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## An inverse approach integrating flowmeter and pumping test data for three-dimensional aquifer characterization

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## 14 **Abstract**

15 The accurate characterization of the underground depositional structure and hydraulic property  
16 distribution is essential to understand flow and solute transport in heterogeneous rocks or soils.  
17 Hydraulic tomography was shown to be an efficient technique to infer the spatial distribution of  
18 hydraulic properties. Due to the fact that information about the sedimentary structures' distribution is  
19 not always available to allow a three-dimensional characterization, many of existing field applications  
20 of hydraulic tomography have been limited to two-dimensional imaging along horizontal layer or  
21 vertical profiles where hydraulic data were collected.

22 In this work, we explore the potential of combining tomographic pumping and flowmeter tests  
23 responses in an inverse approach for three-dimensional aquifer characterization. The tomographic  
24 pumping data provide information about the lateral hydraulic connections between boreholes, while  
25 the flowmeter data constrain the vertical heterogeneity structure. The inverse approach is first  
26 validated using two synthetic models composed of multi-layered depositional structures and  
27 heterogeneous hydraulic properties within each layer. It is shown that adding the information  
28 provided by the flowmeter profiles, the inverted model exhibits more realistic depositional features.  
29 We then apply the proposed approach to characterize the 3D hydraulic conductivity field controlled  
30 by sedimentary structure of an experimental site in layered porous rocks. The inverted hydraulic  
31 conductivity field is in a good agreement with permeability measurement on drilled cores. The  
32 proposed method offers an efficient and low-cost approach for rapid assessment of the hydraulic  
33 properties in 3D and could be extrapolated to other field applications.

## 34        **1. Introduction**

35        The characterization of hydraulic properties, such as hydraulic conductivity and specific storage, is  
36        very important in groundwater modeling and water resources management (Hubbard and Rubin,  
37        2005). Contaminant transport has always been strongly dependent on the accuracy of the hydraulic  
38        properties' characterization. A minor change in hydraulic properties may alter transport behaviors  
39        significantly (Zheng and Gorelick, 2003). Because direct measurements of hydraulic properties are  
40        limited in real-world applications, early analytical analysis of aquifer hydraulic response to  
41        pumping/injection often adopts a homogeneous assumption (e.g., Theis 1935, Cooper and Jacob  
42        1946). It may be enough to infer the bulk aquifer property; however, it cannot capture most of the  
43        transient behavior of the tested aquifer. In addition to pumping tests, several other hydraulic testing  
44        methods, such as slug tests (Yeh et al., 1995) and flowmeter tests (Rehfeldt et al., 1992, Klepikova et  
45        al., 2013, Tamayo-Mas et al., 2018), are being used to provide non-redundant information (with  
46        respect to pumping tests) about the aquifer.

47        Hydraulic tomography (HT) has been developed over the last two decades (e.g., Gottlieb and Dietrich,  
48        1995, Butler et al., 1999, Bohling et al., 2002, Bohling and Butler, 2010, Yeh and Liu, 2000, Zhu and  
49        Yeh, 2005, Zhu and Yeh, 2006, Liu et al., 2002, Liu et al., 2007, Illman et al., 2010, Cardiff et al.,  
50        2009, Zha et al. 2014). This approach has shown a great potential for reconstructing detailed spatial  
51        distributions of hydraulic parameters comparing to the traditional analytical solutions. Hydraulic  
52        tomography yields a detailed two- or three-dimensional map of hydraulic heterogeneity for regions  
53        within between the testing boreholes where constraining hydraulic head responses to cross-hole  
54        pumping are collected. The efficiency of HT has been demonstrated in many laboratory-scale (e.g.,  
55        Liu et al., 2007, Illman et al., 2007, Illman et al., 2010, Zhao et al., 2016, Zhao and Illman 2017) and  
56        field-scale studies (e.g., Bohling et al., 2007, Brauchler et al., 2011, Brauchler et al., 2013, Berg and  
57        Illman, 2011, Cardiff et al., 2012, Fischer et al., 2020).

58        For a full 3D hydraulic tomography, using only one observation from each testing well is not  
59        sufficient and packer tests are often required (Bholing et al. 2007, Berg and Illman 2011, Zha et al.

60 2016, Zha et al. 2017, Cardiff et al. 2012, Zhao and Illman 2017, Wen et al. 2020). However, packer  
61 tests, which are costly and complex to set up, are not always available in each experiment site.  
62 Without packer tests, pumping tests data remain insufficient to capture the three-dimensional aquifer  
63 behavior and may lead to erroneous characterization and sometimes model instability in layered  
64 aquifers.

65 In recent years, other information such as geological and geophysical data have been used to constrain  
66 the inverse process of HT (e.g., Zha et al. 2017, Tso et al. 2016, Soueid Ahmed et al. 2015). The most  
67 widely-used geostatistics-based inverse modelling approaches are the quasi-linear geostatistical  
68 approach (Kitanidis 1995) and the successive linear estimator (SLE) (Yeh et al. 1996). To improve  
69 efficiency when dealing with highly parameterized inverse problems, different approaches were  
70 developed, including principle component geostatistical approach (Kitanidis and Lee 2014), reduced-  
71 order SLE (Zha et al. 2018) and the use of geostatistical reduced order models (Liu et al. 2013).  
72 Previous works have highlighted the benefits of incorporating site-specific geologic structure  
73 information into groundwater models when HT data are limited (Zha et al. 2017, Tso et al. 2016). Zha  
74 et al. (2017) worked on quantitative incorporation of site-specific information into groundwater  
75 models and introduced a general method to derive conditional mean and conditional covariance, that  
76 can be used in HT analysis as prior information. Tso et al. (2016) also concluded that only  
77 incorporating a qualitative facies trend information already yields a better conductivity estimate. Such  
78 improvement can also be seen in hydraulic conductivity estimates through laboratory/ field  
79 applications (Zhao et al. 2016, Zhao and Illman 2017). De Clercq et al. (2020) used electrical  
80 resistivity maps to structure the distribution of the hydraulic properties in a 3D HT.

81 Flowmeter surveys characterize the vertical inflow profile of a given well (Paillet et al. 1998, Molz et  
82 al. 1994, Zlotnik and Zurbuchen 2003, Williams and Paillet. 2002, Day-Lewis et al. 2011). They are a  
83 widely used approach to determine vertical profiles of hydraulic conductivities at well locations.  
84 Complex geological medias are often layered systems and flowmeter analysis has shown its efficiency  
85 to detect the main layers contributing to the total pumped flux (Day-Lewis et al. 2011, Paillet and  
86 Reese 2000). Flowmeter profiling can also be used to detect the well crossing fractures that contribute

