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Modeling of Agricultural Nonpoint-Source Pollution Quantitative Assessment: A Case Study in the Mun River Basin, Thailand

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Abstract: Agricultural nonpoint-source pollution (ANPSP) is a key cause of global environmental problems. However, the estimation of ANPSP, based on agricultural land use type, crop management, and attenuation of pollutants with distance, is lacking. Using the Mun River Basin as an example, this study established quantitative response relationships between subbasin flows and hydrological and water quality parameters. A good matching of the monitored sections and the control area based on flow relationships was achieved. By determining flow paths and flow distances, the overland and in-river transport attenuations of ANPSP were clarified. The overland and in-river transport and attenuation parameters were also quantified. The land use distribution and structure were further refined through crop management, which included crop types and crop rotation (monocropping or double cropping). Based on the above procedures, quantitative relationships among land use pattern, crop management, attenuation of pollutants with distance, and river water quality were established and used to construct six kinds of regression models. Among these models, the best modeling results were obtained when the parameters of water quality, land use structure, crop management, and soil nutrient attenuation were included. The modeling accuracy in the dry season increased from 0.398 to 0.881 when information about attenuation with distance and crop management was included. Similarly, the modeling accuracy in the wet season increased from 0.365 to 0.727. This study's findings indicate that the constructed water quality model is effective and has significance for the quantitative determination of ANPSP.

Keywords: agricultural nonpoint-source pollution; land use patterns; attenuation coefficient; soil nutrient attenuation; water quality

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1. Introduction

In recent decades, aquatic environments and ecosystems have faced enormous threats. Agricultural nonpoint-source (NPS) pollution has become both a research focus and a challenge. Particularly at the basin scale, study findings on the transport of excessive nutrients and sediments by surface flow and the impact of such transport on rivers have provided important information for watershed management [1]. Many studies have shown that rainfall drives as much as 60–92% of the export of sediments and phosphorus [2].

Land use activities have profound impacts on the terrestrial environment and on the transport and transfer of nutrients among the lithosphere, atmosphere, biosphere, and hydrosphere [3]. Land use itself is heterogeneous in terms of structural proportions [4,5], spatial structure, and crop management, and all these factors affect the production, transfer, and transformation of agricultural NPS pollution. Therefore, the accurate determination and quantification of the complex relationships among agricultural NPS pollution, land use, and crop management is of great scientific significance.

Previous studies in China and abroad have drawn different conclusions about the relationships between land use and water quality Wang showed that urban construction and agricultural land cover were significantly positively correlated with the concentrations of pollutants in waterbodies, whereas forest and green space were negatively correlated with pollutant concentrations in waterbodies [6,7]. In contrast, Deng demonstrated a lack of correlation or a negative correlation between agricultural land and pollutant concentrations in waterbodies [8]. Sun-Ah et al. examined the relationship between land use and water quality in the context of urbanization and found that urban and abandoned land cover types were positively correlated with water quality, and forest cover was negatively correlated with water quality [9]. Gyimah et al. studied the effect of different land use types on the physicochemical water quality of a semi-arid coastal basin. Forest cover correlated negatively with water quality although not significantly, and grassland correlated significantly [10]. Lee et al. studied the relationships between reservoir water quality and land use and found that urban area and density significantly influenced water quality [11]. Studies have also shown that water pollution due to land use type is related to the distance between the land and the river [12]. For instance, studies found that cultivated land was related to the concentration of ammonia as a water pollutant. The differences among the study findings indicate that the relationships between land use and water quality are not universal [13,14]. In different regions, variability in the spatial distribution, structure, and mode of land use results in within-basin differences in the relationships between land use and water quality, and even within the same study region, there may be variability between subbasins [15,16].

It is important to use modeling approaches to evaluate and predict NPS pollution, for example, the total maximum daily loads and city behavior in Chinese models. In addition, the inability to obtain long-term data and the reliance on monthly or seasonal data could lead to the underestimation of the severity of water pollution [17,18]. Moreover, the current research mostly addresses the influence of the quantitative structure of land use on pollution [19,20]. Descriptions of crop type and crop management are relatively inadequate. This situation leads to variations in how the relationships between agricultural NPS pollution and land use are interpreted and understood [21,22], and as a result, the management and control measures applied to the aquatic environment are not precise.

The topsoil is the main source of soil nutrient loss [23]. Topsoil erosion can easily exacerbate the loss of nutrient elements, particularly nitrogen and phosphorus, and worsen water pollution [24]. Thus, accurately describing the relationship between topsoil and soil nutrient loss is conducive to guiding land use management. Studies in China and abroad have shown that land use type and crop management have significant impacts on the degree of water pollution. The detailed classification of land use types and the extraction of cultivation activities can provide more accurate information on the estimation of water pollution [25]. Furthermore, the distance between land units and a river can have significant effects on the ecohydrological mechanisms underlying the production, transport, and transformation of pollutants. The availability of such information will make a more comprehensive evaluation of water pollution possible [26].

We performed our study in the Mun River Basin, Thailand. The aims of this paper are (1) to reclassify hydrological units, for which a quantitative correspondence between the confluence subbasin and the water quality monitoring section is established and accurately matched; (2) to calculate the confluence distance, where the confluence path and distance of the whole process are calculated, the overland and channel transport attenuation processes of NPS pollution are clarified, and the corresponding attenuation coefficients are quantified; and (3) to determine a pollution model. Based on the above work, a quantitative relationship model of land use structure, planting mode, soil nutrient attenuation, and water quality is established.

2. Study Area

The Mun River (Figure 1) is located in eastern Thailand; the river length is approximately 673 km, and the watershed has an area of about 82,000 km^2. The Mun River originates on the Korat Plateau and flows through 10 provinces before joining the Mekong River. In the basin, the southwestern areas are plateaus and mountains, and the central and eastern areas are plains. The climate of the Mun River Basin is affected by tropical monsoons. The climate and hydrology within the basin show evident seasonal differences [27]. The basin has distinct wet and dry seasons induced by the seasonal monsoon. The annual temperature is greater than 18 °C, and the average annual rainfall is about 1300–1500 mm.

