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Comparison of Spatial Interpolation Methods to Map Soil Chemical Properties: A Case Study in Chrey Bak Catchment, Cambodia

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Abstract: *Assessing the characteristic of soil properties is important for various purposes, especially for agriculture. The spatial distribution mapping for soil properties in Chrey Bak Catchment can be generated by geospatial analyst (Ordinary Kriging) methods with different semivariogram models: Gaussian model, Exponential model, Pentaspherical model and Hole effect model. The objectives of this study are to: (i) compare and evaluate the most accurate interpolation method for soil properties, and (ii) generate the spatial distribution mapping for soil properties such as pH, Electrical Conductivity (EC), Total Nutrient (TN), potassium (K), Total Phosphorus (TP), Soil Organic Matter (SOM), Cation Exchange Capacity (CEC). Four indicator methods, including (Residual Sum of Squares (RSS), Root Mean Squared Error (RMSE), Mean deviation or Mean error (ME) and Average Kriging Standard Error (AKSE)) were used to evaluate the most accurate interpolation method. The log transformation chosen to estimate the direction or distribution of all parameters with the directional experimental semivariograms is 55^o for all soil parameters. The nugget/sill ratio, RSS, and RMSE of Hole Effect model show the best statistical result than other models of OK interpolation method. And then, the soil properties (pH, EC, TN, K, TP, SOM, CEC) distribution mapping was plotted. These maps revealed the understanding of the soil quality in Chrey Bak Catchment.*

Keywords: Ordinary Kriging (OK); Semivariogram; Soil properties; Geospatial analysis

1. INTRODUCTION

The suitability of the soil for plant growth depends heavily on its structural properties and the nutrient concentration of the soil solution. Soil variability in the field is generally defined with classic statistical methods and is assumed to have a random variability (Parkin, 1993). Soil variability occurs as a result of the effect and interaction of various processes in the soil profile. Soil characteristics generally show spatial dependence (Cemek et al., 2007). Regionally, the closed sampling points share the similarity of its characteristics. However, the classical statistics, assuming the measured data is independent, is not capable to analyze the spatial dependency of the variables (Vieria et al., 1983).

Spatial interpolation methods offer a mean of characterizing a variety of factors or responses over different spatial scales. Characterization over different spatial scales has proven invaluable for pest, crop and soil management, and soil properties mapping (Schloeder et al., 2001).

Interpolation of sampled points is widely used in the engineering field; it is both powerful and time-saving. Soil scientists considered that soil properties vary spatially and have strong fluctuations (Trangmar et al., 1986). Geostatistical interpolation techniques such as Kriging is based on statistics and is used for more advanced prediction surface modelling that also includes some measure of the certainty or accuracy of predictions.

Geostatistical interpolation technique was used to analyze the spatial dependency of soil properties (Burgess & Webster, 1980). Numerous methods have been used for spatial prediction of soil properties. There are several studies analyzing the accuracy of interpolation for numerous methods. (Kravchenko & Bullock, 1999) compared between Normal Ordinary Kriging and Lognormal Ordinary Kriging for soil properties (pH, EC, SOM, TN, TP, K, and CEC) from 58 experimental fields.

The application of geostatistics is the prediction of attribute values at the unsampled location. Prediction is made possible by the existence of spatial dependence between observations as assessed by the correlogram or semivariogram. Modeling of the spatial distribution is a key step between description and prediction. The greater accessibility of geostatistical software has increased the risk

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that geostatistical tools are used without a good command of the underlying theory, in particular in the field of semivariogram modeling (Goovaerts, 1998).

Moreover, in several situations, inappropriate or non-optimal approaches are adopted because scientists are unaware of recent developments, such as factorial kriging, indicator geostatistics or stochastic simulation. In this study, semivariogram models were chosen such as Gaussian model, Exponential model, Pentaspherical model and Hole effect model. There are three parameters that are key features of a semivariogram model description, namely nugget, sill and range (Balasundram et al., 2008).

Given the variability of results obtained by these previous studies the research reported hereafter aims to:

- Assess the accuracy of various well-known interpolation techniques for mapping soil pH, electrical conductivity and organic matter through manipulation of the various parameters attributable to each technique;
- Determine if non-spatial statistics could assist in determining the best interpolation method to implement without using exhaustive test parameters; and
- Identify the spatial prediction method that best illustrates the spatial variability of the soil properties studied. This would enable the identification of areas where remediation is required to improve crop growth.

