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Profile Distribution of Soil Properties on Sloping Cropland in Yingwugou Small Watershed of the Dan River Basin

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Abstract Based on 3 m × 3 m grid in sloping cornfield with soil auger in Yingwugou Small Watershed of the Dan River Basin, a total of 39 sampling points were collected, and soil water content and nutrient content were measured in different soil depths. Meanwhile, the soil properties of different depth have been analyzed by traditional statistical and geo – statistics approaches. The results showed: the mean value of total nitrogen and soil organic carbon reduced as soil depth increased in general. But soil water content increased as the soil depth increased. The change of total phosphorus with soil depth was not obvious. The total nitrogen, soil water content, soil organic carbon and total phosphorus presented a moderate intensity variation and strong spatial dependence. In the four sampling depths, semi – variance model can simulate spatial structure of total nitrogen, soil water content and total phosphorus in 0 to 10 cm and 10 to 20 cm well. But the spatial structure of soil organic carbon was not good, which could not be simulated with semi – variance model. The analysis with Kriging interpolation showed that, the total nitrogen, soil water content and total phosphorus presented layered distribution in 0 to 10 cm and 10 to 20 cm; when the spatial distribution changed to 10 to 20cm from 0 to 10 cm, the average total nitrogen content reduced to from 0.598 g/kg 0.310 g/kg, while the average soil water content and total phosphorus increased from 12.988% to 15.439% and from 0.229 g/kg to 0.366 g/kg, respectively.

Key words Sloping cropland, TN, TP, Soil organic carbon, Profile distribution

Soil organic carbon (SOC), total nitrogen (TN) and total phosphorus (TP), the key indexes for soil quality evaluation, can not only reflect fertility status of the soil but also the quality condition of soil environment, which can be used to evaluate production, environment and health functions of the soil. SOC, the largest component of terrestrial carbon library, plays a key role in terrestrial carbon circulation and is also the important content for global carbon circulation research[1]. The soil water content (SWC) and its distribution influence a series of hydrological processes, such as solute migration, groundwater recharge, matter and energy exchange with atmosphere, *etc.*, and they also relate to runoff generation and soil conservation[2–5]. Soil nutrient has certain spatial distribution characteristics and shows up a certain spatiality and randomness, which is the result of combined action of climate, terrain and human activity factors. Fully understanding spatial variation of soil nutrient serves as the basis for soil nutrient management and reasonable fertilization. It is very necessary to study profile distributions of soil nutrients of different soil layers in an area at the same time and in the same location, which is the basis for adjustment of all management measures and all matter input as well as the acquisition of maximum economic benefits. Long – term fertilization can not only influence the change of nutrient quantity in the soil, but the profile distribution of soil nutrient due to moving downward of the nutrient. As to production, the significance of this profile distribution is two-sided: one is that the downward level of nutrient, exceeding root absorption range, causes leaching loss of nutrient, thus influencing water quality; the second is that moderately moving down of nutrient can enrich the nutrient quantity of subsoil, thus bring unusual benefits to soil fertility cultivation[6–8].

1 Description of study area

Yingwugou Small Watershed, located in Wulipu Village, Chengguan Town, 2 km away from southeast of Shangnan County, Shangluo City of Shaanxi Province, is between east longitude 110° 52′16″ and 110°55′30″, northern latitude 33°29′55″ and 33°33′ 50″. The total area of this watershed is 1.86 km^2, the main channel within the watershed is 3 232.90 m long, and the gradients of the largest main channel and the watershed slope are 0.01 m/m and 0.33 m/m, respectively. And the watershed belongs to polygon drainage. This watershed mostly consists of low mountains and hills. Its ravine is broad with maximum elevation of 600 m and the minimum elevation of 464 m. Mean annual precipitation is 803.2 mm, and the precipitation in July to September, which is mainly in the form of storm, accounts for about 50% in annual precipitation. Yellow brown soil is the main soil in this watershed, which mainly is mainly sand texture and is lack of organic matter and microelement. The study area is mainly covered with farmland, forest land and grassland. Arbors mainly contain oak and pine, shrub species are numerous and miscellaneous, grassland is gramineae grass, and the forest and grass coverage is above 60%. Wheat,

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corn and peanut are the main crops in the farmland.

