Main Nutrient Characteristics and Influencing Factors of Farmland Soils in the Loess Region of Shaanxi (Postprint)

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Abstract

To investigate the characteristics of major soil nutrients and their influencing factors in farmland of the Loess Region of Shaanxi, spatial analysis was performed on soil organic matter (SOM), total nitrogen (TN), available phosphorus (AP), and available potassium (AK) contents using GIS and geostatistical methods, based on data from 5096 sampling points in the 0–20 cm tillage layer of farmland in the study area. The Geodetector model was employed to quantify the explanatory power of 18 influencing factors on the spatial variation of nutrients. The results indicated that the mean contents of SOM, TN, AP, and AK were 14.43 g·kg-1, 0.92 g·kg-1, 18.21 mg·kg-1, and 190.28 mg·kg-1, respectively, all exhibiting moderate variation. The exponential model provided the best fit for all four nutrients, with each nutrient displaying moderate spatial correlation. The combined influence of structural and random factors contributed to spatial differences in nutrient contents. The hierarchy of global spatial correlation among nutrients was: TN > SOM > AK > AP. Regional disparities in nutrient contents were pronounced, following a gradually increasing trend from north to south. Single-factor effects, including annual sunshine duration, annual mean temperature, chemical fertilizer application rate, and geomorphic type, demonstrated stronger explanatory power for the spatial variation of nutrient contents. Two-factor interactions exhibited greater explanatory power than single-factor effects. The study suggests that fertilizer input should be appropriately increased in Northern Shaanxi, intensive cultivation is recommended for the Guanzhong region, and farmland development should account for multiple factors.

Full Text

Main Nutrient Characteristics and Influencing Factors of Farmland Soil in the Loess Plateau of Shaanxi Province

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Abstract

To investigate the main soil nutrient characteristics and their influencing factors in the Loess Plateau of Shaanxi Province, this study conducted spatial analysis of organic matter (SOM), total nitrogen (TN), available phosphorus (AP), and available potassium (AK) content based on 5,096 sampling points from the 0–20 cm cultivated layer using GIS and geostatistical methods. A geographical detector model was applied to explore the explanatory power of 18 influencing factors on the spatial variation of nutrients. The results showed that the mean contents of SOM, TN, AP, and AK were 14.43 $g \cdot kg^{-1}$, 0.92 $g \cdot kg^{-1}$, 18.21 $mg \cdot kg^{-1}$, and 190.28 $mg \cdot kg^{-1}$, respectively, all exhibiting moderate variation. The best-fitting models for all four nutrients were exponential models, with each nutrient showing moderate spatial correlation. The combined effects of structural and random factors caused spatial differences in nutrient content. The global spatial correlation of nutrients followed the order TN > SOM > AK > AP. Regional differences in nutrient content were significant, showing a gradually increasing trend from north to south. Single-factor effects of annual sunshine duration, mean annual temperature, fertilizer application rate, and geomorphic type had stronger explanatory power for spatial variation in nutrient content, though this was weaker than the interaction between two factors. The study indicates that fertilizer input should be appropriately increased in northern Shaanxi, intensive cultivation should be practiced in the Guanzhong region, and farmland construction should consider multiple factors.

Keywords: soil main nutrients; spatial variation; influencing factors; geographical detector model; Loess Plateau of Shaanxi Province

Introduction

Soil nutrient content in farmland directly affects agricultural production efficiency and food security, serving as a crucial indicator for measuring cultivated land quality. Soil provides various nutrients for crops and improves soil physicochemical properties, with organic matter (SOM), total nitrogen (TN), available phosphorus (AP), and available potassium (AK) being key nutrients that influence crop growth and development. The Loess Plateau, as an important ecological unit in the Yellow River Basin, has attracted considerable attention regarding its farmland nutrient research. For instance, Wei et al. used geostatistical methods to study farmland soil SOM in the Weibei Loess Plateau, finding that nutrients in the study area presented a spatial pattern of high in the south and low in the north, and revealed the optimal prediction model. Xie et al. studied farmland soil in the Xiaohe River Basin of the Loess Plateau and found that factors such as fertilization had a stronger influence on nutrient content at this scale.