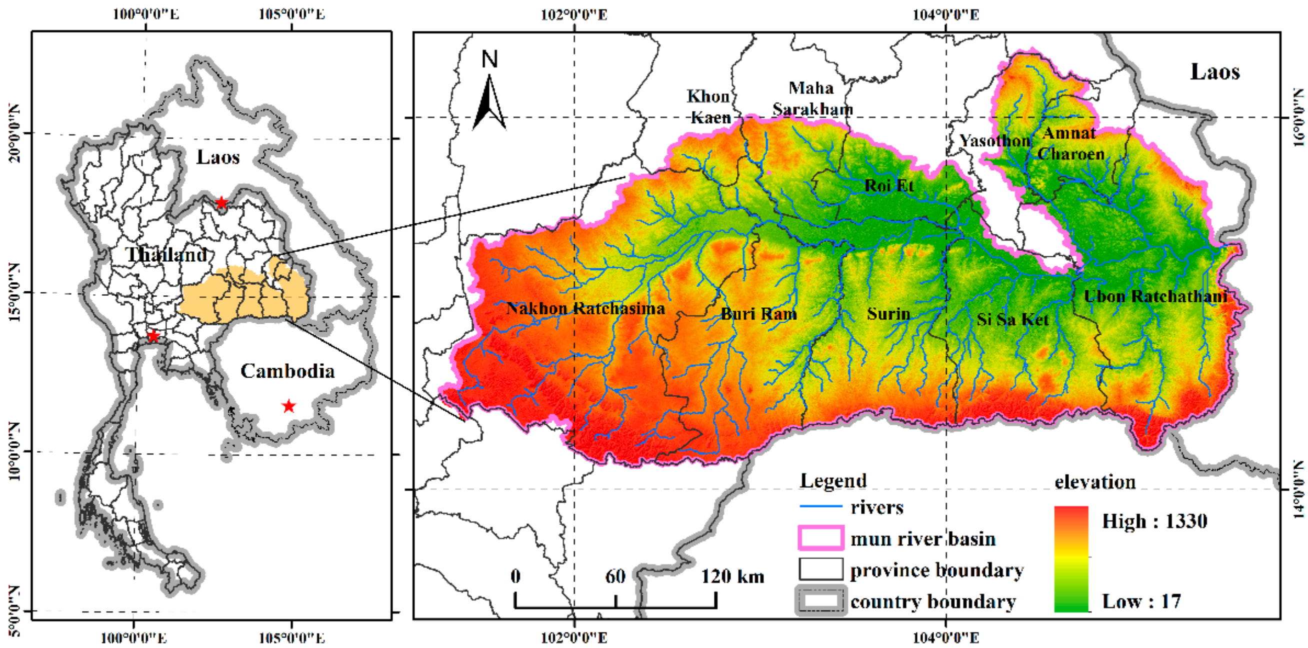

Figure 1. Location of the Mun River Basin.

From May to October each year, the southwest monsoon blowing from the Indian Ocean produces high temperatures and abundant rainfall, generally referred to as the rainy season, with heavy rainfall mostly concentrated in August or September. From November to April of the following year, the northeast monsoon brings low temperatures and dry weather due to the Mongolian cold high-pressure system, and this period is usually referred to as the dry season. The transitional season between the dry season and the rainy season features frequent nondirectional winds [28].

3. Materials and Methods

3.1. Land Use Data

The land use data were produced by the interpretation of remote sensing images in combination with land surveys by Soil Resources and Land Development Agencies in Thailand.

The land use interpretation accuracy was calculated using actual categories as standards. The overall classification accuracy was about 93.4% (Table 1).

3.2. Extraction of Crop Type and Crop Rotations

The MODIS D09Q1 data product has a spatial resolution of 250 m and a temporal resolution of 8 days; this study used data from 2010 to 2020. The detailed processes used to extract the crop type were as follows. First, MODIS normalized difference vegetation index (NDVI) time-series data were extracted, and the NDVI time-series data were filtered to create crop-growing curves using the Savitzky–Golay filtering method. When a larger window width is used, a smoother filtering result is obtained, and the use of a smaller polynomial fitting order yields smoother filtering results. The polynomial fitting order was set to 2. Second, the crop type and crop rotations were determined by the extraction of growing-curve peaks; one peak corresponds to monocropping, whereas two peaks correspond to double cropping. Moreover, pseudopeaks are eliminated according to the restraint set. Peaks with NDVI values less than 0.45 were considered pseudopeaks. When the difference in time between two peaks was smaller than 32 days, the peak with a lower NDVI value was identified as a pseudopeak. Finally, the crop type and rotations were mapped (Figure 2).

Table 1. Land use matrix for accuracy verification.

Identified Classes / Actual Classes	Grassland	Urban Land	Forest	Farmland	Unused Land	Wetland	Gardens	Total
Urban land	1	6		2		3		12
Forest		3	38	8				49
Farmland	2	3	2	505		1	4	517
Unused land					1	1		2
Wetland	1	3		3	1	16		24
Gardens				1			4	5
Total	4	16	40	519	2	21	8	610

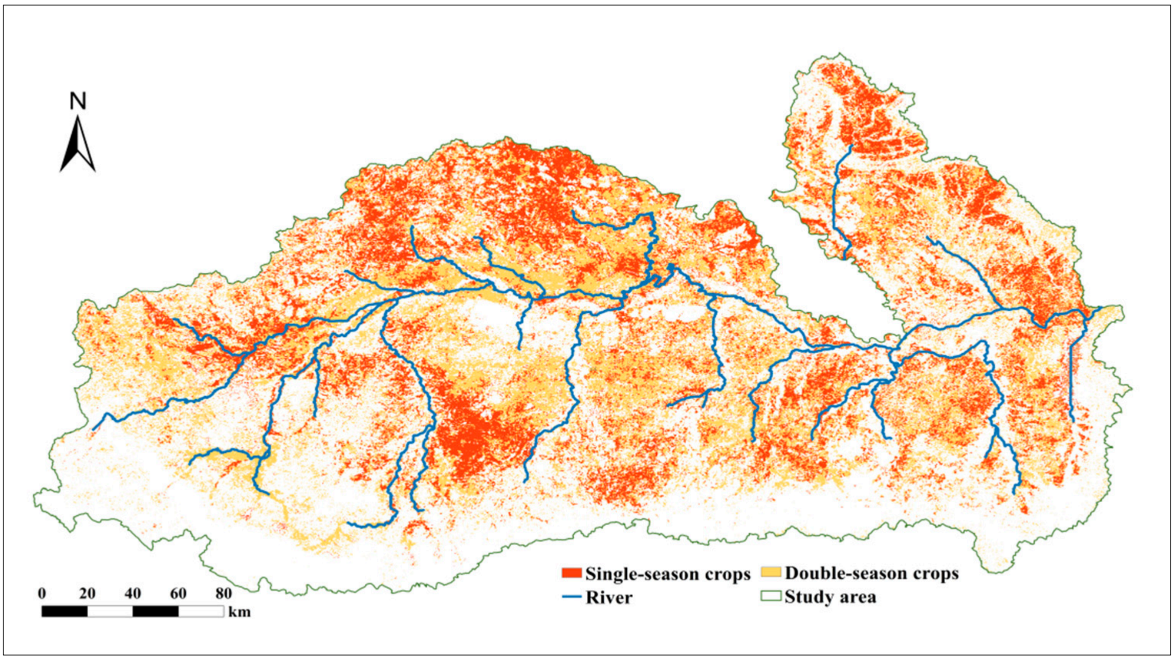

Figure 2. Crop rotation map.

