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Impact of environmental factors on the spatiotemporal variability of soil organic matter: a case study in a typical small Mollisol watershed of Northeast China

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Abstract

Propose Soil organic matter (SOM) content is one critical indicator of agricultural sustainability. Analyzing the spatial distribution and temporal variation of SOM content and its influencing factors at the watershed scale is essential for maintain sustainable soil fertility and productivity in the Chinese Mollisol region.

Materials and methods A total of 292 soil samples at the same sampling points in 2005 and 2016 were used to quantitatively study the spatial heterogeneity of SOM dynamics in Tongshuang small watershed. Effects of land use types and topographic factors (slope gradient, slope positions, slope aspect, elevations, and topography wetness index (TWI)) on the spatiotemporal distribution of SOM dynamics were investigated.

Results and discussion The results showed that the variability of SOM content was moderate variation, with an increase rate of 0.21 g kg^{-1} year^{-1} from 2005 to 2016. The spatial autocorrelation of SOM content was strengthened by 30.37% in 2016 compared with that in 2005. Slope gradient, slope position, slope aspect, elevations, and TWI had significant effects on the SOM content in 2005 and 2016, but not for the variation of SOM content. The explanatory ability of each factor and their interaction to spatial variability of SOM content was strengthened from 2005 to 2016. Slope gradient and TWI could explain over 8.15% of spatial variability in SOM content.

Conclusion A combination of slope position with TWI was the dominant interaction factor that explaining at least 16.0% of the SOM distribution. This study is important for the accurate estimation of carbon reserves, sustainable utilization, and management of soil nutrients and to improve soil productivity in the Chinese Mollisol region.

Keywords Soil organic matter · Spatial variability · Topographic factors · GeoDetector · The Chinese Mollisol region

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1 Introduction

Soil organic matter (SOM) is the largest terrestrial sink of carbon in the global carbon cycle (Fang et al. 2018; Funes et al. 2019; Mayer et al. 2019), which also plays a critical role in keeping the sustainability of soil quality and productivity (Funes et al. 2019; Sun et al. 2018). It has long been recognized that small changes in SOM could influence regional carbon balances (He et al. 2020; Obalum et al. 2017). Therefore, understanding the spatiotemporal distribution and the factors that control SOM variation is significant for estimation of soil carbon storage (Hounkpatin et al. 2018); develop carbon mitigation strategies (Adhikari et al. 2019), and regional ecological environment construction (Lu et al. 2018).
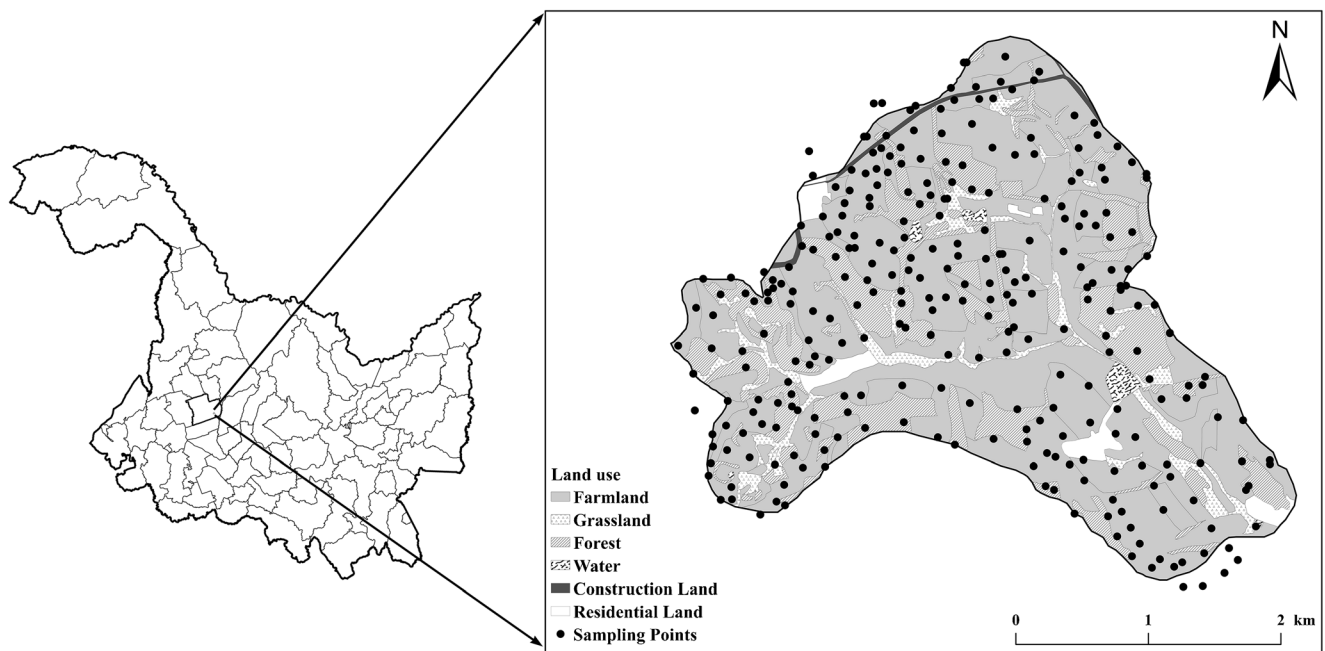
Fig. 1 Location map and land use map of Tongshuang small watershed in 2016

