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Soil Quality Evaluation Based on a Minimum Data Set (MDS)—A Case Study of Tieling County, Northeast China

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Abstract: Soil quality is related to food security and human survival and development. Due to the acceleration of urbanization and the increase in abandoned land, the quality of topsoil has deteriorated, thus resulting in land degradation in recent years. In this study, a minimum data set (MDS) was constructed through principal component analysis (PCA) to determine the indicator data set for evaluating topsoil quality in Tieling County, northeast China. In addition, the soil quality index (SQI) was calculated to analyze the spatial distribution characteristics of the topsoil quality and the influencing factors. The results showed that the MDS included total potassium (TK), clay, zinc (Zn), soil organic matter (SOM), soil water content (SWC), cation exchange capacity (CEC), pH, and copper (Cu), which could replace all other indicators for assessing the topsoil quality in the research region. The overall soil quality of Tieling County showed a trend of being low in the east and high in the west, and it gradually increased from the hilly area to the plain area. The topsoil quality of Tieling County is divided into one to five levels, with grade-I being the best and grade-V being the worst. The proportion of Grade-II and grade-III is the largest, which is 28.5% and 26.3%, respectively, and grade-V is the smallest, which is 9.6%. The evaluation results are consistent with field research, which can provide a reference for other topsoil quality evaluations, and it also provides a basis for the formulation of soil quality improvement measures.

Keywords: soil quality assessment; MDS; principal component analysis; Tieling County

Citation: Qian, F.; Yu, Y.; Dong, X.; Gu, H. Soil Quality Evaluation Based on a Minimum Data Set (MDS)—A Case Study of Tieling County, Northeast China. *Land* **2023**, *12*, 1263. https://doi.org/10.3390/land12061263

Academic Editors: Vincent Chaplot and Adrianos Retalis

Received: 25 April 2023
Revised: 25 May 2023
Accepted: 16 June 2023
Published: 20 June 2023

1. Introduction

Soil is an important natural resource. It is the basis of agricultural production and plays an important role in meeting food needs and maintaining human survival and development. Soil quality is an important attribute for assessing soil conditions and changes, which is mostly defined as "the ability of soil to play a role within the boundaries of natural or managed ecosystems [1]". Higher soil quality means higher productivity and better food security [2]. However, in recent decades, countries have intensively developed their economies and accelerated industrialization, leading to the occupation and conversion of many cultivated lands to land for construction or to developed land. Furthermore, as people's living standards have improved, the urbanization rates have increased, resulting in the abandonment and degradation of cultivated land, as well as the deterioration of soil quality [3,4]. To prevent agricultural land degradation and to improve crop yield, we must carry out soil quality evaluation to grasp soil quality comprehensively and accurately [5]. At the same time, soil quality evaluation is also of great significance for the development of agricultural and cultural industries, poverty alleviation, and rural revitalization.

Since the United States Department of Agriculture (USDA) released the land potential classification system in 1961, many soil quality evaluation methods have been developed [6]. These methods include soil quality cards and test kits [7], the soil quality index (SQI) method [8], the fuzzy correlation method [9], the dynamic soil quality model [10], and the soil management assessment framework [11–14]. Among these methods, the SQI may be the most common method [15] because it fully takes into account the common influence of measured values, weights, and interactions among indicators on the evaluation results. However, due to the complexity of the evaluation indicators, the whole evaluation process is no small challenge. Therefore, the selection of appropriate evaluation indicators is one of the most important factors to consider, and this has a significant impact on soil quality evaluation results. In the selection of evaluation indicators, all indicators, including soil physical, chemical, and biological indicators, should be considered [16]. Additionally, more attention needs to be given to the changes in the indicator system at different spatial and temporal scales. Due to the diversity of soil quality evaluation indicators, the minimum data set (MDS) method was adopted in this paper. An MDS can select the most appropriate indicators from the primary ones through principal component analysis (PCA) to reduce data redundancy [17]. In addition, the weight of selected indicators can be generated during the establishment of an MDS, which reduces the subjective influence of human factors on soil quality and is conducive to the subsequent evaluation of soil quality. At present, many scholars select indicators through an MDS to simplify the evaluation process. For example, Shi Zhihua et al. [18] explored the effects of land use change on environmental quality in a red soil hilly region by establishing minimum data sets. Li Ping et al. [19] established an MDS to evaluate soil quality in a subtropical region. Rahmanipour, F. [20] completed the evaluation of agricultural land soil quality in Ghazvin Province in Iran, and the results proved that the evaluation based on an MDS was superior to the evaluation based on the full data set. Other similar studies have been carried out in coastal areas, woodlands, grasslands, and wetlands [21]. Some researchers have even improved the establishment criteria or an MDS and added soil environmental factors and land use status into the selection principle of indicators, which has resulted in good results being achieved [22]. Zhanjun Liu et al. [23] evaluated the soil quality of high (HPPS), medium (MPPS), and low (LPPS) productive yellow clayey paddy soils by using an MDS and the SQI, and they aimed to identify the factors limiting rice productivity.

In the evaluation of soil quality, many statistical techniques (such as the grey correlation method, artificial neural networks, and principal component analysis) have been widely used for the establishment of MDSs and the calculation of the soil quality index [24,25]. In this study, an MDS was established through principal component analysis and correlation analysis for its strong objectivity, which can ensure the minimum loss of original data information, reflects the impact of indicators on soil quality, reduces the number of independent soil parameters, and solves the multicollinearity problem of indicators to a certain extent. Tieling County was selected as the research object in this study. Research in Tieling County is helpful in exploring the influence of different indicators of the soil quality of different land types. In general, this study has the following objectives: (1) the establishment of an MDS for soil quality evaluation indexes in Tieling County; (2) the formulation of an SQI to quantitatively analyze the spatial distribution of soil quality; and (3) the analysis of the influence of MDS indicators on soil quality.

