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REVIEW PAPER

Spatial variability of soil organic matter in a gravel-sand mulched jujube orchard at field scale

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Abstract

In agricultural ecosystems, soil organic matter (SOM) is a major determinant and indicator of soil fertility and quality. The objectives of this study were to understand the spatial distribution of SOM and the accuracy of two interpolation methods evaluated: Kriging and inverse distance weighting (IDW) in a gravel-sand mulch of northwest China. We are measuring SOM in 256 soil samples collected from 0 to 10, 10–20, 20–30, and 30–50 cm layers at five sampling scales, 32 × 32, 28 × 28, 24 × 24, 20 × 20, and 16 × 16 m, and three sampling spacings, 4, 8, and 12 m. SOM content decreased with depth in each scale, varying from 2.41 to 5.75 g/kg. The SOM was weakly to moderately variable and has a strong spatial autocorrelation. The standard deviation was small for each soil layer, and the variability was low or weakly moderate, indicating that two interpolation methods were applicable to the entire data set. Kriging interpolation was more accurate than IDW. The distribution of SOM differed in the surface layers at the five sampling scales, which was more uniform as the sampling scale decreased. Eight meter is a reasonable sampling spacing. Through the scales effect and spacing change on SOM for fixed-point monitoring, combing the estimate of SOM to reduce the sampling workload will aid the supply of SOM in gravel-sand mulched fields in arid regions.

Keywords Gravel-sand mulch · Soil organic matter · Spatial variation · Kriging interpolation · Inverse distance weighting interpolation

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Introduction

Soil organic matter (SOM) is a key indicator for assessing soil quality and is also important as sources and sinks in global carbon (Marchetti et al. 2012; Thomazini et al. 2015; Klimek et al. 2016). SOM contains more than three times as much carbon as either the atmosphere or terrestrial vegetation globally (Schmidt et al. 2011). And the quantification of organic matter cycling may provide an important guide to the agricultural potential of soils. Assessing SOM variability has become one of the most active areas of research in soil and environmental sciences (Yemefack et al. 2005; Liu et al. 2008; Meyer et al. 2017).

Using gravel-sand mulch, an indigenous farming technique for crop production in the semiarid loessial region of northwestern China may date back to the Qing Dynasty, about 300 years ago (Li 2003). It can improve the soil environment, store water, and maintain soil fertility (Zhao et al. 2017a, 2018). And Zhao et al. (2017b) study the spatial variability of soil salinity in a gravel-sand mulched jujube orchard at different scales and found that gravel-sand mulched could reduce the accumulation of surface salinity. Jujube fruit comes from the small and deciduous jujube tree. The jujube tree is a species of *Ziziphus* in the buckthorn family (Rhamnaceae). It is an important economic tree that has the characteristics of drought resistance and can be planted on a large scale. It is one of the main economic sources of local farmers. However, in recent years, the yield of jujube has a downward trend. The main reason is that the soil organic matter shows a decreasing trend with the increase of tillage years. Because the management of the tillage is extensive, the gravel-sand mulched soil is gradually degraded, and the farmers' lack of understanding of soil organic matter, which leads to the excellent features of soil fertility gradually become decrease with the increase of tillage years (Qiu et al. 2015; Wang et al. 2015). An accurate and objective understanding of SOM content and its spatial variability is therefore of great significance for the sustainable development of gravel-sand mulch.

The spatial variability and distribution of SOM have been studied in China and abroad (Seibert et al. 2007; Wu et al. 2009; Zhang and Zhang 2014), some at large and intermediate scales (Hu et al. 2007; Wang et al. 2010; Huang et al. 2017). And some scholars have analyzed at small scales (Qiu et al. 2016; Cappai et al. 2017). SOM possesses different spatial distribution as a result of differing parental material, climate, topography, land use, and human activities. Estimation of SOM at an acceptable level of accuracy is important; especially in the case when SOM exhibits strong spatial dependence and its measurement is a time- and labor-consuming procedure. Geostatistical analysis is used to define the spatial dependence of soil properties (Western et al. 1998; Fang et al. 2016; Zhao et al. 2017c). Wang et al. (2017) study the spatial variability of reconstructed soil properties using geostatistical analysis. In the geostatistical techniques, Kriging and inverse distance weighting (IDW) are common interpolation methods used to study the spatial characteristics of soil properties (Zimmerman et al. 1999). Mabit and Bernard (2010) found that the patterns of SOM spatial distribution and the relative magnitude of some classes of SOM content differed between the Kriging and IDW methods. Western et al. (1998) noted that the variability apparent in the data would differ from the true natural variability and that this difference was associated with the scale of the measurements. Hu et al. (2014) study the spatial scaling effects on variability of soil organic matter and total nitrogen and found the spatial variability are scale-dependent. Plants can be affected by the distribution of SOM. Hence, research on a single spatial scale cannot fully explore and exploit the information on spatial variation. Field data are often collected at a particular scale, and estimates of SOM are often needed at smaller or larger scales. This study analyzed the effect of scale on the measurements of SOM in a gravel-sand mulched jujube orchard, which is helpful for the precision fertilization.

