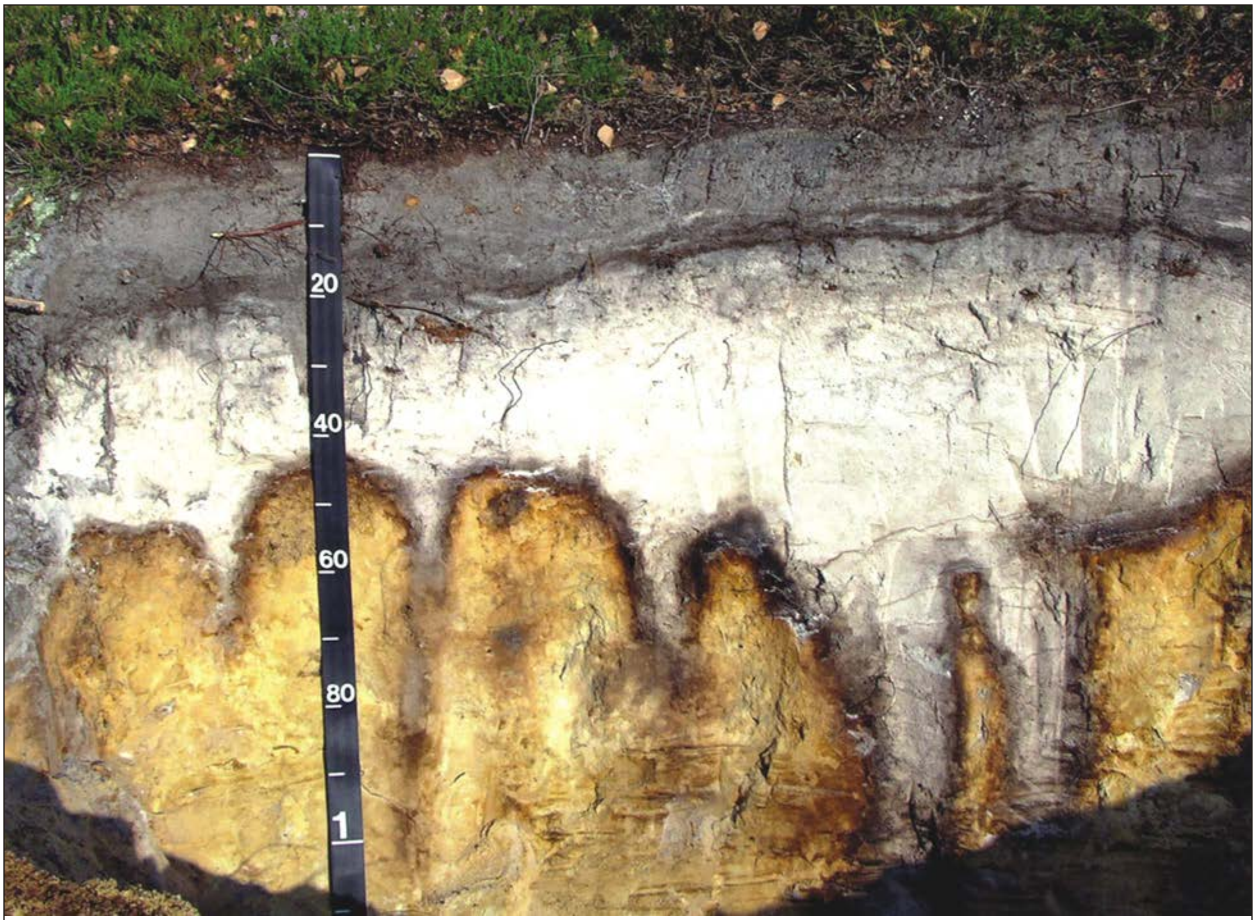

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Spatial Variability of Soil Organic Carbon in Oil Palm