2. Materials and Methods

2.1. Study Area

The study area is Tieling County (Figure 1), which is located in the northern part of Liaoning Province, covering an area of 2262 km^2. Tieling County has a continuous plain area in the west and a low hilly area in the east, with large relief and uneven soil quality levels in the topsoil layer. It belongs to the middle temperate monsoon climate zone. The average annual temperature is 8.2 °C, the average annual precipitation is 670.7 mm, and the average annual relative humidity is 62%. The main soil texture is loam and clay. It has jurisdiction over 15 towns (farms) with a resident population of about 324,400, accounting for 13.58% of the total population of Tieling City. It has a county-cultivated land area of 1087 km^2, mostly concentrated in the central plain area, and a per capita cultivated land area of 0.27 hm^2/person. In 2021, 2 km^2 of high-standard farmland was built, 1.334 km^2 of northeast black land was protected, and grain output reached 0.69 billion kg. The cultivated land resources of Tieling County provide the basis for the grain production of Liaoning Province and even the whole country. Therefore, research on the topsoil of Tieling County is conducive to the rational and efficient utilization of cultivated land resources and provides a reference and guarantee for sustainable development.

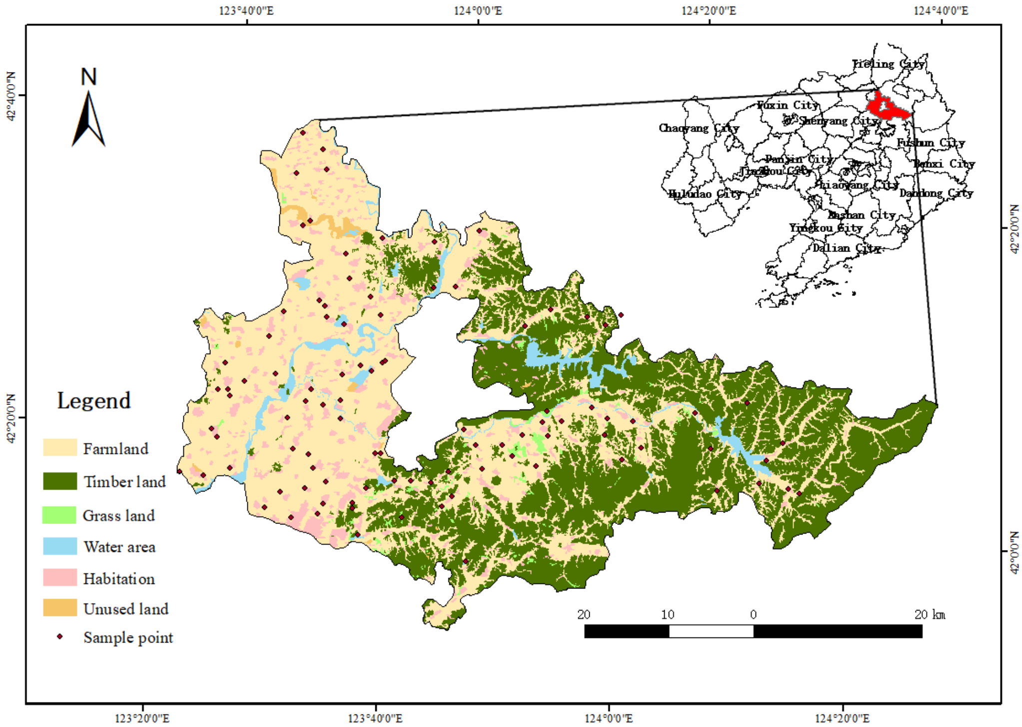

Figure 1. Geographical locations of the study area and soil sampling points.

2.2. Soil Data Sources and Sample Collection

Based on the field soil sampling data in Tieling County from 2021, the basic physical and chemical properties of the soil and heavy metal pollution content were obtained. In this study, 29,677 plots of cultivated lands were used as evaluation units, ArcGIS was used to create a random point tool, and a total of 100 field sampling points were set up to determine the soil's physical and chemical attributes and the total amount of heavy metal elements [26]. Soil sample collection was carried out in October 2021. By using GPS, 100 sampling spots were precisely located, and their latitude and longitude were noted. Based on the geographical location, two to three locations around the sample points were selected to collect 0–20 cm topsoil within a radius of 20 m. The soil samples were collected by sampling, mixing, and placing them into polyethylene self-styled bags afterward; they were sealed and numbered, air-dried indoors, and foreign matter (gravel, brick, plant roots, and other residues) was removed from the soil. Tool grinding was used after agate mortar grinding, with 10 orders (2.00 mm), 20 mesh (0.85 mm), and 100 mesh (0.15 mm) sieves, which were used to determine the physical and chemical properties of the different soil samples in the test of the project analysis.

For the analysis and determination of common physical and chemical soil property indicators, we referred to soil agricultural chemical analysis and the following references: a total of 22 physical, chemical, and metal pollution indicators were measured. Soil bulk density (BD) was determined by the ring tool method [27]. Soil water content (SWC) was determined by the drying method [28]. After the soil samples were collected, they were loaded into the ring knife, weighing the weight of the soil sample with a 0.1 g precision balance to obtain the wet weight of the soil. The soil sample is dried in an oven at 105 °C for 6~8 h to constant weight, and then the dried soil sample is measured to obtain the dry weight of the soil. SWC = the wet weight of the soil/the dry weight of the soil. The particle composition of the soil was determined by a laser particle size analyzer. According to international classification (ISSS), the measurements were as follows: clay (<0.002 mm), silt (0.002–0.02 mm), and sand (0.02–2.0 mm). Soil pH was measured by the potentiometric method (soil–water ratio 1:2.5) [29]. The salt content (WSSC) was determined by the gravimetric method. The content of soil organic matter (SOM) was determined by the potassium dichromate volumetric method and by the external heating method [30]. The content of total nitrogen (TN) was determined by the semi-trace Kelvin method [31]. Total potassium (TK) was determined by the flame photometer method [32]. Total phosphorus (TP) was determined by the alkali fusion–Mo-Sb spectrophotometric method [33]. The available phosphorus (AvP) was determined by the sodium hydrogen carbonate solution-Mo-Sb anti-spectrophotometric method [34]. The available potassium (AvK) was determined by ammonium acetate extraction and flame photometry [35]. The cation exchange capacity (CEC) was determined by the ammonium acetate method [36]. The atomic state contents of the soil heavy metal pollution indicators cadmium (Cd), copper (Cu), zinc (Zn), nickel (Ni), lead (Pb), and chromium (Cr) were analyzed and determined by flame atomic absorption spectrophotometry [37]. Arsenic (As) and mercury Hg were determined by atomic fluorescence spectrometry.

