Environmental factors influencing spatial variability of soil total phosphorus content in a small watershed in Poyang Lake Plain under different levels of soil erosion

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ABSTRACT

Soil erosion can change the migration and deposition patterns of soil particles and alter the regional geographic environment; therefore, it plays an important role in the biogeochemical cycle of soil total phosphorus (STP). Quantifying the influence of environmental factors on STP content under soil erosion is critical for understanding the lateral transfer of STP from soil. Here, we explored the influence of environmental factors on STP content under different levels of soil erosion in the small watershed of Nanliao River, a tributary of Xiu River in the western part of Poyang Lake Plain in Jiangxi Province, China. Soil erosion ranged from 0 to 176.26 t hm⁻² a⁻¹ (15.41 t hm⁻² a⁻¹ on average) across the watershed in 2018, indicating a mild erosion level on the whole. The STP content varied between 0.06 and 1.19 g/kg (0.6 g/kg on average) with a coefficient of variation of 43.33%, indicating moderate variation. An exponential model with a small nugget effect (7.35%) and a small range (2.25 km) could estimate 86.5% of spatial variability in STP content. The STP content showed a strong spatial autocorrelation, and the soil rich in STP was mostly distributed along the Nanliao River. There was a negative correlation between STP content and soil erosion ($r = -0.149$, $P < 0.01$). Each of the 10 selected environmental factors could explain 2.7–21.3% of spatial variability in STP content. Elevation, soil particle size, soil pH, and their interactions with other factors were the main factors influencing STP content, although their influence differed across various erosion levels. This study could provide useful data for controlling STP loss and reducing the impacts of soil erosion on the ecological environment in the Poyang Lake Plain.

1. Introduction

Land surface processes such as soil erosion can interfere with soil development and nutrient cycling in terrestrial and aquatic ecosystems (Berhe et al., 2018). Land degradation caused by soil erosion is a major threat to the global land use and ecological environment (Van Oost et al., 2007). Soil erosion by water is one of the most important forms of soil erosion (Mehri et al., 2018), which results in the separation and migration of soil particles from the soil matrix, leading to the destruction of soil aggregate structure; therefore, soil erosion could cause the losses of soil carbon (C), nitrogen (N), and phosphorus (P), along with surface fragmentation and vegetation degradation (Borrelli et al., 2017). After the lateral transfer of soil nutrients carried by soil particles, most of them are deposited in the terrestrial ecosystem, with a considerable part discharged into the aquatic ecosystem via runoff (Borrelli et al., 2018). Excessive discharge of nutrients (N and P) into the aquatic ecosystem contributes to eutrophication, thus affecting the aquatic environment and ecosystem services (Sun et al., 2014). In order to maintain the functioning of aquatic ecosystems, the priority in eutrophication control is to reduce the amount of nutrients (especially P) entering the water bodies (Carpenter, 2008; Schindler et al., 2008; Schindler and Hecky, 2009).

As the largest freshwater lake in China, the Poyang Lake is a pivot for the regulation of regional water environment in the Yangtze River Basin (Shankman et al., 2010). In addition, the Poyang Lake is an important area of interest for wetland biodiversity conservation in the world, which makes substantial contribution to global ecosystem functioning and biodiversity conservation (Wang et al., 2014). However, under the impacts of human activities and climate change, the water of Poyang Lake has been exposed to a high risk of eutrophication, given its high concentrations of total P (TP) (Wang and Liang, 2015; Wang et al., 2008). As an important source of TP in water, the TP...
carried by sediments from soil erosion may play a dominant role in the eutrophication of Poyang Lake (Borrelli et al., 2018; Song et al., 2017). Moreover, due to the expected impact of global climate change, the rate of soil erosion is still on the rise (Yang et al., 2003). Therefore, it is crucial to explore the mechanisms underpinning lateral transfer of soil TP (STP) under soil erosion, and such knowledge may help us to prevent the eutrophication of Poyang Lake caused by STP pollution.

The lateral transfer of STP is a result of the coupling between soil erosion and the spatial variability of STP content (Cheng et al., 2018), whereas the STP content is influenced by various environmental factors (Cheng et al., 2016). Rainfall, topography, vegetation cover, soil type, soil texture, soil organic matter (SOM), and soil pH have been found to be the key factors driving the spatial variability and biogeochemical cycle of P in soil (Berhe et al., 2018; Cheng et al., 2016; Cheng et al., 2018; Debicka et al., 2016; Liu et al., 2013; Ma et al., 2016; Puustinen et al., 2007; Quinton et al., 2010; Weng et al., 2011). However, the environmental factors dynamically change during the circulation of materials in an ecosystem. In particular, the alterations in soil surface microtopography, vegetation cover, and soil physicochemical properties caused by soil erosion cannot be ignored (Berhe et al., 2018; Cheng et al., 2016; Xu et al., 2015).

In eroded areas, the environmental factors that influence STP content may vary substantially, forming unique environments across different erosion levels. Many studies have comprehensively evaluated the impacts of soil erosion on specific environmental factors (Cheng et al., 2018; Mehri et al., 2018; Borrelli et al., 2017; Borrelli et al., 2018). However, the influence of unique environmental conditions on the lateral transfer of STP under different erosion levels is still poorly understood. Currently, there is a lack of knowledge for formulating specific measures to control the unreasonable transfer of STP into the aquatic environment. Therefore, it is urgent to quantify the influence of environmental factors on STP content under different levels of soil erosion, in order to prevent potential ecological problems.

