Soil electrical conductivity imaging of the soil profile and its relationship to soil properties

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Abstract

The variability of soil properties in space and time is a challenge to their measurement. Currently, apparent electrical conductivity (ECa) of the soil profile can be used to estimate indirectly the spatial variability of the soil properties: salinity, texture, cation-exchange capacity and moisture content. An electromagnetic induction sensor does not require direct contact with the ground, and data collection is relatively easy, rapid, and inexpensive. This allows a larger number of measurements and more comprehensive coverage of sites than is possible with traditional soil sampling methods.

A quasi-2D electromagnetic conductivity model for a field site was developed using electrical conductivity (ECa) data measured by a multi-coil DUALEM-421 sensor and a DUALEM-1s sensor.

Relationships of estimated ECa with volumetric water content (Θv) and cation exchange capacity (CEC) were reasonably accurate (R2 = 0.62 for DUALEM-421 and 0.58 for DUALEM-1s and R2 = 0.68 for DUALEM-421 and 0.58 for DUALEM-1s for Θv and CEC, respectively). These relationships were used to derive depth profile images. As expected, Θv, CEC and the estimated ECa follow similar trends down the soil profile. This soil ECa imaging method shows good potential for predicting 2D depth profiles of certain soil properties.

Background

Variations in water availability across a field due to different soil characteristics or crop needs may require site-specific irrigation management to achieve optimum yields and maximize water use efficiency. An electromagnetic (EM) survey can be used to identify varying soil characteristics and, therefore, the irrigation management zones. Electromagnetic sensors measure the apparent soil electrical conductivity (ECa, mSm-1), which has been shown to be influenced by various soil (e.g. clay content and mineralogy) and hydrological properties (e.g. moisture) (Triantafilis et al., 2013).

If there is one varying feature, such as percent stones, then a relationship can be developed to predict AWC directly from ECa. Also if there is no simple relationship between ECa and soil variability (e.g. due to different soil layering) then a zone-specific AWC can be assigned to each zone. A soil AWC map is useful information for managing any type of irrigation system. It allows irrigation managers to partition paddocks into different management zones, and, in identifying coarse and fine textured soils, it informs the placement of equipment for measuring soil moisture (Hedley et al., 2009).

Triantafilis and Monteiro Santos (2009) illustrated that EM4Soil software can be used to invert single frequency (EM38 and EM31) and multiple coil arrayed DUALEM-421 data to produce a map of exchangeable sodium percentage (Huang et al., 2014) and clay content (Triantafilis et al., 2013).

Our current study focusses on (i) using EM4Soil inversion software to generate a two-dimensional depth profile model of electrical conductivity (ECa, mSm-1) measured by single and multi-coil EM sensor surveys, and (ii) developing a relationship between the calculated vertical profile of conductivities and the measured volumetric moisture contents (Θv, cm3 cm-3) and cation exchange capacity (CEC, meq/100g).

Methods

Study site

The study field is located at Massey University in Palmerston North, New Zealand, (lat. 40°22′57″S, long. 175°35′38″E). The study field is 4 ha and was cultivated and sown with Ryegrass (*Lolium perenne* L.) and clover. The soils are classified as Fluvial Recent soils formed in greywacke alluvium (Pollok et al., 2003; Hewitt 1998).

