Characterizing, Predicting, and Mapping Soil Available Phosphor, pH, and Electrical Conductivity in Rubber Plantation Based on Three Different Methods of Ordinary Kriging in GIS Environment

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Abstract—Soils in rubber plantations have unique characteristics due to their prolonged and excessive uses. These practices have changed soil qualities, production, and the geographical distribution of soil conditions. For this reason, research on the spatial analysis of soil attributes in rubber plantations is essential. Although it is acknowledged that there are proven methods for accounting for geographical variability, their use in rubber plantations is still somewhat restricted. Evidence also demonstrates ongoing debate and variation in the findings on the capacity of methods to predict spatial variability. Therefore, the primary goal of this study is to examine how well various approaches perform when using ordinary kriging to analyze spatial variability of three soil properties: Soil Available Potassium (SAP), pH, and Electrical Conductivity. The methodology employed in this work includes (a) grid sampling for data collection, (b) interpolation using Ordinary kriging with three methods (exponential, spherical, and Gaussian), (c) mapping, and (d) evaluation. The findings of this study demonstrate that semi-variogram analysis using three distinct methods yields somewhat varied outcomes with accuracy in higher order from SAP, soil EC, and soil pH. The results of this study also show that the different methods have unique characteristics when representing spatial structure. These findings suggested that the number of samples and the selection of interpolation techniques are essential factors in studying these three soil properties and determining the accuracy of the results.

Keywords—Soils; spatial analysis; spatial variability; semi-variogram; kriging methods.

I. INTRODUCTION

Rubber plantations have caused detrimental effects on the environment. These negative effects are mainly observed in soils in monoculture rubber plantations [1]. Long-term monoculture rubber plantation has significantly deteriorated soil quality, although these effects did not affect all soil properties [2], [3]. Rubber plantation is a standard land use practice that can potentially affect plant diversity and soil properties in tropical forest ecosystems, even though the evidence is rarely found in tropical Asia. In this study, we examined the effects of these practices on soil chemical properties of a small area in Indonesia through the analyses of the spatial variability of soil properties.

Studies conducted by [4] show adverse effects) of rubber plantations on soil biodiversity (the biodiversity quality index immediately decreased after deforestation, the soil biodiversity in older rubber plantations was low, and the soil chemical properties deteriorated). The increasing and decreasing pattern of soil properties is more likely to occur in different sites than the overall area, which directs different spatial management [5]. Similar studies conducted by [6] show that the spatial variability in soil attributes (N, P, K, Ca, and Mg) affected the nutritional status and growth of the rubber tree clones, which proved that the variability maps of soil properties can be guidance for the planting and management of the rubber tree, which then providing efficient management of plants.

The study conducted by [7] claims that spatial variability results can detect the shortage and excessive of particular nutrients, which are then used for fertilizer recommendation. These studies show that although there are similar conditions for rubber plants, the characteristics of soil properties could differ in magnitude and direction. As a result of this, the study conducted by [8] has endeavored to establish site-specific management zones based on the variability of soil and environmental properties (pH, organic matter, total nitrogen, soil available phosphorus, available potassium, and ecological

variables, namely parent materials, elevation, slope, aspect, mean precipitation, mean temperature, normalized difference vegetation index /NDVI) on rubber plantation land.

Some studies have shown that better soil quality has occurred because of the increase in the age of rubber plants [9]. Another study conducted by [2] indicates that there have been both negative and positive effects on rubber plantation on soil quality. Moreover, there are significant spatial differences in soil quality in rubber plantations [10]. The intrinsic and management factors are believed responsible for changes in different locations.

Interpolation was conducted to display the spatial variability. Interpolation as the method for estimating the values of un-sampled locations from sampled locations [11]–[16] has been prominently used in previous studies [17], [8]. However, it is evidence that the studies are rarely found in elaborating interpolation methods for soil properties in a rubber plantation. Therefore, spatial variability of soil properties is considered an important variable for the management of rubber plantations. Although there have been significant studies accounting for spatial variability, it is very rarely those focusing on how accurately the variability is portrayed. In other words, there have been a limited number of studies accounting for the accuracy assessment of interpolation results in rubber plantations.

For site-specific nutrient management, accuracy issues become critical since the soil is a very dynamic spatial object. Although different interpolation methods do exist, there is no universal one that can be applied to any conditions, and the choice of interpolation depends mainly on the nature of the phenomena and the characteristics of the data [18]. Different spatial interpolation methods resulted in different soil properties being accurately interpolated [19]. Geostatistical techniques have a substantial role in examining how soil fertility qualities vary in other areas [20]. These techniques have been applied in a wide range of disciplines, and the most prominent one is in the study of soil variability [16], [21]–[23].

