SPATIAL SOIL VARIABILITY MAPPING USING ELECTRICAL CONDUCTIVITY SENSOR FOR PRECISION FARMING OF RICE

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ABSTRACT

Accurate and inexpensive methods for measuring soil properties are required to enhance interpretation of yield maps and improve planning for precision farming strategies. The conventional soil sampling is time consuming and requires intensive laboratory analysis. Hence mapping of apparent profile of soil electrical conductivity (EC_a) was developed to identify areas of contrasting soil properties. Such EC_a values are surrogate measures of soil properties. The sensor system, VerisEC model 3100 is used to predict soil nutrients. This system consists of three important parts viz., EC probe, data logger and Differential Global Positioning System (DGPS) receiver. There are six coulter probes where the second and the fifth probes provide the electrical charge while the first and the sixth probe measure the average electrical conductivity (EC_a) for 90 cm depth, and the third and fourth measure EC_a for 30 cm depth. The data logger records EC readings at every second while the DGPS provides the position at sub-meter accuracy. A study was conducted to evaluate the relationships between EC_a and soil properties as well as rice yield in lowland irrigated paddy fields. Grain yield data was obtained by 3 x 3 m crop cutting test at 30 m interval regular grid in the 9-ha plot. Soils were sampled at the same location as the crop cutting test area. The soil samples were analyzed for selected physical and chemical properties. Two study sites were chosen. For the first site, the sensor was pull through a 9-ha plot by a 60-hp tractor in a series of parallel transects spaced about 15 m apart, while for a smaller plot of 0.4 ha field installed with subsurface drainage facility, the path was 7m apart. The kriged map of EC_a was developed to identify the contrast of EC_a. More than 5,200 EC_a data points were collected in 2 hrs for the large plot and 1,800 data points for the smaller plot in 30 minutes. Study site no. 2 has 118 plots covering 132 ha with an average plot size of about 1.2 ha. The EC sensor was pulled by a 35 HP tractor at a speed of about 15 km h^{-1} in a U-shape pattern 15 m apart. The data was later transferred to a notebook computer for generation of EC_a maps using Surfer 7.0 software and ArcGIS 8.3 with Spatial and 3D Analyst extensions. From the analyses, yield and EC_a, nitrogen, potassium, organic carbon and pH show positive correlation. The average values of EC_a are significantly different between shallow and deep depths signifying differences in soil structure. Soil EC_a could provide a measure of the spatial differences associated with soil physical and chemical properties, which for paddy soil may be a measure of soil suitability for crop growth and its productivity. This sensor can measure the soil EC_a through the field quickly for detailed features of the soil and can be operated by just one worker. The EC_a map provides some ideas for future soil management.

Key words: *Bulk Soil Electrical Conductivity, Precision Farming, Kriged Map*

INTRODUCTION

Precision farming is managing each crop production input (e.g. fertilizer, water, lime, herbicide, insecticide and seed) on a site-specific basis to reduce waste, increase profit and maintain the quality of the environment. Without some remarkable enabling assisting technologies, the individual treatment of each plant is impossible and the concept of precision farming would not be feasible. Soil sensor such as the VerisEC sensor is a useful tool in mapping soil electrical conductivity (EC) in order to identify areas of contrasting soil properties. In non-saline soils, EC values are measurements of soil texture –relative amounts of sand, silt and clay. Soil texture is directly related to both water holding capacity and cation exchange capacity, which are key ingredients of productivity [1].

Precision farming relies on geospatial information to facilitate the treatment of small portions of the field as individual management units. Although agriculturalists have long known that fields are heterogeneous, only recently have technologies become available that allow production practices to efficiently take this variability into account. Key technologies include GPS, GIS, electronic sensors, and ruggedized computers for within-field data acquisition and operation control. Although it is now relatively easy to collect geospatial data for precision farming, it is more

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difficult to know how to most effectively use those data in making crop management decisions. An important step in these management decisions is understanding the relationship, on a spatial basis, of crop yields to the myriad of agronomic factors which may potentially be causing yield variations. Sudduth [2] presented a case study, which examines their approach to spatial data collection and the use of statistical analysis and crop growth modeling to relate spatial grain yields to differences in those factors that can affect yields.

