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# Water Table and Permeability Estimation from Multi-Channel Seismoelectric Spectral Ratios

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## Key Points:

- Multi-channel seismoelectric spectral ratios are sensitive to the water table depth and the permeabilities of shallow layers
- Broad learning neural network is introduced to perform the inversion efficiently
- This study allows us to monitor the water table depth from the ground surface for an otherwise pre-defined model

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## 33 **Abstract**

34 Recent developments in predicting and interpreting seismoelectric signals suggest a great potential  
35 for studying near-surface hydrogeological properties, particularly in the vadose zone. Previous  
36 studies have revealed that the seismoelectric spectral ratios obtained from earthquake-triggered  
37 seismoelectric data contain valuable hydrogeological information concerning porous media (e.g.,  
38 permeability, porosity, fluid viscosity, and salinity). This study introduces Multi-Channel  
39 SeismoElectric Spectral Ratios (MC-SESRs) by considering an active seismic source acting on the  
40 ground surface. The frequency- and saturation-dependent excess charge density is adopted to  
41 calculate the cross-coupling coefficients. Applying a supervised learning task based on a flat neural  
42 network, the so-called “broad learning” model, to map and extract the features of MC-SESRs data,  
43 we seek to determine the permeability and the water table depth. Our results indicate that (1) MC-  
44 SESRs are sensitive to the water table depth and permeability; (2) using more traces of SESRs data  
45 for inversion can increase accuracy; (3) the changing water table can be rapidly determined by the  
46 MC-SESRs by resorting to the broad learning inverse model, and it can attain an excellent accuracy  
47 while disturbed by data noise and misspecified model parameters (e.g., porosity and permeability)  
48 with errors of up to 20%. The proposed MC-SESRs inversion has potential applications for non-  
49 invasive monitoring in shallow porous media (e.g., frost thawing and geothermal upwelling).

## 50 **Plain Language Summary**

51 A seismic source acting on the ground or occurring in porous materials containing water will  
52 generate seismic and electromagnetic field waves. The spectral ratios between the electric field  
53 and the seismic field are defined as SeismoElectric Spectral Ratios (SESRs), which are sensitive  
54 to physical properties' contrasts at layer boundaries (e.g., water table and hydrogeological and/or  
55 lithological layer boundaries). Applying SESRs to reconstruct hydrogeological parameters  
56 eliminates the need to know the seismic source function, which greatly facilitates quantitative  
57 interpretation. However, SESRs are often acquired by natural earthquakes in previous studies. It  
58 limits interpreting SESRs to one-trace data. This study uses an active seismic source to obtain the  
59 Multi-Channel SESRs (MC-SESRs). We conduct several experiments on synthetic MC-SESRs  
60 data by using a neural network to obtain water table depths and permeabilities for a layered Earth  
61 model. Our results show that the trained neural network can instantly predict the time-variant water  
62 table depths accurately. This study indicates that the quantitative interpretation of MC-SESRs data

63 allows for effective and rapid characterization of near-surface hydrogeological properties and also  
64 provide a possible approach for the non-invasive monitoring of hydrogeological variations in  
65 shallow porous media by using controllable source.

66

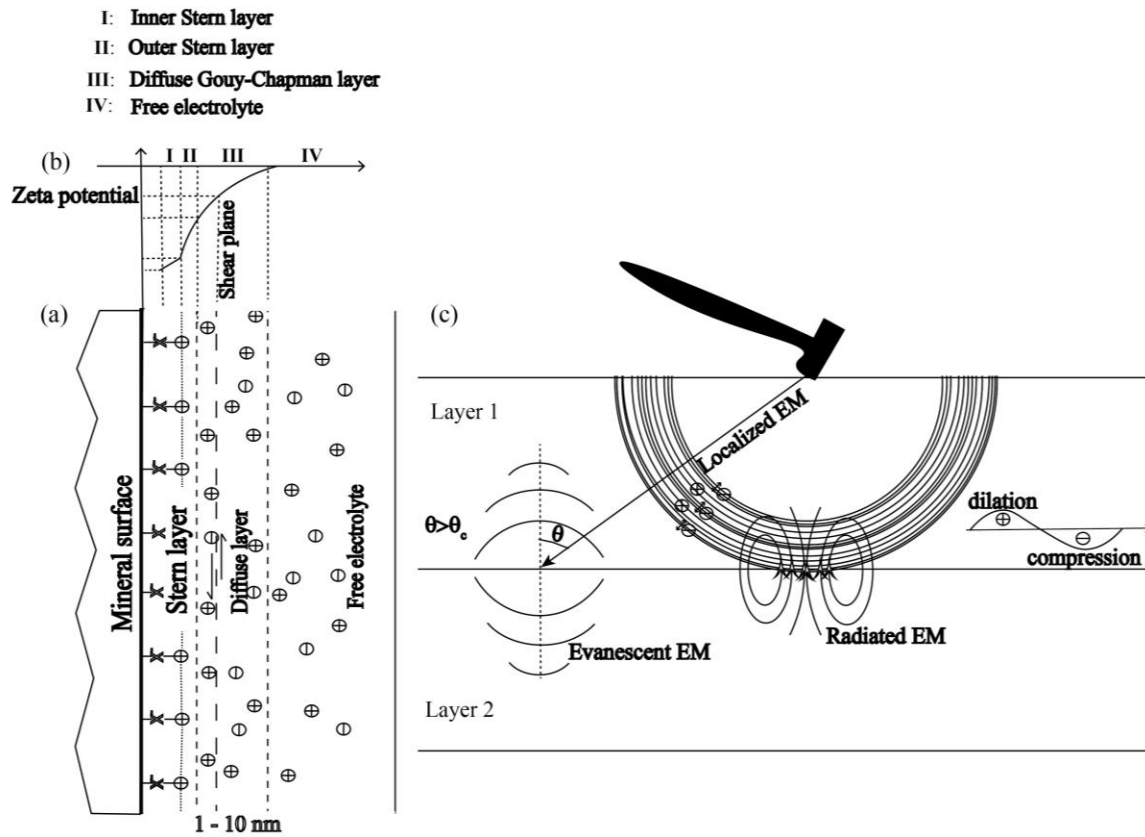
67 **Keywords** Hydrogeophysics; Seismoelectric coupling; Vadose zone; Water table monitoring;  
68 Seismoelectric spectral ratios; Broad learning

## 69 **1. Introduction**

70 In porous media, the surface of the solid grains (e.g., silicate minerals) is typically  
71 negatively charged due to fluid-mineral interactions (Glover & Jackson, 2010; Hunter, 1981; Revil  
72 et al., 2015). Considering the electrical double layer (EDL) model at the microscopic scale (1 - 10  
73 nm) (Figure 1a), a portion of the counterions (cations for negatively charged mineral surfaces)  
74 coats the interface between the mineral surface and pore fluid forming the Stern layer while the  
75 remaining excess charges are distributed in the diffuse Gouy-Chapman layer (Glover & Jackson,  
76 2010; Revil & Jardani, 2013). There is a shear plane in the diffuse Gouy-Chapman layer, beyond  
77 which the pore fluid and ions can move relative to the solid frame. As shown in Figure 1b, the  
78 electrical potential at the shear plane is defined as the Zeta potential (Hunter, 1981; Jougnot et al.,  
79 2020). The Zeta potential is commonly used to estimate the electrokinetic coupling coefficient,  
80 which characterizes the relationship between electrical and hydraulic potential differences  
81 associated with fluid flow within a porous medium (Hunter, 1981). Note that all acronyms used in  
82 this paper are listed in Table A1 of Appendix A.

83 Relative motions occur during the passage of seismic wavefields. Due to the electrokinetic  
84 effect, this process may generate streaming currents and natural electric fields (Pride, 1994; Revil  
85 et al., 2015; Revil & Linde, 2006). This process is commonly called seismoelectric (SE)  
86 conversion. The SE signals contain valuable information concerning the physical properties of  
87 both the pore fluid and the solid skeleton. The SE method can be used to determine  
88 hydrogeological properties provided the data measured on the ground surface or in boreholes are  
89 properly interpreted (Revil et al., 2012). During the past two decades, the SE method has seen  
90 significant development through (1) theoretical studies (e.g., Huang, 2002; Jougnot & Solazzi,  
91 2021; Monachesi et al., 2018; Solazzi et al., 2022; Thanh et al., 2022), (2) numerical modeling  
92 approaches (e.g., Garambois & Dietrich, 2002; Grobde & Slob, 2016; Haines & Pride, 2006; Hu

93 & Gao et al., 2011; Jougnot et al., 2013; Ren et al., 2016a, b; Zheng et al., 2021), (3) physical  
94 laboratory experiments (e.g., Bordes et al., 2015; Devis et al., 2018; Wang et al., 2020; Zhu &  
95 Toksöz, 2013), and (4) field measurements (e.g., Butler et al., 2018; Dupuis & Butler, 2006;  
96 Garambois & Dietrich, 2001; Rabbel et al., 2020; Thompson & Gist, 1993). As the understanding  
97 of SE signals grows, this method is of increasing interest to researchers in near-surface geophysics  
98 (e.g., Grobde et al., 2020). The electromagnetic (EM) wave fields originating from seismic  
99 excitations are regarded as a superposition of three types of patterns (Figure 1c): (1) localized SE  
100 field waves accompanying seismic waves in porous media, which are also commonly referred to  
101 as coseismic electric field waves (Bordes et al., 2015; Jougnot et al., 2013; Pride & Garambois,  
102 2002); (2) radiation waves induced on interfaces or directly converted from a seismic source  
103 (Dupuis et al., 2007; Haartsen & Pride, 1997; Garambois & Dietrich, 2002; Pride & Haartsen,  
104 1996) and (3) evanescent waves generated on interfaces if the seismic incident angle is larger than  
105 the critical angle (Butler et al., 2018; Dzieran et al., 2019; Ren et al., 2016a; Yuan et al., 2021;  
106 Zheng et al., 2021). The generation of interfacial radiation and evanescent SE waves results from  
107 property contrasts at an interface (Garambois & Dietrich, 2002; Ren et al. 2016a, b). Interfacial  
108 radiation SE waves and evanescent SE waves offer a way to examine permeability or porosity  
109 contrasts (Dzieran et al., 2019, 2020), parameters determining the soil moisture characteristic  
110 (Zyserman et al., 2017), strong saturation contrasts such as the water table (Bordes et al., 2015;  
111 Warden et al., 2013), and other parameters (e.g., Archie's parameters, density, bulk, and shear  
112 modulus).



113

114 **Figure 1.** Schematic illustration of the generation of electromagnetic waves by seismoelectric  
 115 conversion. (a) and (b) Electrical double layer and the corresponding electrical potential  
 116 distribution. (c) Generation of localized, interfacial radiated, and evanescent electromagnetic  
 117 wavefields due to an active seismic source.

118 Based on numerical simulation studies, Ren et al. (2016b) put forward the idea that  
 119 evanescent SE waves could be the main contribution to EM signals observed during earthquakes.  
 120 This idea was later adopted by Dzieran et al. (2019) to investigate earthquake-triggered SE signals  
 121 in data from Northern Chile. They show that the SeismoElectric Spectral Ratios (SESRs), defined  
 122 as the ratios between the absolute values of the electric field and the seismic acceleration in the  
 123 frequency domain, have a site-specific frequency dependence with a decreasing amplitude with  
 124 increasing frequency. Dzieran et al. (2019) explain this trend by the fact that the amplitudes of  
 125 evanescent SE waves decay approximately with  $\exp(-\omega p \Delta z)$ , where  $\omega$  is the angular frequency,  $p$   
 126 is the EM wave slowness, and  $\Delta z$  is the separation in depth between the receiver and the interface  
 127 (Ren et al. 2018). Dzieran et al. (2019, 2020) successfully apply the SESRs to interpret shallow  
 128 layered porous media's porosity and fluid salinity. However, Dzieran et al. (2020) state that the

129 SESRs are less sensitive to permeability variations. Inspired by Dzieran et al. (2019, 2020), this  
130 study extends the applications of SESRs data in several ways.

131 First, we change the strategy of calculating the SE coupling coefficient. Dzieran et al.  
132 (2019, 2020) calculate the electrokinetic coupling coefficient defined by Pride (1994), accounting  
133 for the Zeta potential. Instead, we rely on the effective excess charge density to calculate the  
134 electrokinetic coupling coefficient (e.g., Revil & Mahardika, 2013; Revil et al., 2015). Both in  
135 saturated and partially-saturated conditions, the effective excess charge density is highly correlated  
136 with permeability (Guarracino & Jougnot, 2018; Jougnot et al., 2020; Soldi et al., 2019). At low  
137 frequencies, the ratio of the effective excess charge density at partial water saturation to the excess  
138 charge density at full saturation is proportional to the reciprocal of water saturation under the  
139 assumption of a thick EDL model (Linde et al., 2007a; Revil et al., 2007). To account for frequency  
140 dependence, we adopt an approximate empirical formulation by using the relaxation time to relate  
141 the quasi-static to dynamic electrokinetic coupling coefficient proposed by Revil & Mahardika  
142 (2013), which has been tested by experimental measurements and other approaches (Jougnot &  
143 Solazzi, 2021).

144 Second, we consider the case of having both the seismic source and sensors located near  
145 the ground surface, which is very common in active-source SE field measurements (e.g., Butler et  
146 al., 1996, 2018; Dupuis et al., 2007; Garambois & Dietrich, 2001; Mikhailov et al., 1997;  
147 Thompson & Gist, 1993). Three-dimensional SE forward modeling algorithms using the  
148 reflectivity method (e.g., Garambois & Dietrich, 2002; Grobbe & Slob, 2016; Haartsen & Pride,  
149 1997; Ren et al., 2007, 2010) to calculate full waveform simulations for layered media suffer from  
150 highly time-consuming computations when the source and receivers both lie very close to surface.  
151 As the computation of full waveforms relies on numerical integration in the wavenumber domain,  
152 the integrand oscillates strongly with the wavenumber when the depth difference between the  
153 source and the receiver is small, which may cause a slow convergence. Zheng et al. (2021) solved  
154 this convergence problem by adopting the peak-trough averaging method (Zhang et al., 2001,  
155 2003), which selects peak and trough values in a stably oscillating sequence to apply the repeated  
156 average method (Dahlquist & Björck, 1974). Hence it offers an accurate and efficient tool for  
157 active-source SE forward modeling. This allows us to deal with any source-receiver geometries,  
158 particularly ground-based seismic sources. The Amplitude Variation versus Offset (AVO) method  
159 based on multi-channel observation has been widely applied in oil and gas exploration (Rutherford

160 & Williams, 1989). Multi-channel measurements can also be implemented in SE field experiments  
161 for stratified sediments. For example, Butler et al. (2018) presented that the multi-channel high-  
162 resolution EM field data, illustrating multiple modes of SE signals, providing information on  
163 subsurface porous materials complementary to that provided by multi-channel seismic reflection  
164 data. Moreover, Rabbel et al. (2020) document the potential of using the interfacial SE responses  
165 to map the water table by comparing the multi-channel SE measurements with other geophysical  
166 measurements, such as ground-penetrating radar and traditional seismic recordings. Inspired by  
167 AVO and SESRs, we propose a Multi-Channel SESRs (MC-SESRs) method that, in addition to  
168 frequency variations, makes use of the variations of SESRs with respect to the source-receiver  
169 offsets. Thus, we can use more spatial information of SESRs data in the inversions and obtain an  
170 improved reconstruction accuracy.

171 Third, the SESRs are determined by different parameters in different complicated non-  
172 linear ways. For example, the water table variations affect the water saturation distribution, which  
173 determines the effective permeability (e.g., Mualem, 1976; van Genuchten, 1980), the permittivity  
174 (e.g., Linde et al., 2006), the electrical conductivity, the electrokinetic coupling coefficient (e.g.,  
175 Warden et al., 2013; Revil & Mahardika, 2013; Zyserman et al., 2017), the bulk density, the elastic  
176 moduli, the seismic velocity (e.g., Mao et al., 2022; Solazzi et al., 2021) and so on. Dzieran et al.  
177 (2019) mentioned that inverse modeling of SESRs may need a more advanced approach compared  
178 to the conventional linearized inversion algorithm used in their work. Machine learning, which is  
179 enjoying increasing interest in geophysics, may offer a corresponding option.

180 In this study, we rely on the broad learning (BL) model to invert hydrological parameters  
181 using MC-SESRs data. The BL system proposed by Chen and Liu (2017) is a flat neural network  
182 with a single lateral layer neural network, in contrast to deep structured neural networks. It is  
183 developed from the Random Vector Functional Link Neural Network (RVFLNN) (Pao et al., 1994)  
184 to apply an enhancement layer to link the input and output. Broadly expanding the enhancement  
185 nodes may enhance the capacity to approach non-linear problems. It only needs to learn the matrix  
186 weights of the link between the enhancement layer and output. Other matrix weights are randomly  
187 generated. Thus, the RVFLNN is a flat net without hidden layers, which avoids overtraining the  
188 neural network with many adjustable hyperparameters (Pao et al., 1994). Correspondingly, the BL  
189 structure improves the RVFLNN by adding a mapping feature layer to replace the original input  
190 based on the sparse autoencoder. Hence the BL structure first captures the features of input data in

191 the mapping feature layer. Since the BL network structure is fixed, its main advantage is that it  
192 avoids elusive complicated deep architectures and iterative training processes (Gong et al., 2022).  
193 Its efficient capacities for processing noisy time series and text classifications have been verified  
194 (Chen & Liu, 2017; Du et al., 2020; Feng et al., 2019; Gong et al., 2022).

