

Original Research

Spatial Variability and Influencing Factors of Soil P and K in a High-Altitude Mining Area: A Case Study in Southwest China

Xiyao Feng¹, Yu Chen¹, Zhongyou Song¹, Pan Gao¹, Pengfei Chen²,
Fabin Yan², Pei Wang², Pan Zhou²

¹Sichuan Gold Group CO., LTD. Chengdu 610000, PR China

²Sichuan Natural Resources Pengcheng Geological Engineering Technology CO., LTD. Chengdu 610000, PR China

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Abstract

The spatial variation and influencing factors of various forms of P and K in soil from a high-altitude mining area were assessed using a combination of traditional statistical and geostatistical methods. The primary factors affecting the distributions of P and K were identified using correlation analysis. The mean total phosphorus (TP), available phosphorus (AP), inorganic phosphorus (IP), total potassium (TK), quick-release potassium (AK), and slow-release potassium (SAK) were 1280.78 mg kg⁻¹, 8.99 mg kg⁻¹, 554.04 mg kg⁻¹, 15358.60 mg kg⁻¹, 215.14 mg kg⁻¹, and 1381.70 mg kg⁻¹, respectively. The coefficients of variation ranged from 44.79% to 80.89%, indicating that all parameters exhibited strong variation intensity. The block-to-base ratio of semivariance varied from 0.00% to 24.53%, indicating strong spatial autocorrelation. Moran's I analysis revealed significant spatial clustering for TP and TK. However, the spatial distributions of AP, IP, and SAK may be random. Soil pH was negatively correlated with TP and AP, positively correlated with IP, and not correlated with TK, AK, or SAK. SOM was positively correlated with TP and AP and significantly negatively correlated with IP and TK, but not with AK or SAK. Cation exchange capacity was significantly positively correlated with TP, but significantly negatively correlated with TK. Except for IP, there was no significant correlation between soil particle composition and the various forms of P and K. Elevation and aspect had no effect on the distribution of various forms of P and K. NDVI was significantly positively correlated with TP and AP and negatively correlated with IP and TK. Mining activities can strongly affect the availability of P and K. These results have practical significance for soil management and ecological restoration in high-altitude mining areas.

Keywords: mining area, spatial variability, geostatistics, soil phosphorus, soil potassium

*e-mail: chen_yu_sc@163.com

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Introduction

Soil, as a core component of terrestrial ecosystems, is not only a substrate for plant growth but also a key link in biogeochemical cycling and energy flow. Phosphorus (P) and potassium (K) are essential for plant growth and play crucial roles in the health and succession of ecosystems [1]. Soil P is a primary determinant of soil fertility and quality, both of which are common nutrient-limiting factors in many ecosystems, and its content is closely linked to soil productivity [2]. K deficiency strongly affects plant growth, cellular metabolism, and plant resistance to pests [3]. However, the spatial distributions of soil P and K are highly heterogeneous, showing strong spatial discontinuity [4]. Studying the spatial variability of soil nutrients and the factors influencing them can provide valuable data and theoretical guidance for a deeper understanding of the natural environment and ecological restoration, particularly in fragile ecological areas.

With advancements in computational and spatial analysis technologies, the integration of geostatistics and geographic information systems (GIS) has become a widely used approach for studying the spatial variability of soil properties [5]. In recent years, geostatistics, linear models, fuzzy system regression trees, and neural networks have been extensively applied to analyze the spatial variation of soil nutrients. These methods have proven to be effective tools for understanding the dynamic distribution of soil nutrients [6]. Geostatistics is a technique used to estimate soil properties in non-sampled areas or areas with sparse sampling points [7]. Geostatistics is primarily used to predict nutrient variation patterns in space [8]. Owing to the widespread application of methods such as semivariograms and kriging interpolation, the prediction accuracy of geostatistics has gradually improved [9]. The semivariogram model can better reflect the spatial variation structure of soil nutrients and directly affect the accuracy of kriging interpolation [10]. Kriging interpolation is a geostatistical method that uses spatial correlations among measured locations to predict values in unmeasured areas [11]. At present, there are increasing reports on using semivariogram functions to fit spatial variation models of soil nutrients and using kriging interpolation to quantitatively predict the spatial distribution of soil nutrients [12].

The soil is highly heterogeneous and discontinuous. The forms and contents of soil P and K are influenced by internal factors, such as soil pH, soil organic matter (SOM), cation exchange capacity (CEC), and soil particle composition, as well as external factors, such as altitude, slope, aspect, and vegetation coverage, resulting in complex spatial variability [13-15]. Soil pH regulates the bioavailability of P and K by affecting their solubility, chemical reactions, and microbial activity. SOM is an important source and carrier of soil nutrients, including C, N, P, K, and trace elements necessary for plant growth. Its quantity and quality are important indicators

of soil fertility and health [16]. The composition of soil particles is a key factor in determining the soil texture and has a significant impact on soil nutrient cycling and storage [17]. Topography, including slope, aspect, and elevation, is another factor that affects the geochemical behavior of soil P and K. These indicators play decisive roles in the spatial distribution of soil biochemical processes and hydrological conditions [18]. The soil moisture-holding capacity and surface particle migration vary with different slopes, indirectly affecting the soil P and K status [19]. Slope aspect, as an important terrain factor, mainly affects the spatial distribution of soil nutrients by influencing the light intensity and rainfall conditions received by the soil. Elevation affects the temperature, light, and moisture received by the soil, leading to changes in the spatial distribution of soil nutrients [20]. In addition, although the NDVI cannot directly measure soil nutrients, it serves as an effective “indicator” or “proxy variable” that indirectly reflects the overall status of soil and plant nutrient conditions. NDVI is not only related to plant biomass but also to soil properties, such as soil texture and nutrient content [21, 22]. Therefore, NDVI represents not only current vegetation status but also serves as a comprehensive indicator of soil environmental conditions [23].

Alpine ecosystems, typically located in cold, high-altitude regions, are among the most fragile and sensitive environmental systems on Earth. These regions experience harsh climates, short growing seasons, poorly developed soils, and slow biogeochemical processes; once degraded, ecosystem restoration is extremely difficult or even irreversible [24]. Mining activities, as an important driving force for regional economic development, not only bring huge resource dividends to human society but also cause profound and complex disturbances to the local ecological environment. In high-altitude mining areas, owing to their unique geographical location and ecological environment, this disturbance effect is more prominent [25, 26]. The core of ecological restoration in high-altitude mining areas is vegetation reconstruction. The availability of soil nutrients, particularly P and K, is a key limiting factor in determining the success or failure of vegetation restoration. To date, the reports in the literature regarding the distribution characteristics of soil P and K in high-altitude mining areas have been inadequate. In this study, field surveys, sampling, and statistical analysis were applied to investigate: (1) the spatial heterogeneity of soil P and K in high-altitude mining areas and the identification of key factors affecting their distribution; and (2) the impact of mining activities on the distribution of P and K. The research results should provide a solid scientific basis for soil improvement and fertilization planning in high-altitude mining areas, thereby accelerating the ecological succession of degraded mining ecosystems.

Materials and Methods

Overview of the Study Area

This study was conducted in a gold mining area in Sichuan Province, southwest China (Fig. 1). The study area extends from 28°23'09.2253" to 28°23'41.6640"N and from 100°59'08.5604" to 101°00'04.4297"E, covering approximately 1.074 km². The mining area had a plateau river-valley climate. The climate was cold, there was a significant vertical difference, and there were no true summers. Annual precipitation was 818.2 mm, with 80% of it concentrated from June to September. The altitude of the mining area ranged from 3863.2 m to 4102.8 m, featuring a river-valley terrain. The major land use types in the mining area were mining areas, dump sites, transportation roads, and workshops, while the rest were forests and grasslands. There were two types of soil, anthrosols and cambisols, both of which had a loose soil texture with slightly acidic pH ranging from 4.36 to 7.45. Due to the damage to the forest caused by mining activities, the vegetation coverage was only 35%.

