https://pub.isae.in

Journal of Agricultural Engineering (India)

Vol. 59 (3): July-September, 2022

doi: 10.52151/jae2022593.1781

Electrical Conductivity-based Mapping of Paddy Yield using TDR Soil Sensor

Harnoordeep Singh Mann[1], Aseem Verma[2*], Manjeet Singh[3] and Tarandeep Singh[2]

[1]Graduate Engineer, [2]Scientist, [3]Principal Scientist, Department of Farm Machinery and Power Engineering, Punjab Agricultural University, Ludhiana, Punjab, India. *Corresponding author email address: aseemverma@pau.edu

Article Info

Manuscript received:
May, 2022
Revised manuscript accepted:
September, 2022

Keywords: Crop yield, electrical conductivity, heat map, paddy yield, Time Domain Reflectometry (TDR)

ABSTRACT

Electrical conductivity is a physio-chemical property of soil that correlates with soil properties that affect crop productivity. A study was conducted to map the paddy yield on the basis of apparent electrical conductivity (EC_a) at three depth levels (L1 = 76 mm, L2 = 122 mm, L3 = 203.2 mm) measured using the Time Domain Reflectometry (TDR). The statistical correlations between EC_a and paddy yield were established and variations in paddy yield were mapped. The correlation coefficient between crop yield and EC_a was highest (r^2=0.47) for measurements taken at L3, whereas paddy yield was poorly correlated with EC_a measurements at L1 (r^2=0.03). At L3, the highest paddy yield was 6.78 t.ha^{-1} at EC_a of 0.359 mS.m^{-1}; whereas, the lowest (5.63 t.ha^{-1}) was at EC_a of 0.319 mS.m^{-1}. EC_a at L1, L2, and L3 was significantly related to paddy yield with a coefficient of determination value of 0.26. The variability maps of paddy yields would help in better management of paddy fields.

Paddy-wheat cropping system (PWCS) is practiced over 13.5 Mha area in south Asia; mostly in India, Bangladesh, Pakistan, Nepal, and also in large areas in China (Bhatt *et al.*, 2021). This system is highly productive and important for ensuring food security and livelihood in India. Paddy was cultivated in Punjab state in over 3.1 Mha area with a total production of 20.88 Mt during 2020-21 (Anon., 2022).

Understanding the relationships between paddy yield and electrical conductivity of soil is of critical importance in precision farming (Ezrin *et al.*, 2010). Apparent Electrical Conductivity (EC_a) of soil is an accurate and speedy tool for measuring physical and chemical properties of soil that affect crop productivity (Chan *et al.*, 2006; Akanji *et al.*, 2018). Electrical conductivity is the ability of a material to transmit or conduct an electrical current, and is commonly expressed in terms of milli Siemens per metre (mS.m^{-1}). Soil electrical conductivity is one of the important spatially variable properties of the soil (Corwin and Elia, 2020). Soil EC_a is a good indication of the amount of nutrients available for crops to absorb due to the fact that all major and minor nutrients important for plant growth take the form of either cations (positively charged ions) or anions (negatively charged ions) in solution (Akanji *et al.*, 2018). These ions that are dissolved in the soil water carry an electrical charge and thus determine the EC_a level of the soil.

The electrical conductivity of soil water mixtures indicates the aggregate of salts available in the soil which arise from irrigation water, fertilizer, and dissolving soil minerals. Some of the soil salts are very essential for plant growth but excessive salt concentration interrupts plant growth by distressing the soil-water balance. Accordingly, EC_a is considered as the most reliable and frequently used tool in precision farming research for spatio-temporal characterization of edaphic and anthropogenic properties that influence crop yield (Corwin and Elia, 2020). The geospatial measurement of EC_a has played a major role in addressing the field-scale spatial variability characterization issue, particularly in mapping soil salinity, water content, and texture (Corwin and Lesch, 2005; Doolittle and Brevik, 2014). Since, its early agricultural use for measuring soil salinity, the application of EC_a has evolved into a widely accepted means of establishing the spatial variability of a variety of soil physical and chemical properties that either directly or indirectly influence the EC_a measurement (Corwin and Lesch, 2005; Corwin, 2008; Doolittle and Brevik, 2014).

