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

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Abstract

In this research, multi-configuration electromagnetic induction (EMI) measurements were conducted in a corn field to estimate variation in soil electrical conductivity profiles in the roots zone. Electromagnetic forward model based on the full solution of Maxwell's equation was used to simulate the apparent electrical conductivity measured with EMI system (the CMD mini-Explorer). Joint inversion of multi-configuration EMI measurements were performed to estimate the vertical soil electrical conductivity profiles. The inversion minimizes the misfit between the measured and modeled soil apparent electrical conductivity by DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm, which is based on Bayesain approach. Results indicate that soil electrical conductivity profiles have low values close to the corn plants, which indicates loss of soil moisture due to the root water uptake. These results offer valuable insights into future potential and emerging challenges in the development of joint analysis of multi-configuration EMI measurements to retrieve effective soil electrical conductivity profiles.

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 EMI measurements in an arid agriculture field, where corn was irri-

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gated using central pivot system. EMI measurements were carried out with 0.1 m step using CMD-mini explorer sensor (GF Instruments, Czech Republic). Using both horizontal coplanar loop (HCP) and vertical coplanar loop (VCP) 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 evaporation. In this respect, the DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm (Vrugt et al., 2009), which is based on Bayesain approach was used to inversely obtain the subsurface conductivity layering and parameter uncertainty.

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 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:

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

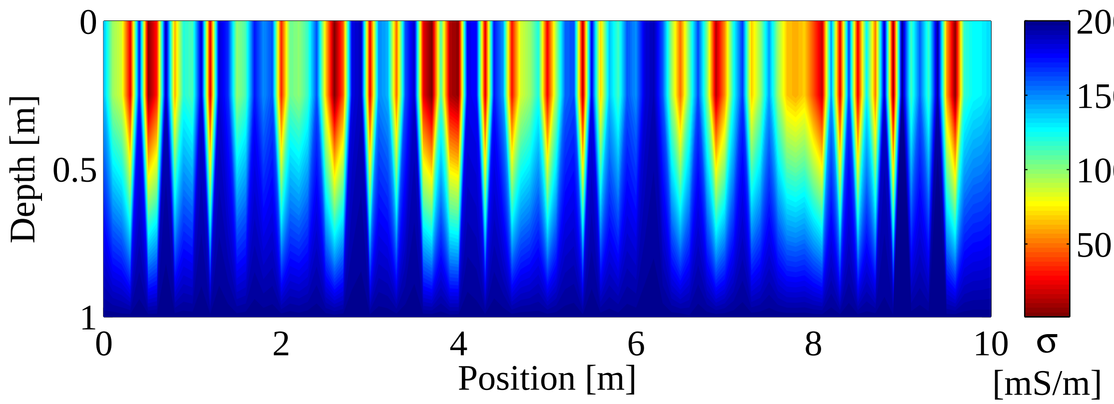

Figure 1 *DREAM optimization applied to the measured EMI data taking into account different offsets and orientations. The 1D models are stitched together for a 2D presentation.*

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.

Results

Figure 1 shows the vertical soil conductivity profiles obtained from joint inversion of multi-configuration EMI measurements via DREAM optimization algorithm. 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 (σ_1, σ_2 and h_1). Figure 1 corresponds to the measurement which was done after 4 days of irrigation. The root water uptakes cause to present low values of conductivities due to the low soil moisture content and the low conductive regions related to the plant locations. The inversion results clearly demonstrate the variations in soil electrical conductivity originate from the evaporation and root water uptake. The root water uptake is mostly in between $0-$ 0.40 cm depth. Near corn plants, the soil apparent electrical conductivity measured with VCP configuration observed low values as compared to HCP configuration measurements as VCP configuration are sensitive to shallow subsurface as compared to HCP (Figure not shown).

To gain more information about the parameter uncertainties, the marginal posterior distribution of the model parameters estimated by the different techniques is plotted in Figure 2. For inversions, the optimization parameter space was set relatively large, covering the whole range of values used for low and high electrical conductivity of soil; namely, $0 < \sigma_1 < 500$ mS/m, $0 < \sigma_1 < 500$ mS/m, and $0 < h_1 <$ 1.5 m. The parameter distributions are obtained using the last 6000 samples generated with DREAM. The marginal posterior distribution for the σ_1 and σ_2 are narrow as compared to the thickness h_1. The posterior distribution of h_1 depends on the the contrast between the σ_1 and σ_2, if contrast is more the posterior distribution of h_1 will be narrow and vice versa.

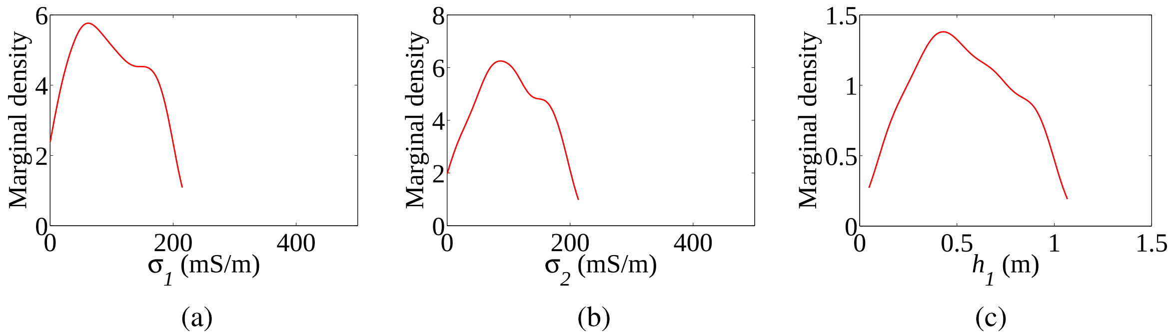

***Figure 2** Marginal posterior probability distribution of the model parameters estimated by DREAM.*

Conclusions

We investigated the ability of the CMD Mini-Explorer, to monitor soil conductivity variations in a corn field 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. Further research is needed to analysis time-lapse EMI measurements for better soil and water management practices.

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