195 Most recently, Yang et al. (2022, 2023) applied the BL neural network to Rayleigh wave  
196 inversion. Considering a 1-D Earth model, Yang et al. (2022) examined the thickness and shear-  
197 wave velocity ranges of each layer by the well-trained BL neural network. Then they used the  
198 optimal ranges as the search space of a Bayesian approach to complement the parameter  
199 optimization. Their results indicated that this two-stage approach can provide more accurate shear-  
200 wave velocity models than without using a priori search space estimated by a BL model. Yang et  
201 al. (2023) also verified that using the BL approach to Rayleigh wave inversion may achieve a  
202 comparable accuracy but consume less training time than deep convolutional neural networks. In  
203 this study, we aim to determine hydrogeological parameters (water table depth and shallow layer  
204 permeabilities) under partially-saturated conditions by MC-SESRs data. For a specific investigated  
205 area whose layered structure had been determined, the well-trained BL model can, if fed with MC-  
206 SESR data, estimate the water table depth and update the permeability in the shallow layer in a  
207 quasi-instantaneous manner. Due to its high training efficiency, BL can easily be retrained to  
208 optimize the network when more MC-SESRs data is obtained. This study may provide a new  
209 monitoring strategy for obtaining the water table depths using the time-lapse MC-SESRs data. It  
210 also has the potential application in long-term observations for assessing groundwater storage and  
211 monitoring volcanic activities.

212 This paper is structured as follows. Section 2 describes the basic SE coupling equations,  
213 numerical simulation of the SE data, and our inversion framework. Section 3 focuses on analyzing  
214 the sensitivity of permeability and depth of water table (dwt) to MC-SESRs. Section 4 tests the  
215 performance of the BL neural network and presents the inversion results. Section 5 discusses the  
216 inversion results, and we provide conclusions in Section 6.

217 **2. Methodology**218 **2.1. Cross-coupling equations**

219 For fluid-saturated isotropic porous media, the cross-coupled constitutive transport  
 220 equations, including macroscopic Ohm's and Darcy's Law, can be expressed in the frequency  
 221 domain through the following governing equations (Pride, 1994; Pride & Haartsen, 1996; Revil &  
 222 Mahardika, 2013):

$$\mathbf{J} = \sigma^*(\omega)\mathbf{E} + L^*(\omega)(-\nabla p_f + \omega^2 \rho_f \mathbf{u}_s), \quad (1)$$

$$-i\omega \mathbf{w} = L^*(\omega)\mathbf{E} + \frac{k^*(\omega)}{\eta_w}(-\nabla p_f + \omega^2 \rho_f \mathbf{u}_s), \quad (2)$$

$$-p_f = C \nabla \cdot \mathbf{u}_s + M \nabla \cdot \mathbf{w}, \quad (3)$$

$$\mathbf{T} = \left[ \left( K_G - \frac{2}{3}G \right) \nabla \cdot \mathbf{u}_s + C \nabla \cdot \mathbf{w} \right] \mathbf{I} + G(\nabla \mathbf{u}_s + \nabla \mathbf{u}_s^T), \quad (4)$$

$$-\rho_b \omega^2 \mathbf{u}_s - \rho_f \omega^2 \mathbf{w} = \left( K_G + \frac{4}{3}G \right) \nabla(\nabla \cdot \mathbf{u}_s) - G \nabla \times \nabla \times \mathbf{u}_s + C \nabla(\nabla \cdot \mathbf{w}) + \mathbf{F}, \quad (5)$$

223 where Equations 1-2 describe the electrokinetic cross-coupling relationship between the electric  
 224 field  $\mathbf{E}$  (V/m) and the volume-averaged fluid filtration displacement  $\mathbf{w}$  (m) =  $\phi(\mathbf{u}_f - \mathbf{u}_s)$ , which  
 225 is defined by the porosity  $\phi$  (m<sup>3</sup>/m<sup>3</sup>) and the volume-averaged fluid and solid displacements ( $\mathbf{u}_f$   
 226 and  $\mathbf{u}_s$ ). The subscripts 'f' and 's' designate fluid and solid properties, respectively. We consider  
 227 a time-harmonic disturbance varying as  $e^{-i\omega t}$  with  $i = \sqrt{-1}$  the imaginary unit,  $\omega = 2\pi f$  the  
 228 angular frequency in rad/s, and  $f$  (Hz) the frequency. The superscript '\*' indicates that a property  
 229 is frequency-dependent and hence complex.  $k^*(\omega)$  thus denotes the frequency-dependent  
 230 permeability (m<sup>2</sup>). Permeability reflects the ability of porous media to allow fluid to flow through  
 231 the pores. Equations 3 and 4 describe the poroelastic relations (Biot, 1956, 1962a, b) with  $\mathbf{I}$   
 232 denoting the identity matrix. The parameters  $C$  (Pa) and  $M$  (Pa) are associated with the elastic  
 233 moduli (Pride, 1994).  $K_G$  (Pa) and  $G$  (Pa) denote the undrained bulk modulus and shear modulus  
 234 of the solid skeleton.  $\rho_b$  (kg/m<sup>3</sup>) and  $\mathbf{F}$  (N) in Equation 5 are the mass density of the porous

235 material and the body force applied on the bulk material, respectively. All parameters and their  
 236 units used in this study are listed in Table A2 of Appendix A.

237 Due to harmonic variations of the bulk-stress tensor  $\mathbf{T}$  (N/m<sup>2</sup>) and the pore fluid pressure  $p_f$   
 238 (Pa), the flow changes from the viscous laminar regime to the inertial laminar regime beyond the  
 239 critical or transition frequency (Revil & Mahardika, 2013; Solazzi et al., 2020, 2022). The  
 240 permeability becomes frequency-dependent and complex-valued beyond the critical frequency,  
 241 and its absolute value decreases with increasing frequency (Solazzi et al., 2020).  $\eta_w$  denotes the  
 242 dynamic viscosity of pore water ( $1.002 \times 10^{-3}$  Pa·s). The macroscopic electrical current density  $\mathbf{J}$   
 243 (A/m<sup>2</sup>) is the superposition of the conduction current density  $\sigma^*(\omega)\mathbf{E}$  and the streaming current  
 244 density  $\mathbf{J}_{ek}^*$  written by:

$$\mathbf{J}_{ek}^* = L^*(\omega)(-\nabla p_f + \omega^2 \rho_f \mathbf{u}_s), \quad (6)$$

245 in which  $\sigma^*(\omega)$ , and  $\rho_f = (1 - S_w)\rho_a + \rho_w$  denote the complex electrical conductivity (S/m) and  
 246 the fluid density (kg/m<sup>3</sup>), respectively.  $S_w$ ,  $\rho_a = 1.21$  (kg/m<sup>3</sup>) and  $\rho_w = 1000$  (kg/m<sup>3</sup>) are the  
 247 water saturation, the density of the air and pore water. Note that we consider pore water as a dilute  
 248 solution with low salinities (commonly around 0.002 mol/L) and, hence, the solute density is  
 249 neglected. For highly saline solutions (e.g., seawater, contaminated water), the mass density of the  
 250 solute would need to be included. Unless mentioned otherwise, the parameters used in this paper  
 251 refer to standard ambient conditions (1 atm and 20 °C). The presence of harmonic electric fields  
 252 usually makes the electrical conductivity of porous materials vary with frequency due to  
 253 polarization effects of electrically conductive mineral grains, interfacial electrochemistry, or  
 254 colloidal chemistry (Revil, 2013). The effective electrical conductivity in the frequency domain  
 255 can be expressed by (Revil et al., 2015):

$$\sigma^*(\omega, S_w) = F^{-1} S_w^n \sigma_w + \sigma_{sur} + i(\sigma_{quad} - \omega \epsilon_0 \kappa). \quad (7)$$

256 Therein,  $n$  denotes the saturation exponent and  $F = \phi^{-m}$  is the electrical formation factor in  
 257 Archie's first and second laws with cementation exponent  $m$  (Archie, 1942).  $\epsilon_0 = 8.85418 \times$   
 258  $10^{-12}$  F/m is the vacuum permittivity.  $\kappa$  denotes the static effective dielectric constant, which is  
 259 the function of the water saturation: (Linde et al., 2006):

$$\kappa(S_w) = \frac{(F-1)\kappa_s + S_w^n \kappa_w + (1-S_w^n)\kappa_a}{F} \quad (8)$$

260 The range of the dielectric constant for most rock-forming minerals is 4-6 and is commonly  
 261 assumed to be  $\kappa_s = 4$  for dry sand grains in near-surface measurements (e.g., Fitterman, 2015;  
 262 Knight & Endres, 2005).  $\kappa_w = 80.1$  and  $\kappa_a = 1$  represent the dielectric constants of the pore  
 263 water and the air, respectively. Based on a volume-averaging method, Equation 8 is derived from  
 264 a two-phase model (i.e. pore fluid and solid grains) by Pride (1994), accounting for the effective  
 265 pore fluid formed by water and air and combining Archie's first and second laws (Linde et al.,  
 266 2006). This equation assumes that the two fluid phases in the pore space are immiscible. The  
 267 physical relationship (Equation 8) has been previously used to simulate seismoelectric signals  
 268 (e.g., Rosas-Carbajal et al., 2020). The surface electrical conductivity  $\sigma_{\text{sur}}$  and the quadrature  
 269 electrical conductivity  $\sigma_{\text{quad}}$  in Equation 7 are related to the fraction and mobility of counterions  
 270 in the diffuse layer and in the Stern layer, respectively (Revil, 2013; Revil et al., 2015). Both  
 271 conductivities are functions of water saturation. More details of these coefficients calculated by  
 272 material properties and saturation levels, can be found in Table A3 of Appendix A.

273 Based on the EDL model (Figure 1a), Equations 1 and 2 express that the poromechanical  
 274 influence contributes to the streaming source current, and the electric field contributes to the pore-  
 275 fluid flow under the electroosmosis effect (Revil & Mahardika, 2013). The critical dynamic  
 276 parameter  $L^*(\omega)$  reflects the cross-coupling relationship. Due to the significance of frequency-  
 277 dependent cross-coupling coefficient  $L^*(\omega)$  in transport equations, its calculation has attracted  
 278 considerable attention in the recent decade (Jougnot & Solazzi, 2021; Jouniaux & Zyserman, 2016;  
 279 Soldi et al., 2020; Thanh et al., 2022; Warden et al., 2013). A popular approach is using the Zeta  
 280 potential to describe the cross-coupling coefficient (Dukhin & Derjaguin, 1974; Pride, 1994;  
 281 Warden et al., 2013; Zyserman et al., 2017). An alternative is to use the movable (effective) excess  
 282 charge density  $\hat{Q}_v^*$  ( $\text{C}/\text{m}^3$ ) and permeability to directly relate the relative flow to streaming current  
 283 generation (Revil & Linde, 2006). The cross-coupling coefficient calculated by both approaches  
 284 explains some experimental measurements (Bordes et al., 2015; Revil & Mahardika, 2013; Zhu &  
 285 Toksöz, 2013). In terms of partially-saturated conditions considering only water and air in the pore

286 space, the latter approach conveniently relates  $L^*(\omega)$  to the effective permeability and  $\widehat{Q}_v^*$  as  
 287 functions of the water saturation by (Revil & Mahardika, 2013; Soldi et al., 2020):

$$L^*(\omega, S_w) = \frac{k^*(\omega, S_w)\widehat{Q}_v^*(\omega, S_w)}{\eta_w}. \quad (9)$$

288 The frequency-dependent (dynamic) characteristics of permeability and effective excess charge  
 289 density are approximately described by the relaxation time or the angular transition frequency  
 290  $\omega_t$  (rad/s), which determines the transition from the viscous (low frequency) to inertial laminar  
 291 flow (high frequency) (Revil & Mahardika, 2013).  $\omega_t(S_w)$  is expressed as a function of water  
 292 saturation by Revil and Mahardika (2013) and Solazzi et al. (2020):

$$\omega_t = \frac{\eta_w \phi S_w}{\rho_w k_0(S_w) \tau_w(S_w)}, \quad (10)$$

293 where  $\tau_w$  denotes the tortuosity related to the topology of the pore space. The saturation-dependent  
 294 tortuosity is equivalent to  $\phi F S_w^{(1-n)}$  based on Archie's law (e.g., Niu & Zhang, 2019; Jougnot et  
 295 al., 2018; Revil et al., 2007; Revil & Jougnot, 2008). Since  $n \geq 1$  ( $1 - n \leq 0$ ), the tortuosity  
 296 increases with the decrease of water saturation (e.g., Ghanbarian et al., 2013; Jougnot et al., 2018),  
 297 while the transition frequency increases with the decrease of water saturation. Here,  $k_0(S_w)$   
 298 denotes the quasi-static ( $\omega = 0$ ) effective permeability as a function of saturation. When the  
 299 frequency-dependent effective permeability and excess charge density are considered, Equation 9  
 300 is written by (Revil & Mahardika, 2013):

$$L^*(\omega, S_w) = \frac{k_0(S_w)\widehat{Q}_{v,0}(S_w)}{\eta_w \sqrt{1 - \frac{i\omega}{\omega_t}}}. \quad (11)$$

301 There are two main approaches to describe this effective excess charge density  $\widehat{Q}_{v,0}$ : either by  
 302 volume-averaging (Linde et al., 2007a) or flux-averaging (Jougnot et al., 2012). In this work, the  
 303 excess charge density at a saturated state is estimated from permeability using (Jardani et al.,  
 304 2007):

$$\log_{10}(\hat{Q}_{v,0}^{\text{sat}}) = -0.82\log_{10}(k_0^{\text{sat}}) - 9.23. \quad (12)$$

305 The superscript ‘sat’ denotes a fully saturated condition. This empirical relationship has been  
 306 applied to various samples ranging from different salinities and lithologies even if it did not  
 307 consider the effect of salinities of pore water on the excess charge density (Jardani et al., 2007;  
 308 Jougnot et al., 2015).

309 Another empirical relationship between the voltage coupling coefficient under saturated  
 310 conditions  $C_0^{\text{sat}}$  (mV/m) and the electrical conductivity of pore water  $\sigma_w$  (S/m) is expressed as  
 311 (Linde et al., 2007b):

$$\log(|C_0^{\text{sat}}|) = -0.895 - 1.319 \log(\sigma_w) - 0.1227[\log(\sigma_w)]^2, \quad (13)$$

312 where  $\sigma_w$  is estimated by the salinity  $C_w$  (mol/L) (Sen & Goode, 1992):

$$\sigma_w = (5.6 + 0.27T - 1.5 \times 10^{-4}T^2)C_w - \frac{(2.36 + 0.099T)C_w^{\frac{3}{2}}}{1 + 0.214C_w}, \quad (14)$$

313 where  $T$  is the temperature in Celsius (°C). Thus, the voltage coupling coefficient  $C_0^{\text{sat}}$  varies with  
 314 pore water salinity. Compared with laboratory and field measurements, Equation 13 works well in  
 315 a range of  $10^{-2} - 10^{0.5}$  S/m for  $\sigma_w$ , which covers typical pore water environments (Linde et al.,  
 316 2007b, Jougnot et al., 2015; Hu et al., 2020). By changing the unit of  $C_0^{\text{sat}}$  to V/m, it can be  
 317 transformed from the static coupling coefficient  $L_0^{\text{sat}}$  (A/m<sup>2</sup>) by:

$$C_0^{\text{sat}} = -\frac{L_0^{\text{sat}}}{\sigma_0}. \quad (15)$$

318 Further,  $C_0^{\text{sat}}$  can be used to express the  $\hat{Q}_{v,0}^{\text{sat}}$  with:

$$\hat{Q}_{v,0}^{\text{sat}} = -\frac{C_0^{\text{sat}} \sigma_0 \eta_w}{k_0^{\text{sat}}}. \quad (16)$$

319 We may use Equation 12 to estimate  $\hat{Q}_{v,0}^{\text{sat}}$  under a known  $k_0^{\text{sat}}$  or we may derive  $\hat{Q}_{v,0}^{\text{sat}}$  by Equations  
 320 13-16 using the salinity of pore water (Jougnot et al., 2015). Otherwise,  $C_0^{\text{sat}}$  can be obtained by  
 321 measuring the voltage differences and hydraulic pressure differences of samples to calculate values  
 322 of  $\hat{Q}_{v,0}^{\text{sat}}$  by Equation 16.

323 For partially saturated conditions, we applied the volume-averaging method to scale  $\hat{Q}_{v,0}$  by  
 324 the effective saturation  $S_e = \frac{S_w - S_{wr}}{1 - S_{wr}}$  (Linde et al., 2007a; Revil & Cerepi, 2004; Revil et al., 2007):

$$\hat{Q}_{v,0}(S_w) = \frac{\hat{Q}_{v,0}^{\text{sat}}}{S_e}, \quad (17)$$

325 where  $S_{wr}$  (unitless) denotes the residual (irreducible) water saturation. Alternative formulations  
 326 have been derived to explicitly describe the dynamic process of  $\hat{Q}_{v,0}$  varying with water saturation  
 327 based on the characteristic pore-size distribution (Jackson, 2010; Jougnot et al., 2012; Soldi et al.,  
 328 2020; Solazzi et al., 2022). Furthermore, the frequency-dependent effective excess charge density  
 329 is calculated by applying a scaling factor  $\sqrt{1 - \frac{i\omega}{\omega_t}}$  (Revil & Mahardika, 2013), which also has been  
 330 further developed by Jougnot and Solazzi (2021) and Thanh et al. (2022).