Numerous research studies have been conducted on geostatistics; however, there is still a great deal of variation in the results. Besides, there also exists significant debate over the best methodologies or techniques and procedures for use when examining spatial variability in detail by using Kriging and how it affects accuracy [24]–[26]. For this reason, this study aims to assess the accuracy of methods for mapping the spatial variability of soil properties in rubber plantation land. Special attention will be provided to three methods in Kriging spatial interpolation (Spherical, exponential, and Gaussian). These three Kriging methods are commonly used in the pure Kriging study and their applications with various results and accuracy. This study's results are expected to contribute to the knowledge and techniques for evaluating the accuracy of the prediction and the mapping of three soil properties (pH, soil available Phosphor, and soil Electrical Conductivity).

II. MATERIALS AND METHODS

A. Preparation

The research was carried out by surveying the study area to determine the terrain conditions at the location. The location identification survey was carried out while tracking with the Global Positioning System (GPS) using Universal Transfer

Mercator UTM) projection. Tracking is carried out to determine the boundaries of the study area, which are then entered into the Geographical Information Systems (GIS). The GIS software used was ArcGIS 10.1. Figure 1 shows the study area, which is located in East Java, Indonesia. This area is the subset of a more extensive area of Rubber plantations. This stage includes the determination of the soil sample's locations for further analysis.
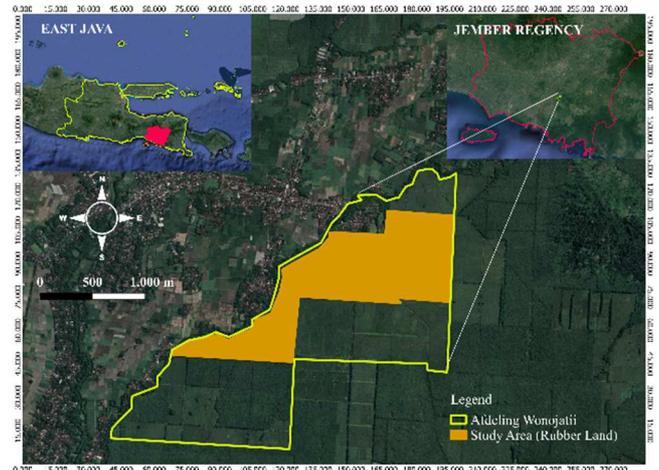
Fig. 1 The Study area

B. Sampling

Soil samples were taken using grid sampling, with 200 meters between samples. The study area is considered flat, and there is homogenous crop management throughout. Figure 2 shows the distribution of soil samples in the study area. As can be seen, 33 sample points were used in this study.
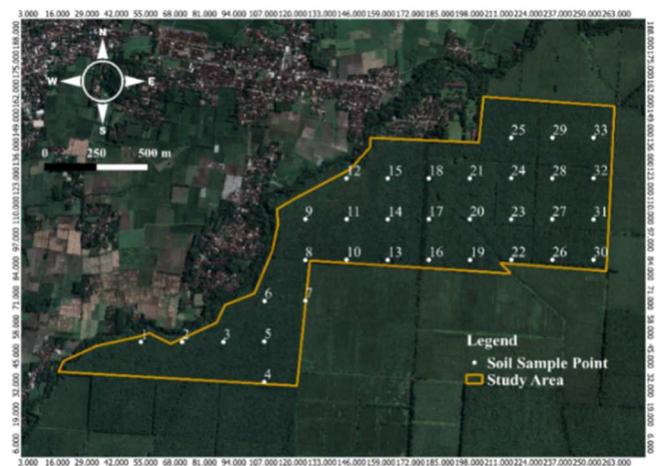
Fig. 2 The distribution of soil samples in the study area

Soil sampling was carried out by digging the soil at 30–40 cm depth. These soil samples were then put into a plastic bag and labeled according to the coordinates of the soil samples. The soil samples obtained were then analyzed in the laboratory using three parameters: soil available phosphorus, pH, and electrical conductivity (EC). The soil available Phosphor (SAP) analysis used the Olsen method, while pH was analyzed using a pH meter. Electrical conductivity (EC) was analyzed using an EC meter.

