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DEVELOPMENT OF REAL TIME SOIL NUTRIENT MAPPING SYSTEM IN PADDY FIELD

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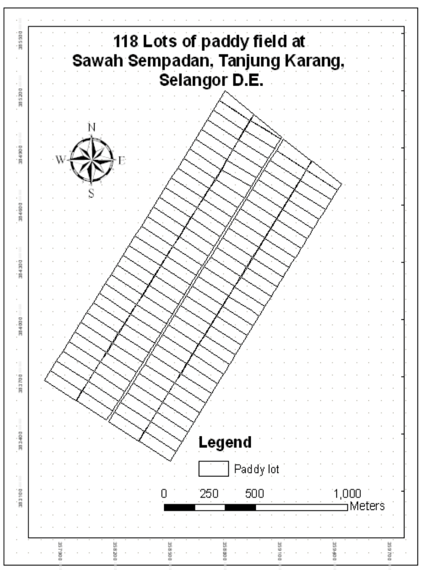
Graphical abstract



Abstract

Application of advanced sensing technology in agriculture has becoming a trend in many countries. Integration of sensors and ICT such as GIS is essential for grower to improve their field management and crop yield. Effective site specific management requires strong and temporally consistent relationship zones that have been identified, underlying soil physical, chemical and biological parameters, and crop yield. Those requirements are possible to be obtained through the use of specialized equipment and state-of-the art technology. This study was carried out to develop a real time system to provide map of soil nutrient such total nitrogen (N), available phosphorus (P) and exchangeable potassium (K) by using electrical conductivity sensor. Results from this study have proven the merit of the developed system in terms of its performance and its reliability. The soil nutrient map produced by this system was nearly identical to a kriging map produced via ArcGIS software and it reliable for use in the site specific application for best fertilizer management practices. This finding indicates that the soil nutrient variability map was possible to be produced in real-time basis without engaging any tedious work in the field. The use of this mapping system as a basis of identifying the soil nutrient variability proved to be a good technique for the farmers to better manage their paddy fields.

Keywords: Apparent Soil Electrical Conductivity (ECa), Nitrogen (N) Fertilizer, Paddy Field, Variability Map

1.0 INTRODUCTION

Macro-nutrients, nitrogen (N), phosphorus (P), and potassium (K), three of the most important nutrients and are the prime ingredients in almost all fertilizers. Measurement of NPK fertilizers in the field is essential in order to deliver the optimum rate of fertilizers according to the crop requirement. Previously, chemical analysis in laboratory is the only procedure being used to measure soil nutrient in the field. The chemical analyses required to develop a precision fertilization scheme involves intensive and complex laboratory testing, which makes sampling and evaluation of soil samples over what could be tens to thousands of acres of farmland physically impractical and cost prohibitive [1]. Thus, fertilizer application has generally been tailored to the extent possible on a scale of hectares (or larger). Generally, fertilizer is broadcasted uniformly throughout a field, although it is known that soil fertility varies considerably within a field and when the amount of fertilizer concentrations in soil increased, the uptake of nutrient by plants is also increasing [2]. From previous research done, it was shown that the fertilizers content is essential to be known in order to apply the fertilizer in the right amount, at the right place and for critical growth stages for best management practices [3]. Thus, a quick measurement tool for soil nutrients such on-the-go device is necessary for the crop field management. On-the-go soil measurement devices and soil sampling approaches have been developed and described by many researchers [4], [5], [6], [7], [8], [9], [10]. The emerging of technology such apparent soil electrical conductivity (ECa) sensor was reported to be reliable to describe field condition as well as nitrogen contents [10]. The ECa sensor is developed for on-the-go measurement of soil properties and is a very practical tool in mapping different soil properties as the soil ECa can be measured quickly with known locations. The apparent Electrical Conductivity (ECa), is affected by several soil properties such as soil water content, clay content, salinity, temperature, organic compounds and also metals [11]. Although many soil factors affecting ECa are relatively fixed over time (e.g., clay content), others may exhibit strong seasonal dynamics. The ECa sensor was also used to determine the relationship between rice yield and soil ECa where the analyses show that ECa value is closely associated with rice yield [12].

Apparent soil electrical conductivity sensor could also help to define management zones with differing productivity and nutrient requirements because of its ability to measure the soil properties [13]. The potential yield can be estimated by determining topsoil thickness with the soil ECa measurements, and then can be used to employ a variable-rate fertilizer [14]. This approach for fertilizer management has been tested and application found to be effective in many types of crops [15].