331 Apart from the effective permeability and excess charge density, other effective parameters  
 332 (e.g., the electrical conductivity  $\sigma^*$ , the mass density of fluid  $\rho_f$ ) in Equations 1 and 2 strongly  
 333 depends on the water saturation as well. Besides, the two fluid phases in the pore space affect the  
 334 mechanical properties (e.g., the effective bulk moduli) that need to be considered in  
 335 hydromechanical modeling of the volumetric strain of porous media and the infiltration  
 336 displacement (Equations 3-5). This indicates that seismic signals could respond to variations in  
 337 water saturation. We summarize the frequency-dependent (dynamic) and saturation-dependent  
 338 parameters in Table A3 of Appendix A. More details with regard to the parameters mentioned  
 339 above as well as the derived equations can be found in Revil & Mahardika (2013).

## 340 **2.2. Multi-Channel SeismoElectric Spectral Ratios (MC-SESRs)**

341 For isotropic layered media, as the SE field and the seismic particle acceleration field are  
 342 triggered by the same seismic source, the seismic source function can be canceled when we  
 343 calculate the ratios of SE fields to the seismic acceleration fields in the frequency domain (Dzieran

344 et al., 2019). Therefore, the SESRs can be represented by the ratio of their Green's functions  
 345  $GE(\omega)$  and  $Ga(\omega)$ , which is expressed as (Dzieran et al., 2019):

$$\text{SESR}(\omega) = \frac{\mathbf{E}(\omega)}{\mathbf{a}(\omega)} = \frac{GE(\omega)}{Ga(\omega)}, \quad (18)$$

346 where  $\mathbf{E}(\omega)$  denotes the SE field spectra.  $\mathbf{a}(\omega)$  denotes the seismic ground acceleration field  
 347 spectra, which also can be replaced by the components of seismic ground velocity spectra with  
 348  $i\omega\mathbf{v}(\omega)$  or displacement spectra with  $-\omega^2\mathbf{u}(\omega)$ . The SESR indicates the ratio of Green's  
 349 functions, which contains the information of stratified porous media. The modulus of SESRs varies  
 350 with position, or offset from the seismic source, represented by:

$$\text{MC-SESR}(\omega, x_i) = \frac{|E_{x,i}(\omega)|}{|a_{x,i}(\omega)|}, \quad i = 1, 2, \dots, B \quad (19)$$

351 where  $i$  denotes the measured points and  $B$  is the total number of measured points. Here,  $E_{x,i}$  and  
 352  $a_{x,i}$  denotes the horizontal electric field and seismic ground acceleration in the frequency domain  
 353 at point  $i$ .

### 354 **2.3. Inversion framework**

355 Deterministic inverse modeling (e.g., Gauss-Newton, Conjugate Gradient, Levenberg-  
 356 Marquardt) algorithms need to construct an objective function, including the data misfit and a  
 357 regularization term. The latter depends on prior and empirical information. In weakly non-linear  
 358 problems, the iterative adjustment of model parameters using gradient-based information enables  
 359 a minimum objective function to be attained. However, it is time-consuming when we deal with  
 360 high-dimension parameter estimation, and these parameters affect the SESRs in a non-linear way.  
 361 Furthermore, such deterministic inversions might fail to recover the true model, although the  
 362 modeling data well match the observed data (Wu et al., 2021).

363 In this study, we aim to reconstruct the permeability and water table depth using the near-  
 364 surface MC-SESRs data. As the water table is affected by land-management practices,  
 365 precipitation, evapotranspiration, and other environmental changes, its depth may change with  
 366 time. Machine learning techniques may allow us to efficiently monitor the dynamic water table. A

367 large number of samples are employed to train a neural network, which can construct the mapping  
 368 process between the input data (MC-SESRs) and the output data (water table depth and  
 369 permeability). Once the neural network is well trained, we can adapt it to a specific region to  
 370 monitor variations of its water table and permeability efficiently. Deep-structured neural networks  
 371 have been employed in solving geophysical inverse problems (e.g., Laloy et al., 2021; Wu et al.,  
 372 2021), which are alternatives for the SESRs inversion. But the many hidden layers included in  
 373 such networks produce a large quantity of hyperparameters, which need large data sets and many  
 374 training epochs to be estimated. Complicated deep architectures empower the neural network to  
 375 project a more complex relationship between the input and output layers. However, the computing  
 376 time is increased due to the iterations of training epochs, and overtrained networks could result.  
 377 Chen and Liu (2017) propose a broad learning (BL) neural network that adopts a flat architecture  
 378 without a complex multilayer structure. Its network structure does not change within the training  
 379 process (Figure 2). It avoids adjusting elusive hyperparameters in the network, and its design  
 380 largely decreases the training time compared with deep networks. Broadly expanding the mapping  
 381 layer enhances the capacity of the neural network to approach complicated projecting  
 382 relationships. More important, the broadly expanding structure can be used for incremental  
 383 learning without retraining the network when additional data are available in input data (Chen &  
 384 Liu, 2017). Compared with the performance of deep structured neural networks (e.g., deep  
 385 convolutional neural networks, deep Boltzmann machines, and deep belief networks) on MNIST  
 386 and NORB data sets, Chen and Liu (2017) demonstrated that the BL system can ensure a  
 387 comparable classification accuracy while vastly reducing the training time. Recently, the BL  
 388 approach has been applied to effectively and efficiently process classification and regression  
 389 problems (Gong et al., 2022). Therefore, the BL approach is considered here to perform water  
 390 table depth and permeability inversions using MC-SESRs data.

391 As a supervised machine learning task, we need to generate a large number of training  
 392 samples. We assume the number of samples is  $N$  for training the network and the number of  
 393 inverted layers of permeability is  $L$ . If there are  $A$  frequencies and  $B$  measured points (traces) in  
 394 Equation 19, the input matrix  $\mathbf{X}$  is MC-SESRs data (Figure 2a). The output matrix  $\mathbf{Y}$  is made up  
 395 of  $N$  depths of the water table written by a vector  $\mathbf{dwt}_{N \times 1}$  and  $N \times L$  permeability matrix written  
 396 by  $\mathbf{K}_{N \times L}$  (Figure 2c). Using the neural-network architecture of the BL model (Chen & Liu, 2017),  
 397 we first need to extract the features of MC-SESRs data as the input layer (Figure 2b):

$$\mathbf{F}_i = \varphi_i(\mathbf{X}\mathbf{W}_i + \boldsymbol{\beta}_i), i = 1, 2, \dots, Q \quad (20)$$

398 where  $\mathbf{F}_i$  denotes the  $i$ th mapped feature matrix.  $\mathbf{W}_i$  and  $\boldsymbol{\beta}_i$  denote the random weighting matrix  
 399 and bias term, which are initially generated by standard uniform distributions in a range of [-1,1].  
 400 Assuming  $A \times B = C$ , the sizes of matrices of  $\mathbf{W}_i$  and  $\boldsymbol{\beta}_i$  are  $C \times P$  and  $N \times P$ , respectively. As  
 401 shown in Figure 2b,  $P$  is the number of feature nodes in each mapping feature group  $i$ .  $Q$  is the  
 402 number of mapping features. The function  $\varphi_i$  maps the sum of matrices  $\mathbf{X}\mathbf{W}_i + \boldsymbol{\beta}_i$  to [-1,1] by  
 403 normalizing the minimum and maximum value each row (1,2, ...,  $N$ ). The sparse autoencoder is  
 404 employed to shrink the input data and extract its mapping features by adapting  $\mathbf{W}_i$  (Chen & Liu,  
 405 2017). As shown in Equation 20, this feature extracting step of the input data can be replaced by  
 406 other extracting approaches from popular artificial neural networks (e.g., deep convolutional  
 407 neural networks) (Gong et al., 2022).

408 The features of input data extracted by mapping feature groups  $\mathbf{F}^Q = [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_Q]$  are  
 409 broadly expanded by  $M$  enhancement nodes with:

$$\mathbf{E}_j = \xi_j([\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_Q]\mathbf{W}_{ej} + \boldsymbol{\beta}_{ej}), j = 1, 2, \dots, M \quad (21)$$

410 where  $\mathbf{E}_j$  denotes the matrix of  $j$ th enhancement node.  $\mathbf{W}_{ej}$  and  $\boldsymbol{\beta}_{ej}$  are randomly generated  
 411 similar to Equation 20. In this study, we used the hyperbolic tangent sigmoid transfer function as  
 412 the non-linear activation function  $\xi_j(\cdot)$ . Each enhancement node is integrated to an enhancement  
 413 layer with  $\mathbf{E}^M = [\mathbf{E}_1, \mathbf{E}_2, \dots, \mathbf{E}_M]$ .

414 The output-layer hydrogeological parameters  $\mathbf{Y} = [\mathbf{dwt}, \mathbf{K}]$  and the last layer integrated by  
 415 input features and the enhancement layer are connected by a weighting matrix  $\mathbf{W}^M$ :

$$\mathbf{Y} = [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_Q | \mathbf{E}_1, \mathbf{E}_2, \dots, \mathbf{E}_M]\mathbf{W}^M, \quad (22)$$

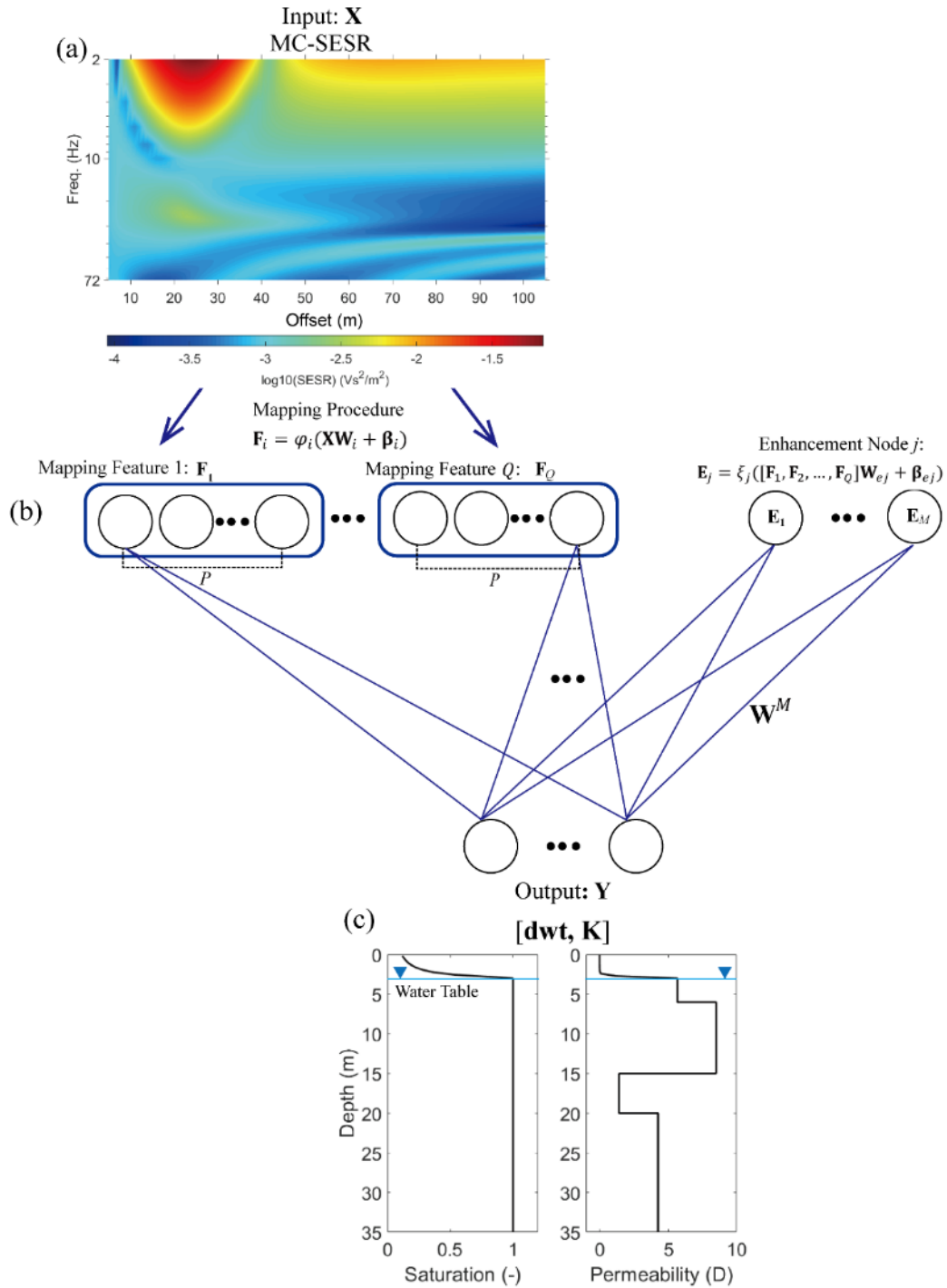
416 Therefore, the training process only needs to estimate the connected-link matrix  $\mathbf{W}^M$  through  
 417 solving the pseudoinverse matrix  $[\mathbf{F}^Q | \mathbf{E}^M]^+$ :

$$\mathbf{W}^M = [\mathbf{F}^Q | \mathbf{E}^M]^+ \mathbf{Y}. \quad (23)$$

418 Following Chen and Liu (2017), the ridge regression approximation is employed to optimize  $\mathbf{W}^M$   
 419 by fulfilling:

$$\arg \min: \|\mathbf{F}^Q \mathbf{E}^M \mathbf{W}^M - \mathbf{Y}\|_2^2 + \lambda \|\mathbf{W}^M\|_2^2, \quad (24)$$

420 where  $\lambda$  denotes a tradeoff regularization factor and  $\|\mathbf{F}^Q \mathbf{E}^M \mathbf{W}^M - \mathbf{Y}\|_2^2$  is the error term of the  
 421 training set. Except for the connected matrix  $\mathbf{W}^M$ , the remaining weight matrices in the network  
 422 are randomly generated. Consequently, we can use the well-trained network with the optimal  
 423 connected weights  $\mathbf{W}^M$  to invert MC-SESRs data. For example, if we acquired more MC-SESRs  
 424 data, we just need to replace Input  $\mathbf{X}$  with the new (untrained) data in Equation 20. By following  
 425 similar computations to the training process by Equations 20-22, we then extract the mapping  
 426 features of the inversion data and use an activation function to learn these features in the  
 427 enhancement layer. Thus, we obtain the newly mapped feature matrices and enhancement matrices.  
 428 Multiplied with the weight matrix derived from the training process (Equations 23 and 24), we can  
 429 obtain the estimated water table depth and permeability (Equation 22).



430

431 **Figure 2.** Broad learning (BL) procedure including (a) the input (MC-SESr data) layer, (b) the  
 432 mapping feature layer and the enhancement layer, and (c) the output (permeability with water  
 433 table) layer employed in this study.

