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USING ELECTRICAL CONDUCTIVITY IMAGING TO ESTIMATE SOIL WATER CONTENT

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Abstract

Measurement of volumetric soil water content (θv cm^3 cm^{-3}) requires collection and analysis of soil samples, which is expensive and time consuming, or soil moisture sensing, which is limited spatially by the number of sensors installed. Apparent electrical conductivity (ECa) of the soil profile can be used as an indicator of a number of soil properties, including soil moisture. Therefore, ECa sensor surveys can be used to efficiently and inexpensively predict θv along a transect or across a field.

In this study, EM4Soil inversion software was used to generate: (i) two-dimensional depth profile models of electrical conductivity (ECa, mSm^{-1}) as measured by a multi-coil DUALEM-421S sensor and a DUALEM 1s sensor, and (ii) a correlation between the calculated conductivity profiles and the measured θv.

ECa survey data were collected along two transects (12 positions) and 8 randomly stratified positions in a field near Palmerston North. Soil samples were taken at 0.30 m increments to a depth of 1.5 m. The θv of these samples was determined in the laboratory. The appropriate calibration between ECa and θv was achieved using inversion parameters of forward modelling, an inversion algorithm and a damping factor. In general, the results show that θv and ECa follow similar trends down the soil profile. Reasonably accurate relationships between ECa and θv were determined using a 'leave-one-out' cross validation approach (R^2 = 0.62 for DUALEM-421S and 0.58 for DUALEM 1s). The cross validation equation for the predicted versus measured θv for 99 samples has a good R^2 (0.62 for DUALEM-421S and 0.58 for DUALEM 1s) and a small RMSE (0.04 cm^{3}cm^{-3} for DUALEM-421S and 0.04 cm^{3}cm^{-3} for DUALEM 1s). We conclude that soil ECa can be used to indirectly estimate (θv) if the predictive power of the ECa for θv is moderated by other soil factors that also affect the EC sensors. For example, if clay content were uniform across the whole, then EC would relate more closely to θv.

Introduction

Agriculture is the biggest water user, with irrigation accounting for approximately 70 percent of all the freshwater withdrawn in the world. Without improved efficiencies, agricultural water consumption is expected to increase globally by about 20% by 2050 (UN water, 2014).

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.

To identify the irrigation management zones based on varying soil characteristics an electromagnetic (EM) survey can be used. Electromagnetic sensors measure the apparent soil electrical conductivity (ECa, mSm^{-1}), which has been shown to be influenced by various soil (e.g. clay and mineralogy) and hydrological properties (e.g. moisture) (Triantafilis et al., 2013).

The DUALEM-421 incorporates an EM transmitter that operated at a fixed low frequency (9 kHz) and 3 pairs of horizontal co-planar (HCP) and perpendicular (PRP) receiver arrays. The depth of ECa measurement is, respectively, 0–1.5 (1mHcon), 0–3.0 (2mHcon) and 0–6.0 m (4mHcon), and 1.1, 2.1 and 4.1 m (PRP) (Triantafilis & Santos, 2013). The DUALEM-1 has 1-m separation between its transmitter and dual receivers, so its dual depths of conductivity measurement are 0.5 m and 1.5 m. Site investigation is essential to check which factors are influencing the soil electrical conductivity. In much of New Zealand, EM variation indicates variations in soil texture and moisture.

If there is one varying feature, such as percent stones, then a relationship can be developed to predict AWC directly from EC. Also if there is no simple relationship between EC and soil variability (e.g. 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 zone paddocks for different management, and to place soil moisture measurement equipment with knowledge of lighter or heavier soil types (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 to produce a map of exchangeable sodium percentage (Huang et al., 2014) and clay (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 correlation relationship between the calculated vertical profile of conductivity with the measured volumetric moisture content (θv, $cm^3\ cm^{-3}$).

Method

Study site

The study field is located in Palmerston North, New Zealand, at Massey University (lat. 40°22′57.4″S, long. 175°35′38.2″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).

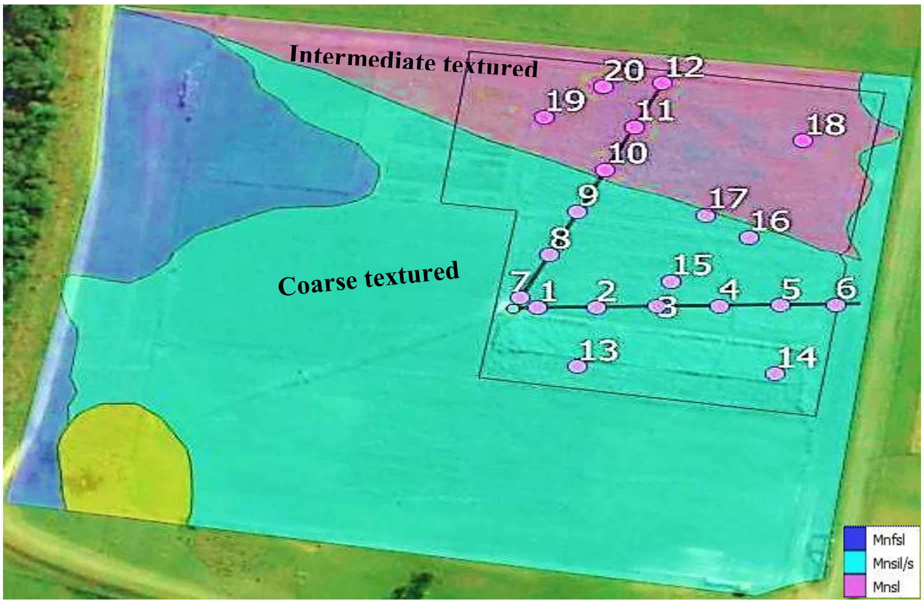


Fig.1. Study area location, EM survey transect soil sampling locations (**Mnfsl**: Manawatu fine sandy loam, **Mnsil/s**: Manawatu silt loam over sand, **Mnsl**: Manawatu sandy loam) *{Pollok, J.A., Nelson, P., Touhy, M.P., Gillingham, S.S., Alexander, M., 2003 Massey University Soil Map. http://atlas.massey.ac.nz/soils/index_soils.asp}*

EM survey (DUALEM-421S and DUALEM-1S), soil sampling and laboratory analysis

The EM survey and collection of ECa data along 2 transects was carried out at a height of 0.25 m (DUALEM-1S) and 0.15 m (DUALEM-421S). To calibrate the inverted ECa data, the calibration sites were selected as shown in Fig 1. On transects 1 and 2, 6 soil samples sites were selected. On transects 1, soil samples were collected at 15.6 m intervals while on transect 2 were at 17 m intervals. At each site, soil samples were taken at 0.30 m to a depth of 1.5m. Sampling was carried out on the same data that the ECa data was acquired (22/09/2016). Laboratory analysis included measurements of gravimetric water soil water content (θg, gg^{-1}) on an oven dry-weight basis and these calculations were then converted to volumetric soil water content (θv, cm^3cm^{-3}) by multiplication with the soil bulk density as in equation: $\theta v = (pb)/(pw) \times \theta g$ where pw is the density of water (g cm-3) (Gardner, 1986).

