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Exploring the Short-scale Spatial Variability of Calcic Red Latosol Soil Using DUALEM-1S Proximal Soil Sensor

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ABSTRACT: *Short-scale spatial variability of soil properties need to be identified for the proper management of soil resources for crop production. Proximally sensing of soil apparent electrical conductivity (ECa) and the application of inversion technique are highly potential approaches to predict the spatial variability of soil properties. This study was carried out to investigate the applicability of ECa data together with inversion technique to predict the spatial variability of soil variability in Calcic Red Latosols. DUALEM-1S sensor was used to perform the ECa survey in an agricultural land (3.2 ha) situated in Allaveddy in the Jaffna district. The acquired ECa data were used to predict ECa at 20 cm depth increments down to 80 cm soil depth. Exploratory data analyses and then local kriging procedure were applied separately for original and inverted ECa data to construct continuous maps. Soil samples were taken from six sample points (at 20 cm depth intervals upto 80 cm from each sample point) using the purposive sampling scheme. Soil samples were analyzed for soil texture, organic matter, electrical conductivity (EC) and pH. Proximally sensed ECaPRP (CV = 45.4%) and ECaHCP (CV = 73.5%) and the depth profiles of different soil properties showed a high vertical and horizontal spatial variability of soil in the site. High correlations were shown between EC (measured at different depths) and both ECaPRP (r >0.60) and ECaHCP (r >0.60) at different depths. However, ECa did not show strong correlations with other soil properties. The high correlations (r > 0.76) between depth specific inverted ECaPRP and ECaHCP measurements and measured EC of respective depths indicated that these ECa data layers can be used to map the soil salinity development in different soil layers. This study revealed a strong short-scale spatial variability of soil properties in the selected Calcic Red Latosol and proximal soil sensing using the DUALEM-1S sensor is a highly potential tool for producing three dimensional maps of the soil EC.*

Keywords: *Apparent electrical conductivity, proximal soil sensing, short-scale spatial variability*

INTRODUCTION

The short-scale spatial variability of soil properties such as soil depth, soil texture and organic carbon is a common phenomenon. The variability of these soil properties influence the soil physical, chemical and biological processes those determine the plant growth. Importantly, soil variability in both, horizontal and vertical directions are equally important in deciding the suitability of a soil for plant growth and thus its management for optimal crop

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production. Therefore, areas having unique combination of vertical patterns of soil properties would serve as uniform land units having different production potentials. Moreover, efficient use of agricultural inputs such as fertilizers and liming materials could be improved by changing the application rates site-specifically based on the variability of soil properties (Winehold and Doran, 2008). The traditional approach to investigate spatial variability of the soil properties is the soil spatial sampling and laboratory analyses followed by mapping, which require high inputs of labour, more time and money. The proximally sensed apparent electrical conductivity (ECa) can be considered as one of efficient, cost-effective and modern approaches to characterize the natural spatial patters of inherent soil properties (Lesch *et al.,* 1995). Proximal soil sensors are used for measuring ECa. Among the available methods, electromagnetic induction (EMI) based methods are becoming more popular among soil surveyors due to their non-destructive nature, rapid response and ease of integration into a mobile platform for obtaining on-the-go measurements. Although the proximally sensed ECa has been used as a reliable tool to predict the horizontal spatial variability of topsoil properties such as clay (Williams and Hoey, 1987), organic matter (Jaynes *et al*., 1996), ECe (Rhoades and Corwin, 1992) and CEC (McBride *et al*., 1990) etc., the patterns of ECa at deeper layers and its relationship with soil properties have been investigated very rarely due to the lack of suitable algorithms to extract ECa in deeper layers using inversion techniques (Santos *et al*., 2011). However, high potential of the EMI based ECa measurements to provide quantitative estimates of the subsoil ECa at different depths have been revealed through ECa data combined with the newly developed inversion techniques (Piikki *et al.*, 2013). EM4SOIL (EMTOMO LDA) is one such software used to invert the proximally sensed ECa acquired from proximal soil sensor (Triantafilis and Santos, 2013). The estimates of ECa are generated by the software for different depths and can be used as secondary information to predict the patterns of soil properties at respective depths. The potential of proximally sensed ECa data of soil of intermediate zone of Sri Lanka to predict the short-scale spatial variability of the different topsoil properties (soil texture, available P, Ca, Mg, K, Na) has been investigated recently (Balasooriya *et al*., 2014; Rathnayaka *et al*., 2014), but the potential use of inverted ECa to predict subsoil properties has not been investigated so far.