Soil nutrients exhibit spatial heterogeneity due to the combined effects of random factors such as soil properties, topography, and climate conditions, as well as structural factors including fertilization, irrigation, and cultivation systems. Understanding the spatial distribution, variation characteristics, and influencing factors of farmland soil nutrients is of great significance for the sustainable development of farmland soil health and for promoting high-quality agricultural development. In recent years, numerous scholars have investigated the distribution of farmland soil nutrients and their influencing factors. Research objects have included major nutrients such as SOM, TN, AP, and AK, as well as trace elements like Fe and Zn. Study areas have covered scales ranging from individual fields and orchards to small and large watersheds and various administrative levels. Geostatistical methods and GIS technology have overcome the limitations of traditional statistics in explaining nutrient spatial variation and are currently among the more effective methods for soil nutrient spatial analysis. Methods such as redundancy analysis, Pearson correlation analysis, regression analysis, and principal component analysis have been widely applied to study influencing factors of farmland nutrients.

However, most current research focuses on small and medium scales, with fewer studies simultaneously examining multiple nutrients at large scales, making it difficult to provide more comprehensive guidance for precision fertilization in farmland. The distribution patterns of large-scale farmland soil nutrients need further revelation. Moreover, most studies have only selected partial influencing factors without comprehensively considering various factors. In this context, this paper takes the Loess Plateau of Shaanxi Province as the study area, considers multiple influencing factors, and investigates the characteristics of major farmland soil nutrients and the effects of influencing factors. The study aims to address the following questions: (1) reveal the spatial distribution pattern of major nutrients in the region to provide theoretical support for regional precision fertilization; and (2) explore the relationship between various factors and farmland soil nutrients at large scales through the geographical detector model, providing references for farmland construction and agricultural soil nutrient management in the Loess Plateau of Shaanxi Province.

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1. Materials and Methods

1.1 Study Area Overview The Loess Plateau of Shaanxi Province is located in the middle of the Loess Plateau, between 33°42 –39°35 N and 106°18 – 111°15 E, with an elevation range of 207–3,754 m. The region spans a large distance from north to south but is narrow from east to west, covering a total area of approximately 2.0$×10^{5}$ km^2, accounting for 97% of the province's area and 38% of the Loess Plateau's area. The main agricultural soil types in the region include loessal soil and aeolian sandy soil in northern Shaanxi, cinnamon soil in the Guanzhong Plain, and fluvo-aquic soil and alluvial soil in river valley floodplains. Based on geomorphic types, the study area is divided from north to south into: the wind-sand beach area along the Great Wall, the loess hilly-gully region of northern Shaanxi, the Weibei loess tableland region, and the Guanzhong Plain. According to climatic conditions, these correspond to: the temperate semi-arid climate zone along the Great Wall, the warm temperate semi-arid climate zone of the northern Shaanxi Plateau, and the warm temperate semi-humid climate zone of the Guanzhong Plain.

1.2 Data Sources

1.2.1 Nutrient Indicators and Soil Sample Collection The abundance of SOM, TN, AP, and AK directly affects crop growth and development and is widely selected as an important indicator for farmland soil fertility research. Moreover, these four nutrients are all major soil nutrients in Shaanxi Province's cultivated land quality evaluation. Therefore, this study focuses on these four nutrients. Considering the administrative location and land use status of the study area, sampling points were laid out comprehensively accounting for terrain, climate, and soil properties. After crop harvest in 2020, 5,096 topsoil samples (0–20 cm) were collected. During sampling, point coordinates and elevation were recorded using GPS, and soil type and crop type at each sampling point were documented. The sample collection and nutrient testing were completed by the Shaanxi Provincial Department of Agriculture's Farmland Quality and Agricultural Environmental Protection Workstation. The sampling locations are shown in [Figure 1: see original paper].