C. Data Processing

The results of the laboratory analysis were then input into ArcGIS software 10.1. Then, further analysis was conducted using the ordinary kriging interpolation method. The semivariogram models used were spherical, exponential, and Gaussian. Then, the accuracy assessment was performed on the maps produced. The following are the formulas used in each semi-variogram model [27]:

$$y(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(xi) - z(xi + h)]2 \qquad (1)$$

The value of the single sample found in the research area at the [i]th location is represented by z(xi) in the equation above, where n is the number of pairs of samples separated by the interval h. The theoretical models (Gaussian, exponential, and spherical) are evaluated on an experimental semi-variogram to select the best-fit model utilizing data. When doing the variogram best fit, nugget effects are set to zero (modeling without nugget effects and it must be ensured that the model closely matches the experimental values. In the equation above, n stands for the number of pairs of samples separated from the interval h, and z(xi) represents the value of the single sample located in the study area with the [i]th position. The theoretical models (Gaussian, exponential, and spherical) are assessed on an experimental semi-variogram to choose the best fit model using data. When doing the variogram best fit, it must be ensured that the model closely matches the experimental values. Formulas (2), (3), and (4) are for Exponential, Spherical, and Gaussian, respectively [14].

Exponential Semi variogram:

$$y(h) = \begin{cases} 0 & h = 0 \\ C_0 + C\left[1 - \exp(-\frac{h}{a})\right] & h > 0 \end{cases} \qquad (2)$$

Spherical Semi variogram:

$$y(h) = \begin{cases} 0 & h = 0 \\ C_0 + C\left(\frac{3h}{2a} - \frac{1h^3}{2a^3}\right), & 0 < h \le a \\ C_0 + C & h > a \end{cases} \qquad (3)$$

Gaussian Semi variogram:

$$y(h) = \begin{cases} 0 & h = 0 \\ C_0 + C\left[1 - exp\left(-\frac{h^2}{a^2}\right)\right], & h > 0 \end{cases} \qquad (4)$$

where a is a range, C is partial sill, C0 is undetermined coefficients, and the sampling interval h is an independent variable. The Moran index is used to show the relationship between one sample and other samples around it with the following formula [26]:

$$I = \frac{N\Sigma_i\Sigma_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\Sigma_i\Sigma_j w_{ij})\Sigma_i(x_i - \bar{x})^2} \qquad (5)$$

where: I = Moran index, N = number of samples, w_{ij} = the matrix of the spatial weight, x_i = value of sample i, x_j = value of sample y and $\bar{x}$ = average value of variable x. The spatial reference unit and the attribute feature values of surrounding spatial units can be compared or correlated using the Moran's I index, whose value ranges from -1 to 1. When Moran's index is larger than 0, there is a positive autocorrelation, according to this formula. Otherwise, it suggests a negative autocorrelation. If the Moran's I index is close to 0, this indicates the absence of spatial autocorrelation [28], [11]. Moran's index is also supported by a random probability value (p-value). P-value is useful for seeing the normal distribution of data.

To error assessment, RMSE was used. Data is said to be accurate if it has the smallest RMSE value. RMSE values are 0 to ∞. The RMSE formula is as below [29], [30]:

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(p_i - a_i)^2}{n}} \qquad (6)$$

where: p_i = the value of the basic simulation result of the observation variable, a_i = the actual value of the observation variable, n = the number of observations.

Finally, the data is then displayed in the form of interpolated maps of soil available-P, pH and EC at an appropriate scale. The map is marked with different colors which will make it easier for the reader to distinguish the distribution of soil available-P, pH and EC nutrient distribution status in the study area.

III. RESULT AND DISCUSSION

A. The characteristics of Soil Properties

Table 1 shows the values of thirty-three samples of SAP, pH and soil EC at the study area. As can be seen, SAP has a minimum value of 4.14, a maximum value of 42.15, the mean of 14.68, a median of 12.33, a mode of 12.33 and a standard deviation of 8.44. The results of available-P values varied widely from 4.14–42.15 ppm. Three soil samples with very low criteria, nine samples with low criteria, ten samples with medium criteria, five samples with high criteria and six samples with very high criteria. The entire rubber plantation area has moderate SAP, ranging from 11.57 to 15.31 ppm. Soil pH has a minimum value of 4.0, a maximum value of 6, the mean of 4.71, a median of 4.8, a mode of 4.8 and a standard deviation of 0.43.