3.3. Soil Sampling in Dry and Wet Seasons

The soil samplings were carried out in February and July 2017, representing the dry season and the rainy season. Soil samples in the profile were taken from representative areas and treated according to the quaternary method upon even mixing, and the remaining 1.5 kg samples were brought back to the laboratory for air drying. After roots, leaves, and stones were removed, the samples were stored for further use. To ensure consistency of the sampling habitat, the slopes of the sampling quadrats were all <5°. The latitude and longitude coordinates of each sample were recorded with GPS. At the same time, the vegetation growth and land use conditions and soil color were recorded; the soil moisture was measured; and the sample sites were photographed. Because only the data pertaining to shallow soil layers were used in this study, the soil sampling depth was set as 0~20 cm. A total of 153 topsoil samples were collected and tested (Figure 3).

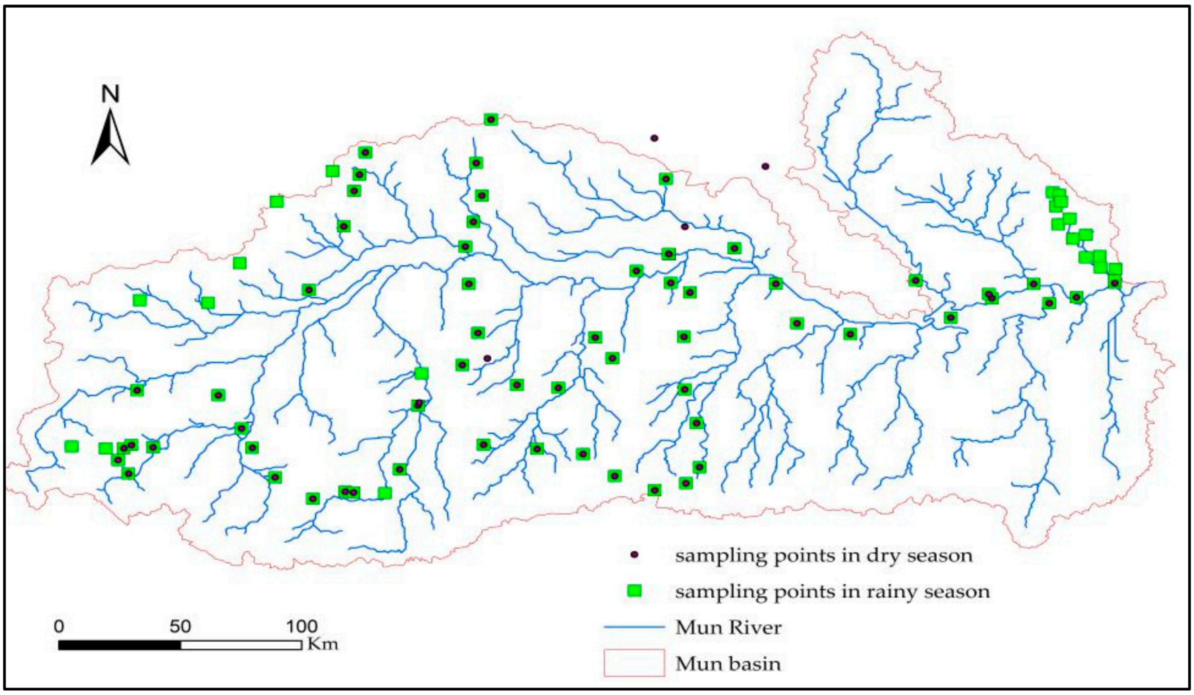

Figure 3. Map of the distribution of soil sampling points [29].

3.4. Flow Network and Flow Distance Calculations

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM)-derived digital elevation model (DEM) differs from real situations to a certain degree. Therefore, prior to further analysis, it is necessary to verify and adjust the original data. Python language programming based on the ArcGIS 10.5 software was used for this purpose. The pixel units in the study region were read individually; for pixels that did not have reasonable values, the data were replaced with the mean elevation values of the surrounding eight pixels.

According to the method for the simulation of DEM-based overland flow, DEM data were used for sink filling, flow direction simulation, and flow path calculation to determine the flow network and subbasin areas. Using the above hydrological analysis, the transport of soil nutrients with runoff under different crop areas could be simulated. Meanwhile, the in-river transport of nutrients was also calculated.

In a river flow network, when the flow accumulation reaches a certain value, surface runoff is generated. Rivers composed of grids with flow accumulation exceeding the threshold constitute the river flow network. The choice of the flow accumulation threshold is one of the key factors in hydrological analysis. Setting different thresholds can generate different river networks, leading to the delineation of different subbasins. At bigger thresholds, fewer grids have a flow accumulation exceeding the threshold, and the river network is simpler. When extracting the river network in the study region, a total of 10 thresholds were set to generate river networks and subbasins. Based on field research and remote sensing images, the threshold of 100,000 pixels was eventually selected as the base value in combination with 10,000 pixels to delineate finer-scale basins. Based on the locations of 19 water quality monitoring stations, the basin was divided into 19 subregions. The overland transport distances and in-river transport distances were calculated (Figure 4).