1.2.2 Selection and Acquisition of Impact Factors Based on previous research results and the actual conditions of the study area, 18 impact factors were selected as shown in . Soil property data and human activity data including irrigation methods, crop types, and cropping systems were obtained from the 2020 cultivated land quality monitoring data of the Shaanxi Provincial

Department of Agriculture's Farmland Quality and Agricultural Environmental Protection Workstation. Slope, aspect, and terrain relief were extracted from 30 m ASTER GDEM data downloaded from the Spatial Geographic Data Cloud (http://www.gscloud.cn/) using ArcGIS. Annual meteorological data including sunshine duration, rainfall, mean temperature, and evaporation were extracted from the Chinese Academy of Sciences' Resource and Environmental Science Data Center (http://www.resdc.cn/). Geomorphic type zones were determined through information on farmland construction released on the official website of the Shaanxi Provincial Department of Agriculture and Rural Affairs (http://nynct.shaanxi.gov.cn/). County-level fertilizer usage data were compiled from statistical yearbooks of various cities.

1.3 Research Methods

1.3.1 Semivariance Model Analysis Semivariance model analysis can reveal the degree of influence of structural and random factors on spatial nutrient content variation. The calculation formula is as follows:

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

where $\gamma(h)$ represents the semivariance function value; h represents the distance between two sampling points (or lag distance); $N(h)$ represents the number of data pairs with spacing h; and $Z(x_i)$ and $Z(x_i + h)$ represent the measured values of variable Z at spatial locations x_i and $x_i + h$, respectively. Important parameters of the semivariance function include nugget value C_0, sill value $C_0 + C$, range A, nugget coefficient $C_0/(C_0 + C)$, and determination coefficient R^2. The nugget coefficient is used to reflect the spatial correlation of variables.

1.3.2 Spatial Autocorrelation Analysis To reflect the overall spatial aggregation state of soil nutrients in the Loess Plateau of Shaanxi Province, the global Moran's I index was calculated and analyzed. The formula is as follows:

$$I = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} \sum_{i=1}^{N} (x_i - \bar{x})^2}$$

where N is the number of samples; W_{ij} is the spatial weight; x_i and x_j are the measured nutrient contents at locations i and j; and $\bar{x}$ is the mean nutrient content. Moran's I index values typically range from -1 to 1, indicating the degree of spatial correlation in nutrient distribution. Z-score testing is usually employed to examine the significance of the index.

1.3.3 Spatial Clustering Analysis Local Moran's I index can reflect regional local spatial autocorrelation, enabling nutrient spatial clustering analysis and spatial outlier identification. The formula is as follows:

$$I_i = \frac{x_i - \bar{x}}{S^2} \sum_{j=1}^{N} W_{ij}(x_j - \bar{x})$$

where $S^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$.

1.3.4 Geographical Detector Model The geographical detector model uses statistical methods to detect spatial stratified heterogeneity and effectively describe the driving forces of various influencing factors behind phenomena. The factor detector is used to detect the explanatory power (interpretive power) of impact factor X on dependent variable Y, measured by the q statistic. The value range of q is [0,1], with larger values indicating stronger factor explanatory power. The formula is as follows:

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

where h represents the number of strata of the impact factor ($h = 1, 2, ..., L$); σ_h^2 represents the variance of the dependent variable in stratum h; σ^2 represents the variance of the dependent variable across the entire range; N is the number of all factors; N_h is the number of factors in stratum h; SSW is the sum of within-stratum variances; SST is the total variance; and q represents the influence power of the factor on dependent variable Y.

The interaction detector describes the explanatory degree of two factors acting together on the dependent variable. By superimposing the stratification of two factors to recalculate the q value and comparing it with the single-factor q values, the strength of the interaction can be determined. Based on this comparison, interactions are classified into several types as shown in .

1.4 Data Processing Outliers in various soil nutrient data from the 5,096 sampling points were removed using the 3-standard-deviation method and neighboring point data comparison method. The number of samples removed were 23, 17, 31, and 19 for SOM, TN, AP, and AK, respectively. Descriptive statistics were performed using SPSS 27.0. Semivariance analysis was conducted using GS+9.0. Spatial autocorrelation analysis, nutrient spatial interpolation, and spatial clustering analysis were performed in ArcGIS 10.7. The geographical detector model was constructed using R language to explore the effects of various factors on soil nutrient content.