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Abstract: This study aimed at quantifying the spatial variability of SOC and estimating SOC concentration in oil palm. This study was carried out in a commercial oil palm plantation bearing 27 year old palms. A systematic design was employed for soil sampling at the 0-20 cm depth based on a cluster of 4 palms that included three operational areas Weeded Circle (WC), Frond Heap (FH) and Harvesting Path (HP). A total of 60 sampling clusters were established. SOC was analyzed using dry combustion method. All measurement points were geo-referenced by a differential Global Positioning System (dGPS). The SOC data were first explored using descriptive statistics, normality check and outlier detection. This followed by variography and interpolation techniques to quantify the spatial variability of SOC. Results showed that all three operational areas exhibited a definable spatial structure and were described by either spherical or exponential models. SOC from WC and HP showed moderate spatial dependence while that from FH showed a strong spatial dependence. The FH had a shorter effective range than other operational areas. Contour maps for WC, FH and HP clearly showed spatial clustering of SOC values. All three operational areas fulfilled the interpolation accuracy criteria. This study suggests that site-specific management could be considered as a strategy to increase SOC sequestration in oil palm.

Key words: Soil organic carbon, spatial variability, oil palm, operational areas, site-specific management, carbon sequestration

INTRODUCTION

The release and sequestration of carbon (C) has received much attention due to its potential impact on global warming. In terrestrial ecosystem, soil plays an essential role in global carbon balance because the C stored in soil is estimated to be four times greater than the total available in living vegetation and its ability to offset greenhouse gas emissions through C sequestration (Lal, 2004). Soil C sequestration is one of the mitigative strategies for minimizing the effects of global warming. Therefore, sequestration of atmospheric carbon in soil is the best long term option for C storage in terrestrial ecosystem (Hutchinson *et al.*, 2006; Follett, 2001; Follett *et al.*, 2001).

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Soil Organic Carbon (SOC) is the main form of sequestered C in the soil and it is related to the proportion of Net Primary Productivity (NPP) returned to the soil (Follett *et al.*, 2001). Processes leading to SOC sequestration include humification, aggregation and translocation of C into the sub-soil. Hence, C sequestration in forest and cultivated soil are potentially offsetting a large portion of CO_2 emitted to the atmosphere (Lal, 2005; Conant *et al.*, 2003; Lal, 2001). Like other soil properties, SOC levels exhibit variability and are known to be influenced by many factors, including climate, vegetation, precipitation, soil physical characteristics, land use changes, topography. These factors typically exhibited spatial variability (Conant *et al.*, 2003; Conant and Paustian, 2002).

In the past, many studies have been focused on the estimation and mapping of soil carbon pools (Wilding *et al.*, 2001). Indeed, measuring spatial variability of SOC is crucial for quantifying the distribution of SOC in order to refine agricultural management strategies that promote sustainable land use. Additionally, spatial variability assessment provides a valuable base against which subsequent and future measurements can be evaluated (Liu *et al.*, 2006). Moreover, it has a potential for faster and more efficient detection of SOC differences, particularly in large areas of cultivated soil (Kravchenko *et al.*, 2006). To study the spatial distribution patterns of SOC, classical and geo-spatial statistical techniques have been widely employed (Jian-Bing *et al.*, 2006; Zhang and McGrath, 2004; McGrath and Zhang, 2003; Chevallier *et al.*, 2000). Geo-spatial statistics are based on the theory of regionalized variable (Webster and Oliver, 2007). It provides advanced tools to quantify the spatial features of soil parameters and to perform spatial interpolation (Liu *et al.*, 2006).

Oil palm, a primary perennial plantation crop in Malaysia has a high potential for soil C sequestration due to its large-scale planting and large biomass production. The total oil palm acreage in 2008 was 4.48 million hectares, an increase of 4.3% as compared to the previous year (Mohd-Basri, 2009). Oil palm biomass consists of Empty Fruit Bunches (EFB), fiber, shell, felled palm trunk, fronds and palm kernel. Shuit *et al.* (2009) stated that total oil palm biomass collected in 2005 was 55.73 million tonnes, where EFB, fiber, shell, trunk and frond and palm kernel contributed to 17, 9.6, 5.9, 21.1 and 2.1 million tonnes, respectively. Below ground oil palm biomass, mainly oil palm root biomass, contributed 20 to 40% of above ground biomass (Henson and Chai, 1997). Thus, large-scale planting and large biomass production of oil palm plantation could contribute to soil C sequestration. However, the amount of soil C sequestration in oil palm plantation is inadequately understood and quantified. As such, the potential of soil C sequestration in oil palm has generated a keen interest for SOC detection. Detection of SOC in oil palm requires precise measurement due to changes in SOC caused by land management practices. Spatial variability assessment of SOC in oil palm should be considered in order to quantify the spatial distribution of SOC as influenced by management practices. Thus, in this study, we investigated the spatial variability of SOC and estimated the total SOC in oil palm cultivation.