The spatial heterogeneity and temporal variation of SOM was influenced by various factors, such as land use (Wang et al. 2020a; Yu et al. 2017), and topographic factors (Hounkpatin et al. 2018; Zadorova et al. 2014). Land use altered soil carbon sequestration process (Hu et al. 2018; Xu et al. 2015) by changing land cover, root activity, and micro-organisms (biotic mechanisms) (Liu et al. 2017). Numerous studies have investigated the SOM dynamics under different land use types (Fang et al. 2018; Lu et al. 2018; Mayer et al. 2019), but have obtained various results. For example, Smal and Olszewska (2008) proposed that Scots pine forests decreased the accumulation of SOM in Poland, while Kalinina et al. (2015) reported that soil carbon stock showed a decrease-increase trend during 1–42 years restoration in the dry steppe zone of Russia. Meena et al. (2018) noted that the returning of degraded farmland ecosystem to forest and grass land ecosystem could increase the accumulation of SOM content in Indian mid-Himalaya region. Thus, the SOM dynamic remains unclear under various land planning strategies (Xu et al. 2015).

Topographic factors, including elevation, topographic wetness index (TWI), slope gradient, slope positions, and slope aspect (Bai and Zhou 2020; Chen et al. 2016; Sigua and Coleman 2010), can modify geomorphologic and hydrological dynamics (Huang et al. 2020; Vos et al. 2019) through abiotic influences by altering land cover pattern and local microclimate (Funes et al. 2019; Wang et al. 2020b). Elevation controls the zonal climatic conditions along the vertical gradient (Zhu et al. 2019b), with different heat conditions, precipitation, and decomposition rates as the increasing elevation, and then resulted in different responses to SOM accumulation (Li et al. 2019b). TWI is used to characterize soil wetness at different landscape positions (Xin et al. 2016). High TWI values within floodplains indicate high soil moisture content for the strong accumulation of SOM (Swetnam et al. 2017). Slope gradient affects SOM distribution through influences soil erosion intensity (Zhang et al. 2020), but varies among soil types (Nabiollahi et al. 2018; Takoutsing et al. 2018). Slope position governed the SOM distribution through soil erosion and decomposition process (Tu et al. 2018), and result in a higher content in the foot slope area than at higher slope positions (Li 2017). Slope aspect represents solar radiation conditions (Zhu et al. 2019a), the SOM on the north slopes generally greater than the south slopes in semiarid regions of the Northern Hemisphere due to lower soil moisture and more drought-tolerant species in south slopes (Yu et al. 2020). In general, the reshaped climatic, hydrological, and ecological conditions by these topographic factors can sharply modify the spatial and temporal patterns of SOM contents (Fan et al. 2020; Kobler

Table 1 The descriptive statistical analysis of SOM content and K-S test

|	Minimum (g kg^{-1})	Maximum (g kg^{-1})	Mean (g kg^{-1})	S.D. (g kg^{-1})	CV (%)	Skewness	Kurtosis	K-S (P)
2005	0.62	102.55	39.01	11.91	30.53	0.73	3.47	0.17
2016	8.45	93.21	41.34	12.39	29.98	0.33	0.86	0.75

Table 2 Isotropic semivariogram theory model and related parameters of SOM content

Year	Nugget coefficient $C_0/C_0 + C$ (%)	Range (m)	R^2	RSS
2005	16.53	342	0.684	5.25E-06
2016	11.51	252	0.763	3.85E-07

et al. 2019). In addition, there existed interaction effect among various topographic factors on soil properties by changing the soil erosion process (He et al. 2020; Obalum et al. 2017). Thus, our understanding of SOM dynamics affected by topographic factors remains incomplete.

Globally, serious soil erosion can result in soil degradation (de Nijs and Cammeraat 2020), the loss of soil nutrients, and the redistribution of SOM content (Hancock et al. 2019). Previous