2. Results

2.1 Statistical Characteristics of Soil Nutrients Statistical analysis of soil nutrient characteristics () showed that the mean contents of SOM, TN, AP, and AK were 14.43 $g \cdot kg^{-1}$, 0.92 $g \cdot kg^{-1}$, 18.21 $mg \cdot kg^{-1}$, and 190.28 $mg \cdot kg^{-1}$, respectively. Compared with the national secondary soil survey nutrient classification standards, SOM and TN were at low levels, AP was at a medium level, and AK was at a relatively high level. The coefficients of variation for the four nutrients were 56.88%, 42.27%, 79.90%, and 42.39%, respectively. According to Nielsen's (1985) classification standard, where CV ≤ 0.1 indicates weak variation and CV ≥ 0.9 indicates strong variation, all soil nutrient indicators exhibited moderate variation intensity. The variation intensity of AP and SOM was relatively high, indicating more obvious regional differences. In subsequent geostatistical analysis, data normalization was required; otherwise, it could lead to bias in variogram analysis and spatial interpolation. The skewness coefficient indicates the degree of data skewness, while the kurtosis coefficient indicates the steepness of the data distribution. A skewness closer to 0 and kurtosis closer to 3 indicates data more approximating a normal distribution. After logarithmic transformation, the four nutrient contents approximately followed a normal distribution.

2.2 Spatial Variation Characteristics of Soil Nutrients

2.2.1 Spatial Variation Characteristics Based on Semivariance Model Semivariance analysis of nutrient distribution in the study area was conducted using GS+9.0 (). The analysis results showed that the best-fitting models for all four nutrients were exponential models, with R^2 values approaching 1, indicating excellent fitting effects. The nugget values (C_0) of each nutrient were greater than 0, which is due to spatial variation caused by sampling error, experimental error, and random human factors within the minimum sampling interval. The nugget coefficient ($C_0/(C_0 + C)$) represents the proportion of variation caused by random factors in the total variation. The nugget coefficients of the four nutrients ranged from 0.25 to 0.75, indicating that nutrient content exhibited moderate spatial correlation, with variability influenced by both structural factors (soil properties, climate conditions, terrain conditions) and random factors (human activities). The nugget coefficient of AP was the largest, indicating it was more affected by human activities compared to other nutrients. The range values showed that the four nutrients had spatial correlation within 40.8 km, 58.9 km, 92.4 km, and 67.3 km, respectively.

2.2.2 Spatial Autocorrelation Analysis of Soil Nutrients To reflect the overall spatial aggregation state of soil nutrients, the global Moran's I index was calculated (). All four nutrients showed extremely significant positive correlation, meaning that the nutrient content value in a small region was positively influenced by the content value of the same nutrient in surrounding areas. The global Moran's I index values for nutrients followed the order TN > SOM > AK

> AP, indicating that TN had the strongest spatial aggregation phenomenon, while AP had relatively weaker spatial aggregation. At the 95% confidence level, all nutrients showed significant autocorrelation.

2.2.3 Spatial Distribution Characteristics of Soil Nutrient Content Based on the parameters obtained from semivariance model fitting, ordinary kriging interpolation was performed. The natural breaks method was used to classify soil nutrient content into five levels. The overall regional differences in the four nutrient contents were significant, showing a spatial distribution characteristic of high in the south and low in the north. SOM and TN content were relatively scarce in Yulin and northern Yan'an, mostly at level 4 (medium) according to national standards. The Xi'an, Baoji, and Weinan areas in the Guanzhong Plain had SOM and TN content at level 3 (relatively high), showing an increasing trend toward the south. The area of level 4 standard was larger, with level 5 mostly located east of Yan'an and Yulin, while level 2 was distributed at the southern edge of Xi'an. AP content showed an increasing trend from northwest to southeast, with low values distributed in Yulin and western Yan'an and high values in the southeastern plain region. AK content was generally at level 3 (medium) in the wind-sand beach area along the Great Wall, while in the Guanzhong Plain area (Xi'an, Baoji, Weinan and surrounding areas), it was at level 2 (relatively high), gradually increasing toward the south.

