Hindawi Publishing Corporation
Applied and Environmental Soil Science
Volume 2009, Article ID 267378, 7 pages
doi:10.1155/2009/267378

Research Article

Small Scale Spatial Variability of Apparent Electrical Conductivity within a Paddy Field

W. Aimrun,[1] M. S. M. Amin,[1,2] and M. H. Ezrin[1]

[1] *Smart Farming Technology Laboratory, Institute of Advanced Technology, Universiti Putra Malaysia, 43400 UPM, Serdang, Selangor, Malaysia*
[2] *Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM, Serdang, Selangor, Malaysia*

Correspondence should be addressed to W. Aimrun, aimrun@gmail.com

Received 19 March 2009; Accepted 29 May 2009

Recommended by Amaresh K. Nayak

Quick variability description is an important component for zone management practices. Precision farming requires topping up of only the nutrients that are lacking in the soil to attain the highest yield with the least input. The apparent soil electrical conductivity (EC_a) sensor is a useful tool in mapping to identify areas of contrasting soil properties. In nonsaline soils, EC_a is a substitute measurement for soil texture. It is directly related to both water holding capacity and Cation Exchange Capacity (CEC), which are key ingredients of productivity. This sensor measures the EC_a across a field quickly and gives detailed soil features (one-second interval) with few operators. Hence, a dense sampling is possible and therefore a high-resolution EC_a map can be produced. This study aims to characterize the variability of soil EC_a within a Malaysian paddy field with respect to the spatial and seasonal variability. The study was conducted at Block C, Sawah Sempadan, Selangor, Malaysia, for three continuous seasons. Soil EC_a was collected after harvesting period. The results showed that deep EC_a visualized the pattern of the former river routes clearly as continuous lines (about 45 m width) at the northern and central regions of the study area. This exploration has shown different maps with higher contrast as compared to the existing soil series map for the study area. Seasonal variability test showed that the EC_a that was acquired during rainy season (collected after harvest in December to January) has the highest value as compared to another season.

1. Introduction

Soil variability in paddy fields is well recognized where its spatial variability and seasonal variability of soil chemical and physical properties within a field are unavoidable. Quick variability description is an important component for zone management practices. Precision farming requires topping up of only the nutrients that are lacking in the soil to attain the highest yield with the least input. Manual soil sampling and the consequent laboratory analysis are expensive, labor-intensive, and require a long time. The use of an on-the-go apparent electrical conductivity (EC_a) sensor can replace the traditional way of acquiring data in a more efficient way.

Since farmers in the study area cultivate rice two seasons a year, it leads to delay in acting for the coming season and will not satisfy the concept of precision farming. Hence, soil nutrient variability is needed for rapid measurement and monitoring. In order to overcome the problems, a sensor device known as VerisEC sensor was introduced. This device can rapidly measure EC_a and exactly know the location. The relationship of EC_a to variation in crop production caused by soil differences have been reported by several authors [1–4]. Rapid spatial measurement of bulk EC_a can be accomplished using noncontact electromagnetic induction sensors [5, 6] or with direct-contact sensors such as rolling coulters that measure electrical resistance directly [7, 8]. In general, EC_a can be affected by a number of different soils properties, including clay content and soil water content [9, 10]. According to Moore and Wolcott [11], they found that EC_a measures texture, nutrients, and crop yields as shown in their study results. They depicted soil EC_a in the surface map using 400 square-foot grid cells. They found that

