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SPATIAL PATTERN AND ITS DRIVING FORCES ANALYSIS OF SOIL AVAILABLE NITROGEN, PHOSPHORUS, AND POTASSIUM IN SEMI-ARID GRASSLAND SURFACE COAL MINING AREAS

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Highlights:

- collected and tested the content of soil available nitrogen, phosphorus, and potassium in the surface coal mining areas;
- analyzed the spatial distribution of soil available nitrogen, phosphorus, and potassium in the semi-arid grassland surface coal mining area;
- quantitative determination of the main driving forces for the spatial distribution of soil available nitrogen, phosphorus, and potassium;
- discussed the impact of surface coal mining on soil available nitrogen, phosphorus, and potassium;
- suggestion for remediation of soil fertility in mining areas.

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Abstract. Mining activities not only provide a large amount of material basis for socio-economic development but also cause great damage to the environment. It is of great significance to study the spatial variation characteristics of soil Available Nitrogen (AN), Available Phosphorus (AP), and Available potassium (AK) in mining areas for land reclamation and ecological protection. Currently, research on soil AN, AP, and AK in mining areas is lacking in large-scale survey, sampling, spatial pattern, and driving force research for surface coal mines in semi-arid grassland areas, and it is not possible to comprehensively grasp the distribution characteristics and driving forces of soil AN, AP, and AK in surface coal mines. Given this, this study took the Shengli Coal Field in Xilinhot City, the hinterland of Xilingol Grassland, as an example to study the spatial pattern and driving forces of soil AN, AP, and AK in the semi-arid grassland surface coal mining areas. The results showed that: (1) There was no strong spatial correlation among AN, AP, and AK in the soil of the study area, and the spatial pattern heterogeneity was strong. The content of AN, AP, and AK in southeast soil was relatively low. (2) The influence degree of each factor on the spatial pattern of AN was ranked as follows: NDVI > Agriculture > Water > Town > Mining > Industry; (3) The influence degree of each factor on the spatial pattern of soil AP was ranked as follows: NDVI > Mining > Water > Industry > Town > Agriculture; (4) The influence degree of each factor on the spatial pattern of soil AK was ranked as follows: NDVI > Town > Agriculture > Water > Mining > Industry; (5) The interaction between two factors presented two relationships: nonlinear enhancement and dual-factor enhancement. The interaction between various factors was higher than that of a single factor.

Keywords: available nitrogen, phosphorus, and potassium, surface coal mining area, spatial pattern, driving forces, semi-arid grassland.

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1. Introduction

The pedosphere is one of the five primary components that constitute the natural environment and is the central link connecting the organic and inorganic worlds. Soil is the material basis and means of production on which human beings depend for survival, as well as the basic ecological environment conditions for the survival and development of human beings and human society. Soil resources produce many important ecosystem goods and services, such as recreation, fiber production, food, recycling or assimilation of waste, and other by-products (Arrouays et al., 2012; Teng et al., 2014). Therefore, soil quality is directly related to the sustainable development of food safety, and economic, social, and human health (Teng et al., 2014; Liu et al., 2013). Soil nutrients are one of the basic attributes of soil, an important indicator of soil comprehensive productivity, and a key factor affecting vegetation growth and succession. Soil nutrients are essential nutrients for plant growth provided by the soil, mainly including 13 elements such as nitrogen, phosphorus, molybdenum, potassium, manganese, calcium, zinc, magnesium, sulfur, iron, boron, copper, and chlorine. Among them, nitrogen, phosphorus, and potassium, as the three essential nutrients for plants, are the main research objects for assessing soil nutrient status, and their content directly reflects the status of soil fertility (Xue et al., 2010). Soil nitrogen, phosphorus, and potassium nutrients are important components of soil fertility. The form and availability of nutrients determine the possibility of nutrients being captured by plant roots and are an important basis for sustainable soil management (Meng et al., 2020). Soil nitrogen nutrients can promote the growth of plant roots, stems, and leaves. Phosphorus plays an important role in plant photosynthesis, respiration, and physiological and biochemical regulation. Potassium can regulate the water potential of plant cells, promote plant photosynthesis, and help improve enzyme activity (Gao et al., 2016). Therefore, it is essential to know the content of the major elements such as nitrogen, phosphorus, and potassium in the soil and to prepare their ideal maps (Navidi & Seyedmohammadi, 2020).

In the past few decades, China has raised many concerns about environmental sustainability and has conducted various soil quality studies throughout the country to provide scientific basis for environmental policy formulation, especially in coal mining areas with serious environmental problems (Teng et al., 2014). Coal is one of the most significance non-renewable energy sources in the world. With the progress of technology, coal will still be a significant energy source in the next 50 years (Thakur et al., 2022). The fact that China is the world's largest coal producer and consumer will not change in the short term (Jing et al., 2018). In terms of the impact of mining, mining projects bring business, employment, infrastructure (such as healthcare), community development, and more to a region (Goswami, 2015). However, large-scale surface and underground coal mining has caused extensive and profound damage to plants, animals, microorganisms, water, soil, topography, landscape ecology, and geological structure in the region, significantly affecting biological communities, landscapes, and the overall environment (Kumar et al., 2021; Thakur et al., 2022; Wu et al., 2019a, 2019b, 2020). Surface coal mining is an important method of mining coal resources. Among China's 52 coal mines with a ten-million-ton level, surface coal mines account for 36.54% and produce 43.12% of the country's coal resources (Ullah et al., 2018; Wang et al., 2022). Surface coal mining produces a large amount of overloaded waste, which is dumped as overloaded waste, which not only occupies a large area but also reduces the soil quality of the land (Gupta & Biswajit, 2015; Thakur et al., 2014). Surface coal mining activities strip topsoil and result in the loss of litter layers, which are indispensable for nutrient storage and exchange. Therefore, the nutrient retention capacity decreases sharply after the disturbance of surface mining (Ma et al., 2019). Surface coal mines are subject to heavy mechanical construction and rolling, resulting in severe soil compaction, poor physical structure, poor water holding, and thermal insulation capacity, and only 20% to 30% of the original topsoil content of AN, AP, and AK, which is not conducive to plant growth (Wang et al., 2016).

