Spatial Heterogeneity of Soil Moisture in Red Beds Area and the Associated Driving Factors

Ping Yan

Sun Yat-sen University

Kairong Lin (✉ linkr@mail.sysu.edu.cn)

Sun Yat-sen University

Chenxi Yu

Sun Yat-sen University

Luobin Yan

Southwest University

Xinjun Tu

Sun Yat-sen University

Luwen Zhuang

Sun Yat-sen University

Research Article

Keywords: soil moisture, spatial heterogeneity, land-use types, driving factors, red beds 35 area

Posted Date: December 21st, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-128738/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Spatial Heterogeneity of Soil Moisture in Red Beds Area and the Associated Driving Factors

Ping Yan¹, Kairong Lin^{1,2,3,*}, Chenxi Yu⁴, Luobin Yan⁵, Xinjun Tu¹, Luwen Zhuang¹

¹ School of Civil Engineering, Sun Yat-sen University, Guangzhou 510275, China;

²Guangdong Key Laboratory of Oceanic Civil Engineering, Guangzhou 510275, China

³Southern Marine Science and Engineering Guangdong Laboratory, Zhuhai 519000, China

⁴School of Environmental Sciences and Engineering, Sun Yat-sen University, Guangzhou 510275, China

⁵ School of Geographical Sciences, Southwest University, Chongqing 400715, China;

*Corresponding author e-mail: linkr@mail.sysu.edu.cn

Abstract:

Soil moisture is one of key factors which influence crop growth and ecological environment construction. Knowledge on the spatial heterogeneity of soil moisture and the associate driving factors is of great importance for water resources allocation and ecological environment management. The present study investigated the spatial heterogeneity of soil moisture under four land-use types (cropland, forestland, grassland and bare land) in the ecologically degraded of a red beds area which located in the Nanxiong basin, China. Geostatistical and classic statistical methods were used to analyze the spatial variance of soil moisture. In addition, the driving factors which affect the spatial variance were discussed. The geostatistical analysis showed that the Gaussian model is the optimal regression model of semi-variance functions for all these four land-use types, among which the model of cropland and forestland had better fitting results comparing with other land-use types. Moreover, the soil moisture in bare land exhibited intermediate spatial autocorrelation, which was affected

by structural and random factors. Using a cross validation method, we found that the precision of the ordinary kriging interpolation (OK) method was better than the inverse distance weighting interpolation (IDW) method, and the OK method more accurately reflected the spatial distribution of soil moisture in all these four land-use types. Furthermore, the spatial heterogeneity of soil moisture was mainly affected by the natural and anthropogenic factors such as structural characteristics of the soil, soil texture, vegetation covered on the surface of the land, local climate, land-use types, and human intervention, among which human intervention is the most important factor.

Keywords: soil moisture; spatial heterogeneity; land-use types; driving factors; red beds area

Introduction

Red beds consist of a list of complex strata including conglomerate, sandstone, siltstone, and argillaceous rock ¹. The red sand gravel layer has high water permeability which increase the difficulty of stabilizing the soil at the top layer. Thus, the lands in red beds areas are often barren. Once vegetation covered on the land is destroyed, the soil at the top layer of a slope lose rapidly which is an irreversible process. Due to these characteristics of red beds, the ecological environment in the red beds areas is fragile. The geology ²⁻³, desertification ⁴⁻⁶, and karst rocky desertification ⁷⁻⁹ of red beds areas have been widely investigated in previous studies. However, few researches have emphasized on the land degradation of the red beds area.

Red beds areas are widely distributed in South China, where the soil erosion problems are usually serious. There are also many "red deserts" in the subtropical humid Pearl River basin where the land degradation is grievous ¹⁰. In Guangdong Province, the exposed red beds cover an area of 28,000 km². The red beds are of various geomorphic patterns ¹¹. Siltstone and clay stone deposited in the middle of the red beds basin are weak in structure and prone to weathering and fragmentation ¹². In the rainy season, there are high risks of collapse, landslide, and debris flow. Slope erosion leads to soil erosion. In the fragile ecologically degraded red beds areas, soil problems reduce ecosystem stability and further affect the economics' sustainable

development. Therefore, how to restore and reverse decertified red beds areas, improve the productivity of forestland, and establish a high-quality, efficient, sustainable, and stable ecological environment are important issues.

Recent studies have discussed and concluded the ecological issues associated with red beds ¹³⁻¹⁴. During the degradation of red beds, the surface organic matter is first eroded. Then, with reverse succession of vegetation, soil moisture content continually decreases. When it reaches the stage of cow liver land, the soil moisture may reduce to lower than 5.64%, due to the loss of vegetation biomass and the decrease of species diversity and accumulated soil organic matter (SOC). Also, the soil erosion in the red beds areas intensifies the loss of soil nutrients, and thus vegetation can hardly survive in this situation ¹¹. Since last decades, human activities have led to an over-exploitation of land and over-use of water resource. The land-use type is a dominant indicator that represents the degree of land utilization in the field of land planning and land evaluation ¹⁵. The land-use type changes significantly which the development of economics, which not only affects the patterns of ground surface (e.g., area of vegetation covered on the land, types of vegetation) but also affected the characteristics of soils such as the soil moisture ¹⁶⁻¹⁷. Soil moisture is often considered as a representative parameter of the characteristics of soil ¹⁸⁻¹⁹. It not only affects the water and soil environment, but also plays a key role in vegetation restoration and ecological environment reconstruction. The soil moisture content depends on the mass and momentum transfer of surface and underground water in the local area, and it dominants material migration, water resources quantity, plant water absorption, yield/biomass of vegetation, and bio-geochemical process ²⁰. Therefore, we used the spatial heterogeneity of soil moisture to evaluate the land degradation, and we took the land-use type into account in the analysis of soil moisture.

