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Assessment of High-Severity Post-Fire Soil Quality and Its Recovery in Dry/Warm Valley Forestlands in Southwest China through Selecting the Minimum Data Set and Soil Quality Index

Xiaosong Qin [1], Yi Wang [1,2,3,*], Dongdong Hou [1] and Yongkang Li [1]

[1] College of Geography and Resources Science, Sichuan Normal University, Chengdu 610101, China; xiaosongqin@stu.sicnu.edu.cn (X.Q.); 20231101076@stu.sicnu.edu.cn (D.H.); lyk@stu.sicnu.edu.cn (Y.L.)
[2] Key Laboratory of Ministry of Education on Land Resources Evaluation and Monitoring in Southwest China, Sichuan Normal University, Chengdu 610066, China
[3] Engineering Research Center for the Development of Farmland Ecosystem Service Functions, Chengdu 610068, China
* Correspondence: wy@sicnu.edu.cn

Abstract: Recurrent wildfires can negatively affect soil quality, and post-fire soil quality recovery is critical for maintaining sustainable ecosystem development. The objective of this study was to evaluate the changes and recovery of soil properties and soil quality in the forests of dry/warm river valleys in southwest China after disturbance by high-severity fires. In this study, the impact of fire on soil properties and soil quality was investigated for three years post-fire. Unburned forest land with a similar natural environment compared to the fire area was used as a control. Soil samples were collected from three different depths of 0–10 cm, 10–20 cm, and 20–30 cm, respectively. Principal component analysis (PCA) combined with the Norm value was used to select the minimum data set (MDS), thus calculating the soil quality index (SQI). The results showed that the soil properties changed significantly after high-severity fires. On average, soil bulk density (0.91 g/cm^3, p = 0.001), total nitrogen (0.12 g/kg, p = 0.000), total phosphorus (0.10 g/kg, p = 0.000), and total potassium (5.55 g/kg, p = 0.000) were significantly lower in the burned areas than in the unburned areas at the first sampling. These indicators increased in the following three years but still did not recover to unburned levels. Compared with the above indicators, soil porosity and organic matter increased post-fire, but gradually decreased over time. Soil clay, geometric mean diameter, and total potassium were included in the MDS. The SQI was ranked as unburned > 3 years > 2 years > 1 year > 6 months. The SQI was significantly (p = 0.001) reduced six months post-fire by an average of 36%, and, after three years of recovery, the soil quality of the post-fire areas could be restored to 81% of soil in unburned areas. Apparently, high-severity fires caused changes in soil properties, thereby significantly decreasing soil quality. Soil quality gradually improved with increasing restoration time. However, the complete recovery of soil quality post-fire in forest land in the dry/warm river valley will take a longer time.

Keywords: forest fires; soil quality index; minimum data set; recovery period

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Citation: Qin, X.; Wang, Y.; Hou, D.; Li, Y. Assessment of High-Severity Post-Fire Soil Quality and Its Recovery in Dry/Warm Valley Forestlands in Southwest China through Selecting the Minimum Data Set and Soil Quality Index. *Forests* **2024**, *15*, 1727. https://doi.org/10.3390/f15101727

Academic Editor: Benjamin L. Turner

Received: 30 July 2024
Revised: 8 September 2024
Accepted: 28 September 2024
Published: 29 September 2024

1. Introduction

As a key component of terrestrial and forest ecosystems, soil is an important medium for regulating nutrient uptake, transformation and decomposition, water supply, and promoting forest land productivity [1]. Soil quality is defined as the ability of soil to maintain plant and animal productivity, protect environmental quality, and support human health and habitation within the ecosystem [2–4]. Different land uses and ecosystem types can affect soil quality within a human-disturbed and temporal variation context [5].

Soil quality is the combination of soil fertility, health, and environmental conditions [6]. Soil quality assessment is a quantitative expression of the internal properties of the soil, which is the expression of the ecological function of a given soil through the selection of soil quality indicators [2,7] to assess and determine the sustainability of soil management practices. The methods of soil quality assessment mainly include comprehensive index methods [8], fuzzy evaluation methods [9], and soil quality index (SQI) methods [10]. Due to the soil quality being influenced by various factors, it cannot be measured accurately using a single indicator. Consequently, the total data set (TDS) indicators of soil properties serve as the foundation for accurately evaluating soil quality [10,11]. However, this also creates problems of rising costs and data redundancy. Therefore, the selection of representative soil physical, chemical, and biological indicators is key to evaluating soil quality [11]. The minimum data set (MDS) has become a common method for selecting key indicators for evaluating soil quality, selecting indicators from the total set of indicators that can maximally represent all the soil characteristics of the evaluation. Principal component analysis (PCA), among mathematical statistical methods, is most widely used in constructing MDS. Many researchers have evaluated soil quality using PCA to construct MDS and combined it with SQI [12–14].

Natural disturbances such as climate change and fire can affect natural ecosystems [14]. The forests or grasslands in most regions and climatic zones of the world are affected by fire, such as Australia, Central Africa, South America, the Mediterranean, North America, and Central and South Asia [15]. Fire damage to ecosystems has also attracted attention, and many reports have been made on fire research [16,17]. Researchers have also used artificial intelligence to accurately predict fire behavior and reduce the destructive consequences of forest fires [18]. Fires can directly or indirectly impact the physical and chemical characteristics of the soil surface by destroying surface vegetation [19,20]. During post-fire vegetation restoration, surface biomass and vegetation density gradually increase, with the growth of subsurface roots and the production of humus causing changes in soil properties, ultimately affecting soil quality. Nevertheless, research on fires in China mainly currently focuses on the Daxing'anling region [21], disregarding the forest fires in southwestern China.

The dry/warm valley in southwest China is rich in forest vegetation types, including mainly mixed coniferous broad-leaved forests dominated by *Pinus yunnanensis* Franch (Franch, 1899). Due to the unique local climatic conditions, the region is highly susceptible to forest fires. According to statistics, there have been 287 forest fires in Sichuan Province since 2019, and 5 severe fires all occurred in the dry/warm valley area of Liangshan Prefecture. This has brought huge safety hazards and economic losses to the lives and properties of local people, and also seriously damaged the local ecological environment.

The severity of forest fires is categorized into three levels of severity based on the extent of damage to forest ecosystems: high-severity fire, moderate-severity fire, and low-severity fire [22,23]. The size of a fire's impact on soil depends largely on its severity and frequency [24–26]. High-severity fires result in the burning of surface vegetation, the destruction of topsoil structures, and drastic changes in soil physical and chemical properties. Several studies have found that high-severity fires can lead to an increased soil bulk density [7], along with destroying soil structure and affecting the stability of soil aggregates [27]. In addition, soil organic matter levels decrease for a short period after fire and gradually increase with recovery time [28]. They also affect different changes in soil nutrient levels such as nitrogen, phosphorus, and potassium [23,29,30]. Fire not only affects soil quality but also leads to the conversion of carbon biopolymers [31], desertification [32], damaging flash floods or mudslides [33,34], and destruction of soil biomes [35]. Additionally, the burned area of the watershed, surface sediments, and ash are identified as the primary drivers of post-fire water pollution, resulting in increased surface water nutrients and dissolved organic carbon, pathogens, and hazardous compounds [36]. Therefore, the evaluation of the impact of fire on soil quality and ecosystems is critical.

The current research on forest fires in the dry/warm valley in southwest China focuses on fire-triggering factors and management measures, with the effects of fires on soil properties and vegetation changes [21]. However, few studies report on the effects of fire on soil quality [7]. Specifically, the impact of fire on soil quality using the soil quality index in the fire-prone forest land of the regions has not been explored to date, nor has the study of the dynamics of soil quality over time post-fire. Our key research question is how high-intensity fire affects soil quality, particularly soil physicochemical properties, in dry/warm valley forest land ecosystems. Here, we hypothesize that soil properties and quality will change dynamically in different post-fire periods, and soil quality can be recovered post-fire, but full recovery may take a longer time due to the importance of soil quality for the sustainability of forest ecosystems. Therefore, the main purpose of this study was to evaluate and compare the effects of high-severity fires on forest land soil quality in a dry/warm river valley in southwest China and the changes in soil quality during natural recovery processes. To address this purpose, we utilized a site after a high-severity forest fire. Meanwhile, an unburned area with a similar natural environment to the burned area was used as a control. Soil samples were collected for 3 years post-fire. Specifically, the study objectives were (1) to analyze the changes in soil properties and the natural recovery process after fire and (2) to quantify soil quality by SQI and MDS during the natural restoration of burned areas with different years of restoration. Basic information and relevant bases for post-fire soil quality changes and ecosystem assessment are provided for dry/warm valley forest land in southwest China.

