Research article

Spatial Variability and Mapping of Soil Properties Using GIS-Based Geostatistic in Myanmar

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Abstract Precise information on the spatial variability of soil is a crucial component for productive intensive agriculture, sustainable development, and the management of natural resources. The primary purpose of the study was to investigate the spatial variability of soil properties of the study site at Yezin Agricultural University Field, Myanmar using geostatistics. A total of 94 composite soil samples were collected from a depth of 0 to 20 cm, in a systematic grid (50 x 50 m^2) at the site in May 2019. Soil pH, electrical conductivity (EC), soil organic matter (SOM), total soil nitrogen (TSN), available phosphorus (Ava-P), and available potassium (Ava-K) were measured using standard analytical methods. Data were analyzed geostatistically based on semivariogram. The exponential model best fitted the semivariogram for pH, EC, Ava-P, and Ava-K; SOM was adapted from the Gaussian model while TSN was adapted from the spherical model. The nugget/sill ratio showed a strong spatial dependence exists for EC, Ava-P, and Ava-K and a moderate spatial dependence for pH, SOM, and TSN. Most of the soil was found to be strongly acidic. It was also found that EC, SOM, and Ava-P are very low in most of the study area. Most of the study area was found to have low TSN levels, while Ava-K content was low over the entire area. With such an analysis, it is possible to plan better nutrient management practices for agricultural production and environmental protection. Therefore, geostatistical analysis with ordinary kriging is a useful tool for studying the spatial variability of soil properties.

Keywords spatial variability, soil properties, geostatistic, semivariogram, kriging

INTRODUCTION

An understanding of the distribution of soil properties is essential for ecological modelling, environmental predictions, precise agriculture, and management of natural resources (Wang et al., 2009). However, soil properties vary spatially from a small to a larger regional area, and are affected by intrinsic (parent materials and climate) and extrinsic factors (soil management practices, fertility status, crop rotation) (Cambardella and Karlen, 1999). Therefore, demands for more accurate

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information on spatial variability of soils are significant for intensive agriculture, sustainable development, and natural resource management (Karlen et al., 2011).

Many studies have used a classical statistical method to quantify spatial characteristics in soil properties (Salehi et al., 2013). However, physico-chemical characteristics of soil often exhibit spatial dependency, which cannot be recorded with classical statistical methods (Lin et al., 2005). To overcome this problem, many researchers apply geostatistical interpolation methods to estimate the spatial variability of soil properties (Cambardella et al., 1994; Webster and Oliver, 2007).

Geostatistics is a set of statistical tools that can be used to investigate and predict the spatial structure of georeference variables and generate soil property maps (Patil et al., 2011). Based on the geostatistical analysis, several studies have been carried out to characterize the spatial variability of various soil properties (Weindorf and Zhu, 2010). Among the various geostatistical methods, ordinary kriging is widely used to map spatial variations in soil fertility because it offers a higher level of predictive accuracy (Song et al., 2013). Therefore, it is important to extend the availability of soil resource information maps to allow the planning of appropriate soil management practices, including fertilization for agricultural production and environmental protection.

OBJECTIVES

The objective of this research is to investigate the spatial variability and mapping of spatial distribution of selected soil properties status in the study area using GIS-based geostatistical analysis.

METHODOLOGY

Study Area, Soil Sampling and Laboratory Analysis

The study area was Yezin Agricultural University Field (19°49'47"19°50'21"N and 96°15'32"-96°16'15"E), Zeyarthiri Township, Nay Pyi Taw Union Territory, in central Myanmar. It has an elevation ranging from 121.547 m to 125.205 m above sea level (Fig 1). The area of the research site is 18.19 ha. The study area has an average temperature of 26.8°C and a mean annual rainfall of about 1420 mm. Summer and monsoon rice are the main crops in the study area and these include both rain-fed and irrigated rice cultivations.

