



1 In-situ estimation of soil hydraulic and hydrodispersive properties by 2 inversion of Electromagnetic Induction measurements and soil 3 hydrological modeling

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16

17 Abstract

18 Determining soil hydraulic and hydrodispersive properties is crucial for the sustainable
19 management of water resources and agricultural land. Due to the local heterogeneity of soil
20 hydrological properties and the lack of fast in-situ measurement techniques, it is hard to assess
21 these properties at the field scale. The present study proposes a methodology based on the
22 integration of Electromagnetic Induction (EMI) and hydrological modeling to estimate soil
23 hydraulic and transport properties at the field scale.

24 To this aim, two sequential water infiltration and solute transport experiments were carried
25 out over a small field plot. The propagation of wetting front and solute concentration along the soil



26 profile was monitored using an EMI sensor (i.e. CMD mini-Explorer), Time Domain
27 Reflectometry (TDR) probes, and tensiometers. Time-lapse apparent electrical conductivity (σ_a)
28 data obtained from the EMI sensor were inverted to estimate the evolution of the vertical
29 distribution of the bulk electrical conductivity (σ_b) over time. The σ_b distributions were converted
30 to water content and solute concentration by using a laboratory calibration, relating σ_b to water
31 content (θ) and soil solution electrical conductivity (σ_w). The hydraulic and hydrodispersive
32 properties were then obtained by an optimization procedure minimizing the deviations between
33 the numerical solution of the water flow and solute transport processes and the estimated water
34 contents and concentrations inferred from the EMI results. The EMI-based results were finally
35 compared to the results obtained from the in-situ TDR and tensiometer measurements.

36 In general, the EMI readings lead to underestimated water contents as compared to the
37 TDR data. And yet, the water content changes over time detected by the EMI closely followed
38 those observed by TDR and contain enough information for effective EMI-based reconstructions
39 of water retention and hydraulic conductivity curves for the soil profile. In addition, this allowed
40 us to reproduce the solute concentration distributions and thus the hydro-dispersive properties of
41 the soil profile. Overall, the results suggest that time-lapse EMI measurements could be used as a
42 rapid, non-invasive, field-scale method to assess soil hydraulic and hydro-dispersive properties,
43 which are critical to hydrological models for agro-environmental applications.

44



45 1. INTRODUCTION

46 Irrigated agriculture plays a crucial role in the food supply in many countries where ecological
47 conditions are characterized by warm and dry summers with high solar radiation and
48 evapotranspiration rates. Evaluating spatio-temporal variability of soil water and solute content is
49 critical for optimal irrigation scheduling in timing, quantity, and quality (Coppola et al., 2019) and
50 soil salinization assessment which depends on the variability of soil hydrological behavior (Chaali
51 et al., 2013; Coppola et al., 2015). Soil hydrological behavior is generally described by solving the
52 Richards' equation (RE) for water flow and the Advective-Dispersive equation (ADE) for solute
53 transport, which is frequently assumed to apply at different spatial scales, from laboratory to field
54 to larger scales (Sposito, 1998). These equations require the soil water retention and the soil
55 hydraulic conductivity functions, as well as the hydro-dispersive properties, to be known at the
56 scale of concern (Basile et al., 2003, 2006; Zech et al., 2015). Thus, the measurement methods
57 and, consequently, the volumes investigated must be able to capture the hydraulic functions and
58 dispersivity at the appropriate scale.

59 Yet, laboratory-scale measurements of hydraulic properties and dispersivity have been
60 frequently used for field-scale studies (Coppola et al., 2011a; Comegna et al., 2012). However,
61 one has to be aware that the validity of these lab-based properties for solving RE and ADE at field
62 scale is essentially related to the size of the volume investigated, which has to appropriately
63 represent the heterogeneity of the medium being studied (Wessolek et al., 1994; Ellsworth et al.,
64 1996; van Genuchten et al., 1999; Inoue et al., 2000; Basile et al., 2003, 2006). An additional
65 concern in lab-scale measurements is determining the hydrological properties of different soil
66 horizons separately and then combining these properties to determine the behavior of the entire
67 soil profile. This is especially important in the case of solute transport, where the transport process



68 may change significantly depending on the solute travel times correlation among different layers
69 (Coppola et al., 2011b).

70 In situ methods also provide the proper properties to solve RE and ADE at the field scale. In
71 situ methods typically evaluate soil hydrological properties by monitoring infiltration and/or
72 redistribution water flow processes, and hydro-dispersive parameters by monitoring mixing
73 processes following pulse or step inputs of a tracer on a large plot or a long field transect (Severino
74 et al., 2010; Coppola et al., 2011b). Inverse modeling is then frequently used to estimate the
75 hydraulic and transport parameters simultaneously (Abbasi et al., 2003; Groh et al., 2018). Tension
76 infiltrometers are also commonly used to monitor infiltration processes in situ for inverse-
77 modeling of parameters (Simunek et al., 1998; Coppola et al., 2011a; Wang et al., 2013); however,
78 the measurement volume is too small to accurately characterize the behavior of a whole soil profile.
79 Thus, in general, for larger scale studies, in situ methods looking at the whole soil profile are
80 generally desirable. Yet, where a large number of field locations have to be characterized, all the
81 in-situ methods remain extremely difficult to implement and it remains critical to finding
82 alternative methods of characterization of soil hydrology, which are fast enough and actually
83 represent the in-situ behavior of the soil.

84 Geophysical methods such as the electrical resistivity tomography (ERT) technique are used
85 as a promising alternative to traditional techniques for soil hydraulic and transport parameters
86 assessment. Many researchers have used the time-lapse ERT data (Binley et al., 2002; Kemna et
87 al., 2002; Singha and Gorelick, 2005; Farzamian et al., 2015a) to monitor temporal water content
88 and solute concentration changes for the estimation of soil hydraulic and transport properties in
89 flow and transport models. The electrical conductivity of any subsurface material is a complex
90 function of different soil properties such as soil texture (Farzamian et al., 2020). However, the



91 dependence of variations of soil electrical conductivity on changes in soil water content and
92 concentration is the key mechanism that permits the use of time-lapse ERT to monitor water and
93 solute movement in time-lapse mode through empirical or semi-empirical relationships (e.g.
94 Archie, 1942) or established in-situ relationships (e.g. Binley et al., 2002; Farzamian et al. 2017).
95 While this method is still widely used for soil hydraulic parameters assessment, the efficiency of
96 this method is limited in the root-zone investigation on a field scale, given the large number of
97 electrodes that need to be installed for shallow investigation.

98 To improve soil electrical conductivity surveying over large areas and within the root zone for
99 agricultural and environmental applications, electromagnetic induction (EMI) can be used as an
100 alternative to the ERT technique as it allows for rapid survey at a relatively low cost for shallow
101 investigation. Apparent electrical conductivity (σ_a) data, obtained from EMI sensors at field-scale
102 has been used to map the geospatial and temporal variability of the soil water content and salinity
103 (Corwin and Lesch, 2005; Bouksila et al. 2012; Coppola et al., 2016; Saeed et al., 2017). However,
104 the usefulness of σ_a is limited when studying the variation of the soil parameters with depth, as σ_a
105 is a depth-weighted, average conductivity measurement and does not represent the soil bulk
106 electrical conductivity (σ_b) distribution with depth (Farzamian et al., 2019).

107 More recently, technological advances have seen the development of multi-coil EM sensors
108 which are designed to collect σ_a at multiple coil spacing and orientations simultaneously in one
109 pass. This allows a rapid investigation of the soil's electrical conductivity at several depth ranges.
110 In addition, several inversion methods have been proposed to obtain the distribution of the σ_b from
111 σ_a measurements (Monteiro Santos, 2004; Farzamian et al., 2015b; Moghadas et al., 2019; Zare et
112 al. 2020; Mclachlan et al. 2020). The EMI survey and inversion algorithm has now led to
113 significant improvement in soil digital mapping and equipped soil scientists with a field-scale and



114 cost-effective technology to obtain soil moisture and salinity (Koganti et al., 2018; Dragonetti et
 115 al., 2018; Farzamian et al., 2019; Paz et al., 2019; 2020a) with depth over large areas quickly and
 116 cheaply. Most recently, time-lapse EMI surveys and inversion modeling have been also used to
 117 study the dynamic of water content (Huang et al., 2016; Whalley et al., 2017) and soil salinity (Paz
 118 et al. 2020b; Farzamian et al. 2021). However, the potential of this method in assessing soil
 119 hydraulic and hydro-dispersive parameters has not been yet studied due to the lack of high-
 120 resolution and well-controlled experiments, required to catch the complexity of water flow and
 121 transport process during infiltration events.