MATERIALS AND METHODS

This study was conducted in a commercial oil palm plantation located at Port Dickson, Negeri Sembilan, Peninsular Malaysia. This trial was conducted between November 2007 and January 2008. A site bearing palms that were 27 Years After Planting (YAP) was selected for sampling. The study site is geographically located at 02°37' North and 101°49' East and has a total planted area of 48 ha. The total sampling area was about 4.2 ha. The site comprised highly-weathered Renggam Series soils (Typic Kandiudults), with a gently sloping to undulating topography (0-4% slope). The oil palm stand had a planting density of 145 palm ha^{-1}, with palms spaced in a triangular pattern at a distance of 9.1×9.1×9.1 m. The annual rainfall ranges between 1700 and 2100 mm.

A systematic design was employed for soil sampling at the 0-20 cm depth based on a cluster of 4 palms (a, b, c and d) that included three operational areas as shown in Fig. 1, Weeded Circle (WC), Frond Heap (FH) and Harvesting Path (HP). A total of 60 sampling clusters were established. Within each cluster, soil samples were obtained from three operational areas using a core auger. Sampling points at the WC were 0.6 m apart from the palm base (a), while sampling points at the FH and HP were both 4.0 m apart from palm base (b and d).

Soil samples were air-dried, ground and sieved to pass through a 1 mm sieve. Soil samples were analyzed for pH in 1:2 soil: water suspension, total Nitrogen (N) using the Kjeldahl method (Bremmer and Mulvaney, 1982), available Phosphorus (P) using the Bray II method (Olsen and Sommers, 1982), exchangeable Potassium (K), Calcium (Ca) and Magnesium (Mg) using 1N NH_4OAc followed by atomic absorption spectrometry and Cation Exchange Capacity (CEC) using the leaching method (Thomas, 1982). A core sampler was used for soil bulk density determination. Soil texture was determined by the pipet method (Gee and Bauder, 1986). Soil samples were analyzed for total C by dry combustion method (Nelson and Sommers, 1982) using a LECO CR-412 carbon analyzer. Since, $CaCO_3$ contribution was minimal, the results were interpreted as SOC. All measurement points were geo-referenced using a differential Global Positioning System (dGPS). The chemical and physical characteristics of the soil used in this study are given in Table 1.

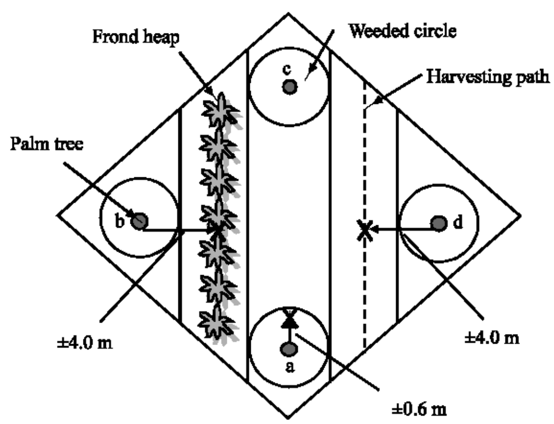

Fig. 1: Sampling distance within a cluster

Table 1: Soil characteristics

Parameters	WC	FH	HP
N (%)	0.15	0.14	0.09
P ($\mu g\ g^{-1}$)	12.37	2.17	traces
K (cmol(+) kg^{-1})	0.21	0.17	0.08
Ca (cmol(+) kg^{-1})	0.47	0.29	0.44
Mg (cmol(+) kg^{-1})	0.14	0.09	0.08
CEC (cmol(+) kg^{-1})	10.40	10.57	7.91
pH (water, 1:2)	3.82-4.38	3.99-4.47	4.03-4.37
Bulk density ($g\ cm^{-3}$)	1.03	1.09	1.44
Texture	Sandy clay	Sandy clay	Sandy clay

