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A floating sensing system to evaluate soil and crop variability within flooded paddy rice fields

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Abstract Continuous paddy rice cultivation requires fields to be flooded most of the time limiting seriously the collection of detailed soil information. So far, no appropriate soil sensor technology for identifying soil variability of flooded fields has been reported. Therefore, the primary objective was the development of a sensing system that can float, acquire and process detailed geo-referenced soil information within flooded fields. An additional objective was to determine whether the collected apparent electrical conductivity (EC_a) information could be used to support soil management at a within-field level. A floating sensing system (FloSSy) was built to record EC_a using the electromagnetic induction sensor EM38, which does not require physical contact with the soil. Its feasibility was tested in an alluvial paddy field of 2.7 ha located in the Brahmaputra floodplain of Bangladesh. The high-resolution (1 × 1 m) EC_a data were classified into three classes using the fuzzy *k*-means classification method. The variation among the classes could be attributed to differences in subsoil (0.15–0.30 m below soil surface) bulk density, with the smallest EC_a values representing the lowest bulk density. This effect was attributed to differences in compaction of the plough pan due to differential puddling. There was also a significant difference in rice yield among the EC_a classes, with the smallest EC_a values representing the lowest yield. It was concluded that the floating sensing system allowed the collection of relevant soil information, opening potential for precision agriculture practices in flooded crop fields.

Keywords Apparent electrical conductivity · EM38 · Flooded soil · Paddy · Bangladesh

Introduction

Floodplain alluvial soils are a valuable natural resource for agricultural crop production in countries like Bangladesh where they occupy almost 80% of the country's area (Brammer

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1996). The most frequent land use of these soils is paddy rice cultivation whereby the fields remain inundated for most of the year. As a consequence, direct methods for the acquisition of information on soil properties are problematic as well as common indirect methods, like air- or space-borne remote sensing. Therefore, these alluvial soils are usually mapped as being fairly homogenous (Alam et al. 1993) and precision agriculture (PA), which aims at adjusting soil management according to the soil variability at a within-field scale, has not been considered. However, at present, technological advances in proximal soil sensing allow high-resolution soil information to be obtained under flooded conditions which can serve as a basis to investigate the possibilities of adopting PA in paddy soils.

Several proximal soil sensors have been introduced for PA under dry land conditions (Sudduth et al. 1997). Among these, the ones based on electromagnetic induction (EMI) are the most commonly used, even at a sub-meter resolution (Simpson et al. 2009). EMI sensors measure the soil apparent electrical conductivity (EC_a) which can be interpreted in terms of soil properties like salinity (Triantafilis et al. 2000), texture (Saey et al. 2009), bulk density or pore volume (Rhoades et al. 1999) and depth to a clay layer (Saey et al. 2008a). Soil EC_a is also linked to the soil moisture status (Brevik et al. 2006), but this source of variation is eliminated under water-saturated conditions. Thus, in a flooded environment, variations in EC_a reflect changes in soil properties except soil moisture. EC_a data have also been used to define management classes which could be linked to variations in crop yield (e.g. Li et al. 2007; Vitharana et al. 2008). However, research relating EC_a and paddy rice yield is rare. One exception is Ezrin et al. (2010), but these authors used soil resistivity measurements (requiring soil contact) under dry land conditions. Yet, they reported a significant positive relation between EC_a and paddy rice yield. Currently, no report is available on the non-invasive use of a proximal soil sensor to analyze the within-field spatial variability of soil properties in paddy fields under flooded conditions.

The main objective of this study was to develop, operate and evaluate a mobile proximal soil sensing system capable of providing relevant information to support PA under flooded paddy field conditions, as in Bangladesh. The within-field variability of rice yield was used to evaluate the relevance of this system.

Materials and methods

The floating sensing system

To acquire high-resolution soil data under wet field conditions (including monsoon rains), a floating sensing system (FloSSy) was developed.