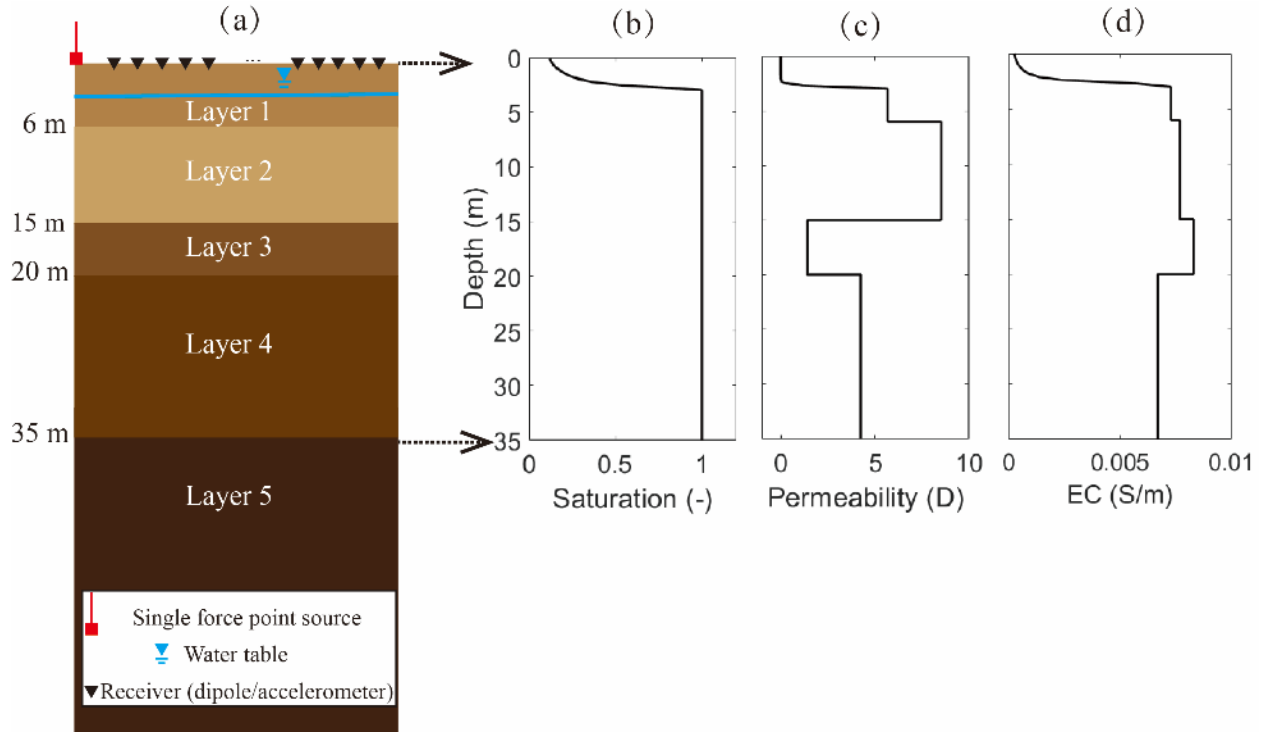
434 **3. Sensitivity Analysis**435 **3.1. Basic test model**

436 We first design a basic test model (Figure 3). It consists of five horizontal layers of porous  
 437 materials. It is assumed that the shallow two layers (layers 1-2) are mainly made up of loamy  
 438 sands, and the deeper two-layer soils (layers 3-4) with lower permeabilities considered as silty  
 439 sands. The bottom layer 5 is assumed as a known layer with lower permeability (0.01 D), porosity  
 440 (0.05), and electrical conductivity (16  $\mu\text{S}/\text{cm}$ ). These hydrogeological parameters are chosen  
 441 based on Carsel and Parrish (1988). The initial water table is set at 3 m, implying that the  
 442 shallowest layer is partially saturated (Figure 3a). The Richards' equation (Richards, 1931) is used  
 443 to solve the hydraulic problem in the vadose zone. The Mualem-van Genuchten (MVG) empirical  
 444 model (Mualem, 1976; van Genuchten, 1980) is used to estimate the relationship between the  
 445 water saturation and the effective permeability with the pore pressure. Based on the MVG model  
 446 by introducing the soil-water characteristic parameters  $\alpha_{\text{VG}}$  ( $\text{m}^{-1}$ ),  $n_{\text{VG}}$  and  $m_{\text{VG}} = 1 - 1/n_{\text{VG}}$ , the  
 447 effective water saturation  $S_e$  and the static permeability  $k_0$  at partially saturated conditions are  
 448 expressed by:

$$S_e = \frac{1}{[1 + (\alpha_{\text{VG}} |H_p|)^{n_{\text{VG}}}]^{m_{\text{VG}}}}, \quad (25)$$

$$k_0 = k_0^{\text{sat}} S_e^{\frac{1}{2}} \left[ 1 - \left( 1 - S_e^{\frac{1}{m_{\text{VG}}}} \right)^{m_{\text{VG}}} \right]^2. \quad (26)$$

449 Here, we assume that the absolute pressure head  $|H_p|$  (m) in the vadose zone is equal to the vertical  
 450 distance between its elevation and the position of the water table (Zyserman et al., 2017). The  
 451 effective electrical conductivity is calculated by Equation 7, whose formulas and the used  
 452 parameters are given in Table A3 of Appendix A and Table S1 of the Supporting Information).  
 453 The water saturation, the effective permeability, and the effective electrical conductivity of the top  
 454 four layers are presented in Figures 3b-d under the assumption that the pore water salinity is  
 455 homogeneous at  $2 \times 10^{-3}$  mol/L at 293.15 K, respectively. Note that the effect of the salinity at  
 456 this level on the fluid mass density is negligible. In contrast, the mass density of the fluid solute  
 457 should be considered in a highly saline environment (e.g., Hu et al., 2023). The specific parameters  
 458 of each layered material are given in Table 1, whose descriptions can be found in Table A2 of  
 459 Appendix A.



460

461 **Figure 3.** Basic test model and its observations. (a) Geometry, (b) water saturation, (c) effective  
 462 permeability, and (d) effective electrical conductivity in the top four layers

463

There is a vertical force point source at the ground marked with a red square in Figure 3a.

464

We assume that the seismic source function  $f_s(t)$  (N) presents as a Ricker wavelet with a peak

465

frequency  $f_p$  of 20 Hz:

$$f_s(t) = -2.506 \times 10^5 \left[ 1 - 2(\pi f_p)^2 \left( t - \frac{2}{f_p} \right)^2 \right] \exp[-(\pi f_p)^2 \left( t - \frac{2}{f_p} \right)^2]. \quad (27)$$

466

The spectrum of this zero-phase wavelet is in a range of  $\sim 70$  Hz. This wavelet and its frequency

467

band are usually considered in seismoelectric simulations (e.g., Jardani et al., 2010). Equation 27

468

is applied to calculate the body force of Equation 5 in forward modeling. Receivers are installed

469

at 0.1 m below the ground surface. The offset ranges from 5 – 105 m with 101 horizontal

470

acceleration sensors and 101 horizontal point dipoles. The offset represents the distance between

471

the source and each accelerometer or central point of each dipole. The interval of two adjacent

472

receivers is 1 m (Figure 3a). Please note that the seismic particle velocity  $\mathbf{v}(\omega)$  obtained by

473

geophones could also be used to calculate SESRs by transforming  $\mathbf{a}(\omega)$  to  $i\omega\mathbf{v}(\omega)$ . As mentioned

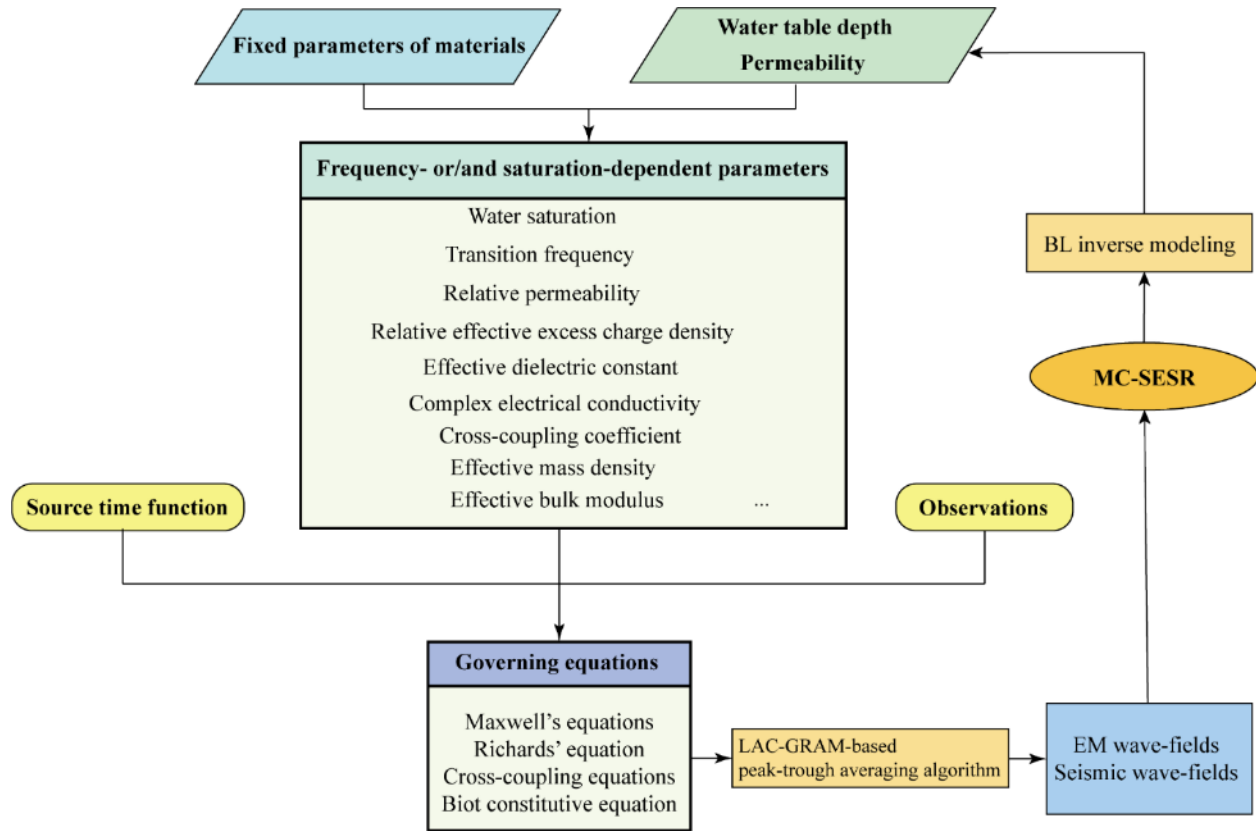
474

in Section 2.2, measuring SESRs does not require knowledge of the seismic source function, so

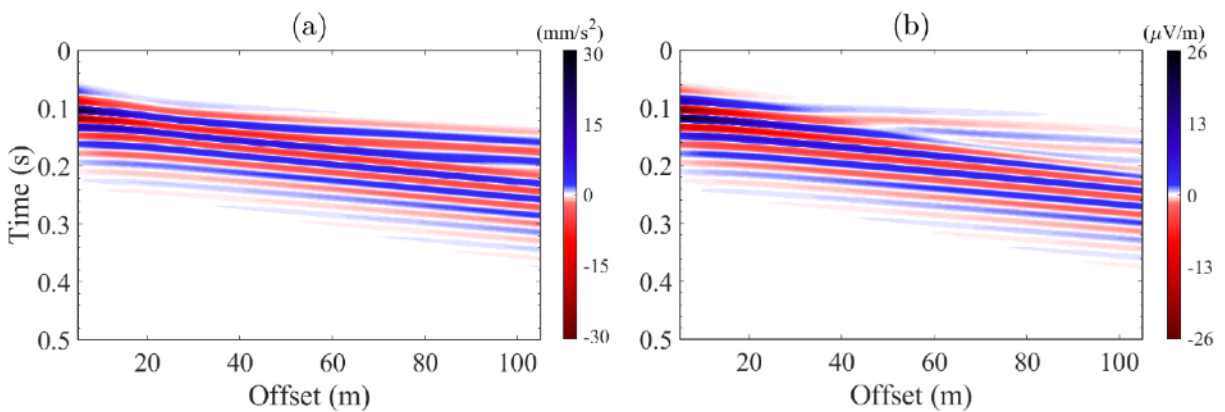
475 we would not need to know the amplitude of the seismic source. Additionally, the SE responses  
476 are proportional to the amplitude of seismic sources, either for explosive sources or weight drops,  
477 demonstrated in the field tests (Butler et al., 1999). Therefore, according to the specific prospecting  
478 conditions, this seismic source function can be replaced with other source functions. However, the  
479 seismic strength and waveform used here are adopted to illustrate that the predicted electric fields  
480 are expected to be measurable for a reasonable seismic source.

481 Based on Section 2.1, with the dynamic and saturation-dependent parameters chosen,  
482 especially the cross-coupling coefficient  $L^*(\omega, S_w)$  in Equation 11, the peak-trough averaging  
483 approach based on Luco-Apsel-Chen Generalized Reflection and Transmission Method (LAC  
484 GRTM) (Zheng et al., 2021) is applied to obtain the frequency solution of the governing equations.  
485 The wave-field components are derived from the numerical integral over the wavenumber domain.  
486 The integrand includes the Bessel function and exponential terms of fast and slow  $P$ ,  $S$ , and EM  
487 waves. Compared with the seismic wavelength, the relatively small source-receiver vertical  
488 differences make integrands more intensively oscillate. Therefore, this situation may cause a slow  
489 convergence computationally (Zheng et al., 2021). The peak-trough averaging approach uses a  
490 certain wavenumber interval in a stably oscillating range to determine peaks and troughs of  
491 integrands and subsequently apply the repeat average method to efficiently compute the numerical  
492 integration (Dahlquist & Björck, 1974). Thus, it allows us to consider more flexible source-  
493 receiver geometries. All used dynamic and saturation-dependent parameters and corresponding  
494 formulations are given in Table A3 of Appendix A, and we summarize a flow chart of the model  
495 generation in Figure 4. We assume that the data recorded from 0 to 0.5 s is digitized by 4096  
496 samples with a sample interval of 0.1221 ms. After the full-waveform computation of this model,  
497 we display the horizontal components of seismic ground acceleration and SE wave fields (Figure  
498 5). Since a zero-phase wavelet was applied to simulate the seismic source (Equation 27), a time  
499 delay is shown in the waveforms (Figure 5). In addition, due to a low saturation ( $S_w = 0.12$ )  
500 occurring on the near-surface ( $\sim 0.3$  m), the corresponding  $S$ -wave velocity is 1242.5 m/s. The  
501 surface waves can have a high apparent velocity to present in longer source-receiver offsets than  
502 the offset range shown in Figure 5. In this case, the maximum absolute horizontal electric field is  
503 26.27  $\mu\text{V}/\text{m}$ . Although the electric-field signals are vulnerable to noise, the environmental noise  
504 level can be managed to below the order of 0.1  $\mu\text{V}/\text{m}$  (see Butler et al., 2007; Dupuis et al., 2007;

505 Thompson & Gist, 1993). The near-surface electric field of this case is, hence, sufficient to be  
 506 observed.



507  
 508 **Figure 4.** Framework of MC-SESRs generation



509  
 510 **Figure 5.** Horizontal components of wave fields under the basic test model (a) seismic ground  
 511 acceleration and (b) seismoelectric wave fields

512 The horizontal components of seismic ground acceleration and SE wave fields recorded in  
 513 the time domain are subsequently transformed into the frequency domain. Then the MC-SESRs  
 514 over the full 0.5s time window are calculated by Equation 19. Here, we take the frequency in the

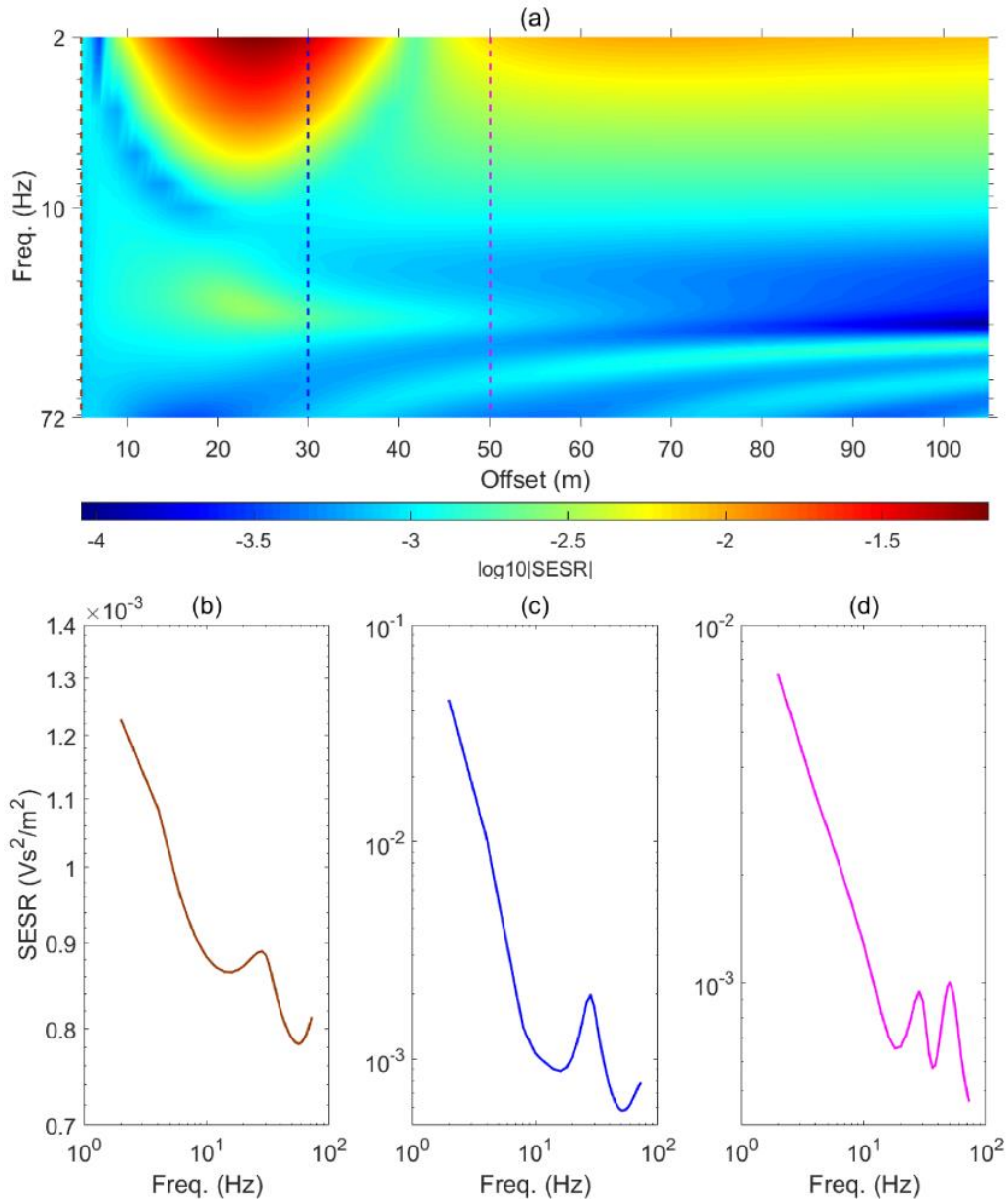
515 range of 2-72 Hz. The MC-SESRs' contour map of this numerical model is shown in Figure 6a.  
 516 The SESRs with greater strength are mainly distributed in a short-offset range (10 - 40 m) and a  
 517 low-frequency range ( $\sim 10$  Hz). Since the SESR concept under the assumption of the localized  
 518 (coseismic) SE field waves are linear with the ground acceleration, the frequency-dependent  
 519 behaviors depend on the evanescent and radiated SE field waves (Dizeran et al., 2019). The  
 520 generation of the radiated SE field waves is commonly regarded as caused by the seismic waves  
 521 nearly vertically arriving at interfaces and the ground surface. Although the radiated EM waves  
 522 generated by the direct SE conversions at the source also depend on the frequency, their strength  
 523 is weak. The subsurface properties' variations barely affect the component of MC-SESRs  
 524 originating from the direct SE conversions.