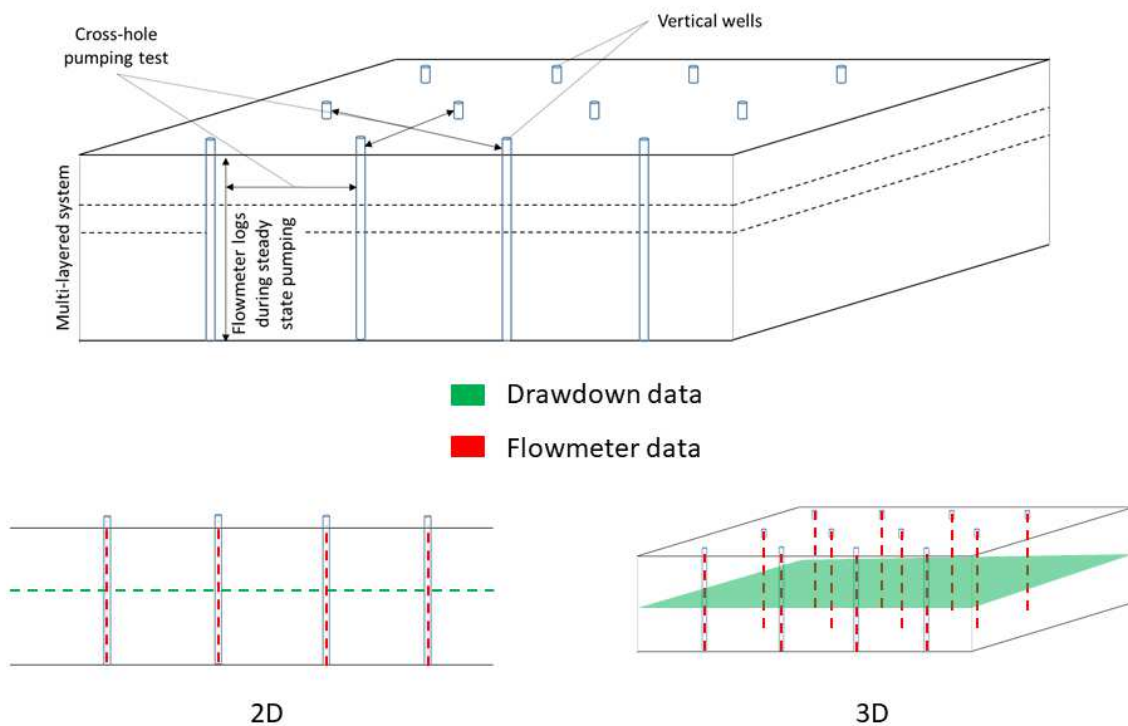
87 to flow (Day-Lewis et al. 2011, Roubinet et al. 2015). Flowmeter tests are easy and cheap but bulky  
88 and the investigated height is limited due to the space taken by the pump and the generated drawdown.  
89 Flowmeter tests may provide a new set of information and have been included in inverse modelling  
90 problems. For instance, Fienen et al. (2004) used a Bayesian inverse approach to interpret the vertical  
91 hydraulic conductivity in a heterogeneous fractured aquifer. Other applications used the interpreted  
92 hydraulic conductivity values from flowmeter tests in the transmissivity map to constrain the  
93 geostatistical inversions (e.g., Rehfeldt et al. 1992; Chen et al. 2001). In other studies, flux  
94 measurements have also been used as observation data additional to hydraulic heads in hydraulic  
95 tomography (Li et al. 2008, Zha et al. 2014, Tso et al. 2016).

96 Combining different hydraulic tests that characterize different parts of the aquifer may lead into a  
97 good characterization; for example, combining flowmeter tests data that give vertical information with  
98 pumping tests data that give lateral information might be a good alternative to obtain a three-  
99 dimensional characterization of the aquifer without packer tests. In this paper, we integrate vertical  
100 hydrogeological information obtained from flowmeter surveys and horizontal information from cross-  
101 hole pumping tests to achieve a 3D transient hydraulic tomographic (THT) characterization of  
102 sedimentary layered rocks. The flowmeter data are incorporated to HT through the construction of  
103 conditional initial mean and covariance of model parameter. We first validate the proposed inversion  
104 framework using synthetic data from a two-dimensional cross-section model and a three-dimensional  
105 model. We then apply the inverse approach to a real-world study in an experimental site composed of  
106 layered porous rocks. In the end, we analyze the data fitting effectiveness and geological coherence of  
107 the inverted hydraulic conductivity fields.

## 108 **2. Methodology**

109 The objective of the study is to integrate two sets of data to obtain spatialized hydraulic conductivity  
110 estimates through hydraulic tomography. The first dataset corresponds to drawdown responses to  
111 pumping tests that give information about lateral variation of hydraulic properties. The second dataset  
112 consists in flowmeter logs measured in every well of the site that give vertical information (see Figure

113 1 for datasets scheme). Flowmeter logs are first interpreted and converted into hydraulic conductivity  
 114 profiles. Then, the interpreted hydraulic conductivity profiles are interpolated using a triangular-base  
 115 bilinear or trilinear interpolation in order to obtain a continuous two- or three-dimensional hydraulic  
 116 conductivity map between the wells and we use ‘nearest neighbors’ interpolation for the rest of the  
 117 inversion domain where the linear interpolation cannot be evaluated. After that, an inverse modelling  
 118 approach is used to reconstruct the hydraulic conductivity distribution using interpolated map as a  
 119 prior information. We use the principal component geostatistical approach, a deterministic iterative  
 120 procedure that updates the conditional mean and the conditional covariance by matching model  
 121 responses to the pumping tests observations.



122

123 **Figure 1:** Data usage scheme. Red dashes correspond to flowmeter log data and green surface  
 124 corresponds to cross-hole pumping tests data. The wells are open hole and the drawdowns are  
 125 sampled at the green z-level.

126 **2.1 Groundwater flow model**

127 We solve the problem of three-dimensional transient fluid flow through a confined, saturated and  
128 heterogeneous porous media. The system is solved in transient regime and is described by the  
129 following equations:

$$130 \quad S_s \frac{\partial h}{\partial t} + \nabla(-K\nabla h) = Q, \quad (1)$$

131 **with**

$$132 \quad h|_{t=0} = h_0, h|_{\varphi} = h_0, \quad (2)$$

133 where  $\nabla$  is the gradient operator,  $S_s$  is the specific storage which assumed constant in this study,  $h$  is  
134 the hydraulic head,  $K$  the hydraulic conductivity,  $Q$  the source term and  $h_0$  is the initial hydraulic head  
135 which remains constant at the boundary conditions  $\varphi$ . The forward flow model is solved using a finite  
136 element method using unstructured mesh (See Figure R3 in supplementary materials).

## 137 **2.2 Flowmeter analysis**

138 The applied approach of flowmeter data analyses is described in Molz et al. (1989), which is based on  
139 the study of flow in a layered, stratified aquifer by Javandel and Witherspoon (1969). Assuming that  
140 the idealized aquifer is layered and the flow quickly becomes horizontal even with high contrast of  
141 hydraulic conductivity between the layers. The flow of a given layer is proportional to the hydraulic  
142 conductivity of that layer and the sum of the different flow rates into the well is equal to the pump  
143 flow rate during the pumping test.

144 During our flowmeter test, water is extracted from an open hole well and, once steady state is reached,  
145 a spinner flowmeter is swept along the well from the bottom of the well to the top and a vertical flow  
146 rate profile is measured. In most common cases, when the pump is located at the top, the flow rate log  
147 will have the trend of an increasing curve starting from a zero value at the bottom to a max value at  
148 the top, that will correspond to the total extracted flux from the well. The increase in flow rate over a  
149 certain depth increment is correlated to the relative hydraulic conductivity profile; higher the  
150 hydraulic conductivity, stronger the rate increase. Flowmeter tests therefore provide relative values of



151 hydraulic conductivity distribution along the borehole. In order to extract the absolute values, an  
 152 effective value of hydraulic conductivity of the well (obtainable from the interpretation single hole of  
 153 a pumping tests) will be used. Single-hole flowmeter data can be analyzed to estimate conductivity  
 154 profiles along boreholes and characterize aquifer compartmentalization (Molz et al. 1989; Kabala  
 155 1994; Paillet et al. 1998).

156 If a well is subject to a pumping with a pump placed at the top of the well working at the rate  $Q_p$ , the  
 157 underground layers connected to that well will contribute to the total extracted flux. Their contribution  
 158 is proportional to their hydraulic conductivity. For the following equations,  $b$  (m) refers to the aquifer  
 159 thickness,  $z_0$  (m) the reference level of the borehole bottom, and  $z$  (m) the height above the bottom  
 160 (Figure 2). In an idealized layered aquifer, the flow into the well from a given layer is proportional to  
 161 the transmissivity of that layer:

$$162 \quad \Delta Q_i = \alpha \Delta z_i K_i, \quad (3)$$

163 where  $\alpha$  (m) is a constant of proportionality,  $\Delta Q_i$  ( $m^3/s$ ) corresponds to the induced flow increments  
 164 observed in the borehole along the  $i^{\text{th}}$  increment of height  $\Delta z_i$  (m) that has a hydraulic conductivity  $K_i$   
 165 (m/s). The average horizontal hydraulic conductivity  $K_{avg}$  can be expressed by:

$$166 \quad K_{avg} = \frac{\sum K_i \Delta z_i}{b}. \quad (4)$$

167 The cumulative flow  $Q_{cum}(b)$  over the aquifer thickness can be expressed as follows:

$$168 \quad Q_{cum}(b) = \int_{z_0}^b Q(z) dz = Q_p = \sum_i \Delta Q_i = \alpha \sum_i \Delta z_i K_i = \alpha K_{avg} b. \quad (5)$$