EM4Soil and 2D inversion of ECa data

EM4Soil is a software package (EMTOMO, 2013) which was developed in order 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 so called ‘full-solution’ of EM fields (FS) (Kaufman and Keller, 1983) is also calculated by the model (results not shown). The modelling is conducted using a 1-dimensional laterally constrained approach (Auken et al., 2002), where 2-dimensional smoothness constraints are imposed. The inversion algorithms (S1 and S2) are based upon the Occam regularization method (e.g. DeGroot and Constable 1990; Sasaki 1989). The latter constrains electromagnetic conductivity images (EMCI) variation around a reference model and is smoother than S1.

For 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 water content and validation of prediction accuracy

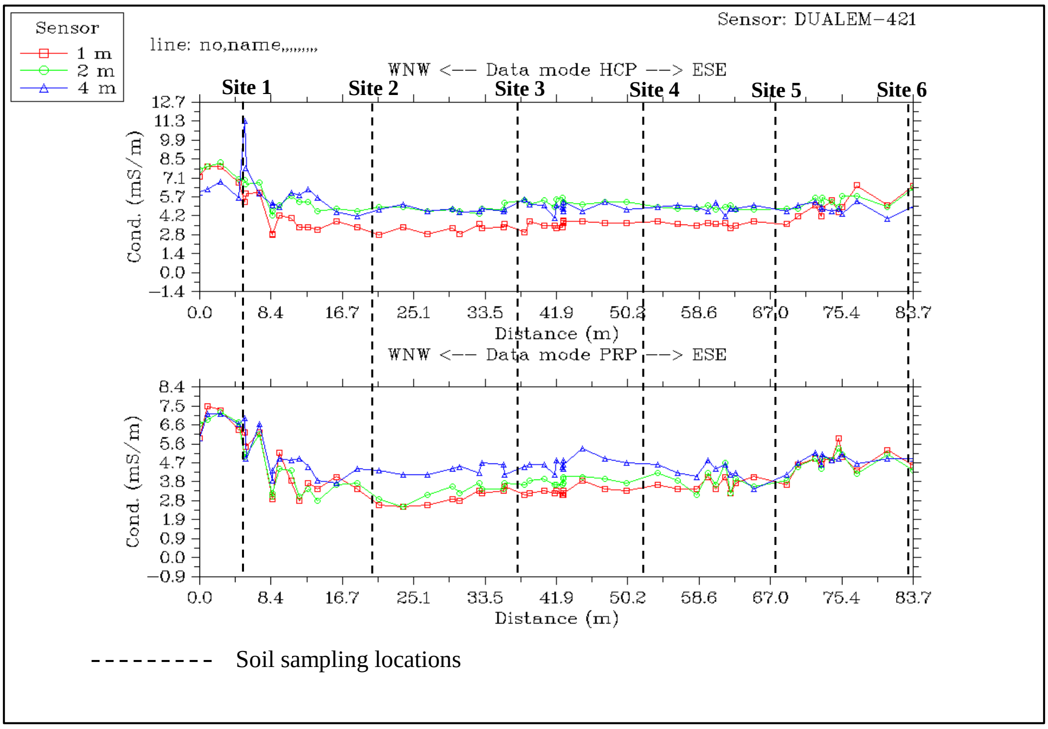
A liner regression was used for developing the calibration relationship between ECa and θv data. This regression model was then validated using a 'leave-one-group-out' cross-validation approach. In this case, the model is repeatedly refit leaving out a single observation and then used to derive a prediction for the left-out observation. Within the literature, it is widely appreciated that 'leave-one-out' is a suboptimal method for cross-validation, as it gives estimates of the prediction error that are more variable than other forms of cross validation and it is a useful and appropriate method for relatively small datasets, such as this one. (Friedman et al., 2001)

The predictive power of the model is described by the average R^2 and RMSE determined from the cross validation process.

Results

Electrical conductivity data (DUALEM 421s)