Two types for sampling method are Grid sampling and Zone sampling. Grid sampling is often conducted on regular grids at spacing of 50 to 100 m or more. It is, therefore, expensive and labor intensive. Zone sampling is sampling based on similar soil property. Through zone sampling, the cost and labor can be reduced by minimizing the number of samples. Soil sampling provides the data used to make maps of the spatial patterns in soil fertility, soil organic matter content, soil pH or soil water. Those maps are then used to make recommendations on the variation of application rates. Currently, farmers manage the field by uniform application over their large fields, based on a single sample of soil cores composite from various areas of the field. But site-specific management or variable rate management introduces zone management in order to reduce cost, maximize yields and benefit the environment.

There are two methods for implementing precision farming or site-specific farming. Each method has unique benefits and can even be used in a complementary or combined fashion. The first method is Map-based that includes the following steps: grid sampling a field, performing laboratory analyses of the soil samples, generating a site-specific map of the properties and finally using this map to operate a variable-rate applicator. During the sampling and application steps, a positioning system, usually DGPS (Differential Global Positioning System), is used to locate the position in the field. The second method is Sensor-based, which utilizes real-time sensors and feedback control to measure the desired properties on-the-go, usually soil properties or crop characteristics, and immediately use this signal to control the variable-rate applicator. This second method does not necessarily require the use of a GPS.

Soil scientists and engineers usually collect the soil samples based on soil map created by semi-detailed sampling. This means one sample is collected from several hectares. Application of inputs follows this recommended or action map, while a good management needs the details of every foot step. Grid sampling will involve few samples per hectare. In a 50 m grid, the total samples for one-hectare field is only 4 samples. Using EC_a sensor to show the contrast of soil properties in the field, the soil EC_a throughout the field can be determined rapidly with detailed features of the soil, and operated by a few workers. Data can be collected every second, therefore numerous data points can be presented on an EC_a map. This paper presents results of a study using the VerisEC sensor in acquiring very detailed soil EC information that can be correlated to some other soil properties for precision farming of rice.

ELECTRICAL CONDUCTIVITY SENSOR

Resistivity measurement involves applying a voltage into the ground through metal electrodes and measuring the resistance to the flow of the electric current. A typical system of resistivity survey consists of four equally spaced metal electrodes [a so-called Wenner array] inserted into the soil. An AC-power source supplies current flow (I) between the two outer electrodes and the resultant voltage difference (V) between the two inner electrodes is measured. The resistance of the soil is given by $R = V / I$. This needs to be standardized over a unit length. The resistance times the length (of the resistor in this case the soil) is called the resistivity. Alternatively, this can be expressed in terms of conductance ($C = 1/ R$, unit ohm^{-1} = Siemens).

VerisEC soil electrical conductivity sensor is used for detecting the ability of soil in conducting electricity. In the Veris Soil EC Mapping System the electrodes are rotating discs placed 6cm into the soil (Fig. 1). As the cart is pulled through the field, one pair of electrodes passes electrical current into the soil, while two other pairs of electrodes measures the voltage drop. The system is set up to switch between two configurations A (shallow) and B (deep). Configuration A uses the four inner discs (2, 3, 4 & 5) as shown in Fig 2. The voltage is measured between the two innermost discs (3 & 4) which are d = m apart. In Configuration B the four outer discs (1, 2, 5 & 6) are used and the voltage is measured between discs 2 and 5. When the electrodes (discs) are d metres apart the conductivity is measured to a depth of roughly 1.5d metres.

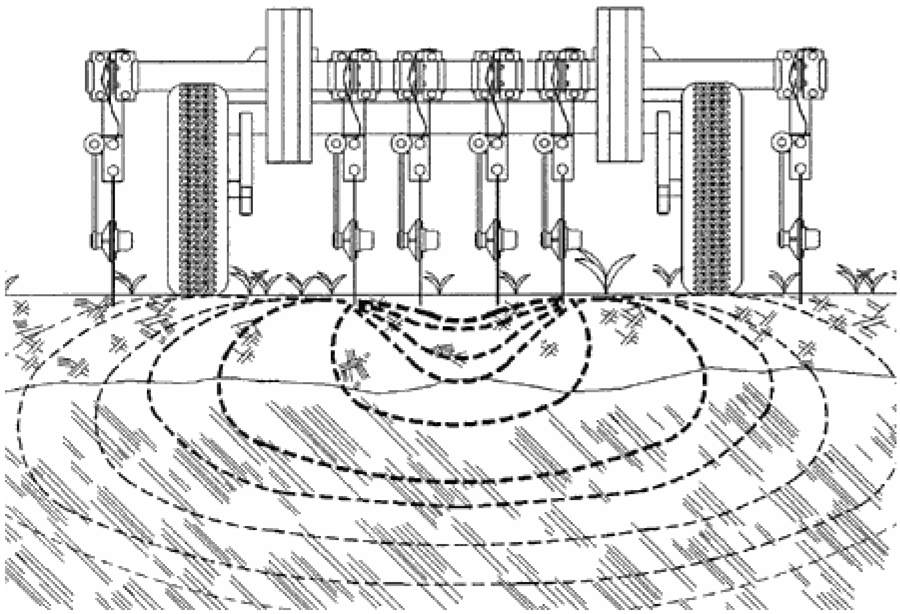

Fig.1: The System Components of Veris Soil EC Mapping-Model: Veris3100.

