Accepted Manuscript

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PII: S0309-1708(17)30061-1
DOI: [10.1016/j.advwatres.2017.10.019](https://doi.org/10.1016/j.advwatres.2017.10.019)
Reference: ADWR 2982

To appear in: *Advances in Water Resources*

Received date: 17 January 2017
Revised date: 19 September 2017
Accepted date: 15 October 2017

Please cite this article as: Davood Moghadas, Khan Zaib Jadoon, Matthew F. McCabe, Spatiotemporal monitoring of soil water content profiles in an irrigated field using probabilistic inversion of time-lapse EMI data, *Advances in Water Resources* (2017), doi: [10.1016/j.advwatres.2017.10.019](https://doi.org/10.1016/j.advwatres.2017.10.019)

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Spatiotemporal monitoring of soil water content profiles in an irrigated field using probabilistic inversion of time-lapse EMI data

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Abstract

Monitoring spatiotemporal variations of soil water content (θ) is important across a range of research fields, including agricultural engineering, hydrology, meteorology and climatology. Low frequency electromagnetic induction (EMI) systems have proven to be useful tools in mapping soil apparent electrical conductivity (σ_a) and soil moisture. However, obtaining depth profile water content is an area that has not been fully explored using EMI. To examine this, we performed time-lapse EMI measurements using a CMD mini-Explorer sensor along a 10 m transect of a maize field over a 6 day period. Reference data were measured at the end of the profile via an excavated pit using 5TE capacitance sensors. In order to derive a time-lapse, depth-specific subsurface image of electrical conductivity (σ), we applied a probabilistic sampling approach, DREAM_(ZS), on the measured EMI data. The inversely estimated σ values were subsequently converted to θ using the Rhoades et al. (1976) petrophysical relationship. The uncertainties in measured σ_a , as well as inaccuracies in the inverted data, introduced some discrepancies between estimated σ and reference values in time and space. Moreover, the disparity between the measurement footprints of the 5TE and CMD Mini-Explorer sensors also led to differences. The obtained θ permitted an accurate monitoring of the spatiotemporal distribution and variation of soil water content due to root water uptake and evaporation. The proposed EMI measurement and modeling technique also allowed for detecting temporal root zone soil moisture variations. The time-lapse θ monitoring approach developed using DREAM_(ZS) thus appears to be a useful technique to understand spatiotemporal patterns of soil water content and provide insights into linked soil moisture vegetation processes and the dynamics of soil moisture/infiltration processes.

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1 Introduction

Non-invasive geophysical techniques have an extensive history of application in the near surface characterizations of soil properties (Hubbard and Rubin, 2000; Robinson et al., 2009; Triantafilis et al., 2012; Huang et al., 2016). Low frequency electromagnetic induction (EMI) is one technique that has received attention for soil proximal sensing due to its mobility, rapid response and real time measurement capability (Moghadas et al., 2012; Callegary et al., 2012; Triantafilis et al., 2012; Jadoon et al., 2015). EMI measures subsurface apparent electrical conductivity (σ_a or ECa - mS/m) that represents a cumulative electrical conductivity distribution over a certain depth range. The commonly used EMI configurations are vertical coplanar loops (VCP) and horizontal coplanar loops (HCP), where HCP mode is more sensitive to the deeper layers (McNeill, 1980; Callegary et al., 2007). Other factors influencing penetration depth are instrument inter-coil spacing (offset) and height of the antenna above the ground. EMI conductivity meters are usually single frequency, since frequency changes do not substantially affect penetration depth (McNeill, 1996; Moghadas et al., 2012).

In the last few decades, time-lapse electromagnetic (EM) measurements have shown considerable potential for field-scale characterization and imaging of soil hydrogeophysical properties (Hubbard and Rubin, 2000; Jadoon et al., 2012). Time-lapse EM measurements allow for inference of hydrological processes, characterization of natural drainage inside the vadose zone, and monitoring of subsurface flow processes (Truss et al., 2007; Robinson et al., 2009). In this respect, monitoring spatiotemporal variations in water content (θ) is important because it provides information relevant to hydrological studies and irrigation management. Increased irrigation efficiency has an important role in improving crop yield and water conservation, reducing drainage and water pollution through excessive runoff.

