RESEARCH ARTICLE

Spatial variability and characteristics of soil organic carbon, total nitrogen, and total phosphorus in cultivated land of Xining, Qinghai, China

Mingyu Zheng[1], Liqun Cai[1, *], Haider Fasih Ullah[2]

[1]College of Resources and Environmental Sciences, Gansu Agricultural University, Lanzhou, Gansu, China.
[2]Key Laboratory of Vegetation Restoration and Management of Degraded Ecosystems, South China Botanical Garden, Chinese Academy of Sciences, Guangzhou, Guangdong, China.

Received: July 3, 2023; **accepted:** August 2, 2023.

Agricultural land is important in ensuring farmland security and promoting sustainable land use. However, the knowledge about characteristics and spatial variability of soil organic carbon (SOC), total nitrogen (TN), and total phosphorus (TP) in the region of Xining, Qinghai, China has yet to be discovered. Therefore, this study aimed to analyze surface soil (0-20 cm) cultivated land in Xining. The research examined this region's characteristics and spatial variability of SOC, TN, and TP. Field collection and laboratory experiments were conducted, and statistical and geostatistical methods were used to analyze data. The results indicated that SOC levels were insufficient, TN content was moderate, and TP content was abundant in Xining. The spatial distribution of SOC, nitrogen (N), phosphorus (P), and stoichiometric ratios exhibited moderate variability. Notably, soil carbon (C)/P, N/P, C/N, and TP displayed strong spatial correlations in Xining, primarily influenced by structural factors. The moderate spatial variation observed in TN and SOC in the soil could be attributed to random and structural factors. Furthermore, the analysis of SOC, TN, TP, and ecological stoichiometric ratios in cultivated soil across Xining demonstrated a positive cluster distribution pattern. The horizontal spatial distribution types of SOC, TN, C/N, C/P, and N/P in the 0-20 cm soil layer of cultivated land in Xining exhibited differentiation from south to north with a gradual increase observed from south to north. No significant correlation was observed among the other indices except for soil C/N, TN, and TP. Overall, this study was of great significance to the characteristics and spatial variability of SOC, TN, and TP in cultivated land in Xining. The findings contributed to understanding farmland security and sustainable land use practices in this region, enabling informed decision-making for land management and agricultural practices.

Keywords: cultivated soil; soil organic carbon; total nitrogen; total phosphorus; ecological stoichiometry; spatial variability.

[*]**Corresponding author:** Liqun Cai, College of Resources and Environmental Sciences, Gansu Agricultural University, Lanzhou 730070, Gansu, China. Email: cailq@gsau.edu.cn.

Introduction

Ecological stoichiometry is a crucial discipline that investigates the balanced relationship between energy and key elements such as carbon (C), nitrogen (N), phosphorus (P), and others in ecosystem interactions [1, 2]. It plays a significant role in unravelling the cycles of organic carbon (OC), N, and P and their interactions within ecosystems. OC, N, and P are fundamental elements in terrestrial ecosystems with OC serving as the main nutrient source and a vital component of the terrestrial soil carbon pool. OC's content directly influences terrestrial ecosystems' stability, carbon dioxide (CO_2) concentrations, and the dynamic balance of the carbon cycle [3, 4]. Soil nitrogen and phosphorus are essential elements that affect plant growth, promote microbial biomass development, and maintain C and N cycles in the soil, acting as limiting factors with significant implications for ecosystem structure and function [5, 6].

Soil, as a crucial component of ecosystems, facilitates the exchange of matter and energy and exhibits extensive connections with soil organisms, plants, and microorganisms [7, 8]. However, the elements of soil C, N, and P are interconnected, and analyzing the dynamics of soil nutrient elements solely from the perspective of a single element cannot fully capture the dynamic changes in soil nutrient elements. Therefore, studying the stoichiometric ecological characteristics of soil nutrients holds significant value in comprehending the cycling patterns of soil nutrients in cultivated land [9, 10]. Several studies have explored the nutritional characteristics and stoichiometric relationships in different ecosystems. Reza, *et al*. analyzed changes in nutritional characteristics in the lower Brahmaputra plains of India [11]. Bollinska, *et al*. identified influential factors in the carbon, nitrogen, phosphorus cycles in the deadwood-soil system of mountain forest ecosystems [12]. Zhang, *et al*. discussed the contents and stoichiometric characteristics of C, N, and P in reclaimed farmland soil using geostatistics to explain the variation of soil nutrients [13]. Du used the geostatistical model and 3S technology to study the spatial variation of N and P ecological stoichiometric in 0-20 cm surface soil in the typical mollic epipenon region of Northeast China and its influencing factors [14]. Additionally, Zhang, *et al*. investigated peatland soil in China, revealing close relationships between water, temperature, precipitation, soil organic carbon, total nitrogen, total phosphorus, and the C/N, C/P, N/P ratios [15].

While stoichiometric studies on grassland, wetland, and forest ecosystems have made significant progress in recent years, research on the stoichiometric characteristics of cultivated soil still requires further investigation, particularly in Xining, Qinghai, China. With the intensification of human disturbance and various factors including changes in land management practices, cultivated soil's physical and chemical properties may vary, affecting soil nutrient content. This study examined soil OC, N, and P based on the stoichiometric ecological characteristics of cultivated land in Xining to uncover the spatial differentiation of soil nutrients in cultivated land in this area and to provide scientific basis for formulating reasonable measures for soil nutrient management in the region. Moreover, this study hypothesized that the spatial variability and characteristics of soil organic carbon (SOC), total nitrogen (TN), total phosphorus (TP) cultivated in Xining would exhibit distinct patterns and relationships. It was also hypothesized that SOC, TN, TP, and their stoichiometric ratios would display spatial correlations primarily influenced by structural factors. Finally, the research predicted a positive cluster distribution pattern for SOC, TN, TP, and ecological stoichiometric ratios in cultivated soil across the area of Xining, Qinghai, China.