Soil Sampling and Analysis

Soil Sampling

The soil sampling was conducted in August 2024. Soil sampling points were arranged using a uniform grid

method covering the whole study area, and additional sampling points were added based on soil types, similar topography, and land use types (Fig. 1). The locations of sampling points were measured using GPS. The interval between sampling points ranged from 50 m to 130 m. At each sampling point, five duplicate samples were uniformly collected within a radius of 5 m to form an X-shaped distribution. Before sampling, weeds and fallen debris were removed from the soil surface. Samples were collected from a depth of 0 to 10 cm using a stainless-steel shovel. Five duplicate soil samples were mixed, larger stones and roots were removed, and 1 kg of the mixed soil sample was weighed and placed in a labeled sample bag. A total of 60 soil samples were collected, covering 6 types of land: mining areas, waste dumps, roads, forests, shrublands, and grasslands. Among them, mining areas, waste dumps, and roads are strongly disturbed by human activities, and the soil is mainly composed of bedrock debris and subsoil. Forests, shrublands, and grasslands are weakly disturbed by human activities and have natural soil.

Laboratory Analysis

The soil samples were ground and sieved through a 2-mm mesh after air-drying. Subsequently, TP was extracted by NaOH fusion in nickel crucibles. AP was analyzed using the hydrochloric acid (HCl)-ammonium fluoride (NH₄F) method [27]. AK, SAK, and TK were

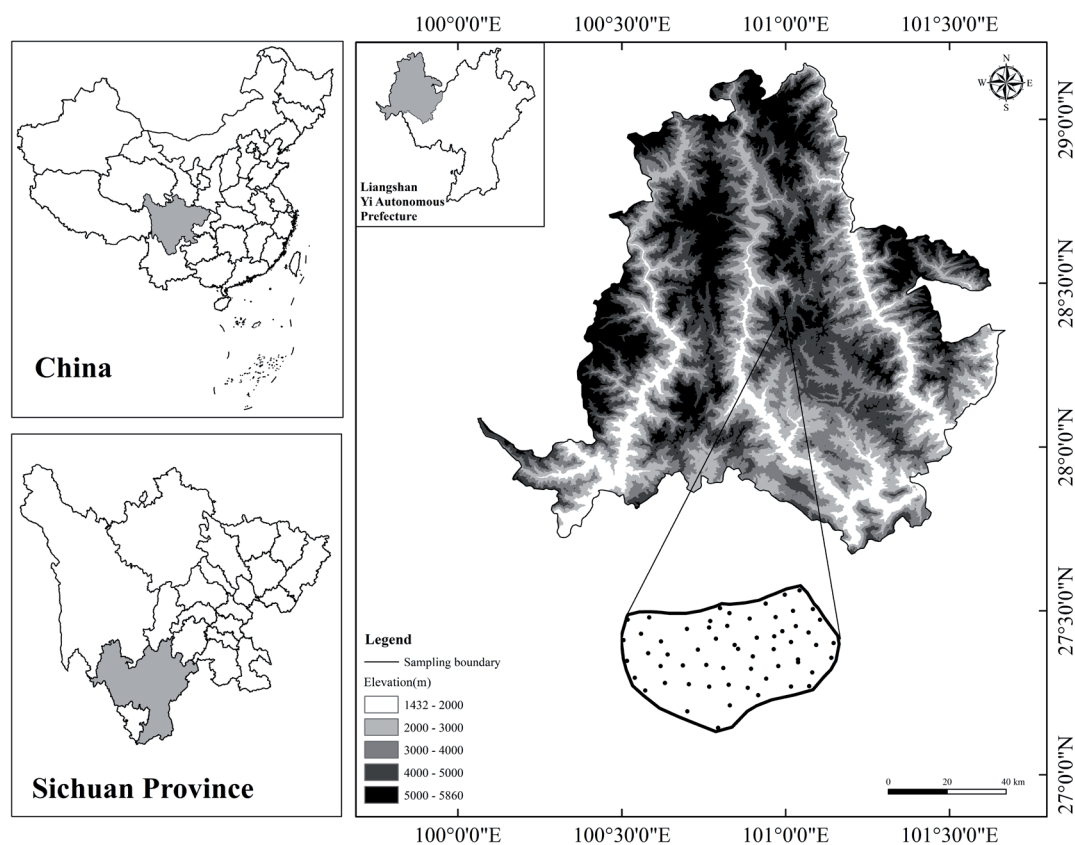


Fig. 1. Location map of the study area and sample points.

analyzed with the conventional methods of 1 mol L⁻¹ neutral ammonium acetate (NH₄OAC), 1 mol L⁻¹ boiling nitric acid (HNO₃), and a mixture of hydrofluoric acid (HF), perchloric acid (HClO₄), and nitric acid (HNO₃), respectively. Soil pH was determined using a pH meter at a 1:2.5 soil-to-solution ratio. The SOM content was determined using the Walkley–Black wet oxidation method [28]. The CEC was determined using the cobalt hexamine trichloride extraction method [29]. The clay, silt, and sand particle contents were determined using standard screening methods [30].

Data Processing

According to the accuracy requirements of the 1:1000 topographic map, the terrain was measured onsite using ARTK, and a topographic map was generated. Elevation, slope, and topographic data were obtained after processing in ArcGIS 10.2 (<http://www.esri.com/arcgis>) based on the topographic map. S2A images (L2A level) were downloaded from the Copernicus Data Center (<https://marine.copernicus.eu/>), and SNAP band resampling (10 m) and ENVI band combination were performed. Radiation calibration was performed using ENVI, followed by NDVI calculations. The NDVI data were exported to ArcGIS for further visualization and analysis, and the sample data were analyzed and processed using classical statistical and geostatistical methods in SPSS Statistics 26 (statistical analysis and Pearson correlation) and GS+9.0 (geostatistical analysis). The kriging method was used to interpolate the data in ArcGIS 10.2.

Geostatistical Analysis

Semivariogram Analysis

Semivariogram analysis is a geostatistical method commonly used to study the spatial variability of factors [31]. Function-fitting methods can accurately summarize the variation characteristics to express the spatial dependence of regional variables [32]. Common models include the exponential, Gaussian, spherical, and linear models. Parameters such as the nugget value, sill value, and range of these models are important regional variables for studying the spatial variability of soil properties [33]. The formula used is as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (1)$$

where h represents the lag distance; $\gamma(h)$ represents the value of the semivariogram function; $N(h)$ is the number of sample pairs separated from h ; i represents the serial number of the sampling point; and $Z(x_i)$ and $Z(x_i + h)$ are the measured values of Z at positions x_i and $x_i + h$, respectively. The nugget value (C_0), abutment value ($C_0 + C$), and range (A) are important parameters

in the semivariogram analysis. The nugget value (C_0) represents the difference between the sample values at a distance of 0. This represents random variations that cannot be explained by spatial distance. The abutment value ($C_0 + C$) represents the stable value reached when the semivariance no longer increases with distance and represents the total degree of variation of regionalized variables within the study area. The range (A) represents the spatial distance that the semivariance must cross from the block to the base value. This defines the scope of influence of spatial autocorrelation. The block-to-base ratio ($C_0/(C_0 + C)$) was used to indicate the degree of spatial variability. When $C_0/(C_0 + C) \geq 75\%$, the variables had weak spatial autocorrelation. When $25\% < C_0/(C_0 + C) < 75\%$, the variables had moderate spatial autocorrelation. When $C_0/(C_0 + C) \leq 25\%$, the variables had strong spatial autocorrelation [34].