Numerous studies have been carried out to map soil moisture changes using EMI (Reedy and Scanlon, 2003; Sherlock and McDonnell, 2003; Abdu et al., 2008). However, these studies have been mainly limited to the qualitative interpretation of the EMI data

without considering depth-dependent electrical conductivity and soil moisture, hampering the accurate quantitative identification of the subsurface hydrogeophysical properties. Obtaining depth-specific information of σ and θ using low frequency EMI is a topic that has not been fully explored due to the limitations associated with this technique. The EM conductivity meters are usually single-frequency and the depth sensitivity of such systems is mainly a function of offset and coil orientation. These systems generally operate under low induction number (LIN) condition (see section EMI forward modeling). As a consequence, they return limited subsurface information in comparison with multi-frequency electromagnetic systems (e.g. radio magnetotelluric) that are not restricted to the LIN assumption. Moreover, in the case of inversion using a high number of layers (more than four), the number of unknown model parameters are more than data, which may influence the final estimates. The non-uniqueness of the solution is also one of the major obstacles for successful inversion of EMI data (Santos et al., 2010; Mester et al., 2011; von Hebel et al., 2014). These issues motivate ongoing efforts to develop and apply robust inversion algorithms for the more accurate subsurface characterizations using low frequency LIN EMI data.

In recent years, a number of approaches have been proposed for the inversion of measured EMI data. Santos (2004) applied a laterally constrained inversion approach which was further developed to the EM4Soil inversion package (EMTOMO, 2014). Mester et al. (2011) developed a novel two-layer inversion algorithm using different sensing depths of multi-orientation, multi-offset, and multi-frequency ECa data. A grid-based inversion approach was proposed by Dafflon et al. (2013) to characterize the spatial variability of active layer and permafrost properties. Jadoon et al. (2015) characterized soil salinity in a drip irrigation system via a two-layered inversion of multi-configuration EMI data. Recently, Huang et al. (2016) monitored spatiotemporal variations of soil water content obtained from electrical conductivity data using the EM4Soil inversion routine. Their approach is a gradient-based optimization technique that is highly dependent on the starting model, i.e., different initial models can produce entirely different results that fit the data to the same degree. To aid in the inversion process, sampling-based stochastic tech-

niques have been designed. One potential sampling routine is the Differential Evolution Adaptive Metropolis algorithm (DREAM) (Vrugt et al., 2009), which has been applied successfully in hydrological and other geophysical applications (Steenpass et al., 2010; Laloy and Vrugt, 2012; Rosas-Carbajal et al., 2013; Moghadas et al., 2015).

In this paper, we performed EMI measurements located along a profile in a maize field using a CMD mini-Explorer (GF Instruments) over a 6 day collection period. In order to determine the soil moisture profiles from the measured apparent electrical conductivity, we examined the use of the DREAM_(ZS) probabilistic inversion approach. The objectives of this study are to: 1) investigate the robustness of DREAM_(ZS) (Vrugt et al., 2009) to image depth profile soil electrical conductivity from measured ECa data; 2) map the spatiotemporal variation of water content with depth and time based on depth-specific conductivity values using petrophysical relationship between σ and θ ; 3) investigate the ability of both the measurement and modeling technique to delineate the temporal wetting front and root zone soil moisture variations; and 4) introduce a strategy for irrigation management, optimizing water use efficiency and a sufficient control of site-specific irrigation using time-lapse EMI measurements.

2 Materials and methods

2.1 Study area and measurements

The study was undertaken at the Tawdeehiya Farm which is located in the desert region of Al-Kharj, approximately 200 km southeast of the capital Riyadh, in Saudi Arabia (Fig. 1). This commercial farm operates approximately 47 fields established on flat desert terrain approximately 380 m above sea level. The region is characterized by an extreme arid climate with hot summer months (average high of 43°C) and an average annual precipitation total of 95 mm (Houborg and McCabe, 2016). EMI measurements were collected from a maize field using a CMD Mini-Explorer (GF Instruments, s.r.o., Brno, Czech Republic) along a 10 m transect and with a 0.2 m increment. The time-lapse measurements were carried out within a 6-day period from November 4-9th, providing a total of 20 dif-

ferent EMI data sets. During this collection period, the average soil moisture in the field increases from around 0.15 to 0.27 vol% on November 4th and from about 0.17 to 0.27 vol% on November 8th, due to the irrigation (see Fig. 11). After each of the irrigation events, the average soil water content decreases gradually due to the root water uptake and evaporation.

At the end of the profile ($X=10$ m), a pit was excavated to a depth of 0.7 m (Fig. 2). 5TE capacitance sensors (Decagon Devices, Pullman, USA) were installed inside this pit at 0.1, 0.15, 0.25, 0.4, and 0.7 m depths. Operating at a frequency of 70 MHz, the 5TE sensor is able to measure soil moisture content, electrical conductivity and temperature in almost any soil including sand, silt and clay (Kizito et al., 2008). The sensor provides soil electrical conductivity values at 25°C (Decagon, 2008). The temperature (T), water content (θ^{ref}) and electrical conductivity (σ^{ref}) were measured with a 2 minute time-step during the 6 day period to provide reference data. These reference data were used to calibrate measured EMI data, to calibrate the petrophysical model and to corroborate the inversely estimated values. Figure 2 shows the excavated pit at the end of the transect. Three distinct soil structures can be observed: 1) 0-0.2 m: root zone (a mixture of fine sand with remnants of roots), 2) 0.2-0.4 m: sand layer, and 3) below 0.4 m: clay layer.