The Poyang Lake Plain is a buffer zone between the aquatic ecosystem of Poyang Lake and the surrounding terrestrial ecosystem. The ecological environment of this plain is a sensitive part of the virtuous cycle in the lake ecosystem (Carmignani and Roy, 2017). Despite the relatively low elevation of Poyang Lake Plain, P fertilizer has been applied frequently due to intensive agricultural activities and the sediments generated by soil erosion thus contain high P content (Guo and Jiang, 2019). In addition, the regional runoff to the Poyang Lake is characterized by shorter transmission paths and higher connectivity. Hence, the influence of regional soil P loss on the Poyang Lake ecosystem could be more pronounced than previously thought (Zhang et al., 2017). Therefore, it is of great significance to clarify the influence of environmental factors on STP content in the Poyang Lake Plain under soil erosion, in order to reduce P pollution and control eutrophication in the Poyang Lake.

In the present study, we selected the small watershed of Nanliao River in the western part of Poyang Lake Plain to explore the influence of environmental factors on STP content under different levels of soil erosion. The objectives of the study were to: (1) estimate soil erosion across the watershed; (2) examine the spatial variability of STP content in relation to soil erosion; and (3) quantify the distinct influence of environmental factors on STP content under different erosion levels.

2. Materials and methods

2.1. Study area

The study was conducted in a small watershed of Nanliao River, a tributary of Xiu River in the western part of Poyang Lake Plain, China (Fig. 1). The geographical coordinates of the study area are 28°68′–80°28′N, 115°08′–115°40′E, with a total area of 202.83 km². This area has a subtropical monsoon climate, with annual average temperature, rainfall, frost-free period, and sunshine hours of 17.3 °C, 1612 mm, 260 days, and 1803 h, respectively. The terrain is generally flat, with an elevation between 31 and 133 m. Most of the landforms are fluvial-alluvial plains and low hills. The major land use types are forests, cultivated land, and orchards. There are two types of soil, anthrosols and cambisols, both of which have a loose soil texture with slightly acidic pH ranging from 5.04 to 5.84. Vegetation cover is 49.01% (see Fig. 2).

2.2. Data acquisition and processing

2.2.1. Soil sampling and laboratory analysis

Considering the landform, land use type, and soil type, we collected 248 soil samples in the Nanliao River watershed through July to August 2018. The sampling was carried out with 201 grids (1 km × 1 km) as the sampling units. The land use type of each grid was determined based on the land type covering the largest area of the grid (Fig. 1). In total, 201 standard sampling points were selected based on the main land use type of each grid, whereas another 47 sampling points were
encrypted in those grids with complex large areas of other land use types, in addition to the main land use type. At each sampling point, five replicate samples were collected evenly within a radius of 5 m, following an X-shaped pattern. The topsoil was collected using a 5.0-cm-diameter stainless steel auger after removal of straw and litter on the soil surface. One kilogram of soil sample was obtained from each sampling point by thoroughly mixing the five replicate samples and the coordinates of the center point were recorded using a handheld GPS device. A total of 98 soil samples were taken in cultivated land (0–20 cm depth), whereas 57 and 93 soils samples were taken in orchards and forests, respectively (0–30 cm depth).

Soil samples were ground and sieved after air-drying in the laboratory. Subsequently, STP content was determined using molybdenum antimony blue calorimetry (Murphy and Riley, 1962). In addition, SOM content was determined using Walkley-Black wet oxidation method (Nelson and Somers, 1982) and soil organic C (SOC) content was obtained by dividing SOM content by a conversion factor of 1.724. Soil pH was measured by potentiometry with a soil/water (w/v) ratio of 1:2.5 (Guo et al., 2018). Soil particle sizes were analyzed using the hydrometer method (Day, 1965).

### 2.2.2. Data processing

Terrain data were derived using GDEMDEM 30 M resolution Digital Elevation Model (DEM) data downloaded from the Geospatial Data Cloud (http://www.gscloud.cn/) (Fig. 2a). Elevation, slope, and topography data were obtained after processing in ArcGIS 10.2 (http://www.esri.com/arcgis) based on DEM data. Annual rainfall data of 2018 were obtained from 35 meteorological stations across Fengxin County (Fig. 2b). Normalized difference vegetation index (NDVI) data were obtained from the infrared band (R) and near-infrared band (NIR) of Landsat-8 images in the four quarters of 2018 and then averaged (Fig. 2c). Soil type data were derived from the soil map of the Second National Soil Survey in China (National Soil Survey Office of China, 1993) (Fig. 2d). Land use data were obtained from Fengxin County Land Use Map for 2017 (Fig. 2e). After elimination of outliers (exceeding three times of standard deviation), all the point data were interpolated using the ordinary Kriging method in ArcGIS 10.2 to obtain the surface raster data covering the entire study area.

### 2.3. Estimation of soil erosion

Soil erosion models are effective tools for the quantitative evaluation of soil erosion, rational utilization of land resources, and scientific planning of soil and water conservation. The Revised Universal Soil Loss Equation (RUSLE), which has reliable parameters and parameter settings, is the most widely used model for the estimation of soil erosion by water (Mehri et al., 2018). Based on the RUSLE, we estimated soil erosion using Eq. (1) (Renard et al., 1997):

$$A = R \times K \times LS \times C \times P$$

where $A$ represents the annual amount of soil erosion (t ha$^{-2}$ a$^{-1}$), $R$ represents the rainfall erosivity factor (MJ mm h$^{-1}$ a$^{-1}$), $K$ represents the soil erodibility factor (t ha$^{-1}$ MJ$^{-1}$ mm$^{-1}$ h$^{-2}$), $LS$ represents the topographic factor (i.e., slope length and steepness factor), $C$ represents the land cover and land use factor, and $P$ represents the conservation practice factor. The $LS$, $C$, and $P$ factors are dimensionless.