Traditional fertilizing recommendation that is commonly used by the farmers in Malaysia for paddy cultivation will slightly cause many detrimental effects to the environment, soil properties, production efficiency and also to the crop itself. It also increased the cost of production in terms of fertilizer use and represents a substantial financial burden to the Government to allocate the fertilizer subsidies to the farmers. Therefore, this study was conducted to develop a rapid system to determine NPK contents in the soil for site specific area to assist farmers and fertilizer provider to control and monitor the NPK requirement for best management practices.

2.0 MATERIALS AND METHODS

A Site Description

The study 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 & Agro-Based Industry Malaysia (MOA). It is in the district of Kuala Selangor at latitude 3°35"N and longitude 101°05"E. The selected study area comprised of 118 lots of paddy field with an average lot size of 1.2ha or less (Figure 1). This granary area was chosen in order to compare the actual nitrogen content in the paddy soil obtained from soil analyses and the predicted nitrogen content derived by the developed system.

B Soil ECa Measurement

A Veris® 3100 Soil EC Sensor was used to measure soil ECa as shown in Figure 2. The sensor consists of six coulters, two of which introduce an electrical potential into the soil. The remaining four coulters are spaced to measure EC over two approximate depths, 0-30 cm for shallow ECa (ECas) and 0-90 cm for deep ECa (ECad). The coulters penetrate the soil surface into a depth of 6 cm. The depth of measurement is based upon the spacing of the coulter-electrodes. The sensor integrated with global navigation satellite system (GNSS) was pulled behind a tractor across each lot within an area of 60 m width and 200 m length. The output data from the logger reflected the conversion of resistance to conductivity (1/resistance = conductivity). A Differential Global Navigation Satellite System (DGNSS) with sub-meter accuracy was used to geo-reference ECa measurements. The soil ECa data obtained from the sensor was used to generate the variability map using ArcGIS version 9.2. The manual classification technique, which was introduced by ArcGIS software, was selected for visual variability as groups. The manual classes were used to compare features to specific and meaning values, emphasize a particular range of values and also can be used for isolating and highlighting ranges of data [16]. The spatial interpolation or kriging method was used to produce a surface of variable values in order to identify the surface coverage or spatial distribution. Kriging technique was chosen over Inverse Distance Weight because it is widely used in practice by many [17].

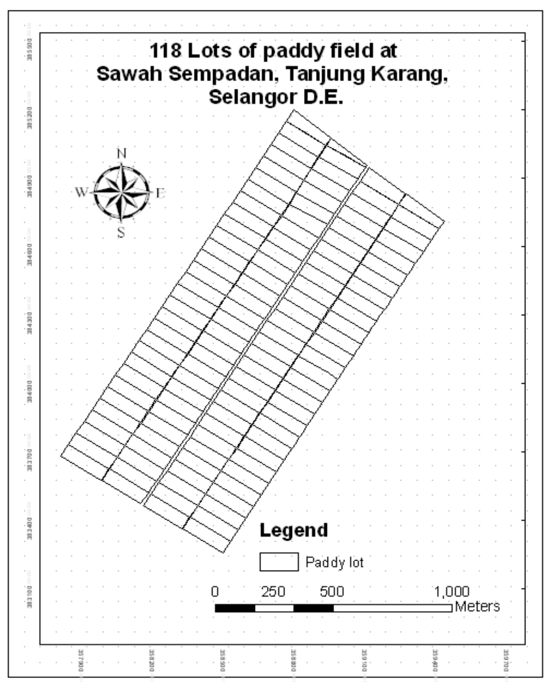


Figure 1 The experimental area at Sawah Sempadan, Tanjung Karang, Selangor\

Figure 2 Soil ECa sensor integrated with Trimble Ag132 DGPS pulled by a tractor

C Soil Nutrient Analyses and Reference Model

The soil sample from each lot was taken within a depth of 30 cm. The sampling task was carried out by using Eijkelkamp soil auger. All the 118 samples were brought to the laboratory to analyze the nutrient content in the respective study area using the Kjeldahl digestion technique [18] for total nitrogen analyses. Exchangeable K and available P were determined by neutral ammonium acetate extraction method (Schollenberger and Simon, 1945) and the Bray II method (Bray and Kurtz, 1945) respectively. The soil nutrients were analyzed for comparison purposes and to measure the reliability level of the developed system.