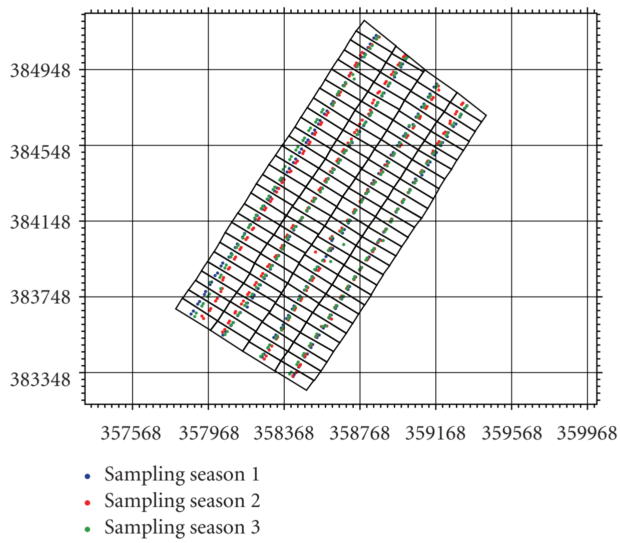

Figure 1: Map of the soil chemical and physical sampling points in block C.

the highest conductivity measurements in the eastern-most portion of the figure fairly accurately depict the denser clay soil in this area. Soil texture affects the amount of fertilizer required to produce optimum crop yields. The surface map may be used as a prescription map for fertilizer input based on soil texture. In a separate study, soil samples were taken from eight specific electrical conductivity zones and analyzed for soil texture and organic matter. There was very high correlation between electrical conductivity and clay content ($r = 0.99$) and between electrical conductivity and organic matter ($r = 0.99$). As mentioned earlier, similar information for paddy soils in the humid tropic is constrained. This study aims to characterize the variability of soil EC_a within a Malaysian paddy field with respect to the spatial and seasonal variability.

2. Methodology

This study uses an on-the-go EC_a sensor for producing EC_a map where its readings can be obtained through this soil-to-instrument contact device that permits rapid soil EC_a measurement without requiring a permanently buried detector. The study was conducted in a paddy field at Block C, Sawah Sempadan, Tanjung Karang, Selangor, Malaysia. The study site has 118 plots covering 145 ha with an average plot size of about 1.2 ha (Figure 1). The EC_a data acquisition was done for three continuous seasons. The first season soil samples were collected on 2nd to 20th June 2003 coinciding with after harvest of the off-season for 2003 and, the second season samples were collected on 16th December 2003 to 3rd January 2004 coinciding with after harvest of the main season for 2003. The third season samples were collected on 9th to 18th June 2004 (off-season 2004).

The Veris 3100 Sensor Cart was pulled across each field behind a tractor in a series of parallel transects spaced about 15 m apart. The plot width was 60 m and the length was 200 m. The instrument was calibrated, as per manufacturer instructions, prior to data collection for each field by checking its resistance of lesser than 2 ohm using ohmmeter. The Veris 3100 has three pairs of coulter-electrodes to determine soil EC_a. The coulters penetrate the soil surface into a depth of 6 cm. One pair of electrodes emits an electrical current into the soil, while the other two pairs detect decreases in the emitted current due to its transmission through soil (resistance). The depth of measurement is based upon the spacing of the coulter-electrodes. The center pair, situated closest to the emitting (reference) coulter-electrodes, integrates resistance between depths of 0 and 30 cm (shallow), while the outside pair integrates between 0 and 90 cm (deep). Output from the Veris data logger was the conversion of resistance conductivity (1/resistance = conductivity). A Differential Global Positioning System (DGPS) Trimble AgGPS132 (Trimble Navigation Ltd., Sunnyvale, Calif, USA) with submeter accuracy was used to georeference EC_a measurements. This differential correction process was done automatically on real-time basis by using available beacon station at Lumut (4° 15.075′′ N and 100° 39.638′′E), Perak, Malaysia (transmission frequency was 298.00 kHz). The Veris data logger recorded latitude, longitude, and shallow and deep EC_a data (mS m^{-1}) at 1-s interval in an ASCII text format. The EC logger was available to log only when DGPS signal was received. The locations of latitude and longitude (WGS84) were then converted to Malaysian Rectified Skew Orthomorphic (RSO) using GPS Pathfinder Office 2.90.