The rainfall erosivity factor $R$ was calculated using Eq. (2) proposed by Wischmeier and Smith (1978) and improved by Arnoldus (1980):

$$R = \sum_{i=1}^{12} \left( 1.735 \times 10^{1.55log_{10} P_{i}^{2.975}} \right)$$

where $P_{i}$ and $P$ represent average monthly rainfall and total rainfall in 2018, respectively, and $i$ represents the month ($i = 1, 2, 3..., 12$).

The Erosion-Productivity Impact Calculator (EPIC) model and USLE nomograph are two most common methods for calculation of the soil erodibility factor $K$ (Xiao et al., 2015; Ganasri and Ramesh, 2016). Compared with the EPIC model, the nomograph method is associated.
with greater difficulty in data collection (e.g., soil aggregation index and tropism index) and is suitable for a narrower range (0–40 g/kg) of SOM content (Auerswald et al., 2014). Therefore, we calculated $K$ values based on the EPIC model using Eq. (3) proposed by Sharpley and Williams (1990):

$$
K = (0.2 + 0.3(q-0.0258(W_i+10000^{0.1})) \times \left( \frac{W_d}{W_i + W_c} \right)^{0.3} \times \left( 1 - \frac{0.25W_c}{W_c + 0.25W_i + 22.13} \right)
$$

(3)

where $W_d$ represents sand content (%), $W_i$ represents silt content (%), $W_c$ represents clay content (%), and $W_v$ represents organic carbon content (%). The calculation results were multiplied by 0.1317 and converted into international units.

The topographic factor $LS$ was calculated using Eqs. (4)–(7) proposed by McCool et al. (1987) and McCool et al. (1989):

$$
LS = \left( \frac{\lambda}{22.13} \right)^N
$$

(4)

$$
\alpha = \left( \frac{\beta}{\beta + 1} \right)
$$

(5)

$$
\beta = \frac{\sin \theta}{3 \times (\sin \theta)^{0.8} + 0.56}
$$

(6)

$$
S = \left\{ \begin{array}{ll}
10.8 \times \sin \theta + 0.03 (x < 9\% , \lambda > 4m) \\
16.8 \times \sin \theta - 0.5 (x < 9\% , \lambda > 4m) \\
3 \times (\sin \theta)^{0.8} + 0.56 (x \leq 4m)
\end{array} \right.
$$

(7)

where $\lambda$ represents slope length (m), $\alpha$ represents an adjustable slope length exponent, $\beta$ represents a coefficient of variation with slope, $\theta$ represents slope angle ($^\circ$), and $x$ represents percentage slope (%).

The land cover and land use factor $C$ was calculated using Eq. (8) proposed by (Cai et al., 2000) for a relatively small watershed, based on the vegetation cover $fc$ (Carlson and Ripley, 1997) calculated using Eq. (9):

$$
C = \left\{ \begin{array}{ll}
1, & fc = 0 \\
0.6508 - 0.3436 \text{log}(fc), & 0 < fc < 78.3% \\
0, & fc \geq 78.3%
\end{array} \right.
$$

(8)

$$
f_c = \left( \frac{NDVI - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \right)
$$

(9)

where $NDVI_{\text{max}}$ and $NDVI_{\text{min}}$ represent the maximum and minimum NDVI values in the region, respectively. $fc \in [0,1]$, the closer the $fc$ is to 1, the higher the vegetation cover.

The conservation practice factor $P$ was calculated as the ratio of soil loss with or without the implementation of soil and water conservation measures (Mehri et al., 2018). $P \in [0,1]$; $P = 0$ indicates that no soil erosion occurs under specific conservation practices, and $P = 1$ represents the status of natural soil erosion when conservation measures are not implemented. We assigned the $P$ factor under various land use types as follows: 0.15 for paddy field, 0.40 for dryland and orchard, 1.00 for forest and grassland, and 0.00 for water and construction land (Wang et al., 2019; Yu et al., 2011).

Based on the RUSLE estimation results, soil erosion in the study area was divided into different levels according to the soil erosion classification and gradation standard (SL190-2007) defined by the Ministry of Water Resources, People’s Republic of China (Ministry of Water Resources of the People’s Republic of China, 2008). This classification standard takes into account the difference in regional climatic conditions, topographical features, and soil properties, which can reflect the differences in soil erosion across various levels. The applicability of the classification standard in Jiangxi Province has been verified (Xiao et al., 2015).

2.4. GeoDetector

GeoDetector (http://www.geodetector.org/) is a statistical tool that can detect spatial variability in geographic phenomena and reveal the key factors driving the variation (Wang et al., 2010). GeoDetector can reflect the explanatory ability of independent variables to dependent variables based on the ratio between the sum of variances of different categories in one independent variable and the sum of variances of dependent variables. GeoDetector has shown compatibility with qualitative factors and superiority in exploring the influence of bivariate interactions on dependent variables (Wang et al., 2016). Therefore, GeoDetector could better reveal the influence of natural conditions and human activities on STP content under different soil erosion levels compared with conventional methods (Wang et al., 2019). GeoDetector is composed of four subdetectors, factor detector, risk detector, interaction detector, and ecological detector. Here we applied the factor detector and the interaction detector to respectively explore the independent and interactive explanatory abilities of environmental factors to STP content.

