STUDY ON THE SPATIOTEMPORAL VARIABILITY OF SOIL NUTRIENTS AND THE FACTORS AFFECTING THEM: ECOLOGICALLY FRAGILE AREAS OF THE LOESS PLATEAU, CHINA

XIA, L. H.[1] – LI, L.[2] – LIU, J.[3*]

[1]*Institute of Land Engineering and Technology, Shaanxi Provincial Land Engineering Construction Group Co., Ltd., Xi'an 710075, China*
(e-mail: 18092729601@163.com)

[2]*Agricultural Inspection and Testing Center of Shaanxi Province, Xi'an 710014, China*
(e-mail: 576427877@qq.com)

[3]*College of Natural Resources and Environment, Northwest Agriculture and Forestry University, Yangling 712100, China*

**Corresponding author*
e-mail: liujing@nwafu.edu.cn

(Received 18th Mar 2022; accepted 11th Jul 2022)

Abstract. The spatial variability of soil nutrients can improve the yield per unit area of food crops and protect the agricultural ecological environment. Geostatistics and geographic information system (GIS) technology were applied to analyse the spatiotemporal variability and main influencing factors in soil organic matter (SOM) and soil total nitrogen (STN) in ecologically fragile regions of the Loess Plateau, China. The results showed that the mean SOM and STN contents significantly increased in the past 40 years. Compared to the 1980 data, both SOM and STN global Moran's I indices are lower, with less spatial structure and an increased role for stochastic factors. The centre of gravity of soil nutrients in the study area mainly to the south-east, a reduction in the area of the ellipse and a tendency to concentrate the spatial distribution of nutrients. And it was concluded that the variation in nutrients was mainly influenced by fertiliser management practices. Therefore, a long time series of soil nutrient study is of great research value to clarify the soil nutrient status of the study area and to improve the efficiency of arable land use, as well as providing a theoretical basis for precision agriculture.
Keywords: *cultivated land, geostatistics, geographic information system, centre of gravity*

Introduction

Cultivated land soil nutrients are essential nutrients for plant growth and development and are important for ensuring the quality of cultivated land and grain yield (Keskinen et al., 2019). Soil organic matter (SOM) and soil total nitrogen (STN) are important factors that determine soil fertility, agricultural product yield and quality. Due to the combined effects of soil type, topography and human activities, soil nutrients have a high degree of spatial variability (Huang et al., 2012; Wang et al., 2009). Studying the temporal and spatial variability laws of soil nutrients has important theoretical and practical guiding significance for precise nutrient management and the promotion of farmland ecological and economic benefits.

In the early 2000s, domestic scholars began to use geostatistics combined with GIS technology to explore the spatiotemporal variability laws of soil characteristics (Xu et al., 2004). Some studies have been conducted at different spatial scales, such as the scale of farmland or paddy field (Duan et al., 2020; Liu et al., 2004, 2014), the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

watershed scale (Wei et al., 2008), and county or larger scales (Chen et al., 2016; Hu et al., 2014; Osat et al., 2016). Recently, an increasing number of studies have focused on the spatiotemporal variability of soil nutrients, e.g., for an agricultural county located in the southern Loess Plateau, China (Chen et al., 2016), five subcatchments in the Ping Gu intermontane basin in Beijing (Zhuo et al., 2019), and the hilly area of the Taihu Lake basin of China (Liao et al., 2017). These studies have provided more in-depth descriptions of the spatiotemporal change process of soil nutrients.

With its advantage of interpolation, the geostatistics method has been widely used in the study of soil spatial variability (Aghasi et al., 2017; Foroughifar et al., 2013). Most scholars have successfully used spatial autocorrelation analysis (Blanchet et al., 2017) and semivariogram analysis (Liu et al., 2013) to describe the spatial variability of soils. However, to date, most studies on the spatiotemporal variability of soil nutrients have used only two phases of data (Guo et al., 2001; Chuai et al., 2012; Wang et al., 2012), and there have been few reports comparing three phases of data with a longer time span. In addition, current studies generally use semivariograms to quantitatively describe spatial characteristics (Hoffmann et al., 2014), and few studies have analysed the spatiotemporal variability laws of soil nutrients from different perspectives. This limited approach will result in researchers not fully understanding the laws of spatiotemporal variability of soil nutrients, which will introduce uncertainty to the formulation of regional soil management measures.

Therefore, this study selects Baishui County, which is a typical region ecologically fragile regions of the Loess Plateau, China, as the research area. The SOM and STN contents in 1980, 2007 and 2020 are employed as the research objects. This study is based on geostatistics and Geographic Information System (GIS) technology, using spatial autocorrelation and Centre of gravity models to reveal the dynamics of the spatial distribution of SOM and STN, and to explore the main factors of nutrient content variation.

The main objectives of this study are (1) to characterise and compare the spatial variability of farmland SOM and STN in the dry plateau area of Weibei; (2) to quantify their spatial distributions and temporal changes; and (3) to clarify the main factors influencing the spatial variability of SOM and STN. Under the current situation of uneven distribution of nutrients in cultivated land, improve the use efficiency of low-nutrient cultivated land, protect the use efficiency of high-nutrient cultivated land, and provide a realistic basis for precision agriculture.

Materials and methods

Description of the study area

Baishui County is located in the transition zone between the Guanzhong Plain and the North Shaanxi Plateau, China, between 109°16′-109°45′ E and 35°4′-35°27′ N (*Fig. 1*). The total area of the district is 986.6 km^2, of which the cultivated area is 525.4 km^2, accounting for 53.2% of the total area. The area is high in the northwest and low in the southeast, with an altitude between 440 m and 1500 m. Baishui County has a temperate continental monsoon climate, an average annual temperature of 11.4 °C, and an average annual precipitation of 577.8 mm. Due to the cutting of each branch gully of the Luo River and Baishui River, the study area has criss-crossed gullies and broken topography. The dominant soil types include loessial soil and cumulic cinnamon soil.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Data collection

Soil data, including the SOM and STN utilised in this study, were obtained from three soil sampling surveys: The second national soil survey in 1980, the 2007 survey of cultivated land quality in Shaanxi Province, and the 2020 survey of cultivated land quality in Shaanxi Province. The three datasets were named “Soil attribute-1980”, “Soil attribute-2007” and “Soil attribute-2020”. The average temperature and climate data were obtained from the Resource and Environment Science Data Center of CAS with a spatial resolution of 1 km×1 km and time taken from 2020.

In the 1980 soil survey, 2007 soil survey and 2020 soil survey, 154 farmland topsoil samples, 156 farmland topsoil samples and 73 farmland topsoil samples (0-20 cm), respectively, were collected from May to June (dry season) after the summer grain harvest. The sampling location was determined by the main topography, soil type and distribution of the sample plot, and the Global Positioning System (GPS) was employed to record the points while avoiding roads, residential areas and other easily disturbed areas when sampling. At each sampling point, 6-8 points were randomly selected and mixed into a soil sample. The collected soil samples were ventilated and dried, and the impurities were removed and finely ground for determination of the SOM and STN content.

