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Spatial variability of soil pH and land use as the main influential factor in redbeds of the Nanxiong Basin, China

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Soil pH is the main factor affecting soil nutrient availability and chemical substances in soil. It is of great significance to study the spatial variability of soil pH for soil nutrient management and soil pollution prediction. In order to explore the causes of spatial variability of soil pH in redbed areas, the Nanxiong Basin in south China was selected as an example, and soil pH was measured in the topsoil by nested sampling (0–20 cm depth). The spatial variability characteristics of the soil pH were analysed by geostatistics and classical statistical methods, and the main factors influencing the spatial variability of soil pH are discussed. The results showed that the coefficient of variation in the redbed areas of Nanxiong Basin was 17.18%, indicating moderate variability. The geostatistics analysis showed that the spherical model is the optimal theoretical model for explaining the soil pH's variability, which is influenced by both structural and random factors. The spatial distribution and pattern analysis showed that soil pH content in the northeast and southwest is relatively high, and is lower in the northwest. These results indicate that topographic factors and land use patterns are the main factors.

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ABSTRACT

Soil pH is the main factor affecting soil nutrient availability and chemical substances in soil. It is of great significance to study the spatial variability of soil pH for soil nutrient management and soil pollution prediction. In order to explore the causes of spatial variability of soil pH in redbed areas, the Nanxiong Basin in south China was selected as an example, and soil pH was measured in the topsoil by nested sampling (0–20 cm depth). The spatial variability characteristics of the soil pH were analysed by geostatistics and classical statistical methods, and the main factors influencing the spatial variability of soil pH are discussed. The results showed that the coefficient of variation in the redbed areas of Nanxiong Basin was 17.18%, indicating moderate variability. The geostatistics analysis showed that the spherical model is the optimal theoretical model for explaining the soil pH's variability, which is influenced by both structural and random factors. The spatial distribution and pattern analysis showed that soil pH content in the northeast and southwest is relatively high, and is lower in the northwest. These results indicate that topographic factors and land use patterns are the main factors.

Subjects Agricultural science, Soil science

Keywords Redbed areas, Soil pH, Spatial variability, Semivariogram, Influencing factors

INTRODUCTION

Soil pH is an indicator of the acidity or alkalinity of soil, which is a reflection of important physical and chemical properties determining soil quality (*Nagy & Kónya, 2007*). Soil pH also has a profound impact on a number of other properties of soil. Extremes in acidity or alkalinity will change the nutrients available and result in element imbalances in plants (*Zhao et al., 2011*).

Spatial heterogeneity refers to the inhomogeneity and complexity of the distribution in space of properties of a system. The spatial heterogeneity of soil parameters such as pH and content of organic matter and of nitrogen, phosphorus and potassium, has an important influence on the distribution and spatial pattern of plants (*Stoyan et al., 2000*; *Augustine & Frank, 2001*; *Li et al., 2008*; *Silvia et al., 2016*). The study of spatial heterogeneity and of the driving factors behind soil properties is significant for revealing ecosystem function and biodiversity (*Augustine & Frank, 2001*).

With the continuous development of geographic information technology, studying the spatial variability of soil properties by a combination of geostatistics and GIS technology has become one of the hot topics in the different fields in which soil is investigated (*Romano, 1993*; *Foroughifar et al., 2013*). Scholars worldwide began to apply geostatistics to the spatial variability of soil properties starting at the end of the

1970s (*Trangmar, Yost, & Uehara, 1986*).

Geostatistics is a widely used method for studying the spatial distribution of regionalized variables (*Liu, Shao, & Wang, 2012*; *Emadi et al., 2016*; *Mohamed et al., 2018*). Many scholars have studied the spatial distribution characteristics of various soil properties by this method (*Zhang & Li, 2002*; *Zhang & Li, 2010*; *Liu, Shao, & Wang, 2011*; *Turgut & Öztaş, 2012*; *Liu, Shao, & Wang, 2013*). However, most of these studies were limited to a single terrain (*Huang et al., 2012; Zhao et al., 2017*), vegetation type (*Riha et al., 1986*; *Zaremehrjardi et al., 2010*), land use (*Mao et al., 2014*; *Miheretu & Yimer, 2017*) or other environmental factors which are rarely analysed in combination.

Previous research revealed that spatial variation in soil pH controls off-season N_2O emission in agricultural soils (*Russenes, Korsaeth, Bakken, & Dörsch, 2016*), that soil parameters are highly variable in space and time (*Bogunovic et al., 2017*; *Griffiths et al., 2017*), and that distributions of soil nutrients and related environmental factors depend on scale. Many studies have shown that soil pH has a negative correlation with many variables, such as organic carbon, total nitrogen, total phosphorus, precipitation, temperature and clay content (*Liu, Shao, & Wang, 2013*). Especially soil pH is a regionalized variable, whose spatial distribution has structural and stochastic characteristics, with implications for crop production (*Liu, Shao, & Wang, 2013*). Reijonen et al. proved that soil pH dictates the accessibility of vanadium V(+V) and V(+IV) by investigating the chemical bioavailability of vanadium species (*Reijonen, Metzler, & Hartikainen，2016*). Therefore, it is important to study the spatial variability of and the factors influencing the regional soil pH, which is important for the regulation of soil acidity and alkalinity, the control of environmental pollution, the sustainable utilization of soil nutrients and the rational management of soil nutrients and structure of the regional ecological environment.

In China, the soil that forms on redbeds is known as 'purple soil'. According to the results of the 34-province-wide soil census, the total area of purple soil is 2.17×10^5 km^2 (*Shinji, 2015*). Many studies have shown that the purple soil formed on redbed parent material is the most seriously eroded of all soil types in the Yangtze River Basin. This is especially visible in humid regions, where severe erosion can threaten the eco-security (*Yan et al., 2017*). The change in soil structure and the removal of topsoil resulting from the erosion may cause nutrient removal and environmental degradation, thereby inhibiting plant growth (*Sheoran, Sheoran, & Poonia, 2010*). Past studies have demonstrated that the extent of soil erosion by water varies with pH (*Luo et al., 2016*; *Kusuma et al., 2012*). The change in soil nutrient availability affects not only crop production and vegetation growth, but also the structure of the ecological environment (*Jin & Jiang, 2002*; *Zhang et al., 2010*). So far, few studies have been made of the factors affecting the spatial variability of soil pH in redbed areas. Therefore, studying the spatial distribution characteristics of soil pH plays an important role in the sustainable utilization and rational management of soil nutrients and the improvement of soil productivity.

The study was carried out in a redbed area in China with the following objectives: (i) to assess the status of soil pH; (ii) to study the spatial variability of soil pH; (iii) to reveal the spatial distribution characteristics of soil pH and the factors influencing it.

MATERIALS AND METHODS

Study area

Nanxiong Basin (24°35′–25°24′ N, 113°50′–114°44′ E) is a narrow basin located in the northeast of

Guangdong Province, China (Fig. 1). A subtropical monsoon climate prevails, with long hot summers and short winters. The average temperature is 19.6 ℃ and the annual precipitation and evaporation are 1555.1 mm and 1678.7 mm, respectively (*Yan et al., 2017*). The total area of Nanxiong Basin is 3692 km^2. Nanxiong Basin is a redbed basin with a severe soil erosion problem due to its dominant purple soil texture (Calcaric Regosols in the FAO taxonomy); the redbeds occupy an area of 1500 km^2 and are mainly distributed in the central part of the basin. Land use mainly includes farmland, woodland and grassland. The main vegetation communities are mixed with Masson Pine and broadleaf trees, secondary forest with mixed deciduous and broadleaf trees, and mainly artificial *Eucalyptus* and pine forests (Fig. 2).

Research method

Soil sample collection

Samples were collected in November 2017 after the crops were fully harvested. ~~Altogether~~ 225 samples were gathered from 0–20 cm depth by the nested sampling method at sampling densities dependent on soil type. The distribution of sample points is shown in Fig. 1. Soil pH was measured in a 1:2.5 soil: water suspension using a PP-50-P11 pH meter (*Liu, Shao, & Wang, 2013*).