The factor detector is mainly used to detect the ability of the independent variable to interpret the spatial variability of the dependent variable. Its strength can be measured using the $q$ value (Wang et al., 2010) calculated as follows:

$$
q = 1 - \frac{\sum_{h=1}^{l} N_h \sigma_h^2}{N^2} = 1 - \frac{SSW}{SST}
$$

(10)

$$
SSW = \sum_{h=1}^{l} N_h \sigma_h^2, \quad SST = N \sigma^2
$$

(11)

where $h$ represents the category of the independent variable ($h = 1, 2,\ldots, L$); $N_h$ and $N$ are the number of units in category $h$ and the entire region, respectively; $\sigma_h^2$ and $\sigma^2$ represent the variance of dependent variable in the category $h$ and the entire region, respectively (Eq. (10)). $SSW$ represents the sum of the category variances of the independent variable, and $SST$ represents the total variance of the dependent variable in the entire region (Eq. (11)). $q$ indicates the ability of independent variables to explain dependent variables, $q \in [0,1]$, the larger the $q$ value, the greater the explanatory ability of the independent variable. In addition, GeoDetector can test the significance of the $q$ value.

The interaction detector has a key advantage in that it can recognize the interaction between two independent variables compared to conventional statistical methods. The $q$ value reflects the ability of bivariate interactions to explain the dependent variable. By comparing the single factor $q$ value and the double factor $q$ value, the direction and mode of interaction between the two factors can be assessed.

Since GeoDetector requires that the input data of the independent variable be type data, we discretized or classified the respective variables extracted from the center point of 200 m × 200 m grids in the GeoDetector analysis. The 30–130 m elevation range was divided into five categories based on 20-m intervals, while the slope was divided into four categories (0–2°, 2–6°, 6–15°, and >15°). The annual rainfall ranged from 1300 to 1900 mm, and was divided into six categories at 100-mm intervals. The NDVI was divided into six categories, < 0 and 0–0.5 at intervals of 0.1. The soil sand, silt, and clay contents were divided into four, three, and two categories, respectively, at intervals of 20%. Soil pH ranged from 5.2 to 5.5, and was divided into three categories at intervals of 0.1. In addition, soil types were classified into soil genus (National Soil Survey Office of China, 1993) and were divided into five categories: red sandy mud red soil, hemp sandy mud red soil, hydromorphic alluvial tide sandy mud paddy, hydromorphic alluvial red sandy mud paddy, and hydromorphic alluvial hemp sandy mud paddy. Land use types were divided into five categories, namely paddy field, dryland, orchard, forest, and other land uses.
2.5. Statistical analysis

2.5.1. Classical statistics

Descriptive statistics were used to describe the quantitative structure (i.e., minimum, maximum, mean, standard deviation [SD], and coefficient of variation [CV]) of STP content across the study area. Correlation analysis was used to reveal the relationship between STP content and soil erosion or environmental factors. Spearman’s correlation coefficients were used to evaluate the relationship between STP content and soil type or land use type, while other relationships were analyzed using Pearson’s correlation coefficients. Descriptive statistics and correlation analyses were performed using IBM SPSS Statistics 22.0 (IBM Corp., Armonk, USA).

2.5.2. Geostatistics

Geostatistics is based on a regionalized variable (Matheron, 1963), which uses Semi-variance analysis to quantify the spatial autocorrelation of STP, thus providing parameters for the Kriging interpolation (Goovaerts, 1999). Semi-variance analysis is a process of calculating the optimal semi-variogram and its characteristic parameters according to the spatial autocorrelation of a variable in the sampled areas. There are three basic characteristic parameters, nugget (C0), sill (C0 + C), and spatial autocorrelation length (range). The ratio of nugget to sill (C0/ (C0 + C), namely the nugget effect, can reflect the proportion of spatial heterogeneity caused by random factors (e.g., land use change) or structural factors (e.g., topography, annual rainfall, and soil type) in total variation. A smaller nugget effect indicates that the spatial variability of STP content is more influenced by structural factors. The range can reflect the complexity of the spatial variability of STP content. A larger range indicates a stronger spatial homogeneity of STP content (Guo and Jiang, 2019).

Using GS + 9.0 (Gamma Design Software, Plainwell, USA), the optimal fitting model for STP content was selected from linear, Gaussian, spherical, and exponential models according to the minimum residual sum of squares (RSS) and the maximum coefficient of determination (R²). Then the optimal fitting model and its characteristic parameters were used for spatial interpolation by ordinary Kriging method in ArcGIS 10.2. The root-mean squared error (RMSE) was applied to cross-validate the interpolation results (Liu et al., 2013).

3. Results

3.1. Soil erosion in Nanliao River watershed

The RUSLE estimation results showed that soil erosion ranged from 0 to 176.26 t hm⁻² a⁻¹ across the Nanliao River watershed in 2018, with an average of 15.41 t hm⁻² a⁻¹. According to the Chinese standard for erosion classification and gradation, soil erosion in the study area could be divided into six levels: slight erosion (< 5 t hm⁻² a⁻¹), mild erosion (5–25 t hm⁻² a⁻¹), moderate erosion (25–50 t hm⁻² a⁻¹), high erosion (50–80 t hm⁻² a⁻¹), extremely high erosion (80–150 t hm⁻² a⁻¹), and severe erosion (> 150 t hm⁻² a⁻¹).