Recently, researchers have shown interest in characterizing soil and topographic variability in relation to crop growth and yield. It has been reported that there is usually little or no significant relationship between crop yield variation and individual soil characteristics such as organic matter, cation exchange capacity, and texture (Kravchenko and Bullock, 2000). However, EC_a which is affected by a number of soil properties such as clay content, soil water content, temperature, salinity, organic compounds, and metals (Kachanoski *et al.*, 1990; Aimrun *et al.*, 2007) has been highly correlated with variations in water storage characteristics, and consequently to yield variations (Kitchen *et al.*, 1999; Joshua and Mokuolu, 2016). According to Corwin and Elia (2020), EC_a is a function of several soil properties (soil salinity, texture, water content), and has sometimes been overlooked in site-specific crop management. Crop yield monitoring data in conjunction with EC_a can be used from a site-specific crop management perspective to (i) identify the soil properties influencing yield (Corwin *et al.*, 2003), and (ii) delineate site-specific management units (Corwin and Lesch, 2010).

Time Domain Reflectometry (TDR) is a proven technology for quick and accurate determination of volumetric water content (VWC) in the soil. TDR is based on soil's effects on primary alternating electric currents transmitted into the soil via embedded electrodes. In reflectometry, the characteristics of alternative current change in response to the dielectric properties of the soil medium, and therefore, other alternating signals are generated. These secondary signals are recorded, and their speed, amplitude, or frequency is analysed. The relationship of EC_a with crop yield is so complex that it has to be modelled for the specific crop production system. Numerous techniques have been applied for modelling the relationship between crop yield and measured soil parameters (Corwin and Elia, 2020). Linear regression is the most popular technique to assess the relationship significance and predictive ability.

The present study was undertaken to map the spatial variations in paddy yields on the basis of apparent electrical conductivity using a TDR sensor. The measured EC_a values and the corresponding paddy yield at the point of measurement were used to develop a relationship between EC_a and paddy yield.

MATERIALS AND METHODS

Site characteristics

The present study was conducted at the Departmental Research Farm, Department of Farm Machinery and Power Engineering, Punjab Agricultural University, Ludhiana (latitude 30°54'38.1"N and longitude 75°49'07.3"E). The experimental field covered an area of 1730 m² as measured with the mobile application "GPS Field Area Measure" and thereafter, the recorded data was established by physical measurement of area.

The soil of the experimental field was sandy loam, and the field was under a conventional paddy-wheat system for more than 7 years. In the present study, paddy cultivar Parmal (PR-122) was grown in all fields. Paddy establishment method typically involved mechanical transplanting of 30-day old mat-type seedlings in puddled soil during the last week of June. All practices of crop establishment, as recommended by Punjab Agricultural University, Ludhiana (Anon., 2022), were followed throughout the cropping season.

Description of Instrument

FIELDSCOUT TDR 350 soil moisture meter with shaft-mounted probe and built-in data logger was used in the present study to record EC_a at selected locations in the paddy field. The data points can be viewed using the FieldScout Mobile app that maps out soil measurements using logged location coordinates. The measurements can also be saved to an external Universal Serial Bus (USB) flash drive when plugged into the built-in USB port. Technical specifications of the instrument are given in Table 1.

In the present study, prior to data collection for each field, the instrument was calibrated as per manufacturer instructions. The operational views of the equipment and user interface are shown in Figs. 1 - 2, respectively.

Data Acquisition

The total study area of 0.4 ha was divided into five plots namely, Plot 1 – 5, with each covering an area of 0.04 ha. Further, each plot was sub-divided into 4 sub-plots namely, A - D.

The EC_a data was recorded at ten data points in each

Table 1. Technical specifications of FIELDSCOUT TDR 350

Sl. No.	Description of component	Specifications
1.	Measurement unit	Percent volumetric water content (VWC) Period (raw sensor reading)
2.	Resolution, Accuracy	VWC: 0.1% increment ±3.0% @ < 2 mS.cm^{-1} 0% to Saturation (Saturation is typically around 50% volumetric water) EC: 0.01 increment; ± 0.1 mS.cm^{-1}; Temperature: 0.1 ˚C; increment: ± 1 ˚C; (-)30 - 60 ˚C Thermistor based; Infrared Optional
3.	Connectivity	USB Type-A, Bluetooth Low Energy
4.	Global Navigation Satellite System (GNSS)	Accuracy 1 m (Galileo), 3.5 – 10 m (Glonass, GPS) WAAS and EGNOS enabled
5.	Power source	4 AA alkaline batteries
6.	Log capacity, measurements	50,000
7.	Display	Backlit, high-contrast, graphic LCD
8.	Weight, kg	1.9
9.	Probe head dimensions, mm	60x35
10.	Shaft dimensions, mm	Extended length: 965 Collapsed length: 584 Width: 35
11.	Available rod dimensions, mm	Turf: 38 Short: 76 Medium: 122 Long: 203.2 Diameter: 5 Spacing: 30