The EC_a data in ASCII format was then transferred through a diskette to an available Geospatial and GIS software such as GS+ version 5.1 and ArcGIS 8.3 with Spatial Analyst extension in order to generate an EC_a map by Kriging technique. The GS+ was used to generate variogram and the best model was selected for use in spatial interpolation (kriging).

The Statistical Analysis System 8e (SAS) was used to determine basic statistical descriptions. The significance test of mean was determined between classes and seasons by Duncan's Multiple Range Test (DMRT) by PROC GLM in SAS.

3. Results and Discussion

3.1. Spatial Variability of Soil EC_a. The aim of this study was to present the variability of EC_a within the study area in a local spatial variability characterization. Since the standard classification did not visualize much variability, then most of the data points fell into a single class. Thus, the classification technique of smart quantiles, which was introduced by ArcGIS software, was selected. This was based on natural groupings of data values. It identifies break points by looking for groupings and patterns inherent in the data. The features are divided into classes whose boundaries are set where there are relatively big jumps in the data values. This is a compromise method between equal interval and quantile, with unequal-sized intervals, such as quantile that generally gets a bit wider at the extremes, but not so much as with

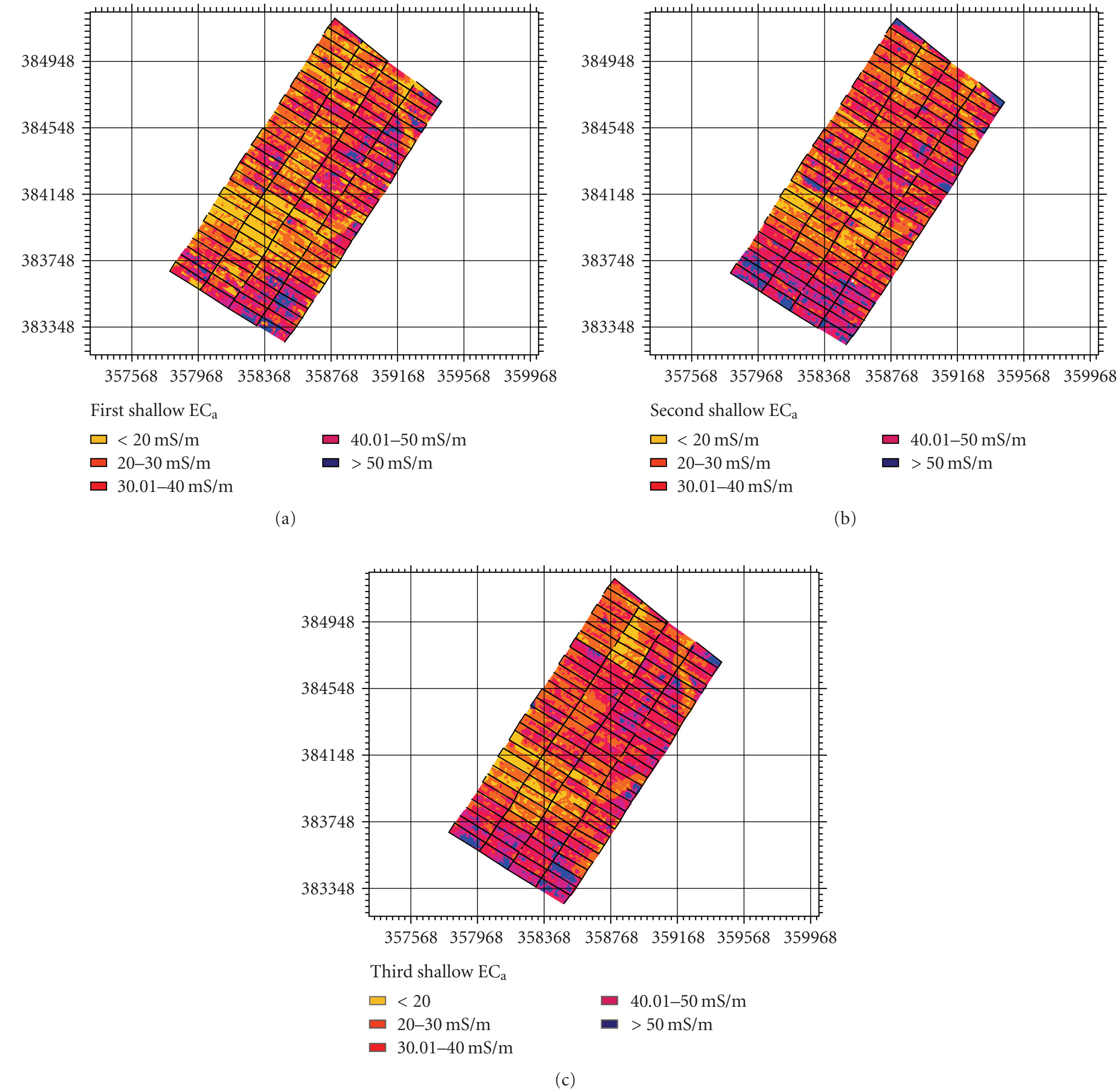

FIGURE 2: Kriged Map for shallow EC_a (mS m^{-1}) classified by smart quantiles (a) Season 1, (b) Season 2, and (c) Season 3.

the quantile method, so there is also a decreasing number of values in the extreme classes. This option tries to find a balance between highlighting changes in the middle values and the extreme values [12]. This study had decided to zone the area into 5 manageable zones classified by smart quantile method with the adjustment of the class value to a single number based on three-season data range. They were less than 20, 20 to 30, 30 to 40, 40 to 50 and more than 50 mS m^{-1} for shallow EC_a. For deep EC_a, they were less than 40, 40 to 60, 60 to 80, 80 to 100 and more than 100 mS m^{-1}. This was to produce a consistence range over the study seasons to use as reference and simplify the comparison.