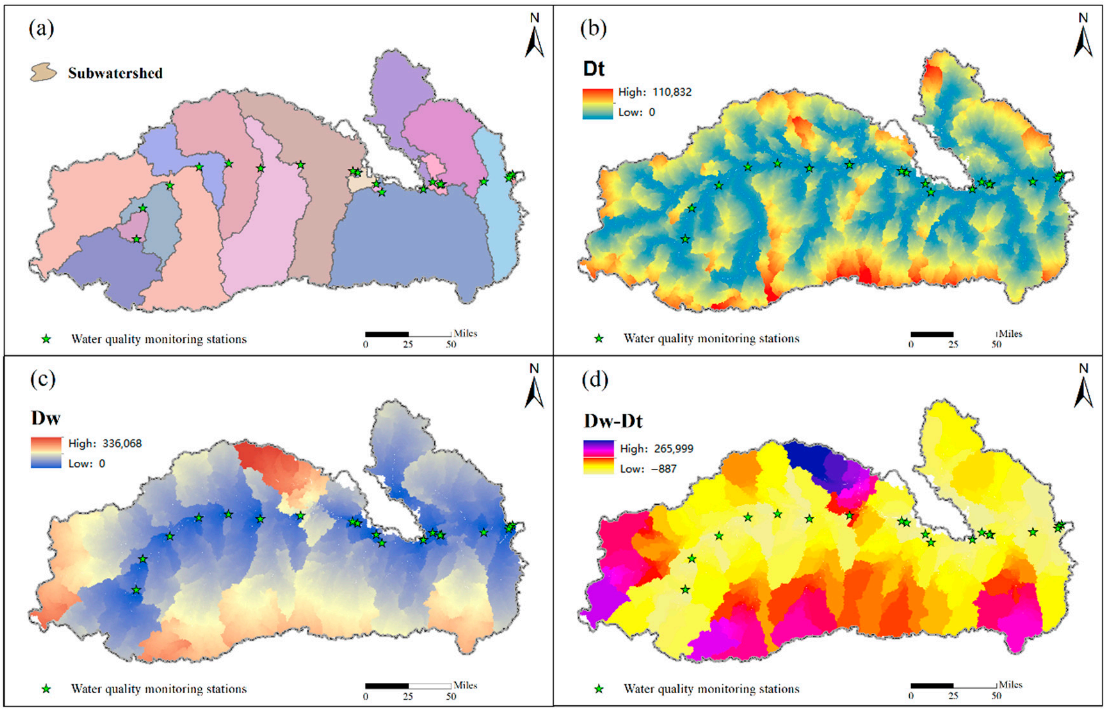

Figure 4. Watershed division and confluence distance. (**a**) Sub-watershed division; (**b**) confluence distance; (**c**) overland transport distance; (**d**) in-river transport distance.

The calculation of overland transport distances and in-river transport distances was mainly performed using the Hydrology module of ArcGIS.

The extracted river channels were gridded. Each grid served as the watershed outlet. The points at which the flow direction diagram and the grids of the river network met were set as the subbasin outlets. The Flow Length tool was then used to calculate the transport distance from each grid unit to the subbasin outlet; this distance was the overland transport distance, Dt. The grid in which a water quality monitoring station was located was set as the watershed outlet. The distance from each grid unit to the water quality monitoring station was calculated as Dw. Using the raster calculator, the river transport distance was calculated as Dw-Dt.

3.5. Selection of Water Quality Elements

The water quality element was selected by principal component analysis (PCA), a multivariate statistical technique that converts a set of possibly correlated variables into a set of linearly unrelated variables through orthogonal transformation. All relevant calculations were performed in SPSS. In this study, 10 variables related to NPS pollution characteristics were selected: NH3-N, NO3-N, NO2-N, total phosphorus (TP), dissolved oxygen (DO), BOD, EC, pH, nephelometric turbidity unit (NTU), and suspended solids (SSs) [30].

3.6. Determination of Attenuation Parameters

The generation of overland flow and transport of soil nutrients to the water quality monitoring stations involves two main processes. The first process is the transport and accumulation of soil nutrients on the land surface. Following transport via surface runoff, soil nutrients become attenuated in the basin, and the eroded nutrients are eventually transported to the subbasin outlet during the process of overland flow. The second process is the transport of soil nutrients from the subbasin outlet to the water quality monitoring station [31,32]. This process includes in-river transport and transformation. The overland flow distance and the in-river transport distance, as well as the attenuation parameters, were measured as part of a quantitative analysis of the relationships between overland soil nutrients and water quality.

The concentrations and attenuations of nutrients along the path between the soil in a given region and the receiving water bodies have been simulated in previous studies using linear functions, exponential functions [33], or a combination of the two [34]. Currently, no unified method or model is used to select functions to quantify the attenuation of nutrients with runoff distance. An inverse distance function, a type of function that has generated good results in previous studies [35], was adopted in this study to separately describe the attenuation of soil nutrients on the basis of between-river overland transport distance and in-river flow distance. The inverse distance function is expressed as follows:

$$f(D) = \left(\frac{1}{D+1}\right)^{\alpha} = \begin{cases} \left(\frac{1}{D_t + 1}\right)^{\alpha} & \text{overland flow} \\ \left(\frac{1}{D_w - D_t + 1}\right)^{\alpha} & \text{in} - \text{river flow} \end{cases} \quad (1)$$

where D represents distance (either the overland transport distance from the land to the river or the in-river transport distance) and a represents the attenuation parameter of soil nutrients with increasing distance. The larger the value of the attenuation parameter, the greater the effects of soil nutrients on water pollution at smaller distances. If $a = 0$, $f(D) = 1$, and the distance has no effect on the water pollution.

For the determination of attenuation parameters, a trial-and-error method was used in this study [30]. Multiple groups of parameters were set and used to quantify the effects of soil nutrients on the water pollution index. The relationships between specific groups of parameters and the water pollution index were compared, and the function with the greatest explanatory power was selected for subsequent analysis and discussion. In this study, five sets of attenuation parameters (0.1, 0.3, 0.5, 0.7, and 1) were used for testing and verification. Because both overland and in-river transport attenuation were involved, it was necessary to determine two sets of attenuation parameters: an overland flow attenuation parameter, a_t, and an in-river flow attenuation parameter, a_i. Theoretically, the speed of overland flow is generally considered to be lower than that of in-river flow. Given the same distance, slopes have greater effects on the water quality index [36]. Therefore, a_t should be greater than or equal to a_i. The determination of each parameter required 15 sets of tests.

3.7. Development of a Water Quality Assessment Model

Water quality here refers to agricultural AP and TN pollution. The models of water quality and planting mode were constructed; 6 kinds of models were adopted; and the best model was selected.

