Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Extraction study of soil mineral ions and microbial influences on phosphorus and sulfur cycling based on principal component analysis

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ABSTRACT

Soil microorganisms and mineral ions play a crucial role in the material cycle and energy flow. Different types of sandy, loamy and gravelly soils were selected as experimental sample plots, and the mineral element and microbial diversity of the soils were analyzed by using the curve method with spiked recovery analysis measurement and Illumina high-throughput sequencing technology. Then, principal component analysis and Pearson correlation analysis were applied to extract the factors affecting phosphorus and sulfur cycling by soil mineral ions and microorganisms, and the results showed that the mineral ions in the three different types of soils were mainly Na+, K+, Mg+, and Ca+. The top ten dominant bacterial phyla in relative abundance in different types of soils were Ascomycetes, Actinobacteria, and so on. The eigenvalues of the first four principal components in the principal component analysis of phosphorus-sulfur cycle influencing factors were greater than 1. Therefore, four principal components were selected: soil water content, soil Mg+ content, soil actinomycetes content, and soil Ca+ content.

Keywords: principal component analysis, Pearson correlation analysis, phosphorus-sulfur cycle, influencing factors, high-throughput sequencing

1. Introduction

Soil is the richest microbial reservoir in nature, and the large number and diversity of microorganisms it contains play an equally important role in regulating ecosystem function [1-2]. Soil microorganisms are not only able to decompose apoplastic materials, improve soil fertility, promote energy flow and nutrient cycling, help plants obtain nutrients and control pests and diseases, but also degrade organic pollutants and reduce heavy metal toxicity [3-5]. Therefore, abundant soil microorganisms are the foundation of soil health. Soil microbial activities control the cycling process of soil carbon, nitrogen, phosphorus, sulfur and other elements to a certain extent, which is the key driving force for the

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Received 15 January 2024; Revised 10 February 2024; Accepted 30 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-351

formation and transformation of various biogenic elements in the soil and the link between the interaction of the soil, atmosphere, lithosphere, hydrosphere and biosphere [6-9]. It is considered as an important engine of elemental biogeochemical cycling, and the elemental cycles of biogenic elements are tightly coupled to regulate and drive biogeochemical processes [10-11]. Although most microorganisms in soil are involved in the biogeochemical processes of key soil elements, whether it is a competitive mechanism or a conditional control mechanism among various microorganisms in a complex microbial environment is a scientific question to be revealed [12].

Carbon is the most basic element that constitutes all organisms, and the carbon cycle, as the most important link in the biogeochemical cycle of nutrient elements, is not only the main form of energy conversion in the biological world, but also the driving factor of nitrogen, phosphorus and sulfur cycles. Literature [13] showed that soil microorganisms can control the inflow and outflow of carbon in soil under the influence of the environment, on the one hand, they can promote carbon sequestration and storage through interaction with plants, on the other hand, they can also participate in the decomposition and mineralization of organic matter to the atmosphere to emit greenhouse gases, thus participating in the global carbon cycle. Literature [14] explored the extent to which the inter-root effect of soil microorganisms affects the subsurface carbon cycle, and found that as the amount of microorganisms increases, the organic carbon metabolism per unit of inter-root soil is accelerated, which enhances the efficiency of the subsurface carbon cycle. Literature [15] investigated the facilitating and inhibiting effects of carbon nanomaterials on soil microbiota function and ecosystem services, and found that in terms of carbon cycling, they altered the carbon cycling efficiency by affecting carbon dioxide fixation and decomposition pathways of organic carbon materials. Literature [16] proposed the incorporation of microbial diversity into ecosystems to construct different Carbon Acquisition Ecological Strategies (CAES), a framework based on which an ecosystem model was constructed to predict soil carbon feedbacks under global change scenarios.

Nitrogen content in soil is one of the key determinants of crop yield and quality, so soil nitrogen cycle is also an important part of biogeochemical cycle of nutrient elements. Literature [17] used biochar to change the physicochemical properties of soil, which in turn affected the structure and activity of soil microbial communities involved in the nitrogen cycle, and improved the efficiency of nitrogen fixation and nitrification in soil, while reducing the total amount of soil ammonia volatilization. Literature [18] examined the effects of crop rotation patterns on nitrogen cycling microorganisms and crop yields, and provided a solid theoretical basis for the realization of soil nitrogen transformation and sustainable agricultural production by identifying the microbial taxa that increase soil nitrogen content. Literature [19] studied the changes of nitrogen cycling functional genes and functional microorganisms in acidified soils based on soil macrogenomics, and found that the reduction of soil pH will lead to an imbalance of the proportion of nitrogen forms in the soil, and at the same time, affect the activities of related enzymes and microbial communities, which reduces the nitrogen conversion and uptake of crops. Literature [20] found that plants with specific traits can be selected to manage nitrogen fluxes in the soil, and that plant species have an impact on the abundance of nitrifying and denitrifying microorganisms in the soil by altering the physicochemical properties of the soil, which in turn affects soil nitrification and nitrate loss.