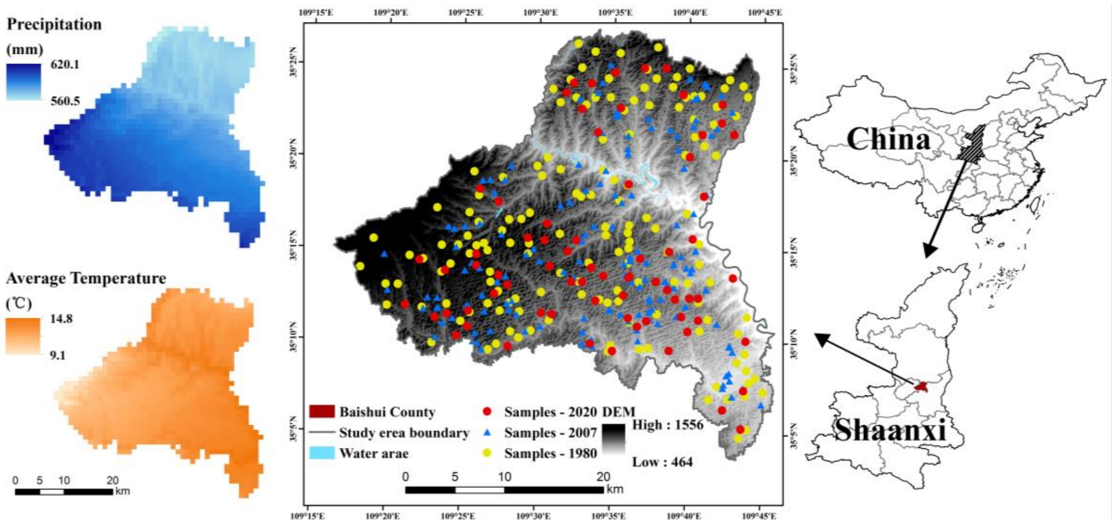

Figure 1. *Map of the soil sample distribution*

In the 1980 soil survey, the SOM content of all 154 soil samples was obtained by the $K_2Cr_2O_7$-H_2SO_4 oxidation method, and the STN of 152 samples was measured by the Kjeldahl method (Agricultural Chemistry Committee of China, 1983). According to this method, the SOM and STN of the soil samples from the 2007 and 2020 surveys were analysed. The sampling point distribution is shown in *Figure 1*.

Data processing and analysis

Data processing

The existence of outliers and the non-normal distribution of data can easily cause the proportional effect of the variogram and increase the estimation error. In this study, we applied the A±3s method to eliminate outliers, where A denotes the average value for

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each variable and s is its standard deviation (Liu et al., 2009). Data that exceed the value (A±3s) were obtained from the raw dataset; we replaced them with the maximum or minimal value of the dataset without outliers. In SPSS 20.0, a one-sample normality test (K-S test) was performed on the sample data after removing outliers. The R-language was applied to perform Box-Cox conversion of the data that did not conform to a normal distribution. The converted data passed the K-S test. The specific parameters are shown in *Table 1*.

Table 1. *Soil nutrient description statistics of cultivated land in three periods (g kg^{-1})*

Variables	Samples	Mean ± standard deviation	Minimum	Maximum	Coefficient of variation (%)	$P_{k\text{-}s}$
SOM-1980	154	10.53 ± 2.36	4.71	17.74	22.4	0.14*
STN-1980	152	0.60 ± 0.09	0.32	1.05	15.6	0.40*
SOM-2007	156	12.49 ± 5.01	2.60	26.40	38.47	0.78*
STN-2007	156	0.64 ± 0.37	0.18	1.11	37.16	0.74*
SOM-2020	73	15.42 ± 4.23	7.96	27.53	27.23	0.43*
STN-2020	73	0.73 ± 0.19	0.38	1.32	27.26	0.74*

Level of significance: * P < 0.05

In this study, we compiled descriptive statistics of soil nutrients using Excel 2016 and performed Kriging interpolation to estimate the spatial distribution and spatial changes of SOM and STN in different years. We calculated the global Moran's I values using ArcGIS 10.6. Sample-independent t tests and a correlation analysis were carried out using SPSS 16.0. A geostatistics analysis was performed by GS + 9.0.

Spatial autocorrelation analysis

Spatial autocorrelation refers to the potential dependence of the same variable at different spatial positions and is a statistical method used to test the correlation between adjacent positions of the studied variables in space (Gelaw et al., 2014). When judging the spatial autocorrelation, the global Moran's I index is often employed to reflect the spatial autocorrelation of the study area. The calculation formula is as follows:

$$I = \frac{n}{S_0} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad \text{(Eq.1)}$$

where n is the total number of samples, Wij is the symmetric binomial spatial weight matrix, and X_i and X_j are the measured values of spatial variable X at different positions i and j, respectively. The value of I ranges from -1 to 1. When I > 0, it means that there is a positive spatial correlation, and larger values indicate stronger spatial correlation. When I < 0, it means there is a negative spatial correlation, and smaller values indicate more obvious spatial differences (Darand et al., 2017).

Semivariogram analysis

The semivariogram is a commonly used function in geostatistical analysis. It can accurately describe the characteristics of the spatial variability of a study area based on known sample points. The semivariogram can reveal the internal relations of variables,

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and the relationship between spatial points in different distances and different directions can be used to obtain the spatial distribution law of variables, which makes the spatial interpolation more accurate (Awais et al., 2017); its calculation formula is as follows:

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

where h is the spatial interval of the sampling points, N (h) is the number of samples with interval distance h, and $Z(x_i)$ and $Z(x_i + h)$ are the measured values of spatial variable Z(x) at the different positions of xi and xi + h, respectively (Balaguer-Beser et al., 2013). There are three important parameters in the semivariogram: the nugget value (C_0), the sill value (C_0 + C) and the range (A). When the step size of h is 0, then r(h) is the nugget value. As the step size of h increases, the semivariogram tends to be in a stable state. At this time, r(h) is the sill value and h is the range (Onyejekwe et al., 2016).

Centre of gravity models and standard deviational ellipse

The centre of gravity model is mostly used to study the process of change in the spatial location of a geographical element in the process of regional development. The model reflects the changing trend of the spatial element through the direction, distance and speed of the centre of gravity migration. This paper uses a centre of gravity model to reveal the spatial aggregation characteristics and trends of soil nutrients. Its calculation formula is as follows:

$$\overline{X} = \sum_{i=1}^{n} M_i X_i / \sum_{i=1}^{n} M_i \quad \text{(Eq.3)}$$

$$\overline{Y} = \sum_{i=1}^{n} M_i X_i / \sum_{i=1}^{n} M_i \quad \text{(Eq.4)}$$

where $\overline{X}$, $\overline{Y}$ are the soil nutrient coordinates at the beginning of the study; M_i is the nutrient content of the ith sample point, g kg^{-1}; X_i, Y_i denote the coordinates of the ith sample point.