Identifying the spatial distribution of soil characteristics is important because it can be used to enhance natural resources management, predict soil properties in non-sampled locations, and improve sampling designs in ecological and environmental studies (Navidi & Seyedmohammadi, 2020). The formation and evolution of soil in mining areas are constrained by various factors such as climate, topography, land use, mining, and industry, so soil nutrients in mining areas exhibit strong spatial variability. A series of coal development activities such as excavation, transportation, and dumping can lead to significant changes in the spatial pattern characteristics of the soil in the mining area (Feng et al., 2019). Studying the spatial pattern and driving forces of soil Available Nitrogen (AN), Available Phosphorus (AP), and Available potassium (AK) in surface coal mining areas is of great significance for ecological restoration in mining areas (Zhao et al., 2020). Meng et al. (2020) took cultivated land and forest land in a typical low groundwater level coal mining subsidence pit in Jiulishan Mine, Jiaozuo, China as the research object, and compared and analyzed the spatial variability of soil AP, AN, total nitrogen, AK, total phosphorus, and total potassium content in different land use types, subsidence slope locations, and section depths. Wang et al. (2021a) analyzed five soil fertility indicators such as soil organic matter, total nitrogen, AP, AK, and soil fine particles in a coal field on the Loess Plateau of China in 2017 and 2019. Vishwakarma et al. (2020) studied the impact of coal mining subsidence on AN, AP, and AK in the primary soil of the southeast coal field in Anupur District, Madhya Pradesh, India. Ahirwal and Maiti (2016) took the Ananta open cast project, Angul district located in Talcher Coalfield, MCL, Odisha, India as an example. Research has shown that the soil nutrient content (N, P, and K) decreased due to the impact of mining. Wang et al. (2021b) collected soil samples twice at 20 sampling points before and after mining in the Caojiatan coal field on the Loess Plateau of China. The results showed that there were significant differences in soil organic matter, total nitrogen, and AP between pre and post-mining. Wang et al. (2019) used multifractal and combined multifractal methods to analyze soil organic matter and total nitrogen before reclamation in the inner waste dump of Antaibao surface coal mine in Pingshuo, Shanxi Province. Han et al. (2019) showed that compared to the control area, except for organic matter, AP, and AK, the soil nutrient content in the open pit mining area has decreased, with the average content of total potassium, total phosphorus, total nitrogen, and alkali hydrolyzable nitrogen decreased by 20.0%, 39.7%, 6.3%, and 47.2%, respectively.

Soil available nutrients refer to the nutrients provided by the soil that are necessary for plant life and easily absorbed and utilized by crops (Wang et al., 2016). Although scholars from various countries have conducted a large amount of research on soil nutrients in mining areas, the current research is mainly focused on the small range of soil nutrients within the mining area, and there is a lack of large-scale investigation, sampling, spatial pattern, and driving force research on AN, AP, and AK in the soil of surface coal mines in semi-arid grassland areas. Therefore, it is not possible to comprehensively grasp the spatial pattern characteristics of AN, AP, and AK in the soil of surface coal mines, It is even more difficult to grasp the impact of surface coal mining on AN, AP, and AK in surrounding farmland and pasture soils, especially for surface coal mining in ecologically fragile areas such as semi-arid grasslands. Given this, this study aims to (1) determine the content of AN, AP, and AK in the soil of Shengli Coalfield and its surrounding areas in Xilinhot City, China; (2) analyze the spatial pattern characteristics of soil AN, AP, and AK in the semi-arid grassland surface coal mining area; (3) analyze the driving forces of spatial pattern of soil AN, AP, and AK in the semi-arid steppe surface coal mining area.

2. Materials and methods

2.1. Study area

The research area is located in Xilinhot City, Xilingol League, China (Figure 1), and is located in the core area of Xilingol Grassland. The map of China on the left in Figure 1 is downloaded from the Standard Map service website of the Ministry of Natural Resources, PRC (http://bzdt.ch.mnr.gov.cn/index.html). The map of the research area on the right in Figure 1 was produced by ArcGIS 10.6 software (https://soft.youxishen.cn/soft/106402.html), and the data source was Landsat remote sensing image. The landform of the mining area includes four units: tectonic denudation terrain, denudation accumulation terrain, erosion accumulation terrain, and lava platform. The zonal soil in the study area is chestnut, and some low-lying areas are meadow soil. The thickness of the soil humus layer is about 20–40 cm, and the content of organic matter is 2.9%–4%. The burial depth of the calcium deposit layer is generally 30–60 cm, with a thickness of 20–40 cm. The soil texture is light loam to medium loam soil, with a high content of fine sand and silt. Once the overlying vegetation is damaged, it is extremely easy to cause soil wind erosion and is difficult to recover. The soil types in the surface mining area mainly consist of chestnut soil, meadow chestnut soil, meadow soil, etc. Due to grassland degradation, sandy and gravelly chestnut soil has been formed, with poor soil fertility. The zonal vegetation type in the study area belongs to a typical grassland type. The grassland is subdivided into semi-humid and semi-arid grassland areas of temperate zone in central and eastern Inner Mongolia. The plant composition includes Stipa crenata, Stipa grandis, Cryptocarpus scabra, Artemisia frigida, Leymus chinensis, Cha grass, Icegrass, Caragana, etc.