First, the FloSSy consists of a soil sensor which was put in a waterproof housing on a raft (Fig. 1). Preference was given to EMI as a geophysical technique because it does not require physical contact with the soil, so the sensor can be operated floating on water. More details on EMI are given by Corwin et al. (2008). The EM38 (Fig. 1; Geonics Limited, Canada) was used because of its robustness, structural simplicity, light weight (about 3.5 kg) and small physical dimension (1.05 × 0.16 × 0.05 m). The inter-coil distance of the EM38 is 1 m, resulting in a depth of influence of about 1.5 m in the vertical orientation under conditions of a homogeneous soil. So, given the limited water depth of a paddy field (0.10–0.25 m) there is still sufficient influence of the topsoil to be measured. More technical details on the EM38 sensor are given by McNeill (1980). The EM38 sensor can also be operated in a horizontal orientation which receives its major influence from the

Fig. 1 The floating soil sensing system (FloSSy) during field measurement of EC_a. The different components are indicated as follows: *i* laptop, *ii* GPS, *iii* water proof sensor housing, *iv* floating platform, *v* the power tiller

near-surface soil (Saey et al. 2008). However, the vertical orientation to ensure a major influence of the soil beneath the water layer was used here.

Next, a GPS (NL-422MP manufactured by NAVILOCK®, Zehlendorf, Berlin, Germany) and a field laptop (Dell ATG 6400 model) with real time data processing of both the sensor and GPS signals was adapted to be operational in a waterproof environment. A 1.8 m long PVC pipe was put vertically on the raft to enable the data communication cables to be connected to the field computer. On top of this pipe the GPS receiver was fixed so that its position corresponded to the centre of the EM38 sensor. A real-time path guidance software was created to display the traversing path, otherwise it would be impossible in a flooded field to track the previously measured path to guarantee that the entire field was covered. The laptop was placed inside a polyethylene jacket to guard against the splashes of field mud and rain and made visible to the vehicle driver. The raft was sufficiently light to be trailed at some distance (1.8 m) by the usual 12 HP vehicle operating on muddy inundated fields (called a 'power tiller') (Fig. 1).

The computer language G from LabVIEW (National Instruments 2003) was used to develop software for the simultaneous acquisition and processing of signal output from the FloSSy. Functionality of the operational system during the EC_a survey was monitored from the graphical user interface (GUI) by checking the raw and processed data from both the EM38 and GPS. In the flooded field, the traversing path of the FloSSy could be displayed on the computer screen in real-time to guide the distance between measured parallel lines.

Study site

A 2.7 ha experimental paddy field of the Bangladesh Agricultural University in Mymensingh was selected as a study area to test the operational performance of FloSSy and to evaluate the soil spatial variability of the field. It has been under continuous paddy cultivation for more than 35 years. The field (with central co-ordinates 24.72450°N and 90.42317°E) is located in the floodplain of the Brahmaputra. In general, these alluvial deposits consist mainly of fine sand to silty material with less than 5% clay. According to Brammer (1981), the soil in the area of the experimental field has a silt texture.

To reduce the loss of water and dissolved nutrients, paddy fields are puddled during land preparation. During puddling, the topsoil is inundated and the subsoil is compacted by repeated ploughing at the same depth (approximately at a depth of 0.17–0.20 m). An additional advantage of flooding is the effective control of weeds during the growing period.

EC_a survey and data processing

The EC_a survey with FloSSy was conducted in July 2009, after the usual field preparation by puddling and before the seasonal planting of rice seedlings. At the time of measurements, the water height on the field was approximately 0.18–0.20 m. The traversing speed was approximately 3.6 km h^{-1} and the measurement frequency was 4 Hz. Measurement lines were separated 1 m apart and care was taken to orient them as much as possible parallel. The measurements were averaged to one value per square meter, so the processed data resolution was 1 observation per m^2. EC_a measurements were post-corrected for instrumental drift and standardized to a reference temperature of 25°C by the method of Sheets and Hendrickx (1995):

$$EC_{a_{25}} = EC_{a_{obs}}\left(0.4470 + 1.4034.e^{-T/26.815}\right) \quad (1)$$

with $EC_{a_{25}}$, the standardized EC_a values at 25°C and $EC_{a_{obs}}$, the observed EC_a values at soil temperature T (°C). During the field survey, soil temperature was recorded every hour by a bimetal sensor pushed in the soil to a depth of 0.25 m below soil surface. It remained stable during the survey at 30°C. In the remaining part of this article, all EC_a values refer to $EC_{a_{25}}$.