2. METHODOLOGY

2.1 Study Area

This study was conducted in Stung Chrey Bak Catchment located in Kampong Chhnang province, Cambodia (Fig. 1).

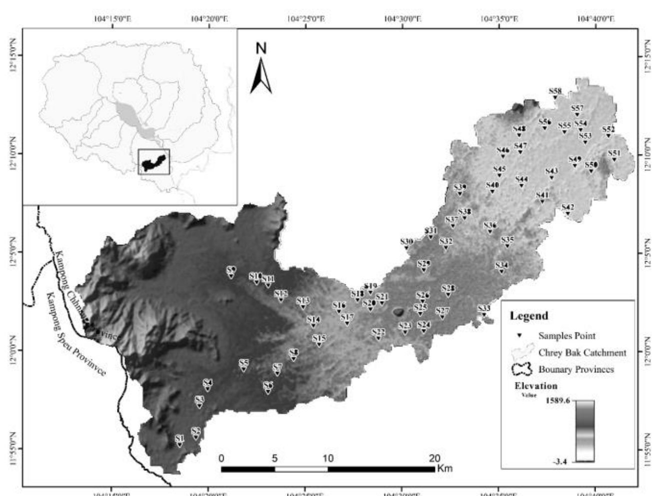

Fig.1. Geographic location of sampling points in Chrey Bak Catchment (UTM zone 48N coordinate system)

Stung Chrey Bak catchment is one of the tributaries of the Tonle Sap River (Chem et al., 2011). Soil type was divided into six main types, including Lithosols, Alluvial, Ferrasols, Argic, Histosols, and Acrisols. Obviously, 55 percent of the catchment area accounts as agricultural land, 32 percent of the catchment area accounts as forestland and 11 percent accounts as grassland (Oeurng et al., 2015).

2.2 Soil sampling and measurement

The field monitoring was conducted in October 2017 and collected a total of 58 samples through random sampling from the whole study area. The selected samples at a depth of 0-20 cm were collected from 12-15 points of sub-soil from within a diameter of 30 m (Fig.2). Then the samples were well-mixed in a bucket. Additionally, the soil samples were air dry in the laboratory for seven days at room temperature and sieved (2mm) for texture analysis. Soil parameters pH, EC (µS/cm), SOM (mg/L), TP (mg/L), TN (mg/L), K (mmol/L), and CEC (cmol/Kg) were determined using standard soil analysis methods properly.

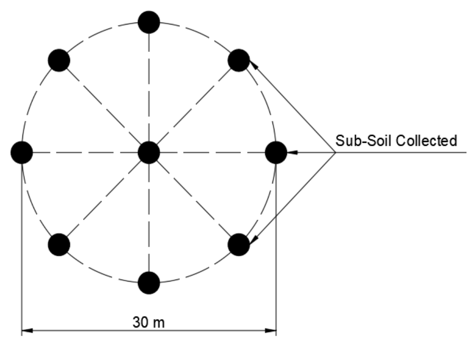

Fig.2. Sub-soil collected for soil sampling

Fig. 2 shows the elevation of the study area and sampling location. Due the difficulties to access the field, the samples were collected in the middle and downstream more than upstream.

2.3 Exploratory data analysis

This section describes the overall framework of the research. The first step is to apply the statistic method for geostatistical. The statistic method was applied to identify the most important transformation of data. The second step is to apply the semicariogram method that will find the best method for each parameter by used statistics between observe data with prediction data.

