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Relationship between Rice Yield and Apparent Electrical Conductivity of Paddy Soils

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Abstract: Problem statement: Understanding the relationships between rice yield and soil properties such as bulk electrical conductivity is of critical importance in precision farming. The apparent Electrical Conductivity of soil (ECa) is influenced by a combination of physico-chemical properties including soluble salts, clay content and mineralogy, soil water content, bulk density, organic matter and soil temperature. Accordingly, ECa is considered as the most reliable and frequently used tools in precision farming research for the spatio-temporal characterization of edaphic and anthropogenic properties that influence crop yield. Many researchers have found positive correlation of ECa to crop yield such as corn and soy bean but not rice paddies. This study discussed on the relationship between ECa and rice yield for best practice management on paddy field. **Approach:** The analyses had used two reliable methods in six selected paddy lots at Sawah Sempadan, Selangor, Malaysia. Stepwise Linear Regression (SLR) and Boundary Line Analysis (BLA) techniques were used. External factors such as weather conditions, disease outbreaks, labor shortage and other factors were not considered in the data analysis and interpretation. **Results:** The results indicate that deep ECa (ECad) is significantly related to rice yield with R^2 = 0.1246 and R^2 = 0.4156 from SLR and BLA analyses, respectively. **Conclusion:** Results of this study can benefit farmers and researchers to understand the influence of ECa to the crop productivity.

Key words: Apparent electrical conductivity, precision farming, regression analysis, boundary line analysis

INTRODUCTION

Researchers and producers alike have recently shown interest in characterizing soil and topographic variability in relation to crop growth and yield. Several researchers (Kravchenko and Bullock, 2000) have reported that there is usually little or no significant relationship between crop yield variation and individual soil characteristic such as organic matter, cation exchange capacity and texture. However, apparent Electrical Conductivity (ECa), which is affected by a number of soil properties such as the clay content, soil water content, temperature, salinity, organic compounds and metals (Kachanoski *et al*., 1990) has been highly correlated with claypan topsoil thickness Doolittle *et al*. (1994); Sudduth *et al*. (2001) causing variations in water storage characteristics and consequently to yield variations in average precipitation crop years (Kitchen *et al*., 1999).

Corwin *et al*. (2003) observed that, although the crop yield inconsistently correlates with soil apparent Electrical Conductivity (ECa), there are specific instances where yield correlates with ECa. Johnson *et al*. (2003), in a 250 ha dry land experiment, mapped ECa against wheat and corn yields and found the corn yield to have positive correlations with ECa. They expressed the possibility of using ECa to make decisions on prescription maps for input metering and yield determination. Amidst all these contradicting results, ECa is one sensor-based measurement parameter that has shown promise for precision farming. It is also clear that ECa's relationship to crop yield is so complex that it has to be modeled for the specific crop production system.

Numerous techniques have been applied for modeling the relationship between crop yields and measured soil and site parameters. Linear regression is the most popular technique to perform the relationship

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significance and predictive ability. Linear analyses of investigating yield response consisting of empirical analysis of large, spatial and multivariate data sets have often been reported in the literature. Several authors have found that linear correlations between yield and soil properties, or between two soil properties, vary greatly both within and between fields (Drummond *et al*., 1995; 2003; Khakural *et al*., 1999; Pierce *et al*., 1994; Lamb *et al*., 1997) and can also exhibit strong temporal variability (Lark *et al*., 1997).

Non-linear models can also be applied, but with a prerequisite of assuming the relationship between the dependent and independent variables, which in most cases may be unknown. Kitchen *et al*. (1999) investigated the relationship of apparent Electrical Conductivity (ECa) of claypan soils (Udollic Ochraqualfs) and grain yield of five site-years of corn, seven site-years of soybean and one site year of grain sorghum. They used a boundary log-normal function fit to the upper edge of the scatter plots between yield and ECa to quantify the widely varying yield response. A significant relationship between grain yield and ECa was reported. They mentioned that more information on climate, crop type and specific field parameters were needed to explain the shape of the possible yield by ECa interaction.