Since field measurements could not be conducted exactly on a grid basis, the soil EC_a data were interpolated to a fixed resolution using ordinary point kriging (OK) (Goovaerts 1997). This was conducted with the program Surfer (Golden Software Inc., Golden, USA) and the final EC_a map had a pixel resolution of 1 × 1 m.

The interpolated EC_a data were classified using a fuzzy *k*-means classification procedure. Therefore the FuzMe 3.0 software (Minasny and McBratney 2006), based on the modified fuzzy *k*-means for predictive classification as described by de Gruijter and & McBratney (1988), was used. The fuzziness performance index (FPI) and the modified partition entropy (MPE) were used to guide the classification (McBratney and Moore 1985). The optimum number of classes was determined when these two measures were minimal.

Soil and crop sampling

Within the field, 50 soil samples were collected according to a fixed spacing of 20 × 20 m. At each sampling location, three replicate samples were taken within 1 m^2 at three depths (0.0–0.15 m, 0.15–0.30 m and 0.30–0.45 m). Given the flooded conditions of the land, a custom-built hand-operated paddy field sampler was designed (Fig. 2). It contains a metal tube attached to the top of the soil-sampling core which has three holes to drain water out of the drill when the sampler is pushed into the flooded muddy soil. To avoid loss of soil during withdrawal, pneumatic pressure was maintained inside the core with a one-way gate valve attached to the top of the sampling core. During insertion of the sampler, opening of the valve allowed reduction of air pressure inside the core. A pulley controlled shutter gate was provided to open and close the bottom during insertion and removal from the soil, respectively. The oven dried (105°C) weight of the soil samples allowed calculation of its bulk density given the known volume of the sampler (0.75 L).

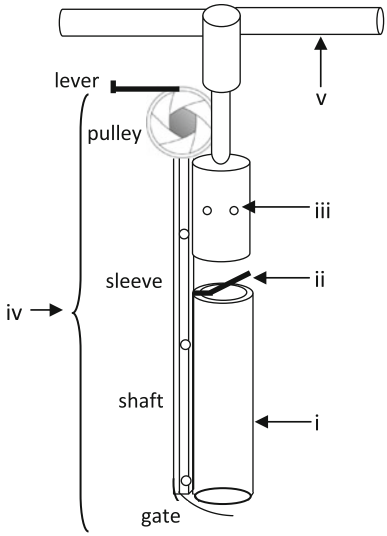

Fig. 2 Schematic overview of the paddy field soil sampler: *i* 150 × 80 mm soil core, *ii* One-way gate valve, *iii* excess water draining holes, *iv* shutter with lever, pulley, sleeve, shaft and gate; *v* handle rod

At each of the 50 sampling locations, the paddy grain yield was determined by harvesting manually 1 m^2. The weight of the unhusked fresh grains was measured, adjusted to a moisture content of 18%, and expressed as t ha^{-1}.

Results and discussion

EC_a

The 30 396 EC_a measurements ranged between 22 and 49 mS m^{-1} with a mean of 34.7 mS m^{-1} and a variance of 21.4 (mS $m^{-1})^2$, so the coefficient of variation was 13%. The distribution was close to Gaussian with coefficients of skewness (0.16) and kurtosis (2.8) approaching normal values (0 and 3, respectively). The variogram was best described by a spherical model:

$$\gamma(h) = \begin{cases} C_0 + C_1 \cdot \left[1.5\left({}^{h}\!/_{a}\right) - 0.5\left({}^{h}\!/_{a}\right)^3\right] & \text{if} \quad 0 < h \le a \\ C_0 + C_1 & \text{if} \quad h > a \end{cases} \tag{2}$$

