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A Study of the Spatial Difference of the Soil Quality of The Mun River Basin during the Rainy Season

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Abstract: The Mun River basin is one of the main grain-producing areas of Thailand, and the rainy season is the main period for crop planting after being idle during the dry season. However, the soil conditions are variable, so an assessment of soil quality during the rainy season is necessary for improving soil condition and crop production. The aim of this study was to conduct a soil quality assessment based on soil samples. To attain that, a minimum data set theory was used to screen evaluation indicators and geographically weighted regression was performed to obtain spatial interpolations of indicators, while the fuzzy logic model was used to determine the soil quality results. The results showed that the contents of indicators had similar spatial trends as their contents declined from the western to the eastern region of the basin. The soil quality results showed that the poor soil was in the middle of the basin, where the main land use is paddy fields, and the good soil was in the southwest of the basin, where forests and dry fields are widely distributed. The results indicated that the soil quality in the Mun River basin varied greatly, especially for farmland, so these findings will be helpful for improving soil conditions and grain production in the Mun River basin.

Keywords: Thailand; soil quality; geographically weighted regression model; fuzzy logic model; rainy season

1. Introduction

Soil is an important natural resource and the carrier of most natural and social environments. Soil quality has a strong influence on the growth of vegetation, especially on crops [1], which makes soil quality a crucial attribute for food security, human health and the sustainable development of the environment [2]. No definition of soil quality has been universally accepted, but most experts emphasize that soil productivity depends on soil quality, so most research results of soil quality assessments are based on soil nutrient indicators [3,4].

Much research has been performed in the area of soil quality assessment, focusing on forests, grasslands, farmlands and so on [5–7]. Meanwhile, research methods have evolved from qualitative descriptions and statistical analyses to multi-data modeling [8,9], such as principal component analysis (PCA) [4], regression analysis, analytic hierarchy process (AHP) and fuzzy models [10]. According to previous results, there are some problems in the assessment process: First, data redundancies are common among the selected indicators owing to a lack of indicator screening processes [11,12]; second, most research projects are based on a point scale and the results are not extended to the entire area. In addition, geostatistical models, such as ordinary kriging and cokriging, are commonly used in a small number of spatial research projects [13,14], the accuracies of which are highly dependent on the number of sampling points, with the result maps consistently displaying a "bullseye" phenomenon [15]. Moreover, there are some unreasonable conditions in the threshold setting processes of indicators and assessment results; for example, most research indicators are often standardized or directly graded according to the indicator values [16], and then the grade values are used as evaluation parameters for overlay analysis [17]. This strict grading method has been questioned in term of its reasonability, though there is no recognized classification standard of soil quality [18].

The Mun River basin is located in the Nakhon Ratchasima Plateau of northeast Thailand, and although it is considered a main grain-producing area of Thailand, its production is very low. The tropical monsoon climate gives this area obvious dry and rainy seasons [19], and most farmland is idle because of the lack of rain in the dry season, while the paddy fields are widespread in the rainy season [20]. Research on soil quality in tropical areas is less common than that dealing with other temperature zones; additionally, tropical monsoon areas that have distinctive features, such as the Mun River basin, are relatively unstudied. In fact, there have been no related soil quality studies on the Mun River basin until the present study. Based on the above, the object of this study was to evaluate the soil quality of the Mun River basin and to analyze the differences over the study area. To attain it, the minimum data set theory was introduced as the indicator screening method [21,22]. The geographically weighted regression model was selected to finish the spatial extensions of the evaluation indicators, as this method is not highly dependent on the number of samples and takes the spatial locations of samples into consideration [23]. The fuzzy logic model was used to generate the final assessment results based on its membership theory in the indicator grading process [24].

The assessment of soil quality in rainy seasons in this area will not only have scientific significance for the recognition of tropical soil characteristics but also have practical significance by providing data supporting soil remediation and improvement.

2. Data Collection

2.1. Study Area

This study was conducted in the Mun River basin, which is located in the northeast of Thailand and includes 10 provinces (Figure 1). The Mun River is the right tributary of the Mekong River. The coordinates of the basin site are from 14°07′–16°23′ N and 101°16′–105°38′ E, with a total area of approximately 70,435.94 km^2. The elevation of the basin ranges from 17 m to 1330 m, which gradually decreases from the west to the east, and the south and west boundaries are primarily mountainous. The basin has a tropical monsoon climate, with annual precipitation between 800 mm and 1800 mm in the rainy season, which lasts from mid-May to mid-October, and a temperature between 25 °C and 30 °C. The maximum precipitation occurs in August or September. By contrast, the dry season has low precipitation from mid-October to the end of April of the next year. According to the Land Development Department of Thailand, the main land use type is cultivated land, which accounts for approximately 78% of the study area, and approximately 75% of the cultivated land is paddy fields. Of the paddy fields, approximately 90% are rain-fed, so most of the cultivated land in the dry season is idle, while the rainy season is the main period of crop planting. The food crops are mainly rice and corn, and the cash crops include sugar cane and cassava, so there are many factories that make tapioca starch. Other industries include light industry, such as sugar mills and alcohol plants. Most of the natural vegetation is tropical evergreen broad-leaved forest, which is dominated by tall trees, followed by shrubs, with relatively few herbs, concentrated on both sides of rivers or valleys.