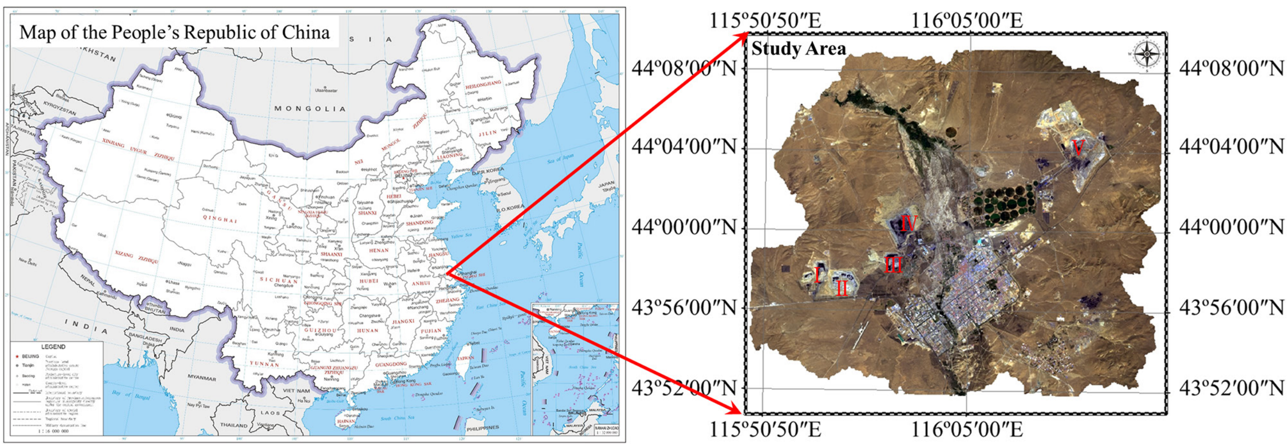
2.2. Data source and processing

The main data used in this study are: DEM data, Landsat OLI data, and 2017 land use classification data in the study area (Table 1). Use ENVI 5.3 software to perform atmospheric correction and other preprocessing work on Landsat OLI, and calculate the Normalized Difference Vegetation Index (NDVI) using the band calculation method according to the formula in Table 2.

Table 1. Data resources

Data type	Data resources	Acquisition method
DEM	Geographic Information Monitoring Cloud Platform (http://www.dsac.cn/)	Free download
Landsat OLI	United States Geological Survey website (https://glovis.usgs.gov/)	Free download
Land use classification data	Existing research results of the author (Wu et al., 2021, 2022) (Figure 2)	

2.3. Collection and testing of soil samples



Note: I – Surface germanium mine; II – West No. 2 surface mine; III – West No. 3 surface mine; IV – No. 1 surface mine; and V – East No. 2 surface mine.

Figure 1. Location of the study area

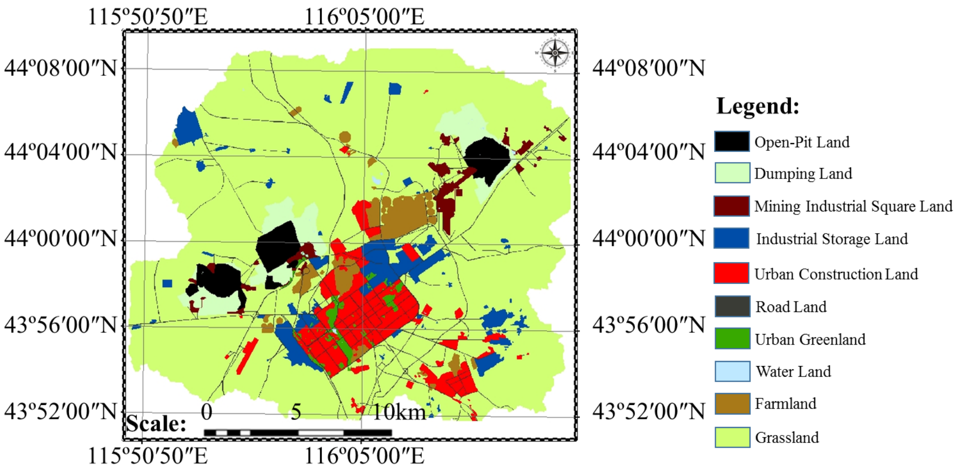


Figure 2. Land use classification map of the study area

In this study, 152 soil samples were collected, taking into account factors such as land cover type and site conditions (Figure 3a). The collection depth of soil samples is 0–20 cm. Each sample was composed of a central point and four peripheral subsamples (Figure 3b). AN was determined by the alkali-diffusion method. The AP was determined by 0.5 mol/L sodium bicarbonate extraction method. The AK was determined by ammonium acetate extraction-flame spectrophotometry.