The new classification results for the shallow EC_a displayed the appearance of the former water routes (once upon a time, they were rivers), but they were still blur (Figure 2). However, the previous classification method was unable to justify them. Most of the area was occupied by classes 2 and 3 for all the seasons for more than 50 ha (34.50%) except for class 3 in season 1. Class 1 occupied the area of 32.56 (22.49%), 14.66 (10.13%), and 14.25 ha (9.84%) for seasons 1, 2, and 3, respectively. This indicated that the area of low shallow EC_a (<20.00 mS m^{-1}) was less than 23% of the total area. Class 5 of more than 50 mS m^{-1} occupied the smallest area (less than 6%) for all seasons (Table 1).

The new classification approach should be justified for its strength. Strength of the classification approach can be illustrated by compactness and isolation [13, 14]. The compactness is referred to low within class variance or all

Table 1: Summary of kriged shallow EC_a maps for three seasons classified by smart quantiles.

Class	Count	Area	Min	Max	Range	Mean*	Std. Deviation
Season 1		(ha)			dS m^{-1}		
1	7586	32.56 (22.49%)	1.68	20.00	18.32	14.92e	4.02
2	12562	53.92 (37.25%)	20.00	30.00	10.00	25.04d	2.82
3	8841	37.95 (26.21%)	30.00	40.00	10.00	34.48c	2.86
4	3421	14.68 (10.14%)	40.00	50.00	10.00	44.07b	2.79
5	1318	5.66 (3.91%)	50.00	91.17	41.16	57.49a	7.17
Season 2							
1	3415	14.66 (10.13%)	2.56	20.00	17.44	16.55e	2.98
2	12292	52.76 (36.45%)	20.00	30.00	10.00	25.43d	2.80
3	11702	50.23 (34.70%)	30.00	40.00	10.00	34.57c	2.86
4	4529	19.44 (13.43%)	40.00	50.00	9.99	44.07b	2.78
5	1789	7.68 (5.30%)	50.01	112.29	62.27	57.80a	8.18
Season 3							
1	3319	14.25 (9.84 %)	4.94	20.00	15.06	17.16e	2.35
2	12240	52.54 (36.29%)	20.00	30.00	10.00	25.49d	2.81
3	12167	52.22 (36.07%)	30.00	40.00	10.00	34.51c	2.81
4	4675	20.07 (13.86%)	40.00	49.99	9.99	43.88b	2.75
5	1327	5.70 (3.93%)	50.01	141.31	91.30	55.76a	6.99
Total area		**144.77**					