2.3. Soil Quality Evaluation Method

2.3.1. Indicator Selection

The multidimensional attribute of soil quality covers many dimensions, such as nature, the social economy, and the ecological environment. As the basis of agricultural production and development, natural conditions, including hydrogeology, soil type, geomorphic characteristics, and other aspects, are decisive indicators related to the quality of cultivated land. The slope has a significant impact on topsoil quality in Tieling County. Hence the index system takes this into account. The natural quality of soil reflects the background characteristics of cultivated land resources. Because the climate environment and planting system of land resources at the county level are similar, the differences were mainly in topography, effective soil layer thickness, and soil nutrient level. With the rapid advancement of urbanization, soil heavy metal pollution has become an important factor affecting crop growth and the regional ecological environment, and soil heavy metal content is a key indicator of environmental quality, so soil heavy metal is considered a natural indicator. Due to the correlation among the influencing factors, it is necessary to select indicators with a high acquisition, strong stability, a large influence degree, and indicators that can reflect the difference in soil quality to carry out the relevant evaluation. In this study, SPSS 26.0 software was used for the correlation analysis so as to preliminarily determine whether the primary indicators are suitable for inclusion in the soil quality evaluation indicator system.

2.3.2. Principal Component Analysis (PCA)

Due to the selection capability of the MDS, principal component analysis was used as a data reduction tool to select the most appropriate indicators. SPSS 26.0 software was used to import the data of various indicators, analyze their correlation, remove the repetitive information, and convert it into a group of irrelevant variables. The new group of variables generated after transformation is called the principal component (PC). The PC with an eigenvalue > 1 was screened, and the indicator with a load number greater than 0.5 on each PC was classified into a group. If the load number of the indicator was greater than 0.5 in multiple PCs, the correlation coefficient between the indicator and the other indicators in the group was observed; the indicator was included in the group unless the indicator was not significantly correlated with all other indicators. If the indicator is not significantly correlated or significantly correlated with other indicators in the same group in different groups, it will be classified into a group with a smaller distribution range of correlation coefficients. If the load number of the indicator in the PC is less than 0.5, these indicators will be separately divided into a group. After grouping all of the indicators, each group was observed, and the indicators whose Norm value reached 10% of the maximum Norm value of the group were screened. These indicators were screened, and correlations between these indicators were observed. If all indicators in this group are not significantly correlated (r < 0.5), all indicators in this group will be included in the MDS. If the correlation level of the indicators in this group is different, the indicator with the largest Norm value will be selected for the MDS. These indicators selected by PCA [38] can reduce the number of independent variables and eliminate problems related to multicollinearity.

2.3.3. Weight Assignment

After determining the MDS, the weight of each indicator is calculated based on the common factor variance, and the formula is [39]:

$$w = C_i / S_i \tag{1}$$

where w is the weight of each indicator, C_i is the common factor variance of the indicator, and S_i is the sum of the common factor variance.

2.3.4. Indicator Scoring

The influence of each indicator on soil quality is a relatively fuzzy concept [40]. To evaluate soil quality more accurately, the data of each indicator are uniformly converted by a membership function. The expert experience method was used to evaluate the influence of grade scores or the actual measured values of each indicator on soil quality, and the corresponding membership degree of the indicator was determined. The relationship equation between the indicator values and membership degree was determined by a scatter plot and a fitting curve, and the corresponding membership function of the indicator was finally constructed, as shown in Table 1.

Table 1. Types of membership functions.

Indicators	Type of Membership Function	Membership Function Expression	Parameter		Unit
			a	b	
TK	Type S	$\mu_{(x)}=\begin{cases} 1 & x \geq b \\ 0.9(x-a)/(b-a)+0.1 & a < x < b \\ 0.1 & x \leq a \end{cases}$	17.583	27.423	g kg^{-1}
SOM			13.321	43.431	g kg^{-1}
SWC			14.462	50.883	%
CEC			6.947	57.451	cmol kg^{-1}
Zn	Type reverse S	$\mu_{(x)}=\begin{cases} 1 & x \leq a \\ 0.9(x-b)/(a-b)+0.1 & a < x < b \\ 0.1 & x \leq a \end{cases}$	26.186	86.979	mg kg^{-1}
Cu			19.83	43.337	mg kg^{-1}
Clay	Type parabola	$\mu_{(x)}=\begin{cases} 1 & b_2 \geq x \geq b_1 \\ 0.9(x-a_1)/(b_1-a_1)+0.1 & a_1 < x < b_1 \\ 0.9(x-a_2)/(b_2-a_2)+0.1 & a_2 > x > b_2 \\ 0.1 & x \leq a_1 \text{ or } x \geq a_2 \end{cases}$	7.225	16.253	%
pH			4.345	6.946	

(1) x is the measured value of the indicator, and a and b are the lower and upper limits of the indicator. TK = total potassium; SOM = soil organic matter; SWC = soil water content; CEC = cation exchange capacity. (2) Parameters a and b were obtained through interpolation analysis of the sampled data of each indicator.

2.3.5. Developing the Soil Quality Index

After calculating the weight of each indicator and the score of each area, the soil quality index was further calculated:

$$\mathrm{SQI} = \Sigma A_i \cdot X_i' \tag{2}$$

where type of A_i is each evaluation indicator's weight and X_i' is each evaluation indicator's membership degree value.

2.3.6. Spatial Interpolation Analysis and Quality Classification

As the study area is under continuous monitoring and sampling, the data is incomplete. This study predicted values between sampling points through Kriging interpolation analysis to generate a continuous surface, predict possible results of missing areas, and estimate missing data to produce finer analysis results. The natural break classification was used to categorize numeric data into multiple classes, identify abrupt changes or threshold points in the data, and find natural groupings of the data. This approach avoids the subjectivity of manually specifying classification intervals and can discover natural patterns in the data. The two methods intuitively reflect the characteristics of spatial variation and can provide a data basis for further analysis of results.