Red Latosol (Typic Ustipsamments) is the most dominant soil great group distributed in the Jaffna peninsula which is extensively used for the agriculture (Mapa *et al., 2010)*. Except few studies (Ketheeshwaren, 2005) less attention has been given for the spatial characterization of red latosols. Moreover, potential of using novel technologies such as proximal soil sensing in spatial characterization of this soil have not been investigated for Red Latosols. The applicability of proximally sensed data to predict subsoil properties become a very important research area related to optimization of the efficient use of agricultural inputs. The objective of this study was to investigate the potential of using the proximal soil sensing technique for the characterization of short-scale soil variability of red latosol at different depth intervals.

METHODOLOGY

An agricultural field (3.2 ha) located at Allaveddy in Jaffna district of Sri Lanka (20 m elevation, 9° 47' 12.8" N, 80° 0' 32.21" E) was selected for the study (Figure 1). The study field is located in the upper position of the soil catena and Red Calcic Latosol is the dominant great soil group (Panabokke, 1996). Onion is the commonly cultivated crop in the selected agricultural field.

DUALEM-1S (Dualem Inc) proximal soil sensor was used to perform the ECa survey. It is one of very popular second generation EMI based proximal sensors which consists of one transmitter coil (Tx) and two receiver coils (Rx) spaced at 1 m. The transmitter coil and one of the receivers in the pair have horizontal coil windings and these components form the horizontal co-planar geometry (HCP). The other receiver in the pair has vertical coil windings. It combines with the transmitter to form the perpendicular coplanar geometry (PRP). The Tx is energized from an alternating current (9 kHz) and it produces a primary magnetic field around the Tx. This primary magnetic field induces small alternating current in the soil which induces a proportionate secondary magnetic field in the soil. This induced magnetic field is superimposed on the primary field and both are measured by two receiver coils (Saey *et al.*, 2009). Thus, the DUALEM-1S soil sensor measures two ECa values as perpendicular coplanar ECa (ECaPRP) and horizontal coplanar ECa (ECaHCP) simultaneously. Perpendicular coplanar ECa is highly sensitive to the conductivity of the topsoil, whereas ECaHCP is highly sensitive to the conductivity of the subsoil (DUALEM-1S user manual, 2012). Therefore, the sensor gives provision for the investigation of soil properties at both topsoil and subsoil.

The DUALEM-1S was attached to a wooden sled and pulled at a speed approximately 3.5 kmh^{-1} along parallel lines spaced at 2 m. The field computer attached to the sensor recorded ECa at 1 second time intervals. Thus, ECa measurements were taken at a density of 2 m x 2m. Exploratory data analysis was performed separately for ECaHCP and ECaPRP measurements. Local kriging interpolation procedure was used to interpolate ECa data using VESPER 1.6 software. The local kriging process calculates variograms for each interpolation search window assuring a best liner interpolation of data measured at high density (Sun *et al.*, 2010). The raster maps showing the spatial variability of ECaHCP and ECaPRP were developed using ArcGIS 10.3 software. The smaller area of the study field was selected for the investigation of the spatial patterns of the selected soil properties in relation to the ECa patterns. The sample points were spatially selected by adopting purposive sampling (Bianchini and Mallarino, 2002) approach (Figure1). Thus, comprehensive spatial representation ECa patterns was achieved.

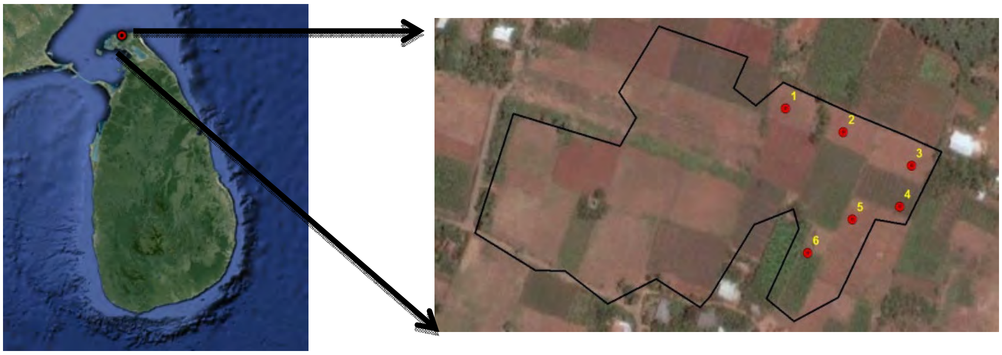


Fig. 1. The location of study field in Sri Lankan map and the satellite image showing spatial distribution of study field boundary and sample points