Materials and Methods

Overview of the study area

The location of Xining is at 36°34'3" ~ 37°28'3" north latitude and 101°49'17" ~ 101°54'17"east longitude on the eastern edge of the Qinghai-Tibet Plateau, Huangshui Valley, a tributary of the Yellow River. The city's terrain inclines from north to south with high in the southwest and low in the northeast and is distributed in a ribbon of east-west direction. Xining belongs to the continental plateau semi-arid, plateau alpine cold temperature climate. The average sunshine duration of the year is 2,510.1 h. The average annual temperature is 7.6°C with the highest of 34.6°C and the lowest of -18.9°C. It is 2,168 ~ 4,622 meters above sea level with an average altitude of 2,261 m. The annual average precipitation is 330 ~ 450 mm, and the evaporation is 1,363.6 mm, more in the west than in the east. The valley land has high potential fertility, good structure and good fertilizer, and water retention performance. However, the soil cultivability is poor. The soil is loose with serious soil erosion in the alpine and middle-high mountain areas. The total land area of Xining is 7,613.91 km², while the cultivated land area is about 2,133.61 km², of which the irrigated land area is 102.85 km² and the dry land area is 2,030.76 km².

Sample collection

(1) Layout of sample points

Considering soil type, administrative division, cultivated land utilization, cultivated land grade, and soil quality, the research area for this study included the five districts and two counties of Xining, Qinghai, China. The cultivated land area of Xining in 2020 served as the basis for the analysis. A sample point of 666.67 hectare of cultivated land was set up, and 306 sampling points were set up in Xining (Figure 1).

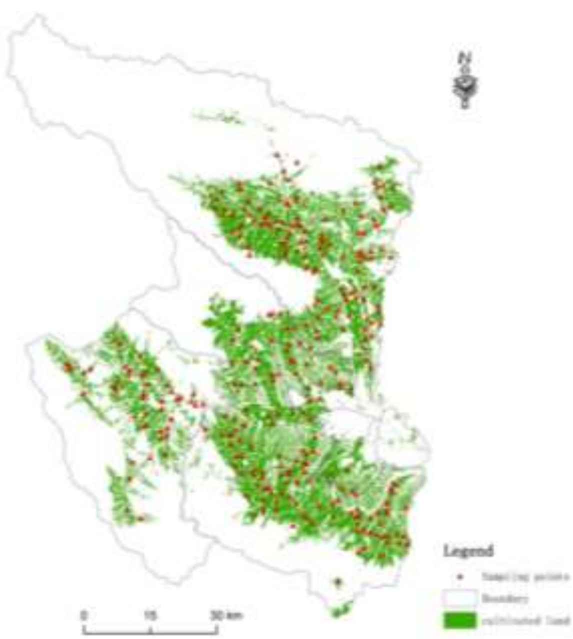

Figure 1. Location and grid map of the study area (Xining, Qinghai, China).

(2) Soil sample collection and measurement

A 5-point sampling method was adopted for each sampling point. The five points were the center point of the two diagonal lines of the field and the four points on the diagonal line that were 2.5 km away from the center. The soil at the edge of the field was avoided. Each sampling point was accurately located by using GPSMAP® 64 system (Garmin, Olathe, Kansas, USA). The soil sampling depth was 0 - 20 cm after removing the topsoil layer. A total of 306 sampling points were selected. Each soil sample was packed into a PVC bag, and labels were affixed inside and outside, indicating the sampling number, name, sampling depth, sampling location, date, sampling person, and the latitude and longitude of the center point, and the altitude. The samples were then transported to the laboratory within 24 hours. After natural air drying and crushing, the plant roots and gravel were picked out. The soil sample was made through a 2 mm soil screen, and then put into a sealed bag and stored for testing.

According to the method of soil agrochemical analysis [16], the SOC concentrations were determined by using the potassium dichromate volumetric method ($K_2Cr_2O_7/H_2SO_4$) [17], which involved oxidizing 0.5 g of soil with a solution of $K_2Cr_2O_7$ and H_2SO_4 at 170°C followed by titrating excess dichromate with 0.25 mol/L $FeSO_4$. The TN concentrations were measured by applying Kjeldahl nitrogen method [18] and K9840 Kjeldahl nitrogen analyzer (Drawell Scientific Instrument, Shanghai, China), which involved the digestion of 1.0 g of soil with a catalyst (H_2SO_4-K_2SO_4-$CuSO_4$-Se mixture) at 380°C and distillation sample by adding 30 mL of NaOH. Released ammonium was captured in 10 mL of H_3BO_3. The titer of formed ammonium borate was measured by the addition of 0.05 N H_2SO_4 using a methyl red and bromocresol green indicator. The TP concentrations were measured by using TU-1901 UV-Vis spectrophotometer (Beijing General Analytic Instrument, Beijing, China) and NaOH melt-molybdenum-antimonic resistance colorimetric method after $HClO_4$-H_2SO_4 digestion [19]. The major reagents for SOC, TN, and TP measurements were from China National Pharmaceutical Group Corporation, Beijing, China.

Statistical analysis

(1) Semi-variance function

Semi-variation function is one of the most widely used methods to describe the spatial pattern of soil in geostatistics [20]. It was a function of the semi-variation value of data points and the distance between data points, which was used to study soil's spatial structure and spatial correlation. The formula for the semi-variance function was as follows:

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

where y (h) was the semi-variance function, h was the spatial distance between sample points, *N* (h) was the sampling pick-up distance, h was the total logarithm of points, *Z* (xi) and *Z* (xi + h) were the observed values of *Z* (x) at the spatial positions xi and xi + h, respectively. The semi-variance function had three important parameters, which were the bullion value (C_0), the base value ($C_0 + C$), and the range [21]. The bullion value represented the constant at which the variance function remained unchanged at a distance of 0, while the base value represented the constant at which the variance function became stable as the distance increased. Spatial variability could be divided into two types including random and structural variations. The strength of spatial variability could be reflected by the ratio of the nugget value to the base value (nugget coefficient), which could also be called the nugget effect C_0 / (C_0 + C). The bullion coefficient could reflect the proportion of random factors in the total variation factors. The larger the bullion coefficient was, the stronger the influencing factors of random variation were and the weaker the spatial correlation was, and vice versa. The variable range referred to the range of spatial continuity of patches with certain correlation properties. When the maximum variable range was exceeded, the spatial structure change would not be affected, and the spatial variables within the variable range had spatial autocorrelation.