* Mean values in column were significant at $\alpha = 0.05$ by DMRT.

Table 2: Summary of kriged deep EC_a maps for three seasons classified by smart quantiles.

Class	Count	Area	Min	Max	Range	Mean*	Std. Deviation
Season 1		(ha)			mS m^{-1}		
1	4176	17.92 (12.38%)	0.89	40.00	39.11	26.11e	10.59
2	6375	27.36 (18.90%)	40.00	60.00	20.00	50.84d	5.75
3	9035	38.78 (26.79%)	60.00	80.00	20.00	70.04c	5.73
4	7469	32.06 (22.14%)	80.00	100.00	19.99	89.54b	5.75
5	6673	28.64 (19.78%)	100.00	166.02	66.02	113.75a	10.25
Season 2							
1	1528	6.56 (4.53%)	15.44	40.00	24.56	32.04e	6.17
2	5366	23.03 (15.91%)	40.00	59.99	19.99	51.28d	5.65
3	7640	32.79 (22.65%)	60.00	80.00	19.99	70.05c	5.68
4	6702	28.77 (19.87%)	80.01	100.00	19.99	89.50b	5.73
5	12492	53.62 (37.04%)	100.00	278.44	178.44	129.33a	22.22
Season 3							
1	2007	8.61 (5.95%)	8.50	40.00	31.50	31.44e	6.67
2	6350	27.26 (18.83%)	40.01	60.00	19.99	50.87d	5.71
3	8924	38.30 (26.46%)	60.01	80.00	19.99	70.22c	5.64
4	7729	33.18 (22.92%)	80.00	99.99	19.99	89.45b	5.76
5	8718	37.42 (25.85%)	100.00	208.41	108.41	116.93a	11.76
Total area		**144.77**					

* Mean values in column were significant at $\alpha = 0.05$ by DMRT.

objects within a class are highly similar to each other. The isolation is referred to high distance between classes or the objects within a class are dissimilar to objects in all other classes. This study chose the statistical method of grouping test, such as DMRT and LSD to identify the isolation of the class where their mean values should be significantly different from each other.

The labeled letter for mean values at each class indicated significant difference ($P < .001$) showing the isolation between classes when classified by adjusted smart quantiles