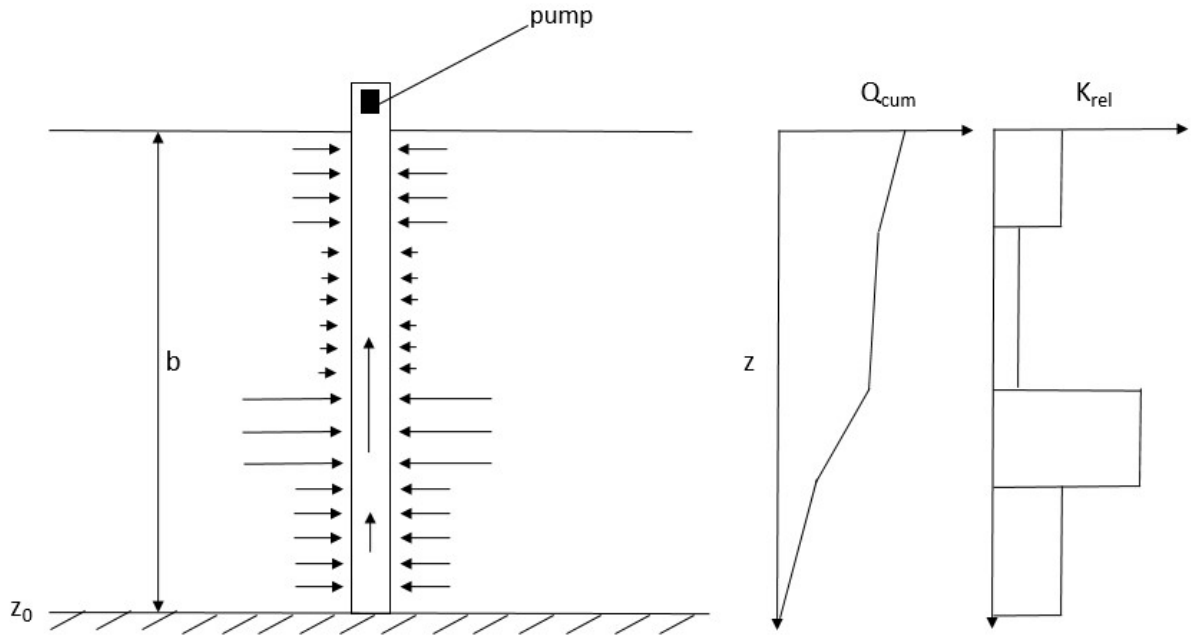
169 By substituting the sum,  $\alpha$  can be solved as:

$$170 \quad \alpha = \frac{Q_p}{K_{avg} b}. \quad (6)$$

171 Then, the hydraulic conductivity of each layer can be quantified by:

172

$$K_i = \frac{\Delta Q_i K_{avg} b}{Q_p \Delta z_i} . \quad (7)$$



173

174

**Figure 2:** Flowmeter setup scheme with an interpretation example.  $Q_{cum}$  is the cumulative flow rate

175

and  $K_{rel}$  is the interpreted relative permeability from flow log.

## 176 2.2 Principal component geostatistical approach

177 In order to optimize the hydraulic conductivity field in the model we use the principal component

178 geostatistical approach (PCGA) (Kitanidis and Lee 2014). The observation equation that links the  $m$

179 unknown hydraulic conductivities, stored in a vector  $\mathbf{s}$ , to the observation data (hydraulic heads)

180 stored in a matrix  $\mathbf{y}$  is (Kitanidis 1995):

$$181 \quad \mathbf{y} = \mathbf{h}(\mathbf{s}) + \mathbf{v}, \quad (8)$$

182 where  $\mathbf{h}(\cdot)$  is the forward model,  $\mathbf{v}$  is the observation error with a random normal distribution with

183 mean 0 and variance  $\mathbf{R}$ , which is usually the error measurement multiplied by the identity matrix. The

184 prior probability of  $\mathbf{s}$  is a Gaussian distribution with mean  $\mathbf{X}\boldsymbol{\beta}$  generalized by a covariance matrix  $\mathbf{Q}$ .

185  $\mathbf{X}$  is a  $m$ -vector of ones and  $\boldsymbol{\beta}$  represents the mean hydraulic conductivity value. The posterior

186 probability density function (objective function  $\mathbf{L}$ ) of  $\mathbf{s}$  and  $\boldsymbol{\beta}$  is given by:

187 
$$\mathbf{L} = \frac{1}{2}(\mathbf{y} - \mathbf{h}(\mathbf{s}))^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{h}(\mathbf{s})) + \frac{1}{2}(\mathbf{s} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{Q}^{-1}(\mathbf{s} - \mathbf{X}\boldsymbol{\beta}) . \quad (9)$$

188 The optimization of the hydraulic conductivity values is obtained by minimizing this objective  
 189 function through an iterative method.

190 Inversion process requires the calculation of the sensitivity matrix (Jacobian matrix) which require as  
 191 much forward model simulations as unknowns  $m$ . Despite the computer science advancement, the  
 192 forward model itself can be time consuming when dealing with high dimensional problems (3D  
 193 simulations, fine mesh, presence of complex structures). In order to bypass this difficulty, the  
 194 principal component geostatistical approach which avoids the full Jacobian matrix calculation, was  
 195 proposed. The reduced order successive linear estimator ROSLE (Zha et al. 2018) based on SLE (Yeh,  
 196 1996) can be one alternative to the PCGA. These methods use a singular value decomposition and  
 197 then a truncation based on the eigenvalues and Eigen functions of the covariance matrix  $\mathbf{Q}$ . The  
 198 covariance matrix can be rewritten with its decomposed form as:

199 
$$\mathbf{Q} = \mathbf{V}\mathbf{S}\mathbf{V}^T , \quad (10)$$

200 where  $\mathbf{V}$ 's columns correspond to the eigenvectors of the covariance matrix and  $\mathbf{S}$  is a diagonal matrix  
 201 of its eigenvalues  $\lambda$  which are decreasingly organized. The eigenvectors and eigenvalues are then  $\mathbf{k}$ -  
 202 rank truncated. The  $\mathbf{k}$  first eigenvalues and its corresponding eigenvectors are kept. The compressed  
 203 covariance can be calculated as:

204 
$$\mathbf{Q}_k = \mathbf{V}_k \mathbf{S}_k \mathbf{V}_k^T , \quad (11)$$

205 where

206 
$$\mathbf{Q}_k \approx \mathbf{Q} , \quad (12)$$

207 It can be also written as a sum:

208 
$$\mathbf{Q}_k = \mathbf{V}_k \mathbf{S}_k \mathbf{V}_k^T = \sum_{i=1}^k \xi_i \xi_i^T , \quad (13)$$

209 where

$$210 \quad \xi_i = \sqrt{\lambda_i} \mathbf{V}_i. \quad (14)$$

211 The accuracy of the low-rank covariance depends on the truncation number. However, it is already  
 212 shown that a much smaller truncation number than the number of unknowns ( $\mathbf{k} \ll m$ ) can be used  
 213 (Kitanidis and Lee, 2014). The quasi-Linear geostatistical approach (Kitanidis, 1995) updates the  
 214 actual best estimate  $\bar{\mathbf{s}}$  for the next iteration as:

$$215 \quad \bar{\mathbf{s}} = \mathbf{X}\bar{\boldsymbol{\beta}} + \mathbf{Q}\mathbf{H}^T\bar{\boldsymbol{\xi}}, \quad (15)$$

216 where  $\mathbf{H}$  is the Jacobian matrix and the accentuation-bar denotes the best estimate.  $\bar{\boldsymbol{\beta}}$  and  $\bar{\boldsymbol{\xi}}$  are solved  
 217 from the following linear system:

$$218 \quad \begin{bmatrix} \mathbf{H}\mathbf{Q}\mathbf{H}^T + \mathbf{R} & \mathbf{H}\mathbf{X} \\ (\mathbf{H}\mathbf{X})^T & \mathbf{0} \end{bmatrix} \begin{bmatrix} \bar{\boldsymbol{\xi}} \\ \bar{\boldsymbol{\beta}} \end{bmatrix} = \begin{bmatrix} \mathbf{y} - \mathbf{h}(\bar{\mathbf{s}}) + \mathbf{H}\bar{\mathbf{s}} \\ \mathbf{0} \end{bmatrix}. \quad (16)$$

219 The minimized objective function  $\mathbf{L}$  can also be written as:

$$220 \quad L = \frac{1}{2} \left( \mathbf{y} - \mathbf{h}(\mathbf{X}\boldsymbol{\beta} + \mathbf{Q}\mathbf{H}^T\boldsymbol{\xi}) \right)^T \mathbf{R}^{-1} \left( \mathbf{y} - \mathbf{h}(\mathbf{X}\boldsymbol{\beta} + \mathbf{Q}\mathbf{H}^T\boldsymbol{\xi}) \right) + \frac{1}{2} \boldsymbol{\xi}^T \mathbf{H}\mathbf{Q}\mathbf{H}^T \boldsymbol{\xi}. \quad (17)$$

221 In PCGA, the sensitivity matrix  $\mathbf{H}$  is not fully calculated and an alternative way to approximate it is  
 222 proposed.