The procedure of boundary line analysis, detailed by Webb (1972), selects a subset of points from the original data that are the best performing in terms of some response variable (e.g., yield). The boundary line analysis works best when data sets are large. The boundary line analysis procedure assumes that there is a significant biological response between the potential limiting factor and the response variable in order to imply the cause-and-effect relationship (Lark *et al*., 1997; Webb, 1972). A weakness of the analysis is that it is a single factor analysis, like simple correlation and assumes insignificant joint effects with other factors at the boundary (Lark *et al*., 1997). Webb (1972) asserted that boundary line analysis is a procedure for exploring response relationship for the purpose of indicating where attention should be directed for the greatest prospect of increasing yield. For this analysis, it must be recognized that soil ECa per se is not a direct measure of a yield-limiting factor. However, it is an estimate of numerous soil properties of the top soils that mediate crop growth.

An insight into the relationship between soil properties, plant stand and yield potential will pave the way for maximizing the production through an appropriate decision-making strategy. In order to understand the relationship, a necessary step in this process is the search for techniques that enable to identify functional relationships between ECa and crop yield. This study will focus on rice as a correspondence crop to relate with soil ECa. The main goal of this study was to investigate rice yield relationship to variability of soil ECa.

MATERIALS AND METHODS

Study site: The research was conducted at the paddy fields of Sawah Sempadan, Tanjung Karang, Selangor, managed by the Integrated Agricultural Development Area (IADA) under the Ministry of Agriculture Malaysia authority. It is in the district of Kuala Selangor and Sabak Bernam at latitude 3°35”N and longitude 101°05”E. Sawah Sempadan covers 2300 ha. and it is divided into 24 blocks namely Blocks A to X and Block C was chosen as the study area. It has 118 lots with 1.2 ha each. Six lots were selected randomly for this research namely lots 3117, 3121, 3155, 3168, 3172 and 3176. According to the previous research, lots 3117 and 3121 are located in peat area where the former river was found in that area Aimrun *et al*. (2008). In this condition, any supplemental input (lime, fertilizer and water) will be absorbed more by the soil rather than crop due to high infiltration rate of the soil.

Data collection and analyses: The rice yield data was collected on April 2007 based on Crop Cutting Test (CCT) technique at 24 randomly selected sampling points within the selected lots Fig. 1. The latitude and longitude position of each sampling point was recorded using a handheld DGPS Pro-XR. The 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 (transmission frequency was 298.00 kHz). The area of cut at each sampling point was 0.5×0.5 m and the collected grains from the cut crops were weighed and recorded.

The ECa data was measured by using Veris 3100 soil electrical conductivity sensor. The sensor integrated with DGPS was pulled across each lot behind a tractor within a typical paddy field size of 60 m width and 200 m length. 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 sensor has three pair of coulter-electrodes to determine soil ECa. The coulters penetrate the soil surface into a depth of 6 cm. One pair of electrodes functioned to emit 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.

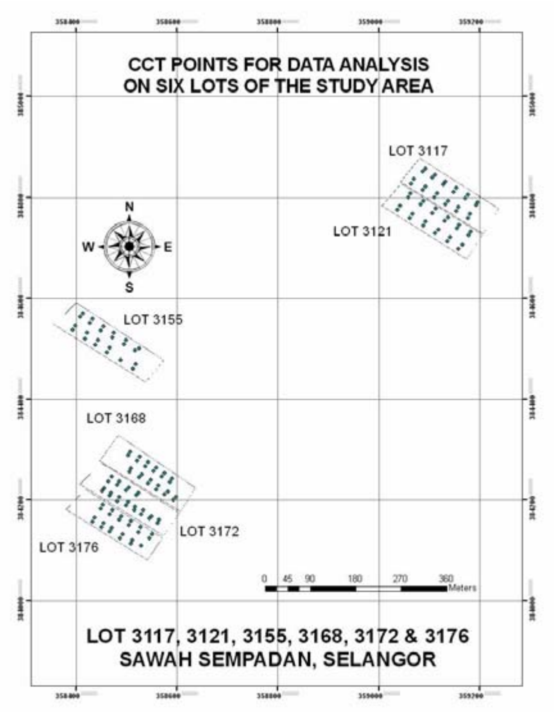


Fig. 1: The CCT sampling points for six selected lots in the study area

The center pair, situated closest to the emitting (reference) coulter-electrodes, integrate resistance between depth of 0-30 cm, while the outside pair integrate between 0-90 cm. Output from the data logger reflected the conversion of resistance to conductivity (1/resistance = conductivity).