Soil samples were collected from each sample point at 20 cm depth increments down to 80 cm depth. The samples were air-dried and passed through 2 mm sieve to separate gravel, and analyzed for the soil texture, soil organic matter, pH and EC. Soil texture determination was done using the pipette method (Gee and Or, 2002). The procedure proposed by Walkley and Black (1934) was used for the determination of soil organic matter (OM%). Soil pH and EC of each soil sample were determined separately in 1:2.5 and 1:5 soil/water suspensions respectively, using an EC meter (Eutech COND 6+) and pH meter (Eutech pH 700) to measure EC and pH.

The depth profiles of clay%, sand%, OM%, pH and EC developed for each sample point were used to investigate the vertical spatial variability of the selected soil properties.

The depth response curves of the ECaHCP and ECaPRP models are provided in Figure 2 and these measurements provide values of ECa by integrating conductivities of thin layers of the soil. EM4SOIL inversion software (EMTOMO LDA) was used to invert ECaHCP and ECaPRP to obtain ECa of the soil depths of 20, 40, 60 and 80 cm. The exploratory data analysis was separately done for inverted ECa data set obtained for different depths.

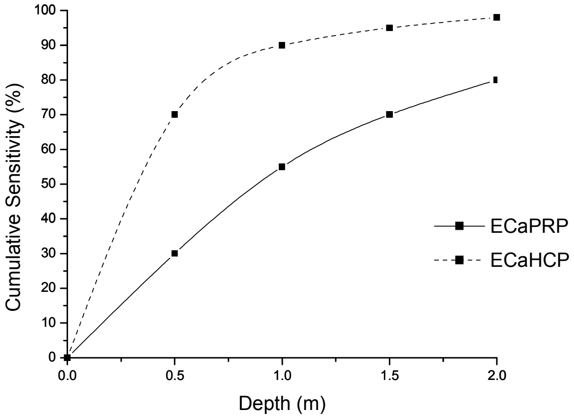


Fig. 2. The cumulative sensitivity in percentage of ECaPRP and ECaHCP for the different depths of soil

Local kriging procedure was performed to interpolate ECa data estimated through inversion technique using VESPER 1.6 software. The interpolated ECa data, estimated through inversion were used to develop maps showing the spatial variability of ECa at different depths. ArcGIS 10.3 software was used to prepare maps. The ECa of each sample location at four depths were extracted from the corresponding interpolated maps using ArcGIS 10.3 software. The applicability of the original and estimated ECa produced by inversion to predict the patterns of inherent soil properties were determined considering the correlations between measurements of different soil properties and respective original and inverted ECa data extracted from the sample location at different depth.

RESULTS AND DISCUSSION

Variability of proximal sensor measured ECaHCP and ECaPRP

The ECa surveys followed by exploratory data analysis resulted in 5884 ECaPRP and 5890 ECaHCP point measurements. Table.1 shows the summary statistics of the apparent electrical conductivity (ECa) measured with DUALEM-1S sensor.

ECaPRP measurements ranged from 6.1 mSm^{-1} to 67.7 mSm^{-1} with the mean of 25.07 mSm^{-1} and the coefficient of variation (CV) of 45.35% while ECaHCP measurements ranged from -12.4 mSm^{-1} to 37.39 mSm^{-1} with the mean of 11.73 mSm^{-1} and the CV of 73.49%. Moreover, ECaPRP had moderate variability (between 12% and 60%) and ECaHCP had high variability (>60%) according to the classification of CV by Warrick and Nielsen (1980). The coefficients of skewness and kurtosis of each ECa data type indicate that both the distributions are positively skewed and platykurtic.