The standard deviation ellipse is a visual representation of the state of aggregation of soil nutrients and their tendency to shift, and consists mainly of the angle of rotation θ, the standard deviation along the major axis (long axis) and the standard deviation along the minor axis (short axis). The long half-axis of the ellipse indicates the direction of the soil nutrient distribution and the short half-axis indicates the extent of the soil nutrient distribution. In this study, standard deviation ellipses were constructed to reflect the spatial pattern of soil nutrients on the basis of the centre of gravity model.

Results

Descriptive statistics

The descriptive statistical results of the data after eliminating the outliers in the three periods are summarised in *Table 1*. It can be seen that the average contents of SOM and STN of the cultivated soil in the study area in 1980 were 10.53 g kg^{-1} and 0.60 g kg^{-1}, respectively. In 2007, the average SOM content and STN content in the cultivated soil in the study area were 12.49 g kg^{-1} and 0.64 g kg^{-1}, respectively; in 2020, the corresponding values were 15.42 and 0.73 g kg^{-1}, respectively. Compared with 1980,

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the average SOM content and STN content in 2007 increased by 2.48 g kg^{-1} and 0.04 g kg^{-1}, respectively. From 2007 to 2020, the contents of the two nutrients increased by 2.41 g kg^{-1} and 0.09 g kg^{-1}, respectively. Although the data do not depend on the sample t test, the mean value presents a significant difference (*Table 2*). The coefficient of variability of the soil nutrients in the cultivated land in the study area in the three phases was between 15.6 and 38.47%, which indicated moderate variability.

Table 2. *Significance test of soil nutrients in 1980, 2007 and 2020*

Variables	P		Variables	P
SOM (1980-2007)	0.005**		SOM (2007-2020)	0.002**
STN (1980-2007)	0.03*		STN (2007-2020)	0.021*

Level of significance: * $P < 0.05$; ** $P < 0.01$

Spatial autocorrelation analysis

The spatial statistical results of the soil nutrients of the cultivated land in the three phases are shown in *Table 3*. It can be seen from the table that the global Moran's I index of SOM and STN decreased from 0.41 and 0.44 to 0.26 and 0.17, respectively, from 1980 to 2007. In 2020, the global Moran's I index of SOM and STN were 0.25 and 0.21, respectively. By normalizing the global Moran' s I index, all Z values were greater than 2.56, which indicates that at the current sampling density, the three-stage SOM and STN show a very significant positive spatial correlation at the 0.01 statistic level, and their spatial distribution is characterised by agglomeration. By further comparing the global Moran's I index, the global Moran's I index of SOM and STN in 2007 and 2020 is higher than that of SOM and STN in 1980. This finding shows that SOM and STN in 1980 have stronger spatial dependence and better spatial structure, with weaker random variability.

Geostatistics analysis

The optimal fitting of the theoretical model revealed that SOM-1980, STN-1980, SOM-2020 and STN-2020 fit the exponential model, while SOM-2007 and STN-2007 conform to the linear model. The coefficient of determination (r^2) is between 0.785 and 0.995; the proximity of these values to 1 indicates that the excellent fit of the semivariogram (*Fig. 2*). The parameters of the model are listed in *Table 3* (i.e., nugget, sill and nugget/sill ratio). The nugget/sill ratio of SOM and STN in the three periods ranges from 42.27 to 76.14%, which indicates that the spatial correlation is moderate and the spatial continuity is average. The nugget/sill ratios of SOM and STN in 2007 were 76.14% and 66.56%, respectively, which is higher than in 1980 (SOM with 42.95% and STN with 42.27%). The nugget/sill ratio of SOM and STN in 2020 has not changed substantially from 2007 and is also higher than that in 1980. The strong spatial variability in 2007 and 2020 indicates that they may be affected by more external factors, such as fertilization and irrigation. These results are consistent with the analysis results of the global Moran's I values.

The spatial range of soil SOM and STN in the three periods is 5050 to 17,350 m, which is considerably larger than the average sampling interval (2500-4000 m). This finding shows that the number of sampling points in the three periods is sufficient for analysing the spatial distribution of nutrients on the county scale.

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Table 3. *Semivariance model of soil nutrients in three periods and Moran's I index*

Variables	Model	Nugget (C_0)	Sill (C_0 + C)	Nugget/sill (%)	Range (m)	R^2	Moran's I	Z
SOM-1980	E	0.1188	0.2766	42.95	6470	0.995	0.41**	32.36
STN-1980	E	0.0238	0.0563	42.27	5050	0.957	0.44**	35.48
SOM-2007	L	2.129	2.796	76.14	17350	0.867	0.26**	24.89
STN-2007	L	0.0547	0.0823	66.56	16280	0.816	0.17**	19.06
SOM-2020	E	0.0748	0.1315	56.88	9950	0.824	0.25**	24.96
STN-2020	E	0.0304	0.0638	47.64	11800	0.785	0.21**	17.56

E is the exponential model, L is the linear model
Level of significance: ** P < 0.01