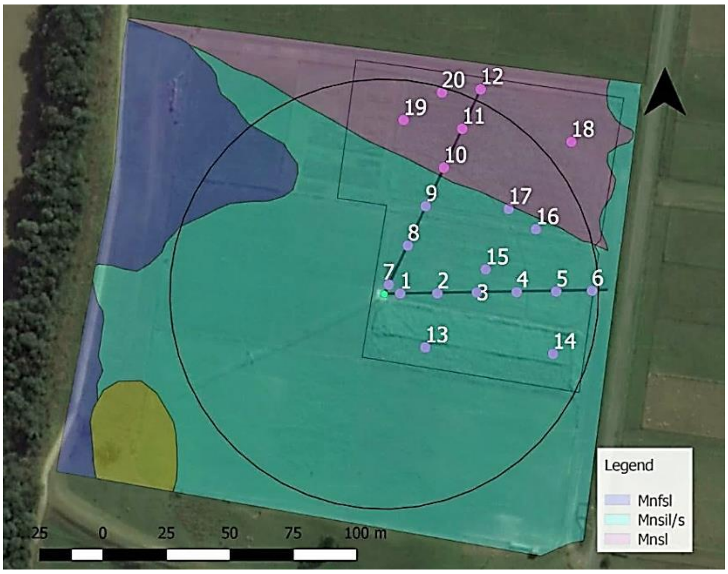

Figure 1. Study area location, EM survey transect soil sampling locations
(Mnfsl: Manawatu fine sandy loam, Mnsil/s: Manawatu silt loam over sand, Mnsl: Manawatu sandy loam)
{Pollok et al. 2003 Massey University Soil Map.}
http://atlas.massey.ac.nz/soils/index_soils.asp}

EM survey, soil sampling and laboratory analysis

The EM surveys were carried out at 6 m swath widths and collect a total of 2,435 ECa georeferenced ECa data points at a height of 0.25 m (DUALEM-1s) and 2,531 ECa georeferenced data points at 0.15 m above the surface (DUALEM-421). To calibrate the inverted ECa data, the calibration sites were selected as shown in Figure1. On transect 1 (locations 1 – 6) and transect 2 (locations 7 – 12), six soil sample sites were selected. On transect 1, soil samples were collected at 15.6 m intervals while on transect 2 they were collected at 17 m intervals. At each site, soil samples were taken at 0.30 m intervals to a depth of 1.5 m. Both the soil sampling and the ECa surveys were carried out on the 22 September, 2016. Laboratory analysis included measurements of gravimetric soil water content (Θg, g g-1) on an oven dry-weight basis and these calculations were then converted to volumetric soil water content (Θv, cm3 cm-3) by multiplication with the soil bulk density (ρb , g cm-3) using the equation: Θv = (ρb)/(ρw) x Θg where ρw is the density of water (g cm-3) (Gardner, 1986). Cation exchange properties (CEC, meq/100g) were determined by 1 M ammonium acetate (pH 7) method (Blakemore et al., 1974).

EM4Soil and 2D inversion of ECa data

EM4Soil is a software package (EMTOMO, 2013) which was developed to invert ECa data acquired at low induction numbers. The algorithm is described by Monteiro Santos et al. (2010). In this study, the forward modelling is based upon the cumulative function (CF) (McNeill, 1980; Wait, 1962). The modelling is conducted using a 1-dimensional laterally constrained approach (Auken et al., 2002), where 2-dimensional smoothness constraints are imposed.

When running EM4Soil, a smoothing or damping factor (λ) is required. A large value of λ will achieve a very smooth model where λ leads to equilibrium between data misfit and smoothness of the EMCI model (Triantafilis et al., 2013). In this study, we used the FS model, S2 algorithm and λ = 0.04. Inversion of ECa was generated with a maximum of 10 iterations. We calculated ECa (σ) using an initial model (σ = 35 mSm-1).

Estimating the soil properties and validation of prediction accuracy
A liner regression was used to develop the relationship between ECa and Θv, and between ECa and CEC data. This regression model was then validated using a 'leave-one-group-out' cross-validation approach (Friedman et al., 2001). The predictive power of the model is described by the average R2 and RMSE determined from the cross validation process.

Thin plate spline regression (fields package) (Nychka et al., 2015) was used in R version 3.3.2 and RStudio 1.0.136 (R Core Team., 2016) for generating the cation exchange capacity image or model. Thin plate spline regression is described as fitting a thin plate spline surface to irregularly spaced data. The smoothing parameter is chosen by generalized cross-validation. The assumed model is additive Y = f(X) + e where f(X) is a d dimensional surface. This function also works for just a single dimension and is a special case of a spatial process estimate (Kriging).