studies (Adhikari et al. 2019; Olson et al. 2016; Zhang et al. 2013) reported that the conversion of forest to farmland resulted in SOM stock decreased approximate 10–52% during 100–150 years, which had threaten the sustainable development of local agriculture (Cui et al. 2007; Zhang et al. 2007; Zhang et al. 2018b). To prevent soil erosion and enhance soil carbon accumulation, Chinese government has established the "Grain for Green" program since the 1980s (Sun et al. 2018), which involved in returning farmland into forestlands and grasslands (Li et al. 2019a; Wei et al. 2008; Zhang et al. 2011). Numerous studies noted that vegetation restoration can recover the soil properties in the serious eroded areas (Burst et al. 2020; Funes et al. 2019; Li et al. 2019a; Miao et al. 2014; Zhang et al. 2016). Thus, understanding the SOM dynamics during vegetation restoration processes is becoming increasingly important (Meena et al. 2018). However, few studies have systematically investigated the spatial distribution patterns and temporal variation of the
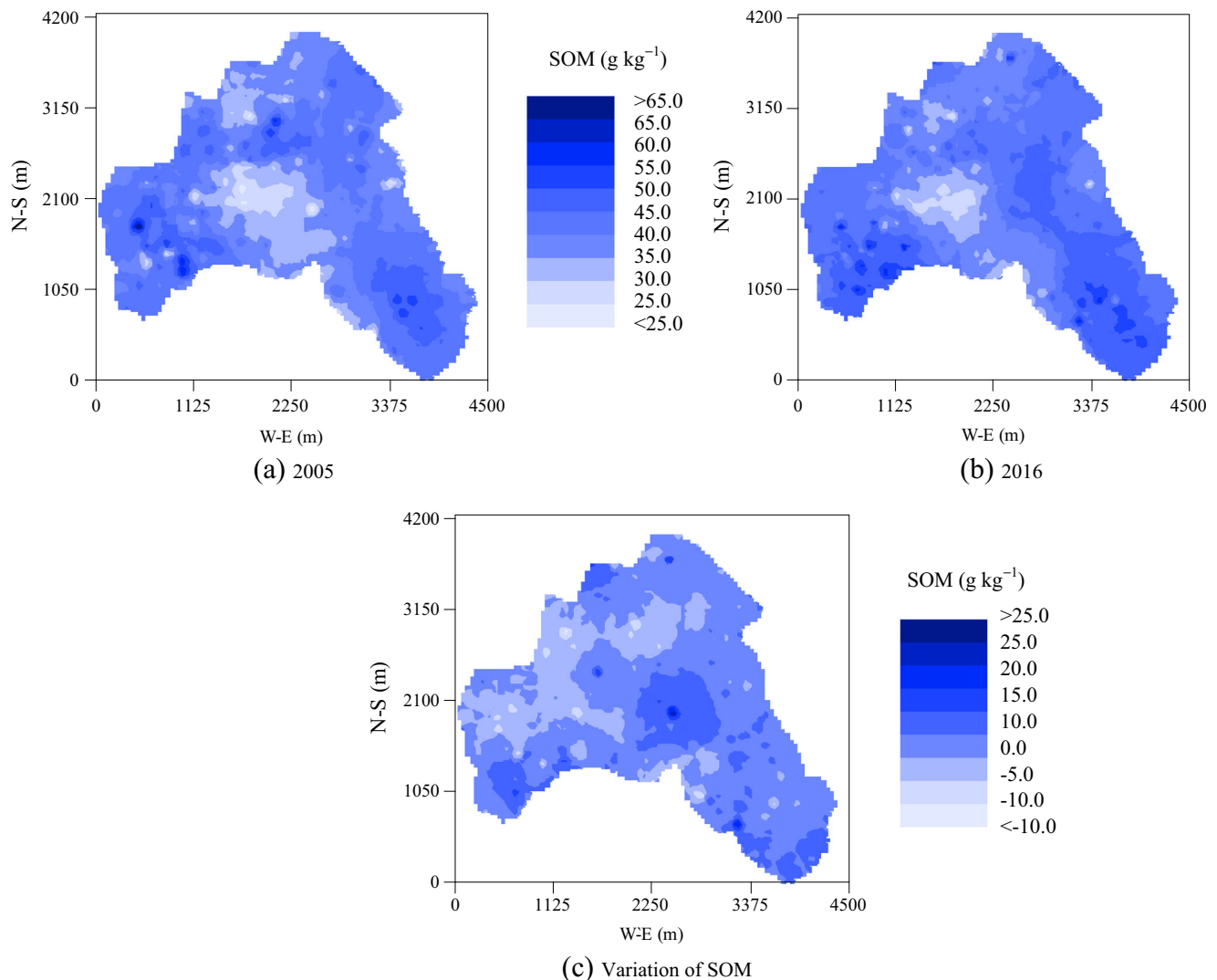
Fig. 2 Spatial distribution of SOM content in the 2005 (**a**), 2016 (**b**), and the variation (**c**)
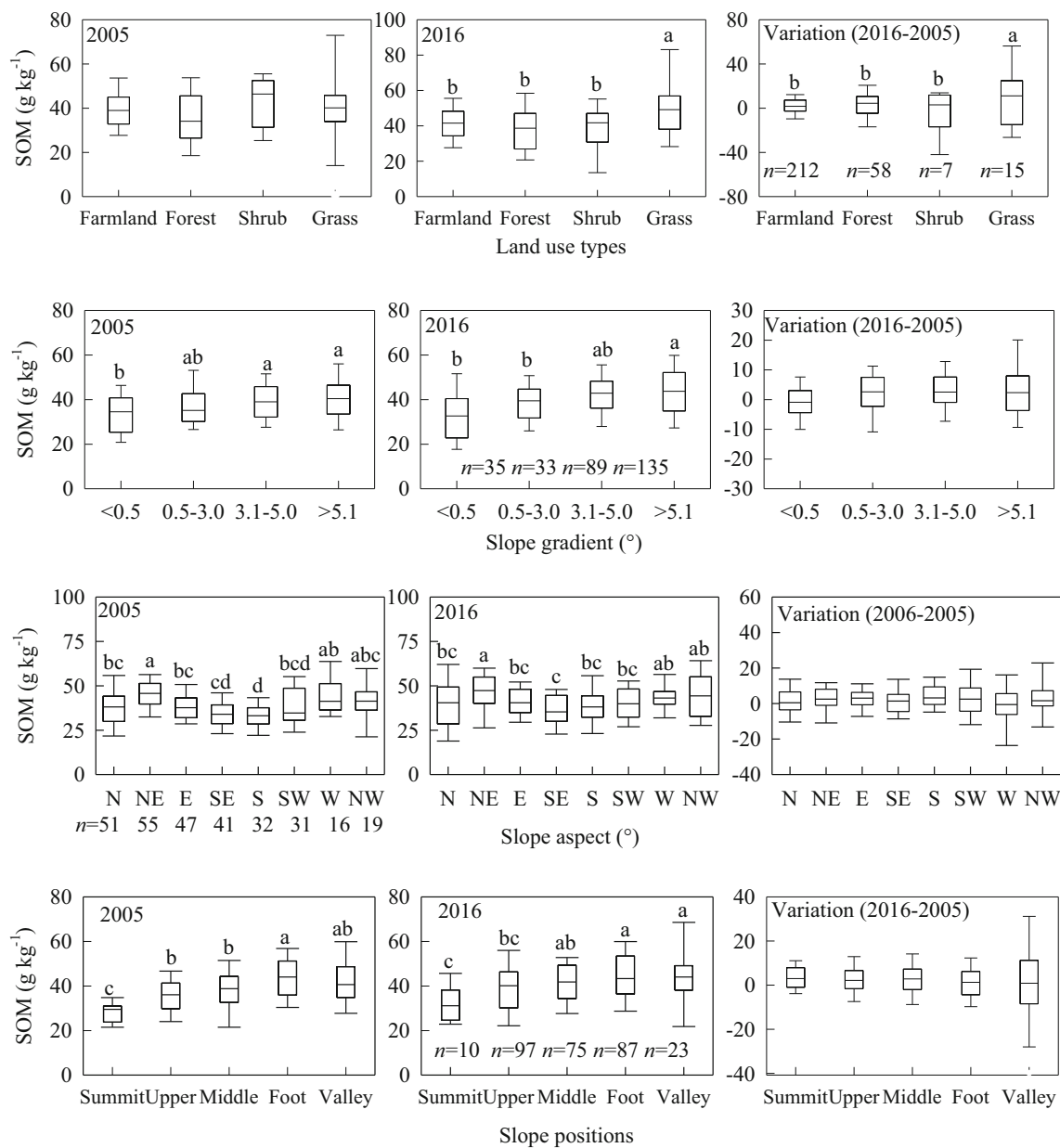
Fig. 3 Box plots showing the influence of land use types, slope gradient, slope position, and slope aspect on the SOM content. The central divider of the box is the median of the SOM data of each land use type. The box delimits the inter-quartile range (lower quartile Q1 and upper quartile Q3), and the whiskers indicate the variation outside this interquartile range. The same in Fig. 4