525 Once the seismic incident angle is larger than the critical angle  $\theta_c$ :

$$\theta_c = \arcsin\left(\frac{V_{\text{sei}}}{V_{\text{EM}}}\right), \quad (28)$$

526 where  $V_{\text{sei}}$  (m/s) and  $V_{\text{EM}}$  (m/s) denote the seismic wave velocity and EM wave velocity,  
 527 respectively, the SE conversion leads to the generation of evanescent SE waves. Actually,  $\theta_c$   
 528 approaches zero due to  $V_{\text{EM}} \gg V_{\text{sei}}$ . The existence of physical properties' contrasts causes the  
 529 interfacial SE responses, mainly containing evanescent SE field waves. The superposition of  
 530 different modes of SE conversions makes the spectral ratios between the SE responses and the  
 531 ground acceleration are of frequency dependence. Thus, the SESR modulus decreasing with the  
 532 increasing frequency mainly attributes to the evanescent SE waves, which approximately decay  
 533 with a factor  $\exp(-\omega p \Delta z)$  (Ren et al., 2018). The horizontal EM wave slowness  $p$  relies on the  
 534 incident angle of the seismic waves arriving at the interface and inducing the localized SE waves.  
 535 The spatial variations of SESRs presumably are complicated due to the presence of a vadose zone.  
 536 The multi-channel SE field waves combined with the ground acceleration field waves are sensitive  
 537 to water table variations (e.g., Rabbal et al., 2020). Using MC-SESRs facilitates the inversion of  
 538 hydrogeological parameters due to without reconstructing the seismic source function. Selecting  
 539 SESRs from near- and far-offset receivers, we show the SESRs varying over frequency for three  
 540 receivers with different offsets of 5 m, 30 m, and 50 m, respectively. As shown in Figures 6b-d,  
 541 the SESRs at different offsets have a similar frequency dependence. The SESR generally increases  
 542 as the frequency decreases, and their log-scale variations show an approximately linear correlation

543 in the low-frequency domain ( $\sim 10$  Hz), and it oscillates at higher frequencies. Notably, the  
 544 oscillating signatures are more notable in the far-offset range (Figures 6c-d). These oscillatory  
 545 characteristics may originate from the electric field induced by the guided *P*-wave traveling in the  
 546 upper two layers.



547

548 **Figure 6.** The MC-SESRs of the basic test model with (a) the contour map of MC-SESRs in  
 549 logarithmic scale showing variations both with frequency and offsets. Sample SESR curves as a  
 550 function of frequency at different offsets: (b) 5 m, (c) 30 m and (d) 50 m.

551

552 **Table 1**553 *Parameters of the basic test model*

Property	Units	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
Thickness	m	6	9	5	15	Inf.
$\phi$	$\text{m}^3/\text{m}^3$	0.41	0.43	0.46	0.38	0.05
$\alpha_{\text{VG}}$	$\text{m}^{-1}$	12.4	-	-	-	-
$n_{\text{VG}}$	-	1.89	-	-	-	-
$S_{\text{wr}}$	-	0.1585	-	-	-	-
$\rho_{\text{s}}$	$\text{kg}/\text{m}^3$	2650	2650	2650	2650	2700
$\rho_{\text{w}}$	$\text{kg}/\text{m}^3$	1000				
$\rho_{\text{a}}$	$\text{kg}/\text{m}^3$	1.21	-	-	-	-
$\rho_{\text{b}}^{\text{sat}}$	$\text{kg}/\text{m}^3$	1973.5	1940.5	1891	2023	2615
$C_{\text{w}}$	mol/L	$2 \times 10^{-3}$				
$\sigma_0^{\text{sat}}$	S/m	0.0073	0.0077	0.0083	0.0067	0.0016
$\eta_{\text{w}}$	Pa·s	$1 \times 10^{-3}$				
$\eta_{\text{a}}$	Pa·s	$1.8 \times 10^{-5}$	-	-	-	-
$T$	K	293.15				

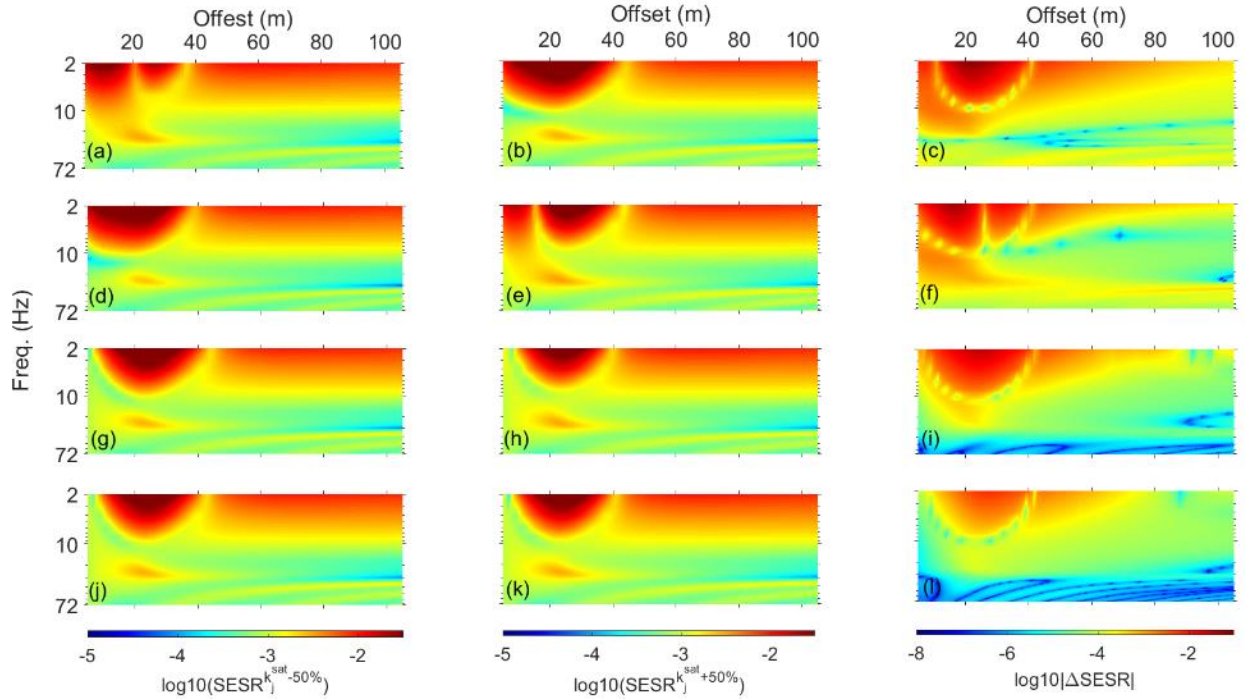
$\kappa_s$	-	4				
$\kappa_w$	-	80.1				
$\kappa_a$	-	1				
$m$	-	1.35				
$n$	-	1.85				
$K_s$	GPa	35	35	35	35	36
$G$	GPa	2.49	2.49	14.08	14.08	15
$K_{fr}$	GPa	2.84	2.84	14.4	14.4	20
$K_w$	GPa	2.25				
$K_a$	Pa	$1.43 \times 10^5$	-	-	-	-

555           **3.2. Analysis of permeability**

556           First, we test the sensitivity of SESRs with respect to permeability. The considered typical  
 557 ranges in the critical zone refer to Carsel and Parrish (1988). The saturated permeability  $k_j^{\text{sat}}$  of  
 558 the top four layers ( $j = 1,2,3,4$ ) in the basic test model is 5.67, 8.51, 1.42, and 4.26 D, respectively  
 559 (Figure 3c). By changing the saturated permeability of shallow layers ( $j = 1,2,3,4$ )  $\pm 50\%$ , we  
 560 calculated the absolute MC-SESRs difference concerning the original model by:

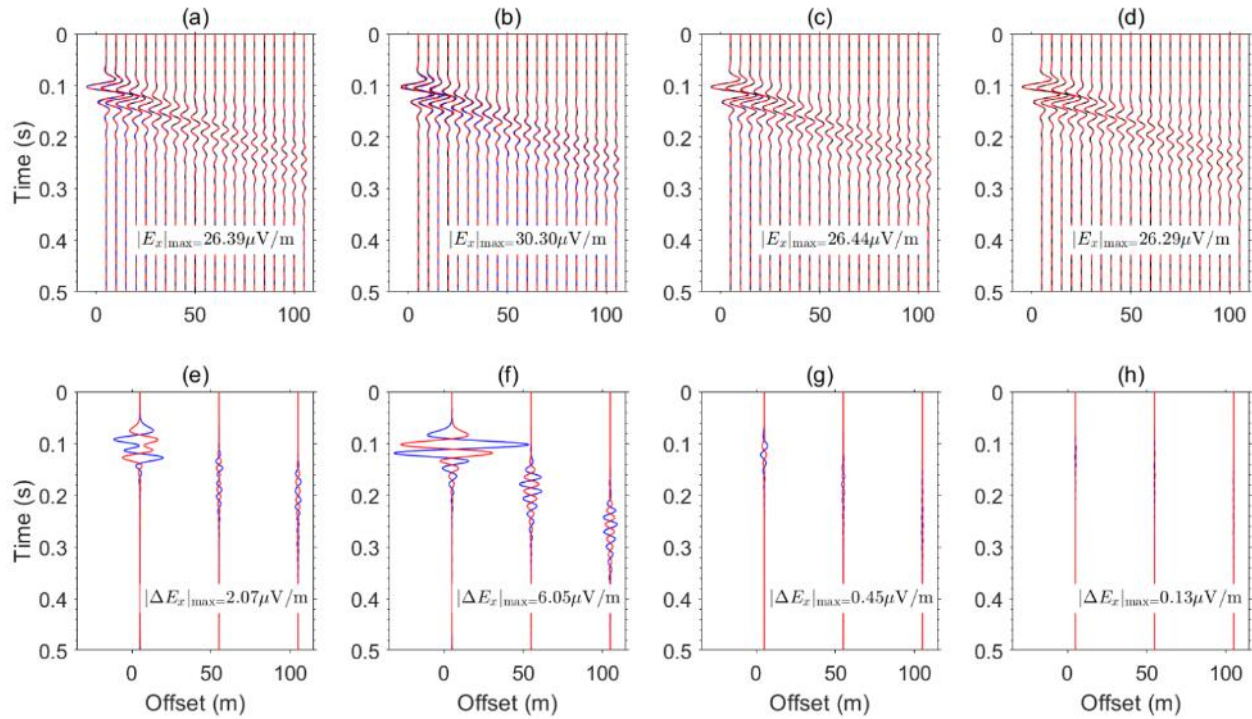
$$\Delta\text{SESR}(\omega, x_i, j) = \left| \text{SESR}(\omega, x_i)^{k_j^{\text{sat}+50\%}} - \text{SESR}(\omega, x_i)^{k_j^{\text{sat}-50\%}} \right|, \quad (29)$$

561 where the horizontal offset  $x_i$  ranges from 5 to 105 m with the number of receivers  $i =$   
 562 1,2, ..., 101. The short-offset (~20 m) SESRs have more changes when the permeability of shallow  
 563 layers has been changed than the permeability of deep layers has been changed (Figure 7). Their  
 564 maximum absolute differences with changing the saturated permeability of each layer decrease in  
 565 depth, which is 0.0877, 0.0636, 0.0377, and 0.0069 (Figures 7c, 7e, 7h, and 7l), respectively. The  
 566 MC-SESRs mainly change in near-offset traces ( $x_i < 45$  m) and low frequencies ( $f < 10$  Hz). The  
 567 absolute differences of SESRs are less when the permeability in the lower zone changes (Figure  
 568 7l), whose maximum absolute difference of SESRs is an order of magnitude smaller than for layers  
 569 1 and 2. As shown in Figure 7, by changing the permeability of different layers, the absolute  
 570 differences of SESRs produce different variations either in frequency or laterally.



571  
 572 **Figure 7.** The MC-SESRs in logarithmic scale with respect to (a-d-g-j) 50% decrease and (b-e-h-  
 573 k) 50% increase the basic test model of (a-c) layer 1, (d-f) layer 2, (g-i) layer 3, and (j-l) layer 4.  
 574 (c-f-i-l) The absolute MC-SESRs difference in logarithmic scale of the corresponding layers  
 575 calculated by Equation 29.

576 To test the behaviors of SE wave-fields by changing the permeability of each layer, we  
 577 compare the differences between the original waveforms with the changed waveforms in Figure 8.  
 578 As shown in Figures 8e-h, the variations of SE wave fields are largest when the permeability of  
 579 layer 2 changes (Figures 8b and 8f). Layer 2 is saturated and provided with the highest saturated  
 580 permeability in the basic test model. Interestingly, the differences by changing the permeability of  
 581 layer 1 (Figure 8e) show a very different trend within 0.06 – 0.14 s in contrast with other layers  
 582 (Figures 8f-h). Layer 1 is a partially saturated zone, which produces a different behavior on  
 583 waveforms compared with other layers.



584

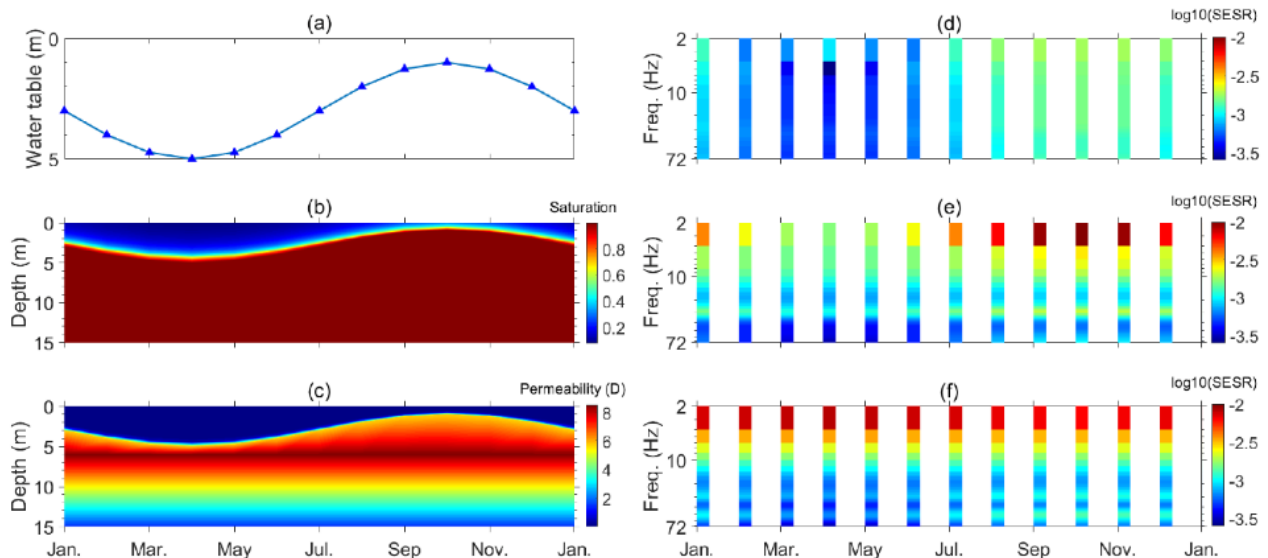
585 **Figure 8.** (a-d) Horizontal components of SE wave fields for the basic test model (black solid  
 586 lines) and for cases of 50% increase (red lines) and decrease (blue lines) in the permeability of  
 587 layers 1-4 respectively. (e-h) Differences between SE wave fields obtained for cases of 50%  
 588 increased (red lines)/decreased (blue lines) permeability in layers 1-4 respectively compared to  
 589 those obtained for the original model, at three particular offsets, whose amplitudes are amplified  
 590 by a factor of 8 compared to those in (a-d).

### 591 3.3. Analysis of water table

592 Second, we test how the different depths of the water table or partially-saturated conditions  
 593 influence the distributions of MC-SESRs. Accounting for a static partially-saturated state, the VG  
 594 model is used to determine the water saturation (van Genuchten, 1980). The water table of the  
 595 basic test model is assumed to vary seasonally in a year. In this case, we assume the rainy season  
 596 is from September to November with higher water levels, and the period of March to May is the  
 597 dry season with lower water levels (Figure 9a). Correspondingly, the water saturation and the  
 598 effective permeability at the shallow layer change with the water table (Figures 9b-c). As the used  
 599 parameter  $\alpha_{\text{VG}}$  ( $12.4 \text{ m}^{-1}$ ) of the VG model is large, the permeability is rather low at low  
 600 saturations. Note that the contour map of permeabilities shown in Figure 9c is an interpolation

601 result in the time and space domain. Permeabilities below the water level in each layer are different  
 602 constants, as the basic test model presented in Figure 2c. The SESRs with the short (5 m), medium  
 603 (30 m), and long (50 m) source-receiver offset are collected to show their responses to the  
 604 variations of the water table (Figures 9d-f). The absolute ratios increase in the rainy season with  
 605 higher water levels and decrease in the dry season with lower water levels.

