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ARTICLE

Spatial variability of bulk soil electrical conductivity in a Malaysian paddy field: key to soil management

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Abstract On-the-go EC sensor is a useful tool in mapping the apparent soil electrical conductivity (EC_a) to identify areas of contrasting soil properties. In non-saline 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 (1-s interval) with few operators. Hence, a dense sampling is possible and therefore a high resolution EC_a map can be produced. This paper presents experiences in acquiring detailed EC_a information that is correlated to other soil properties for precision farming of rice. The study was conducted on a 9 ha rice plot in MARDI Seberang Prai Station, Penang. The VerisEC3100 was pulled across the field in a series of parallel transects spaced about 15 m apart. The study showed that shallow and deep EC_a had high correlation and shallow EC_a had significant correlation to P. Deep EC_a had significant correlation to P, K and yield. Regression equations showed that N and P could be estimated by shallow EC_a but, pH, K and yield were better estimated by deep EC_a. This study was able to draw some basic ideas of nutrient zone management according to precision farming technique.

Keywords Area of contrast · High resolution map · Precision farming · Site specific fertilizer application

Introduction

Soil sensor such as the VerisEC sensor is a useful tool in mapping apparent soil electrical conductivity (EC_a) 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 (Veris Technologies 2001). The crop management system known as precision farming relies on geospatial information to facilitate the treatment of small portions of fields as individual management units. Although agriculturalists have long known that fields are heterogeneous, only recently the technologies become available that allow production practices to efficiently take this variability into account. Key technologies include GPS, GIS, electronic sensors, and ruggedized computers are being used for within-field data acquisition and operation control. Although it is now relatively easy to collect geospatial data for precision farming, it is difficult to apply effectively those data in making crop management decisions. An important step in these management decisions is to understand the relationship, on a spatial basis, of crop yields to the myriad of agronomic factors which may potentially be causing yield variations.

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Soil scientists collect soil samples based on soil map created by semi-detailed sampling which means only one sample from several hectares. Then, agricultural inputs were added following this prescription or action maps, while a good management needs the details of every foot step. Grid sampling involves few samples per hectare. For 50-m grid sampling, four samples will be collected for a hectare field. Using EC_a sensor to show the contrast of soil properties in the field, the soil EC_a across the field can be determined rapidly with detailed features of the soil, and operated by a few workers. Data can be collected for every second. Therefore, numerous data points can be presented on an EC_a map.

Soil EC_a measurements can provide information on soil texture, in addition to estimating soil water content. Williams and Hoey (1987) used electromagnetic (EM) measurements of EC_a to estimate within-field variations in soil clay content. Doolittle et al. (1994) found that EM measurements were highly correlated with the topsoil depth above a subsurface claypan horizon. They then used an automated EM sensing system to map topsoil depth over a number of fields. It was necessary to obtain calibration measurements with a soil probe at a number of locations within a field to remove the effects of temporal variations in soil water content and temperature. Since soil EC_a integrates texture and moisture availability, two characteristics that both vary over the landscape and also affect productivity, EC_a sensing also shows promise in interpreting grain yield variations, at least in certain soils (Sudduth et al. 1995; Jaynes et al. 1995).

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 (Jaynes et al. 1994), clay content (Williams and Hoey 1987), and cation exchange capacity (McBride et al. 1990). These properties have a significant effect on water and nutrient-holding capacity, which are major drivers of yield (Jaynes et al. 1995). The relationship between soil EC_a and yield has been reported and quantified by others (Kitchen and Sudduth 1996; Fleming et al. 1998).

Sudduth et al. (1998) 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. Fraisse et al. (1999) 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 et al. (1998) showed that sampling according to soil management zones identified with a soil conductivity map can be more effective than grid sampling. Most of the works mentioned above concerned measurement of EC_a of upland soil in temperate areas. To the best knowledge of the authors, a similar data for paddy soils in the humid tropic is limited. Therefore, this paper presents results of using VerisEC sensor in acquiring detailed soil EC_a information that correlates to soil properties for precision farming of rice. With the acquired information, the zones of EC_a and yield were characterized to be used as a key to zone management.