223 In order to estimate  $\mathbf{H}\mathbf{Q}$  and  $\mathbf{H}\mathbf{Q}\mathbf{H}^T$ ,  $\mathbf{k}$  forward runs are needed to be solved in addition to the  
 224 forward run of the actual best estimate, the forward models are used to calculate  $\boldsymbol{\eta}$  defined as follows:

$$225 \quad \boldsymbol{\eta}_i = \mathbf{H}\boldsymbol{\xi}_i \approx \frac{1}{\delta} [\mathbf{h}(\mathbf{s} + \delta\boldsymbol{\xi}_i) - \mathbf{h}(\mathbf{s})], \quad (18)$$

226  $\delta$  is the finite difference interval from the Taylor series expansion (Kitanidis and Lee, 2014). Then  
 227  $\mathbf{H}\mathbf{Q}$  and  $\mathbf{H}\mathbf{Q}\mathbf{H}^T$  are defined as:

$$228 \quad \mathbf{H}\mathbf{Q} \approx \mathbf{H}\mathbf{Q}_k = \mathbf{H} \sum_{i=1}^k \boldsymbol{\xi}_i \boldsymbol{\xi}_i^T = \sum_{i=1}^k (\mathbf{H}\boldsymbol{\xi}_i) \boldsymbol{\xi}_i^T = \sum_{i=1}^k \boldsymbol{\eta}_i \boldsymbol{\xi}_i^T, \quad (19)$$

229 
$$\mathbf{H}\mathbf{Q}\mathbf{H}^T \approx \mathbf{H}\mathbf{Q}_k\mathbf{H}^T = \mathbf{H}[\sum_{i=1}^k \xi_i \xi_i^T]\mathbf{H}^T = \sum_{i=1}^k (\mathbf{H}\xi_i)(\mathbf{H}\xi_i)^T = \sum_{i=1}^k \eta_i \eta_i^T. \quad (20)$$

230 In order to estimate  $\mathbf{H}\mathbf{X}$ , one (columns of  $\mathbf{X}$ ) forward run is needed, following:

231 
$$\mathbf{H}\mathbf{X}_i \approx \frac{1}{\delta} [\mathbf{h}(\bar{\mathbf{s}} + \delta\mathbf{X}_i) - \mathbf{h}(\bar{\mathbf{s}})]. \quad (21)$$

232 In order to estimate  $\mathbf{H}\bar{\mathbf{s}}$ , one forward run is needed in addition to the forward model of the actual best  
 233 estimate, following:

234 
$$\mathbf{H}\bar{\mathbf{s}} = \frac{1}{\delta} [\mathbf{h}(\bar{\mathbf{s}} + \delta\bar{\mathbf{s}}) - \mathbf{h}(\bar{\mathbf{s}})] + \mathbf{O}(\delta) \approx \frac{1}{\delta} [\mathbf{h}(\bar{\mathbf{s}} + \delta\bar{\mathbf{s}}) - \mathbf{h}(\bar{\mathbf{s}})]. \quad (22)$$

235 In total, each iteration requires  $\mathbf{k}+3$  forward runs; 1 forward run of the actual best estimate, 1 forward  
 236 run to estimate  $\mathbf{H}\bar{\mathbf{s}}$ , 1 forward run to estimate  $\mathbf{H}\mathbf{X}$  and  $\mathbf{k}$  forward models to estimate  $\mathbf{H}\mathbf{Q}$  and  $\mathbf{H}\mathbf{Q}\mathbf{H}^T$ .  
 237 The above steps are repeated iteratively until convergence of the objective function value is reached.

### 238 *2.3 Prior information*

239 The approach of conditional mean and conditional covariance using geological information as  
 240 presented in Zha et al. (2017) work is used in this study. The two main prior information are the initial  
 241 guess and the initial covariance matrix. The prior input of the inversion is constructed using  
 242 interpreted flowmeter data. The 3D interpolated conductivity is mapped into inversion grid, stored in  $\mathbf{s}$ ,  
 243 and used as an initial guess for the first iteration instead of using an initial mean.; an interpolation  
 244 or/and an extrapolation might be often used. It also allows identifying the main facies and  
 245 constructing the prior covariance accordingly (Zha et al. 2017). However, the covariance matrix  $\mathbf{Q}$  is  
 246 constructed as a sum of different covariance sub-matrixes (Zha et al., 2017): a) a covariance matrix  
 247 that defines the different facies (layers) will be of high importance and its construction is achieved  
 248 only by using a strong correlation between the cells that belong to the same facies, b) another  
 249 covariance matrix that defines the correlation between the cells of the same facies, defined as an intra-  
 250 facies covariance, c) a third covariance matrix, defined as an inter-facies covariance, can be used on  
 251 the global inverted domain. By conditioning the prior covariance with facies information

252 distinguished from flowmeter data, we try to incorporate the vertical information into the inversion  
253 process and constrain its convergence path.

### 254 **3. Validation of concept**

255 The main objective of the paper is the use of two different datasets which are easily available to better  
256 characterize the hydraulic conductivity of a multi-layered sedimentary structure constitutive of the  
257 aquifer. The first dataset corresponds to flowmeter data along the profile of each well. Flowmeter logs  
258 are obtained by pumping in the top of each well and the flowmeter tool is swept under the pump to get  
259 the flow contribution along the borehole. The second dataset corresponds to measured hydraulic  
260 response (drawdowns) to pumping tests. Here we try to perform a 3D inversion of the hydraulic  
261 conductivity field to characterize the aquifer on the basis of pumping tests data and incorporating  
262 flowmeter information. In order to validate this concept, the proposed inverse approach is first applied  
263 on two synthetic cases. The first case is performed in 2D and the second one in 3D.

#### 264 **3.1. 2D synthetic case**

265 By using a two-dimensional random field generator tool (Paul Constantine 2021), a random hydraulic  
266 conductivity field is generated following an exponential correlation function using the parameters of  
267 standard deviation  $\sigma=1.5$ , the correlation length in x direction  $L_x=100$  m, the correlation length in y  
268 direction  $L_y=5$  m. With such set of parameters, the obtained hydraulic conductivity field displays  
269 multi-layered hydraulic properties (see Figure 3.a). We consider the obtained 2D map as a vertical  
270 cross-section of an aquifer centered on the inverted domain which is extended using a buffer area until  
271 the boundary conditions. The dimensions of the inverted domain are 70 m by 50 m; the dimensions of  
272 the buffer area are 700 m by 50 m. The lateral boundaries are set to constant zero hydraulic head  
273 while the upper and lower boundaries are set to no flow condition. The initial condition is set to zero  
274 hydraulic head in the whole domain. For forward flow simulations, we use the subsurface flow  
275 module of Comsol Multiphysics (COMSOL AB 2018). We assume the aquifer to be confined. The  
276 specific storage is assumed constant and a value of  $S_s = 10^{-4}$  was used.