606 Furthermore, the strength of SESRs in the high-frequency domain is increased when the  
 607 water table is in the shallow zone (e.g., September-November). The amplitudes of evanescent SE  
 608 signals decay exponentially with the normal direction of the interfaces (Ren et al., 2016b; Ren et  
 609 al., 2018). This implies that deep water tables cause weaker SE signals than shallow water tables.  
 610 This characteristic is also embodied in the SESRs data obtained at the source-receiver offset of 30  
 611 m (Figure 9e). Nevertheless, the sensitivity of the SESRs obtained at a more extended offset (50  
 612 m) responding to the dynamic water table depth is considerably weakened (Figure 9f). This test  
 613 implies we may use the time-lapse MC-SESRs data in short source-receiver traces to monitor the  
 614 water table depth variations.



615 **Figure 9.** The modeling results with the water table vary over time. (a) The depth of the water  
 616 table, (b) the time-lapse variations of the water saturation with depth, (c) the effective permeability,  
 617 and the SESRs in logarithmic scale collected at a source-receiver distance of (d) 5 m, (e) 30 m and  
 618 (f) 50 m.

## 620 4. Inversion Results

621           Employing synthetic seismic and SE data generated for the basic test model introduced in  
 622 Section 3.1, we carry out a three-step strategy to perform MC-SESRs inversion. We assume that  
 623 the depth and properties of the bottom layer 5, and all other layer depths and properties except for  
 624 the water table depth and the permeabilities of layers 1-4 are known. The prior information could  
 625 have been determined by drilling and other geophysical methods (e.g., Dzieran et al, 2019). This  
 626 could represent a scenario where there was interest to monitor temporal changes in depth to the  
 627 water table and to determine permeabilities of the near surface layers (to 35 m depth) for  
 628 hydrogeological applications.

629           To begin, we generated random samples by drawing permeabilities for each of layers 1 - 4  
 630 from predefined reasonable ranges, and drawing a water table depth in layer 1 randomly from the  
 631 range of 1 - 5 m. We account for the ranges of hydraulic conductivity  $K_j^{\text{sat}}$  of layers 1-2, referring  
 632 to materials consisting of loamy sands. Layers 3-4 with a lower range of the soil permeabilities are  
 633 considered to contain more silty sands (Carsel & Parrish, 1988). The hydraulic conductivity of  
 634 layers 1-2 ranges from 3 to 35 cm/h and layers 3-4 ranges from 0.02 to 15 cm/h, which can be  
 635 transformed to the ranges of permeability  $k_j^{\text{sat}}$  by is equal to  $\frac{K_j^{\text{sat}}\eta_w}{\rho_w g}$ , where  $g$  ( $\text{m/s}^2$ ) denotes the  
 636 gravitational acceleration ( $9.81 \text{ m/s}^2$ ). Following the flowchart of the model generation (Figure  
 637 4), we calculated MC-SESRs of 7000 random samples. Therefore, the first step is to obtain the  
 638 7000 input-output pairs.

### 639 4.1. Performance of the BL neural network

640           In the second step, we randomly selected 5000 from the 7000 input-output pairs for training  
 641 the BL neural network (Figure 2). In addition, 1500 randomly generated samples were split into  
 642 the original validation dataset (500 samples) and the original testing dataset (1000 samples). The  
 643 input MC-SESRs data of the training samples are noise-free synthetic data, and output data are the  
 644 dwt and the permeability of layers 1-4 ( $k_1, k_2, k_3, k_4$ ) (Figure 2c). First, to accurately extract and  
 645 map features of the input data, we need to set the number of mapping groups ( $Q$ ) and feature nodes  
 646 ( $P$ ) of each group and their corresponding enhancement nodes ( $M$ ) based on the BL architecture  
 647 (Figure 2) introduced in Section 2.3. After that, the BL network is fixed. We tested different

648 configurations of the BL neural network to present the root-mean-squared errors (RMSEs) of  
 649 training models (water table depth and permeability):

$$RMSE^j = \sqrt{\frac{\sum_1^n (\text{Output\_}Y_i^j - \text{True\_}Y_i^j)^2}{n}}, \quad (30)$$

650 where  $j$  denotes the corresponding numbers of different parameters ( $j = 1$  for dwt, and  $j = 2 - 5$  for  
 651 k1-4 respectively).  $n$  is the number of samples for training the network, which is 5000 in this case.  
 652  $\text{Output\_}Y_i^j$  and  $\text{True\_}Y_i^j$  are the reconstructed and true output of the  $j$ th parameter of the  $i$ th  
 653 sample. Here, we separately present the RMSEs of different parameters since the output dataset  
 654 indicate different properties and in different scales. The ranges of  $P$ ,  $Q$  and  $M$  are [10:5:100],  
 655 [10:5:100], and [10:10:500], respectively. The regularization coefficient is set to  $10^{-8}$  (see Chen  
 656 & Liu, 2017). The optimum sets of parameters for training models are given in Table 2. The  
 657 RMSEs of water table depth can be limited to 0.034 m. The RMSEs of permeability of layer 1 are  
 658 much higher than layers 2-4. In contrast with deep layers, the permeability of the top layer is easier  
 659 to be directly investigated in situ. k2 and k3 reach their optimum under  $P=15$ ,  $Q=10$  and  $M=500$ ,  
 660 and correspondingly, the RMSEs for estimating the dwt and k4 are satisfactory with the same  
 661 setting.

662 **Table 2**

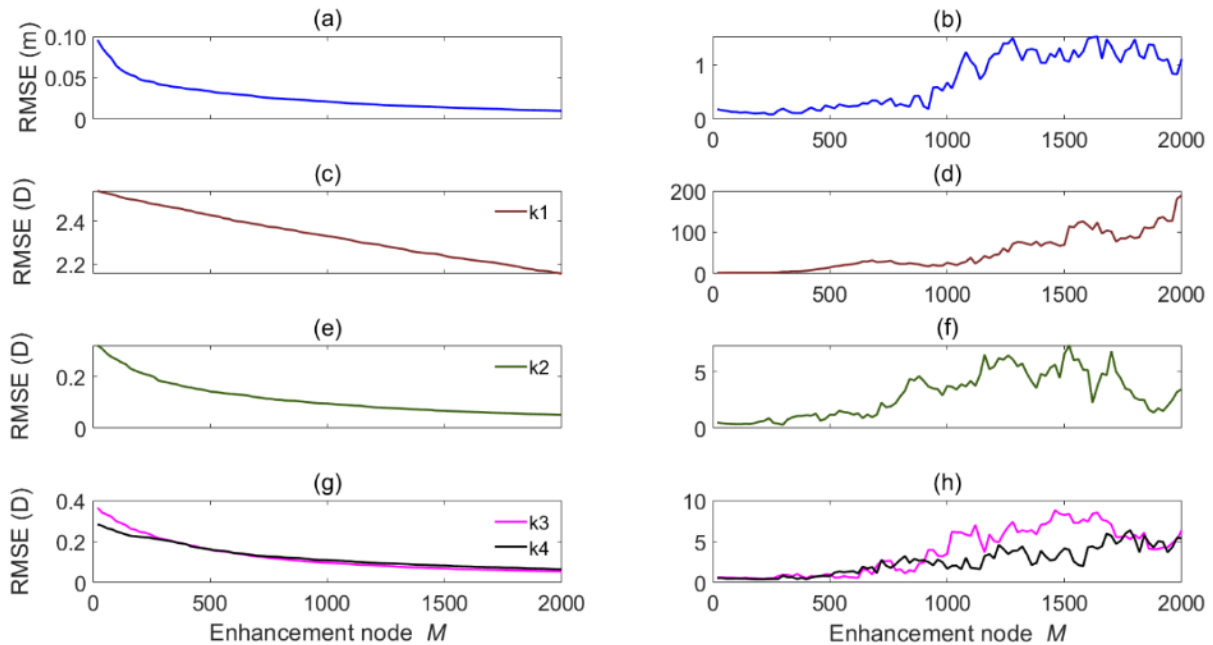
663 *RMSEs of training data set with different configurations of the BL model (bold numbers denote*  
 664 *the corresponding minimum RMSEs)*

Parameters of BL model			RMSE of training models				
$P$	$Q$	$M$	dwt (m)	k1 (D)	k2 (D)	k3 (D)	k4 (D)
100	100	500	<b>0.0210</b>	2.4174	0.1462	0.1899	0.1526
80	40	500	0.0271	<b>2.4090</b>	0.1713	0.2005	0.1644
15	10	500	0.0339	2.4274	<b>0.1415</b>	<b>0.1603</b>	0.1616
10	10	500	0.0336	2.4239	0.1473	0.1628	<b>0.1500</b>

665 As the parameters' estimation accuracy is the highest when the number of enhancement  
 666 nodes ( $M$ ) reaches the maximum in the search range, we expanded this range to search for an  
 667 appropriate neural network. The neural network gets more complex structures with a large number  
 668 of groups, mapping feature nodes, and enhancement nodes, which may empower the BL model to  
 669 describe the approximate mapping relationship between the input and output data from the training

670 data set. As shown in Figure 2b,  $M$  directly reflects the complexity of the connected matrix for  
671 linking the integration of the feature mapping layer and the enhancement layer with the output  
672 layer. To examine whether the RMSEs would be reduced by keeping increasing the enhancement  
673 nodes and fixing  $P = 15$  and  $Q = 10$ , we display the RMSEs varying with the number of  
674 enhancement nodes (Figure 10). In addition, we utilized 500 untrained samples from the validation  
675 dataset to test the inverted performance with increasing  $M$ . Further, the measured data in practice  
676 ineluctably contain some noise. With the improvement of pre-and post-processing techniques on  
677 near-surface SE applications, the signal-to-noise ratio (SNR) can be achieved to 20 – 45 dB (Butler  
678 & Russel, 2003; Butler et al., 2007). Thereby, to account for the possible interferences from self-  
679 noise and background noise, we add 5% random noise of the mean amplitude of synthetic SESRs  
680 at each trace (SNR  $\approx$  26 dB) to the initial validation and testing datasets without noise  
681 contamination. Similar to the treatment of the training dataset, the RMSEs of the validation dataset  
682 are calculated by replacing the number of samples in Equation 30 to 500 and updating the  
683 corresponding output dataset. Slightly though, the RMSE set keeps decreasing with  $M$  increasing  
684 (Figures 10a, 10c, 10e, and 10g), which indicates the neural network has been adapted to the  
685 training data set. However, there are different trends shown in untrained samples (Figures 10b,  
686 10d, 10f, and 10h).

687 The parameter estimation using untrained noisy data as input performs better when  $M$  is  
688 lower than 300 (Figures 10b, 10d, 10f, and 10h). The number of enhancement nodes of each  
689 parameter reaching a minimum RMSE is given in Table 3. To show the influence of chosen  $M$  on  
690 the inversion accuracy, we contrast the true and reconstructed models by inputting noisy MC-  
691 SESRs of the validation dataset under the BL neural networks trained by  $M = 50, 200, 500,$  and  
692 1000, respectively. Taking the water table depth as an example to display (Figure 11), the majority  
693 of reconstructed models are visually closer to the true models with increasing  $M$ , but the RMSE  
694 increases when  $M \geq 200$  (Figures 11c-d). The reconstructed permeability also presents a similar  
695 trend (see Figures S1-S3 of Supporting Information). It can be attributed to the large departure of  
696 a few estimations from the true models. Finally, to detect the dynamic water table, we choose  $M =$   
697 240 as the number of enhancement nodes to train the BL model.

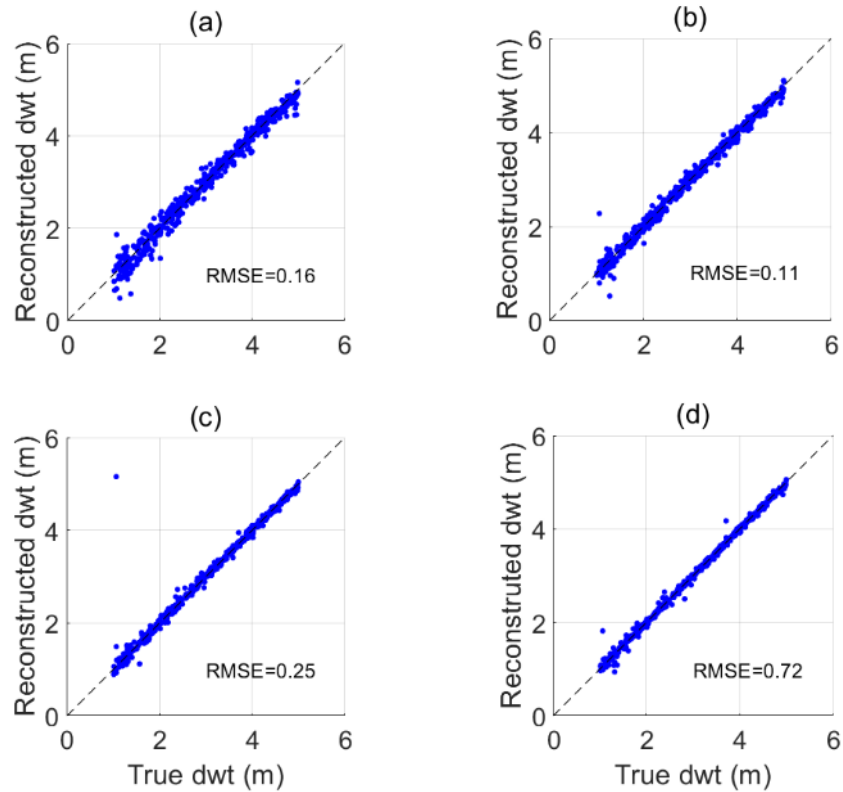


698  
 699 **Figure 10.** RMSEs of output data (a-b: water table depth, c-d: permeability of layer 1, e-f:  
 700 permeability of layer 2, and g-h: permeability of layers 3-4) vary with the number of enhancement  
 701 nodes ( $P=15$ ,  $Q=10$ ). Panels in the left column (a, c, e, g) represent the training data set and panels  
 702 in the right column (b, d, f, h) represent the validation noisy dataset.

703 **Table 3**

704 *RMSEs of validation data set with the optimum number of enhancement nodes (bold numbers*  
 705 *denote the corresponding minimum RMSEs)*

Enhancement node	RMSE of validation models					
	$M$	dwt (m)	k1 (D)	k2 (D)	k3 (D)	k4 (D)
240		<b>0.0895</b>	2.7884	0.8879	0.5321	0.4339
20		0.1839	<b>2.6092</b>	0.4798	0.6212	0.5654
300		0.1945	4.5221	<b>0.3084</b>	0.9505	0.8540
220		0.1196	2.7551	0.6383	<b>0.4510</b>	0.4140
200		0.1117	2.8753	0.5839	0.4730	<b>0.4101</b>



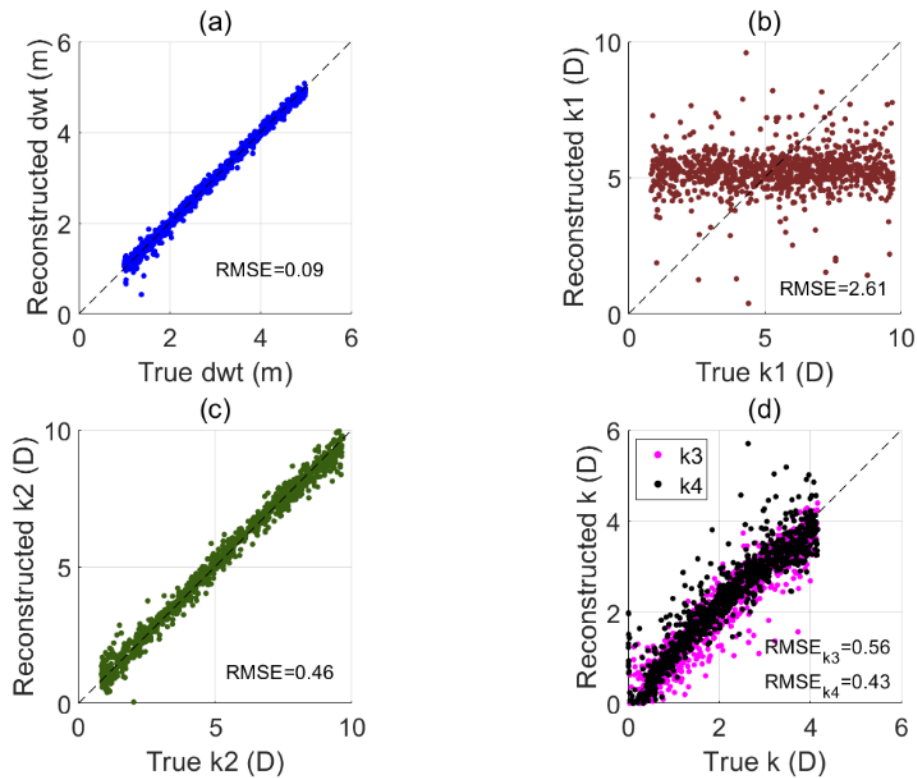
707

708 **Figure 11.** Comparisons of the true and reconstructed depth of water table (dwt) of the validation  
 709 dataset with (a)  $M = 50$ , (b)  $M = 200$ , (c)  $M = 500$ , and (d)  $M = 1000$

