Application of Electromagnetic Induction to Monitor Changes in Soil Electrical Conductivity Profiles in Arid Agriculture

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Application of electromagnetic induction to monitor changes in soil electrical conductivity profiles in arid agriculture field

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Abstract

Introduction

Low frequency electromagnetic induction (EMI) is a powerful tool to map the electrical conductivity variations in the vadose zone due to the sensitivity to soil moisture and salinity. The use of EMI is largely motivated by the need of robust and compact system design, easy to use, rapid acquisition, and capability to produce a large number of georeferenced measurements that can be associated with the spatial variability of subsurface at the field scale (Corwin, 2008). Several inversion algorithms have been developed for EMI measurements to improve the resolution of subsurface features and the assessment of soil properties (Hendrickx et al., 2002; Lavoue et al., 2010; Triantafilis and Monteiro Santos, 2013; Jadoon et al., 2015). Generally these inversion algorithms are robust and provide useful estimates of subsurface properties in terms of optimal model parameters, analysis of parameter uncertainty and correlation is often left unaddressed. Parameter uncertainty can be associated to the measurement errors (acquisition geometry, instrumental calibration and human error), modelling errors (assumptions in the electromagnetic forward model and petrophysical relationships), prior assumptions or constraints, parametrization, and inversion or estimation methods. For instance, Minsley (2011) used synthetic data considering the characteristics of shallow ground-based EMI system, geophex GEM-2, to estimate parameters uncertainty for a three layer model via Bayesian Markov Chain Monte Carlo (MCMC) approach. They showed that combine multiple configuration EMI measurements have significantly reduced total error, best able to capture the shallow interface and have reduced regions of uncertainty at depth.

In this research, we performed time-lapse EMI measurements along a 10 m transect in an arid agriculture field. EMI measurements were carried out with 0.1 m step using CMD-mini explorer sensor (GF Instruments, Jecna, Brno, Czech Republic). Using both VCP and HCP configurations, the CMD-mini explorer operates at 30 kHz frequency with 0.32, 0.71, 1.18 m transmitter-receiver offsets offering different depth sensitivities. Assuming soil conductivity as a surrogate measure of the water content, this study aims at investigating the soil moisture variations due to the root water uptakes and surface evaporations. In this respect, the subsurface conductivity layering was inversely estimated using DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm which is based on Bayesain approach (Vrugt et al., 2009).

Electromagnetic forward model

Given a layered earth model, to calculate the forward EMI response is to solve the Maxwell-based full solution for the magnetic field measured over a horizontal layered medium given by Keller and

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Frischknecht (1966) and Anderson (1979). The electromagnetic forward model for a horizontal and vertical dipole source-receiver combination with an offset ρ over a multilayered earth can be written as:

$$\sigma_a^{HCP}(x,\rho) = \frac{-4\rho}{\omega\mu_0}\mathrm{Im}\left[\int_0^\infty R_0 J_0(\rho\lambda)\lambda^2 d\lambda\right] \tag{1}$$

$$\sigma_a^{VCP}(x,\rho) = \frac{-4}{\omega\mu_0}\mathrm{Im}\left[\int_0^\infty R_0 J_1(\rho\lambda)\lambda d\lambda\right] \tag{2}$$

In this expression, J_0 and J_1 are the zero-order and first-order Bessel functions, λ is the radial wave number, μ_0 is permeability of the free space and ω is angular frequency. The reflection factor R_0 is obtained recursively beginning with the lowest layer N+1, where $R_{N+1} = 0$:

$$R_n(h_n,\sigma_n) = \frac{\frac{\Gamma_n-\Gamma_{n+1}}{\Gamma_n+\Gamma_{n+1}} + R_{n+1}\exp(-2\Gamma_{n+1}h_{n+1})}{1+\frac{\Gamma_n-\Gamma_{n+1}}{\Gamma_n+\Gamma_{n+1}}R_{n+1}\exp(-2\Gamma_{n+1}h_{n+1})} \tag{3}$$

$$\Gamma_n = \sqrt{\lambda^2 + \omega\mu_0 j\sigma_n} \tag{4}$$

whereas $\sigma_0 = 0$, h_n is the height, and σ_n is the electrical conductivity for the n^{th} layer. This formulation assumes that electrical conductivities from layer to layer and each layer is homogenous and of infinite horizontal extent. This electromagnetic forward model is not based on the LIN assumption and returns more reliable apparent electrical conductivity values than the standard sensitivity curves.