Water quality and land use:

$$WQ_k = \sum_{i=0}^{6} L_i \cdot A_i + H \quad (2)$$

Water quality and land use structure:

$$WQ_k = \sum_{i=1}^{6} L_i \cdot A_i + \sum_{j=1}^{3} F_j B_j + H \quad (3)$$

Water quality and land use + crop management:

$$WQ_k = \sum_{i=1}^{6} L_i \cdot A_i + \sum_{j=1}^{3} F_j B_j + \sum_{l=1}^{2} P_l C_l + H \quad (4)$$

Water quality and land use + soil nutrient attenuation:

$$WQ_k = \sum_{i=0}^{6} L_i \cdot A_i + \sum_{m=1}^{2} Q_m D_m + H \quad (5)$$

Water quality and land use structure + soil nutrient attenuation:

$$WQ_k = \sum_{i=1}^{6} L_i \cdot A_i + \sum_{j=1}^{3} F_j B_j + \sum_{m=1}^{2} Q_m D_m + H \quad (6)$$

Water quality and land use structure + cultivation mode + soil nutrient attenuation:

$$WQ_k = \sum_{i=1}^{6} L_i \cdot A_i + \sum_{j=1}^{3} F_j B_j + \sum_{l=1}^{2} P_l C_l + \sum_{m=1}^{2} Q_m D_m + H \quad (7)$$

where WQ_k = the area controlled by the kth section, k = 1, 2, 3, . . . , 19;

L_i = the ith type of land use, and A_i = the contribution coefficient of the ith type of land use to the river water quality, with $i = 0, 1, 2, \ldots, 6$;

F_j = the jth type of land use structure, and B_j = the contribution coefficient of the jth type of land use structure to the river water quality, with $j = 0, 1, 2, \ldots, 6$;

P_l = the lth type of cultivation mode, and C_l = the contribution coefficient of the lth type of cultivation mode, with $l = 1, 2$;

Q_m = the mth type of soil nutrient attenuation, and D_m = the contribution coefficient of the mth type of soil nutrient attenuation, with $m = 1, 2$;

H = a constant.

4. Results

4.1. Analysis of Spatial Distribution of Soil Nutrients

The descriptive statistical analysis of soil nutrients was performed with SPSS 25.0 software, and the Kolmogorov–Smirnov (K-S) test was used to perform nonparametric tests with the significance levels 0.01 and 0.05. Spatial autocorrelation analysis, semi-variance function analysis, optimization, selection of models and simulations, calculation of parameters, and selection of the best-fitting models were all performed with GS+ 7.0 Statistics software, which in turn provided parameters for spatial interpolation. The kriging spatial interpolation was performed using ArcGIS 10.5 software. The spatial distributions of the soil parameters are shown in Figures 5 and 6 [29].

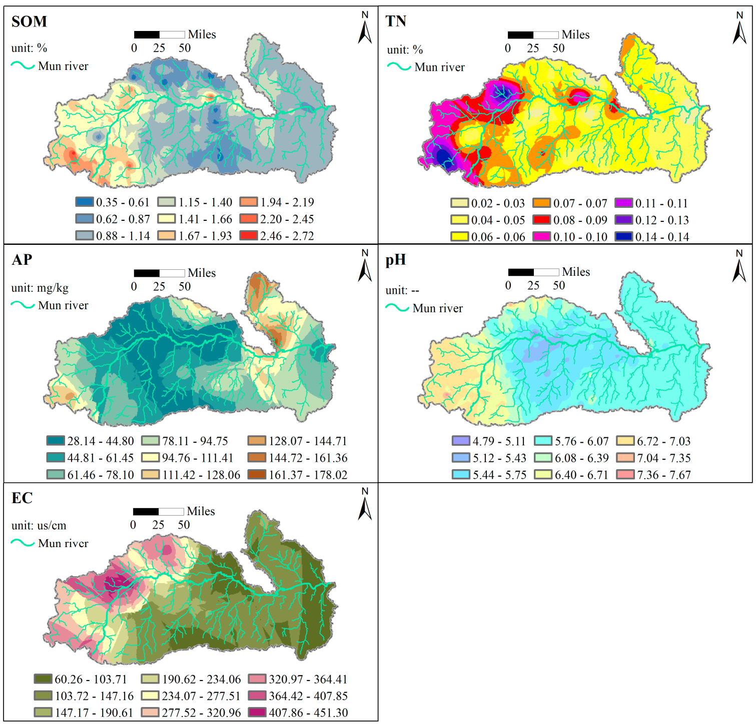

Figure 5. Spatial patterns of SOM, TN, AP, pH, and EC in the dry season.

