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Soil Quality Variation under Different Land Use Types and Its Driving Factors in Beijing

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Abstract: With the advancement of urbanization, land resources are becoming increasingly strained, particularly for urban greening purposes. In this context, a large number of newly cultivated lands dominated by construction waste and backfill soil are emerging in cities. Assessing the soil quality of these newly cultivated lands and achieving their rational utilization accurately and quantitatively has become an urgent issue. In this study, soil samples of five land use types, namely newly cultivated land (NCL, control), adjacent cropland (CL), arbor–shrub mixed forest (ASF), arbor forest (AF), and shrubland (SL) were selected around Beijing, China. ASF, AF, and SL are also newly cultivated lands composed of construction waste and backfill before greening. Based on principal component analysis (PCA), a total data set (TDS) and a minimum data set (MDS) were used to construct the soil quality index (SQI) model. Soil quality indicators covering the physical and chemical characteristics of the soil and their relationships with land use types were studied with the Partial Least Squares Path Model (PLS-PM). The results were summarized as follows: (1) The soil quality index under different land use types in the Beijing plain area were in the order of arbor–shrub mixed forest (ASF) > arbor forest (AF) > shrubland (SL) > cropland (CL) > newly cultivated land (NCL). (2) Soil organic carbon (SOC), soil water content (SWC), maximum water-holding capacity (MWHC), capillary water-holding capacity (CWHC), Pb, and Cd were identified as the MDS. The MDS of the soil quality assessment model showed a linear relationship with the TDS ($y = 0.946x + 0.050$, $R^2 = 0.51$). (3) Land use types have an indirect impact on soil quality by changing the content of Pb. The chemical indicators' coefficient (0.602) contributed more to the SQI than did the physical indicators' (0.259) and heavy metal elements' (−0.234). In general, afforestation and agricultural production could improve the newly cultivated lands' soil quality, but afforestation is much better than agricultural production. These results will help to evaluate the SQI in the Beijing plain area objectively and accurately, and they have significant implications for soil restoration and management.

Keywords: soil quality index; land use types; PLS-PM; soil physicochemical property; heavy metal

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1. Introduction

Soil is an important carrier and the major source of nutrients for plant growth. Soil is also a critical factor to support ecosystem biodiversity, structure, and function [1]. Soil quality is defined as the capacity of soil to sustain plant and animal productivity and maintain human and environment health in natural or human ecosystems [2,3]. Reasonable land use types have been considered as an effective method to improve soil structure, contributing to ensure crop yields and improve environmental quality [4]. Nevertheless, unreasonable land use types will degrade the soil and decrease the soil quality, lead to slow vegetation growth, and finally even vegetation death [5]. It is difficult to evaluate soil quality accurately. Numerous soil quality evaluation methods have been developed to comprehensively assess soil quality, such as the matter–element method and the grey correlation analysis method. Yu et al. evaluated the land eco-security of nine cities with the theory of entropy weight and the matter–element model [6]. Tang et al. evaluated the effects of land use type on soil characteristics by using grey correlation analysis [7]. The matter–element method has a relatively complicated calculation process, and the grey correlation analysis method is prone to lose information with discrete values of indicators. However, the soil quality index (SQI) is an effective approach which integrates multiple soil properties into a comprehensive index and is widely used to assess the impact of natural and anthropic factors on soil quality because of its flexibility and simplicity [8,9]. There are numerous factors that affect soil quality; thus, when evaluating soil quality, it is necessary to identify indicators that can truly and effectively reflect the soil conditions. [10]. Principal component analysis (PCA), reducing the complexity of the total data sets by reducing redundancy and improving the reliability and usefulness of the results, has become the most used method for selecting soil quality evaluation indicators.

With the expansion of cities and the increase in population, urban land resources are becoming increasingly strained, leading to more severe ecological security issues. Since 2012, in the plain area of Beijing, a lot of newly cultivated land containing construction waste and backfill has appeared in the urban and suburban areas, and afforestation projects have been implemented on this area, forming different land use types. These newly cultivated lands' soil has problems, such as unreasonable structure, nutrient deficiency, and heavy metal pollution [11]. Different land use types have a profound impact on soil and vegetation. Therefore, how to evaluate soil quality and rationally utilize it is an urgent problem to be solved at present. In most studies of soil quality assessment, the characteristics of soil quality have been emphasized, with attention being given to soil physical indicators, nutrient indicators, and microbial indicators [12]. It is reported that construction waste may cause heavy metal pollution in soil. Heavy metal pollution of urban soil has been a hot topic in recent research [13]. Wang et al. [14] stated that construction waste pollution in Beijing was at a moderate level, and the main pollution factors were Pb and Cd. Soil heavy metals, which are persistent, difficult to degrade, and easy to accumulate, will lead to the deterioration of soil environmental quality. In this paper, we choose soil samples of five different land use types in Fangshan District, Beijing for study, including newly cultivated land (NCL, control), adjacent cropland (CL), arbor–shrub mixed forest (ASF), arbor forest (AF), and shrubland (SL). ASF, AF, and SL are also newly cultivated lands composed of construction waste and backfill before greening. We measured 15 indicators, including physical, nutrient, and heavy metal elements. Principal component analysis was used to screen soil indexes, and the nonlinear scoring method was used to calculate soil quality. The main objectives of this study were to (1) compare the differences in soil properties among different land use types, (2) screen the soil quality evaluation indicators and establish a soil quality evaluation model based on the minimum data set to evaluate the soil quality of different land use types, and (3) analyze the relationship between soil quality, soil indicators, and land use types. The results are expected to provide a scientific basis and data support for quantitative land assessment and rational planning and utilization in the Beijing Plain and similar areas.