Likelihood function

The DREAM optimization algorithm was used to estimate the optimal values of the model parameters and their uncertainties (Vrugt et al., 2009). DREAM is a Markov chain Monte Carlo sampling approach and run multiple chains CH in parallel. Assuming θ as a vector of model parameters to be optimized, the likelihood function $L(\theta_i)$ of each point of CH, $(i = 1,...,N)$ is calculated. In our case, the vector θ contains thickness and electrical conductivity of the layers, i.e., $\theta_i = [h_1,h_2,...h_{n-1},\sigma_1,\sigma_2,....\sigma_n]$ in which n is the number of layers. Given M to be the total number of data points, the likelihood function is calculated as:

$$L(\theta_i) = -\frac{M}{2}\ln(2\pi) - \sum_{m=1}^{M}\ln(\delta_m(t)) - \frac{1}{2}\phi(\theta_i) \tag{5}$$

where the last term $\phi(\theta_i)$ represents the data misfit or objective function defined as:

$$\phi(\theta_i) = \sum_{m=1}^{M}\left[\frac{\sigma_{a,i}^{meas} - \sigma_{a,i}^{mod}}{\sigma_{a,i}^{meas}}\right]^2 \tag{6}$$

where $\sigma_{a,i}^{meas}$ and $\sigma_{a,i}^{mod}$ are the measured and modeled apparent electrical conductivity, respectively. The joint multi-configuration inversion will be possible by including the data from all offsets and coil orientations in the likelihood function. During the optimization process, a convergence diagnostic R is calculated using the last 50% of the samples in each chain (Brooks and Gelman, 1998). The convergence criteria is when R = 1.2 is satisfied for all unknown parameters. After convergence, the last 25% of the samples in each chain are utilized to summarize the posterior distribution.

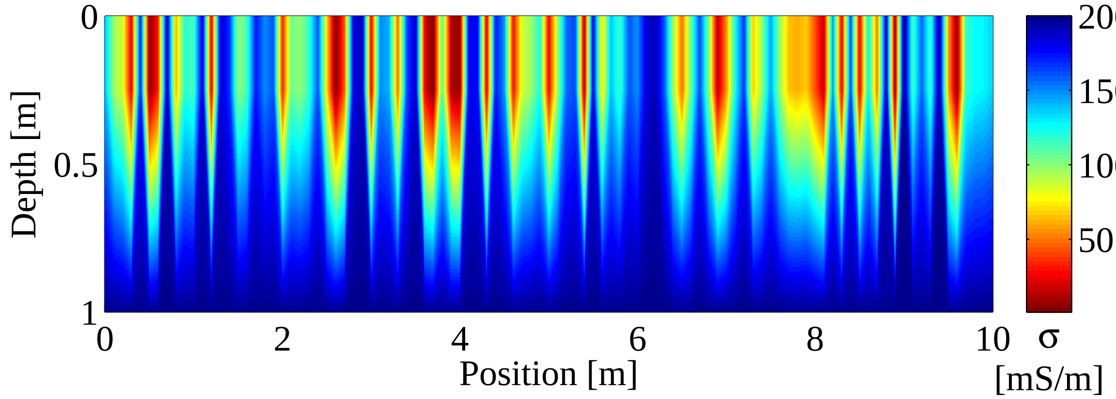

Figure 1 *DREAM optimization applied to the measured EMI data taking into account different offsets and orientations. The 1D models are stitched together for a 2D presentation.*

Results

Figure 1 shows the vertical soil conductivity profile obtained using DREAM approach. The 1D models are stitched together for a 2D presentation. The inversion was implemented by considering two layer model resulting to have three model parameters. The thickness of the first layer was fixed to 0.25 m. Figure 1 corresponds to the first measurement which was done shortly after the irrigation. The low conductive regions related to the plant locations. The root water uptakes cause to present low values of conductivities due to the low soil moisture content. The inversion results for the next measurements (not presented here) clearly demonstrate the rate of soil conductivity variations originate from the evaporation and root water uptake.

Conclusions

We investigated the ability of the CMD Mini-Explorer, to monitor soil conductivity variations in a a farm land using Bayesian inversion scheme. The approach allows for the quantitative mapping of spatial electrical conductivity variations and can be used for soil management. Moreover, joint inversion results provide conductivity variations with respect to the depth, which supplies additional information as compared to traditional apparent conductivity imaging. This study offers promising perspectives in mapping electrical properties of the shallow soil subsurface, which is particularly relevant in environmental and agricultural applications.

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