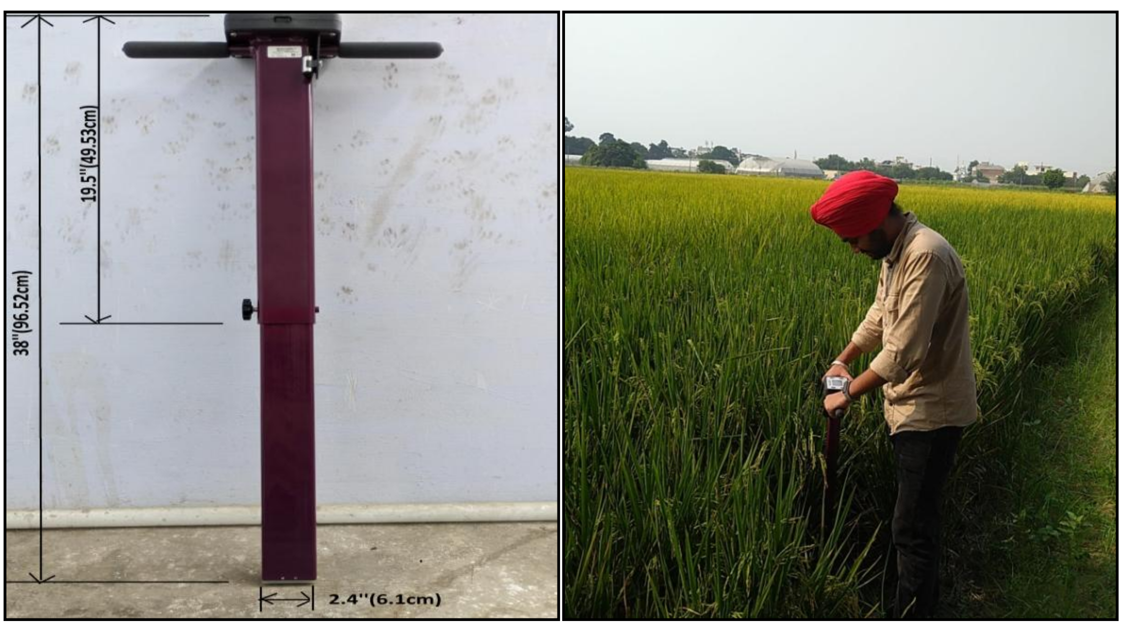


Fig. 1: A view of FIELDSCOUT TDR 350 equipment

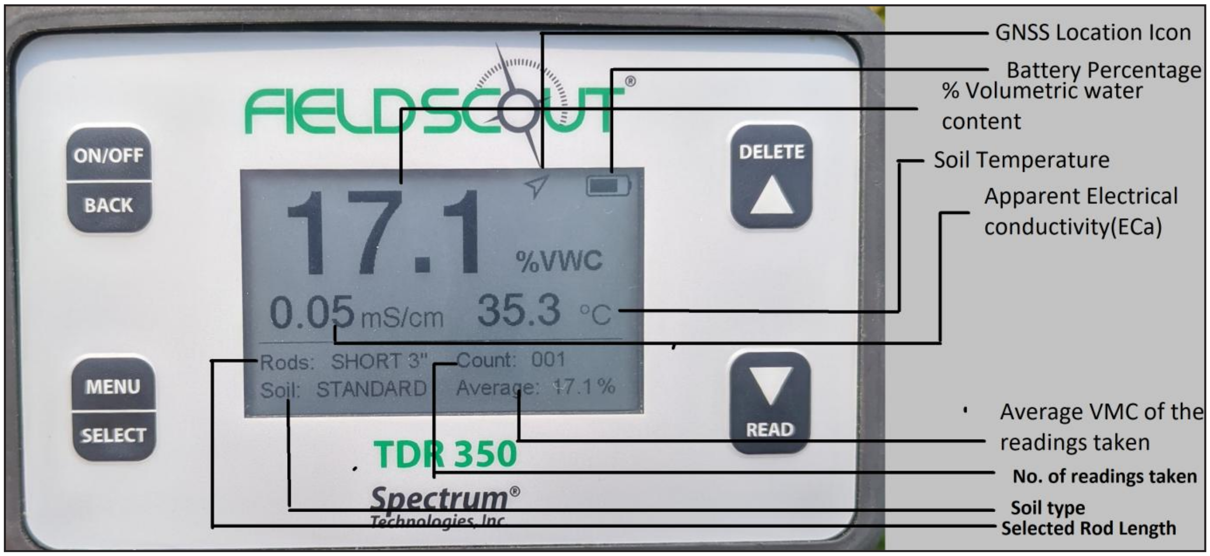


Fig. 2: A view of user interface

sub-plot, thus in total 200 readings were collected from the field with each probe length L1 = 76 mm, L2 = 122 mm, and L3 = 203 mm. Paddy yield data were collected at 20 sampling points (1×1 m^2 each) within the selected sub-plots covering all points of EC_a measurements.