122 With these premises, we propose a procedure based on a sequence of water infiltration and
 123 solute transport experiments, both monitored by an EMI sensor, with the objective of estimating
 124 field soil hydraulic and solute dispersivity parameters with a non-invasive sensor and relatively
 125 short field experiments. The sequence of water and solute infiltration has the main aim to
 126 discriminate the contribution of the water content and the soil solution electrical conductivity to
 127 the EMI-based σ_b . This issue will be clarified in detail in the Hydro-Geophysical approach section.
 128 The goodness of these parameter estimations will be evaluated by comparing the EMI-based
 129 hydraulic and hydrodispersive properties to those obtained from in-situ TDR and tensiometer
 130 measurements.

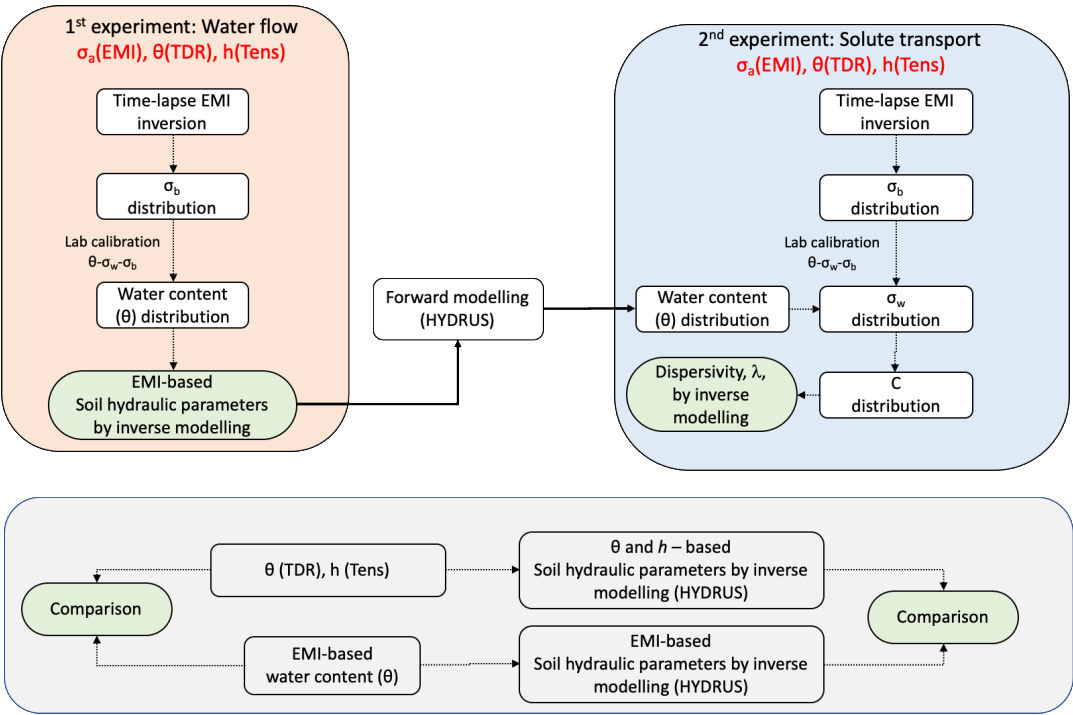
131 2. HYDRO-GEOPHYSICAL APPROACH

132 A six-step procedure, schematized in Fig. 1, was taken in order to investigate the potential of
 133 the EMI method in estimating the soil hydraulic and hydro-dispersive properties: 1) inversion of
 134 time-lapse σ_a data obtained during two experiments to generate EMI-based σ_b distributions for
 135 each experiment; 2) laboratory calibration of θ - σ_b - σ_w in order to convert σ_b distributions to water
 136 content (first experiment) and solute concentrations, $[Cl^-]$, (second experiment); 3) converting σ_b



137 distributions obtained from the first experiment to as many water content distributions, to be used
 138 in the next step; 4) numerical simulation (by using the HYDRUS-1D model) of the first water
 139 infiltration process in order to estimate the van Genuchten-Mualem model (vG-M) parameters
 140 through an inversion procedure based on the water contents inferred from step 3; 5) converting σ_b
 141 distributions inferred from the second experiment to $[Cl^-]$ distribution in order to estimate
 142 longitudinal dispersivity. In this step, the soil solution electrical conductivity (σ_w) distribution was
 143 estimated by using the laboratory θ - σ_b - σ_w calibration. The θ distribution in the second experiment
 144 was simulated based on the vG-M parameters obtained in step 4. This is a crucial step in the
 145 proposed procedure, as this allows to discriminate the contribution of the soil water electrical
 146 conductivity to the EMI-based σ_b . The σ_w distributions were thus converted to $[Cl^-]$ by a calibration
 147 σ_w - $[Cl^-]$; 6) numerical simulation of the second solute infiltration process in order to estimate
 148 dispersivity through an inversion procedure based on the concentrations coming from step 5.

149 An alternative dataset of θ and σ_b obtained from direct TDR measurements, as well as
 150 tensiometer pressure head (h) readings, collected during the two experiments, allowed us to obtain
 151 independent hydraulic and hydrodispersive properties to be used as a reference to evaluate the
 152 EMI-based parameter estimation.



153

154 Figure 1: Schematic diagram of the proposed Hydro-Geophysical approach

155

156 **3. MATERIAL AND METHODS**

157 **3.1. Study area**

158 The experiment was performed at the Mediterranean Agronomic Institute of Bari (CIHEAM-
159 IAM), south-eastern coast of Italy. The study area is located at an altitude of 72 m with 41° 3'
160 13.251" N, the longitude of 16° 52' 36.274" E, and elevation of about 68 m a.s.l. with a typical
161 Mediterranean climate with rainy winters and very hot dry summers. The soil is a Colluvic Regosol
162 consisting of silty loam layers of an average depth of 70 cm on a shallow fractured calcareous
163 rock. The soil is frequently tilled at 25-30 cm, and scattered calcareous fragments are present due



164 to the frequent breaking and grinding of the bedrock using heavy machinery to improve the soil
165 structure and increase soil depth for plantation.