TABLE I
THE RESULTS OF LABORATORY ANALYSIS OF SOIL AVAILABLE P, PH AND SOIL EC

Sample Point	Soil available P (ppm)	Classified P	pH	Classified pH	EC (dS/m)	Classified EC
1	4.49	Very low	4.5	Very Strong Acid	0.021	Non-Saline
2	14.42	Medium	4.4	Broad Ordinary Acid	0.031	Non-Saline
3	12.92	Medium	4.4	Extremely Acid	0.022	Non-Saline
4	9.18	Low	4.4	Extremely Acid	0.022	Non-Saline
5	16.55	High	4.8	Very Strong Acid	0.025	Non-Saline
6	24.32	Very high	4.5	Very Strongly Acid	0.03	Non-Saline
7	30.45	Very high	4.3	Extremely Acid	0.038	Non-Saline
8	4.14	Very low	5.0	Very Strong Acid	0.023	Non-Saline
9	16.07	High	5.3	Strongly Acid	0.031	Non-Saline
10	11.57	Medium	4.2	Extremely Acid	0.022	Non-Saline
11	42.15	Very high	4.8	Very Strong Acid	0.038	Non-Saline
12	19.05	High	4.0	Extremely Acid	0.025	Non-Saline

Sample Point	Soil available P (ppm)	Classified P	pH	Classified pH	EC (dS/m)	Classified EC
13	12.39	Medium	4.6	Very Strong Acid	0.027	Non-Saline
14	8.38	Low	4.8	Very Strong Acid	0.023	Non-Saline
15	23.44	Very high	4.8	Very Strong Acid	0.031	Non-Saline
16	9.59	Low	5.0	Very Strong Acid	0.023	Non-Saline
17	10.95	Medium	4.2	Extremely Acid	0.025	Non-Saline
18	15.31	Medium	4.8	Very Strong Acid	0.023	Non-Saline
19	29.1	Very high	4.5	Very Strong Acid	0.044	Non-Saline
20	4.23	Very low	4.1	Extremely Acid	0.022	Non-Saline
21	8.35	Low	5.2	Strongly Acid	0.019	Non-Saline
22	11.62	Medium	4.8	Very Strong Acid	0.023	Non-Saline
23	8.65	Low	5.2	Strongly Acid	0.035	Non-Saline
24	8.97	Low	4.8	Very Strong Acid	0.02	Non-Saline
25	7.15	Low	4.6	Very Strongly Acid	0.019	Non-Saline
26	29.51	Very high	4.2	Extremely Acid	0.036	Non-Saline
27	11.6	Medium	5.1	Strongly Acid	0.02	Non-Saline
28	9.8	Low	4.8	Very Strongly Acid	0.032	Non-Saline
29	12.98	Medium	4.8	Very Strongly Acid	0.027	Non-Saline
30	8.85	Low	5.6	Slightly Acid	0.033	Non-Saline
31	17.96	High	6.0	Slightly Acid	0.023	Non-Saline
32	17.96	High	4.5	Very Strong Acid	0.02	Non-Saline
33	12.33	Medium	4.6	Very Strong Acid	0.022	Non-Saline

The range values of soil pH from 4–6 and consisted of 4 criteria, namely six samples (extremely acid criteria), twenty-one samples (very strongly acid), four samples (strongly acid) and two samples (moderately acid). Therefore, rubber plantation land in the study area is dominated by very strongly acidic soil pH, with the range of pH values is 4.5–5. Soil EC has a minimum value of 0.019, a maximum value of 0.044, an average of 0.027, a median of 0.023, a mode of 0.023 and a standard deviation of 0.006. The overall results of the analysis show that the rubber plantation soil in the study area is a non-saline soil with an EC value <0.7 dS/m. Based on these characteristics, it is clear that the study area shows varying values of SAP, pH, and soil EC in thirty-three samples and the plantation has moderate SAP, highly acidic pH, and non-saline soil, proving that his condition is suitable for rubber plantation. The next step is finding the spatial pattern of the three soil properties in the study area.

Table 2 shows the results of spatial pattern analysis of three soil properties using Moran Index. As shown, the results of Moran indices confirm that the spatial pattern of point data of three soil properties is not significantly different to random. In other words, randomness, and lack of spatial autocorrelation. Lack of spatial autocorrelation refers to the absence of a relationship between the values of a variable and their spatial locations. As can be seen in Table 2, the values of Moran indices were: -0.054 (SAP), 0.100 (Soil pH) and -0.218 (Soil EC). The negative values indicates that adjacent data values tend to show the contrasting values, whereas positive ones relate to the similarity of values of samples in closer distances [30].The

results of Moran analysis show that SAP and Soil EC have different characteristics of values between adjacent locations of soil samples. In contrast, pH is likely to have similar values amongst sample locations.