Statistical Analysis

Correlation and regression-based analyses were conducted to determine the association between variables (paddy yield and soil EC_a). Because of their uniformity in all sub-plots, the influence of external factors such as weather conditions, disease outbreaks, insect attacks, and labour use on crop yield was not considered in the data analysis and interpretation.

Data analysis was done using the programming language 'Python'. The techniques adopted consisted of (1) Linear Regression (LR) and correlation analysis, and (2) Visual map analysis. Correlation analysis was done using heat maps in 'Seaborn for Python' (Seaborn, 2021). To analyse data, linear regression was implemented by using the regression plot in 'Seaborn for Python', and the coefficient of determination (R^2) was determined with real data points. Besides, Pearson's correlation was executed to indicate the strength and direction of the linear relationship between soil EC_a and paddy yield.

RESULTS AND DISCUSSION

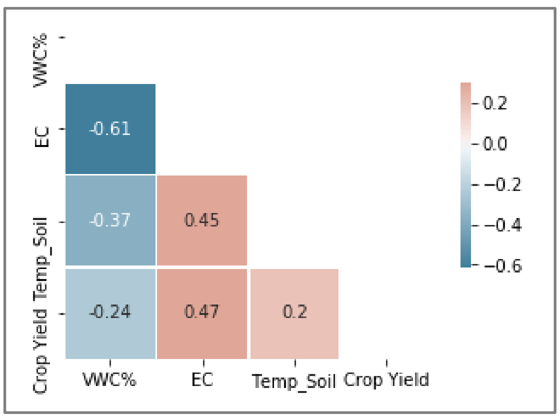
Apparent Electrical Conductivity Variations with Crop Yield

The soil EC_a varied down the soil profile and spatially across the experimental field. Paddy yield and EC_a showed a significant correlation coefficient of 0.47 at 1% level of significance. This might be due to the underlying soil property relationships that both data sets had in common, as electrical conductivity levels might serve as an indirect indicator of the amount of water and water-soluble nutrients available for plant uptake. Akanji et al. (2018) also reported that higher soil EC_a revenues richer nutrient concentration, which is needed for crop growth and yield. The average EC_a at depth levels L1, L2, and L3 ranged between 0.181-0.284 (mean 0.245), 0.223-0.305 (mean 0.267), and 0.316-0.390 (mean 0.349) $mS.m^{-1}$, respectively (Table 2). Highest paddy yield recorded was 6.78 $t.ha^{-1}$ (EC_a 0.359 at L3) in sub-plot 2; whereas, the lowest recorded yield was 5.63 $t.ha^{-1}$ in sub-plot 4 (EC_a 0.319 at L3). The trend of EC_a at L3 was likely to be synchronized to the yield obtained. The data showed that a high yield was obtained when EC_a at L3 was 0.359-0.390 $mS.m^{-1}$. The correlation coefficient between paddy yield and EC_a at L1, L2, and L3 depths, determined using heat maps in 'Python', are presented in Fig. 3. The other correlation coefficients *i.e.* volumetric water content (VWC %) and soil temperature (Temp_soil) were also determined to understand field variability in these properties. The overall correlation between paddy yield and EC_a at different depth levels is shown in Fig. 4.

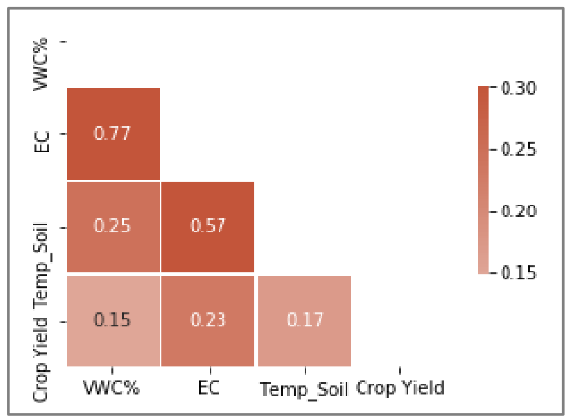
As shown in Fig. 5, the coefficient of correlation (r) between paddy yield and EC_a was highest (0.47) at the depth L3, followed by L2 (0.23), and L1 (0.033). The value of EC_a at L3 resulted in a positive correlation with paddy yield. Results were in line with Ezrin *et*