2. Materials and Methods

2.1. Study Area

The study was conducted at the southeast of Fangshan District (115°25′~116°15′ E and 39°30′~39°55′ N), Beijing, which is dominated by plains with an elevation of approximately 20–60 m (Figure 1). The region belongs to a continental monsoon climate with a mean annual temperature of 10–12 °C and a mean annual frost-free period of 202 days. The climate is characterized by four distinct seasons (spring, summer, autumn, and winter). The mean annual rainfall is approximately 587 mm, where about 85% falls from June to August. Fangshan District is rich in plant resources, with natural vegetation dominated by temperate deciduous broad-leaved forests, followed by temperate coniferous forests. The dominant greening tree species include *Populus* L., *Salix babylonica* L., *Ulmus pumila* L., *Styphnolobium japonicum* (L.) Schott, and *Larix gmelinii* (Rupr.) Kuzen. *Platycladus orientalis* (L.) Franco, and the main shrubs are *Vitex negundo* var. *heterophylla* (Franch.) Rehd. and *Ziziphus jujuba* var. spinosa (Bunge) Hu ex H.F.Chow. The soil type is classified as Anthrosols [15], and the average soil thickness is 60 cm.

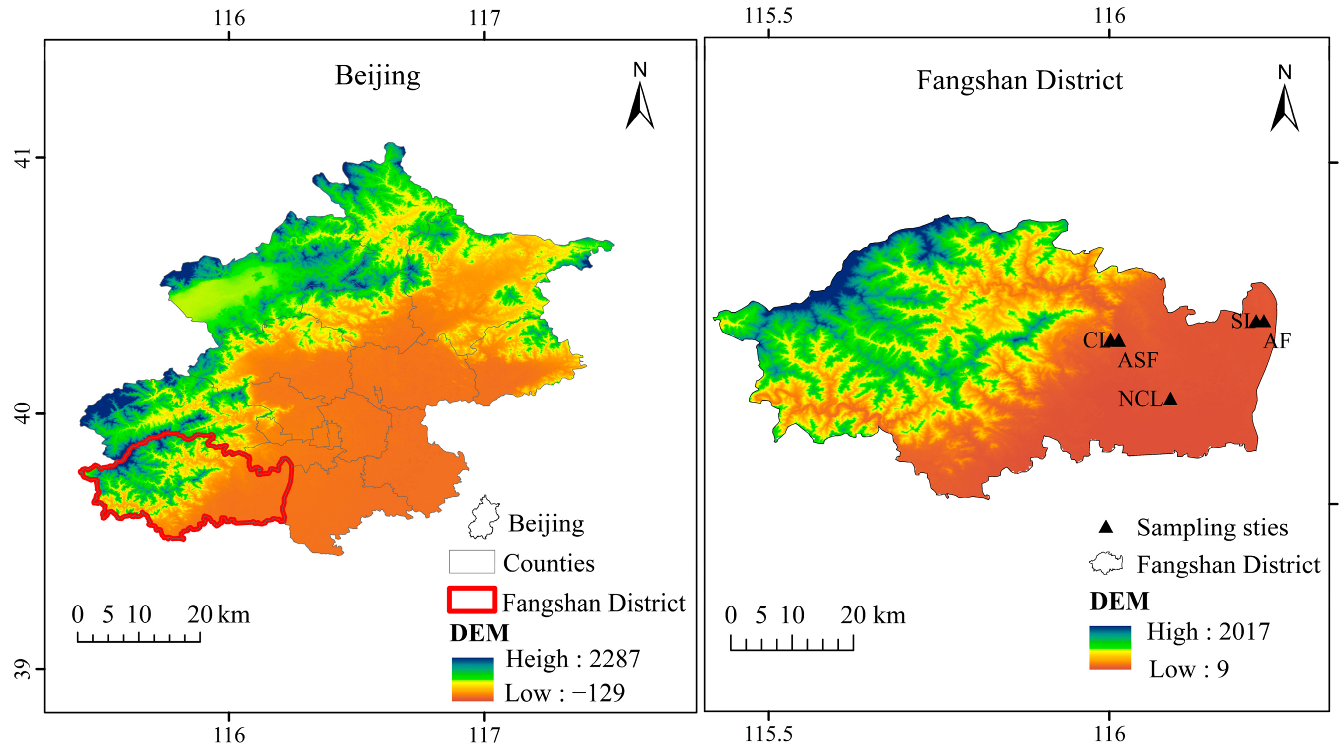

Figure 1. Location map of the study area.

2.2. Soil Sampling and Laboratory Analyses

Through comprehensive field research and investigation in the afforestation area of the Beijing Plain, we selected five different land use types in the plain area of Fangshan District, including newly cultivated land mainly composed of construction waste and backfill, as well as arbor–shrub mixed forest, arbor forest, and shrubland planted on the newly cultivated land, as well as nearby cropland (Table 1). An area of 20 m × 20 m was selected on each field plot for investigation and sampling. At each sampling spot, we excavated three soil profiles with a depth of 60 cm, which were divided into four layers vertically from the surface, namely 0–10 cm, 10–20 cm, 20–40 cm, and 40–60 cm. Soil samples were collected using the cutting-ring method. Three ring knife samples were taken from each layer for replication to determine the physical properties of the soil. Meanwhile, 500 g mixed soil samples were taken from the same soil layer, packed into the cloth bags, and taken back to the laboratory for wind drying to test the chemical characteristics and heavy metals.

Table 1. Basic information for each sampling site.