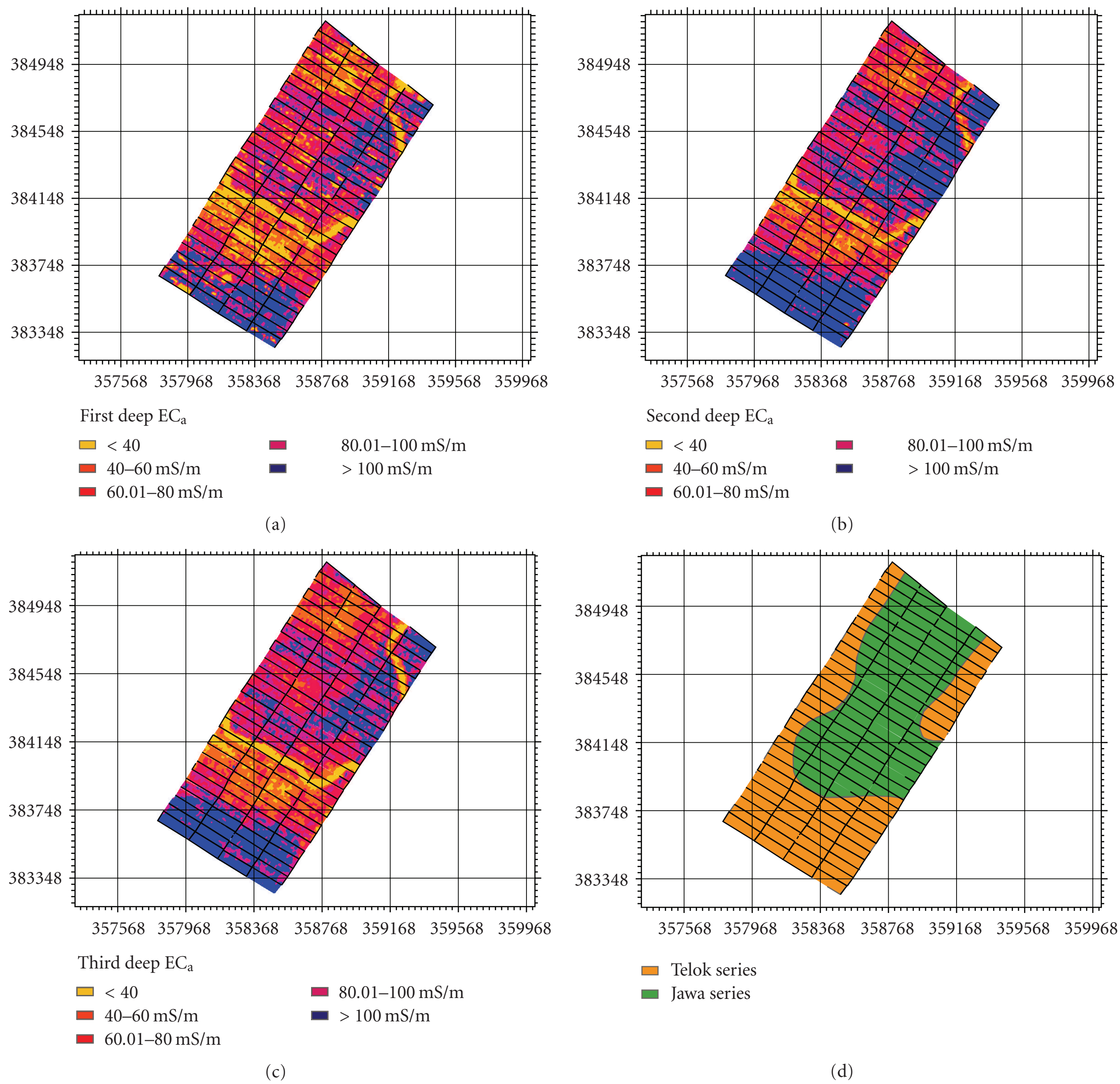

Figure 3: Kriged map for deep EC_a ($mS\,m^{-1}$) classified by smart quantiles: (a) Season 1, (b) Season 2, (c) Season 3, and (d) Soil series map.

Table 3: Mean of the EC_a for Seasons 1, 2, and 3.

Soil Properties	Season 1	Season 2 $mS\,m^{-1}$	Season 3
Shallow EC_a	28.71c (n = 93884)	32.17a (n = 65618)	31.46b (n = 63578)
Deep EC_a	72.53c (n = 85811)	92.59a (n = 65667)	80.44b (n = 63571)

Means within a row followed by the same letters are not significant at α = 0.05 level by DMRT.

approach. The standard deviation, especially for classes 2, 3, and 4, indicated the compactness of the classification approach, when the standard deviations low and only classes 1 and 5 had higher standard deviations due to unlimited values within the class. Therefore, this adjusted smart quantiles classification approach was accepted due to its classification strength.