Data analysis

Some basic statistics were calculated, such as the minimum, maximum and mean values of measurements and their coefficient of variation (CV). The Kolmogorov–Smirnov (K-S) test and correlation analysis of the soil pH were performed to analyse the data distribution using the statistics software SPSS 19 (SPSS Inc., USA). GS+7 (Gamma Design Software, Plainwell, MI, USA) software was used to do the geostatistical analysis. The K-S method was used to evaluate data normality and asymmetry in terms of skewness and kurtosis because these factors have important implications on the performance of the interpolation methods.

A semivariogram is the basic tool of geostatistics (*Oliver & Webster, 1986*; *Goovaerts, 1999*; *Nasseh et al., 2016*). The formula used to calculate the semivariogram is:

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

In the formula, $N(h)$ is the logarithm of the distance when the distance equals h, and $Z(x_i)$ is the value at location x_i; $Z(x_i + h)$ is the value at distance h from x_i (*Yang et al., 2016*; *Rosemary et al., 2017*). Appropriate model functions were fitted to the semivariograms. The semivariograms were used to determine the degree of spatial variability on the basis of the classes of spatial dependence distinguished by Cambardella (1994): strong spatial dependence ($C_0/(C_0 + C) > 75\%$), moderate spatial dependence ($25\% < C_0/(C_0 + C) < 75\%$) and weak spatial dependence ($C_0/(C_0 + C) < 25\%$). In ArcGIS 9.2, we used kriging interpolation in the geostatistics module to draw the soil pH spatial distribution map and trend analysis chart in order to analyse the spatial variability characteristics. According to the soil type map, slope, aspect, elevation, and land use type distribution map, the degree of influence and main control factors of the soil's spatial variation of pH were analysed.

RESULTS

Descriptive statistics of soil pH

Descriptive statistics of the soil pH are presented in Table 1. The soil pH of the study area ranged between 7.50 and 8.50, with an average value of 8.04, and a median of 8.05. The mean soil pH for the redbed region is higher than the estimated mean soil pH for the whole of China (6.8) and lower than the mean soil pH for the Loess Plateau region (8.49), ~~which was calculated from 225 soil samples~~. The pH could be mainly attributed to the ~~region's~~ humid climate and to the relatively high contents of calcium carbonate in the soft rock underlying the redbeds. The criteria proposed by Wilding (1985) were used to classify the parameters into most (CV > 35%), moderate (CV 15–35%) and least (CV < 15%) variable classes. The standard deviation of the soil pH was 0.66 and the CV value for the pH in this area was 17.18%. Accordingly, the pH in this area could be classified as moderately variable. In general, pH is considered to be a stable soil parameter. Similar CV values were reported by *Fu et al.* (2010), *Liu et al.* (2013) and *Tsui et al.* (2004); in all these studies, variability was moderate. According to the observed trend in the accumulation frequency of the soil pH (Fig. 3), the pH value in the study area was mainly in the range of 7.95–8.20. Based on the K-S test, the pH values of the sample points showed a normal distribution, and thus meet the requirements of geostatistics analysis (Table 1).

Spatial variability of soil pH

Isotropic semivariogram of soil pH

GS+7.0 software was used to fit the soil pH in the study area to the theoretical model (Table 2). The variogram's fitting model was selected based on the nugget effect, the coefficient of determination (R^2) and the range of variation (*Bogunovic, Trevisani, Seput, Juzbasic, Durdevic, 2017*). As can be seen from Table 2, the value for nugget (C_0) is 0.12, the value for sill ($C_0 + C$) is 0.18, the ratio of nugget (C_0) and sill ($C_0 + C$) is 66.67%, and the determining coefficient (R^2) is 0.812. High coefficients of determination indicated that the models fitted the semivariogram well (*Jeloudar et al., 2014*). The nugget–sill ratio of 66.67% indicated that the soil pH had a moderate spatial dependence (*Cambardella, 1994*). The variation of the soil pH in the study area was modelled best with the spherical model. The main structural factors consisted of the climate, parent material and terrain; these can enhance the spatial dependency of soil pH. In contrast, the random factors, which are the result of human activity such as farming and fertilization, can make the spatial dependency of soil pH weaker (*Isaaks & Srivastava, 1989*). This moderate spatial dependence of soil pH in the redbeds implies that the spatial variation of soil pH in the study area is mainly caused by both structural and random factors.

According to Figure 4, when the separation distance is more than 161 m, the semivariance fluctuates only slightly, and then stabilizes. This trend might be caused by differences in directional variation. The variance at 250 m implies that the range of the spatial dependence is much wider than the sampling interval. Therefore, the current sampling design was appropriate for this study.

In order to understand the characteristics of spatial variation in soil pH, the semivariogram was drawn in four directions, E–W (0°), NE–SW (45°), S–N (90°) and SE–NW (135°), using the GS+7.0 software. As shown in Figure 5, the spatial variation exhibits large differences in different directions, showing the heterogeneity. Table 3 shows that the best-fitting models in the four directions are all spherical. The nugget (C_0) and sill ($C_0 + C$) values are different and their ratio ranges from 25% to 75%, indicating moderate variation.

As shown in Figure 5, The range of the soil pH values from the northeast to the southwest (45°) and from the southeast to the northwest (135°) is significantly smaller than from east to west (0°) and from north to south (90°), indicating that the variation in the 0° and 90° directions is more complex than those at 45° and 135°.

From east to west (0°), when the separation distance is greater than 161 m, the difference in the semivariance of the soil pH begins to fluctuate, first increasing and afterward decreasing to around 0.0388. The semivariance from north to south (90°) shows the same trend, alternating between high and low, but the degree of fluctuation in the east–west (0°) direction is smaller. When the separation distance is larger than 169 m, the variation of the soil pH in the NE–SW (45°) and SE–NW (135°) directions is more stable near 0.0388, and the degree of variation is not very different. The main reason is that the area is near the badlands hills in the NE–SW and the SE–NW directions; the topography and parent materials are of great influence, and in the SE–NW direction there are more hills and larger undulations. However, in the N–S and E–W directions (0° and 90°, respectively), the soil pH shows high spatial homogeneity because the relief is low and the only land use is farmland in these directions. Taken together, the soil pH in this study area has an obvious spatial heterogeneity, which is suitable for further interpolation analysis.

Analysis of the spatial distribution of soil pH

The effect of trends is a prerequisite for and the basis of prediction by kriging interpolation. The lower the order of the trend effect is, the smaller the number of parameters will be that are required for kriging interpolation. Thus, a lower order of the trend effect can reduce error, and many scholars take the lower-order trend among two trends as the trend to be used in conducting prediction by interpolation (*Li et al., 2013*). Trend analysis can provide a study area sampling point and a three-dimensional perspective with information for the attribute value on the *z*-axis. The global trend in sampling data can be is analysed from different perspectives.

As shown in Figure 6, soil pH decreases from northeast to southwest, which is consistent with the result of semivariogram analysis. The soil pH values are higher in the northeast and southwest; this pattern can be explained by the different land use. In the northeastern and southwestern parts, the land is unused land with a high relief. Arable land is mainly distributed in the northwest, where the relief is low and the land is strongly affected by human activities such as the use of nitrogen fertilizer, which might cause a reduction of the pH value in soil (*Yüksek et al., 2009*).

Spatial distribution pattern of soil pH

Based on the semivariance function model and the spatial distribution trend analyses, the spatial distribution pattern of soil pH in the study area was analysed by interpolation analysis of the 3D map constructed with the GS+7.0 software (*Nasseh et al., 2016*). Kriging analysis of the 3D map shows that the soil pH varies greatly in the horizontal direction in the study area (Fig. 7); the soil pH is higher in the northeast and the southwest, increases towards the southwest, and decreases towards the northwest. The result of inverse distance weighting interpolation of the 3D map shows that the overall trend for the pH in the study area is consistent with the results from kriging interpolation (Fig. 8).