A Differential Global Positioning System (DGPS) Trimble AgGPS132 (Trimble Navigation Ltd., Sunnyvale, CA) with sub-meter accuracy was used to geo-reference ECa measurements. This differential correction process was done automatically on real time basis by using the OmniSTAR DGPS System. The Veris data logger recorded latitude, longitude, shallow and deep ECa data (mS m^{-1}) at 1-s interval in an ASCII text format. The restriction of the EC logger was available to log only when DGPS signal was received. The location of latitude and longitude (WGS84) were next converted to Malaysia Rectified Skew Orthomorphic (RSO) using GPS pathfinder Office 2.90. The ECa data in ASCII format were then transferred through a diskette to an available Geospatial and GIS software such as GS + version 7 and ArcGIS 9.2 with spatial analyst extension in order to generate spatial map by using kriging technique.

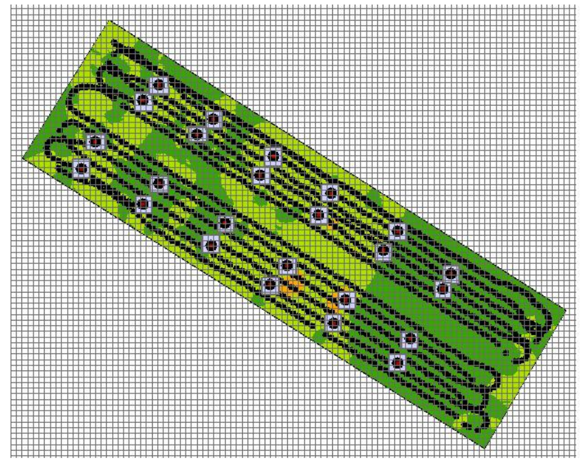


Fig. 2: The composite map in grid format

The spatial map produced from GIS then would be compiled in one single map consisting of shallow ECa (ECas) layer, deep ECa (ECad) layer and rice yield layer. The composite map was divided into several parts using grid format in the GIS for uniformity area distribution Fig. 2. A new average data were next selected based on CCT points as shown in Fig. 1. This procedure was executed in order to get ECa data and rice yield data in the same position with the same number of data points.

Statistical data analysis: Several methods of statistical analysis were used in this study to relate rice yield based on CCT to soil ECa. External factors such as weather conditions, disease outbreaks, shortage of labor force and others were not considered in the data analysis and interpretation.

Before performing data analysis, the data was imported into GIS software and was rasterized. This method created a map of cells for each layer that correspond to the same geographic cells in the other layers such as yields or soil ECa. The cell data then was analyzed in the GIS, or logged into a database or spreadsheet programme for analyses. The techniques adopted in this study consist of (1) stepwise Linear Regression (SLR) and correlation analysis, (2) Boundary Line Analysis (BLA) and (3) visual map analysis.

The stepwise linear regression was implemented by using SPSS version 11.5 to analyze all the data. The coefficient of determination (R^2) measures of how well the regression line approximates the real data points. An R^2 of 1.0 indicates that the regression line perfectly fits the data. Beside, the Pearson's correlation was also executed to indicate the strength and direction of linear relationship between soil ECa and rice yield.

The boundary line analysis was implemented in this investigation. This method isolates the upper boundary points for each soil ECa range and fits a non-linear line or equation to represent the top performance parameters within each soil ECa range. When viewed in a two-dimensional scatter plot, this upper boundary represents the conditions of that data set, the maximum possible response to ECa measurements. Points below the boundary line represent conditions where other factors have limited rice yield. The 95 and 75 percentile ranking were used to indicate how well the performance relative to the other cells in data spreadsheet similar to ECa values. Since this subset of data points were lying on the upper edge of the whole data, any questionable points need to be scrutinized.