According to VerisTech [1], some benefits of the soil conductivity map which can be derived by Veris 3100 are: (a) determine the layout of the site, (b) used in the interpolation of yield maps, (c) guide soil sampling, (d) design on-farm trials, and (e) help derive input recipes for seed, nutrients and crop protection chemicals.

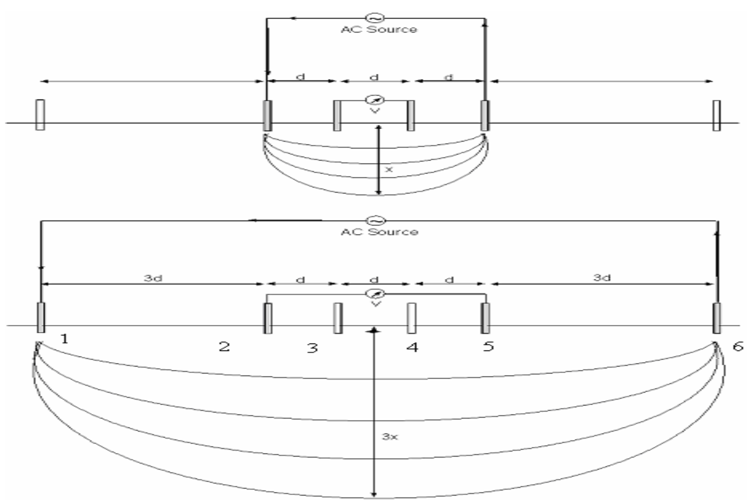

Fig. 2: Schematic of Configuration A-Shallow <30 cm (top) and B-Deep <90 cm(below).

It is not surprising that maps of soil physical properties and yield maps show visible correlation. Soil EC_a can serve as a proxy for soil physical properties such as organic matter [3], clay content [4], depth to claypan [5], and cation exchange capacity [6]. These properties have a significant effect on water and nutrient-holding capacity, which are major drivers of yield [7]. The relationship between soil EC_a and yield has been reported and quantified by others [8], [9], [10].

Sudduth [2] found that within field variation in soil properties could be explained with soil conductivity measurements. They found a significant relationship between soil conductivity and topsoil depth and Fraisse [11] added to this work by using soil electrical conductivity for zone delineation. Both of these works concentrated on using soil EC_a to characterize local spatial variability. Lund [12] show that sampling according to soil management zones identified with a soil conductivity map can be more effective than grid sampling.

MATERIALS AND METHOD

The study was conducted at two paddy areas, one in Penang, and the other in Selangor, about 300 km apart. The objective was to evaluate the relationships between EC_a and soil properties as well as rice yield in lowland irrigated paddy fields. Grain yield data was obtained by 3 x 3 m crop cutting test at 30 m interval regular grid. Soils were sampled at the same location as the crop cutting test area. The soil samples were analyzed for selected physical and chemical properties. For the first site, the sensor was pull through a 9-ha plot by a 60-hp tractor in a series of parallel transects spaced about 15 m apart, while for the smaller plot of 0.4 ha field installed with subsurface drainage facility, it was pulled through in a u-shaped path 7m apart in each of the three similarly sized sub-plots. The kriged map of EC_a was developed to identify the contrast of EC_a. Study site no. 2 has 118 plots covering 132 ha with an average plot size of about 1.2 ha. The VerisEC cart was pulled by a 35 HP tractor at a speed of about 15 km h^{-1} in a U-shape pattern 15 m apart. The data was later transferred to a notebook computer for generation of EC_a maps using Surfer 7.0 software and ArcGIS 8.3 with Spatial and 3D Analyst extensions.