2. Materials and Methods

2.1. Study Area

The study area is located in the southwest dry/warm valley area of Mianning County, Liangshan Yi Autonomous Prefecture, Sichuan Province (101°38′~102°25′ E, 28°05′~29°02′ N), where a high-severity fire occurred on 20 April 2021 (Figure 1). The region is dominated by mountainous terrain, with an altitude of between 1249 and 5267 m. It has a typical subtropical monsoon climate, with an average annual rainfall of about 995.6 mm, and an average annual temperature of 17.2 °C. The soils in the study area are derived from sand shale parent material sediments, which can be classified as Lixisol according to the World Reference Base (WRB, 2015) international soil classification system [37], with the following soil profile: A (humus layer) is 0–16 cm, B (deposition layer) is 16–34 cm, and C (parent material layer) is 34–100 cm. Soil texture is mostly sandy loam. The forest cover reaches 60%, which is mainly large concentrated and continuous *Pinus yunnanensis* forests, accompanied by *Schima superba* Gardn and Champ, *Abies fabri* (Mast.) Craib, and *Lithocarpus glaber* in the forest. The shrub layer mainly consists of *Dodonaea viscosa* (Linn.) Jacq., *Vaccinium bracteatum* Thunb, *Coriaria nepalensis* Wall, and *Rhododendron parvifolium* Adams. Herbaceous plants are mainly *Elymus dahuricus* Turcz, *Cyperus rotundus* L., and *Leonto podium leontopodioides* (Willd.) Beauv. Fading pine needles, pine cones, and other dead leaves and branches make it easy to form a thick humus layer in the forest understory, with a high load of combustible materials. In addition, the region’s rainfall pattern is highly unequal throughout the year, with the wet period from May to October, when about 80% of the year’s rainfall falls, and the dry period from November to April, when only about 10% of the year’s rainfall falls [38]. In winter and spring, there is a lot of sunshine, high evaporation, and dry air. Combined with the complex topography of the region, steep slopes, and significant foehn wind effects, this period is highly susceptible to forest fires.

2.2. Methods

2.2.1. Soil Sampling

Based on the field investigation, this fire was a high-severity fire or a severe surface fire. This fire burned over an area of 41 hm^2, with a flame height greater than 3 m, and all the ground vegetation was burned out, leaving a large number of stumps, with trunks all blackened and no green leaf cover. Before the fire, the forest land was mainly composed of *Pinus yunnanensis*, with a simple and aged mature stand structure that was roughly 70 years old.

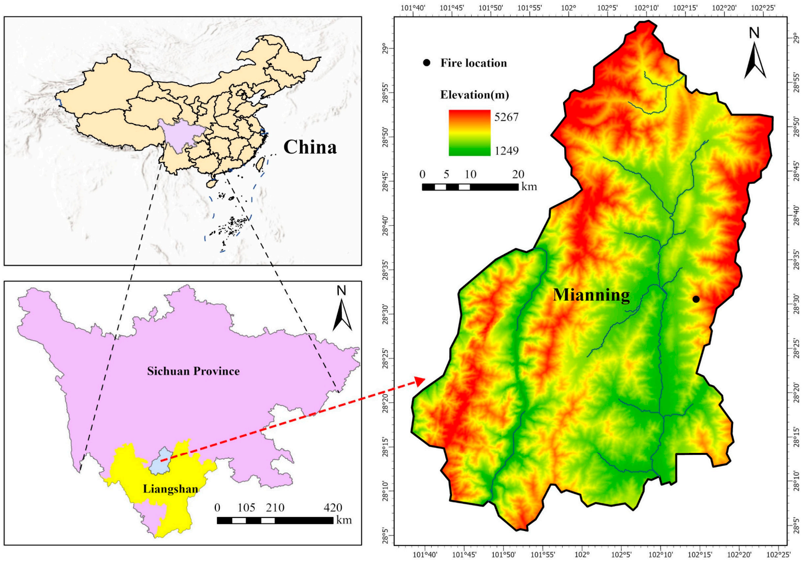

Figure 1. Location of the study and fire site.

In this study, a slope with an area of about 380 m long × 310 m wide was selected as the study object (Figure 2), and an unburned area of mixed *Pinus yunnanensis* forest at a straight-line distance of about 1.5 km from the burnt areas was also selected as the control to determine whether the fires degraded the soil quality. The unburned areas were consistent with the burned areas in terms of forest age, vegetation type, soil thickness, and soil texture. Three representative sample plots were selected on the top, medium, and bottom slopes of the burned areas and unburned areas, respectively, to better represent the overall soil quality condition of the sampling area, with an interval of about 80 m between each slope. There were no significant environmental differences between the sample plots. Each sampling area was 20 m × 20 m, which were marked to facilitate the subsequent stationary monitoring and sampling.

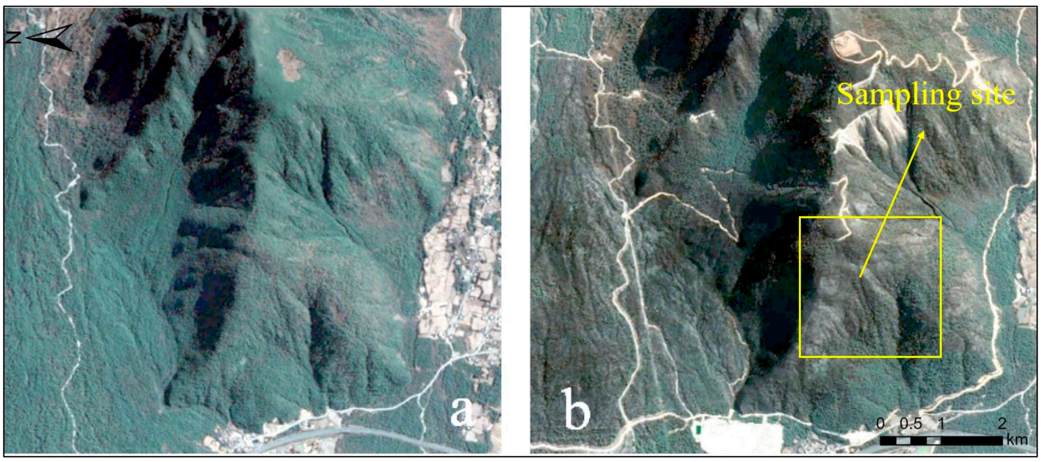

Figure 2. Before and after fire comparison ((**a**): pre-fire, (**b**): post-fire).

The first sampling was scheduled for October 2021, six months after the occurrence of the fire. The purpose was to observe the condition of soil quality in a short period. Taking into account the post-fire accessibility and the effect of rainy season precipitation, soil enzymes and microbial in spring are more active [39]. Soil samples were collected in April 2022, April 2023, and April 2024 at different times of natural succession (1 year, 2 years, and 3 years), respectively (Figure 3). For each sampling, three sampling points were arranged in an "S" shape within the sample plot, and soil was sampled from 0–10 cm, 10–20 cm, and 20–30 cm layers in each sampling point, respectively. The samples were homogenized into a 2 kg sample to be analyzed for the basic chemical characterization of the soil. Original soil was collected from each soil layer using a core method with a 100 cm^3 volume to determine soil bulk density, total porosity, and water content, with additional portions of original soil samples taken for analysis of soil aggregates.

Figure 3. Different recovery periods of burned areas ((**a**): six months, (**b**): 1 year, (**c**): 2 years, (**d**): 3 years).

2.2.2. Soil Analyses

The obtained soil samples were brought back to the laboratory to undergo pre-treatment such as air drying and sieving. Soil bulk density (BD), water content, and porosity (POR) were measured by the core method. Soil particle sizes (clay, silt, sand) were determined by the Master-Sizer 2000 method laser particle sizer [12]. The content of water-stable aggregates using the wet sieve method were calculated for the mean weight diameter (MWD) and the geometric mean diameter (GMD) [27]. Soil organic matter (SOM) was determined by dichromate oxidation using the Walkley and Black method [40]. Total nitrogen (TN) was determined using the Kjeldahl digestion method. Total phosphorus (TP) was determined using the Molybdenum antimony colorimetric method. Total potassium (TK) was determined using the Flame photometric method.