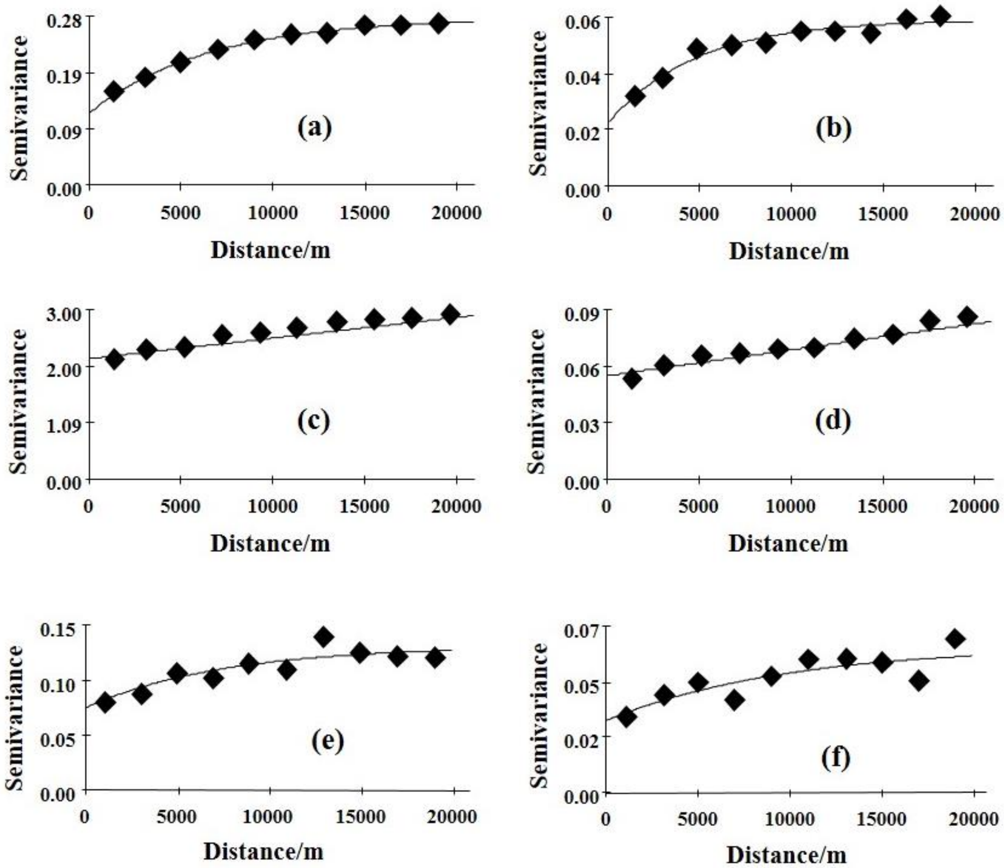

Figure 2. *Fitted models of SOM and STN in 1980 (a-b), 2007 (c-d), and 2020 (e-f). SOM: soil organic matter; STN: soil total nitrogen*

Spatial distribution characteristics

The spatial interpolation results of soil SOM and STN in the three periods are shown in *Figure 3*. It can be seen from the figure that the spatial distribution characteristics of soil SOM content in the three phases are similar: the distribution characteristics are low in the northwest and high in the southeast (*Fig. 3a-c*). In 1980, the SOM content in the study area was at a low-medium level, while the content in the central region was relatively low. The area with a content greater than 13 g kg^{-1} was only 1.47 km^2. In

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2007, the soil SOM content in the study area increased steadily, and the area with a content greater than 13 g kg^{-1} increased to 228.06 km^2. In 2020, the SOM content increased significantly, which shows high spatial distribution characteristics in the east and low spatial distribution characteristics in the west. Only 78.98 km^2 remained in the study area where the SOM content was less than 13 g kg^{-1} (*Table A1* in the *Appendix*).

As SOM and STN have a significant positive correlation, they show similar spatial distribution characteristics (*Fig. 3d-f*). In 1980, the content of STN was low and mostly concentrated from 0.55 to 0.65 g kg^{-1}. In 2007, the STN content was distributed in blocks, and the content in some areas increased significantly, mainly in the southern part of the study area. In 2020, the STN content was at a relatively high level, with a content greater than 0.75 g kg^{-1} concentrated in the southeast part of the study area, with an area of 165.37 km^2, which accounts for 30.88% of the total study area (*Table A2*).

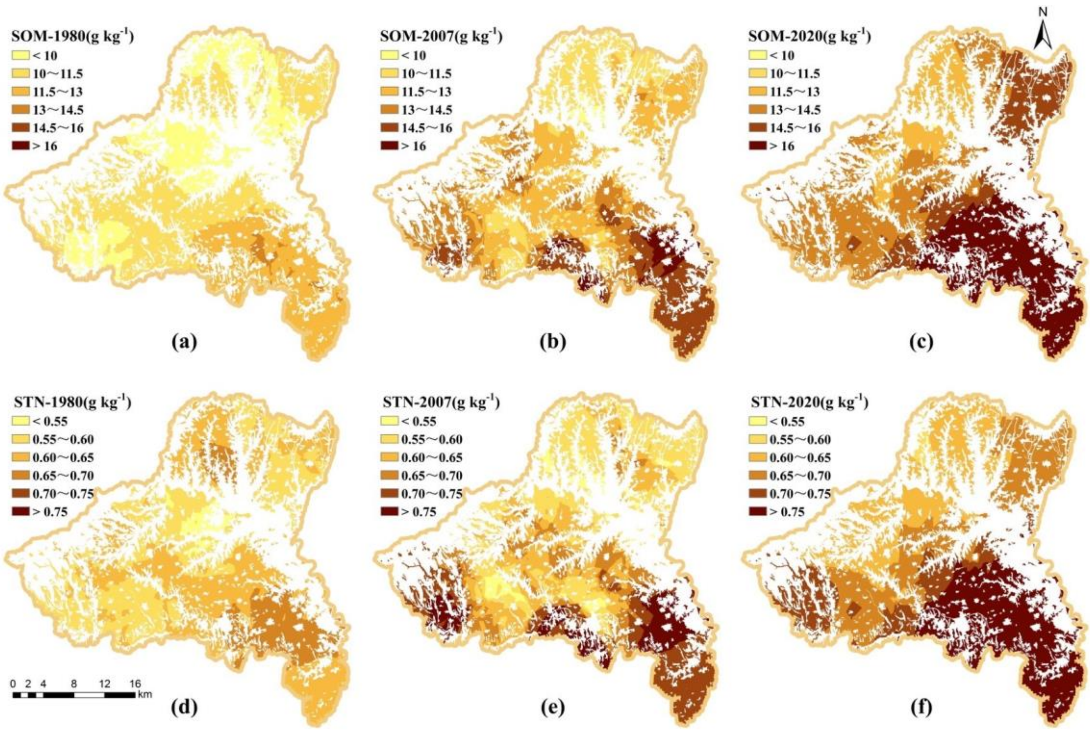

Figure 3. *Distribution map of SOM and STN in three different periods (a – f). SOM: soil organic matter; STN: soil total nitrogen*

Temporal and spatial characteristics

We employed the ArcGIS vector mask extraction tool and raster calculator to calculate the rate of change according to the formula "(x2007-x1980)/x1980 and (x2020-x2007)/x2007". The results are shown in *Figure 4*.

From 1980 to 2007, the soil SOM and STN content in the study area showed an overall increasing trend, but the degree of change was different in different regions. The area where the SOM increased accounted for 94.97% of the study area, with an area of 499.07 km^2. Compared with SOM, the increase in STN was relatively weak, and the increase was mainly concentrated in the range 0-15%, which accounts for 44.55% of the total area. The data reveals that 31.14% of the cultivated land exhibits a decrease in STN content (*Table A3*).