A number of previous studies have reported that soil moisture exhibits high levels of spatial heterogeneity owing to the effects of, e.g., topography, soil, and vegetation ²¹⁻²⁵. Recently, Wiebke et al. ²⁶ indicated that the spatial heterogeneity and its influence factors of soil moisture is affected by various natural factors. Zhang et al. ²⁷ showed that soil moisture has strong spatial heterogeneity in both horizontal and

vertical directions. Fend et al.²⁸ found that soil moisture has significant spatial heterogeneity on different scales. However, especially in typical red beds fragile ecological environment, there are few studies on the spatial heterogeneity and its influence factors of soil moisture under different land-use types. Therefore, the spatial heterogeneity of soil moisture in the red beds area is of great ecological significance for vegetation construction and restoration of ecological management. However, none has studied the spatial heterogeneity of soil moisture in red bed areas.

In view of this, the purpose of this study were (1) to learn about the spatial heterogeneity of soil moisture and its influencing factors in cropland, forestland, grassland and bare land; (2) to explore which optimal geostatistical analysis method can be applied to the study of spatial heterogeneity of soil moisture.

Study area and methods

Study area

Nanxiong basin is a fault basin controlled by the Nanxiong fault along the northern margin with an area of 1800 km² spanning Guangdong and Jiangxi provinces (24° 56' 59"~25° 25' 20" N, 113° 55' 30"~114° 44' 38" E¹¹. The annual average temperature is 19.6 °C, in the winter half of the year, it is controlled by continental high pressure, cold temperatures, and little rain, frost, and freezing weather. The annual average minimum temperature is in January with a prevailing northeast wind and continental climate characteristics. In the second half of the year, it is affected by a subtropical ocean weather system with a prevailing southwest wind. The total rainfall is abundant (average annual rainfall 1555.1 mm)¹⁴. There are four types of natural soil: yellow, red, red lime, and purple. The soil texture in the selected red bed area belongs to purplish sand soil. According to a field survey conducted by the project team all year round, the soil sampling area in the present study was in the northeast of the Nanxiong basin (Figure 1). There were evidently different types of red vegetation communities in this area with different soil patterns, which is the best area to analyze the spatial heterogeneity of soil properties.

Figure 1. Study area: Nanxiong basin, which is a typical red beds landscape type in Guangdong province.

Sample Collection and Field Investigation

Soil moisture is very important in agricultural production in red bed area, the results of sampling in different seasons, such as before and after the rainy season, may be quite different. To reduce the effect of seasonal precipitation on the research results, we unified the field sampling work after the rainy season during which there was no

precipitation. The samples were collected after the crops were completely harvested in November 2017. 225 samples were randomly collected in the selected area. The distance between each sampling point ranged within 50–300 m. We classified the lands into four catalogues (i.e., cropland, forestland, grassland, and bare land) based on the types of vegetation covered on the land (see Figure 2 and Table 1). As shown in Table 2, we collected 59 samples from cropland, 68 samples from forestland, 57 samples from grassland, and 41 samples from bare land. The sampling depth was 0–0.2 m, as most crop roots and humus were distributed within this set of range. Same sampling depth has been commonly adopted by previous studies^{29–31}. Of course, the plants were able to extract water far beyond this depth. We don't enter the controversy here. Each sampling point was 10–20 m from the center of the field, and 3–7 samples were collected according to an "s" shape and mixed evenly. Then 1 kg of soil samples was left by the quartering method. At the same time, the vegetation coverage and rock exposure rates around the sampling point were recorded.

Figure 2. Distribution of the four land-use types in the studied area: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Land-use types	Vegetation covered on the land
Cropland	Rice
Forestland	<i>Pinus massoniana</i> , <i>Pinus elliottii</i> , <i>Leucaena forest</i>
Grassland	<i>Lagerstroemia indica</i> , <i>Rosa parviflora</i>
Bare land	Dry slope land

Table 1. Vegetation covered on different types of lands.

Laboratory Analysis

All the samples were stored with plastic bags with labels. The gravimetric method was used to determine the soil moisture of the samples. The weights of the samples were measured before and after a 10 h laboratorial drying at 105–108 °C³². The physical characteristics of soil (bulk density, capillary water capacity, total porosity, capillary porosity, and non-capillary porosity) were determined using the bulk density ring method³³. Soil pH was determined using a pH meter equipped with a calibrated combined glass electrode³⁰. Soil organic matter was measured using a potassium dichromate-oxidation external heating method³⁴. Soil total nitrogen was analyzed using the Kjeldahl digestion procedure³⁵, and hydrolysed nitrogen was measured by alkaline dissociation diffusion method³⁶. Soil total phosphorus was determined by alkaline digestion³⁷. Soil available phosphorus was detected using spectrophotometry and flame photometry method³⁸. Total potassium was determined by the sodium hydroxide alkali melting method³⁹, and available potassium was determined by the ammonium lactate solution method⁴⁰.

