PERFORMANCE OF FREQUENTLY USED INTERPOLATION METHODS TO PREDICT SPATIAL DISTRIBUTION OF SELECTED SOIL PROPERTIES IN AN AGRICULTURAL WATERSHED, ETHIOPIA

Hailu Kendie Addis, Andreas Klik, Stefan Strohmeier

Institute of Hydraulics and Rural Water Management, University of Natural Resources and Life Sciences, Vienna, Austria

Gondar Agricultural Research Center, Soil and Water Management Directorate, Gondar, Ethiopia

International Center for Agricultural Research in the Dry Areas, Amman, Jordan

ABSTRACT. *Soil maps of an agricultural watershed provide a wealth of knowledge and can be a vital tool for implementing site specific soil managements. Hence, watershed based soil assessment was conducted to select an optimum spatial interpolation method, while aiming for sustainable soil managements. Thus, intensive soil sampling was undertaken to investigate the performance of ordinary kriging (OK), inverse distance weighting (IDW) and radial basis functions (RBF) for predicting the spatial distribution of soil texture, pH, soil organic carbon (SOC) and available phosphorus (AP). The 72ha study area was divided into a 100m by 100m grids and approximately at the center of each grid, topsoil (10-15cm) samples were collected over 75 locations across the entire study area. The exponential and Gaussian models were best fitted in the semivariogram of the measured soil variables. The performance of each interpolation method was assessed quantitatively in terms of Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d). The interpolated maps generated based on the highest value of E displayed OK was best performed for SOC and sand. RBF was most suitable* *for mapping of AP and clay, while IDW gave better result when applied to pH. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP. Generally, the methodology used in this study was adequate for spatial interpolation and evaluation of measured soil properties and can serve as a general method for surface map generation in future studies of similar regions.*

Keywords: *Agricultural watershed, radial basis functions, semivariogram, interpolation.*

INTRODUCTION

Soils continually undergo development and vary over a wide range of spatial and temporal scales. Spatial scales reach from the micro-environment (quite small area) to the watershed and beyond, while temporal scales extend from seconds to centuries and longer (Addis et al., 2015). Therefore, any effort to enhance soil productivity in different types of cropping method may not yield appropriate results without a careful understanding of soil variability. The spatial variability of soil is often measured using a number of interpolation methods. Selecting an ideal spatial interpolation method for map generation is crucial in surface analysis (Zandi et al., 2011).

The goal of spatial interpolation is to estimate the magnitude of the variable (Z_0) at location X_0, Y_0 using surrounding points with known X and Y coordinates and magnitude of variable (Z) (Meijerink et al., 1994). However, spatial interpolation and interpretation is predominantly human dependent, and therefore subjective (Furrer and Genton, 1999). The spatial interpolation methods, including geostatistics, have been developed for and applied in various disciplines (Zhou et al., 2007). Numerous factors including sampling density, sample volume, spacing, sampling design and variation in the data affect the predictive ability of a spatial interpolation method (Li and Heap, 2008). These factors make it difficult to select an appropriate spatial interpolation method for a given input dataset (Burrough and McDonnell, 1998).

The precision of various spatial interpolation techniques for predicting unmeasured values have been documented by a number of researchers (Weber and Englund, 1992; Nalder and Wein, 1998; Kravchenko and Bullock, 1999). Nevertheless, there have been many conflicting findings regarding the relative performance of different spatial interpolation methods and the use of basic statistics to predetermine both interpolation techniques and their parameters (Robinson and Metternicht, 2005).

Spatial interpolation techniques are developed for specific data types or a particular variable (Li and Heap, 2008). Most of the methods perform at an acceptable level for estimating soil attributes in gentle terrain, whereas few perform well in rugged terrain (Pandey et al., 2010; Yao et al., 2013). Three of the most popular interpolation methods, IDW, RBF and ordinary kriging have been commonly used in agricultural research (Zandi et al., 2011). Several studies, however, have found that IDW to be more accurate than kriging for mapping of soil organic matter (SOM) and soil NO_3 levels (Gotway et al., 1996) and for mapping of P and K levels (Wollenhaupt et al. 1994). Similarly, research conducted by Robinson and Metternicht, (2005) reported that IDW predicted the subsoil pH with greater accuracy than kriging and spline. However, kriging has been the preferred method for predicting agricultural yield data (Birrell et al., 1996; Batchelor et al., 2002; Whelan et al., 2002), topsoil pH (Robinson and Metternicht, 2005) and for mapping of soil Zn (Leenaers et al., 1990). In contrast, research conducted by Zandi et al. (2011) showed that RBF outperformed OK and IDW for interpolating topsoil pH and this study tried to test the validity of such methods at a sub-watershed scale. Surface soil map generation for an agricultural watershed provide a wealth of information and can be an important tool for implementing various site specific soil managements but, such information for soil of Gumara-Maksegnit agricultural watershed is lacking and hence, need to be assessed. Considering these different and conflicting findings, the objectives of this research were to i) analyze the performance of frequently used spatial interpolation techniques (IDW, OK and RBF) for predicting topsoil pH, soil organic carbon (SOC), available phosphorus (AP) and texture; and, ii) determine the optimum spatial interpolation method for mapping of selected soil properties in agricultural watershed.