2.4. Making of spatial pattern map of soil AN, AP, and AK

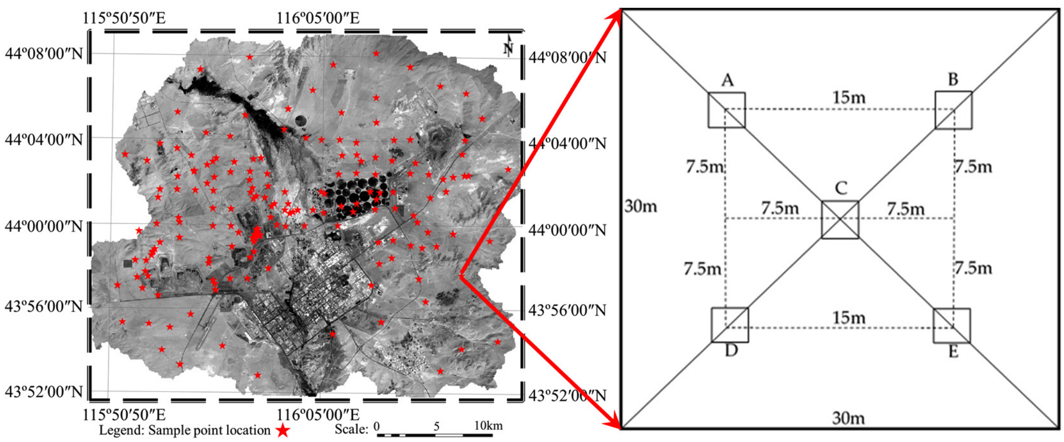
Trend effect analysis, Kriging interpolation, and cross-validation were conducted on the ArcGIS platform, map editing was carried out, and spatial pattern maps of soil AN, AP, and AK were prepared (Zhao et al., 2020). The kriging method is one of the most powerful interpolation techniques. The value of the experimental variogram for a separation distance of h is half the difference of mean squared between the value of $Z(x_i)$ and $Z(x_i + h)$ as follows:

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

where $\gamma(h)$ is the semivariance at lag distance h, $Z(x_i)$ is the value of the variable Z at location x_i, h is the lag and $N(h)$ is the number of pairs of sampling points separated by h (Wang & Shao, 2011).

Experimental variograms were obtained by calculating variogram at different lags. Spherical and exponential models were chosen for experimental variogram modelling and getting information on appropriate spatial structure as well as input parameters for prediction performance in kriging method. The spherical and exponential models are defined as Equations (2) and (3) respectively:

$$\gamma(h) = \begin{cases} C_0 + C\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] & 0 < h \le a \\ C_0 + C & h > a \\ 0 & h = 0 \end{cases}; \quad (2)$$



a) Spatial distribution of sample plots **b)** Layout of quadrat

Figure 3. Space distribution of soil sample plots and layout of quadrat

$$\gamma(h) = C_0 + C\left[1 - \exp(-\frac{h}{a})\right], \tag{3}$$

where C_0 is the nugget variance, C_0 + C sill variance and a range.

The nugget effect to sill ratio can be used to evaluate the spatial structure of the data in the fitted model. The class of spatial structure is strong, moderate and weak when this ratio is <0.25, 0.25–0.75 and 0.75<, respectively (Navidi & Seyedmohammadi, 2020).

2.5. Analysis method of spatial pattern driving force of AN, AP, and AK in surface coal mining area

According to the characteristics of the study area and the needs of this study, the selection of driving factors is shown in Table 2. In this study, the driving force analysis is carried out by using the geographical detector method. The geographical detector consists of four parts, namely, factor detection, interaction detection, risk detection, and ecological detection. The first two parts are applied in this study (Wang & Xu, 2017; Wang et al., 2016). Use the Create Random Points function of ArcGIS to generate 10000 random points at an interval, and then extract the value of each factor using the random points.

Table 2. Natural and human factors affecting spatial pattern of soil AN, AP, and AK in the study area

Category	Factors	Explanation
Natural factors	NDVI	$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$ (ρ_{Red} and ρ_{NIR} represent red and near-infrared bands, respectively)
	Elevation	Spatial resolution of 30 m
	Slope	Calculated from DEM data with a resolution of 30 m
	Aspect	
	Distance to the nearest water land	Based on the land use classification data, the Euclidean distance method in the ArcGIS spatial analysis module is used to calculate
Human factors	Distance to the nearest mining land	
	Distance to the nearest Town commercial and residential service land	
	Distance to the nearest industries and storage land	
	Distance to the nearest agricultural land	
	Distance to the nearest road network land	

(1) Spatial differentiation and factor detection. The spatial differentiation of probe y (AN, AP, and AK) and the extent to which the probe factors explain the spatial differentiation of attribute y (AN, AP, and AK). Measured with a q value, the expression is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}, \tag{4}$$

where q represents the interpretation rate of the influencing factor, with a value range of 0 to 1. The larger the q value, the stronger the interpretation rate. The X and Y variables are superimposed in the Y direction to form an L layer, represented by h = 1, 2, 3,..., L. N_h and N are the sample numbers of the subregion h and the entire region, respectively. σ_h^2 and σ^2 is the discrete variance of the subregion h and the entire region Y.

(2) Interaction detection. Interaction detectors are used to detect whether the influencing factors are independent or interactive (Chen et al., 2021).