RESULTS

Linear regression analysis: The relationship between soil EC and yield has been reported and quantified by others. It is becoming increasingly common for precision agriculture service providers to create scatter plots and calculate bi-variate regression correlation coefficients for paired data. When this is applied to ECa and yield data sets, as shown in Fig. 3, the results typically show statistically significant correlation. The yield and soil EC from these Sawah Sempadan paddy fields have a statistically significant (at the 1% significance level) correlation co-efficient of 0.1246. Much of this is due to the underlying soil property relationships that both data sets have in common. Beside, the density at which both data sets are collected influence to the analysis result. The virtually continuously-sensed, dense data collected with the mobilized EC mapping system (Veris 3100) and from the CCT yield data from similar locations in the field, reduced the errors induced by interpolating sparser data.

This study, involved two different approaches of statistical analyses. The 143 data points in six selected lots of the study area have been acquired for the investigation as shown in Table 1. Yield, ECas and ECad from 24 data points in each lot have been interpreted for the analysis. However, lot 3155 has one missing data point due to an error during the rice yield measurement task.

As shown in Table 1, lots 3117 and 3121 produced only 6.49 and 4.73 ton ha^{-1} of rice yield, respectively, the lowest yield production in the lots studied. The highest yield was in lot 3172 with 10.32 ton ha^{-1}.

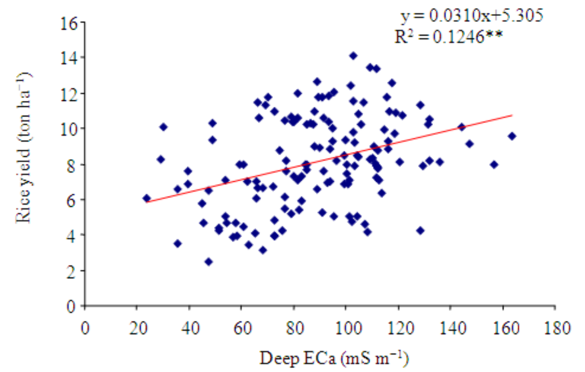


Fig. 3: Least square linear-line of rice yield versus ECad in all lots of the study area

Table 1: Rice yield and soil ECa values in six lots of the study area

Lot	n	Average yield (ton ha^{-1})	Average ECas (mS m^{-1})	Average ECad (mS m^{-1})
3117	24	6.49	29.34	67.80
3121	24	4.73	31.97	65.95
3155	23	9.03	30.29	103.12
3168	24	10.20	34.61	98.94
3172	24	10.32	32.65	101.09
3176	24	8.01	49.44	101.32
All lots	143	8.13	34.75	89.61

The average of ECas data was approximately 30 mS m^{-1} all lots accept for the lot 3176 which indicated almost 50 mS m^{-1} of ECas, while the averages of ECad values fluctuated ranging from 66-100 mS m^{-1}. The trends of ECad were likely synchronized to the yield production. It shows that high yields were obtained when ECad is around 90 mS m^{-1}.

The graph in Fig. 3 represents the linear relationship between ECad and rice yield production. The coefficient of determination (R^2), indicates a significant relationship at 0.01 level. The pattern of the graph and the R^2 value show that ECad has a positive linear relationship to rice yield and more reliable to be used as independent variables for the statistical analysis compared to the ECas which only perform 0.0003 of R^2 Fig. 4.

In order to find the best model to relate rice yield and soil ECa, the linear regression analysis was carried out by using ECas and ECad data as independent variables and rice yield data as dependent variable. The stepwise method produced the best selection model in the analysis as shown in Table 2. According to the results, both ECas and ECad are significantly related to the rice yield and generated high coefficient of determination value at 0.001 level ($R^2 = 0.161$).