2.2.4 Spatial Clustering Analysis of Soil Nutrients Based on the ordinary kriging interpolation results, with county/district as the evaluation unit, the average interpolation results within each county/district were spatially connected to the evaluation units, and local Moran's I index calculations were performed to form LISA cluster maps ([Figure 3: see original paper]). Spatial clustering analysis divides the study area into: not significant, high-high (high value clustering), high-low (high value surrounded by low values), low-high (low value surrounded by high values), and low-low (low value clustering) regions, representing different relationships between regions. The results showed that the low-value clustering areas of SOM and TN were distributed in Yulin and northern Yan'an, while high-value clustering areas were distributed in Xi'an and its surrounding areas, with most areas of Baoji also included. The low-value clustering areas of AP were distributed in the central-western part of the study area, while high-value clustering areas were mostly distributed in Xi'an and its surrounding areas, with a small high-high area in northern Xianyang. The low-high clustering areas of AK were distributed in Yulin and northwestern Yan'an, while high-high clustering areas were mostly distributed in Xi'an, Xianyang, and Weinan.

2.3 Detection of Influencing Factors

2.3.1 Single-Factor Detection The factor detector was used to calculate the q statistic for 18 impact factors on the spatial distribution of the four nutrients to represent their explanatory power. Except for the aspect factor, which had no significant influence on the four nutrient contents ($P > 0.01$), all other factors reached significant levels. The factor detection results ([Figure 4: see original paper]) showed that the explanatory power (q value) of each impact factor on regional nutrient spatial differentiation varied significantly. Overall, the explanatory power of each factor for SOM and TN was significantly higher than for AP and AK, indicating that various factors participated more in the farmland nutrient cycle of SOM and TN compared to AP and AK. For SOM, the factors with the highest explanatory power were annual sunshine duration (0.496), geomorphic type (0.484), fertilizer application rate (0.468), and crop cropping system (0.421). For TN, the top factors were annual sunshine duration (0.512), mean annual temperature (0.508), fertilizer application rate (0.505), and geomorphic type (0.492). For AP, the top factors were mean annual temperature (0.297), geomorphic type (0.289), annual sunshine duration (0.287), and elevation (0.283). For AK, the top factors were mean annual temperature (0.356), annual sunshine duration (0.348), elevation (0.342), and fertilizer application rate (0.336). For any single nutrient, the top explanatory factors all included annual sunshine duration, mean annual temperature, geomorphic type, and fertilizer application rate.

2.3.2 Interaction Detection The interaction detector was used to explore whether the effects of various influencing factors on soil nutrient content were independent or interactive, and if interactive, whether they enhanced or weakened each other. The interaction factors with the greatest explanatory power for each nutrient are shown in . The results showed that the interaction effects of factors had stronger explanatory power for nutrient spatial differentiation than single factors, with the top interactions all having q values greater than 0.5. The interaction effects on SOM and TN were the strongest, with the highest q values of 0.621 and 0.618, respectively, from the interaction between annual temperature and fertilizer application rate, indicating that the interaction between human and natural factors had stronger explanatory power for these two nutrients. The interaction effects on AP and AK were slightly weaker, ranking 4th and 5th, respectively. The interaction factors with the greatest explanatory power for SOM and TN were the same (annual temperature and fertilizer application rate), partly because both factors directly affect SOM and TN content, and partly because they influence the transformation of SOM and TN storage. The interaction heatmap ([Figure 5: see original paper]) showed that the interactive explanatory power of various factors on farmland nutrients in the Loess Plateau of Shaanxi Province was higher than single-factor effects, manifesting as two-factor enhancement and single-factor nonlinear enhancement.