3. Results

3.1. Spatial pattern of AN, AP, AK in the surface coal mining area

As shown in Figure 4, the soil AN content in the western part of the study area is significantly higher than that in other regions, especially in the northwest side of the No. 1 surface mine, west No. 3 surface mine, west No. 2 surface mine, and surface germanium mine, while the soil AN content in other regions has a high heterogeneity. The soil AP content in the northern part of the study area is significantly higher than that in other regions, especially in the Xilin River Basin wetland, where the soil AP content is the highest, and in other regions, the soil AP content is relatively homogeneous. Soil AK content is higher in the west and northeast of the study area, especially in the north of the No. 1 surface mine, and the heterogeneity of soil AK content is higher in the study area. There is no strong spatial correlation among AN, AP, and AK in the soil of the study area, and the spatial pattern heterogeneity is strong. The content of AN, AP, and AK in the soil in the southeast of the study area is relatively low.

3.2. Driving forces analysis of the spatial pattern of soil AN

(1) Single-factor analysis of detection factors

The q value of soil AN in NDVI, the distance to the nearest town land, the distance to the nearest agricultural land, the distance to the nearest mining land, and the distance to the nearest water land are all more than 0.8, indicating that NDVI, town, agriculture, mining, and water have a strong driving effect on the spatial pattern of soil AN in the study area. The q value of the distance to the nearest industrial storage land exceeds 0.6, indicating that

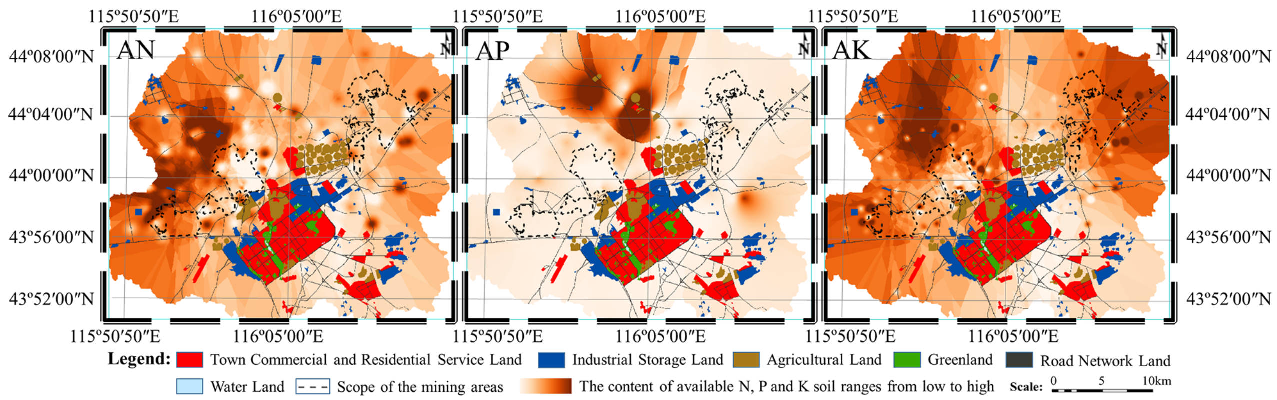


Figure 4. Spatial pattern map of soil AN, AP, AK in the study area

the industry has a significant driving effect on the spatial pattern of soil AN in the study area. The *q* values of distance to the nearest road network land, elevation, slope, and aspect are all less than 0.4, indicating that these four driving factors have no significant driving effect on the spatial pattern of soil AN in the study area.

From the perspective of the entire study area, natural factors have a higher impact on the change of AN than human factors, and the order of the impact of various factors on the spatial pattern of AN is as follows: NDVI(0.994816)>Agriculture (0.931306)>Water (0.926628)>Town (0.913076)>Mine (0.803338)>Industry (0.622229). Among natural factors, NDVI and water have the most significant impact. The *q* values of NDVI and water are 0.994816 and 0.926628, respectively, with an interpretation rate of over 90%. Among human factors, agriculture, town, and mining have a significant impact on the spatial pattern of AN, with *q* values of 0.931306, 0.913076, and 0.803338, respectively, with an explanatory power of over 80% (Figure 5).

(2) Analysis of interaction between detection factors

The interaction between two factors presents two kinds of relations, namely nonlinear enhancement and double-factor enhancement, and there is no independent factor. Among the interactions among factors, the explanation rate of interactions between Town, Agriculture, Mine, NDVI, and Water and all other factors is above 0.85. The interpretation rate of the interaction between two factors on the spatial pattern of AN is 1.000000 for 9 groups: Town ∩ NDVI, Agriculture ∩ Mine, Agriculture ∩ Water, Agriculture ∩ NDVI, Industry ∩ Water, Mine ∩ Water, Mine ∩ NDVI, Road ∩ NDVI, and Altitude ∩ NDVI.

3.3. Driving forces analysis of the spatial pattern of soil AP

(1) Single-factor analysis of detection factors

From Figure 6, it can be seen that NDVI, the distance to the nearest mining land, and the distance to the nearest water land all exceed 0.8 for the *q* value of soil AP, indicating that NDVI, mining, and water have a strong driving effect on the spatial pattern of soil AP in the study area. The *q* value of the distance to the nearest town land, the distance to the nearest agricultural land, and the distance to the nearest industrial storage land exceed 0.6, indicating that the driving effect of town, agriculture, and industry on the spatial pattern of soil AP in the study area is also relatively obvious. The *q* values of distance to the nearest road network land, elevation, slope, and aspect are all less than 0.4, indicating that these four driving factors have no significant driving effect on the spatial pattern of soil AP in the study area.