2.3. Soil Quality Assessment Methods

2.3.1. Construction of the Minimum Data Set

Eleven commonly used indicators reflecting soil properties of post-fire areas were selected for this study. These included soil clay, silt, sand, bulk density, porosity, mean weight diameter of aggregates, geometric mean diameter, soil organic matter, total nitrogen, total phosphorus, and total potassium, constituting a TDS of indicators for evaluating soil quality. PCA combined with the Norm value method was used for the construction of the MDS. The specific steps are to extract the principal components with eigenvalues $\geq$1 and organize index factor loadings with absolute values $\geq$0.5 to a set. When an indicator has loadings >0.5 in various principal components extracted, it will be included in a less relevant group among the indexes. The Norm values of the indicators in groups are calculated individually, and the indicators within 10% of the greatest Norm value within the group are selected. Whenever there is more than one indicator in a group, a Pearson's correlation factor is required to identify the appropriate index for selection. When a correlation coefficient r < 0.5 indicates a low correlation between indicators, the indicators can be maintained; whereas, if the correlation coefficient r $\geq$ 0.5 indicates a strong correlation between indicators, the maximum Norm value is selected to be included as the MDS. The Norm value is expressed as the vector norm strength of this indicator on the multidimensional dimension consisting of the elements, and, the longer the strength, the greater the combined loading of this index on account of all the principal components, hence its capacity for explaining the combined messages will be stronger [41]. The formula is calculated as follows:

$$N_{ik} = \sqrt{\sum_{i=1}^{k} (U_{ik}^2 * \lambda_k)} \tag{1}$$

where N_{ik} is the combined loading of the variable i onto the principal components of eigenvalue ≥ 1; U_{ik} stands for the loading of the variable i onto the principal component k; λ_k is the characteristic value of the principal component k [42,43].

2.3.2. Indicator Scoring

When evaluating soil quality, since the soil indicators are of different scales and orders of magnitude, it is necessary to convert each indicator into a score value from 0 to 1 by dimensionless quantization. Therefore, in this study, we used both linear [1] and nonlinear [44] scoring methods to transform the data.

2.3.3. Calculation of Soil Quality Index

The soil quality index is a general expression for soil quality, and the greater its value, the greater the soil quality. It is calculated using the following formula:

$$SQI_A = \sum_{i=1}^{k} \frac{S_i}{k} \tag{2}$$

$$SQI_W = \sum_{i=1}^{k} W_i * S_i \tag{3}$$

where SQI_A is the soil quality index by using additive methods, SQI_W is the soil quality index by using weighted additive methods, W_i is the weight of the index i, S_i is the score of the index i (linear or nonlinear), and k is the number of the soil evaluation index [14,45,46]. The weight of the selected indicator is equal to the ratio of the common factor variance of each indicator to the sum of the common factor variance.

In this present study, eight SQIs were calculated—the linear scoring additive TDS (SQI-LT-A) and weighted additive (SQI-LT-W), the linear scoring additive MDS (SQI-LM-A) and weighted additive (SQI-LM-W), the nonlinear scoring additive TDS (SQI-NLT-A) and weighted additive (SQI-NLT-W), and the nonlinear scoring additive MDS (SQI-NLM-A) and weighted additive (SQI-NLM-W).

2.4. Statistical Analysis

Routine statistics for soil physicochemical properties on upper, middle, and bottom slopes of unburned areas and burned areas with different years of restoration were performed in Excel 2019. One-way analysis of variance (ANOVA) was used to analyze the differences in soil physicochemical properties between the unburned areas and the burned areas with different restoration years. Tests of variance and normal distribution were performed before statistical analysis to satisfy the statistical assumption test. Pearson correlation analysis was used to investigate the correlation between soil physicochemical properties and different modes of soil quality indexes, respectively. The results of the soil quality index for total and minimum data sets were analyzed by linear fitting. The above results were reported at the $p < 0.05$ significance level. All statistical analyses were performed in IBM SPSS Statistics 26.0 (IBM Corp., Armonk, NY, USA) statistical software.

3. Results

3.1. Post-Fire Temporal Trends in Soil Properties

The physical and chemical properties of soil at different times of natural succession in the burned areas and the unburned areas are shown in Table 1. The soil particle composition of the burnt areas showed no significant difference at different times of natural restoration compared with unburned areas ($p > 0.05$). The amount of clay and silt particles decreased each year after the fire, but the sand content gradually increased. The maximum sand particles of 80.68% was recorded in the two years of the fire. In comparison, BD in the unburned areas was significantly greater ($p = 0.001$) than the different recovery periods after the fire. The lowest BD was observed six months after the fire, decreasing to 69% of the unburned area, and increasing from 0.91 g/cm^3 to 0.99 g/cm^3 with increasing years of restoration. Correspondingly, POR in the unburned areas was significantly lower ($p = 0.001$) than in different recovery periods after the fire. POR of burned areas was the largest in six months, increasing to about 1.75 times more than the unburned areas and decreasing yearly from 50.13% to 46.36%. The MWD ($p = 0.312$) and the GMD ($p = 0.116$) of the soil water-stable aggregates in the burned areas showed no significant differences in the early stages of the succession. Meanwhile, TN, TP, and TK in the soil of the unburned areas were remarkably higher than those in the burned areas at different times of natural restoration ($p = 0.000$). The TN, TP, and TK in the six months after the fire were only 11.22%, 15.38%, and 25.32% of those in the unburned areas, but all of them showed a tendency to increase year by year. After three years of restoration, TN, TP, and TK were able to reach 72.89%, 81.54%, and 87.04% of the unburned areas, respectively. However, SOM contents showed a different tendency, with a significant increase in surface organic matter content after the fire. The highest SOM content was found six months after the fire, with 2.61 times more than the unburned areas. Moreover, it decreased from 70.64 g/kg to 37.32 g/kg, reduced by about 47% with increasing recovery time, and the SOM content after three years of restoration was still 27.28% higher than the unburned areas. Analyzing the coefficients of variation for each indicator, we found that the degree of variation for soil bulk density, porosity, and soil aggregate structure was relatively low. Fire can lead to relatively high variation in soil nutrient content indicators, including TN, TP, TK, and SOM.

Table 1. Soil property indicators of different years of natural restoration of burned areas and unburned areas (mean ± standard deviation).

Indicators	UB	T0	T1	T2	T3	CV/%
Clay/%	7.92 ± 0.84 a	7.44 ± 0.72 ab	7.20 ± 0.47 ab	5.99 ± 1.15 b	6.38 ± 0.09 ab	13.78
Silt/%	16.82 ± 1.96 a	17.27 ± 1.99 a	16.52 ± 1.00 a	13.33 ± 3.37 a	14.50 ± 0.30 a	14.73
Sand/%	75.26 ± 2.80 a	75.28 ± 2.70 a	76.29 ± 1.39 a	80.68 ± 4.49 a	79.12 ± 0.38 a	4.19
BD (g/cm^3)	1.31 ± 0.10 a	0.91 ± 0.03 b	0.95 ± 0.04 b	1.02 ± 0.02 b	0.99 ± 0.13 b	15.50
POR/%	29.07 ± 5.47 b	50.73 ± 1.74 a	48.54 ± 2.40 a	44.62 ± 1.33 a	46.36 ± 6.87 a	19.83
MWD (mm)	3.30 ± 0.51 a	2.35 ± 0.01 a	2.26 ± 0.58 a	2.73 ± 0.14 a	2.92 ± 0.90 a	20.28
GMD (mm)	1.65 ± 0.38 a	1.15 ± 0.02 ab	1.24 ± 0.36 ab	1.25 ± 0.02 ab	1.12 ± 0.07 b	22.15
TN (g/kg)	1.07 ± 0.20 a	0.12 ± 0.01 c	0.24 ± 0.03 c	0.82 ± 0.05 b	0.78 ± 0.02 b	63.63
TP (g/kg)	0.65 ± 0.05 a	0.10 ± 0.01 d	0.22 ± 0.04 c	0.52 ± 0.03 b	0.53 ± 0.07 b	53.75
TK (g/kg)	21.92 ± 2.10 a	5.55 ± 1.01 d	9.57 ± 1.10 c	17.41 ± 1.09 b	19.08 ± 1.51 b	44.01
SOM (g/kg)	27.03 ± 3.38 c	70.64 ± 4.62 a	52.41 ± 0.70 b	40.29 ± 16.02 bc	37.32 ± 3.63 bc	36.90

Note: UB—unburned; T0—6 months after fire; T1—1 year after fire; T2—2 years after fire; T3—3 years after fire. Clay—clay content; Silt—silt content; Sand—sand content; BD—bulk density; POR—porosity; MWD—mean weight diameter; GMD—geometric mean diameter; TN—total nitrogen; TP—total phosphorus; TK—total potassium; SOM—soil organic matter. Different lowercase letters in the same row indicate significant differences among restoration years ($p < 0.05$).

3.2. Post-Fire Temporal Trends in Soil Quality Index

Soil quality indicators were analyzed by PCA (Table 2). Three principal components (PCs) were withdrawn for eigenvalues ≥ 1, and their eigenvalues were 5.693, 3.280, and 1.018, respectively, with a cumulative variance contribution of 90.824%. These three principal components were able to explain more than 90% of the information, which shows that the MDS composed of them can represent the TDS to assess the soil quality for this study. Following the grouping principle of factor loading value ≥0.5, the 11 soil indicators were categorized into 3 groups. Indicators included in group 1 were BD, POR, MWD, TN, TP, TK, and SOM. Although the loading value of MWD on the third principal component also satisfied ≥ 0.5, it was shown by correlation analysis (Figure 4) that its correlation with the indicators in group 3 was stronger, so it was classified in group 1. Group 2 consisted of clay, silt, and sand particles, reflecting soil texture. The GMD was classified in group 3.