Materials and methods

The study was conducted in a 9 ha paddy experimental plot within the Malaysian Agricultural Research and Development Institute (MARDI) Seberang Perai Station, Penang State (Fig. 1). This plot is currently used to conduct soil and water management research for rice production. The soil samples and VerisEC data were collected on 20 March 2003, during the fallow period after harvesting.

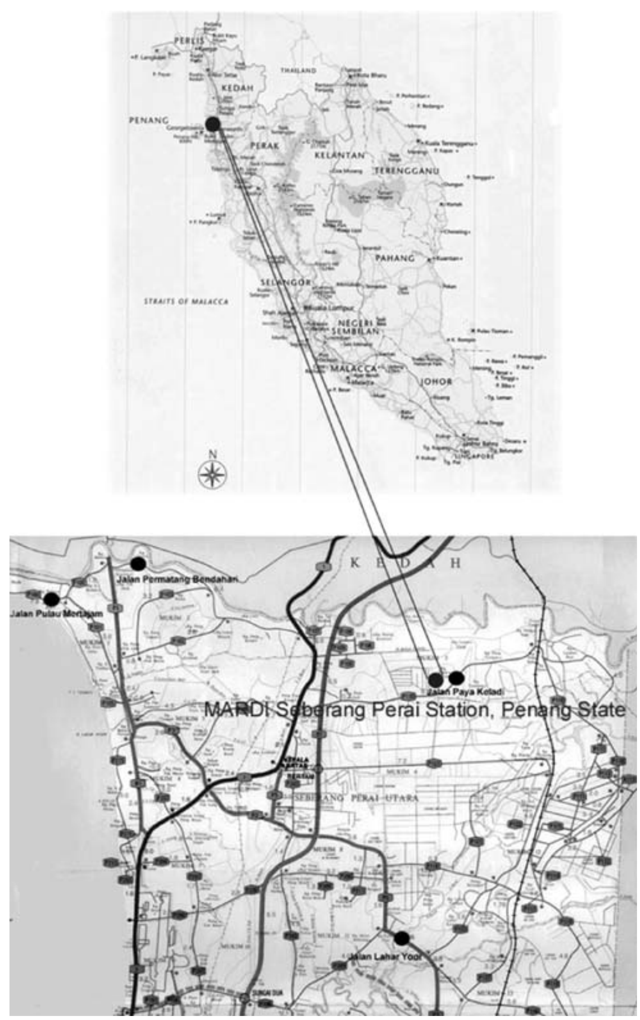

Fig. 1 The study area (MARDI Seberang Perai) located in Penang State, North of Malaysia

EC data acquisition and EC map

The Veris 3100 Sensor Cart was pulled across the field behind a tractor in a series of parallel transects spaced of about 15 m apart for the plot (Fig. 2). The Veris 3100 used three pairs of coulter-electrodes for determination of 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 conductivity (1/resistance = conductivity). A Trimble AG132 DGPS system (Trimble Navigation Ltd., Sunnyvale, CA) with submeter 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) by 1 s intervals in an ASCII text format.

Soil and yield samples

Soil samples were collected by grid method spacing of about 30 × 30 m at 0–30 cm and total soil samples were 99 (Fig. 3). Samples were then transferred to the laboratory for further analyses of some selected chemicals and physicals properties. Soil chemical properties were pH, C, N, P, CEC and K and soil physical properties were clay, silt and sand. Rice yields were harvested at the same grid point of soil samplings by one meter square area size. They were then interpolated to per hectare basis (kg/ha).