There was substantial spatial variability in soil erosion level across the Nanliao River watershed (Table 1 and Fig. 3). Slight erosion and mild erosion were most prevalent, which accounted for 72.8% of the study area and mainly occurred in the alluvial plain of Nanliao River with an elevation of 60 m. Moderate erosion and high erosion accounted for 19.1% and 7.7% of the study area, respectively, which were

<table>
<thead>
<tr>
<th>Erosion level</th>
<th>Slight erosion</th>
<th>Mild erosion</th>
<th>Moderate erosion</th>
<th>High erosion</th>
<th>Extremely high erosion</th>
<th>Severe erosion</th>
<th>Entire region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil erosion (t hm⁻² a⁻¹)</td>
<td>2.02</td>
<td>11.99</td>
<td>35.92</td>
<td>57.57</td>
<td>91.79</td>
<td>158.27</td>
<td>15.41</td>
</tr>
<tr>
<td>STP (g/kg)</td>
<td>0.62</td>
<td>0.60</td>
<td>0.56</td>
<td>0.54</td>
<td>0.52</td>
<td>0.47</td>
<td>0.60</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>59.57</td>
<td>62.36</td>
<td>67.54</td>
<td>75.50</td>
<td>83.7</td>
<td>90.97</td>
<td>63.06</td>
</tr>
<tr>
<td>Slope (%)</td>
<td>2.22</td>
<td>2.58</td>
<td>3.06</td>
<td>5.27</td>
<td>8.1</td>
<td>10.99</td>
<td>2.72</td>
</tr>
<tr>
<td>Sand content (%)</td>
<td>41.72</td>
<td>42.81</td>
<td>44.76</td>
<td>45.12</td>
<td>45.95</td>
<td>48.15</td>
<td>42.83</td>
</tr>
<tr>
<td>Silt content (%)</td>
<td>32.73</td>
<td>30.95</td>
<td>28.79</td>
<td>28.16</td>
<td>27.14</td>
<td>25.55</td>
<td>31.20</td>
</tr>
<tr>
<td>Clay content (%)</td>
<td>20.52</td>
<td>20.38</td>
<td>19.87</td>
<td>20.02</td>
<td>19.67</td>
<td>18.60</td>
<td>20.33</td>
</tr>
<tr>
<td>pH</td>
<td>5.31</td>
<td>5.30</td>
<td>5.31</td>
<td>5.30</td>
<td>5.30</td>
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<td>SOM (g/kg)</td>
<td>35.16</td>
<td>33.97</td>
<td>33.83</td>
<td>34.99</td>
<td>34.64</td>
<td>32.60</td>
<td>34.62</td>
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<tr>
<td>NDVI</td>
<td>0.25</td>
<td>0.25</td>
<td>0.27</td>
<td>0.27</td>
<td>0.26</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>Annual rainfall (mm)</td>
<td>1695.16</td>
<td>1698.8</td>
<td>1696.28</td>
<td>1752</td>
<td>1743.63</td>
<td>1771.51</td>
<td>1700.77</td>
</tr>
<tr>
<td>Area (km²)</td>
<td>100.93</td>
<td>46.25</td>
<td>38.56</td>
<td>15.52</td>
<td>0.82</td>
<td>0.02</td>
<td>202.1</td>
</tr>
<tr>
<td>Area ratio (%)</td>
<td>49.94</td>
<td>22.88</td>
<td>19.08</td>
<td>7.68</td>
<td>0.41</td>
<td>0.01</td>
<td>100.00</td>
</tr>
</tbody>
</table>

STP, Soil total phosphorous content; SOM, soil organic matter content; and NDVI, normalized difference vegetation index.

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Table 1
Classification of soil erosion and corresponding soil total phosphorous (STP) content and environmental factors in the study area in 2018.

Fig. 3. Spatial variability of soil erosion levels in the study area in 2018.
scattered in the hilly and gently sloping area with slightly higher elevations. The total area that experienced extremely high erosion and severe erosion accounted for less than 0.5% of the study area and were mainly distributed on hilly slopes with low vegetation cover in the central and northern parts of the watershed. Overall, the entire region of Nanliao River watershed was under mild erosion, although there was a local risk of high erosion.

3.2. Soil total phosphorous in Nanliao River watershed

3.2.1. Classical statistic results

Descriptive statistics of 242 soil sample data were obtained after the exclusion of six outliers. The STP content ranged from 0.06 to 1.19 g/kg across the Nanliao River watershed, with an average of 0.60 g/kg. The coefficient of variation in STP content was 43.33%, indicating moderate variation. According to the soil nutrient classification standard of the Second National Soil Survey in China, the STP content in the study area were at the third level, i.e., the medium level. Kolmogorov-Smirnov test results revealed that the STP content had a normal distribution, which satisfied the requirements of subsequent semi-variance analyses of geostatistics.

3.2.2. Optimal semi-variogram

The semi-variogram fitting results (Fig. 4) showed that the exponential model was an optimal model for fitting STP content ($R^2 = 0.865$, RSS close to 0), which could reflect the spatial characteristics of STP content adequately. The nugget effect for STP content was 7.35%, indicating high spatial autocorrelation of STP content (nugget effect < 25%). The spatial aggregation of STP content was strong, which, in turn, indicates that its spatial variability was mainly influenced by structural factors. The range of spatial autocorrelation for STP content was 2.25 km and the spatial aggregation of STP content was significant in the range.