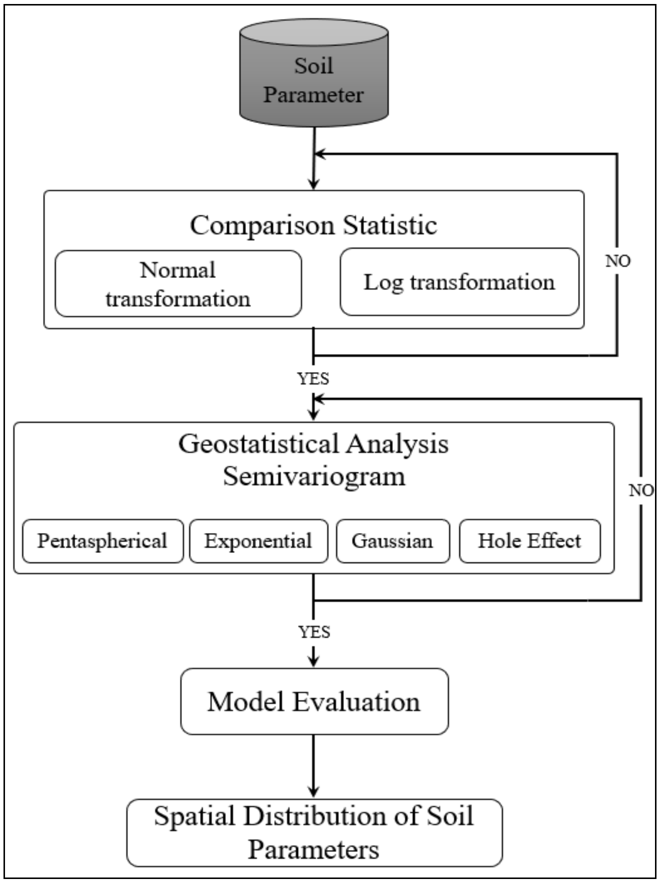

Fig. 3. Framework of Geostatistical Analysis

2.4 Visualization and exploratory data analysis

A technique applied and summarized the methods in a case study for spatial prediction and comparative evaluation of soil properties. The visual analysis by screening the data values to identify incorrect coordinate information and illogical data point. Data value description is achieved via basic summary statistics including means, medians, skewness, and Kurtosis (Robinson & Metternicht, 2006).

2.4.1 Examining the distribution of data

The different interpolation methods were tested to obtain the best result. To ensure a good result, two transformation distribution methods were used. Generally, the important features of the distribution are its central value, its spread, and its symmetry. Thus, it is important to understand the distribution (Johnston et al., 2001).
There are two proposed hypotheses to compare different interpolation methods:

- For normal distribution, there are symmetric around mean and median, both are equal.
- The coefficient of skewness is a measure of the symmetry of a distribution. For a symmetric distribution, the coefficient of skewness is zero. If is defined formally from the third moment about the mean (Webster & Oliver, 2007):

$$\text{Skewness}=\frac{1}{N}\sum_{i=1}^{N}\left[z(x_i)-\bar{z}(x_i)\right]^3 \qquad (\text{Eq.}1)$$

If a distribution has a long right tail of large values, it is positively skewed, and if it has a long-left tail of small values, it is negatively skewed. The mean is larger than the median for positively skewed distributions and vice versa for negatively skewed distributions.

- Kurtosis is based on the size of the tails of distribution and provides a measure of how likely the distribution will produce outliers. This obtained from the fourth moment about the mean:

$$\text{Kurtosis}=\frac{1}{N}\sum_{i=1}^{N}\left[z(x_i)-\bar{z}(x_i)\right]^4 \qquad (\text{Eq.}2)$$

2.5 Spatial prediction methods of Ordinary Kriging

Kriging provides a solution to the condition of estimation predicted on a continuous model of stochastic spatial variation. It creates the best existing knowledge by taking account of the way that a property varies in space through the variogram model. Ordinary kriging is by significantly the most common type of kriging in practice (Webster & Oliver, 2007). The value of experimental variogram for a separation distance of h is half the average squared difference between the value at $z(x_i)$ and the value at $z(x_i+h)$ (Lark, 2000). The following approach used exploratory analysis including examining for normality and skewness, and the data changed when necessary. Isotropic experimental semivariogram was then constructed using the following equation:

$$\gamma(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}[z(x_i)-z(x_i+h)]^2 \qquad (\text{Eq.}3)$$

Where $z(x_i)$ and $z(x_i + h)$ represent pairs of observations separated by a distance h (or lag size), n is the number of data pairs and $\gamma(h)$ is the semivariance. (Corstanje et al., 2006).

2.6 Variogram modeling

In practice, the average squared distance was obtained for all pairs separated by a range of distances and these average squares differences were plotted against the average separation distance. A theoretical model might be fitted to the semivariogram, and the coefficient of this model could be used for kriging. In this study, four existing theoretical models were used as following:

- **Gaussian model**

Other function with inverted curvature near the origin keeps coming in the geostatistical and software. For Gaussian model semivariogram expression is:

$$\gamma(h)=C\left(1-\exp\left(-\frac{h^2}{L^2}\right)\right) \quad (Eq.4)$$

C_o is the nugget variance; C is the partial sill, and C_o+C represents the amount of spatial variabsility.