TABLE II
RESULTS OF MORAN INDICES OF THREE SOIL PROPERTIES

No	Soil Property	Indicator (S)	Value	Result
1	Soil Available Phosphor	Moran index	-0.054	Not significantly different from random
		Variance	0.018	
		Z-Score	-0.170	
		P Value	0.864	
2	Soil pH	Moran index	0.100	Not significantly different from random
		Variance	0.019	
		Z-Score	0.947	
		P Value	0.343	
3	Soil EC	Moran index	-0.218	Not significantly different from random
		Variance	0.019	
		Z-Score	-1.326	
		P Value	0.185	

B. Semi variogram of Soil Available P, pH, and EC

Figure 3 shows the semi-variogram of soil available Phosphorus, pH, and EC, which are selected for those three soil properties for every kriging method, while Table 2 shows the summary of the variogram properties for each soil property.
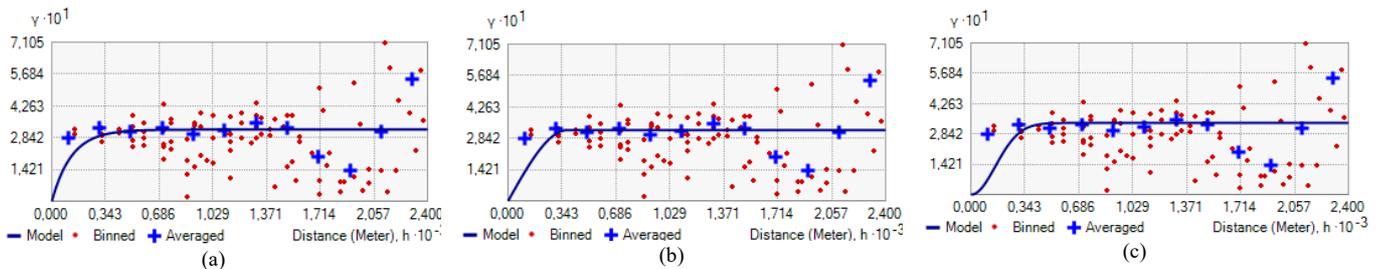
Fig. 3 Semivariograms of Soil Available-Phosphor for (a) Exponential, (b) Spherical and (c) Gaussian

As can be seen in Figures 3, 4, and 5, there are different patterns of semivariogram of each soil property. This distinct pattern is expected due to the various ways of representing spatial structure. These figures also show that although different patterns are observed, similarities also occur. As can be seen in Figure 4, pH is the only soil property that best fits the empirical semivariogram. On the other hand, soil EC and SAP seem to have deviations, which is mainly due to the nature of the data. As previously described, a higher standard deviation was observed in SAP than in other soil properties (pH and EC). Table 3 shows the values of semivariogram components: nugget, sill, and range.
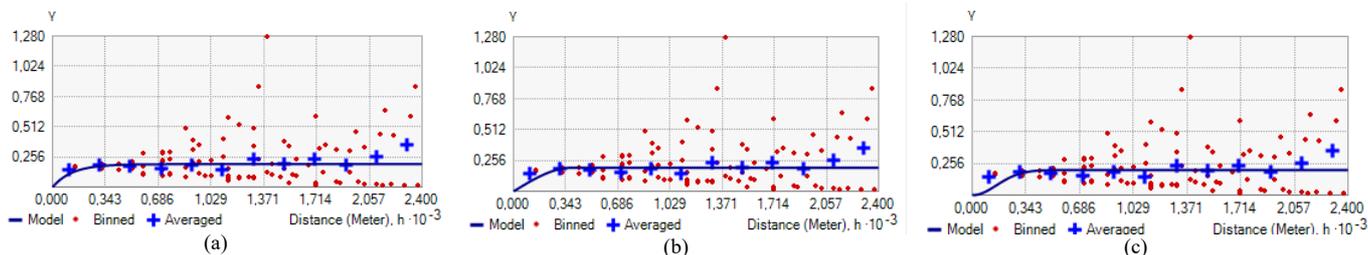
Fig. 4 Semivariograms of Soil pH for (a) Exponential, (b) Spherical and (c) Gaussian
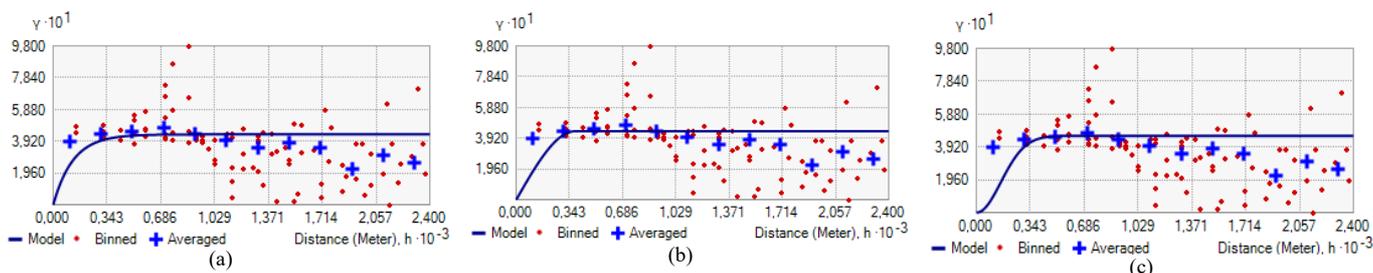
Fig. 5 Semi variograms of Soil EC for (a) Exponential, (b) Spherical, and (c) Gaussian