EC Data Acquisition and EC Map

The instrument for the Veris 3100 Sensor was calibrated, as per manufacturer instructions, prior to data collection for each field. The Veris 3100 uses three pairs of coulter-electrodes to determine soil EC_a. The coulters penetrate the soil surface to depth of about 6 cm. One pair of electrodes functions 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. The center pair, situated closest to the emitting (reference) coulter-electrodes, integrates resistance between depths of 0 and 30 cm, while the outside pair integrates between 0 and 90 cm. Output from the Veris Data Logger reflects the conversion of resistance to conductivity (1/resistance = conductivity). A Trimble AG132 DGPS system (Trimble Navigation Ltd., Sunnyvale, CA) with sub-meter accuracy was used to geo-reference the EC_a measurements. The Veris data logger records latitude, longitude, and shallow and deep EC_a data (mS m^{-1}) by one second intervals in an ASCII text format. The EC_a data in ASCII format is then transferred to Surfer software for generating an EC_a map. The basic statistical analysis such as mean, minimum value, maximum value and standard deviation is described in order to understand the basic features of the soil EC_a. Fig. 3 shows the Veris EC 3100 cart mounted with GPS antenna pulled by a tractor fitted with GPS receiver and data logger.

Fig. 3: VerisEC 3100 and GPS Pulled by a Tractor

RESULTS AND DISCUSSION

The study found that the operation time for the small plot of 1.2 ha (3 acres) was only about 30 minutes and the sensor can collect more than 300 data points. And the operation time for the big plot (9ha) was about 2 hours and the sensor can collect more than 5,000 data points. The other methods such as grid sampling or random sampling techniques will require more time to cover the acreage.

The EC_a values at shallow depth (0-30 cm) for the small plot ranged from 7.4 to 49.4 mS/m with the average of 24.4 mS/m. The standard deviation was 6.6 mS/m and the total 357 data points. The deep (0-90 cm) EC_a values ranged from 4.6 to 60.7 mS/m with the average and the standard deviation of 24.8 mS/m and 7.7 mS/m, respectively. The total number was 347 data points.

Fig. 4 shows the variation of the shallow EC_a at the small plot. The EC_a values were divided into 5 classes with the binning method of Equal Number. High EC values were found at the northern part of the study area while the southern part was lowest. The distribution of deep EC_a values was similar to shallow EC_a, where EC_a in the northern part were higher than in the south (Fig. 5).

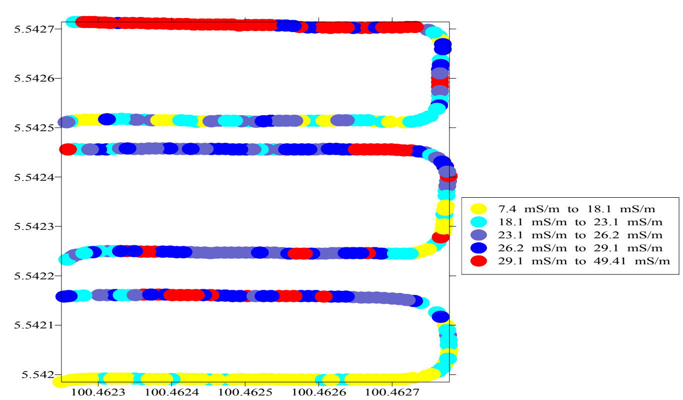

Fig. 4: Map of Shallow EC_a for the 1.2 ha Plot.

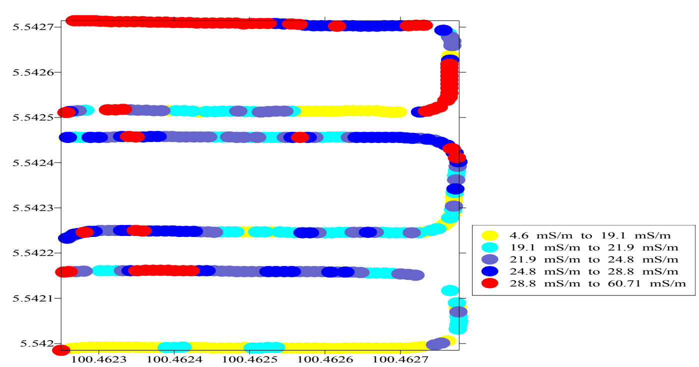

Fig. 5: Map of Deep EC_a for the 1.2 ha Plot.

For the big plot, the EC_a values at shallow depth ranged from 0.9 to 64.1 mS/m with the average and the standard deviation of 5.7 mS/m and 3.0 mS/m, respectively. The total data points collected was 5454 points (Fig.6). The deep EC_a value ranged from 1.3 to 48.9 mS/m with the average and the standard deviation of 9.1 mS/m and 6.8 mS/m, respectively. The total number was 5205 data points (Fig. 8). The average value of the deep ECa was higher than that of the shallow depths. This indicates some differences in soil properties within the root zone (<30 cm) and sub layer below the root zone. More than 5,200 EC_a data points were collected in 2 hrs for the large plot and 1,800 data points for the smaller plot in 30 minutes.