Land Use Types	Slope/(°)	Elevation/(m)	Main Plant Species	Coverage/(%)
Newly cultivated land (NCL)	0–5	40	*Eleusine indica* (L.) Gaertn., *Setaria viridis* (L.) Beauv., *Artemisia caruifolia* Buch.-Ham. ex Roxb.	10
Cropland (CL)	0–5	100	*Helianthus annuus* L., *Ipomoea batatas* (L.) Lam., *Artemisia argyi* H. Lév. & Vaniot, *Setaria viridis* (L.) Beauv., *Xanthium strumarium* L.	50
Arbor forest (AF)	0–5	50	*Populus tomentosa* Carrière, *Larix gmelinii* (Rupr.) Kuzen.	80
Shrubland (SL)	0–5	50	*Prunus mume* 'Meiren'	60
Arbor–shrub mixed forest (ASF)	0–5	90	*Populus tomentosa* Carrière, *Larix gmelinii* (Rupr.) Kuzen., *Vitex negundo* var. *heterophylla* (Franch.) Rehd.	90

The detailed methods for measuring and analyzing soil indicators are shown in Table 2 [16–18].

Table 2. Soil indicators measurement.

Soil Indicators	Measurement Methods
Soil water content (SWC)	The drying method (oven-drying method (105 °C, 12 h))
Soil bulk density (BD) Maximum water-holding capacity (MWHC), capillary water-holding capacity (CWHC), capillary porosity (CP), non-capillary porosity (NCP)	The ring knife method
Soil organic carbon content (SOC)	The potassium dichromate oxidation method
Soil total nitrogen (TN)	Kjeldahl method
Soil total phosphorus (TP)	NaOH melting-molybdenum antimony colorimetric method
pH	The PHS-3E meter (INESA, Shanghai, China) (the water–soil ratio was 2.5:1)
The metal elements (Cd, Cu, Pb, Fe, Zn)	Inductively coupled plasma–optical emission spectrometry (PRODIGY-XP, Leeman Labs, Hudson, USA) (RF power: 1150 W; cooling air flow: 1.0 L/min; injection cleaning time: 30 s; integration time: 30 s; flushing pump speed: 45 r/min; analyzing pump speed: 45 r/min)

2.3. Soil Quality Evaluation Methods

This study used the SQI method to evaluate the soil quality of different land use types in the Beijing plain afforestation area. The total data set and the minimum data set are used to identify appropriate indicators. One-way analysis of variance (ANOVA) was performed on the 15 indicators to assess the influence of different land uses on soil indicators. Only the indicators showing significant treatment differences ($p < 0.05$) were chosen as members of the total dataset [4]. The indicators of the minimum data set are screened out through principal component analysis of the standardized data matrix of the total dataset [4,19]. The calculation process of soil quality includes the following four steps: (1) identification of the minimum data set, (2) calculation of membership degrees, (3) determination of indicator weights, and (4) calculation of the SQI [19–21].

2.3.1. Identification of the Minimum Data Set (MDS)

To reduce redundancy and information overlap, this study established a minimum dataset to screen out the most representative indicators. Firstly, the loadings of each soil indicator on the principal components (PCs) with eigenvalues ≥ 1 are calculated, and the explained total variance is greater than 85%. For each PC, the indicators with loadings within 10% of the maximum weighted loading are retained to represent that PC. If multiple indicators are retained for a PC, the correlation between the indicators needs to be considered to determine whether they should be included in the minimum dataset. If the remaining indicators are positively correlated, the indicator with the highest correlation coefficient with the rest of the indicators is selected, otherwise, all indicators in that group are included in the minimum dataset [22].

The calculation formula for the norm value is as follows:

$$N_{ik} = \sqrt{\sum_i^k \left(U_{ik}^2 \lambda_k\right)} \tag{1}$$

where N_{ik} is the comprehensive loading of the i-th variable on the first k principal components with eigenvalues ≥ 1; U_{ik} is the loading of the i-th variable on the k-th principal component; and λ_k is the eigenvalue of the k-th principal component.

2.3.2. Calculation of Membership Degrees

The data are converted to values between 0 and 1 using a nonlinear scoring function method, where 1 represents a high level of the indicator and 0 represents a low level of the indicator.

According to the contribution of indicators to soil quality, they are divided into "more is better" and "less is better" types. The formula is as follows:

$$F(x) = \frac{1}{1 + (x/x_{max})^b} \tag{2}$$

where $F(x)$ is the nonlinear score of the indicator, x is the observed value of the indicator, and x_{max} is the average observed value of the indicator. b is the slope of the equation. For "more is better" type curves, b is -2.5, and for "less is better" type curves, b is 2.5.

2.3.3. Determination of Indicator Weights

In order to objectively evaluate soil quality, the weights of each soil indicator in this study are determined using PCA. First, the indicators are analyzed using PCA to obtain the common factor variance of each indicator. Then, the weight of each indicator is calculated by dividing its common factor variance by the sum of common factor variances of all indicators.

2.3.4. Calculation of the SQI

The calculation formula for the SQI is as follows:

$$SQI = \sum_{i=1}^n R_i \times F(x_i) \tag{3}$$

where R_i is the weight of the soil indicator, $F(x_i)$ is the membership degree of the soil indicator, and n is the number of soil indicators.

2.4. PLS-PM Method

The PLS-PM includes the measurement model and the structural models. The measurement model is used to define the latent variables. The structural model is used to reflect the relationship between the latent variables [23,24]. The formulas are as follows:

$$x = \Lambda_x \xi + \delta \tag{4}$$

$$y = \Lambda_y \eta + \varepsilon \tag{5}$$

where x represents exogenous indicators and y represents endogenous indicators. Λ_x and Λ_y are the matrix of factor loadings of ξ to x and η to y. δ and ε refer to the measurement error. The formula is as follows:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{6}$$

where η is the endogenous latent variable, ξ is the exogenous latent variable, B and Γ refer to the regression path coefficient of the effect between different η and the effect of ξ on η. ζ represents the regression residuals.

2.5. Statistical Analysis

The data were processed and calculated using Excel 2010. The statistical analysis of the data was performed using SPSS 26.0, including one-way analysis of variance and principal component analysis. The driving factors of soil quality differences were analyzed using SmartPLS 4 for PLS-PM analysis. The figures were plotted using Origin 2018.