As can be seen in Table 3, the nugget effect is set to nil (modelling without nugget effect is not shown in the table), the differences are on the sill, while the range values are the same for every soil property and for all semi-variogram models.

TABLE III
SEMI-VARIOGRAM COMPONENT OF THREE SOIL PROPERTIES

Soil Properties	Semi variogram Model	Semi variogram Component	
		Sill	Range
SAP	Exponential	0.321	378.118
	Spherical	0.322	378.118
	Gaussian	0.336	378.118
pH	Exponential	0.195	378.118
	Spherical	0.195	378.118
	Gaussian	0.203	378.118
EC	Exponential	0.435	378.118
	Spherical	0.437	378.118
	Gaussian	0.458	378.118

The leading cause of this can be attributed to the differences in representing spatial structure used in the model. As Table 3 shows, pH is the soil's properties that have stronger spatial dependencies than the others (smaller values of sills than the other two soil properties). On the other hand, the highest values of sill were found in soil EC for all semi-variogram models used, proving that there exists little spatial autocorrelation amongst soil samples, as also evidenced by the analysis of Moran indices. This shows that SAP, pH, and EC are highly variable in space, which potentially affects crop production [31],[32] claims that the range in the Gaussian and exponential models could exceed the provided in Table 3 because they do not the valid ranges.

C. The Results of Interpolation

Table 4 shows the differences between the interpolated and the original data of three soil properties, showing the variability of accuracy due to data characteristics. As can be seen, there are differences between original and interpolated values of SAP, soil pH, and soil EC. Considering the maximum values, it is apparent that the Gaussian model tends to overestimate the values, while others (exponential and spherical) generally underestimate the original data. For the soil properties of SAP and pH, the minimum values seem to be overstated by three semi-variogram models. An interesting difference is observed for the maximum values of SAP for Gaussian model which tends to overestimate maximum values, resulting in significant errors compared to exponential and spherical kriging. EC shows the least differences, possibly because of its lower standard deviation (0.006) and positive Moran Index compared to pH (0.43) and SAP (0.56). This shows that the characteristics of data are the factors determining the accuracy of interpolated values of soil properties. This agrees with previous studies [19], [20] claiming that data characteristics determine accuracy of interpolated soil property values, with smaller sill resulting in smaller RMSE, as observed in pH. As Table 4 shows, the values of RMSE also show a similar pattern, in that SAP is having much higher RMSE compared to those in pH and EC. This shows that for the soil properties having smaller sill (as shown in table 3), it is most likely to result in smaller RMSE. This clearly evidence that the spatial structure determine the accuracy of interpolated values [33],[34].

TABLE IV
THE DIFFERENCES OF INTERPOLATED AND THE DATA VALUES

Soil Properties	Semi variogram Model	Data Values		Interpolated Values		Differences		RMSE
		Min	Max	Min	Max	Min	Max	
SAP	Exponential	4.14	42.15	4.320	41.445	-0.180	0.705	9.292
	Spherical			4.224	41.879	-0.084	0.271	9.808
	Gaussian			3.858	44.485	0.282	-2.335	11.22
pH	Exponential	4.0	6.0	4.018	5.963	-0.018	0.037	0.465
	Spherical			4.007	5.988	-0.007	0.012	0.442
	Gaussian			3.929	6.143	0.071	-0.143	0.425
EC	Exponential	0.019	0.044	0.019	0.043	0	0.001	0.737
	Spherical			0.018	0.044	0.001	0	0.863
	Gaussian			0.016	0.046	0.003	-0.002	1.064