3. Results

3.1. Statistical Analysis of Indicators and Establishment of MDS

Descriptive statistical analysis was carried out on the quantitative indicators (Table 2). The average effective soil layer thickness was 38 cm, indicating that the soil had good fertility. The mean slope of the terrain was 1.35°, which was flat and suitable for crop growth. The average soil BD was 1.25 g cm^{-3}, which was relatively moderate. The mean pH value was 5.78, which was slightly acidic. The average soil water content was 26.35%. The mean value of EC was 50.85 µS cm^{-1}, which was greater than the critical point of the crop growth barrier. Soil improvement should be carried out in areas with values greater than 50 [41]. The mean soil organic matter was 21.14 g kg^{-1}. The mean values of total nitrogen, total carbon, total potassium, and total phosphorus were 1.33 g kg^{-1}, 12.31 g kg^{-1}, 24.71 g kg^{-1}, and 0.63 g kg^{-1}, respectively, which were relatively high. The mean value of available phosphorus was 34.49 mg kg $^{-1}$. The mean value of available potassium was 101.73 mg kg^{-1}. The mean value of cation exchange capacity was 15.19 cmol kg^{-1}. The mean values of copper, zinc, and lead were 31.11 cmol kg^{-1}, 60.88 cmol kg^{-1}, and 23.19 cmol kg^{-1}, respectively, which were all relatively high. There were significant differences between the maximum and minimum contents of soil elements in Tieling County, with the coefficient of variation between 0.03–1.41. Generally, coefficient of variation (CV) $\leq$ 0.1 is considered to indicate a weak variation, 0.1 < CV < 1.0 is considered to indicate a moderate variation, and CV $\geq$ 1.0 is considered to indicate a strong variation [42]. In conclusion, the pH, bulk density, silt, and total potassium of the soil in Tieling County showed weak variation, and the factors were relatively stable with a small variation range. SWC, EC, clay, SOM, and TN showed moderate variation. The ESLT and slope had strong variation, and the elements were unstable with a large variation range.

Table 2. Descriptive statistics of the soil indicators.

	Unit	Minimum	Maximum	Mean	SD	CV
ESLT	cm	0.00	150.00	38.00	53.56	1.41
Slope	°	0.00	5.00	1.35	1.71	1.27
BD	g cm^{-3}	0.95	1.58	1.25	0.11	0.09
pH		4.54	6.89	5.78	0.36	0.06
SWC	%	14.65	49.67	26.35	5.08	0.19
EC	µS cm^{-1}	29.58	90.18	50.85	9.59	0.19
WSSC	%	0.12	0.37	0.21	0.04	0.19
Clay	%	7.93	16.28	12.15	1.44	0.12
Silt	%	68.57	79.17	74.62	2.04	0.03
Sand	%	7.02	19.83	13.22	2.45	0.19
SOM	g kg^{-1}	13.37	39.65	21.14	3.91	0.19
TN	g kg^{-1}	1.01	2.13	1.33	0.16	0.12
TC	g kg^{-1}	7.92	22.40	12.31	2.28	0.19
TK	g kg^{-1}	17.96	27.52	24.71	1.59	0.06
TP	g kg^{-1}	0.38	1.02	0.63	0.12	0.18

Table 2. *Cont.*

	Unit	Minimum	Maximum	Mean	SD	CV
AvP	mg kg^{-1}	7.38	99.82	34.49	10.87	0.32
AvK	mg kg^{-1}	47.30	360.07	101.73	27.03	0.27
CEC	cmol kg^{-1}	7.41	55.41	15.19	5.05	0.33
Cu	mg kg^{-1}	19.96	43.46	31.11	4.21	0.14
Zn	mg kg^{-1}	26.29	87.52	60.88	7.72	0.13
Pb	mg kg^{-1}	9.82	48.12	23.19	4.53	0.20
Hg	mg kg^{-1}	0.01	0.22	0.09	0.04	0.46
As	mg kg^{-1}	1.64	15.39	9.84	2.94	0.30
Cd	mg kg^{-1}	0.02	0.22	0.06	0.02	0.33
Ni	mg kg^{-1}	18.38	68.32	32.17	6.41	0.20
Cr	mg kg^{-1}	46.65	279.04	90.06	26.07	0.29

(1) The number of samples was 100. (2) ESLT = effective soil layer thickness; BD = bulk density; SWC = soil water content; EC = electrical conductivity; WSSC = water-soluble salt content; SOM = soil organic matter; TN = total nitrogen; TC = total carbon; TK = total potassium; TP = total phosphorus; AvP = available phosphorus; AvK = available potassium; CEC = cation exchange capacity.

As can be seen from Tables 3 and 4, PCA was carried out on 26 indicators, and seven principal components with eigenvalues greater than 1 were selected, and their eigenvalues were 6.118, 4.072, 3.589, 2.706, 1.854, 1.186, and 1.094. The cumulative contribution rate reached 79.307%. Finally, eight indicators, including TK, clay, Zn, SOM, SWC, CEC, pH, and Cu, were selected for the MDS.

Table 3. Principal component analysis results.

Component	Initial Eigenvalues		
	Total	Percentage of Variance	Accumulation (%)
1	6.118	23.532	23.532
2	4.072	15.662	39.194
3	3.589	13.805	52.999
4	2.706	10.409	63.408
5	1.854	7.130	70.538
6	1.186	4.560	75.098
7	1.094	4.209	79.307

Table 4. Indicators included in the Minimum data set.

Indicators	Component							Group	Norm	Included
	1	2	3	4	5	6	7			
TK	−0.756	−0.214	0.336	−0.098	−0.255	0.073	0.099	1	2.074	Yes
Slope	0.704	−0.043	0.036	−0.204	0.003	0.027	−0.251	1	1.805	
Ni	0.689	−0.327	0.253	0.439	−0.009	−0.116	0.253	1	2.064	
As	−0.652	0.270	0.250	0.058	−0.443	−0.024	0.036	1	1.884	
TP	0.599	−0.422	0.357	0.279	0.132	0.297	−0.077	1	1.956	
Silt	0.592	0.518	0.217	0.055	−0.100	−0.058	−0.156	1	1.881	
Cr	0.591	−0.364	0.209	0.459	0.013	−0.152	0.349	1	1.909	
Pb	0.574	−0.066	0.454	0.003	−0.078	−0.147	0.101	1	1.693	
ESLT	0.548	−0.067	0.138	−0.297	−0.024	−0.015	−0.294	1	1.512	
Cd	−0.545	0.129	0.161	0.277	−0.434	0.437	−0.009	1	1.681	
SOM	0.431	0.693	−0.455	0.104	0.072	0.228	0.163	2	2.026	Yes
TC	0.429	0.689	−0.456	0.103	0.074	0.233	0.170	2	2.019	
Sand	−0.315	−0.676	−0.407	0.315	0.062	−0.005	0.113	2	1.866	
TN	0.497	0.671	−0.320	−0.062	0.150	0.285	0.203	2	2.008	
AvP	0.006	−0.618	0.432	−0.139	0.366	0.299	0.119	2	1.666	