The post map of the shallow EC_a for the big plot is shown in Fig. 6. The values were divided into 5 classes with the binning method of Equal Number. High EC values are distributed in the middle part of the study area. Fig.7 shows the kriging map of the raw data. Based on the maps, the spatial variability of soil ECa within a field or the adjacent field is clearly shown. For deep EC_a, the higher values are distributed in the northern part and higher than in the south as shown in Figs. 8 and 9. The average EC_a values from both plots (small and big) show that the small plot installed with subsurface drainage system has higher EC_a than the larger plot. The soils of the smaller plot has higher clay content. Based on previous yield records, the small plot produces higher yield than the big plot. Further work is being carried out to determine the correlation of rice yield with EC_a measurement and other soil fertility parameters in the paddy field.

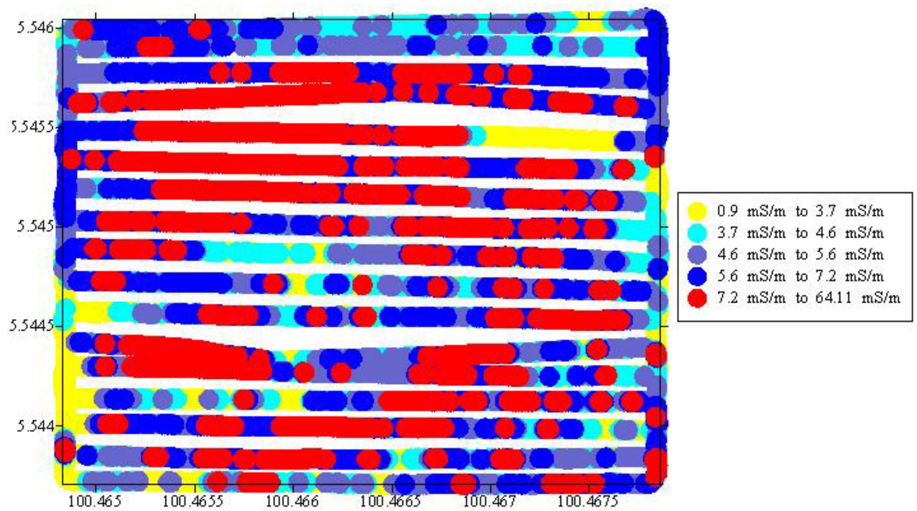

Fig. 6: Map of Shallow EC_a for the 9 ha Plot.

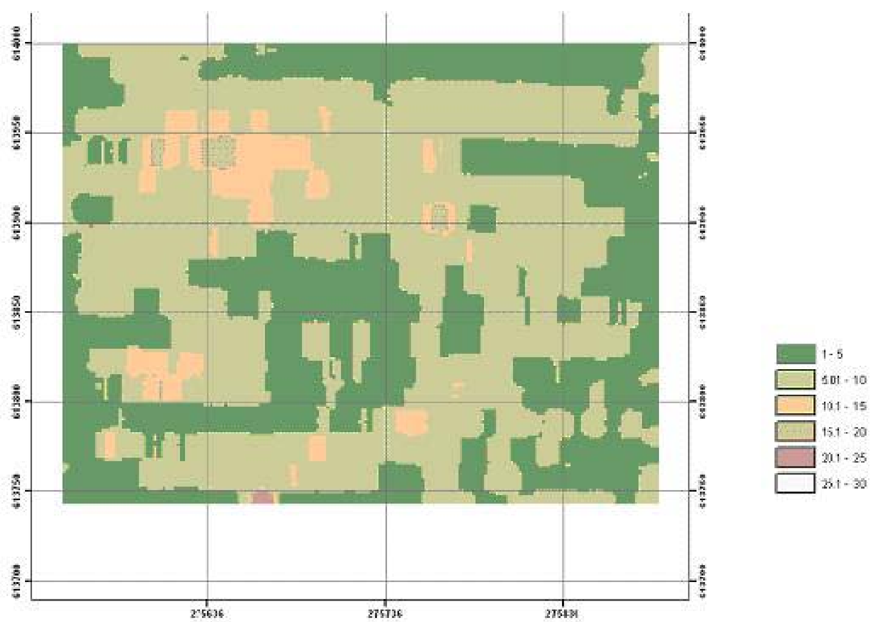

Fig. 7: Kriging Map of Shallow EC_a for the 9 ha Plot.