Analysis of influential factors

Although the spatial variation of soil pH in the study area is determined by structural factors such as topographic factors, and the random factors of human fertilization, it is still not known what extent each factor affects the spatial variation of soil pH. Therefore, two factors (topographic factors and land use) will be further discussed here to demonstrate their influence.

Topographic factors

(1) Influence of slope and position along the slope on the spatial distribution of soil pH

Severe soil erosion can cause a decrease in the pH value (*Schindelbeck et al., 2008*). Due to the humid monsoon climate and the high erodibility of purple soil caused by its high content of sandy particles, the pH value is generally lower than in the weathering sediments of redbeds, which have a pH value higher than 8. Table 4 shows that the pH value of the 0–20 cm soil layer tends to decrease from downslope to middle slope to upper slope; this decrease is especially significant at slopes of 20° and 25° ($P < 0.05$). This is mainly caused by the transportation of weathering products from the upper slope to the downslope, and as a result the downslope position becomes a sink of soil eroded higher up.

In general, soil pH varied significantly between different slopes and positions along the slope (*Henkel, 2003*). Therefore, the pH of surface soil (0–20 cm) varies with the slope and position along the slope, reflecting the geomorphic process.

(2) Influence of aspect on the spatial distribution of soil pH

Different slope aspects experience different solar radiation, temperature and water conditions. The vegetation coverage is also different. Therefore, there are differences in physical, chemical and biological processes in the topsoil correlated with different aspect directions, which lead to a heterogeneity of pH content and distribution in the topsoil (*Vieira et al., 2009*; *Salehi, Esfandiarpour & Sarshogh, 2011*). By combining the aspect distribution map of the study area and the geostatistical analysis module in the ArcGIS software, the spatial distribution map of the soil pH was analysed synthetically (*Figures 9 and 10*). The result shows that the average pH value varies with aspect of the slope in the study area. The soil pH values on north- and southwest-facing slopes are relatively higher than on slopes of other aspects.

Land use pattern

Different systems of land use result in different levels of human land-use activities and have different effects on soil properties. The results showed that land use had a significant effect on surface soil pH ($P < 0.05$). As shown in Figure 11, among the four categories of land use patterns (farmland, woodland, grassland and bare land), the average soil pH differed significantly between different land uses ($P < 0.05$). Among them, there is not much difference between woodland and grassland, though. The soil pH between different land use patterns varied from 8.09 for farmland to 7.98 for bare land, 7.97 for grassland and 7.96 for woodland. A comparison of the pH values in farmland and woodland topsoils shows that the pH value of farmland is lowest. An explanation for this might be that the tree species on woodland is pine (*Pinus massoniana* Lamb), which has an acidifying effect on soil.

The pH of bare land had the lowest CV with 14.21%, and the pH of grassland and woodland was lower than that of farmland. However, previous research established that the pH of forest and cultivated land had the lowest CV, which could be the result of the uniform conditions in the region such as small changes in slope and its direction that led to a uniformity of soil in this region (*Cambardella, 1994; Kavianpoor et al., 2012*; *Jeloudar et al., 2014*). The possible reasons require further investigation.

On the whole, the spatial distribution of soil pH is closely related to land use (*Mao et al., 2014*). This might be caused by the application of urea fertilizer, which has been proven to increase the soil pH (*Petrie & Jackson, 1984*).

DISCUSSION

Human activities and the natural environment always interact with each other. Natural factors such as climate, topography and soil properties will greatly affect the way and method of land use by human beings (*Morales et al., 2009*; *Wang, Zhang & Huang, 2009*; *Zucco et al., 2014*). The human choice for different land uses will also act on natural factors in turn, such as vegetation types, soil physical, chemical and biological properties.

A large number of studies have shown that the spatial variability of soil pH is related to many factors (*Riha, Senesac & Pallant, 1986*; *Kuzel et al., 1994*; *Russenes, Korsaeth et al., 2016*). The results of this study are that the CV is 17.18%, which can be classified as moderate variation, and is the result of both structural factors (parent material, topography, climate) and random factors (soil biology, human disturbance, sampling design and measurement error).

The study area is located in the humid redbed area in south China. It is representative for the concentrated distribution of soft rock in redbeds. The best fitting models were all spherical, with a high degree of fit for the spatial variability of soil pH and verified in relevant studies (*Liu, Shao, & Wang, 2013*; *Wang et al., 2011*), indicating that the soil pH had good spatial structure in the study area.

The effects of topographic factors on soil pH were discussed in this study. The pH of soil is highest on the downslope, followed by the middle slope, and is lowest on the upper slope. Similar results were reported by Tsui (2004), who confirmed that slope, which is involved in the transport and accumulation of solutes, resulted in higher pH. It can be seen that to some extent factors affecting soil erosion have an influence on the change in soil pH.

In addition, as we know, the topography is a structure factor influencing the spatial variability of soil pH. In the E–W and N–S directions (0° and 90°, respectively), the soil pH shows high spatial homogeneity because the relief is low and the only land use is farmland. In this study, one rarely acknowledged but important result is that the topography influences the soil pH mainly through the slope and indirectly via the effect of topography on land use patterns.

Kerry and Oliver (2004) indicated that as a rough guide, in future sampling intervals should be chosen to be less than half the variogram range. According to the results of this study, future sampling intervals for monitoring pH should be 80–100 m.

Numerous studies have shown a decreasing soil pH with increasing number of cropping years (*Meng , Li & Liu, 2000*; *Zhao, Wu & Liu, 2000*). The average soil pH in is highest farmland, followed by grassland and bare land, and the average pH in woodland is lowest. *Rosemary et al.* (2017), by studying the spatial variability of soil properties in an Alfisol soil catena, arrived at similar conclusions, namely that soil pH in paddies is high.

CONCLUSION

The investigated parameters follow a normal distribution. For pH, the best-fitting variogram model was a spherical one. A practical application of our research results may be that the inclusion of the models we established for application in directional semivariograms in interpolation analysis can improve the reliability of local assessments of the analysed soil pH, thus reducing the cost of the production cycle. In order to reduce production costs, a sampling interval of 80–100 m is recommended for soil pH. The spatial distribution maps based on the kriging interpolation method were successfully applied in soil pH studies.

This study shows that soil pH in the study area has moderate spatial autocorrelation, which means that the soil pH is affected by both structural and random factors. This study focused on the spatial variability of soil pH as a result of the interaction of topographic factors, soil and land use patterns. In general, studying the spatial variability of soil pH can provide a theoretical basis for the restoration and improvement of soil quality, including the rapid restoration of soil in the redbed ecosystem and ecological reconstruction in the moist environment of south China.

ADDITIONAL INFORMATION AND DECLARATIONS

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Competing Interests

The authors declare there are no competing interests.

Author Contributions

- Ping Yan conceived and designed the experiments, performed the experiments, analysed the data, prepared figures and/or tables, authored or reviewed drafts of the paper and approved the final draft.
- Hua Peng conceived and designed the experiments, contributed reagents/materials/analysis tools, authored or reviewed drafts of the paper and approved the final draft.
- Luobin Yan conceived and designed the experiments, performed the experiments, analysed the data, authored or reviewed drafts of the paper and approved the final draft.
- Shaoyun Zhang conceived and designed the experiments, prepared figures and/or tables, authored or reviewed drafts of the paper and approved the final draft.
- Aimin Chen conceived and designed the experiments, authored or reviewed drafts of the paper and approved the final draft.

Field Study Permissions

The following information was supplied relating to field study approvals (i.e., approving body and any reference numbers):
The field permit for biological sample collection was granted by the Institute of Ecological Environment Technology in Guangdong Province, China : Permit number 455858580.

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Figure 1

Figure 1 Location map of the study area.