Phosphorus is one of the bulk nutrients necessary for plant growth, along with sulfur. Phosphorus in soil can be categorized into organic and inorganic forms, and organic phosphorus compounds contain three types of phytochemicals, nucleic acids and phospholipids [21]. The biogeochemical cycle of soil phosphorus mainly contains the processes of organic phosphorus mineralization, inorganic phosphorus dissolution, inorganic phosphorus biosynthesis, and inorganic phosphorus hydrolysis [22]. And the biogeochemical cycle of elemental sulfur mainly includes sulfur oxidation and reduction processes [23]. However, relatively few studies have been conducted on microorganisms and soil biogeochemical cycling of phosphorus and sulfur elements, and further research is urgently needed to understand the mechanism and process of microbial involvement.

In this paper, sandy, loamy and gravelly soils were selected as samples to analyze the mineral element content of the soils by collecting soil samples of each type with the spiking and recovery method of curvilinear method. The soil samples were subjected to Illumina high-throughput sequencing to analyze the community composition of microorganisms in different types of soils at the phylum classification level. The influence of soil mineral ions and microorganisms on phosphorus-sulfur cycle was analyzed using principal component analysis method and Pearson correlation, and the main influence factors of phosphorus-sulfur cycle were extracted.

2. Involvement of mineral ions and microorganisms in the phosphorus and sulphur cycles

The main chemical elements that make up soil minerals Minerals are naturally occurring in the earth's crust with a certain chemical composition, physical properties and internal structure of the object, is the basic unit of the composition of the rock. There are many types of minerals, totaling about 3,300 or more. The composition of soil mineral elements is mainly composed of more than 100 kinds, including oxygen, silicon, aluminum, iron, calcium, magnesium, titanium, potassium, sodium, phosphorus, sulfur, and some trace elements such as manganese, zinc, copper, molybdenum and so on. Among them, oxygen and silicon are the two most abundant elements in soil minerals, accounting for 49% and 33% of the weight of soil respectively. Iron and aluminum are the next most abundant elements, while the remaining 90 elements together account for about 10%. The chemical composition of soil minerals fully reflects the dispersion and enrichment characteristics of elements and bioaccumulation in the process of soil formation. It inherits the genetic properties of the chemical composition of the earth's crust, while some chemical elements such as oxygen, silicon, carbon and nitrogen increase during soil formation, while others decrease significantly, such as calcium, magnesium, potassium and sodium.

Soil mineralization potential can characterize the supply capacity of soil nitrogen nutrients. Mineralization potential refers to the gross/net increase in the conversion of organic nitrogen into inorganic nitrogen by soil microorganisms per unit of time under suitable conditions, which is mainly influenced by microbial activity and soil mineral content. As an important component of terrestrial ecosystems, soil microorganisms play an important role in regulating soil ecological functions and driving biogeochemical cycles. At the same time, soil microorganisms are extremely sensitive to changes in the external environment and soil disturbances, and they can influence important ecological processes related to soil biogeochemical cycling by changing the composition, structure and function of their own communities. These processes can lead to elevated CO2, greenhouse gas emissions, nutrient loading and water depletion, and can be exacerbated by changes in the Earth's interaction loop. Therefore, a comprehensive understanding of the diversity and abundance of microbial taxonomic composition and functional genes is critical to better understand microbial-mediated biogeochemical processes and their critical role in current global change. The phosphorus cycle mainly consists of organic phosphorus mineralization, inorganic phosphorus mineralization, inorganic phosphorus synthesis and inorganic phosphorus solubilization processes [24]. The sulfur cycle mainly consists of sulfuric acid oxidation and reduction processes, and fewer studies have been reported on the effects of temperature changes on the phosphorus and sulfur cycles [25].

Phosphorus activation by sulfate reduction can be achieved through two main pathways: direct organic matter (OP) mineralization and indirect dissolution by Fe-P reduction. In general, sediments with high content of active organic matter and OP (e.g., large amount of debris after the death of red tide algae in the late red tide stage) have strong sulfate reduction and fast rate of mineralization of organic matter, and the biogenic OP is mainly reactivated through sulfate reduction. In addition, sulfate reduction products of dissolved sulfide will rapidly diffuse to the surrounding pore water, and co-precipitation with Fe2+ will also continue to consume iron oxides, i.e., cause iron chemical reduction.

Originally adsorbed and passivated Fe-P with the dissolution of iron oxide reduction is released, and the reduction products whether mackinawite or pyrite on the adsorption of phosphorus are weak, indirectly caused by Fe-P activation. Thus, strong sulfate reduction is often an important process controlling phosphorus activation, especially in coastal zone sediments with high biogenic and terrestrial sources of phosphorus, and may outweigh the contribution of Fe-isomerization reduction, leading to decoupling of pore-water dissolved Fe and phosphorus distributions as well as coupling of dissolved sulfide and phosphorus distributions.

3. Methodology for the analysis of impact factors

3.1. Pearson correlation analysis method

Impact studies can reflect the phosphorus-sulfur cycle more comprehensively. Correlation analysis and regression analysis are commonly used to study the relationship between variables. In this paper, the correlation coefficients of soil mineral ions and microorganisms on the phosphorus-sulfur cycle were calculated by using Pearson correlation analysis, and the strength of the linear relationship was determined according to the size of the correlation coefficients, and the influence of the indicators was evaluated and ranked by the strength of the linear relationship.