The SOC data were first analyzed using Exploratory Data Analysis (EDA), which included descriptive statistics, normality check and outlier detection (Balasundram *et al.*, 2008). Descriptive statistics and normality check were computed using statistic version 8.1 (Analytical Software). Normality check was performed using the Shapiro-Wilk Test while outlier testing was performed using the Extreme Studentized Deviate (ESD) method, also known as Grubb' Test. Following the EDA, SOC data were spatially analyzed using variography and interpolation techniques. Variography characterizes and models the spatial variance of data using semivariogram. The semivariogram determines the increase in variance between samples collected at increasing separation distances from one another. The semivariogram was estimated using the following formulae (Isaaks and Srivastava, 1989):

$$\gamma(h) = 0.5n(h)\sum_{i=1}^{n(h)}\left[z_i - z_{i+h}\right]^2$$

where, h is the separation distance between location x_i or x_{i+h}, z_i or z_{i+h} are the measured values for the regionalized variable at location x_i or x_{i+h} and n(h) is the number of pairs at any separation distance h.

The semivariogram is generally fitted with an authorized model, such as spherical, exponential or Gaussian model (Webster and Oliver, 2007). These models provide information about the spatial structure as well as the spatial attributes which are the input parameters for interpolation. These models are typically described by three parameters, namely nugget, sill and range. Nugget is defined as a measure of the amount of variance due to errors in sampling, measurement and other unexplained sources of variance. Sill is the total vertical scale of the variogram whereby the semivariance becomes constant when the distance between sample locations increases. Range refers to the distance at which the samples become spatially independent and uncorrelated with one another. This indicates that at separation distances greater than the range, sampled points are no longer spatially correlated. Interpolation is used to predict values in areas that have not been sampled and is often carried out using kriging. Kriging uses the modeled variance to estimate the values between samples (Balasundram *et al.*, 2008). Semivariogram and kriging operations were computed using GS+version 7.0 (Gamma Design Software, Plainwell, MI). Point kriging method was used to estimate SOC at unsampled location. Measured and kriged values were mapped using Surfer Version 8.06 (Golden Software, Inc., Golden, Co). Spatial dependence was defined using nugget to sill ratio (Cambardella *et al.*, 1994), where:

Ratio	Inference
Nugget:Sill<0.25	Strong spatial dependence
0.25<Nugget:Sill<0.75	Moderate spatial dependence
Nugget:Sill >0.75	Weak spatial dependence

Kriged values were cross-validated (Balasundram *et al.*, 2006, 2008; Webster and Oliver, 2007; Isaaks and Srivastava, 1989) using the following procedure:

- Firstly, the interpolated Mean Error (ME) should be close to zero. The ME is calculated as follows:

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left[\bar{z}(x_i) - z(x_i)\right]$$

where, n is the number of sample points, $\bar{z}$ is the predicted value of the variable at point x_i and $z(x_i)$ is the measured value of the variable at point x_i.

- Secondly, the Mean Squared Error (MSE) should be less than the sample variance. The MSE is given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[\bar{z}(x_i) - z(x_i)\right]^2$$

- Thirdly, the ratio of the theoretical and calculated variance, called the Standardized Mean Squared Error (SMSE), should be approximately close to one. The SMSE is given by:

$$SMSE = \frac{\frac{1}{n-1}\sum_{i=1}^{n}\left[\bar{z}(x_i) - z(x_i)\right]^2}{\sigma^2}$$

where, σ^2 is the theoretical variance.

Cross-validation enables comparison between estimated and actual (measured) values using information available in the sample data set. This would allow the selection of the best model. This comparison can be used to compare methods of estimation and to justify the use of kriging as an estimation method (Webster and Oliver, 2007). The ME should be close to zero because kriging is unbiased. It also indicates that overestimation and underestimation within the data set are in balance. MSE, which included the mean or bias and the spread of the error distribution, should be less than the sample variances. MSE gives a better indication when comparing different estimation methods. SMSE enables comparison between the magnitudes of actual and predicted error and gives an idea about adequacy of the model and its parameters (Webster and Oliver, 2007; Wackernagel, 2003; Goovaerts, 2001). Cross validation facilitates reexamination and reformulation of the models to better conform to the data at hand.