The semi-variance function included four models as the spherical model, the exponential model, the gaussian model, and the linear model [22]. The calculation formula of each model was as follows:

Spherical model:

$$y(h)=\begin{cases}0, & h=0\\ C_0+C\left(\frac{3h}{2a}-\frac{h^3}{2a^3}\right), & h>a\\ C_0+C, & h<a\end{cases} \quad (2)$$

Exponential model:

$$y(h)=\begin{cases}0, & h=0\\ C_0+C\left(1-e^{-\frac{h}{a}}\right), & h>0\end{cases} \quad (3)$$

Gaussian model:

$$y(h)=\begin{cases}0, & h=0\\ C_0+C\left(1-e^{-\frac{h^2}{a^2}}\right), & h>0\end{cases} \quad (4)$$

Linear model:

$$y(h)=\begin{cases}C_0+C\left(\frac{h}{a}\right), & 0\le h\le a\\ C_0+C, & h>a\end{cases} \quad (5)$$

where C_0 was the bullion coefficient, *C* was structural variance, (C_0 + C) was the base value, a was variable range. The semi-variance function was analyzed by using GS+ 9.0 software (Gamma Design Software, Plainwell, Michigan, USA) to calculate the optimal function model of each index and determine the parameters of each index according to the minimum residual error and maximum determination coefficient.

(2) Moran's index

Spatial autocorrelation analysis tests whether the observed value of a spatial position variable is significantly correlated with the observed value of its adjacent spatial points. In this study, global Moran's I was selected to quantify soil C, N, and

P's spatial autocorrelation characteristics and demonstrated the spatial correlation between things globally with the calculation formula below [23].

$$\text{Moran's } I = n / \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \bar{y})(y_j - \bar{y}) / \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \sum_{j=1}^{n}(y_i - \bar{y})^2 \quad (6)$$

where n represented the total number of units in the space, and y_i and y_j represented the value of the variable y at the space points i and j, respectively. $\bar{y}$ was the mean and W_{ij} was the weight of the distance between the sample points. The value range of the Moran's I was [1, -1] with the Moran's I < 0 as the spatial region anomaly, the Moran's I close to -1 as strong spatial diversity, and the Moran's I > 0 as the space having agglomeration. The closer the value was to 1, the stronger the spatial autocorrelation. The Moran's I = 0 indicated that there was no spatial autocorrelation, and the random distribution. The scatter plot of Moran's I had 4 quadrants, from the first to the fourth quadrant. There were 4 distribution types of "high-high", "low-high", "low-low", and "high-low". In the first and third quadrants, it belonged to the "high-high" and "low-low" cluster distribution types, while, in the second and fourth quadrants, it belonged to the "low-high" and "high-low" isolated distribution types. By using GeoDa software (The University of Chicago, Chicago, Illinois, USA), the global Moran's I was selected to quantify the spatial autocorrelation and analyze the clustering or isolated spatial distribution type.

(3) Data analysis

SOC, TN, and TP data were processed by using Microsoft Excel (Microsoft, Redmond, Washington, USA). The descriptive statistical analysis was conducted by using SPSS 24.0 software (IBM, Armonk, New York, USA). Kolmogorov-smolov test (K-S test) was used for testing, and correlation analysis was conducted. The optimal model of each index was used for ordinary Kriging method interpolation by using ArcGIS 10.6 (ESRI, Redlands, California, USA), and the spatial distribution characteristics of OC, TN, and TP in Xining were obtained.

Results and discussion

Descriptive statistical analysis

The nutrient analysis results were presented in Table 1, showing the variation range of nutrients in the order of TP > SOC > TN. Additionally, Table 2 assessed the nutrient levels in cultivated land in Xining. The results indicated that SOC fell into the fourth grade, indicating a lack of content. TN was classified as the third grade, representing moderate content. On the other hand, TP fell into the first grade, indicating extremely rich content. These findings suggested that the area's overall quality of soil nutrients was generally low, except for TP. It was important to utilize TP based on specific local conditions effectively. The distribution of soil nutrients was analyzed by using a normal distribution test. All indexes showed a non-normal distribution except for SOC. However, after applying root-mean-square conversion, TN and TP followed a normal distribution. Similarly, after logarithmic conversion, the ratios of C/N, C/P, and N/P also exhibited a normal distribution. Consequently, a semi-variance function analysis was conducted on each index. Table 1 presented the coefficient of variation for the cultivated soil indexes in Xining. The values ranged from 10% to 100% with a concentration between 40% and 75%. These coefficients indicated a moderate intensity of variation for all indexes. Notably, the C/P and N/P ratios exhibited relatively large coefficients of variation, surpassing 70%. On the other hand, the coefficients of variation for SOC, TN, TP, and C/N were similar. The study revealed distinct spatial patterns and variability of SOC, TN, and TP in the cultivated land of Xining. The results showed that SOC levels were insufficient, TN content was moderate, and TP content was abundant. This spatial variability of nutrient levels could be attributed to various factors such as soil hydrothermal conditions, vegetation cover, and agricultural practices [24]. The higher SOC and TN contents in the study area compared to the

Table 1. Basic content characteristics of soil indexes.