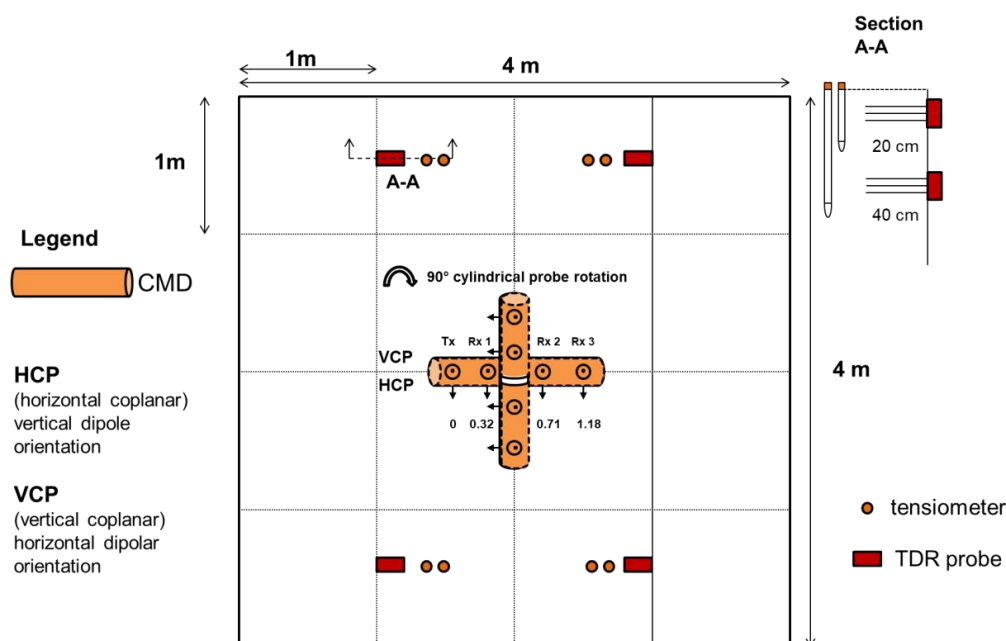
166 **3.2. Experimental set-up**

167 A layout of the experimental setup is shown in Fig. 2. The plot sizes 4×4 m. Water was applied
168 by using a drip irrigation system consisting of 20 lines, with drippers spaced 0.20 m and delivering
169 a nominal flow rate of 10 l h^{-1} . The drip irrigation system was placed on a metallic grid to be easily
170 moved away from the plot and whenever EMI measurements were taken on the ground soil. The
171 experimental plot was covered with a plastic sheet about four months prior to the experiment to
172 keep the experimental plot under dry and a uniform water content condition at the beginning of
173 the experiment.

174 Prior to the water infiltration experiments, eight three-wire TDR probes, 7 cm long, 2.5 cm
175 internal distance, and 0.3 cm in diameter, were inserted horizontally at 2 depths – 20 and 40 cm,
176 corresponding to the Ap and the Bw horizon – in the 4 corners of the experimental plot (at 1 m
177 distance from the plot edge), as shown in Fig. 2. A Tektronix 1502C cable tester (Tektronix Inc.,
178 Baverton, OR) was used in this study, enabling simultaneous measurement of water content, θ ,
179 and bulk electrical conductivity, σ_b , of the soil volume explored by the probe (Robinson et al.,
180 2003; Coppola et al., 2011a, b; 2013). Furthermore, eight tensiometers were vertically inserted
181 near each TDR probe to acquire water potentials by a Tensicorder sensor (Hydrosense3 SK800).
182 The experimental plot was firstly irrigated by using tap water with an electrical conductivity of
183 about 1 dS m^{-1} . Eleven irrigation supplies were applied at regular intervals during one day at a 1 h
184 frequency. Overall, an average water volume of 2000 l was supplied.



185 The propagation of the wetting front along the soil profile was monitored by using an EMI
186 sensor (i.e. CMD mini-Explorer, GF Instruments, Czech Republic), positioned horizontally in the
187 middle of the plot (see Fig. 2) in order to measure the apparent electrical conductivity, σ_a , in the
188 soil profile in VCP (vertical coplanar, i.e., horizontal magnetic dipole configuration) mode and
189 then HCP (horizontal coplanar, i.e., vertical magnetic dipole configurations) mode by rotating the
190 probe 90° axially to change the orientation from VCP to HCP mode. The CMD Mini-Explorer
191 operates at 30 kHz frequency and has three receiver coils with 0.32, 0.71 and 1.18 m distances
192 from the transmitter coil, referred to hereafter as ρ_{32} , ρ_{71} , and ρ_{118} . The manufacturer indicates
193 that the instrument has an effective depth range of 0.5, 1.0 and 1.8 m in the HCP mode, which is
194 reduced to half (0.25, 0.5, and 0.9 m) by using the VCP orientation. As a consequence, this EMI
195 sensor returns six different σ_a values (utilizing three offsets with two coil orientations) with each
196 corresponding to different depth sensitivity ranges. All measurements were performed five
197 minutes after each water pulse application by temporarily removing the irrigation grid. The
198 infiltration was also monitored by TDR probes and tensiometers in order to monitor the space-
199 time evolution of water content, θ , pressure head, h , as well as bulk electrical conductivity, σ_b . The
200 distance of the TDR probes and tensiometers to the middle of the plot was specifically designed
201 to avoid any interference with the EMI measurements.



202

203 Figure 2. Layout of the experimental and monitoring set-up

204

205 At the end of the 1st water infiltration experiment, the soil was allowed to dry again (by
 206 drainage and evaporation) to bring the distribution of water content along the profile similar to the
 207 initial one (observed before the water infiltration test). Afterward, a similar infiltration experiment
 208 (2nd) was carried out but using saline water at an electrical conductivity of 15 dS m⁻¹, and obtained
 209 by mixing CaCl₂ into the tap water. Again, eleven saline water supplies were provided at intervals
 210 of 1h apart. In the 1st experiment, an average saline water volume of 2000 liters was supplied for
 211 all irrigation events. The propagation of the water and chloride during the 2nd infiltration
 212 experiment was monitored similarly to the 1st experiment using TDR probes, tensiometers, and the
 213 CMD Mini-Explorer sensor.



214 3.3. Site-specific calibration θ - σ_w - σ_b

215 The relationship among bulk electrical conductivity (σ_b), the electrical conductivity of the soil
 216 solution soil water (σ_w) and the water content were obtained by using the model proposed by
 217 Malicki and Walczak, (1999):

$$218 \sigma_w = \frac{\sigma_b - a}{(\varepsilon_b - b)(0.0057 + 0.000071S)}, \quad (1)$$

219 where ε_b (-) is the dielectric constant, which is related to the water content. The parameters $a = 3.6$
 220 d Sm^{-1} ; $b = 0.11$ were obtained in a laboratory experiment reported in Farzamian et al. (2021). An
 221 additional linear calibration, obtained by using solutions at different concentrations of calcium
 222 chloride was used to relate soil water concentrations, Cl^- , to σ_w .

223 3.4. Forward modeling and time-lapse inversion of EMI σ_a data

224 Time-lapse (TL) σ_a data obtained during the experiments were inverted using a modified
 225 inversion algorithm proposed by Monteiro Santos et al. (2004) to obtain σ_b distribution in time.
 226 The aim of the inversion is to minimize the penalty function that consists of a combination
 227 between the observations' misfit and the model roughness (Farzamian et al., 2019). The earth
 228 model used in the inversion process consists of a set of 1D models distributed according to the
 229 number of time-lapse measurements. All the models have the same number of layers (7) whose
 230 thickness is kept constant. The parameters of each model are spatially and temporally constrained
 231 using their neighbors through smooth conditions. The forward modeling is solved based on the
 232 full solution of the Maxwell equations (Kaufman and Keller, 1983) to calculate the σ_a responses
 233 of the model. The TL inversion algorithm is Occam-regularization and the objective function was
 234 developed based on Sasaki, (2001). Therefore, the corrections of the parameters, in an iterative
 235 process are calculated solving the system:



$$[(J^T J + \eta C^T C)] \delta p = J^T b \quad (2)$$

where δp is the vector containing the corrections applied to the parameters (logarithm of block conductivities, p_i) of an initial model, b is the vector of the differences between the logarithm of the observed and calculated σ_a [$b_i = \ln(\sigma_a^o/\sigma_a^c)_i$], J is the Jacobian matrix whose elements are given by $(\sigma_j/\sigma_{ai}^c) (\partial \sigma_{ai}^c / \partial \sigma_j)$, the superscript T denotes the transpose operation, and η is a Lagrange multiplier that controls the amplitude of the parameter corrections and whose best value is determined empirically. The elements of matrix C are the coefficients of the values of the roughness of each 1D model, which is defined in terms of the two neighbor's parameters and the constraint between the parameters of the different models on time. In this regard and in our temporal 1D experiment, each cell is constrained spatially by its vertical neighbors, while the temporal constraints are imposed using its lateral neighbors. An iterative process allows the final models to be obtained, with their response fitting the data set in a least-square sense. In terms of η , generally, large values will produce smooth inversion results with smoother spatial and temporal variations.

3.5. Numerical simulation of water flow and chloride transport in soil

The water and the chloride propagation monitored during the experiments were also simulated by using the HYDRUS-1D model (Simunek et al., 1998). HYDRUS-1D simulates water flow and solute transport by solving the Richards equation and the Advection-Dispersion equation, respectively.