Deep EC_a maps which were classified according to adjusted smart quantiles method visualized clearer the former water routes. The new classification for the deep EC_a was identified as less than 40, 40 to 60, 60 to 80, 80, to 100 and more than 100 $mS\,m^{-1}$. The former water routes where deep EC_a was very low (class 1) had clear shape with the width of about 45 m. They were found in the northeastern part as a short distance and another crossing the study area from the east to the west. Low deep EC_a was also found at the edge surrounding the former water routes. Most of the high EC_a

were distributed in the south and central east as illustrated by the darker color of class 5. This appearance of the former water routes found in all seasons indicated that deep EC_a was a good indicator to describe the variability pattern over the period (Figure 3). Most of the deep EC_a values fell into class 3 (more than 20.00% of the total area), class 4, and class 5 (Table 2). Class 1 (<40 mS m^{-1}) was found in small areas of less than 12% of the total area for all the seasons. Season 2 had the smallest area of the lowest deep EC_a. This indicates that most of the area had high (>40 mS m^{-1}) EC_a values in the subsoil layer.

Count number of raster cells showed the areas that were occupied by each class. The significant difference between the mean of deep EC_a values at 95% confidence level (α = 0.05) indicated the isolation of the classification, while low variance (standard deviation), except for classes 1 and 5 which was wide range, indicates the compactness. Hence, there was the effectiveness of classification method.

Both shallow and deep EC_a maps showed the difference to soil series map. This was because of the different sampling scale, where soil EC_a was more intensive sampling points as compared to detailed soil survey map, which was at about 200 m grid. According to Aimrun et al. [15], deep EC_a zone can delineate rice yield and soil K where low deep EC_a area has a significant low yield and a significant high K when tested by LSD at 5% level.

3.2. Seasonal Variability of Soil EC_a. Mean shallow and deep EC_a values had similarly changed from one season to another season (the same range of c, a, and b). Season 2 had significantly highest mean values for shallow and deep EC_a as compared to seasons 1 and 3 (Table 3). The period of seasons 1 and 3 was during the first cultivation of the year (January to May) and the EC_a data was acquired during June. The similarity of means shallow and deep EC_a for a season indicated strong relationship between shallow and deep values. On the other hand, in a season that had high mean shallow EC_a value, mean deep EC_a value was also high even though the population numbers were different. The highest EC_a values found in season 2 was due to high water content in the field (above saturation point) caused by heavy rain in December.

4. Conclusions

Spatial variability of the soil properties were found to be different over the studied seasons, but both shallow and deep EC_a retained their patterns even though the mean values were different. Deep EC_a showed the pattern of the former river routes clearly as continuous lines (about 45 m width) at the northern and central regions of the study area. Most of the high EC_a levels were found in the southern and central regions. All the three seasons showed that the pattern of the map retained the same shape (clear former water route in low EC_a zone and zone of high EC_a). This exploration has shown different maps with higher contrast as compared to the existing soil series map for the study area. It showed that very detailed (as collected at every one meter) soil zoning map can be produced and delineated faster using soil EC_a sensor at a submetre grid (less than 1 m) collected at every 1-second interval. Seasonal variability test showed that the EC_a that was acquired during rainy season (collected after harvest in December to January) has the highest value as compared to another season. The significance of the study to the research problem is that soil EC_a map can be as a supplementary to soil series map. For conventional practice, soil series were used to describe the soil condition at the field. So far, EC_a map can be produced more intensive, faster, lower cost, and less labor, therefore, EC_a map can be an alternative way to describe the field condition.

Acknowledgments

Cooperation from MACRES, DOA, MARDI, and IADA is acknowledged. The assistance of all staff at the Smart Farming Laboratory, ITMA, and the Department of Biological and Agricultural Engineering, Faculty of Engineering UPM is highly appreciated. Special thanks to Professor Mohd Sapuan Salit for reviewing this manuscript and giving good comments.