a) Transect 1



b) Transect 2

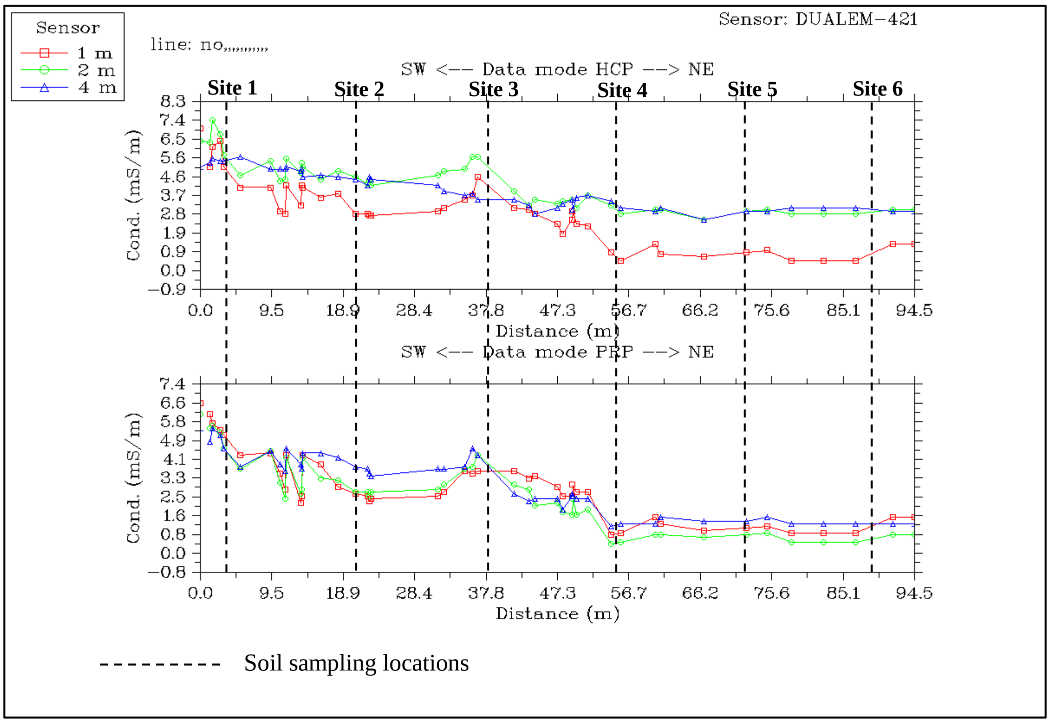
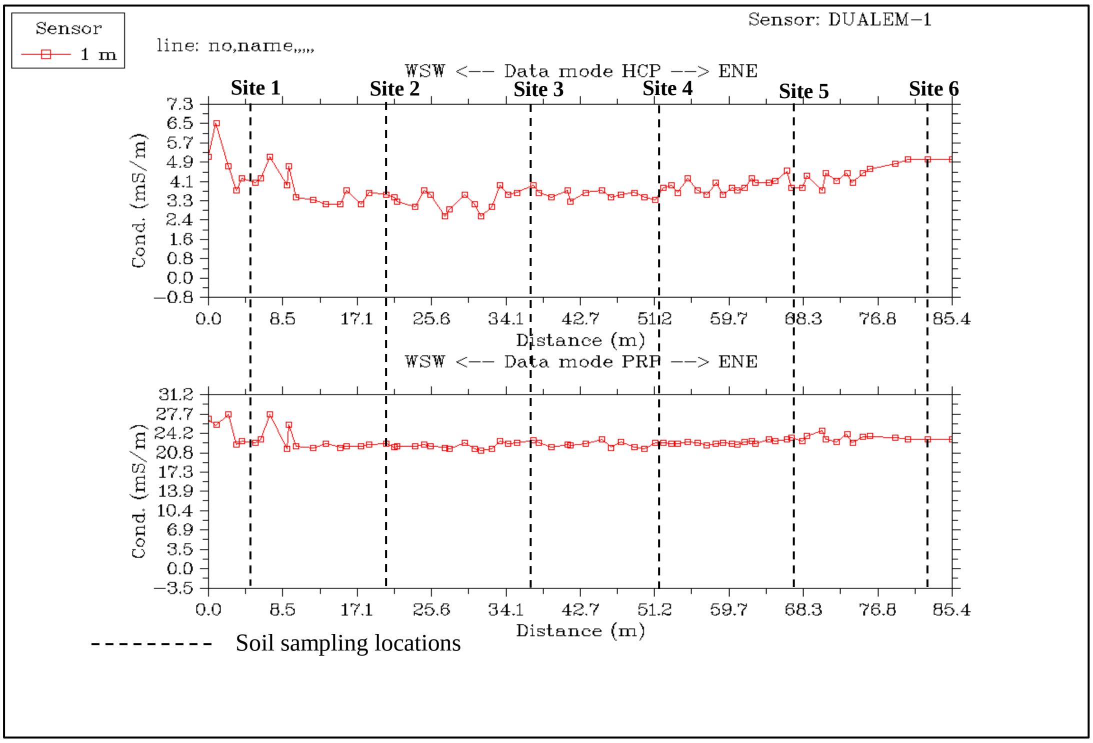


Fig.2. Measured apparent soil electrical conductivity (ECa, mSm^{-1}) along transect 1 and 2 using the DUALEM-421 sensor in horizontal coplanar (Hcon) and perpendicular coplanar (Pcon) for spacing (a) 1, (b) 2 and, (c) 4 m

Electrical conductivity data (DUALEM 1s)

a) Transect 1



b) Transect 2

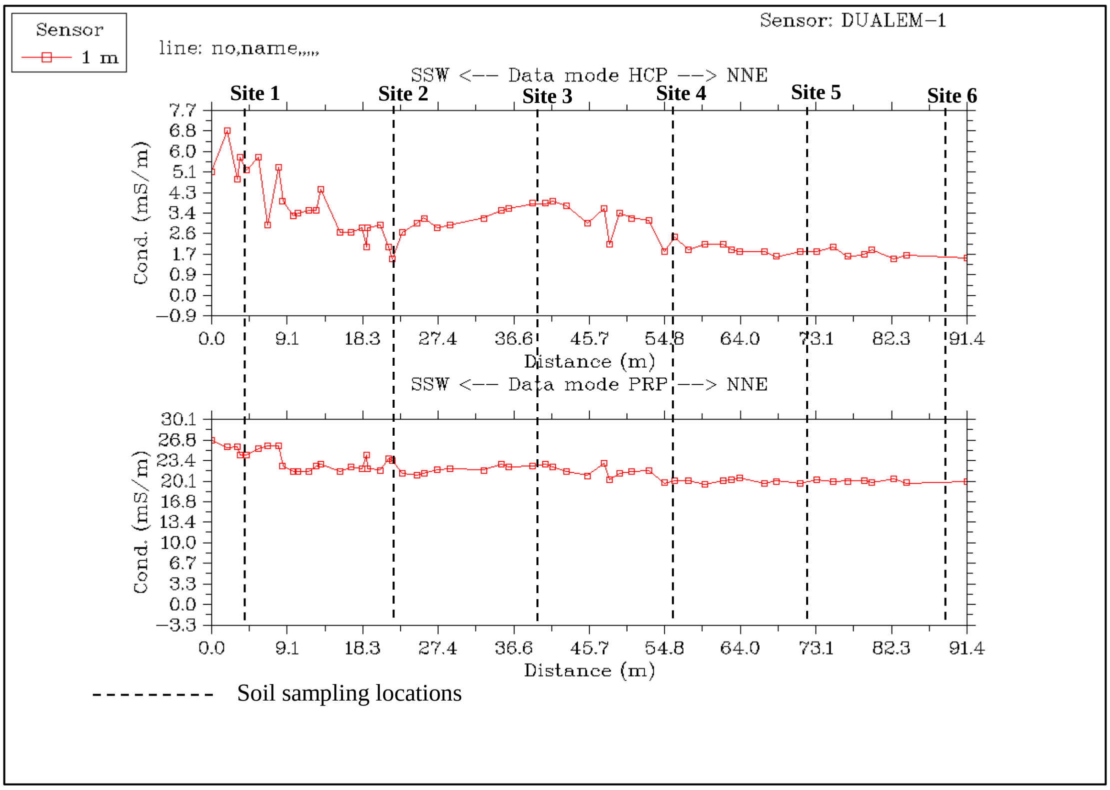
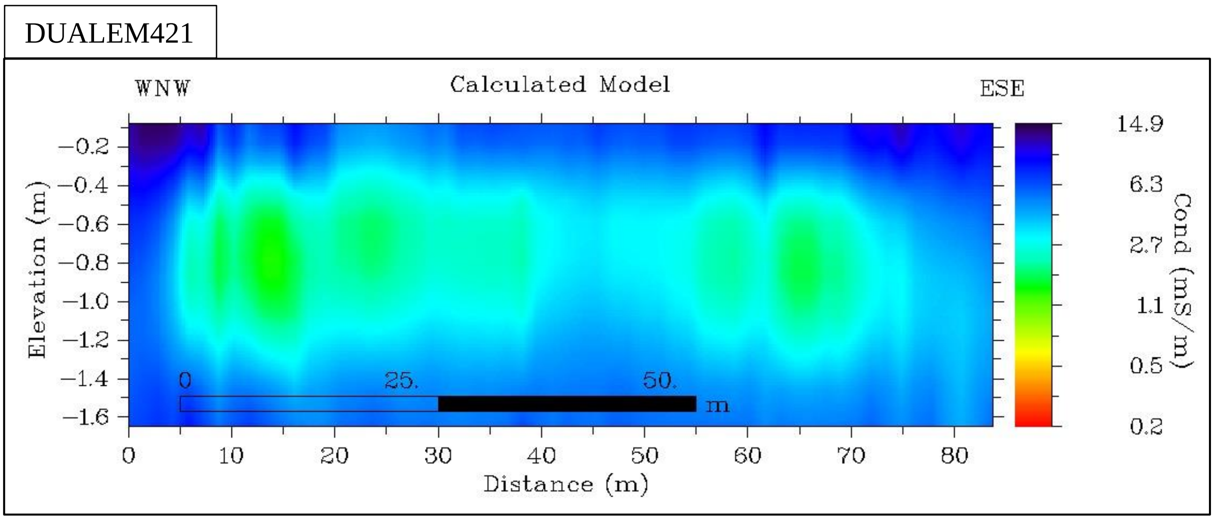