A CMD Mini-Explorer allows for ECa measurement in both VCP and HCP modes using 0.32, 0.71 and 1.18 m offsets. The system operates at 30 kHz frequency. McNeill (1980) introduced a simple form of spatial sensitivity analysis using a measure of an instrument's distribution of sensitivity in the subsurface (cumulative response). According to the McNeill (1980) definition, the effective penetration depth of EMI instruments for each configuration are when the corresponding cumulative response has a value of 0.3. In other words, about 30% of the measured response is referable to material at depths 0.76 of the inter-coil spacing (Callegary et al., 2007). For the CMD Mini-Explorer system, the effective penetration depths in HCP mode are 0.5, 1.0 and 1.8 m for 0.32, 0.71 and 1.18 m offsets, respectively. These values are reduced to 0.25, 0.5 and 0.9 m using VCP mode. As a consequence, for each measurement point (combining both HCP and VCP configurations), the system returns six different ECa values, each of which correspond

to a specific depth range. It is worth noting that in the presence of metallic objects in the subsurface (very high conductive anomalies), EMI systems return negative apparent electrical values (Everett, 2013).

2.2 EMI forward modeling

McNeill (1980) presents a model based on an assumption of a linear relationship between the soil apparent electrical conductivity and the ratio of the quadrature components of the primary and secondary electromagnetic fields, referred to as the low induction number (LIN) condition. This model is independent of frequency and is valid when the electrical conductivity of the soil is less than 100 mS/m (Hendrickx et al., 2002). In very conductive media where $\sigma_a > 100$ mS/m, or high induction number (HIN) condition, a more complex model based on the full solution of Maxwell's equation is applied (Wait, 1954; Ward and Hohmann, 1987). In this paper, we applied the full-EM model, which is valid for both LIN and HIN conditions. The electromagnetic forward model for a horizontal and vertical dipole source-receiver combination with an offset ρ over a multi-layered earth can be written as:

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

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

In these expressions, σ_a^{HCP} and σ_a^{VCP} , respectively, correspond to apparent electrical conductivity measured in horizontal and vertical coplanar mode, 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 $R_{N+1} = 0$:

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

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

whereas $\sigma_0 = 0$, h_n is the height, and σ_n is the electrical conductivity for the n^{th} layer.

2.3 EMI data processing

After data collection, the following processing steps were implemented to prepare the EMI data for later inversion:

Temperature correction: the reference temperature data measured from different depths (see section Reference data) were used for temperature correction of the EMI data to 25°C, based on the approach proposed by Sheets and Hendrickx (1995).

Calibration: considering reference electrical conductivity values, σ^{ref} , as inputs for the full-EM model (equations 1 and 2), the reference apparent electrical conductivities, $E\text{Ca}^{ref}$, were calculated. Note that σ^{ref} signifies depth profile electrical conductivity (conductivity layering), while $E\text{Ca}^{ref}$ implies a cumulative electrical conductivity distribution over a certain depth range (cumulative conductivity). The reference data were measured down to 0.7 m, while the maximum effective penetration depth of CMD Mini-Explorer is 1.8 m. In our calculations, we assumed that the electrical conductivity below 0.7 m is equal to the electrical conductivity of the last layer of reference conductivity profile as proposed by Lavoué et al. (2010). Considering measured ECa data from X=10 m and their corresponding $E\text{Ca}^{ref}$ values from 20 measurement time periods, a linear regression was implemented to derive calibration parameters. These parameters were applied to the entire EMI data to correct instrument shift. Employing measured data along the profile, this calibration approach was originally proposed by Lavoué et al. (2010) and later modified by Moghadas et al. (2012) and Jadoon et al. (2015). We applied a similar methodology using temporal data to find calibration parameters.

It is important to note that EMI calibration using spatial reference data has some limitations. Lavoué et al. (2010) used electrical resistivity tomography (ERT) data to derive reference electrical conductivity values. However, non-uniqueness issues in inversion of

the ERT measured data can be the source of error in the calculation of the calibration parameters and also reference values. Moghadas et al. (2012) used electrical conductivity data directly measured from several soil cores taken along the EMI transect. This method requires interpolation of the data to find lateral variation of the reference electrical conductivity along the EMI transect, causing to neglect any horizontal small-scale variations in the reference data. Here we considered one location and the electrical conductivity values were measured over time. The ECa values used for the calibration procedure were measured at different temperatures, but the temperature corrections described above standardised these to 25°C. Consequently, inaccuracies in the inversion, lateral heterogeneities, and temperature do not overtly influence the calibration procedure. However, we compared 5TE electrical conductivity values measured using a frequency of 70 MHz with EMI data measured at 30 kHz frequency. Therefore, our approach assumes a frequency independent electrical conductivity in this frequency range.