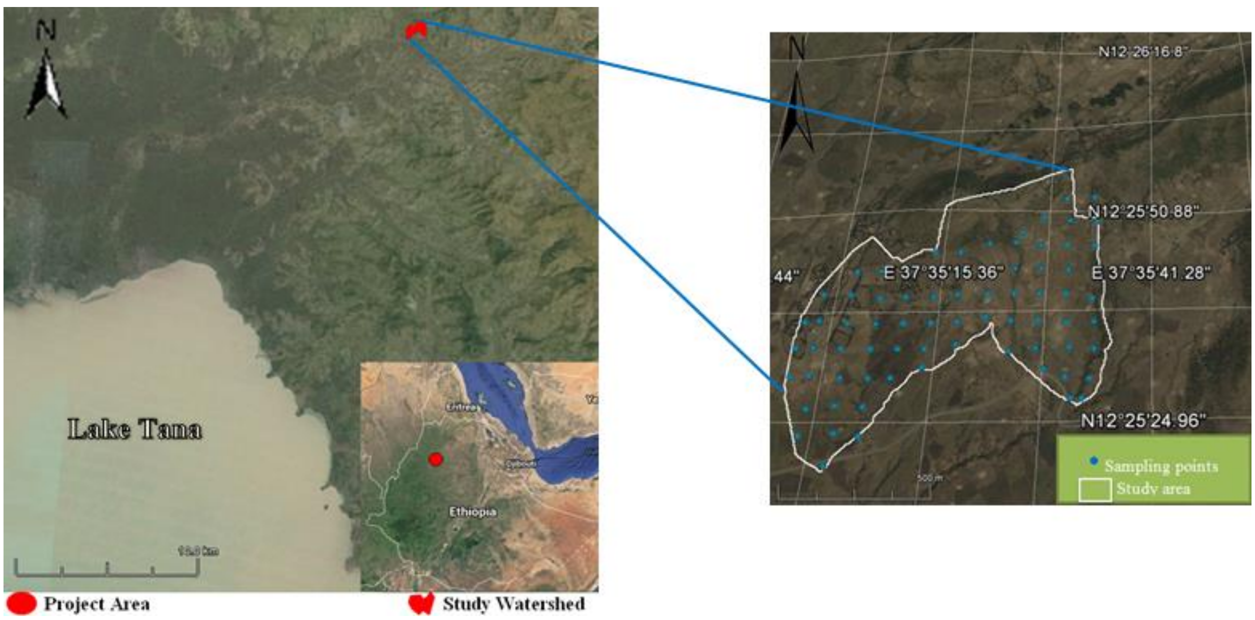

Figure 1. Location of the study sub-watersheds and the distribution of observed soil samples.

MATERIALS AND METHODS

STUDY AREA DESCRIPTION

The study was carried out in the Ayeye and Aba-Kaloye sub-watersheds ($37^0$35'15"E, $12^0$25'50"N), which are located near Lake Tana basin in the northwestern Amhara region, Ethiopia (fig. 1). The two sub-watersheds have a total area of 72 ha and the elevation ranges from 1,997 m to 2,532 m, while the hillslopes range from nearly flat (< 2%) to extremely steep (> 50%). The climate of the area is characterized by intense rainfall events occurring mainly between June and

August and a dry period between November and April; average annual rainfall is 1170 mm (Addis et al., 2015). The study area, which is part of the northern highlands of Ethiopia, belongs to the Trapp series of Tertiary volcanic eruptions (Mohr, 1963). In the study sub-watersheds, some of the factors causing considerable nutrient depletion in agricultural lands are related to soil erosion by water, the cultivation of the steep and fragile soils, limited recycling of cow dung and crop residue, deforestation, and overgrazing.

SOIL SAMPLING METHOD

The study sub-watersheds were under agricultural land-use system (crop production) with varying landscape features, including elevation, slope, aspect, soil categories and land management. The soil sampling sites were selected using a well-organized regular sampling interval in a GIS environment, coupled with a systematic selection of the most representative soil-landscape features as it was described by Buttafuoco *et al.* (2012). The systematic method is the most commonly used technique and provide more accurate results than random sampling pattern (Wang and Qi, 1998; Kavianpoor et al., 2012) and is an appropriate method when no other information is available regarding the soil variability prior to sampling. Therefore, the 72 ha study area was divided into a 100 m by 100 m square grid using arcgis and a total of 75 soil samples across the entire sub-watersheds were collected from the topsoil horizon with the best available tool (bucket auger) for analyses. The pH value of the soil was measured with a pH meter in the supernatant suspension of 1:2.5 ratios (sample to water mixture). Soil texture was measured following the procedure as described by Gee and Or (2002), and organic carbon was determined by wet oxidation method as described by De Vos et al. (2007). Available Phosphorus (AP) was extracted using sodium bicarbonate solution at pH 8.5 following the procedure described by Olsen (1954). In this study, classical statistical analyses were used to describe soil properties and geo-statistical analyses were used to select an optimum spatial interpolation method.

SPATIAL INTERPOLATION TECHNIQUES

Frequently used spatial interpolation techniques (OK, RBF and IDW) were selected to predict the spatial continuous surfaces of soil properties in the study sub-watersheds. Naturally, the selected interpolation techniques are commonly described as weighted average methods, and they all share the same basic mathematical formulation (Webster and Oliver, 2001; Li and Heap, 2008) and calculated as:

$$\check{z}(x_0) = \sum_{i=0}^{n} \lambda_i \, z(x_i) \qquad (1)$$

Where n represents the number of sampled points used for the prediction, $\check{z}$ is the predicted value of an attribute at the point of interest x_0, z is the observed value at the sampled point x_i, and λ_i is the weight assigned to the sampled point (Webster and Oliver, 2001).

Kriging

Kriging is a statistical procedure for interpolating values at unmeasured locations between locations with sampled data (Nielsen and Wendroth, 2003). Kriging analysis is applicable for environmental disciplines such as agricultural yield mapping (Blackmore, 1999), spatial continuous soil surface generation (Goovaerts, 1999), spatial variability assessment of rainfall (Naoum and Tsanis, 2004) and air pollution modelling (Wong et al., 2004). Ordinary kriging is a type of kriging that considers the mean is constant but unknown across the spatial domain of interest (Li and Heap, 2008). Kriging utilizes the spatial variance structure available in a semivariogram and provides a best linear unbiased estimate of an unmeasured value calculated from weighted values measured in a local neighborhood (Nielsen and Wendroth, 2003).

Semivariance (γ) is an important concept in geostatistics (Webster and Oliver, 2001) and can be estimated from the observed values as follows:

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

Where h is the distance between point x_i and x_0 and $\gamma(h)$ is commonly referred to as semivariogram (Webster and Oliver, 2001), $N(h)$ is the number of data pairs within a given class of distance and direction. A plot of $\gamma(h)$ against h is known as the experimental semivariogram, which displays several important features (e.g. nugget, sill and range) (Burrough and McDonnell, 1998). If the ratio of nugget to sill is close to 1, it reflects a weak degree of spatial dependency (Cambardella et al., 1994).The "range" is a value of distance at which the "sill" is reached (Li and Heap, 2008) and the range provides information about the size of a search window used in the spatial interpolation methods (Burrough and McDonnell, 1998). GS+ was used to obtain the semivariogram model of each observed soil properties (Robertson et al., 2008) and model with the least reduced sum of squares (RSS) was further examined to find the number of neighbors that returned the best cross-validation result (Robinson and Metternicht, 2005).