Table 2. Paddy yield and EC_a at different soil depth levels

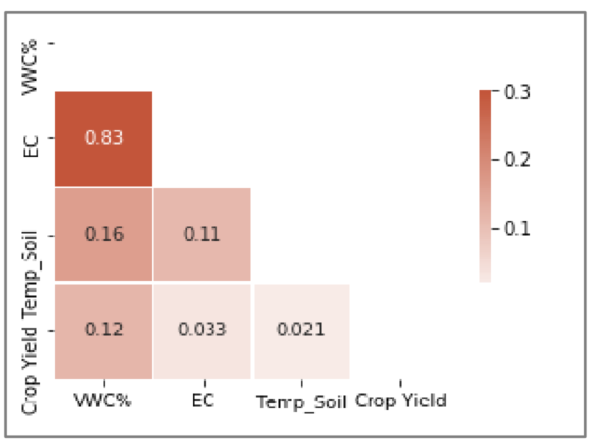
Plot number	Average EC_a, $mS.m^{-1}$			Average yield, $t.ha^{-1}$
	L3	L2	L1	
1	0.390	0.305	0.254	6.58
2	0.359	0.262	0.273	6.78
3	0.316	0.223	0.181	6.18
4	0.319	0.236	0.237	5.63
5	0.362	0.311	0.284	6.68
Mean	0.349	0.267	0.245	6.37
Standard Deviation	0.028	0.035	0.036	0.42
Standard Error	0.013	0.016	0.016	0.19



(a) L3



(b) L2



(c) L1

Fig. 3: Heat maps for the coefficient of correlation (r) for different probes

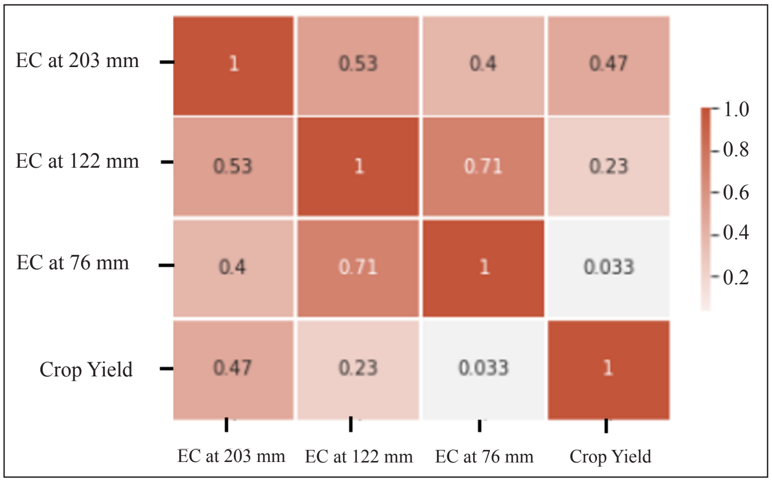


Fig. 4: Correlation coefficient (r) between paddy yield and EC_a at different soil depths

al. (2010), who also found a statistically significant relationship between paddy yield and apparent electrical conductivity of paddy soils with correlation coefficient of 0.1246. The linear regression plots between paddy yield and EC_a for different depth levels are shown in Fig. 5.

The coefficient of determination (R^2), as calculated from linear regression analysis, was highest (0.221) for EC_a at depth L3, whereas it was lowest (0.001) for EC_a at depth L1.

The yield predicting linear regression equations with EC_a at L1, L2, and L3 as explanatory variables are:

For L3: Yield = 0.3186 + 0.9090 (EC_a); $R^2 = 0.221$ ...(1)

For L2: Yield = 0.5269 + 0.4088 (EC_a); $R^2 = 0.052$ ...(2)

For L1: Yield = 0.6242 + 0.0496 (EC_a); $R^2 = 0.001$ ...(3)

In order to find the best model to relate paddy yield and soil electrical conductivity, the linear regression analysis considering EC_a (L3), EC_a (L2), and EC_a (L1) as independent variables and paddy yield as a dependent variable improved the coefficient of determination (R^2) from 0.221 to 0.260.

The multiple linear regression analysis in 'Python' produced the best selection model as

Yield = 0.952 (EC_a at L3) + 0.309 (EC_a at L2) - 0.430 (EC_a at L1) + 0.326; R^2=0.26 ...(4)

The results showed that EC_a (L3), EC_a (L2), and EC_a (L1) are significantly related to the paddy yield, and generated a high coefficient of determination value (R^2 =0.26); although, the EC_a (L3) contributed more to the significant relationship factor rather than EC_a (L2), and EC_a (L1).