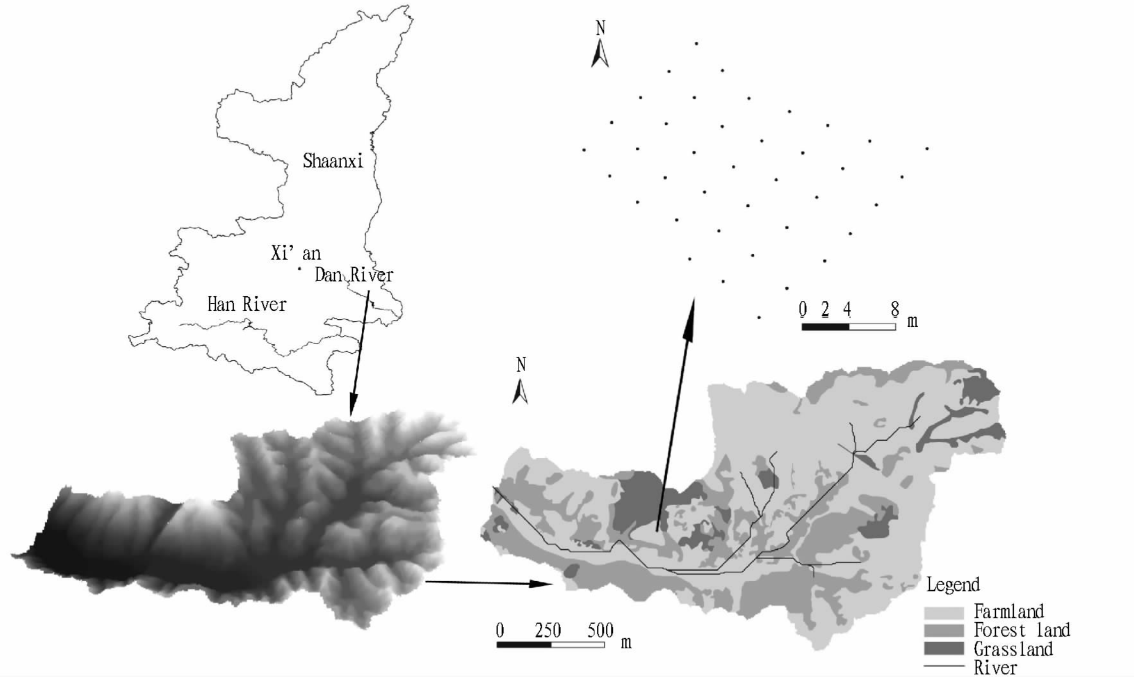

Fig. 1 Location of study area and distribution of sampling points

2 Materials and methods

2.1 Soil sampling Soil sampling was conducted based on 3 m ×3 m grid with soil auger in sloping cornfield of study area from August 28 to September 1, 2011, and a total of 39 sampling points are collected (Fig. 1). Sampling depth reaches 60 cm. A total of 4.0 kg of soil samples are collected in four soil layers (weighs 1.0 kg for each layer) with their respective depths of 0 – 10 cm, 10 – 20 cm, 20 – 40 cm and 40 – 60 cm and were taken back to laboratory for analysis. After air drying, the soil samples will be ground respectively, then screened with soil sieve (the sample analyzed with all elements is 0.25 mm, available nutrient is 1 mm) and loaded in paper bags for later use. Soil depths of 0 – 10 cm, 10 – 20 cm, 20 – 40 cm and 40 – 60 cm were represented as A1, A2, A3 and A4.

2.2 Soil analysis After air drying and screening of soil samples, 0.5 to 1.0 g were weighed and put into Kelvin bottle, add sulfuric acid and catalyst into the bottle and lixiviate them for one hour, then determine total nitrogen content of the soil with Foss 8400 Automatic kieldahl apparatus. (2) Use Discrete Chemistry Analyzer (ADA, CleverChem200, Germany) to determine total phosphorus. (3) Use TOC analyzer (N/C 2100 Analyzer) to determine total content of soil organic carbon. (4) Adopt aluminum specimen box drying method to determine soil water content, the method is drying the soil for 8 hours.

2.3 Data processing method The descriptive parameters were calculated using Micro – soft Excel (version 2003) and SPSS for Windows (version 16.0). All maps were produced using GIS software ArcMap (version 9.3) with its Geostatistical Analyst extension. The geostatistical analyses were performed with the geostatistical software GS + (version 7.0).