The objectives of this paper are to (1) characterize the spatial variability of SOM using geostatistical techniques, (2) through the scales effect and spacing change on SOM for fixed-point monitoring, combing the estimate of SOM to reduce the sampling workload, and (3) to determine the better interpolation method for simulating the spatial distribution and provide a theoretical basis for the supply of SOM, which are important for crop growth and planting management.

Materials and methods

Status of the study area

The study was conducted in a jujube orchard near the test site of Lanzhou University of Technology in Jingtai County, the province of Gansu, northwestern China (Fig. 1). The soil type is mainly arctic ash and desert soil. Jingtai County is in the transition zone between monsoon and non-monsoon regions. Precipitation is rare but heavy and is unevenly distributed throughout the year. Mean annual rainfall is 185 mm, 61.4% of which falls from July to September. Mean annual evaporation is 3038 mm, 16-fold more than the precipitation. Mean annual temperature is 8.2 °C, with temperatures ranging from − 27.3 to 36.6 °C. Solar-thermal resources are rich with the annual sunshine time which is about 2725 h and a sunshine percentage of 62%; the mean annual solar radiation is about 147.8 kcal/cm^2; and the mean frost-free period is 141 days (Zhao et al. 2017a, b, c).

Sample collection

The jujube trees were planted on a gravel-sand mulched jujube orchard with a mulching thickness of 10 cm 5 years ago for studying the spatial variability of SOM content. In the past 5 years, we do not fertilizer application. The study area was 1.5 hm^2, the sampling area was 32 × 32 m, and jujube was planted every 4 m along two perpendicular. The rectangular sampling was performed for 1 × 1 m quadrats 4 m apart, center to center, for a total of 64 sampling locations, and soil samples (60–70 g) were collected with a soil auger from the 0–10, 10–20, 20–30, and 30–50 cm layers (Fig. 2). We tested five sampling scales of 32 × 32 m, 28 × 28 m, 24 × 24 m, 20 × 20 m, and 16 × 16 m from the northwestern to the southeastern corner of the study area. Sampling spacings: The sampling density was varied by extracting sampling points from 1 to 2 points in the east-west and north-south directions, respectively, representing an increase in sampling spacing and the pitch in each of all the original measurement data to get. The data in a geostatistical analysis will not be reliable if the spacing is too large, so we analyzed only three sampling spacings (4, 8, and 12 m) for determining their effects on the spatial variation. SOM was estimated by dichromate oxidation (Walkley and Black 1934).

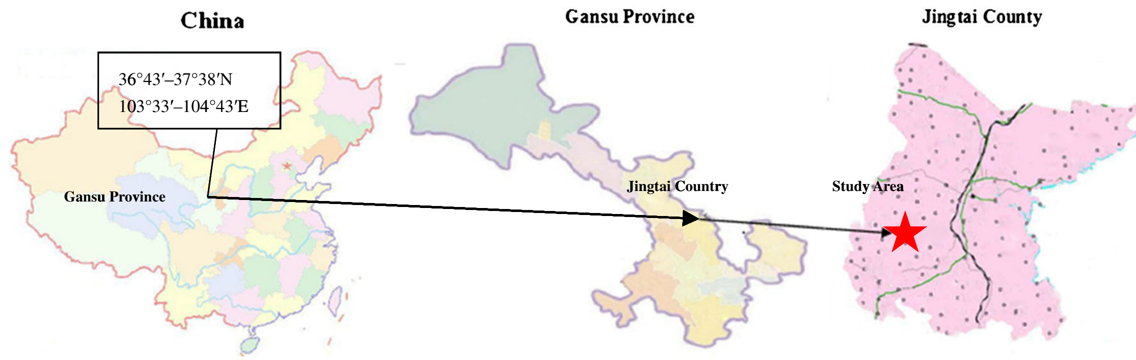

Fig. 1 Study area and the soil sampling locations in the study area situated in Gansu, China

Data processing

The data were analyzed using Microsoft Excel (version 2010, Microsoft Corporation, Redmond, USA) and SPSS 20.0 software (SPSS Inc., Chicago, IL, USA); Kriging and IDW interpolation were carried out using GS+ (version 9.0, Gamma Design Software, Michigan, USA). The three-dimensional spatial distribution of SOM content was drawn using Surfer (Version 11.0, Golden Software, USA).

The coefficient of variation (CV) is calculated as (Lei et al. 1988):

$$\mathrm{CV} = \frac{S}{\overline{x}} \tag{1}$$

where S is the standard deviation and $\overline{x}$ is the average. Geostatistical methods were used to calculate the semivariogram as follows: the formula for the semivariogram is shown in (Pham 2016):

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

where h is the spatial sampling interval, $\gamma(h)$ is the semivariance for interval h, $N(h)$ is the total number of sample pairs for the separation interval h, and $Z(x_i + h)$ and $Z(x_i)$ are measured samples at points $x_i + h$ and x_i, respectively.