Table 4. *Cont.*

Indicators	Component							Group	Norm	Included
	1	2	3	4	5	6	7			
SWC	−0.441	0.498	0.237	0.424	0.183	−0.331	−0.155	6	1.794	Yes
Cu	0.031	0.044	0.739	0.390	−0.249	0.211	0.118	3	1.635	Yes
Hg	0.285	0.056	0.580	−0.427	0.227	−0.209	−0.128	3	1.568	
pH	−0.324	0.435	0.542	−0.254	−0.203	0.073	0.177	3	1.689	Yes
Avk	0.088	−0.075	0.474	−0.348	0.399	0.421	−0.121	6	1.345	
BD	−0.167	−0.340	−0.457	0.138	−0.234	0.247	−0.326	6	1.341	
Clay	−0.300	0.420	0.388	−0.615	0.036	0.090	0.028	4	1.720	Yes
Zn	0.428	0.316	0.440	0.489	−0.285	0.222	−0.091	6	1.784	Yes
EC	−0.553	0.148	0.094	0.443	0.564	0.158	−0.143	1	1.799	
WSSC	−0.553	0.148	0.094	0.443	0.564	0.158	−0.143	1	1.799	
CEC	−0.368	−0.048	−0.017	−0.366	0.270	0.034	0.572	5	1.314	Yes

ESLT= effective soil layer thickness; BD = bulk density; SWC = soil water content; EC = electrical conductivity; WSSC = water-soluble salt content; SOM = soil organic matter; TN = total nitrogen; TC = total carbon; TK = total potassium; TP = total phosphorus; AvP = available phosphorus; AvK = available potassium; CEC = cation exchange capacity.

The correlation analysis of eight indicators in the MDS (Table 5) showed that the correlation coefficients among all of the indicators were less than 0.5, indicating a weak correlation. The MDS reduced data redundancy and could better replace the full data set to evaluate the topsoil quality in the study area.

Table 5. Correlation coefficients of MDS indicators.

	pH	SWC	Clay	SOM	TK	CEC	Cu	Zn
pH	1.000	0.360	0.464	−0.129	0.483	0.328	0.427	0.124
SWC	0.360	1.000	0.187	−0.003	0.244	0.169	0.238	0.115
Clay	0.464	0.187	1.000	−0.062	0.391	0.322	0.070	−0.113
SOM	−0.129	−0.003	−0.062	1.000	0.412	−0.197	−0.197	0.295
TK	0.483	0.244	0.391	0.412	1.000	0.335	0.306	−0.256
CEC	0.328	0.169	0.322	−0.197	0.335	1.000	0.015	−0.251
Cu	0.427	0.238	0.070	−0.197	0.306	0.015	1.000	0.470
Zn	0.124	0.115	−0.113	0.295	−0.256	−0.251	0.470	1.000

SWC = soil water content; SOM = soil organic matter; TK = total potassium; CEC = cation exchange capacity.

3.2. Spatial Interpolation Analysis

Since the indicator data quantity of the sampling points could not replace the entire data, interpolation analysis was carried out on the graded data of the entirety of Tieling County, and the total number of map spots was 29,677. The interpolation results for all the MDS indicators are shown in Figure 2. As Figure 2 shows, the spatial distribution of indicators in the MDS is inconsistent. The overall distribution trends of pH, SWC, TK, and CEC are high in the western plain, low in the eastern mountains and hills, and at their highest in the southern part of the clay. The content of the remaining areas increases gradually from east to west. The content of SOM in the eastern parts is the highest, and in the central parts, it is low, and the distribution of the other areas is relatively uniform; the content of Cu is the highest in the central parts, and the content of Zn is highest in the central and eastern parts. All of the spatial distribution features are related to slope, soil type, and human activities. Due to the large slope in the eastern hilly area and the infiltration of rain, the content of SWC is low. At the same time, as the slope increases, it is easy for the soil particles to migrate downslope, so the content of clay is less in the eastern parts. In the middle of the study area, the sandy soil is not conducive to SOM accumulation, while the loam and clay areas have relatively high SOM.