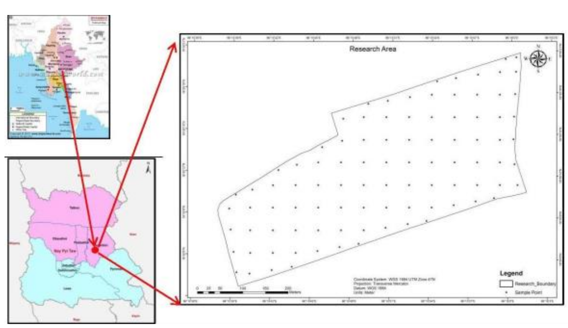

Fig. 1 Georeferenced sampling sites of the research area

A total of 94 composite soil samples were collected at a depth of 0 to 20 cm based on a systematic grid (50 x 50 m^2) determined with the help of a hand-held GPS device, in May 2019. Soil samples were air-dried and ground so as to pass through a 2-mm sieve. Soil pH and electrical conductivity (EC) were measured in a 1:5 soil/water extract, soil organic matter (SOM) was determined by Heanes wet oxidation method, total soil nitrogen (TSN) was analyzed by the Semi-micro Kjeldahl steam distillation method, available phosphorus (Ava-P) was measured by the Olsen-P method, and available potassium (Ava-K) was determined by extraction with 1M ammonium chloride (Rayment and Lyons, 2011).

Geostatistical Analysis

The geostatistical analysis, consisting of semivariogram calculation, cross-validation, and mapping, was performed with the Geostatistical Analyst Extension Tool of ArcGIS 10.7. The spatial variation of soil properties was analyzed using geographical semivariogram to quantify the spatial variation of a regionalized variables which derives important parameters used for ordinary kriging (OK) spatial interpolation (Krige, 1951). The semivariogram is used as a fundamental tool to study the spatial distribution structure of soil properties. The semivariogram analyzes were performed before the application of OK interpolation, as the semivariogram model determines the interpolation function (Goovaerts, 1997), defined as:

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

where, γ (h) is the experimental semivariogram value in a distance interval h (in meters or km), N (h) is the number of sample pairs that are located by a particular distance (h) from each other. z (x_i) and z ($x_i + h$) are the values of a regionalized variable at location x_i and $x_i + h$, respectively (Wang and Shao 2013).

Theoretical semivariogram models fit the empirical semivariogram obtained from the data to generate geostatistical parameters, including nugget variance (C_0), structured variance (C), sill variance (C_0+C), and distance parameters (A). The nugget/ sill ratio, C_0/ (C_0 + C) is calculated to characterize the spatial dependency of the values. A nugget/ sill ratio is classified as strongly spatially dependent if the ratio is less than or equal to 0.25, moderately spatially dependent if the ratio is between greater than 0.25 and less than or equal to 0.75 while it is classified as a weak spatial dependent if it is greater than 0.75 (Cambardella et al., 1994).

Several semivariogram models were evaluated to select the best fit with the data. The model, spherical, Gaussian, or exponential that offers the best fit varies depending on the soil parameters (Ramzan and Wani, 2018). A cross-validation technique was used to evaluate and compare the performance of the OK interpolation method. The lowest RMSE (Root Mean Square Error) value indicates the best fit for the variogram model (Panday et al., 2018). The predictive maps of soil properties are then created using a semivariogram model through OK.

Assessment of Accuracy of Interpolation Map

The effectiveness of interpolation was evaluated based on Goodness-of-Prediction Estimate (G) Eq. (2). A "*G*" value of 100% indicates a perfect prediction, positive values (i.e., 0 to 100%) show that the predictions are more reliable than the use of the sample mean, and negative values indicate that the predictions are less reliable than using the sample means (Laekemariam et al., 2018).

$$G = \left[1 - \frac{\sum_{i=1}^{N} \left[z(x_i) - \hat{z}(x_i) \right]^2}{\sum_{i=1}^{N} \left[z(x_i) - \hat{y} \right]^2} \right] \times 100 \qquad (2)$$

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Where, $z(x_i)$ is the observed value at location i, $\check{z}(x_i)$ is the predicted value at location i, N is the sample size, and $\hat{y}$ is the sample mean.

RESULTS AND DISCUSSION

Geostatistical Analysis

The semivariogram parameters obtained from the best-fit model are in Table 1. An exponential model produced the best fit to semivariogram for pH, EC, Ava-P, and Ava-K. This model is one of the standard models used in the study of soil properties (Cambardella et al., 1994; Reza et al., 2016). The spherical model was the best suited to the semivariogram of TSN, while a Gaussian model was the best fit for SOM.

The range for all soil properties varies from 96.76 m to 276.68 m, and therefore the length of the spatial autocorrelation is much longer than the sampling interval of 50 m. According to Goovaerts (1997), the current sample design is appropriate for this study, and it is expected that the interpolated map will display good spatial structure.