References

[1] D. B. Jaynes, T. S. Colvin, and J. Ambuel, "Yield mapping by electromagnetic induction," in *Proceedings of the 2nd Site-Specific Management for Agricultural Systems*, P. C. Robert, et al., Ed., pp. 383–394, University of Minnesota Extension Service, Minneapolis, Minn, USA, March 1994.

[2] N. R. Kitchen, K. A. Sudduth, and S. T. Drummond, "Soil electrical conductivity as a crop productivity measure for claypan soils," *Journal of Production Agriculture*, vol. 12, no. 4, pp. 607–617, 1999.

[3] A. Luchiari, J. Shanahan, D. Francis, et al., "Strategies for establishing management zones for site specific nutrient management [CD- ROM]," in *Proceedings of the 5th International Conference on Precision Agriculture*, P. C. Robert, Ed., Minneapolis, Minn, USA, July 2000.

[4] N. Zhang and R. Taylor, "Applications of a field level geographic information system (FIS) in precision agriculture [CD-ROM]," in *Proceedings of the 5th International Conference on Precision Agriculture*, P. C. Robert, Ed., Minneapolis, Minn, USA, July 2000.

[5] J. D. McNeil, "Rapid, accurate mapping of soil Salinity by electro magnetic ground conductivity meters," in *Advances in Measurements of Soil Physical Properties: Bringing Theory into Practice*, pp. 201–229, SSSA, Madison, Wis, USA, 1992.

[6] K. A. Sudduth, S. T. Drummond, and N. R. Kitchen, "Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture," *Computers and Electronics in Agriculture*, vol. 31, no. 3, pp. 239–264, 2001.

[7] E. D. Lund, C. D. Christy, and P. E. Drummond, "Practical applications of soil electrical conductivity mapping," in *Proceedings of the 2nd International Conference on Precision Agriculture*, J. V. Stafford, Ed., pp. 771–779, Odense, Denmark, July 1999.

[8] K. A. Sudduth, N. R. Kitchen, and S. T. Drummond, "Soil conductivity sensing on claypan soils: comparison of electromagnetic induction and direct methods," in *Proceedings*

of the 4th International Conference on Precision Agriculture, vol. 2, pp. 979–990, St. Paul, Minn, USA, July 1999.

[9] R. G. Kachanoski, E. G. Gregorich, and I. J. Van Wesenbeeck, "Estimating spatial variations of soil water content using noncontacting electromagnetic inductive methods," *Canadian Journal of Soil Science*, vol. 68, no. 4, pp. 715–722, 1988.

[10] C. L. S. Morgan, J. M. Norman, R. P. Wolkowski, B. Lowery, G. D. Morgan, and R. Schuler, "Two approaches to mapping plant available water: EM-38 measurements and inverse yield modeling [CD-ROM]," in *Proceedings of the 5th International Conference on Precision Agriculture*, P. C. Robert, et al., Ed., Minneapolis, Minn, USA, July 2000.

[11] S. H. Moore and M. C. Wolcott, "Mapping and interpreting electrical conductivity in production fields. Louisiana Agriculture," *Summer*, vol. 44, no. 3, pp. 25–27, 2001.

[12] ESRI, *Using ArcGIS Geostatistical Analyst*, ESRI, Redlands, Calif, USA, 2001.

[13] R. M. Cormack, "A review of classification," *Journal of the Royal Statistical Society, Series A*, vol. 134, pp. 321–367, 1971.

[14] A. D. Gordon, *Classification*, Chapman & Hall, London, UK, 1981.

[15] W. Aimrun, M. S. M. Amin, D. Ahmad, M. M. Hanafi, and C. S. Chan, "Spatial variability of bulk soil electrical conductivity in a Malaysian paddy field: key to soil management," *Paddy and Water Environment*, vol. 5, no. 2, pp. 113–121, 2007.