In statistics, the Pearson product-moment correlation coefficient is used to measure the interrelationship between two variables X and Y, and its value ranges between -1 and +1 [26]. Pearson's correlation coefficient is widely used in academic research to measure the strength of linear correlation between two variables. The Pearson's correlation coefficient between two variables is defined as the quotient of the product of the covariance of the two variables and the standard deviation of the two variables, that is:

$$\rho_{xy} = \frac{\operatorname{cov}(X,Y)}{\sigma_x \sigma_y} = \frac{E(X-\mu x)(Y-\mu y)}{\sigma_x \sigma_y} \tag{1}$$

Equation (1) defines the overall correlation coefficient ρ_{xy}. If the covariance and standard deviation calculated for the sample are used instead of the covariance and standard deviation of the whole, then it is the sample correlation coefficient, which is usually denoted by r:

$$r = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i - \bar{X}}{S_x}\right)\left(\frac{Y_i - \bar{Y}}{S_Y}\right) \tag{2}$$

3.2. Principal component analysis

To investigate the relative magnitude of the effect of having each influence factor on the phosphorus-sulfur cycle, we used principal component analysis.

Principal components are p specific linear combinations of random variables $X_1, X_2, ..., X_p$. Geometrically, these linear combinations represent a new coordinate system obtained by rotating the original system with $X_1, X_2, ..., X_p$ as the axis. The new coordinate axes represent the directions with maximum variability and provide a simpler and more concise description of the covariance structure. So the principal components depend only on the matrix Σ (or correlation matrix ρ) of the covariance $X_1, X_2, ..., X_p$ [27].

Let the random vector $x = [X_1, X_2, ..., X_p]$ have covariance matrix Σ with eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. Consider linear combinations:

$$\begin{aligned} Y_1 &= a_1' X = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \\ Y_2 &= a_2' X = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \\ &\vdots \\ Y_p &= a_p' X = a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p \end{aligned} \tag{3}$$

From there, you can get:

$$\begin{aligned} Var(Y_i) &= a_i' \Sigma a_i \qquad i = 1, 2, \ldots, p \\ Cov(Y_i, Y_k) &= a_i' \Sigma a_k \quad i, k = 1, 2, \ldots, p \end{aligned} \tag{4}$$

Principal components are those uncorrelated linear combinations whose variance is as large as possible $Y_1, Y_2, ..., Y_p$. Principal components are linear combinations with maximum variance.

First principal component = maximization of linear combination $a_1' X$; $Var(a_1' X)$ satisfies $a_1' a_1 = 1$.

Second principal component = maximization of linear combination $a_2' X$; $Var(a_2' X)$ satisfies $a_2' a_2 = 1$, $Cov(a_1' X, a_2' X) = 0$.

The i st principal component = the maximization of the linear combination $a_i' X$; $Var(a_i' X)$ satisfies $a_i' a_i = 1$, and $Cov(a_i' X, a_k' X) = 0$, where $k < i$.

It can be concluded that Σ is the covariance matrix associated with the random vector $X = [X_1, X_2, ..., X_p]$. Σ has eigenvalue-eigenvector pairs $(\lambda_1, e_1), (\lambda_2, e_2), ..., (\lambda_p, e_p)$ and $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$.

Then the i th principal component by can be given by Eq. (5):

$$\begin{aligned} Y_i = e_i' X &= e_{i1} X_1 + e_{i2} X_2 + \cdots + e_{ip} X_p \qquad i = 1, 2, ..., p \\ Var(Y_i) &= e_i' \Sigma e_i = \lambda_i \qquad i = 1, 2, \ldots, p \\ Cov(Y_i, Y_k) &= e_i' \Sigma e_k = 0 \qquad i \neq k \end{aligned} \tag{5}$$

If some λ_i are equal, the choice of the corresponding eigenvectors e_i and principal components Y_i is not unique. Also the principal components are uncorrelated and their variance is equal to the eigenvalues of Σ. And has the property shown in equation (6):

$$\sum_{i=1}^{p} Var(X_i) = tr(\Sigma) = \sum_{i=1}^{p} Var(Y_i) \tag{6}$$

Overall variance:

$$\sigma_1 1 + \sigma_{22} + \cdots + \sigma_{pp} = \lambda_1 + \lambda_2 + \cdots + \lambda_p \tag{7}$$

Therefore, the proportion of total variance due to the k first principal component is:

$$\begin{aligned} &\text{Proportion of the population variance caused by the KTH principal component} \\ &= \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_p}{k} \\ &k = 1, 2, ..., p \end{aligned} \tag{8}$$

For data with a large number of indicators p if the majority of the overall variance (e.g., 80% to 90%) can be attributed to the first, first two, or first three principal components, then these principal components can "replace" the original p variables without losing much information. Observational analysis of correlation coefficients and correlations can also be used to better explain the principal components.

When conducting principal component analysis on variables measured at different scales or different ranges on a common scale, it is necessary to standardize the variables as shown in Equation (9):

$$z_j = \begin{bmatrix} \dfrac{x_{j1}-\overline{x}_1}{\sqrt{s_{11}}} \\ \dfrac{x_{j2}-\overline{x}_2}{\sqrt{s_{22}}} \\ \vdots \\ \dfrac{x_{jp}-\overline{x}_p}{\sqrt{s_{pp}}} \end{bmatrix} j=1,2,...,n \tag{9}$$