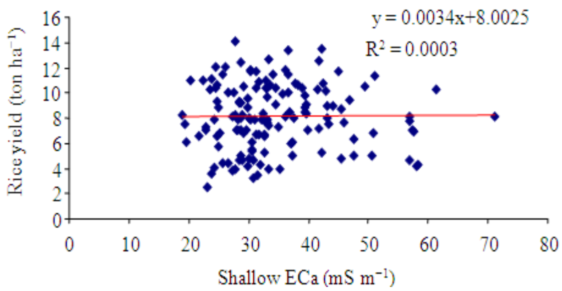


Fig. 4: Least square linear-line of rice yield versus ECas in all lots of the study area

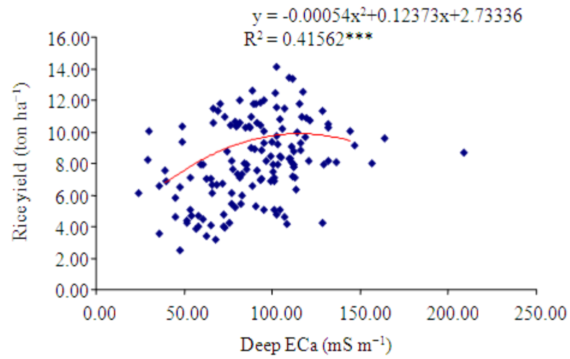
Table 2: Results of linear regression analysis for rice yield, ECad and ECas

Lot	All lots
n	143
Average ECas (mS m^{-1})	34.75
Average ECad (mS m^{-1})	89.61
Average yield (ton ha^{-1})	R^2
R^2	0.161***
Model	yield = 0.042(ECad)-0.058(ECas)+6.418^{ab}

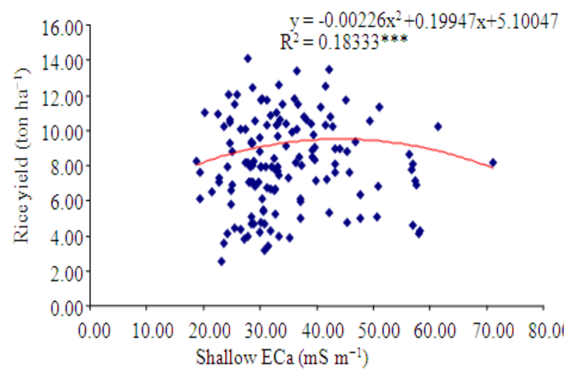
Nevertheless, the ECad contributed more to the significant relationship factor rather than ECas as shown in Table 3. The ECas only assist to perform better linear regression as suggested by stepwise method.

Boundary line analysis: The Boundary Line Analysis (BLA) was carried out in this investigation as a non-linear analysis. The same data was used to identify the relationship and the results were compared with the linear regression analysis. The analysis was divided into two categories. The first category was carried out by using ECad and rice yield and the second category by using ECas and rice yield. Each category of analyses was executed in both 95 and 75 percentile rankings to perform the non-linear model Table 4 and 5. The analysis was successfully performed to determine the relationship between rice yield and soil ECa. The best relate to rice yield was ECad which represented the highest R^2 value in both 95 and 75 percentile ranking (0.3903 and 0.4156, respectively) when compared to the R^2 values found in ECas (0.0999 and 0.1833, respectively).

The pattern of the graphs in Fig. 5 presents both low and high ECa values are associated with a decrease in productivity. The mid-range of ECa values are associated with high rice yield in both ECad and ECas conditions. The curve fit line indicated higher yield when ECa reach approximately to 100 and 35 mS m^{-1} for deep and hallow ECa, respectively.



(a)



(b)

Fig. 5: Non-linear line of rice yield versus (a) ECad and (b) ECas based on 75 percentile ranking of boundary line analysis

Table 3: Correlations of rice yield, shallow ECa and deep ECa for all lot of study area

		Rice yield	ECas	ECad
Rice yield	Pearson correlation	1.000	0.016	0.353**
	Sig. (2-tailed)	----	0.850	0.000
	n	143.000	143.000	143.000
ECas	Pearson correlation	0.016	1.000	0.510**
	Sig. (2-tailed)	0.850	0.143	0.000
n	143		143.000	
ECad	Pearson correlation	0.353**	0.510**	1.000
	Sig. (2-tailed)	0.000	0.000	0.143
	n	143.000	143.000	

**: Correlation is significant at the 0.01 level (2-tailed)

The rice yield response to soil ECa is highly associated in non-linear compared to the linear regression analysis. The BLA isolates the top yielding points for each soil EC range and fits a non-linear line or equation to represent the top-performing yields within each soil EC range. This method knifes through the cloud of EC/yield data and describes their relationship when other factors are removed or reduced.