SOM content at the same sampling points within the controlled watershed. In addition, the influence of unique environmental factors and their interactions on the dynamics of SOM content is still poorly understood at the controlled watershed with certain land use patterns. Hence, a typical controlled Mollisol watershed in Northeast China, where the soil had higher SOM content and is known as "black soil" (Liu et al. 2008; Liu et al. 2012; Zhang et al. 2018b), was selected as the study case. The objectives of this study were to (1) examine the spatial and temporal variability of SOM content at the same sampling points during 2005–2016; and (2) quantify the distinct influence of environmental factors on SOM dynamics.

2 Materials and methods

2.1 Study area

The study has been conducted in Tongshuang small watershed (126° 14' 45– 126° 17' 15' 'E, 47° 26' 00– 47° 28' 30 N), which is located in the southeastern of Baiquan county, Heilongjiang province, Northeast China (Fig. 1). It covers an area of 992 ha. This region has a typical temperate monsoon climate, which was characterized by short warm summer and long cold winter, with annual average temperature and precipitation of 1.28 °C and 490 mm (Wei et al. 2006). The rainy
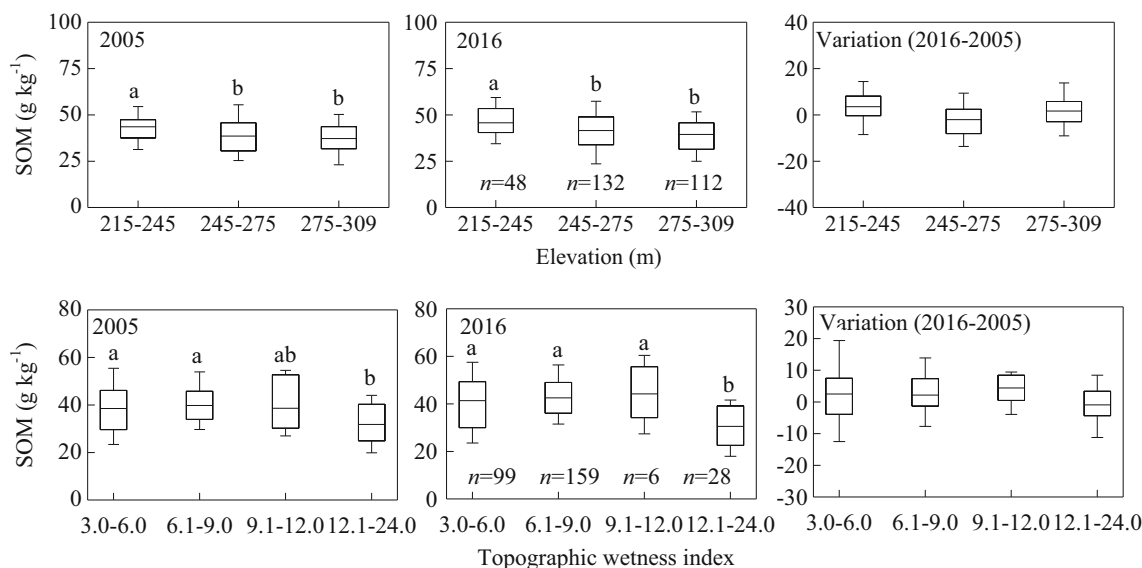
Fig. 4 Box and whiskers plots showing influence of elevation, and topographic wetness index on the SOM content