The normalized matrix representation is shown in Eq. (10), i.e., the normalized matrix Z of the vector is obtained:

$$\begin{aligned} \mathrm{Z} &= \begin{bmatrix} z_1' \\ z_2' \\ \vdots \\ z_n' \end{bmatrix} = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1p} \\ z_{21} & z_{22} & \cdots & z_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{np} \end{bmatrix} \\ &= \begin{bmatrix} \dfrac{x_{11}-\vec{x}_1}{\sqrt{s_{11}}} & \dfrac{x_{12}-\vec{x}_2}{\sqrt{s_{22}}} & \cdots & \dfrac{x_{1p}-\vec{x}_p}{\sqrt{s_{pp}}} \\ \dfrac{x_{21}-\vec{x}_1}{\sqrt{s_{11}}} & \dfrac{x_{22}-\vec{x}_2}{\sqrt{s_{22}}} & \cdots & \dfrac{x_{2p}-\vec{x}_p}{\sqrt{s_{pp}}} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{x_{n1}-\vec{x}_1}{\sqrt{s_{11}}} & \dfrac{x_{n2}-\vec{x}_2}{\sqrt{s_{22}}} & \cdots & \dfrac{x_{np}-\vec{x}_p}{\sqrt{s_{pp}}} \end{bmatrix} \end{aligned} \tag{10}$$

The correlation between the variables can be known by the correlation coefficient matrix, and if the correlation between the variables does not reach the degree of correlation, then it is not suitable for principal component analysis. Based on the standardized data matrix, covariance matrix R is established, and matrix R is a statistical index reflecting the degree of correlation between standardized data. The larger its value, the more it represents the need to perform principal component analysis on the data.

The correlation coefficient matrix is shown in equation (11):

$$R = \frac{1}{n-1} Z'Z = \frac{1}{n-1} \begin{bmatrix} \dfrac{(n-1)s_{11}}{s_{11}} & \dfrac{(n-1)s_{12}}{\sqrt{s_{11}}\sqrt{s_{22}}} & \cdots & \dfrac{(n-1)s_{1p}}{\sqrt{s_{11}}\sqrt{s_{pp}}} \\ \dfrac{(n-1)s_{12}}{\sqrt{s_{11}}\sqrt{s_{22}}} & \dfrac{(n-1)s_{22}}{s_{22}} & \cdots & \dfrac{(n-1)s_{2p}}{\sqrt{s_{22}}\sqrt{s_{pp}}} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{(n-1)s_{1p}}{\sqrt{s_{11}}\sqrt{s_{pp}}} & \dfrac{(n-1)s_{2p}}{\sqrt{s_{22}}\sqrt{s_{pp}}} & \cdots & \dfrac{(n-1)s_{pp}}{s_{pp}} \end{bmatrix} \tag{11}$$

The normalized vector matrix Z is the normalized matrix of the data and $z_1, z_2, ..., z_n$ is the normalized set of vectors whose covariance matrix is R. Then the expression of the i th principal component of the normalized data is shown in equation (12):

$$\begin{aligned} U_i = e_i' Z = e_{i1} z_1 + e_{i2} z_2 + \cdots + e_{ip} z_p \quad & i = 1, 2, ..., p \\ Var(U_i) = \lambda_i \quad & i = 1, 2, ..., p \\ Cov(U_i, U_k) = 0 \quad & i \neq k \end{aligned} \tag{12}$$

$$\sum_{i=1}^{p} Var(U_i) = tr(R) = p = \lambda_1 + \lambda_2 + \cdots + \lambda_p \tag{13}$$

$(\lambda_1, e_1), (\lambda_2, e_2), ..., (\lambda_p, e_p)$ is the eigenvalue-eigenvector pair of the covariance matrix R, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$. U_1 as the first principal component, U_2 as the second principal component, ..., U_p as the p th principal component.

The principal component analysis method determines the weights directly based on the information represented by the original data to achieve the evaluation analysis. In the principal component analysis method, the variance contribution rate of the principal components is directly used as the weight of the corresponding principal components, in other words, the information contribution rate of the principal components is the weight of the principal components. The principal component composite score is shown in equation (14):

$$H = \Sigma_{i=1}^{p} f_i U_i \tag{14}$$

In the established principal component model the weights are calculated by the ratio of the sum of the corresponding eigenvalues of each principal component to the total eigenvalues. Following the idea of weighting, the composite score was calculated by adding the multiplier of each principal component score and the corresponding weight. The calculated composite score provides data support for the comprehensive evaluation of the research objectives.

4. Research on the analysis of factors affecting the phosphorus-sulfur cycle based on principal component analysis

4.1. Mineral ion content of different soil types

According to the different soil types, sandy, loamy and gravelly soils were selected as experimental sample plots, i.e. Space1~Space3.

Sample collection:In early September 2024, 1.0 m×1.0 m sample squares were set up in each experimental sample plot, and the dominant and subdominant species of plants in the sample squares were mowed in the same place, bagged in separate species, and 3 samples of each plant species were collected in each sample plot as replicates, dried and stored for spare; meanwhile, soil samples were collected in corresponding sample plots by soil auger method (0-10 cm, 10-20 cm, 20-30 cm. 30-40 cm, 40-60 cm), with 3 replicates, 30-40 cm, 40-60 cm), 3 replicates, dried and preserved; meanwhile, soil samples were collected by soil auger method.

Sample treatment:The plant samples were firstly pre-treated by distilled water rinsing and drying; the soil samples were pre-treated by drying, grinding and passing through 100 mesh (2 mm) sieve, then digested with HClO4 and HNO3 (V:V, 1:4), and then fixed to be ready for on-line testing.