Spatial Autocorrelation Analysis

Spatial autocorrelation analysis based on Moran's I coefficient was used to further explore the spatial distributions of soil P and K. Moran's I coefficient was used to measure the similarity of the unit attribute values between adjacent cells in a region. The formula was as follows:

$$I_i = \frac{Z_i - \bar{Z}}{\sigma^2} \sum_{j=1, j \neq i}^n [W_{ij} (Z_j - \bar{Z})] \quad (2)$$

where I_i is the autocorrelation function of the lag distance i . A Moran's I coefficient > 0 indicates positive spatial autocorrelation, where similar values are gathered together in space. A Moran's I coefficient < 0 indicates negative spatial autocorrelation, where different values are spatially clustered, meaning that high values are surrounded by low values, or vice versa. When Moran's I coefficient $= 0$, there is no spatial autocorrelation, and the values are randomly distributed in space, making it impossible to predict their values based on their location [35].

Results

Descriptive Statistics

Table 1 presents the descriptive statistics of the different forms of soil P and K in the mining area. The mean TP, AP, IP, TK, AK, and SAK were averaged at 1280.78 mg kg⁻¹, 8.99 mg kg⁻¹, 554.04 mg kg⁻¹, 15358.60 mg kg⁻¹, 215.14 mg kg⁻¹, and 1381.70 mg kg⁻¹, respectively. The coefficients of variation of SAK (80.89%) $>$ AP (78.1%) $>$ IP (66.55%) $>$ AK (59.6%) $>$ TK (47.29%) $>$ TP (44.79%) indicated that these six indicators had strong variation intensity. All skewness values were greater than zero, indicating that the distribution was positively skewed. The data were

Table 1. Statistical characteristics of soil TP, AP, IP, TK, AK, and SAK.

Soil nutrients	Min	Max	Mean	Standard deviation	Skewness	Kurtosis	Coefficient of variation (%)
TP	435.00	2797.50	1280.78	573.66	0.812	-0.216	44.79%
AP	0.55	44.60	8.99	7.02	2.445	10.268	78.10%
IP	45.00	1445.00	554.04	368.72	0.365	-0.914	66.55%
TK	4362.00	33156.00	15358.60	7263.45	0.260	-0.806	47.29%
AK	38.98	671.44	215.14	128.22	1.117	1.712	59.60%
SAK	313.12	5608.12	1381.70	1117.61	3.230	9.856	80.89%

concentrated on the left side of the distribution, while there were a few extremely large outliers on the right side. The kurtosis of AP and SAK was much greater than 3, indicating that the data of these two indicators were more concentrated around the mean value, and the probability of outliers occurring was higher than that of a normal distribution. The kurtosis of TP, IP, TK, and AK was relatively small, indicating that the data distribution of these indicators was more dispersed and was not concentrated around the mean value.

Spatial Variability

Semivariogram Analysis of Spatial Variation

The variability in soil P and K in the mining area was also investigated. The spatial variabilities of the different forms of P and K were estimated based on the nugget effect. The nugget, sill, and range parameters were analyzed for each empirical semivariogram (Table 2). Different forms of P and K were fitted using different models, and the spherical model was applicable to AP. Variations in TP, IP, and SAK were better described using the exponential model. TK and AK were better fitted by Gaussian models. The fitted semivariogram curves (Fig. 2) revealed significant differences in the distributions of P and K forms.

As shown in Table 2, except for TK, the nuggets of the indicators were all very small, ranging from 0.00 to 0.236, indicating the spatial variability of the soil properties [36]. The ranges of the various forms of P and

K in this study ranged from 98.73 m to 666 m. IP had the highest spatial autocorrelation distance, while TK had the lowest. The sampling design scale was 35–300 m, which met the requirements of geostatistical sampling and could reflect the spatial pattern information of the different forms of P and K in the mining area. The block-to-base ratios were as follows: IP (24.53%) > AK (8.5%) > TK (4.3%) > AP (0.09%) > TP (0.06%) > SAK (0.03%), and all were less than 25%, which means that soil TP, AP, IP, TK, AK, and SAK had strong spatial autocorrelations, and the spatial variability was mainly caused by endogenous variation.

Spatial Autocorrelation Analysis

Moran's I coefficients for the spatial autocorrelation of various forms of P and K were calculated using ArcGIS 10.5. As shown in Table 3, Z scores for TP and AK were >1.96, and P values were <0.01, indicating that Moran's I coefficient passed the significance test at the 99% confidence level, and that Moran's I was >0, indicating significant spatial clustering of these two indicators. The P-values for AP, IP, and SAK were >0.05, indicating that the null hypothesis could not be rejected for these three indicators, and their spatial distributions may be random.

Fig. 3 shows the variation in Moran's I coefficients for TP, AP, IP, TK, AK, and SAK with interval distance (step size). The positive correlation distance roughly reflects the average radius of the patches with similar properties. As shown in the figure, TP, IP, TK,

Table 2. Semivariance model and its parameters for soil TP, AP, IP, TK, AK, and SAK.

Soil nutrients	Theoretical model	Nugget (C_0)	Sill (C_0+C)	Nugget /Sill (%)	Range (m)	Determining coefficient	Residual SS
TP	Exponential	0.000	0.17	0.00	249.00	0.826	0.002
AP	Spherical	0.001	1.18	0.00	137.00	0.902	0.032
IP	Exponential	0.236	0.96	24.53	666.00	0.834	0.069
TK	Gaussian	41.000	954.00	4.30	98.73	0.834	72416.000
AK	Gaussian	0.035	0.41	8.54	195.72	0.852	0.017
SAK	Exponential	0.000	0.31	0.00	396.00	0.819	0.013