#### 710 4.2. Comparisons of reconstructed and true models

711 After the 500 validation samples validated the BL model obtained by the 5000 training  
 712 samples, we took the third step to attain MC-SESRs inversion. We applied this BL neural network  
 713 configured by  $P=15$ ,  $Q=10$ , and  $M=240$  to invert the water table depth and permeability of 1000  
 714 testing samples with the same amount of noise contamination as the original testing MC-SESRs  
 715 dataset. The testing dataset is independent of the training or validation datasets. The RMSEs of the  
 716 testing dataset are calculated similarly to the validation dataset (Equation 30). The reconstructed  
 717 depth of the water table has great consistency with corresponding true values (Figure 12a), whose  
 718 RMSE is 0.09 m. The inversion results can nicely reconstruct the permeability of layer 2 (Figure  
 719 12c), whose RMSE is 0.46 D. the reconstructed permeability of layers 3 and 4 deviates more from  
 720 true values than layer 2 (Figure 12d), while their RMSEs are acceptable (0.56 D and 0.43 D,  
 721 respectively). Nevertheless, the permeability of the partially saturated layer 1 cannot be

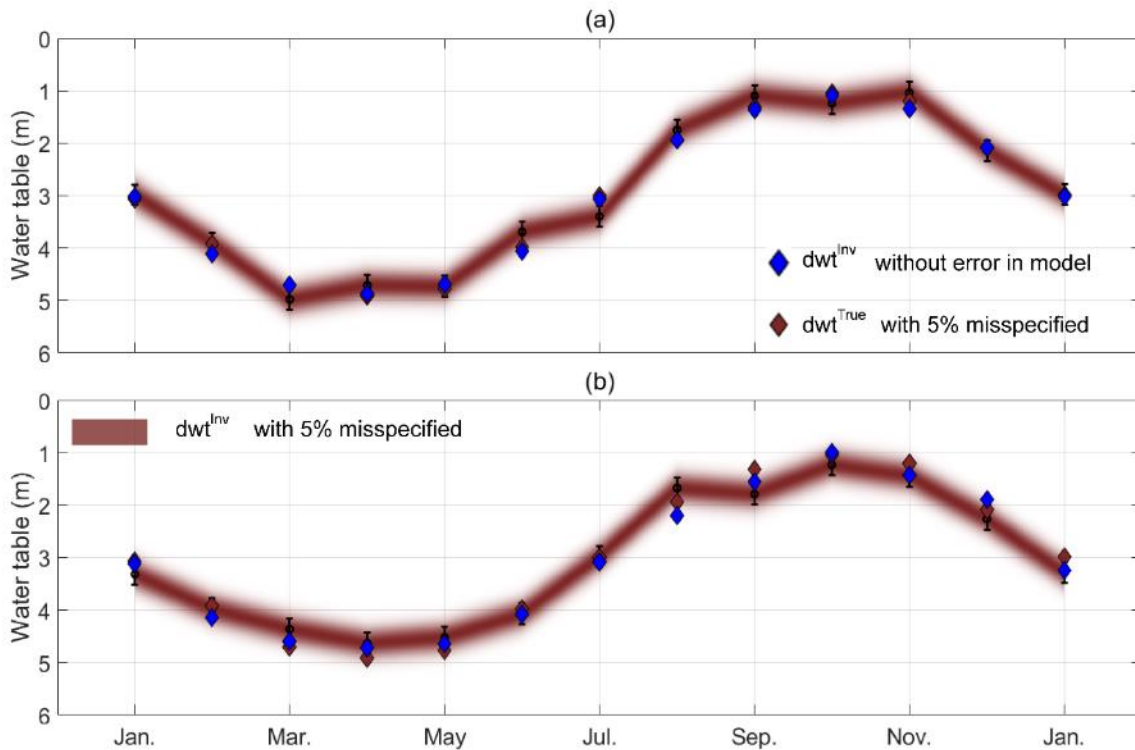
722 reconstructed, which concentrates around 5 D. It reflects that the SESRs data did not constrain the  
 723 permeability of the unsaturated layer well since the low saturation makes a very low effective  
 724 permeability to obtain a small SE coupling coefficient (Equation 11).



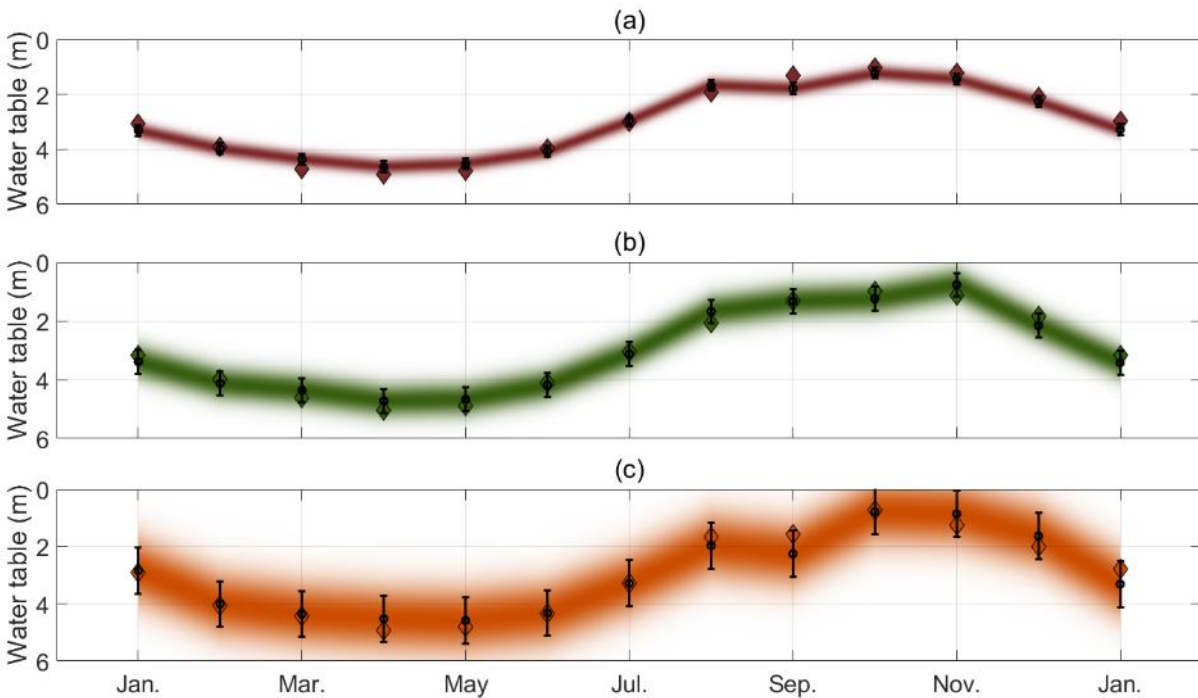
725  
 726 **Figure 12.** Comparisons of the true and reconstructed (a) depth of water table, (b) permeability of  
 727 layer 1, (c) permeability of layer 2 and (d) permeability of layers 3-4 using noisy MC-SESRs data  
 728 (SNR  $\approx$  26 dB).

729 Based on the settings of the basic test model, we used the SESRs data introduced in Section  
 730 3.3 to characterize variations in the water table depth. As the data uncertainty not only can originate  
 731 from the noise but also possibly contains the errors of the model parameters, here, we assumed  
 732 five-percent errors of dwt, permeability, and porosity included in the basic test model. Still, the  
 733 data are assumed to be contaminated by five-percent random noise in the following tests.  
 734 Meanwhile, as the sensitivity analysis of SESRs to the dwt in Section 3.3 shows, the short-offset  
 735 SESRs are more sensitive than the long-offset SESRs to the variations of dwt, we test to apply the  
 736 different number of channels to reconstruct the dynamic dwt. All 101 channels' or 26 short-offset  
 737 channels' SESRs data used to invert the dwt can obtain comparable accuracy under five-percent  
 738 errors in model parameters (Figure 13). This test indicates that we can reconstruct dynamic shallow

739 dwt by using less short-offset MC-SESRs data. Since higher errors may occur in realistic  
 740 measurements, we compare the inversion accuracy under five-percent, ten-percent, and twenty-  
 741 percent errors in the pre-defined model using 26 short-offset channels' SESRs in Figure 14. The  
 742 inverted water table depths are more deviated from the true values by enhancing errors. However,  
 743 the overall inverted values are consistent with the true values with twenty-percent errors in the  
 744 known model parameters, except for the result in September (Figure 14c).

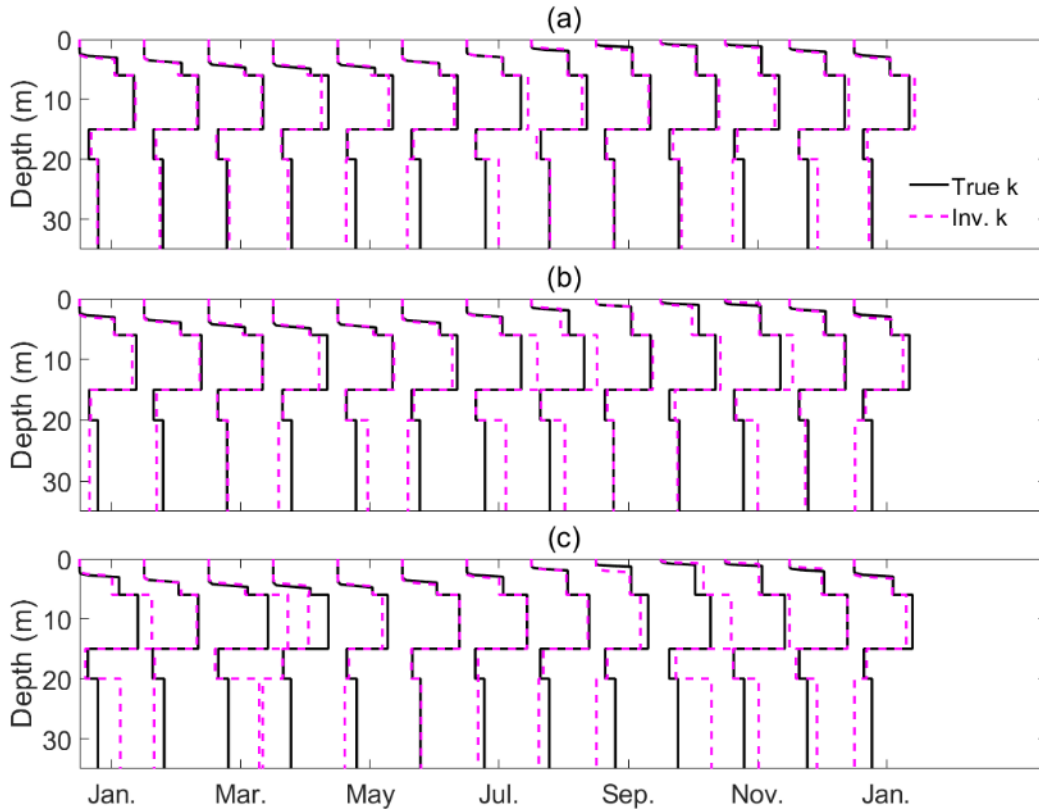


745  
 746 **Figure 13.** Detection of the water table depth using noisy MC-SESRs data collected from (a) 101  
 747 traces (5 - 105 m) and (b) 26 traces (5 - 30 m). The blue diamonds represent the inverted value  
 748 without the model errors; The red diamonds represent the true values with 5%-misspecified errors  
 749 in pre-defined model parameters; The circles represent the inverted values, whose misspecified  
 750 levels are indicated by the shaded areas and error bars.



751  
 752 **Figure 14.** Detection of the water table depth using the noisy 26-channel SESRs data with  
 753 misspecified errors of (a) 5%, (b) 10%, and (c) 20% in pre-defined model parameters. Diamonds  
 754 represent the true values; The circles represent the inverted values, whose misspecified levels are  
 755 indicated by the shaded areas and error bars.

756 As the absolute pressure head in the vadose zone is assumed to be the distance between its  
 757 elevation and the water table level, the effective permeability and water saturation are calculated  
 758 by the MVG model. We show that the true and the inverted permeabilities vary with time in Figure  
 759 15. The permeability can still be reconstructed in the time-lapse profiles (Figure 15a). The  
 760 predicted accuracy is also reduced when errors added to the model are enhanced (Figures 15b and  
 761 15c). Particularly, the inverted errors of permeability increase in layer 4 due to the increasingly  
 762 attenuated seismic and SE signals strength. The model parameters may be misspecified by larger  
 763 errors, which causes lower inverted accuracy in deep layers due to the fragile signals.



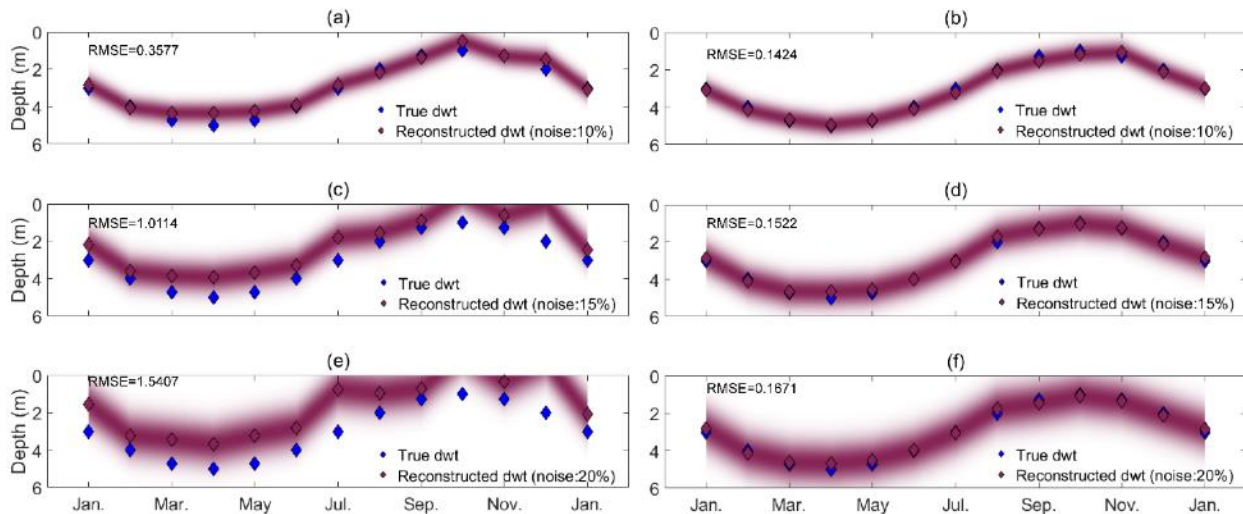
764

765 **Figure 15.** Comparison of true (black lines) and inverted (pink) permeability with the changing  
 766 water table depth by accounting for errors of (a) 5%, (b) 10% and (c) 20% in pre-defined model  
 767 parameters.

## 768 5. Discussion

769 To test the capability of this neural network in the presence of noise, we decrease the SNR  
 770 to 20 dB, 16 dB, and 14 dB by considering different random noise levels (10%, 15%, and 20%)  
 771 into synthetic MC-SESRs data. Based on the assumptions in Section 4.3, we attempt to use the  
 772 SESRs data at different noise levels to detect the changing water table levels. As shown in Figure  
 773 16, the inverted accuracy is reduced when the noise is enhanced from 5% to 10% and more. In this  
 774 case, the water table detection can be achieved at a 10% noise level when 26-channel SESR data  
 775 (5 – 30 m) have been involved in the inversion (Figure 16a). This scenario can be improved by  
 776 increasing the data by using more traces. The RMSE reaches 0.1671 m at a 20%-noise level when  
 777 the used channels increase to 101. Correspondingly, the source-receiver offset ranges from 5 to  
 778 105 m (Figures 16b, 16d, and 16f). The inverse modeling may be able to perform well for stronger  
 779 noise levels when the used MC-SESR data are sufficient. Note that the monitoring test in Section

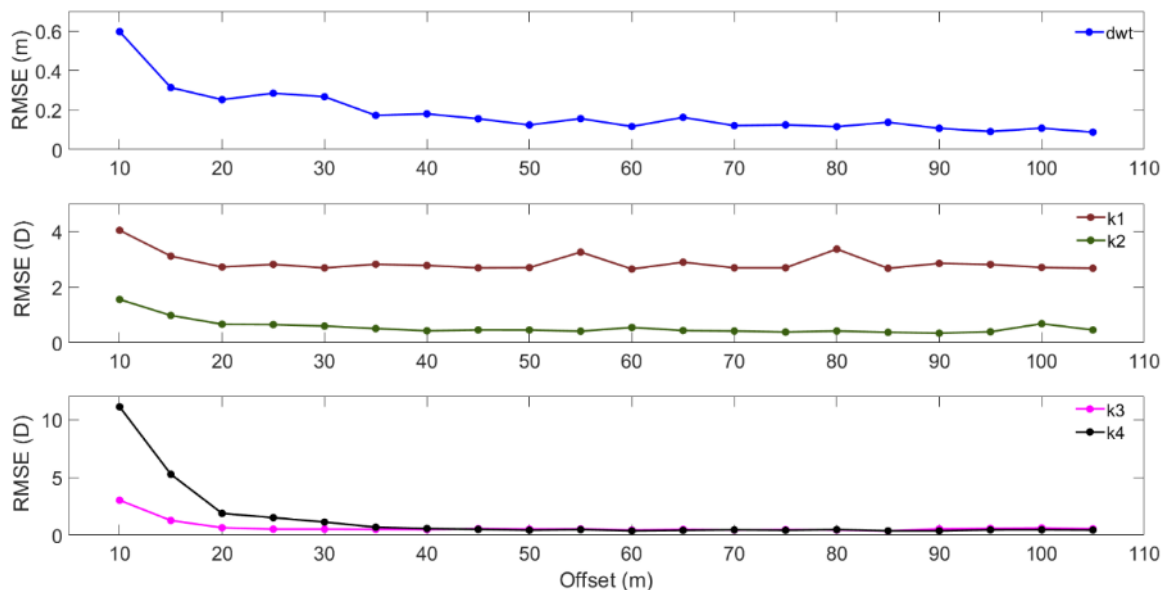
780 4.2 discussed the influence of different levels of errors in model parameters (Figures 13-15).  
 781 Ideally, although the water table and permeability changed with time and contained model  
 782 perturbations, the well-trained network (Figure 2) can recover their true values for a specific site.  
 783 Therefore, the inverted values are still close to the true values using 26-channel data with mixing  
 784 the noise level of 5% (Figure 13). However, the porosity of each layer is also assumed to be  
 785 misspecified. Thus, the increased errors in the pre-defined model decrease the inverted accuracy  
 786 of the water table depth and permeability.