From the perspective of the entire study area, natural factors have a higher impact on the change of AP than human factors, and the order of the influence of various factors on the spatial pattern of AP is as follows: NDVI

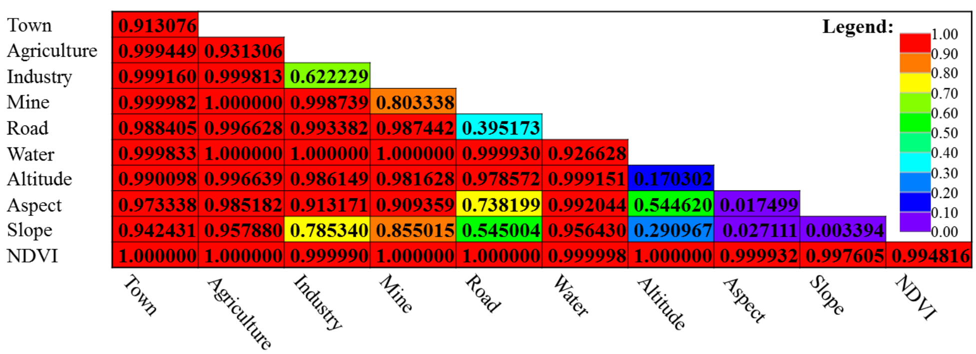


Figure 5. Interaction detector results of spatial pattern driving factors of AN

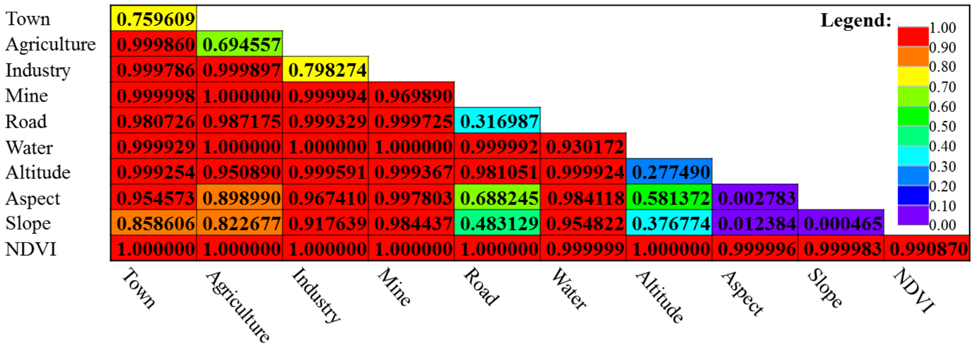


Figure 6. Interaction detector results of spatial pattern driving factors of AP

(0.990870)>Mine (0.969890)>Water (0.930172)>Industry (0.798274)>Town (0.759609)>Agriculture (0.694557). NDVI and water have the most significant effects on soil AP among natural factors. The q values of NDVI and water are 0.990870 and 0.930172, respectively, with an interpretation rate of over 90%. Among human factors, mining, industry, town, and agriculture have a significant impact on the spatial pattern of AP, with q values of 0.969890, 0.798274, 0.759609, and 0.694557, respectively, with an explanatory power of over 65% (Figure 6).

(2) Analysis of interaction between detection factors

The interaction between two factors presents two types of relationships, namely, nonlinear enhancement and dual-factor enhancement. There are no independent factors that act. Among the interactions among factors, the explanation rate of interactions between Town, Agriculture, Mine, NDVI, and Water and all other factors is above 0.8. The 10 groups with an interpretation rate of 1.000000 for the spatial pattern of soil AP by the interaction between two factors are: Town ∩ NDVI, Agriculture ∩ Water, Agriculture ∩ Mine, Agriculture ∩ NDVI, Industry ∩ Water, Industry ∩ NDVI, Mine ∩ Water, Mine ∩ NDVI, Road ∩ NDVI, and Altitude ∩ NDVI.

3.4. Driving forces analysis of the spatial pattern of soil AK

(1) Single-factor analysis of detection factors

From Figure 7, it can be seen that NDVI, the distance to the nearest town land, the distance to the nearest agricultural land, the distance to the nearest mining land, and the distance to the nearest water land all exceed 0.85 for the q value of soil AK, indicating that NDVI, town, agriculture, mining, and water have a strong driving effect on the spatial pattern of soil AK in the study area. The q value of the distance to the nearest industrial storage land exceeds 0.65, indicating that industry has a significant driving effect on the spatial pattern of AK in the soil in the study area. The q values of the distance to the nearest road network land, elevation, slope, and aspect are all less than 0.41, indicating that these four driving factors have no significant driving effect on the spatial pattern of soil AK in the study area.

From the perspective of the entire study area, the order of the impact of various factors on the spatial pattern of soil AK is as follows: NDVI (0.996468)>Town (0.904748)>Agriculture (0.902045)>Water (0.889276)>Mine (0.872485)>Industry (0.684817). Among natural factors, NDVI and water area have the most significant impact. The q values of NDVI and water are 0.996468 and 0.889276, respectively, with an interpretation rate of over 85%. Among human factors, town, agriculture, mining, and industry have a significant impact on the spatial pattern of soil AK, with q values of 0.904748, 0.902045, 0.872485, and 0.684817, respectively, with an explanatory power of over 80% (Figure 7).

(2) Analysis of interaction between detection factors

The interaction between two factors presents two types of relationships, namely, nonlinear enhancement and dual-factor enhancement. There are no independent factors that act. Among the interactions among factors, the explanation rate of interactions between Town, Agriculture, Mine, NDVI, and Water and all other factors is above 0.8.

