A peer-reviewed version of this preprint was published in PeerJ on 30 January 2019.

View the peer-reviewed version (peerj.com/articles/6342), which is the preferred citable publication unless you specifically need to cite this preprint.

Yan P, Peng H, Yan L, Zhang S, Chen A, Lin K. 2019. Spatial variability in soil pH and land use as the main influential factor in the red beds of the Nanxiong Basin, China. PeerJ 7:e6342 https://doi.org/10.7717/peerj.6342
Spatial variability of soil pH and land use as the main influential factor in redbeds of the Nanxiong Basin, China

Ping Yan 1, Hua Peng 1, Luobin Yan Corresponding Author, Shaoyun Zhang 1, Aimin Chen 1

1 School of Geography and Planning, Sun Yat-sen University, Guangzhou, Guangdong Province, China
2 School of Geographical Sciences, Southwest University, Chongqing, Chongqing Province, China

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

Ping Yan¹, Hua Peng¹, Luobin Yan², Shaoyun Zhang¹, Aimin Chen¹

¹ School of Geography and Planning, Sun Yat-sen University, Guangzhou, China
² School of Geographical Sciences, Southwest University, Chongqing, China

Corresponding Author:
Luobin Yan²
No. 2 Tiansheng Road, Beibei district, Chongqing, 400715, P.R. China
Email address: yanlb@mail2.sysu.edu.cn
Spatial variability of soil pH and land use as the main influential factor in redbeds of the Nanxiong Basin, China

Ping Yan¹, Hua Peng¹, Luobin Yan², Shaoyun Zhang¹, Aimin Chen¹

¹ School of Geography and Planning, Sun Yat-sen University, Guangzhou, China
² School of Geographical Sciences, Southwest University, Chongqing, China

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 factor, which are rarely analysed in combination.

Previous research revealed that spatial variation in soil pH controls off-season N₂O 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 × 10⁵ km² (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 °C 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 km². 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 km² 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:

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

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

Funding
This work was supported by the National Natural Science Foundation of China (41771088) and the Special Project for Key Basic Research of the Chinese Ministry of Science and Technology (2013FY111900). The funders played no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Grant Disclosures
The following grant information was disclosed by the authors:
National Natural Science Foundation of China: 41771088.
Special Project for Key Basic Research of the Chinese Ministry of Science and Technology: 2013FY111900.

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.
REFERENCES

Augustine DJ, Frank DA. 2001. Effects of migratory grazers on spatial heterogeneity of soil nitrogen properties in a grassland ecosystem. *Ecology* 82(11): 3149-3162 DOI 10.2307/2679841.

Bogunovic I, Trevisani S, Seput M, Juzbasic D, Durdevic B. 2017. Short-range and regional spatial variability of soil chemical properties in an agro-ecosystem in eastern croatia. *Catena* 154: 50-62 DOI 10.1016/j.catena.2017.02.018.

Cambardella CA. 1994. Field-scale variability of soil properties in central iowa soils. *Soil Science Society of America Journal* 58: 1501-1511.

Emadi M, Shahriari AR, Sadegh-Zadeh F, Seh-Bardan BJ, Dindarlo A. 2016. Geostatistics-based spatial distribution of soil moisture and temperature regime classes in mazandaran province, northern iran. *Archives of Agronomy & Soil Science* 62(4): 502-522 DOI 10.1080/03650340.2015.1065607.

Foroughifar H, Jafarzadeh AA, Torabi H, Pakpour A, Miransari M. 2013. Using geostatistics and geographic information system techniques to characterize spatial variability of soil properties, including micronutrients. *Communications in Soil Science & Plant Analysis* 44(8): 1273-1281 DOI 10.1080/00103624.2012.758279.

Fu WJ, Tunney H, Zhang CS. 2010. Spatial variation of soil nutrients in a dairy farm and its implications for site-specific fertilizer application. *Soil & Tillage Research* 106(2): 185-193 DOI 10.1016/j.still.2009.12.0.

Goovaerts P. 1999. Geostatistics in soil science: state-of-the-art and perspectives. *Geoderma* 89(1-2): 1-45 DOI 10.1016/S0016-7061(98)00078-0.

Griffiths NA, Hanson PJ, Ricciuto DM, Iversen CM, Jensen AM, Malhotra A, McFarlane KJ, NorbyRJ, Sargsyan K., Sebestyen SD, Shi XY, Walker AP, Eric JW, Warren JM, Weston DJ. 2017. Temporal and spatial variation in peatland carbon cycling and implications for interpreting responses of an ecosystem-scale warming experiment. *Soil Science Society of America Journal* 81(6): 1668-1688 DOI 10.2136/sssaj2016.12.0422.