IDW interpolation method as shown in (Chen and Liu 2012):

$$Z'(s_0) = \sum_{i=1}^{n}\lambda_i Z(s_i) \tag{3}$$

$$\lambda_i = \frac{1/d_i}{\left(\sum_{i=1}^{n}\frac{1}{d_i}\right)} \tag{4}$$

where $Z'(s_o)$ was the estimated value at point S_0, n was the number of known points around the point to be estimated, λ_i the weight of each sample, and $Z(s_i)$ was the sample value at point S_i.

Mean error (ME) and root mean square error (RMSE) were used to evaluate the performance of the regression models as shown in (Phogat et al. 2010):

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{6}$$

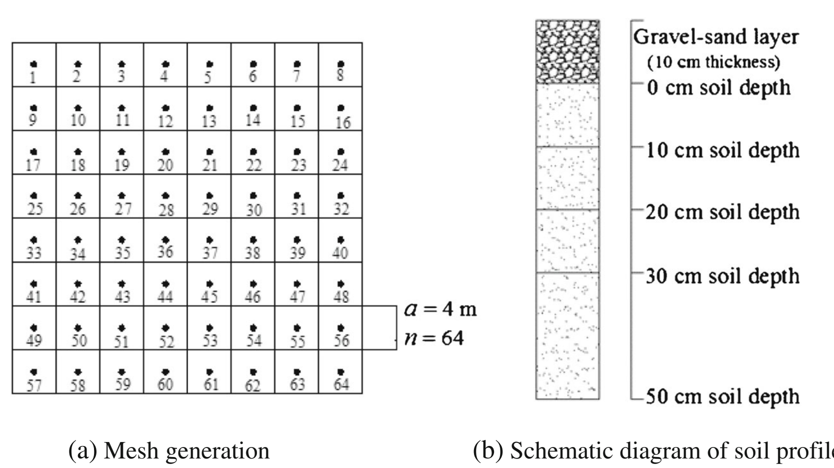

Fig. 2 Distribution map of sampling points of (a) mesh generation, (b) schematic diagram of soil profile (Note: a is mesh size and n is total sampling points)

where O_i and P_i are the measured and predicted values, respectively, and n is the number of observations in the validation data set.

Moran's I is similar to the correlation coefficient and ranges from − 1 to 1. Moran's I is calculated as (Monica et al. 2010):

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N}\omega_{ij}\right)\sum_{i=1}^{N}\left(x_i-\overline{x}\right)} \tag{7}$$

where x_i and x_j are the observed values of spatial element x in spatial units i and j, respectively; $\overline{x}$ is the average x; ω_{ij} is the adjacent weight (binary weight is now commonly used; ω_{ij} is defined as 1 if adjacent sampling sites i and j are correlated, otherwise as 0); and N is the total number of spatial units.

Soil particle size of different depth

The soil particle sizes at the various depths are shown in Table 1. The particle sizes were measured by a laser diffraction particle size analyzer (Malvern Instruments 2000, Malvern, England). The range of sizes for this instrument is 0.02–2000 μm, which provides a continuous volume percentage of sizes with a repeated measurement error < 2%.

Results and discussion

Statistical eigenvalue analysis of SOM content

Statistical eigenvalue analysis of SOM content under different sampling scales

The characteristics of SOM content to a depth of 50 cm for the five sampling scales are shown in Table 2. SOM content are ranging from 2.41 to 5.75 g/kg, which belongs to the lowest degree while refers to the second national soil grading standard (National Soil Survey Office Chinese Soils 1998), which indicates that the fertility level was classified as barren. In the same soil layer, the mean, maximum, and minimum values of SOM at the five scales have almost the same values. The SOM mean values at 32 × 32, 28 × 28, 24 × 24, 20 × 20, and 16 × 16 m scales of the 0–10 cm were 4.95, 4.88, 4.84, 4.84, and 4.92 g/kg. A large number of jujube trees are planted in the study area, the surface layer of the soil accepts the litter of surface vegetation, and there are a large number of fine roots of plants. The source of SOM is rich, the time of soil formation is short, and the amount of SOM decomposition loss is lower than the amount of SOM added, so the content of organic matter is higher. With the increase of depth, the buried time of soil layer increases, and the source of SOM decreases, while the time of soil formation increases. Therefore, the content is differed significantly between layers and has a decreasing trend with increasing depth in the same scale, which was consistent with the results of Chen et al. (2005) on the evolution mechanism of soil organic matter depth distribution.

The CV is an important index for describing the degree of spatial variation of regionalization. In Nielsen's classification (Nielsen and Bouma 1985), a CV < 10% indicates low variability, and 10% ≤ CV < 100% indicates moderate variability. The CV ranged between 4.41 and 11.89%, indicating weakly to moderately variable. The CV for the same layer tended to decrease as sampling scale decreased. The CV for SOM content was lowest in the 0–10 cm layer, perhaps because the soil was shallow and vulnerable to human factors such as tillage and fertilization and to biological factors such as animals, plant debris, and microorganisms. The decomposition and synthesis of organic compounds in the surface soil concentrates the distribution of organic matter. Many studies have also confirmed that the surface soil organic matter content of space continuity is strong (Wu et al. 2009; Yang et al. 2014).