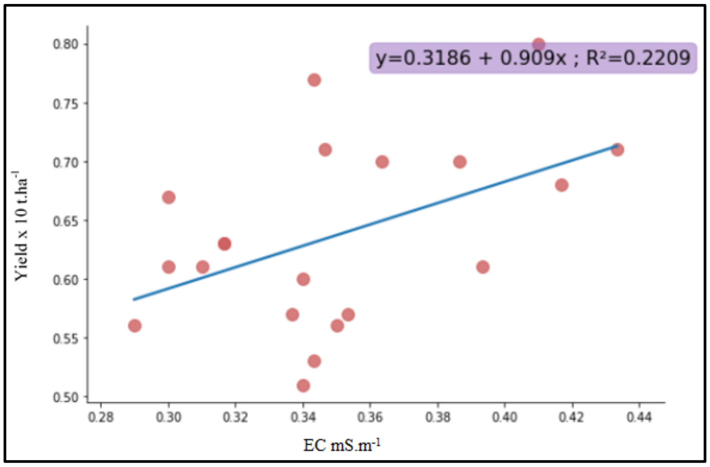
Yield Map

Analysis of yield maps showed that the areas of higher yield were concentrated in plot 5. The lower yield was scattered mostly in plots 3 and plot 4. Plot 3 located in the northern area of the experimental site had a lower EC_a value compared to the other plots. The visual analysis of maps also indicated a similar trend of high paddy yield associated with the higher values of EC_a in the field (Fig. 6 and 7).

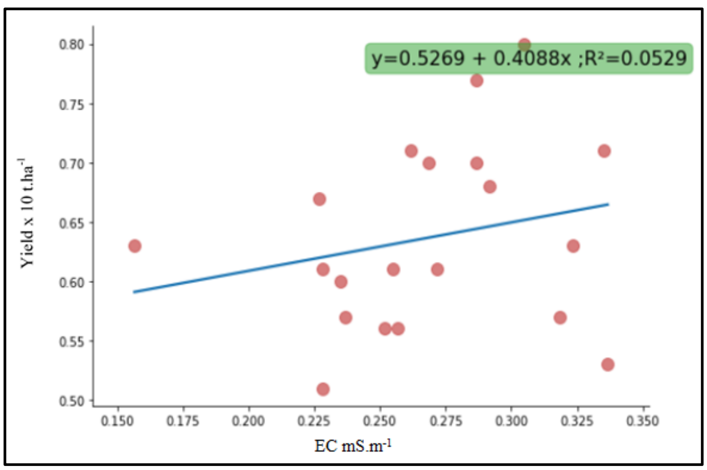
The analysis of data showed that EC_a (L3), EC_a (L2), and EC_a (L1) are important parameters in determining the relationship evidence between paddy yield and soil EC_a. The step-wise method suggested that EC_a (L3), EC_a (L2), and EC_a (L1) are necessary variables to generate linear regression models. However, the EC_a (L3) contributed more to the significant relationship than EC_a (L2) and EC_a (L1). For obtaining the threshold of EC_a corresponding to maximum paddy yield, more data needs to be collected from large field areas having different soil conditions and from different paddy cultivars.

CONCLUSIONS

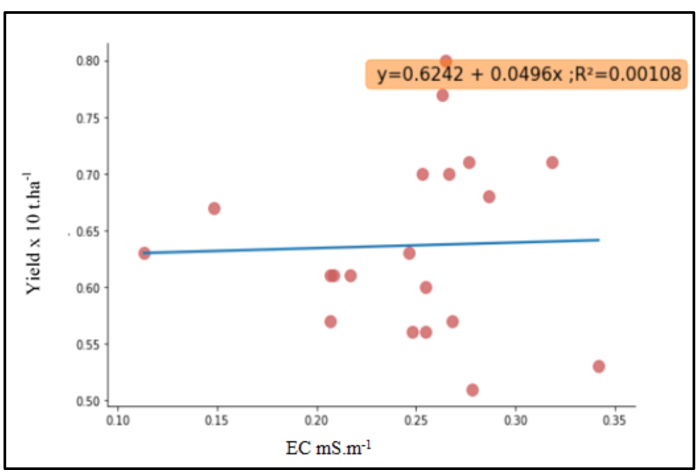
Time Domain Reflectometry (TDR) sensor-based field survey was conducted to map paddy yield on the basis of apparent electrical conductivity (EC_a) measured at three soil depths (L1 = 76 mm, L2 = 122 mm, and L3 = 203.2 mm). Statistical correlations between EC_a and paddy yield were established and variations in paddy yield were mapped. A significant correlation was