Offset overlap: for each receiver, half of the inter-coil spacing is considered as its corresponding measurement point. Given the measurement step of 0.2 m, the transmitter-receiver offsets overlap between measurement points. As a consequence, to find the corresponding apparent electrical conductivity values for each measurement point, offset overlap along the profile should be taken into account. Figure 3 demonstrates the full arrangement of the offsets along the EMI transect. In this graph, ρ_1 , ρ_2 , ρ_3 signify data from 0.32, 0.71 and 1.18 m offsets, respectively. The superscripts denote the coil orientations. For instance, regarding the third measurement point, data from the third point (ρ_1^{HCP} and ρ_1^{VCP}), the second point (ρ_2^{HCP} and ρ_2^{VCP}) and the first point (ρ_3^{HCP} and ρ_3^{VCP}) overlap. Consequently, ECa values obtained from these offsets should be considered together for the third measurement point.

2.4 Probabilistic EMI inversion

The Markov Chain Monte Carlo (MCMC) sampling is based on the Bayesian approach in which the posterior distribution of the parameters of the model can be derived by conditioning the behavior of the model on measurements of the observed system response.

To increase the efficiency of the MCMC method, the DREAM algorithm was introduced running multiple chains, Φ , in parallel. Assuming φ as a vector of model parameters to be optimized, the measured (σ_a^{meas}) and modeled (σ_a^{mod}) data vectors define as:

$$\sigma_a^{meas} = \begin{pmatrix} \sigma_a^{meas,HCP} \\ \sigma_a^{meas,VCP} \end{pmatrix}, \quad \sigma_a^{mod}(\varphi_i) = \begin{pmatrix} \sigma_a^{mod,HCP}(\varphi_i) \\ \sigma_a^{mod,VCP}(\varphi_i) \end{pmatrix} \quad (5)$$

where $i = 1, 2, \dots, \Phi$. The Bayes' theorem is described in a general form as:

$$p(\varphi_i | \sigma_a^{meas}) = \frac{p(\varphi_i) p(\sigma_a^{meas} | \varphi_i)}{p(\sigma_a^{meas})} \quad (6)$$

where $p(\varphi_i)$ and $p(\varphi_i | \sigma_a^{meas})$ are the prior and posterior parameter distribution, respectively, $L(\varphi_i) = p(\sigma_a^{meas} | \varphi_i)$ denotes the likelihood function and $p(\sigma_a^{meas})$ is the evidence (i.e. the evidence that the data were generated by the model). In our case, the vector φ contains the thickness and logarithm of conductivity of the layers, i.e., $\varphi_i = [h_1, h_2, \dots, h_{n-1}, \log(\sigma_1), \log(\sigma_2), \dots, \log(\sigma_n)]$. The evidence acts as a normalization factor and can be removed without harm from equation 6, leaving us with the following proportionality equality:

$$p(\varphi_i | \sigma_a^{meas}) \propto p(\varphi_i) p(\sigma_a^{meas} | \varphi_i) \quad (7)$$

DREAM renders several likelihood functions depending on the applications. We used a likelihood model that assumes a zero-mean uncorrelated and homoscedastic normal distribution for the residual errors. Given M to be the total number of data points, the log-likelihood function, $l(\varphi_i)$, is calculated as:

$$l(\varphi_i) = -\frac{M}{2} \ln \left(\sum_{m=1}^M [\sigma_a^{meas} - \sigma_a^{mod}(\varphi_i)]^2 \right) \quad (8)$$

Thus, the joint multi-configuration inversion will be possible by including the EMI data from HCP and VCP modes in the log-likelihood function. This log-likelihood function is a homoscedastic Gaussian likelihood in which the measurement errors are integrated out. To assure the convergence of the algorithm, the $\hat{R}$ statistic of Gelman and Rubin (1992) is

employed, which calculates the ratio of between-chain variance to with-in chain variance. The threshold of $\hat{R}=1.2$ is usually applied for convergence diagnosis of the DREAM algorithm. After convergence, the last 25% of the samples in each chain are utilized to summarize the posterior distribution accounting for the burn-in period. We refer to the solution of the problem as a posteriori distribution. DREAM allows for specifying different options for initialization of the algorithm, including: 1) a uniform prior distribution, 2) Latin hypercube sampling (LHS) and 3) a multivariate normal distribution. The RMS error between observed and calculated data is formulated by:

$$RMS = \sqrt{\frac{1}{M} \sum_{m=1}^M (\sigma_a^{meas} - \sigma_a^{mod})^2} \quad (9)$$

It is important to note that DREAM cannot be directly used in high-dimensional inversions (over 5000-10000 dimensions). As a consequence, dimensional reduction approaches were developed that can be coupled with DREAM to produce more tractable results (Laloy et al., 2015).