Soil properties	N	Min	Max	Mean	Median	S.D.	Range	C.V. (%)	D.T.
SOC (g/kg)	306	2.61	43.69	14.49	13.608	5.93	41.08	40.92	no
TN (g/kg)	306	0.27	4.06	1.54	1.46	0.53	3.79	34.42	square
TP (g/kg)	306	0.51	4.02	1.56	1.79	0.74	3.51	47.44	square
C/N	306	3.60	87.07	9.49	9.38	4.65	83.47	49.00	log
C/P	306	1.40	57.29	12.67	8.53	9.46	55.89	74.66	log
N/P	306	0.15	4.31	1.35	0.94	0.95	4.16	70.37	log

Notes: N: number of soil samples, S.D.: standard deviation, C.V.: coefficient of variation, D.T.: distribution type.

Table 2. Soil nutrient classification standards of the second national soil survey.

Grade	Trophic grade	SOC (g/kg)	TN (g/kg)	TP (g/kg)
First	Rich	＞40	＞2.00	＞1.0
Second	Richer	[30, 40]	[1.50, 2.00]	[0.8, 1.0]
Third	Medium	[20, 30]	[1.00, 1.50]	[0.6, 0.8]
Fourth	Lack	[10, 20]	[0.75, 1.00]	[0.4, 0.6]
Fifth	Lesser	[6, 10]	[0.50, 0.75]	[0.2, 0.4]
Sixth	Less	[0, 6]	[0.00, 0.50]	[0.0, 0.2]

Table 3. Optimum semi-variance function model and parameters of soil nutrients.

Soil properties	Fitted model	C_0	C_0+C	C_0/C_0+C (%)	A(m)	R^2	RSS
SOC	Exponential	0.3980	0.81	49.14	51850	0.926	5.933×10^{-3}
TN	Exponential	0.03066	0.06142	49.92	49450	0.844	7.125×10^{-5}
TP	Gaussian	0.013	0.436	2.98	80890	0.987	3.032×10^{-4}
C/N	Exponential	0.0056	0.0952	5.88	990	0.106	6.868×10^{-4}
C/P	Gaussian	0.1780	1.2880	13.82	60360	0.991	3.53×10^{-3}
N/P	Gaussian	0.139	1.1430	12.16	57020	0.993	2.613×10^{-3}

Notes: C_0: nugget, C_0+C: sill, C_0/(C_0+C): nugget/still, A (m): range, RSS: residual sum of squares.

national average could be explained by favorable conditions for organic matter decomposition such as abundant water sources and suitable soil hydrothermal conditions in Xining. These factors contributed to the accumulation of carbon and nitrogen nutrients in the soil, making it relatively fertile. Additionally, applying nitrogen-based fertilizers in agricultural production might have contributed to the moderate TN content [25]. The high content of TP in the soil could be attributed to the intensive use of phosphorus fertilizers in the study area [26]. However, the alkaline nature of the soil and the presence of carbonate in calcareous soil could lead to a strong fixation of phosphorus, resulting in a high content of TP [27], which suggested that phosphorus fertilizers applied in the region might not be fully available to plants, and appropriate measures should be taken to improve phosphorus availability [28].

Spatial structure analysis

Geostatistical analysis using GS+ software was conducted to investigate the spatial characteristics of SOC, TN, TP, and their ecological stoichiometric ratios in cultivated soil in Xining. The results were presented in Table 3. The fitting models for SOC, TN, and C/N in cultivated soil were found to be exponential models, while Gaussian models provided the best fit for other indicators. The fitting degrees, as indicated by the R^2 values, were generally good, except for soil C/N which had a lower reasonable degree. SOC, TP, C/P, and N/P exhibited high fitting degrees with values above 0.885, suggesting an excellent fit. The spatial autocorrelation analysis revealed that SOC, TN, and TP exhibited strong spatial autocorrelation within relatively small ranges of 51,850, 49,450, and 80,890 meters, respectively. However, their spatial continuity was poor, indicating discontinuity in their distribution. On the other hand, the spatial continuity of C/N, C/P, and N/P was also poor, with range values of 990, 60,360, and 57,020 meters, respectively, suggesting limited spatial consistency in the distribution of these ratios in Xining soil. The results presented in Table 3 demonstrated the order of the bullion effect for soil indexes as TN > SOC > C/P > N/P > C/N > TP. Except for the block-based ratio of TN and SOC, the bullion effect for other indexes was less than 25%. The results showed that the carbon to phosphorus, nitrogen to phosphorus, carbon to nitrogen and total phosphorus had strong spatial correlation. These indices were mainly affected by structural factors such as climate and terrain, with a relatively weak impact from random factors (e.g., human activities). The bullion effects of TN and SOC were 49.92% and 49.14%, respectively, indicating that the spatial variations of TN and SOC in the soil were mainly attributed to random and structural factors that contributed to a moderate spatial correlation in TN and SOC distribution. The study found strong spatial correlations among soil C/N, C/P, N/P, and TP, which indicated that the spatial distribution of these nutrients was primarily influenced by structural factors such as climate and terrain [29]. The positive correlation between SOC and TN and SOC and ecological stoichiometric ratios highlighted the important role of OC as a nutrient source and its influence on soil fertility and the C cycle. TN was positively correlated with C/P and N/P, and negatively correlated with TP, indicating that the difference of TN and TP contents would affect soil fertility and plant growth. The interactions between C, N, and P ecological stoichiometric characteristics collectively affected soil fertility and nutrient availability. The stoichiometric ratios provided insights into nutrient imbalances and could guide nutrient management practices in cultivated land [30, 31].

Spatial autocorrelation analysis

Spatial autocorrelation analysis of soil nutrients and ecological stoichiometric ratios in cultivated land in Xining was conducted by using GeoDa software. The results revealed positive global Moran's I values for SOC, TN, and TP (Figure 2), which were mainly distributed in the first and third quadrants, indicating a clustering pattern of "high-high" and "low-low" for these soil nutrients. The analysis demonstrated that the spatial distribution of SOC, TN, and TP in cultivated land exhibited adjacent characteristics in areas with high and low values, which suggested that certain regions within Xining had consistently high or low levels of these soil nutrients. Furthermore, the global Moran's I of the ecological stoichiometric ratios of soil nutrients in cultivated land was also positive with a similar distribution pattern in the first and third quadrants, which indicated that the ecological stoichiometric ratios exhibited adjacent characteristics in the study area's low-value and high-value regions.