Inverse Distance Weighted (IDW)

Inverse Distance Weighted (IDW) is a deterministic method that uses a weighted average of nearby locations, with closer points to the center of the cell being estimated having greater weight in the averaging process (Zeiler, 2010). The most important factor that affects the accuracy of IDW is the value of the power parameter (Isaaks and Srivastava, 1989). IDW is commonly used for estimating soil properties or (attributes) (Leenaers et al., 1990; Wollenhaupt et al., 1994; Gotway et al., 1996) using the following formula:

$$z(x_0) = \frac{\sum_{i=1}^{n} z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \quad (3)$$

Where x_0 is the estimation point and x_i are the data points within a chosen neighborhood. The weights (r) are related to distance by d_{ij}, which is the distance between the estimation point and the data points. One of the concerns with the IDW method is that higher or lower values of the site under consideration will be overlooked if they are not sampled (EPA, 2012) so if the peaks and valleys of the data are not represented in the sample, this technique may be wildly inaccurate in some locations. Since IDW is a deterministic technique, it does not take into account the spatial structure of the sample points. Thus, the results can be influenced by sampling density and sampling interval. In addition, if the sampling of input points is sparse or uneven, the results may not sufficiently represent the desired surface (Watson and Philip, 1985).

Radial Basis Functions (RBF)

Radial Basis Functions (RBF) is a family of five deterministic exact interpolation techniques: thin-plate spline, spline with tension, completely regularized spline, multi-quadratic function and inverse multi-quadratic function (Zeiler, 2010). The differences among RBFs are small, so the generated surfaces are almost similar (Burrough and McDonnell, 1998). Unlike IDW (which is also an exact interpolator), RBF can predict values above the maximum or below the minimum of the measured values (Zeiler, 2010). RBFs are used to produce smooth surfaces from a large number of sample points. The functions produce good results for gently varying surfaces such as elevation. However, the techniques are inappropriate when large changes in the surface values occur within short distances and/or when you suspect the sample data is prone to measurement error or uncertainty (Zeiler, 2010).

MODEL EVALUATION TECHNIQUES

Spatial interpolation methods are increasingly used in a wide range of disciplines despite increasing concern about their accuracy and precision (Hartkamp et al., 1999; Huo et al., 2012). The concern about their accuracy and precision is because they were developed either for specific disciplines or even for specific variables based on the data properties modelled and each method has its own specific assumptions and features (global versus local, exact versus inexact, deterministic versus stochastic, and gradual versus abrupt) (Li and Heap, 2008). Therefore, several error measurement methods have been used to assess the accuracy and precision of the interpolation methods (Li and Heap, 2008, 2011).

In this study, cross-validation with a single variogram was used to assess the performance of each spatial interpolation method. Cross-validation is an appropriate method to evaluate models when two independent datasets (calibration and validation) cannot be built because of the reduced number of data points (jack-knifing) (Guisan and Zimmermann, 2000). The model is fit to a portion of the data, and then the attained equation is applied to the remaining data points to determine their estimated values (Davis, 1987; Li and Heap, 2008). The estimated values from cross-validation were used to calculate an error estimator (Willmott, 1982). The performance of each interpolation method was assessed quantitatively in terms of mean error (ME), mean squared error (MSE), root mean squared error (RMSE), Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d).

Nash-Sutcliffe Efficiency (E)

The Nash-Sutcliffe efficiency (E) is a normalized statistic that explains the relative magnitude of the residual variance ("noise") associated with the observed data variance (Nash and Sutcliffe, 1970; Moriasi et al., 2007). The efficiency E documented by Nash and Sutcliffe, (1970) is defined as follows:

$$E = 1 - \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad (4)$$

Where n is the number of observations or samples, O_i is the observed value of sample *i*, E_i is the estimated value of sample *i*, and Ō is the mean of observed values.

The range of E lies between −∞ and 1.0 with E = 1 describing a perfect fit. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicate that the mean observed value is a better predictor than the estimated value (unacceptable performance) (Moriasi et al., 2007). The key weakness of the Nash-Sutcliffe efficiency is the fact that larger values in a dataset are strongly overestimated whereas lower values are neglected (Legates and McCabe, 1999).

Coefficient of Determination (R^2)

The coefficient of determination, R^2, is the squared value of the coefficient of correlation (Krause et al., 2005). It is defined as follows:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})\,(E_i - \bar{E})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(E_i - \bar{E})^2}}\right]^2 \qquad (5)$$

Where n is the number of observations or samples, O_i is the observed value of sample *i*, E_i is the estimated value of sample *i*, Ō is the mean of observed values and Ē is the mean of estimated values.

The range of R^2 lies between 0 and 1, and describes how much of the observed value is explained by the predicted value (Krause et al., 2005). A value of 1 means the predicted value is equal to the observed value, where a value of zero means there is no correlation between the predicted and observed values.

Index of Agreement (d)

The index of agreement, d, as reported by Willmott (1981) is a standardized measure of the degree of model accuracy. The range of d is the same as R^2 ranging from1 (perfect fit) to 0 (no correlation) (Moriasi et al., 2007). The index of agreement is described as follows:

$$d = \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(|\check{E}_i| + |\check{O}_i|)^2} \qquad (6)$$

Where n is the number of observations or samples, O_i is the observed value of sample i, E_i is the estimated value of sample i, $\bar{O}$ is the mean of observed values, $\check{O}_i$ is the difference between the observed value for sample i and the mean observed value $(O_i – \bar{O})$, and $\check{E}_i$ is the difference between the estimated value of sample i and the mean observed value $(E_i – \bar{O})$.

Krause et al. (2005) have reported relatively high value of d (more than 0.65) even for poor model fits. It has also been found that d is overly sensitive to extreme values due to the squared differences (Legates and McCabe, 1999).

Table 1. Descriptive statistics summary for soil physical and chemical properties of the study sub-watersheds.

Soil attributes	No. of samples	Minimum	Maximum	Range	Mean	SD[b]	se (mean) [b]	CV[b]	Skewness	Kurtosis
SOC (%)[a]	75	0.13	5.22	5.09	1.81	0.97	0.11	0.53	0.67	0.81
AP (ppm) [a]	75	0.32	155.92	155.60	22.98	38.95	4.50	1.69	2.32	4.92
pH	75	5.68	7.37	1.69	6.57	0.34	0.04	0.05	0.18	-0.15
Clay (%)	75	10	58	48	29.19	10.22	1.18	0.35	0.17	-0.22
Silt (%)	75	18	62	44	35.64	6.51	0.75	0.18	0.49	2.96
Sand (%)	75	16	62	46	35.17	10.55	1.22	0.30	0.73	-0.17

[a] SOC is soil organic carbon and AP is available phosphorous.