- **Exponential model**

A function that is also much used in geostatistics is the negative exponential:

$$\gamma(h)=C\left(1-\exp\left(-\frac{h}{L}\right)\right) \quad (Eq.5)$$

Nevertheless, for practical purposes it is convenient to assign it an effective range, and this is usually taken as the distance at which γ(h) equals 95% of the sill variance, approximately 3L. Its slope at the origin is C/L (Webster & Oliver, 2007).

- **Pentaspherical model**

Matérn (1960), and McBratney & Webster (1986) extended the line of reasoning to obtain the five-dimensional analog of the above, the pentaspherical function:

$$\gamma(h)=\begin{cases} C\left[\frac{15h}{8L}-\frac{5}{4}\left(\frac{h}{L}\right)^3+\frac{3}{8}\left(\frac{h}{L}\right)^5\right] & \text{for } h \le L \\ C & \text{for } L < h \end{cases} \quad (Eq.6)$$

It is useful in that is curve is somewhat more gradual than that of the spherical model. Its gradient at the origin is 15c=8a.

- **Hole-Effect model**

For Hole-Effect model semivariogram expression is expressed by:

$$\gamma(h)=\sigma^2\left(1-\left(1-\frac{h}{L}\right)\exp\left(-\frac{h}{L}\right)\right) \quad (Eq.7)$$

Where σ^2>0 and L>0 and are two parameters.

2.7 Criteria for comparison

2.7.1 Residual sum of square (RSS)

The residual sum of square is a measure of the discrepancy between the data and an estimation model. A small RSS indicates a tight fit of the model to the data. The RSS between experimental semivariance data and the model by optimizing the model parameter: nugget, still and range values. The RSS can be calculated using Eq. 8.

$$RSS=\sum_{i=1}^{N}\left(z_i-\hat{z}_i\right)^2 \quad (Eq.8)$$

2.7.2 Criteria for comparison of cross-validation

Cross-validation is attained by reducing information. Generally, one observation at the same time, estimating the value at that location with the rest of the data and then computing the difference between the actual and predicted value for each and every data location. The cross-validation approach is used to choose the best variogram model among the candidate model and also to search radius and lag distance that minimizes the kriging variance (Davis, 1987).

One way of choosing between competing models is to use them for kriging and see how well they perform. Except in research studies, this would waste information, and validation is usually done by a process known as "cross-validation" (Webster & Oliver, 2007). It works as follows:

1. An experimental variogram is computed from the whole set of sample data, and plausible models are fitted to it.
2. For each model, Z is estimated from the data and the model by kriging at each sampling point in turn after excluding the sample value there. The kriging variance is also calculated
3. Three diagnostic statistics are calculated from the results

To compare different interpolation techniques, the difference between the observed data and the predicted data of all 58 sample points were analyzed using:

- Mean error or mean prediction error, ME, given by:

$$ME=\frac{1}{N}\sum_{i=1}^{N}[\hat{Z}(x_i)-z(x_i)] \quad (Eq.9)$$

- Root-mean-square prediction errors,

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}[\hat{Z}(x_i)-z(x_i)]^2} \quad (Eq.10)$$

- Average kriging standard error,

$$AKSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\sigma^2(x_i)} \quad (Eq.11)$$

Where $\hat{Z}(x_i)$ is the predicted value from cross-validation, $z(x_i)$ is the observed (known) value, and N the number of values in the dataset (Johnston et al., 2001).

The mean error should ideally be zero if the interpolation method is unbiased. The calculated ME, however, is a weak diagnostic for kriging because it is insensitive to inaccuracies in the variogram. The value of ME also depends on the scale of the data. If the model for the variogram is accurate, then the variability is accurate, then the RMSE should equal the kriging variance, so the RMSE should equal 1.

3. RESULTS AND DISCUSSION

3.1 Comparative Statistics

As a result, the skewness and kurtosis values of log transformation is smaller than a normal distribution (Table 1). Therefore, the log transformation was chosen to estimate the direction or distribution of all parameters. The soil properties differed in spatial dependence, and the most fitted directional experimental semivariograms are 55º for all soil parameters.