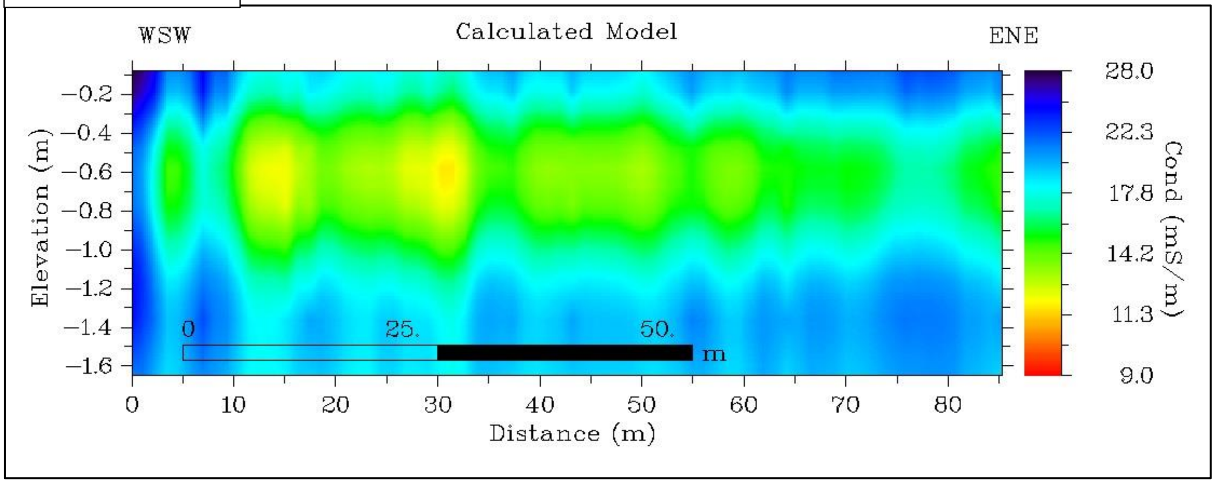
Fig.3. Measured apparent soil electrical conductivity (ECa, mSm^{-1}) along transect 1 and 2 using the DUALEM1S sensor in horizontal coplanar (Hcon) and perpendicular coplanar (Pcon) for spacing 1m