Henkel TW. 2003. Monodominance in the ectomycorrhizal dicymbe corymbosa (caesalpiniaceae) from guyana. *Journal of Tropical Ecology* 19(4): 417-437 DOI 10.1017/S0266467403003468.

Huang Y, Chen L, Fu B, Huang Z, Gong J, Lu X. 2012. Effect of land use and topography on spatial variability of soil moisture in a gully catchment of the loess plateau, china. *Ecohydrology* 5(6): 826–833 DOI 10.1002/eco.273.

Isaaks EH, Srivastava RH. An introduction to applied geostatistics.1989

Jeloudar ZJ, Shabaanzadeh S, Kavian A, Shokri M. 2014. Spatial Variability of Soil Features Affected by Landuse Type using Geostatistics. *Ecopersia* 2: 667-679 http://journals-old.modares.ac.ir/article_12810.html.

Jin J, Jiang C. 2002. Spatial variability of soil nutrients and site-specific nutrient management in the p.r. china. *Computers & Electronics in Agriculture* 36(2-3): 165-172 DOI 10.1016/S0168-1699(02)00099-6.

Kavianpoor H, Ouri AE, Jeloudar ZJ, Kavian A. 2012. Spatial variability of some chemical and physical soil properties in nesho mountainous rangelands. *American Journal of Environmental Engineering* 2: 34-44 DOI 10.5923/j.ajee.20120201.06.
Kerry R, Oliver MA. 2004. Average variograms to guide soil sampling. *International Journal of Applied Earth Observation & Geoinformation* **5**: 307-325 DOI 10.1016/j.jag.2004.07.005.

Kusuma GJ, Shimada H, Sasaoka T, Matsui K, Nugraha C, Gautama RS, Rudy SG, Budi S. 2012. Physical and geochemical characteristics of coal mine overburden dump related to acid mine drainage generation. *Memoirs of the Faculty of Engineering Kyushu University* **72**: 23-38 http://kenkyou.eng.kyushu-u.ac.jp/memoirs-eng/bulletin/72/2/paper1(72-2).pdf.

Kuzel S, Nýdl V, Kolár L, Tichý R. 1994. Spatial variability of cadmium, pH, organic matter in soil and its dependence on sampling scales. *Water Air & Soil Pollution* **78**(1-2): 51-59. DOI 10.1007/BF00475667.

Li J, Okin GS, Alvarez L, Epstein H. 2008. Effects of wind erosion on the spatial heterogeneity of soil nutrients in two desert grassland communities. *Biogeochemistry* **88**(1): 73-88 DOI 10.1007/s10533-008-9195-6.

Li WH, Wang C, Yang M, Wang L. 2013. Trend effect and an isotropy of soil particle composition in the chengdu plain. *Journal of Agricultural Science* **5**(2): 56-63 DOI 10.5539/jas.v5n2p56.

Liu ZP, Shao MA, Wang, YQ. 2011. Effect of environmental factors on regional soil organic carbon stocks across the loess plateau region, china. *Agriculture Ecosystems & Environment* **142**(3): 184-194 DOI 10.1016/j.agee.2011.05.002.

Liu ZP, Shao MA, Wang, YQ. 2012. Large-scale spatial variability and distribution of soil organic carbon across the entire loess plateau, china. *Soil Research* **50**: 114-124 DOI 10.1071/SR11183.

Luo W, Shi S, Lu Y, Zou S, Chen Z, Chen L. 2016. Optimization Study of Outburst Prevention Measures for Tuzhu Coal Mine Based on Fixed Weight Clustering Analysis. *Journal of Environmental Protection* **7**(2): 160-169 DOI 10.4236/gep.2016.41016.

Mao Y, Sang S, Liu S, Jia J. 2014. Spatial distribution of ph and organic matter in urban soils and its implications on site-specific land uses in xuzhou, china. *Comptes Rendus Biologies* **337**(5): 332-337 DOI /10.1016/j.crvi.2014.02.008.

Meng HG, Li Z, Liu YJ. 2000. Characteristics of the physical and chemical properties in the protected vegetable soils. *Bulletin of Chinese Soil Science* **31**: 70-82.

Miheretu B A, Yimer AA. 2017. Spatial variability of selected soil properties in relation to land use and slope position in gelana sub-watershed, northern highlands of ethiopia. *Physical Geography* **3**: 1-16 DOI 10.1080/02723646.2017.13809.

Mohamed JEH, Abdelkader L, Mohamed F, Mohamed S. 2018. Spatial distribution of regionalized variables on reservoirs and groundwater resources based on geostatistical analysis using GIS: case of Rmel-Oulad Ogbane aquifers (Larache, NW Morocco). *Arabian Journal of Geosciences* **11**(5):104 DOI 10.1007/s12517-018-3430-9.
Morales J, Rodriguez A, Alberto V, Machado C, Criado C. 2009. The impact of human activities on the natural environment of the canary islands (spain) during the pre-hispanic stage (3rd–2nd century bc to 15th century ad): an overview. *Environmental Archaeology* **14**(1): 27-36 DOI 10.1179/174963109X400655.

