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Research Article

Soil Organic Carbon Storage and Influencing Factors in Southwest Mountainous Area

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Abstract: As the biggest "carbon sinks" and "carbon source" of terrestrial ecosystems, soil organic carbon plays a crucial role in global warming and agricultural production. Both of natural and human factors has a momentous influence on soil organic carbon. The cultivated soil of mountainous and hilly area located in Yunyang County was selected as the object area of research. Elevation, slope, parent materials, slope position and Topography Wetness (TWI) are considered as essential factors for soil organic carbon. In addition, category variables were introduced into the regression model through path analysis, the mechanism of factors on cultivated Soil Organic Carbon (SOC) density was discussed. The variability of SOC density was gained by border analysis and anisotropic analysis. The results show that the average, 0-20 cm, cultivated SOC density is 2.91 kg/m^2 and the cultivated soil carbon storage is 1838.75×106 kg in the study area. The correlation between elevation and SOC density is significant (0.329**). Topography wetness index (TWI) also has great correlation with SOC density (0.256**). Areas covered by Gray-brown purple mud (shale) efflorescence and Purple sand and mud (shale) efflorescence have lower SOC density. The sequence of SOCD in different slope position is: Valley>slope foot>ridge>slope shoulder>slope back. From spatial variation aspect, anisotropic analysis illuminates that, spatial variability of SOC density is more drastic in south-north orientation than in east-west orientation.

Keywords: Anisotropic, impact factors, soil organic carbon

INTRODUCTION

Soil Organic Carbon (SOC) is an import ant soil component in farming systems. It is essential to improve soil and water quality and hence sustains food production (Singh *et al*., 2007; Longbottom *et al*., 2014). As the largest carbon reservoir in terrestrial ecosystems (Li *et al*., 2002), soil carbon library has an important effect on the greenhouse effect and global climate change4.

There is strong spatial variation in Soil Organic Carbon (SOC) (Xie *et al*., 2004; Grüneberg *et al*., 2010) and both of natural and human factors can bring a great influence on spatial variability of the SOC (Mou *et al*., 2005; Somaratne *et al*., 2005; Tan *et al*., 2004a). The significance of impact factors varies from scale to scale (Powers and Schlesinger, 2002). Likewise, the influence of different geographical regions on main controlling factors of the spatial distribution is different (Dai and Huang, 2006). In recent years, studies on the mechanism and spatial variation of Impact Factors affecting soil organic carbon have become a research hotspot. The traditional soil organic carbon analysis was often based on qualitative procedures (FAO, 1976). Recently, with the rapid development of computers and information technology (Soil Survey Staff, 1993; USDA, 2007), a more quantitative approach has been developed that may replace the traditional inventory techniques.

The method of agricultural management, cropping systems, vegetation, climate, terrain conditions and other factors are generally considered to have significant effects on soil organic carbon (Vallejo *et al*., 2008). To quantify the qualitative variables into regression model to analyze the influences of these factors on cultivated soil organic carbon density, using the above factors as auxiliary data has become possible. As it has a significant effect on the predicted accuracy, that the soil parent material as the spatial variable, introduced into the soil organic carbon prediction model (Cresser *et al*., 2007). Alejandra function was used to quantify the qualitative factors and the soil parent material was introduced into the multiple regression models to realize the soil organic carbon density spatial prediction and mapping, where the results indicated that the prediction accuracy was improved (Cresser *et al*., 2007).

At present, researches on effects of soil parent material on soil organic carbon density and spatial prediction are of great importance but largely missing.

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Meanwhile, effects of soil parent material on soil organic carbon density remain to be further explored. Hence, we have to quantify qualitative soil parent material to analyze inherent soil organic carbon variation caused by the interaction of different soil forming factors accurately.

Extensive literatures have reported the distribution patterns and spatial characteristics of soil organic carbon reserves from small scale to large scale (Tan *et al*., 2004b; Greenland and Szabolcs, 1994). However, due to the difficulties encountered in obtaining accurate information of soil organic carbon from the local scale, researches on the same region often draw different conclusions (Yu *et al*., 2005; Wang *et al*., 2000). Although numerous studies have reported on field scale, the researches on regional soil organic carbon storage and distribution are still largely missing (Don *et al*., 2007). There is a need for further study of soil organic carbon content in small hilly areas, especially on regional scale, with limited data availability and considerable inherent soil variation caused by the interaction of different soil forming factors, in order to improve the accuracy of the carbon cycle from the regional, national and global scale.

Here, we focused on SOC content because these properties are important driving factors behind crop production and can be used in crop growth simulation models as indicators of soil fertility. We thoroughly analyzed influencing factors and the spatial variability of cultivated soil organic carbon at the regional scale, based on 5893 soil samples taken in the surface layer (0-20 cm) in the period from 2008 to 2010.This study may provide scientific guidance for farming and agricultural regional planning and have 4 main objectives: 1. to evaluate the soil organic carbon storage of Yunyang area; 2. to analyze quantitative relations of SOC and Impact Factors (including Soil parent material, soil type and topographical variables); 3.to analysis direct or indirect influence of Impact Factors on soil organic carbon and the influence path; and 4.to assess spatial distribution and variation characteristics of soil organic carbon.