Table 4: Results of boundary line analysis for rice yield and ECad in six lots of the study area

Lot	n	Average of ECad (mS m^{-1})	Average rice yield (ton ha^{-1})	95th percentile R^2	95th percentile Model	75th percentile R^2	75th percentile Model
All lots	143	89.61	8.13	0.3903***	yield = -0.00031 (ECad)^2 + 0.08099 (ECad)+6.29212	0.4156***	yield = -0.00054 (ECad)^2+0.12373 (ECad)+2.73336^b

^{b}: Boundary line model to be used for map generation; ***: R^2 values in column are significant at the 0.001 level

Table 5: Results of boundary line analysis for rice yield and ECas in six lots of the study area

Lot	n	Average of ECas (mS m^{-1})	Average rice yield (ton ha^{-1})	95th percentile R^2	95th percentile Model	75th percentile R^2	75th percentile Model
All lots	143	34.75	8.13	0.0999**	yield = -0.00170 (ECas)^2 +0.13122 (ECas)+8.71453	0.1833***	yield = -0.00226 (ECas)^2 +(0.19947 (ECas)+5.10047^b

^{b}: Boundary line model to be used for map generation; **: R^2 value in column is significant at the 0.01 level; ***: R^2 value in column is significant at the 0.001 level

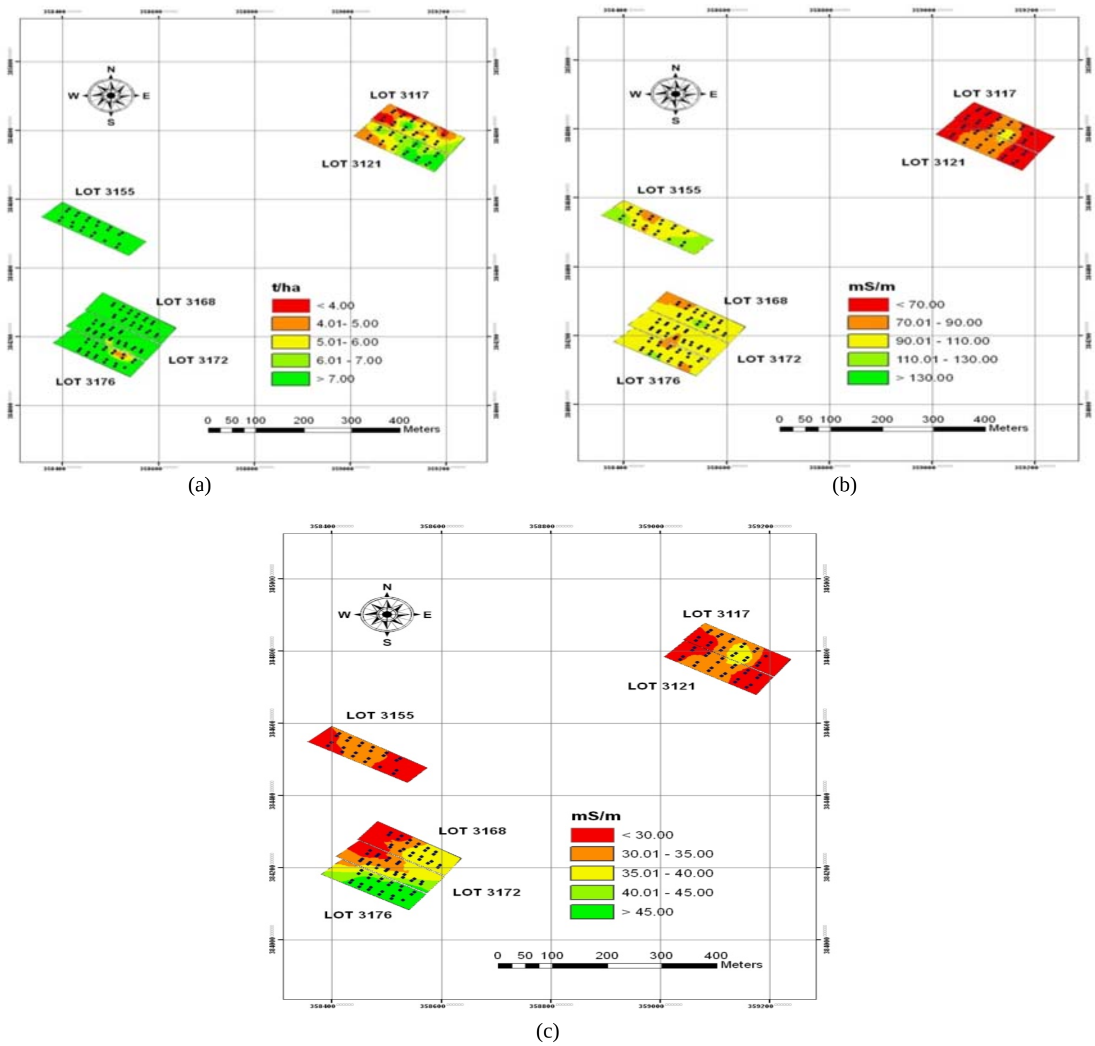


Fig. 6: The kriging maps of (a) rice yield, (b) ECad and (c) ECas classified by manual method

Figure 4 is a scatter plot of a Sawah Sempadan paddy field which does not show a statistically significant relationship when both data sets are correlated in their entirety. It would seem that ECas explains zero percent of the yield variability on this field. Yet a relationship does appear to exist at the upper yield limits as shown in Fig. 5b. This relationship is clarified using the boundary line method which shows that ECas explains almost 20% of the yield limiting factors on this field. Further more, the relationship of rice yield is significantly more related to ECad as shown in Fig. 5a which explains almost 50% of the yield variability. The upper boundary represents the maximum yield for each soil EC range. Nevertheless, there may be a number of factors causing yields to be lower than the boundary that need to be investigated further.

Visual map analysis: The classification approach using raster calculator, which was available in the spatial analyst for calculating the ECa reading and calculated maps were produced. Since the standard classification did not visualize much variability, thus the classification technique of manual, which was introduced by ArcGIS software, was selected to visual variability as groups. This study decided to zone the area into 5 zones (respectively for ECa reading and rice yield) which could be manageable and also easy to compare.