Fig. 2 Veris 3100 sensor cart pulled behind a tractor across a paddy field

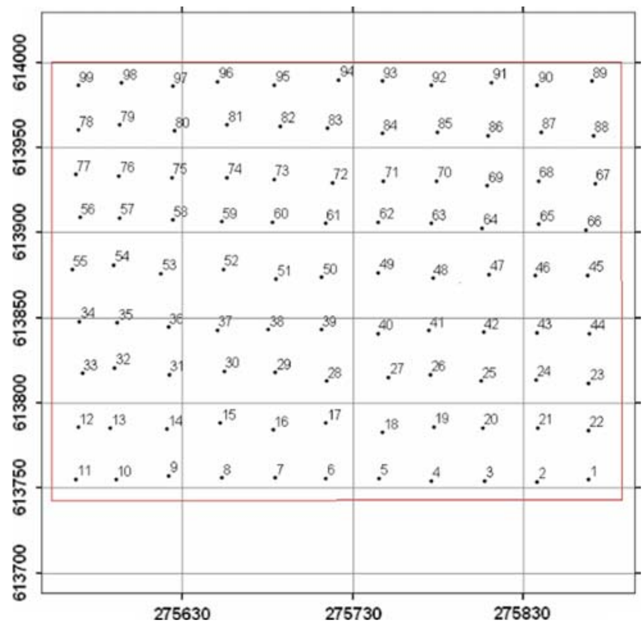

Fig. 3 Sampling points map within 9 ha paddy field

Data analyses

EC_a, soil properties and yield data were analysed by statistical software for their statistics description, correlation and regression. They were also kriged and mapped using ArcGIS 8.3 for spatial variability description. Through the use of spatial analyst extension on ArcGIS, zonal statistics were performed.

Results and discussion

Classical statistics

The study found that the operation took about 2 h to cover 9 ha area and the sensor could collect 5,205–5,454 data points. Other methods such as grid sampling or random sampling would require more time to cover the same acreage.

Table 1 shows shallow EC_a ranged from 0.90 to 64.10 mS/m with the average and the standard deviation of 5.67 and 3.04 mS/m, respectively. The total data points collected was 5,454. The deep EC_a values ranged from 1.30 to 48.90 mS/m with the average and the standard deviation of 9.09 and 6.81 mS/m, respectively. The total number of data points was 5,205. The average value of the deep EC_a was higher than that at the shallow depths. This indicates some differences in soil properties between the root zone (0–30 cm) and sub layer below the root zone (30–90 cm). Soil pH had low variation (2.58%), while deep EC_a had the

Table 1 Statistical description of soil properties and yield

Parameters	Min	Max	Mean	SD	CV (%)
EC_{as} (mS/m)	0.90	64.10	5.67	3.04	53.62
EC_{ad}	1.30	48.90	9.09	6.81	74.92
pH	4.24	4.90	4.65	0.12	2.58
C (%)	0.54	0.91	0.71	0.08	11.27
N	0.06	0.15	0.10	0.02	20.00
Sol. P (ppm)	6.40	10.10	7.75	0.82	10.58
CEC (meq/100 g)	6.40	11.20	8.21	1.03	12.55
Exch. K	0.09	0.35	0.18	0.05	27.78
Clay (%)	13.80	28.80	21.68	3.55	16.37
Silt	9.90	18.70	13.80	2.28	16.52
Sand	56.40	73.70	64.52	3.80	58.90
Yield (kg/ha)	978.00	4,000.00	2,222.89	705.83	31.75

highest (74.92%) variation. The average yield was 2,222.89 kg/ha and its variation was 31.75%.

Correlations

The study showed that shallow EC_a was positive significantly correlation with deep EC_a and soluble P at 0.01 level. Deep EC_a too had positive significant correlation with soil P and yield at 0.05 level but negative significant correlation with exchangeable K at 0.01 level (Table 2). However, sand had significant correlation with many parameters, such as pH, CEC, clay and silt.

Regression analyses

A technique of curve estimation regression showed that shallow EC_a was a good indicator to estimate N and soluble P and deep EC_a was good for pH, exchangeable K, soluble P, and yield. However, shallow EC_a was better to estimate soluble P rather than deep EC_a since their R values were 0.40** and 0.21*, respectively. Most of the models were in the form of cubic and quadratic functions except for soluble P and exchangeable K in exponential and logarithmic forms, respectively.