MATERIALS AND METHODS

Study site: Our study located in southwestern China covers an area of 3649 km^2 with an elevation ranging from 139 to 1809 m above sea level

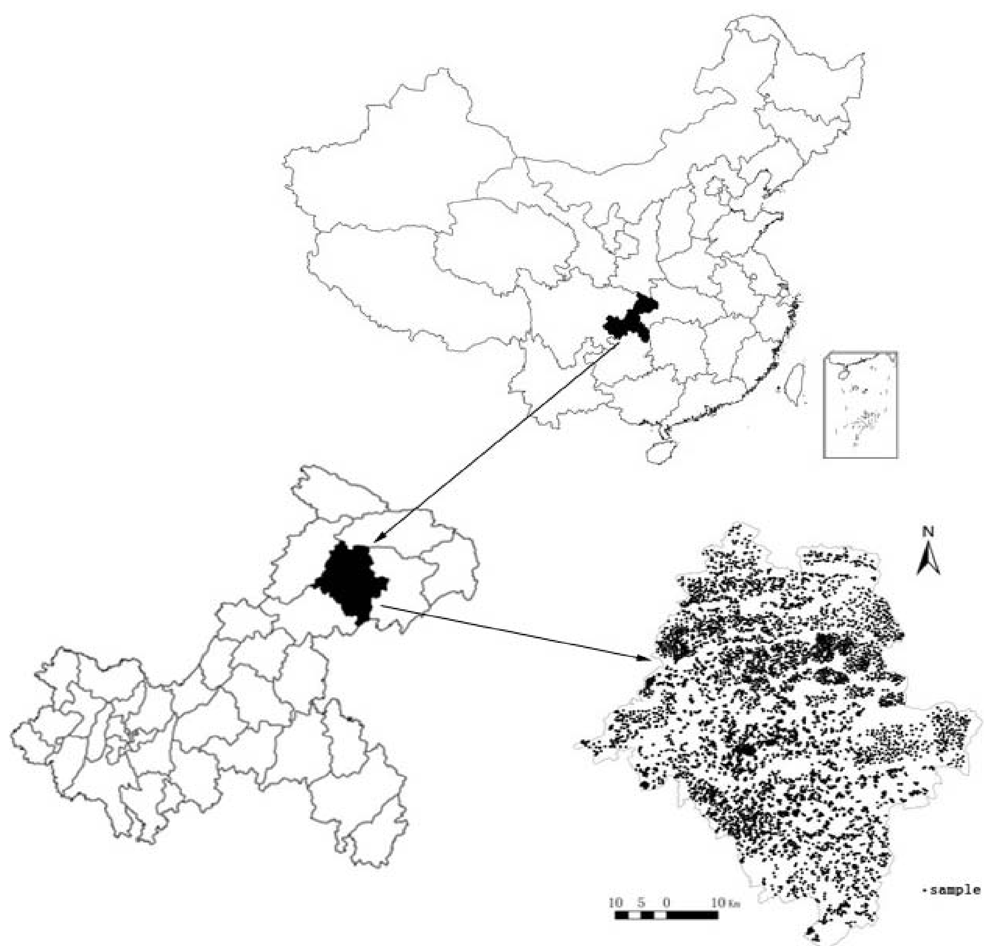

Fig. 1: Distribution of sampling points

(108°24′32″~109°14′51″E, 30°35′6″~31°26′30″N). The area is generally characterized by Karst and hilly to mountainous topography. The climate is subtropical moist monsoon with a mean annual precipitation of 1165.8 mm and a mean annual temperature of 184°C. Based on the FAO (1976) soil classification, dominant soils in the study area are paddy soils, purple soils, yellow soils and limestone.

Soil sampling: A fertility survey of the farmland was carried out in Yunyang County in 2011 and all the sample data used in this study were obtained from this fertility survey data set of 2008-2010 (Yunyang Soil Testing and Formulated Fertilization Database). Following the farmland productivity evaluation survey and quality technical procedures, a total of 5893 soil samples were collected from a depth of 0-20 cm of cultivated horizon soil. The soil organic matter content and soil volume was determined using the dichromate oxidation (external heat applied) method and Ring knife method, respectively (Nelson and Sommer, 1975). The location of each soil sample was recorded with Geographical information systems (ArcGIS9.3) according to the latitude and longitude coordinates (Fig. 1).

Soil organic carbon density was calculated with the following equation (Zhang *et al*., 2005):

$$SOCD = 0.58 \times (1 - A) \times H \times B \times SOM \qquad (1)$$

where, A is gravel content (%), B is volume mass (g/cm^3), SOM is organic matter content (g/kg) and 0.58 is the conversion factor of Bemmelen.