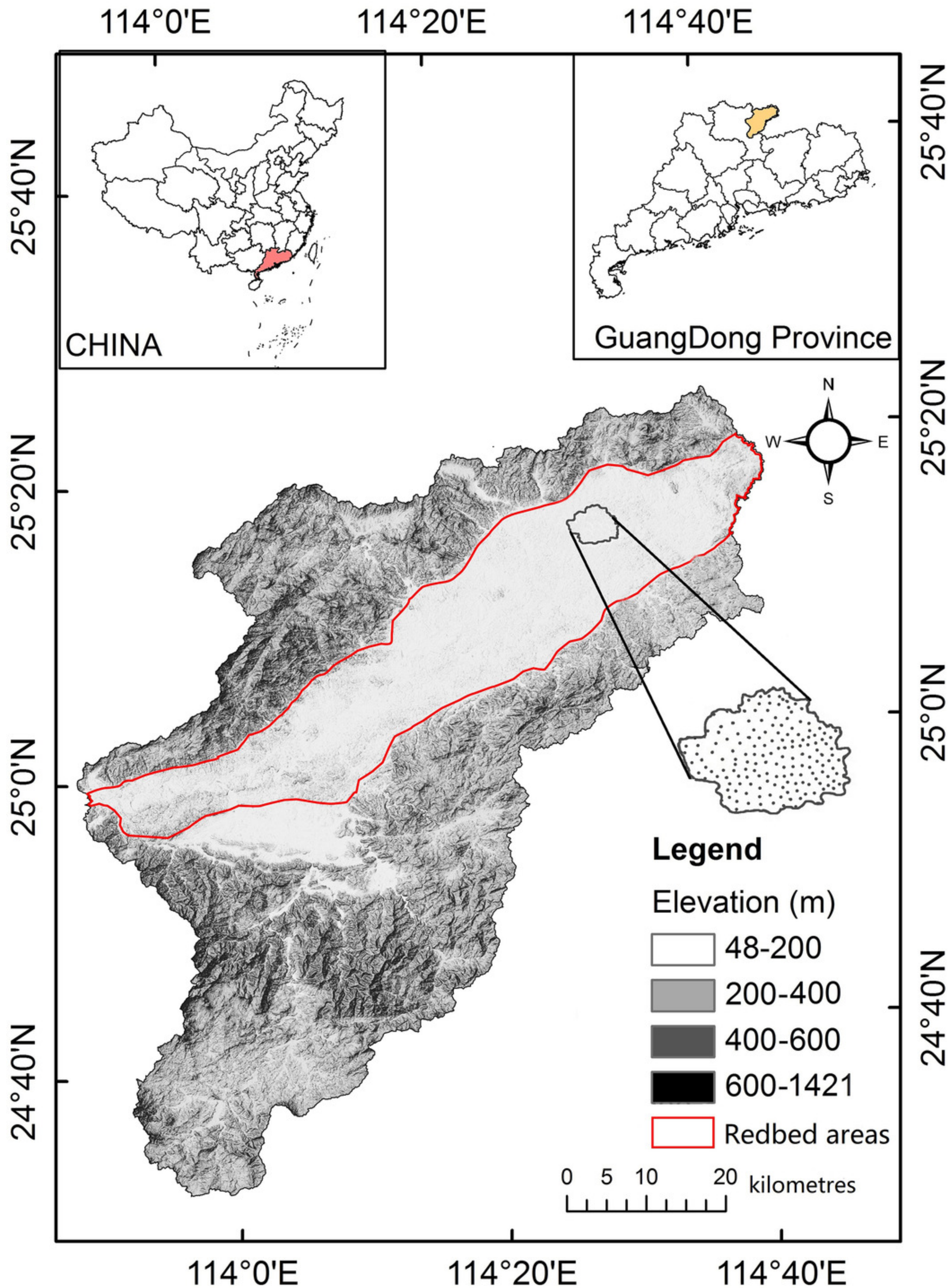
114°0'E
114°20'E
114°40'E
25°40'N
25°20'N
25°0'N
24°40'N
CHINA
GuangDong Province
N
W
E
S
Legend
Elevation (m)
48-200
200-400
400-600
600-1421
Redbed areas
0 5 10 20 kilometres

Figure 2

Figure 2 Location map of sampling point.

Figure 3

Figure 3 Trend of the cumulative frequency of soil pH.

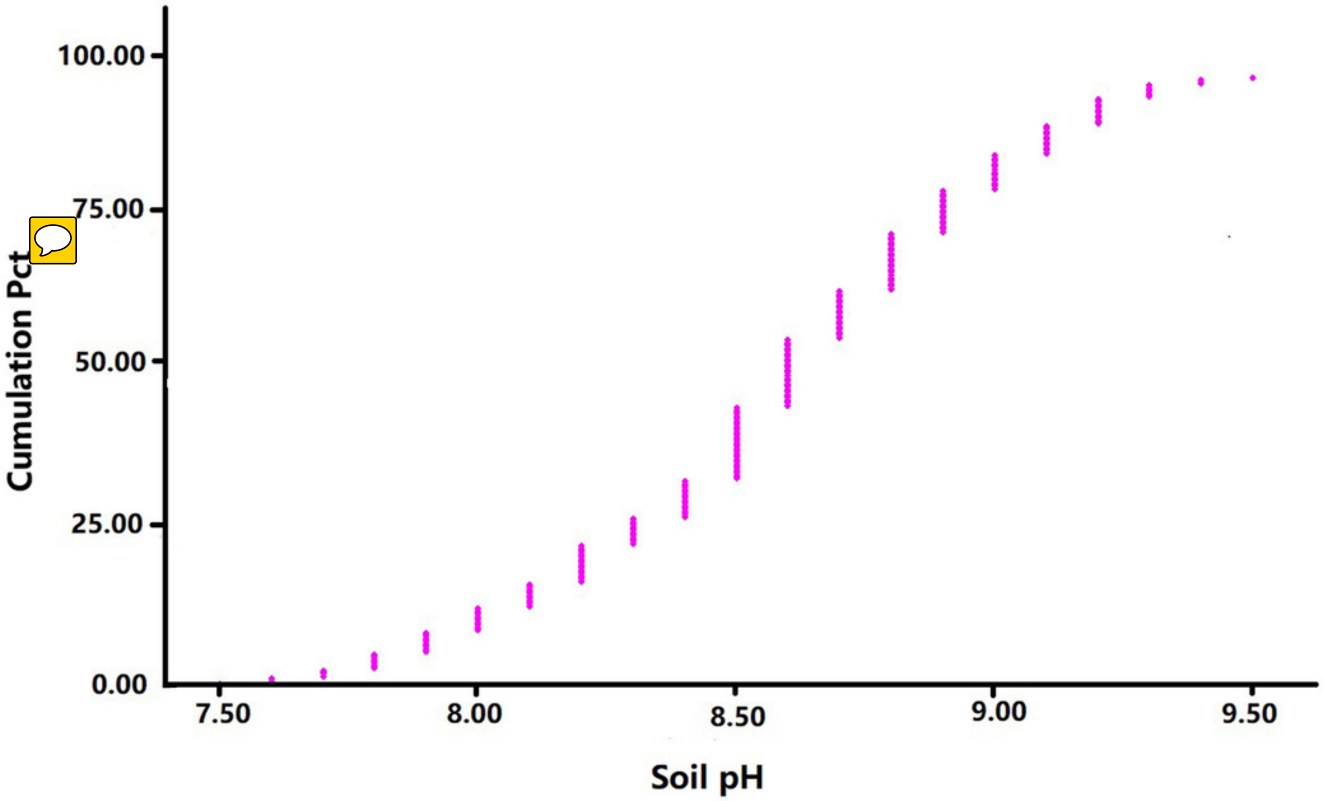

Figure 4

Figure 4 Isotropic semivariance of soil pH.