Richards equation can be written for one-dimensional, unsaturated, non-steady state flow of water in the vertical direction as follows:

$$C_w(\theta) \frac{\partial h}{\partial t} = \frac{\partial}{\partial z} \left[K(h) \frac{\partial h}{\partial z} + K(h) \right] \quad (3)$$



where $C_w(\theta)$, the water capacity, is the slope of the water retention curve, θ is the volumetric water content [L^3L^{-3}], h is the soil water pressure head [L], $K(h)$ is the unsaturated hydraulic conductivity [LT^{-1}].

The Advection-Dispersion equation governing the transport of a single non-reactive and non-adsorbed (a tracer, chloride in our case) ion in the soil can be written as:

$$\frac{\partial(\theta C)}{\partial t} = \frac{\partial}{\partial z} \left[\theta D \frac{\partial C}{\partial z} - qC \right] \quad (4)$$

where q is the darcian flux, C is the solute concentration in the liquid phase [ML^{-3}], D (L^2T^{-1}) is the effective dispersion coefficient, which can be assumed to come from a combination of the molecular diffusion coefficient, D_{diff} (L^2T^{-1}) and the hydrodynamic dispersion coefficient, D_{dis} (L^2T^{-1}):

$$D = D_{diff} + D_{dis} \quad (5)$$

where the hydrodynamic dispersion is the mixing or spreading of the solute during transport due to differences in velocities within a pore and between pores. The dispersion coefficient can be related to the average pore water velocity $v=q/\theta$ through:

$$D = \lambda v \quad (6)$$

where λ [L] is the dispersivity, a characteristic property of the porous medium. To solve the Richards equation (Eq. 3), the water retention function, $\theta(h)$, and the hydraulic conductivity function, $K(h)$, must be defined. In this paper we adopted the van Genuchten-Mualem model (vG-M), (Van Genuchten, 1980):

$$S_e = [1 + (\alpha|h|)^n]^{-m} \quad (7)$$

$$K(h) = K_s S_e^\tau \left[1 - (1 - S_e^{1/m})^m \right]^2 \quad (8)$$



279 In the Equations 7 and 8, $S_e = \frac{(\theta - \theta_r)}{(\theta_s - \theta_r)}$ is the effective water saturation, θ_s the saturated water
 280 content, θ_r the residual water content, α , n and m are fitting parameters with m taken as $m=1-1/n$,
 281 K_s is the saturated hydraulic conductivity and τ is the pore-connectivity parameter.

282

283 **3.6. Inverse estimation of soil hydraulic and solute transport parameters**

284 The obtained EMI-based spatiotemporal distribution of σ_b during the water infiltration
 285 experiment (the 1st experiment) was converted to a θ distribution in order to estimate the temporal
 286 evolution of θ during the infiltration process. These water content data were then used in an
 287 optimization procedure by using the HYDRUS-1D model, in order to estimate the hydraulic
 288 properties of the different horizons in the soil profile. The simulations were carried out by using
 289 the actual top boundary flux conditions during the experiment, including the irrigation events. For
 290 the bottom boundary, free drainage was considered. A simulation domain 150 cm depth was
 291 considered. The same procedure was repeated using the direct measurements of θ (TDR) and
 292 pressure head (Tensiometers) in order to obtain independent hydraulic parameters to be compared
 293 to those inferred from EMI. A three-layer soil profile (0-25; 25-70; 70-150 cm), reflecting the
 294 actual pedological layering (i.e. Ap, Bw, and bedrock) were used in all simulations.

295 As for the solute transport experiment, a HYDRUS-1D simulation was carried out with the
 296 EMI-based hydraulic properties obtained from the 1st experiment to simulate the water content
 297 distributions in correspondence with the EMI measurement times. The simulations of water
 298 infiltration and solute transport in the 2nd experiment was carried out by using the top boundary
 299 fluxes conditions used during the 2nd experiment along with the same simulation domain, three-
 300 layer soil profile, and the bottom boundary described above. Thus, for each monitoring time, we



301 had available the σ_b distributions obtained from the EMI and θ from the HYDRUS-1D simulations.
 302 These distributions allowed us to estimate as many σ_w (and thus C) distributions by using the θ -
 303 σ_b - σ_w relationship obtained in the laboratory. These C distributions were used in a new HYDRUS-
 304 1D simulation to estimate the longitudinal dispersivity of the investigated soil. The simulated
 305 concentrations, with the optimized dispersivity, were compared to those obtained from the TDR
 306 and tensiometer data.

307

308 4. RESULTS AND DISCUSSION

309 4.1. Water infiltration – 1st experiment

310 4.1.1. Time-lapse σ_a data and estimation of σ_b distribution

311 Figure 3 shows the σ_a values observed during the water infiltration experiment. Both VCP and
 312 HCP modes show a relatively similar pattern of σ_a values with $\rho 32$ and $\rho 118$ being the highest and
 313 lowest respectively. HCP mode shows higher values compared to the VCP mode in the same
 314 receivers. This pattern of σ_a distribution suggests the presence of a conductive zone over a resistive
 315 zone which is expected in this experiment as a result of the waterfront being infiltrated into the
 316 soil profile and the presence of a resistive bedrock. In terms of temporal σ_a variabilities, the σ_a
 317 increases consistently in both VCP and HCP modes during the first three hours of the experiment.
 318 Afterward, σ_a did not change significantly toward the end of the experiment. The range of σ_a
 319 variations is relatively small in both VCP and HCP modes with the former in the 10-30 mS m⁻¹
 320 range and the latter in the 10-50 mS m⁻¹ range.