Statistical Analysis

SPSS 19.0 was used to carry out soil moisture content of descriptive statistics, multiple comparisons, and single sample nonparametric Kolmogorov-Smirnov test under four land-use types. GS+7.0 software was used for geostatistical analysis. Variogram was used for geostatistical analysis. The formula used to calculate variogram was as follows:

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

where $N(h)$ is the value of the distance is equal to h of the point logarithm; $Z(x_i)$ is the mean of position x_i ; and $Z(x_i + h)$ is the mean of distance of $x_i + h$ ⁴¹⁻⁴².

Using ArcGIS 10.5, 225 sample points were digitized to generate a spatial database of sample points distribution for geostatistical analysis. The key fields and soil moisture data of four land-use types of each point were connected to form-attributed data matching with the geographic coordinates of the sample points.

Then geostatistical analysis was carried out with the geostatistical analysis module in ArcGIS 10.5, including statistical analysis of sample data, elimination of outliers, calculation of variogram, structural analysis of variogram, optimal fitting, and testing of the theoretical variogram model. Furthermore, the undetermined area was measured by the inverse distance weighting (IDW) and ordinary kriging (OK) interpolation methods according to the theoretical variogram model. The results of cross validation between the measured and predicted values under different land-use types were obtained by interpolation calculation of the soil moisture status, and the scatter diagram and its related parameters were used for model fitting evaluation. Different theoretical models were mainly compared through statistical indicators, such as mean error (ME), mean standard error (MSE), average standard error (ASE), root mean square standardized error (RMSSE), and root mean square error (RMSE), and the best fitting model was selected⁴¹. The relevant formulate were as follows:

$$ME = \frac{\sum_{i=1}^n [\hat{Z}(x_i) - Z(x_i)]}{n} \quad (2)$$

$$MSE = \frac{\sum_{i=1}^n [\hat{Z}(x_i) - Z(x_i)] / \hat{\sigma}(x_i)}{n} \quad (3)$$

$$ASE = \sqrt{\frac{\sum_{i=1}^n \hat{\sigma}(x_i)}{n}} \quad (4)$$

$$RMSSE = \sqrt{\frac{\sum_{i=1}^n \left\{ [\hat{Z}(x_i) - Z(x_i)] / \hat{\sigma}(x_i) \right\}^2}{n}} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n [\hat{Z}(x_i) - Z(x_i)]^2}{n}} \quad (6)$$

where, $\hat{\sigma}(x_i)$ is the prediction standard error; $\hat{Z}(x_i)$ is the prediction of the *i*th sample at position *x*; *Z*(*x*_{*i*}) is the measurement of the *i*th sample at position *x*; and *n* is the number of sampling points.

At the same time, combining the interpolation windows in GS+7.0, we carried

out IDW and OK to obtain the three-dimensional spatial distribution map of soil moisture in cropland, forestland, grassland and bare land. Finally, the Redundancy Analysis method (RDA) was carried out in the multivariate analysis software Canoco 4.5, Canodraw, and TWINSpan.

Results

Statistical Analysis of soil moisture

Under different land-use types, soil moisture content was different. Among all sampling points, bare land (8.85%) had the lowest value, and forestland (22.31%) had the highest soil moisture (Table 2). The results of one-way ANOVA showed that there was a significant differences of soil moisture in cropland, forestland, grassland and bare land. The results indicated that the mean value of soil moisture in grassland and bare land was significantly lower than that in cropland and forestland. However, there was no significant difference between cropland and forestland.

The coefficient of variation (CV) reflects the variation degree in characteristic parameters and reveals the dispersion degree of regional variables^{34, 43}. The CVs of soil moisture in cropland, forestland, grassland, and bare land was 4.33%, 4.52%, 7.92%, and 10.06%, respectively. The CV value of grassland and bare land was significantly higher than others, and that in bare land was the highest (intermediate variation).

Figure 3 shows the frequency of soil moisture in cropland, forestland, grassland and bare land. The range of soil moisture content of cropland and forestland was mainly between 21.25% and 22.75%, and that of grassland was mainly between 11.75% and 12.25%. Although the values were relatively centralized, there was no evident skewed distribution. The skewness and kurtosis values listed in Table 2 also represent this statistical distribution. The result of the K-S test is between 0.45-0.64, which indicated that the soil moisture was normally distributed and fitted the requirements of geostatistical analysis in cropland, forestland, grassland and bare land.

types	Sample size	Min	Max	Mean	Standard deviation	Kurtosis	Skewness	Coefficient of variation (%)	K-S test
Cropland	59	20.25	24.25	22.16a	0.96	-0.57	-0.014	4.33	0.45
Forestland	68	20.25	24.50	22.31a	1.01	-0.55	-0.065	4.52	0.58
Grassland	57	9.75	14.00	11.87b	0.94	-0.25	-0.081	7.92	0.59
Bare land	41	7.20	10.60	8.85c	0.89	-0.95	0.087	10.06	0.64

Table 2. Statistical characteristics of soil moisture.

Note: the letters after the mean value indicate the difference of average soil moisture under four land-use types, and the significance is tested by Duncan multiple comparison method ($P < 0.05$).