D. Distribution of Soil properties

The spatial variability maps are useful for finding out how soil properties have changed spatially between fields [35]. Changes of variability of a soil property could lead the management of that soil. The following figures (Figure 6, 7 and 8) show the distribution of soil available P, soil pH and soil EC in the study area, respectively. As can be seen in these figures, there do exist the similarities in the patterns of the distributions modelled using three different methods of kriging (exponential, spherical and Gaussian), although different pattern of spatial distribution does exist for each soil property. SAP, for instance, provides similarities in the maps produced by using exponential, spherical and Gaussian. This similar pattern of spatial distribution also occurred for soil pH and soil EC.
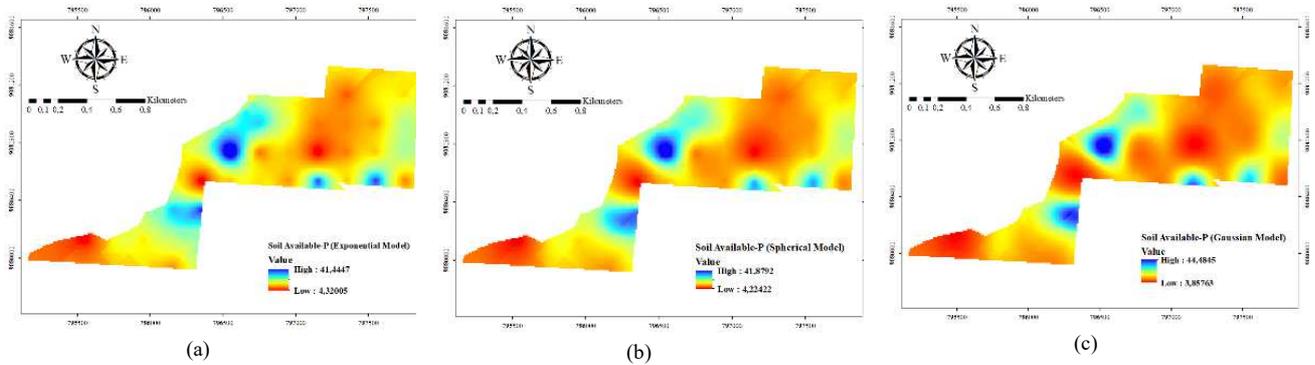
Fig. 6 Interpolated values of soil Available-P using (a) Exponential, (b) Spherical and (c) Gaussian

As can be seen in Figure 6, the high and low values of SAP occur in the same locations, with the high values (blue color) distributed in the Northwest, Southeast and Southwest parts of the study area. Most of the SAP is in the low to medium categories. The high value of SAP may be attributed to the localized practices of fertilizer application. This pattern of SAP clearly shows that for the purpose of rubber management, the addition of P fertilizers is urgently required.

Spatial distribution of pH is different to SAP. The distribution of soil pH tends to be spotty amongst low and large values (Figure 7). A particular attention is the high values of pH in the middle part of the study area. Smooth surface of high values in this middle area is observed in the map resulted from Gaussian model. On the other hand, comparing the results of exponential and spherical, smoothing seems to be more prominent in spherical. This clearly shows that the smoothing effects of kriging methods become higher in the order from exponential, spherical and Gaussian, although this may not perform in the entire study area [36]. The previous arguments made evident how important maps are for revealing information about the spatial variability of soil characteristics. This variability has the implication on the future soil management [25]
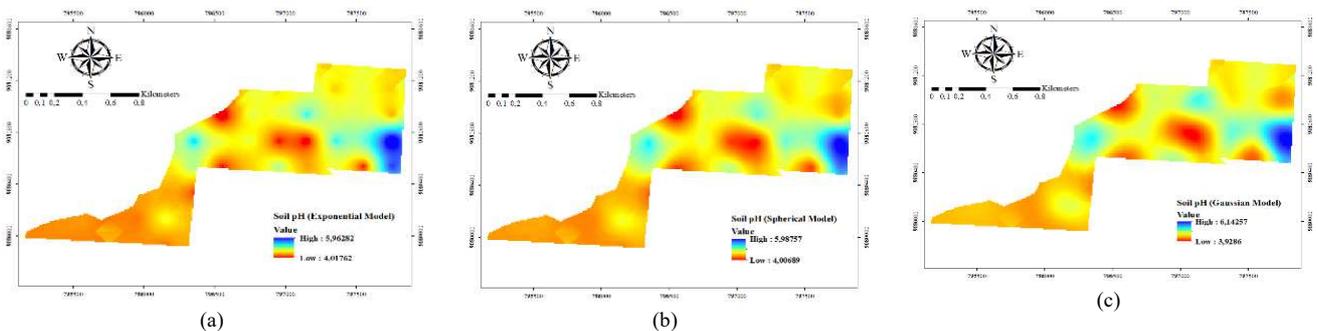
Fig. 7 Interpolated values soil pH using (a) Exponential, (b) Spherical and (c) Gaussian