DUALEM-1S sensor usually gives positive values as proximally sensed ECa values for soil. Apparent electrical conductivity measures the ability of solid and solution phases in soil to transmit an electrical current. The charged colloids such as clay and humic substances highly contribute to the ECa from soil solid phase, while dissolved ions contribute to ECa from soil solution phase (Ristolainen *et al.*, 2009). The sensor provided negative values as proximally sensed ECaHCP for some locations. Moreover, those negative values were concentrated to five specific areas in the study field. The negative values for proximally sensed ECa for soil are usually resulted by the sensor when it is oriented perpendicular to a high conductive buried objects such as iron or steel in soil (Stanton and Schrader, 2001). Therefore, it revealed that the spatial variability of the conductivity of studied soil has been altered by the anthropogenic activities

Table1. Statistical parameters of ECaHCP and ECaPRP measurements proximally sensed using DUALEM-1S sensor

Variable	N	Min.	Max.	Mean	SD	CV	Skewness	Kurtosis
ECaPRP(mSm^{-1})	5890	6.1	67.7	25.07	11.37	45.35	0.539	-0.119
ECaHCP(mSm^{-1})	5884	-12.4	37.9	11.73	8.62	73.49	0.173	0.048

Maps of both ECaPRP and ECaHCP, produced through local kriging procedure showed identifiable short-scale spatial variability in the study field (Figure 3). The pattern of ECaPRP and ECaHCP are different from each other implying differences in spatial variability of conductivity at topsoil and subsoil or vertical heterogeneity of soil conductivity.

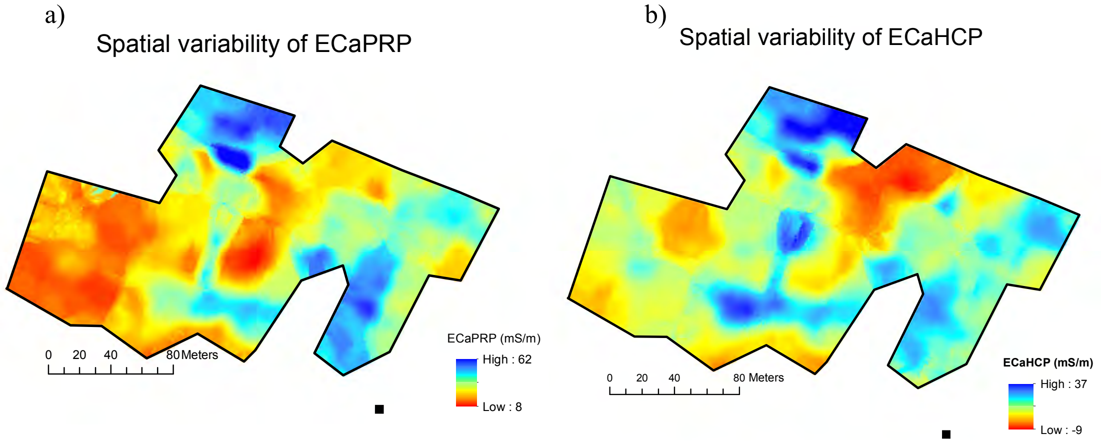


Fig. 3. **Maps showing the spatial variability of the proximally sensed (a) ECaPRP and (b) ECaHCP**

Variability of soil properties in vertical and horizontal directions

The depth profiles developed for individual soil properties showed a vertical spatial variability of each sampling point (Figure 4a-4e). Depth profiles indicated considerable variability of all properties at different depth intervals. The surface soil clay content (0–20 cm) ranged from 8% to 30% across sample points. This variability increased as the depth increases. According to the USDA classification, subsurface layers with a significantly higher percentage of phyllosillicate clay (1.2 times or more than clay percentage in elluvial horizon) overlying soil materials are known as argillic horizon (USDA survey staff, 2014). All the profiles showed the evidence of presence of argillic horizons. However, the argillic horizon occurring depth differs from one sample point to another. The clay profiles of sample locations 2, 5 and 6 showed a presence of argillic horizons at depth of 40-60 cm whereas, those of sample locations of 3 and 4 exhibited argillic horizons from 60 cm onwards upto 80cm or more. Moreover, the presence of argillic horizon of sample point 1 could be seen from 20-60 cm. Huang *et al.* (2011) have showed some limitations to crop growth in the presence of argillic horizon such as poor drainage with purched water table and acting as a barrier to the root penetration. The main possible reason for increasing clay content at deeper layers is due to the translocation (elluviations) of clay particles from surface horizon and deposition in subsurface horizons (Kozlovskii *et al*., 2001). The profile diagrams (Figure 4a) showed variation of the elluviations and illuviation processes at six sample locations and consequently larger variability of clay content in deeper horizons. The % OM content of the top soil layer ranged between 1.2–6.6% (Figure 4c). The depth profiles showed accumulation of OM in the surface layer. Rusco *et al.* (2001) stated that accumulation of OM mainly occurs in the surface horizon due the continuous input of plant biomass and high activity of soil microorganisms.