Figure 3. Frequency map of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Spatial Heterogeneity of Soil Moisture

In Table 3, C_0 is the nugget value, indicating the nugget effect, reflecting the possible degree of internal randomness of regionalized variables. There are various positive base effects caused by short-distance variation, sampling error, inherent variation and random. C is the structural variance, also known as the off-base station value, which indicates the structural variation caused by non-human regional factors, such as soil, terrain, parent material, and climate; $C_0 + C$ is the base-station value, which indicates the total variation in the system. Nugget value/abutment value ($C_0 / (C_0 + C)$) is also known as the nugget coefficient, which indicates the degree of spatial heterogeneity, and a high ratio indicates that random factors play a leading role and spatial variation is relatively high. Conversely, the degree of spatial variation caused by structure factors is relatively high⁴⁴. Generally, it is considered that $< 25\%$

variables have strong spatial autocorrelation, 25–75% variables have intermediate spatial autocorrelation, and > 75% variables have weak spatial autocorrelation, and the variation is mainly random, which is not suitable for spatial interpolation. If the nugget coefficient is close to 1, then there is constant variation over the whole scale. According to Table 3, the nugget values of cropland, forestland, grassland, and bare land were 0.001, 0.052, 0.036, and 0.094, respectively, indicating that there was variation caused by sampling error, short-distance variation, and random factors within the current sampling scale. The nugget coefficients for cropland, forestland, grassland and bare land were 1.25%, 5.31%, 4.15%, and 27.72%, respectively.

Through the determination coefficient (R^2) and residuals, linear, gaussian, exponential, and spherical models were selected to fit the variogram. The results showed that the Gaussian model had a good fit with the cropland and forestland and a high determination coefficient (0.876, 0.853). The range represents the range of spatial continuity of patches with similar properties. The spatial variables within the range were spatially autocorrelated, but there was no spatial autocorrelation outside the range.

From Table 3 and Figure 4, the range of soil moisture in four land-use types, i.e. the maximum spatial correlation distance, was 156.12–467.65 m. The lag distance of soil moisture on the regional scale was greater than 300 m in the field sampling (Figure 4). This also shows that the current sampling design reflects the spatial distribution patterns of soil moisture, indicating that the soil moisture in cropland, forestland, grassland and bare land, which is continuously distributed in this spatial range, and that it is spatially autocorrelated.

Land-use types	Theoretical model	Nugget (C0)	Sill (C0+C)	Nugget/Sill (%)	Range (m)	Coefficient of determination (R2)	Residual
Cropland	Gaussian	0.001	0.800	1.25	316.96	0.876	0.110
Forestland	Gaussian	0.052	0.980	5.31	467.65	0.853	0.019
Grassland	Gaussian	0.036	0.866	4.15	381.05	0.616	0.039
Bare land	Gaussian	0.094	0.339	27.72	156.12	0.615	0.333

Table 3. Parameters of semi-variogram model of soil moisture.

Figure 4. Semi-variogram of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Spatial Distribution of Soil Moisture

With the support of the GS + 7.0 software, we used Inverse distance weighting (IDW) and Ordinary kriging (OK) interpolation methods to interpolate the soil moisture of the four land-use types. Figs. 5 and 6 show the interpolation results obtained from the OK method, and IDW method, respectively. In the spatial distribution map of soil moisture, red area denotes high soil moisture content, whereas the green area means low values of soil moisture.

Here, we used two interpolation techniques (OK method and IDW method) to interpolate the soil moisture data at the sampling points, because we think that all the mathematical models including interpolation model have unavoidable calculation inaccuracies. In our case, we have the soil moisture data of the sampling points, whereas the field data of the soil moisture is unknown. Therefore, we cannot check whether the interpolation results fit well with the real situation for the whole area. From this consideration, introducing a second interpolation technique and comparing the results of these two methods is helpful for us to obtain an estimation that closer the truth values.

First, we can see from Figs. 5 and 6 that the spatial distributions determined by

the IDW method and the OK method for different land-use types were similar (Figs 5 and 6). It means that both the IDW and OK interpolation methods are suitable for the spatial interpolation of soil moisture. Comparing with the interpolation results estimated with the IDW method, the distribution map of soil moisture estimated by the OK method was relatively smooth with less fluctuation. The different levels of fluctuation mainly result from the differences of the interpolation algorithms. This is also why we conducted the interpolation with two methods rather than using a representative one.

In general, both the two interpolation methods showed that the soil moisture at different land-use types of the studied area was significantly different. In particular, the variance of soil moisture between forestland and bare land is significant. The soil moisture of bare land was significantly lower than those of cropland, forestland and grassland, whereas the fluctuation of soil moisture of bare land was smaller than those of others.

For grassland, the high soil moisture areas were distributed in the whole area. The soil moisture in the southeast direction of cropland was significantly higher than other land-use types. Soil moisture in the middle part of forestland was significantly higher than that in the surrounding areas. For the bare land, the low soil moisture areas were mainly distributed in the northeast of the selected area, with the rate of variation ranged from 8.2% to 9.5%. These low soil moisture areas are mainly near Dagongkeng, Shangzhitian, and Piankeng villages in the Nanxiong basin. The common feature of these areas is that they have a large area of shoddy red beds. The coverage of vegetation is significantly lower than other areas, and thus the ecological environment is much more frangible.