[b] SD is standard deviation, se (mean) is standard error of mean and CV is coefficient of variation.

RESULTS AND DISCUSSION

According to laboratory measurements soil texture was rather heterogeneous across the study area, primarily clay loams, loams and sandy loams with the clay contents ranging from10% to 58%, and sand contents from16% to 62%. The descriptive statistical summary of the measured soil physical and chemical properties of the study sub-watersheds is presented in table 1.Variability of soil properties can be described by the minimum and maximum values, standard deviation (SD), and coefficient of variation (CV). Among these values, the coefficient of variation (CV) is the most selective factor as it is a useful statistic for comparing the degree of variation from one data series to another, even if the means are drastically different from each other (Wei et al., 2008). According to the soil variability guidelines provided by Wilding (1985), the property shows low variability when CV is less than or equals to 0.15, moderate variability when the CV is between 0.15 to 0.35, and the most variability when the CV is greater than 0.35. Based on these guidelines, AP, SOC and clay contents were the most variable soil properties, while silt and sand contents had moderate variability, and pH was the least variable (table 1). A similar study by Sun et al., (2003) and Addis et al. (2015) documented that AP showed the highest variation, while pH had the least, based on the CVs. The range of SOC increased from 0.13% at the outlet to greater than 3.2% at upper catchment areas. A lognormal ordinary kriging was used for AP as the coefficient of skewness is greater than 1 (table 1).

Table 2. Coefficients of the theoretical semivariogram statistic produced for different ordinary kriging models of the selected soil properties.

Variable	Model type	Nugget [Co]	Sill [Co+C]	Range Ao (m)	RSS[a]	$R^{2[a]}$	nugget/sill ratio [Co /(Co+C)]
SOC	Linear	0.32	1.07	497.85	1.21	0.92	0.30
	Spherical	0.35	1.06	282	8.72E-03	0.97	0.33
	Exponential	0.23	1.88	711	0.01	0.94	0.12
	Gaussian	**0.18**	**1.01**	**503**	**8.01E-03**	**0.97**	**0.18**
Lognormal AP	Linear	1.64	3.17	497.85	5.35	0.65	0.52
	Spherical	0.001	2.85	246	0.11	0.93	0.00
	Exponential	0.001	3.03	119	0.17	0.9	0.00
	Gaussian	**0.22**	**2.86**	**118**	**0.09**	**0.94**	**0.08**
pH	Linear	0.09	0.41	497.85	2.04E-03	0.79	0.22
	Spherical	0.09	0.37	1979	1.06E-04	0.79	0.24
	Exponential	0.09	0.37	1097	1.13E-04	0.77	0.24
	Gaussian	**0.09**	**0.39**	**1104**	**9.11E-05**	**0.92**	**0.23**
Clay	Linear	0.0063	0.011	497.85	7.91E-07	0.93	0.57
	Spherical	0.006	0.014	1074	6.50E-07	0.94	0.43
	Exponential	**0.0059**	**0.02**	**1110**	**5.58E-07**	**0.95**	**0.30**
	Gaussian	0.0071	0.014	541	1.35E-06	0.88	0.51
Silt	Linear	0.0035	0.005	497.85	4.90E-06	0.85	0.70
	Spherical	0.0035	0.007	1634	1.64E-07	0.86	0.50
	Exponential	**0.0034**	**0.007**	**749**	**1.30E-07**	**0.89**	**0.49**
	Gaussian	0.0039	0.008	824	2.80E-07	0.75	0.49
Sand	Linear	0.0073	0.012	497.85	1.39E-06	0.86	0.61
	Spherical	0.007	0.014	1037	1.19E-06	0.88	0.50
	Exponential	**0.0069**	**0.02**	**1067**	**1.07E-06**	**0.89**	**0.35**

	Gaussian	0.0082	0.017	651	2.24E-06	0.77	0.48

[a] RSS is residual sum squares and R^2 is coefficient of determination. Bolded RSS values were chosen as the best model.

COMPARISON OF THE INTERPOLATION METHODS

The spatial variability of selected soil properties was assumed to be identical in different directions and the isotropic experimental semivariogram for each observed soil variable was calculated using Eq. (2). The results of the experimental semivariograms show that the exponential and Gaussian models were best fitted and the model with the least residual sum of squares (RSS) was chosen (table 2). Selecting an appropriate spatial interpolation method for a given input dataset is difficult, as they are data-specific or even variable-specific. Therefore, the choice of spatial interpolation techniques is subjective (Furrer and Genton, 1999). This study does not overlook the possibility of anisotropy and directional semivariograms have been examined but the directional semivariograms are not very good, thus, the study end up using an isotropic semivariogram. The isotropic semivariograms for the selected soil properties are shown in figures 2a-2f. The semivariograms of clay, silt and sand contents were best-fitted with the exponential function and each of their coefficients of determination (R^2) is greater than 0.89, which suggested that clay, silt, and sand contents had stronger spatial structure.

Typically, the nugget to sill ratio or relative nugget effect [Co/(Co+C)] reflects the spatial autocorrelation (Li and Reynolds, 1995). The relative nugget effect was calculated for each observed soil properties and used to assess the degree of spatial dependence and correlation related with each soil variables (Jabro et al., 2010). The relative nugget effect of each observed soil properties were then classified into one of the three classes to describe the spatial dependence (Cambardella et al., 1994). If the relative nugget effect was less than or equal to 0.25, the soil property was categorized as strongly spatially dependent; if the relative nugget effect was greater than 0.25 and less than 0.75, the soil property was categorized as moderately spatially dependent; and if the relative nugget effect was greater than 0.75, the soil property was categorized as weakly spatially dependent (Cambardella et al., 1994; Jabro et al., 2010). The relative nugget effect of clay, silt, and sand for the best fitted model ranged from 0.30 to 0.49, indicating moderately spatially dependent.