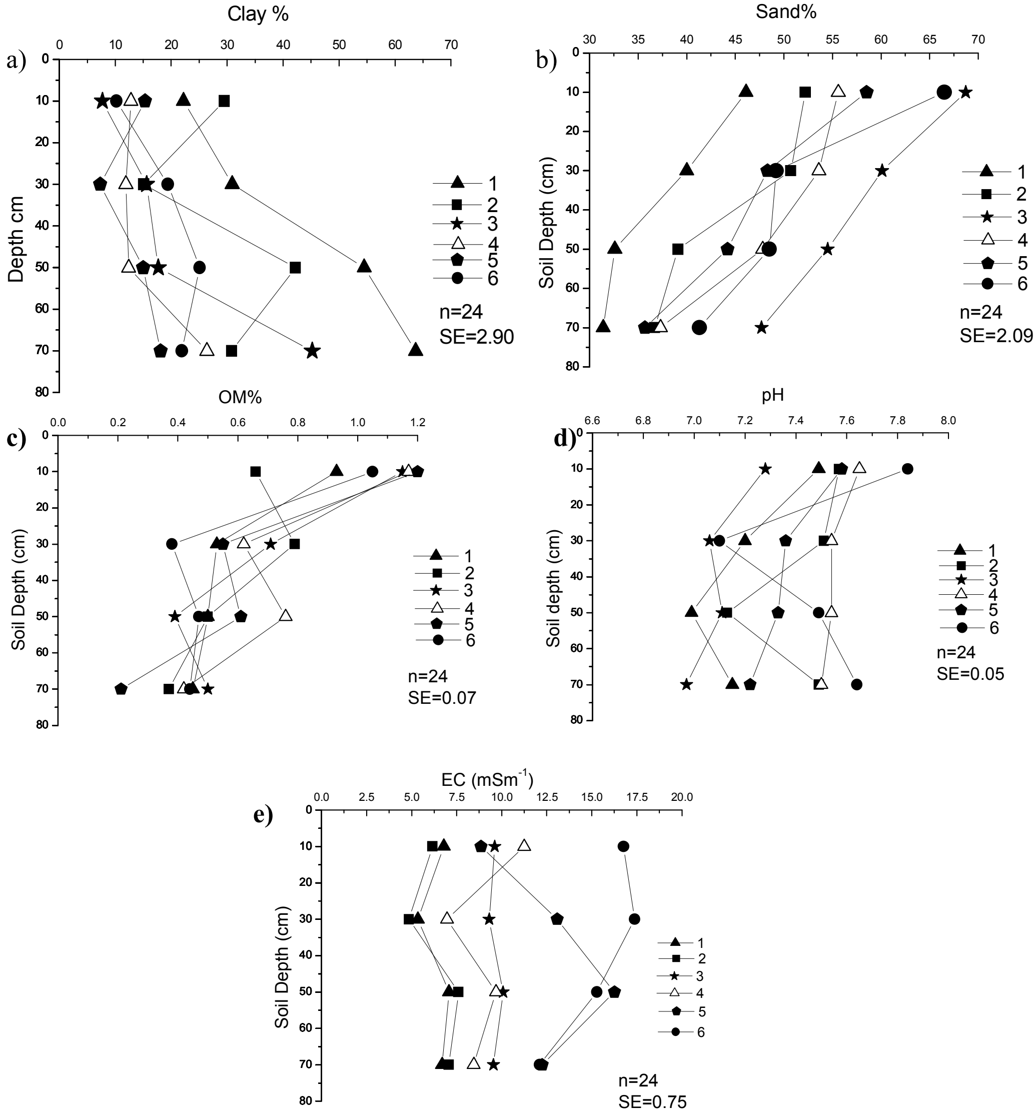


Fig. 4. The depth profiles of (a) clay%, (b) sand%, (c) OM%, (d) pH and (e) EC

Soil pH (Figure 4d) showed a moderate variability within the surface soil (7.3–7.8). This did not change drastically along vertical direction of the soil. According to soil pH classification by Hornek *et al.* (2011), pH values of all the layers at each sample point were within the range of neutral or moderately alkaline. Calcic Red Latosol is a type of Red Latosol, developing on the marine sediments, near to the coastal area (Panabokke, 1996). Marine sediments are rich in $CaCO_3$.Thus, the resultant Red Calcic Latosol soil is also composed of high amount of $CaCO_3$. This would lead to an increase of soil pH throughout the soil profile. Soil EC of the surface soil (Figure 4e) showed a considerable variability (5-17.5 mSm^{-1}). However, this variability narrowed at deeper soil layer (60-80 cm). All EC profiles except sampling points 5 and 6 showed small variation along the depth. The EC profiles of sample point 5 and 6 showed large variation along the depth. The EC depth profiles of most of the sample locations showed comparatively higher values at surface soil layer and deeper soil layers, while lower EC in middle most layers. The water evaporation followed by accumulation of dissolved salts continuously at surface layer due to high temperature in the area, may be the reason for high EC in surface layer. The leaching of the dissolved salts from middle most layers to the deeper layers may be the reason for lower EC in deeper layers.

Relationships between proximal sensed ECa and soil properties

The measurements of ECaHCP and ECaPRP were highly correlated with the measured EC at different depths (Table 2). Moreover, EC measured at 0–20 cm, 20–40 cm and 40-60 cm showed stronger correlations with ECaPRP than ECaHCP. This proved a representation of the conductivity of surface and subsurface layers by ECaPRP measurement. The cumulative response curve of ECaPRP (Figure 2) shows that 75% of its response is attributed to the soil layer 0–60 cm. In