For five kinds of sample scale of 0–50 cm soil layer, the mean CV and the sampling area were fitted. The relationship is shown in Fig. 3, where y is the CV and x is the sampling area. The fitted results indicated that the CV increased with sampling area. This is mainly due to the introduction of new variability factors along with the increase of the study area; that is, some of the factors that affect the distribution of SOM in larger scales may have relative consistency within a relatively small scale. When the scale is increased, its effect on the SOM distribution is reflected so that its coefficient of variation increases.

Table 1 Soil particle size of different depth

Soil depth (cm)	Clay	Silt	Sand				
			Extremely fine sand	Fine sand	Medium sand	Coarse sand	Extremely coarse sand
	< 0.002 mm	0.002~0.05 mm	0.05~0.1 mm	0.1~0.25 mm	0.25~0.5 mm	0.5~1 mm	1~2 mm
0–10	2.95	52.86	28.5	13.83	1.85	0.03	0
10–20	3.66	60.86	28.05	7.43	0	0	0
20–30	3.16	57.53	27.52	9.91	1.81	0.07	0
30–50	3.1	57.24	30.26	8.29	0.99	0.10	0

Table 2 Statistics parameters of horizontal soil organic matter in 0–50 cm layers for all scales

Item	Depth (cm)	Max (g/kg)	Min (g/kg)	Mean (g/kg)	SD	Kurtosis	Skew	CV(%)
32 × 32	0–10	5.75	4.25	4.95	0.27	0.8857	0.2229	6.04
	10–20	4.73	3.52	4.12	0.32	− 0.7827	− 0.0071	7.81
	20–30	3.73	2.61	3.26	0.25	− 0.3662	− 0.2798	7.60
	30–50	3.61	2.41	2.86	0.34	− 0.4670	0.6940	11.89
28 × 28	0–10	5.25	4.25	4.88	0.22	1.230	− 0.7382	4.52
	10–20	4.73	3.52	4.13	0.34	− 0.9482	− 0.0893	8.17
	20–30	3.73	2.84	3.29	0.22	− 0.8570	− 0.1396	6.60
	30–50	3.67	2.41	2.77	0.28	0.9480	1.0546	10.30
24 × 24	0–10	5.23	4.25	4.84	0.22	1.3174	− 0.9941	4.44
	10–20	4.66	3.52	4.07	0.33	− 1.2049	− 0.0919	8.21
	20–30	3.61	2.92	3.27	0.19	− 0.9252	0.0471	5.78
	30–50	3.61	2.56	3.07	0.34	− 0.9503	0.1977	10.08
20 × 20	0–10	5.25	4.46	4.84	0.19	− 0.1783	− 0.1738	3.90
	10–20	4.61	3.34	4.00	0.37	− 1.1361	0.1278	9.29
	20–30	3.61	3.06	3.29	0.16	− 0.9643	0.3910	4.96
	30–50	3.60	2.55	3.02	0.29	− 0.6759	− 0.0131	9.57
16 × 16	0–10	5.25	4.25	4.92	0.24	1.5207	− 0.5751	4.86
	10–20	4.66	3.61	4.20	0.30	− 0.7554	− 0.3646	7.05
	20–30	3.61	2.84	3.27	0.23	− 0.8198	− 0.0604	7.09
	30–50	3.67	2.42	2.87	0.32	0.0861	0.5721	11.28

Statistical eigenvalue analysis of SOM content under different sampling spacings

When the sampling spacing is changed from 4 to 12 m, the statistical analysis of the SOM content is shown in Table 3. The SOM content and coefficient of variation in all soil layers do not change much, and they fluctuate around a fixed value. The mean values of the coefficient of variation were 6.05%, 7.9%, 8.01%, and 11.88%, respectively. It can be seen that the variation coefficient of SOM content in the study area is affected by the depth of soil layer, while the sampling spacing has almost no effect on it. Hence, within a certain study area, the actual coefficient of variation of SOM can still be obtained by appropriately increasing the sampling spacing.

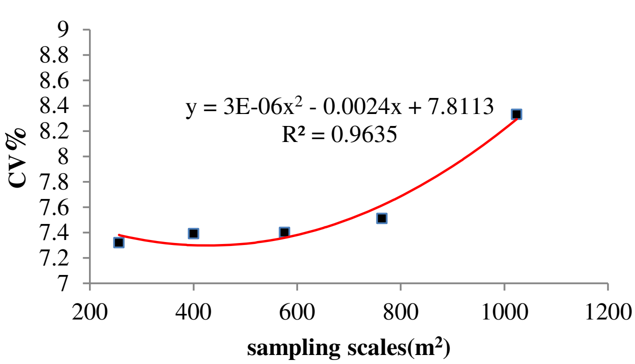

Fig. 3 The effect of scale for SOM variation coefficient

Spatial variability analysis of SOM content

Spatial variability analysis of SOM content under different sampling scales

Classical statistical analyses of SOM only identify changes in magnitude and do not take spatial structure into account, thus cannot reflect its spatial structure, randomness, and correlation. Analyzing and discussing the spatial structures of the SOM using geostatistical methods combined with the spatial position of the sampling point are therefore necessary. The GS+ program provided the best models of the SOM at each scale and showed the parameters for each semivariogram. For all data, the spherical, Gaussian, and exponential models could describe the omnidirectional semivariogram well. The results of the semivariance analysis of SOM content in the soil samples are shown in Table 4.