The predicted model for soil nutrients were derived from the previous study [19]. The soil ECa was identified to be reliable to measure soil nutrients at the study site for both dry and wet seasons. The statistical analysis shows that soil ECa was significantly related to total N, available P and exchangeable K at 0.01 level. The model based on soil ECa can be described as follow:

$$Total\ N = 0.1070 + (11.5606 / ECad)$$

$$Available\ P = e^{2.5932+(13.7757/ECad)}$$

$$Exchangeable\ K = e^{-0.4907-(32.065/ECad)}$$

D Program Development

The MATLAB software version 7.4.0 was used to develop the application program. It was designed to produce the nitrogen variability map during on-the-go measurement of soil ECa. The program was developed to plot the NPK in real time basis and the plotting map to be displayed on the robust computer screen mounted in a tractor cab. The coordinates of plotted data point were retrieved from DGNSS which was connected to the robust computer. The developed program was facilitated with interpolation function to generate the variability map based on the plotting data obtained from the ECa sensor. This function provides three selection methods; automatic interpolation, equal interval and K-means, and also a manual interpolation which allows user to insert the desired minimum and maximum range. The program was mounted as a very user-friendly tool with interactive GUI for user to access as shown in Figure 3. It is a simple system with many selections of panels and easy to use.

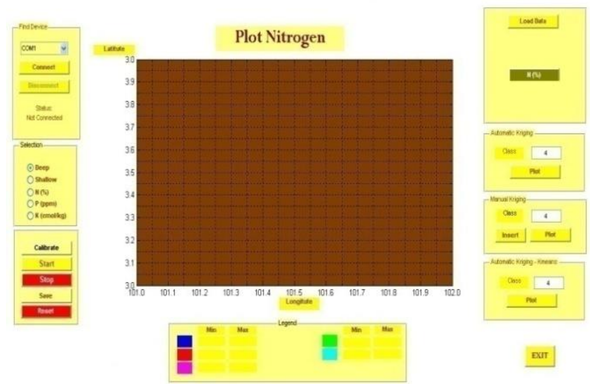


Figure 3 Graphical User Interface (GUI) of the developed program

E System Setup

The developed system consist of various devices such DGNSS, ECa sensor, a robust computer, a software and a tractor integrated as a system to provide the necessary information as shown in Figure 4. The DGNSS and ECa sensor were connected to the robust computer which mounted in the tractor cabin. The developed program was installed in the robust computer as a tool or software to synchronize the DGNSS and ECa sensor. The data obtained from the system will appear automatically as a map based in the software when the synchronization was successful. The tractor was a prime mover to pull the ECa sensor for data acquisition task within the paddy field. All the electronic devices were supplied by the 12 volts power source from the tractor's battery.

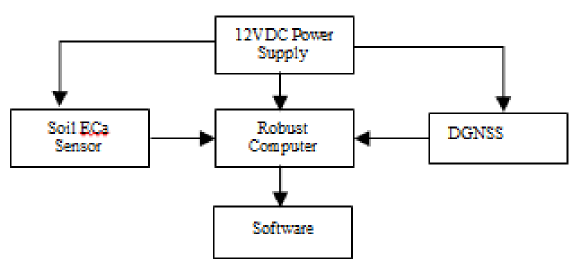


Figure 4 Diagram of the developed system comprising of various devices

3.0 RESULTS AND DISCUSSIONS

Validity Test

The ECa data obtained from the sensor were integrated over a soil depth of 30 cm and 90cm for shallow ECa (ECas) and deep ECa (ECad), respectively. The total number of ECa data points was 21,642 for 118 lots. The number of data is dependent on the speed of the tractor and the condition of the soil surface. The logging interval of one second, a slow drive can collect more data points [20]. Table 1 shows the descriptive statistics of soil ECa. The values of ECas (mS/m) were found to be 0.70, 296.90 and 74.94 for minimum, maximum and mean value, respectively. The value of ECad (mS/m) was slightly higher compared to ECas values; it was 21.20, 388.50 and 51.92 for minimum, maximum and mean value, respectively. The coefficient of variation (CV) for ECas and ECad were 38.89 % and 62.60 %. This means ECad reading varies more than ECas. The variability of ECad may be caused by the difference of soil textures in the soil profile to a depth of 90 cm [21].