Soil parent material and soil type: According to a soil map (map-scale: 1:50,000) and Soil Chronicles of Yunyang, there are 7 soil parent materials in the study area: dolomite weathered material (Pmd), River alluvium (Pma), gray-brown purple mud (shale) efflorescence (Pmm), limestone weathering (Pmt), feldspar quartz sandstone weathering (Pmf), purple sand and mud (shale) efflorescence (Pmp) and reddish brown thick mudstone (Pmb). Among 5893 points, 429 locations are for dolomite weathered material, 146 locations are for river alluvium, 1472 locations are for gray-brown purple mud (shale) efflorescence, 1410 locations are for feldspar quartz sandstone weathering, 956 locations are for Purple sand and mud (shale) efflorescence and 799 locations are for reddish brown thick mudstone. The basic statistics of soil sample points are presented in Table 1.

Topographical variables: Elevation data was obtained by 30-m grid DEM (digital elevation model) (Fig. 2). Three topographical variables were derived from the DEM: (1) Topographic Wetness Index (TWI), (2) slope position and (3) slope. The topographic wetness index can accurately portray the terrain changes and their impact on soil runoff is an effective indicator to characterize soil moisture content (Zhang *et al*., 2005). It can be written as Wilson and Gallant (2000) and Claessens *et al*. (2006):

$$TWI = \ln(\alpha / \tan\beta) \qquad (2)$$

where,
α = The specific catchment area (SCA, m^2/m)
β = The local gradient

SCA is defined as the upstream catchment area of a unit contour.

Based on the similarity weighted fuzzy reasoning method (Qin *et al*., 2007, 2009), five slope positions, namely, ridge (Spr), shoulder (Sps), slopeback (Spb), footslope (Spf) and valley (Spv) were divided in this study. Among 5893 points, 937 locations are for ridges, 1330 locations are for shoulders, 1771 locations are for slopeback, 1410 locations are for footslope and 454 locations are for valleys. The basic statistics of sampling points are shown in Table 1.

All these variables were calculated using software SimDTA-V1.0.3 and ArcGIS9.3.

Table 1: Descriptive statistics of categorical auxiliary in the study area

				SOCD (kg/m^2)			
Category	Variable	Code	Number	Max.	Min.	Mean	S.D.
Soil parent material	Dolomite weathered material	Pm_d	429	6.87	0.12	3.07	1.31
	River alluvium	Pm_a	146	6.04	0.29	2.90	1.13
	Gray-brown purple mud (shale) efflorescence	Pm_m	1472	6.38	0.01	2.82	1.05
	Limestone weathering	Pm_t	681	7.60	0.11	3.06	1.18
	Feldspar quartz sandstone weathering	Pm_f	1410	6.44	0.01	2.93	1.09
	Purple sand and mud (shale) efflorescence	Pm_p	956	6.76	0.01	2.92	1.14
	Reddish brown thick mudstone	Pm_b	799	6.28	0.09	2.85	1.10
Slope position	Ridge	Sp_r	937	6.55	0.10	2.88	1.11
	Shoulder	Sp_s	1330	7.60	0.01	2.75	1.11
	Slopeback	Sp_b	1771	6.87	0.09	2.87	1.08
	Footslope	Sp_f	1401	6.58	0.06	2.98	1.14
	Valley	Spv	454	6.42	0.01	3.08	1.28

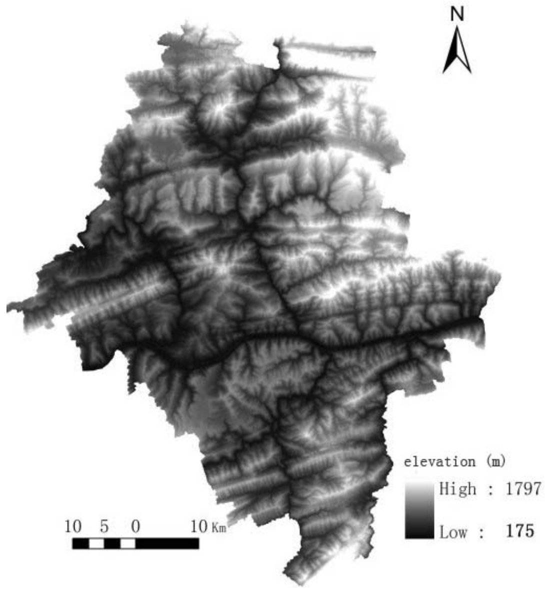

Fig. 2: Maps of DEM

Path and geo statistical analyses: Qualitative variables were converted to binary variables (Vallejo *et al*., 2008) by using Alejandra function before the correlation analyst.