Spatial distribution pattern

By using the ordinary Kriging method in the statistical analysis module of ArcGIS software to carry out spatial interpolation, the spatial variation characteristics of cultivated soil in Xining were directly captured. The resulting horizontal spatial distribution maps of SOC, TP, TN, C/N, C/P, and N/P in the 0 - 20 cm soil layer were shown in Figure 3. The spatial distribution pattern of soil nutrients and ecological stoichiometric ratios exhibited noticeable variations across the study area. SOC displayed a bipolar distribution trend with slightly higher values in the north and south and lower values in the central region. TN followed a similar distribution trend to SOC although the higher values were not as widespread. The southern region exhibited higher TP content, while the northern region generally had lower TP levels. Moreover, the soil ecological stoichiometric ratio of cultivated land showed a gradual increase

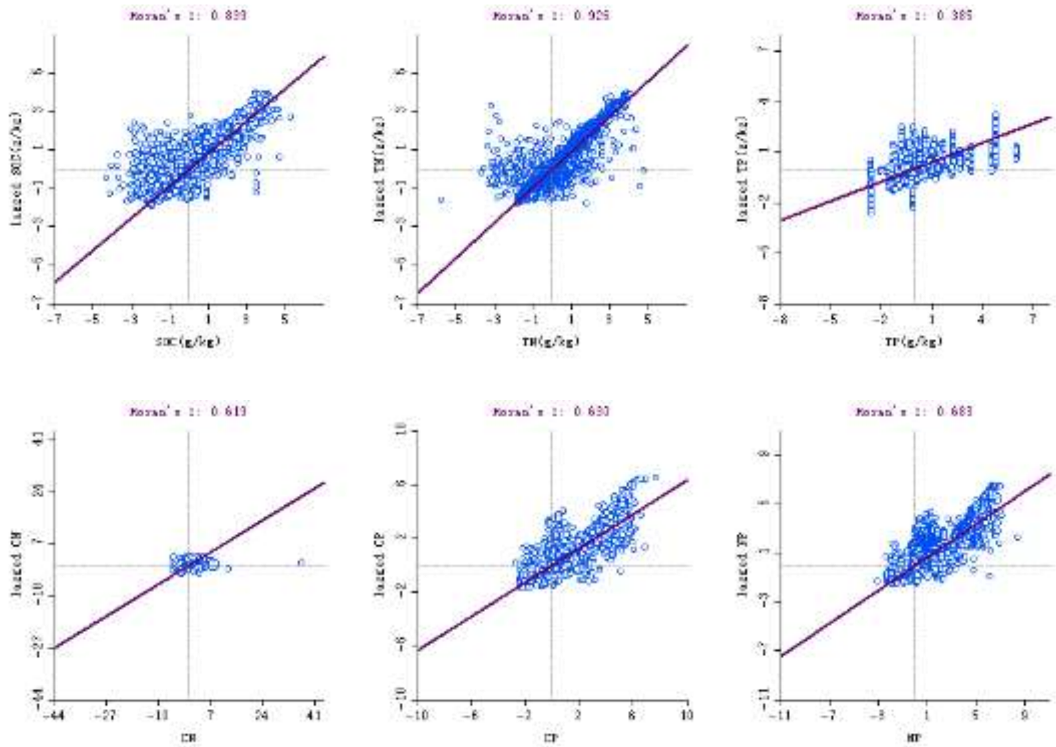

Figure 2. Scatterplot of the global Moran's I of soil nutrients.

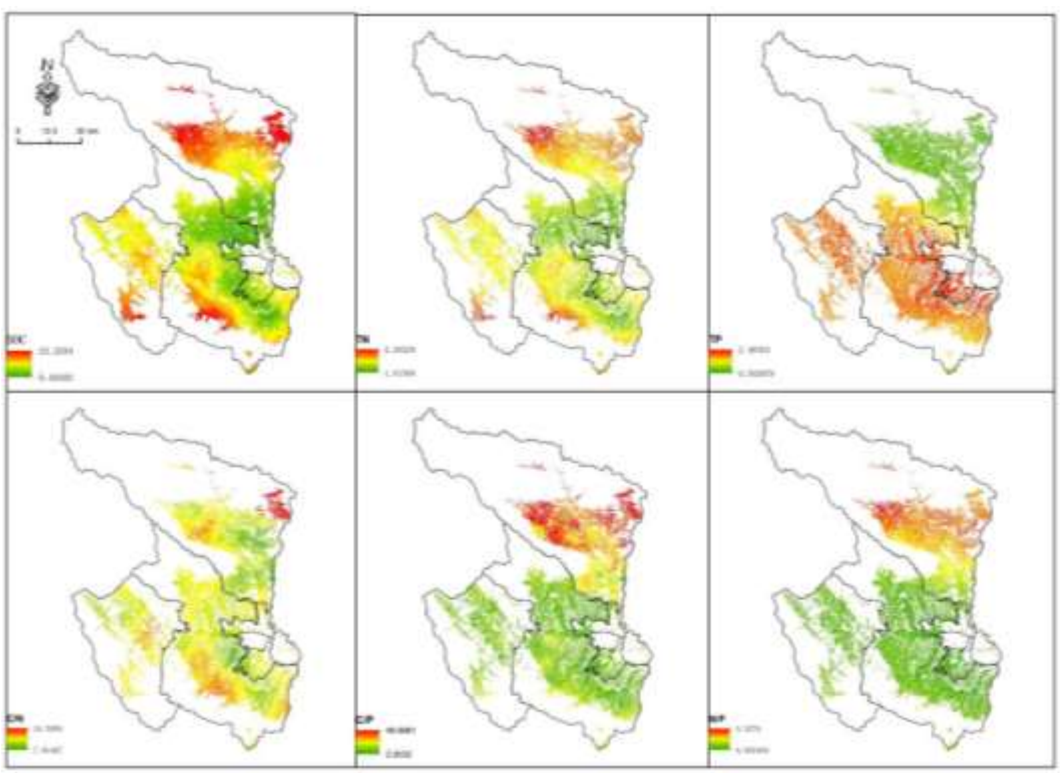

Figure 3. Spatial distribution characteristics of soil nutrient indexes.