Table 1 Descriptive statistics for ECas and ECad in the experimental area

Description	ECas (mS/m)	ECad (mS/m)
Number of Data	21642	21642
Min	0.70	21.20
Max	296.90	388.50
Mean	74.94	51.92
Range	296.20	367.30
Std. Deviation	29.14	32.50
Variance	849.38	1056.03
Coefficient of Variation (C.V.)	38.89	62.60

The descriptive statistics of predicted NPK content in the experimental area is shown in Table 2. The predicted NPK was derived by the developed system and the number of data was obtained from the ECa sensor. The developed system was field tested during the soil sampling task. The C.V. for predicted NPK was 26.30 %, 12.58% and 26.76% for total N, available P and exchangeable K in the entire experimental area, respectively. It can be explained that the system has predicted heterogeneous NPK content in the study area. The actual macro nutrient of NPK was also measured for comparison purposes. The numbers of data to measure NPK were 118 as shown in Table 3. The number of data was smaller compared to the data from predicted NPK because it was based on the sampling points collected in each lot of the experimental area. The mean values of actual NPK were found to be 0.16, 19.73 and 0.35 for total N, available P and exchangeable K, respectively. The mean values of actual P and K were almost similar compare to predicted P and K. The mean value of actual total nitrogen was varied compare to the predicted total N. The C.V. for actual NPK were 50%, 23.57% and 43.86% for total N, available P and exchangeable K, respectively. The higher value of C.V. shows that the actual NPK is more varied than the predicted NPK. It can be explained that the number of data points will influence the hypothesis.

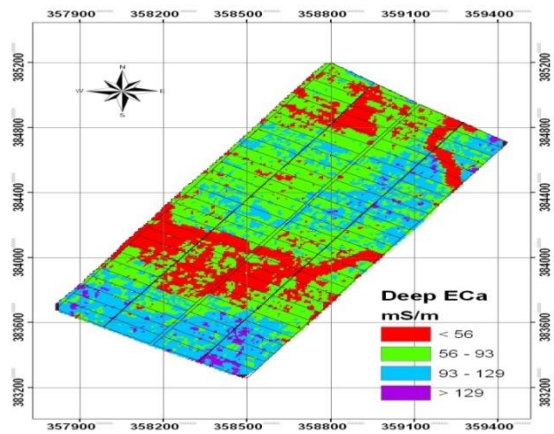
Table 2 Descriptive statistics for predicted NPK in the experimental area

Description	Predicted Total N (%)	Predicted Ava. P (mg/kg)	Predicted Exc. K (cmol/kg)
Number of Data	21642	21642	21642
Min	0.14	13.86	0.13
Max	0.65	25.61	0.56
Mean	0.38	18.67	0.30
Range	0.51	11.75	0.43
Std. Deviation	0.10	2.35	0.08
Variance	0.01	5.54	0.01
Coefficient of Variation (C.V.)	26.30	12.58	26.76

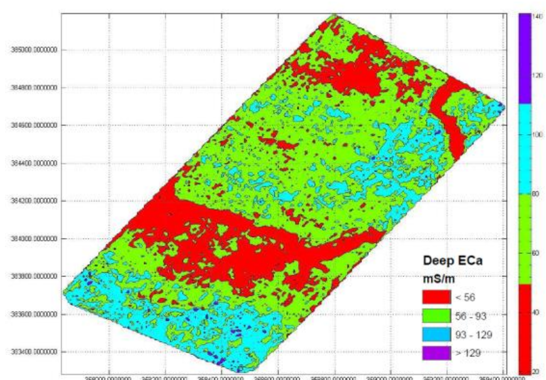
Table 3 Descriptive statistics for actual NPK in the experimental area

Description	Actual Total N (%)	Actual Ava. P (mg/kg)	Actual Exc. K (cmol/kg)
Number of Data	118	118	118
Min	0.03	9.00	0.13
Max	0.30	37.00	0.86
Mean	0.16	19.73	0.35
Range	0.27	28.00	0.73
Std. Deviation	0.08	4.65	0.15
Variance	0.01	21.65	0.02
Coefficient of Variation (C.V.)	50.00	23.57	43.86