Regarding the inversion, we considered a three-layer model in which electrical conductivities and thicknesses of the layers are free variables, resulting in 5 unknown parameters. We considered the feasible parameter space from which the initial state of each of the chains is described using LHS (uniform random sampling). In this respect, the parameter spaces were relatively large, covering the whole range of values used for low and high electrical conductivity of soil: $1 < \sigma_n < 200$ mS/m and $0.1 < h_n < 0.5$ m. The DREAM scheme also allows for boundary handling of the unknown parameters if the generated parameters are outside their respective ranges. We used the "reflect" option since it is somewhat more refined and treats the boundary of the search space as a mirror through which each individual parameter value is reflected backwards into the search space. In this paper, we applied DREAM_(ZS) (Vrugt et al., 2009), which is based on the original DREAM algorithm, but employs sampling from an archive of past states to generate candidate points in each individual chain. The reader is referred to Vrugt (2016) for further information regarding DREAM and DREAM_(ZS) approaches and their features.

2.5 Petrophysical model

There are numerous empirical and conceptual petrophysical models to relate soil electrical conductivity and water content according to relationship with soil type and salinity (Rhoades et al., 1976, 1989; Shutko and Reutov, 1982; Wang and Schmugge, 1980; Wagner et al., 2011). Moghadas et al. (2014) showed that for high EM frequencies (MHz or GHz), the models of Shutko and Reutov (1982) and Wang and Schmugge (1980) should be taken into account because of the dispersion phenomenon (ECa increases with frequency). Due to the low operating frequency of the EMI, frequency-dependent petrophysical models are not relevant for our case. Among the range of empirical models proposed by soil scientist to relate ECa with θ , the most commonly used is Rhoades et al. (1976). Rhoades et al. (1989) extended this model to account for mobile, continuous and immobile, discontinuous aqueous phases, and also for different solid-liquid conducting pathways. This model allows for a better description of ECa and θ , but the increased number of difficult-to-obtain empirical parameters limits its applicability. As a consequence, we applied the model of Rhoades et al. (1976), which has been shown to be robust in relating apparent electrical conductivity to soil water content (Huang et al., 2016). In addition, this model has proven to be applicable for different soil types including organic, sand, and mixed sand and clay soils (Rhoades et al., 1976, 1989; Friedman, 2005; Huang et al., 2016). When information on soil texture is available, one can obtain the calibration parameters for this model as described in Rhoades et al. (1990). For more accuracy, we calibrated the Rhoades et al. (1976) model for different soil types using measured reference data.

The model of Rhoades et al. (1976) is described as:

$$\sigma = (a'\theta^2 + b'\theta) \sigma_w + \sigma_s \quad (10)$$

in which a' and b' are soil specific parameters, σ_w is the electric conductivity of the soil water and σ_s is the electrical conductivity of the dry soil (also known as surface conductivity). Since we measured reference conductivity and water content for different depths

at the end of the profile, we inversely estimated Rhoades parameters for each depth using $\text{DREAM}_{(ZS)}$. In this respect, we assumed $a = a'\sigma_w$ and $b = b'\sigma_w$, resulting in three unknown parameters (a , b , and σ_s). The calculated parameters for each depths were utilized to find the depth profile water content (θ^{inv}) from inversely estimated electrical conductivity values (σ^{inv}).

3 Results and discussion

3.1 EMI data

After EMI data processing, the one dimensional (1D) subsurface ECa data were plotted together considering no lateral constraints between adjacent sites (1D assumption). Doing this provides a two dimensional (2D) subsurface conductivity pseudosection down to 1.8 m depth, which is the maximum effective penetration depth of the system (see section Study area and measurements). In other words, the measured values for each offset-coil configuration were plotted versus their corresponding effective penetration depth (i.e. generalized penetration depth) making a 2D subsurface apparent electrical conductivity model down to 1.8 m depth. The 1D assumption was also considered for the inversion of the EMI data as we will see in the following sections. For the case of a 2D earth, more advanced forward and inverse modeling techniques are required (Guillemoteau et al., 2012). Figure 4 shows the measured apparent electrical conductivity values along the 10 m transect for the first measurement, carried out on the afternoon of November 4th. The 5TE capacitance sensor and location of the maize plantings are shown by black dots and triangles, respectively. As attested in the excavated profile (Fig. 2), three distinct layers could be discriminated for the subsequent inversion process. Based on all 20 measurements (not presented here), the apparent electrical conductivity ranges from 15-130 mS/m. As a result, we considered $1 < \sigma_n < 200$ mS/m for $\text{DREAM}_{(ZS)}$ to cover the entire conductivity ranges.