3 Results

3.1 Statistic character analysis of soil properties under different depths See Table 1 for the basic statistic characters of TN, SWC, SOC and TP in the four sampling depths in sloping cropland of Yingwugou Small Watershed. The mean values of TN show A1 > A2 > A3 > A4, which means that total nitrogen content decreases as the depth of soil increases. SOC also decreases as the depth of soil increases in general. However, in contrast, the mean values of SWC show A1 < A2 < A3 < A4, which means that SWC content increases as the depth of soil increases, as surface soil moisture is active with dramatic changes and the soil water content will increase rapidly with the occurrence of rainfall and decrease gradually with soil evaporation and continuous water absorption of plants. Compared with surface layer, the water content of deep soil is relatively stable. Before sampling, there is only one rainfall with 39.6 mm on August 21, and it is mostly cloudy from that day to the sampling day, which results in a larger soil water content in surface layer. The layered distribution of soil water will make a significant impact on water infiltration and pollutants migration, therefore, in order to understand soil water storage in a certain deep soil, it is very important to strengthen the research on water content of sloping cropland[9–10]. The change of TP with soil depth was not obvious. Variable coefficient, a cardinal number without dimension, which indicates the variation of unit quantity and can be used for intercomparison, reflects heterogeneity of soil. Variable coefficients of TN, SWC, SOC and TP, all belonging to medium variations, are all between 0.10 and 1.00. All variable coefficients of SWC are small under the four sampling depths, indicating that the variation of SWC is weaker than TN, SOC and TP. In A2 and A3 layers, SWC is in significant positive correlation with TN ($P<0.05$), while in A1 and A2 layers, SOC is also in significant positive correlation with TN ($P<0.05$), and TP does not have an obvious correlation with the other three soil properties. Since the maximum prediction accuracy of normal distribution data is contributed by Kriging method, it is necessary to inspect whether the soil property data meets normal distribution before geo-statistical analysis. From K-s Normality Test, we know that TN, SWC and SOC obey normal distribution basically, but only TP disobey it. Accordingly, TP, disobeying normal distribution, will be conducted log conversion, then, after the conversion, the TP data will be in normal distribution ($P>0.05$), thus meeting the requirements of the next analysis.

Table 1 Statistic characters of soil properties under different depths

Soil properties	Min.	Max.	Average	Skewness	Kurtosis	Standard deviation	Variable coefficient	K-S (*P* value)
TN_A1	0.18	1.90	0.62	1.69	3.42	0.39	0.63	0.24
TN_A2	0.04	0.79	0.32	0.66	−0.66	0.20	0.64	0.37
TN_A3	0.01	0.60	0.27	0.17	−1.20	0.17	0.61	0.35
TN_A4	0.01	0.90	0.32	0.89	0.17	0.23	0.71	0.42
SOC_A1	1.96	9.32	5.56	0.22	−0.14	1.68	0.30	1.00
SOC_A2	1.56	11.93	5.48	0.50	−0.01	2.39	0.44	0.90
SOC_A3	1.47	11.93	5.54	0.87	0.89	2.39	0.43	0.31
SOC_A4	0.20	8.77	3.81	0.35	−1.01	2.66	0.70	0.54
SWC_A1	5.46	20.23	13.12	0.28	0.70	3.10	0.24	0.40
SWC_A2	10.19	22.84	15.64	0.18	−1.15	3.58	0.23	0.69
SWC_A3	9.60	23.02	17.59	−0.16	−0.84	3.48	0.20	0.57
SWC_A4	3.35	23.95	17.88	−1.35	2.34	4.22	0.24	0.08
TP_A1	0.09	0.48	0.22	0.62	−1.10	0.12	0.54	0.06
TP_A2	0.18	0.92	0.37	2.48	6.76	0.15	0.40	0.00
TP_A3	0.06	0.45	0.16	2.05	3.39	0.09	0.60	0.00
TP_A4	0.05	0.69	0.26	0.81	−0.23	0.17	0.64	0.02

Note: K-S (P), Kolmogorov-smirnov, normal inspection reached significant level: $P\geqslant0.05$. The units of TN, SOC and TP are all g/kg; and the unit of SWC is %.