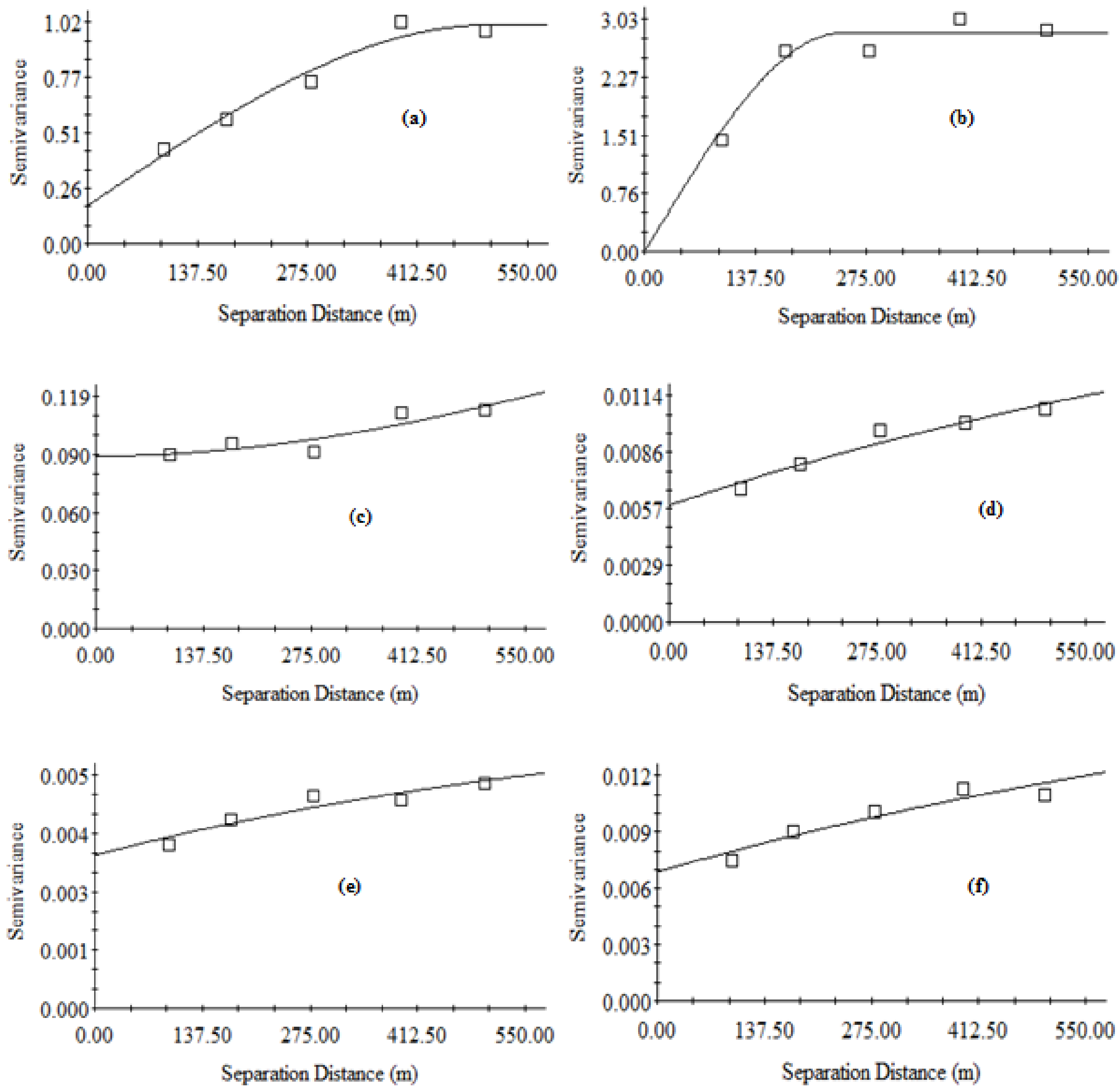

Figure 2. Fitted semivariogram for the selected soil property of (a) SOC using the Gaussian model, (b) AP using the Gaussian model, (c) pH using the Gaussian model, (d) clay using exponential model, (e) silt using exponential model and (f) sand using exponential model.

The semivariograms of SOC, AP and pH were well fitted to the Gaussian model and each of their coefficients of determination (R^2) is greater than or equal to 0.92, which suggest that SOC, AP, and pH had stronger spatial structure. The spatial analysis of SOC and pH shows a clear structure with a strong to moderate relative nugget effect (0.8 to 0.49) (table 2). A similar study by Cambardella et al. (1994) documented that pH and silt had strong spatial dependence. The ranges of spatial dependencies were large and differ between 118 m for AP to 1110 m for clay indicating that the optimum sampling interval varies greatly among different soil properties.

The quantitative summary of the performance of each interpolation method is shown in table 3. In this study, 5 to 25 neighboring points were considered for each interpolation method. Meanwhile, a power of 1, 2, and 3 were tested and the best weighting parameter for IDW was found to be a power of two. With regards to RBF, the five kernel functions were tested although the best kernel function was found to be completely regularized spline. Ordinary kriging for observed soil property and lognormal ordinary kriging for available phosphorous were also tested.

The mean error (ME), mean squared error (MSE) and root mean squared error (RMSE) were calculated as measures of accuracy and the Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d) were determined as measures of effectiveness for each observed soil property (table 3). The lowest root mean square error (RMSE) for clay, silt and sand contents were found with a neighborhood of 15, 5 and 16 points, respectively. The lowest root mean square error (RMSE) for SOC, AP and pH were found with a neighborhood of 5, 8 and 15 points, respectively. The predictions of the selected soil properties except AP were relatively unbiased as the mean errors (ME) were almost equals to 0 (table 3).