3. Discussion

In terms of spatial patterns and variation characteristics, statistical analysis showed that farmland soil nutrients in the Loess Plateau of Shaanxi Province were generally low, which is closely related to the region's complex natural conditions of soil, climate, and terrain, as well as extensive cultivation methods and management systems. Although the coefficient of variation of AP was as high as 79.90%, significantly higher than other nutrients, because phosphorus is easily fixed by soil and more susceptible to human fertilization and irrigation factors, the semivariance function model results showed that all four nutrients exhibited moderate spatial correlation, with nutrient content influenced by both structural and random effects. The main reason for this difference may be that long-term environmental protection and agricultural cultivation management have caused certain changes in soil nutrients, gradually strengthening the influence of random factors. The spatial distribution patterns and clustering status of nutrients showed that SOM and TN were deficient in Yulin and northern Yan'an, possibly because this area is mostly covered by aeolian sandy soil and loessal soil, which are inherently poor, and environmental conditions cause severe nutrient loss. Straw return and organic fertilizer application can not only provide rich organic matter and nitrogen, phosphorus, and potassium for farmland soil but also improve soil structure, making them suitable for promotion in this region. In the Xi'an, Baoji, and Weinan area, located in the Guanzhong Plain with fertile soils such as fluvo-aquic soil and cinnamon soil, relatively flat terrain, and strong soil water and nutrient retention capacity, these areas are mostly nutrient enrichment zones.

Regarding influencing factors, soil properties affect soil nutrient content by determining water and nutrient retention capacity, aeration, and cultivation difficulty. Among soil properties, soil texture had higher explanatory power than others because lighter-textured soils have greater permeability, making them more prone to SOM and other nutrient loss and unfavorable for nutrient accumulation, while heavier-textured soils often have higher clay content, which more easily adsorbs and fixes AP and AK. Climate conditions often determine the large-scale spatial pattern of nutrients. Sunshine duration, precipitation, temperature, and evaporation affect nutrient content by influencing crop photosynthesis, regional water-heat balance, and microbial activity. Among these, sunshine duration had the most obvious effect, with nutrient content in the study area generally increasing as sunshine duration decreased. Topography and geomorphology mainly affect nutrient content by influencing the spatial redistribution of water and solar radiation. Geomorphic type and elevation control regional differences in climate, soil, and hydrology within certain areas, making them important factors restricting farmland nutrients. Regarding human activities, fertilizer application rate, as a direct source of cultivated land nutrients, has stronger explanatory power for nutrient content spatial differences, while cultivation patterns and management systems also indirectly affect nutrient content. Interaction detection showed that two-factor interactions had stronger effects on nutrients than single factors, indicating that nutrient content is affected by the combined action of various factors, consistent with the research results of Wang et al. in this region. During farmland construction, multiple factors affecting crop yield should be considered, and human activities should be adapted to local conditions according to soil properties, terrain conditions, and climate factors.

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4. Conclusion

1) According to the nutrient classification standards of the second national soil survey, SOM and TN in the Loess Plateau of Shaanxi Province are at relatively low levels, AP is at a medium level, and AK is at a relatively high level. All soil nutrient indicators exhibit moderate variation intensity.
2) The best-fitting models for all four nutrients are exponential models, with each nutrient showing moderate spatial correlation. The combined effects of structural and random factors cause spatial differences in farmland soil nutrient content in the study area. The global Moran's I index indicates that all four nutrients show extremely significant positive correlation. Kriging interpolation shows that nutrient content has obvious regional differences, characterized by high in the south and low in the north. Spatial clustering analysis shows that low-value clustering areas are mostly distributed in Yan'an and Yulin, while high-value clustering areas are mostly distributed in Xi'an, Baoji, and Weinan. It is recommended to appropriately increase fertilizer input and adopt more water and nutrient conservation measures in northern Shaanxi, practice intensive cultivation in the Guanzhong region to improve grain yield and nutrient use efficiency.
3) Annual sunshine duration, mean annual temperature, fertilizer application rate, and geomorphic type have stronger explanatory power for the spatial variation characteristics of each nutrient content, and the explanatory power of two-factor interactions on nutrients is stronger than that of single factors.

References

[References are preserved in their original format as provided in the source text]

Note: Figure translations are in progress. See original paper for figures.