Table 2. Soil index factor loads and Norm values based on PCA.

Soil Indicators	PC1	PC2	PC3	Norm Value	Group
Clay	−0.047	0.990	−0.002	1.796	2
Silt	−0.285	0.933	−0.078	1.823	2
Sand	0.217	−0.960	0.057	1.815	2
BD	0.814	0.377	−0.251	2.074	1
POR	−0.814	−0.377	0.251	2.074	1
MWD	0.631	0.070	0.690	1.664	1
GMD	0.567	0.397	0.588	1.643	3
TN	0.949	−0.106	−0.208	2.282	1
TP	0.949	−0.170	−0.053	2.285	1
TK	0.952	−0.138	−0.065	2.286	1
SOM	−0.900	−0.033	0.094	2.150	1
Eigenvalue	5.693	3.280	1.018		
Variance explained (%)	51.752	29.820	9.251		
Cumulative variance (%)	51.752	81.572	90.824		

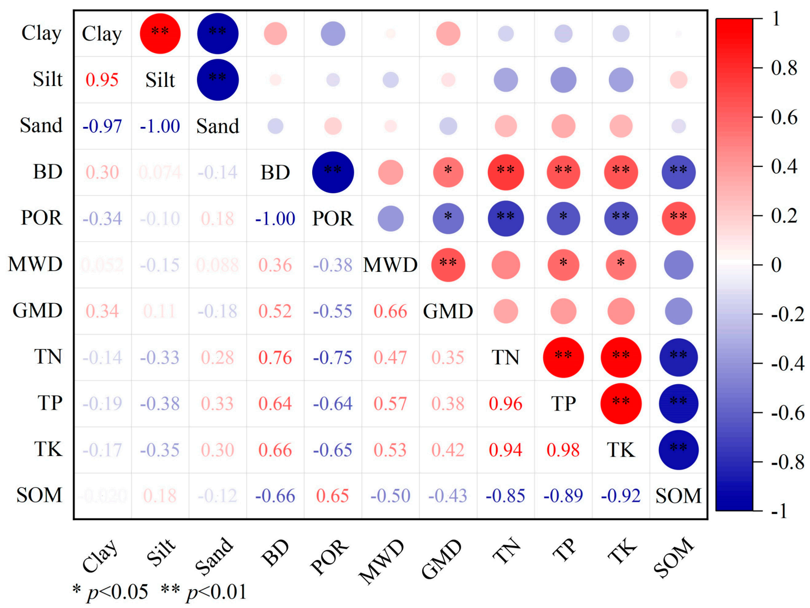

Figure 4. Correlation among soil quality evaluation indexes. Note: Clay—clay content; Silt—silt content; Sand—sand content; BD—bulk density; POR—porosity; MWD—mean weight diameter; GMD—geometric mean diameter; TN—total nitrogen; TP—total phosphorus; TK—total potassium; SOM—soil organic matter.

According to the principle of MDS establishment, the Norm value of the soil quality indicators in the three groups above needed to be calculated by Formula (1). The greatest Norm value in group 1 was for TK, which was 2.286, and the indicators within its 10% range were BD, POR, TN, TP, and SOM. In group 2, the largest Norm value was for silt at 1.823, and both clay and sand were within its 10% range. Group 3 had only a GMD indicator. By analyzing the correlation between the groups of indicators, it was determined that the indicators that ended up in the minimum dataset were silt, GMD, and TK.

PCA was used to obtain the common factor variance and weights for each indicator in TDS and MDS (Table 3). The soil indicator score values were calculated using linear and nonlinear scoring methods. The "smaller is better" model was used for BD and sand, and the "greater the better" model for the rest of the soil quality indexes was used in this study. As shown in Table 3, clay (0.098) had the greatest weight in TDS, followed by sand (0.097), silt (0.096), TN (0.096), TP (0.093), TK (0.093), MWD (0.088), BD (0.087), POR (0.087), GMD (0.083), and the smallest weight was SOM (0.082). In MDS, the weights of the indicators from the largest to the smallest were silt (0.347), GMD (0.337), and TK (0.316). In this study, soil physical indicators had a greater influence on soil quality during the period of restoration of burnt areas.

Table 3. Common factor variance and weight of soil quality evaluation index.

Soil Indicators	TDS		MDS	
	Common Factor Variance	**Weight**	**Common Factor Variance**	**Weight**
Clay	0.982	0.098		
Silt	0.958	0.096	0.906	0.347
Sand	0.972	0.097		
BD	0.868	0.087		
POR	0.868	0.087		
MWD	0.880	0.088		
GMD	0.826	0.083	0.878	0.337
TN	0.955	0.096		
TP	0.933	0.093		
TK	0.929	0.093	0.824	0.316
SOM	0.820	0.082		

Note: Clay—clay content; Silt—silt content; Sand—sand content; BD—bulk density; POR—porosity; MWD—mean weight diameter; GMD—geometric mean diameter; TN—total nitrogen; TP—total phosphorus; TK—total potassium; SOM—soil organic matter.

Finally, Equations (2) and (3) were used to calculate the soil quality index. The statistical parameters of SQI are summarized in Table 4. The soil quality index in different restoration years of burned areas and unburned areas ranged from 0.426 to 0.692 for SQI-LT-W, 0.398 to 0.568 for SQI-NLT-W, 0.296 to 0.879 for SQI-LM-W, 0.354 to 0.682 for SQI-NLM-W, 0.424 to 0.685 for SQI-LT-A, 0.399 to 573 for SQI-NLT-M, 0.301 to 0.884 for SQI-LM-A, and 0.347 to 0.686 for SQI-NLM-A. The eight SQIs were statistically significant ($p < 0.05$), except SQI-LT-W and SQI-LT-A. The weighted additive scoring methodology reduced F-values and CVs. The SQI variations ranged from 10% to 40% and were all moderately sensitive. Eight SQI results showed that it was lowest after six months of natural recovery in high-severity fire, with an average reduction of 36%, and the soil quality after three years of recovery was significantly higher than the recovery after six months, with an average improvement of 27.97%. However, the soil quality after three years of recovery still did not reach the level before the fire, and it was improved by 81.28% on average compared with the unburned areas (Figure 5).

The linear relationship of SQI between the TDS and MDS in scoring methods (linear and nonlinear) and soil quality index methods (additive and additive weighted) is shown in Figure 6. TDS and MDS had a significant positive correlation ($p = 0.00$), indicating that the evaluation index system based on the minimum data set can replace the total data set for the evaluation of the soil quality of the burnt areas in this study. It was further found that the nonlinear SQIs were better than the linear SQIs due to the high R^2 and F-value. Meanwhile, the MAE and SEE of the soil quality index fitting effects of the nonlinear scores were lower than those of the linear scores, showing that the nonlinear scoring method was more applicable in this study. By Pearson correlation analysis, the eight SQIs were significantly positively correlated with each other (Table 5), implying that each of them can be used to assess soil quality.