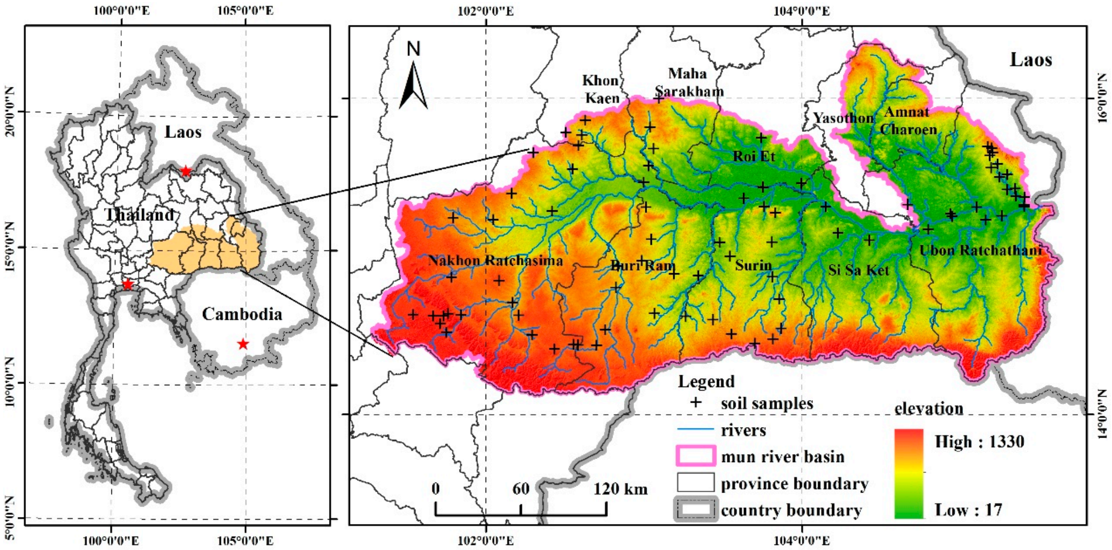


Figure 1. Study area and soil sample locations.

2.2. Soil Sampling and Analysis

This study used surface soil as the study object and the soil was sampled from 15 August 2017 to 25 August 2017. Combined with land use types, soil types and distribution of roads, a 10 × 10 km grid was created for sampling. However, the accessibility or operability were always unsatisfied; some sample points had to be replaced by points near the originally designed locations, and certain areas had access restrictions, which led to the final samples not being spatially uniform. Soil from 0–20 cm under the soil surface was collected, and each sample was put into an aluminum box. The locations of all samples were recorded with a handheld GPS (Global Position System), and a total of 86 samples were sampled. Some samples were collected outside the study area because of accessibility limitations (Figure 1). All samples were air-dried in ovens and then passed through a 2 mm sieve before physical and chemical analyses in the laboratory.

According to the advice of native professors and local residents regarding the soil quality assessment and spatial analysis of the soil properties, eight indicators were selected in advance, which were available phosphorus (AP), total nitrogen (TN), soil pH, soil particle size distribution (clay, silt and sand), soil organic matter (SOM) and soil electronic conductivity (EC). A laser particle analyzer was used to determine the soil particle size distribution. The Walkley-Black method [10] was used to measure the content of SOM. The Kjeldahl digestion method [25] was used to measure the content of TN. AP was determined by extracting samples with a 0.5 mol/L sodium bicarbonate solution, and then detected with a spectrophotometer. Soil pH was measured by the electrometric method on a soil/water suspension. EC was detected by a conductivity meter (SMET100).

2.3. Auxiliary Data

The auxiliary data, which were used as explanatory variables in the processes of indicator interpolation and spatial analysis, included elevation, terrain curvature, topographic index, distance to rivers, land use information (Figure 2), soil textures, normalized differential vegetation index (NDVI), environmental vegetation index (EVI), modified soil adjusted vegetation index (MSAVI) and meteorological data. The land use status of 2016 was generated from the Land Development Department of Thailand and modified by interpreting 2017 Landsat Thematic Mapper (TM) remote sensing images from the USA, from which the spatial distribution of the rivers was extracted and the distance to the rivers was calculated using the Euclidean distance method in ArcGIS software. The elevation, terrain curvature and topographic index were extracted from a digital elevation model (DEM), which was obtained from the Geospatial Data Cloud (http://www.gscloud.cn/). The NDVI, EVI and MSAVI were MODIS data products, which were retrieved from the online Data Pool courtesy of the NASA Land Processes Distributed Active Archive Center (LP DAAC), United States Geological Survey (USGS)/Earth Resources Observation and Science (EROS) Center, with the 2017 MOD13Q1 data used. Finally, the soil textures and meteorological data were obtained from the Land Development Department of Thailand. All of the datasets were projected into the WGS84-based Transverse Mercator orthographic projection coordinate system and resampled to a 250 m spatial resolution, which was also the study unit. Additionally, we conducted a questionnaire survey on land fertilization and crop yield during the field sampling to properly analyze the soil conditions in the study area.