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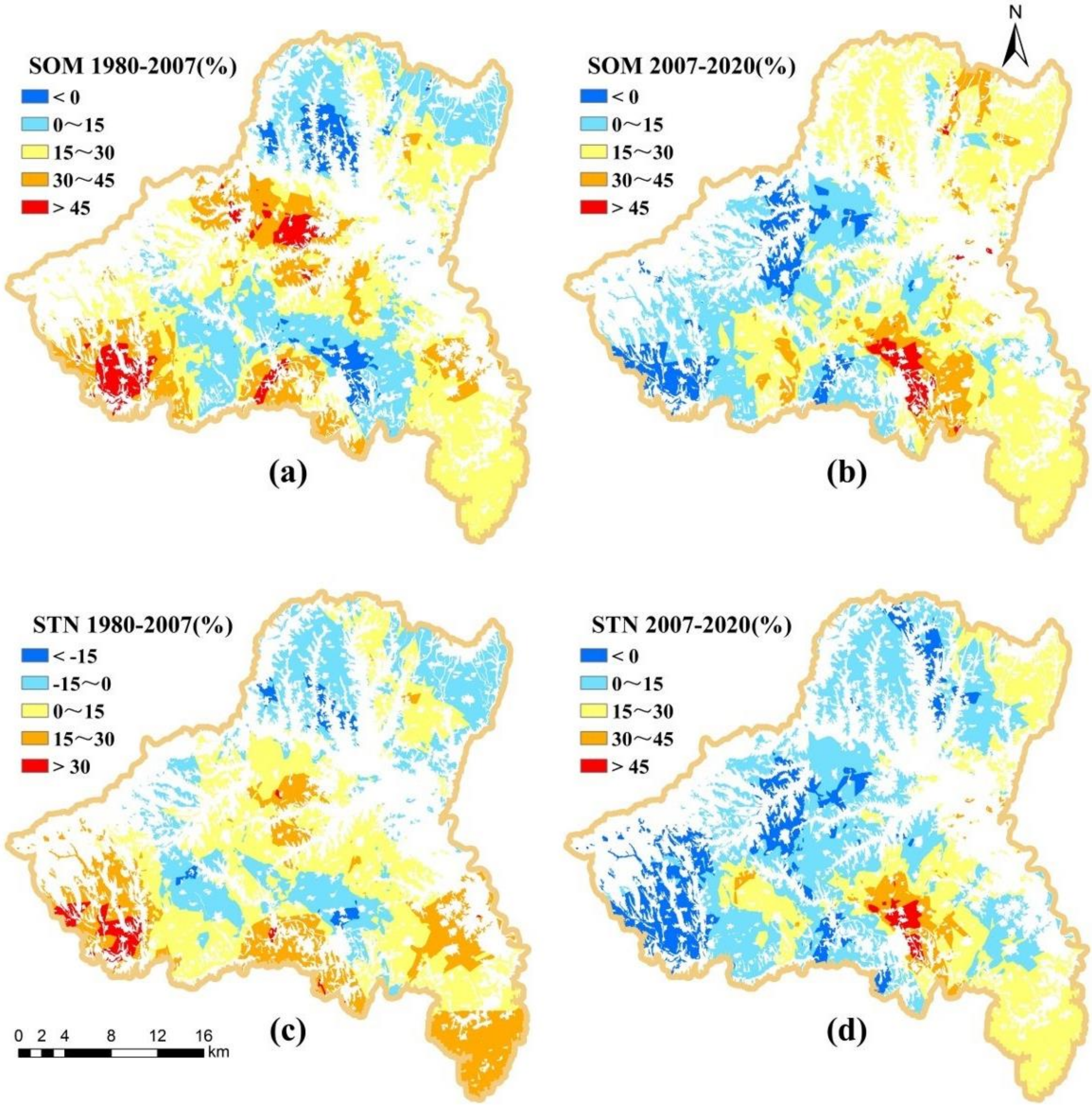

Figure 4. *Spatial distribution map of SOM (a) and STN (b) changes in Baishui County from 1980 to 2007, and the spatial distribution map of the changes in soil SOM (c) and STN (d) Baishui County from 2007 to 2020. SOM: soil organic matter; STN: soil total nitrogen*

From 2007 to 2020, the content of SOM and STN in the study area increased steadily, with a relatively large increase in the east and a relatively small increase in the west. The SOM and STN content decreased in only a few areas. The growth rates of SOM and STN are similar, and the growth rates are mainly concentrated from 0 to 30%, which accounts for 79.52% of the study area and 79.75% of the study area, respectively (*Table A4*).

Centre of gravity models and standard deviational ellipse

The centre of gravity model was used to obtain the direction and distance of soil nutrient centre of gravity migration for each period respectively, and the results are shown in *Tables 4* and *5* and *Figure 5*, which show that the nutrient changes in the study area are mainly divided into the following two stages:

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From 1980-2007, the centre of gravity of soil nutrients shifted towards southeast. Since the 1980s, farmers have been practising intensive farming and have begun to focus on land management, so the centre of gravity of soil nutrients has moved a long way. From 2007 to 2020, the centre of gravity of soil nutrients as a whole shifted 922.96 m and 1030.95 m to the southeast, respectively, a relatively short distance (*Table 4*). The centre of gravity as a whole shifted to the south-east as the lower ground made it easier for people to cultivate. In summary, it can be seen that the centre of gravity of soil nutrients in the study area has generally shifted to the south-east over the past 40 years, with a decreasing trend in the distance shifted.

Table 4. *Soil nutrient gravity shift 1980-2020*

Shift of gravity centre	SOM		STN	
	1980-2007	2007-2020	1980-2007	2007-2020
Moving direction	South-east	South-east	South-east	South-east
Movement distance (m)	3579.31	922.76	3903.31	1030.95

Table 5. *Changes in standard deviational ellipse parameters for soil nutrients 1980-2020*

Year	SOM			STN		
	1980	2007	2020	1980	2007	2020
Rotation (°)	56.32	72.63	61.98	51.49	70.71	63.66
Standard deviation along the x-axis (km)	14.72	13.38	13.29	14.58	13.49	13.31
Standard deviation along the y-axis (km)	13.48	11.63	12.32	13.25	11.59	12.37
Ellipse area (km^2)	623.69	514.61	489.24	618.76	514.61	491.54

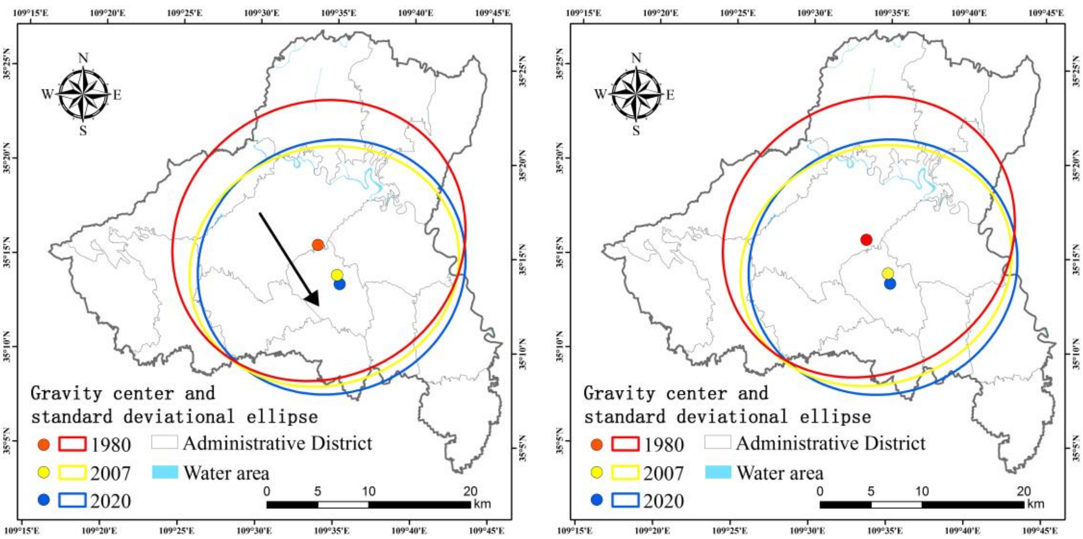

Figure 5. *Soil nutrient gravity shift 1980-2020*

As can be seen from *Figure 5*, there is a certain directionality to the change in the standard deviation ellipse in the study area, which correlates with the shift in the centre of gravity. Throughout the study period, the angle of rotation shows an 'increasing-

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DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

decreasing' pattern, with an increasing spatial distribution in the southeast. As can be seen from *Table 5,* the area of the standard deviation ellipse gradually decreases, indicating that the spatial distribution of soil nutrients in the study area gradually tends to concentrate and the nutrient content becomes more stable.