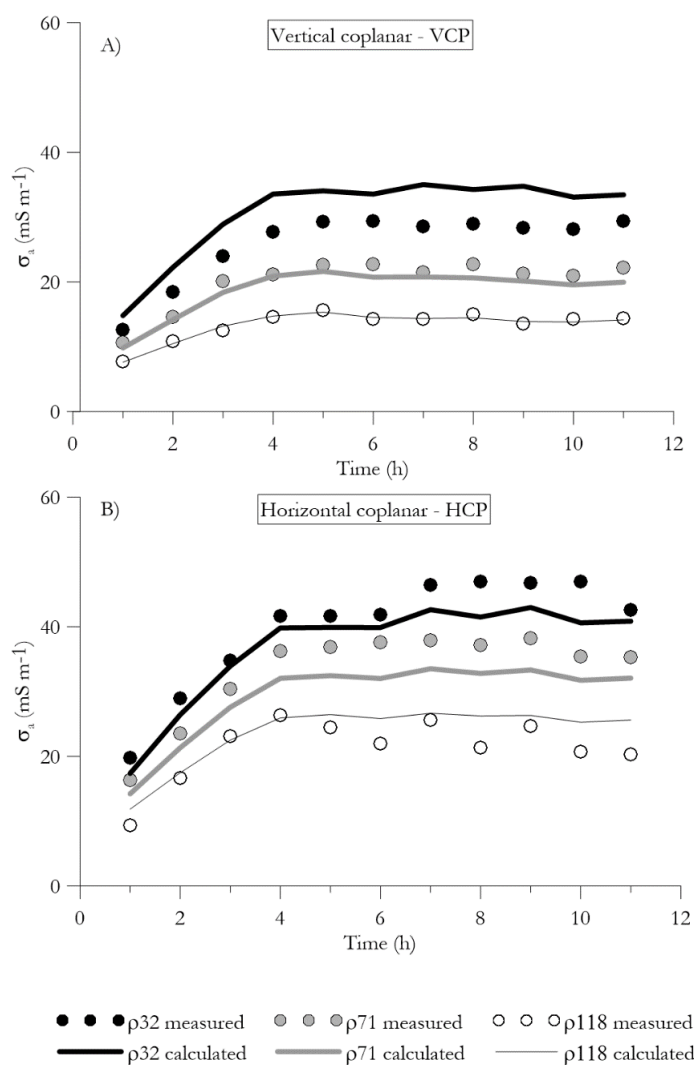


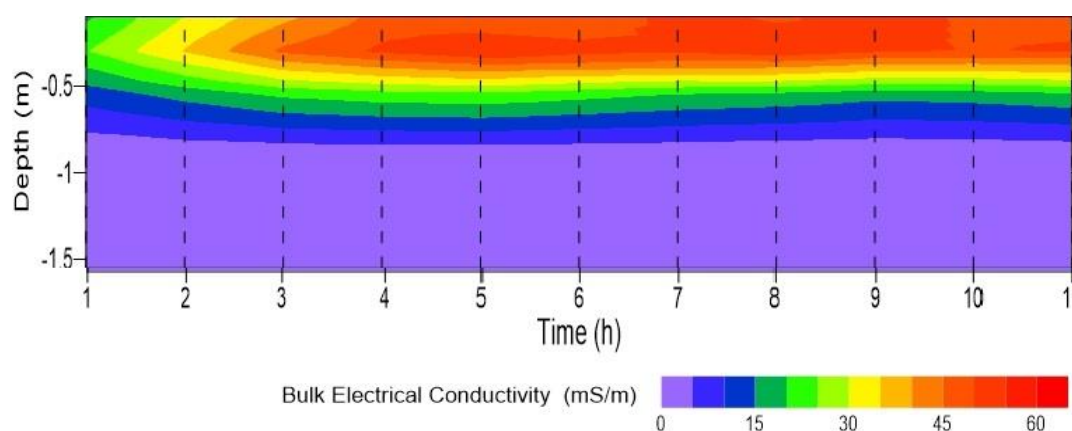
Figure 3: σ_a values observed during the water infiltration experiment. (A) VCP, (B) HCP. The symbols represent the measured data whereas the lines represent the values calculated after the inversion.

321 Fig. 4 depicts the time-lapse σ_b modeling results of σ_a shown in Fig. 3. The model shows clearly
 322 the evolution of the conductive zone into the soil profile shortly after the irrigation started as
 323 expected from the σ_a data. The resistive zone beneath a conductive zone corresponds to the bedrock



324 layer in the experimental plot. The σ_b of the resistive zone remains below 5 mS m^{-1} and does not
 325 vary significantly during the experiment, while, in contrast, the σ_b of the upper layers increased
 326 significantly from an average of 20 mS m^{-1} at the beginning of the experiment to more than 50 mS
 327 m^{-1} after the 5th irrigation. The conductivity of this zone does not increase largely since then,
 328 suggesting that the soil is fairly saturated after the 3rd irrigation.

329



330

331 Figure 4. Time evolution of bulk electrical conductivity (σ_b) distribution with depth during the
 332 water infiltration experiment.

333

334 4.1.2. Comparison between TDR measurements and EMI-based σ_b and θ distribution

335 Figure 5 shows the temporal σ_b changes inferred from TDR and EMI observations at two
 336 depths, 20 and 40 cm, where the TDR probes monitored the water infiltration experiment. As
 337 reported by many authors (e.g. Coppola et al., 2016; Dragonetti et al., 2018), both techniques
 338 provide σ_b estimations but a direct comparison between σ_b by TDR and EMI is not straightforward
 339 due to different volumes of sensor investigation as well as the different nature of measurements.
 340 However, this comparison can be used as a means to investigate the consistency of the σ_b trends



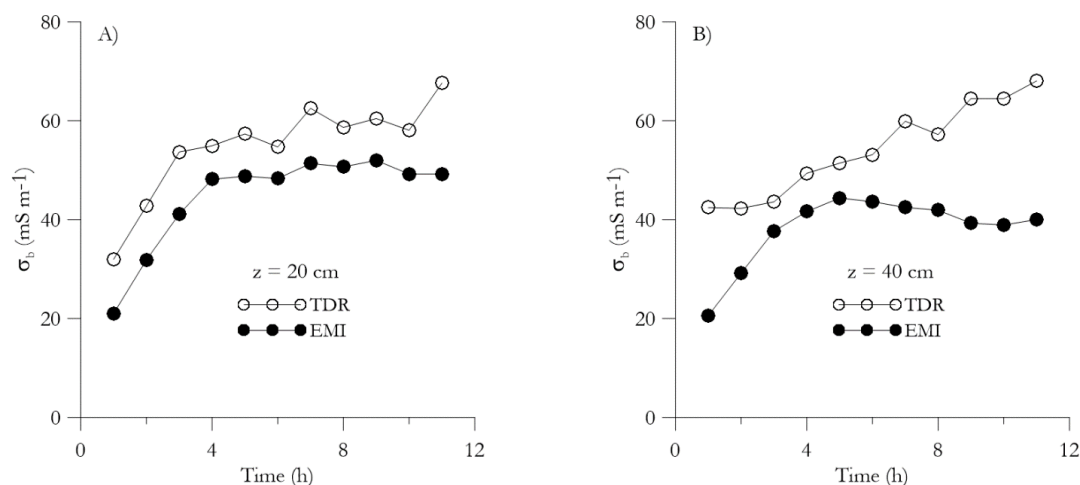
and to provide an insight into the uncertainty associated with the EMI survey and inversion process in resolving the water infiltration process into the soil profile. Focusing on the σ_b series inferred from both TDR observations and EMI inversion, a similar time pattern of σ_b variability is evident, but in general, the EMI model underestimates the σ_b obtained by TDR. A better agreement was observed at 20 cm in terms of both absolute σ_b values and trend ($r=0.94$; Mean Error=10.1 mS m⁻¹). In contrast, at 40 cm, the mismatch between TDR observations and EMI inversions becomes larger at the end of the experiment, but still in an acceptable range ($r=0.54$; Mean Error=16.1 mS m⁻¹). The EMI σ_b values – especially at 40 cm depth – remain rather invariant in the last part of the infiltration experiment. The general outcome that for both layers the EMI σ_b values underestimate the TDR σ_b measurements has been frequently found in the literature (e.g. Coppola et al., 2015; Dragonetti et al., 2018; Visconti and De Paz, 2021). von Hebel et al. (2014) also found a similar behavior when comparing their EMI results with ERT surveys. In that case, the σ_a values measured by EMI systematically underestimated the σ_a generated by applying EMI forward modeling to the σ_b distribution retrieved by ERT.

Figure 6 shows the evolution of θ at the same two depths, 20 and 40 cm as observed by TDR and EMI sensors. While TDR provides direct measurements of θ , in order to estimate θ from EMI observation, σ_b values extracted at these depths (Fig. 4) were converted to θ by the calibration performed in the laboratory, as detailed in Farzamian et al., (2021). A rapid increase of θ is visible shortly after injection in both EMI-based and TDR measurements. The EMI-based θ estimation is able to detect the similar water content evolution (similar water content differences over time) observed by direct TDR measurements but at a slightly different water content level. Specifically, EMI water contents were mostly lower than the TDR ones but the two series showed a quasi-



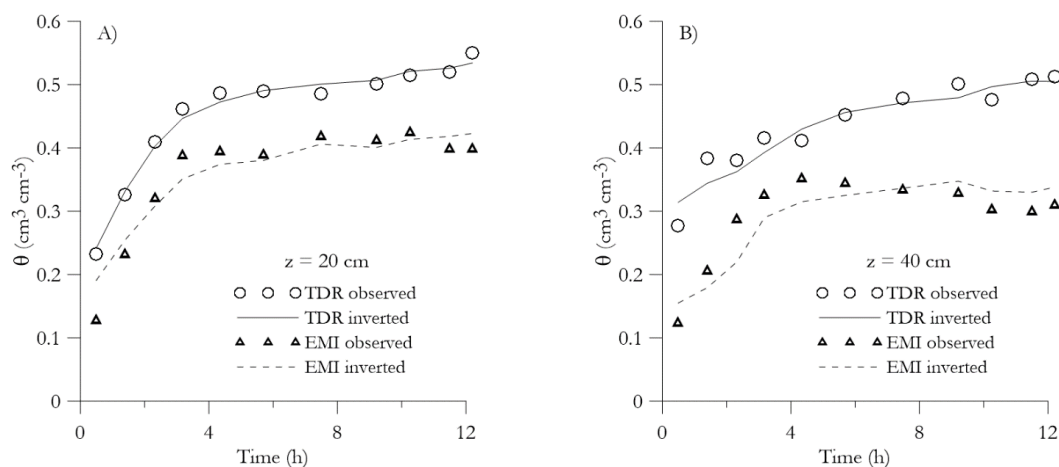
parallel evolution at 20 cm depth ($r=0.98$; Mean Error= $0.09 \text{ cm}^3 \text{ cm}^{-3}$), while diverging for longer
 times at 40 cm depth ($r=0.60$; Mean Error= $0.17 \text{ cm}^3 \text{ cm}^{-3}$).