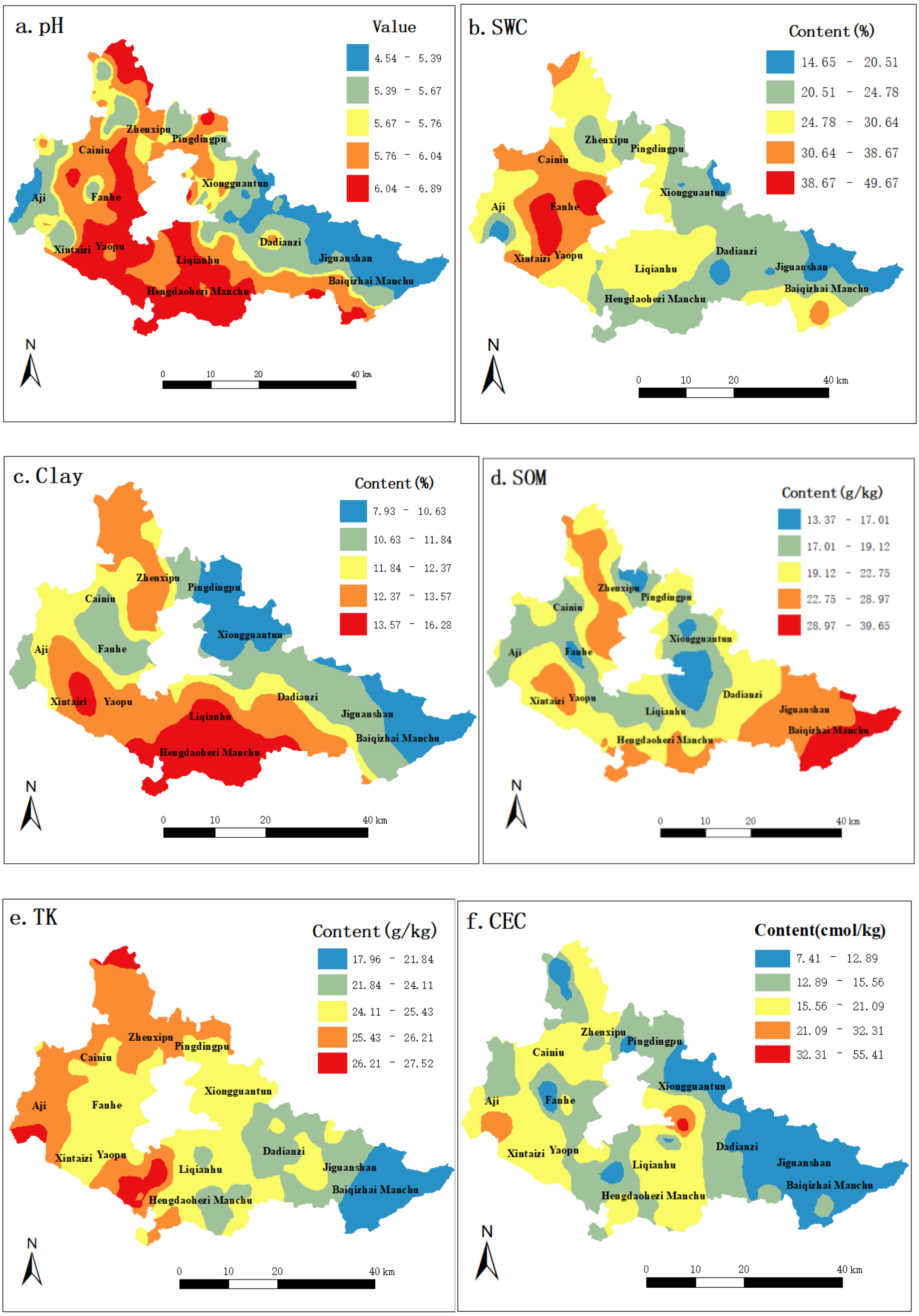

Figure 2. *Cont.*

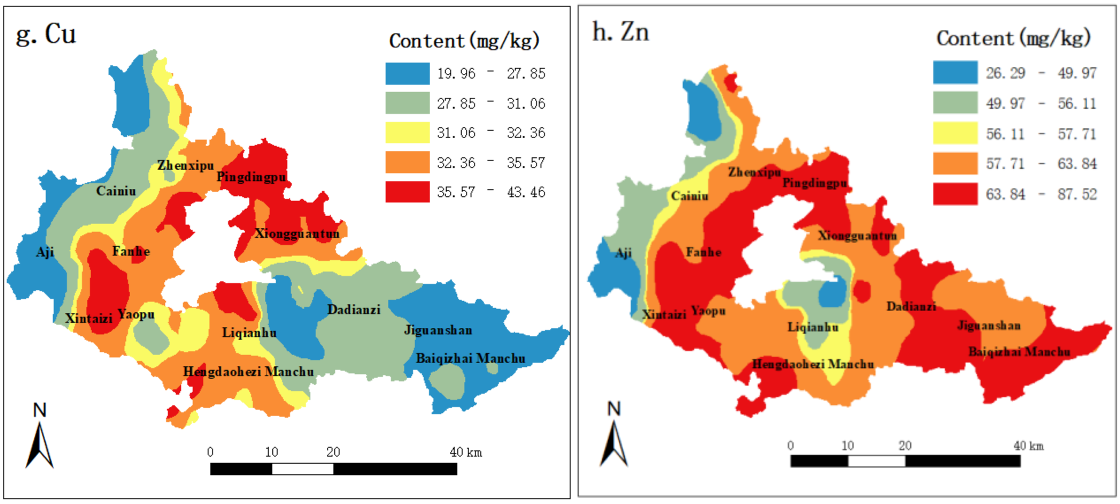

Figure 2. Interpolation result for the indicators. **Note:** SWC = soil water content; SOM = soil organic matter; TK = total potassium; CEC = cation exchange capacity; Cu = copper; Zn = zinc.

3.3. Soil Quality Evaluation Based on MDS

The weight of indicators in the MDS was calculated according to the variance of common factors (Table 6). The soil quality index of Tieling County was calculated according to the membership value and weight of each indicator (Table 7). The range of soil quality index scores of each evaluation unit was 0.395–0.677, with an average value of 0.518. Based on the ArcGIS-natural breakpoint method, soil quality was classified into I–V levels; the I-level soil quality was the best, V-level soil quality was the worst, and the spatial distribution map of soil quality based on the MDS was created (Figure 3).

Table 6. Weights of soil indicators in the Minimum data set.

Indicator	Common Factor Variance	Weight
TK	0.849	0.119
Clay	0.808	0.114
Zn	0.858	0.121
SOM	0.977	0.137
SWC	0.847	0.119
CEC	0.526	0.074
PH	0.73	0.103
Cu	0.809	0.114
Total	7.113	1

SWC = soil water content; SOM = soil organic matter; TK = total potassium; CEC = cation exchange capacity; Cu = copper; Zn = zinc.

Table 7. Soil quality index distribution.

SQI	Grade	Area (km^2)	Proportion (%)
0.589–0.677	I	141.31	17.0
0.539–0.589	II	245.11	28.5
0.503–0.539	III	224.96	26.3
0.462–0.503	IV	166.49	18.6
0.395–0.462	V	71.48	9.6

SQI = soil quality Index.