3. Results

3.1. Changes in Measured Soil Indicators

Significant differences were found for all soil properties, except for noncapillary porosity (NCP). A total of 14 soil indicators were chosen as members of the total data set. Then, we used PCA to reduce redundant indexes of the SQI calculation, including four chemical indicators, five physical indicators and five trace element indicators.

As shown in Table 3, the NCL had a higher pH (8.04) and lower SOC (0.45 $g \cdot kg^{-1}$), TN (0.05 $g \cdot kg^{-1}$), and TP (0.18 $g \cdot kg^{-1}$) compared with those of the other four land use types, and showed a significant difference in TN. ASF was characterized by higher SOC (1.79 $g \cdot kg^{-1}$) and TN (0.23 $g \cdot kg^{-1}$) compared with those of the other land use types, and showed a significant difference in SOC, except for CL. For TP, CL was the highest (1.52) and had a significant difference with other land use types.

In terms of physical properties, NCL has the largest MWHC and CWHC among the five land use types, which are 38.98% and 31.29%, respectively, while its soil BD is the smallest (1.05 $g \cdot cm^{-3}$). The SWC of ASF (15.69%) is significantly higher than that of CL (11.67%), AF (8.46%), and SL (8.16%), but there is no significant difference between ASF and NCL (14.93%). AF has the largest CP (36.55%) without a significant difference from SL (36.01%) and ASF (33.63%). There is no significant difference in NCP among the five land use types.

ASF has significantly higher Cu (25.77 $mg \cdot kg^{-1}$) and Fe (26.70 $mg \cdot kg^{-1}$) contents than NCL, AF, and SL, but there is no significant difference between ASF and CL. CL has significantly higher Cd (0.05 $mg \cdot kg^{-1}$) and Pb (19.53 $mg \cdot kg^{-1}$) contents than the other four land use types, which are approximately five times and 1.2–1.8 times higher, respectively. CL's Zn (106.28 $mg \cdot kg^{-1}$) content is about 1.7 times higher than AF and SL, but there is no significant difference between CL and NCL (94.32 $mg \cdot kg^{-1}$) or ASF (104.73 $mg \cdot kg^{-1}$).

Table 3. The statistical features of soil indicators under different restoration modes.

Soil Index	Land Use Types														
	NCL			**CL**			**AF**			**SL**			**ASF**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
SOC ($g\cdot kg^{-1}$)	0.45 ± 0.09b	0.10	0.96	1.18 ± 0.32ab	0.33	2.98	0.91 ± 0.23b	0.32	2.18	0.62 ± 0.13b	0.25	1.37	1.79 ± 0.42a	0.33	3.38
pH	8.04 ± 0.03a	7.86	8.17	7.26 ± 0.09c	6.90	7.74	7.90 ± 0.04a	7.71	8.09	7.61 ± 0.09b	7.08	7.90	7.34 ± 0.15c	6.78	8.09
TN ($g\cdot kg^{-1}$)	0.05 ± 0.02b	0.01	0.19	0.20 ± 0.04a	0.08	0.42	0.15 ± 0.03a	0.04	0.32	0.15 ± 0.02a	0.09	0.25	0.23 ± 0.05a	0.08	0.50
TP ($g\cdot kg^{-1}$)	0.18 ± 0.06b	0.02	0.52	1.52 ± 0.52a	0.14	4.62	0.37 ± 0.06b	0.18	0.69	0.72 ± 0.03b	0.56	0.83	0.79 ± 0.10b	0.36	1.23
SWC (%)	14.93 ± 0.42a	12.84	18.59	11.67 ± 0.34b	10.42	13.96	8.46 ± 0.69c	4.62	12.28	8.16 ± 0.67c	4.92	12.67	15.69 ± 0.37a	12.89	17.00
BD ($g\cdot cm^{-3}$)	1.05 ± 0.02d	0.97	1.16	1.51 ± 0.05a	1.27	1.78	1.36 ± 0.02b	1.23	1.46	1.26 ± 0.02c	1.18	1.38	1.24 ± 0.03c	1.10	1.41
MWHC (%)	38.98 ± 0.32a	37.14	40.91	26.17 ± 1.65c	18.71	36.25	31.82 ± 0.87b	27.37	37.22	33.60 ± 1.03b	28.76	38.86	33.19 ± 1.16b	26.39	40.62
CWHC (%)	31.29 ± 0.35a	29.12	33.72	21.60 ± 1.44c	16.34	32.68	27.00 ± 0.74b	24.01	31.50	28.63 ± 1.39ab	22.03	37.70	27.37 ± 1.01b	20.99	34.55
CP (%)	32.71 ± 0.64bc	28.29	36.20	32.13 ± 1.46c	24.75	44.69	36.55 ± 0.93a	32.64	42.70	36.01 ± 1.49ab	27.77	44.52	33.63 ± 0.92abc	28.17	38.18
NCP (%)	8.05 ± 0.36a	5.08	9.53	6.65 ± 1.12a	1.47	13.30	6.43 ± 1.04a	1.34	11.69	6.30 ± 0.93a	1.36	11.59	7.07 ± 1.04a	0.88	13.96
Cd ($mg\cdot kg^{-1}$)	0.01 ± 0.00b	0.01	0.01	0.05 ± 0.02a	0.01	0.15	0.01 ± 0.00b	0.01	0.02	0.01 ± 0.00b	0.01	0.02	0.01 ± 0.00b	0.01	0.02
Cu ($mg\cdot kg^{-1}$)	10.90 ± 1.07b	5.33	14.88	23.61 ± 1.68a	15.65	30.20	8.15 ± 0.23b	6.88	8.88	8.20 ± 0.49b	6.63	10.60	25.78 ± 0.55a	22.90	27.90
Fe ($mg\cdot kg^{-1}$)	13.32 ± 0.29c	12.04	14.77	24.68 ± 2.00a	19.64	36.05	16.90 ± 0.79b	12.48	19.25	17.22 ± 0.19b	16.56	18.28	26.70 ± 0.47a	24.10	28.25
Pb ($mg\cdot kg^{-1}$)	10.95 ± 0.12d	10.35	11.28	19.53 ± 1.09a	16.18	25.63	10.87 ± 0.08d	10.58	11.30	12.60 ± 0.56c	11.20	15.75	16.80 ± 0.38b	14.68	17.85
Zn ($mg\cdot kg^{-1}$)	94.32 ± 3.11a	83.10	110.58	106.28 ± 9.49a	66.00	152.33	59.46 ± 2.32b	47.70	69.00	63.02 ± 3.06b	55.15	80.38	104.73 ± 3.82a	89.70	134.68