3.2 Spatial structure analysis of soil properties under different depths Conduct semi-variance function simulation on soil properties under four depths with GS + 7.0 to obtain their own semi-variance models and the parameter values, and then conclude the statistical parameters for the four soil layers in Table 2. The optimum model refers to that with maximum degree of fitting (R^2) and minimum residual sum of squares (RSS). In four sampling depths, determination coefficients of TN, SWC and TP are higher at above 0.90 in A1 and A2 and their residual sums of squares are both smaller, which indicates that the extremely high fitting precision of model can reflect A1 and A2 spatial structure characters well. However, the determination coefficients of SOC in A1 and A2 are smaller, and the fitting precision of model is also lower. Therefore, this research mainly conducts the further analysis on spatial variations of TN, SWC and TP in A1 and A2. Variation range reflects the scope of influence by regionalized variable, or to say, autocorrelation range of this variable. The maximum variation range for the four soil properties is 3.19 m, if the range is greater than the spacing (3 m) of this grid sampling, it is deemed to meet the requirements of spatial analysis. In A1 and A2 layers, TN, SWC and TP are mainly in spherical models, while the variation ranges of TN and TP get smaller from A1 to A2, their spatial autocorrelation ranges will also diminish gradually. The situation of SWC is just the opposite. The reason for this is that, TN and TP are influenced by the migration from surface layer to deep layer of soil and interflow. The deeper the soil layer, the weaker the migration process and interflow action. While for SWC, the reason is that it is under the effect of lower layer water as the soil moisture is evaporated from the top to the bottom.

Nugget denotes spatial heterogeneity of random part, and a larger Nugget indicates that a certain process in a smaller scale can't be ignored. The larger Partial Sill denotes a higher total spatial heterogeneity. Nugget coefficient is the ratio of Nugget and Partial Sill. If the value is relatively high (>0.5), the random part may cause a higher level of spatial heterogeneity; if the value approaches to 1, one variable in landscape may have constant variation in the entire scale[2,11]. From Table 2, we know that the Nuggets for TN, SWC and TP are all smaller under four soil depths, which indicates that spatial heterogeneity caused by random part is relatively small. The Nugget of SOC in A1 and A2 layers is relatively large, indicating a larger impact of random part. The Partial Sill of TN and TP is relatively small, showing a lower level of total spatial heterogeneity and a relatively small numerical difference in each soil layer. But the Partial Sill of SOC and SWC is relatively large, showing a higher level of total spatial heterogeneity and a relatively large numerical difference in each soil layer. SOC(A1) and TP(A3) are in random distribution, as their Nugget coefficients are 1, that is to say, variable does not have spatial correlation; beyond that, the Nugget coefficients of TN, SOC, SWC and TP are basically smaller than 0.25, indicating their strong spatial dependence, and their variations are mainly caused by structural factors (climate, terrain, parent material, *etc*.) instead of random factors (cultivation, fertilization, *etc*.)[12-14].

Table 2 Spatial structure characters of soil properties under different depths

Soil properties	Nugget	Partial Sill	Variation range // m	Determination coefficient/ R^2	Nugget coefficient	Model	RSS
TN_A1	0.02	0.26	6.62	0.92	0.07	Spherical	1.93E-04
TN_A2	0.02	0.45	5.95	0.91	0.05	Spherical	3.45E-04
TN_A3	0	0.03	7.03	0.88	0.09	Spherical	5.50E-06
TN_A4	0.17	1.09	8.73	0.88	0.16	Exponential	3.25E-03
SOC_A1	2.86	2.86	9.87	0	1	Linear	/
SOC_A2	0.16	4.54	8.07	0.76	0.04	Exponential	1.33E-01
SOC_A3	0.61	5.98	3.42	0.6	0.1	Exponential	1.42E-02
SOC_A4	4.38	12.86	25.06	0.97	0.34	Gaussian	1.05E-01
SWC_A1	0.28	7.87	5.3	1	0.04	Spherical	1.01E-04
SWC_A2	0.54	12.17	12.09	1	0.04	Spherical	1.67E-03
SWC_A3	0.44	11.8	5.39	0.29	0.04	Spherical	2.90E+00
SWC_A4	0.01	16.65	3.19	0	0	Gaussian	/
TP_A1	0.01	0.03	18.07	1	0.22	Gaussian	1.89E-07
TP_A2	0	0.02	16.2	1	0.01	Spherical	1.57E-08
TP_A3	0.01	0.01	9.88	0	1	Linear	/
TP_A4	0	0.03	10.26	0.98	0.04	Exponential	8.64E-07