The equations can be shown as:

$$N = -\,0.0111 + (0.0570EC_{as}) - [0.0087(EC_{as})^2] + [0.0004(EC_{as})^3]\ R = 0.27^{*} \quad (1)$$

$$P = 5.3441 + (1.1978\ EC_{as}) - [0.2029(EC_{as})^2] + [0.0114(EC_{as})^3]\ R = 0.40^{**} \quad (2)$$

$$pH = 4.6650 - (0.0066\ EC_{ad}) + [0.0004(EC_{ad})^2]\ R = 0.23^{*} \quad (3)$$

$$P = 7.4555 \times e^{(0.0032EC_{ad})}\ R = 0.21^{*} \quad (4)$$

$$K = 0.2252 - (0.0225 \times \ln EC_{ad})\ R = 0.29^{*} \quad (5)$$

$$Yield = 2048.67 - (41.9250EC_{ad}) + [8.2479(EC_{ad})^2] - [0.2381(EC_{ad})^3]\ R = 0.34^{**} \quad (6)$$

Further study to evaluate the soil properties affecting the EC_a found that shallow EC_a was mainly affected by soluble P, while deep EC_a was affected by exchangeable K. The stepwise linear regression equations can be shown as follows:

$$EC_{as} = 0.473 + 0.697(sol.P)\ R = 0.32^{**} \quad (7)$$

$$EC_{ad} = 16.955 - 35.748(exch.K)\ R = 0.28^{**} \quad (8)$$

Table 2 Correlation of soil properties and yield (n = 99)

	EC_{as}	EC_{ad}	pH	C	N	Sol. P	CEC	Exch. K	Clay	Silt	Sand	Yield
EC_{as}	1	**				**						
EC_{ad}	0.469	1				*		**				*
pH	–0.090	0.168	1					*			*	
C	–0.014	0.063	0.098	1								
N	–0.088	–0.040	0.071	–0.053	1							
Sol. P	0.316	0.214	–0.004	0.127	0.086	1						
CEC	–0.089	–0.153	0.116	0.024	–0.014	0.115	1		*		**	
Exch. K	0.027	–0.283	–0.211	0.042	–0.174	–0.150	0.020	1				
Clay	0.032	–0.041	–0.177	0.126	–0.123	0.034	–0.225	–0.040	1	*	**	
Silt	0.026	0.084	–0.061	–0.125	0.027	–0.023	–0.101	0.056	–0.205	1	**	
Sand	–0.045	–0.012	0.202	–0.043	0.099	–0.019	0.271	0.004	–0.811	–0.407	1	
Yield	–0.127	0.255	0.098	0.148	–0.008	0.056	0.128	–0.044	–0.060	0.066	0.016	1

EC_{as} is shallow EC_a and EC_{ad} is deep EC_a

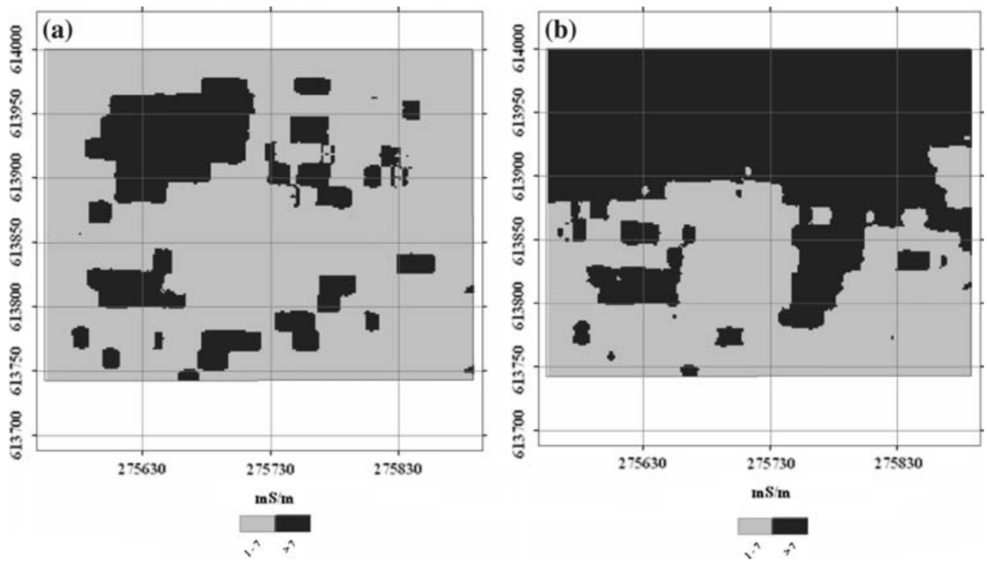

Fig. 4 Spatial variability of **a** shallow and **b** deep EC_a within the study area (mS/m)