Spatial variability and correlation among variables within a range in the semivariance function model are usually expressed by nugget (C_0), sill ($C + C_0$), and the range (A). The nugget variance ($C_0/(C_0 + C)$) represents the proportion of spatial variability due to random factors. Based on the concept proposed by Cambardella et al. (1994), when the $C_0/(C_0 + C)$ were low than 0.25 or between 0.25 and 0.75, this indicates that the variables are strongly spatially correlated or moderately autocorrelated. When it is > 0.75, the autocorrelation of the variables is weak, and the mutation is mainly

Table 3 Statistics parameters of horizontal soil organic matter content in 0~50 cm layers of sampling spacing

Depth (cm)	Sampling spacing (m)	Max (g/kg)	Min (g/kg)	Mean (g/kg)	SD	Kurtosis	Skew	CV(%)
0–10 cm	4	5.75	4.25	4.95	0.27	0.8857	0.2229	6.04
	8	5.50	4.25	4.91	0.29	0.0218	0.1043	5.98
	12	5.50	4.25	4.99	0.31	− 0.3152	− 0.0811	6.13
10–20 cm	4	4.73	3.52	4.12	0.32	− 0.7827	− 0.0071	7.81
	8	4.73	3.56	4.13	0.29	0.2771	− 0.0860	6.92
	12	4.66	3.24	4.04	0.60	− 0.4815	− 0.4081	8.97
20–30 cm	4	3.73	2.61	3.26	0.25	− 0.3662	− 0.2798	7.60
	8	3.73	2.70	3.28	0.27	− 0.3107	− 0.8524	8.02
	12	3.73	2.70	3.28	0.28	− 0.2101	− 0.7144	8.42
30–50 cm	4	3.61	2.41	2.86	0.34	− 0.4670	0.6940	11.89
	8	3.61	2.41	2.87	0.34	0.7369	− 0.2559	11.75
	12	3.60	2.42	2.85	0.34	0.9056	− 0.0381	12.00

composed of random mutations. At this time, the spatial interpolation method is not suitable for prediction. C_0 was stable, and the degree of change was small between the sampling scales (Table 4), indicating that the spatial variation was low under the influence of random factors such as soil property, sampling error, or measurement error. The range (A) varied widely with sampling scale, with means of 53.67, 51.96, 88.31 51.86, and 25.12 m for 32 × 32, 28 × 28, 24 × 24, 20 × 20, and 16 × 16 m, respectively, indicating spatial dependence, which showed that range in all data was closely related to spatial variation and the spatial autocorrelation distance differed between the scales. $C_0/(C_0 + C)$ was < 0.25, indicating that the SOM content to a depth of 50 cm was strongly spatially correlated. The overall variation of the random factor was relatively small.

In this case, the correlation is determined using spatial interpolation. Moran's *I* describes the spatial dependence of the variables. Moran's $I > 0$ denotes positive spatial correlation, and the larger the value, the stronger the spatial correlation. Moran's $I < 0$ denotes negative spatial correlation, and the

Table 4 Semivariance models and fitted parameters of soil organic matter for each layer at different scales

Scale	Soil depth(cm)	Semivariogram model	C_0	$C_0 + C$	$C_0/(C_0 + C)$	A(m)	R^2
32 × 32	0–10	Exponential	0.007	0.048	0.139	75.33	0.873
	10–20	Exponential	0.012	0.109	0.109	10.11	0.816
	20–30	Gaussian	0.049	0.183	0.262	96.00	0.849
	30–50	Gaussian	0.044	0.190	0.231	33.22	0.991
28 × 28	0–10	Spherical	0.032	0.086	0.367	61.00	0.808
	10–20	Spherical	0.037	0.116	0.320	14.19	0.744
	20–30	Gaussian	0.065	0.526	0.124	76.31	0.948
	30–50	Gaussian	0.041	0.243	0.171	56.34	0.981
24 × 24	0–10	Exponential	0.028	0.120	0.236	153.00	0.704
	10–20	Gaussian	0.011	0.117	0.094	5.83	0.732
	20–30	Exponential	0.026	0.078	0.327	153.00	0.716
	30–50	Gaussian	0.035	0.282	0.124	41.40	0.998
20 × 20	0–10	Exponential	0.022	0.074	0.302	92.46	0.886
	10–20	Exponential	0.084	0.265	0.317	84.72	0.760
	20–30	Gaussian	0.016	0.034	0.459	16.65	0.990
	30–50	Gaussian	0.020	0.116	0.182	13.63	0.996
16 × 16	0–10	Exponential	0.032	0.090	0.353	37.11	0.978
	10–20	Gaussian	0.023	0.362	0.163	31.80	0.991
	20–30	Spherical	0.004	0.059	0.164	8.10	0.934
	30–50	Gaussian	0.058	0.222	0.261	23.48	0.996

smaller the value, the larger the spatial difference. Moran's I = 0 indicates random spatial correlation. A function diagram of Moran's I and its model fitting is shown in Fig. 4 (using 32 × 32 m as an example). The trend of Moran's I for SOM content was decrease at 0–21.33 m, and the whole variation range is small, which is between 0.548 and 0.548, indicating that SOM content was strongly spatially correlated.