2-D depth profile modelling of electromagnetic conductivity

a) Transect 1

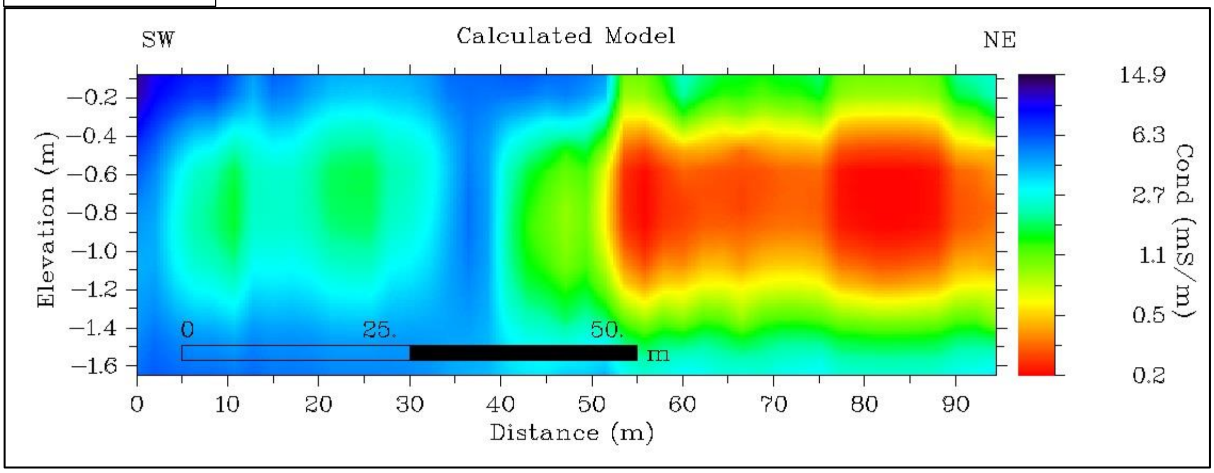


DUALEM1S



b) Transect 2

DUALEM421



DUALEM1S

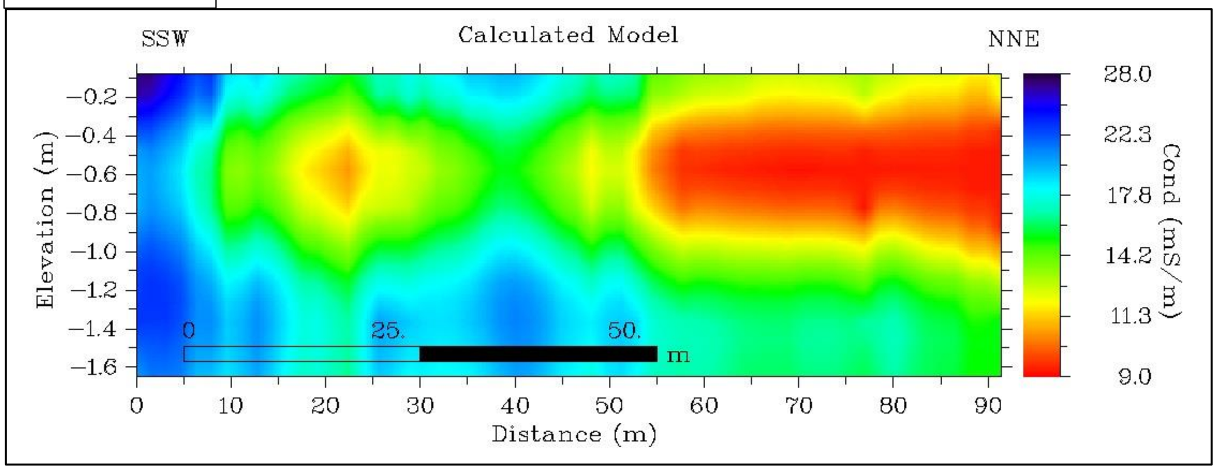
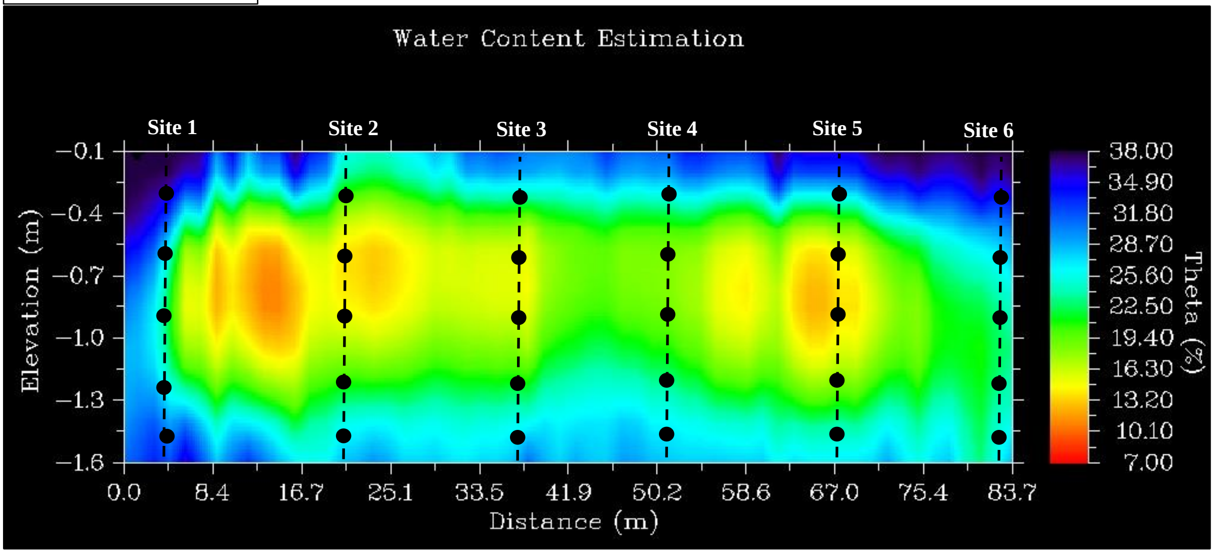


Fig.4. Vertical conductivity profiles derived from the Q2D (quantitative 2D) model for the two transects

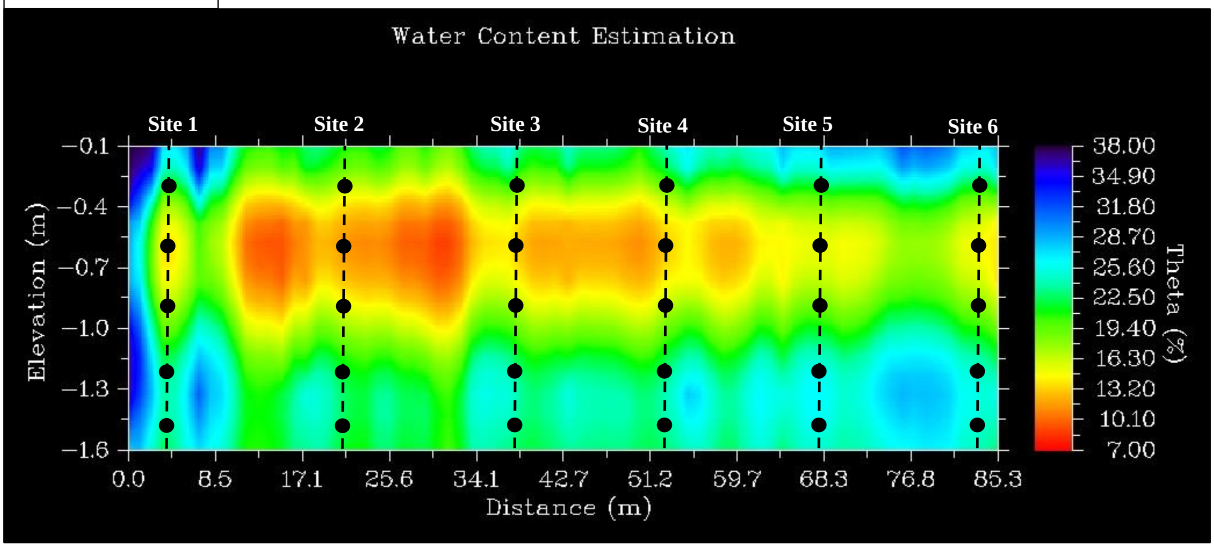
2-D depth profile modelling of predicted soil moisture (cm^3, cm^{-3}) content along two transects