where EC_{as} is shallow EC_a in mS/m, EC_{ad} is deep EC_a in mS/m, N is in %, soluble P is in ppm, exchangeable K is in meq/100 g and yield is in kg/ha.

Spatial variability

The study divided the values of EC_a into two dominant classes according to smart quantiles classification approach (ESRI 2001). Two zones were selected based on the manageable area within the site. The smart quantiles indicated that the critical values for EC_a were 7.00 mS/m for both shallow and deep EC_a. The variability maps showed that high shallow EC_a values (>7.00 mS/m) were scattered within the study area, while high deep EC_a covered the northern part of the study area (Fig. 4). Class 1 shallow EC_a occupied bigger area than class 2 for about 77.66 and 22.34%, respectively. This indicated that most of the top soil (0–30 cm) had low EC_a. Class 2 deep EC_a occupied bigger area than class 1 for more than half of the study area (55.04 and 44.96%, respectively). However, mean values for classes 1 and 2 for shallow and deep EC_a were significantly different, which indicated the isolation of the classification (Table 3). On the other hand, the classification was acceptable.

Table 3 Zonal statistical description for shallow and deep EC_a

Class	Area m^2 (%)	Min (mS/m)	Max (mS/m)	Range (mS/m)	Mean (mS/m)	SD (mS/m)
Shallow EC_a						
1	67,164.70 (77.66)	1.35	7.00	5.65	4.90a	1.17
2	19,324.40 (22.34)	7.00	27.06	20.06	9.39b	2.22
Deep EC_a						
1	38,888.10 (44.96)	1.49	7.00	5.51	4.06a	1.27
2	47,601.00 (55.04)	7.00	33.75	26.75	14.94b	5.82

Spatial variability of soil chemical and physical properties showed that most of the high values for soil properties can be found in the pattern of north/south or else east/west. Some properties joined from the opposite sides (Figs. 5, 6). However, K was found to be similar to deep EC_a where K had the highest significance to deep EC_a.

Zonal statistics

Shallow EC_a zones

There were two zones that could be delineated by shallow EC_a. One zone (<7 mS/m) had 75 sampling points and another (those above 7 mS/m) had 24 sampling points. Zonal Statistics for shallow EC_a indicated that the zone was able to delineate deep EC_a and P. Zone of high shallow EC_a had high deep EC_a and P (Table 4). This finding agreed to the correlation and regression tests where P was found to have good correlation to shallow EC_a and P can be estimated from shallow EC_a.

Deep EC_a zones

The zones that were delineated by deep EC_a showed good delineation of shallow EC_a, K and yield. The zone of high deep EC_a values had high shallow EC_a and yield, but the reverse for K. The significant differences of soil properties within deep EC_a zones are indicated by different letters (Table 5). Zone of high deep EC_a had 55 sampling points while, low deep EC_a (<7 mS/m) had 44 sampling points.