with $\gamma(h)$ the variogram at lag distances h, the nugget variance $C_0 = 1.2$ (mS $m^{-1})^2$, the sill $C_0 + C_1 = 14.3$ (mS $m^{-1})^2$ and the range $a = 38$ m. Thus, the EC_a data were characterized by a strong spatial structure with a very low noise component as indicated by a nugget to sill ratio of 8.4%. The EC_a map interpolated with OK is shown in Fig. 3a. The EC_a map shows patterns of fluctuating EC_a values across the field, however, without a systematic trend. Therefore, the field was classified in zones to delineate management classes using the fuzzy *k*-means algorithm. The optimal number of EC_a classes was identified as three since the FPI and NCE were minimum at this number. Figure 3b shows a map of these three classes: EC_a class-1 grouped low EC_a values around a centroid value of 29.2 mS m^{-1}, EC_a class-2 represented intermediate EC_a values with a centroid value of 35.0 mS m^{-1} and EC_a class-3 combined the high EC_a values with a centroid value of

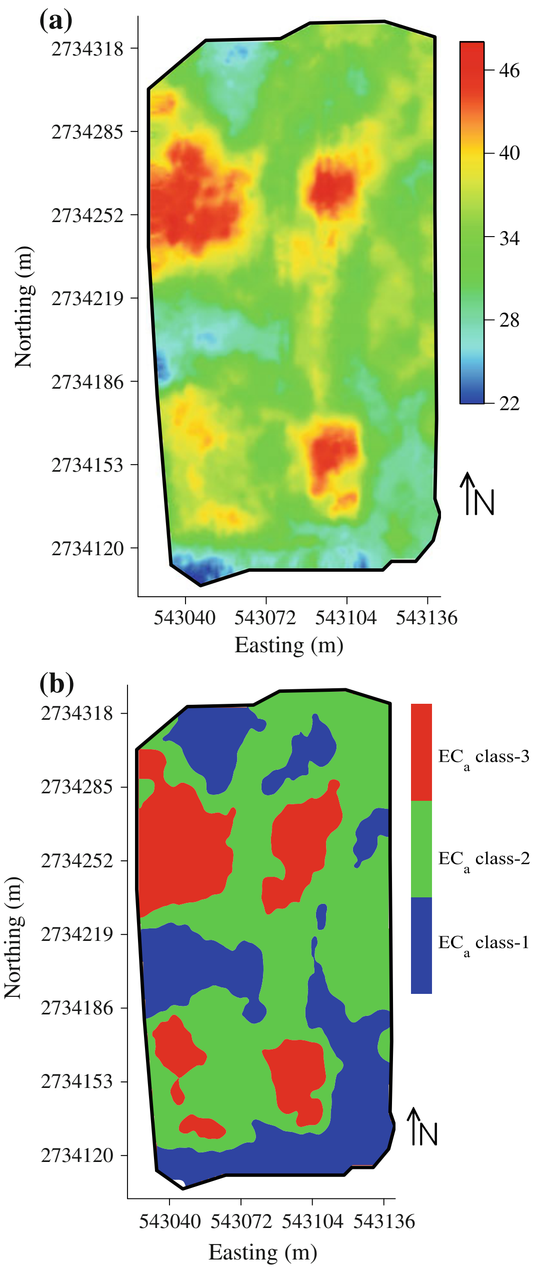

Fig. 3 **a** The interpolated EC$_a$ (mS m^{-1}) map of the paddy field. The co-ordinates are expressed in m, conforming to the Bangladesh Transverse Mercator projection with map datum Gulshan 303 and **b** Delineated EC$_a$ classes of the field

41.3 mS m^{-1} (areas less than 15 m^2 were merged with the surrounding class for practical reasons). These classes represented 28, 60 and 12% of the area, respectively, but only class-2 consisted of one contiguous zone. Class-1 and -3 contained several zones (map polygons) which occurred over the entire field.