Notes: Different lowercase letters indicate significant differences among different land use types (one-way ANOVA, $p < 0.05$).

3.2. Selecting MDS Indicators

As shown in Table 4, the first four PCs had eigenvalues > 1.0 and explained >86.65% of the variance of the original data (Table 4). The first PC explained 36.39% of the total variance. The highest loading value is Pb. Cu had a loading value within 10% of the highest loading value. Pb and Cu were significantly ($p < 0.01$) correlated with each other (Table 5). Therefore, only Pb was selected as the indicator of PC1. The second PC explained 26.15% of the total variance and met the selection requirements in four indicators, which were SOC, N, MWHC, and CWHC. SOC had the highest loading value. SOC and TN were significantly ($p < 0.01$) correlated with each other, but TN was not chosen. However, the correlations among MWHC, CWHC, and SOC were insignificant, these two indicators were kept in the MDS as the indicator of PC2. The third PC explained 15.62% of the total variance. Only SWC was retained as the indicator of PC3. Similarly, only Cd was reserved as the indicator of PC4. The final indicators of SQI determined by PCA are Pb, SOC, MWHC, CWHC, SWC, and Cd.

Table 4. Results of principal component analysis of the TDS.

Soil Indicators	PC1	PC2	PC3	PC4	Communalities
SOC	0.47	<u>0.75</u>	−0.06	−0.29	0.92
pH	−0.70	−0.39	0.14	0.38	0.87
TN	0.47	0.71	−0.26	−0.30	0.93
TP	0.44	0.48	−0.47	0.57	0.97
SWC	0.27	0.42	<u>0.78</u>	0.11	0.89
BD	0.54	−0.60	−0.51	−0.14	0.95
MWHC	−0.55	<u>0.72</u>	0.34	0.08	0.94
CP	−0.27	0.50	−0.46	−0.31	0.98
CWHC	−0.56	<u>0.74</u>	0.14	−0.13	0.98
Cd	0.35	0.53	−0.47	<u>0.59</u>	0.97
Cu	0.90	0.10	0.29	0.12	0.96
Fe	0.83	−0.27	0.13	−0.08	0.88
Pb	<u>0.93</u>	−0.11	0.09	−0.11	0.92
Zn	0.63	0.04	0.59	0.13	0.77
Eigenvalue	5.09	3.66	2.19	1.19	
Variance (%)	36.39	26.15	15.62	8.50	
Cumulative variance (%)	36.39	62.53	78.15	86.65	

Notes: Red highlighting factor loading values are considered highly weighted. Red highlighting and underlined loading values correspond to the soil indicators included in the MDS.

Table 5. Correlation matrix for the TDS.

	SOC	pH	TN	TP	SWC	BD	MWHC	CWHC	CP	Cd	Cu	Fe	Pb	Zn
SOC	1													
pH	−0.66 **	1												
TN	0.84 **	−0.74 **	1											
TP	0.15	−0.31 *	0.38**	1										
SWC	0.25	−0.07	0.08	−0.12	1									
BD	−0.07	−0.30 *	0.05	0.26 *	−0.52 **	1								
MWHC	0.13	0.27 *	0.00	−0.26 *	0.46 **	−0.91 **	1							
CWHC	0.16	0.20	0.08	−0.26 *	0.33 *	−0.75 **	0.84 **	1						
CP	0.19	−0.05	0.29 *	0.14	−0.16	−0.01	0.23	0.59 **	1					
Cd	0.27 *	−0.02	0.23	0.48 **	−0.18	0.06	0.05	−0.04	0.09	1				
Cu	0.48 **	−0.50 **	0.34 **	0.13	0.56 **	0.16	−0.20	−0.26 *	−0.28 *	0.11	1			
Fe	0.29 *	−0.50 **	0.30 *	0.35 **	0.20	0.50 **	−0.52 **	−0.52 **	−0.18	0.09	0.78 **	1		
Pb	0.40 **	−0.77 **	0.47 **	0.28 *	0.23	0.33 **	−0.37 **	−0.35 **	−0.21	0.00	0.79 **	0.81 **	1	
Zn	0.22	−0.21	0.04	0.02	0.69 **	−0.09	−0.04	−0.12	−0.36 **	−0.23	0.72 **	0.48 **	0.51 **	1

Notes: ** Correlation is significant at $p < 0.01$ level. * Correlation is significant at $p < 0.05$ level.