277 The wells are modeled explicitly with a radius of  $r_w=0.1$  m. We attribute to wells a high hydraulic  
278 conductivity ( $K=1$  m.s<sup>-1</sup>) and a low specific storage ( $10^{-10}$  m<sup>-1</sup>) (see Figure S1 in supplementary

279 material). The spacing of wells in the x direction is 15m (Figure 3a). We simulate five cross-hole  
280 pumping tests, which are considered as the ‘data’ for inversion. The location of selected wells is  
281 indicated in Figure S4. We simulate flowmeter data for each well by using a point source at the top of  
282 the well and applying a steady-state pumping flow rate. Once the steady-state flow regime is reached,  
283 we evaluate the vertical velocity along a line in the middle of the well. In our flow simulations, extra  
284 fine meshes are adopted to discretize the well domain (Figure R3). Examples of simulated flowmeter  
285 measurements for the 2D case can be found in supplementary material (Figure R2). For cross-hole  
286 pumping tests dataset to be used in HT, we simulate the transient hydraulic heads using a point source  
287 in the middle of explicitly modelled wells. The black dots shown in Figure 3 are the position of the  
288 points to be used as point source for the pumping tests and the monitoring points. For hydraulic head  
289 data, we sample at five different time steps covering the early to middle times for all pumping tests.  
290 The total number of drawdown data used for inversions are 5 (number of time steps) \* 5 (number of  
291 pumping tests) \* 4 (number of observation wells) = 100.

292 The simulated vertical velocity curves are converted into hydraulic conductivity distributions  
293 following the procedure described as follows (An example of the manipulation is provided in the  
294 supplementary information file).

- 295 - Step1: Discretize the vertical velocity profile into depth intervals  $\Delta z$
- 296 - Step2: In each interval, evaluate the change in velocity  $\Delta v_i$  corresponding to the change in  
297 depth  $\Delta z_i$
- 298 - Step3: Use Equation 7 to estimate  $K_i$  for each  $\Delta z_i$
- 299 - Step4: Hydraulic conductivity profile is obtained in each well.

300 The hydraulic conductivity profiles are then interpolated using a triangular-base bilinear interpolation  
301 to obtain a hydraulic conductivity map for areas within between the wells. For the rest of the inversion  
302 domain where the linear interpolation cannot be evaluated, we use a nearest neighbors’ extrapolation.  
303 In the next step, we construct a nested covariance using the interpolated hydraulic conductivity map.  
304 The nested covariance is constructed by the combination of multiscale correlated heterogeneities (Zha  
305 et al. 2017). For example, a geological facies from another survey can be used a soft constraint added

306 into the initial covariance matrix for HT. The interface between different facies or zones may exhibit  
307 an abrupt change of hydraulic properties. On the other hand, the variability inside a particular facies or  
308 zone (compared to its large-scale mean) can be described by a zero mean and a small-scale covariance  
309 function.

310 The covariance matrix used in HT of the 2D study is either calculated using a covariance model  
311 similar to the one used to generate the true random field (Figures 3b and 3c), or built from a nested  
312 covariance which is a sum of different covariance matrices: a covariance matrix built using a  
313 covariance model similar to the one used to generate the true random field plus a covariance matrix  
314 defining the important facies of flowmeter interpreted map (Figure 3e and 3f). The first covariance  
315 matrix is simply calculated using an exponential covariance model with standard deviation=1.5,  
316 correlation length in x direction  $L_x=100$  m and correlation length in y direction  $L_y=5$  m. For the  
317 second covariance matrix that defines the facies, we simply identify the facies from flowmeter map  
318 (Figure 3g) and we build a binary covariance that correlates the cells that belong to the same facies.

319 In the inverse problem, a structured grid is used to discretize the model domain. For the two-  
320 dimensional cases, the number of grid blocks in x and y directions are  $n_x = 30$  and  $n_y = 15$  respectively  
321 (See Figure R3). As a result, the total number of unknown K parameters is 450. For PCGA setup, we  
322 use a truncation number of  $k=20$  for a number of unknowns  $n=30*15$ ,  $R=0.001*Id$  where Id is the  
323 identity matrix, and  $\delta=0.0001$  for the finite difference interval. The specific storage was kept constant  
324 in the inversion and the value is the same as in the forward simulation, i.e.,  $S_s = 10^{-4} \text{ m}^{-1}$ . Figure 3  
325 shows the results of the two-dimensional validation case. Figure 3a corresponds to the generated,  
326 considered true, hydraulic conductivity field. Figure 3b is the inverted hydraulic conductivity field  
327 using a classical hydraulic tomography that used similar covariance information as in the generation  
328 of the random field. Figure 3d shows the interpreted hydraulic conductivity from flowmeter analysis.  
329 Figures 3c, 3e and 3f show the inverted hydraulic conductivity by integrating flowmeter  
330 interpretations into prior information of the inversion; Figure 3c used the interpreted hydraulic  
331 conductivity in Figure 3d to initialize only the parameter; Figure 3e used the interpreted hydraulic  
332 conductivity in Figure 3d to initialize both the parameter and the covariance matrix which remained  
333 constant during inversion iterations; Figure 3f used the interpreted hydraulic conductivity in Figure 3d

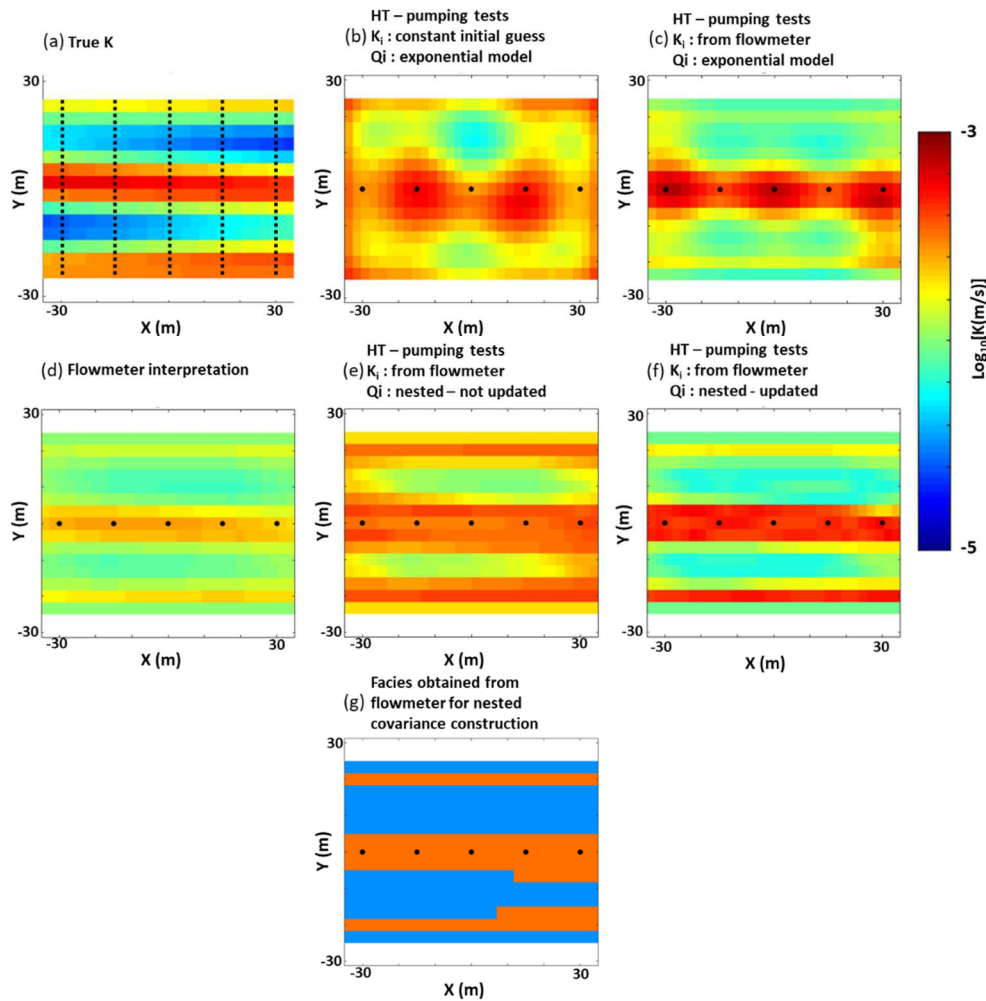


334 to initialize both the parameter and the covariance matrix which was updated during inversion  
335 iterations.