Path analysis is the supplement and extension of regression analysis (Batjes, 1996). Multivariate linear regression equation was developed to achieve path analysis in SPSS18.0. MLR equation can be expressed as (Du and Chen, 2012):

$$y = a + \sum_{i=1}^{n} b_i x_i + \varepsilon_i = 1, 2, 3, ...n \tag{3}$$

where,
y = Soil organic carbon density
x_i = The Impact factor
a = The constant
b_i = The regression coefficient
ε = The error

Geo statistics uses the semi-variogram to quantify the random and structured spatial variation of a regionalized variable and relevant statistical analysis methods to analyze the spatial distribution. The semi-variogram is depicted as follows:

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i + h) - z(x_i) \right]^2 \tag{4}$$

where, N(h) is the number of pairs of sample points separated by h, h the lag distance and $z(x_i)$ the value of the variable z at location of x_i. As the most suitable model of semi-variogram to obtain the semivariogram in this study, Spherical model is described as:

$$\gamma(h) = C_0 + C_1 (1.5(h/a) - 0.5(h/a)^3) \tag{5}$$

where,
C_0 = The nugget value
C_1 = The base value and a the distance parameter

Trend and anisotropic analysis in ArcGIS 9.3 were used to compare SOC densities in South-North (SN), Southeast-Northwest (SE-NW), West-East (WE) and Northeast-Southwest (NE-SW) direction. The semi-variogram value were calculated and exported in GS+9.0 and the theoretical variogram and test fitting effect were obtained by using matlab7.0 to fit semivariogram in each direction.

RESULTS

Descriptive statistics: The Kolmogorov-Smirnov test was used to analyze the level of the variables conformance to a normal distribution. The results (Table 2) showed that the values of skewness and kurtosis are close to 0 and Kolmogorov-Smirnov test (p = 2.9) at a significance level of higher than 0.05, implying that the data conforms to normal distribution. The standard deviation, basic statistical means are shown in Table 2. SOC concentration ranges from 0.01 to 7.60 kg/m^2, with the arithmetic mean of 2.91 kg/m^2. We integrated the standard deviation and arithmetic mean to obtain the coefficient of variation and the result shown SOC has a relatively moderate C.V. (38.49%).

With qualitative variables assigned by using formula 4, we got three basic statistical results of continuous variables shown in the Table 3 and the statistics of each qualitative variable shown in Table 1. For soil parent material, The rank order of mean SOC density was (1) dolomite weathered material, (2) limestone weathering, (3) feldspar quartz sandstone weathering, (4) purple sand and mud (shale) efflorescence, (5) reddish brown thick mudstone, (6) gray-brown purple mud (shale) efflorescence. For slope position, the rank order of mean SOC density was (1) valley, (2) footslope, (3) ridge, (4) slopeback, (5) shoulder.

Correlation analysis: The results of the correlation analysis between SOCD and the variables are shown in Table 4. According to the results, there were highly significant (p<0.01) correlations of SOC with all the selected topographic and soil parent material properties, as well as between these properties. SOCD was positively correlated to elevation, slope, topographic wetness, footslope and valley, but negatively correlated to ridge, slope shoulder, slopeback and gray-brown purple mud (shale) efflorescence. Extremely significantly positive correlations were observed between slope and reddish brown thick mudstone (r = 0.036, p<0.01), elevation and ridge (r = 0.085, p<0.01).

Table 2: Classical statistical parameters of the SOCD in the study area

	Number	Min.	Max.	Mean	S.D.	Variance	Skewness	Kurtosis	K-S
SOCD (kg/m^2)	5893	0.01	7.60	2.91	1.12	1.26	0.05	-0.75	2.91

Table 3: Descriptive statistics of continuous auxiliary variables in the study area

	Code	Max.	Min.	Mean	S.D.
Slope	Sl	54.45	0	15.66	8.000
Topographic wetness index	TWI	15.15	1.01	6.690	1.570
Elevation (m)	Alt	1655	175	586.78	247.02

Table 4: Correlation coefficient

Item	SOCD	Sl	Alt	TWI	Pm_d	Pm_t	Pm_f	Pm_a
SOCD	1							
Sl	-0.021	1						
Alt	0.329**	0.012	1					
TWI	0.256**	-0.069**	-0.099**	1				
Pm_d	0.006	-0.025	-0.018	0.012	1			
Pm_t	0.013	-0.006	0.009	0.002	-0.137**	1		
Pm_f	-0.001	-0.007	0.001	-0.008	-0.170**	-0.179**	1	
Pm_a	0.010	-0.006	0.010	0.011	-0.061	-0.064**	-0.079**	1
Pm_p	-0.013	-0.009	0.027*	0.006	-0.152**	-0.160**	-0.199*	-0.071**
Pm_b	0.007	0.036**	0.009	-0.026*	-0.130	-0.137**	-0.170	-0.061
Pm_m	-0.032*	0.013	-0.026*	0.006	-0.226**	-0.238**	-0.296**	-0.106**
Sp_v	0.470**	-0.007	-0.070**	0.344*	-0.006	-0.035**	-0.014	-0.012
Sp_f	0.182**	-0.012	-0.046	0.031*	-0.024	0.010	-0.018	0.012
Sp_b	-0.088**	0.005	0.001	-0.068*	0.016	0.023	0.031*	-0.002
Sp_s	-0.347**	0.021	0.060	-0.190*	0.000	-0.003	0.003	0.012
Sp_r	-0.308**	-0.012	0.085**	-0.158**	0.021	0.005	-0.006	-0.016
Item	Pm_p	Pm_t	Pm_m	Sp_v	Sp_f	Sp_b	Sp_s	Sp_r
SOCD								
Sl								
Alt								
TWI								
Pm_d								
Pm_t								
Pm_f								
Pm_a								
Pm_p	1							
Pm_b	-0.153**	1						
Pm_m	-0.265*	-0.227**	1					
Sp_v	0.028*	-0.005	0.027*	1				
Sp_f	0.000	0.016	0.010	-0.277*	1			
Sp_b	-0.006	-0.029*	-0.029*	-0.300	-0.320**	1		
Sp_s	-0.022	0.020	-0.002	-0.282*	-0.301*	-0.326	1	
Sp_r	0.001	-0.004	-0.006	-0.143**	-0.153**	-0.166**	-0.156**	1