a) Transect 1

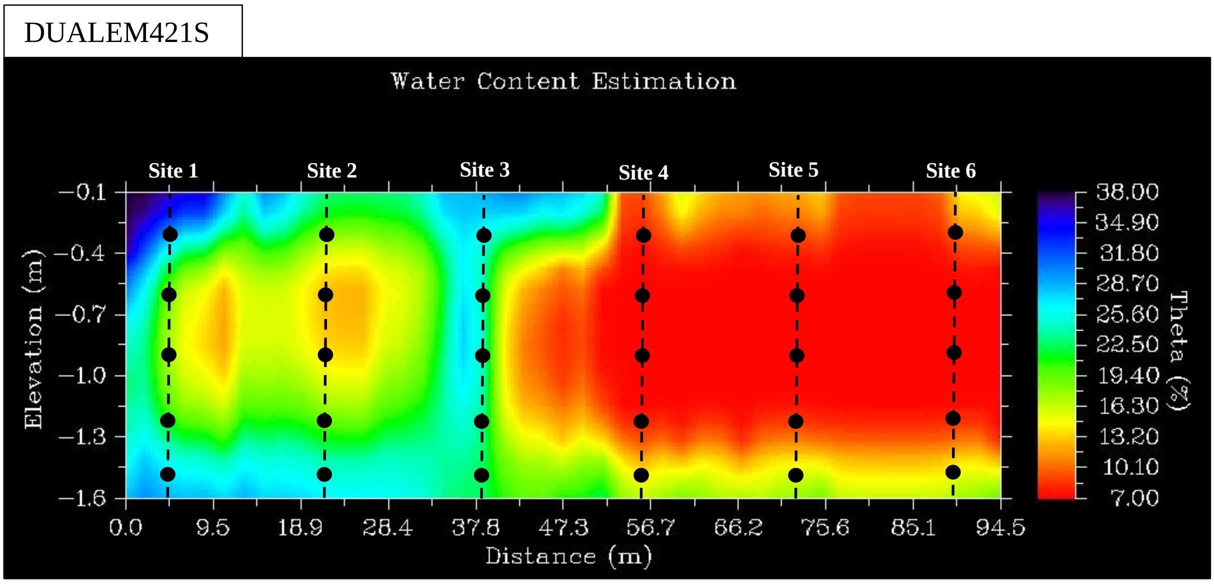
DUALEM421S



DUALEM1S



a) Transect 2



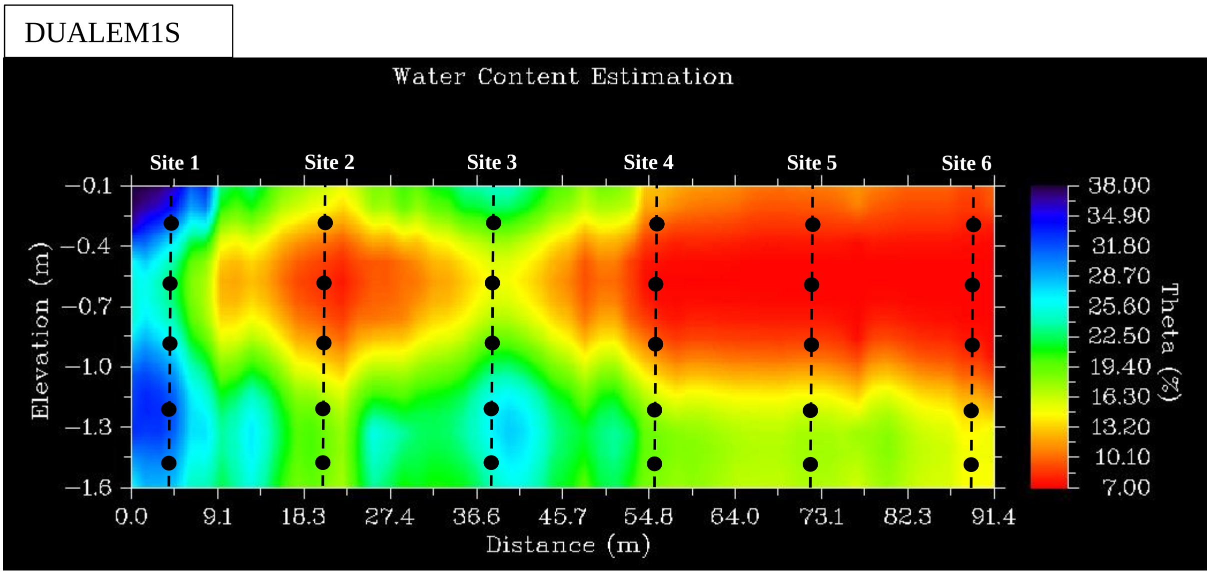
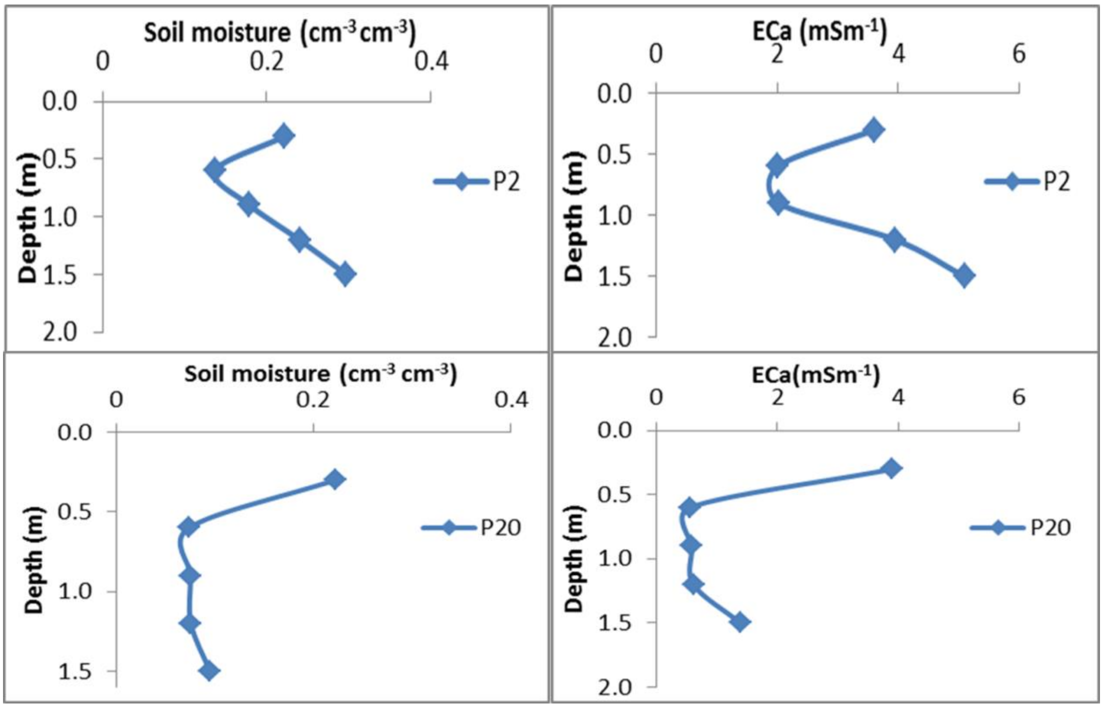