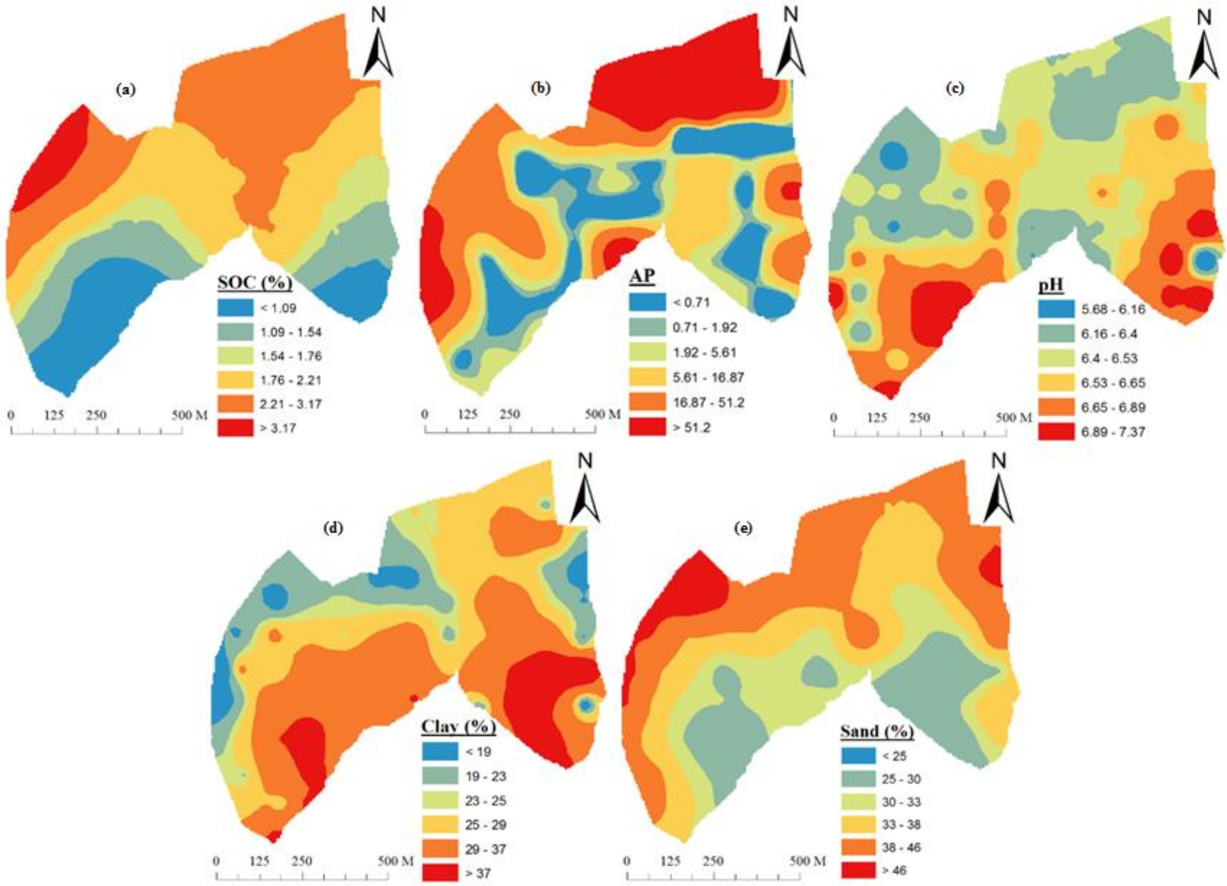

Figure 3. Best interpolated soil map of (a) SOC using ordinary kriging, (b) AP using RBF, (c) pH using IDW, (d) clay using RBF and (e) sand using ordinary kriging.

The interpolated maps generated based on the highest value of the Nash-Sutcliffe efficiency (E) resulted from the cross-validation of the selected soil properties can be seen in figure 3. Interpolation of SOC using the Gaussian model with the highest Nash-Sutcliffe efficiency of 0.44 is shown in figure 3A. The study area had SOC that ranges from 0.13% to 5.22% and the highest SOC (> 3.17%) was occurred in northwest of Aba-Kaloye sub-watershed. The lowest SOC (0.13% to 1.54%) values occur on the central to the outlets of the sub-watersheds which were intensively cultivated. Interpolation of AP using RBF with the highest Nash-Sutcliffe efficiency of 0.51 is shown in figure 3B. AP content in the central part of the study area was less than the mean value

(22.98 ppm), and areas where AP content was twice the mean value was observed in northeast of Ayeye sub-watershed (figure 3B). Interpolation of pH over the study sub-watersheds using IDW technique with E equals to 0.45 is shown in figure 3C. These results disagreed with those found by Laslett et al. (1987) and Robinson and Metternicht (2005) where topsoil pH was better estimated by using OK than by using IDW. The observed soil pH data had a value ranged from 5.68 to 7.37 which suggests the area is very good for crop production. The areas where pH was lower than the mean value (6.57) was observed in northwest of Aba-Kaloye sub-watershed, and areas where pH was greater than the mean value were found around the outlets of the sub-watersheds (figure 3C). Meanwhile, RBF proved to be the better method for interpolating clay content of the study sub-watersheds with the Nash-Sutcliffe efficiency of 0.17 (figure 3D). The areas where clay contents were lower than the mean value (29.19%) were observed in northwest of Aba-Kaloye sub-watershed, and areas where clay contents were greater than the mean value were found at the outlets of the sub-watersheds (figure 3D). Exponential ordinary kriging proved to be the best method for interpolating sand contents with E equals to 0.17 (figure 3E). The Nash-Sutcliffe efficiency for all measured soil properties except silt showed a positive value (table 3). Silt was the only measured soil property for which the resulting Nash-Sutcliffe efficiency of each interpolation method had a negative value (less than –0.34), that suggested the prediction would have been more reliable if the sample mean had been used instead. Generally, the methodology used in this study was adequate for spatial interpolation and evaluation of measured soil properties and can serve as a general method for spatial continuous surfaces map generation in future studies of similar regions.

Table 3. Quantitative summary of the performance of the three interpolation methods for the study sub-watersheds.

Variable	Interpolation methods																	
	OK[a]						IDW[a]						RBF[a]					
	ME[b]	RMSE[b]	MSE[b]	d[b]	E[b]	R^2	ME	RMSE	MSE	d	E	R^2	ME	RMSE	MSE	d	E	R^2
SOC	0	0.72	0.51	0.78	0.44	0.44	-0.01	0.73	0.53	0.75	0.43	0.43	0	0.72	0.52	0.76	0.44	0.44
AP	1.48	32.35	1046.8	0.67	0.30	0.30	0.09	31.04	963.69	0.72	0.36	0.36	0.01	27.2	739.67	0.83	0.51	0.51
pH	0	0.32	0.1	0.58	0.16	0.17	0	0.3	0.1	0.65	0.18	0.19	0	0.33	0.11	0.59	0.17	0.17
Clay	0.06	9.34	87.17	0.58	0.15	0.17	0.04	9.28	86.09	0.61	0.16	0.17	0.04	9.23	85.21	0.62	0.17	0.18
Silt	0.03	7.49	56.17	0.33	-0.34	0	0.07	7.58	57.48	0.32	-0.37	0	0	7.49	56.15	0.33	-0.34	0
Sand	-0.08	9.51	90.44	0.64	0.17	0.18	-0.44	10.08	101.66	0.54	0.11	0.13	-0.09	9.99	99.89	0.57	0.14	0.16

[a] OK is ordinary kriging, IDW is inverse distance weight and RBF is radial base function.