336 The flowmeter interpretation allows the detection of the main layers in the system (Figure 3d) while  
337 the attempt of an inversion using only pumping tests data couldn't assess the vertical profiles of  
338 hydraulic conductivity (Figure 3b). Figure 3c, 3e and 3f show better K estimates. Flowmeter data  
339 clearly carry non-redundant information on the vertical hydraulic conductivity profiles along the wells.

340 By only using the obtained hydraulic conductivity map from flowmeter interpretation as an initial  
341 guess, the inverted conductivity already contains vertical profile information and show different layers  
342 (Figure 3c). The inverted hydraulic conductivity shown in (Figure 3e) is also representative of a  
343 layered system but clearly not better than the inverted hydraulic conductivity shown in (Figure 3c).

344 On the contrary, when the nested covariance has the freedom to update through inversion iterations,  
345 the best parameter estimate was obtained compared to all other configurations (Figure 3f).

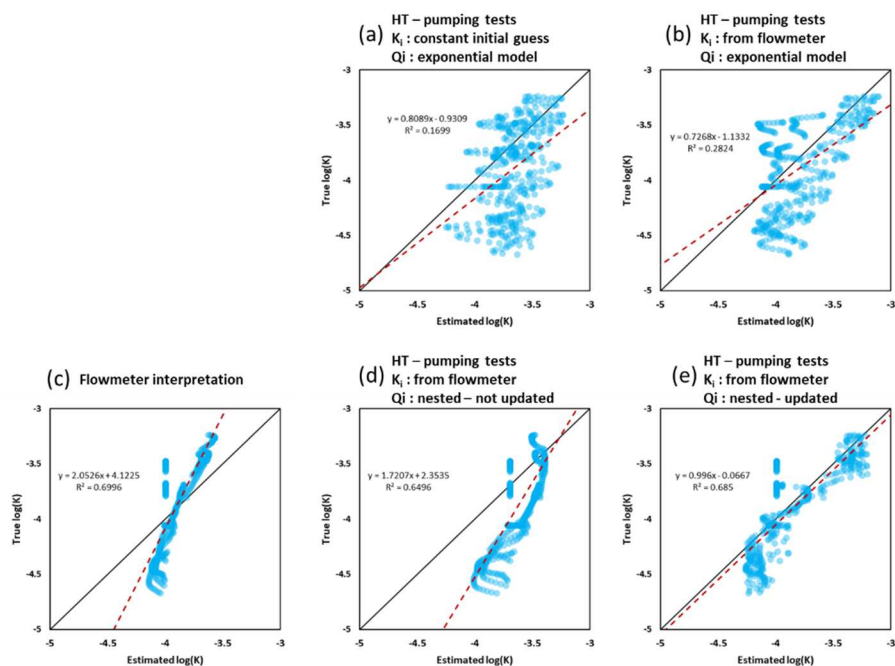


346

347 **Figure 3:** Two-dimensional validation case – results of HT using different prior information. a) true  
 348 hydraulic conductivity, d) interpreted hydraulic conductivity from flowmeter tests, b, c, e and f are  
 349 inverted hydraulic conductivities using different prior models.  $K_i$  and  $Q_i$  correspond to the initial  
 350 hydraulic conductivity and initial covariance matrix respectively, g) is the constructed facies from  
 351 flowmeter analyses to use in order to construct the nested covariance.

352 Figure 4 shows a scatter plot of true hydraulic conductivity and estimated hydraulic conductivity  
 353 shown in Figure 3. In each scatter plot we plot a linear model of data fitting (red dashed line) and  
 354 calculated the coefficient of determination, i.e.,  $R^2$  shown in Figure 4. The solid line is the first  
 355 bisector line of  $y=x$ . Figures 4a and 4b present results of using pumping tests and an exponential  
 356 covariance model for inversion. The difference is that in Figure 4a the initial guess of hydraulic  
 357 conductivity was assumed constant while in Figure 4b the hydraulic conductivity distribution  
 358 constructed by interpolating measured flowmeter profiles was used as the initial model. When the

359 flowmeter data are integrated, the inverted hydraulic conductivities represent the true model better ( $R^2$   
 360 of Figure 4b is lower than that of Figure 4a). On the other hand, Figure 4c confirms that the flowmeter  
 361 data can capture the true K distribution to some extent indicated by the strong linear trend and high  
 362 value of  $R^2$ . However, the variance of the hydraulic conductivity estimates seems underestimated. The  
 363 improved hydraulic conductivity estimation is obtained when flowmeter data are used to construct  
 364 both the initial model and the covariance model (Figure 4d). Comparing results shown in Figures 4d  
 365 and 4e indicates that allowing the update of the nested covariance improves the estimation  
 366 considerably.



367  
 368 **Figure 4:** Scatterplots of true hydraulic conductivity versus estimated hydraulic conductivity for the  
 369 different cases of the two-dimensional synthetic case. c) scatter plot of true K versus interpreted K  
 370 from flowmeter. a, b, d and e are scatter plots of true K versus inverted K using different prior models.

### 371 3.2. 3D synthetic case

372 We extend the approach to a three-dimensional synthetic case and try to show if flowmeter data can  
 373 provide the vertical information for a 3D aquifer characterization instead of packer tests. Similar to  
 374 the simplified two-dimensional case, we use a three-dimensional random field generator (Rass et al.  
 375 2019) to generate a three-dimensional synthetic hydraulic conductivity map using the following  
 376 parameters (Correlation function: exponential, standard deviation = 1.5,  $L_x=100$  m,  $L_y=100$  m and  $L_z=$

377 5 m). Such parameters provide a hydraulic conductivity map that is representative of a multilayered  
378 system. The dimensions of the inverted domain are length=70 m, width=70 m and height=30 m; the  
379 lateral dimensions of the buffer area are length=700 m and width=700 m; the buffer was not extended  
380 in the vertical direction. The outer boundaries are set to constant zero hydraulic head while the upper  
381 and lower boundaries (top and bottom) are set to no flow condition. The initial condition is set to zero  
382 hydraulic head in the whole domain. The specific storage is assumed constant and a value of  $S_s = 10^{-4}$   
383  $m^{-1}$  was used.