Analytical items: Cu, Zn, Fe, Mn, Co, Ni, K, Na, Ca, Mg, P, Li, Sr, Pb, Cr, Cd, etc.

Analytical method:Cu, Zn, Fe, Mn, Co, Ni, K, Na, Ca, Mg, Li, Sr and other elements using flame atomic absorption instrument standard curve method spiked recovery analysis test:

1) Pb and other elements were spiked and recovered by flow injection hydrogenation method atomic absorber standard curve method.

2) Tested by graphite furnace atomic absorber standard curve method, V for soil and B for plant.

3) P was tested by the standard curve method with spiked recovery using a 721 spectrophotometer.

Analyzing instrument: TAS-986 atomic absorption spectrophotometer (Beijing Pudian General Co.,

Ltd.).

WHG-103A flow injection hydride generator (Beijing Haotianhui Co., Ltd.).

GFH-986 Atomic Absorption Graphite Furnace Power Supply (Beijing Puritic General Co., Ltd.).

721 Spectrophotometer (Shanghai Second Analytical Instrument Factory).

AR1140 electronic balance (Chaus Corp. Pine Brock, NJ, USA).

Plant growth and development needs from the supply of mineral element nutrition in the soil, after the fall of the yellowing of the plant body will be partially returned to the soil environment, through the digestion and decomposition of soil microorganisms, which will return the mineral element to the soil, the mineral element is so for the vibrant green grassland, through the interface between the plants and the soil through the interface shuttle, in the form of different ionic or chemical compounds and cyclic pathways, carrying out the mineral element The biological phosphorus and sulfur cycle. The vertical band spectrum of mineral elements in soil is characterized by the spatial distribution pattern of mineral elements consistent with the topography and landscape. Therefore, according to the hypothesis of the "starvation effect" of mineral elements, mineral elements accumulate and differentiate due to the "starvation effect". On the contrary, the accumulation and differentiation of mineral elements in plants due to the nutritional supply of mineral elements, resulting in the growth and development of plants and then affected, interacting with each other and restricting each other, under the action of the biological phosphorus and sulfur cycle of mineral elements, unique vegetation communities and landscapes are formed, and the spatial distribution pattern of mineral elements consistent with the topography and landscape is also formed. It should be noted that, under the limitations of environmental conditions such as alpine, drought and oxygen deficiency, the biological phosphorus-sulfur cycling between plants and mineral elements in soil has a tendency to weaken with the increase of altitude, and the mineral elements in each experimental sample plot are as shown in Table 1, and the mineral ions in the soil mainly include Na+, K+, Mg+, Ca+ and so on. It is related to the limitation of ambient temperature, moisture and other climatic conditions, that is, under lower temperature or moisture conditions, the activity of mineral element migration and ion transfer decreases, which is not conducive to the uptake of mineral element nutrients by the plants, and therefore, the accumulation of differentiation due to the relative insufficiency of the mineral element uptake during the growing period of the plants. Note: a, b and c represent significant differences between different sites for the same plant of the same element, $p<0.05$.

Table 1. The elements of the vegetation in the vegetation of the field(mg/kg)

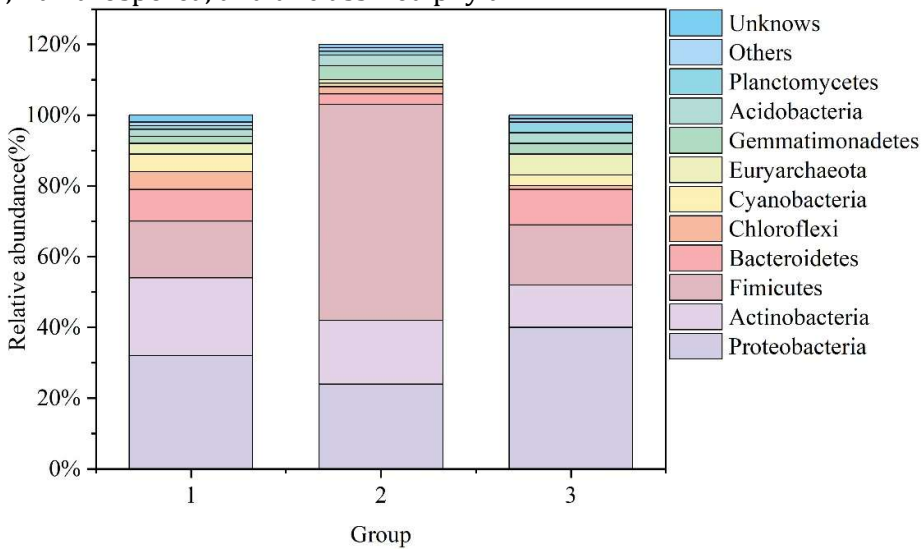
	Space1		Space2		Space3	
	Degraded	Enclosed	Degraded	Enclosed	Degraded	Enclosed
Na+ Vegetation	7.725±4.852 a	6.132±4.784 b	9.174±5.497a	7.894±4.796 b	10.56±5.054a	7.295±4.784 b
Na+ Soil	14.02a	24.2b	21.36a	23.25b	20.96a	18.89b
K+ Vegetation	57.16±9.523 a	50.21±24.21 b	72.39±29.3a	56.38±22.78 b	53.89±12.58a	61.94±30.25 b
K+ Soil	45.23a	112.2b	102.3a	432.5b	88.26a	78.79b
Mg+ Vegetation	175.6±80.42 a	84.25±114.6 b	140.5±63.58a	164.8±98.5b	140.2±42.63a	165.28±94.56b
Mg+	12945a	14875b	13945a	14898b	14897	14226