**: $p<0.01$, *: $p<0.05$

Table 5: ANOVA of the regression model for prediction SOCD

Item	Quadratic sum	df	MSE	F	Sig.
Regression	4127.730	9	458.637	817.278	0.000
Residual	3301.397	5883	0.56100		
Total	7429.127	5892			

Table 6: The results of regression coefficient

	Unstandardized coefficients				
Model	B	Std. Error	Standardized coefficients	T	Sig.
1(Constant)	1.264	0.061		4.328	0.0200
Sp_v	1.396	0.044	0.863	54.297	0.0000
Alt	0.002	0.000	0.354	46.245	0.0004
Sp_b	0.172	0.041	0.456	28.455	0.0010
Sp_s	-0.602	0.041	-0.227	14.545	0.0113
TWI	0.038	0.007	0.054	5.714	0.0130
Pm_m	-0.114	0.023	-0.046	-5.042	0.0260
Pm_p	-0.084	0.028	-0.027	-2.973	0.0030

Among the negative correlations, topographic wetness index and elevation was highest ($r = -0.99$, $p<0.01$).

Stepwise regression: Relationships of SOCD with topographic and soil parent material properties were obtained by multiple linear regression analysis with the stepwise method. Taken seven factors as dummy variables into regressions formula 5. The results (Table 5) of variance analysis (ANOVA) which sum of squares of regression and residua was 4127.73 and 3301.40, respectively, F statistic was 817.3 ($p<0.05$) indicated the regression equation was effective. The standard errors, standard coefficient (path coefficient) and the T test results corresponding regression coefficient in the regression equation were shown in Table 6. T test showed that the independent variables had significant impact on the dependent variable implying the path coefficient was effective. Multiple linear regression models predicting SOC was achieved as follows:

$$SOCD_{regression} = 1.264+1.396*Spv+0.002*Alt+0.172*Spb-0.602*Sps+0.038*TWI-0.114*Pmm-0.084*Pmp\ (R^2 = 0.54)$$

Path analysis: Path analysis (cf. Table 7) indicated that valley (b = 0.8630, R^2 = 0.1253) had the highest value of positively direct path coefficient and determination coefficient, followed by slope back (b = 0.4560, R^2 = 0.2079), however their indirect path coefficients and determination coefficients through other variables were lower. By contrast, elevation (b = 0.354, R^2 = 0.1253) and topography wetness index (b = 0.054, R^2 = 0.0.0029) had higher values of positive direct path coefficients, whereas others had negative direct path coefficients.

As shown in Table 4, elevation had extremely significantly positive correlations with SOCD, indicating SOCD increases as the increase of elevation, but an extremely significantly negative correlation with topographic wetness index, meaning that the soil moisture content in the high altitude areas is less. Path analysis (Table 7) showed elevation (b = -0.035) and SOCD had negative indirect path coefficients through topographic wetness index, as well as topographic wetness (b = -0.0053) index through elevation.

Purple sand and mud (shale) efflorescence (Pmp) and gray-brown purple mud (shale) efflorescence