season is from June to August. The elevation ranges from 215.6 to 309.1 m. The slope gradient ranges from 0° to 19°. This watershed with hilly landscape, with the soil classified as Mollisols (USDA Taxonomy). The main cultivation is corn-soybean rotation. Various ecological programs, including farmland (such as terraces and contour tillage), forest land, shrub land, and grassland, have been implemented on hillslopes since 1980s due to the drastic erosion in the late 1970s. The shrub vegetation includes *Salix monglica* and *Salix viminalis*, and forest vegetation includes *Larix dahurica* and *Pinus sylvestris* Var. *mongolica* (Wei et al. 2008).

2.2 Soil sampling and measurements

A 500 by 500 m grid was used for collecting soil samples according to different land use, topographic factors, and representative principles in the field survey. A total of 292 soil samples in the top layer of 20 cm (plowed layer), where > 50% of soil organic carbon was distributed (National Soil Survey Office 1997), were collected at the same sampling points within the watershed in June 2005 and June 2016 (Fig. 1). Each soil sample was a composite of five subsamples based on the four corners and center points of the 1 by 1 m square. A subsample of 1 kg per mixed sample was isolated for laboratory analysis. Sample sites were laid on different slope positions including summit, upper,

middle, foot, and valley slope (Wei et al. 2008). The sampling sites were recorded by the global positioning system (GPS) (Fig. 1). Soil samples of SOM were air-dried and sieved at 0.25 mm, and analyzed by using an elemental analyzer (Vario EL III, Germany) (Slepetiene et al. 2008). Because the soils were free of carbonates, soil organic carbon (SOC) was assumed to be equivalent to total carbon (Liang et al. 2009; Zu et al. 2011).

2.3 Mapping of land use types and the calculation of topographic factors

Field mapping of land use types based on a relief map of scale 1:10,000 and Landsat-8 image (ETM+ of August, 2016, 15 m resolution). A digital map of land use types was built according to a triangulation network calculated from contour lines with 1 m intervals using ArcGIS 10.2 (ESRI 2013, ArcGIS Desktop: Redlands, CA: Environmental Systems Research Institute).

Four topographic factors, including elevation, TWI, slope gradient, and slope aspect, were calculated from DEM. According to the techniques standard for comprehensive control of soil erosion in the black soil erosion SL 446-2009, Ministry of Water Resources, China, the contour tillage, vegetated earth bund, and terrace were suitable for built at the slope gradient < 3°, 3°–5°, and > 5° perpendicular to the

Table 3 Correlation analysis between environmental factors and SOM content

	Land use types	Slope gradient	Slope aspect	Slope position	Elevation	TWI
SOM_{2005}	0.016	0.172[**]	0.026	0.157[**]	− 0.195[**]	− 0.181[**]
SOM_{2016}	0.083	0.244[**]	0.053	0.122[*]	− 0.211[**]	− 0.274[**]
$SOM_{variation}$	0.075	0.086	0.030	− 0.031	− 0.025	− 0.111

[**] $p < 0.01$; [*] $p < 0.05$

Table 4 q values of single factors influencing the spatial variability of SOM content under different topographic factors

	Slope gradient	Slope position	Elevation	TWI
SOM$_{2005}$	0.034	0.099	0.028	0.043
SOM$_{2016}$	0.0815**	0.057	0.037	0.0820*

** $p < 0.01$; * $p < 0.05$

sloping farmland, respectively (Ministry of Water Resources 2009); thus, the slope gradient was grouped into 4 classes (< 0.5°, 0.5°–3.0°, 3.1°–5.0°, > 5.1°). Slope aspect was designated as north (N), northeast (NE), east (E), southeast (SE), south (S), southwest (SW), west (W), and northwest (NW).

2.4 Statistical methods

2.4.1 Classical statistical analysis

The descriptive statistics was performed using the statistical software SPSS 21.0 (IBM SPSS Statistics for Windows, IBM Corp., Armonk, NY, USA). Analysis of variance (ANOVA) was conducted to examine significant differences in SOM. For the results of multiple comparisons, the method of least significant difference (LSD) procedure was used, and the values were statistically significant at the 95% confidence level. The correlation analysis between land use types and topographical factors with SOM was also investigated.

2.4.2 Geostatistics analysis

Spatial variations in SOM were analyzed by using GS + 9.0 (Gamma Design Software, Plainwell, MI, USA). Besides, the Kriging spatial interpolation was applied to draw the spatial distribution map of SOM dynamics. The semivariogram was calculated using the following equation:

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

where $\gamma(h)$ is the experimental semi-variogram value at distance interval h, $N(h)$ is the logarithm of the distance when the distance equals h, $Z(x_i)$ is the value at location x_i; and $Z(x_i + h)$ is the value at a distance h from x_i.

2.4.3 GeoDetector method

Spatial heterogeneity of geographic phenomena and its key driving factors could be analyzed by GeoDetector (http://www.geodetector.org/). Both numerical data and qualitative data can be detected in geodetector method (Wang et al. 2010). There are four modules of GeoDetector, involved in factor detector, risk detector, interaction detector, and ecological detector(Wang et al. 2016).