Spatial variability analysis of SOM content under different sampling spacings

The spatial variability of soil organic matter content under different sampling spacing is shown in Table 5. At different sampling spacings, the semivariance models for 0~10 cm soil layers and10~20 cm are exponential and Gaussian for 20~30 cm soil layers and 30~50 cm soil layers are Gaussian. From Table 5, it can be further known that the C_0 tends to increase when the sampling spacing increases from 4 to 12 m, which may be due to the fact that the structural features of the organic matter variation process within a short distance are overshadowed by larger distances. There is no significant change in the $C_0 + C$. In the three sampling spacing, the range is greater than the corresponding sampling spacing, indicating that the sampling spacing is reasonable and fewer samples can still obtain reasonable results. Most of the $C_0/(C_0 + C)$ are less than 0.25, and the rest are between 0.25 and 0.50, indicating that when the sampling spacings are different, the SOM content showed a strong spatial autocorrelation overall in the 0–50 cm soil layer.

Estimation using Kriging and IDW interpolation

Sampling introduces errors, so we studied the spatial variability of SOM content at various scales in order to reduce the error. The Kriging is usually sufficiently effective for estimating values at unsampled locations. IDW is simple and quick. So, comparing the interpolation accuracy of the two methods makes sense. We used the 32 × 32 m scale as an example for comparing estimated and measured values using Kriging and IDW interpolation. RMSE and average ME of the estimated values were calculated using cross-validation as the evaluation index. The smaller the RMSE is, the smaller the average prediction error (ME) and the higher the accuracy of the interpolation model (Zhang et al. 2012). The estimated data were compared with the measured data (Table 6).

The conditions of climate, hydrology, water resources, and soil parental material that determine the SOM content at different depths in this area are not completely independent but are spatially correlated to some extent. The Kriging and IDW interpolation produced the same values as the mean of the estimated values (Table 6). The maximum estimated value was lower than the maximum measured value. The minimum estimated value was larger than the minimum measured value, and the range of variation

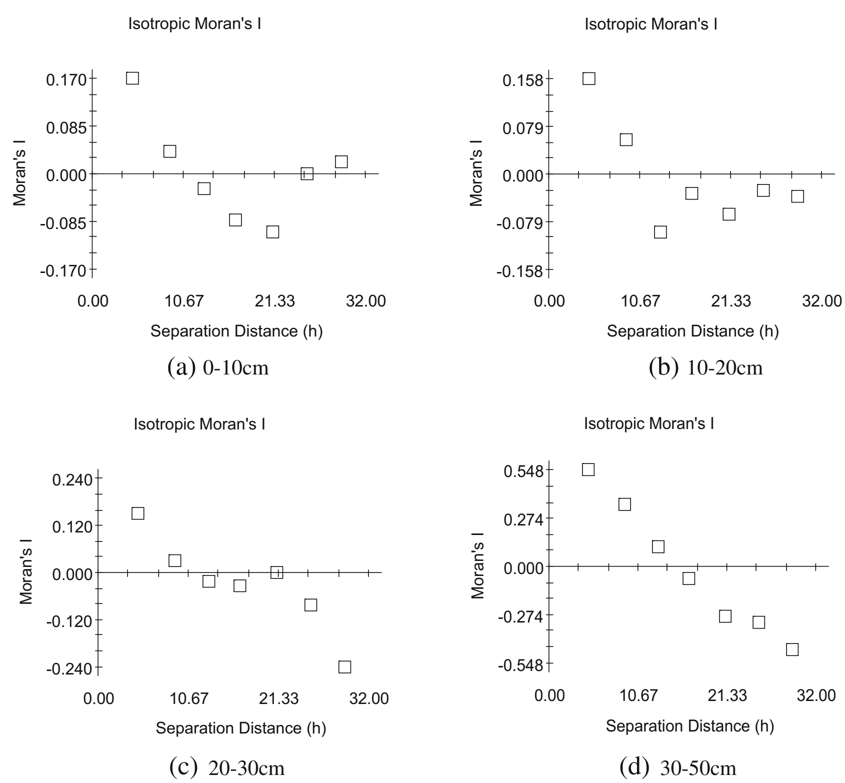

Fig. 4 Soil organic matter Moran's I figure of each soil layer at 32 × 32 m scale of (a) 0-10cm, (b) 10-20cm, (c) 20-30cm, (d) 30-50cm

Table 5 Effects of sampling spacing on semivariogram parameter of SOM in 0~50 cm layers