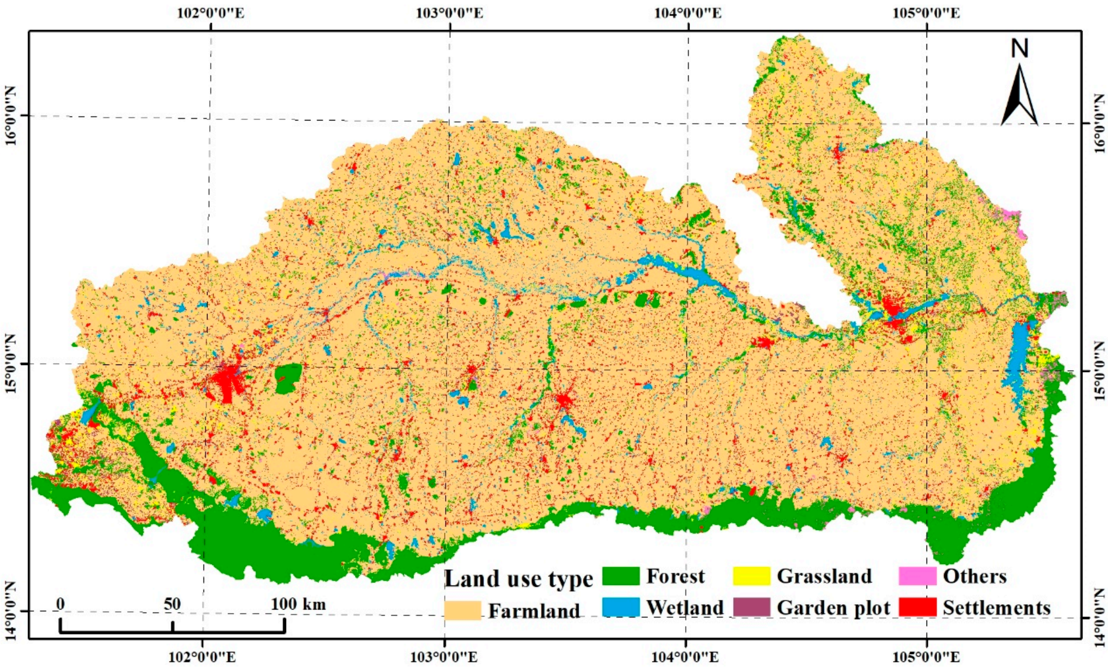


Figure 2. Spatial distributions of different land use types.

3. Methods

3.1. Geographically Weighted Regression

Geographically weighted regression (GWR) is an extension of traditional multiple linear regression and takes the spatial location of samples into consideration [25]. A GWR model can be expressed as follows:

$$y(u) = \beta_0(u) + \sum_{j=1}^{n} \beta_j(u) x_j(u) \tag{1}$$

where $y(u)$ is the dependent variable, $x_j(u)$ is the jth independent variable value, $\beta_0(u)$ is the intercept, $\beta_j(u)$ is the regression coefficient of the jth independent variable and n is the number of independent variables. The coefficients at each location in the study area need to be estimated using the weighted least squares approach as follows:

$$\hat{\beta}(u) = \left[X^T W(u) X\right]^{-1} X^T W(u) Y \tag{2}$$

where Y is an $(m \times 1)$ dependent data matrix, m is the number of observed data points in the local regression at location u, X is an $[m \times (n \times 1)]$ independent data matrix that includes a column of intercepts, and $W(u)$ is an $(m \times m)$ spatial weighting diagonal matrix, which can be described as:

$$W_{ij} = e^{-0.5(d_{ij}/r)^2} \tag{3}$$

where W_{ij} is the weight of the observed point at location j for predicting the dependent variable at location i and r is the bandwidth. The function shows that the weight of the observed point decreases with the distance from the predicted point, and a corrected Akaike information criterion (AICc) method is always used to obtain the appropriate bandwidth r as it reduces model complexity and instances of under-smoothing [26]. All of the above equations can be solved in ArcGIS software.

All soil samples were divided into two parts, 66 of which were training samples for interpolation. The remaining samples were used to verify accuracy.

3.2. Fuzzy Logic Model

Fuzzy membership is the probability of one indicator belonging to some grades but not to a certain grade; this method uses fuzzy functions to evaluate the fuzzy memberships of the different indicators belonging to all grades and then determines a specific grade according to some principles [27]. The common fuzzy membership function is as follows:

$$MF_{x_i} = \left[1/\left(1 + ((x_i - b)/d)^2\right)\right] \quad (4)$$

where MF_{x_i} is the fuzzy membership of indicator i (its range was $0 < MF_{x_i} \leq 1$); x_i is the value of i; d is the transition width of i, which is always set as the indicator value difference when the membership values are 0.5 and 1. Index b is the indicator value when the membership value is 1 (Figure 3).

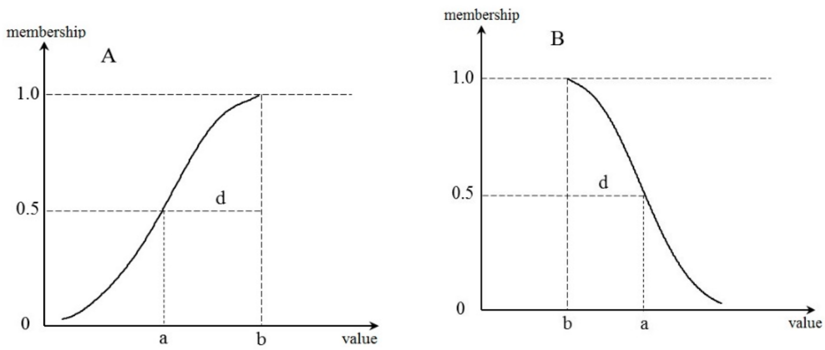


Figure 3. Indexes of the fuzzy logic model. (**A**) is for positive indicators and (**B**) is for negative indicators.