3.2 Comparison of Geostatistical Performance

The Pentaspherical, exponential, Gaussian and Hole effect models were fitted to the experimental variogram, and the model with the lowest RSS was chosen as optimal (Robinson & Metternicht, 2006). The comparable RSS values in Table 2 indicate that the four models are comparable. From the RSS value, the maximum likelihood is calculated for each model. A Hole Effect model has a parameter that its residual sum of squares is lower than other parameters such as pH, EC, Total N, P, SOM, CEC, and K.

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Soil properties differed in spatial dependence as shown in Fig.4. The predicted directional experimental semivariogram was fitted in the direction of 55º for each soil property. Table 2, shows the soil properties where variable characteristics were generated from the semivariogram model. The high ratio indicates that the spatial variability is primarily caused by stochastic factors, such as fertilization, farming measures, cropping systems, and other human activities. The lower ratio suggests that structural factors, such as climate, parent material, topography, soil properties, and other natural factors, play a significant role in spatial variability (Shit et al., 2016). The quantity of spatial autocorrelation was detailed by the ratio of nugget and sill, if it is smaller than 25%-75%, it indicates the system gets the medium spatial autocorrelation; if the ratio greater than 75% advised the weak spatial autocorrelation (Yang et al., 2008).

In Table 2, the nugget/sill ratio calculated from Hole effect model for pH, TN, TP, K, and CEC parameters reached the best result which means it shows the strong correlation between each location of these parameters. According to results in Table 2, the Hole Effect model had the lowest RSS value for some parameters such as pH, EC, TN, SOM, TP, and K. On the other hand, SOM and CEC, its RSS by the Exponential model is greater than Hole Effect model. Otherwise, the RMSE of Hole Effect model produced a smaller value than Exponential (Table 2). To sum up, according to the overall statistical result of these four methods for all seven parameters, the Hole Effect model is the most fitted model of OK interpolation method which provided the best performance for generating the budget soil properties distribution map in the study area.

Table 1. The result of skewness and kurtosis for seven parameters (the bold values represent the comparative statistic of skewness and kurtosis, the direction/distribution of all parameters is selected based on the small value of these indicators)

Parameters	Normally Distribution				Log transformation				Comparison
	Mean	Median	Skew.	Kur.	Mean	Median	Skew.	Kur.	
pH	6.19	6.00	1.06	3.96	1.81	1.79	**0.84**	**3.43**	Log trans.
EC	22.89	11.7	4.86	30.18	2.69	2.46	**1.18**	**4.44**	Log trans.
SOM	0.85	0.77	0.62	**2.91**	-0.35	-0.26	**-1.41**	5.59	Log trans.
Total N	0.05	0.05	4.26	26.18	-3.05	-3.01	**0.00**	**4.93**	Log trans.
P	2.83	2.24	1.57	4.44	0.75	0.80	**0.34**	**2.32**	Log trans.
K	0.32	0.13	3.31	15.26	-1.86	-2.04	**0.55**	**2.31**	Log trans.
CEC	6.16	4.70	1.72	5.89	1.60	1.54	**0.26**	**2.64**	Log trans.

Table 2. The result of statistical indicator comparison (the values in yellow and blue/green highlight represent the comparative statistic of EC and P for each geospatial model, respectively)