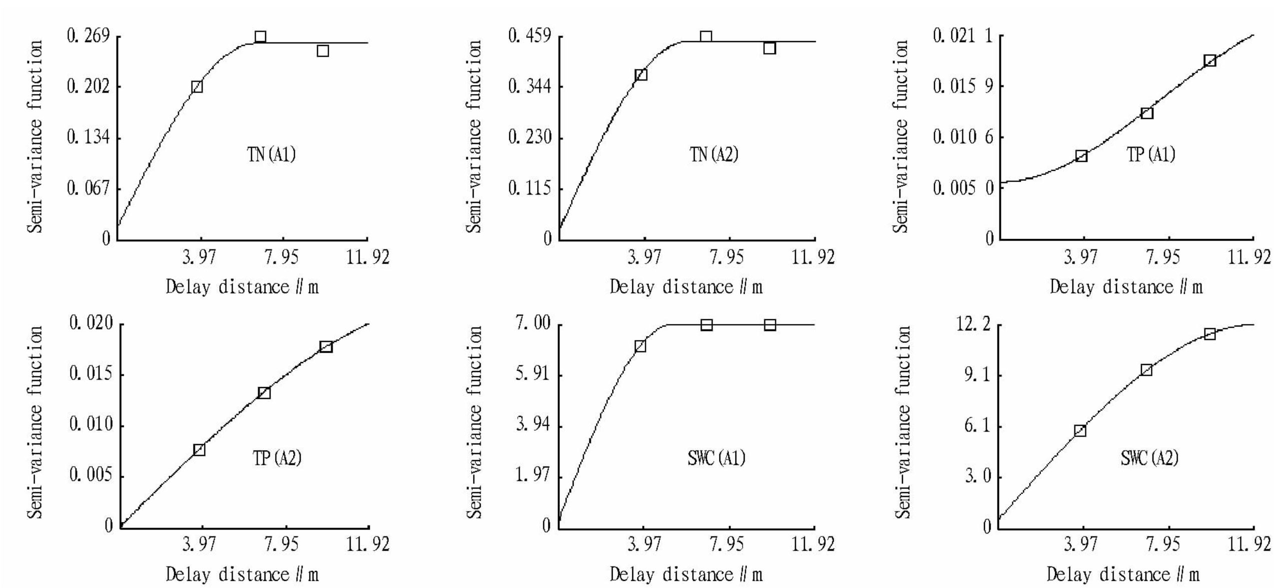

Fig. 2 Semi-variance function theoretical model of TN, TP and SWC in A1 and A2

To compare the effects of sampling depths on geo-statistics results of TN, TP and SWC, conduct analog computation on their semi-variance function theoretical models with GS+ software, see Fig. 2 for details. As can be seen, semi-variation model can make a relatively accurate analog on A1 and A2. Except that Gaussian model serves as the optimal model of TP in A2, the optimal models of the other three properties are all spherical models in A1 and A2. The spatial heterogeneity of soil property variation has been highly concerned, which can influence sampling method and the results of Kriging interpolation. Therefore, this article analyzes anisotropy of semi-variance function of soil properties. And it is concluded that TN, TP and SWC are anisotropic in A1 and A2.

3.3 Analysis on spatial interpolation Conduct Kriging interpolation on TN, TP and SWC values in A1 and A2 and draw the spatial distribution maps of TN, TP and SWC under two soil layers in sloping cropland, so as to reflect spatial distribution of soil properties more intuitively. From Fig. 3, we know the variation range of TN in A1 is larger than that in A2, and TN is in layered distribution in A1, presenting an increasing trend from northwest to southeast. The variation range of SWC and TP in A1 is smaller than that in A2, and the distribution of SWC in A2 is similar to that in A1, showing that the water content is higher in the lower soil in sloping cropland. For TP, it is large in the middle layer and small in both upper and lower ends in A1 layer, while in A2 layer, it is in a relatively obvious patch distribution. In addition, from A1 to A2, the average TN content decreases to 0.310 g/kg from 0.598 g/kg, while the average SWC and TP contents increase to 15.439% and 0.366 g/kg from 12.988% and 0.229

g/kg, respectively.

The results of Kriging interpolation also indicate that, in a small scale, this interpolation method has still eliminated a part of areas in which TN, TP and SWC contents are larger or smaller. And the method has an obvious smooth effect in general, making the mottling distribution disappearing basically, and the effect is particularly apparent in the area with higher content. However, Kriging interpolation is able to show the spatial distribution trend of TN, TP and SWC well. Some differences exist between Kriging interpolation result and measured value, which is mainly attributed to that "the Kriging interpolation theory, being used to evaluate conditional mathematical expectation of random function describing spatial distribution of a property and possessing obvious smooth effect, belongs to linear regression theory, which is applicable for interpolation and distribution characters presentation of the spatial properties with little variation but lack of good ability to express a mutation of data"[2,15].