Nagy NM., Kónya J. 2007. Study of pH-dependent charges of soils by surface acid–base properties. *Journal of Colloid & Interface Science* **305**(1): 94-100 DOI 10.1016/j.jcis.2006.09.040.

Nasseh S, Moghaddas NH, Ghafoori M, Asghari O, Bazaz, JB. 2016. Spatial variability analysis of subsurface soil in the city of mashhad, northern east iran. *International Journal of Mining and Geo-Engineering* **50**(2): 219-229 DOI 10.22059/ijmge.2016.59832.

Oliver MA, Webster R. 1986. Semi-variograms for modelling the spatial pattern of landform and soil properties. *Earth Surface Processes & Landforms* **11**(5): 491-504 DOI 10.1002/esp.3290110504.

Petrie SE, Jackson TL. 1984. Effects of fertilization on soil solution ph and manganese concentration1. *Soil Science Society of America Journal* **48**: 315-318 DOI 10.2136/sssaj1984.03615995004800020018x.

Reijonen I, Metzler M, Hartikainen H. 2016. Impact of soil pH and organic matter on the chemical bioavailability of vanadium species: The underlying basis for risk assessment. *Environmental Pollution* **210**: 371-379 DOI 10.1016/j.envpol.2015.12.046.

Riha SJ, Senesac G, Pallant E. 1986. Effects of forest vegetation on spatial variability of surface mineral soil ph, soluble aluminum and carbon. *Water Air & Soil Pollution* **31**(3-4): 929-940 DOI 10.1007/BF00284238.

Romano N. 1993. Use of an inverse method and geostatistics to estimate soil hydraulic conductivity for spatial variability analysis. *Geoderma* **60**(1-4): 169-186 DOI 10.1016/0016-7061(93)90025-G.

Rosemary F, Vitharana UWA, Indraratne SP, Weerasooriya R, Mishra U. 2017. Exploring the spatial variability of soil properties in an alfisol soil catena. *Catena* **150**: 53-61 DOI 10.1016/j.catena.2016.10.017.

Russenes AL, Korsaeth A, Bakken LR, Dörsch P. 2016. Spatial variation in soil ph controls off-season N2O emission in an agricultural soil. *Soil Biology & Biochemistry* **99**: 36-46 DOI 10.1016/j.soilbio.2016.10.017.

Salehi MH, Esfandiarpour I, Sarshogh M. 2011. The effect of aspect on soil spatial variability in central zagros, iran. *Procedia Environmental Sciences* **7**: 293-298 DOI 10.1016/j.proenv.2011.07.051.

Schindelbeck RR, Es HMV, Abawi GS, Wolfe DW, Whitlow TL, Gugino BK, Idogu OJ, Moebius-Clune BN. 2008. Comprehensive assessment of soil quality for landscape and urban management. *Landscape & Urban Planning* **88**(2-4): 73-80 DOI 10.1016/j.catena.2016.10.017.

Sheoran V, Sheoran AS, Poonia P. 2010. Soil reclamation of abandoned mine land by revegetation: a review. *International Journal of Soil Sediment & Water* **3**: 1-21 http://works.bepress.com/as_sheoran/1/.

Shinji M. 2015. Prevention of Acid Mine Drainage (AMD) by Using Sulfur-Bearing Rocks for a Cover Layer in a Dry Cover System in View of the Form of Sulfur. *Inzynieria Mineralna* **2**: 29-35 http://yadda.icm.edu.pl/yadda/element/bwmeta1.element.baztech-4d2e9347-db56-4751-be57-b4affc7ca575.

Silvia P, Escalante AE, Noguez AM, Felipe GO, Celeste MP, Cram SS, Eguiarte LE, Souza. 2016.
Spatial heterogeneity of physicochemical properties explains differences in microbial composition in arid soils from Cuatro Cienegas, Mexico. *PeerJ* 4(9): e2459. DOI 10.7717/peerj.24.

Stoyan H, De-Polli H, Böhm S, Robertson GP, Paul EA. 2000. Spatial heterogeneity of soil respiration and related properties at the plant scale. *Plant & Soil* 222(1-2): 203-214 DOI 10.1023/A:100475405147.

Trangmar BB, Yost RS, Uehara G. 1986. Application of geostatistics to spatial studies of soil properties. *Advances in Agronomy* 38(1): 45-94 DOI 10.1016/S0065-2113(08)60673-2.

Tsui CC, Chen ZS, Hsieh CF. 2004. Relationships between soil properties and slope position in a lowland rain forest of southern taiwan. *Geoderma* 123: 131-142 DOI 10.1016/j.geoderma.2004.01.031.