Soil depth (cm)	Sampling spacing (m)	Semivariogram model	C_0	$C_0 + C$	$C_0/(C_0 + C)$	A(m)	R^2
0~10 cm	4	Exponential	0.007	0.048	0.139	75.33	0.873
	8	Exponential	0.015	0.099	0.148	20.39	0.776
	12	Gaussian	0.065	0.456	0.143	115.72	0.696
10~20 cm	4	Exponential	0.012	0.109	0.109	10.11	0.816
	8	Exponential	0.008	0.087	0.197	10.86	0.604
	12	Gaussian	0.109	0.604	0.180	122.10	0.814
20~30 cm	4	Gaussian	0.049	0.183	0.262	96.00	0.849
	8	Gaussian	0.042	0.085	0.499	31.10	0.744
	12	Gaussian	0.060	0.257	0.235	99.65	0.736
30~50 cm	4	Gaussian	0.044	0.190	0.231	33.22	0.991
	8	Gaussian	0.061	0.164	0.369	30.95	0.973
	12	Gaussian	0.018	0.144	0.122	22.50	0.967

was smaller for the predicted than the measured content. The range of variation of SOM content was similar for Kriging and IDW interpolation, likely because the Kriging interpolation method in order to achieve the smoothness of the estimate values line increases the smaller numerical, reducing the gap between the maximum and minimum, resulting in the standard deviation and coefficient of estimated values less than the measured value. The accuracy of IDW interpolation was higher at the smaller scales. The standard deviation was small for each soil layer, and the variability was low or weakly moderate, so two interpolation methods were applicable to the entire data set. The Kriging interpolation was more accurate than IDW: RMSE was lowest for Kriging, and average ME was close to 0. This result was consistent with related studies (Yasrebi et al. 2009; Mabit and Bernard 2010).

Spatial distribution of SOM content

We have found that Kriging interpolation was the more accurate method. So we choose the Kriging interpolation, and first, the data for SOM were transformed to a normal distribution. After the interpolation, the SOM was transferred to obtain more data. The horizontal and vertical spatial distributions of SOM content in the 0–10 cm layer at the five scales and three spacings are shown in Fig. 5.

Each layer had peaks and valleys. The magnitude of the peaks and the SOM content decreased gradually with depth, and magnitude of the valleys remained about the same. The distribution of SOM was more uniform in the surface soil, perhaps because shallow soil is more susceptible to rain, evaporation, artificial tillage, and other external factors. The peaks and valleys became more uniform as the scale decreased,

Table 6 Comparison of measured and estimated values by two interpolation methods of soil organic matter

Soil depth	Estimated method	Point of estimated	Max	Min	Mean	CV	SD	RMSE	ME
0–10 cm	Measured		5.75	4.25	4.95	6.04	0.30		
	Kriging	94	5.18	4.77	4.94	1.95	0.09	0.2857	− 0.0097
	IDW	94	5.17	4.78	4.56	2.19	0.11	0.2899	− 0.1094
10–20 cm	Measured		4.73	3.52	4.12	7.81	0.32		
	Kriging	94	4.32	3.87	4.12	2.80	0.12	0.3154	0.0136
	IDW	94	4.37	3.78	4.14	3.04	0.13	0.3234	0.0159
20–30 cm	Measured		3.73	2.61	3.26	7.60	0.25		
	Kriging	94	3.43	2.85	3.26	3.68	0.12	0.2319	− 0.0020
	IDW	94	3.41	3.07	3.27	2.69	0.09	0.2361	0.0126
30–50 cm	Measured		3.61	2.41	2.86	11.89	0.34		
	Kriging	94	3.57	2.47	2.86	10.15	0.29	0.2228	− 0.0003
	IDW	94	3.25	2.57	2.85	7.84	0.22	0.2384	− 0.0250