In the present study, factor detector and interaction detector were used to detect the independent and interactive explanatory abilities of environmental factors to SOM dynamics, respectively. Factor detector can detect the ability of the independent variable to interpret the spatial variability of the dependent variable (Wang et al. 2019), which can express as q value (ranged from 0 to1, the larger q value represents the greater the explanatory ability), the significance of the q value also can be test (Wang et al. 2010). The q values can be calculated as follows:

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

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2, \quad SST = N\sigma^2 \quad (3)$$

where $h = 1, ..., L$ is the classification of independent variable; N_h and N are the number of sample units in classification h and the whole region, respectively; σ_h^2 and σ^2 are the variance in the classification h and the whole region, respectively; SSW and SST mean within sum of squares and total sum of squares, respectively (Wang et al. 2010; Wang et al. 2016).

Interaction detector can identify the interaction between two independent variables by comparing the q values of single factor and the interaction q values as compared with conventional statistical methods (Wang et al. 2016). There are five types of interaction between two covariates, as long as interaction exists, it can be detected (Wang et al. 2019).

3 Results

3.1 Description statistics of SOM content

The SOM contents increased from 39.01 to 41.34 g kg^{-1} from 2005 and 2016. The increase rate of SOM content was 0.21 g kg^{-1} year^{-1} (Table 1). The coefficient variations (CV) of SOM in 2005 and 2016 were 30.53% and 29.98%, respectively, indicating moderate variation. The SOM contents were normally distributed, as indicated by the shape parameters (skewness and kurtosis) of the data ($p > 0.05$), which met the requirement of geostatistic analysis.

3.2 Spatial and temporal variability in SOM content

The exponential model gave the best fit for the SOM contents in 2005 and 2016 (Table 2). The nugget coefficient in 2005 and 2016 was lower than 25%, indicating high spatial autocorrelation of SOM content and the spatial variability was mainly influenced by structural factors. The spatial autocorrelation of SOM content was strengthened in 2016; the nugget coefficient value in 2016 was lower 30.37% than that in 2005.

The range of spatial autocorrelation decreased 90 m from 2005 to 2016.

In 2005 and 2016, the SOM distributions presented ribbon and plaque shapes (Fig. 2). The higher SOM content was distributed in the northeast, southwest, and southwest areas and the lower SOM content was distributed in the middle area. In addition, the SOM content increased in east, southwest, and southwest areas, but decreased in the west and northwest areas during 2005–2016.

3.3 Analysis of influencing factors on SOM content

The SOM content in grassland was significantly greater than that in other land use types in 2016 (Fig. 3, $p < 0.05$). The value in grassland was 1.23, 1.32, and 1.31 times greater than that in farmland, forestland, and shrub land, respectively. In addition, the variation rate of SOM content in grassland was 4.14, 3.96, and 3.07 times greater than that in farmland, forestland, and shrub land, respectively ($p < 0.05$).

The mean SOM content increased with the increasing slope gradient, and the values increased by 1.20 and 1.33 times as slope increased in 2005 and 2016, respectively (Fig. 3, $p < 0.05$). SOM content increased by 3.36%, 6.51% and 7.82% in 0.5°–3°, 3°–5°, and > 5.1°, respectively, while decreased by 2.84% in the slope of < 0.5° from 2005 to 2016 ($p > 0.05$).

For different slope aspects, the mean SOM content significantly decreased from N slopes to SE and S slopes, and then increased to NW slopes in 2005 and 2016 (Fig. 3, $p < 0.05$). The values in NE slopes were 1.29 to 1.37 times, and 1.22 to 1.29 times greater than those in S and SE slopes in 2005 and 2016, respectively. The SOM content increased in all slope aspect except in W slopes, which decreased by 1.68% from 2005 to 2016 ($p > 0.05$).

For different slope positions, the mean SOM content increased from the summit slope to valley slope, the values increased by 1.54 and 1.41 times in 2005 and 2016, respectively (Fig. 3, $p < 0.05$). SOM content increased by 1.90%, 3.65%, 7.45%, 9.19%, and 12.05% in foot, valley, upper, middle, and summit slope, respectively from 2005 to 2016 ($p > 0.05$).

The mean SOM content decreased with elevation, and its content decreased by 13.63% and 15.10% as elevation decreased in 2005 and 2016, respectively (Fig. 4, $p < 0.05$). SOM content increased by 5.00% and 6.82% in 275–309 m

and 215–245 m, respectively, while decreased by 6.11% in 245–275 m from 2005 to 2016 ($p > 0.05$).

For different TWI intervals, the mean SOM content in 3.0–6.0 and 6.1–9.0 TWI intervals was significantly greater than that in 12.1–14.0 TWI intervals, and the values were 1.21 and 1.27 times and 1.33, 1.40 times greater than that in 12.1–14.0 TWI intervals in 2005 and 2016, respectively (Fig. 4, $p < 0.05$). SOM content increased by 6.33%, 6.64%, and 10.10% in 3.0–6.0, 6.1–9.0, and 9.1–12.0, respectively, while decreased by 3.31% in 12.1–24.0 from 2005 to 2016 ($p > 0.05$).