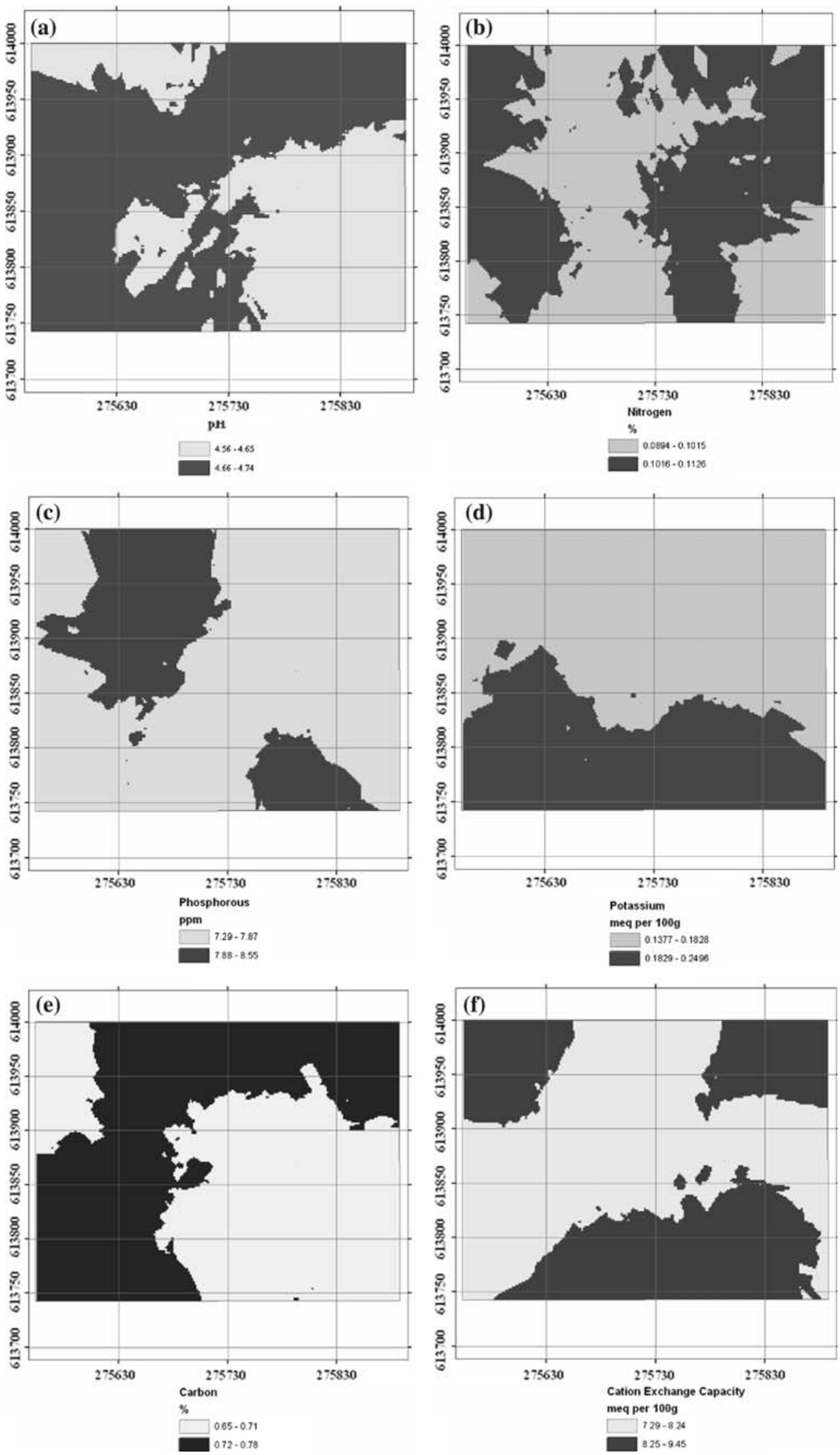

Fig. 5 Spatial variability maps of **a** soil pH, **b** nitrogen (%), **c** phosphorous (ppm), **d** potassium (meq/100 g), **e** carbon (%) and **f** cation exchange capacity (meq/100 g)

Fig. 6 Spatial variability maps of **a** clay (%), **b** silt (%) and **c** sand (%)