Table 7: Results of path analysis

Independent variable	Direct impact	Direct determination coefficient	Indirect effect on y: Path	Indirect path coefficients	Indirect determination coefficient	Total effect	Decision coefficient
Alt	0.3540	0.1253	Alt↔TWI→ y	-0.0350	-0.0701	0.3290	0.186
			Alt↔Sp_v→y	-0.0248	-0.0496		
			Alt↔Sp_b →y	0.0004	0.0007		
			Alt↔Sp_s→y	0.0212	0.0425		
			Alt↔Pm_m→y	-0.0092	-0.0184		
			Alt↔Pm_p→y	0.0096	0.0191		
TWI	0.0540	0.0029	TWI↔Alt→y	-0.0053	-0.0038	0.2560	0.023
			TWI↔Sp_v→y	0.0186	0.0321		
			TWI↔Sp_b→y	-0.0037	-0.0033		
			TWI↔Sp_s→y	-0.0103	-0.0047		
			TWI↔Pm_m→y	0.0003	0.0000		
			TWI↔Pm_p →y	0.0003	0.0000		
Spv	0.8630	0.7448	Sp_v↔Atl→y	0.0604	0.0428	0.4700	0.470
			Sp_v↔TWI→y	0.2969	0.0321		
			Sp_v↔SP_b→y	-0.2589	-0.2361		
			Sp_v↔SP_s→y	-0.2434	-0.1105		
			Sp_v↔Pm_m→y	0.0233	-0.0021		
			Sp_v↔Pm_p→y	0.0242	-0.0013		
Spb	0.4560	0.2079	Sp_b↔Alt→y	0.0023	0.0016	-0.0880	-0.040
			Sp_b↔TWI→y	-0.0310	-0.0033		
			Sp_b↔Sp_v→y	-0.1368	0.2361		
			Sp_b↔Sp_f→y	0.0141	0.0185		
			Sp_b↔Sp_s→y	-0.1487	-0.0675		
			Sp_b↔Pm_m→y	-0.0132	0.0012		
			Sp_b↔Pm_p→y	-0.0027	0.0001		
Sps	-0.2270	0.0515	Sp_s↔Alt→y	0.0136	0.0096	-0.3470	-0.120
			Sp_s↔TWI→y	-0.0431	-0.0047		
			Sp_s↔Sp_v →y	-0.0640	-0.1105		
			Sp_s↔Sp_b→y	-0.0740	-0.0675		
			Sp_s↔Pm_m→y	-0.0005	0.0000		
			Sp_s↔Pm_p→y	-0.0050	0.0003		
Pmm	-0.0460	0.0021	Pm_m↔Alt→y	-0.0012	-0.0008	-0.0320	-0.0006
			Pm_m↔TWI→y	-0.0003	0.0000		
			Pm_m↔Sp_v→y	-0.0013	-0.0022		
			Pm_m↔Sp_b→y	0.0013	0.0012		
			Pm_m↔SPs→y	-0.0001	0.0000		
			Pm_m↔Pm_p→y	0.0122	-0.0007		
Pmp	-0.0270	0.0007	Pm_p↔Alt→y	-0.0007	-0.0005	-0.0130	-0.0017
			Pm_p↔TWI→y	-0.0002	0.0000		
			Pm_p↔Sp_v→y	-0.0008	-0.0013		
			Pm_p↔Sp_b→y	-0.0002	-0.0001		
			Pm_p↔Sp_s→y	0.0006	0.0003		
			Pm_p↔Pm_m→y	0.0072	-0.0007		

(Pmm) had inhibitory effect on SOCD in correlation analysis, but the former did not reach a significant level. As far as both in the regression equation was concerned, inhibitory effect of purple sand and mud (shale) efflorescence (R^2 = -0.0017) was greater than gray-brown purple mud (shale) efflorescence (R^2= -0.0006), this could be explained by the inhibitory effect strengthened in Pmp↔Spv→y path.

Geostatistical analysis: There was a strong spatial anisotropy of soil organic carbon density in the study area from overall trend analysis. Four directional semi–variograms which took range and semi–variogram as coordinates obtained by scatter diagram and spherical model were shown in Fig. 3. Nugget was the intercept of fitted curve and vertical axis given by Spherical model, as well as the base value. The variation as the step of the base value, Theoretical semivariogram model parameters for different directions were shown in Table 8.

Different sill value and the range of the theoretical semivariogram model (Table 8) suggested a zonal anisotropy of SOC density in the study area. The ratio of nugget value and base value in the four directions ranged from 25% to75%, indicating a strong spatial dependence of SOC density in the four directions. In the NE-SW (45°) direction (Sill is 1.174, Range is 8.7 km) the spatial variability of SOCD was the strongest and the spatial correlation function of the sample points range reached to the minimum. The spatial variability of SOCD in NE-SW (45°) and N-S (0°) directions were significant. In the W-E (90°) direction (Sill is 0.58 and Range is 10.25km) the spatial variability of SOCD was the weakest and the spatial correlation function of the sample points range is the maximum. Compared to the W-E (90°) direction, the spatial variability of SOCD in SE-NW (135°) was greater.