Setting the suitable range for each indicator is necessary according to the specific object. The membership value of each indicator can be gained through fuzzy function when the indicator value is in the range; otherwise, the membership value will be set as 0 or 1. The suitable range of each indicator is always confirmed by consulting previous research, documentation and standard specifications—it is an important and difficult process. The final evaluation is calculated by the integrated weighting method:

$$MF = \sum_{i=1}^{n} MF_{x_i} w_i \quad (5)$$

where w_i is the weight of indicator i, and an analytic hierarchy process is used to generate the weights of all indicators. Additionally, not all indicators were used for the soil quality assessment because of the redundancy among them, so the minimum data set theory was selected for indicator screening. Principal component analysis (PCA) is a common method used in establishing a minimum data set (MDS); indicators with high factor loadings in the components with eigenvalues ≥1 were selected as the soil properties that best represented the soil quality.

Additionally, SPSS software was used in the statistical analysis process of the data in the study and ArcGIS software was used in the process of spatial data processing analysis process. All spatial data sets were projected to a WGS84-based Transverse Mercator orthographic projection coordinate system and were resampled to a 30 × 30 m spatial resolution, and the final maps had the same resolution as the data sets.

4. Results

4.1. Descriptive Statistics

Initially, we conducted outlier tests on each indicator value of the soil samples, and values exceeding the range $(u - 3s,\ u + 3s)$ (where u is the mean of the indicator value and s is the standard deviation of the indicator value) were treated as outliers, which were then modified to the maximum or minimum of the remaining values. The results showed that there was one outlier in SOM, three outliers in TN and three outliers in AP, all of which were modified. Table 1 shows the descriptive statistics of the final data.

Table 1. Descriptive statistics of all soil indicators.

	Minimum	Maximum	Mean	SD	Skewness	Kurtosis	K-S Test	CV
pH	4.69	9.30	6.11	1.07	1.64	2.72	0.01	17.50
EC (us/cm)	4.11	133.00	28.87	38.52	3.52	13.71	0.00	133.43
Clay (%)	0.60	46.70	14.15	9.67	1.15	0.90	0.01	68.34
Sand (%)	49.00	97.70	80.81	11.56	−0.90	0.21	0.03	14.31
Silt (%)	0.50	17.20	4.95	3.86	1.40	1.39	0.01	77.87
SOM (%)	0.05	2.84	1.13	0.64	0.88	0.40	0.14	56.19
AP (mg/kg)	6.88	139.47	32.06	32.43	2.34	4.88	0.00	101.16
TN (%)	0.03	0.16	0.08	0.03	0.98	0.37	0.06	44.79

SD: standard deviation; CV: coefficient of variation.

Table 1 reveals that most indicators had a moderate variation as the coefficients of variation (CVs) were less than 100% with the exceptions of EC and AP, which showed strong variation with their coefficients exceeding 100%. Compared to the soil nutrient standard described by Wu [10], the contents of SOM and TN were low, but AP was abundant. The sand content in the soil was high, and the soil was mainly acidic as the pH values of 63 samples were lower than 6.5; only TN and SOM were in a normal distribution based on the *k-s* (Kolmogorov-Smirnov) test results. The correlation among the different indicators is shown in Table 2.

Table 2. Correlation coefficients among all of the indicators.

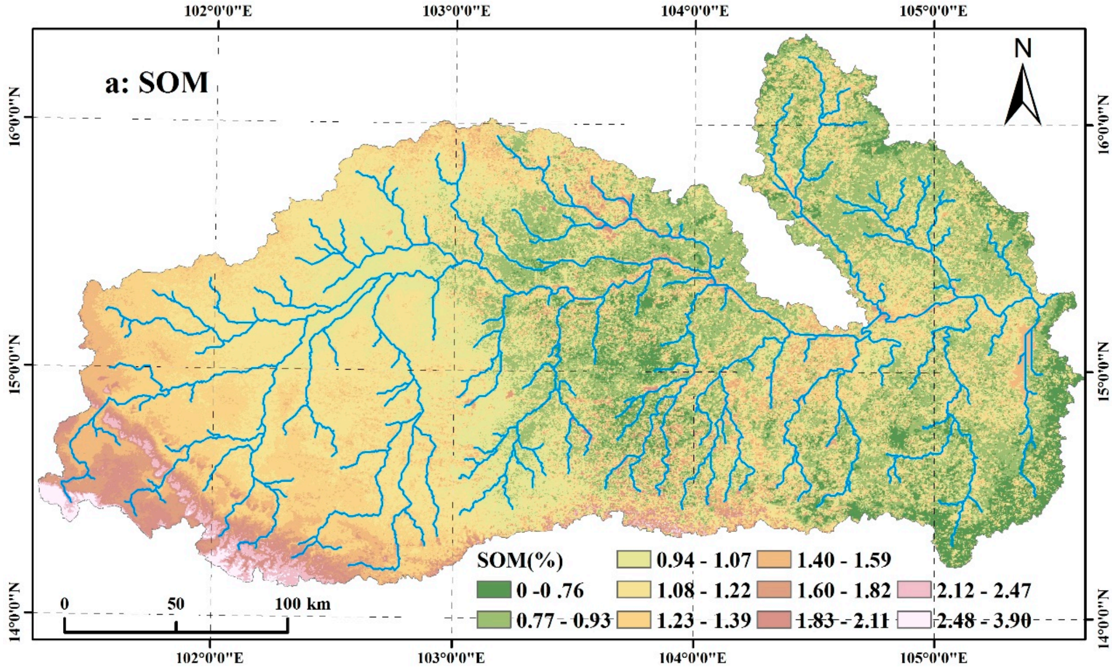
	SOM	AP	TN	Clay	Sand	Silt	pH	EC
SOM	1							
AP	0.24 *	1						
TN	0.92 **	0.13	1					
Clay	0.60 **	−0.01	0.64 **	1				
Sand	−0.59 **	0.03	−0.64 **	−0.95 **	1			
Silt	0.28 **	−0.08	0.33 **	0.37 **	−0.63 **	1		
pH	0.20	0.07	0.21	0.20	−0.18	0.04	1	
EC	0.27 *	0.03	0.31 **	0.29 **	−0.31 **	0.21	0.54 **	1