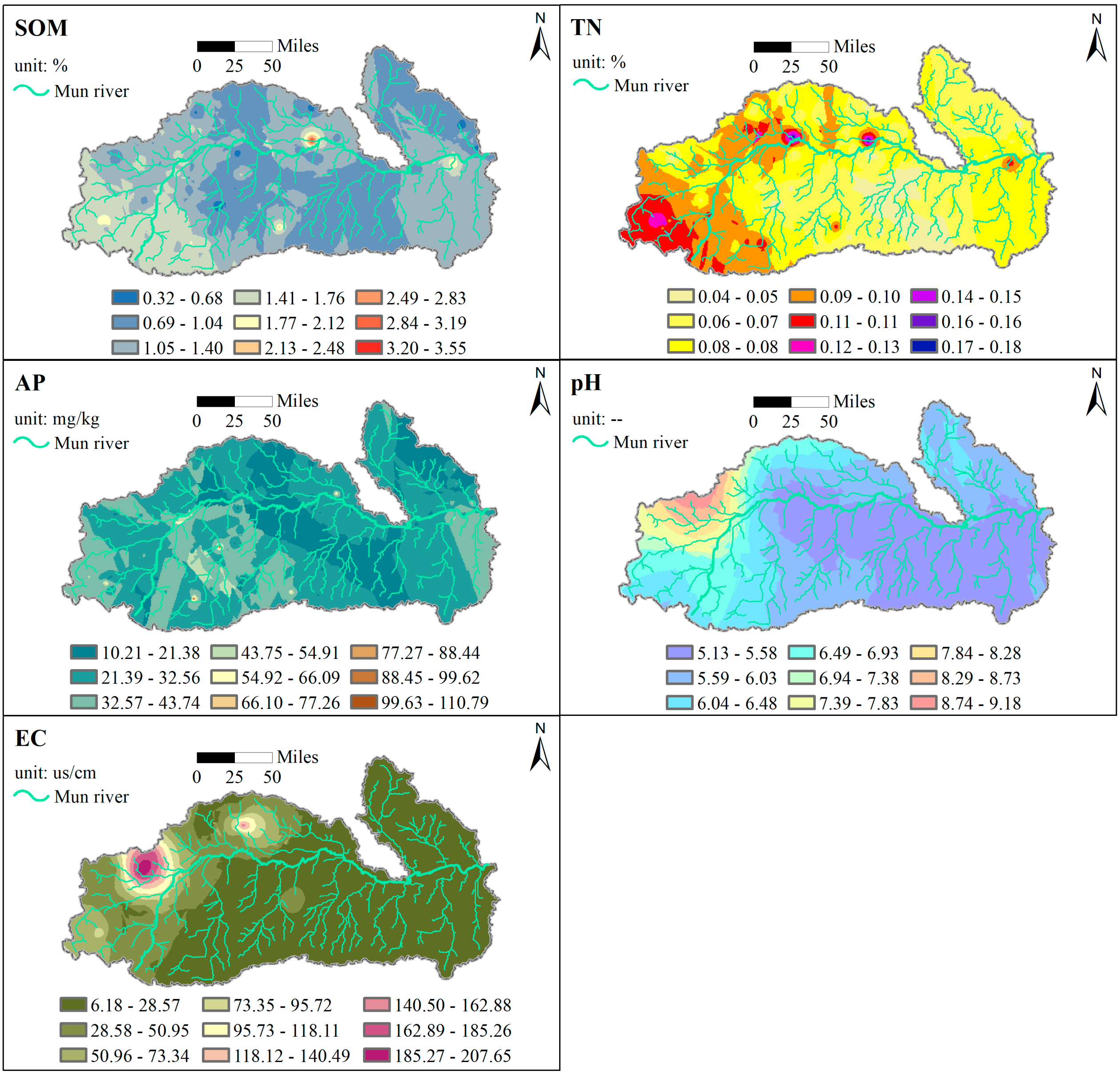

Figure 6. Spatial patterns of the SOM, TN, AP, pH, and EC in the rainy season.

4.2. Analysis of the Water Pollution Index

The water quality factors NH3-N, NO3-N, NO2-N, TP, DO, BOD, EC, pH, NTU, SSs, and other pollution indicators were used in the PCA analysis, and the comprehensive pollution index was calculated for the 19 water quality monitoring stations (Figure 7) [29]. A higher score indicates more severe pollution, and the assignment of scores makes it possible to analyze the degree of pollution at individual monitoring stations. The specific results are shown in Table 2.

The results show that the water quality was worse during the rainy season than during the dry season. This effect was mainly related to agricultural practices and to the increased discharge of pollutants during the rainy season. In the rainy season, the water quality was better in the upper reaches of the river than in the lower reaches. The water quality gradually deteriorated from upstream to downstream.

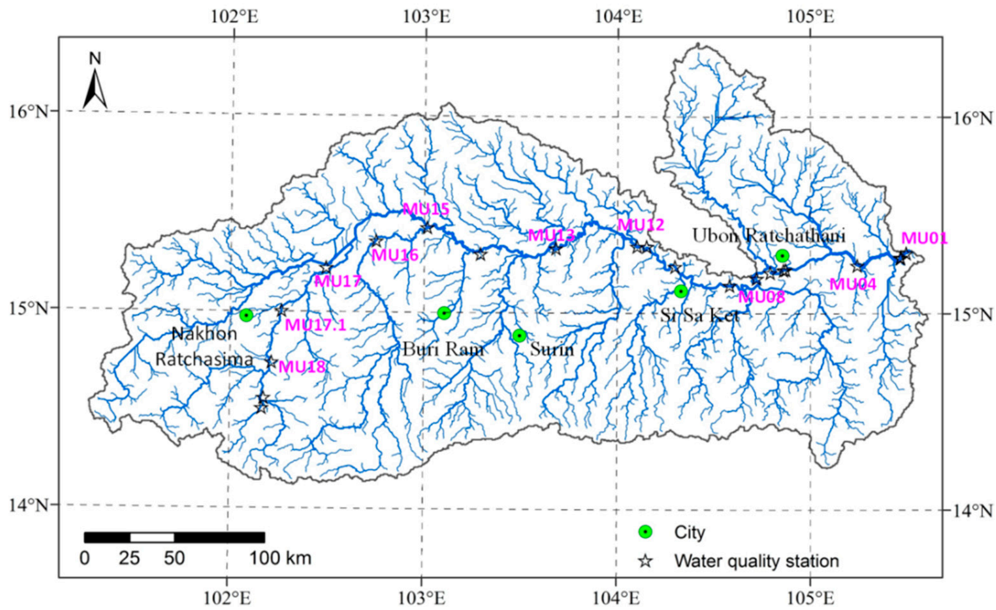

Figure 7. Distribution of the water quality monitoring stations in the Mun River.

Table 2. Principal component analysis of the water pollution index.

Stations	Pollution Score in the Dry Season	Pollution Score in the Rainy Season
MU18	−172.54	−117.76
MU17.1	−203.90	−88.14
MU17	−184.19	−117.34
MU16	−148.14	−112.81
MU15	−143.58	−137.82
MU14	−167.97	−117.69
MU13	−131.38	−87.32
MU12	−62.53	−79.90
MU11	−62.93	−59.61
MU10	−58.78	−19.85
MU09	−56.13	−50.07
MU08	−13.52	−54.37
MU07	−26.23	−45.30
MU06	−29.24	−49.50
MU05	−27.82	−48.11
MU04	−42.79	−33.92
MU03	−34.02	−27.39
MU02	−28.20	−28.37
MU01	−29.47	−19.25

4.2.1. Water Quality Modeling in the Dry Season

As shown in Table 3, in the dry season, the R2 values for the relationships between water quality and land use, water quality and land use structure, water quality and land use + cultivation mode, water quality and land use + soil nutrient attenuation, water quality and land use structure + soil nutrient attenuation, and water quality and land use structure + cultivation mode + soil nutrient attenuation were 0.398, 0.652, 0.772, 0.729, 0.802, and 0.881, respectively. The results show that the integration of water quality, cultivation mode, and soil nutrient attenuation generated better results for the correlation analysis in the dry season, explaining 88.1% of the variation. Hence, the inclusion of cultivation mode and soil nutrient attenuation with distance significantly enhanced the ability to explain water pollution.

Table 3. Regression model parameters for water pollution in the dry season.

R^2	Farmland (A0)	Gardens (A1)	Grassland (A2)	Wetlands (A3)	Forests (A4)	Other Land (A5)	Urban Land (A6)	Other Farm-land (B1)	Paddy Field (B2)	Dryland (B3)	Single Season (C1)	Double Season (C2)	P-Decay (D1)	N-Decay (D2)	Constant (H)
0.398	0.0003	−0.0025	0.0042	−0.0023	0.0004	0.0040	−0.0036								−84.8908
0.652		0.0243	0.0069	0.0025	−0.0021	−0.0069	−0.0010	0.0016	0.0003	−0.0011					−75.9622
0.772		0.0346	0.0081	0.0102	−0.0030	−0.0052	−0.0033	−0.0013	0.0017	−0.0003	−0.0025	−0.0027			−76.9617
0.729	0.0003	−0.0022	−0.0017	0.00002	−0.0003	0.0073	−0.0026						9.1396	113,273.2368	−221.1177
0.802		0.0140	0.0041	0.0017	−0.0013	0.0029	−0.0006	0.0003	−0.00004	−0.0007			6.1364	144,308.2920	−180.2528
0.881		0.0246	0.0064	0.0084	−0.0022	−0.0004	−0.0026	−0.0015	0.0014	−0.0002	−0.0022	−0.0019	4.3823	171,466.8839	−160.3606

Other farmland refers to farmland types other than paddy fields and dryland (the same holds for Tables 5 and 6).