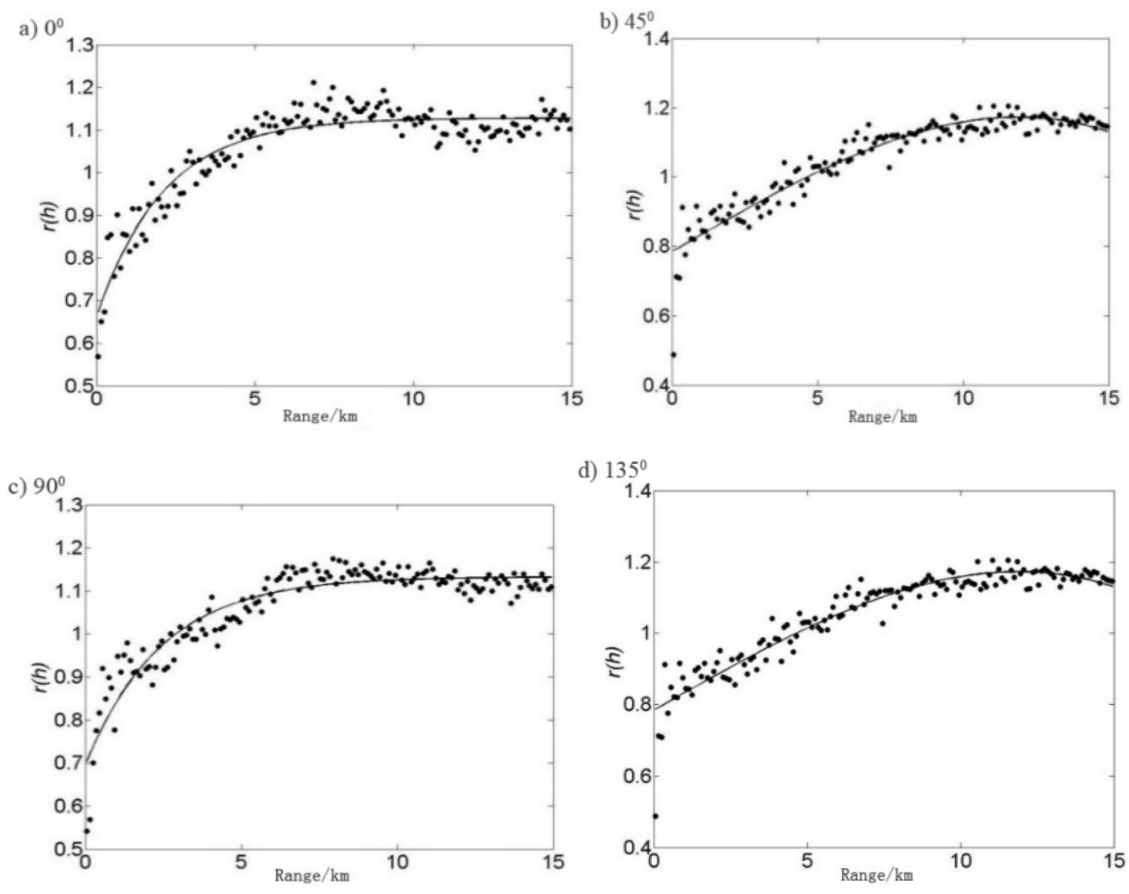

Fig. 3: Map for Semi-variogram in four orientation: a) 0 °, b) 45°, c) 90°, d) 135°

Table 8: Theoretical semivariogram model parameters for different directions

Direction	Model	Nugget (Co)	Sill (C+Co)	Range (km)	Co effect	R^2
N-S (0°)	Spherical	0.66	1.128	6.250	0.59	0.884
NE-SW (45°)	Spherical	0.786	1.174	8.700	0.67	0.905
W-E (90°)	Spherical	0.240	0.580	10.25	0.41	0.850
SE-NW (135°)	Spherical	0.210	0.610	6.780	0.34	0.871

DISCUSSION

Effect of altitude and TWI on SOCD: SOC density increased obviously as the increase of elevation in this study is in agreement with the results of Xianfu Cheng and Tan (Chen and Xie, 2009; Chuai *et al*., 2012). There were highly positive significant correlations of SOC density with elevation, topography wetness index and valley; however topography wetness index and the distribution probability of valleys decreased with increasing elevation. A similar finding was made by Wang *et al*. (2012) in North China, nonetheless, such a result was surprising, elevation had a critical effect on SOC density and less susceptible to interference from other variables. This may be explained by indirect determination coefficient of SOC density through topography wetness index and valley was -0.0701 and -0.0496, respectively. Direct determination coefficient of SOC density, by contrast, was 0.1253. Other studies (Xu *et al*., 2010) showed that the increase of altitude lead to a decrease of temperature, reducing the decomposition of organic carbon, which was also one of the reasons in favor of organic carbon accumulation. Further study will take the temperature into account, which is ignored in this study.

Topographic wetness index had highly significantly positive correlation with SOC density (0.256**) in this research, which consist with research results of Miao *et al*. (2010), who reported soil organic carbon content is high in the great soil moisture area lately. Meanwhile, probability distribution of the valley was large in the high topography wetness area, therefore, the accumulation of SOC may be explained by the repetition between topography wetness and valley. However, there was a contrasting result in our study; total decision coefficient of topographic wetness (0.023) on SOC density was not great. It was not difficult to find that the effect of topographic wetness index through TWI↔Spv→y path on soil organic carbon density (0.0321) was greater than the direct effect on organic carbon (0.0029).