SOM content was significant positive correlated with slope gradient and slope positions, but negative correlated with elevation and TWI in 2005 and 2016 (Table 3, $p < 0.05$). But there was no correlation among $SOM_{variation}$ and topographic factors. The factors that had no significant correlation with SOM content was excluded from the subsequent analysis.

3.4 Relationships between spatial variability of SOM content and topographic factors

3.4.1 Influence of single factors on spatial variability of SOM content

According to the factor detector, the factors influencing SOM content were differed in 2005 and 2016 (Table 4). There was no dominant factor influence the spatial variability of SOM content in 2005; while in 2016, TWI was the dominant factor, its explanatory ability was 8.20%; followed by slope gradient with an explanatory ability of 8.15%.

3.4.2 Influence of interactions between factors on spatial variability of SOM content

The influence of interactions between various factors was enhanced compared with the influence of single factors (Table 5). In 2005, the interactions of slope position with TWI, elevation, and slope gradient were the dominant factors influencing SOM content, and their explanatory abilities increased by 6.1%, 3.5%, and 2.5%, respectively, compared with those of slope position alone. However, different interactions of factors were observed in 2016, when the explanatory ability of each interaction was much higher than that in 2005; the explanatory abilities of slope position with TWI

Table 5 q values for the interactions between factors influencing the spatial variability of SOM content under different topographic factors

	SOM_{2005}	SOM_{2016}
Dominant interaction 1	Slope position ∩ TWI	Slope position ∩ TWI
q	0.160	0.161
Dominant interaction 2	Slope position ∩ Elevation	Slope gradient ∩ Elevation
q	0.135	0.158
Dominant interaction 3	Slope position ∩ Slope gradient	Slope gradient ∩ Slope position
q	0.125	0.147

were the highest (16.1%), and the interactions of slope gradient with elevation (15.8%) and slope position (14.7%) became the dominant factors influencing SOM content.

4 Discussion

4.1 Dominant factors influencing the spatial variability of SOM content

In the present study, the spatial variability of SOM content was mainly affected by structural factors, including topography factors, climate, and parent material, which drove the soil heat and water (Fan et al. 2020; Yu et al. 2020; Zhu et al. 2019a), solar radiation condition (Bai and Zhou 2020; Sigua and Coleman 2010), and soil erosion (Zhang et al. 2007). The spatial dependence of SOM was affected little by human factor in the present study, and the continuity of disturbance from human factor is not high (Zhu et al. 2019b). According to the factor detector, slope gradient and TWI could explain the spatial variability of SOM content. This indicated that the slope gradient and TWI-induced variations in soil temperature and moisture were the main controls of SOM spatial patterns in the present study areas.

Slope gradient affected the redistribution of SOM content through alter soil erosion process (Miheretu and Yimer 2018; Zhang et al. 2020). SOM content was significant positive correlated with slope gradient. This was also reported in previous studies, but the increment of SOM content could attribute to the increase of rock exposure rate in the karst region of southwest China (Hu et al. 2018), or attribute to the reduced actual inclusion area of the slope on the China's Loess Plateau (Zhang et al. 2020); while in the present study, this phenomenon could attribute to the implementation of ecological programs (Ministry of Water Resources 2009) that enhanced the accumulation of SOM content (Zhang et al. 2020). However, contradictory results have also been reported, such as decreased (Nabiollahi et al. 2018; Takoutsing et al. 2018), no change (Tu et al. 2018), and exist a slope threshold (Zhang et al. 2018a). The inconsistency of these abovementioned observations suggests that the spatial distribution of SOM content is site-dependence (Bai and Zhou 2020; Sigua and Coleman 2010).

TWI is used to characterize soil wetness at different landscape positions (Xin et al. 2016; Swetnam et al. 2017). SOM content was significant negative correlated with TWI in the watershed. This was different with previous report (Liu et al. 2017; Zadorova et al. 2014) that higher TWI values indicate higher soil water content and resulted in the slower decomposition rates and mineralisation rate of organic matter (di Folco and Kirkpatrick 2011). One possible reason was that water movement from upslope to downslope is more divergent in lower areas (Hounkpatin et al. 2018) and result in TWI may

not capture the movement of water flow well at lower sites (Fan et al. 2020). Another possible reason was that different ecological programs changed the topographic concavo-convex, which exhibit different underlying condition influence the redistribution of water and sediment (including the transport of organic matter). The above reasons may reduce TWI control on the distribution of SOM content (Li et al. 2018).

Various factors may interact with each other to influence the spatial variability of SOM content (He et al. 2020; Obalum et al. 2017) through influence the local microclimate, which directly affect the decomposition rate and plant production (Qin et al. 2016). In the current study, the interaction of slope position with TWI had the highest explanatory ability to the spatial variability of SOM content, followed by slope position/ slope gradient with elevation, and slope position with slope gradient. The fine particles combined with organic matter in the summit and upper slope were transport (Wei et al. 2008; Xu et al. 2015) and deposited on the foot and valley slope (Li 2017; Tu et al. 2018) along the gentle and long slope in this region. Moreover, TWI and elevation determines alter soil water (Li et al. 2019b; Liu et al. 2017) and heat conditions (Xin et al. 2016; Zadorova et al. 2014). Due to the relatively low elevation (215 − 309 m), temperature changed little by the increasing elevations (Hu et al. 2018), the wetter and warmer conditions in lower elevations promote the increase of the biomass productivity and organic carbon inputs (Zhu et al. 2019b); while the SOM in high elevation areas could be easily lost and concentrated in valley lowlands (Yu et al. 2020). In addition, ecological programs set at different slope gradient intervals can not only effectively reduced soil erosion (Ministry of Water Resources 2009), but also enhanced the accumulation of SOM (Zhang et al. 2020). Different results also been reported, Zhu et al. (2019a) and Zhang et al. (2020) proposed that the spatial distribution of SOM was significantly affected by the interaction of elevation and slope aspect, slope gradient and slope aspect. This could be attributing to that interaction of the topographic factors affected the SOM content through their indirect influences on the microclimate and vegetation type (Fan et al. 2020; Yu et al. 2020; Zhu et al. 2019a).