Bulk density

To interpret the observed variation of EC_a in the flooded paddy field, it was not feasible to turn to published information. The reconnaissance soil survey reported that these flood-plain soils are not saline and fairly homogenous in terms of texture and drainage class (Brammer 1981), but no information on the detailed scale of the study is available, so this general statement should be considered with some caution. Nevertheless, as a first approximation, the alluvial parent material, soil genesis processes and general land use activities of the studied field were assumed to be fairly uniform resulting in a limited variability in clay and organic matter. Therefore, bulk density as a soil property influencing EC_a was considered (Rhoades et al. 1999). Besides, bulk density is a key soil parameter for wetland paddy cultivation. Low bulk density of the ploughed topsoil facilitates paddy root growth whereas high bulk density of the subsoil restricts leaching of nutrients. Bulk density values are also used to indicate the degree of ploughed soil softness and subsoil compaction. In light textured soils, as is the case for the studied field, a high bulk density value indicates a well-formed plough pan.

To investigate the relationship between EC_a and bulk density, the 50 observations of bulk density at the three depth intervals were grouped according to the EC_a classes. Table 1 gives the summary statistics together with a statistical comparison of the mean values. For all three depth intervals, the significantly smallest mean bulk density values were found in EC_a class-1, i.e. the class with the smallest EC_a values. For EC_a classes -2 and -3 the differences were also significant for the first two depth intervals, but not for the 0.30–0.45 m interval. So, in general, soil bulk density followed the same trend as the EC_a values, i.e. the higher the EC_a, the higher the bulk density. Although the aim of this article was not to find a cause for this relationship, it seems to indicate that the finer the saturated soil pores are, the larger their electrical conductivity becomes.

Within each EC_a class, the soil bulk density increased from 0.0–0.15 m to 0.15–0.30 m and decreased in the deeper layer (0.30–0.45 m). Low bulk density values in the topsoil indicated topsoil softness, while the high bulk density of the 0.15–0.30 m layer represents compaction by puddling and the formation of a plough pan. Both topsoil softness and

Table 1 Descriptive statistics and mean comparison of soil bulk density [Mg m^{-3}] among the EC_a classes

Soil depth (m)	Soil bulk density [Mg m^{-3}]				
	EC_a class	Mean*	Minimum	Maximum	SD
0.0–0.15	Class-1	1.26[a]	1.17	1.33	0.05
	Class-2	1.32[b]	1.28	1.36	0.02
	Class-3	1.37[c]	1.32	1.41	0.03
0.15–0.30	Class-1	1.44[a]	1.42	1.45	0.01
	Class-2	1.63[b]	1.42	1.76	0.11
	Class-3	1.76[c]	1.65	1.79	0.05
0.30–0.45	Class-1	1.43[a]	1.42	1.44	0.01
	Class-2	1.46[b]	1.43	1.53	0.04
	Class-3	1.46[b]	1.37	1.51	0.04

* Within a soil depth, means followed by the same letter do not differ significantly ($P = 0.05$) according to Fisher's least significant difference test; number of samples per EC_a class = 16, 25 and 9 for class-1, class-2 and class-3 respectively; SD = Standard deviation

subsoil compaction are required for a high paddy rice yield. However, the large variation in the 0.15–0.30 m layer of bulk density (between 1.42 and 1.79 Mg m^{-3}) indicated that soil compaction was not uniform within this field.

Paddy rice yield

Table 2 provides the summary statistics of the rice yield data. A difference of 2.0 t ha^{-1} was found between the lowest and highest yield, which is considerable given an average yield of 4.9 t ha^{-1}. To evaluate the link between EC_a and rice productivity, the yield data were also grouped according to the EC_a classes and the significance of the differences between the classes were analyzed statistically. The average rice yield was the lowest (4.4 t ha^{-1}) for EC_a class-1, increased significantly in class-2 (5.2 t ha^{-1}) and stabilized in class-3 (mean = 5.4 t ha^{-1}, not significantly different from the mean of class-2).

The general relationship between EC_a and rice yield was best modeled by a second order polynomial (the adjusted R^2 of a linear model was 0.68 and of a second order polynomial 0.80):

$$\text{Yield} = -8.295 + (0.672 * EC_a) - \left(0.00821 * {EC_a}^2\right) \quad R^2 = 0.80 \tag{3}$$

with yield in t ha^{-1} at a moisture content of 18% and EC_a in mS m^{-1} at 25°C (dashed curve in Fig. 4).