**, *: significant correlation at the 0.01 level and the 0.05 level, respectively.

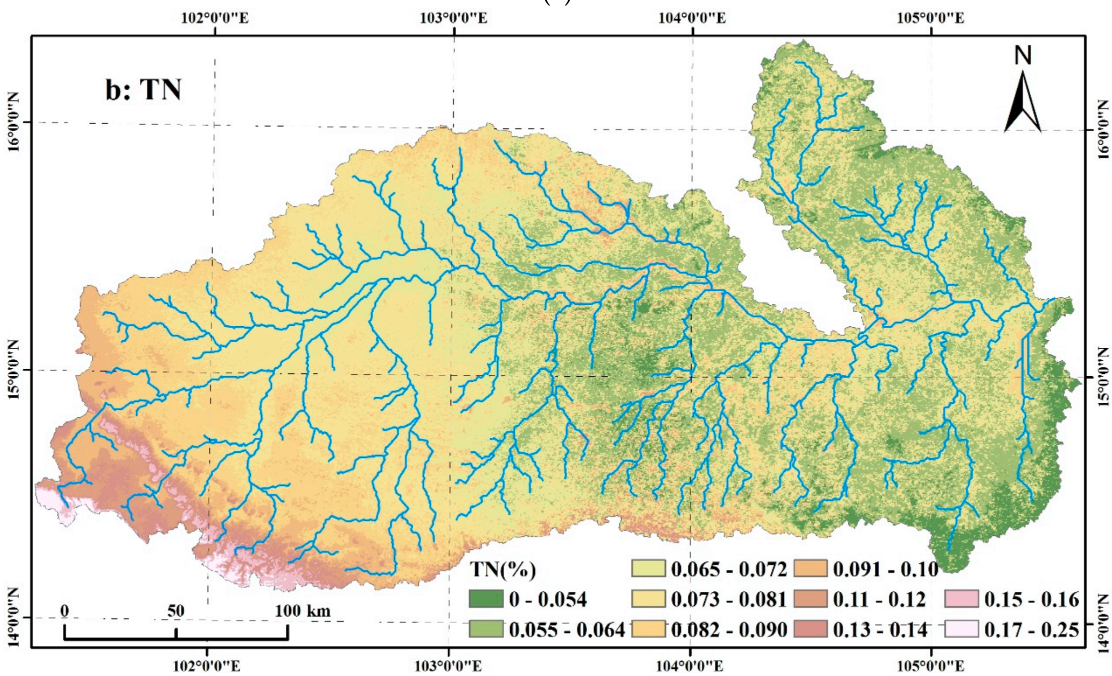
Table 2 indicates that most of the correlation coefficients among different indicators were significant at the 0.01 and 0.05 levels. SOM was highly related to most indicators at the 0.01 level, and the soil physical properties might be very influential on SOM and TN as the correlation coefficients among them were extremely significant at the 0.01 level.

4.2. Soil Indicator Interpolation

In this study, we only selected four indicators for soil quality assessment based on the minimum data set (MDS) theory, a widely used method in similar research. The four indicators chosen were SOM, TN, AP and pH. Elevation, terrain curvature, topographic index, distance to rivers, NDVI, EVI and MSAVI were preselected as explanatory variables for indicator interpolation; however, only NDVI and elevation were used in GWR because the multivariate collinearity among other variables exceeded the tolerance according to the stepwise regression calculation in SPSS software. Additionally, there were no explanatory variables selected for pH in GWR, so ordinary kriging was used to generate the spatial distribution of pH. The results are shown in Figure 4 below.