RESULTS AND DISCUSSION

Variation Among Operational Areas

SOC data from three operational areas were examined using Analysis of Variance (ANOVA). Mean and standard error values are shown in Fig. 2. The results demonstrated heterogeneity of SOC among operational areas. This indicates that land management practices had a significant effect on SOC distribution. Higher SOC content (%) was found in the WC as compared to other operational areas, indicating the essential role of oil palm roots in soil C sequestration. It has been reported that root growth and turnover results in increasing SOC (Rasse *et al.*, 2005). Kumar *et al.* (2006) stated that large amounts of C contributed by root lysis and root exudates were deposited in sub-surface soil. In comparison to surface soil, these deposits have potential for a greater contribution to long-term soil C sequestration as a result of slow oxidation. Meanwhile, the FH registered a moderate amount of SOC while the HP had the lowest SOC. For the FH area, SOC levels are affected by frond heap accumulation. The lower SOC, in comparison to WC, might be due to lesser stacking of fronds. In addition, the palms at this area were almost at the end of their life cycle and fruit production was relatively low. The lowest SOC levels in the HP area could

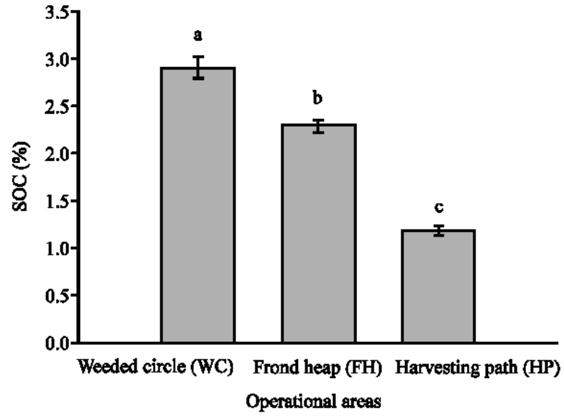

Fig. 2: Soil organic C content (%) at the three operational areas (WC, FH and HP) at 0-20 cm depth

Table 2: Descriptive statistics of SOC (%) at three operational areas

Operational areas*	n[1]	Mean	Median	CV (%)	Skewness[2]	Kurtosis[2]	Normality[3]
WC	59	2.90	2.79	29.57	0.491	-0.188	0.974^{ns}
FH	60	2.30	2.25	21.83	0.470	-0.316	0.976^{ns}
HP	59	1.18	1.09	27.40	0.446	-0.077	0.972^{ns}

*WC: Weeded circle, FH: Frond heap, HP: Harvesting path. [1]No. less than 60 indicate that non-spatial outliers were removed from the data set. Non-spatial outliers were detected using the Extreme Studentized Deviate (ESD) method. [2]Significant if the absolute value of skewness or kurtosis is ≥2 times its standard error. The standard error of skewness = $(6/n)^{0.5}$ while the standard error of kurtosis = $(24/n)^{0.5}$. [3]Estimated using the Shapiro-Wilk test. If the test stastistic W is significant ($p<0.05$) thus the distribution is not normal. ns: Not significant ($p>0.05$)

be attributed to high bulk density, as compared to the other operational areas (Lal and Kimble, 2001). SOC data from these operational areas should be analyzed separately due to different SOC levels.

Classical Statistics

Based on the Shapiro-Wilk statistic, data from all three operational areas were normally distributed (Table 2). The coefficients of skewness and kurtosis describe the shape of the sample distribution. The coefficient of skewness from all three operational areas was positive, indicating that the sample distribution had a long tail of high values to the right (median<mean). The coefficient of kurtosis from all three operational areas was negative, indicating that the sample distribution was relatively flat. The Coefficient of Variation (CV), defined as the ratio of standard deviation to the mean, from all three operational areas ranged from 22 to 30%, indicating low variability in the data set.

Spatial Structure and Attributes

Semivariograms of SOC from the three operational areas are given in Fig. 3. The semivariograms of SOC from WC, FH and HP were constructed based on an active lag of 188 m and lag class interval of 18, 16.5 and 19 m, respectively.

All operational areas exhibited a definable spatial structure for SOC. The SOC data from WC and HP were described by a spherical model, while that of FH was described by an exponential model (Fig. 3a-c). The spatial dependence of SOC from WC and HP were moderate with the nugget to sill ratio of 0.5 and 0.4, respectively. However, SOC from FH exhibited strong spatial dependence with a nugget to sill ratio of 0.11. This infers that the explainable proportion of the total variation of WC, FH and HP were 50, 89 and 60%, respectively, while the remaining variations can be attributed to random sources.