3.3. Soil Quality Index under Different Land Uses

We used the nonlinear scoring methods to transform the soil indicators in the TDS and MDS. The parameters of nonlinear equations, and the weights for the selected indicators, are shown in Table 6. Finally, the comparative SQI can be described as follows:

$$\text{SQI-NLT} = 0.072 \times \text{C} + 0.067 \times \text{pH} + 0.072 \times \text{N} + 0.080 \times \text{P} + 0.071 \times \text{SWC} + 0.077 \times \text{BD} + 0.077 \times \text{MWHC} + 0.052 \times \text{CP} + 0.073 \times \text{CWHC} + 0.080 \times \text{Cd} + 0.076 \times \text{Cu} + 0.065 \times \text{Fe} + 0.075 \times \text{Pb} + 0.063 \times \text{Zn}$$

$$\text{SQI-NLM} = 0.170 \times \text{C} + 0.168 \times \text{SWC} + 0.159 \times \text{MWHC} + 0.166 \times \text{CWHC} + 0.169 \times \text{Cd} + 0.168 \times \text{Pb}$$

Table 6. The parameters and weights in the TDS and MDS.

Indicators	Mean	Slope	Weight 1	Weight 2
SOC	0.99	−2.50	0.072	0.170
pH	7.63	2.50	0.067	
TN	0.16	−2.50	0.072	
TP	0.72	−2.50	0.080	
SWC	10.89	−2.50	0.071	0.168
BD	0.12	2.50	0.077	
MWHC	1.28	−2.50	0.077	0.159
CP	0.33	−2.50	0.052	
CWHC	0.34	−2.50	0.073	0.166
Cd	0.07	2.50	0.080	0.169
Cu	0.41	−2.50	0.076	
Fe	0.27	−2.50	0.065	
Pb	0.02	2.50	0.075	0.168
Zn	15.32	−2.50	0.063	

As shown in Table 7, the differences in soil quality among different land use types calculated based on the TDS and the MDS are similar. The order of SQI values from high to low for the five land use types is as follows: ASF > AF > SL > CL > NRL. The SQI values of the other four land use types are both higher than that of NCL, indicating that compared to NCL, both afforestation and agricultural production can improve soil quality.

Table 7. The soil quality evaluation results.

Restoration Pattern	TDS	MDS
NCL	0.466	0.485
CL	0.485	0.510
AF	0.493	0.519
SL	0.488	0.515
ASF	0.503	0.527

As shown in Figure 2, the linear fitting of the MDA and the TDS gives a fitted equation of y = 0.946x + 0.050 with $R^2 = 0.51$, indicating a significant positive correlation between the two methods.

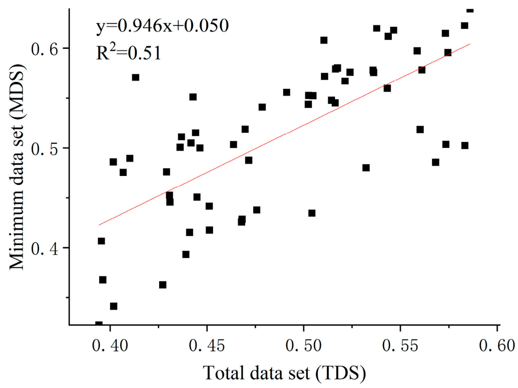

Figure 2. Linear fitting of soil quality.

3.4. Analysis of Driving Factors of Soil Quality under Different Land Uses

To illustrate the relationship between soil quality and soil physicochemical factors and heavy metal elements under different land use types, a Partial Least Squares Path Model (PLS-PM) was constructed (Figure 3). Chemical indexes (SOC, TP), physical indexes (CP, MWHC), and Pb were the key factors contributing to changes in soil quality under different land use types. The meanings of parameters in the model are shown in Table 8 [25–27]. The results of the VIF test, the reliability and validity of the model, and the loadings for each of the manifest factors are shown in Table 9. The path validity tests of the model are shown in Figure 3.

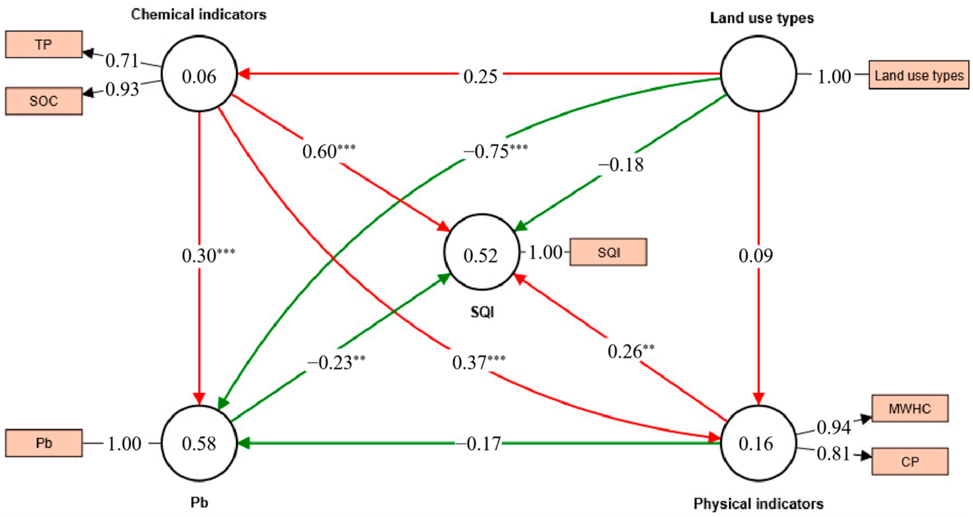

Figure 3. Path model (PM) analysis and validity of the effects of chemical indicators, physical indicators, Pb, and land use types on the soil quality index (SQI). Red arrows indicate negative effects and green arrows represent positive effects. Numbers adjacent to arrows are path coefficients (p-values) indicating the effect size of the relationship. **, and *** represent $0.01 < p < 0.05$, and $p < 0.01$, respectively.

Table 8. The meanings of parameters in PLS-PM.

Parameters	**Meanings**
Variance inflation factor (VIF)	Measure the severity of multicollinearity
Reliability and validity	Validate the accuracy of the PLS-PM results
Composite reliability (CR, not <0.6)	Evaluate the reliability of internal coherence
Extracted average variance (AVE > 0.5)	Verify the convergence validity

Table 9. Modeling (PLS-PM) of the variance inflation factor (VIF) of each indicator and the PLS-PM reliability and validity evaluations.