The results demonstrated the influence of land-use types on the spatial distribution of soil moisture. It further confirmed that the spatial distribution of soil moisture is affected by the factors associated with land-use types such as the vegetation covered on the land, the underground roots, and the surface evapotranspiration affected by vegetation. These factors affect soil moisture via influencing the soil-water interaction process and the momentum and mass flux of water in soils. We

may deduce that the vegetation covered on the land increase the water conservation capacity of soil.

Figure 5. Ordinary kriging (OK) interpolation of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 6. Inverse distance weighting (IDW) interpolation of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Comparison of OK and IDW methods

The spatial distribution of soil moisture was tested using OK and IDW interpolation methods in geostatistical analysis module of ArcGIS 10.5 under four land-use types. The closer the MSE and ME values to 0, the closer the response values to 1, and the RMSE being close to ASE infers better model performance ⁴⁴. From Table 4, the values of ME and ASE were close to 0 both OK and IDW under four land-use patterns. The values of RMSE and ASE of OK were closer than IDW, and the RMSE values of OK was closer to 1 than IDW. This result shows that the precision of the OK interpolation method is better, and the spatial distribution maps can more accurately reflect the distribution characteristics of soil moisture.

Land-use types	Methods	ME	RMSE	MSE	ASE	RMSSE
Cropland	OK	0.0172	0.8433	0.0035	0.7895	0.9615

	IDW	0.0531	0.2536	0.0126	0.5623	0.9112
Forestland	OK	-0.0005	1.0237	0.0019	0.9552	1.0651
	IDW	0.0187	1.0515	0.0035	0.9123	0.8546
Grassland	OK	0.0073	0.9599	0.0079	0.9545	1.0043
	IDW	0.0081	0.9717	0.0561	0.9549	0.8917
Bare land	OK	0.0117	0.8668	0.0127	0.9333	0.9732
	IDW	0.0455	0.9034	0.0464	0.9256	0.9486

Table 4. Cross-validation indices for IDW and OK methods.

Analysis of the Influencing Factors using the RDA method

To directly reflect the influence of environmental factors on soil moisture, the Redundancy Analysis method (RDA) was carried out for soil physical and chemical factors and environmental factors related to soil moisture. Thirteen soil properties factors and seven environmental factors were selected to analyze the influencing factors of spatial distribution of soil moisture in cropland, forestland, grassland and bare land.

According to Table 4, the cumulative interpretation of soil characteristics in cropland, forestland, grassland and bare land of the first two axes of RDA analysis of cropland was 60.7%, 50.7%, 81.1% and 68.1%, respectively. And the cumulative interpretation of the properties and environment relation was 77.8%, 87.3%, 86.6% and 84.8%, respectively.

In cropland, from Figure 7(a), the soil moisture is positively related to capillary water capacity, organic matter, hydrolytic nitrogen, total phosphorus, pH, available potassium, and vegetation coverage, and negatively related to altitude, slope direction, non-capillary porosity, available phosphorus, and rock exposure. Among them, the angle between soil moisture and capillary water holding capacity, hydrolytic nitrogen, and organic matter was the smallest, which indicates that the capillary these factors of cropland have the greatest effect on soil moisture.

In forestland, according to the RDA analysis sequence diagram, the soil moisture content was positively correlated with hydrolytic nitrogen, total porosity, vegetation coverage, total phosphorus, available phosphorus, and total nitrogen (Figure 7(b)). The angle between soil moisture and altitude was 90°, and there was no correlation. It

was negatively correlated with slope, slope direction, available potassium, rock exposure rate, and soil temperature. Among them, the angle between soil moisture and hydrolytic nitrogen, total porosity, and vegetation coverage was the smallest, indicating that these factors of forestland have the greatest effect on soil moisture.

In grassland, from the RDA analysis sequence diagram (Figure 7(c)), the soil moisture content had a significant positive correlation with hydrolytic nitrogen, available phosphorus, capillary porosity, vegetation coverage, total potassium, and available potassium, and a significant negative correlation with slope, soil bulk density, slope direction, rock exposure rate, and soil temperature. Among them, the angle between soil moisture and capillary porosity, available phosphorus and vegetation coverage was the smallest, which indicates that these factors have the greatest effect on soil moisture.

In bare land, from the RDA analysis sequence diagram (Figure 7(d)), the soil moisture was significantly positively correlated with total porosity, available potassium, vegetation coverage, total phosphorus, and capillary water capacity, and significantly negatively correlated with soil bulk density, altitude, slope direction, rock exposure rate, and soil temperature. Among them, the angle between soil moisture and total porosity, available potassium, and vegetation coverage was the smallest, which indicates that these factors have the greatest effect on soil moisture.