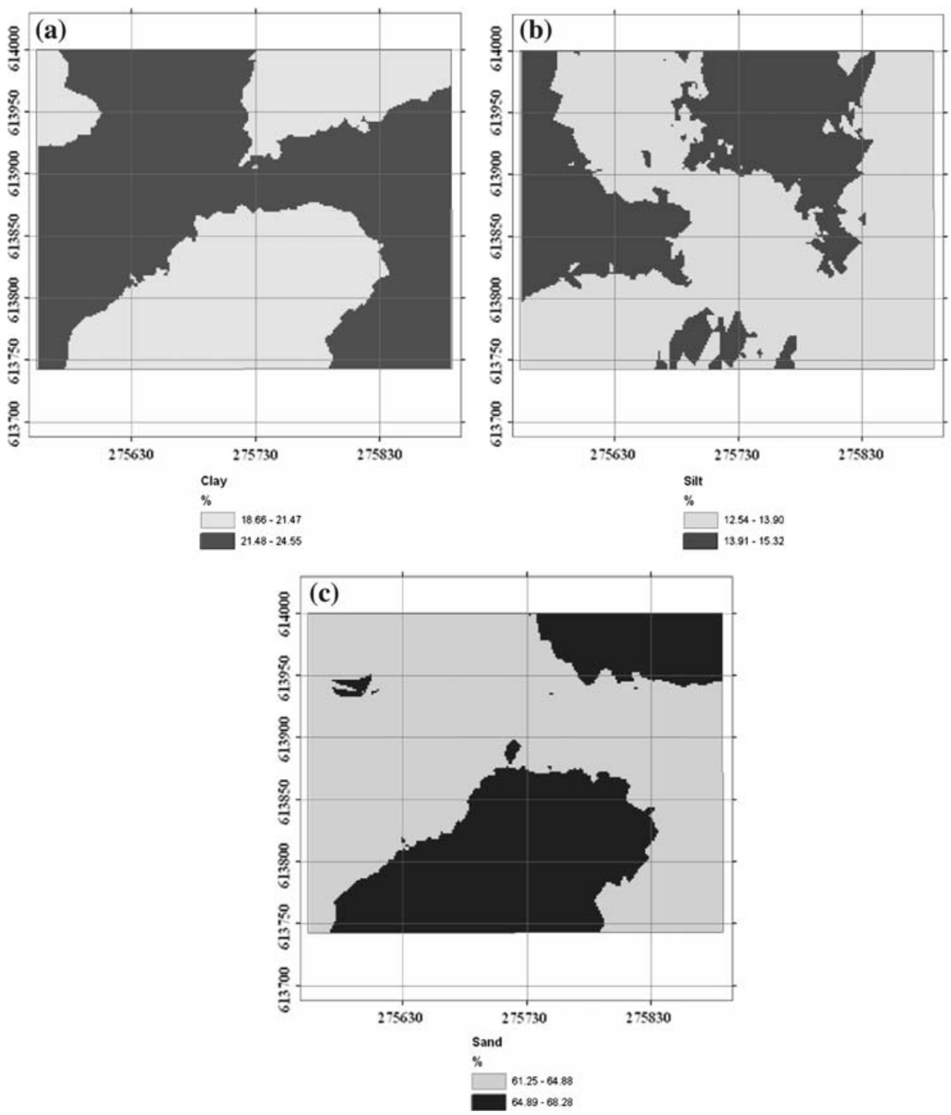

Table 4 Mean soil properties and yield within two shallow EC_a zones

Parameters	Zone 1 (n = 75)	Zone 2 (n = 24)
Shallow EC_a	4.90b	9.39a
Deep EC_a	9.52b	14.04a
pH	4.65a	4.66a
C	0.7079a	0.7142a
N	0.0997a	0.1079a
P	7.63b	8.15a
CEC	8.17a	8.31a
K	0.18a	0.17a
Clay	21.68a	21.69a
Silt	13.84a	13.67a
Sand	64.48a	64.64a
Yield	2,239.50a	2,171.00a

Means within a row followed by the same letters are not significant at the 5% level by LSD

Yield zones

Low yield zone (< 2289.9 kg/ha) occupied the biggest area of about 67.36% and the high yield occupied about 32.64% of the total area. High yielding areas were mostly found in the north (Fig. 7). There were 34 points within zone of higher yield and 65 points within low yielding area. According to yield zonal analysis, it showed that deep EC_a and K had good correlation to yield. Yield increase with increase in deep EC_a and decrease in K (Table 6).