3.2 Reference data

The depth profile reference data measured at $X=10$ m are shown in figure 5. Measurements were carried out at different depths corresponding to 0.1, 0.15, 0.25, 0.4 and 0.7 m. The reference conductivity data (figure 5a) provided almost a constant temporal variation, except on the 4th and 8th of November, which coincided with the irrigation periods. The reference water content values (figure 5b) demonstrate the drying and irrigation patterns over the 6-day period, which are prominent for the top sand layer. One might expect to see these variations in the depth-specific models of σ and θ over time. The temperature data (figure 5c) depicted considerable spatial and temporal variation. In particular, after November 8th, the temperature reduced to around 16°C for the shallower layers reflecting the applied irrigation waters. These temperature values were used to correct EMI data to 25°C (before EMI data calibration).

3.3 Calibration of Rhoades model

The Rhoades model (equation 10) was calibrated by fitting depth-specific reference electrical conductivity and soil water content data using $DREAM_{(ZS)}$. The estimated parameters, as well as RMS errors between measured and modeled data, are also presented in Table 1. Due to the presence of different soil structures with depth (see figure 2), calculated calibration parameters had different values. It is important to note that the σ_s related to the 0.7 m depth presented a value of -0.405. Han et al. (2015) also reported negative σ_s and considered this an indication of negligible grain surface conductivity. Negative values of surface conductivity have no physical meaning but are sometimes encountered in sand. However, due to the increasing clay content, we expected to observe an increase in value of surface conductivity. As mentioned by Rhoades et al. (1976), dry soil conductivity does not depend on water content and salinity of soil solutions. On the other hand, clay content and also grain size are influential in σ_s values (surface conductivity is larger for finer-textured soils). We believe that the negative value of σ_s encountered here is still relevant, since the inversion approach provided acceptable fitting for this depth (RMS=3.34).

3.4 Inversion results

Figure 6 shows depth profile electrical conductivity estimated using $\text{DREAM}_{(ZS)}$ for 10 different measurements. These models were derived based on maximum a posteriori (MAP) probabilities. The results were interpolated in both horizontal and vertical directions to more appropriately demonstrate 2D variations. To maintain consistency with the reference data, we presented the inversion results down to 0.7 m. The RMS errors between measured and modeled data vary between 1.13 (measurement 8) to 3.82 (measurement 2), which entailed acceptable fitting for the whole data set. As seen, the 2D depth profile models illustrated lateral variations of σ along the transect. Three layers with relatively sharp conductivity contrast can be recognized, which are more pronounced in the water content models, as we will see later. Measurements from November 4th and 8th clearly show the effect of irrigation on data by presenting lower conductivity ranges in comparison with the other measurements (figures 6b and 6g). Presentation of the inversion results in 1D assists to better demonstrate differences between the separate layers. Figure 7 shows 1D inversely estimated (blue lines) and reference (red lines) electrical conductivity values related to $X=10$ m for three different measurement times. The gray regions represent the 95% uncertainty bounds. Both reference and estimated conductivity models present a three layered model. However, some disagreements between them can be observed. In particular, the thickness of the second layer cannot be well resolved. For the first measurement (figure 7a), both σ_2 and h_2 present some uncertainties. These issues will be further discussed in the analysis of the posterior distribution.

The inversely estimated electrical conductivity values, σ^{inv} , were converted to soil water content using the Rhoades et al. (1976) model. The spatiotemporal variations of θ^{inv} are shown in figures 8. Three significantly distinguished water content layers can be observed in the data: 1) root zone (0-0.2 m), 2) sand layer (0.2-0.4 m), and 3) clay layer (below 0.4 m). These results are in agreement with the soil structures demonstrated in figure 2. The constant low values of σ^{inv} and θ^{inv} over the top 0.2 m are observed, and are due to the soil structure (a mixture of fine sand with remains of the roots) in this area. The first measurement (figure 8a) was carried out in a dry field condition, resulting in a

resistive layer with low water content for the root zone. The second measurement (figure 8b) was carried out shortly after the first irrigation and as a result, the root zone showed relatively high water content, with the first and second layers having almost the same θ values. Afterwards, due to evaporation and root water uptake, the root zone became dryer. This pattern continued until measurement 15 (figure 8g) at which the second irrigation was performed. After that, the drying pattern commenced, although its intensity was lower than the first drying process.