365



366

367 Figure 5. σ_b evolution estimated from the TDR and EMI measurements at 20 cm (A) and 40 cm
 368 (B) depths.



369

370 Figure 6. Evolution of θ measured by TDR (circles) and estimated from EMI measurements
 371 (triangles) at 20 cm (A) and 40 cm (B) depths. Continuous lines for TDR and dashed lines for EMI
 372 refer to the estimation obtained by the inversion procedure of the water infiltration process (see
 373 Sect. 4.1.3 below).



4.1.3. Estimation of hydraulic properties

In order to estimate hydraulic properties parameters, an inversion procedure was performed using the HYDRUS-1D model. The first set of hydraulic parameters was obtained by optimizing soil water content measured by TDR and pressure head measured by tensiometers (hereafter TDR-based for sake of simplicity). The second set of hydraulic parameters was obtained by optimizing soil water content estimated by EMI measurements (hereafter EMI-based). The inversion simulations were carried out by fixing $\theta_r=0$ and $\tau=0.5$, while θ_s , α , n and K_s were optimized for all the layers considered. The hydraulic properties of the bedrock were fixed to $\theta_r=0.068$, $\theta_s=0.354$, $\alpha=0.055$, $n=3.67$, $\tau=0.5$ and $k_s=19.02$ according to Caputo et al. (2010; 2015).

Figure 6 reports a comparison between water contents measured (symbols) and estimated (lines) by the inversion procedure. The θ distribution was properly estimated at 20 cm depth in both approaches. However, a lower agreement was obtained at 40 cm but still acceptable. Table 1 reports the parameters of the hydraulic functions, estimated for the first two horizons. Figure 7 reports the water retention curves and the hydraulic conductivity curves corresponding to the parameters shown in table 1 for a better comparison between TDR-based and EMI-based hydraulic properties assessment.

As for water retention, the TDR and EMI water retention curves showed similar shapes but with slightly different saturated water contents. As discussed earlier, the slightly lower saturated water content is not surprising for the EMI-based estimation due to the overall underestimation of water content. The two curves almost overlapped once scaling the EMI curve by the ratio of the saturated water contents. Obviously, this result is consistent with the underestimation of EMI-based θ distributions as shown in Fig. 6.



396 As for the hydraulic conductivity, TDR-based and EMI-based hydraulic conductivity curves
 397 at both 20 and 40 cm appear to almost overlap, with similar saturated hydraulic conductivity and
 398 curve shape. This result is expected because the hydraulic conductivity is mainly a function of the
 399 variation of θ and not the absolute value of θ itself. It is worth mentioning that the same top
 400 boundary flux and different water contents in the soil profile provided similar EMI-based and
 401 TDR-based hydraulic conductivity. These conditions lead to two different water flow processes,
 402 with simulations predicting higher water stored in the soil profile and lower downward fluxes (data
 403 not shown) when TDR-based results are compared to the EMI-based results.

404 Table 1. vG-M Hydraulic parameters (Eqs. 7 and 8) and dispersivity, λ (Eq. 6) for Ap and Bw
 405 horizons

Soil hydraulic and transport parameters		Ap		Bw	
		TDR- based	EMI- based	TDR- based	EMI- based
θ_r	[cm ³ cm ⁻³]	0.00	0.00	0.00	0.00
θ_s	[cm ³ cm ⁻³]	0.54	0.45	0.52	0.45
α	[cm ⁻¹]	0.006	0.003	0.009	0.007
n	[-]	1.70	1.54	1.50	1.41
k_s	[cm min ⁻¹]	0.06	0.02	0.28	0.29
τ	[-]	0.5	0.5	0.5	0.5
λ	[cm]	10	12	0.5	0.8

406

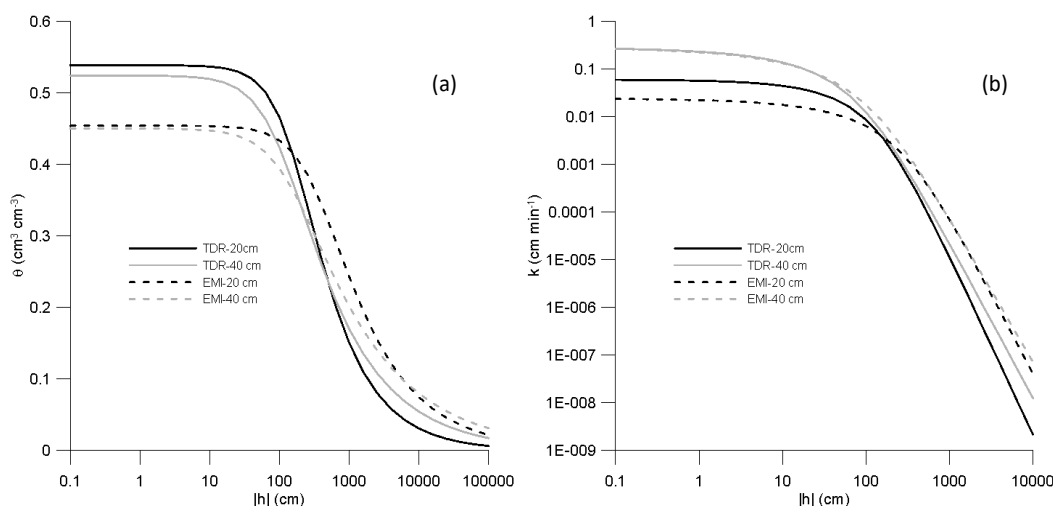
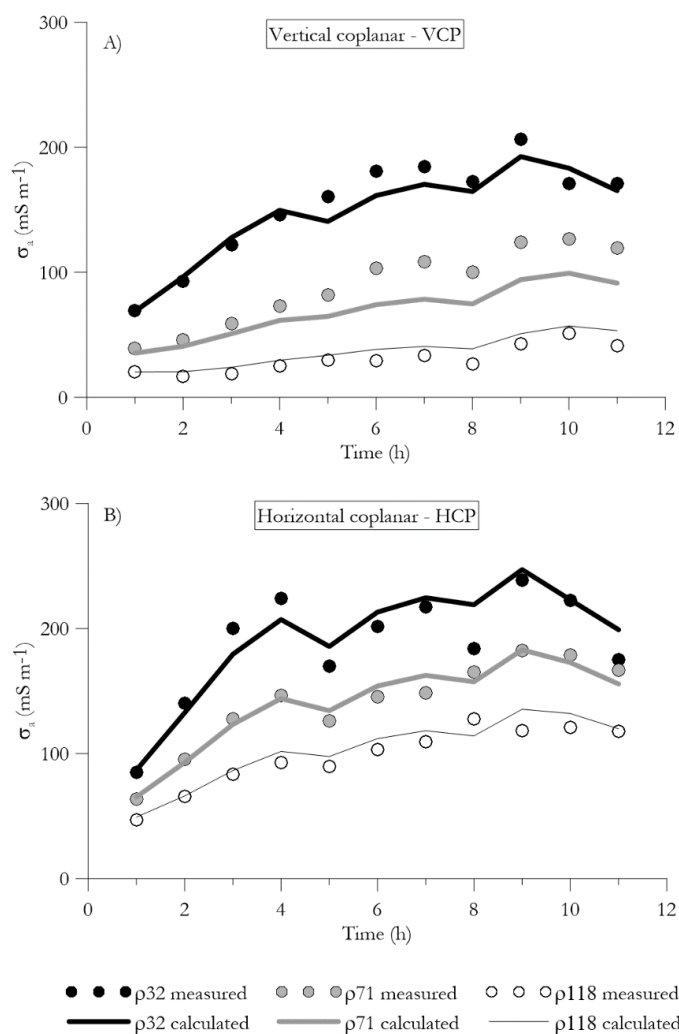


Figure 7. Soil water retention (A) and unsaturated hydraulic conductivity (B) curves, estimated from the TDR and EMI measurements at 20 cm and 40 cm depths.

