderma* **2016**, *282*, 70–79. [CrossRef]
47. Ranjbar, A.; Emami, H.; Khorassani, R. Soil quality assessments in some iranian saffron fields. *J. Agric. Sci. Technol.* **2016**, *18*, 865–878.
48. Jin, H.; Minmin, J.; Chen, G. Evaluation indicators of cultivated layer soil quality for red soil slope farmland based on cluster and PCA analysis. *Trans. Chin. Soc. Agric. Eng.* **2018**, *34*, 155–164. [CrossRef]
49. Qi, Y.; Darilek, J.L.; Huang, B.; Zhao, Y.; Sun, W. Evaluating soil quality indices in an agricultural region of Jiangsu Province, China. *Geoderma* **2009**, *149*, 325–334. [CrossRef]
50. Li, P.; Zhang, T.; Wang, X.; Yu, D. Development of biological soil quality indicator system for subtropical China. *Soil Tillage Res.* **2013**, *126*, 112–118. [CrossRef]
51. Guo, L.; Sun, Z.; Ouyang, Z.; Han, D.; Li, F. A comparison of soil quality evaluation methods for Fluvisol along the lower Yellow River. *Catena* **2017**, *152*, 135–143. [CrossRef]
52. Andrews, S.S.; Mitchell, J.P.; Mancinelli, R.; Karlen, D.L.; Munk, D.S. On-farm assessment of soil quality in California's Central Valley. *Agron. J.* **2002**, *94*, 12. [CrossRef]