Soil						
Ca+ Vegetation	636.8±146.3a	245.5±130.2b	14896	411.2±186.3b	485.3±112.4a	512.5±162.4b
Ca+ Soil	245.8±130.5b	778.2b	14225	887.1	822.9	780.5

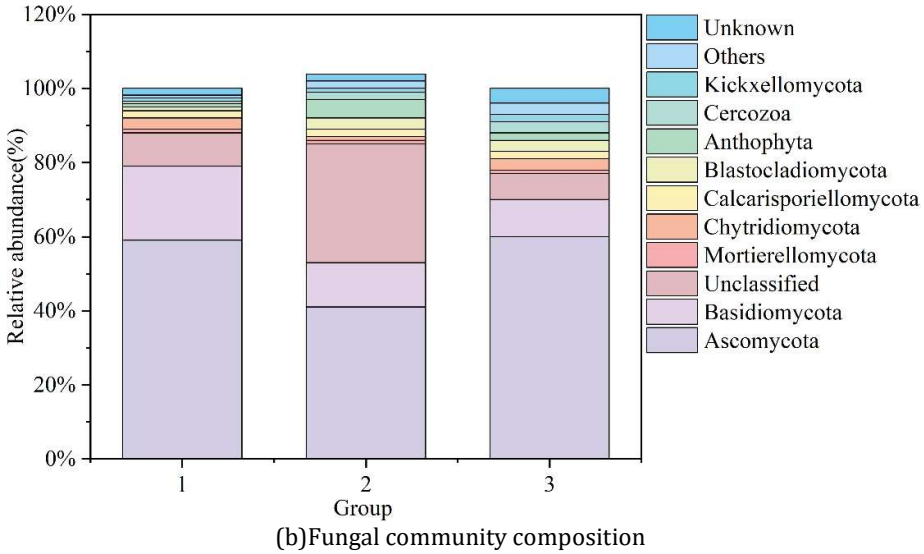
4.2. Microbial diversity of different soil types

Microorganisms are the main force driving the biochemical cycles of the earth, and they have a great impact on the metabolism of carbon, nitrogen, phosphorus, and sulfur, organic matter degradation, nitrogen efflux, and phosphorus loss in the environment.

Soil samples from each sample zone in the study area were subjected to Illumina high-throughput sequencing technology to analyze the information mainly through three steps of sequence splicing, filtering, and removing chimeras, and the quality of the sequencing data was evaluated through statistical sequencing to finally obtain valid sequences that could be used for conducting subsequent analysis. The community composition of different types of soil microorganisms under the phylum classification level is shown in Fig. 1, from which it can be seen that the top ten dominant bacterial phyla in relative abundance in different types of soils (sandy, loamy and gravelly soils) were Ascomycetes, Thick-walled Bacteria, Actinobacteria, Anaplastic Bacteria, Acidobacteria, Broad Archaea, Green Curved Bacteria, Cyanobacteria, Bacteromonas, and Floating Molds. The relative abundance of Firmicutes in loamy soil was 61%, which was much higher than sandy and gravelly soil. The first soil-dominant bacterial phylum with the highest relative abundance in sandy and gravelly soils was Proteobacteria, with relative abundance of 32% and 40%, respectively. The top ten dominant fungal phyla in terms of relative abundance in different soil types were Ascomycetes, Peridinomycetes, Stachybotrys, Combretum, Peridinomycetes, Filamentospora, Chytridiomycota (Potamomycetes), Botrytis cinerea, Kalkarosporea, and unclassified phyla.



(a) Bacterial community composition



(b)Fungal community composition

Fig. 1. Microbial community composition

4.3. Analysis of factors affecting the phosphorus-sulfur cycle

This study focuses on the relationship between soil mineral ions, microorganisms and phosphorus-sulfur cycle. In order to accurately determine the correlation of the influencing factors, Pearson correlation analysis was used to analyze the correlation coefficients and significance of soil mineral ions, microbial factors and phosphorus-sulfur cycle. The correlation results were shown in Table 2, and the factors were significantly related to the phosphorus-sulfur cycle. Mean annual precipitation and mean annual air temperature were significantly correlated with the phosphorus-sulfur cycle at the 0.01 level, with correlations of 0.756**, 0.869**, respectively. Phosphorus-sulfur cycle and soil moisture content in the factor showed positive correlation. r = 0.912**, significantly correlated at the 0.01 level. It indicates that the higher the soil water content, the more P, S content in the phosphorus-sulfur cycle. Phosphorus-sulfur cycle and capacity value soil are negatively correlated, correlation is -0.742**, $p<0.01$ significant correlation at 0.01 level, the smaller the capacity value the greater the P, S content of the phosphorus-sulfur cycle. There is a positive correlation between the phosphorus-sulfur cycle content and the K+ content of soil factors, r=0.635**, the correlation is relatively strong. $p<0.01$, the significance is relatively good. It indicates that the more soil K+ content, the more P, S content of phosphorus-sulfur cycle. The correlation between phosphorus-sulfur cycle P, S content and soil Na+ content is 0.522**, $p<0.01$, significant at 0.01 level. It indicates that the more soil Na+ content in the horizontal direction of the study area, the greater the P, S content of the phosphorus-sulfur cycle. The P, S content of phosphorus-sulfur cycle and soil pH were negatively correlated with a correlation of -0.526**, $p<0.01$. Within the range of soil pH in the study area, the greater the soil pH, the lower the P, S content of phosphorus-sulfur cycle. Soil Mg+, Ca+ factors also had a significant effect on phosphorus-sulfur cycle. Soil bacteria, fungi and actinomycetes were positively correlated with phosphorus-sulfur cycle content at the 0.01 level. The correlation coefficients were 0.089, 0.578** and 0.663**, respectively. There was no significant correlation between soil carbon to nitrogen ratio and phosphorus to sulfur cycle.