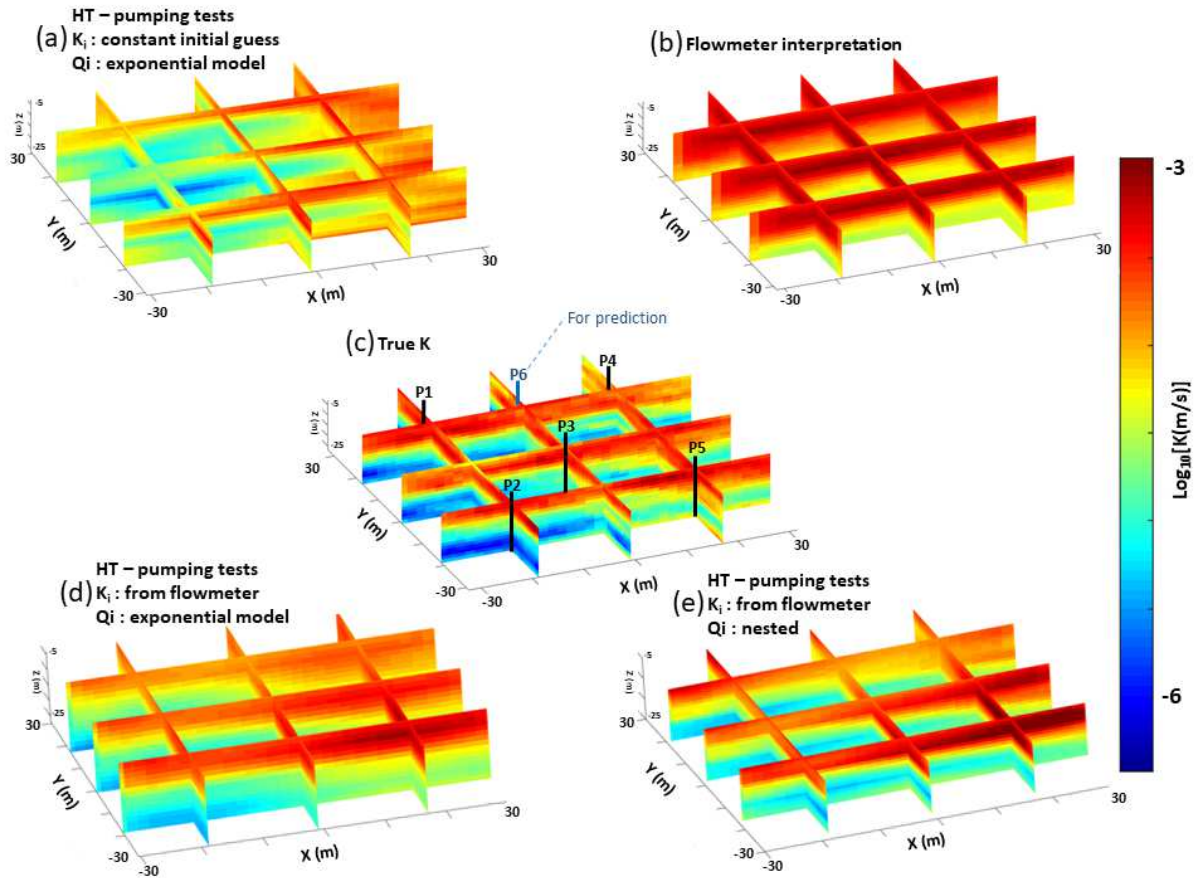
384 As for the two-dimensional case, we simulate flowmeter and cross-hole datasets by modelling explicit  
385 wells and point source pump (the point source in the top for the flowmeter simulation and in the  
386 middle for cross-hole tests simulations). Extra fine meshes are adopted to discretize the well domain  
387 (Figure R3). See Figure R2 in supplementary material for an example of simulated flowmeter  
388 measurements for the 3D case. Five cross-hole pumping tests data are simulated and considered as the  
389 'data' for the inversions. The location of selected wells is indicated in Figure S4. As for the 2D cases,  
390 the total number of observations for the 3D cases is 100. The flowmeter data are interpreted and the  
391 hydraulic conductivity profiles are then interpolated using a triangular-base trilinear interpolation to  
392 fill the area between the wells. The rest of the inversion domain where the linear interpolation cannot  
393 be evaluated, we use a nearest neighbors' extrapolation.

394 We construct a nested covariance using the interpreted flowmeter map as described for the two-  
395 dimensional case. In the inverse problem, a structured grid is used to discretize the model domain. For  
396 the three-dimensional cases, the number of grid blocks in x, y and z directions are  $n_x = 20$ ,  $n_y = 20$ ,  $n_z$   
397  $= 8$  respectively (See Figure R3). For PCGA setup, we use a truncation number of  $k=30$  for a number  
398 of unknowns  $n=20*20*8$ ,  $R=0.001*Id$  where  $Id$  is the identity matrix and  $\delta=0.0001$  for the finite  
399 difference interval. The specific storage was kept constant ( $S_s = 10^{-4} m^{-1}$ ) in the inversion and we  
400 focus on the characterization of K fields.

401 Figure 5 shows the results of the three-dimensional validation case. Figure 5c corresponds to the  
402 generated, considered true, hydraulic conductivity field. Figure 5a is the inverted hydraulic  
403 conductivity field using a classical hydraulic tomography that used same covariance information as in  
404 the random field generation. Figure 5b shows the interpreted hydraulic conductivity from flowmeter

405 analysis. Figures 5d and 5e show the inverted hydraulic conductivity by integrating flowmeter  
406 interpretations into prior information of the inversion; Figure 5d used the interpreted hydraulic  
407 conductivity in Figure 5b to initialize only the parameter; Figure 5e used the interpreted hydraulic  
408 conductivity in Figure 5b to initialize both the parameter and the covariance matrix which was  
409 updated during inversion iterations.

410 The results of the 3D validation case agree with the observed results of the 2D validation case. The  
411 flowmeter interpretation allows vaguely the detection of the main layers in the system (Figure 5b)  
412 while the attempt of an inversion using only pumping tests data couldn't assess the vertical profiles of  
413 hydraulic conductivity (Figure 5a). Figures 5d and 5e show better characterization in the vertical  
414 profiles due to non-redundant added information brought by flowmeter data. Using the flowmeter's  
415 interpreted hydraulic conductivity as an initial guess in the inversion already improves considerably  
416 the results (Figure 5d). Also, as seen in the 2D validation case, the best K estimate was obtained when  
417 flowmeter interpretation was used to initialize both the parameter and the covariance matrix (Figure  
418 5e).



419

420

**Figure 5:** Three-dimensional validation case - results of HT using different prior information; b)

421

interpreted hydraulic conductivity from flowmeter tests, c) true hydraulic conductivity, a, d and e are

422

inverted hydraulic conductivities using different prior models.  $K_i$  and  $Q_i$  correspond to the initial

423

hydraulic conductivity and initial covariance matrix respectively.

424

These results obtained with the 3D synthetic case are similar to the ones obtained with the 2D

425

synthetic case, and thus confirm that adding flowmeter information allows improving the hydraulic

426

permeability field. This conclusion is consistent with the fact that flux, in addition to hydraulic head

427

measurements, enhance K values estimate (Yeh et al. (2011, 2015a, 2015b), Mao et al. (2013a,

428

2013b), Tso et al. 2016).

429

To better evaluate the quality of the estimated hydraulic conductivity field, we simulate a transient

430

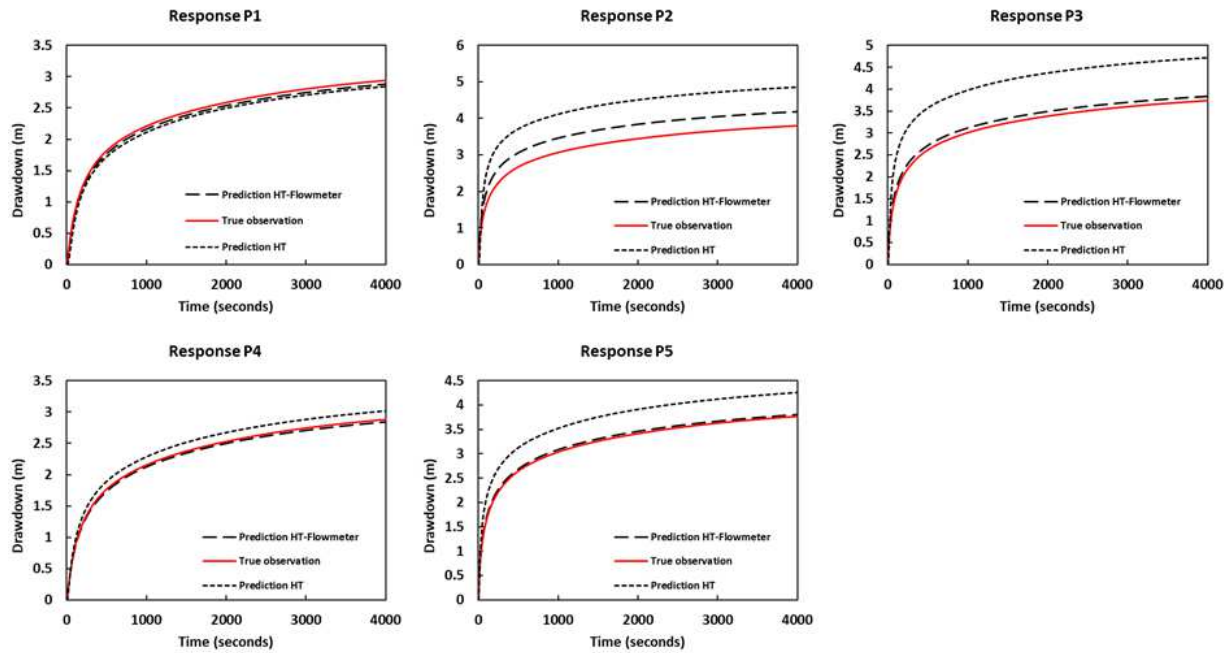
pumping test in well P6 (see Figure 5c) using this inverted hydraulic conductivity map and compare

431

the simulated drawdowns to the simulated drawdowns obtained with the true hydraulic conductivity

432

field (see Figure 6).