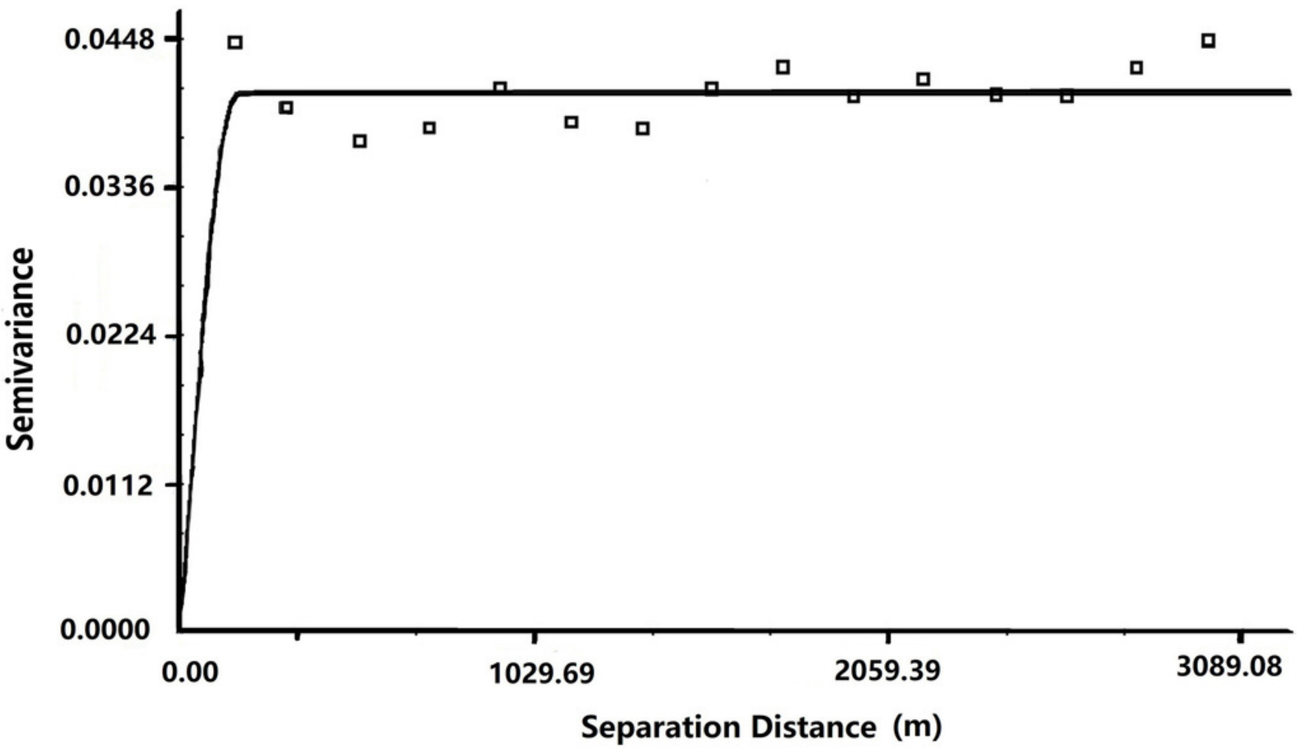

Figure 5

Figure 5 Anisotropic semivariance of soil pH.

The semivariogram of the spatial variation in soil pH was drawn in directions of E–W (0°) in Figure 5 (A); the semivariogram of the spatial variation in soil pH was drawn in directions of NE–SW (45°) in Figure 5 (B); the semivariogram of the spatial variation in soil pH was drawn in directions of S–N (90°) in Figure 5 (C); the semivariogram of the spatial variation in soil pH was drawn in directions of SE–NW (135°) in Figure 5 (D).