Model	Soil parameters	RSS	Nug	Sill	Nug./Sill	Error		
						RMSE	ME	AKSE
Pentaspherical	pH	14.686	0.007	**0.007**	1.000	0.574	0.013	0.712
	EC	**63979.782**	0.524	**0.524**	1.000	**35.019**	2.793	4.209
	SOM	3.867	0.221	0.515	**0.429**	0.504	-0.044	0.738
	Total N	0.039	0.135	0.321	0.422	**0.046**	**0.001**	0.166
	P	290.436	0.508	0.508	1.000	2.431	**0.016**	1.552
	K	14.357	1.174	1.210	0.970	0.545	0.034	0.704
	CEC	922.844	0.359	0.434	0.827	4.781	**-0.133**	2.156
Exponential	pH	13.822	0.006	**0.007**	0.954	0.5653	**0.002**	0.712
	EC	**63979.782**	0.524	**0.524**	1.000	**35.019**	2.793	4.209
	SOM	**2.366**	**0.172**	0.525	0.328	0.508	-0.035	0.702
	Total N	0.064	0.193	0.321	0.602	0.047	**0.001**	0.178
	P	290.436	0.508	0.508	1.000	2.431	**0.016**	1.552
	K	14.264	1.195	1.207	0.990	0.542	0.034	0.706
	CEC	**645.729**	0.301	0.433	0.695	4.718	-0.011	2.104
Gaussian	pH	14.355	0.006	**0.007**	0.969	**0.567**	**0.002**	0.712
	EC	64645.303	**0.510**	0.529	**0.965**	35.281	**2.513**	4.220
	SOM	7.361	0.307	0.528	0.581	0.506	**-0.053**	0.782
	Total N	0.102	0.282	0.324	0.868	0.048	0.001	0.186
	P	284.349	0.500	0.510	0.981	**2.400**	0.050	1.537
	K	13.988	1.142	1.221	0.935	0.542	0.031	0.702
	CEC	849.497	**0.350**	**0.433**	0.808	4.7184	-0.010	2.146
Hole Effect	pH	**9.821**	**0.005**	**0.007**	**0.800**	0.571	0.004	0.707
	EC	**63979.782**	**0.524**	**0.524**	1.000	**35.019**	2.793	4.209
	SOM	6.224	0.278	**0.499**	0.557	**0.485**	-0.048	0.764
	Total N	**0.027**	**0.112**	**0.317**	**0.353**	0.048	0.001	0.159
	P	**244.494**	**0.459**	**0.507**	**0.904**	2.462	0.032	0.572
	K	**7.764**	**0.744**	**1.204**	**0.618**	**0.541**	**0.017**	0.682
	CEC	933.650	0.346	0.436	**0.794**	**4.65**	-0.035	2.103