In relation to that, classification approach using raster calculator, by doing spatial analysis for calculating the variables and to produce map was carried out. The map was used to compare the ECa spatial distribution to the map produced from the developed system. The map was classed into 4 zones which means more manageable and easy to compare between the maps. The ECa zones were 1) very low, 2) low, 3) moderate and 4) high. The ECas was not considered in this comparison since the reference model that has been used in this study was only significant to the ECad. According to the map in Figure 5(a), the kriging map produced via ArcGIS software was almost similar to the map produced by the developed system in Figure 5(b). The areas in both maps were mostly occupied by low ECad. The moderate ECad seemed to be concentrated in the south and was scattered in the middle part of the study area. Furthermore, the highest ECad zone was not able to distinguish in the variability maps. The similarity between both maps in Figure 5 shows that the developed system was able to produce an accurate soil ECa map and reliable to define the ECa zones very quick.



(a)

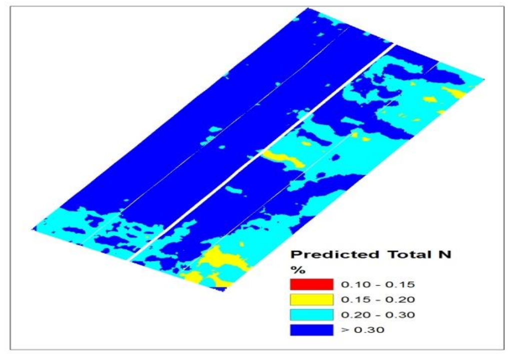


(b)

Figure 5 Comparison of Kriging map produced from ArcGIS 9.2 (a) and from the developed system (b)

Reliability Test

The developed system has successfully produced the NPK maps based on 21642 soil ECa data points as shown in Figure 6(a), 6(b) and 6(c) for total nitrogen, available P and exchangeable K, respectively. According to the map in Figure 6(a), the 118 lots of the study area mostly occupied with higher level of nitrogen content. The lower nitrogen content was found in a small portion in south-eastern part of the study area. The area was also occupied with low level of available phosphorus as shown in Figure 6(b). Some of the paddy lots in the study area were found to be occupied with moderate level of the phosphorus content. Nevertheless, the variation of available phosphorus is lower compared to the variation of exchangeable potassium as mentioned in the Table 2. The exchangeable potassium was proven more varied compared to the phosphorus as shown in Figure 6(c) and statistical analysis in the Table 2. According to the map in the Figure 6(c), the higher level of exchangeable potassium was found in the eastern part of the area. The western part was mostly occupied with low level of potassium and some of the paddy lots in the study area were occupied with very low of exchangeable potassium. The maps in the Figure 6 show that the developed system is reliable to produce nutrient information that possible to be used by the farmers.



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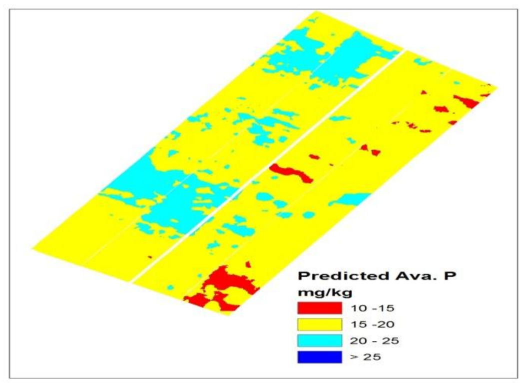

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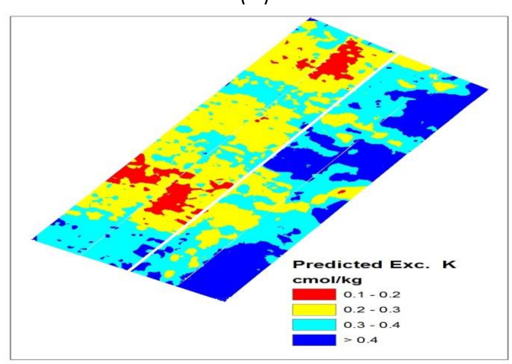
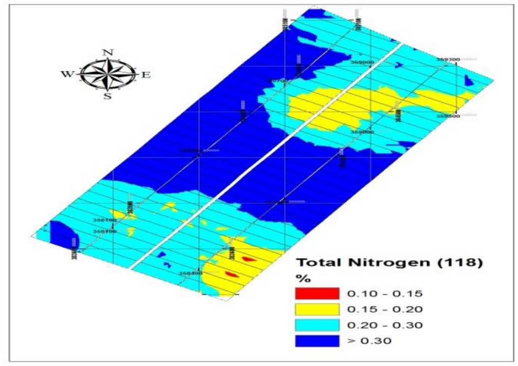