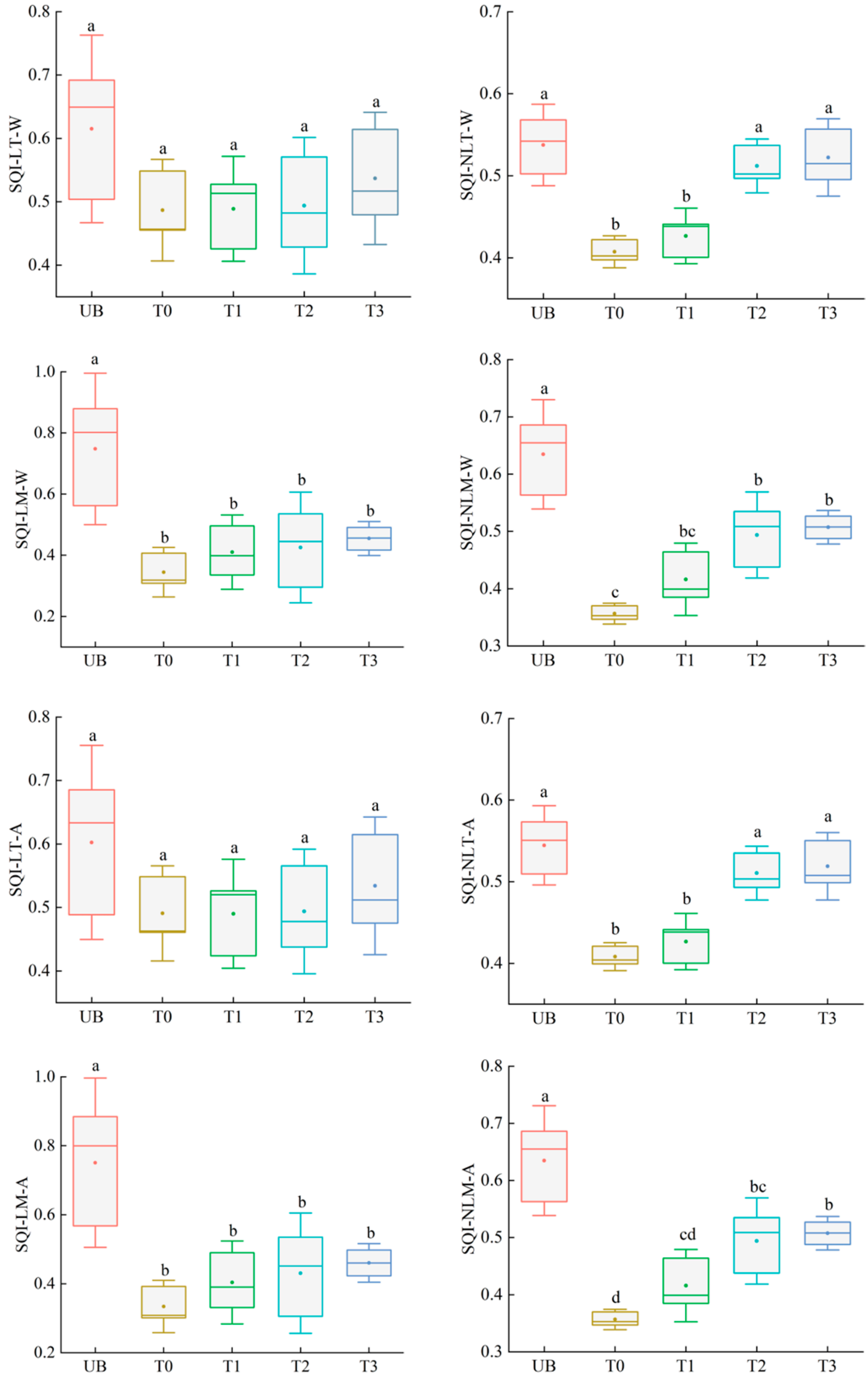

Figure 5. SQI of unburned and burned areas with different restoration years (UB—unburned; T0—6 months after fire; T1—1 year after fire; T2—2 years after fire; T3—3 years after fire). Different lowercase letters were significantly different ($p < 0.05$). Note: SQI-LT-A—the linear scoring additive TDS; SQI-LT-W—the linear scoring weighted additive; SQI-LM-A—the linear scoring additive MDS; SQI-LM-W—the linear scoring weighted additive; SQI-NLT-A—the nonlinear scoring additive TDS; SQI-NLT-W—the nonlinear scoring weighted additive; SQI-NLM-A—the nonlinear scoring additive MDS; SQI-NLM-W—the nonlinear scoring weighted additive.

Table 4. Statistical eigenvalues of soil quality index in TDS and MDS.

Soil Quality Index	Change Range	Mean Value	Standard Deviation	F	*p*-Value	CV/%
SQI-LT-W	0.426~0.692	0.524	0.079	1.761	0.213	15.05
SQI-NLT-W	0.398~0.568	0.481	0.059	16.443	0.000	12.32
SQI-LM-W	0.296~0.879	0.476	0.169	6.986	0.006	35.51
SQI-NLM-W	0.354~0.682	0.482	0.100	16.691	0.000	20.73
SQI-LT-A	0.424~0.685	0.522	0.075	1.375	0.310	14.43
SQI-NLT-A	0.399~0.573	0.482	0.060	18.974	0.000	12.37
SQI-LM-A	0.301~0.884	0.476	0.171	7.628	0.004	36.01
SQI-NLM-A	0.347~0.686	0.482	0.104	18.586	0.000	21.49

Note: SQI-LT-A—the linear scoring additive TDS; SQI-LT-W—the linear scoring weighted additive; SQI-LM-A—the linear scoring additive MDS; SQI-LM-W—the linear scoring weighted additive; SQI-NLT-A—the nonlinear scoring additive TDS; SQI-NLT-W—the nonlinear scoring weighted additive; SQI-NLM-A—the nonlinear scoring additive MDS; SQI-NLM-W—the nonlinear scoring weighted additive.

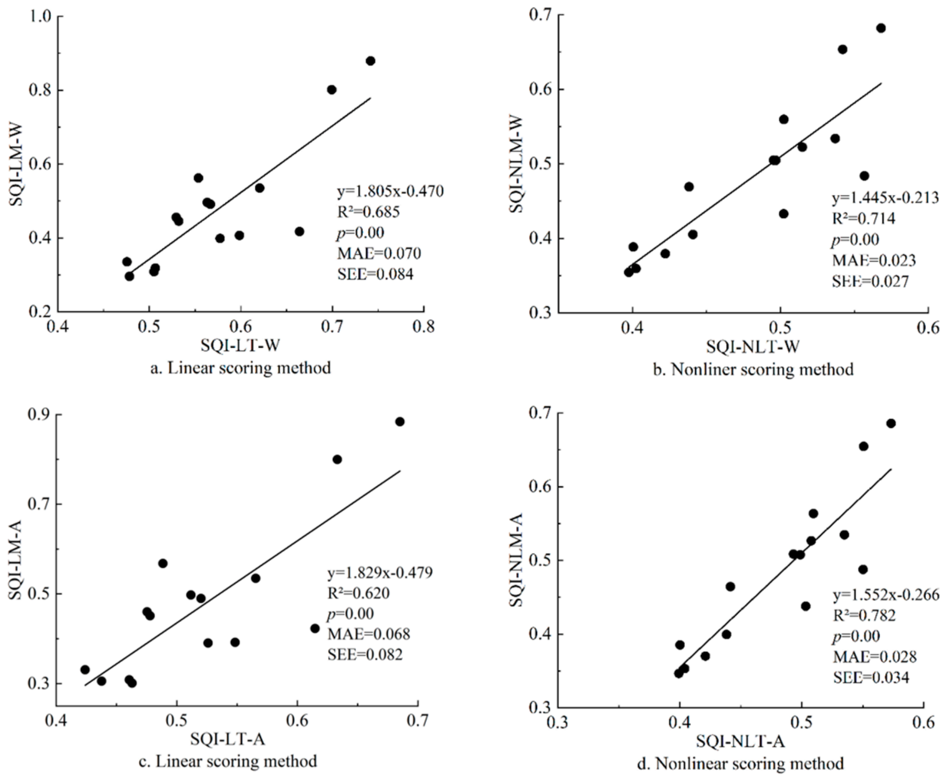

Figure 6. Relationship between TDS and MDS of SQI based on two scoring methods. MAE—mean absolute error; SEE—standard error of estimate.

Table 5. Correlation of eight soil quality indexes.

	SQI-LT-W	SQI-NLT-W	SQI-LM-W	SQI-NLM-W	SQI-LT-A	SQI-NLT-A	SQI-LM-A	SQI-NLM-A
SQI-LT-W	1							
SQI-NLT-W	0.697 **	1						
SQI-LM-W	0.842 **	0.680 **	1					
SQI-NLM-W	0.744 **	0.857 **	0.933 **	1				
SQI-LT-A	0.996 **	0.677 **	0.811 **	0.706 **	1			
SQI-NLT-A	0.705 **	0.997 **	0.715 **	0.884 **	0.683 **	1		
SQI-LM-A	0.836 **	0.704 **	0.999 **	0.946 **	0.804 **	0.739 **	1	
SQI-NLM-A	0.731 **	0.869 **	0.920 **	0.999 **	0.693 **	0.894 **	0.935 **	1

Note: SQI-LT-A—the linear scoring additive TDS; SQI-LT-W—the linear scoring weighted additive; SQI-LM-A—the linear scoring additive MDS; SQI-LM-W—the linear scoring weighted additive; SQI-NLT-A—the nonlinear scoring additive TDS; SQI-NLT-W—the nonlinear scoring weighted additive; SQI-NLM-A—the nonlinear scoring additive MDS; SQI-NLM-W—the nonlinear scoring weighted additive; ** significant at the 0.01 probability level.