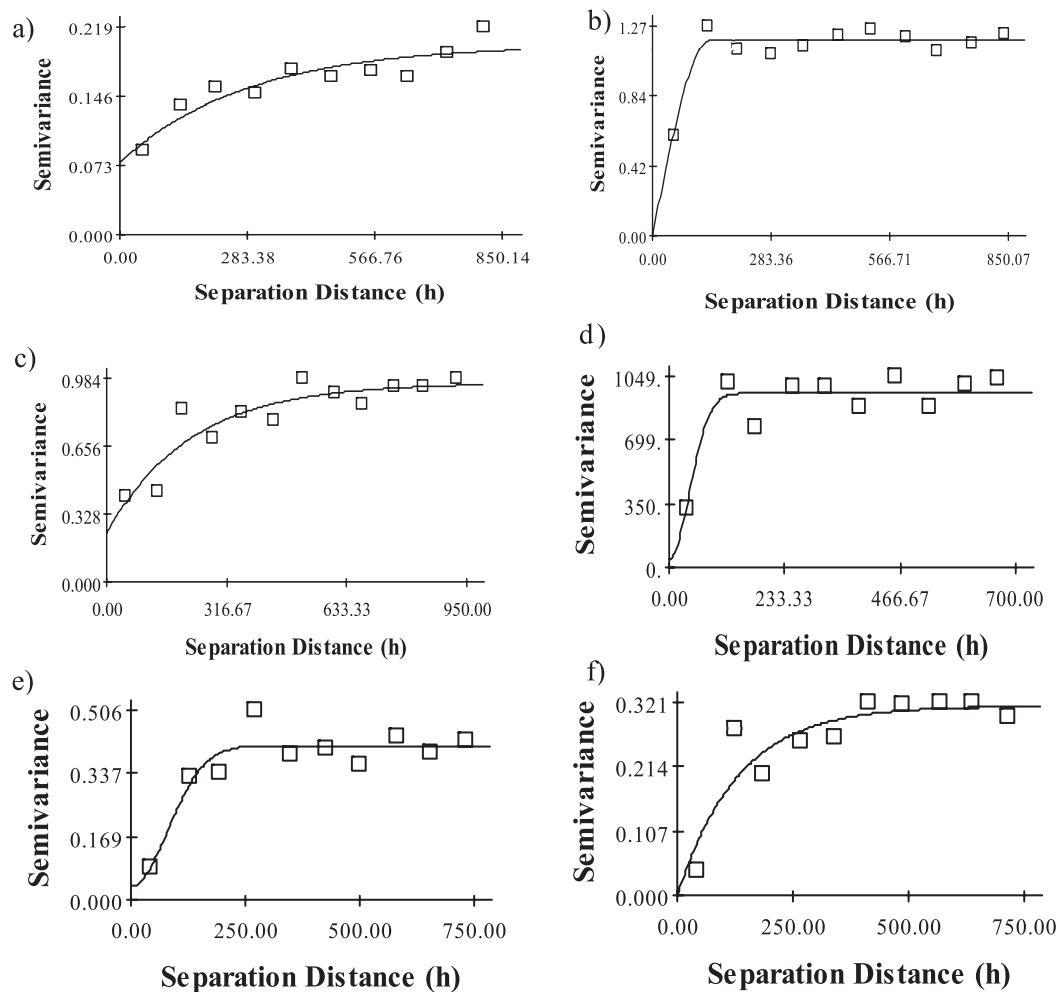


Fig. 2. Semivariograms and fitted models of soil a) TP, b) AP, c) IP, d) TK, e) AK, and f) SAK.

and AK exhibited similar trends with increasing distance, indicating that they had similar spatial structures. A positive spatial correlation between soil TP and IP was obtained when the step size was smaller than 248.81 m. Soil TK and AK also showed a positive spatial correlation when the step size was <119.66 m. Within this range, both curves decreased rapidly, indicating that the spatial processes of TK and AK had a relatively limited range of action. Fig. 3 shows that the curves were all characterized by fluctuations, indicating

the existence of multi-scale spatial structures of P and K in the study area, which may be related to mining activities, soil erosion, and plant growth.

Spatial Distribution Characteristics

The kriging method in the ArcGIS 10.5 geostatistical module was used to draw spatial distribution contour maps of soil P and K (Fig. 4). As shown in Fig. 4, the various forms of soil P and K in the mining area exhibited significant spatial heterogeneity and good spatial continuity. In general, in terms of regional distribution, the contents of TP, AP, and IP in the southwestern part of the study area were higher than those in other regions. The lowest contents of TP and IP were mainly distributed in the northwestern part of the study area, while the lowest content of AP was mainly distributed in the middle of the study area, near the waste dump. In terms of land type, the maximum contents of TP and AP were distributed in forest areas at 2797.5 mg/kg and 44.6 mg/kg, respectively, while the maximum content of IP occurred on the road at 1445 mg/kg.

Table 3. Moran's I coefficients of soil TP, TK, AP, and AK.

Soil nutrients	Moran's I	Z	P
TP (mg/kg)	0.2979	3.4553	0.000550
AP (mg/kg)	-0.0741	-0.6877	0.491647
IP (mg/kg)	0.1088	1.3729	0.169796
TK (mg/kg)	0.1690	2.0316	0.042190
AK (mg/kg)	0.2692	3.1908	0.001419
SAK (mg/kg)	0.1348	1.8195	0.068842

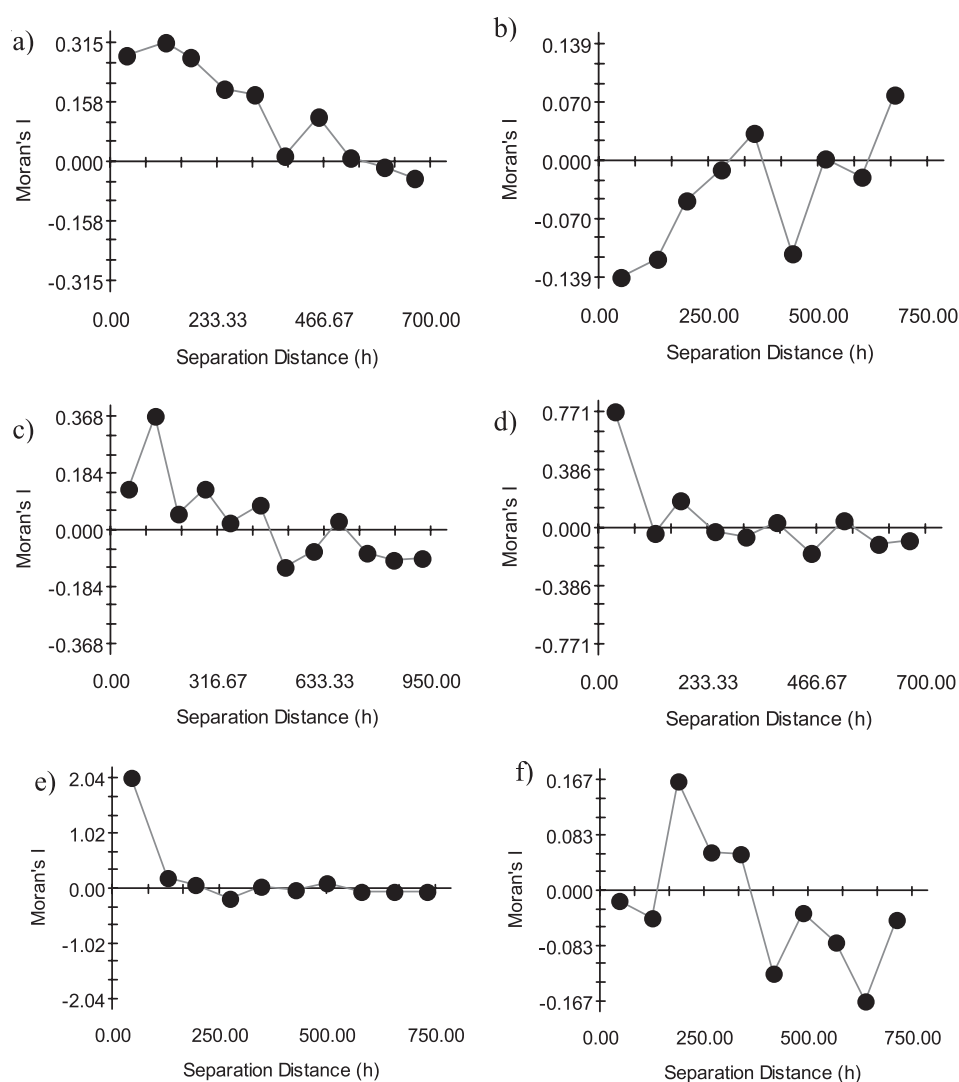


Fig. 3. Spatial intercorrelograms of soil a) TP, b) AP, c) IP, d) TK, e) AK, f) SAK.

In terms of regional distribution, the highest levels of AK and SAK were distributed in the southwestern part of the study area, whereas the highest levels of TK were mainly in the central and northeastern parts. In terms of land type, the three sampling points with the highest TK content were found in the mining area and waste dumps, with concentrations of 33156 mg/kg, 28178 mg/kg, and 27,622 mg/kg. High values of AK were mainly distributed in the forest land and waste dumps in the southwest of the study area, while the AK in the mining area was relatively low. The high-value areas of SAK existed in the study area in the form of islands. In particular, the SAK values of Y18, Y24, Y10, and Y17 ranged from 4721.96 mg/kg to 5608.12 mg/kg, which were much higher than the SAK content of other sampling sites (<2000 mg/kg). The land types in the high-value areas of SAK were mainly mining areas and waste dumping sites, as well as forestland between the two.