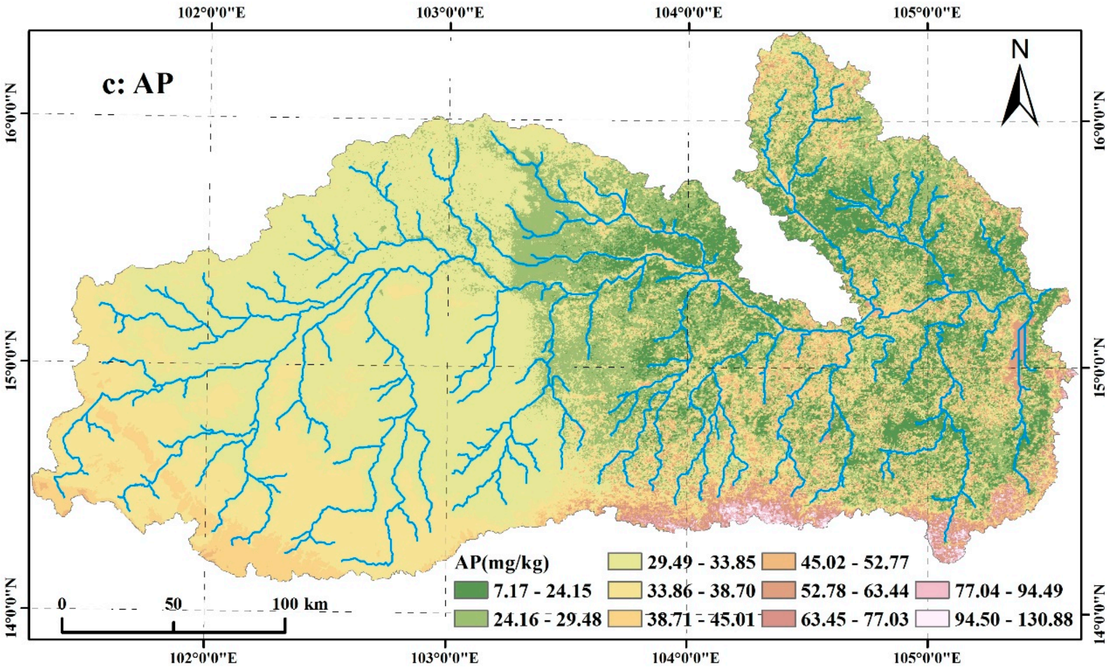


(**a**)



(**b**)

Figure 4. *Cont.*



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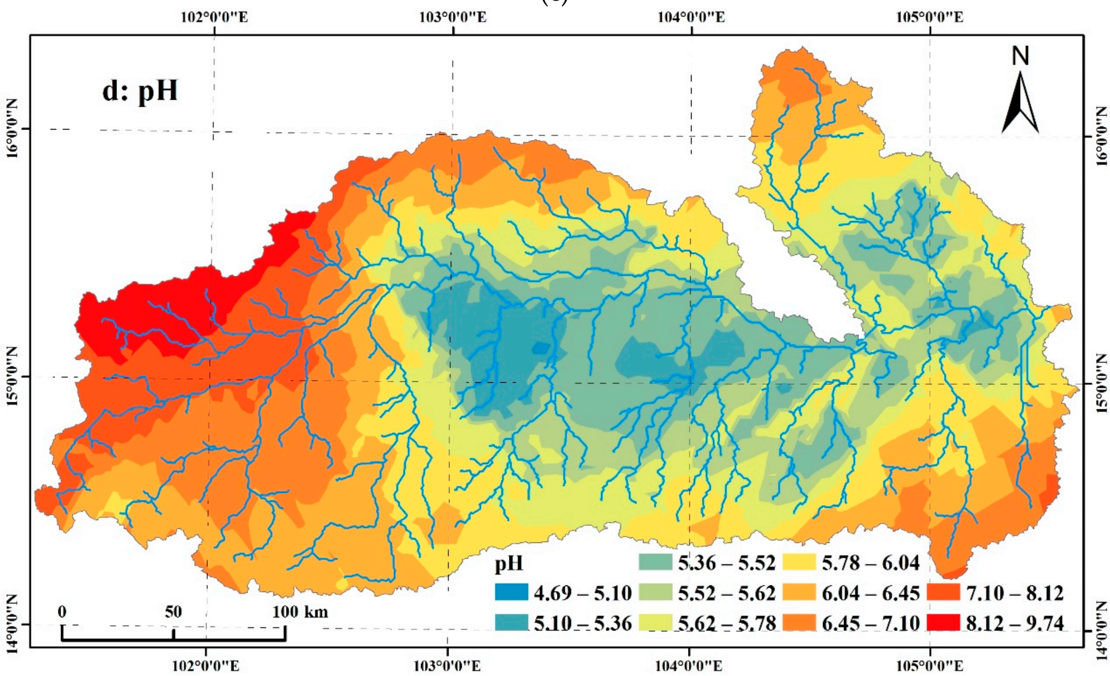

(**d**)

Figure 4. Spatial distributions of the assessment indicators. (**a**–**d**): the contents of SOM, TN, AP and pH.

The figure showed that the spatial distributions of all of the indicators were regular and that the accuracies of the four indicators were also satisfactory, with the mean errors close to 0 and root mean square errors not exceeding 0.5. The content of SOM gradually declined from the western to the eastern region of the basin, and it displayed different spatial characteristics near the upstream and downstream tributaries of the Mun River. Specifically, the content of SOM was lower along the rivers than other areas in the upstream direction and higher along the rivers than other areas in the downstream direction. The highest content of SOM was distributed in the southwest part of the basin, where the topography is mainly mountainous. The spatial distribution of TN was similar to that of SOM, with an obvious boundary in the middle of the study area, and the content of TN gradually declined from the western to the eastern region of the basin. The highest content was found in the mountainous southwest region of the basin, but the southeast mountains of the basin had the lowest content of TN. Compared to SOM, the influence from rivers was weaker as the contents of TN along the rivers was similar to those of other areas near the rivers. The content of AP was more abundant than those of other indicators over the basin and showed the highest values in the southeast of the basin; this indicator also declined from the western to the eastern region of the basin, though there were some high values in the downstream area except near rivers. The soil was mainly acidic throughout the basin, as shown in Figure 4, and the pH value was higher in the periphery compared to the interior of the basin. The lowest value was approximately 4.69 in the middle of the basin, while the highest value was approximately 9.74 in the northwest of the basin, where the soil was mainly alkalic.

For further analysis, the land use types (Figure 2) were overlain with the spatial distribution of the different indicators, and their mean values in different land use types are shown in Table 3.

Table 3. Statistics of all of the assessment indicators in different land use types.