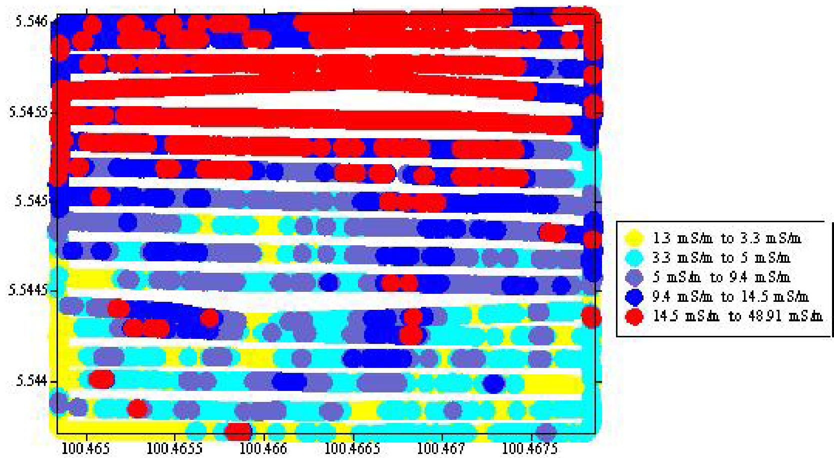

Fig. 8: Map of Deep EC_a for the 9 ha Plot.

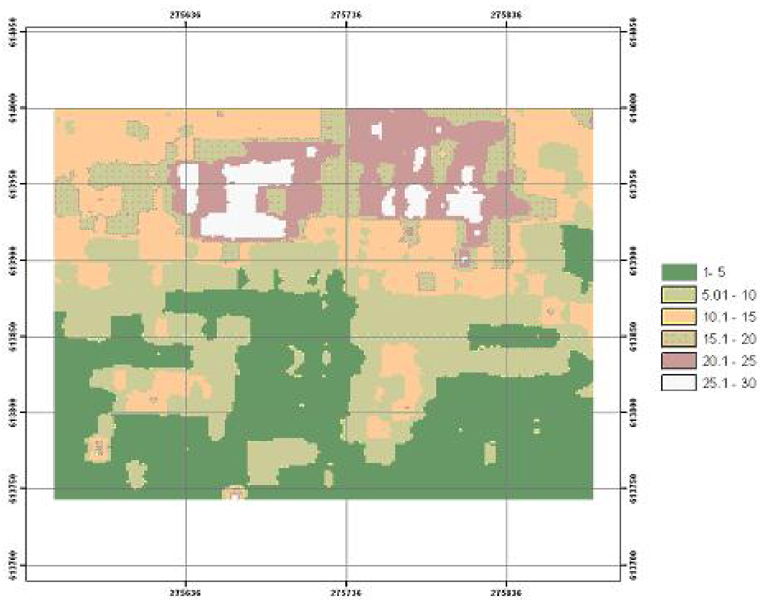

Fig. 9: Kriging Map of Deep EC_a for the 9 ha Plot.

Study site no. 2 has 118 plots covering 132 ha with an average plot size of about 1.2 ha. The VerisEC cart was pulled by a 35 HP tractor at a speed of about 15 km h^{-1} in a U-shape pattern 15 m apart. The data was later transferred to a notebook computer for generation of EC_a maps using Surfer 7.0 software. Results of kriging is shown in Fig. 10. A closer look at one paddy plot typically owned by one farmer is shown in Figs. 11 and 12. The farmer with this map in his possession will be able to apply variable rate of fertilizer according to the delineated zones. From laboratory analyses of manual soil sampling conducted earlier, yield and EC_a, Nitrogen, Phosphorus, organic carbon and pH show positive correlation. Fig. 13 shows results of regression analysis of rice yield in relation to EC, N and P. All show positive correlation to yield. The average values of EC_a are significantly different between shallow and deep depths signifying differences in soil structure. Soil EC_a could provide a measure of the spatial differences associated with soil physical and chemical properties, which for paddy soil may be a measure of soil suitability for crop growth and its productivity. This sensor can measure the soil EC_a through the field quickly for detailed features of the soil and can be operated by just one worker. The EC_a map provides some ideas for future soil management. Further studies are being undertaken to relate ECa to rice yield obtained by a yield sensor mounted on the combine rice harvester complete with GPS and data logger.