Discussion

Temporal changes in SOM and STN

The distribution patterns of soil SOM and STN in the study area are similar. During the 38-year period from 1980 to 2020, the content of soil SOM and STN in Baishui County increased significantly. Generally, some agricultural practices can reduce soil carbon by soil disturbance and mineralization (Ma et al., 2016a). Some studies have focused on the impact of land use changes on SOM and STN content. For example, the conversion from cultivated land to orchard land increases the risk of nutrient loss in the watershed (Chen et al., 2019). Compared with farmland, the organic matter and total nitrogen content in the surface soil of orchard land increases (Lu et al., 2016). When the original grassland is changed to vegetable land (Kong et al., 2006), both the soil organic carbon (SOC) content and STN content increase. More research focuses on the impact of agricultural activities on SOM and STN content. In Kansas, the application of animal droppings (Schlegel et al., 2017) and the presence of plateau pikas in the Qinghai-Tibet Plateau significantly (Yu et al., 2017) increased the STN and SOC content. The average SOC content and STN content in the Tai Lake Basin increased during a 20-year period (1980-2000) (Liu et al., 2014a); and the STN and SOM content in the ecologically fragile area of the Loess Plateau increased (Guan et al., 2020). These findings show that fertilization measures and planting management methods may cause changes in soil nutrients. Therefore, it can be seen that the transformation of land use patterns and various agricultural practices will affect the soil SOM content and STN content to varying degrees. In this study, the general increase in SOM and STN content may be attributed to the implementation of the household contract responsibility system, the distribution of land to households, the widespread use of fertilizers, the improvements in irrigation and drainage facilities, and the intensive cultivation of farmers.

Among the major apple-producing areas in the country, Baishui County is the only county that meets the seven indicators used to identify the most suitable apple production areas, and the region has very superior natural conditions. Therefore, apples have become the main agricultural industry in the county. For apples, the content of organic matter in the soil is very important. It can not only improve the quality of apples but also fertilize the soil and improve the soil environment. The SOM content in the study area showed an increasing trend, which provided a strong guarantee for increasing apple output, rural residents' incomes and sustainable agricultural development.

Temporal changes of their spatial variability

Judging from the variability of the soil nutrients in the study area, the coefficient of variability of the nutrients in the three phases is between 15.6 and 38.47%, and the spatial heterogeneity is weak. From the spatial autocorrelation and semivariogram analysis, we obtain the same analysis results for the three-phase SOM and STN. The nugget/sill ratios of SOM and STN in 2007 and 2020 are higher, and the global Moran's I index is lower, which indicates that the spatial autocorrelation of SOM and STN is

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DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

weakened, the distribution tends to be fragmented, and the proportion of random variability increases.

The global Moran's I index describes the spatial aggregation characteristics of the research variables from the perspective of correlation and uses the standard deviation of the approximate normal distribution hypothesis in random conditions to standardise it to determine whether the spatial autocorrelation is significant (or extremely significant). However, the global Moran's I index cannot provide a basis for spatial interpolation and is unable to adequately describe the spatial patterns of variables (Martin et al., 2014). A semivariogram can better compensate for the lack of interpolation of a spatial autocorrelation analysis. A semivariogram can not only quantitatively reveal the spatial correlation degree of regional variables and the scale range of spatial variability using indicators such as the block base ratio and variable range but also perform Kriging interpolation on a parameter basis; however, it cannot provide a statistical test for positive and negative spatial correlation significance, such as Moran's I standardised Z value (Ma et al., 2016).

Factors that influence an increase in SOM and STN

Topographic influence

To explore the influence of topography, the average SOM and STN content of different elevations and topography types were calculated (*Tables 6* and *7*). From 1980 to 2007, additional SOM and STN were accumulated in low-altitude areas. For example, SOM and STN content increased by 2.422 g kg^{-1} and 0.051 g kg^{-1} (<600 m), and high-altitude areas only increased by 1.899 g kg^{-1} and 0.034 g kg^{-1} (>900 m). This pattern also appeared from 2007 to 2020. This phenomenon may be caused by flat terrain in low-altitude areas, excessive agricultural production activities, and excessive fertilization, which produced greater biological residues and nitrogen accumulation in the soil (Zhu et al., 2019).

Table 6. *Average SOM and STN content (g kg^{-1}) at different elevations. SOM: soil organic matter; STN: soil total nitrogen*

Variables	Elevation			
	< 700 m	**700-800 m**	**800-900 m**	**> 900 m**
SOM-1980	11.511 ± 2.374	11.230 ± 2.446	9.986 ± 2.309	10.429 ± 1.975
SOM-2007	13.933 ± 4.132	13.503 ± 5.779	12.148 ± 4.315	12.328 ± 4.537
SOM-2020	17.091 ± 2.895	17.717 ± 4.936	14.419 ± 3.671	13.281 ± 2.487
Increment (1980-2007)	2.422	2.273	2.162	1.899
Increment (2007-2020)	3.158	4.214	2.271	0.953
STN-1980	0.618 ± 0.087	0.635 ± 0.091	0.592 ± 0.090	0.601 ± 0.081
STN-2007	0.669 ± 0.217	0.663 ± 0.261	0.629 ± 0.203	0.635 ± 0.249
STN-2020	0.811 ± 0.131	0.821 ± 0.223	0.683 ± 0.135	0.653 ± 0.145
Increment (1980-2007)	0.051	0.028	0.037	0.034
Increment (2007-2020)	0.142	0.158	0.054	0.018

Table 7 shows the comparison results of the changes in the SOM and STN content for different landform types. From 1980 to 2007, the SOM and STN content in the

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valley terrace increased by 2.747 g kg^{-1} and 0.031 g kg^{-1}, respectively, while the increase in SOM and STN content in the middle mountain were negative. The changes in the SOM and STN content from 2007 to 2020 also showed this pattern.