4. Discussion

4.1. Temporal Variation of Soil Properties in Post-Fire Areas with Natural Succession

High-severity fires cause drastic changes in soil properties, but the physical and chemical properties of burned areas recover gradually in the course of natural succession (Table 1). In general, forest fires affect the physical properties of soils primarily by altering soil temperature and soil structure through the burning of organic matter. The sand content increased during the early stages of succession in this study. On the one hand, high-severity fires destroyed surface vegetation leading to surface exposure, which increased the sand content due to the massive loss of clay and silt particles under the raindrop splashing and water erosion. On the other hand, the high-severity fire destroyed soil minerals, and the mineral decomposition produced oxides and hydroxides that led to particle cementation, which formed sand-sized particles [19,47]. However, with the gradual recovery of vegetation, the content of silt and clay particles increased. Soil bulk density of burned areas decreased by 30.53% in six months after the fire compared with unburned areas and had the highest porosity, which was 1.75 times higher than the unburned areas. This may be related to changes in soil structure due to high temperatures at the time of the fire [47]. Hofstede [48] also showed that soil capacity decreased after fire burning. Meanwhile, due to the reduction of surface vegetation, increased temperatures can cause drying and cracking of the soil surface [49], leading to a reduction in BD and an increase in POR. The decomposition of decaying root systems of underground dead vegetation also increases porosity. During its subsequent natural succession, the BD gradually increases and the POR gradually decreases, but it is still higher than the unburned areas. This reason is probably because the surface vegetation decreases and the direct strike of raindrops on the ground makes the soil taut. As the surface cracks of the soil are gradually filled with small particles, the soil POR is reduced [49]. In addition, this study also found that high-severity fire caused a significant decrease in soil aggregate indicators (MWD and GMD) and destroyed soil aggregates. Sharifi et al. [27] and Mataix-Solera et al. [50] also studied soil properties after fire. They indicated that fire can destroy the soil aggregate stability, consistent with our results, and the impact of fire on aggregates is related to the severity of the fire. Furthermore, the high-temperature environment under high-intensity fires also destroys soil mineral cementation, which reduces soil aggregate stability. With the extension of natural succession, the input of various cementing substances, such as soil organic matter and root and microbial secretions, improved the stability of the aggregates to resist water erosion.

Researchers have come to inconsistent conclusions about the dynamic variation in soil nutrient content after fire [35,51]. Francos et al. [52] and Muqaddas et al. [53] showed that fire dramatically decreased soil TN levels. In addition, Hosseini et al. [54] considered that TN and TP contents increased following the fire. Soil nutrient content was affected by the fire intensity, with high-severity fires significantly destroying soil nutrients more than low-severity fires. Burning of surface vegetation and destruction of soil aggregates can easily result in the loss of soil nutrients during high-severity rainfall during the rainy season. In this study, we found that soil TN, TP, and TK were significantly lower in the early post-fire period compared with the unburned areas (Table 1), and these averaged about 17% of the unburned areas in the six months after the fire, consistent with other results [7]. It was probably due to the high temperatures that evaporated TN. Nevertheless, phosphorus mainly exists in the form of an organic state in the soil, and high-severity fire destroys the surface vegetation, resulting in the easy loss of phosphorus under the influence of rainfall [55]. Unlike carbon and nitrogen, potassium does not exist in a gaseous form, so the high temperatures associated with burning do not cause potassium to be lost as a gas. However, the ash formed by the fire was easily lost in surface runoff, which reduced TK. After three years of restoration, the soil nutrient content increased significantly and on average could reach about 80% of the unburned areas. The post-fire environment promotes the renewal rate of vegetation, and nutrient elements are absorbed by plants and then stored in the plants. After plants decay and decompose back into the soil, this is the main reason for the increase in soil nutrient content after fire [56]. SOM content increased by 61.74% in six months after the fire compared with the unburned areas. Paladines et al. [20] also indicated that the organic matter content increased by about 30% under fire. The increase in SOM after the fire is probably caused by the ingress of ash and charred material into the soil [10,57,58]. Furthermore, other results showed that the evaporation of organic matter by fire and rainfall erosion caused a reduction in SOM content [59]. As the restoration time increased, the SOM content of the burned areas gradually decreased, but it was still higher than the unburned areas. In general, soil chemical properties are more affected by high-severity fire than soil physical properties.

It has been shown that fire leads to the formation of forest ecosystems and soils [32]. After undergoing high-severity fires, the vegetation communities of forests are altered, causing a secondary succession of top vegetation [33]. The changes in vegetation, on the other hand, can have a greater impact on the surface cover and belowground root system, further leading to changes in soil texture and soil structure, as found in this study. Soil enzymes are important factors in soil biochemical processes, which promote material cycling and energy flow in forest ecosystems. When high-severity fire burning occurs, nutrient levels such as nitrogen, phosphorus, and potassium are significantly reduced, and soil microorganisms die out directly in the heat [60], which directly reduces the source of soil enzymes. Therefore, the developing process of the soil is interrupted and the soil quality is affected by the above-mentioned factors. With the slow recovery of vegetation, soil microorganisms, and enzyme activities [7], the improvement of soil physicochemical properties has an important contribution to the formation of soil.

4.2. Temporal Variation of Soil Quality in Post-Fire Areas with Natural Succession

Choosing soil indicators properly is an essential part of assessing soil quality accurately. This research utilized principal component analysis incorporating Norm values for screening the MDS for soil quality evaluation of burned areas (Table 2). The main indicators selected included silt, which is related to soil texture, GMD, the key indicator that is sensitive to external physical conditions [44], and TK, which promotes plant growth (Table 3). The soil quality indexes were calculated for burned areas based on both linear and nonlinear scoring methods. SQI results indicated that the greatest in unburned areas and the lowest six months after the fire (Figure 5). The high-severity fire severely damaged the surface vegetation and soil structure, superimposed on the large loss of soil nutrients due to rainfall, resulting in significantly lower soil quality within six months of the fire. However, the SQIs of burned areas all increased with the number of years of restoration, consistent with previous studies [39,61]. During natural succession, soil structure and soil nutrients improve with the recovery of vegetation and root growth [29,30,61,62], and soil quality increases gradually.

In addition, The SQIs were relatively high three years after the fire, reaching an average of 81.28% of the unburned areas (Figure 5). Raisei and Pejman [7] studied soil quality after a wildfire in central Iran, and they indicated that the SQI obtained two years after the fire using linear and nonlinear scoring methods were 74% and 69% of those that had not been burned by the fire, consistent to our results, soil quality restoration after fire may take a longer time. According to the comparison and validation of the indexes (Figure 6), the nonlinear scoring method is better than the linear scoring method, Yu et al. [44] and Askari and Holden [45] also showed that non-linear scoring methods are greater than linear scoring in evaluating the soil quality. However, some research indicated that the linear scoring method is much more sensitive and superior to the nonlinear scoring method [12,14,63]. This may be due to the differences in the study population and the selection of soil property indicators, resulting in some variability in the results of each study. Moreover, this study mainly focused on soil physical and chemical indicators but lacked the selection of soil biological indicators. Raisei and Pejman [7] indicated that microbial indicators are also sensitive indicators for evaluating soil quality, for soil enzymes also affect the production and decomposition of organic matter and promote nutrient cycling.

To more reasonably evaluate the soil quality, it is necessary to continuously improve the evaluation index system.

5. Conclusions

This study showed that high-severity fire significantly reduced soil quality in *Pinus yunnanensis* forest land in a dry/warm valley in southwest China. Using the soil quality index method to evaluate the effect of fire on soil quality has favorable applicability. To avoid data redundancy, the use of the minimum data set can effectively replace the total data set. Under climatic conditions with unbalanced rainfall distribution, high-intensity rain erosion during the rainy season may slow down the recovery of soil quality. Therefore, soil quality after fire takes longer to recover, and vegetation recovery plays an important role in soil quality. Changes in soil quality over three years may be short-term, with subsequent observations over a longer recovery period should be considered to better reflect the status of soil quality recovery after fire. In addition, the selection of evaluation indicators and evaluation methods need to be considered for a more accurate evaluation of soil quality.

Author Contributions: Writing—original draft, X.Q.; writing—review and editing, Y.W.; conceptualization, X.Q. and Y.W.; formal analysis, X.Q.; data curation, D.H.; funding acquisition, Y.W.; investigation, X.Q., D.H. and Y.L; methodology, X.Q.; resources, Y.W.; software, Y.L.; project administration, Y.W.; validation, X.Q. and Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Key Laboratory of Land Resources Evaluation and Monitoring in Southwest (Sichuan Normal University), Ministry of Education, China (TDSYS202310).

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors wish to express their appreciation to Jingru Ruan and Wei He for their assistance in the field experiment.