Fig.5. Soil moisture content (Theta) and their location derived from the Q2D model for the two transects.

Measured θv and ECa data at specific depths

a)



b)

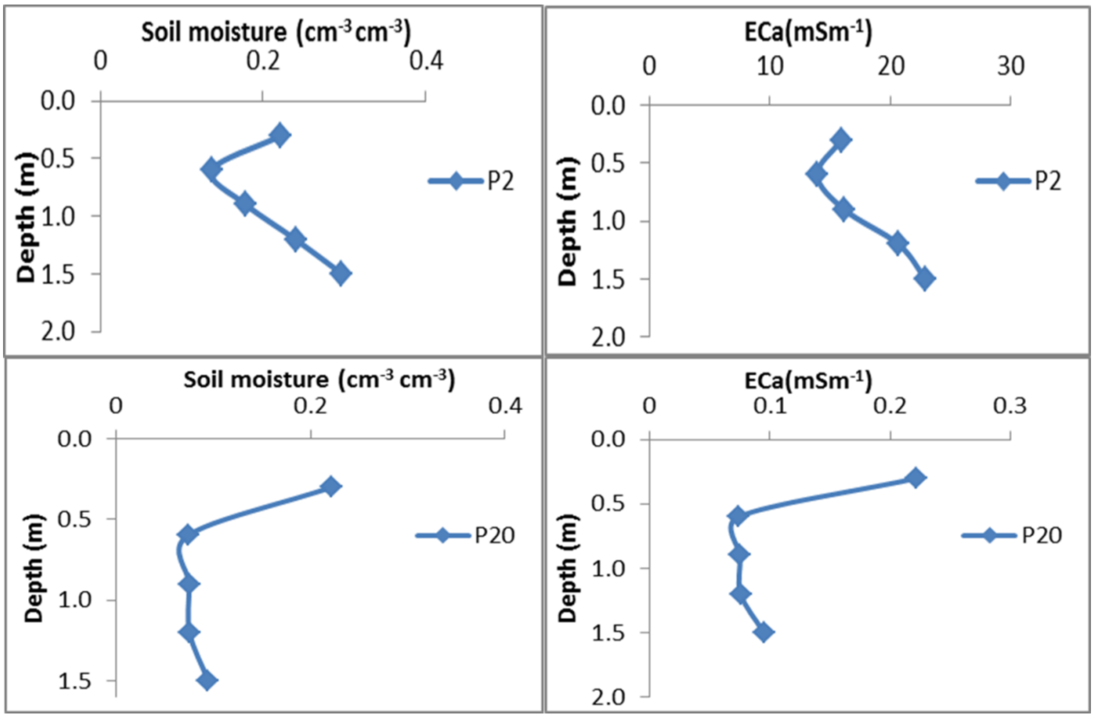


Fig.6. a) Volumetric soil content (θv, cm^3cm^{-3}) and estimated soil electrical conductivity (ECa, mSm^{-1}) values for position 2 and position 20 measured in the lab at 5 depths (a) DUALEM-421s (b) DUALEM-1S

Validation of estimated θv (cm^3cm^{-3})

a) DUALEM421s

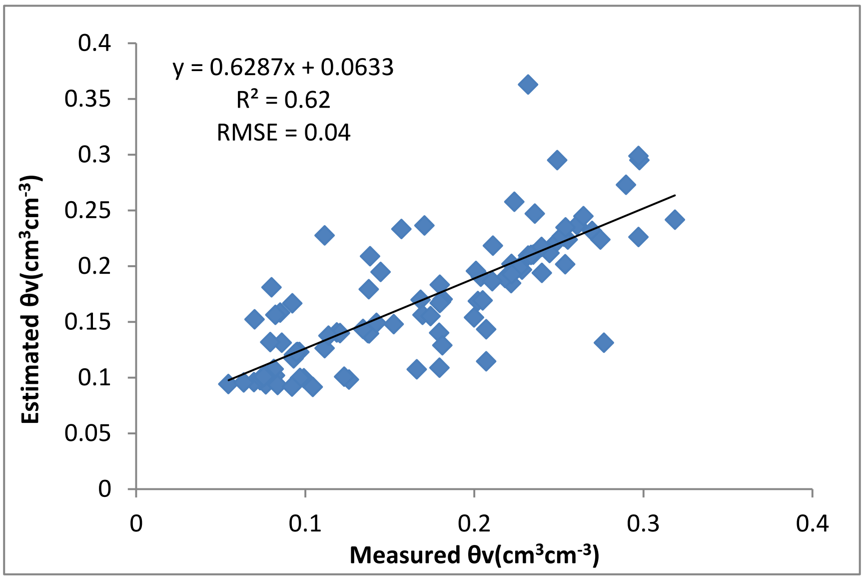


Fig.7. Predicted soil water content (θv, cm^3cm^{-3}) derived from electrical conductivity (DUALEM-421S) versus measured soil water content (θv, cm^3cm^{-3}).