Figure 8 shows the spatial distribution of soil EC. As shown, similarity was found for soil EC distribution resulted from exponential, spherical and Gaussian methods. A minor difference was observed in the low values (lower part of the study area with blue color). This may due the effect of smoothing in Gaussian method [37]. Overall, the results provide the evidence that the spatial distribution of soil properties depends on intrinsic and management factors [21]. Intrinsic factors relate to soil forming processes, while the management component relates to the management of rubber plantation land. In relation to intrinsic factors, the study area is most likely to have similar soil forming factors, because the study area is small area having relatively homogenous topography, climate, parent material, and soil age (time).

(a)   (b)   (c)
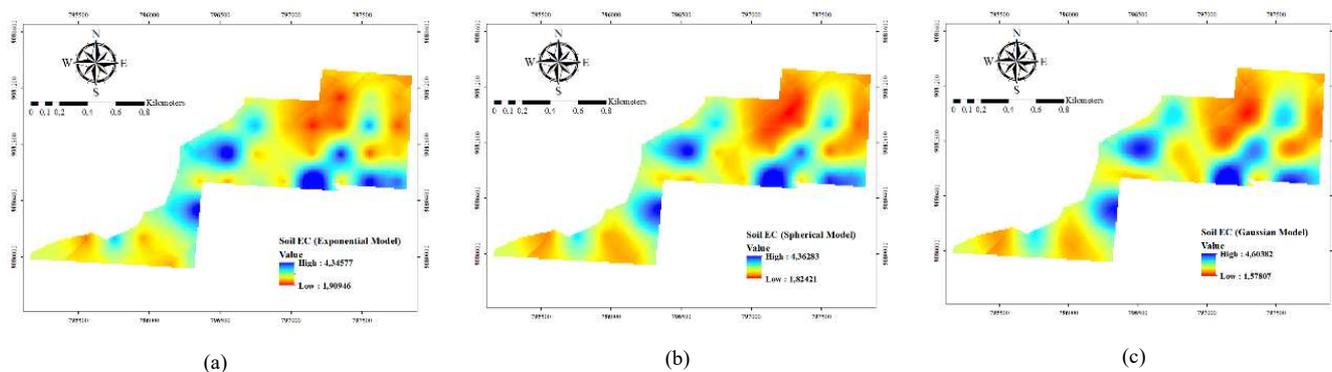
Fig. 8 Interpolated values of soil EC using (a) Exponential, (b) Spherical, and (c) Gaussian

The result of texture analysis shows that the percentage ranges of texture components are 29.5%-20.7% (sand), 10%-20.78% (silt), and 41.5%-55.9% (clay). This textural composition shows that all samples were categorized as having clay soil texture. Clay texture in the study area seems to be an important factor responsible for the similarity of the pattern observed. Considering this, it can be argued that the study area would provide a strong spatial dependence because texture is theoretically the main property determining other soil properties, but this does not occur in the study area. Although Kriging is a spatial interpolation that can provide accurate estimates [18], [38], and [39], the results show that this does not occur for SAP. Indeed, the spotty pattern of maps may be attributed to the management factor. The management of rubber plants, particularly the fertilization practices, is the most likely factor contributing to the differences in spatial patterns.

IV. CONCLUSION

The results of this study show that based on the values of RMSE, kriging with three different methods is quite capable of providing accurate predictions of pH and soil EC, although this is not the case for SAP. This does not mean that kriging is not an appropriate interpolation for the study area. Still, the number of samples, the configuration of samples, and the variability of management of rubber plantation may need attention. This means that although kriging is applied for the small study area, the number of soil samples must be able to provide appropriate spatial autocorrelation. Otherwise, the results of interpolation would be poorly displayed. This research also shows that there may be smaller variations in the data, and increasing the number of samples potentially leads to an improvement in accuracy in the prediction. Therefore, adding the number of samples in the study area could improve accuracy.

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