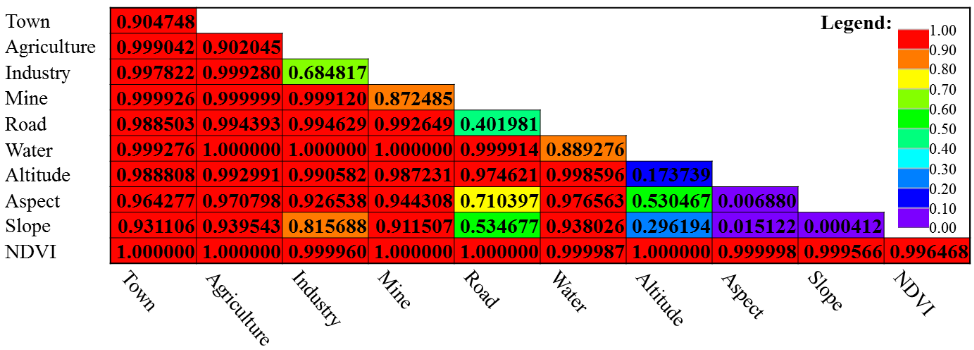


Figure 7. Interaction detector results of spatial pattern driving factors of AK

The interpretation rate of the interaction between the two factors on the spatial pattern of soil AK is 1.000000 for 8 groups: Town ∩ NDVI, Agriculture ∩ Water, Agriculture ∩ NDVI, Industry ∩ Water, Mine ∩ Water, Mine ∩ NDVI, Road ∩ NDVI, and Altitude ∩ NDVI.

4. Discussion

4.1. Effects of Town, Agriculture, NDVI, and Water on soil AN, AP, and AK

Among the interactions among factors, the explanation rate of interactions between Town, Agriculture, NDVI, and Water, and all other factors is above 0.8 for soil AN, AP, and AK. In the process of urban development, atmospheric subsidence, urban non-point source, and point source emissions will input nutrients such as carbon, nitrogen, phosphorus, potassium, and sulfur into the soil, changing the biochemical cycle of soil elements (Xie et al., 2019). Although nutrients such as nitrogen, phosphorus, and potassium fertilizers can improve soil fertility while promoting crop growth, excessive nutrient inputs can cause widespread contamination, which can degrade soil and water quality (Navidi & Seyedmohammadi, 2020). NDVI not only reflects the vegetation cover and growth status but also is closely related to soil moisture, temperature, organic matter content, and other environmental factors. These environmental factors jointly affect the spatial distribution of soil AN, AP, and AK. Water indirectly affects the cycling process of nitrogen, phosphorus, and potassium in soil by influencing the moisture status of the soil (Cai, 2020).

4.2. Effects of surface coal mining on AN, AP, and AK in surface soil

Most of China's large surface mines are located in arid/semi-arid areas with extremely fragile ecological environments, such as the Inner Mongolian Plateau, the Loess Plateau, and the Gobi Desert in Xinjiang. The perennial evaporation capacity of these areas is far greater than the precipitation. Long-term and intensive mining activities have led to serious soil pollution, drastic changes in soil fertility, and frequent water and soil erosion. However, surface mining is the direct stripping of topsoil and overlying strata of coal seams, exposing coal seams to mining, which severely damages the ecological environment and land resources, and severely restricts the socio-economic development of mining areas (Yu, 2017).

During the process of stripping, excavation, transportation, and dumping in open-pit coal mines, the exposed surface is prone to rain splashes and sunlight exposure. Heavy vehicles repeatedly roll the soil, causing loss of soil biological crusts and damage to soil pores, which further affect rainfall infiltration, water conduction, and erosion potential. The original soil structure and properties have undergone significant changes, and soil AN, AP, and AK have been severely damaged. These factors make it difficult for plants to obtain sufficient water due to insufficient rainfall infiltration during the initial stage of ecological restoration, and it is difficult to trigger the automatic soil restoration mechanism (Zipper et al., 2013; Ahirwal & Maiti, 2018; Feng et al., 2019). It can also be seen from Figures 5, 6, and 7 that there is a strong correlation between surface vegetation, mining, and soil AN, AP, and AK. The q value of NDVI for soil AN, AP, and AK is above 0.99, and the interpretation rate of the interaction between NDVI and all other driving factors for the spatial pattern of soil AN, AP, and AK is above 0.99. The q values of AN, AP, and AK in soils affected by mining were 0.803338, 0.969890, and 0.872485, respectively. The interpretation rate of the interaction between mining and all other driving factors on the spatial pattern of soil AN, AP, and AK is above 0.85.

4.3. Remediation of soil fertility in mining areas

The surface coal mining area is one of the most severely degraded ecosystems currently. Soil is a prerequisite for ecosystem restoration (Guo et al., 2020). When the biological and abiotic resources of an ecosystem are sufficient to self-develop without any external assistance, the ecosystem is referred to as repair and restoration (Maiti, 2013). In recent years, to restore the ecological environment of the mining area, land reclamation has been carried out in succession. Due to the disturbance caused by the reclamation process, the original physical and chemical structure of the soil has been completely changed. The soil conditions after reclamation will directly affect the local agricultural and animal husbandry production, thereby affecting the effectiveness of the ecological environment construction of the entire region (Wang, 2016; Liu et al., 2016; Zhao et al., 2020). Soil fertility largely determines the survival and growth of natural grassland vegetation, determines the productivity level of vegetation around the mining area, and plays an extremely important role in the development of ecosystems, especially vegetation communities (Bi et al., 2020). The restoration of soil fertility in the semi-arid grassland surface coal mining area is the application of physical, chemical, biological, and engineering measures to eliminate pollution in the soil, improve the environmental quality of the reconstructed soil, and fertilize and improve the soil to make it more suitable for plant growth, recover and improve the productivity of the reconstructed soil in a relatively short time, laying a good foundation for subsequent vegetation reconstruction (Hu, 2022; Jing, 2014; Hu et al., 2005). The main purpose of soil fertility remediation is to optimize soil conditions and accelerate soil maturation (Wang et al., 2016).