(a) L3



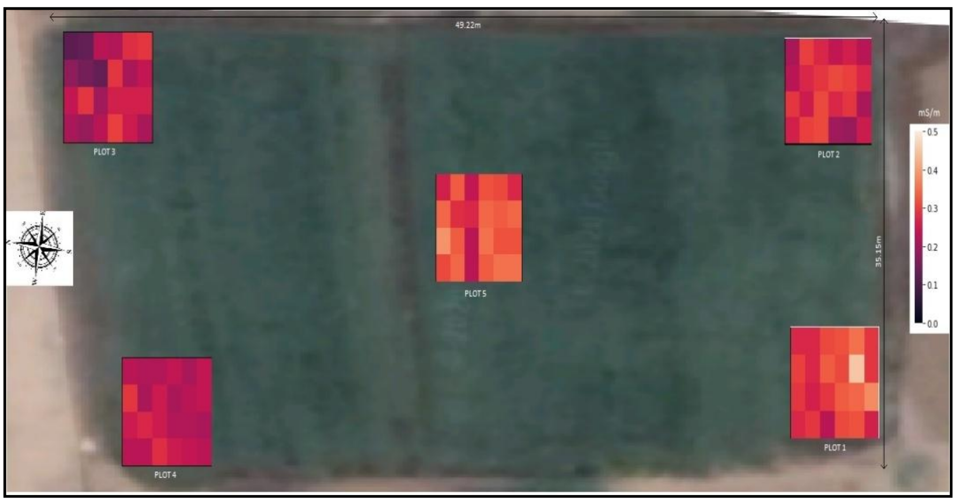
(b) L2



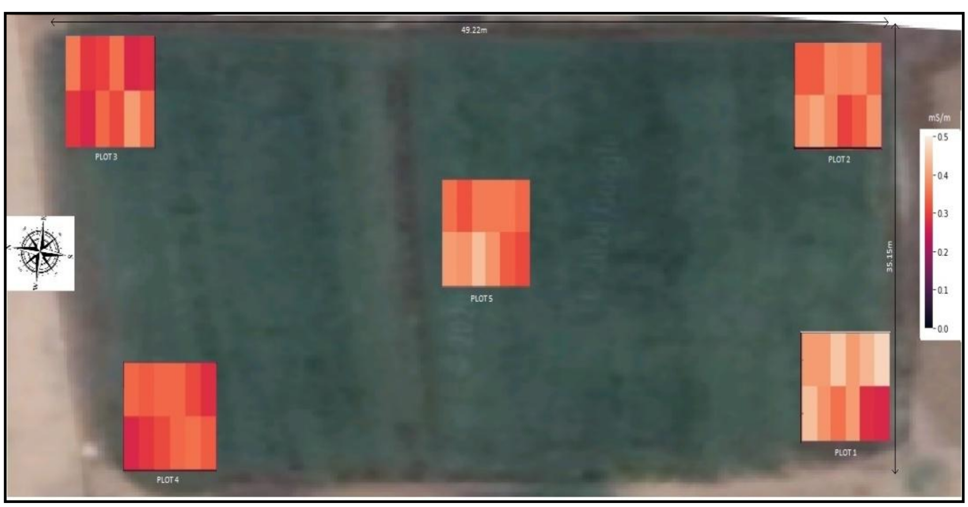
(c) L1

Fig. 5: Regression plots between paddy yield and EC_a for all experimental plots

(a) L1



(b) L2



(c) L3

Fig. 6: Mapping of EC_a at different soil depth levels

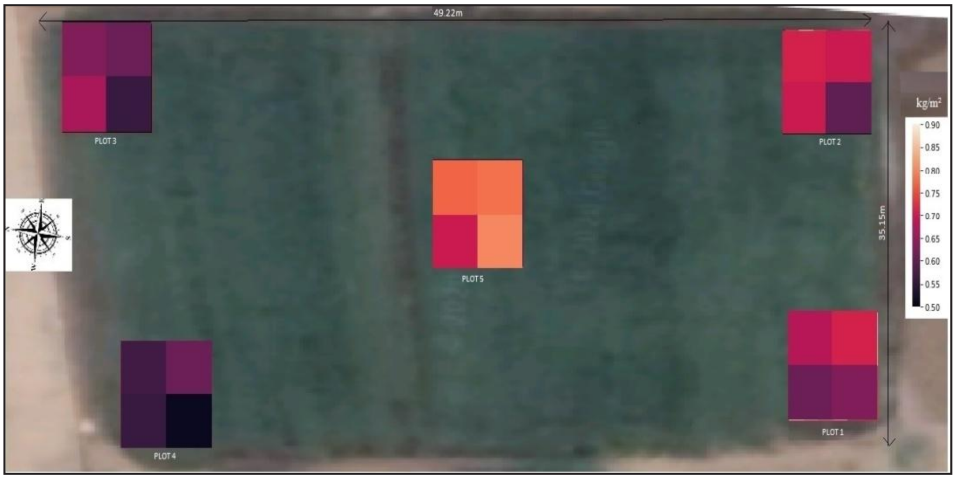


Fig. 7: Mapping of crop yield in study area

observed between EC_a and paddy yield. The regression-based analysis revealed that EC_a at L1, L2, and L3 had significant influences on paddy yields with a coefficient of determination of 0.26. The yield variability maps developed on the basis of soil EC_a could be used to adopt better soil and crop management practices in paddy. The findings showed the potential of TDR based EC_a measurements in precision farming to understand yield variations in paddy fields. Large-scale trials are needed to confirm the results with data from different soil and crop conditions.

ACKNOWLEDGMENT

The authors would like to thank ICAR-NAHEP-CAAST and Punjab Agricultural University, Ludhiana (India) for providing the equipment and other facilities for accomplishing this study.

REFERENCES

Aimrun W; Amin M S M; Ahmad D; Hanafi M Ecad; Chan C S. 2007. Spatial variability of bulk soil electrical conductivity in a Malaysian paddy field. Paddy Water Environ., 5, 113-121.

Akanji M A; Oshunsanya S O; Alomran A. 2018. Electrical conductivity method for predicting yields of two yam (Dioscorea alata) cultivars in a coarse textured soil. Int. J. Soil Water Conserv. Res., 6(3), 230-236.

Anon. 2022. Package of Practices for Crops of Punjab, Kharif 2022. Punjab Agricultural University, Ludhiana, 39(1), pp: 184. Available at https://www.pau.edu/content/ccil/pf/pp_kharif.pdf

Bhatt R; Singh P; Hossain A; Timsina J. 2021. Rice–wheat system in the northwest Indo-Gangetic plains of South Asia: Issues and technological interventions for increasing productivity and sustainability. Paddy Water Environ., 19, 345-365.

Chan C S; Amin M S M; Lee T S; Mohammud C H. 2006. A new technique in predicting soil productivity. J. Inst. Eng. Malaysia, 67(4), 45-55.