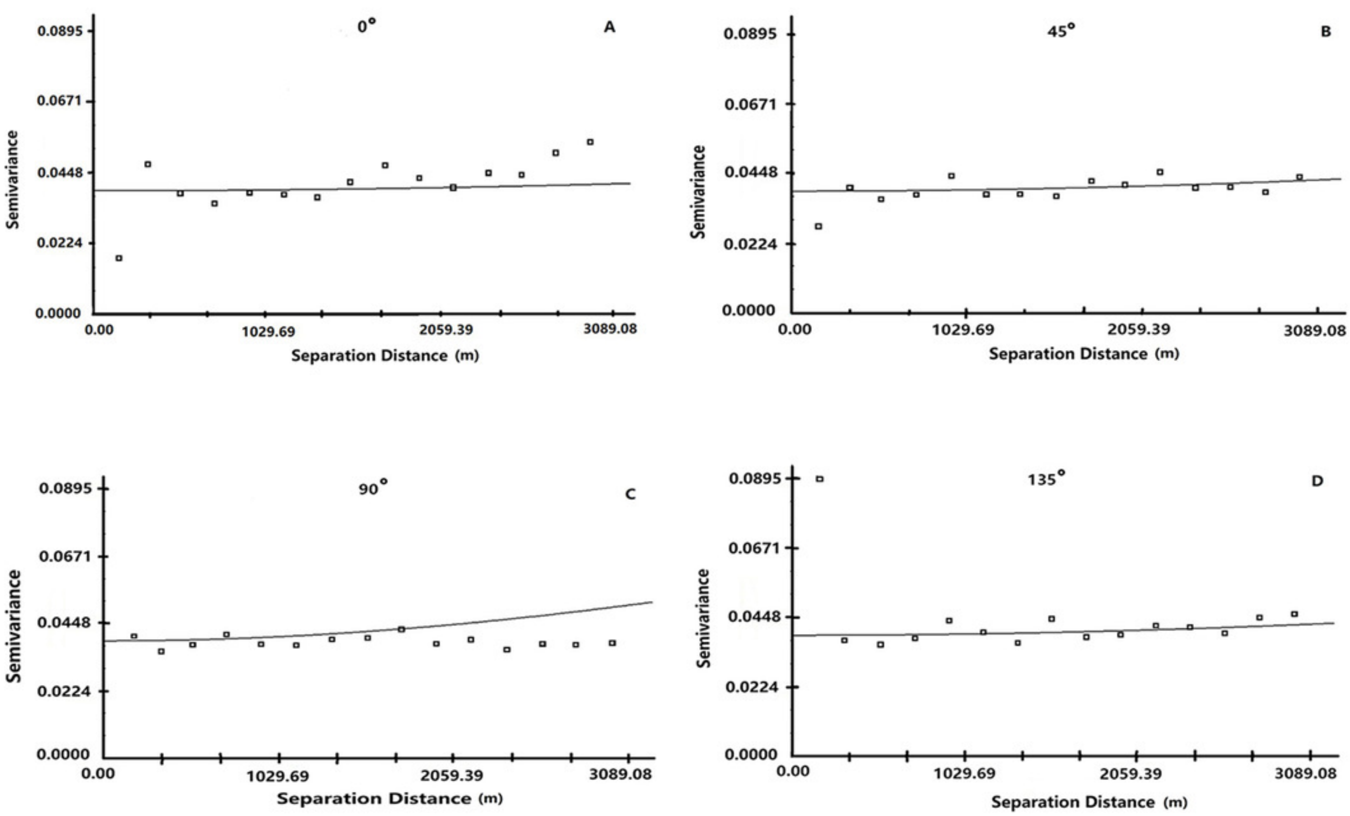

Figure 6

Figure 6. Analysis of soil pH trend. 6

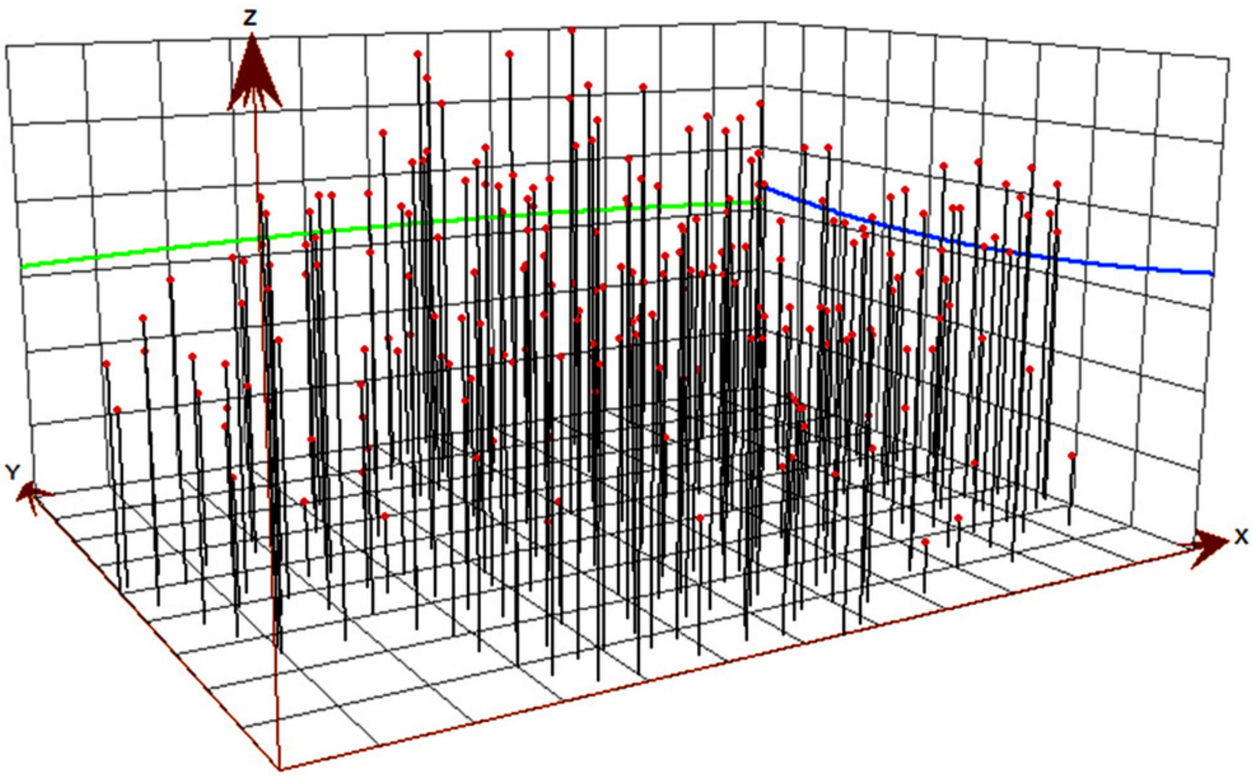

Figure 7

Figure 7 Kriging interpolation map of 3D Map of soil pH.

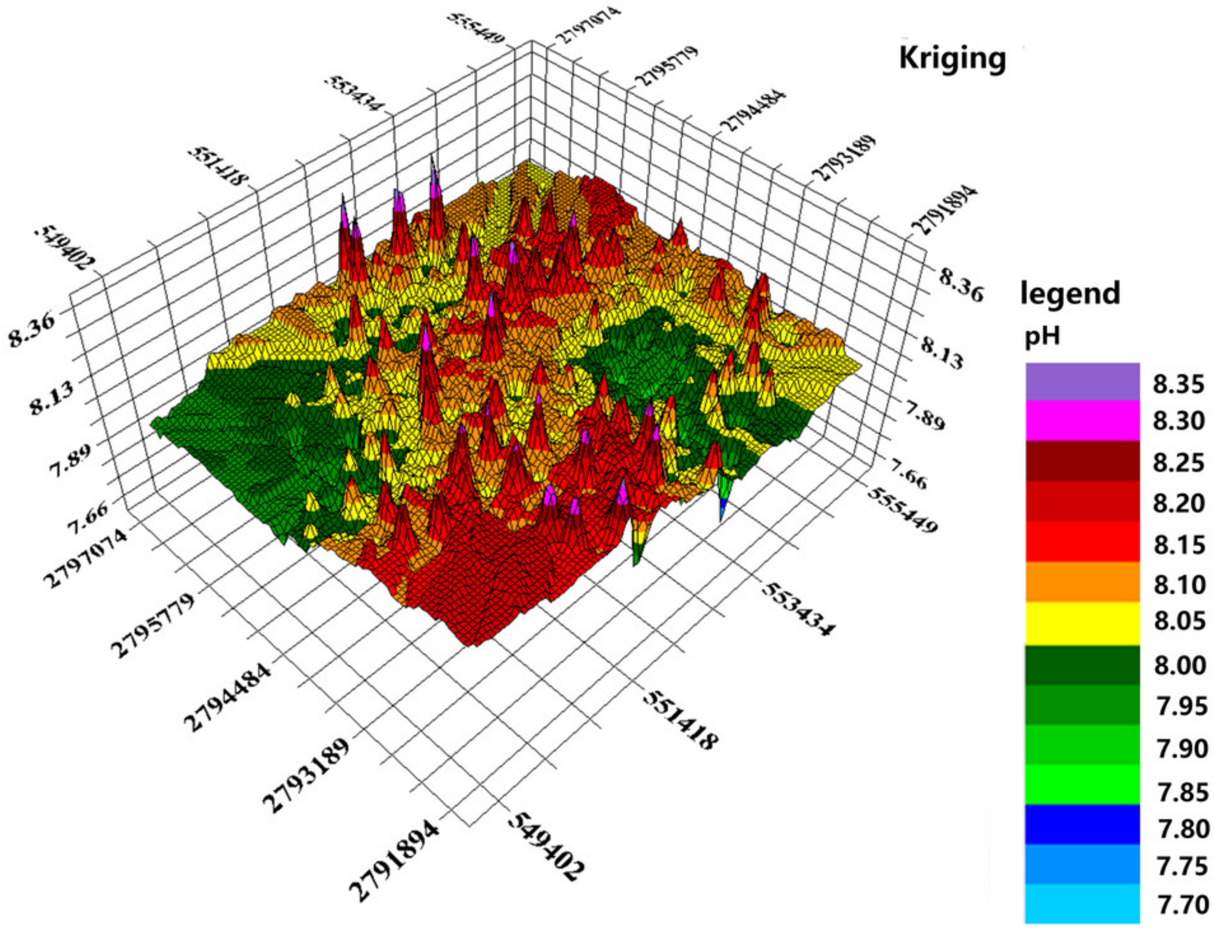

Figure 8

Figure 8 Inverse distance weighting interpolation map of 3D Map of soil pH.