b) DUALEM1S

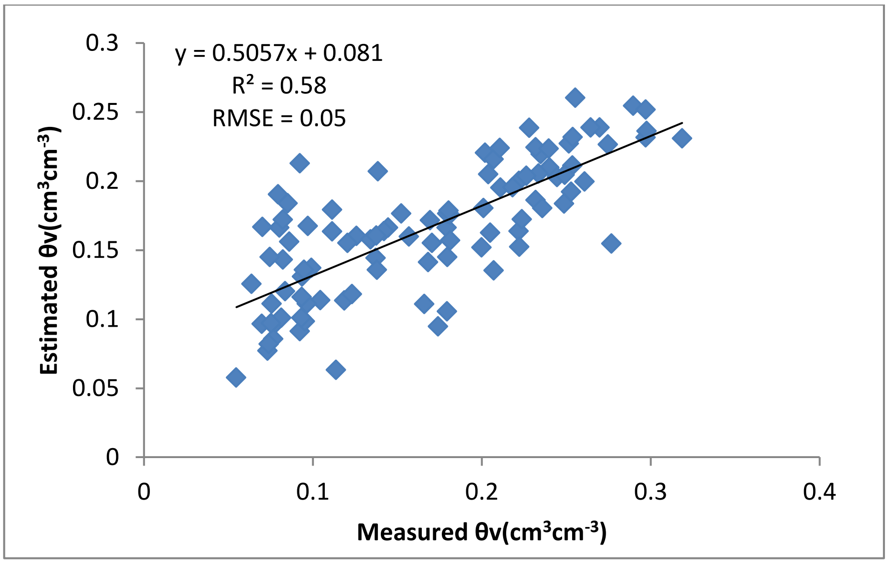


Fig.8. Predicted soil water content (θv, cm^3cm^{-3}) derived from electrical conductivity (DUALEM-1S) versus measured soil water content (θv, cm^3cm^{-3}).

Discussion

Fig.2 and Fig.3 are showing the ECa values for three DOE (depths of exploration) obtained using the three coil system (DUALEM-421) and one DOE for the one coil system (DUALEM-1S) for transect 1 and transect 2, respectively. The average values of the DUALEM-421S ECa data for 1m Pcon and 1m Hcon = 3.3 mSm^{-1} (exploration depth 0.5 and 1.5 m respectively) and are slightly higher than for 2m Pcon = 3.1 mSm^{-1} (exploration depth 1 m). Similarly, the DUALEM-1S ECa data shows the average values of 1m Pcon (exploration depth 0.5m) = 21.9 mSm^{-1} which are higher than for 1m Hcon (exploration depth 1.5m) = 3.1

mSm^{-1}. This suggests a slightly higher conductor in the topsoil and the deep subsoil (0-0.5m and 1-1.5m) than subsoil (0.5-1m). Transect 2 ECa values started higher then decrease rapidly to north which suggests that transect 2 is located in a contrasting soil (texture). Decreasing ECa values are likely to indicate a coarser and/or drier soil, and investigation of the soil map (Pollok et al., 2003) showed that this area of soils is sandier (see Fig.1) also the lab measurements of θv were lower in this area which relates to the coarser textured soil type.

Fig.4 shows 2-D maps of vertical conductivity profiles derived from the Q2D model. ECa values are higher in the top soil then decrease in the subsoil then increase into the deep subsoil and this indicates the impact of wetness and/or soil texture. The inverted ECa values show two distinct regions for transect 2 which relate to the two different soil types (see Fig. 1). We attribute that the last two positions located in a Manawatu sandy loam soil as described by a previous investigation (Pollok et al., 2003). The ECa values show a similar trend to soil moisture data so that a relationship between ECa and θv has been established at this field site.

Fig.5 shows the 2-D map of estimated soil water content along transect 1 and 2 using the inverted ECa data at different depths. One important observation is that there is an over estimated value for θv for the topsoil at the first location (5m), and we attributed this to an elevated ECa value due to soil compaction, where a higher bulk density value was recorded. It is suggested that the topsoil has a high value of θv which then decreases in the subsoil and then increases into the deeper subsoil which gives a quite similar indication to our soil moisture data.

Fig.6 (a, b) shows the results of volumetric soil water content (θv, cm^3cm^{-3}) and estimated soil electrical conductivity (ECa, mSm^{-1}) for positions 2 and 20 at 5 depths (0-30, 30-60, 60-90, 90-120, and 120-150). Our result indicates that θv and ECa follow similar trends down soil profiles. The trends of soil moisture to the subsoil (0.6-0.9m) decreases then increases into the shallow subsoil (0.9-1.5m) in positions (P1, P3, P6, P8) while in P2 it starts increasing from 0.6 to 1.5m (results only shown for P2 and P20). There is a fluctuation in the soil moisture trend in P4, P7, P5 and P10 where in P4 and P7 it increases to the subsoil (0.6-0.9m) then decreases form (0.9-1.2m) then increase again into the shallow subsoil (1.2-1.5m) while it decreases suddenly in P2 (due to stone contents where the sample was taken into 0.9-1.33m due to finding stones layer>1.30m) and slightly decreases in P10. In general, these findings suggest these ECa variations relate to variations in soil layering and soil type.

A leave-one-out cross validation approach was used to correlate the estimated ECa (mSm^{-1}) and measured θv (cm^3cm^{-3}) and it indicates a good average R^2 (0.62 for DUALEM-421S and 0.58 for DUALEM 1s) and a small RMSE (0.04 cm^3cm^{-3} for DUALEM-421S and 0.04 cm^3cm^{-3} for DUALEM 1s) (Fig.7 and Fig.8).

Conclusion

The inversion model (EM4soil) has been shown to be a useful tool for mapping ECa (mSm^{-1}) which is then related to measured θv (cm^3cm^{-3}). This can assist in irrigation management as explained below. The inversion method estimates ECa (mSm^{-1}) at specific depths which are then used to produce (i) a 2-D ECa map and (ii) by establishing a correlation between ECa (mSm^{-1}) and θv (cm^3cm^{-3}), it can be used to produce a 2-D soil moisture depth profile map. This map gives an indication about the areas at higher risk to deep drainage (i.e. the wetter zones), the spatial variability of soil moisture at different layers and this guided placement of soil moisture sensors into the field. Integrating the EM data as a reasonable tool for representing the spatial variability of the soil with soil moisture sensors data (temporal change in θv) could be useful in improving irrigation management. Future work could be developing a calibration between ECa, particle size and CEC.

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