4.2. Solute Infiltration – 2nd Experiment

4.2.1. Time-lapse σ_a data and estimation of σ_b distribution

Figure 8 shows the σ_a data collected during the solute infiltration experiment. Again, as for the water infiltration experiment, both VCP and HCP modes show a relatively similar pattern of σ_a values with ρ_{32} and ρ_{118} being the highest and lowest respectively. HCP mode shows higher values on average compared to the VCP mode. Similarly, to the water infiltration experiment, σ_a increases consistently during the first three hours of the experiment, then it does not change significantly or consistently until the end of the experiment. Much higher ranges of σ_a variations were measured in both VCP and HCP configurations, with σ_a values ranging in 20-200 and 50-250 mS m⁻¹ respectively.



422

423 Figure 8: σ_a values observed during the solute infiltration experiment. (A) VCP, (B) HCP. The
 424 symbols represent the measured data whereas the lines represent the values calculated after the
 425 inversion.

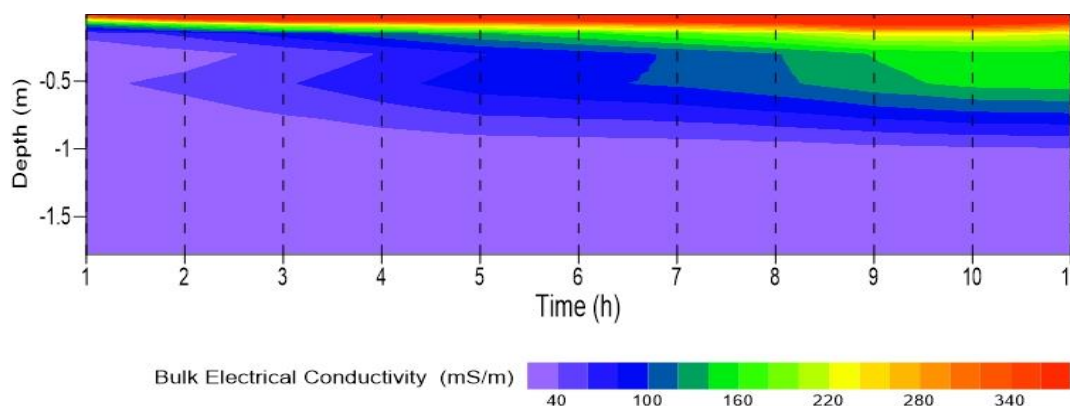
426

427 Figure 9 depicts the σ_b evolution for the solute infiltration experiment, obtained by time-lapse
 428 inversion of σ_a data. The results show the rapid evolution of the conductive zone to the soil profile
 429 shortly after the irrigation started. In comparison to the obtained σ_b in the 1st experiment, the results



430 reveal significantly higher soil conductivity in topsoil but a much slower evolution. The
 431 conductivity of the top layer exceeds 300 mS m^{-1} shortly after the irrigation. The higher topsoil
 432 conductivity results from injection of high-saline water (about 15 dS m^{-1}) that dramatically
 433 increases soil conductivity whereas the smaller evolution of the conductive zone is caused by
 434 significantly slower concentration propagation into the soil profile.

435



436

437 Figure 9. Time evolution of bulk electrical conductivity (σ_b) during the solute infiltration
 438 experiment.

439

440 4.2.2. Comparison between TDR measurements and EMI-based σ_b and $[Cl^-]$ distribution

441 Figure 10 shows the comparison between the σ_b values obtained by the TDR measurements
 442 and those obtained from the EMI inversion (Fig. 9) during the 2nd experiment. As discussed above,
 443 this comparison is to provide an insight into the potential of the EMI survey and inversion process
 444 in monitoring a solute transport experiment into a soil profile. The comparison shows a similar
 445 time pattern of σ_b variability, but in general, the EMI model slightly underestimates the σ_b obtained
 446 by TDR. The results of this comparison agree with the 1st experiment where, again, the EMI-based



447 σ_b are lower compared to those measured by the TDR. In contrast to the 1st experiment, the
 448 differences between the two techniques and in terms of the absolute σ_b values are of minor concern.
 449 This is expected to be due to the larger conductivity contrast that tracer introduced into the soil
 450 profile in the 2nd experiment which became easier to detect by using the EMI sensor. On the other
 451 hand, the TDR probes show more fluctuations in σ_b measurements, especially at 20 cm. We
 452 attribute these fluctuations to the smaller volume of investigation of the TDR probes which are
 453 very sensitive to the process taking place very close to the probe and, therefore, strongly influenced
 454 by small-scale local variability.

455 The next step in the procedure allows us to determine the distribution of Cl^- concentrations by
 456 both TDR and EMI sensors. TDR-based Cl^- distributions were obtained directly in the field from
 457 a direct measurement of the impedance Z along the TDR transmission line embedded in the soil.
 458 As for the EMI-based Cl^- concentrations, a forward HYDRUS-1D simulation was carried out using
 459 the EMI-based hydraulic properties obtained from the 1st experiment and reported in Table. 1 to
 460 estimate the water content distributions in correspondence with the EMI measurement times of the
 461 2nd experiment. These water contents, combined with the available σ_b distribution obtained from
 462 the EMI inversion, allowed us to obtain the σ_w distributions (through the θ - σ_b - σ_w calibration
 463 relationship) for both depths and, consequently, the Cl^- distributions. Finally, the latter was used
 464 again for estimating the longitudinal dispersivity of the two soil layers investigated (Sect. 4.2.3.).

465

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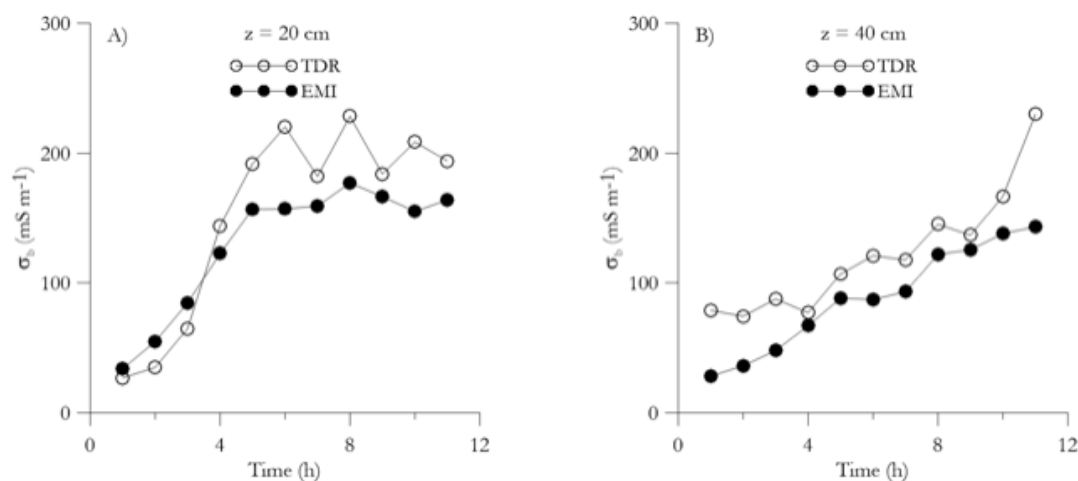


Figure 10. σ_b evolution estimated by TDR and EMI measurements at 20 cm (a) and 40 cm (b) depth.