Table 4 shows the correlation between dry-season water quality and cultivation mode. Dry-season water quality was positively correlated with soil available phosphorus attenuation with distance, with a correlation coefficient of 0.615. Dryland cover in farmland was significantly negatively correlated with water quality, with a correlation coefficient of −0.436.

Table 4. Correlation analysis of water quality and planting patterns in the dry season.

	Water Quality	AP	TN	Farmland	Gardens	Grassland	Wetlands	Forests	Other Land	Urban Land	Other Farm-land	Paddy Field	Dryland	Double Season	Single Season
water quality	1	0.615 **	0.270	−0.108	−0.164	0.031	−0.115	−0.123	0.247	−0.233	0.076	0.023	−0.436 *	−0.096	−0.034
AP		1	0.450 *	−0.483 *	−0.217	−0.278	−0.553 **	−0.258	−0.223	−0.484 *	−0.373	−0.457 *	−0.349	−0.521 *	−0.475 *
TN			1	−0.464 *	−0.275	−0.488 *	−0.505 *	−0.369	−0.287	−0.449 *	−0.400 *	−0.458 *	−0.241	−0.470 *	−0.468 *
farmland				1	0.733 **	0.854 **	0.908 **	0.734 **	0.432 *	0.964 **	0.884 **	0.955 **	0.595 **	0.977 **	0.931 **
gardens					1	0.801 **	0.524 *	0.915 **	0.417 *	0.766 **	0.655 **	0.531 *	0.764 **	0.617 **	0.478 *
grassland						1	0.802 **	0.834 **	0.582 **	0.832 **	0.760 **	0.754 **	0.641 **	0.810 **	0.764 **
wetlands							1	0.619 **	0.469 *	0.876 **	0.758 **	0.893 **	0.482 *	0.923 **	0.937 **
forests								1	0.553 **	0.725 **	0.683 **	0.567 **	0.557 **	0.611 **	0.515 *
other land									1	0.323	0.681 **	0.434 *	0.114	0.415 *	0.344
urban land										1	0.793 **	0.868 **	0.731 **	0.931 **	0.862 **
other farmland											1	0.893 **	0.406 *	0.865 **	0.781 **
paddy field												1	0.388	0.975 **	0.963 **
dryland													1	0.563 **	0.425 *
double season														1	0.962 **
single season															1

** Significant correlation at layer 0.01 (double tailed). * The correlation was significant at 0.05 layers (double tailed).

4.2.2. Water Quality Modeling in the Rainy Season

As shown in Table 5, in the rainy season, the R2 values for the relationship between water quality and land use, water quality and land use structure, water quality and land use + cultivation mode, water quality and land use + soil nutrient attenuation, water quality and land use structure + soil nutrient attenuation, and water quality and land use structure + cultivation mode + soil nutrient attenuation were 0.365, 0.501, 0.560, 0.532, 0.676, and 0.727, respectively. The results show that the use of rainy-season water quality, cultivation mode, and soil nutrient attenuation generated better results for the correlation analysis. Hence, the inclusion of cultivation mode and soil nutrient attenuation with distance significantly enhanced the ability to explain water pollution.

Table 5. Regression model parameters for water pollution in the rainy season.

R^2	Farmland (A0)	Gardens (A1)	Grassland (A2)	Wetlands (A3)	Forests (A4)	Other Land (A5)	Urban Land (A6)	Other Farm-land (B1)	Paddy Field (B2)	Dryland (B3)	Single Season (C1)	Double Season (C2)	P-Decay (D1)	N-Decay (D2)	Constant (H)
0.365	0.00005	−0.0025	0.0022	−0.0014	−0.0001	0.0034	−0.0009								−60.2969
0.501		0.0077	0.0036	0.0011	−0.0008	−0.0052	−0.0006	0.0014	−0.0002	−0.0005					−55.6722
0.560		0.0119	0.0040	0.0043	−0.0012	−0.0040	−0.0016	0.0002	0.0006	−0.00009	−0.0010	−0.0012			−56.0109
0.532	0.00009	−0.0071	0.0030	−0.0017	0.0001	0.0024	−0.0008						69.1513	−16,830.8122	−123.8904
0.676		0.0031	0.0044	0.0009	−0.0005	−0.0064	−0.0004	0.0014	−0.0002	−0.0005			83.1247	−28,384.0053	−126.5728
0.727		0.0075	0.0051	0.0040	−0.0009	−0.0075	−0.0013	0.0005	0.0004	−0.0002	−0.0011	−0.0007	77.5100	−23,328.8338	−124.7021

Table 6 shows that rainy-season water quality was positively correlated with soil total nitrogen attenuation with distance, with a correlation coefficient of 0.444. Urban land was negatively correlated with water quality, with a correlation coefficient of −0.458.

Dryland cover in farmland was negatively correlated with water quality, with a correlation coefficient of −0.458.

Table 6. Correlation analysis of water quality and planting patterns in the rainy season.

	Water Quality	AP	TN	Farmland	Gardens	Grassland	Wetlands	Forests	Other Land	Urban Land	Other Farm-land	Paddy Field	Dryland	Double Season	Single Season
water quality	1	0.444 *	0.403 *	−0.354	−0.290	−0.163	−0.324	−0.246	0.140	−0.425 *	−0.132	−0.241	−0.458 *	−0.335	−0.285
AP		1	0.926 **	−0.563 **	−0.297	−0.541 *	−0.600 **	−0.416 *	−0.273	−0.525 *	−0.477 *	−0.576 **	−0.212	−0.570 **	−0.583 **
TN			1	−0.453 *	−0.270	−0.458 *	−0.481 *	−0.348	−0.242	−0.439 *	−0.382	−0.445 *	−0.236	−0.454 *	−0.452 *
farmland				1	0.733 **	0.854 **	0.908 **	0.734 **	0.432 *	0.964 **	0.884 **	0.955 **	0.595 **	0.977 **	0.931 **
gardens					1	0.801 **	0.524 *	0.915 **	0.417 *	0.766 **	0.655 **	0.531 *	0.764 **	0.617 **	0.478 *
grassland						1	0.802 **	0.834 **	0.582 **	0.832 **	0.760 **	0.754 **	0.641 **	0.810 **	0.764 **
wetlands							1	0.619 **	0.469 *	0.876 **	0.758 **	0.893 **	0.482 *	0.923 **	0.937 **
forests								1	0.553 **	0.725 **	0.683 **	0.567 **	0.557 **	0.611 **	0.515 *
other land									1	0.323	0.681 **	0.434 *	0.114	0.415 *	0.344
urban land										1	0.793 **	0.868 **	0.731 **	0.931 **	0.862 **
other farmland											1	0.893 **	0.406 *	0.865 **	0.781 **
paddy field												1	0.388	0.975 **	0.963 **
dryland													1	0.563 **	0.425 *
double season														1	0.962 **
single season															1

** Significant correlation at layer 0.01 (double tailed). * The correlation was significant at 0.05 layers (double tailed).