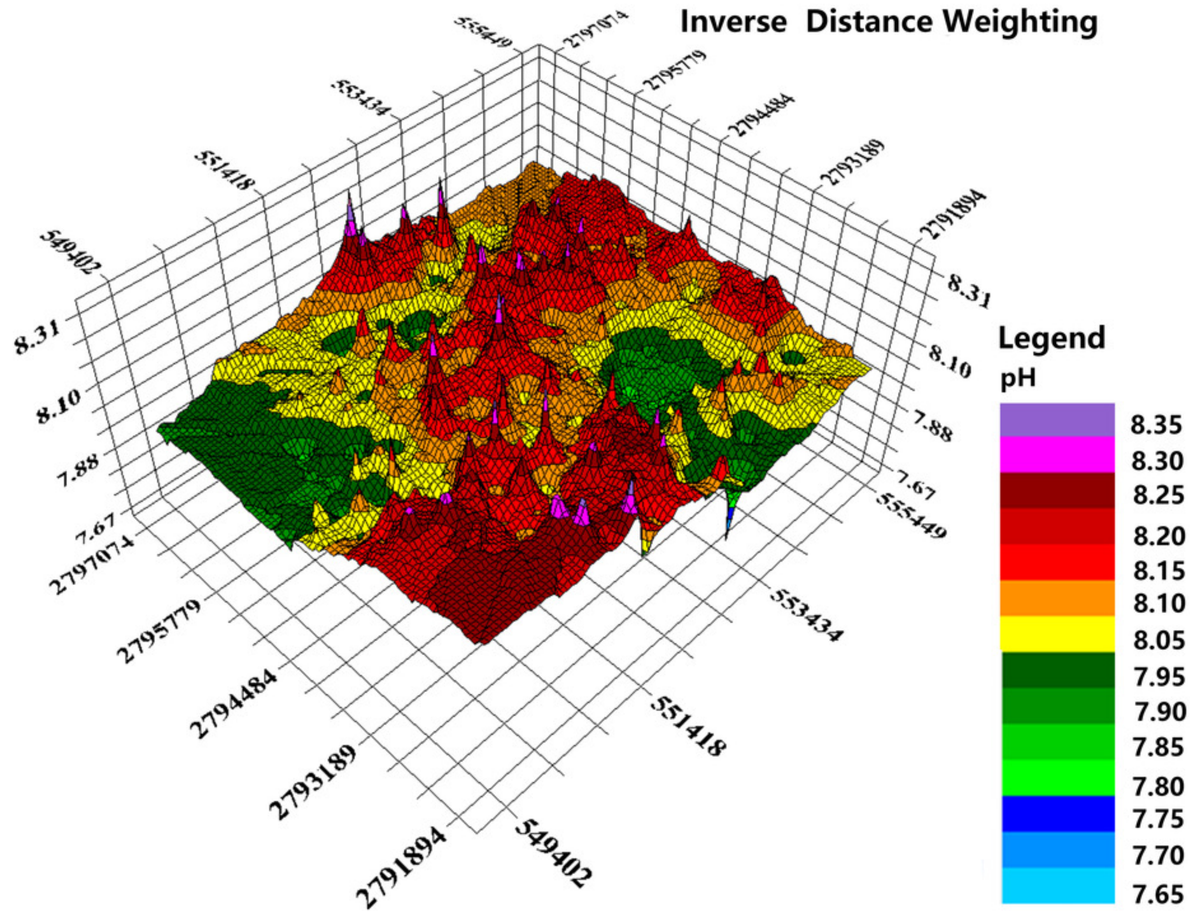

Figure 9

Figure 9. Slope distribution map of the study area.

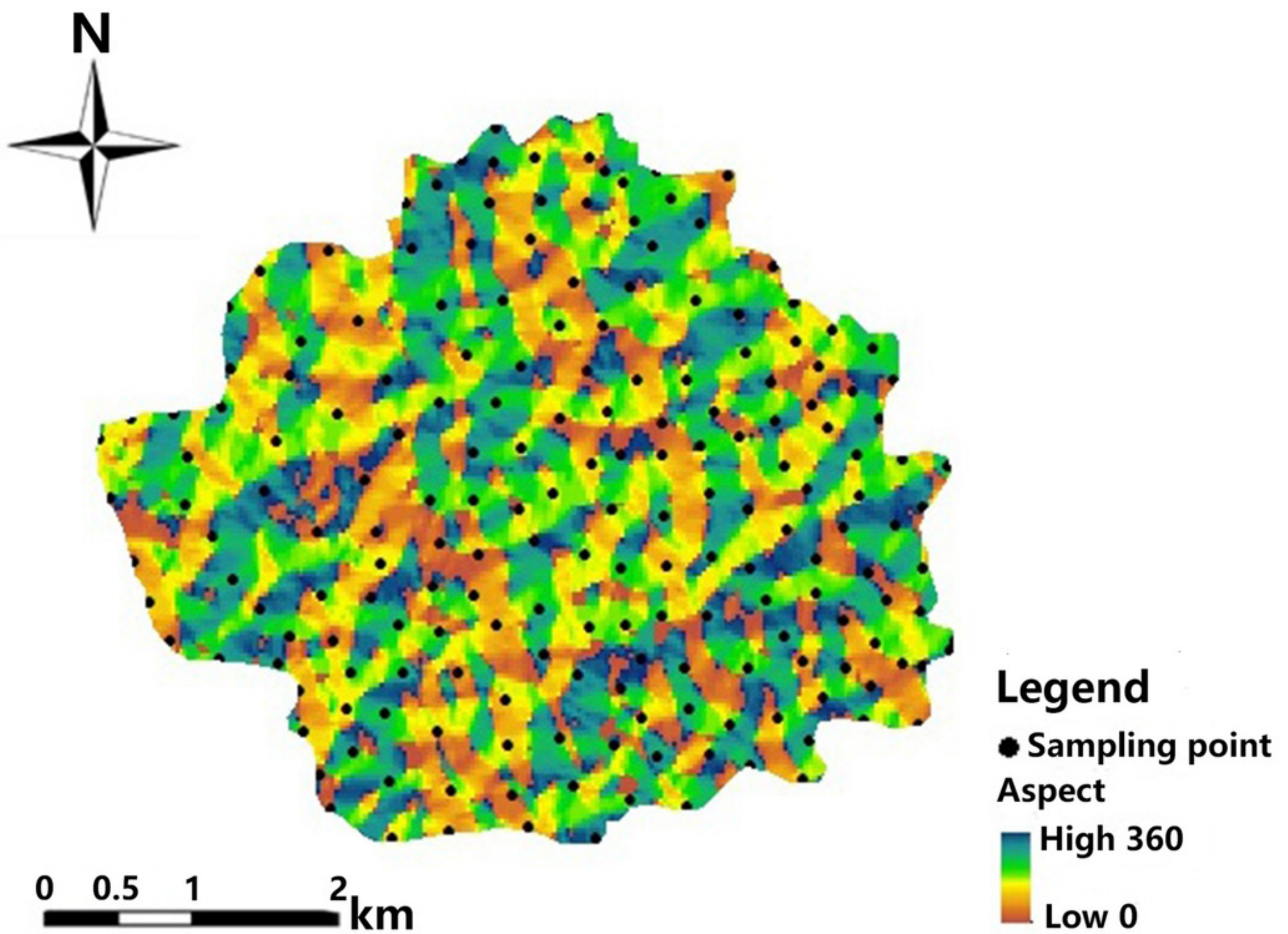

Figure 10

Figure 10. Spatial distribution map of soil pH.

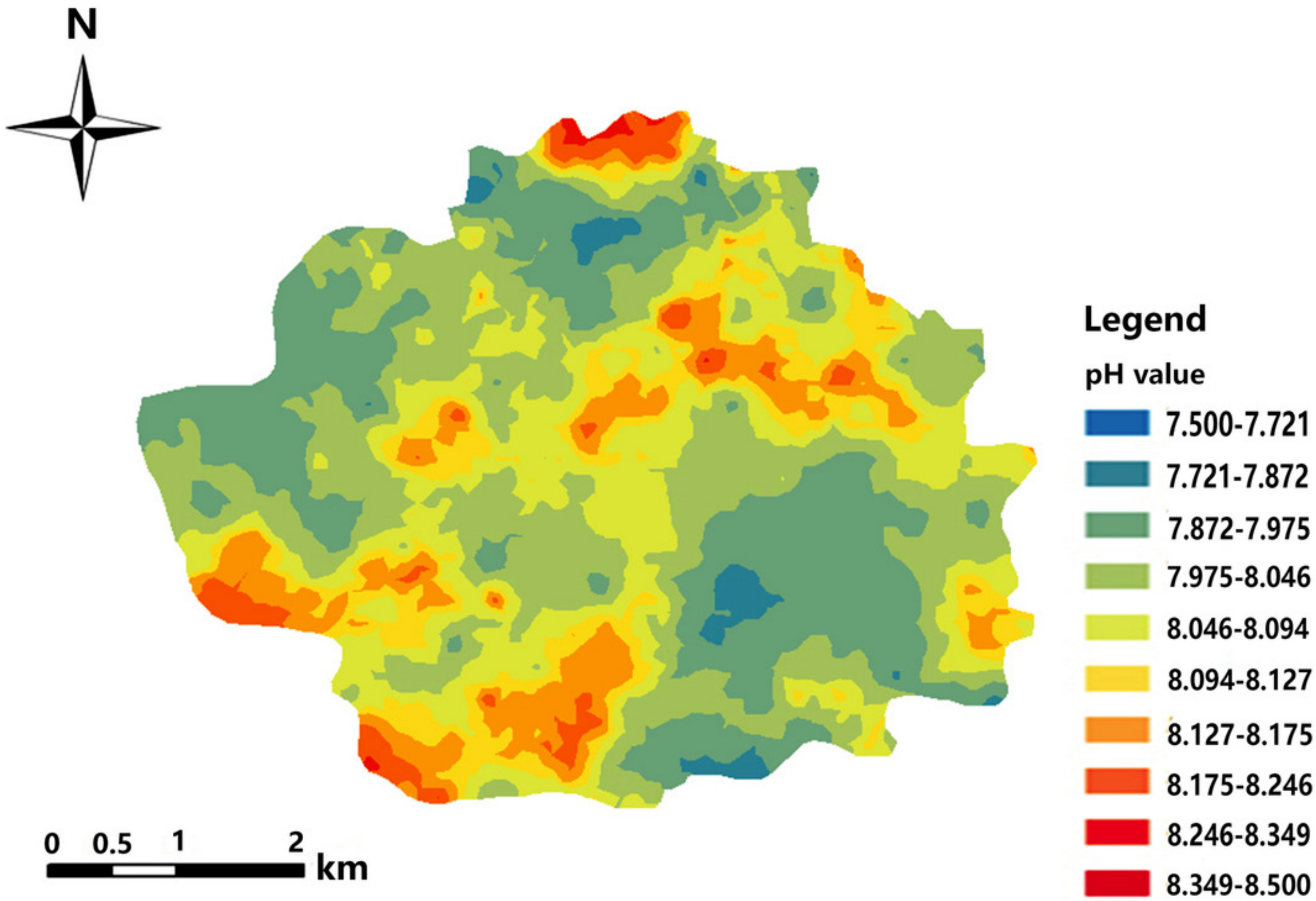

Figure 11

Figure 11 Different land use patterns of soil pH in the study area.