3.4 Analysis on spatial autocorrelation To study the correlativity of a spatial variable with the variables in its surrounding locations, we can calculate spatial correlation degree with statistical approach to analyze the interrelation of these variables in spatial terms[2]. And spatial dependence will be expressed mainly by statistical parameter Moran's I. Moran's I ranges from -1 to $+1$[16]. When the positive value is larger, it means that the spatial correlation will be higher and adjacent location areas tend to get together more. When the negative value is smaller, it indicates that the data researched is in interaction in spatial terms. When the value of Moran's I equals to 0, it means that there is no correlation in spatial terms. The closer the value to 0, the lower the correlation was[17-18]. As seen in Fig. 4, TN is in positive spatial correlation under the depth less than 6 m in A1 layer, and the spatial autocorrelation will weakens as the distance increases; meanwhile, the positive autocorrelation distance of TN in A2 layer is reduced to 5 m. SWC and TP are in similar spatial autocorrelation characteristics in A1 and A2 layer, only the positive and negative autocorrelation distances are different. Furthermore, the positive autocorrelation distances of SWC and TP both increase from A1 to A2.

The spatial distribution information of TN, TP and SWC in the soil plays a particularly important role in land management and the evaluation of soil nitrogen and phosphorus losses in the watershed and their impacts on water quality[19-21]. Nitrogen and phosphorus may threaten the surface water and downstream water either by migration loss (for example, nitrogen migration may pollute the underground water) or soil erosion. The input parameters of all prediction models for nitrogen and phosphorus losses are targeted for certain regions and may not be applicable for water source area in southern Shaanxi under "south water to north" project, therefore, this research is of reference value in the application of nitrogen and phosphorus loss models of southern Shaanxi.