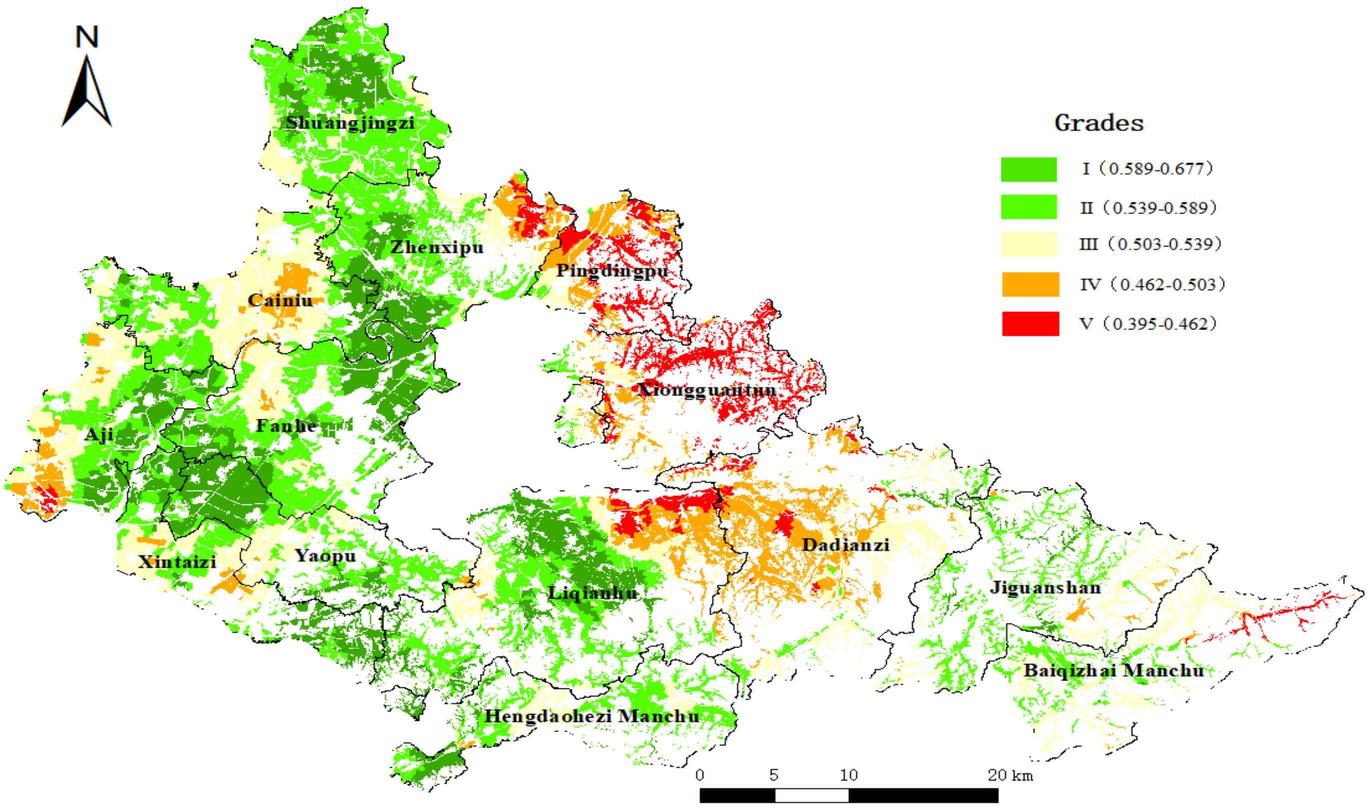

Figure 3. Spatial distribution of the soil quality.

It can be seen from Figure 3 that the spatial distribution of the soil quality in the study area has a strong regularity. In general, the soil quality in the northwest of the study area was better than that in the southeast, and the main grades were grades II and III. The soil quality gradually increased from the hilly area to the plain area, which was consistent with the field survey results, indicating that the results were reliable and that the indicators in the constructed MDS had certain applicability for soil quality evaluation in the study area. According to the statistical analysis, the proportion of soil mass area of each grade in the study area was as follows: Grade II (28.5%) > Grade III (26.3%) > Grade IV (18.6%) > Grade I (17.0%) > Grade V (9.6%). The I-level SQI is between 0.589 and 0.677, covering an area of 184.72 km^2. The I-level land has the highest quality, mainly distributed in the western and central parts of the plain. The average SOM in the I-level land is 34.66 g kg^{-1}, and the content is high, which is the dominant factor. The average CEC is 33.16 cmol kg^{-1}, the content is high, and the pH is neutral, which is suitable for crop growth. The comprehensive indicator characteristics of these places are better, so the topsoil quality is high. The II-level soil quality index is distributed between 0.539 and 0.589, with an area of 309.60 km^2, accounting for the largest proportion. It is mainly distributed in the western and central areas and is mostly clustered around the I-level area. The SOM content in the II-level area is high, but it is lower than that in the I-level area, with an average value of 28.36 g kg^{-1}. The CEC content is high, the indicator is better, and the average value is 39.37 coml kg^{-1}. The Cu content is lower, the Zn content is high, which is the main limiting factor. The pH is neutral, and the topsoil quality is high. The III-level soil quality index is between 0.503–0.539 and covers an area of 285.37 km^2. Most of the soil is distributed in the northwest and southern parts of the plain in massive form, and some parts of the soil are distributed in the eastern hilly area. Clay and TK are the main influencing factors in the soil. The content of Clay and TK is high, the content of SOM is not high, and the content of Cu and Zn is a little high. The three are the main limiting factors, which lead to the high quality of the topsoil. The level IV soil quality index ranges from 0.462 to 0.503, covering an area of 202.40 km^2, mainly distributed in the east-central region, that is, near the junction of the plain and hills. The content of Clay and SOM in the level IV area is less, which is the main limiting factor. The content of TK and CEC is more, but the content of Cu and Zn is more, and the two are the main influencing factors. On the whole, the quality of topsoil is relatively poor. The V-level soil quality index is distributed in the range of 0.395–0.462, with an area of 104.52 km^2. It is mainly distributed in the eastern hilly area with poor geographical conditions, such as Baiqizhai Manzu Township. The content of Cu and Zn in this area is high, which is the dominant factor, and the content of SOM, Clay, TK and CEC is low, which is the main limiting factor, so the topsoil quality is poor.

4. Discussion

In contrast to Figures 2 and 3, it can be deduced that the distribution pattern of topsoil quality for pH, SWC, TK, and SOM is "high in the northwest and low in the southeast", as can also be seen from Table 6. This is because these four indicators have a high weight. The pH content is higher in the western and central parts, which is neutral and conducive to soil microbial activity and crop growth, so the soil quality is higher. The other regions have more acidic or alkaline soil, so the soil quality also decreases to different degrees. The influence of SWC, TK, and SOM content on soil quality is like that of pH, and their contents result in higher soil quality. The high Cu and Zn contents in the eastern part of the study area have a negative effect on soil quality, and the low SOM content has a small effect on the improvement of soil quality, so the soil quality is poor. However, in the western parts, low Zn, Cu and high SWC, CEC, TK, and neutral pH are conducive to the improvement of SOM and soil evolution, and thus the soil quality is higher. From the perspective of a single indicator, its influence on soil quality is apparent. However, for a given land unit, it is affected by multiple indicators. For example, even if the SOM content is high in that land unit, if the SWC is low and Cu and Zn contents are high, the overall quality of that land unit is not necessarily high.