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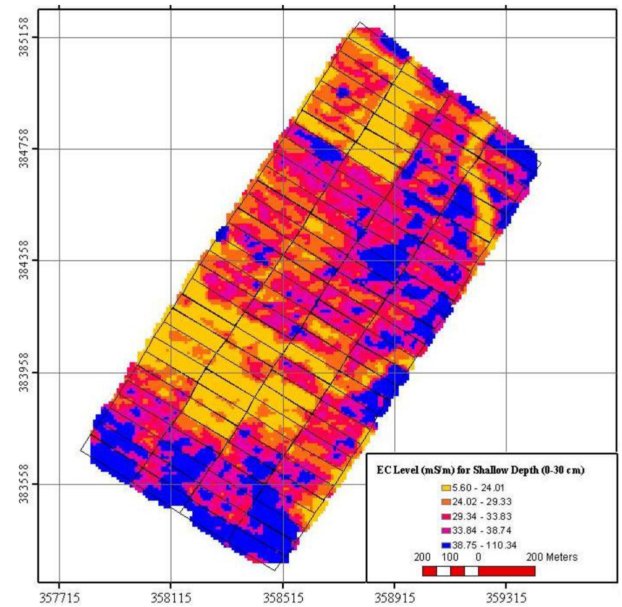

Fig. 10. Kriging map of EC_a for 132 ha Irrigation Block at PBLS, Malaysia.