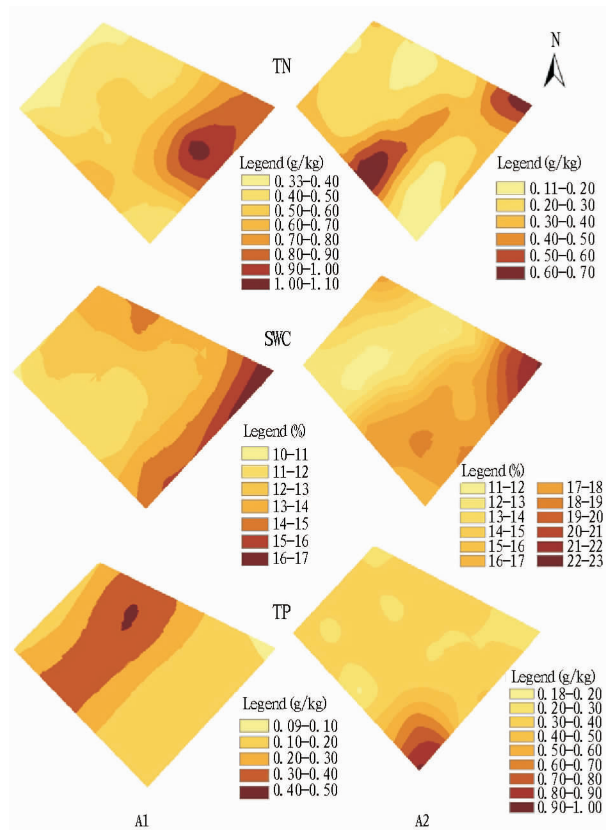

Fig. 3 Spatial interpolation results of TN, TP and SWC in A1 and A2

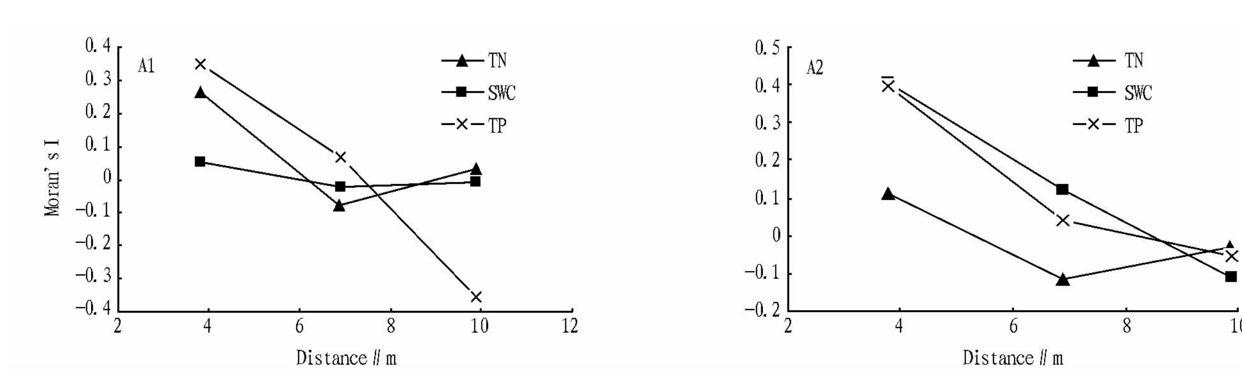

Fig. 4 Spatial autocorrelation of TN, TP and SWC in A1 and A2

4 Conclusions

(1) In general, the average value of TN and SOC decreased with the increase of soil depth. In contrast, the average value of SWC showed as A1 < A2 < A3 < A4, which means the SWC content increases as the soil depth increases. The change of TP with soil depth was not obvious.

(2) Variable coefficients of TN, SWC, SOC and TP, all belonging to medium variations, were all between 0.10 and 1.00; and their Nugget coefficients were all smaller than 0.25 basically, indicating their strong spatial dependence.

(3) In four sampling depths, semi-variance model can simulate the precisions of TN, SWC and TP in A1 and A2 well. The spatial structure of SOC was poorer, which could not be simulated with semi-variance model well.

(4) The analysis with Kriging interpolation showed that, TN, SWC and TP were in layered distribution in A1 and A2; when the spatial structure changed to A2 from A1, the average TN content reduced to 0.310 g/kg from 0.598 g/kg, while the average SWC and TP content increased to 15.439% and 0.366 g/kg from 12.988% and 0.229 g/kg, respectively.

(5) With the increase of depth, the positive autocorrelation distance of TN got smaller from A1 to A2, while the positive autocorrelation distances of SWC and TP both increased.

References

[1] ZHANG XY, CHEN LD, LI Q, *et al*. Effects of agricultural land-use on soil nutrients and the vertical distributions in traditional cultivated region, Northern China[J]. Journal of Agro – Environment Science, 2006, 25(2): 377 –381. (in Chinese).
[2] ZHAO PP. Spatial distribution of soil water content and sediment in the dam farmlands in a small catchment of the Loess Plateau[D]. Shaanaxi Yangling: Research Center of Soil and Water Conservation and Ecological Environment, Chinese Academy of Sciences, 2010. (in Chinese).
[3] ZHANG X, LIU XQ, WANG YP, *et al*. Evaluation on benefits of soil and water conversation in ecological function region of Qinling Mountain[J]. Research of Soil and Water Conservation, 2012, 19(2): 86 – 90. (in Chinese).
[4] LIU MH, WANG F, LI R, *et al*. Discrepance of surface soil moisture between forestland of earth – rock mountain and farmland of loess tableland rural section[J]. Research of Soil and Water Conservation, 2011, 18(3): 187 –190. (in Chinese).
[5] FAN RG, WANG CC, CHEN SQ, *et al*. Spatial distribution of total nitrogen and organic material in surface soil around Chaohu Lake[J]. Environmental Science & Technology, 2011, 34(5): 117 –120. (in Chinese).
[6] GUO JW, ZHANG YB, LIU SC, *et al*. Vertical distribution of soil nutrients in sugarcane field in Changning, Yunnan[J]. Chinese Journal of Soil Science, 2007, 38(6): 1072 –1075. (in Chinese).
[7] ZOU JL, SHAO MA, GONG MH. Effects of different vegetation and soil types on profile variability of soil moisture[J]. Research of Soil and Water Conservation, 2012, 18(6): 12 –17. (in Chinese).
[8] GAO C, ZHU JY, ZHU JG. Effects of extreme rainfall on the export of nutrients from agricultural land[J]. Acta Geographica Sinica, 2005, 60(6): 991 –996. (in Chinese).
[9] WANG HB. Study on the relations between characters and sediment yield and runoff from plots with different soil and water conservation measures [J]. Research of Soil and Water Conservation, 2011, 18(5): 63 –66. (in Chinese).
[10] GONG Y, ZHANG J, CHEN LW. Characteristic of typical rainfall – runoff on different vegetation types in the river basin in the upper Jialing River [J]. Journal of Soil and Water Conservation, 2010, 24(2): 35 – 39. (in Chinese).
[11] WANG SY, LU P, WANG JL, *et al*. Spatial variability and distribution of soil organic matter and total nitrogen at different scales: a case study in Pinggu County, Beijing[J]. Acta Ecologica Sinica, 2008, 28(10): 4957 – 4964. (in Chinese).
[12] Gao XJ, HU XF, WANG SP, *et al*. Nitrogen losses from flooded rice field [J]. Pedosphere, 2002, 12(2): 151 –156.
[13] ZHAO J, LIU HJ, SUI YY, *et al*. Analysis for spatial heterogeneity of organic matter content and available nutrients in black soil crop area with different scales[J]. Journal of Soil and Water Conservation, 2006, 20(2): 41 –44. (in Chinese).
[14] YANG QY, YANG JS. Spatial variability of soil organic matter and total nitrogen at different scales[J]. Journal of Soil and Water Conservation, 2010, 24(6): 100 –104. (in Chinese).
[15] LI BG, HU KL, CHEN DL, *et al*. Conditional simulation of soil surface saturated hydraulic conductivity at field scale[J]. Journal of Hydraulic Engineering, 2002, 36(2): 36 –40. (in Chinese).
[16] Cliff A. Spatial Processes[M]. London: Pion., 1981: 266.
[17] Wang Y Q, Zhang X C, Huang CQ. Spatial variabilityof soil total nitrogen and soil total phosphorus under different land uses in a small watershed on the LoessPlateau, China[J]. Geoderma, 2009, 150(1/2): 141 –149.
[18] Moran P A. Notes on continuous stochastic phenomena[J]. Biometrika, 1950, 37(1/2): 17 –23.
[19] Bennett L T, Adams M A. Indices for characterisingspatial variability of soil nitrogen semi – arid grasslands of Northwestern Australia[J]. Soil Biol. Biochem., 1999, 31(5): 735 –746.
[20] Page T, Haygarth P M, Beven K J. Spatial variabilityof soil phosphorus in relation to the topographic index and critical source areas: sampling for assessing risk to water quality[J]. J. Environ. Qual., 2005, 34(6): 2263 – 2277.
[21] LIU JP, LIU JX, YU Y, *et al*. Study on spatial variability of available nitrogen in different sampling scale——A case study on cropland soil in Yushu City[J]. Research of Soil and Water Conservation, 2012, 19(2): 107 –109. (in Chinese).