Driving Factors	**Soil Indicators**	**Variance Inflation Factor (VIF)**	**Outer Loadings**	**Cronbach's Alpha**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Chemical indicators	SOC	1.19	0.93	0.57	0.73	0.69
	TP	1.19	0.71			
Physical indicators	CP	1.46	0.81	0.72	0.85	0.77
	MWHC	1.46	0.94			
Pb		1	1	/	/	/
Land use types		1	1	/	/	/
SQI		1	1	/	/	/

Notes: "/" is meaningless.

In the PM, the path coefficients of SQI with different land use types, chemical indexes, physical indexes, and Pb were −0.18, 0.60, 0.26, and −0.23, respectively.

4. Discussion

4.1. Soil Indicators under Different Land Use Types

Vegetation has a profound influence on soil physicochemical properties [28]. In this study, the soil chemical properties of NCL, which served as a control, were obviously lower than the other four land use types. These results confirmed that vegetation affects soil parameters significantly, which is consistent with the conclusions of a previous study by Wu et al. [29]. The highest SOC and TN contents were found in ASF, which indicated that ASF had a more significant effect on improving soil chemical properties. The cover on land or incorporation of plant litter within the top-soil layer is a major source of soil organic matter. Litter is transformed into humus through microbial decomposition and a slow decomposition process, which can be stably preserved in soil for a long time to maintain carbon storage [30]. In addition, less tillage can reduce the decomposition rate of organic carbon, thereby increasing the soil organic carbon content [31]. In this study, the ASF accumulated more soil organic carbon because of its larger vegetation coverage, higher stand density, and greater amount of litter. Some studies have shown that deciduous broad-leaved tree species have a better effect on soil organic carbon accumulation than conifer species [32]. Research has shown that compared to monoculture forests, mixed forests significantly increase the total organic carbon and active organic carbon content of forest soil [33]. In this study, the ASF mainly consists of deciduous broad-leaved tree species, such as *Populus tomentosa* and *Vitex negundo*, which increases the content of soil organic carbon. The TP content of CL is significantly higher than the other four land use types, which is induced by artificial application of P fertilizer. Studies have shown that crops can absorb a small fraction of P. Therefore, long-term fertilization leads to the accumulation of P in CL soil.

Soil physical properties also showed significant differences among different land use types. Soil bulk density and soil porosity can reflect the compactness of soil and can be affected by tillage methods and soil microstructure [34,35]. Most previous studies on soil bulk density under different land use patterns have shown that newly cultivated land has a higher bulk density than forest and grassland [36,37]. However, in this study, the bulk density of NCL is the lowest, where the primary reason for this observation is the lack of human intervention in the land use of NCL compared to other sites. The foreign soil changes the original microstructure of the soil, affecting the aggregate structure of the soil, and thereby reducing the soil bulk density. Higher BD in the cropland can be attributed to frequent cultivation and mechanical compaction, which caused a reduction in soil porosity and deterioration of the soil structure. Soil water-holding capacity is affected by multiple factors, such as soil bulk density, soil porosity, and land use type [38]. In the current study, the water-holding capacity of soil is directly proportional to porosity and inversely proportional to bulk density. Different land use types also affect SWC. There are differences in surface vegetation types and root distribution in soil under different land use types, which in turn affect the process of soil water infiltration and circulation [39]. The highest soil water content in ASF was due to the good soil structure, which was conducive to water content. In addition, the high vegetation coverage has a shading effect, reducing the evaporation of soil moisture. We found that NCL also has a high SWC, which is consistent with the results of Wang et al. [37]. This may be due to the fact that there is little vegetation in NCL, and therefore no vegetation consumption of soil water in NCL.

Previous studies have demonstrated that livestock manure serves as the primary source of trace elements in agricultural soil, particularly Cu and Zn [40,41]. Conversely, mineral fertilizer predominantly contributes to Cd contamination, with phosphate fertilizers generally exhibiting high levels of Cd content [42]. In this study, the higher concentrations of Cu and Zn in CL may be attributed to the application of livestock manure. The TP in CL is significantly higher compared to the others, indicating a greater usage of P fertilizer, which consequently leads to a significantly elevated Cd content. The fertilization also influences soil pH and cation exchange capacity, subsequently affecting the levels of heavy metal elements content [43]. Despite the presence of construction waste and backfill soil in other land use types, variations in plant root absorption and human activities contribute to differences in heavy metal content. For instance, plant extraction is an economical and environmentally friendly method that utilizes special plants to remove heavy metals from contaminated soil, thereby reducing their concentration to a safe level [44]. Additionally, human activities affect both the input and migration redistribution of heavy metals in soil [45].