Principal Component Analysis (PCA)

PCA was used to reduce the dimensionality of the data on the spatial variability of soil P, K, and soil physicochemical properties. The biplot chart (PC1 + PC2) showed that PC1 and PC2 explained only 51.041% of the total variance (Table 4). Moreover, the graph showed that the sample distribution was relatively scattered (Fig. 5a)). Therefore, PCs with eigenvalues greater than 1 and cumulative contributions greater than 70% were selected. This reflects most of the information in the original data. The cumulative contribution rate of PC1 was 31.319%, and the loadings of SOM and clay were relatively high. The contribution rate of PC2 was 19.722%, and AK, CEC, and SAK had significant positive values. AK and SAK were soil nutrient indicators, and CEC reflected the soil's ability to retain nutrients. The contribution rate of PC3 was 14.97%, and the silt and pH loadings were relatively high, indicating that the third principal component described silt and pH content. The contribution rate of PC4 was 8.757%, and

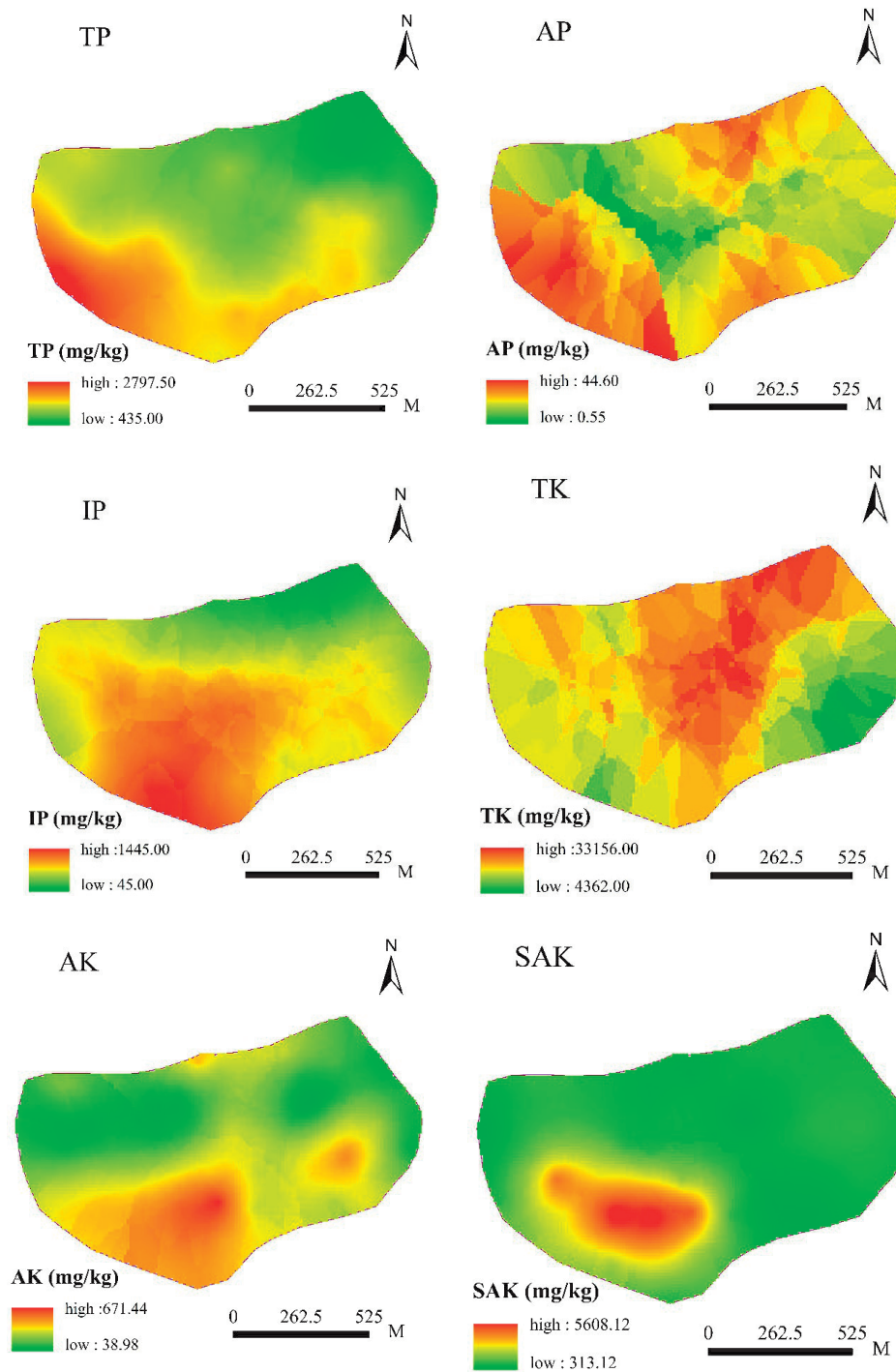


Fig. 4. Kriging interpolation map of soil TP, AP, IP, TK, AK, SAK.

AP and IP had significant positive vector values. AP and IP reflected the soil's ability to provide phosphorus.

PCA was used to reduce the dimensionality of the data and analyze the spatial variability of soil P, K, and other environmental factors; the biplot chart (PC1 + PC2) showed that PC1 and PC2 explained only 42.3% of the total variance (Table 5). Moreover, the graph showed that the sample distribution was relatively scattered (Fig. 5b)). Therefore, the PCs having eigenvalues greater than 1 and cumulative contributions greater than 70% were selected. The cumulative contribution rate of PC1

was 21.986%, and the loadings of NDVI, elevation, and slope had significantly positive values. The contribution rate of PC2 was 20.310%, and NDVI had significantly positive values. The contribution rate of PC3 was 12.747%, and the aspect, elevation, and slope loadings were relatively high. All three were topographic indicators. The contribution rate of PC4 was 11.265%, and the slope and aspect had significantly positive vector values. The contribution rate of PC5 was 10.115%.

Table 4. Loadings of soil parameters via principal component analysis.

Factor	PC1	PC2	PC3	PC4
TP	0.257	0.375	-0.218	0.322
AP	0.191	-0.075	-0.236	0.708
IP	-0.352	0.254	0.145	0.414
TK	-0.237	-0.439	-0.095	0.084
AK	-0.034	0.450	-0.031	0.058
SAK	-0.063	0.366	0.054	-0.362
pH	-0.345	0.084	0.449	0.133
SOM	0.457	0.115	-0.167	-0.090
CEC	0.203	0.401	0.278	-0.044
clay	0.411	-0.193	0.103	-0.087
silt	0.172	-0.088	0.608	0.210
sand	-0.381	0.183	-0.419	-0.060
Eigenvalue	3.758	2.367	1.796	1.05
Variability (%)	31.319	19.722	14.97	8.757
Cumulative %	31.318	51.041	66.011	74.769

Discussion

Correlation among P, K, and Soil Physicochemical Properties

Soil pH plays an important role in determining the availability of nutrients to plants. The soil pH in the research area ranged from 4.36 to 7.41 (Fig. 6). In the correlation matrix (Fig. 7), pH was negatively correlated

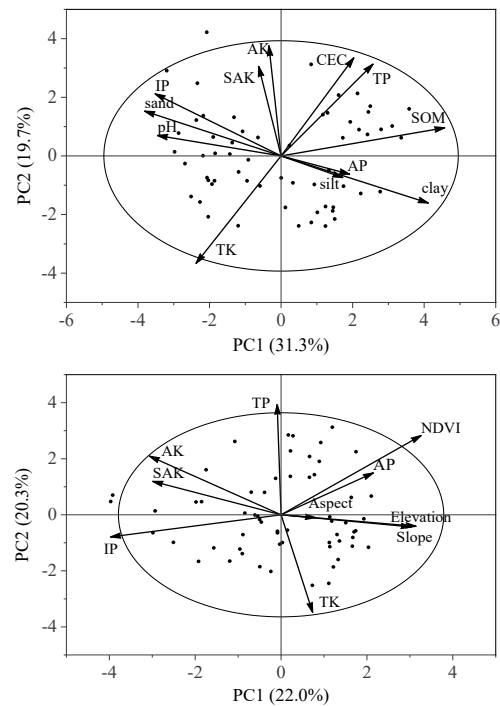


Fig. 5. PC1 vs. PC2 biplots of a) soil parameters and b) other environmental factors.

with TP and AP and positively correlated with IP. Soil pH can regulate the adsorption-precipitation mechanism of P. In acidic environments ($\text{pH} < 6.5$), active Fe and Al in the soil bind with P, forming insoluble Fe/Al phosphates, which reduces P availability [37]. In alkaline conditions ($\text{pH} > 7.5$), active Ca combines with P to form insoluble Ca phosphates. Only within the pH range of 6.5-7.5, where the activity of Fe, Al, and

Table 5. Loadings of other environmental factors by principal component analysis.