3.2.3. Spatial variability of STP content based on ordinary Kriging

The spatial variability of STP content was visualized by ordinary Kriging interpolation using the optimal semi-variogram and its corresponding parameters. Cross-validation of the interpolation results revealed that the RMSE of the model fitting was $2.46 \times 10^{-3}$, which indicates a good fitting. The spatial interpolation results showed obvious spatial aggregation of STP content across the study area (Fig. 5), which confirms the small-scale spatial autocorrelation reflected by the small range in the optimal semi-variogram. The high-value area was distributed in an east-west strip in the middle part of the watershed, corresponding to the flow trend of Nanliao river. Conversely, the low-value area was mainly distributed in the northeastern and southwestern hilly areas. The average STP contents of paddy field, dryland, orchard, forest, and other land use type were 0.63, 0.65, 0.58, 0.55, and 0.64 g/kg respectively.

3.2.4. Spatial variability of STP content under different erosion levels

Based on the spatial variability of STP content (Fig. 5) and soil erosion level (Fig. 3), we found that the areas with high STP content were mostly associated with low soil erosion, while the areas with low STP content largely overlapped with the areas under high soil erosion. From slight to severe level of soil erosion, the average STP content generally decreased, i.e., 0.62, 0.60, 0.56, 0.54, 0.52, and 0.47 g/kg, respectively. With increasing erosion level, STP content generally decreased, and larger decreases were found under moderate erosion and severe erosion compared with the previous level. The correlation analysis revealed that there was a significant negative correlation between STP content and soil erosion ($r = -0.149$, $P < 0.01$).

3.3. Factors influencing spatial variability of STP content

According to the results of semi-variance analysis, the spatial variability of STP content in the study area was mainly influenced by structural factors, but the interference of random factors could not be ruled out. The environmental factors influencing STP content spatial variability might also vary considerably under different soil erosion levels. Therefore, we selected elevation, slope, soil type, soil sand, silt, and clay contents, soil pH, SOM, NDVI, and annual rainfall as structural factors, and land use type as a random factor to explore the independent interpretation and interaction abilities of environmental factors on STP content under different erosion levels.

Fig. 4. Optimal semi-variogram of soil total phosphorus content in the study area.

Fig. 5. Spatial variability of soil total phosphorus (STP) content in the study area.
3.3.1. Correlation between STP content and environmental factors

The correlation analysis revealed that (Table 2) STP content was negatively correlated with elevation, slope, soil sand content, soil pH, NDVI, annual rainfall, and land use type \( (P < 0.01) \). Conversely, STP content was positively correlated with soil type, SOM, and silt content \( (P < 0.01) \). In terms of the absolute value of correlation coefficient, the top three factors correlated STP content were soil silt content \( (r = 0.503) \), elevation \( (r = -0.493) \), and soil sand content \( (r = -0.383) \). This result indicates that the spatial variability of STP content was largely influenced by structural factors, confirming the results of the semi-variance analysis. Because soil clay content had no significant correlation with STP content, it was excluded from the subsequent analysis.

3.3.2. Influence of single factors on spatial variability of STP content under different erosion levels

The results obtained using the factor detector (Table 3) showed that the environmental factors influencing STP content differed across various erosion levels. Horizontally, in areas with slight erosion, the explanatory ability of each factor to spatial variability of STP content ranged from 5.4% (annual rainfall) to 26.0% (elevation). In areas with mild erosion, elevation was still a dominant factor, but its explanatory ability was only 14.3%. In areas with moderate erosion, the explanatory ability of soil type and pH was identical (13.0%), both of which were the major factors influencing the spatial variability of STP content. In areas with high to severe erosion, only five factors appeared to be significant with an average explanatory ability of 24.7%, and the strongest explanatory factor was annual rainfall with an explanatory ability of 30.8%. Longitudinally, elevation, soil type, soil sand content, soil pH, and annual rainfall had significant influence on STP content under different erosion levels, while slope, SOM, NDVI and land use type had significant influence only in areas with slight or mild erosion, and silt content had no significant influence in areas with severe erosion.

3.3.3. Influence of interactions between factors on spatial variability of STP content under different erosion levels

The results obtained using the interaction detector (Table 4) revealed that under different levels of soil erosion, the influence of interactions between various environmental factors was enhanced compared with the influence of single factors. Across the entire region, the interactions of elevation with soil type, SOM content, and pH were the dominant factors influencing STP content, and their explanatory abilities increased by 15.5%, 12.7%, and 11.2%, respectively, compared with those of elevation alone. In areas with slight erosion, the dominant interactions were similar to those observed for the entire region, but the explanatory ability of each interaction was higher. In areas with mild erosion, the interaction of elevation and soil type showed the second highest explanatory ability, whereas the explanatory ability of interaction between soil mechanical composition and pH substantially increased. Similar interactions of factors were observed in areas with moderate erosion, albeit their relatively low average explanatory ability. However, different interactions of factors were observed in areas with high to severe erosion, where the explanatory ability of each interaction was much higher than that in other areas; in particular, the explanatory abilities of soil type and pH were the highest, and the interactions of annual rainfall with soil sand content and pH became the dominant factors influencing STP content.

### Table 2

Correlation coefficients between soil total phosphorus (STP) content and environmental factors.