Results

Exploratory data analysis
The summary statistics of ECa (mSm-1) for the two soil zones measured by the DUALEM-421 across the study area are provided in Table 1 [Mean, min, max].

Table 1: Summary of whole field ECa datasets in Zone 1 and 2

DUALEM421s	Zone 1			Zone 2		
	Mean	Min	Max	Mean	Min	Max
Pcond (0.5m)	1.8	0.2	6.4	4.3	0.1	10.1
Pcond (1m)	1.3	0.1	4.5	4	0.5	10.9
Hcon (1.5m)	1.7	0.1	4.8	4.2	1	11.4

The linear regression model of estimated electrical conductivity (ECa, mSm-1) modelled by inversion (EM4Soil) for DUALEM-421 and DUALEM-1s versus the measured volumetric water content (Θv, cm3 cm-3) are shown in Figure 2.

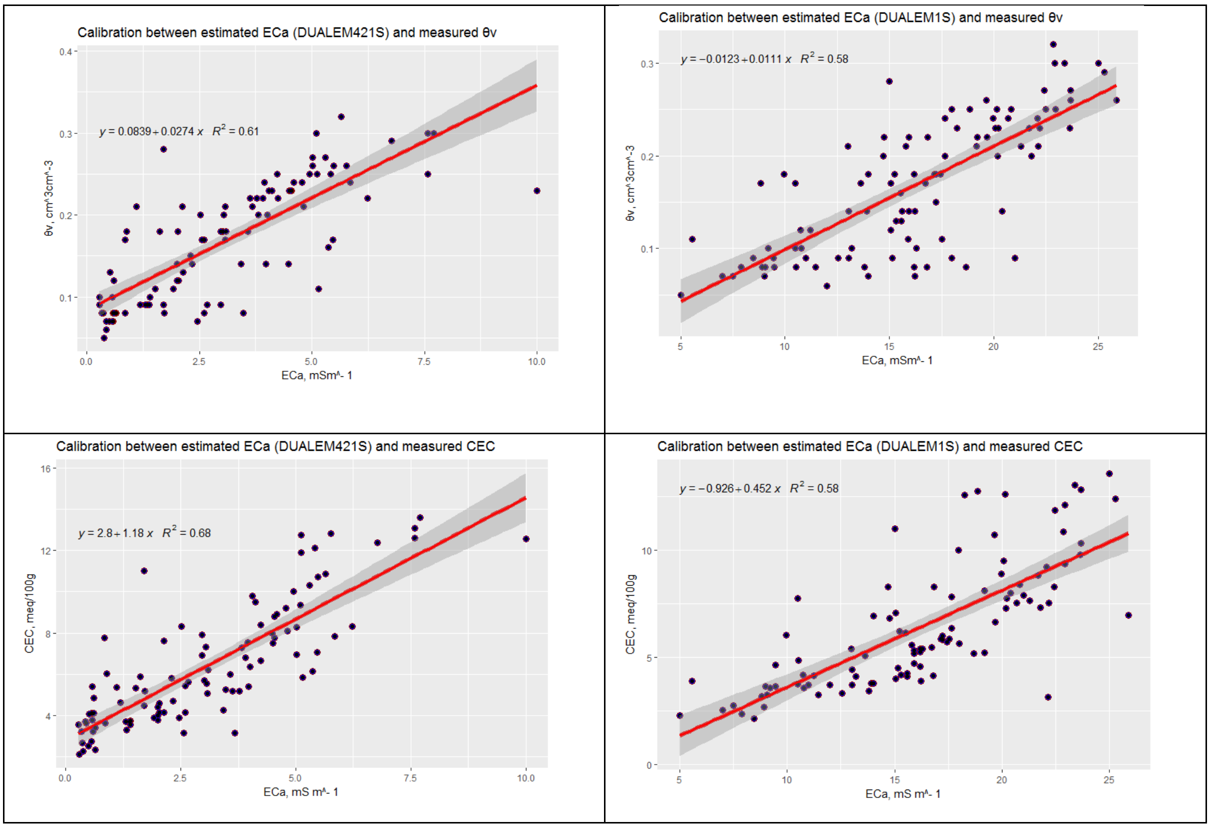

Figure 2. The relationships of estimated ECa (mSm-1) with (Θv, cm3 cm-3) and (CEC, meq/100g) using the available data of 99 samples

Figure 3 shows the predicted volumetric water content (Θv, cm3 cm-3) along two transects as generated using a quasi-2D model and the inversion of bulk apparent electrical conductivity (ECa, mSm-1) collected using a DUALEM-421 and DUALEM-1s.