Factor	PC1	PC2	PC3	PC4	PC5
TP	-0.011	0.589	-0.152	0.090	0.159
AP	0.257	0.224	-0.104	0.417	0.609
IP	-0.476	-0.118	-0.068	0.169	0.309
TK	0.088	-0.521	-0.153	0.454	0.065
AK	-0.367	0.314	0.389	0.255	0.078
SAK	-0.358	0.179	0.264	0.334	-0.488
Elevation	0.377	-0.061	0.378	-0.039	-0.123
Slope	0.363	-0.065	0.336	0.540	-0.144
Aspect	0.096	-0.015	0.645	-0.337	0.400
NDVI	0.391	0.424	-0.211	-0.004	-0.254
Eigenvalue	2.199	2.031	1.275	1.126	1.012
Variability (%)	21.986	20.310	12.747	11.265	10.115
Cumulative %	21.986	42.296	55.043	66.308	76.423

Ca is low, does P primarily exist in a form that can be efficiently absorbed by plants [38]. However, in our study area, only 30% of the soil samples had a neutral pH. Metwally et al. (2019) also found a negative correlation between pH and AP in purple soil from the hilly areas of Sichuan Province, China [39]. Unlike P, K has two core mechanisms in soil: ion exchange equilibrium and primary mineral dissolution kinetics, both of which are controlled by pH. The soil in the research area is mainly acidic. When it is acidic, H^+ can directly accelerate the release of K from mineral structures into the solution. Moreover, high concentrations of H^+ and dissolved Al^{3+} can also displace K^+ at ion exchange sites, forcing K^+ into the soil solution, increasing its leaching probability, and reducing the bioavailability of K [40]. Generally, a higher soil pH (slightly alkaline to neutral) increases K availability [41]. However, there was no significant correlation between pH and TK, AK, or SAK contents in our research area. This may be due to interference from mining activities.

SOM is known to influence soil properties. SOM has a high affinity for P ions, which makes it easy for P ions to be adsorbed and retained by SOM and minerals in the soil [42]. This can explain why there was a highly significant positive correlation between SOM and TP in our research area. Similarly, there was a positive correlation between SOM and AP. The influence of SOM on soil AP content is not determined by a single mechanism but rather by an interconnected network involving four main pathways: competitive adsorption, organic acid activation, microbial turnover, and indirect physicochemical effects [43]. Under the framework of nutrient cycling theory, SOM essentially acts as a pivotal mediator that transforms P from inorganic fixed forms into organic and dissolved states. Its decomposition products occupy adsorption sites, complex with metal ions, and release organic P, while its own mineralization forms a critical pathway for P conversion from organic to inorganic dissolved forms. From the perspective of mineral weathering theory, the organic acids produced by SOM serve as one of the key acidic media driving the chemical dissolution of P-containing primary minerals [44]. High levels of SOM lead to better retention and availability of K ions [45]. In general, soils with higher SOM content often have higher levels of AK. However, in our study area, there was no correlation between SOM and AK or SAK. SOM showed a highly significant negative correlation with TK, which means that the lower the SOM, the higher the TK. As shown in Fig. 6, the areas with lower SOM content were the mining area and waste dump, indicating that the TK content was higher in these areas. This may be because the vicinity of the mineral veins in the study area was tuff, which is a type of rock with a high K content. Moreover, this type of rock can easily be broken into fine particles or powders when exposed to the surface. During mineral mining, tuff particles are easily dispersed in mining areas, waste dumps, and transportation roads, leading to an increase in the TK content (Fig. 4). These areas also

often had a low SOM content.

CEC refers to the ability of soil to exchange cations, and high levels of SOM can increase soil CEC. Therefore, there was a significant positive correlation between SOM and CEC in the research area. Similarly, there was a significant positive correlation between the CEC and TP. CEC usually indirectly affects P through Ca, Mg, and Al in a specific pH environment. For K, CEC is a direct parameter that determines the distribution pattern of soil K forms [46]. According to the theory of nutrient cycling, CEC essentially specifies the maximum capacity of exchangeable K reservoirs. High-CEC soils can temporarily adsorb and store a large amount of K ions after fertilization or release through mineral weathering, which can be gradually absorbed by plants, while low-CEC soils are prone to K ion leaching with runoff. The soil CEC in the study area ranges from 0.77 cmol/kg to 18.77 cmol/kg, with 62% of soil sites having a CEC of less than 10 cmol/kg, indicating weak soil fertility and easy loss of cations such as K. Therefore, there is no correlation between CEC and AK or SAK, and there is even a negative correlation between CEC and TK, which may be due to strong soil erosion or mining effects in the study area.

In terms of the influence of soil-particle composition on P and K content, only IP showed a highly significant negative correlation with clay and a highly significant positive correlation with sand, indicating that soil sand particles are the main carriers of IP. However, there was no significant correlation between the clay, silt, and sand contents and TP, AP, TK, AK, or SAK. This is inconsistent with the general conclusion that soil clay components are key reservoirs for the enrichment of P and K [47]. This may be due to the complex interaction of multiple mechanisms, such as the differentiation of mineral weathering material sources, the offsetting effect of soil development and weathering intensity, and the bidirectional nature of adsorption fixation and morphological transformation under specific environmental conditions in high-altitude mining areas. Notably, this study only explored the response of soil nutrient content to soil physicochemical properties, but did not delve into the interactions between various factors. These soil properties interact with each other and collectively affect the soil function and fertility. However, each soil attribute has a unique formation mechanism and influencing factors; therefore, the correlation between them is not always significant [48].