4.2. Soil Quality Indexes and Effects of Land Use Types on Soil Quality

The SQI has emerged as a robust and widely adopted approach for assessing soil quality in numerous scientific investigations. TDS and MDS, two commonly used methods for calculating SQI, each have their own advantages and limitations. The TDS can provide a more comprehensive set of soil indicators, while the MDS is simpler and more cost-effective. In this study, six indicators (Pb, SOC, MWHC, CWHC, SWC, and Cd) with highly weighted factors were selected in the MDS for evaluation. The indicators of SOC, MWHC, CWHC, and SWC have been widely adopted as the minimum data set in numerous previous studies [4,22,46,47]. SOC serves as a pivotal indicator for assessing soil quality, exerting positive influences on various physical, chemical, and biological indicators of soil. For instance, the presence of organic carbon enhances soil structure, augments soil fertility, and stimulates the activities of soil fauna and microorganisms [22]. The SWC, MWHC, and CWHC indexes are all closely associated with soil moisture, which is a vital determinant of plant and microorganism survival, directly impacting their ecological conditions. Given the water scarcity in the arid and semi-arid study area, the accurate assessment of soil quality necessitates a comprehensive evaluation of soil moisture indicators. Previous studies on soil quality assessment have rarely included heavy metal indicators; however, given the presence of construction waste in our study site, it is imperative to acknowledge the significant impact of heavy metals associated with such waste [13,14]. Through the principal component analysis and minimum data set screening, Cd and Pb were identified as indicators for evaluating soil quality in this study. The concentrations of Cd and Pb in soil are influenced by both natural geological background and human activities [48]. Wang et al. [14] conducted an analysis on the pollution characteristics of heavy metals in construction waste in Beijing, revealing mild and severe contamination of Pb and Cd, respectively. Consistent with the minimum data set indicator selected in this study, Joimel et al. [49] proposed using Pb as an indicator to assess soil quality. The presence of Cd in agricultural soil in China is highly concerning, with an average annual input of 0.004 mg/kg/a [50]. Furthermore, Cd exhibits pronounced migratory capabilities, facile absorption by plants, and toxicity towards both plants and soil microorganisms. After Cd enters the human body through the food chain, it may lead to deadly diseases such as cancer [11]. Consequently, the higher the Cd concentration in soil, the greater ecological risk it poses.

The soil quality varies among different land use types in this study (Table 6). The SQI results for various land use types indicate that ASF > AF > SL > CL > NCL. Meng et al. [51] have indicated that the growth of vegetation and the application of fertilizers can enhance the physical and chemical properties of soil, thereby improving its quality, which is in line with our findings. In this study, the *Vitex negundo* in the ASF are characterized as shallow-rooted plants. Previous research has demonstrated that mature trees predominantly utilize deep soil moisture, whereas shrubs primarily absorb surface soil moisture [52]. Consequently, there appears to be minimal water competition among different plant species within the ASF. Additionally, the high vegetation coverage and diverse plant species in ASF contribute to a substantial accumulation of litter, leading to significant nutrient cycling. Consequently, ASF exhibits elevated levels of soil organic matter and nitrogen content, thereby enhancing soil fertility. As a result, the soil quality improvement of ASF is more pronounced compared to AF. However, due to the relatively shallow roots, single plant species, and small biomass of the SL, its soil quality improvement effect is comparatively lower than ASF and AF. The lower soil quality of CL compared to forestland may be attributed to long-term cultivation, which damages the soil structure and mechanically disrupts soil aggregates, thereby accelerating the mineralization rate of organic matter. Additionally, farmers' harvesting practices also contribute to a decline in soil nutrient content [53]. Fertilization induces alterations in heavy metal content and soil pollution, resulting in lower soil quality on CL compared to forestland. The lowest soil quality observed on NCL suggests that both afforestation and agricultural practices contribute to improving the soil quality, with afforestation exhibiting a superior effect.

4.3. The Dominant Factor Analysis of Soil Quality Change

This study employed PLS-PM to investigate the impact of variables on soil SQI. The findings revealed that variables exerted both direct and indirect effects on soil SQI by influencing other variables. For instance, in this study, the soil chemical indexes (SOC and TP), physical indexes (MWHC and CP), and heavy metal element (Pb) were found to directly influence SQI, with corresponding influence coefficients of 0.602, −0.234, and 0.259, respectively. Moreover, chemical indexes exhibited highly significant influences while physical indexes and heavy metal elements showed significant influences on SQI. However, the direct impact of land use types on SQI was not found to be statistically significant. The land use types, with a path coefficient of −0.752, exert a significant influence on Pb levels, which aligns with the findings reported by Zheng et al. [54] in Beijing. Hence, it is evident that land use types primarily influence SQI through alterations in soil Pb levels, subsequently exerting an indirect impact on SQI. Lead is a highly toxic chemical element that can persist in the environment and has detrimental effects on both animals and humans. It predominantly occurs in soil, where it cannot be biodegraded, posing a significant threat to plant health and human well-being. Lead primarily originates from atmospheric and rainwater deposition, the introduction of lead-containing waste, sludge, and organic fertilizers, as well as the application of pesticides containing lead. The elevated lead content observed in CL may be attributed to the application of chemical fertilizers and pesticides. These findings align with results reported by Li et al. [55], demonstrating that land use types play a significant role in the accumulation and impact of lead in cropland.

In this study, the influence coefficient of chemical indexes on SQI (0.602) surpassed that of physical indexes (0.259) and heavy metal elements (−0.234), aligning with the findings by Zou et al. [56]. This suggests the crucial role of soil chemistry indicators in soil quality restoration. Previous studies have demonstrated that agricultural and forestry practices can effectively enhance soil organic matter content, while the application of fertilizers and improvements in soil structure contribute to increased levels of SOC and TN, thereby augmenting the capacity for carbon and nitrogen sequestration in soils [57]. Furthermore, the augmentation of SOC and TN content can enhance soil structure and improve soil permeability and drainage, thereby mitigating nitrogen loss in the soil [58].

5. Conclusions

Except for NCP, there are differences in soil physical and chemical indicators and heavy metal content among different land use types in the study area. The minimum data set comprised six indicators, including one soil chemical indicator (SOC), three soil physical indicators (MWHC, CWHC, and SWC), and two heavy metal indicators (Cd and Pb). The SQI values of the TDS and the MDS followed the order of ASF > AF > SL > CL > NCL. Afforestation and agricultural practices exhibited improvements in soil quality, with a more pronounced effect observed for afforestation. The land use type has a significant impact on the soil Pb content. Therefore, in the evaluation of urban soil quality, attention should be paid to the heavy metal elements. The future land use types in the study area should be determined according to the needs of production practices, selecting the most rational utilization types. If the primary objective is solely to improve soil quality, then the ASF should be prioritized.

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