Corwin D L. 2008. Past, present, and future trends of soil electrical conductivity measurement using geophysical methods. In: Allred B J; Daniels J J; Ehsani M R (Eds.), Handbook of Agricultural Geophysics, Boca Raton, FL: CRC Press, 17-44.

Corwin D; Elia S. 2020. Field-scale apparent soil electrical conductivity. Soil Sci. Soc. Am. J., 84, 1405-1441.

Corwin D L; Lesch S M; Shouse P J; Soppe R; Ayars J E. 2003. Identifying soil properties that influence cotton yield using soil sampling directed by apparent soil electrical conductivity. Agron. J., 95(2), 352-364.

Corwin D L; Lesch S M. 2005. Apparent soil electrical conductivity measurements in agriculture. Comp. Elect. Agric., 46(1-3), 11-43.

Corwin D L; Lesch S M. 2010. Delineating site-specific management units with proximal sensors. In: Oliver M (Ed.), Geostatistical Applications in Precision Agriculture, Springer, New York, 139-165.

Doolittle J A; Brevik E C. 2014. The use of electromagnetic induction techniques in soil studies. Geoderma, 33-45, 223-225.

Ezrin M H; Amin M S M; Anuar A R; Aimrun W. 2010. Relationship between paddy yield and apparent electrical conductivity of paddy soils. Am. J. Appl. Sci., 7 (1), 63-70.

Joshua E O; Mokuolu A O. 2016. Electrical resistivity based empirical model for predicting cassava plant (TMS 98/0505) tuber yield on sandy-loam soil. Int. J. Sci. Res., 5, 1957-1963.

Kachanoski R G; Van-Wesenbeeck I J; DeJong E. 1990. Field scale patterns of soil water storage from non-contacting measurements of bulk electrical conductivity. Can. J. Soil Sci., 70, 537-541.

Kitchen N R; Sudduth K A; Drummond S T. 1999. Soil electrical conductivity as a crop measure for claypan soils. J. Prod. Agric., 12, 607-617.

Kravchenko A N; Bullock D G. 2000. Correlation of corn and soybean grain yield with topography and soil properties. Agron. J., 92, 75-83.

Seaborn. 2021. A library for making statistical graphics in Python. https://seaborn.pydata.org. (Accessed on 23 March, 2021)