Land-use types	RDA	Axis				Total
		1	2	3	4	
Cropland	Eigenvalues	0.449	0.158	0.070	0.056	1.000
	Properties-environment correlations	0.967	0.741	0.969	0.966	
	Cumulative percentage variance					
	Of properties data %	44.9	60.7	67.6	73.2	
	Of properties-environment relation %	57.5	77.8	86.7	93.9	
	Sum of all eigenvalues					1.000
	Sum of all canonical eigenvalues					0.780
Forestland	Eigenvalues	0.372	0.134	0.046	0.014	1.000
	Properties-environment correlations	0.727	0.807	1.000	0.989	
	Cumulative percentage variance					
	Of properties data %	37.2	50.7	55.3	56.7	
	Of properties-environment relation %	64.1	87.3	95.2	97.6	
	Sum of all eigenvalues					1.000

	Sum of all canonical eigenvalues	0.581			
	Eigenvalues	0.673	0.137	0.051	0.049
	Properties-environment correlations	0.972	0.983	0.995	0.992
	Cumulative percentage variance				
Grassland	Of properties data %	67.3	81.1	86.1	91.0
	Of properties-environment relation %	71.9	86.6	92.0	97.2
	Sum of all eigenvalues	1.000			
	Sum of all canonical eigenvalues	0.936			
	Eigenvalues	0.449	0.232	0.069	0.039
	Properties-environment correlations	0.965	0.909	0.962	0.770
	Cumulative percentage variance				
Bare land	Of properties data %	44.9	68.1	75.1	79.0
	Of properties-environment relation %	56.0	84.8	93.5	98.4
	Sum of all eigenvalues	1.000			
	Sum of all canonical eigenvalues	0.803			

Table 4. RDA analysis results of soil properties and environmental factors under the four land-use types.

Figure 7. RDA ordinary diagram of soil physical and chemical properties and environmental factors under cropland. (a): Cropland; (b): Forestland; (c): Grassland; (d): Bare land, with X1: Soil moisture, X2: Bulk density, X3: Capillary water capacity, X4: Total porosity, X5: Capillary

porosity, X6: Non-capillary porosity, X7: pH, X8: Organic matter, X9: Total nitrogen, X10: Hydrolyzed nitrogen, X11: Total phosphorus, X12: Available phosphorus, X13: Total potassium, X14: Available potassium, X15: Elevation, X16: Slope, X17: Aspect, X18: Vegetation coverage, X19: Rock exposure rate, X20: Soil temperature.

Discussion

The spatial heterogeneity

One striking feature observed from this study is that soil moisture's degree of variation of is relatively weak, and the soil moisture's CV is smaller than other soil properties. Similar pheromones also have been observed by ²². The derivation of soil moisture at different spatial locations may result from the retrograde succession of vegetation due to human interferences ⁴⁵. This confirms the assumption that human activity is a key factor that influence the spatial variation of soil moisture content. The results show that the Gauss model had a good fit with the cropland and forestland and a high determination coefficient (0.876, 0.853). The results show that the soil moisture in the study area has a good spatial structure.

We can obtain from the ordination kriging interpolation map that the soil moisture of bare land was significantly lower than those of cropland, forestland and grassland, whereas the fluctuation of the soil moisture of bare land was smaller than those that of others. We may deduce that the vegetation covered on the land increase the water conservation capacity of soil.

It should also be noted that comparing with the interpolation results estimated with the IDW method, the distribution map of soil moisture estimated by the OK method was relatively smooth with less fluctuation. The cross-validation shows that the OK interpolation method has a better prediction precision. Thus, the choose of interpolation method is also an important issue for evaluating the spatial distribution of soil moisture.

The driving factors

The driving factors have been analyzed using the RDA method in the driving factors of the spatial heterogeneity of soil moisture can be concluded two-folds:

random factors (e.g., irrigation, fertilization, and farming) and structural factors (e.g., parent material, climate, biology, and topography). The spatial heterogeneity of soil moisture results from the interaction of natural environment factors and human activities ²³. The land-use types reflect the levels of human intervention and levels of over-utilization. When people planting or building constructions on the land, these activities may change the characteristics of the soil, and thus affect the water content in soil. There was a strong spatial autocorrelation among cropland, forestland, and grassland, which demonstrated that structural factors rather than the random factors played a key role in the spatial heterogeneity of soil moisture for all these land-use types.

By RDA redundancy analysis, we have estimated the degree of correlation between soil moisture and each driving factor, and determined the most influential factor. Yang et al. has shown that if the cumulative interpretation of the relationship between species and environment in the first three ranking axes is > 40%, the ranking results are effective ²². RDA results show that the total porosity and vegetation coverage of soil are key factors affecting soil moisture content.

Furthermore, the spatial heterogeneity and distribution of soil moisture are affected by various factors, such as structural characteristics of the soil itself, vegetation, climate, and changes in land-use types.

Conclusion

In the present study, the spatial heterogeneity of soil moisture and the associate driving factors of a typical red beds area which located in the southern of China are discussed under four land-use types. Comparing with previous studies, the present results are relevant to the study of soil spatial variation at smaller spatial scale in the red beds area. Through the selection of interpolation parameters and the comparison of interpolation accuracy, we found that the OK interpolation method has a better accuracy than the IDW method, and thus its results can more accurately reflect the spatial distribution of the soil moisture. The spatial heterogeneity of the soil moisture plays an important role in the sustainable development of soil and water resources in

the red beds ecological area. In the future, to investigate the mechanisms underlying the land degradation, the effect of biological and environmental factors, such as geology, soil, vegetation, topography, and human activities, should also be comprehensively considered. In addition, the spatial heterogeneity of soil moisture content on a larger scale will further be studied to improve our understanding of the mechanisms underlying land degradation in this region.

Author Contributions

Author contributions were as follows: Ping Yan and Kairong Lin conceived the original ideas. Kairong Lin and Xinjun Tu acquired the funding support. Ping Yan, Chenxi Yu and Luobin Yan designed and performed the experiments. Ping Yan, and Luobin Yan outlined the paper. Ping Yan wrote the paper under guidance from Kairong Lin, and Ping Yan and Luobin Yan collected soil samples in the field. Luwen Zhuang improved the paper and corrected English.