4.2 Temporal characteristics of the SOM content

During 2005–2016, the spatial autocorrelation of SOM content strengthened but the spatial autocorrelation range decreased; this indicated that the spatial autocorrelation distance and heterogeneity decreased. This was inconsistent with previous study in the corn belt of Northeastern China over 1980s to 2005 (Miao et al. 2014), when the spatial autocorrelation of SOM content was weakened and the range increased, which could mainly attributed to the effects of land-use and land cover changes, crop productivity increase, and agricultural managements (Zhu et al. 2019a). In addition, the influence

of single factors and the interactions between various factors was enhanced in 2016 as compared with that in 2005. This indicated that topographic factors enhanced the spatial variability of SOM content after 11 years implementation of ecological programs, which also confirming the results of the semi-variance analysis.

Based on the balance theory of SOC, the evolution of SOM on sloping farmland was driven by soil erosion and non-erosive natural evolution before ecological program implemented (Zhang et al. 2013). The former depends on topsoil loss per year, namely as soil erosion modulus, the latter depends on the soil mineralization rate and humification rate of the existing farmland management mode (de Nijs and Cammeraat 2020; Hounkpatin et al. 2018; Zadorova et al. 2014). After the implementation of ecological programs, the evolution process of SOM was driven by soil erosion, equilibrium point, and the returned biomass, the increase of returned biomass leads to the root and litter increased, and finally result in the increase of SOM content (Van Oost 2007).

Numerous studies (Fang et al. 2018; Gong et al. 2007; Zhang et al. 2017) have investigated that land use caused by human activities was the predominant factor affecting the variation of the SOM content (Deng et al. 2017; Li et al. 2012), which affected SOM sequestration by alter canopy coverage, root distribution and activity (Burst et al. 2020; Gao et al. 2020), litter and soil microbial biomass (Chen et al. 2017; Hu et al. 2018). In the current study, grassland had greater SOM dynamics than that in other land use types because grassland has more favorable soil water conditions and a shorter life cycle (Deng et al. 2014; Karhu et al. 2011; Laganière et al. 2010), and less disturbed by human activities (Miheretu and Yimer 2018; Obalum et al. 2017; Xie et al. 2014). However, land use types had no correlation with SOM dynamics. The possible reason was that the ecological programs typically designed based on local topography condition and land use types, and this special land use patterns resulted in the influence of land use types on SOM overlaps with the influence of topographic factors may be diluted at some extent (Gao et al. 2020; Yu et al. 2017).

In addition, the initial SOM contents had significant effect on the variation in SOM content (Lal 2001). Previous study (Zhao et al. 2018) reported that initial SOM content accounted for over 30% of the variation in SOM stocks. The increment in carbon inputs was the primary reason result in the increase of SOM content in the low initial SOM contents areas (Xie et al. 2021). However, in the present study, the initial SOM content in the sloping farmland of the study areas was very low before 1980 (Wei et al. 2008). With the continuous plant-derived carbon inputs increased (Zhao et al. 2018), the soil in the study area could maintain relatively high-level SOM content over a long time period (1980–2005), and then resulted in a small increase during 2005–2016 as compared with other studies (Fang et al. 2018; Lu et al. 2018). The variation of SOM

content was a complex process affecting by the specific topography (Hounkpatin et al. 2018; Zadorova et al. 2014), vegetation restoration period (Xu et al. 2015; Yu et al. 2017), and human disturbances (e.g., the ecological program design) (Gao et al. 2020). Therefore, to better evaluate and clarity the mechanisms of driving factors behind SOM change, long-term monitoring is required for future research.

5 Conclusions

In the current study, a total of 292 soil samples at the same sampling points were used to investigate the spatial and temporal variations in SOM content over the period of 2005–2016, and identified the dominant factors of the spatial distribution of SOM content. Results showed that the SOM content increased at a rate of $0.21 \mathrm{~g~kg}^{-1} \mathrm{~year}^{-1}$ over the 11 years, and belongs to moderate variation. The spatial autocorrelation of SOM content was strengthened but the range decreased over the 11 years. SOM content was significant positive correlated with slope gradient and slope positions, but negative correlated with elevation and TWI in 2005 and 2016. No factor was identified as the dominant driver of the increment in SOM content. In addition, the explanatory ability of each factor and their interaction to spatial variability of SOM content was enhanced over the 11 years. No dominant driving factors were found in 2005, while slope gradient ($q = 0.0815$) and TWI ($q = 0.0820$) were the main drivers of the spatial variability of the SOM content in 2016. The interaction of slope position with TWI (q values of 0.160 and 0.161) predominantly explained the spatial heterogeneity of the SOM content. This study could provide scientific guidance for soil conservation, environment protection, and agricultural production planning in the study region.

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