Table 2. Correlation

Influencing factor	Correlation	
	r	P
Soil moisture content	0.912**	0.001
Soil ph	-0.526**	0.002
Capacity value	-0.742**	0.001
Na+	0.522**	0.001
K+	0.635**	0.001
Mg+	0.984**	0.001
Ca+	0.989**	0.001
C, N ratio	0.224	0.056
Bacteria	0.089	0.642
Fungi	0.578**	0.001
Actinomycetes	0.663**	0.001
Annual average temperature	0.869**	0.001
Annual average precipitation	0.756**	0.001

In nature, the phosphorus-sulfur cycle content is jointly affected by several influencing factors. And there is covariance between each influencing factor, using principal component analysis for dimensionality reduction to exclude covariance between influencing factors.KMO and Barlett's detection is shown in Table 3, and KMO and Bartlett's test are firstly carried out in factor analysis. In this analysis KMO detection value is 0.812>0.7 and Bartlett's test of sphericity significance is 0.00, which indicates that our principal component analysis is feasible and suitable for factor analysis.

Table 3. KMO and Barlett's tests

KMO and Barlett's tests		
KMO metric for sampling sufficient degree		0.812
	Approximate card	598.963
Bartlett's spherical test	Freedom	79
	Significance	0.001

The results of the principal component analysis are shown in Table 4, in the principal component analysis we extracted four principal components of the original data, and the four principal component data retained 86.27% of the information before transformation. These four factors contain most of the information of the original impact factor, indicating that the principal component analysis is feasible.

Table 4. Main component analysis results

Influencing factor	Main component				Factor extraction rate
	1	2	3	4	
C/N ratio	0.093	0.072	-0.046	0.655	84.22%
Soil moisture content	0.223	0.041	-0.154	0.231	80.03%
Capacity value	-0.182	0.136	-0.154	-0.135	74.25%
Soil ph	-0.124	0.023	0.145	0.415	70.25%
Bacteria	-0.146	-0.094	0.568	-0.053	74.23%
Fungi	-0.095	0.053	0.441	0.098	74.89%
Na+	0.178	-0.563	0.078	-0.06	99.56%
K+	-0.136	0.514	-0.058	0.079	98.27%
Actinomycetes	0.320	-0.174	-0.234	-0.009	70.12%
Annual average temperature	0.142	-0.02	0.046	-0.120	83.27%

Annual average precipitation	0.152	-0.194	0.22	-0.203	78.25%
Mg+	0.18	0.036	-0.006	0.04	95.33%
Ca+	0.145	0.06	0.04	-0.032	94.58%
Cumulative contribution	35.62%	55.26%	73.28%	86.27%	

The gravel plot of the principal component analysis of the influence factors is shown in Figure 2. In the gravel plot of principal component analysis, the eigenvalues of the first four principal components are greater than 1, and it is feasible to select four principal components.