In the present study, the nugget/ sill ratio showed that EC, Ava-P, and Ava-K were strongly dependent spatially whereas, pH, SOM, and TSN were moderately dependent spatially. The strong spatial dependency suggests that intrinsic factors, such as climate, parent material, topography, soil properties, and other natural factors, play important roles in spatial variability. The weak spatial dependency indicates that the spatial variability is mainly caused by extrinsic factors, such as fertilization, local farming practice, cropping systems, and other human activities. The moderate spatial dependency shows that spatial variability is caused by a mix of extrinsic and intrinsic factors (Bhunia et al., 2018; Cambardella et al., 1994).

The G-values are greater than zero for all soil parameters. This value indicated that spatial prediction using semivariogram parameters is better than assuming that the mean of observed values is the best value for an unsampled location. This result also shows that semivariogram parameters obtained from fitting experimental semivariogram values describe the spatial variation reasonably (Reza et al., 2010).

Table 1 Geostatistical parameters of the fitted semivariogram models for soil properties

Parameters	Model	Nugget	Sill	Range (m)	Nugget / Sill	DSD	RMSE	G (%)
Soil pH	Exponential	0.1037	0.1822	253.34	0.57	Moderate	0.41	6.11
EC	Exponential	0.0000	0.4822	96.76	0	Strong	0.03	13.25
SOM	Gaussian	0.0900	0.2869	276.68	0.31	Moderate	0.34	47.43
TSN	Spherical	0.0005	0.0008	227.30	0.38	Moderate	0.03	25.08
Ava-P	Exponential	0.0856	0.6445	178.09	0.13	Strong	6.71	25.66
Ava-K	Exponential	0.0000	214.0108	108.58	0	Strong	12.26	39.90

DSD: Degree of Spatial Dependence, RMSE: Root Mean Square Error, G: Goodness of Prediction

Spatial Distribution of Soil Properties

The parameter of the fitted semivariogram models is used for OK to produce a spatial distribution map of soil properties in the study area. The spatial distribution of soil properties such as pH, EC, SOM, TSN, Ava-P, and Ava-K are shown in (Fig. 2a-e). The distribution of the predicted soil pH map (Fig. 2a) shows that 0.77%, 80.92%, and 18.31% of the study area were very strongly acid, strongly acid, and moderately acid, respectively. Most of the soils were strongly acid which may be caused by a mixture of the nature of the soil mineralogy, the use of acidic fertilizers, low input of organic materials,

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and removal of base nutrients (Rawal et al., 2018). The predicted map of EC (Fig. 2b) shows that 89.22% and 10.78% of the soil in the study area, can be described as very low and low, respectively. According to the soil guide (Moore, 2001); low EC levels only have a minimal impact on plant growth.