<table>
<thead>
<tr>
<th>Soil property</th>
<th>Elevation</th>
<th>Slope</th>
<th>Soil type</th>
<th>Sand content</th>
<th>Silt content</th>
<th>Clay content</th>
<th>pH</th>
<th>SOM</th>
<th>NDVI</th>
<th>Annual rainfall</th>
<th>Land use type</th>
</tr>
</thead>
<tbody>
<tr>
<td>STP</td>
<td>(-0.493)**</td>
<td>(-0.168)**</td>
<td>0.247**&lt;sub&gt;0.01&lt;/sub&gt;</td>
<td>(-0.383)**</td>
<td>0.503**</td>
<td>(-0.012)</td>
<td>(-0.374)**</td>
<td>0.209**</td>
<td>(-0.222)**</td>
<td>(-0.040)**</td>
<td>(-0.068)**&lt;sub&gt;0.01&lt;/sub&gt;</td>
</tr>
</tbody>
</table>

SOM, soil organic matter content; and NDVI, normalized difference vegetation index. ** \( P < 0.01 \), * \( P < 0.05 \).

### Table 3

q values of single factors influencing the spatial variability of STP content under different erosion levels.

<table>
<thead>
<tr>
<th>Erosion level</th>
<th>Elevation</th>
<th>Slope</th>
<th>Soil type</th>
<th>Sand content</th>
<th>Silt content</th>
<th>Soil pH</th>
<th>SOM</th>
<th>NDVI</th>
<th>Annual rainfall</th>
<th>Land use type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slight</td>
<td>0.260**</td>
<td>0.033**</td>
<td>0.123**</td>
<td>0.104**</td>
<td>0.135**</td>
<td>0.093**</td>
<td>0.051**</td>
<td>0.075**</td>
<td>0.065**</td>
<td>0.054**</td>
</tr>
<tr>
<td>Mild</td>
<td>0.143**</td>
<td>0.001**</td>
<td>0.096**</td>
<td>0.108**</td>
<td>0.118**</td>
<td>0.126**</td>
<td>0.025**</td>
<td>0.038**</td>
<td>0.035**</td>
<td>0.032**</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.108**</td>
<td>0.002**</td>
<td>0.130**</td>
<td>0.056**</td>
<td>0.089**</td>
<td>0.130**</td>
<td>0.007**</td>
<td>0.007**</td>
<td>0.045**</td>
<td>0.009**</td>
</tr>
<tr>
<td>High to severe</td>
<td>0.205**</td>
<td>0.011**</td>
<td>0.301**</td>
<td>0.222**</td>
<td>0.052**</td>
<td>0.201**</td>
<td>0.008**</td>
<td>0.065**</td>
<td>0.308**</td>
<td>0.010**</td>
</tr>
<tr>
<td>Entire region</td>
<td>0.213**</td>
<td>0.027**</td>
<td>0.121**</td>
<td>0.113**</td>
<td>0.130**</td>
<td>0.101**</td>
<td>0.034**</td>
<td>0.052**</td>
<td>0.047**</td>
<td>0.054**</td>
</tr>
</tbody>
</table>

SOM, soil organic matter content. ** \( P < 0.01 \), * \( P < 0.05 \).
looser and more influenced by hydraulic erosion (Rodrigo Comino et al., 2016). Considering the relative severity of soil erosion and its negative correlation with STP content in the Nanliao River watershed, controlling soil erosion would be critical to minimize STP losses and potential ecological damage in the Poyang Lake Basin.

4.2. Relationship between spatial variability of STP content and soil erosion

The spatial variability of STP content across the Nanliao River watershed was roughly consistent with the trend of soil erosion level, and this relationship could be confirmed by the significant negative correlation between STP content and soil erosion. Cheng et al. (2018) also found that the erosion level of topsoil varied across a small watershed of the Loess Plateau, with higher STP content occurring in areas with lower erosion levels. The findings from the current and previous studies indicate that soil erosion plays a decisive role in the spatial variability of STP content.

The influence of soil erosion on the spatial variability of STP can be explained in the following two aspects (Berhe et al., 2018; Quinton et al., 2010): (1) During the course of soil erosion, runoff directly transports sediments that contains P; and (2) Soil erosion alters the physicochemical properties of the soil and consequently influencing the retention of P. For instance, soil erosion can lead to the loss of SOM, whereas the decline in SOM content will in turn reduce the adsorption capacity of soil for P (Debicka et al., 2016), thereby causing the loss of STP. In the Nanliao River watershed, the dramatic decreases in STP content under moderate erosion and severe erosion levels corresponded to the rapid decline in SOM content. Undoubtedly, the alteration in environmental factors by soil erosion is not restricted to cause the loss of SOM. Under the influence of soil erosion, unique environments may be formed across various erosion levels (Berhe et al., 2018), which could explain the distinct influence of environmental factors on STP content.

4.3. Global influence of environmental factors on spatial variability of STP content

In the present study, many environmental factors were found to influence the spatial variability of STP across the Nanliao River watershed. Each of the following five single factors (elevation, soil silt content, soil sand content, soil type, and soil pH) could explain over 10% of the spatial variability of STP content across the entire region. STP content was significantly negatively correlated with elevation and slope, which is consistent with the study of Liu et al. (2013) conducted on the Loess Plateau. The STP in high-elevation areas could be lost due to the complexity of the soil erosion process, various factors may interact with each other to influence the spatial variability of STP content (Cheng et al., 2018). In the current study, the average STP content was higher in areas experiencing slight erosion. According to the results obtained using GeoDetector, elevation and its interactions with soil type, SOM, and pH were the dominant factors influencing STP content across the slight erosion area. First, the fluvial alluvial plain at low elevations is the accumulation area of sediments migrated after soil erosion with rich STP and SOM (Liu et al., 2013). In addition, anthrosols developed from the Quaternary red clay is the main soil type in these areas. Due to its highest clay content compared with other soil types, it is easier for the anthrosols to absorb and preserve P. Moreover, P fixation by acidic soil could contribute to the conservation of STP. Taken together, sediment deposition, organic matter conservation, clay