contrast, soil EC measured at 60–80 cm showed a strong correlation with ECaHCP which is more sensitive for deeper soil layers (Table 2). However, most soil properties such as OM% ($r < 0.59$), pH ($r < 0.33$) and sand% ($r > -0.59$) showed poor to moderate correlations with both ECaPRP and ECaHCP. Proximally sensed ECa measurements have shown strong positive correlations with OM% (Jaynes *et al.,* 1994), clay% (Williams and Hoey, 1987), CEC (McBride *et al.*, 1990) in non-saline soil. In saline soils, ECa measurements have shown a strong positive correlation with the electrical conductivity of the soil solution (Rhoades and Corwin, 1992). Although, the selected field is not saline, the proximal sensed ECa showed a strong correlation with the EC of soil solution. Moreover, as indicated by Amexketa (2007), strong positive correlations between ECa measurement and other soil properties can be masked by the soil electrical conductivity being the major factor contributing to the measured ECa values.

Table 2. Correlation coefficients of measured EC with ECa extracted from interpolated ECa maps (both ECaHCP and ECaPRP) and depth specific inverted ECa from corresponding interpolated inverted ECa maps at sampling point

	EC measurements (mSm^{-1})			
	(0-20cm)	**(20-40cm)**	**(40-60cm)**	**(60-80cm)**
ECaPRP	0.724	0.848	0.596	0.728
ECaHCP	0.601	0.792	0.592	0.770
Depth specific inverted	0.809	0.913	0.762	0.777

The results of the exploratory data analysis of ECa data at different depths are given in Table 3. The predicted ECa at 10 cm, 30 cm and 50 cm showed a moderate spatial variability (12-60%) and the predicted ECa at 70 cm showed high spatial variability (> 60%) according to classification of CV proposed by Warrick and Nielsen (1980). The predicted ECa at depths of both 10 cm and 30 cm are almost the same. All the distributions of predicted ECa of different depths are positively skewed and platykurtic.

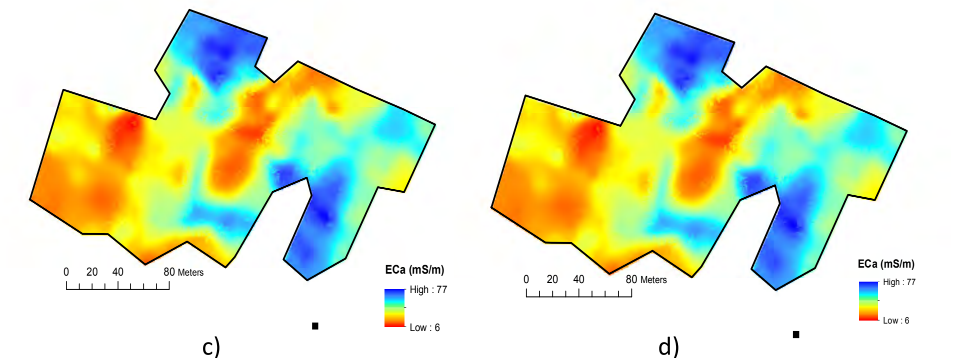
Table 3. Summary statistics for the predicted ECa (mSm^{-1}) for different depth using inversion technique of EM4SOIL Inversion software