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

References

1. Zhang, G.L.; Bai, J.H.; Xi, M.; Zhao, Q.Q.; Lu, Q.Q.; Jia, J. Soil quality assessment of coastal wetlands in the Yellow River Delta of China based on the minimum data set. *Ecol. Indic.* **2016**, *66*, 458–466. [CrossRef]
2. Doran, J.W.; Coleman, D.C.; Bezdicek, D.F.; Stewart, B.A. *Defining Soil Quality for a Sustainable Environment*; Soil Science Society of America and American Society of Agronomy: Madison, WI, USA, 1994; p. 7. [CrossRef]
3. Karlen, D.; Andrews, S.; Doran, J. Soil quality: Current concepts and applications. *Adv. Agron.* **2001**, *74*, 1–40. [CrossRef]
4. Raiesi, F. A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. *Ecol. Indic.* **2017**, *75*, 307–320. [CrossRef]
5. Gong, L.; Ran, Q.Y.; He, G.X.; Tiyip, T. A soil quality assessment under different land use types in Keriya river basin, Southern Xinjiang, China. *Soil Till Res.* **2015**, *146*, 223–229. [CrossRef]
6. Oscar, K.M.; Shisanya, C.; Cournac, L.; Raphael, M.J.; Gitari, H.; Muriuki, J. Integrating no-tillage with agroforestry augments soil quality indicators in Kenya's dry-land agroecosystems. *Soil Till Res.* **2023**, *227*, 105586. [CrossRef]
7. Raiesi, F.; Pejman, M. Assessment of post-wildfire soil quality and its recovery in semi-arid upland rangelands in Central Iran through selecting the minimum data set and quantitative soil quality index. *Catena* **2021**, *201*, 105202. [CrossRef]
8. Li, W.X.; Zhang, X.X.; Wu, B.; Sun, S.L.; Chen, Y.S.; Zhao, D.Y.; Cheng, S.P. A comparative analysis of environmental quality assessment methods for heavy metal-contaminated soils. *Pedosphere.* **2008**, *18*, 344–352. [CrossRef]
9. Ghaemi, M.; Astaraei, A.R.; Mahalati, M.N.; Emami, H.; Sanaeinejad, H.H. Spatio-temporal soil quality assessment under crop rotation irrigated with treated urban wastewater using fuzzy modelling. *Int. Agrophys.* **2014**, *28*, 291–302. [CrossRef]
10. Rahmanipour, F.; Marzaioli, R.; Bahrami, A.H.; Fereidouni, Z.; Bandarabadi, R.S. Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. *Ecol. Indic.* **2014**, *40*, 19–26. [CrossRef]
11. Liu, Z.J.; Zhou, W.; Li, S.T.; He, P.; Liang, G.Q.; Lv, J.L.; Jin, H. Assessing soil quality of gleyed paddy soils with different productivities in subtropical China. *Catena* **2015**, *133*, 293–302. [CrossRef]
12. Guo, S.; Han, X.; Li, H.; Wang, T.; Tong, X.G.; Ren, G.X.; Feng, Y.Z.; Yang, G.H. Evaluation of soil quality along two revegetation chronosequences on the Loess Hilly Region of China. *Sci. Total Environ.* **2018**, *633*, 808–815. [CrossRef] [PubMed]

13. Meitasari, R.; Hanudin, E.; Purwanto, B.H. Comparison of two soil quality assessment models under different land uses and topographical units on the southwest slope of Mount Merapi. *Soil Water Res.* **2024**, *19*, 77–89. [CrossRef]
14. Zhou, Y.; Ma, H.B.; Xie, Y.Z.; Jia, X.Y.; Su, T.T.; Li, J.P.; Shen, Y. Assessment of soil quality indexes for different land use types in typical steppe in the loess hilly area, China. *Ecol Indic.* **2020**, *118*, 106743. [CrossRef]
15. Pereira, G.M.; Gonçalves, N.; Amraoui, M. The influence of wildfire climate on wildfire incidence: The case of Portugal. *Fire* **2024**, *7*, 234. [CrossRef]
16. Pereira, G.M.; Calado, J.T.; DaCamara, C.C.; Calheiros, T. Effects of regional climate change on rural fires in Portugal. *Clim Res.* **2013**, *57*, 187–200. [CrossRef]
17. Chebykina, Y.E.; Abakumov, V.E.; Kimeklis, K.A.; Gladkov, V.G.; Andronov, E.E.; Dymov, A.A. Wildfires'effect on soil properties and bacterial biodiversity of postpyrogenic histic podzols (Middle Taiga, Komi Republic). *Forests* **2024**, *15*, 145. [CrossRef]
18. Shaddy, B.; Ray, D.; Farguell, A.; Calaza, V.; Mandel, J.; Haley, J.; Hilburn, K.; Mallia, V.D.; Kochanski, A.; Oberai, A. Generative Algorithms for Fusion of Physics-Based Wildfire Spread Models with Satellite Data for Initializing Wildfire Forecasts. *Artif. Intell. Earth Syst.* **2024**, *3*, 3. [CrossRef]
19. Heydari, M.; Rostamy, A.; Najafi, F.; Dey, D.C. Effect of fire severity on physical and biochemical soil properties in Zagros oak (Quercus brantii Lindl.) forests in Iran. *J. For. Res.* **2016**, *28*, 95–104. [CrossRef]
20. Paladines, C.V.; Fries, A.; Hinojosa, B.M.; Oña, A.; Álvarez, J.L.; Benítez, A.; Rodríguez, L.F.; Ruiz, G.R. Effects of low-severity fire on soil physico-chemical properties in an Andean Páramo in Southern Ecuador. *Fire* **2023**, *6*, 447. [CrossRef]
21. Yang, Y.; Hu, X.W.; Han, M.; He, K.; Liu, B.; Jin, T.; Cao, X.C.; Wang, Y.; Huang, J. Post-fire temporal trends in soil properties and revegetation: Insights from different wildfire severities in the Hengduan Mountains, Southwestern China. *Catena* **2022**, *213*, 106160. [CrossRef]
22. Brewer, C.K.; Winne, J.C.; Redmond, R.L.; Opitz, D.W.; Mangrich, M.V. Classifying and mapping wildfire severity: A comparison of methods. *Photogramm. Eng. Remote Sens.* **2005**, *71*, 1311–1320. [CrossRef]
23. Li, X.Y.; Jin, H.J.; Wang, H.W.; Wu, X.D.; Huang, Y.D.; He, R.X.; Luo, D.L.; Jin, X.Y. Distributive features of soil carbon and nutrients in permafrost regions affected by forest fires in northern Da Xing'anling (Hinggan) Mountains, NE China. *Catena* **2020**, *185*, 104304. [CrossRef]
24. DeBano, L.F.; Neary, D.G.; Ffolliott, P.F. *Fire's Effects on Ecosystems*; John Wiley & Sons: New York, NY, USA, 1998.
25. Bento-Gonçalves, A.; Vieira, A.; Úbeda, X.; Martin, D. Fire and soils: Key concepts and recent advances. *Geoderma* **2012**, *191*, 3–13. [CrossRef]
26. Pellegrini, A.F.A.; Ahlström, A.; Hobbie, E.S.; Reich, B.P.; Nieradzik, P.L.; Staver, C.A.; Scharenbroch, C.B.; Jumpponen, A.; Anderegg, L.R.W.; Randerson, T.J.; et al. Fire frequency drives decadal changes in soil carbon and nitrogen and ecosystem productivity. *Nature* **2018**, *553*, 194–198. [CrossRef] [PubMed]
27. Sharifi, Z.; Azadi, N.; Certini, G. Fire and tillage as degrading factors of soil structure in Northern Zagros oak forest, West Iran. *Land Degrad Dev.* **2016**, *28*, 1068–1077. [CrossRef]
28. Gomes, F.D.V.Y.D.; Ana, O.D.P.P.; Tiago, S.D.P.; Carvalhoda, E.N.S. Prescribed fire application in a Brazilian mountain environment: Changes in soil organic matter quality in the short and medium term. *Catena* **2023**, *232*, 107418. [CrossRef]
29. Alcañiz, M.; Outeiro, L.; Francos, M.; Farguell, J.; Úbeda, X. Long-term dynamics of soil chemical properties after a prescribed fire in a Mediterranean forest (Montgrí Massif, Catalonia, Spain). *Sci. Total Environ.* **2016**, *572*, 1329–1335. [CrossRef]
30. Verma, S.; Singh, D.; Singh, K.A.; Jayakumar, S. Post-fire soil nutrient dynamics in a tropical dry deciduous forest of Western Ghats, India. *For. Ecosyst.* **2019**, *6*, 67–75. [CrossRef]
31. Dymov, A.A.; Startsev, V.V.; Milanovsky, E.Y.; Valdes-Korovkin, I.A.; Farkhodov, Y.R.; Yudina, A.V.; Donnerhack, O.; Guggenberger, G. Soils and soil organic matter transformations during the two years after a low-intensity surface fire (Subpolar Ural, Russia). *Geoderma* **2021**, *404*, 115278. [CrossRef]
32. Neary, G.D. Forest soil disturbance: Implications of factors contributing to the wildland fire nexus. *Soil Sci. Soc. Am. J.* **2019**, *83*, S228–S243. [CrossRef]
33. Stavi, I. Wildfires in grasslands and shrublands: A review of impacts on vegetation, soil, hydrology, and geomorphology. *Water* **2019**, *11*, 1042. [CrossRef]
34. Stiefel, C.L.; Cooley, C.S.; Johnson, G.B. Increased colluvial hollow discharge and subsequent recovery after a low intensity wildfire in the Blue Ridge Mountains, USA. *Hydrol. Process.* **2021**, *35*, e13971. [CrossRef]
35. Alex, A.A.; Simon, A.; Thomas, D.A.; Richard, A. A review of the effects of forest fire on soil properties. *J. For. Res.* **2022**, *33*, 1419–1441. [CrossRef]
36. Niels, N.; Pedro, J.N.; Joana, P. Assessing post-fire water quality changes in reservoirs: Insights from a large dataset in Portugal. *Sci. Total Environ.* **2023**, *912*, 1694. [CrossRef]
37. IUSS Working Group WRB. *World Reference Base for Soil Resources 2014, Update 2015. International Soil Classification System for Naming Soils and Creating Legends for Soil Maps*; World Soil Resources Reports No. 106; FAO: Rome, Italy, 2015.
38. Li, X.X.; Ye, M.; Wang, L.H.; Mu, C.L.; Deng, X.B.; Wang, Z.L.; DU, J.C. Leaf physiological characteristics, flowering and fruit rate of five *Olea europaea* species in three ecological regions. *J. West China For. Sci.* **2022**, *51*, 49–55. (In Chinese) [CrossRef]
39. Abellán, A.M.; Córdoba, P.I.M.; Saucedo, G.F.; Baena, W.C.; Morote, G.A.F.; Caballero, R.E.; Morneo, L.J.; Bastida, F.; García, C.; Serrano, L.R.F. Application of a soil quality index to a mediterranean mountain with post-fire treatments. *Forests* **2023**, *14*, 1745. [CrossRef]