Although electrical conductivity layers demonstrated sharp lateral variations, the water content profiles presented almost smooth lateral fluctuations. In particular, the boundary between the second and third layers is relatively flat, except for some small variations that may reflect inversion artifacts (artificial images constructed by the inversion). Nimmer et al. (2008) showed that the presence of sharp resistivity (conductivity) contrasts between subsurface layers (as we observe here) may result in inversion artifacts. Depth-specific electrical conductivity and soil moisture profiles present different lateral changes that can be assigned to the fact that soil structures also have a strong impact on the conductivity values (Friedman, 2005). In addition, the Rhoades et al. (1976) model (equation 10) is not a linear relationship and as a result, having such a clear delineation in the prescribed layers after converting σ^{inv} to θ^{inv} can be pertinent. It is interesting to note that the spatiotemporal models of θ better illustrate the root water uptake and evaporation than those provided by σ . In addition, the clay layer had the maximum conductivity (up to around 190 mS/m) and water content for all models, which can be misinterpreted as a water layer. This is important, since in many electrical and electromagnetic geophysical surveys, distinguishing between water and clay layers is challenging and requires using other geophysical methods to provide complementary information (Behroozmand et al., 2012).

3.5 Posterior distribution

The posterior distribution supplies probabilities of each variable providing valuable insights into the uniqueness of the inverse solution and parameter correlations. Figure 9

shows the histogram of marginal distributions and two dimensional correlation plots of posterior parameter samples (left-hand plots). The numbers reflect the correlation coefficient (r) between parameter pairs. The right-hand plots correspond to the marginal density of the individual estimated parameters along with the maximum a posteriori (MAP) probabilities (blue stars). The posterior distribution is related to the first measurement for the reference point ($X=10$ m). Although this analysis is slightly limited in terms of location validation, it assists to better understand the behavior of the DREAM_(ZS) during the entire process. The marginal distribution of the σ_3 follows a normal distribution whereas the histograms of the other parameters deviate considerably from normality. The parameter pairs $(\sigma_1 - \sigma_2)$ and $(\sigma_2 - \sigma_3)$ have negative correlations, while the other parameter groups present positive correlations. In general, correlation coefficients of any pair of parameter groups are low and only $(\sigma_1 - h_1)$ and $(\sigma_3 - h_1)$ share moderate r values of 0.5381 and 0.5019, respectively. In this case, conductivity-thickness products (conductance) are much better resolved than conductivities and thicknesses separately, illustrating model equivalence (Unsworth et al., 1999; Constable and Constable, 2004; Sattel, 2004; Shireesha and Harinarayana, 2013). The uncertainties in derivation of the h_2 and σ_2 were also observed in the 1D electrical conductivity profile presented in figure 7a. This may be attributed to the fact that the second layer constitutes a transitional layer in the sense of conductivity, through which the routine attempts to reconstruct a sharp boundary.

3.6 Evaluation of the inversion results

In order to evaluate the inversion strategy and the accuracy of the estimated depth profile σ and θ , we illustrate a 2D time-depth model of these values for $X=10$ m in figure 10. Figure 10a and b show spatiotemporal variations of electrical conductivity and soil water content related to the reference measurement point ($X=10$ m), respectively. The temporal variation of measured ECa data (as shown in Fig. 4) for the reference point was also presented in figure 10c. Although, σ^{inv} (figure 10a) and σ^{ref} (figure 5a) presented some agreement (the RMS error between modeled ECa and ECa^{ref} was 9.02), discrepancies can be observed. In particular, the inversely estimated conductivity values versus time

demonstrated highly oscillating behavior in comparison with the corresponding reference data. Moreover, the boundary between the layers had a smoother shape for the reference data, with irrigation periods clearly visible in this model. For the inversion results, the conductivity contrasts due to the irrigation are hard to distinguish. In this case, the thicknesses of the first layer for most of the measurement points are also higher than those predicted by the reference data.

The reasons for the inaccuracy in estimation of σ^{inv} might be related to: 1) the measured ECa data versus time also had some oscillations for this point, which can be attributed to the presence of incoherent noise in the EMI data (see figure 10c). Since repeated EMI surveys were not performed for each measurement time, increasing signal to noise ratio is not possible using stacking; 2) uncertainties in deriving the conductivities and thicknesses of the layers during the inversion (see Figure 9) influenced the final estimated model, and 3) the EMI system returned cumulative subsurface response associated with the area below the source-receiver combination, while the 5TE capacitance sensors provided reference data from a smaller area between instrument electrodes, i.e., different measurement footprints of the 5TE and CMD Mini-Explorer sensors may have affected correlations between the two. This is perhaps the most important factor influencing the EMI data calibration and also evaluation of the inversion. Figure 10b presents spatiotemporal variation of θ^{inv} for the reference measurement point. As can be seen, the clay layer (below 0.4 m) was well distinguished and consistent with the reference data (figure 5b). From November 6-8th, the soil water content had values around 0.1 for the first layer. Afterwards, the soil water content increased due to the irrigation. It is interesting to note that inversely estimated soil moisture profiles present fewer oscillations in time in comparison with σ^{inv} , resulting in a better demonstration of evaporation, root water uptake and subsurface processes.