Conclusion

The use of VerisEC 3100 sensor in a paddy field produced a very dense soil EC_a dataset with less time as compared to normal grid sampling. Deep EC_a had the

Table 5 Mean soil properties and yield within two deep EC_a zones

Parameters	Zone 1 (n = 44)	Zone 2 (n = 55)
Shallow EC_a	5.27b	6.37a
Deep EC_a	4.06b	14.94a
pH	4.64a	4.66a
C	0.7050a	0.7129a
N	0.0984a	0.1044a
P	7.62a	7.87a
CEC	8.24a	8.18a
K	0.20a	0.16b
Clay	22.21a	21.26a
Silt	13.76a	13.83a
Sand	64.03a	64.91a
Yield	1,980.09b	2,417.13a

Means within a row followed by the same letters are not significant at the 5% level by LSD

Table 6 Mean soil properties and yield within two yield zones

Parameters	Zone 1 (n = 65)	Zone 2 (n = 34)
Shallow EC_a	6.06a	5.53a
Deep EC_a	8.10b	15.43a
pH	4.64a	4.67a
C	0.7003a	0.7268a
N	0.1017a	0.1018a
P	7.76a	7.74a
CEC	8.08a	8.46a
K	0.19a	0.16b
Clay	21.99a	21.10a
Silt	13.73a	13.94a
Sand	64.28a	64.96a
Yield	1,938.23b	2,767.09a

Means within a row followed by the same letters are not significant at the 5% level by LSD

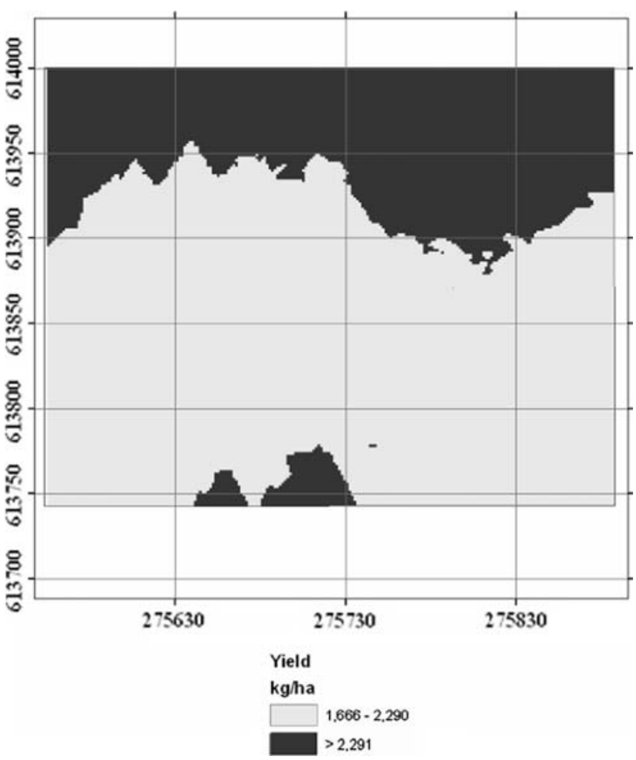

Fig. 7 Spatial variability map of rice yield (kg/ha)

highest (74.92%) variation coefficient, and pH was the lowest (2.58%). Correlation test showed that shallow and deep EC_a had high correlation and shallow EC_a had significant correlation to P. Deep EC_a had significant correlation to P, K and yield. The regression analysis showed that N and P could be estimated by shallow EC_a but, pH, K and yield were better estimated by deep EC_a. However, shallow EC_a was mainly contributed by soil P, while K was the main contributor to deep EC_a. In contrast, the EC_a of paddy soil was not affected by soil texture and CEC. Zonal statistical analysis proved that shallow EC_a can delineate the zone of P, while deep EC_a can delineate K and yield.

This study was able to draw some basic ideas of nutrient zone management according to precision farming technique. The spatial variability map showed the zone of high and low yield indicating land productivity suggesting that low yielding area may need special treatment. Site specific fertilizer application and its economics will be further studied based on the nutrient management zones derived from EC_a.

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