40. Nelson, D.W.; Sommers, L.E. Total carbon, organic carbon, and organic matter. In *Methods of Soil Analysis*; Page, A.L., Miller, R.H., Keeney, D.R., Eds.; American Society of Agronomy: Madison, WI, USA, 1982; pp. 539–579. [CrossRef]
41. Jin, H.F.; Shi, D.M.; Chen, Z.F.; Liu, Y.J.; Lou, Y.B.; Yang, X. 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. (In Chinese) [CrossRef]
42. Tian, K.; Zhang, B.; Zhang, H.D.; Huang, B.; Darilek, L.J.; Zhao, Y.C.; Yang, J.S. Evaluation of soil quality in major grain-producing region of the North China Plain: Integrating minimum data set and established critical limits. *Ecol Indic.* **2020**, *117*, 106–163. [CrossRef]
43. Wu, C.S.; Liu, G.H.; Huang, C.; Liu, Q.S. Soil quality assessment in Yellow River Delta: Establishing a minimum data set and fuzzy logic model. *Geoderma* **2019**, *34*, 82–89. [CrossRef]
44. Yu, P.J.; Han, D.L.; Liu, S.W.; Wen, X.; Huang, Y.X.; Jia, H.T. Soil quality assessment under different land uses in an alpine grassland. *Catena* **2018**, *171*, 280–287. [CrossRef]
45. Askari, S.M.; Holden, M.N. Indices for quantitative evaluation of soil quality under grassland management. *Geoderma* **2014**, *230–231*, 131–142. [CrossRef]
46. Li, X.Y.; Wang, D.Y.; Ren, Y.X.; Wang, Z.M.; Zhou, Y.H. Soil quality assessment of croplands in the black soil zone of Jilin Province, China: Establishing a minimum data set model. *Ecol. Indic.* **2019**, *107*, 105251. [CrossRef]
47. Chief, K.; Young, H.M.; Shafer, S.D. Changes in soil structure and hydraulic properties in a wooded-shrubland ecosystem following a prescribed fire. *Soil Sci. Soc. Am. J.* **2012**, *76*, 1965–1977. [CrossRef]
48. Hofstede, R.G. The effects of grazing and burning on soil and plant nutrient concentrations in Colombian páramo grasslands. *Plant Soil.* **1995**, *173*, 111–132. [CrossRef]
49. Perkins, J.P.; Diaz, C.; Corbett, S.C.; Cerovski-Darriau, C.; Stock, J.D.; Prancevic, J.P.; Micheli, E.; Jasperse, J. Multi-stage soil-hydraulic recovery and limited ravel accumulations following the 2017 Nuns and Tubbs Wildfires in Northern California. *J. Geophys. Res. Earth Surf.* **2022**, *127*, e2022JF006591. [CrossRef]
50. Mataix-Solera, J.; Cerdà, A.; Arcenegui, V.; Jordán, A.; Zavala, L.M. Fire effects on soil aggregation: A review. *Earth Sci. Rev.* **2011**, *109*, 44–60. [CrossRef]
51. Alcañiz, M.; Outeiro, L.; Francos, M.; Úbeda, X. Effects of prescribed fires on soil properties: A review. *Sci. Total Environ.* **2018**, *613–614*, 944–957. [CrossRef]
52. Francos, M.; Stefanuto, E.B.; Úbeda, X.; Pereira, P. Long-term impact of prescribed fire on soil chemical properties in a wildland-urban interface. Northeastern Iberian Peninsula. *Sci. Total Environ.* **2019**, *689*, 305–311. [CrossRef]
53. Muqaddas, B.; Zhou, X.Q.; Lewis, T.; Wild, C.; Chen, C.G. Long-term frequent prescribed fire decreases surface soil carbon and nitrogen pools in a wet sclerophyll forest of Southeast Queensland, Australia. *Sci. Total Environ.* **2015**, *536*, 39–47. [CrossRef]
54. Hosseini, M.; Geissen, V.; González-Pelayo, O.; Serpa, D.; Machado, I.A.; Ritsema, C.; Keizer, J.J. Effects of fire occurrence and recurrence on nitrogen and phosphorus losses by overland flow in maritime pine plantations in north-central Portugal. *Geoderma* **2017**, *289*, 97–106. [CrossRef]
55. Zhao, M.; Zhang, X.M.; Yang, M.J. Effects of forest fire disturbance on species diversity and soil physicochemical properties in *Pinus tabuliformis* coniferous forests. *Acta Ecol. Sin.* **2023**, *43*, 7412–7421. (In Chinese) [CrossRef]
56. Badía, D.; Martí, C. Fire and Rainfall Energy Effects on Soil Erosion and Runoff Generation in Semi-Arid Forested Lands. *Arid Land Res. Manag.* **2008**, *22*, 93–108. [CrossRef]
57. Downing, A.T.; Imo, M.; Kimanzi, J.; Otinga, N.A. Effects of wildland fire on the tropical alpine moorlands of Mount Kenya. *Catena* **2017**, *149*, 300–308. [CrossRef]
58. Shakesby, A.R.; Bento, P.C.; Ferreira, S.C.; Ferreira, J.D.A.; Stoof, R.C.; Urbanek, E.; Walsh, P.D.R. Impacts of prescribed fire on soil loss and soil quality: An assessment based on an experimentally-burned catchment in central Portugal. *Catena* **2013**, *128*, 278–293. [CrossRef]
59. Granged, P.J.A.; Jordán, A.; Zavala, M.L.; Muñoz-Rojaset, M.; Mataix-Soleraal, J. Short-term effects of experimental fire for a soil under eucalyptus forest (SE Australia). *Geoderma* **2011**, *167–168*, 125–134. [CrossRef]
60. Wüthrich, C.; Schaub, D.; Weber, M.; Marxer, P.; Conedera, M. Soil respiration and soil microbial biomass after fire in a sweet chestnut forest in southern Switzerland. *Catena* **2002**, *48*, 201–215. [CrossRef]
61. Wang, L.; Fu, Q. Soil quality assessment of vegetation restoration after a large forest fire in Daxing'anling, northeast China. *Can. J. Soil Sci.* **2020**, *100*, 162–174. [CrossRef]
62. Yu, Y.; Jia, Q.Z. Changes in soil organic carbon and nitrogen capacities of *Salix cheilophila* Schneid. along a revegetation chronosequence in semi-arid degraded sandy land of the Gonghe Basin, Tibet Plateau. *Solid Earth* **2014**, *5*, 1045–1054. [CrossRef]
63. Nehrani, H.S.; Askari, S.M.; Saadat, S.; Delavar, A.M.; Taheri, M.; Holden, M.N. Quantification of soil quality under semi-arid agriculture in the northwest of Iran. *Ecol Indic.* **2020**, *108*, 105770. [CrossRef]