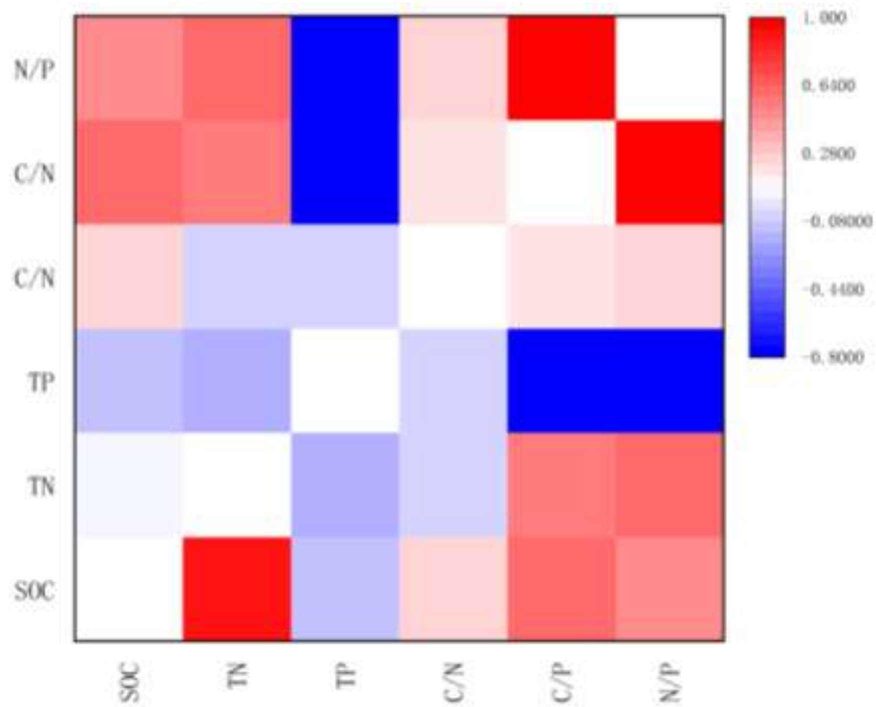

Figure 4. Correlation analysis between SOC, TN, TP, and ecological stoichiometric characteristics.

from south to north, the distribution trend was consistent with TN. These findings demonstrated an overall difference from south to north with a gradual increase from south to north, consistent with the TN distribution trend and provided valuable insights into the spatial patterns of soil nutrients and ecological stoichiometry in Xining, highlighting distinct regional variations and the importance of considering both spatial and stoichiometric characteristics for effective land management. Soil properties, land use practices, and environmental conditions could influence these spatial distribution patterns [32-34]. The variations observed highlighted the importance of considering spatial heterogeneity when implementing soil nutrient management strategies in the study area [35].

Relationship between soil stoichiometric ratio and soil C, N, and P

The results of the Pearson linear correlation analysis conducted using SPSS software were presented in Figure 4. SOC showed a significant positive correlation with TN, C/N, C/P, and N/P (P < 0.01). SOC also had a significant negative correlation with TP at a confidence level (P < 0.05). The results suggested that SOC, derived from plant and animal residues and soil parent material, was crucial in supplementing other nutrient indexes, leading to significant correlations. Furthermore, soil TN exhibited a significant positive correlation with C/P and N/P (P < 0.01), while it showed a significant negative correlation with TP (P < 0.01). Similarly, soil TP was negatively correlated with C/P and N/P (P < 0.01). These findings indicated that TN and TP content variations could inhibit soil fertility, influencing vegetation growth and development. Similarly, the ecological stoichiometric characteristics of C/N, C/P, and N/P all demonstrated significant positive correlations (P < 0.01), which suggested that the interplay between C, N, and P ratios collectively influenced and restricted soil fertility and plant growth. By presenting these correlation results, we could observe the interrelationships between soil nutrient parameters and their implications for soil fertility and plant development.

Limitations of the study

This study focused only on the cultivated land of Xining, Qinghai, China, which might not comprehensively represent the nutrient characteristics and spatial variability of other land types or regions. The findings might not apply to different soil types or land uses. Furthermore, the analysis was limited to surface soil (0 - 20 cm) and did not consider deeper soil layers. Nutrient distribution patterns and variability at deeper depths could provide additional insights into soil fertility and nutrient availability. Also, the study did not investigate the underlying causes and mechanisms driving the observed spatial patterns and correlations. Further research is needed to explore the factors such as soil hydrothermal conditions, vegetation cover, land management practices, and agricultural activities contributing to nutrient variability in the study area [36]. Moreover, the study might have yet to capture temporal variability in soil nutrient levels and distribution patterns. Soil nutrient dynamics could vary throughout the year due to seasonal changes, crop rotation, and management practices [37]. Long-term monitoring and analysis would provide a more comprehensive understanding of nutrient variations [38].