<table>
<thead>
<tr>
<th>Dominant interaction 1</th>
<th>Elevation</th>
<th>Silt content</th>
<th>Elevation</th>
<th>Soil type</th>
<th>Elevation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil type</td>
<td>0.368</td>
<td>∩ Soils type</td>
<td>0.270</td>
<td>∩ pH</td>
<td>0.247</td>
</tr>
<tr>
<td>q</td>
<td>0.368</td>
<td>∩ Soils type</td>
<td>0.270</td>
<td>∩ pH</td>
<td>0.247</td>
</tr>
<tr>
<td>Dominant interaction 2</td>
<td>Elevation</td>
<td>Silt content</td>
<td>Annual rainfall</td>
<td>Elevation</td>
<td>Elevation</td>
</tr>
<tr>
<td>Soil type</td>
<td>0.340</td>
<td>∩ Soils type</td>
<td>0.256</td>
<td>∩ pH</td>
<td>0.236</td>
</tr>
<tr>
<td>q</td>
<td>0.340</td>
<td>∩ Soils type</td>
<td>0.256</td>
<td>∩ pH</td>
<td>0.236</td>
</tr>
<tr>
<td>Dominant interaction 3</td>
<td>Elevation</td>
<td>Sand content</td>
<td>Annual rainfall</td>
<td>Elevation</td>
<td>Elevation</td>
</tr>
<tr>
<td>Soil type</td>
<td>0.325</td>
<td>∩ Soils type</td>
<td>0.232</td>
<td>∩ pH</td>
<td>0.232</td>
</tr>
<tr>
<td>q</td>
<td>0.325</td>
<td>∩ Soils type</td>
<td>0.232</td>
<td>∩ pH</td>
<td>0.232</td>
</tr>
</tbody>
</table>

Table 4: q values for the interactions between factors influencing the spatial variability of soil total phosphorus content under different erosion levels.
adsorption, and P fixation under acidic soil conditions might contribute to the high STP content in these areas with slight erosion. In areas with mild erosion, elevation was still the dominant single factor influencing STP content, followed by soil pH in terms of their explanatory ability. The interaction between elevation and soil type became the second dominant, whereas the interaction between soil pH and silt content became the first dominant in influencing STP content. In these areas, cambisols is commonly developed from acidic crystalline salt weathering, which contains abundant iron/aluminum oxides with high silt content and low soil pH. All these factors might facilitate the fixation of STP in soil. In areas with moderate erosion, the interaction between soil type and soil pH, as well as their interactions with elevation and silt content, played a major role in influencing the spatial distribution of STP content. In these areas, cambisols covers 62.31% of the total area, and this value is 6.72% and 4.03% higher than those in other areas with slight erosion and mild erosion, respectively. Similar to the situation in areas with mild erosion, acidic cambisols could significantly influence spatial distribution of STP in areas with moderate erosion. However, under the influence of more serious soil erosion, moderate erosion areas would experience more STP losses than slight and mild erosion areas, leading to lower STP content.

Furthermore, rainfall is an important factor involved in soil erosion and biogeochemical cycles of soil nutrients (Wu et al., 2018). In areas experiencing severe erosion, the explanatory ability of annual rainfall increased substantially and it became the dominant factor influencing the spatial variability of STP content. In these areas, which received more topographic rain, annual rainfall was higher than in the other areas (Table 1). Moreover, the soil had higher sand content and soil pH in these areas, which could limit the occurrence of P fixation by soil. Under the influence of strong runoff caused by heavy rainfall, the STP might be seriously lost.

5. Conclusion

In this study, the RUSLE model was used to estimate soil erosion in the small watershed of Nanliao River, which comprehensively considered the rainfall erosivity factor (R), soil erodibility factor (K), topographic factor (LS), land cover and land use factor (C), conservation practice factor (P), and rainfall erosivity factor (R). The results showed that soil erosion ranged from 0 to 176.26 t ha⁻¹ a⁻¹ across the Nanliao River watershed in 2018. The soil erosion in the study area could be divided into six levels, among which slight erosion was the most prevalent, accounting for 49.94% of total area. However, in terms of average soil erosion, the entire region was under mild erosion. According to classical statistics, STP content ranged from 0.06 to 1.19 g/kg, with an average of 0.6 g/kg. Geostatistics analysis revealed that an exponential model had the best performance in explaining the spatial variability in STP content. The nugget effect of the model was 7.35% and the range was 2.25 km, indicating that structural factors played a dominant role in spatial variability of STP content. Ordinary Kriging interpolation based on the optimal semi-variogram showed that the spatial variability of STP was consistent with the flow trend of Nanliao River. Correlation analysis revealed that there was a significant negative correlation between STP content and soil erosion. Soil erosion influenced STP content and played an important role in the migration and deposition of STP. The influence of unique environment on STP content under soil erosion could be explained by GeoDetector. Across the entire region, elevation, soil particle size, and soil pH were the key factors influencing STP content. In other words, sediment deposition, clay adsorption, and P fixation under acidic soil conditions were the key processes determining STP content and its loss in soil. However, it should be noted that the key factors differed across various erosion levels. This study clarified the spatial variability of STP content in a terrestrial ecosystem and the influence of soil erosion on STP content. The results could improve our understanding of the spatial patterns of STP migration in soil, and provide support data for controlling the potential P pollution and maintaining the ecological balance in aquatic ecosystems such as freshwater lakes.

Declaration of Competing 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.

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