According to the yield map Fig. 6a, the areas were mostly occupied by the higher yield and it seemed to be concentrated in the south. The lower yield were scattered mostly in lots 3117 and 3121 in the north of the area. The variability of ECad map Fig. 6b illustrated that class 3 (the moderate values of ECad) was covered almost more than half of the area and concentrated in the south. The lots 3117 and 3121 located in northern area have lower ECa values compared to the other lots. Previous research was established that lots 3117 and 3121 are located in peat area where a former river was found in that area Aimrun *et al*. (2008). In this condition, any supplemental inputs (water and fertilizer) will be absorbed more by the soil rather than crop due to high infiltration rate on the soil. For that reason, the irrigated and stagnant water in those particular lots become lesser and influenced the ECa values as previously discussed.

DISCUSSION

The analyses in this study showed that both ECad and ECas are important parameters in determining the relationship evidences between rice yield and soil ECa. The stepwise method was suggested both ECad and ECas are necessary variables to generate linear modeling. However, the ECad contributed more to the significant relationship factor rather than ECas. Beside, an approach of Boundary Line Analysis (BLA) technique proved that the rice yield is significantly related to ECad which explains almost 50% of the yield variability. The analyses results show that both low and high ECa values are associated with a decrease in yield productivity. The mid-range of ECa values correspond high rice yield in both ECad and ECas conditions.

According to the kriging maps observation, the Sawah Sempadan paddy fields produced higher yield in southern area associate with the moderate values of ECad. There was no obvious relationship between yield and ECas considered not contributing any influence factor to the rice yield as visualized in ECas kriging map. It can be concluded, that visual observation and statistical analysis indicated the same results and the trends could be observed in most areas of the paddy field for several planting season.

CONCLUSION

These findings indicate the potential for technology of precision farming to understand and control variation in Malaysian production fields. Additional research is needed to confirm the results with data from other fields and crops.

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