Turgut B, Öztas T. 2012. Assessment of spatial distribution of some soil properties with geostatistics method. *Ziraat Fakültesi Dergisi - Süleyman Demirel Üniversitesi* 7(2): 10-22 http://edergi.sdu.edu.tr/.../3118.

Vieira SR, Filho OG, Chiba MK, Cantarella H. 2009. Spatial variability of soil chemical properties after coffee tree removal. *Revista Brasileira De Ciência Do Solo* 33(5): 1507-1514 http://www.redalyc.org/html/1802/180214068041/index.html.

Wang Y, Shao M, Zhu Y, Liu Z. 2011. Impacts of land use and plant characteristics on dried soil layers in different climatic regions on the loess plateau of china. *Agricultural & Forest Meteorology* 151: 437-448 DOI 10.1016/j.agrformet.2010.11.016.

Wang Y, Zhang X, Huang C. 2009. Spatial variability of soil total nitrogen and soil total phosphorus under different land uses in a small watershed on the loess plateau, china. *Geoderma* 150(1): 141-149 DOI 10.1016/j.geoderma.2009.01.021.

Wilding LP. 1985. Spatial variability: its documentation, accommodation and implication to soil survey. *Spatial Variations* 166-194.

Yan LB, He RX, Kašanin-Grubin M, Luo GX, Peng H, Qiu JX. 2017. The dynamic change of vegetation cover and associated driving forces in nanxiong basin, china. *Sustainability* 9(3): 443-457 DOI 10.3390/su903044.

Yang J, Chen H, Nie Y, Zhang W, Wang K. 2016. Spatial variability of shallow soil moisture and its stable isotope values on a karst hillslope. *Geoderma* 264: 61-70 DOI 10.1016/j.geoderma.2015.10.003.

Yüksek T, Göl C, Yüksel F, Yüksel EE. 2009. The effects of land-use changes on soil properties: the conversion of alder coppice to tea plantations in the humid northern blacksea region. *African Journal of Agricultural Research* 4(7): 665-674 http://www.academicjournals.org/AJAR.

Zaremehrjardi M, Taghizadehmehrjardi R, Akbarzadeh A. 2010. Evaluation of geostatistical techniques for mapping spatial distribution of soil pH, salinity and plant cover affected by environmental factors in southern iran. *Notulae Scientia Biologicae* 2(4): 92-103 http://www.notulaebiologicae.ro.

Zhang C, Li W. 2010. Regional-scale modelling of the spatial distribution of surface and subsurface textural classes in alluvial soils using markov chain geostatistics. *Soil Use & Management* 24(3): 263-272 DOI 10.1111/j.1475-2743.2008.00165.x.

Zhang JH, Li Y. 2002. Spatial variability of soil moisture on the hillslopes, southwestern china. *Archives*
Zhang Q, Yang ZP, Li Y, Chen DL, Zhang JJ, Chen MC. 2010. Spatial variability of soil nutrients and gis-based nutrient management in yongji county, china. *International Journal of Geographical Information Science* 24(7): 965-981 DOI 10.1080/13658810903257954.

Zhao BH, Li ZB, Li P, Xu G, Gao HD, Cheng YT, Chang EH, Yuan SL, Zhang Y, Feng ZH. 2017. Spatial distribution of soil organic carbon and its influencing factors under the condition of ecological construction in a hilly-gully watershed of the loess plateau, china. *Geoderma* 296: 10-17 DOI 10.1016/j.geoderma.2017.02.010.

Zhao FY, Wu FZ, Liu D. 2000. Studies on the physical and chemical properties of the protected vegetable soils. *Soil and Fertilier* 2: 11-23.

Zhao J, Dong Y, Xie X, Li X, Zhang XX, Shen X. 2011. Effect of annual variation in soil pH on available soil nutrients in pear orchards. *Acta Ecologica Sinica* 31(4): 212-216 DOI 10.1016/j.chnaes.2011.04.001.

Zucco G, Brocca L, Moramarco T, Morbidelli R. 2014. Influence of land use on soil moisture spatial-temporal variability and monitoring. *Journal of Hydrology* 516(6): 193-199 DOI 10.1016/j.jhydrol.2014.01.043.
Figure 1

Figure 1 Location map of the study area.
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.
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. Slope distribution map of the study area.
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

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 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 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 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 | Lower 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 Semivariogram models and model parameters for soil properties in four land uses.

| Model | Parameter | Value 1 | Value 2 | Value 3 |
|-------|-----------|---------|---------|---------|
| Model A | Variance | 0.5     | 0.6     | 0.7     |
| Model B | Range    | 10      | 12      | 15      |

(continued on next page)
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                        |