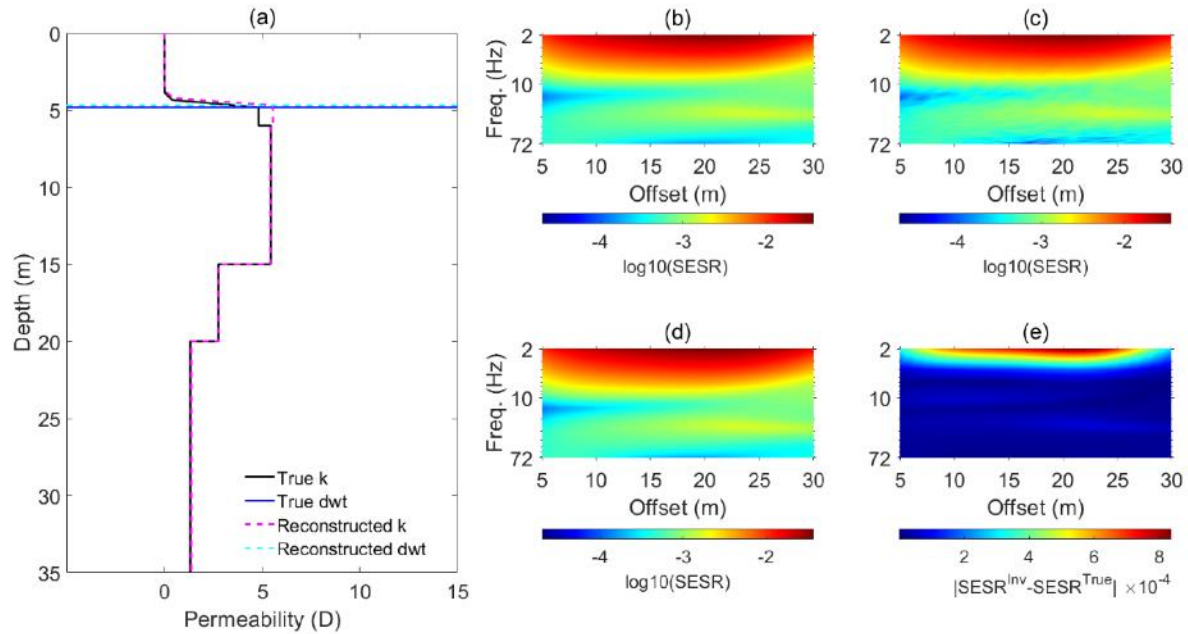
787  
 788 **Figure 16.** Comparison of true (blue) and predicted (purple) water table depth by adding (a-b)  
 789 10%, (c-d) 15% and (e-f) 20% random noise into data. The left panels (a, c, and e) use 26-channel  
 790 SESRs data and the right panels (b, d, and f) use 101-channel SESRs data. The shaded areas  
 791 indicate the misspecified levels.

792 As aforementioned sensitivity of permeability and water table depth in Sections 3.2-3.3,  
 793 the SESRs at different source-receiver offsets respond to the variations of different layers. The  
 794 number and locations of sensors used for inversion may affect the inverted results. We test the  
 795 inverted RMSEs using MC-SESRs with different offsets by 1000 untrained random models. The  
 796 interval distance of adjacent sensors is kept at 1 m. It starts from offset = 10 m, which means that  
 797 MC-SESRs data obtained by 6 traces in the range of 5 – 10 m are used for inversion (see Section  
 798 2.3 X:  $\text{SESR}_{5000 \times 36 \times 6}$ ). Figure 17 shows that the RMSEs dropped considerably when the used  
 799 offsets increased to 30 m, but they continued reducing to a lesser extent. Generally, more SESRs  
 800 data used for inversion should obtain higher inverted accuracy.

801 Picking a model to contrast the true with reconstructed parameters, the predicted  
 802 permeability can reconstruct the effective permeability above the capillary fringe based on the  
 803 water table estimation. However, the predicted saturated permeability of layer 1 deviates from its  
 804 true value (Figure 18a). The inverted saturated permeability of the top layer poorly fits the true  
 805 value embodied in the whole test set (Figure 12b). As the effective permeability drops considerably  
 806 at low water saturations, the SE coupling coefficient is rather small. Thus, the information of the  
 807 saturated permeability in layer 1 cannot be extracted by the mapping feature layer of input MC-  
 808 SESRs data. The water table depth and permeability of layers 2-4 of the model are well estimated.  
 809 Although the noisy MC-SESRs data for inversion are affected by disturbances (Figure 18c), the  
 810 MC-SESRs data calculated by the predicted model (Figure 18d) well fit the synthetic MC-SESRs  
 811 data (Figure 18b). The fitting errors concentrate in 10 – 25 m and low frequencies ( $\sim 3$  Hz) (Figure  
 812 18e). The inversion accuracy for this case is satisfactory by using data from 26 channels ( $\sim 30$  m)  
 813 to train and invert the water table depth and permeability. One estimation with lower accuracy is  
 814 presented in the Figure S4 of Supporting Information, whose modeling result from the inverted  
 815 parameters can recover the overall shape and trend of the original data, but the maximum absolute  
 816 difference is one order of magnitude larger than Figure 18e.



817  
 818 **Figure 17.** RMSEs between inverted and true models vary with the offset (SNR  $\approx 26$  dB). (a)  
 819 water table depth, (b) permeability of layers 1-2 and (c) permeability of layers 3-4



820

821 **Figure 18.** Comparisons of the true model and the reconstructed model using 26-channel SESR  
 822 data. (a) The blue (solid) and cyan (dashed) lines represent the true and predicted water table depth,  
 823 respectively. The black (solid) and pink (dashed) lines represent the true and reconstructed  
 824 permeability, respectively. (b-d) display the 26-channel synthetic and noisy SESR data modeling  
 825 by (b-c) the true model and (d) the inverted model. (e) shows SESRs difference between the data  
 826 modeling by the true model and the inverted model.

## 827 6. Conclusions

828 In this paper, we propose using MC-SESRs to process multi-channel SE signals and  
 829 seismic signals recorded at the ground surface. By analyzing the sensitivity of MC-SESRs to the  
 830 water table depth and permeability, the results indicate that MC-SESRs data obtained by different  
 831 offsets respond to the variations of different water table depths and permeability. Moreover, we  
 832 introduce a simple and efficient BL approach to interpret MC-SESRs data to quantitatively infer  
 833 the water table depth and permeability of layered-porous materials. As a type of non-invasive  
 834 measurement, MC-SESRs obtained by surface observations can supplement traditional piezometer  
 835 installations. It can be applied to rapidly and accurately detect the water table for a specific  
 836 investigated field even though pre-defined model parameters are misspecified by 20%. This feature  
 837 of monitoring the water table has potential applications for assessing groundwater storage and  
 838 studying frost thawing and volcanic eruption. Nevertheless, as aforementioned, the dynamic

839 effective excess charge density using the scaling factors by volumetric average and relaxation time  
 840 suffers several limits as predictions, particularly at the pore scale. We suggest considering explicit  
 841 frequency- and saturation-dependence in the future (Jougnot & Solazzi, 2021; Solazzi et al., 2022;  
 842 Thanh et al., 2022).

843

## 844 **Appendix A**

845 Tables A1 and A2 list the acronyms as well as the notation and description of symbols used  
 846 in the manuscript, respectively. The formulations of frequency-dependent (dynamic) and  
 847 saturation-dependent parameters are summarized in Table A3.

848 **Table A1.** Acronyms and meaning

<b>Acronyms</b>	<b>Meaning</b>
SE	SeismoElectric
SESR	SeismoElectric Spectral Ratio
MC-SESR	Multi-Channel SeismoElectric Spectral Ratio
EDL	Electrical Double Layer
AVO	Amplitude variation Versus Offset
BL	Broad Learning
RVFLNN	Random Vector Functional Link Neural Network
EM	ElectroMagnetic
MVG	Mualem-van Genuchten
VG	van Genuchten
LAC GRM	Luco-Apsel-Chen Generalized Reflection and Transmission Method
dwt	Water table depth

849 **Table A2.** Nomenclature of the Material Properties

<b>Symbol</b>	<b>Unit</b>	<b>Description</b>
$\omega$	rad/s	Angular frequency
$f$	Hz	Frequency
$\omega_t$	Hz	Angular transition frequency
$\theta_c$	rad/s	The critical angle of evanescent electromagnetic waves
$S_w$	-	Water saturation
$S_{wr}$	-	Residual water saturation
$S_e$	-	Effective water saturation
$\sigma^*$	S/m	Complex electrical conductivity
$\sigma_w$	S/m	Electrical conductivity of pore water
$\sigma_0$	S/m	Static bulk electrical conductivity
$\mathbf{E}$	V/m	Electric field
$\mathbf{J}$	A/m <sup>2</sup>	Total current density
$L^*$	A/m <sup>2</sup>	Streaming cross-coupling coefficient
$L_0^{\text{sat}}$	A/m <sup>2</sup>	Streaming cross-coupling coefficient at the saturated condition in low frequency
$\hat{Q}_{v,0}^{\text{sat}}$	C/m <sup>3</sup>	Saturated effective excess charge density in low frequency
$\hat{Q}_{v,0}$	C/m <sup>3</sup>	Effective excess charge density in low frequency
$\hat{Q}_v^*$	C/m <sup>3</sup>	Complex effective excess charge density
$CEC$	C/kg	Cation exchange capacity
$\beta_+$	m <sup>2</sup> /sV	Mobility of the counterions in the diffuse layer
$\beta_+^{\text{sur}}$	m <sup>2</sup> /sV	Mobility of the counterions in the Stern layer
$f_Q$	-	Fraction of counterions in the Stern layer
$C_0^{\text{sat}}$	V/m	Streaming voltage coupling coefficient
$C_w$	mol/L	Salinity of pore water
$F$	-	Electrical formation factor
$m$	-	Cementation exponent of Archie's law
$n$	-	Saturation exponent of Archie's law
$p_f$	Pa	Pore-fluid pressure
$\rho_f$	kg/m <sup>3</sup>	Mass density of fluid
$\rho_s$	kg/m <sup>3</sup>	Mass density of solid
$\rho_b^{\text{sat}}$	kg/m <sup>3</sup>	Saturated bulk mass density
$\mathbf{u}_s$	m/s	Averaging solid displacement
$\mathbf{u}_f$	m/s	Averaging pore-fluid displacement
$\mathbf{w}$	m/s	Averaging filtration displacement
$k^*$	m <sup>2</sup>	Frequency-dependent permeability
$k_0$	-	Effective permeability in low frequency

$k_0^{\text{sat}}$	$\text{m}^2$	Saturated permeability in low frequency
$\phi$	$\text{m}^3/\text{m}^3$	Porosity
$\alpha_{\text{VG}}$	$\text{m}^{-1}$	Parameters of van Genuchten model
$n_{\text{VG}}$	-	Parameters of van Genuchten model
$\tau_w$	-	Tortuosity
$\eta_w$	$\text{Pa}\cdot\text{s}$	Dynamic viscosity of pore-water
$\alpha$	-	Biot coefficient
$\alpha^{\text{sat}}$	-	Saturated Biot coefficient
$T$	$^{\circ}\text{C}$ or $\text{K}$	Temperature
$\epsilon_0$	$\text{F}/\text{m}$	Vacuum permittivity
$\kappa_w$	-	Dielectric constant of water
$\kappa_a$	-	Dielectric constant of air
$\kappa_s$	-	Dielectric constant of solid phase
$K_s$	$\text{Pa}$	Bulk modulus of solid phase
$G$	$\text{Pa}$	Frame shear modulus
$K_{\text{fr}}$	$\text{Pa}$	Frame bulk modulus
$K_w$	$\text{Pa}$	Bulk modulus of water
$K_a$	$\text{Pa}$	Bulk modulus of air
$K_G$	$\text{Pa}$	Undrained bulk modulus
$C$	$\text{Pa}$	Biot modulus
$M$	$\text{Pa}$	Biot modulus

850 **Table A3.** Frequency- and saturation-dependent parameters and corresponding formulations

Parameter	Unit	Expression	References
Angular transition frequency $\omega_t(S_w)$	Hz	$\frac{\eta_w \phi S_w}{\rho_w k_0(S_w) \tau_w(S_w)}$	Revil & Mahardika, 2013; Solazzi et al., 2020
Tortuosity $\tau_w(S_w)$	-	$\phi F S_w^{1-n}$	Revil & Jougnot, 2008; Jougnot et al., 2018
Dynamic permeability $k^*(\omega, S_w)$	-	$\frac{k_0(S_w)}{1 - \frac{i\omega}{2\omega_t}}$	Revil & Mahardika, 2013
Effective water saturation $S_e(S_w)$	-	$\frac{S_w - S_{wr}}{1 - S_{wr}}$	

Quasi-static effective permeability $k_0(S_w)$	-	$k_0^{\text{sat}} S_e^{\frac{1}{2}} \left[ 1 - \left( 1 - S_e^{\frac{1}{m_{VG}}} \right)^{m_{VG}} \right]^2$ $m_{VG} = 1 - n_{VG}^{-1}$	Mualem, 1976; van Genuchten, 1980
Specific moisture capacity $C_m(S_w)$	$m^{-1}$	$\frac{\alpha_{VG} m_{VG} \phi (1 - S_{wr}) S_e^{\frac{1}{m_{VG}}} \left( 1 - S_e^{\frac{1}{m_{VG}}} \right)^{m_{VG}}}{1 - m_{VG}}$	Richards, 1931; van Genuchten, 1980
Frequency-dependent effective excess charge density $\hat{Q}_v^*(\omega, S_w)$	-	$\hat{Q}_{v,0}(S_w) \sqrt{1 - \frac{i\omega}{\omega_t}}$	Revil & Mahardika, 2013
Complex electrical conductivity $\sigma^*(\omega, S_w)$	S/m	$\frac{S_w^n \sigma_w}{F} + \sigma_{\text{sur}}(S_w) + i[\sigma_{\text{quad}}(S_w) - \omega \epsilon_0 \kappa(S_w)]$	Revil et al., 2015
Effective surface conductivity $\sigma_{\text{sur}}(S_w)$	S/m	$\frac{2}{3} m \frac{(F-1)}{F} S_w^{n-1} \beta_+ (1 - f_Q) \rho_s CEC$	Revil, 2013; Revil & Mahardika, 2013
Effective quadrature conductivity $\sigma_{\text{quad}}(S_w)$	S/m	$-\frac{2}{3} m \frac{(F-1)}{F} S_w^{n-1} \beta_+^{\text{sur}} f_Q \rho_s CEC$	Revil, 2013; Revil & Mahardika, 2013
Dielectric constant $\kappa(S_w)$	-	$\frac{(F-1)\kappa_s + S_w^n \kappa_w + (1 - S_w^n) \kappa_a}{F}$	Linde et al., 2006
Biot coefficient $\alpha(S_w)$	-	$\frac{S_w - S_{wr}}{1 - S_{wr}} \alpha^{\text{sat}}$	Revil & Mahardika, 2013
Mass density of fluid $\rho_f(S_w)$	$\text{kg/m}^3$	$S_w \rho_w + (1 - S_w) \rho_a$	
Bulk modulus of fluid $K_f$	Pa	$\frac{1}{\frac{S_w}{K_w} + \frac{1 - S_w}{K_a}}$	

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## 864 **Open Research**

865 The data set and the main codes for inversion related to this manuscript can be found in the  
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867 subroutines of the broad learning system can be found at <https://broadlearning.ai/> (Chen & Liu,  
868 2017). The used code of the peak-trough averaging algorithm is located at  
869 [https://datadryad.org/stash/share/xXcw75yKN0M\\_C\\_MMcqYVKQxb-qAvGjf7ICPnahRBH4Y](https://datadryad.org/stash/share/xXcw75yKN0M_C_MMcqYVKQxb-qAvGjf7ICPnahRBH4Y)  
870 (Zheng et al., 2021).

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