Acknowledgments

This work was funded by the Research Fund for the National Natural Science Foundation of China (No.51779279, No.51822908 and No.41771008), the Fundamental Research Funds for the Central Universities of China (No. 20lgy158) and the Project Funded by China Postdoctoral Science Foundation (No. 2020M672941). We would like to thank the members of the team. In addition, the authors gratefully acknowledge Jiayi Chen from South China Institute of Environmental Science, Ministry of ecological environment for helping with the experiment treatment. The authors also acknowledge Ms Zhenzhu Meng from Swiss Federal Institute of Technology in Lausanne for improving the manuscript.

Additional Information

Competing Interests: The authors declare that they have no competing interests.

Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References:

1. Motaghian, H.R. & Mohammadi, J. Statistical and geostatistical appraisal of spatial variability of

- aggregate stability and aggregate-associated organic carbon content on a catchment scale in a semi-arid region, central Iran. *Desert* **17**, 27-39 (2012).
2. Buseck, P.R., Tsipursky, S.J. & Hettich, R. Fullerenes from the geological environment. *Science* **257**, 215-217 (1992).
3. Lin, N.F. & Tang, J. Geological environment and causes for desertification in arid-semiarid regions in china. *Environmental Geology* **41**, 806-815 (2002).
4. Houérou, H.N.L. Climate change, drought and desertification. *Journal of Arid Environments* **34**, 133-185 (1996).
5. D'odorico, P. *et al.* Global desertification: drivers and feedbacks. *Advances in Water Resources* **51**, 326-344 (2013).
6. Eskandari, H., Borji, M., Khosravi, H. & Mesbahzadeh, T. Desertification of forest, range and desert in, tehran province, affected by climate change. *Solid Earth* **73**, 905-915 (2016).
7. Huang, Q.H.; Cai, Y.L. Assessment of karst rocky desertification using the radial basis function network model and gis technique: a case study of guizhou province, china. *Environmental Geology* **498**, 1173-1179 (2006).
8. Wang J.X. *et al.* Erosion-creep-collapse mechanism of underground soil loss for the karst rocky desertification in chenqi village, puding county, guizhou, china. *Environmental Earth Sciences* **72**, 2751-2764 (2014).
9. Xie, L.W. *et al.* Evaluation of soil fertility in the succession of karst rocky desertification using principal component analysis. *Solid Earth* **6**, 515-524 (2015).
10. Peng, H. *et al.* A preliminary study of desertification in red beds in the humid region of Southern China. *Acta Geographica Sinica* **70**, 1699-1707 (2015).
11. Yan, L.B. *et al.* The dynamic change of vegetation cover and associated driving forces in Nanxiong Basin, China. *Sustainability* **9**, 1-15 (2017).
12. Yan, L.B. *et al.* The spatial patterns of Red Beds and Danxia Landforms: Implication for the formation factors-China. *Scientific reports* **9**, 1-10 (2019).
13. Zhu, X. & Zhu, B. Diversity and abundance of soil fauna as influenced by long-term fertilization in cropland of purple soil, China. *Soil & Tillage Research* **146**, 39-46 (2014).
14. Yan, P. *et al.* Spatial variability of soil physical properties based on GIS and geo-statistical methods in Nanxiong Basin, China. *Polish Journal of Environmental Studies* **28**, 1-12 (2019).
15. Cai, Z.Q. *et al.* Land-use type strongly shapes community composition, but not always diversity of soil microbes in tropical China. *Catena* **165**, 369-380 (2018).
16. Foley, J.A. Global consequences of land use. *Science* **309**, 570-574 (2005).
17. Ning, J. *et al.* Spatiotemporal patterns and characteristics of land-use change in china during 2010-2015. *Journal of Geographical Sciences* **28**, 547-562 (2018).
18. Wang, Y.Q., Shao, M.A. & Liu, Z.P. Spatial variability of soil moisture at a regional scale in the Loess Plateau. *Advances in Water Science* **23**, 310-316 (2012).
19. Janik G. Spatial variability of soil moisture as information on variability of selected physical properties of soil. *International Agrophysics* **22**, 35-43 (2008).
20. Brocca, L. *et al.* Spatial-temporal variability of soil moisture and its estimation across scales. *Water Resour. Res.* **46**, 1-14 (2010).
21. Cantón, Y.; Solé-Benet, A. & Domingo, F. Temporal and spatial patterns of soil moisture in semiarid badlands of SE spain. *Journal of Hydrology* **285**, 199-214 (2004).
22. Yang, J. *et al.* Dynamic variations in profile soil water on karst hillslopes in southwest china.