The self-repair of soil is a very slow and complex process (Burke et al., 1989; Li et al., 2007; Hu et al., 2015). The recovery of surface soil nutrients is slower in arid and semi-arid regions. Some soil components can even take 50 to 100 years to recover naturally (Derose et al., 1995; Li et al., 2007). Artificial methods can promote the formation of soil fertility. The restoration of soil fertility should follow its natural development laws, fully consider the self-repairing ability of reclaimed soil, and take targeted soil fertility measures based on actual needs. First of all, it is necessary to increase the content of organic fertilizer in the reclaimed soil and accelerate the degree of soil maturation. Generally speaking, high soil ripening is the fundamental guarantee for high and stable crop yields, and soil ripening is mainly due to the thickening of the active soil layer and the role of organic fertilizers. Organic fertilizer is the material basis for fertilizing and maturing soil. The combination of organic and inorganic mineral source fertilizers can not only meet the nutrient requirements of crops but also increase the content of organic matter in the soil and improve the soil structure. It is an effective way to combine nutrition and utilization.

In addition, vegetation reconstruction is an effective measure to accelerate the restoration of topsoil, as artificial vegetation has a significant fertilizing effect on the soil and can accelerate the improvement of soil fertility (Gong et al., 2004; Zhang et al., 2003). The vegetation restoration process can effectively improve the water holding capacity and pore state of the soil, reduce the soil bulk density, and improve the stable infiltration efficiency of the soil. The direct interpenetration of vegetation and the indirect protection of litter increase the structural stability of soil, thereby improving soil fertility. Secondly, after falling, vegetation will form dead branches and leaves, which contain a large amount of nutrients. Soil microorganisms act as decomposers to decompose the litter, forming humus, returning nutrients to the soil, and improving soil fertility. The roots of vegetation increase the nutrient content of soil by secreting various substances such as amino acids, vitamins, and organic acids into the soil (Zhang et al., 2018).

4.4. Construction of a multi-scale mining area soil investigation and monitoring system

Soil investigation and monitoring are the foundation and basis for conducting research on soil issues and formulating soil remediation plans and policies. Soil investigation and monitoring is a systematic measurement of various soil properties to check and record the temporal and spatial changes of these properties. Many countries around the world, such as China, the United States, Austria, and Denmark, have established official soil monitoring frameworks (Teng et al., 2014).

Soil investigation and monitoring in mining areas include investigation and monitoring of existing soil problems and soil remediation effects. Mining areas have caused varying degrees of pollution and impact on soil worldwide. If various possible pollution and impacts can be predicted in advance with less cost, and response plans can be formulated in advance, the risk of various negative impacts of coal mines on the soil will be greatly reduced. At present, 3S integration technology has been very mature and widely used in various environmental and disaster monitoring and database construction. If a multi-scale and large-scale mining area soil investigation and monitoring system and network can be constructed, and a mining area soil database can be built, from surface to point, from macro to micro, from real-time to historical, which will greatly benefit the protection and restoration of global mining area soil.

5. Conclusions

This study took the Shengli Coal Field in Xilinhot City, Xilingol League, China, as an example to study the spatial pattern and driving forces of soil AN, AP, and AK in the semi-arid grassland surface coal mining area. The results showed that: (1) The soil AN content in the western part of the study area is significantly higher than that in other regions, especially in the northwest side of the No. 1 surface mine, west No. 3 surface mine, west No. 2 surface mine, and Surface germanium mine. The heterogeneity of soil AN content in other regions is high. The soil AP content in the northern part of the study area is significantly higher than that in other regions, especially in the Xilin River Basin wetland, where the soil AP content is the highest, and in other regions, the soil AP content is relatively homogeneous. The soil AK content in the west and northeast of the study area is relatively high, especially in the north of the No. 1 surface mine. The soil AK content heterogeneity in the study area is high. (2) The impact degree of each factor on the spatial pattern of AN is ranked as follows: NDVI (0.994816)>Agriculture (0.931306)>Water (0.926628)>Town (0.913076)>Mining (0.803338)>Industry (0.622229); (3) The impact degree of each factor on the spatial pattern of AP is ranked as follows: NDVI (0.990870)>Mining (0.969890)>Water (0.930172)>Industry (0.798274)>Town (0.759609)>Agriculture (0.694557); (4) The impact degree of each factor on the spatial pattern of soil AK is ranked as follows: NDVI (0.996468)>Town (0.904748)>Agriculture (0.902045)>Water (0.889276)>Mining (0.872485)>Industry (0.684817); (5) The interaction between two factors presents two types of relationships: nonlinear enhancement and dual-factor enhancement, and the interaction between each factor is higher than that of a single factor.

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Conflict of interest

The authors declare no conflict of interest.

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