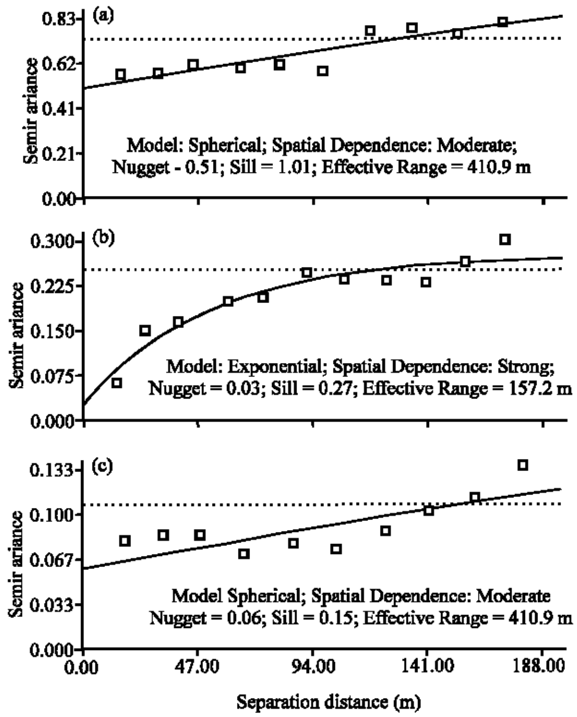

Fig. 3: Spatial structure and attributes of SOC for (a) WC, (b) FH and (c) HP

The SOC data from both the WC and HP had an Effective Range (ER) of 410.9 m while that from FH had a shorter ER of 157.2 m. Soil C content has been found to have stronger spatial dependence with relatively large spatial correlation range as compared to other soil properties (Kravchenko *et al.*, 2006; Wang *et al.*, 2002; Cambardella *et al.*, 1994). At separation distance greater than the ER, sampling points will not be subjected to spatial correlation. This has great implication on sampling design. Sampling design should use separation distances that are shorter than ER in order to understand the spatial pattern of a given property. In addition, spacing between sampling points are recommended to be from 0.25 to 0.5 of the ER (Mulla and McBratney, 1999). Based on the ER value, sample spacing in FH should be closer than WC and HP.

Spatial Variability

The distribution and pattern of both measured and kriged values of SOC from WC, FH and HP are represented as contour maps (Fig. 4a-c). SOC level (%) for each operational area was classified based on mean and Standard Deviation (SD) values. The classes generated were as follows:

Class	Interpretation
High	Mean+2SD
Somewhat high	Mean+SD
Medium	Mean
Somewhat low	Mean-SD
Low	Mean-2SD