Prospects and recommendations

Conducting detailed studies to understand the factors driving the observed spatial patterns and correlations of this study would provide valuable insights, which could involve investigating the effects of specific environmental factors, land management practices, and agricultural activities on soil nutrient distribution and stoichiometric ratios [39-41]. Extending the analysis to include a larger spatial scale and different land uses would help understand regional soil nutrient variability patterns and would be beneficial to assess nutrient characteristics in various land types including croplands, grasslands, forests, and wetlands to capture the full range of ecological and agricultural systems [42]. Implementing long-term monitoring programs to track changes in soil nutrient levels and distribution patterns over time would provide valuable data for sustainable land management and would help identify trends, assess the impacts of land use practices, and guide nutrient management strategies. Based on the findings of this study, there is a need to develop targeted nutrient management strategies to address nutrient imbalances and optimize nutrient availability in the study area. These strategies should consider specific soil properties, crop requirements, and environmental conditions to enhance soil fertility and promote sustainable agricultural practices [43]. Involving local farmers, land managers, and policymakers in the research process and disseminating findings could facilitate the adoption of appropriate nutrient management practices. Collaboration with stakeholders would ensure that research outcomes were practical, relevant, and effectively implemented. By addressing these limitations and pursuing the recommended prospects, a more comprehensive understanding of soil nutrient variability and management strategies could be achieved, leading to improved soil fertility and sustainable land use practices in the study area and beyond.

Conclusion

This study provided crucial insights into soil nutrient characterization and distribution in Xining, Qinghai, China. C, N, and P emerged as key indicators of soil nutrient status. The results revealed that N primarily limited the stoichiometric ecological characteristics of cultivated soil, as indicated by its smaller variation coefficient than other indices. The spatial variation of TN and SOC resulted from random and structural factors, while other soil indices were influenced mainly by structural factors. Spatial autocorrelation analysis indicated clustering patterns for SOC, TN, TP, and ecological stoichiometric ratios, showing a north-south differentiation. The study highlighted the scarcity of SOC and TN resources in Xining. Effective land management practices tailored to local conditions were essential for ecosystem protection. Recommended measures based on spatial distribution patterns included air sowing, sealing, soil and water conservation, grazing prohibition, management, and rotational practices in suitable grassland areas. This study contributed valuable information for understanding soil nutrient variation and distribution, emphasizing the importance of sustainable land management and targeted interventions to preserve and enhance soil nutrient resources in the region.

References

1. Elser JJ, Sterner RW, Gorokhova E, Fagan WF, Markow TA, Cotner JB, *et al*. 2000. Biological stoichiometry from genes to ecosystems. Ecol Letters. 3(6):540–550.
2. Elser, O'Brien, Dobberfuhl, Dowling. 2000. The evolution of ecosystem processes: growth rate and elemental stoichiometry of a key herbivore in temperate and arctic habitats. J Evolution Biol. 13(5):845–853.
3. Xu Z, Yu G, Zhang X, He N, Wang Q, Wang S, *et al*. 2017. Soil enzyme activity and stoichiometry in forest ecosystems along the North-South Transect in eastern China (NSTEC). Soil Biol Biochem. 104:152–163.
4. Xu X, Thornton PE, Post WM. 2013. A global analysis of soil microbial biomass carbon, nitrogen and phosphorus in terrestrial ecosystems: Global soil microbial biomass C, N and P. Glob Ecol Biogeogr. 22(6):737–749.
5. Amaral F, Abelho M. 2016. Effects of agricultural practices on soil and microbial biomass carbon, nitrogen and phosphorus content: a preliminary case study. Web Ecol. 16(1):3–5.
6. Asada K, Kanda T, Yamashita N, Asano M, Eguchi S. 2022. Interpreting stoichiometric homeostasis and flexibility of soil microbial biomass carbon, nitrogen, and phosphorus. Ecological Modelling. 470:110018.
7. Albornoz FE, Prober SM, Ryan MH, Standish RJ. 2022. Ecological interactions among microbial functional guilds in the plant-soil system and implications for ecosystem function. Plant Soil. 476(1–2):301–313.
8. Sun K, Cai J, Liu X, Yang L, Li H, Wang G, *et al*. 2023. Effects of nitrogen and phosphorus supply levels and ratios on soil microbial diversity-ecosystem multifunctionality relationships in a coastal nontidal wetland. Sci Total Environ. 874:162472.
9. Cao Y, Chen Y. 2017. Coupling of plant and soil C:N:P stoichiometry in black locust (*Robinia pseudoacacia*) plantations on the Loess Plateau, China. Trees. 31(5):1559–1570.
10. Li T, Zeng J, He B, Chen Z. 2021. Changes in soil C, N, and P concentrations and stoichiometry in Karst Trough Valley area under ecological restoration: the role of slope aspect, land use, and soil depth. Forests. 12(2):144.
11. Reza SK, Baruah U, Sarkar D, Singh SK. 2016. Spatial variability of soil properties using geostatistical method: a case study of lower Brahmaputra plains, India. Arab J Geosci. 9(6):446.
12. Błońska E, Piaszczyk W, Lasota J. 2023. Patterns and driving factors of ecological stoichiometry in system of deadwood and soil in mountains forest ecosystem. Sci Rep. 13(1):5676.
13. Zhang Z, Xue Z, Lyu X, Tong S, Jiang M. 2017. Scaling of soil carbon, nitrogen, phosphorus and C:N:P ratio patterns in peatlands of China. Chin Geogr Sci. 27(4):507–515.
14. Du H. 2022. Spatial differentiation of ecological stoichiometry of nitrogen and phosphorus in mollic epipedon of China. Int J Chem Eng. 2022:1-8.
15. Zhang P, Liu G, Yu Y. 2023. Ecological stoichiometry of soil carbon, nitrogen and phosphorus in reclaimed farmland in coal mining subsidence area. J Soil Sci Plant Nutr. 23(2):2498–2511.
16. Dolobeshkin EV, Gumbarov AD, Bandurin MA. 2021. Monitoring of arable land fertility based on agrochemical analysis and dynamics of changes in soil organic matter reserves. IOP Conf Ser: Earth Environ Sci. 666(5):052064.
17. Jia Z, Zhang J, Ding S, Feng S, Xiong X, Liang G .2016. Based on GIS and statistical HuangFan District spatial variation of soil phosphorus - in Zhoukou, for example. J Appl Ecol. 27(04): 1211-1220.
18. Bremner JM. 1960. Determination of nitrogen in soil by the Kjeldahl method. J Agric Sci. 55(1):11–33.
19. Kowalenko CG, Babuin D. 2007. Interference problems with phosphoantimonylmolybdenum colorimetric measurement of phosphorus in soil and plant materials. Commun Soil Sci Plant Anal. 38(9-10):1299–1316.
20. Yao X, Yu K, Deng Y, Zeng Q, Lai Z, Liu J. 2019. Spatial distribution of soil organic carbon stocks in Masson pine (*Pinus massoniana*) forests in subtropical China. CATENA. 178:189–198.
21. Eljebri S, Mounir M, Faroukh AT, Zouahri A, Tellal R. 2019. Application of geostatistical methods for the spatial distribution of soils in the irrigated plain of Doukkala, Morocco. Model Earth Syst Environ. 5(2):669–687.
22. Nourzadeh M, Mahdian MH, Malakouti MJ, Khavazi K. 2012. Investigation and prediction spatial variability in chemical properties of agricultural soil using geostatistics. Arch Agron Soil Sci. 58(5):461–475.
23. Pinto EP, Pires MA, Matos RS, Zamora RRM, Menezes RP, Araújo RS, et al. 2021. Lacunarity exponent and Moran index: A complementary methodology to analyze AFM images and its application to chitosan films. Physica A: Statistical Mechanics and its Applications. 581:126192.
24. Zhang Y, Shangguan Z. 2018. Interaction of soil water storage and stoichiometrical characteristics in the long-term natural vegetation restoration on the Loess Plateau. Ecol Eng. 116:7-13.
25. Harindintwali JD, Zhou J, Muhoza B, Wang F, Herzberger A, Yu X. 2021. Integrated eco-strategies towards sustainable carbon and nitrogen cycling in agriculture. J Environ Manage. 293:112856.
26. Liu Q, Xu H, Yi H. 2021. Impact of fertilizer on crop yield and C:N:P stoichiometry in arid and semi-arid soil. IJERPH. 18(8):4341.
27. Han W, Li Y, Yin H. 2021. The Influence of mechanical composition and mineral composition of calcareous soil on slope farmland on phosphorus fixation. Appl Sci. 11(9):3731.