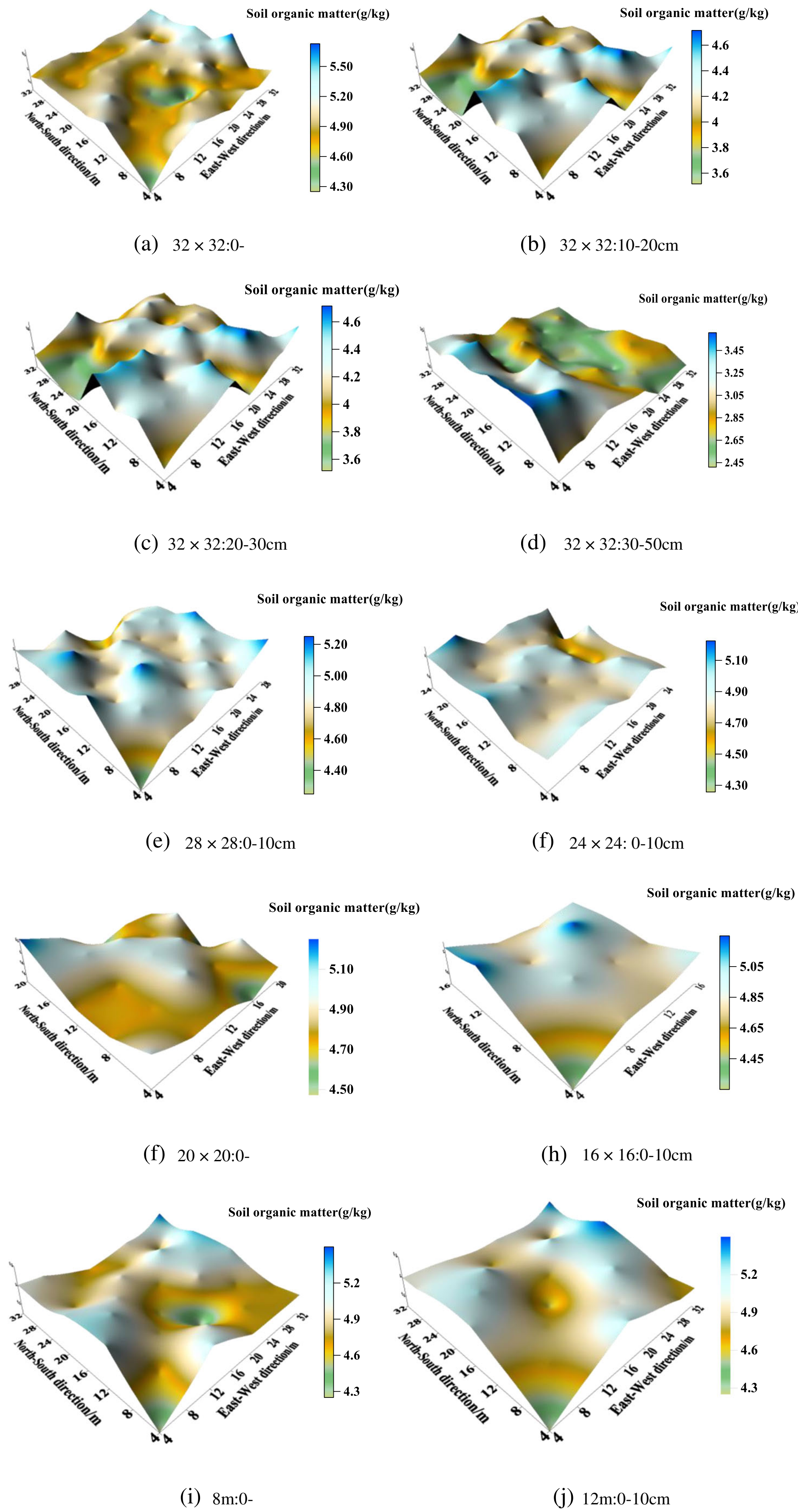

Fig. 5 Spatial distribution of soil organic matter at each scale of (a) 32 × 32:0-10cm, (b) 32 × 32:10-20cm, (c) 32 × 32:20-30cm, (d) 32 × 32:30-50cm, (e)28 × 28:0-10cm, (f)24 × 24: 0-10cm, (g) 20 × 20:0-10cm, (h) 16 × 16:0-10cm, (i) 8m:0-10cm, (j) 12m:0-10cm

which may have been due to the terrain. From the a, i, and j plots in Fig. 5, the spatial distribution of SOM content in 0–10 cm soils at different sampling spacing is approximately the same, but the distribution pattern tends to be uniform as the sampling distance increases. When the sampling spacing is 8 m, although the pattern tends to be uniformed, the spatial distribution map with a sampling spacing of 4 m has little difference, which can better characterize the spatial distribution characteristics of SOM, and when it is 12 m, compared with 4 and 8 sampling spacing, the distribution characteristics are too uniform which can no longer characterize the actual spatial variability. Therefore, the sampling spacing of 8 m in this study is reasonable, which can greatly reduce the workload of sampling on the basis of reliable experimental results.

Conclusions

(1). The variability of SOM content decreased with scale for the same layer. The CV was lowest in the 0–10 cm layer. $C_0/(C_0 + C)$ was < 0.25, indicating that the SOM content to a depth of 50 cm was strongly spatially autocorrelated. SOM content was strongly spatially correlated, with Moran's I ranging between −0.548 and 0.548. Under the condition of different sampling spacing, the CV did not change much. This indicates that when the sampling scale is fixed, the change of sampling spacing cannot change the factors affect the variation of SOM content. With the increase of sampling spacing, the C_0 basically shows an increasing trend, and the SOM content shows a strong spatial autocorrelation as a whole.

(2). The standard deviation was small for each soil layer, and the variability was low or weakly moderate, so two interpolation methods were applicable to the entire data set. The Kriging interpolation was more accurate and practical than IDW. The spatial distribution of SOM content under the different sampling spacing has the same overall trend, but with the increase of sampling spacing, the distribution pattern tends to be uniform. The sampling spacing of 8 m can better characterize the spatial distribution characteristics of SOM.

(3). The spatial variability of SOM is scale-dependent. So comparing the results by sampling at different spatial scales and spacing, it is important to master how SOM changes at each scale. Field scales are foundation for reasonable layout of crops, to improve the field management and increase efficiency of soil.

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