(From page 110)

[13] SU JH. Duncan multiple comparisons, data filling methods and its application[J]. Shanghai Statistics, 2003(3): 23 –24. (in Chinese).
[14] Cantón Y, Solé – benet A, de Vente J, *et al*. A review ofrunoff generation and soil erosion across scales in semiaridsouth – eastern Spain[J]. Journal of Arid Environments, 2011, 75(12): 1254 –1261.
[15] GU ZJ. Study on remote-sensing monitoring of vegetation restoration and generation mechanism of current under forest in the water erosion region [D]. Nanjing: Institute of Soil Science, Chinese Academy Sciences, 2008. (in Chinese).
[16] ZI SH, WU BZ, DUAN QS, *et al*. Control effect of grass strips of African green bristlegrass on runoff and soil loss in sloping fields[J]. Research of Soil and Water Conservation, 2006, 13(5): 183 –185. (in Chinese).
[17] YANG JH, WU SJ, WANG P, *et al*. Study on soil and water conservation benefits of Pueraria lobata Ohwi[J]. Journal of Shandong Forestry Science and Technology, 1990(4): 37 –40. (in Chinese).
[18] YU RG, ZUO CQ, YANG J, *et al*. Hydrological effects of soil and water conservation forest in red-soil erosion region[J]. Bulletin of Soil and Water Conservation, 2007, 27(6): 194 –198. (in Chinese).
[19] Kinnell P I A. Event soil loss, runoff and the Universal Soil Loss Equation family of models: a review[J]. Journal of Hydrology, 2010, 385(1/4): 384 –397.
[20] de Baets S, Poesen J, Knapen A, *et al*. Root characteristics of representative Mediterranean plant species and their erosion – reducing potential during concentrated runoff[J]. Plant and Soil, 2007, 294(1): 169 –183.
[21] XIE SH, ZHENG HJ, YANG J, *et al*. Effect of runoff reduction through vegetation measures of soil and water conservation in the hilly – land area southern China[J]. Journal of Soil and Water Conservation, 2010, 24(3): 35 –38. (in Chinese).