Land Use Type	Area Proportion (%)	SOM (%)	TN (%)	AP (mg/kg)	pH
Farmland	72.138	1.096	0.073	31.669	6.111
Forest	13.062	1.327	0.087	40.980	6.226
Grassland	3.423	1.135	0.075	32.095	6.211
Wetland	4.060	1.260	0.079	35.826	5.987
Garden plot	0.824	1.283	0.084	33.861	6.304
Others	0.430	0.949	0.063	40.119	6.123
Residence	6.062	1.155	0.076	32.752	6.140

Figure 2 and Table 3 show that farmland and forest are the main land use types in the Mun River basin, with the total proportion of both reaching more than 85%. From the above figure and table, we note that forest is mainly distributed toward the southern boundary of the basin, which is mountainous. The forest region had higher contents of SOM, TN and AP than those of the other land use types, and its soil was more neutral as assessed by the mean pH value. Farmland had the widest distribution over the basin, but the soil indicators were not ideal; for example, the contents of SOM, AP and TN were all found to be at low levels and the soil was more acidic. Additionally, the mean values of the indicators in paddy fields and dry fields, which were included in farmland, made a significant difference. The mean values of the four indicators were 1.238, 0.082, 83.491, 33.862 and 6.724 in the dry fields and 1.064, 0.071, 30.991 and 5.977 in the paddy fields, respectively.

4.3. Soil Quality Assessment and Analysis

The optimum ranges of all of the selected indicators used for the soil quality assessment in the Mun River basin were designated according to research results, in addition to expert advice, policy standards and the actual situations of the indicators [28,29] (Table 4). Then, indexes b and d were generated based on the ranges and fuzzy logic function, and the membership values of all of the indicators of soil quality were calculated according to the function. However, pH was a double trend indicator, as it was positive when its value was lower than 7 and negative when its value was higher than 7.

Table 4. Membership thresholds of the assessment indicators.

Indicator	Range	b	d	Tendency
TN	0.01–0.075	0.075	0.025	Positive
AP	20–120	120	50	Positive
pH	5.5–7	7	1	Positive
pH	7–8.5	7	1	Negative
SOM	0.6–1.5	1.5	0.5	Positive

The integrated weighting method was selected to complete the soil quality assessment, and the indicator weights were obtained from each indicator communality that was generated in the PCA process (Table 5); the weight of each indicator was the proportion of its value to the total value.

Table 5. Weights of the assessment indicators.

Indicator	Communality	Weight
pH	0.80	0.25
SOM	0.83	0.26
AP	0.71	0.22
TN	0.85	0.27

Assessment results of each study unit were generated using the integrated weighting method. The soil quality was divided into six grades, ranging from grade I to grade VI, according to the natural breakpoint method (which was based on the principle of minimizing the sum of the variations in each level to select the graded breakpoint), with ranges of ≤0.37, 0.37–0.46, 0.46–0.55, 0.55–0.64, 0.64–0.73 and ≥0.73. Grade VI was the highest soil level. The spatial distribution of the soil quality is shown in Figure 5.

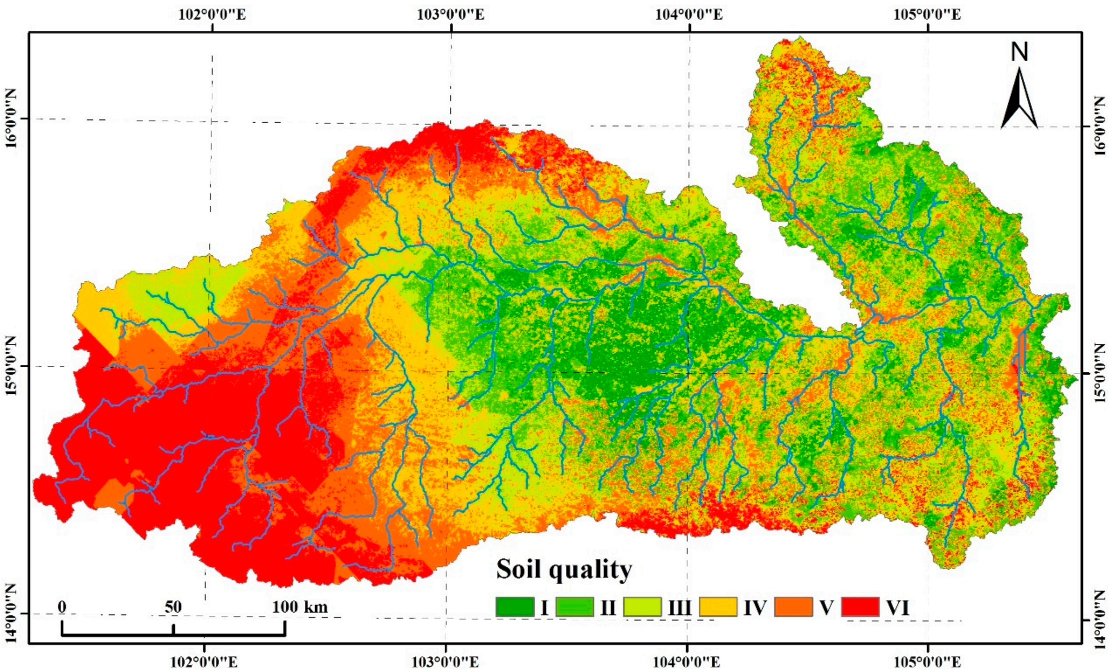

Figure 5. Spatial distributions of soil quality in the Mun River basin during the rainy season.