When the spatial distribution of the contents of the indicators is combined with different cultivated land types in the statistical analysis (Table 8), the area of dryland is the largest, 849.43 km^2, accounting for more than 78%, and its average soil quality is the highest, followed by the paddy field and the irrigated land. As can be observed, dry land is primarily used for agriculture in the study region, followed by paddy fields. In the dryland, the paddy field, and the irrigated land, the proportion of excellent land (grade III and above) was close. They all exceeded 70%, and the distribution of the three types was the highest in grade II and the lowest in grade V, which was the same as with the overall soil quality distribution—indicating that the land use structure of different land types in the study area was reasonable and the overall quality was good. For example, Fayez Raiesi obtained important indicators for arid and semi-arid land by studying soil quality in different land types and environments and quantified land use conversion effects on soil quality [43].

In this study, the SQI was used to characterize topsoil quality in Tieling County, and the MDS was constructed by comprehensive means such as PCA, correlation analysis, and Norm value. There were 26 primary indicators in total. After MDS screening, the soil quality evaluation system in the study area was composed of eight indicators: TK, clay, Zn, SOM, SWC, CEC, pH, and Cu, and the filtering rate of the indicators reached more than 60%. Before, the comprehensive weighted index method was used to cover all the factors, but there were too many factors, and the results were redundant and complicated. The MDS system established in this study was simple and practical, with accurate characterization and easy application, but judging by its results, a lack of soil bulk density and effective soil layer thickness, which were selected frequently, were not included in the MDS. From the perspective of the construction of the system, soil bulk density was grouped with SWC and Zn in the screening process of MDS indicators. However, the Norm value of SWC was the largest and highly correlated with other indicators in the group, so the soil BD did not enter the MDS; similarly, the effective soil layer thickness did not enter the MDS. From the perspective of data analysis, the range of BD in the study area was 0.95 to 1.58 g cm^{-3}, the mean value was 1.25 g cm^{-3}, the standard deviation was 0.11, and the coefficient of variation was 0.09, indicating that the BD data were relatively centralized and had little change, and could not be used as a key indicator to distinguish the soil quality of each unit. The same was true for the thickness of the effective soil layer. Therefore, the construction of the MDS should be combined with the region, research scale, and local land use status. The MDS is constructed by soil quality evaluation in different regions and different scales is different [44].

Compared with other county-scale topsoil quality evaluations, this study also has some advantages. First, previous studies mostly used full data to evaluate the soil in the study area in question, and the evaluation process in such studies was complicated and laborious. In this study, the full data were screened and filtered, and the MDS was constructed through PCA to evaluate the soil quality, simplify the indicator system, and streamline the evaluation process [45]. Secondly, the membership function is used in this study to transform the indicator value uniformly, which is convenient for the accurate calculation of the SQI. However, there are also some shortcomings in this study. One is that the indicator system only uses natural indicators but not site indicators [46], so it is impossible to analyze the impact of site characteristics on topsoil quality in the study area. Another problem is that the study area was not analyzed on a time scale, and it is impossible to know the long-term changes of various indicators and their effects on soil quality [47]. Therefore, we will strengthen the research on these two aspects in the future to build a more complete MDS system.

Table 8. Distribution of soil mass in different soils.

Classification		I	II	III	IV	V	Total
Dry land	Area (km^2)	141.31	245.11	224.96	166.49	71.48	849.43
	Proportion (%)	16.64	28.86	26.48	19.60	8.41	100
Paddy field	Area (km^2)	40.25	58.91	55.96	33.83	29.94	218.89
	Proportion (%)	18.39	26.91	25.57	15.46	13.68	100
Irrigable land	Area (km^2)	3.16	5.59	4.44	2.08	3.10	18.38
	Proportion (%)	17.22	30.40	24.18	11.32	16.88	100
Total	Area (km^2)	184.72	309.60	285.37	202.40	104.52	1086.61
	Proportion (%)	17.00	28.49	26.26	18.63	9.62	100

5. Conclusions

In this study, eight indicators, including TK, clay, Zn, SOM, SWC, CEC, pH, and Cu, were selected from 26 indicators to form the soil quality indicator system of Tieling County. By using the MDS method, the MDS indicators can replace all the primary indicators to evaluate soil quality in Tieling County. The soil quality index in Tieling County ranges from 0.395 to 0.677, with an average value of 0.518. Based on the ArcGIS-natural breakpoint method, the soil quality was classified into I-V grades, with the I grade having the best soil quality and the V grade having the worst soil quality. Evidently, the soil quality in Tieling County demonstrated a conspicuous spatial pattern of decreasing from west to east, concomitant with a gradual enhancement transformed from hilly areas to plain regions. The main grades of soil quality were II (28.5%) and III (26.3%), and the V area was the smallest, accounting for 9.6%. The spatial distribution of the soil quality is similar to the results of previous studies. However, there are still some limitations in this study, such as the absence of site indicators in the indicator system and the lack of evaluation studies on a time scale.

The results of this study reveal the need for accurate monitoring of soil quality. Continuous anthropogenic influences and environmental changes can lead to continuous soil quality degradation and affect the implementation of soil remediation measures. For example, especially near farmland with good quality, the establishment of factories should be reduced. Meanwhile, attention should be paid to the maintenance of soil texture, reducing pollutant content, and avoiding nutrient loss. Moreover, the soil quality requires persistent monitoring. The assessment indicators ought to be upgraded dynamically, adapting to indigenous scenarios. Both temporal variations and spatial heterogeneity deserve substantial attention to construct a foundation for enacting conservative strategies.

Author Contributions: Conceptualization, H.G.; methodology, F.Q. and Y.Y.; software, F.Q.; validation, X.D. and F.Q.; formal analysis, Y.Y.; investigation, F.Q.; resources, H.G.; data curation, F.Q.; writing—review and editing, X.D. and Y.Y.; All authors have read and agreed to the published version of the manuscript.

Funding: National Natural Science Foundation of China (42077149), National Key R&D Program of China (2021YFD1500200).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are not publicly available.

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

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