Table 7. *Average SOM and STN content (g kg^{-1}) for different terrains. SOM: soil organic matter; STN: soil total nitrogen*

Variables	Topography		
	Valley terrace	**Loess tableland**	**Middle mountain**
SOM-1980	10.881 ± 2.394	10.496 ± 2.109	10.982 ± 2.949
SOM-2007	13.628 ± 3.754	12.881 ± 4.142	10.400 ± 4.537
SOM-2020	17.354 ± 4.152	15.627 ± 4.210	11.278 ± 3.285
Increment (1980-2007)	2.747	2.385	-0.582
Increment (2007-2020)	3.726	2.746	0.878
STN-1980	0.606 ± 0.077	0.605 ± 0.086	0.590 ± 0.103
STN-2007	0.637 ± 0.193	0.632 ± 0.247	0.540 ± 0.249
STN-2020	0.750 ± 0.008	0.721 ± 0.185	0.574 ± 0.213
Increment (1980-2007)	0.031	0.027	-0.05
Increment (2007-2020)	0.113	0.089	0.034

The study revealed that the valleys and rivers located in the valley terrace of the study area have flat terrain with relatively satisfactory farming performance, which greatly improves the supply and utilization of carbon and nitrogen in the soil (Weihrauch and Opp, 2018). According to the survey results, the use of chemical fertilizers has increased steadily in recent years. The combined application of phosphate fertilizers and organic fertilizers, the increase in agricultural production input and the high degree of cultivation and maturation facilitate the accumulation of organic matter, which causes a steady increase in the SOM content in the study area.

Soil-type influence

The main soil types in Baishui County mainly include cumulic cinnamon soil and loessial soil. The effects of two soil types on the SOM and STN content were calculated separately (*Fig. 6*). It can be seen from the figure that there are significant differences in the content of SOM and STN in the two soil types. For example, in 1980, the average SOM content and STN content of Cumulic cinnamon soil were 10.704 g kg^{-1} and 0.612 g kg^{-1}, respectively, while the average SOM content and STN content of loessial soil were only 9.985 g and 0.558 g kg^{-1}. From 1980 to 2007, the SOM content and STN content of cinnamon soil increased to 13.266 g kg^{-1} and 0.648 g kg^{-1}, respectively, and the SOM content and STN content of loess soil increased to 12.916 g kg^{-1} and 0.642 g kg^{-1}, respectively. From 2007 to 2020, the SOM and STN content in the two soil types also showed an increasing trend. These differences could be attributed to the different textures, parent materials, and soil formation processes that are associated with these soil types.

Cumulic cinnamon soil is a kind of anthropogenic soil that is neutral to slightly alkaline, has a deep plough layer, and has excellent water and fertility retention (Yan et al., 2019). Loessial soil is loose and soft with a light soil colour. Due to the lack of obvious profile development and serious soil erosion, loessial soil has weak water and fertilizer retention capabilities (Xin et al., 2016). Therefore, cumulic cinnamon soil has a higher SOM and STN content. Therefore, it can be concluded that soil type also has a substantial influence on the spatial changes of farmland SOM and STN.

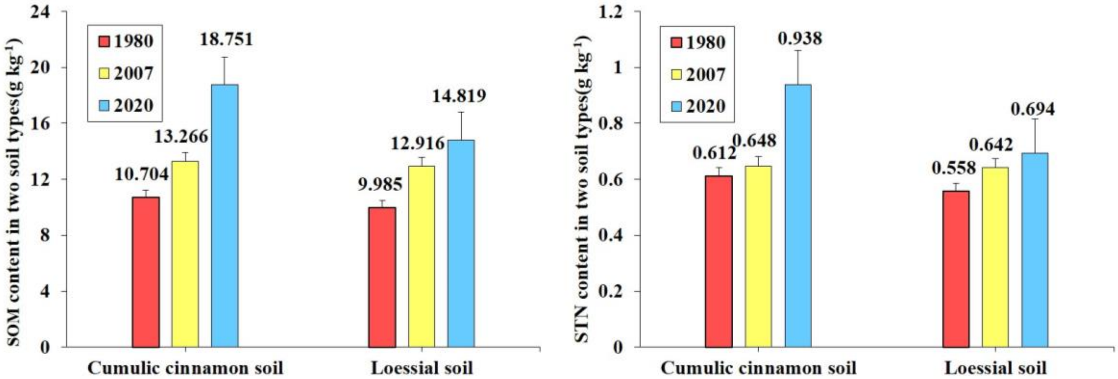

***Figure 6.** Bar graphs for average SOM and STN content for two different soil types. SOM: soil organic matter; STN: soil total nitrogen*

Impact of land use practices

In addition to the influence of soil type, changes in land use patterns should not be ignored. In the 1980s, the land use pattern in Baishui county was mainly dry land. With the construction and improvement of farmland water conservancy facilities, dry land gradually decreased, watered land increased, and the effective irrigated area of arable land increased significantly. As can be seen from *Figure 7*, from 1980 to 2007, except for the soil STN decreased under dryland-watered conditions, all the others showed an increase; from 2007 to 2020, the soil nutrient content increased regardless of the change in cropland use, with the highest increase in cropland maintained as watered land for a long time, with SOM and STN increasing by 3.74 g kg^{-1} and 0.148 g kg^{-1} respectively. Due to the favourable irrigation conditions on the watered land and the fine tillage management, the soil nutrient content increased significantly. It shows that the change in the use of arable land leads to a different pattern of change in soil nutrient content.

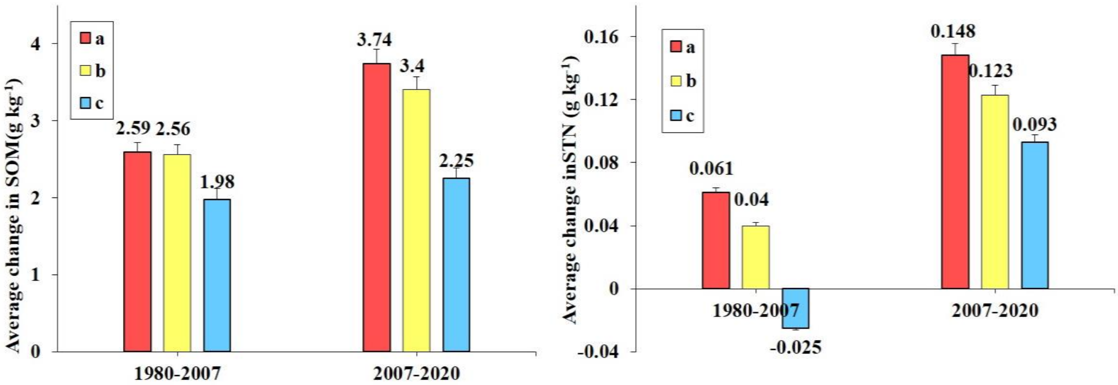

***Figure 7.** Changes in soil nutrients in arable land under different land use practices. (a) Watered land-Watered land; (b) Dryland-Dryland; (c) Dryland-Watered land*

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DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

Farming management practice influence

In agricultural production, various farming practices, such as fertilizer application, irrigation, and crop residue returned to the field can significantly affect the SOM and STN dynamic change. In 1980, the lower SOM and STN contents on farmland reflected a long cultivation history with little or no fertilizer input (2542 t in 1980). Most crop residues were also taken off and used as fuel for cooking and heating. Since the early 1980s the Household Responsibility System has been implemented. The farmers were then given the authority to manage the contracted land, including all decisions regarding production. In order to get higher yield, more chemical fertilizers were used by farmers. After reviewing the Shaanxi Statistical Yearbook (Shaanxi Provincial Bureau of Statistics, 1980-2020), the amount of chemical fertilizer used in the study area increased from 2,542 t in 1980 to 70,643 t in 2020. Meanwhile, there has been a significant increase of organic manure applications and return of crop residues into the soil. It is clear that the use of organic manure and higher chemical fertilizers inevitably resulted in increased cropland SOM and STN levels.