[b] ME is mean error, RMSE is root mean square error, MSE is mean square error, d is index of agreement and E is Nash-Sutcliffe efficiency.

The spatial interpolation techniques used for each soil properties indicated that values of R^2 range from 0.00 to 0.51. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP using RBF (table 3). A comparison of E with r^2 displays the fact that the two criteria had a strong positive correlation with the correlation coefficient (r) equals to 0.92. The correlation between E and index of agreement (d) was also significantly positively correlated (r = 0.98). Similarly, the correlation between R^2 and index of agreement (d) was also significantly positively correlated (r = 0.96).

CONCLUSIONS

This study aims to analyze the performance of frequently used spatial interpolation techniques (IDW, OK and RBF) and determine the optimum spatial interpolation method for mapping of selected soil properties, which were sampled in mountainous agricultural sub-watersheds, Ethiopia. The descriptive analyses revealed that AP, SOC and clay contents were the most variable soil properties, with CV greater than 0.35 while, silt and sand contents were moderately variable, with CV vary from 0.18 to 0.30. Cross-validation was used to get the best agreement between the observed data and the predicted values of selected spatial interpolation methods. This study considered 5 to 25 neighboring points for each interpolation method. Meanwhile, the five kernel functions and a power of 1, 2, and 3 were tested for RBF and IDW, respectively. The best kernel function for RBF was found to be completely regularized spline, while the best weighting parameter for IDW was found to be a power of two.

The Nash-Sutcliffe efficiency (E) for each soil property except silt showed a positive value of ($E \geq 0.17$), therefore, the methodology used in this study can serve as a general method for surface map generation in future studies of similar regions. When comparing the resulting values of the efficiency criteria, for each interpolation technique, the OK method was best performed for SOC and sand contents. RBF method was produced more accurate maps for AP and clay contents, while IDW performed best for interpolating topsoil pH. The surface maps for the selected soil properties indicated that values of R^2 range from 0.00 to 0.51. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP using RBF. The results of the accuracy measuring parameters for each spatial interpolation method showed that there was no single interpolation method that significantly outperformed the others.

The choice of spatial interpolation techniques were project and user dependent, which may play a significant role in the resultant prediction maps. Therefore, future research in the area should consider the different spatial interpolation methods, land management practices, land-use and topography to improve the outputs. Finally, environmental models which use soil map as an input might consider the influence of the soil map produced by different spatial interpolation techniques.

ACKNOWLEDGMENTS

The research was made possible by Austrian Development Agency (ADA). The author is gratifying to Gondar Agricultural Research Center, Soil and Water Management Research Directorate staff for collecting the soil samples in difficult topography.

REFERENCES

Addis, H. K., A. Klik, and S. Strohmeier. 2015. Spatial Variability of Selected Soil Attributes under Agricultural Land Use System in a Mountainous Watershed, Ethiopia. *Int. J. Geosci.* 6: 605–613.

Batchelor, W. D., B. Basso, and J. O. Paz. 2002. Examples of strategies to analyze spatial and temporal yield variability using crop models. *Eur. J. Agron.* 18: 141–158.

Birrell, S. J., K. A. Sudduth, and S. C. Borgelt. 1996. Comparison of sensors and techniques for crop yield mapping. Comput. *Electron. Agric.* 14: 215–233.

Blackmore, S. 1999. Remedial correction of yield map data. *Precis. Agric.* 1: 53–66.

Burrough, P.A., and R. A. McDonnell. 1998. Creating continuous surfaces from point data. In: Burrough, P. A., M. F. Goodchild, R. A. McDonnell, P. Switzer, and M. Worboys. (Eds.), Principles of Geographic Information Systems. Oxford University Press, Oxford, UK.

Buttafuoco, G., M. Conforti, P. P. C. Aucelli, G. Robustelli, and F. Scarciglia, 2012. Assessing spatial uncertainty in mapping soil erodibility factor using geostatistical stochastic simulation. *Environ. Earth Sci.* 66: 1111–1125.

Cambardella, C. A., T. B. Moorman, J. M. Novak, T. B. Parkin, D. L. Karalan, R. F. Turco, and A. E. Konopka. 1994. Field scale variability of soil properties in central Iowa soils. Soil *Sci. Soc. America J.* 58(5): 1501–1511.

Davis, B. M. 1987. Uses and abuses of cross-validation in geostatistics. *Math. Geol.* 19: 241–248.

De Vos, B., S. Lettens, B. Muys, and J. A. Deckers. 2007. Walkley–Black analysis of forest soil organic carbon: recovery, limitations and uncertainty. *Soil Use Manag.* 23: 221–229.

EPA, U. S. A. 2012. *Developing Spatially Interpolated Surfaces and Estimating Uncertainty*. BiblioGov.

Furrer, R., and M. G. Genton. 1999. Robust spatial data analysis of Lake Geneva sediments with S+ SpatialStats. *Syst. Res. Inf. Sci.* 8: 257–272.

Gee, G. W., and D. Or. 2002. 2.4 Particle-size analysis. Methods Soil Anal. Part 4: 255–293.

Goovaerts, P. 1999. Geostatistics in soil science: state-of-the-art and perspectives. *Geoderma* 89: 1–45.

Gotway, C. A., R. B. Ferguson, G. W. Hergert, and T. A. Peterson. 1996. Comparison of kriging and inverse-distance methods for mapping soil parameters. *Soil Sci. Soc. Am. J.* 60: 1237–1247.

Guisan, A., and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecol. Model.* 135: 147–186.

Hartkamp, A. D., J. W. White, and G. Hoogenboom. 1999. Interfacing geographic information systems with agronomic modeling: a review. *Agron. J.* 91: 761–772.

Huo, X. N., H. Li, D. F. Sun, L. D. Zhou, and B. G. Li. 2012. Combining geostatistics with Moran's I analysis for mapping soil heavy metals in Beijing, China. *Int. J. Environ. Res. Public. Health* 9: 995–1017.

Jabro, J. D., W. B. Stevens, R. G. Evans, and W. M. Iversen. 2010. Spatial variability and correlation of selected soil properties in the AP horizon of a CRP grassland. *Appl. Eng. Agric.* 26(3): 419–428.

Isaaks, E. H., and R. M. Srivastava. 1989. Applied Geostatistics. Oxford University Press, New York, 561 pp.