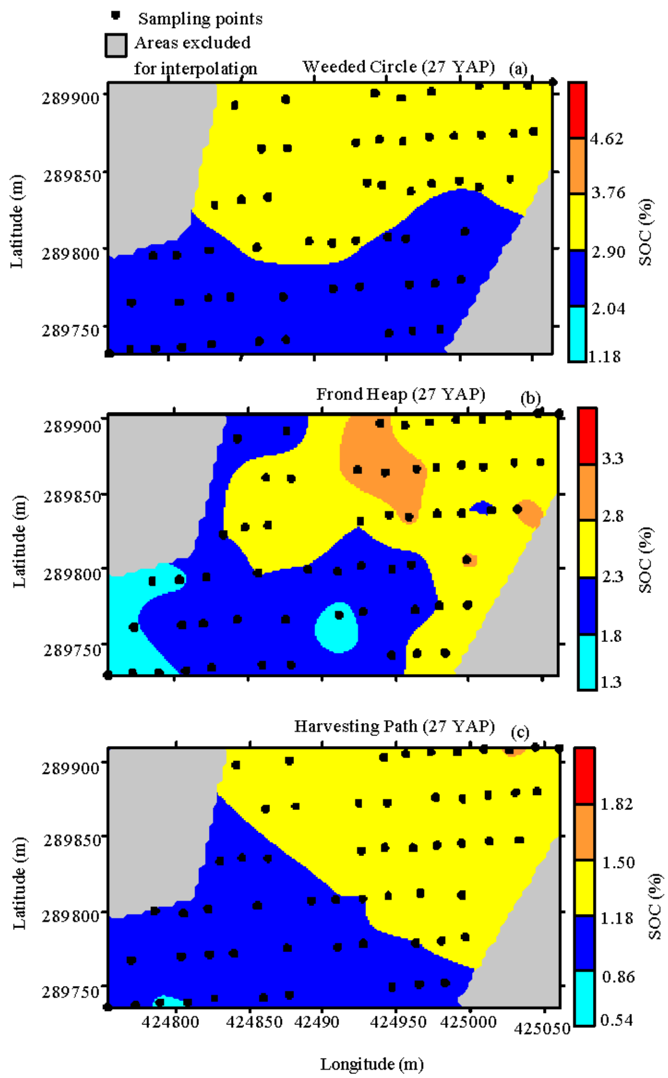

Fig. 4: Spatial distribution of SOC for (a) WC, (b) FH and (c) HP (based on measured and kriged values)

The SOC from the WC was spatially clustered with 53% of the study area showing the average value of 3.33 and 47% with values below the average. For FH, 46% of the study area was clustered within the average value of 2.55, 47% with values below the average and 7% with values above the average. For HP, 55% of the study area was clustered close to the average value of 1.34%, while the remaining area had values below the average. Contour maps for WC, FH and HP demonstrated a similar trend, whereby higher SOC concentrations were located at the north-east portion of the study area. This could be due to topography of the study area, which was gently sloping to undulating with 0-4% slope. Topography is one of the main factors driving spatial distribution and variability of soil C (Kravchenko *et al*., 2006). Lower SOC concentration might be located at gently sloping areas

Table 3: Cross-validation statistics of kriged values for SOC (%) at the operational areas

Operational areas*	Sample variance	ME[1]	MSE[2]	SMSE[3]
WC	0.7363	0.0214	0.5823	0.8045
FH	0.2511	0.0012	0.1837	0.7438
HP	0.1045	0.0003	0.0855	0.8315

*WC: Weeded circle, FH: Frond heap, HP: Harvesting path. [1]Mean Error, [2]Mean Squared Error, [3]Standardized Mean Squared Error

while higher SOC concentration is typically located at almost flat areas. However, the spatial distribution pattern of SOC was distinctly different among the three operational areas, inferring high SOC variability. It appears that the oil palm frond influence the SOC concentration and variability in oil palm plantation. Oil palm frond accumulation over time will increase SOC levels, as well as potentially decrease the spatial variability of SOC. The amount of oil palm fronds accumulated in this area could have also affected the variability of SOC, as evidenced in the contour map. Higher SOC concentration might result from accumulation of large amounts of oil palm frond as compared to other areas and vice versa. Therefore, application of proper management practices in FH area is required in order to increase SOC concentration and reduce its variability.

Cross-validation statistics showed that all operational areas fulfilled the interpolation accuracy criteria (Table 3). This indicates that interpolation using kriging technique is an appropriate method to estimate SOC in oil palm without having to perform field sampling and laboratory analyses. Kriging is practical technique for SOC because SOC does not change significantly over time (Conant and Paustian, 2002; Cambardella *et al*., 1994).

CONCLUSION

Spatial variability of SOC at the Weeded Circle (WC), Frond Heap (FH) and Harvesting Path (HP) in a 27 year old oil palm stand was manifested in this study. SOC variation was observed among and within the operational areas. All three operational areas exhibited a normal distribution with CV ranging from 22 to 30%. All operational areas also exhibited a definable spatial structure for SOC. SOC data from WC and HP were described by a spherical model, while that of FH was described by an exponential model. The spatial dependence of SOC from WC and HP were moderate while that from FH was strong. Additionally, FH had a shorter ER in comparison to the other operational areas, indicating that sample spacing in FH should be closer than those of WC and HP. Contour maps for WC, FH and HP, based on the measured and kriged values, clearly showed spatial clustering of SOC values. The spatial distribution pattern of SOC was distinctly different among the three operational areas, inferring high SOC variability. All three operational areas fulfilled the interpolation accuracy criteria. Results suggest that it is practical to detect SOC using spatial analysis. SOC does not change significant overtime. Nevertheless, land management practices can change significantly over time. Site-specific management should be considered as a strategy to increase SOC sequestration in oil palm. It may be necessary to quantify the spatial variability of SOC across different palm ages.

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