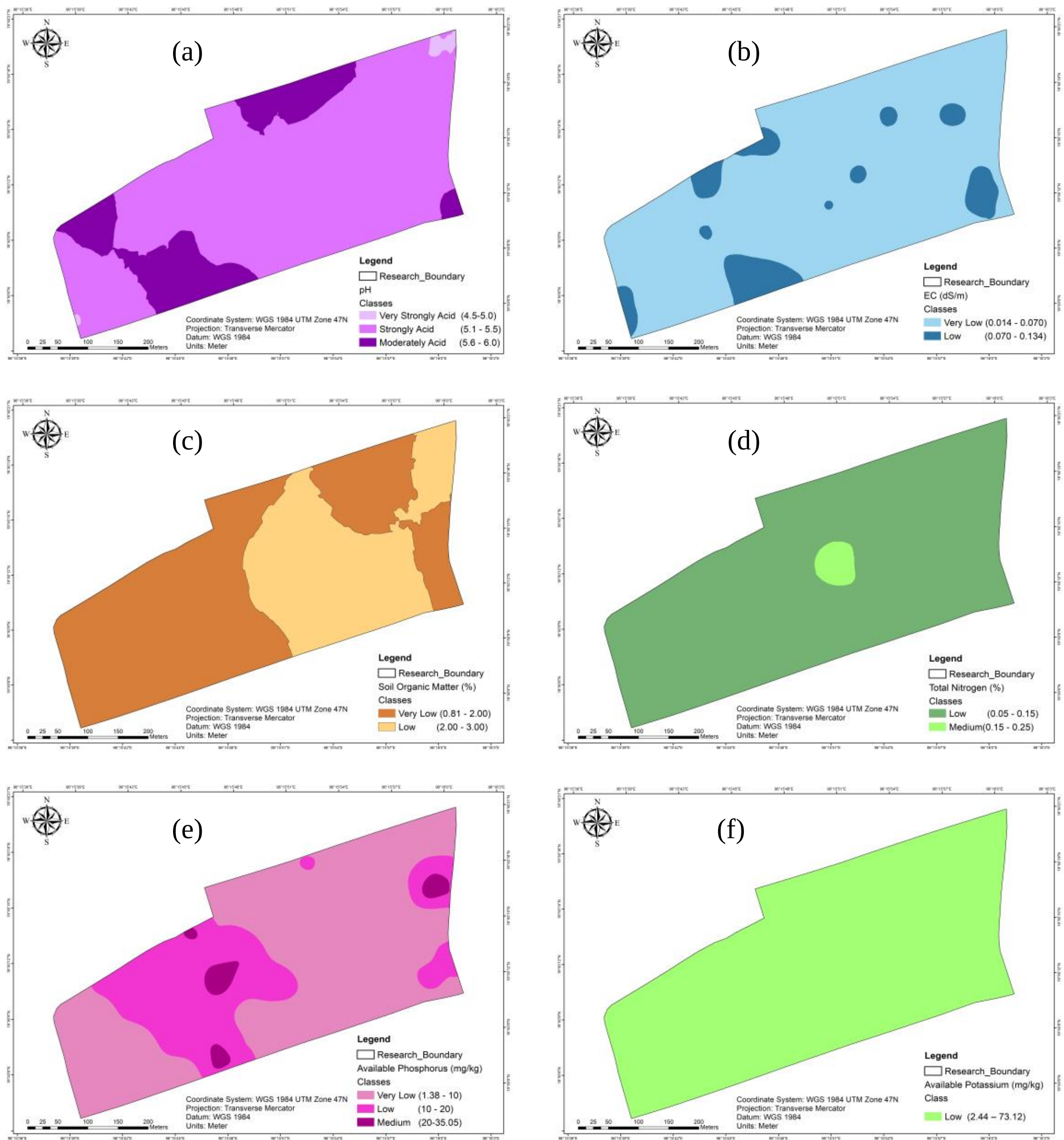

Fig. 2 Spatial distribution maps for (a) pH, (b) EC, (c) SOM, (d) TSN, (e) Ava-P and (f) Ava-K

The distribution of SOM (Fig. 2c) ranged from very low (62.73%) to low (37.27%), but low levels were most prevalent. The lower organic matter content in these soils can be attributed to the poor management practices such as intensive cropping, the complete removal of crop residues, and lack of addition of organic fertilizer sources (Gebreselassie, 2002). The majority of the soils were low (97.75%) in total nitrogen content, whereas 2.25% of the study area is rated at a medium level (Fig. 2d). The low nitrogen levels in most areas could be as a result of continuous cereal-based cropping, lower external organic-N inputs (like plant residues, animal manures), N (nitrate ions) leaching problem, and addition of a low amounts of SOM (Patil et al., 2011). The Ava-P map (Fig. 2e) shows that, in terms of area coverage, 68.83%, 28.42%, and 2.75% of the study area has very low, low, and medium levels respectively. This result indicates that, in general, the majority (97.25%) of the study area is deficient in phosphorus. The reason for low soil phosphorus levels may be due to the intensive cropping system, low pH (acidic) soils, the imbalanced use of fertilizer, and nutrient mining (Sertsu and Ali, 1983). The whole of the study area can be classified with a low rating for Ava-K content (Fig. 2f). The lowest Ava-K in the study area might be due to the lowest SOM and the continuous removal of potassium by cereal crops, as the field has been intensively cultivated for a long period.

CONCLUSION

Most of the soil was strongly acidic. The selected soil properties had a distribution showing low content levels in most of the study area. The distribution of variability of the soil properties across the landscape might be sufficient to construct fertility maps. The generated spatial distribution and fertility maps can serve as a powerful tool for farmers, decision-makers, and planners to understand the existing soil conditions and make sensible decisions to better manage the soil for sustainability and productivity. These results show that geostatistical analysis with kriging is an effective tool for studying the spatial variability of soil properties and that it will be useful technique for future soil sampling campaigns in Myanmar.

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