Mean soil pH in 0-20 cm soil layers under four land uses. Difference lowercase letters denote significant differences determined by Duncan's Multiple Range Test (*p* <0.05).

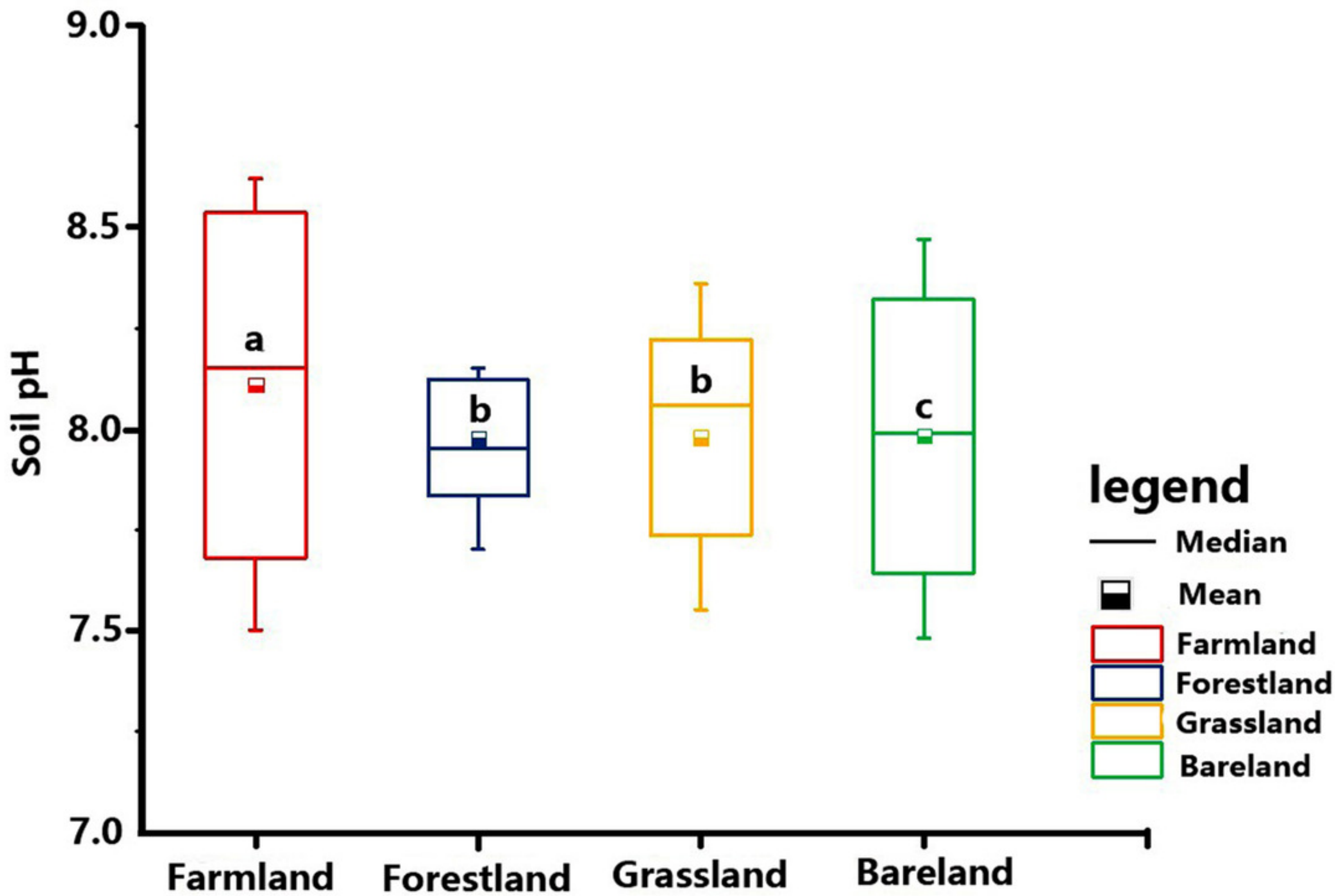

Table 1(on next page)

Table 1 Statistical characteristic values of soil pH.

Table 1 Statistical characteristic values of soil pH.

Soil properties	Sample size	Range	Median	Mean	Standard deviation	Skewness	Kurtosis	Coefficient of variation (%)	K-S test
pH	225	7.50-8.50	8.05	8.04	1.38	-0.25	-0.42	17.18	0.10

Table 2(on next page)

Table 2 Isotropic semivariogram theory model and related parameters of soil pH.

Table 2 **Isotropic semivariogram theory model and related parameters of soil pH.**

Soil property	Theoretical model	Nugget (C_0)	Sill (C_0+C)	Nugget/Sill (%)	Range (m)	Determining coefficient (R^2)
Soil pH	Spherical model	0.12	0.18	66.67	161	0.812

Table 3

(on next page)

Table 3 Anisotropic semivariogram theory model and related parameters of soil pH.

Table 3 Anisotropic semivariogram theory model and related parameters of soil pH.

Soil property	Direction	Theoretical model	Nugget (C_0)	Sill (C_0+C)	Nugget/Sill (%)	Range (m)	Determining coefficient (R^2)
Soil pH	0°	Spherical model	0.27	0.39	69.23	161	0.539
	45°	Spherical model	0.32	0.47	68.09	172	0.586
	90°	Spherical model	0.29	0.48	60.42	169	0.612
	135°	Spherical model	0.35	0.51	68.62	182	0.509

Table 4(on next page)

Table 4 The influence of slope and slope position on soil pH.

The difference between the letters in the same column is significant ($P < 0.05$), and the letters in brackets indicate significant difference ($P < 0.05$).

Table 4 The influence of slope and slope position on soil pH. The difference between the letters in the same column is significant ($P < 0.05$), and the letters in brackets indicate significant difference ($P < 0.05$).

Slope	0-20 cm Soil layer		
	Upper slope	Middle slope	Down slope
10°	8.41±0.11a(a)	8.39±0.02a(a)	8.01±0.09b(a)
15°	8.32±0.14a(a)	8.29±0.01a(a)	8.15±0.01b(a)
20°	8.09±0.09b(b)	8.02±0.02b(b)	8.26±0.06ab(a)
25°	7.95±0.22b(b)	7.88±0.53b(b)	8.35±0.12a(a)

Table 5(on next page)

Table 5 Semivariogram models and model parameters for soil properties in four land uses.

Table 5 Semivariogram models and model parameters for soil properties in four land uses.

Land use patterns	Theoretical model	Coefficient of variation (%)	Nugget (C_0)	Sill (C_0+C)	Nugget/Sill (%)	Range (m)	Determining coefficient (R^2)
Farmland	Spherical model	17.25	0.22	0.37	59.15	195	0.62
Forestland	Spherical model	17.09	0.31	0.48	63.49	180	0.58
Grassland	Spherical model	16.95	0.21	0.34	62.12	175	0.56
Bareland	Spherical model	14.21	0.19	0.29	65.59	181	0.59