Impact of Other Environmental Factors on the Distribution of P and K

A correlation matrix chart of soil P, K, and other environmental factors in the study area is shown in Fig. 8. In previous studies, soil P and K have an extremely significant positive correlation with terrain factors, elevation, and aspect [49]. This is because the altitude decreased and the number of plants decreased, resulting in a decrease in soil P and K content. Adequate sunlight

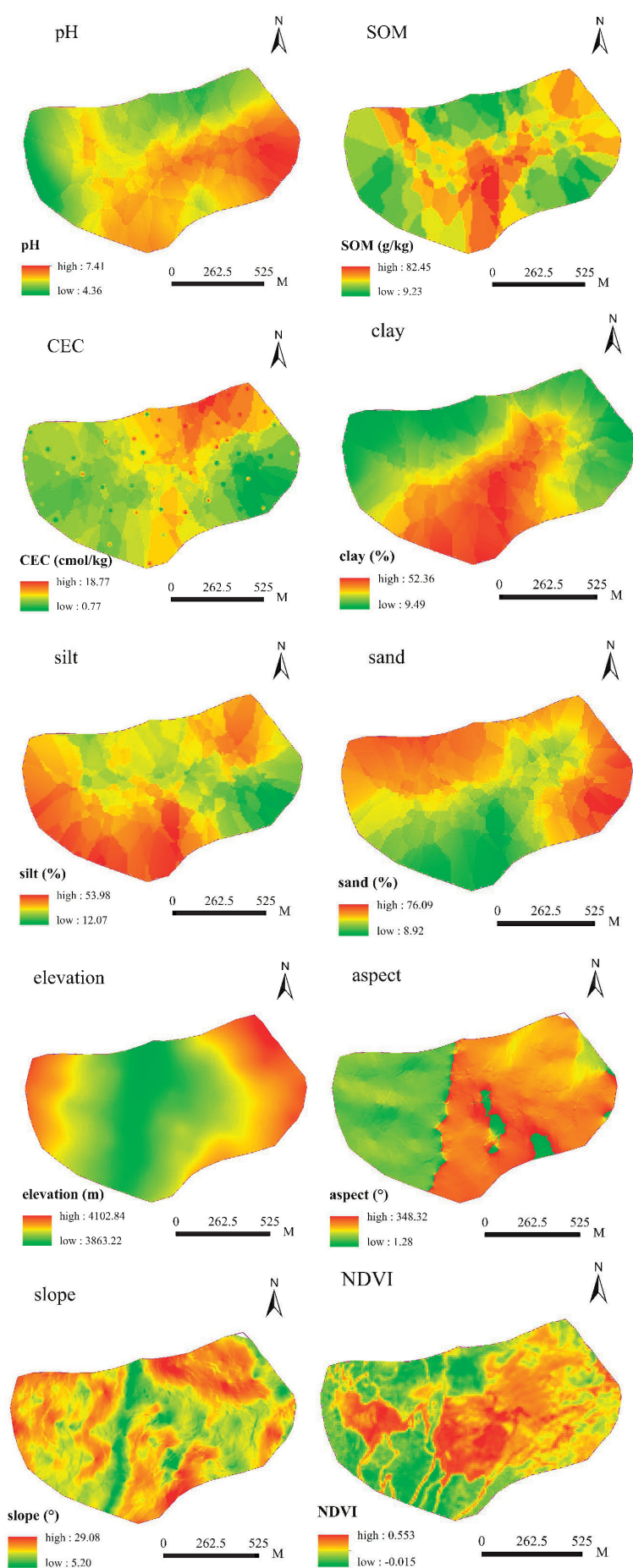


Fig. 6. Distribution of soil physicochemical properties, topography, and NDVI in the research area.

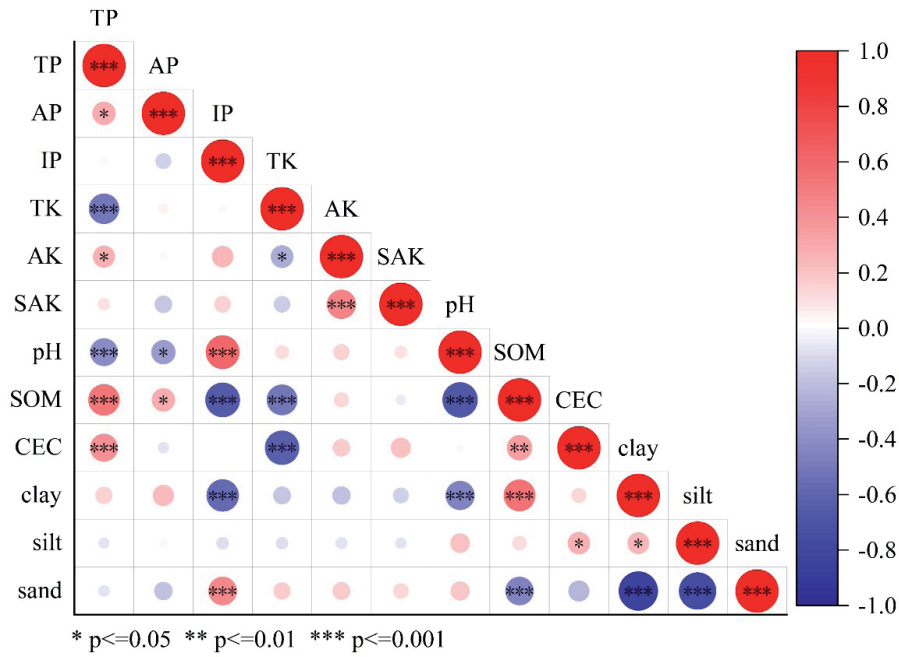


Fig. 7. Pearson correlation coefficient of soil indicators.

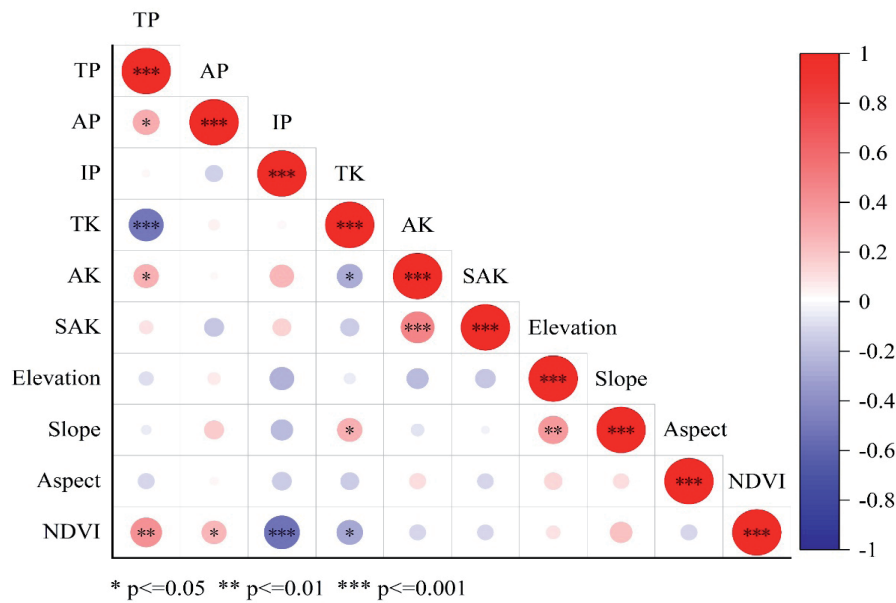


Fig. 8. Pearson correlation coefficient of other environmental factors.

on sunny slopes can enhance plant growth and microbial activity, which is beneficial for the accumulation of soil P and K. In a mango orchard in China's Dry-Hot Valley, principal component analysis indicated that slope aspect accounted for 59.6% of the variance in soil nutrients [50]. TP and TK are negatively correlated with elevation [51]. However, in our research area, no correlation was found between elevation or aspect and the content of various forms of P and K. This may be because the elevation in our study area ranges from 3863.22 m to 4102.84 m (Fig. 6, elevation), which is a small height

difference; therefore, the impact of elevation on the differences in P and K content was not significant. Moreover, in our research area, the river valley ran from north to south and was relatively open (Fig. 6, aspect), with sunlight reaching all areas and no obvious shady slopes. Therefore, aspect also had no significant impact on soil P and K contents. Of course, as macro terrain factors, the influence of elevation and aspect on soil P and K may also be overshadowed by the stronger driving force of mining activities. Li et al. (2011) reported that there was no significant difference in soil nutrient