Figure 11 shows the average of the soil moisture (θ^{avg}) over time considering both inversely estimated and reference values. As seen, after the first irrigation (November 4th), the θ^{avg} starts to decrease gradually until the second irrigation on November 8th. After that, the second drying period begins. Although, inaccuracies in the estimation of θ^{inv}

present small oscillations in θ^{avg} during the drying periods, the wetting fronts (dashed lines) are clearly visible in the graph. Root zone soil moisture in vegetated regions has a significant influence on evaporation and transpiration rates. These results clearly demonstrate that one can detect temporal root zone soil moisture changes using the proposed EMI measurement and modeling technique.

In the context of the spatiotemporal monitoring of soil conductivity and water content, the proposed time-lapse monitoring approach developed using probabilistic inversion renders a fast real-time measurement capability and a more accurate subsurface characterization. Moreover, it permits to monitor soil water changes with root water uptake and evaporation, which are key factors for plant growth and transport of water and nutrients in the soil-plant system. Furthermore, it provides a possibility to detect dry and wet zones developed in soil due to water uptake by plant roots and irrigations. Although we believe that the proposed methodology is promising, there are caveats associated with the application of this technique. As already mentioned, the capacitance sensor and EMI operate in different frequencies that could affect calibration of the EMI data. Also, differences of measurement type and sensor influence (differences between the 5TE sensor readings and the EMI data) are perhaps the most important factors in interpretation of the data. However, this is inherent to practically every calibration of geophysical data. We corrected for the EMI data offset combined with signal drift and calibration (considering one specific point where the reference data were collected) providing comparable data sets to evaluate spatiotemporal variations along the profile. Since data were collected over a short period of time in a high conductive environment, the impact of signal drift (mainly induced through ambient and instrument temperature variations) is negligible. Also, the effect of signal drift is aggravated when data sets are recorded over longer periods of time and/or in more resistive environments. We presented an efficient approach which integrates reliable long-term calibration data. An alternative strategy, might be repeated electrical soundings conducted at the same time as the EMI profile measurements. However, this is not a practical or cost-effective approach. Overcoming the limitations of gathering four-dimensional (4D) calibration data is a topic that requires further examination, including

aspects such as the spatial coverage, and increased sensing depth.

4 Conclusion

In this paper, we applied DREAM_(ZS) on time-lapse EMI data to monitor depth profile variations of soil electrical conductivity and soil water content over the time. To do this, we used the Rhoades et al. (1976) petrophysical model to derive soil moisture profile from inversely estimated electrical conductivities. Although finding a valid petrophysical model is a major challenge in hydrogeophysics, we believe that the relationship used herein is adequate, since this model has previously been shown to be robust for many geophysical applications. Despite some relatively small discrepancies between inversely estimated and reference values, the proposed approach allows for the monitoring of the spatiotemporal variation of soil electrical conductivity and soil water content. In particular, the estimated water content profile rendered more relevant results than depth-specific electrical conductivity to monitor subsurface flow processes. Furthermore, the applied measurement and modeling technique permits a delineation of the temporal wetting front and root zone soil moisture variations. Nevertheless, more measurements at different sites must be performed to further investigate the reliability of the approach proposed here. In terms of agricultural applications and in particularly irrigation management, these time-lapse measurements may provide some important insights. For instance, it offers a timely and precise characterization of spatial and temporal soil water content in the root zone for sustainable agricultural and irrigation management. Moreover, the proposed approach provides the possibility to evaluate the uniformity of irrigation in a field, as well as optimizing water use efficiency by providing a sufficient control of site-specific irrigation management.

5 Acknowledgments

This work was supported by the Water Desalination and Reuse Center, King Abdullah University of Science and Technology (KAUST), Saudi Arabia. Three anonymous re-

viewers helped to improve the manuscript by providing insightful comments which is acknowledged.

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Figure 1: Location of the Tawdeehiya commercial farm in Saudi Arabia (Houborg and McCabe, 2016). The red circle represents the location of the experiment.

Figure 2: The excavated pit at the end of the transect ($X=10$ m) which was used to obtain reference data. Three discernable soil structures can be observed: 1) 0-0.2 m: root zone, 2) 0.2-0.4 m: sand layer, and 3) below 0.4 m: clay layer.

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Table 1: Calculated Rhoades parameters determined by fitting depth-specific reference electrical conductivity and soil water content data using DREAM_(ZS) scheme.

Depth [m]	a	b	σ_s	RMS error
0.10	2.736	-0.375	0.026	3.28
0.15	2.482	-0.200	0.006	4.33
0.25	4.659	-0.924	0.054	3.25
0.40	1.369	-0.543	0.197	3.88
0.70	-5.773	3.582	-0.405	3.34