5. Discussion

5.1. Effects of the Inclusion of Attenuation with Distance on Modeling Accuracy

The ecohydrological processes of pollution generation and its transport via surface runoff to the monitored sections were investigated in this study. The land units and the monitored sections were accurately delineated, and attenuation through overland and in-river transport was included in a model designed to describe the factors influencing water pollution from different perspectives [37].

Most previous studies focused on the number of land use characteristics when addressing the relationships between land use and water pollution; the results of these studies had highly variable explanatory power for pollutant input into the river and high uncertainty. By quantifying the transport of pollutants, the current study accurately matched the information from different water quality monitoring sections and land units. The inclusion of information that had been neglected in previous studies can effectively improve our ability to explain water pollution.

5.2. Effects of Land Use on Water Quality

Whether the scale of land use is related to the level of water pollution is a question that has been extensively investigated by scholars [38]. The water quality regression model constructed in this study can be used to help clarify the impact of land use on water pollution. The study findings show that combining the information about differences in land use type and cultivation mode and in overland and in-river transport and attenuation processes can enhance the accuracy of water pollution modeling [34].

Urban and built-up land was negatively correlated with water quality, which is mainly due to domestic sewage. The influence of the rainy season was greater than that of the dry season. Surface runoff is mainly generated in the rainy season and causes domestic sewage to flow into the river. The pollution is primarily transport-limited in the dry season. Therefore, reducing runoff should be the first measure to restrict the transport of NPS pollution on land surfaces.

In addition, paddy fields were negatively correlated with water quality in both the dry and wet seasons. (1) Dryland was positively correlated with water quality in both the dry and wet seasons. Dryland reduction can lessen water pollution and protect water quality. (2) Forest plantations were positively correlated with water quality in the dry season and negatively correlated with water quality in the wet season. This finding indicates that forest plantations are a source of pollution in the wet season; however, in the dry season, the lack of nutrients allows forest plantations to resorb or reduce pollutants from the surface runoff, thereby alleviating water pollution.

The above results are consistent with the findings of a survey administered in the form of a questionnaire in 2017 in the basin. Applying fertilizers at 230.4 kg/ha. in dryland areas caused light water pollution. Applying fertilizers at 378.0 kg/ha. in paddy fields caused water pollution. Applying fertilizers at 488.25 kg/ha. in forest plantations caused more severe water pollution than the application of fertilizers in paddy fields.

With respect to crop rotation, the effects of double cropping on the degree of water pollution were greater than the effects of monocropping, and the degree of water pollution was greater in the wet season than in the dry season. This situation occurred because the wet season is the growing season, during which agricultural activities include the application of fertilizers and pesticides. The result is also related to rainfall-induced surface runoff and the resulting transport of nutrients to the water in the wet season.

5.3. Limitations

Due to the complexities and uncertainties regarding water quality, land use structure, and cultivation modes, this study has some limitations. For instance, the research methodology could be improved; more comprehensive and in-depth consideration of factors is needed; and the conclusions should be better organized and more concise. The main limitations of this study are elaborated below.

1. Unevenness in the distribution of soil sampling locations was a limitation. Compared to the area of the study region, the number of soil samples collected was relatively small. In addition, the spatial distribution of the sampling points was uneven. The use of a small number of soil samples collected from unevenly distributed sampling points to comprehensively analyze the spatial variability in soil nutrients throughout the entire study region resulted in a relatively low accuracy. Furthermore, given the complexity of the soil system, the use of the kriging method to identify the spatial pattern of soil nutrients based on a small number of samples from areas with different topographies and land use types resulted in uncertainty.
2. Water quality was sampled twice a year. The lack of time-series data did not permit sufficient characterization of river water quality under different hydrological conditions. In addition, the water quality data consisted of data from 19 monitoring cross-sections in the mainstream of the river, including measured water quality data in the dry and wet seasons. The data were not sufficient to reflect water quality under different hydrological conditions and could be used to describe the water quality for the whole year.
3. Point-source pollutants, such as domestic sewage and garbage, and endogenous pollutants in rivers may affect the water quality in specific river sections. Because the potential effects of point-source discharge of pollutants and endogenous pollutants on water quality in the basin were not analyzed, the data may not have been sufficient to reveal the response of the water quality of the river section to pollution from basin NPSs.

6. Conclusions

In this study, GIS spatial analysis technology is used to describe the whole process of soil nutrient attenuation with distance and channel migration attenuation with distance. According to the characteristics of land use spatial distributions and planting patterns, soil nutrients increase instantaneously with increasing distance attenuation and channel migration distance, and during the whole process, the analysis of water pollution, planting patterns, and other related factors is based on the relationship between the quantitative soil nutrients and the distances of the overland and in-river attenuation processes. Information about land use and the related processes of water pollution and planting patterns that influence water quality is also discussed.

1. On the basis of the inverse distance function and the trial-and-error method, the overland and in-river attenuation coefficients of soil AP and TN with distance in the dry season and rainy season were calculated. The attenuation coefficients of AP in the dry season were ai = 0.1 and at = 0.1, and they were ai = 0.1 and at = 0.3 in the rainy season. In the dry season, the soil TN attenuation coefficients were ai = 0.3 and at = 0.5, and they were ai = 0.3 and at = 0.3 in the rainy season, where at is the overland confluence attenuation parameter and ai is the in-river confluence attenuation parameter.
2. Multiple factors and water pollution scores were used for regression. The relationships between water quality and land use, water quality and land use structure, water quality and land use + plantation mode, water quality and land use + soil nutrient attenuation, water quality and land use structure + soil nutrient attenuation, and water quality and land use structure + plantation mode + soil nutrient attenuation were determined, and the optimal simulation model was selected. The simulation results showed that the relationship between water quality and land use structure + plantation mode + soil nutrient attenuation was better, with R2 values of 0.881 in the dry season and 0.727 in the rainy season, and the selected factors could explain the factors influencing water quality in the basin.

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