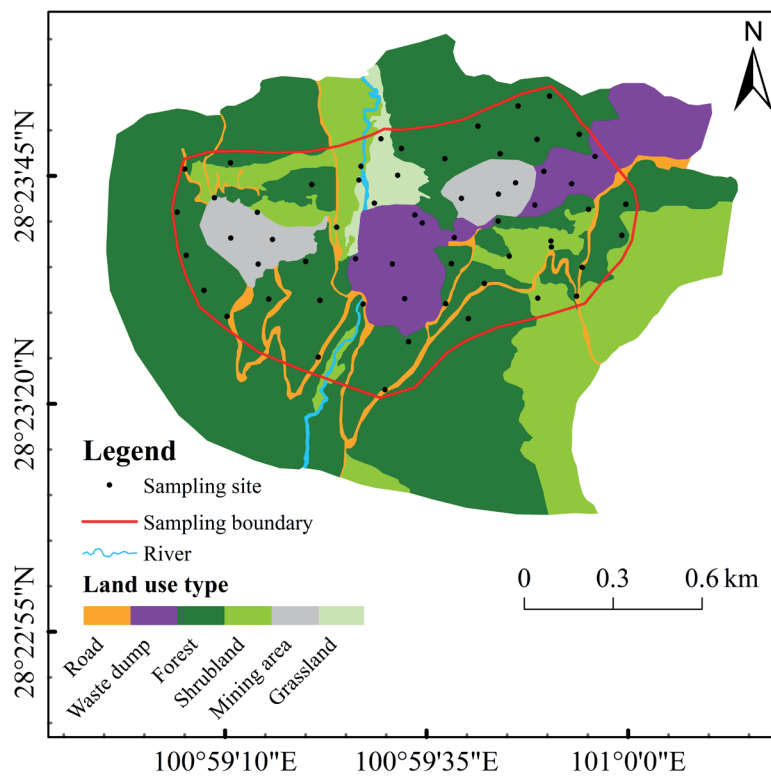


Fig. 9. Land type map of the study area.

content with elevation in a mining area in southwestern China, while in undisturbed native grasslands in the same region, the available N, P, and K contents showed a clear decreasing trend with altitude [52]. In terms of slope, the slope in the research area is between 5.20° and 29.08°. Only TK content is positively correlated with slope. K is an element that migrates easily. Usually, the steeper the slope, the easier it is for K to be lost [53]. However, the opposite situation occurred in our study area, possibly because the steeper the slope, the smaller the soil particles that are more likely to be lost with water, leaving behind coarser primary mineral particles. Often, these primary mineral particle structures contain abundant K; therefore, in the study area, the steeper the slope, the higher the TK content. Jakši et al. (2021) reported that the AP and AK contents in the soil of Niš, Serbia, showed a decreasing trend with an increasing slope [54]. NDVI was significantly positively correlated with TP and AP, possibly because, in areas with high NDVI, vegetation is lush, and plant litter entering the soil can improve soil fertility and significantly increase the content of TP and AP in the soil. Mazur et al. also found a significant positive correlation between NDVI and soil pH, P, and K after studying a corn planting area in central Poland [55]. The NDVI is negatively correlated with IP, which may be because the lower the NDVI, the more exposed the soil and the lower the organic matter content; therefore, soil P is mainly inorganic P. TK is negatively correlated with NDVI because areas with low NDVI are mainly mining areas, waste disposal sites, and transportation roads, which are areas with scattered

K-containing tuff particles. Therefore, there was a negative correlation between NDVI and TK.

The Impact of Mining Activities on P and K

The study area comprises 6 types of land use: roads, waste dumps, forests, shrublands, grasslands, and mining areas, with specific distribution details shown in Fig. 9. Among them, the mining areas, waste dumps, and roads are regions heavily impacted by mining activities, accounting for 34.2% of the research area, while forests, shrublands, and grasslands are areas less affected by mining, accounting for 65.8% of the research area. Based on the land use type map (Fig. 7) and the spatial distribution map of different forms of P and K (Fig. 4), the content of TP, AP, AK, and SAK in the soil of mining areas, waste dumps, and roads is relatively low, while the content of TK in the soil is relatively high in these areas. In areas such as forests, shrublands, and grasslands, the content of TP, AP, AK, and SAK in the soil is relatively high. The main reason for this phenomenon is the destruction of topsoil and vegetation caused by mining activities, which has led to intensified soil erosion. The characteristic of this process is that the original organic-rich topsoil layer is stripped or buried, replaced by broken rock fragments from deep bedrock. Its mineral composition, chemical properties, and degree of weathering are significantly different from natural topsoil, and it is usually dominated by primary minerals, lacking secondary clay minerals and organic matter accumulated through long-term soil

formation processes. The soil cation exchange capacity is limited, so the available P and K content is relatively low. Another important reason is the destruction of vegetation. The root exudates of vegetation, such as organic acid anions and phosphatases, can activate insoluble P and slow-release K in the soil, accelerating the conversion of mineral nutrients to available forms [56]. The destruction of vegetation will reduce or hinder this process. Vegetation destruction can also lead to increased soil erosion, loss of particle-adsorbed P and K with clay and sand, and loss of dissolved P and K with runoff. These reasons result in generally low levels of AP and AK in mining areas, waste dumps, and road areas. However, in mining areas and waste dumps, the TK content is relatively high. This may be because fresh broken rock fragments from bedrock contain abundant primary minerals such as K feldspar and mica, such as the widely distributed tuff in the study area, which results in high TK content in the soil in these areas. The low content of TP in mining areas and waste dumps may be due to the low P content in bedrock minerals. SAK mainly exists in the interlayer positions of mica-layered silicate minerals, and can supplement soil solution K through interlayer release when exchangeable K is consumed. The content of SAK is highly dependent on the degree of weathering of primary minerals [57], and the content of SAK is also lower in mining areas and waste dumps, possibly due to the lower degree of weathering of newly exposed mica-layered silicate minerals. Furthermore, it should be pointed out that mining disturbance, vegetation destruction, soil heterogeneity, and soil erosion do not act independently, but form a complex interactive network in the ecosystem of high-altitude mining areas, jointly affecting the spatial distribution pattern of different forms of P and K in the soil of mining areas.

Conclusions

The spatial distribution and influencing factors of soil P and K in a high-altitude mining area in southwestern China were analyzed using geostatistical methods and correlation analysis. The results showed: (1) The coefficients of variation for TP, AP, IP, TK, AK, and SAK were all relatively large, indicating that these six indicators had strong variation. The block-to-base ratios were all greater than 25%, indicating that these six indicators had strong spatial autocorrelation; (2) Moran's I coefficients indicate that TP and AK followed a spatial agglomeration distribution. However, the null hypothesis cannot be rejected for AP, IP, and SAK, and their spatial distribution may be random; (3) The contents of TP, AP, and IP in the southwestern part of the study area are higher than those in other regions. The highest contents of AK and SAK were distributed in the southwestern part of the study area, while the areas with the highest TK content were mainly in the central and northeastern parts; (4) Through

correlation analysis, it can be concluded that pH has a significant impact on TP, AP, and IP, organic matter has a significant impact on TP and AP, and CEC has a significant impact on TP. Except for IP, the composition of soil particles in the study area had no effect on the contents of various forms of P and K; (5) Elevation and aspect had no effect on the distribution of TP, AP, IP, TK, AK, or SAK. The higher the NDVI, the higher the TP and AP, but the lower the TK, which may be due to mining activities spreading the K-bearing tuff; (6) The content of TP, AP, AK, and SAK in the soil of mining areas, waste dumps, and roads is relatively low. However, the TK content is relatively high in these areas. In forests, shrublands, and grasslands, the content of TP, AP, AK, and SAK in the soil is relatively high. Mining activities can strongly affect the availability of P and K. Future research should focus on temporal effects, especially the impact of freeze-thaw cycles caused by seasonal changes on the geochemical behavior of P and K, to support the restoration and management of soil quality in mining areas.

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Conflict of Interest

The authors declare no conflicts of interest.

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