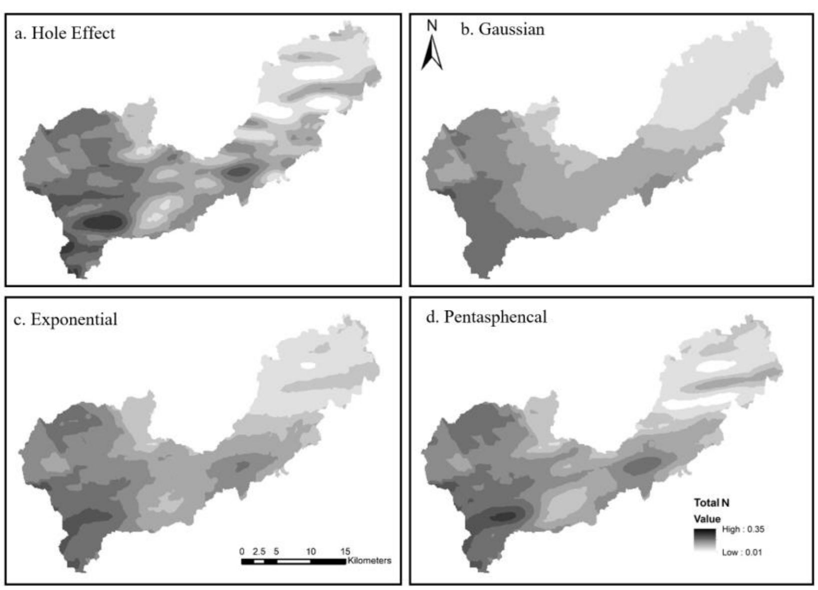

Fig.4. Comparison map of Total N

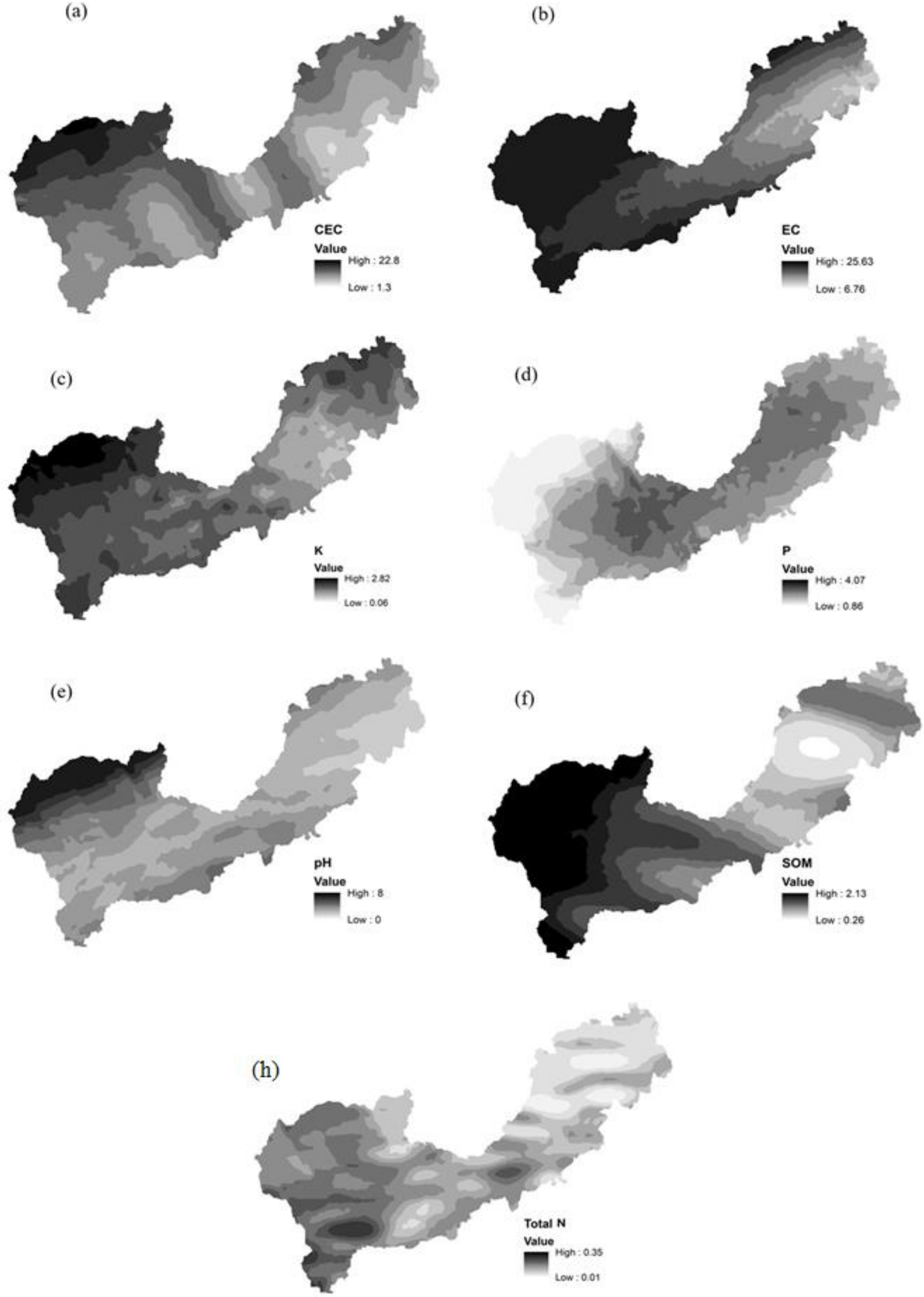

Fig. 5. The map interpolation of Hole Effect: (a). CEC, (b). EC, (c). K, (d). P, (f). pH, (g). SOM, (h). Total N

4. CONCLUSIONS

Understanding the spatial distribution and accurately mapping of soil properties at large scale is essential for precision farming, environmental monitoring, and modelling. This study showed that geostatistical model was an applicable soil interpolation method for all parameters, those are pH, EC, TN, K, TP, SOM, CEC. The OK interpolation methods are calculated for soil properties with four most commonly used mathematical models (Pentaspherical, Exponential, Gaussian and Hole Effect). The methods are evaluated using efficiency and error estimates of interpolation techniques. The efficiency is assessed by RSS, and errors are represented by the RMSE.

The geostatistical performance of soil quality parameters showed that Hole Effect model has better performance than other models. The Hole effect model is more appropriate to parameters that follows structured spatial distribution due to lithology (like pH, CEC and probably EC, TN, TP and K in the second order). SOM can be more influenced by land use and follow different pattern. In addition, the Hole Effect model is better than another interpolation model in this study area with the log transformation. However, due to the field accessibility, the sample can be collected mostly in the rice field close to the road, which does not present the variability of the parameters. Therefore, it is recommended that the sampling point selection procedure should strictly follow the grid which was assigned.

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