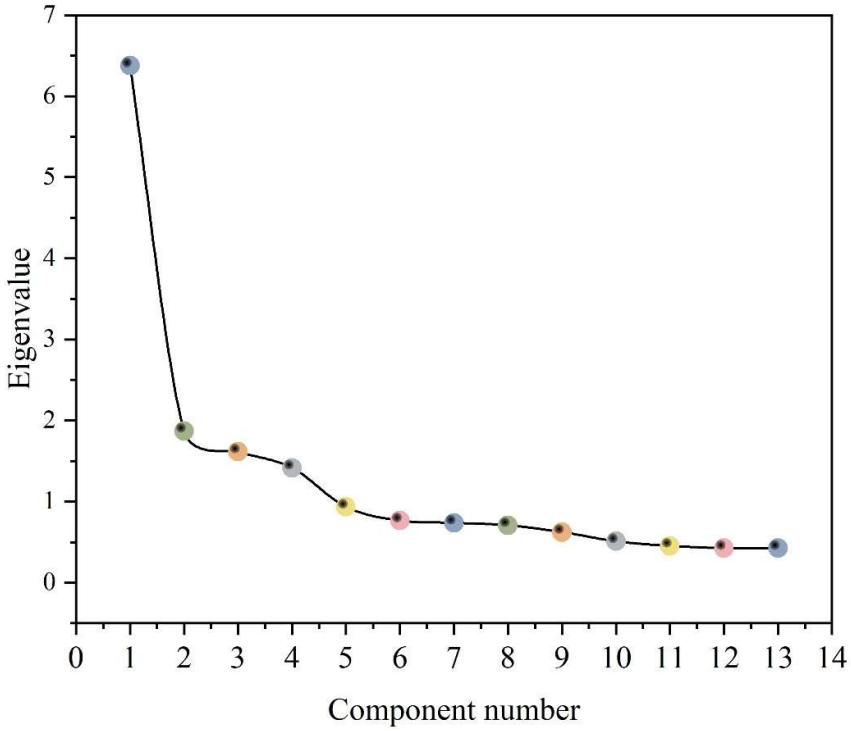


Fig. 2. Influence factor main component analysis

Regression analysis was done on the principal components of the extracted influencing factors and the standardized phosphorus-sulfur cycle, and the factors explained 95.4% of the phosphorus-sulfur cycle, and the significance of the regression equation was 0.000, with a DW value of 2.114, which indicated that the regression equation was meaningful and well-fitted. The regression analysis is meaningful. The regression coefficient matrix and principal component score matrix were obtained after combining the regression as shown in Table 5, and the regression coefficients of each influence factor were obtained.

Table 5. Impact factor regression analysis

Principal component	Regression coefficient	T	Significance
1	0.874	23.517	0.001
2	0.356	9.056	0.001
3	0.294	7.846	0.001
4	-0.04	-0.9	0.08

The relative degree of influence of each influencing factor on phosphorus and sulfur cycle was derived from the regression coefficients as shown in Table 6. In the table, the influence of annual average temperature and annual precipitation among climatic factors is 10.54% and 9.96%, respectively. Soil moisture content among the soil physical factors has the greatest influence on phosphorus-sulfur cycle with a weight of 12.54%. The influence of soil bulk weight value on

phosphorus-sulfur cycle was 11.63%. The effect of soil pH on phosphorus-sulfur cycle was 5.01%. The combined effect of soil Na+, K+ was 5.1%. The proportion of Mg+ in soil was 12.35%. The effect of soil Ca+ content on phosphorus-sulfur cycle was 11.72%, and the combined effect of soil bacteria and fungi and actinomycetes on phosphorus-sulfur cycle was 17.91%.

Table 6. Relative influence

Influencing factor	Regression coefficient	Relative influence
C/N ratio	0.07	4.75%
Soil moisture content	0.22	12.54%
Capacity value	-0.16	11.63%
Soil ph	-0.08	5.01%
Bacteria	0.02	1.21%
Fungi	0.07	4.56%
Na+	0.03	1.89%
K+	0.06	3.21%
Actinomycetes	0.17	12.14%
Annual average temperature	0.15	10.54%
Annual average precipitation	0.15	9.96%
Mg+	0.17	12.35%
Ca+	0.18	11.72%

The distribution of influencing factors is shown in Fig. 3. In summary, the main factors affecting the phosphorus and sulfur cycle content in the horizontal direction are soil water content, soil Mg+ content, soil actinomycetes content, and soil Ca+ content.

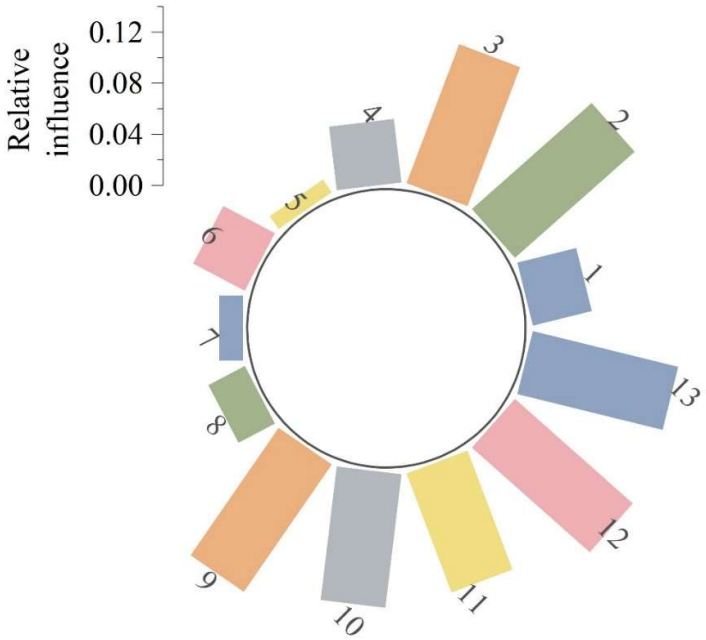


Fig. 3. Influence factor profile

5. Conclusion

In this paper, the main components were extracted by principal component analysis and Pearson correlation analysis to derive the regression coefficients and the eigenvalues of the principal components to analyze the effects of mineral ions (Na+, K+, Mg+, Ca+), microorganisms (bacteria, fungi,

and actinomycetes), and other factors (water content, precipitation, and pH, etc.) on phosphorus-sulfur cycling at the scale of different types of soils. The results of the study showed that the correlation coefficients of bacteria, fungi and actinomycetes in the soil were 0.089**, 0.578** and 0.663**, respectively, which were significantly correlated with phosphorus-sulphur cycle at 0.01 level. Soil mineral Na+, K+, Mg+, and Ca+ contents were also significantly and positively correlated with phosphorus-sulfur cycle. There was no significant correlation between soil carbon and nitrogen ratios and phosphorus and sulfur cycling, and there was a negative correlation between pH and bulk weight values of soil. The four main factors affecting the phosphorus-sulfur cycle were soil water content, soil Mg+ content, soil actinomycetes content, and soil Ca+ content.

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