Effect of soil parent material on SOCD: Purple sand and mud (shale) efflorescence had not shown significant correlation with SOC density (r = -0.013) and gray-brown purple mud (shale) efflorescence highly significant correlation (r = -0.032*). However, purple sand and mud (shale) efflorescence expressed a greatly negative impact on SOC density. A reasonable explanation was given by the multivariate statistical analysis. In the Pearson correlation, purple sand and mud (shale) efflorescence had significant positive correlation with elevation (positively correlated with SOCD), but negative with clouds weathered shale, limestone weathering and river alluvium (positively correlated with SOCD). Conversely, significantly negative correlation was found between gray-brown purple mud (shale) efflorescence and elevation and cannot be offset by the negative correlation with dolomite weathered material, limestone weathering and river alluvium. As the mainly parent material of purple (Fig. 4) soil in the study area, gray-brown purple mud

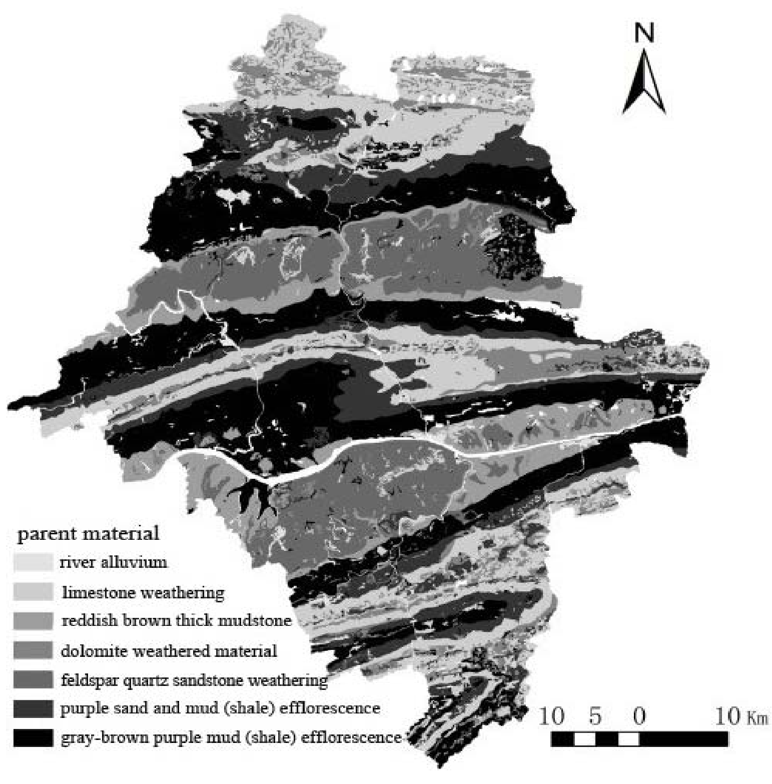

Fig. 4: Maps of parents materials

(shale) efflorescence developed into thick bony sandy soil may result in more soil erosion, leading to SOC decline also (Martin *et al*., 2010).

In all soil parent material, the maximum average SOC density (3.07kg/m^2) distributed in dolomite weathering area. As one of the main soil parent material, dolomite weathered material weathered into yellow soil by the impact between mountainously cold climate and coniferous forest. Level of Yellow Soil claying is not deep and organic matter accumulates a lot, therefore, soil organic carbon density is relatively high.

Effect of slope position on SOCD: Slope position contains different characteristics of soil properties in different topographic positions and becomes an important factor in geographical or ecological process model (Milne, 1934; Guo *et al*., 2010). Slope position was divided into three categories in the research of Guo *et al*. (2010) and Lu *et al*. (2013), who reported SOC content is highest on the bottom of the slope and lowest at the top of the slope lately. In our study, slope position was divided into five categories and results are in agreement with the consequences of previous studies. Moreover, the results suggest that the classification in our study can clarify the influence mechanism of SOC density and slope positions more accurately.

Correlations between SOC densities and slope position are found to be positive in valley and footslope, while negative in ridge, slopeback and shoulder. This is necessarily an indication that valley and footslope increased SOC accumulation, but others decreased. Slope and reddish brown thick mudstone shows extremely significant positive correlation with SOC density, implying palm red thick mudstone mainly distributed in relatively steeper slope. As the maximum in direct impact coefficients, valley on SOC density is 0.8630. It can be assumed that relatively soil erosion may result in redistribution of soil and water, leading to runoff and sediment rom the top of slope position accumulation in low-lying valley area. Consequently, more SOC concentrated in bottom of trench.

CONCLUSION

Overall, our study has revealed the average SCOD is 2.91 kg/m^2, below the national average level of cultivated land (3.0 kg/m^2) and the total SOC storage is 1838.75×106kg on 0-20cm surface soil in the study area. High-density areas of SOC tend to distribute in limestone soil and yellow soil area. Clearly, high elevation, high topographic wetness, valley and dolomite weathered material have led to SOC density accumulation, in which elevation has the strongest relationship with SOC density. Reforestation, terracing, more organic fertilizer may necessary to increase SOC in low altitude, ridge or shoulder area, also no tillage and reduced tillage planting mode may necessary to increase agricultural soil carbon sequestration capacity. Likewise, the spatial anisotropic analysis have shown that spatial variability in NE-SW (45°) direction is strongest and the spatial correlation function of the sample points range reached to the minimum, followed by N-S (0°), however, weakest and maximum in the W-E (90°) direction. Further refinement of the quantitative qualitative variables is needed to express a certain variable on SOC density.

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