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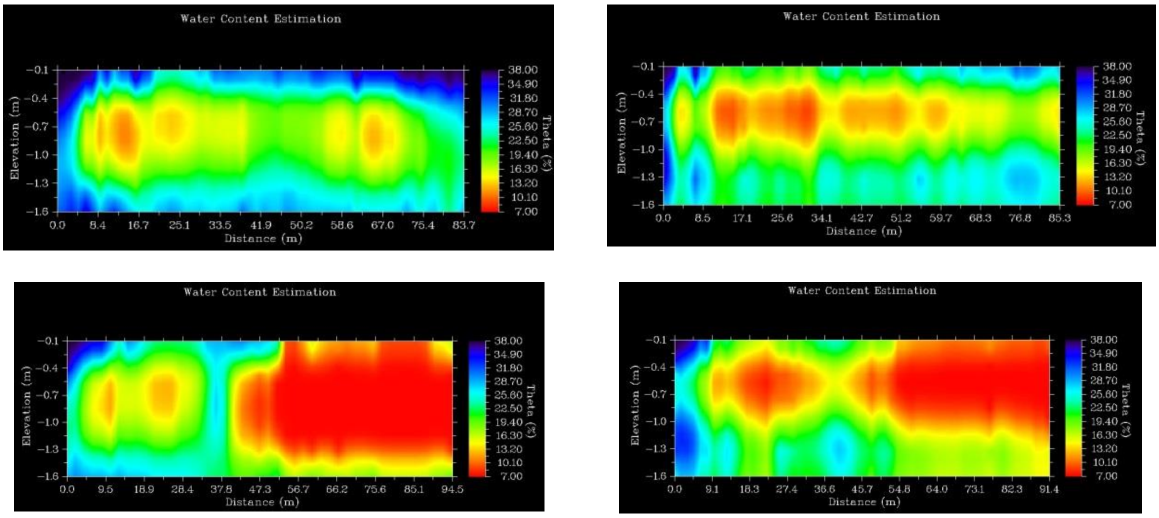

Figure 3. Soil moisture content derived from the Q2D model (1-dimensional laterally constrained technique inversion) for the two transects (Transect 1: top; Transect 2: bottom).

Figure 4 shows the predicted cation exchange capacity (CEC, meq/100g) along two transects as generated using the thin plate spline regression between the estimated ECa and the measured CEC for a DUALEM-421 and DUALEM-1s.

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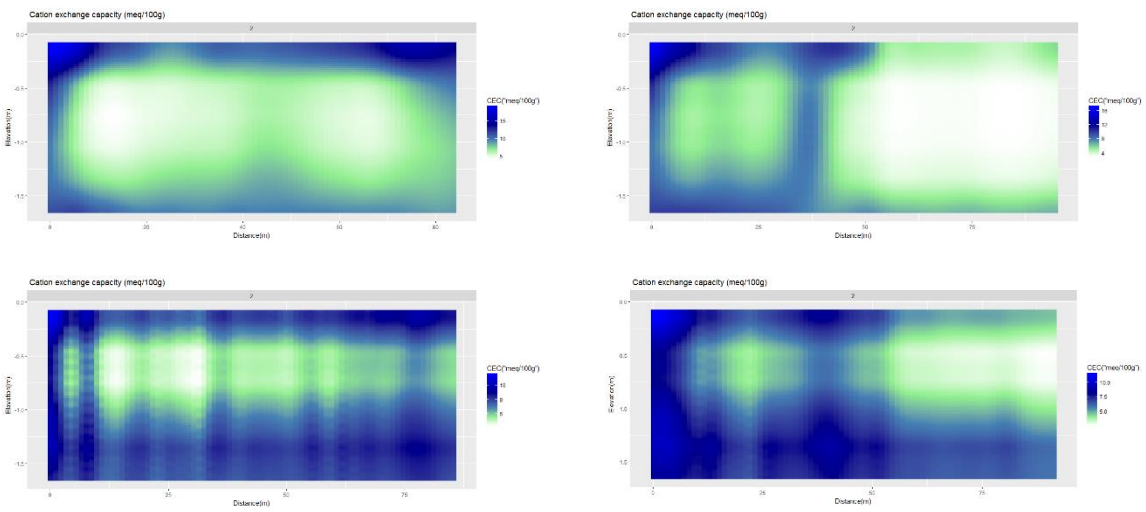