Figure 5 shows that the upstream region of the basin had the best soil condition with grades of mainly V and VI. Most of the middle and downstream areas featured low grades, being especially true for the middle area, where the soil grade was mainly I. The soil conditions near rivers were better than those of other areas in the downstream region. The statistics of the different soil quality grades showed that grades III, IV and V had similar areas over the basin and were also the most widely distributed, with areas of 13,360.39 km^2, 13,387.41 km^2 and 13,608.93 km^2, respectively, and grade I was the smallest, with an area of 5348.33 km^2, distributed primarily in the middle of the basin. Grade VI was mainly found in the upstream region, with an area of 12,782.43 km^2 (Table 6). Additionally, the spatial distribution of soil quality was overlaid with the land use types, and the results showed that the mean values of soil quality in farmland and forest were 0.56 and 0.63, which belonged to grade IV, respectively.

Table 6. Areas of all of the soil quality grades in different land use types.

Land Use Type \ Grade	I	II	III	IV	V	VI	Total
Farmland	4186.90	9261.92	10,285.84	10,302.06	9988.29	6786.07	50,811.08
Forest	661.63	1290.69	1131.80	951.83	1274.38	3890.04	9200.38
Grassland	139.84	391.61	496.46	429.69	452.19	501.50	2411.30
Wetland	89.99	269.69	464.85	687.31	928.62	419.54	2859.99
Garden plot	29.75	79.12	74.61	67.29	87.85	241.71	580.33
Others	52.52	76.69	52.87	42.44	39.16	39.47	303.14
Residence	187.70	578.71	853.95	906.80	838.44	904.11	4269.71
Total	5348.33	11,948.44	13,360.39	13,387.41	13,608.93	12,782.43	70,435.94

Table 6 shows the areas of different land use types in the six soil quality grades, and it can be seen that most farmland areas were of grades III and IV. The areas of grades I and II were also very large; however, the total area of grades I, II and III was approximately 46.75% of the farmland, which indicated that the soil quality was not perfect for farmland and that some improvements should be carried out for the sustainable use of land. However, there was still approximately 33% of farmland distributed in high grades of V and VI, which were mainly in the western and northern regions of the basin. Dry fields had a better soil quality than paddy fields, as approximately 78.44% of dry fields were in grades IV, V and VI, while the proportion was only 47.45% for paddy fields. The soil condition of forest was better than that of farmland, as most forests had high grades of soil quality and were also mainly distributed upstream. In comparison, the soil of the forest in the southeast area was poorer.

5. Discussion

The accuracy of the soil quality assessment in this study was not verified due to a lack of related research, but we were able to make a general judgment through comparison of the spatial distributions of different indicators to that of soil quality as we had confirmed the accuracy of interpolation of all indicators. Furthermore, compared to previous studies by Zhao [30,31], more details were expressed in this research, which also proved that the geographically weighted regression model was more applicable. The spatial distribution of soil quality was similar to those of SOM and TN throughout the basin as their weights were heavy in the assessment process, and the influence of AP on soil quality was mainly seen in the south of the basin, where the high content of AP led to good soil quality. The high values of soil quality in the northwest of the basin were indicated by the pH. Based on the above parameters, we consider that the assessment results were reasonable.

The study results showed some obvious patterns not only according to space but also according different land use types. First, most forests were natural, with little human interference, and the soil nutrients had accumulated for many years from the decomposition of dead branches and leaves, which led to rich SOM, AP and TN; humus could also regulate the pH of the soil, which made the soil neutral. Second, the soil quality in farmland was not that good over the basin, though the soil quality was better in dry fields than in paddy fields because dry fields can be cultivated continuously throughout the year with multiple fertilizations. Meanwhile, paddy fields remained idle because of the lack of rain and nutrient supply, and these fields were not all fertilized even in the rainy season according to our questionnaire surveys. Third, the land was variable in the western part of the basin, with forests and dry fields mainly distributed there, so the soil quality was better than that of other areas. The land was smooth in the middle and east part of the basin, where the main land use type was paddy fields, which were idle in dry months, with all of these factors leading the soil quality to be poor. Some areas in proximity to the downstream rivers were still available for cultivation throughout the year, and in those areas fertilization played a role in improving soil quality according to our questionnaire survey.

The assessment was reasonable to some extent, especially considering that the spatial patterns were in line with expectations according to the questionnaire surveys; however, there still were some insufficiencies in this study. First, the number of samples was too small and the samples were randomly distributed over the study area, which led to great uncertainty in the spatial interpolations of all indicators and soil quality assessment. Furthermore, the spatial details could not be displayed fully, especially in the southeast of the basin, where the samples were very rare. Second, compared to other studies on soil quality assessment [4,10], the selected indicators in this study were relatively lower, and biological indicators were not included because of the restrictions of the experimental conditions. Fortunately, we will continue our research in the Mun River basin and may be able to solve these problems through the use of other methods in the near future.

6. Conclusions

Soil nutrient indicators had obvious spatial patterns in the Mun River basin, and the contents of SOM and TN were at low levels over the basin. The spatial distributions of the two indicators were similar, with high values in the west and low values in the east of the basin, and a gradual decline from the west to the east of the basin. The content of AP was at a high level over the basin, and its spatial trend was similar to that of SOM; however, the highest AP values appeared to the southeast of the basin. The pH measurements indicated that soil was very acidic in the middle of the basin and very alkalic in the northwest of the basin. The soil quality assessment results showed bad soil in the middle of the basin, where the main land use is paddy fields, and good soil in the southwest of the basin, where forests and dry fields are widely distributed. All of the above indicated that the variability of soil quality over the Mun River basin was large and especially for farmland, the soil quality was not ideal. These findings will be useful for soil quality improvement during the farming period, for example to increase soil nutrients that are lacking. Additionally, the limited soil samples and incomplete indicators system gave the assessment results great uncertainty, and solving these issues is an opportunity for future research.

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