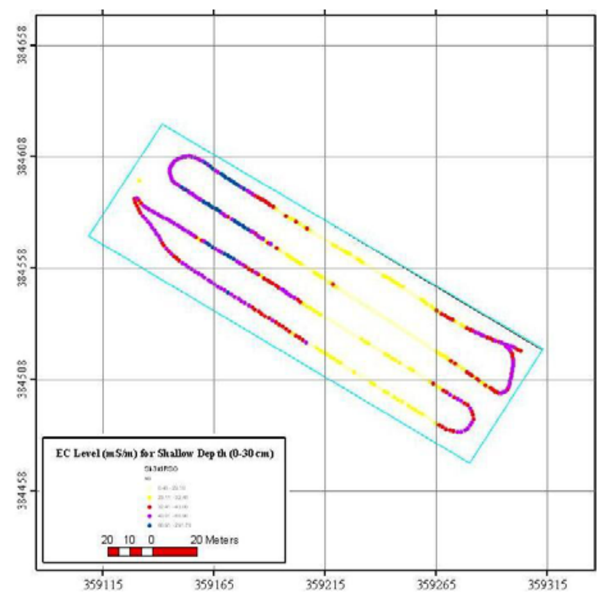

Fig. 11. EC_a Data from Four Passes of The Sensor In A 1.2 Ha Paddy Field

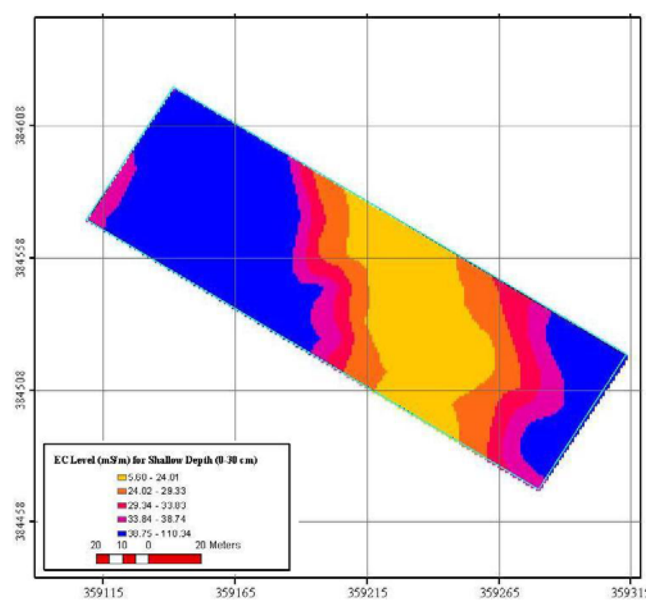

Fig. 12. Kriged Map of Shallow Ec_a for The 1.2 Ha Field

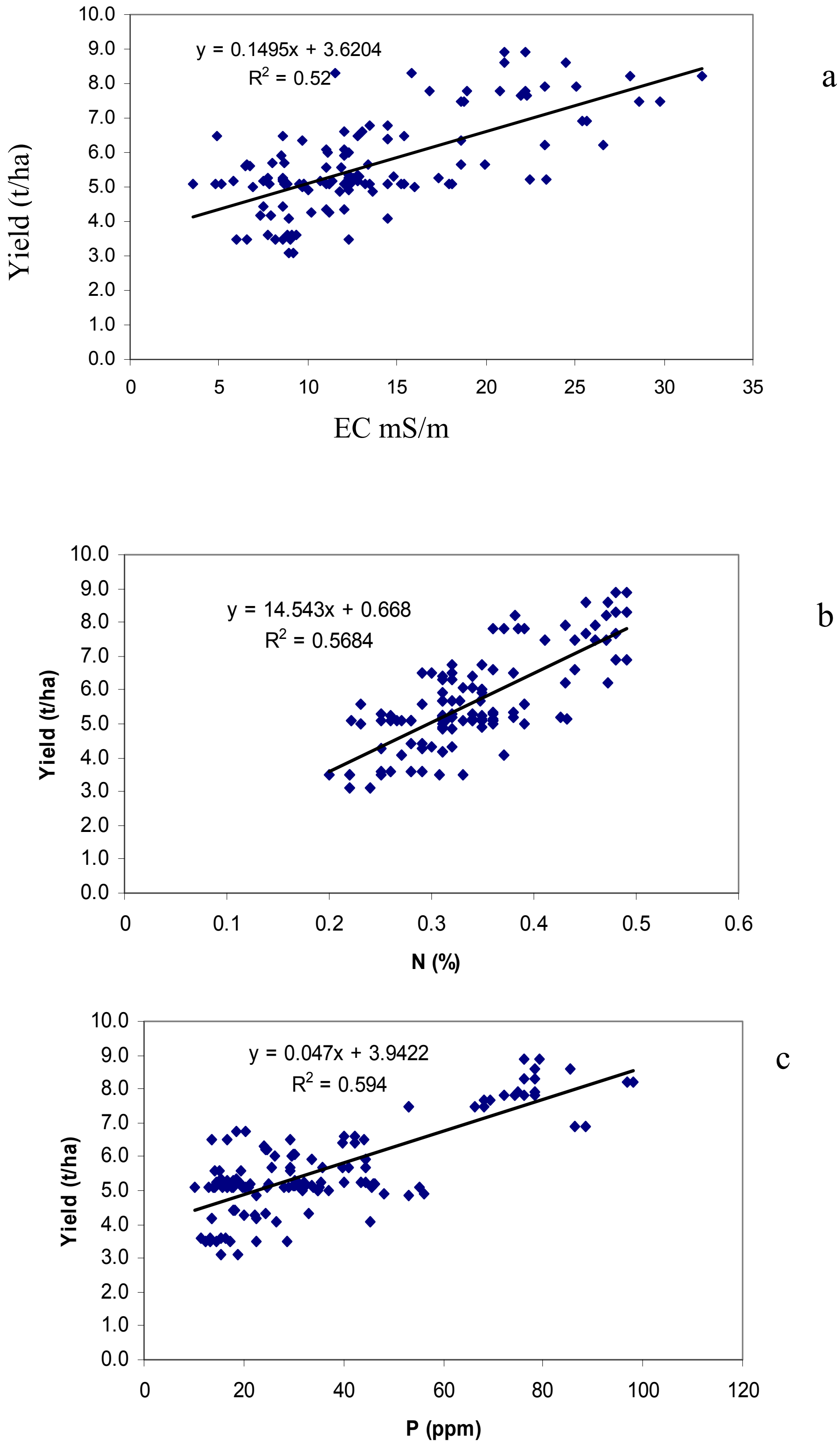

Fig. 13. Correlation of Rice yield with a) EC, b) N, and c) P, Respectively

CONCLUSION

Spatial soil variability mapping using electrical conductivity sensor is a very useful technology for precision farming. VerisEC is one such on-the-go EC_a sensor that collects soil EC_a data while the tractor is moving. With the logging interval of one second, a slow drive will collect more data points. A tractor moving at 15 km/h with a swath width of 15m can collect about 500 EC data points. Hence, the advantage of this sensor is that it can collect almost 50 to 100 times more data points than direct sampling or grid sampling techniques. EC_a measurements can show the variability of soil properties in detail and rapidly using simple equipment with less cost and labour force. Action maps will then be produced for farmers to apply fertilizers at different rates according to the delineated zones.

Based on the concept of on-the-go multi-sensor, this EC_a sensor is currently the most suitable device where its data is able to be correlated to some other soil properties (since it does not only measure one parameter) through ground truthing or scouting. The variability map will provide some ideas for soil management to fulfill the concept of precision farming.

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