28. Yang H, Feng J, Weih M, Meng Y, Li Y, Zhai S, *et al.* 2020. Yield reduction of direct-seeded rice under returned straw can be mitigated by appropriate water management improving soil phosphorus availability. Crop Pasture Sci. 71(2):134.
29. Hua D, Li J, Xu Y. 2020. Influence of topographical factors on spatial distribution characteristics of soil nutrients in Qinba Mountain area. IOP Conf Ser: Earth Environ Sci. 558(3):032025.
30. Zhang J, Liu Y, Zheng T, Zhao X, Liu H, Zhang Y. 2021. Nutrient and stoichiometric characteristics of aggregates in a sloping farmland area under different tillage practices. Sustainability. 13(2):890.
31. Li L, Li X, Liu B, Lei J, Yue Z, Li C. 2020. Imbalanced stoichiometric patterns in foliar nutrient resorption response to N and P addition in grazing alpine grassland. Acta Oecologica. 102:103505.
32. Niu X, Liu C, Jia X, Zhu J. 2021. Changing soil organic carbon with land use and management practices in a thousand-year cultivation region. Agric Ecosyst Environ. 322:107639.
33. De Godoy Fernandes PH, De Souza ALT, Tanaka MO, Sebastiani R. 2021. Decomposition and stabilization of organic matter in an old-growth tropical riparian forest: effects of soil properties and vegetation structure. For Ecosyst. 8(1):13.
34. Jakšić S, Ninkov J, Milić S, Vasin J, Živanov M, Jakšić D, *et al*. 2021. Influence of slope gradient and aspect on soil organic carbon content in the region of Niš, Serbia. Sustainability. 13(15):8332.
35. Gao X, Xiao Y, Deng L, Li Q, Wang C, Li B, *et al*. 2019. Spatial variability of soil total nitrogen, phosphorus and potassium in Renshou County of Sichuan Basin, China. J Integr Agric. 18(2):279–289.
36. Gomez Gimenez M, Della Peruta R, De Jong R, Keller A, Schaepman ME. 2016. Spatial differentiation of arable land and permanent grassland to improve a land management model for nutrient balancing. IEEE J Sel Top Appl Earth Observations Remote Sensing. 9(12):5655–5665.
37. Bimantara PO, Kimani SM, Kautsar V, Egashira H, Kikuchi S, Tawaraya K, *et al*. 2022. Seasonal changes in soil properties caused by slash and burn agriculture practice in a humid temperate region of northeast Japan. Soil Sci Plant Nutr. 68(1):81–87.
38. Nerger R, Klüver K, Cordsen E, Fohrer N. 2020. Intensive long-term monitoring of soil organic carbon and nutrients in Northern Germany. Nutr Cycl Agroecosyst. 116(1):57–69.
39. Zhu Q, Liao K, Lai X, Lv L. 2021. Scale-dependent effects of environmental factors on soil organic carbon, soil nutrients and stoichiometry under two contrasting land-use types. Soil Use Manage. 37(2):243–256.
40. Liliana VJ, Gutierrez Boem F, Garcia F, Rubio G. 2020. Long-term fertilization does not affect soil carbon/nitrogen/sulfur ratios or the proportion between labile and nonlabile fractions in Mollisols. Soil Sci Soc Am j. 84(3):798–810.
41. Zhang J, Yang X, Song Y, Liu H, Wang G, Xue S, *et al*. 2020. Revealing the nutrient limitation and cycling for microbes under forest management practices in the Loess Plateau – Ecological stoichiometry. Geoderma. 361:114108.
42. Bader C, Müller M, Schulin R, Leifeld J. 2018. Peat decomposability in managed organic soils in relation to land use, organic matter composition and temperature. Biogeosciences. 15(3):703–719.
43. Lago-Olveira S, El-Areed SRM, Moreira MT, González-García S. 2023. Improving environmental sustainability of agriculture in Egypt through a life-cycle perspective. Sci. Total Environ. 890:164335