Since the yield statistics of EC_a class-1 were different from those of EC_a classes -2 and -3 (Table 2), this relationship was investigated separately within class-1 and within the grouped classes -2 and -3. For both groups of data, a linear regression was found to be a better fit than a second order polynomial on the basis of the adjusted R^2 (full curves in Fig. 4). For class-1 the regression was:

$$\text{Yield} = -7.437 + (0.402 * EC_a) \quad R^2 = 0.83 \tag{4}$$

and for the combined class-2 and class-3 data:

$$\text{Yield} = 3.309 + (0.052 * EC_a) \quad R^2 = 0.46 \tag{5}$$

The difference in slope of both regressions clearly indicate a difference in soil-yield relationship within both EC_a zones (class-1 vs. class-2 and class-3).

Since EC_a class-1 had both the lowest soil bulk density values within the 0.15–0.30 m layer and the lowest rice yield, it would be reasonable to assume that both are related. After

Table 2 Descriptive statistics and mean comparison of the paddy yield observations [t ha^{-1}] for the whole field and stratified per EC_a class

	Yield observations [t ha^{-1}]				
	n	Mean*	Minimum	Maximum	SD
Whole field	50	4.9	3.6	5.6	0.5
EC_a class-1	16	4.4^a	3.5	5.0	0.4
EC_a class-2	25	5.2^b	4.6	5.6	0.2
EC_a class-3	9	5.4^b	4.7	5.5	0.3

* Means followed by the same letter do not differ significantly ($P = 0.05$) according to Fisher's least significant difference test; *n* = number of samples, SD = Standard deviation

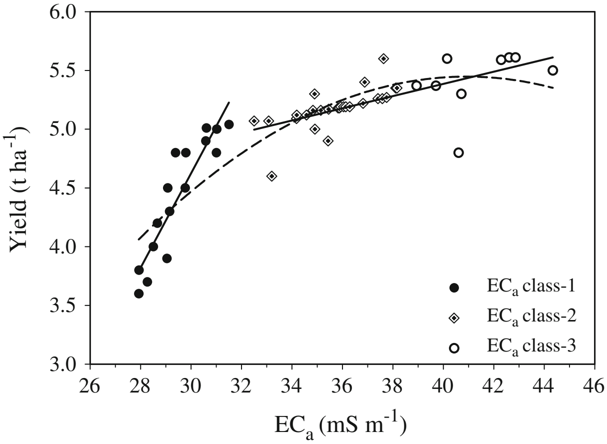

Fig. 4 Relation between EC_a and paddy yield for the field as a whole (*dashed curve*) and per EC_a zone (*full curves*). One EC_a zone consisted of EC_a class-1, while the other zone grouped EC_a class-2 and -3. Points were symbolized according to the EC_a class

all, under flooded conditions, a less compacted subsoil will result in an increased leaching of nutrients, although more research is needed to confirm this statement.

Conclusions

An efficient system for measuring the within-field variation of soil properties of flooded fields is a prerequisite to introduce precision agriculture in such a type of land use. EMI was chosen for this purpose and implemented in a FloSSy which was successfully used to measure in detail the soil EC_a of a field which is not easily accessible for soil sampling due to the almost permanent inundation, as in the intensively cropped paddy areas of Bangladesh. The EC_a measurements showed a clear spatial pattern of varying values. These data were optimally classified in three EC_a classes. The differences among these classes showed significant differences in soil bulk density in the first two depth intervals and were the largest in the puddled subsoil (0.15–0.30 m below surface). In general, the larger the EC_a, the higher the bulk density.

The first EC_a class had a significantly lower paddy rice yield compared to the yield of the other two classes with a clearly different linear relationship between EC_a and yield. This indicated a different soil-yield relationship among the delineated EC_a zones. Since the yield was the lowest in the EC_a class with lowest subsoil bulk density, it was postulated that a poorly compacted plough pan might have facilitated the leaching of nutrients reducing its crop yield potential.

It can be concluded that an EMI-based floating sensing system is useful in collecting EC_a data which can support the evaluation of relevant soil and crop properties allowing the within-field management of flooded paddy rice fields.

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