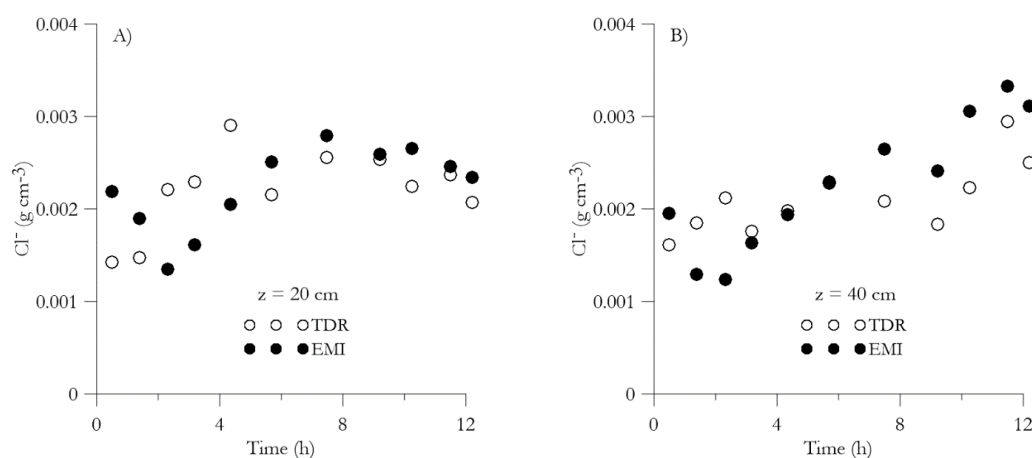


Figure 11. Cl^- distributions inferred from EMI and TDR measurements.

Figure 11 shows the Cl^- distributions inferred from EMI compared to the TDR measurements. The comparison suggests a good agreement between the two time series. The EMI-based concentrations underestimate the TDR-based ones by 4% and by 7% at 20 cm and 40 cm depths,



475 respectively. The time evolution of the two data series reveals marked differences, as shown by
476 the very different correlation: $r = -0.04$ for the 20 cm depth and $r = 0.70$ for the 40 cm depth. The
477 difference between the two data series at both depths can be mostly explained by the differences
478 between σ_b distributions shown in Fig. 10. Additionally, another point of difference may arise from
479 the assumption that the water content distribution obtained from the HYDRUS-1D simulation can
480 be used as a substitute for the water content measurements, in order to obtain $[Cl^-]$ from the EMI
481 readings. However, this is different compared to the direct measurements of TDR in the 2nd
482 experiment and therefore introduces more mismatch between $[Cl^-]$ plots.

483

484 4.2.3. Estimation of longitudinal dispersivity

485 Inverse HYDRUS-1D simulations were conducted using concentration data provided by both
486 the TDR and EMI results, in order to estimate the longitudinal dispersivity λ for both Ap and Bw
487 horizons. The results are reported in Table 1. TDR-based and EMI-based procedures provide
488 similar values of λ . Specifically, for the Ap horizon, the obtained values agree with those
489 frequently found in the literature for either large columns or field-measured dispersivity (e.g.,
490 Vanderborght and Vereecken, 2007; Coppola et al., 2011b). The TDR and EMI-based estimation
491 of dispersivity for the Bw horizon shows one order of magnitude lower values compared to the Ap
492 horizon. These values are more consistent with values measured in the laboratory (Coppola et al.,
493 2009).

494



505 5. CONCLUSION AND OUTLOOK

506 In this study, we carried out two sequential water infiltration and solute transport experiments
 507 and conducted time-lapse EMI surveys to examine how well this methodology can be used to i)
 508 monitor water content dynamic after irrigation and to estimate the soil hydraulic van Genuchten–
 509 Mualem parameters from the first experiment and ii) to monitor solute concentration, C , and to
 510 assess solute dispersivity. We then compared the obtained results to those estimated by direct TDR
 511 and tensiometer probes measurements. Based on our study, the following main conclusions can be
 512 drawn:

513

514 1. The EMI-based estimation of θ can detect the similar water content evolution in time when
 515 compared to direct TDR measurements in the 1st experiment, however, a significant
 516 underestimation was observed in the EMI-based estimation of θ . This is expected when we
 517 compare σ_b evolution from the inversion of σ_a data with the TDR-based σ_b measurements.
 With regard to the 2nd experiment, a similar time pattern of σ_b variability can also be seen
 between the two approaches. However, the differences between the two approaches are of
 minor concern in both σ_b distribution and $[Cl^-]$. We attribute the smaller underestimation of
 σ_b distribution and $[Cl^-]$ in the 2nd experiment to the larger conductivity contrast that tracer
 introduced into the soil profile in the 2nd experiment which became easier to detect by using
 the EMI sensor.

514 2. The proposed methodology for the estimation of vG-M parameters proved to be effective for
 515 both Ap and Bw horizons. The overall EMI-based underestimation of θ did not impact the
 516 hydraulic conductivity curves significantly as the hydraulic conductivity is the main function
 517 of the variation of θ . On the other hand, this underestimation resulted in lower saturated



518 water content which also appeared in the water retention curve. The overall approach shows
 519 the high potential of the EMI sensor to replace TDR and tensiometer probes in the field-scale
 520 assessment of soil hydraulic properties. In practice, one could monitor a relatively short
 521 infiltration experiment with an EMI sensor and use the water content estimations in an
 522 inversion procedure to estimate the hydraulic properties. The latter can be simply converted
 523 to more accurate water content distribution by direct measurement of the actual saturated
 524 water content at the end of the experiment using TDR probes or even by taking samples and
 525 laboratory measurements.

526 3. In terms of the longitudinal dispersivity, λ , there was a very good agreement between EMI-
 527 based and TDR-based estimation for both Ap and Bw horizons. The finding results are also
 528 in very good agreement with previous in-situ and laboratory measurements which suggests
 529 that the proposed methodology can be used in the field-scale assessment of the longitudinal
 530 dispersivity, λ which is indeed an important parameter in soil salinity simulations in salt-
 531 affected regions across the world. However, this method requires that the hydraulic
 532 properties of the investigated soil at the scale of concern be assessed prior to the application
 533 of this method to discriminate the contribution of water content and concentration in the
 534 EMI-based σ_b estimation.

535 4. The application of EMI for detailed investigation of the infiltration process has several
 536 limitations apart from the overall underestimation of water content and concentration and
 537 requires further investigation. Resolving the wetting zone during the water injection is one
 538 source of uncertainty in this approach. The water content sharply decreases with depth in
 539 this zone to near the initial water content of the soil and causes dramatic resistivity variation.
 540 In addition, a very shallow resistive bedrock exists in the study site which added to the



541 complexity of resolving three zones with very different resistivity. The limited number of σ_a
542 measurements (total of 6) is not sufficient for recovering the sharp σ_b variability that takes
543 place during the infiltration. In addition, a smoothness constraint was performed in the
544 inversion process to stabilize the inversion process which further smooths the layer
545 boundaries in this approach. Measuring σ_a at different heights enables us to collect more σ_a
546 data to better resolve changes that occur over short depth increments. More importantly, the
547 application of a coupled Hydro-Geophysical approach (e.g. Hinnell et al. 2010; Huisman et
548 al. 2010) can improve the estimation of the parameters by considering all of the hydrologic
549 and geophysical data in a single inversion. In the coupled approach, geophysical data are not
550 inverted individually and a regularization/smoothness constraint is no longer required to
551 stabilize the geophysical component of the inverse problem.

552 5. Water irrigation and soil salinity management and thus hydrological investigations are
553 usually large-scale challenges. The EM method is a non-invasive, fast, and cost-effective
554 technique, covering large areas in less time and at a lower cost. Our study reveals the
555 potential of this method for hydrological studies on large scales. However, our study was
556 limited to a controlled experiment on a plot scale. More investigations have to be conducted
557 in this area to evaluate the potential of EMI sensors under different soil conditions and within
558 the larger 2D and 3D investigations to further address the limitations of this methodology at
559 desired field scale. Our study also shows that we cannot use geophysical imaging alone and
560 we need to use other in-situ data to support Hydro-Geophysical approach. Last but not least,
561 proper estimation of soil hydraulic and hydrodispersive properties relies on an appropriate
562 understanding of both geophysical and hydrogeological data and modeling approaches and
563 requires close collaboration of geophysicists and hydrologists.



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