In addition, with the development of irrigation and water conservation activities, many non-irrigated farmlands were transformed into irrigated lands, especially in the low-elevation areas. To reveal the irrigation effect, the average SOM and STN contents for different cropland types are calculated and their increment is shown in *Figure 8*. During the period from 1980 to 2020, the highest increment of SOM was in the cropland that changed from dry land to irrigated land, whereas for STN the largest increase occurred for the irrigated land (over the whole period). Generally speaking, SOM and STN in irrigated cropland increased relatively most. Thus, it can be seen that irrigation has a clear influence on the change of farmland SOM and STN.

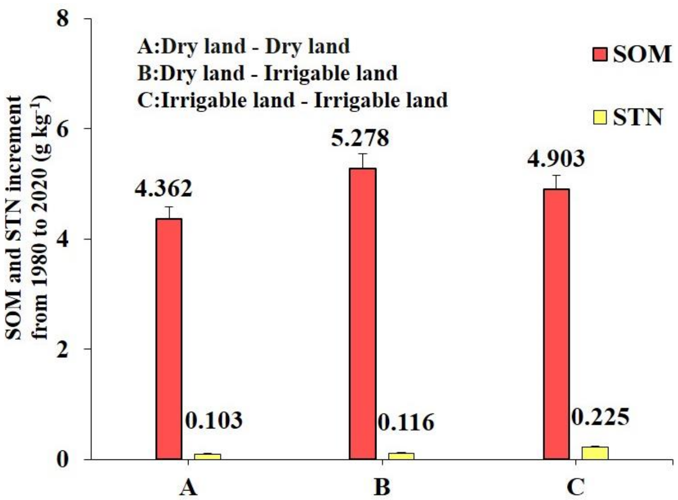

Figure 8. *Average increase of SOM and STN content between 1980 and 2020 for different cropland types. SOM: soil organic matter; STN: soil total nitrogen*

Conclusions

In this study, a combination of geostatistical and GIS techniques was used to quantitatively study and explore the spatial and temporal variability characteristics of the SOM and STN of cultivated soils in Baishui County, a typical region in ecologically fragile regions of the Loess Plateau, China. The main findings are as follows:

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DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

1. The average SOM content increased by 2.48 g kg^{-1} and 2.41 g kg^{-1} during 1980-2007 and 2007-2020, respectively, and the average STN content increased by 0.04 g kg^{-1} and 0.09 g kg^{-1}, respectively.
2. The coefficients of variability of soil nutrients on cultivated land in three years ranged between 15.6% and 38.5%, which represented moderate variability. Compared with 1980, the SOM and STN contents in 2007 and 2020 showed a higher nugget/sill ratio and a lower global Moran's I index, which indicates the spatial variability and weak spatial structure of SOM and STN.
3. The centre of gravity of soil nutrients generally shifted towards southeast, moving 922.96 m and 1030.95 m respectively. The spatial distribution pattern of the soil nutrient standard deviation ellipse is consistent with the direction of distribution in the study area, shifting to the southeast. The Rotation show an "increasing-decreasing" pattern of change, with the oval area decreasing and the spatial distribution of soil nutrients tending to concentrate.
4. We also found moderate spatial variation in both SOM and STN content as a result of a combination of intrinsic factors (topography, soil type, and land use patterns) and extrinsic factors (agricultural management practices). However, the main factors causing nutrient variation was agricultural management practices.

Acknowledgements. This research was supported by the National Natural Science Foundation (grant number 42071240) and Analysis of the Evolution of Spatial and Temporal Patterns of Arable Land in the Northern Weibei Dry Plateau Area and its Driving Forces (DJNY2022-36).

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APPENDIX

Table A1. *Statistical table of SOM in three periods*

SOM (g kg^{-1})	1980		2007		2020	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)
< 10	144.64	27.53	4.27	0.8	-	-
10-11.5	236.81	45.06	102.54	19.51	-	-
11.5-13	135.02	25.69	190.59	36.27	78.98	15.03
13-14.5	9.02	1.72	105.69	20.11	180.61	34.37
14.5-16	-	-	102.57	19.52	105.04	19.99
> 16	-	-	19.83	3.77	160.86	30.61

SOM: soil organic matter

Table A2. *Statistical table of total nitrogen content in three periods*

STN (g kg^{-1})	1980		2007		2020	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)
< 0.55	15.74	3.00	22.60	4.30	-	-
0.55-0.6	201.05	38.26	158.49	30.16	5.90	1.10
0.6-0.65	228.90	43.56	124.34	23.66	128.66	24.03
0.65-0.7	79.80	15.19	71.54	13.61	151.34	28.26
0.7-0.75	-	-	93.58	17.81	74.23	13.86
> 0.75	-	-	54.96	10.46	165.37	30.88

Table A3. *Area and percentage of soils with increased SOM and STN contents between 1980 and 2007*

Variables and item	Different categories of content increase (%)					
	<-15	-15-0	0-15	15-30	30-45	>45
SOM						
Area (km^2)	-	26.42	157.56	218.32	98.98	24.21
Percentage (%)	-	5.03	29.98	41.55	18.84	4.61
STN						
Area (km^2)	8.22	155.42	234.12	117.13	10.61	-
Percentage (%)	1.56	29.58	44.55	22.29	2.02	-

SOM: soil organic matter; STN: soil total nitrogen

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DOI: http://dx.doi.org/10.15666/aeer/2005_38533872

Table A4. *Area and percentage of soils with increased SOM and STN contents between 2007 and 2020*

Variables and item	Different categories of content increase (%)					
	<-15	**-15-0**	**0-15**	**15-30**	**30-45**	**>45**
SOM						
Area (km^2)		43.28	150.73	267.18	53.02	11.29
Percentage (%)		8.24	28.68	50.84	10.09	2.15
STN						
Area (km^2)		75.79	248.36	170.71	23.87	6.75
Percentage (%)		14.42	47.26	32.49	4.54	1.28

SOM: soil organic matter; STN: soil total nitrogen

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2005_38533872