(c)

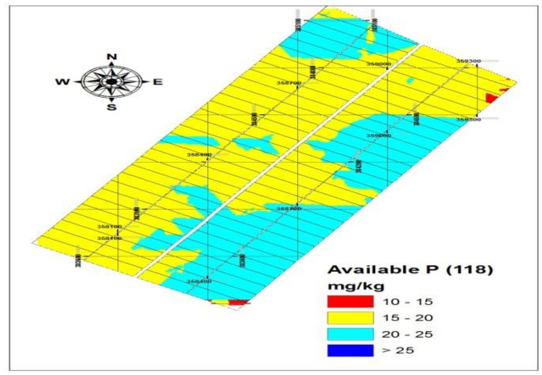
Figure 6 Variability maps of total nitrogen (a), available phosphorus (b), and exchangeable potassium (c) produced by the developed system for 118 lots of the study area.

The actual nutrient maps were also produced by the ArcGIS software as shown in Figure 7 for comparison purposes. The maps were based on 118 data points and the kriging technique was used to produce the variability maps. According to the map in Figure 7 (a), the actual nitrogen content in 118 lots of paddy field was slightly higher in most of the area especially in the middle part of the study area. The nitrogen content is varied where some of the area was occupied with low nitrogen content. The variation of the map was supported by the statistical analyses where the coefficient of variation was 50% as shown in Table 2. In Figure 7(b), the low level of available phosphorus was found being occupied in most of the area and some of the area was occupied with moderate level of the phosphorus. However, the variation of available phosphorus was lesser compared to the variation of total nitrogen in the study area. The map of exchangeable potassium was also being produced as shown in Figure 7(c). According to the map, the exchangeable potassium for 118 lots of paddy field seems to be concentrated especially on the south-eastern part. Some of the area was occupied with low level of exchangeable potassium. The variation of the maps in the Figure 7 shows that the area was heterogeneous and the fertility level was varied among the paddy lots.

In this study, patterns of the predicted NPK maps in Figure 6 were slightly different compared to the actual NPK maps in Figure 7. The different pattern was due to the number of data used for interpolation process. The dense number of data may give the best interpolation map and more accurate. However, the dense data is only possible to be obtained by using the sensor without the tedious field work compared to the conventional method. The map in Figure 6(a) shows that the nitrogen content was saturated in most of the area and this map was supported with the actual nitrogen map where the nitrogen content was concentrated in most of the area especially in the middle part of the area as shown in the Figure 7(a). The developed system also produced the predicted map of the available phosphorus in the study area where most of the area was found to have low level of available phosphorus as shown in Figure 6(b). This interpretation can be supported with the actual available phosphorus map where most of the areas have low level of phosphorus as shown in Figure 7(b). From the hypothesis, it was shown that the predicted NPK map can be interpreted as similar to the actual NPK map even though the pattern was different.



(a)



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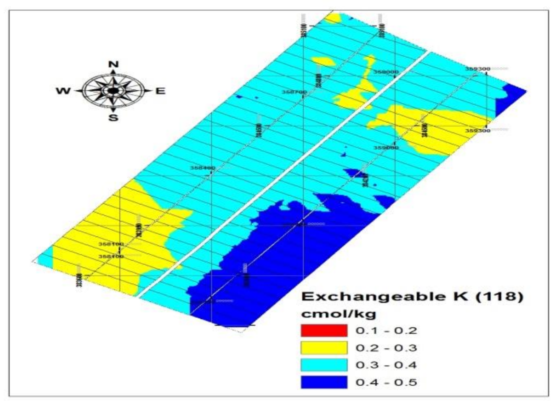

(c)

Figure 7 Variability maps of actual total nitrogen (a), available phosphorus (b), and exchangeable potassium (c) for 118 lots of the study area

4.0 CONCLUSIONS

This study was carried out in order to develop on-the-go mapping system to measure the nutrient level in the paddy soil on real time basis. The result of this study showed that the developed system was capable of producing NPK maps and can be interpreted as good as actual measurement of NPK. The map was reliable to assist the farmers to manage their farm better and indirectly will optimize the cost of production and reduce the environmental degradation by applying optimum quantity of the required nutrients.

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