Kavianpoor, H., A. E. Ouri, Z. J. Jeloudar, and A. Kavian. 2012. Spatial variability of some chemical and physical soil properties in Nesho Mountainous Rangelands. *Am. J. Environ. Eng.* 2: 34–44.

Krause, P., D. P. Boyle, and F. Bäse. 2005. Comparison of different efficiency criteria for hydrological model assessment. *Adv. Geosci.* 5: 89–97.

Kravchenko, A., and D. G. Bullock. 1999. A comparative study of interpolation methods for mapping soil properties. *Agron. J.* 91: 393–400.

Laslett, G. M., A. B. McBratney, P. J. Pahl, and M. F. Hutchinson. 1987. Comparison of several spatial prediction methods for soil pH. *J. Soil Sci.* 38:325–341.

Leenaers, H., J. P. Okx, and P. A. Burrough. 1990. Employing elevation data for efficient mapping of soil pollution on floodplains. *Soil Use Manag.* 6: 105–114.

Legates, D. R., and G. J. McCabe. 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* 35: 233–241.

Li, H., and J. F. Reynolds. 1995. On definition and quantification of heterogeneity. Oikos. 73: 280–284.

Li, J., and A. D. Heap. 2008. A review of spatial interpolation methods for environmental scientists, Record 2008/23. Geoscience Australia, Canberra.

Li, J., and A. D. Heap. 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: performance and impact factors. *Ecol. Inform.* 6: 228–241.

Meijerink, A. M., H. A. de Brouwer, C. M. Mannaerts, and C. R. Valenzuela. 1994. *Introduction to the use of geographic information systems for practical hydrology*. UNESCO.

Mohr, P. A. 1963. The Geology of Ethiopia. Vol. 1, University College of Addis Ababa Press, Addis Ababa.

Moriasi, D. N., J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans ASABE* 50: 885–900.

Nalder, I. A., and R. W. Wein. 1998. Spatial interpolation of climatic normals: test of a new method in the Canadian boreal forest. *Agric. For. Meteorol.* 92: 211–225.

Naoum, S., and I. K. Tsanis. 2004. Ranking spatial interpolation techniques using a GIS-based DSS. *Glob. Nest* 6: 1–20.

Nash, J. E., and J. V. Sutcliffe. 1970. River flow forecasting through conceptual models: Part 1. A discussion of principles. *J. Hydrology* 10(3): 282–290.

Nielsen, D. R., and O. Wendroth. 2003. *Spatial and temporal statistics: sampling field soils and their vegetation.* Catena Verlag.

Olsen, S. R. 1954. Estimation of available phosphorus in soils by extraction with sodium bicarbonate.

Pandey, V., and P. K. Pandey. 2010. Spatial and temporal variability of soil moisture. *Int. J. Geosci.* 1: 87–98.

Robertson, G. P. 2008. GS+: *Geostatistics for the Environmental Sciences.* Gamma Design Software, Plainwell.

Robinson, T. P., and G. Metternicht. 2005. Comparing the performance of techniques to improve the quality of yield maps. *Agric. Syst.* 85: 19–41.

Sun, B., S. Zhou, and Q. Zhao. 2003. Evaluation of Spatial and Temporal Changes of Soil Quality Based on Geostatistical Analysis in the Hill Region of Subtropical China. *Geoderma*, **115**, 85-99. http://dx.doi.org/10.1016/S0016-7061(03)00078-8

Wang, X. J., and F. Qi. 1998. The effects of sampling design on spatial structure analysis of contaminated soil. *Sci. Total Environ.* 224: 29–41.

Watson, D. F., and G. M. Philip. 1985. A Refinement of Inverse Distance Weighted Interpolation. *Geoprocessing*, 2: 315-327.

Weber, D., and E. Englund. 1992. Evaluation and comparison of spatial interpolators. *Math. Geol.* 24: 381–391.

Webster, R., and M. A. Oliver. 2001. *Geostatistics for Environmental Scientists.* Hoboken, N.J.: John Wiley and Sons Inc.

Wei, J. B., D. N. Xiao, H. Zeng, and Y. K. Fu. 2008. Spatial variability of soil properties in relation to land use and topography in a typical small watershed of the black soil region, northeastern China. *Environ. Geol.* 53: 1663–1672.

Whelan, B.M., McBratney, A.B., Minasny, B., 2002. Vesper 1.5–spatial prediction software for precision agriculture, in: Precision Agriculture, Proc. 6th Int. Conf. on Precision Agriculture, ASA/CSSA/SSSA, Madison, WI, USA.

Wilding, L. P., 1985. Spatial variability: it's documentation, accommodation and implication to soil surveys, In: Soil Spatial Variability, Nielson, D. R. and J. Bouma (Eds.). Pudoc, Wageningen, the Netherlands, pp: 166–194.

Willmott, C. J. 1981. On the validation of models. *Phys. Geogr.* 2: 184–194.

Willmott, C. J. 1982. Some comments on the evaluation of model performance. *Bull. Am. Meteorol. Soc.* 63: 1309–1313.

Wollenhaupt, N. C., R. P. Wolkowski, and M. K. Clayton. 1994. Mapping soil test phosphorus and potassium for variable-rate fertilizer application. *J. Prod. Agric.* 7: 441–448.

Wong, D. W., L. Yuan, and S. A. Perlin. 2004. Comparison of spatial interpolation methods for the estimation of air quality data. *J. Expo. Sci. Environ. Epidemiol.* 14: 404–415.

Yao, X., B. Fu, Y. Lü, F. Sun, S. Wang, and M. Liu. 2013. Comparison of four spatial interpolation methods for estimating soil moisture in a complex terrain catchment. *PloS One* 8(1): 1–13.

Zandi, S., A. Ghobakhlou, and P. Sallis. 2011. Evaluation of spatial interpolation techniques for mapping soil pH. In: Shanmuganathan, S., and P. Sallis (Eds). MODSIM2011, 19th International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 2011, pp. 1153-1159.

Zeiler, M. 2010. *Modeling our world*: the ESRI guide to geodatabase concepts. ESRI press.

Zhou, L., Dickinson, R. E., Tian, Y., Vose, R. S., Dai. Y. 2007. Impact of vegetation removal and soil aridation on diurnal temperature range in a semiarid region: Application to the Sahel. *Proc. Natl. Acad. Sci.* 104: 17937–17942.