- Catena* **172**, 655-663 (2019).
23. Rosenbaum, U. *et al.* Seasonal and event dynamics of spatial soil moisture patterns at the small catchment scale. *Water Resources Research* **48**, 3472-3476 (2012).
 24. Liu, Z.P.; Shao, M.A. & Wang, Y.Q. Scale-dependent correlations between soil properties and environmental factors across the loess plateau of china. *Soil Research* **51**, 112-123 (2013).
 25. Gebreslase, S. M. *et al.* Spatial variability of soil moisture in newly implemented agricultural bench terraces in the ethiopian plateau. *Water* **11**, 2134 (2019).
 26. Wiebke, N. *et al.* Spatial-temporal soil moisture dynamics under different cocoa production systems, *Catena* **158**, 340-349 (2017).
 27. Zhang, K. *et al.* Ground observation-based analysis of soil moisture spatiotemporal variability across a humid to semi-humid transitional zone in china. *Journal of Hydrology* **574**, 903-914 (2019).
 28. Feng, Q. *et al.* Spatial Heterogeneity of Soil Moisture and the Scale Variability of Its Influencing Factors: A Case Study in the Loess Plateau of China. *Water* **5**, 1226-1242 (2013).
 29. Liu, Z.P.; Shao, M.A. & Wang, Y.Q. Scale-dependent correlations between soil properties and environmental factors across the loess plateau of china. *Soil Research* **51**, 112-123 (2013).
 30. Liu, Z.P.; Shao, M.A. & Wang, Y.Q. Large-scale spatial interpolation of soil pH across the loess plateau, china. *Environmental Earth Sciences* **69**, 2731-2741 (2013).
 31. Liu, Z.P.; Shao, M.A. & Wang, Y.Q. Estimating soil organic carbon across a large-scale region: a state-space modeling approach. *Soil Science* **177**, 607-618 (2012).
 32. Zhang, J.H. & Li, Y. Spatial variability of soil moisture on the hillslopes, southwestern china. *Archives of Agronomy and Soil Science* **48**, 357-362 (2002).
 33. De Marins, A.C. *et al.* Crambe grain yield and oil content affected by spatial variability in soil physical properties. *Renewable & Sustainable Energy Reviews* **81**, 464-472 (2018).
 34. Teng, M.G. *et al.* Spatial variability of soil organic carbon in three gorges reservoir area, china. *Science of the Total Environment* **599**, 1308-1316 (2017).
 35. Fang, X. *et al.* Soil organic carbon distribution in relation to land use and its storage in a small watershed of the Loess Plateau, China. *Catena* **88**, 6-13 (2012).
 36. Bremner, J.M. & Tabatabai, M.A. Use of an ammonia electrode for determination of ammonia in Kjeldahl. *Analysis* **3**, 159-165 (1972).
 37. Murphy, J. & Riley, J.P. A modified single solution method for the determination of phosphate in natural water. *Analytica Chimica Acta* **27**, 31-36 (1962).
 38. Bogunovic, I. *et al.* Short-range and regional spatial variability of soil chemical properties in an agro-ecosystem in eastern Croatia. *Catena* **154**, 50-62 (2017).
 39. Zhu, X.G.; Han, B.J. & Zhao J. Spatial and temporal variability of soil nutrients in the black soil area of northeast China. *Journal of Food Agriculture and Environment* **11**, 1386-1389 (2013).
 40. Egnér, H.; Riehm, H. & Domingo, W.R. Untersuchungen über die chemische Bodenanalyse als Grundlage für die Beurteilung des Nährstoffzustandes der Böden. II. Chemische Extraktionsmethoden zur Phosphor-und Kaliumbestimmung. *Kungliga Lantbrukshögskolans Annaler* **26**, 199-215 (1960).
 41. Mohamed, N. *et al.* Depositional systems, composition and geochemistry of triassic rifted-continental margin redbeds of the internal rif chain, morocco. *Sedimentology* **57**, 312-350 (2010).
 42. Oliver, M.A. & Webster, R. Semi-variograms for modelling the spatial pattern of landform and soil properties. *Earth Surface Processes & Landforms* **11**, 491-504 (2010) .
 43. Guan, F. *et al.* Spatial variability of soil nitrogen, phosphorus and potassium contents in moso bamboo forests in yong'an city, china. *Catena* **150**, 161-172 (2017).

- 541 44. Zhao, Y. *et al.* Study on Soil Nutrients Spatial Variability in Yushu City. *Computer and*
542 *Computing Technologies in Agriculture* **369**, 1-7 (2012).
- 543 45. Jin, Y.L. *et al.* Discussion on desertification of humid region in southern China. *Progress in*
544 *Geography* **34**, 772-780 (2015).

Figures

Figure 1

Study area: Nanxiong basin, which is a typical red beds landscape type in Guangdong province.

Figure 2

Distribution of the four land-use types in the studied area: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 3

Frequency map of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 4

Semi-variogram of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 5

Ordinary kriging (OK) interpolation of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 6

Inverse distance weighting (IDW) interpolation of soil moisture: (a) Cropland, (b) Forestland, (c) Grassland, and (d) Bare land.

Figure 7

RDA ordinary diagram of soil physical and chemical properties and environmental factors under cropland. (a): Cropland; (b): Forestland; (c): Grassland; (d): Bare land, with X1: Soil moisture, X2: Bulk density, X3: Capillary water capacity, X4: Total porosity, X5: Capillary porosity, X6: Non-capillary porosity, X7: pH, X8: Organic matter, X9: 366 Total nitrogen, X10:Hydrolyzed nitrogen, X11: Total phosphorus, X12: Available phosphorus, X13: Total potassium, X14: Available potassium, X15: Elevation, X16: Slope, X17: Aspect, X18: Vegetation coverage, X19: Rock exposure rate, X20: Soil temperature.