Figure 4. Soil CEC derived from the thin plate spline regression (fields package) for the two transects (Transect 1: top; Transect 2: bottom).

Discussion

Table 1 shows the summary statistics of apparent electrical conductivity (ECa, mSm-1) measured by a DUALEM-421 (867 ECa locations for zone 1 and 1,664 for zone 2). The mean values in Table 1 quantify the difference in ECa between the soils where, as expected, the lowest value is measured for zone 1 with coarser-textured soils and higher value for zone 2 with finer- textured soils (Pollok et al., 2003).

The soil moisture content and cation exchange capacity values are typically higher in the top soil then decrease in the subsoil before increasing again in the deep subsoil (Figures 3 and 4). This pattern indicates the impact of wetness and/or soil texture. The predicted Θv values for transect 2 show two distinct regions which relate to the two different soil types (see Figure 1). Positions 10, 11 and 12 are located in the Manawatu sandy loam soil as described by a previous investigation (Pollok et al., 2003). The inverted ECa values at certain depths show a similar trend to Θv and CEC data so that relationships could be established for this field site.

Soil moisture decreases in the subsoil (0.6-0.9m) and then increase in the deep subsoil (0.9-1.5m) at positions P1, P3, P6, and P8, while at P2 it starts increasing from 0.6 to 1.5m (results not shown). At P4 and P7, soil moisture increases in the 0.6-0.9 m depth, then decreases from 0.9-1.2 m and then increases again in the 1.2-1.5 m depth. At P2 it decreases suddenly due to a higher stone content with a stone layer at approximately 1.30 m. In general, these findings suggest that these ECa variations relate reasonably well to variations in soil layering and soil type. This relationship can be used to guide the placement of soil moisture sensors in the field

The linear regression model was used to correlate the estimated ECa (mSm-1) with measured Θv (cm3 cm-3) and CEC (meq/100g) (R2 = 0.62 for DUALEM-421 and 0.58 for DUALEM-1s and R2 = 0.68 for DUALEM-421 and 0.58 for DUALEM-1 for Θv and CEC, respectively). RMSE was 0.04 cm3 cm-3 for DUALEM-421 and 0.05 cm3 cm-3 for DUALEM-1s and 1.6 meq/100g for DUALEM-421 and 2.65 meq/100g for DUALEM-1s for Θv and CEC, respectively.

Conclusion

The inversion model (EM4soil) has been shown to be a useful tool for mapping ECa (mSm-1) down the soil profile as a 2D ECa map Inversion modelling has also been used to relate ECa to measured Θv (cm3 cm-3) and CEC (meq/100g) for a soil depth profile and so it can be used to predict 2D soil property depth profile images. The Θv depth profile image indicates the areas where more rapid deep drainage occurs (e.g. the wetter zones). Integrating the EM data, which represents soil spatial variability, with soil moisture monitoring (reliable measurement of temporal changes in Θv) could be useful for improving irrigation management. In addition, future research will investigate if the development of a relationship between ECa and CEC can be used as an indicator of clay and organic matter content in the soil profile.

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