Variable	N	Min.	Max.	Mean	SD	CV	Skewness	Kurtosis
ECa(10cm)	2430	10	99.5	38.98	17.57	45.07	0.320	-0.658
ECa(30cm)	2430	10	99.5	38.98	17.57	45.07	0.320	-0.658
ECa(50cm)	2430	22	68.9	26.20	12.29	46.91	0.435	-0.381
ECa(70cm)	2430	1.4	38.5	10.75	7.22	67.16	1.027	1.370

The interpolated maps showing the spatial variability of ECa for different depths are given in the Figure 5. The patterns of spatial variability of all the maps are slightly different from one to another. However, the coefficient of variation for the inverted ECa has increased with the depth. It proved that deeper layers have inverted ECa with high variability due to smaller population means and relatively high standard deviations.

a) Spatial variability of predicted ECa at the depth of 20cm

b) Spatial Variability of predicted ECa at the depth of 40cm



c) Spatial variability of predicted ECa at the depth of 60cm

d) Spatial variability of predicted ECa at the depth of 80 cm

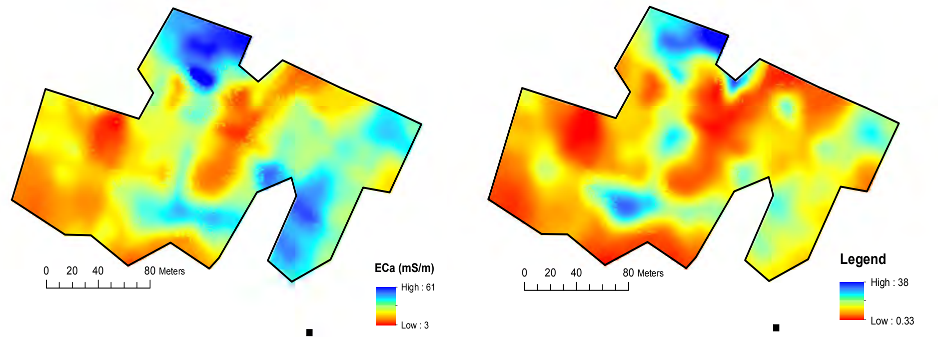


Fig. 5. The maps showing the spatial variability of ECa predicted by inversion technique at the depth of (a) 20 cm, (b) 40cm, (c) 60 cm and (d) 80cm

The inverted ECa data at four depths showed strong correlations with corresponding EC (Table 2). The soil EC measurements showed a stronger correlation with estimated inverted

ECa than either ECaHCP or ECaPRP proving that relationships between sensor measured ECa and soil properties can be strengthened through the data inversion. However, inverted ECa data at four depths showed unexpected very poor correlations with other measured soil properties such as OM% ($r < 0.36$), clay% ($r < -0.31$), sand% ($r >0.35$), and pH ($r < 0.43$).

CONCLUSION

The proximal soil sensing revealed a strong spatial heterogeneity of apparent electrical conductivity of both in the surface and subsurface horizons of the calcic red latosol soil. Investigation of clay, sand, silt, OM%, pH and soil solution EC at four depth intervals at five sampling locations showed a strong variability of these soil properties in both vertical and horizontal directions. In Calcic Red Latosols, considerable variability of soil properties at short-scale can be expected. The prediction of soil properties such as Clay%, Sand%, OM% and pH by proximally sensed ECa have been concealed due to the dominant influence of soil solution EC. The overall results suggest that the proximal soil sensing has a high potential of mapping the salinity development in the calcic red Latosols in the Jaffna peninsula. The calculation of depth specific ECa by inverting ECaPRP and ECaHCP measurements indicated that these ECa data layers can be used to map the soil salinity development in different soil layers. Thus, proximal soil sensing using the DUALEM-1S sensor can be considered to be a highly potential tool for producing three dimensional maps of soil salinity in the Calcic Red Latosols.

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