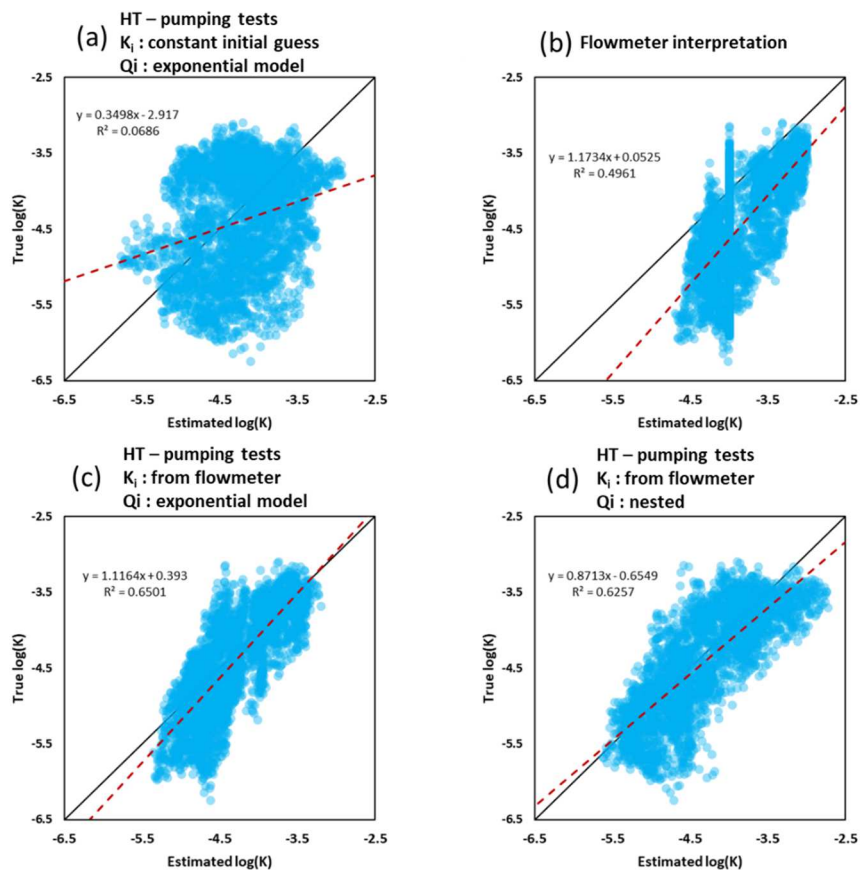
433

434 **Figure 6:** Hydraulic head response to simulated pumping tests in the new added well P6. Solid red,  
 435 dotted and dashed black curves correspond to the simulated drawdowns using respectively the true  
 436 conductivity, the hydraulic conductivity map obtained from hydraulic tomography and the hydraulic  
 437 conductivity map obtained from the hydraulic tomography conditioned by flowmeter analysis data.

438 Figure 6 compares different drawdowns obtained on 5 boreholes in response to a pumping test in the  
 439 new added prediction well P6. The drawdowns were simulated by using different hydraulic  
 440 conductivity fields; the curves represented by solid red lines correspond to simulated drawdowns  
 441 using true hydraulic conductivity; the curves represented by dotted black lines correspond to  
 442 simulated drawdowns using inverted hydraulic conductivity obtained from hydraulic tomography  
 443 using other pumping tests observation data (Figure 5a); the curves represented by dashed black lines  
 444 correspond to simulated drawdowns using inverted hydraulic conductivity obtained from hydraulic  
 445 tomography using other pumping tests observation data and conditioned by flowmeter data (Figure  
 446 5e). The results clearly show that the dashed lines (HT + flowmeter data) are closer to the solid red  
 447 lines (true drawdown) compared to the dotted lines (classical HT). Such observation confirms that  
 448 incorporating flowmeter data in the hydraulic tomography leads to better K estimates.

449 We also show a scatter plot of true hydraulic conductivity and estimated hydraulic conductivity in  
 450 Figure 7. Each scatter plot has a linear model of data fitting represented by a red dashed line with a

451 linear regression expression and a coefficient of determination. The solid line is the first bisector line  
 452 of  $y=x$ . Figure 7a shows the result of using pumping tests and an exponential covariance model.  
 453 Figure 7b presents the result of hydraulic conductivity comparison based on flowmeter interpretation.  
 454 The small bias toward high absolute values of hydraulic conductivities indicates that the effective  
 455 hydraulic conductivity is overestimated by the interpolation of flowmeter profiles. When the  
 456 interpreted hydraulic conductivity distribution from flowmeter is used as initial guess for the inversion,  
 457 we observe that the characterization of hydraulic conductivity becomes considerably better (compare  
 458 Figure 7c to Figure 7a). The incorporation of multiscale heterogeneity with the nested covariance  
 459 model generates a different representation, but the hydraulic conductivity estimates is considerably  
 460 improved as well (Figure 7d). This demonstrates the importance of integrating flowmeter data.

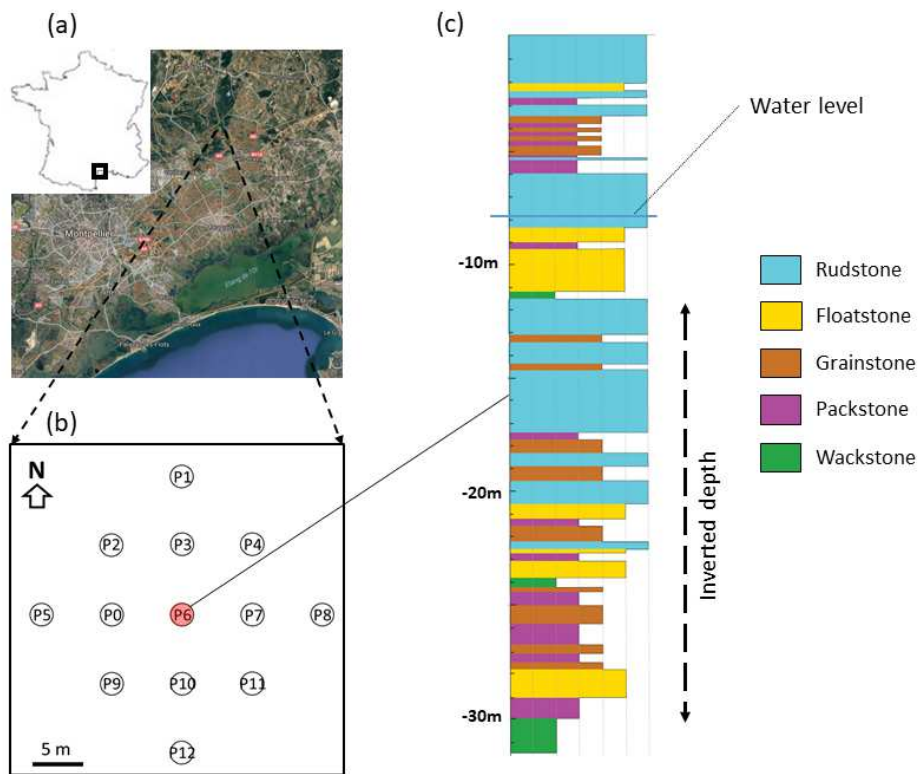


461  
 462 **Figure 7:** Two-dimensional validation case – scatterplots of true hydraulic conductivity versus  
 463 estimated hydraulic conductivity for the different cases of the two-dimensional synthetic case. b)  
 464 scatter plot of true  $K$  versus interpreted  $K$  from flowmeter. a, c and d are scatter plots of true  $K$  versus  
 465 inverted  $K$  using different prior models.



466 **4. Application**

467 In this section, the approach is applied to an experimental field site on the basis of real field data. The  
468 experimental site is located in Southern France, 20 km northeast of Montpellier (Figure 8a). The site's  
469 aquifer is composed of mollusc shells of late Burdigalian. The deposit is a dune system constructed  
470 during Miocene's tidal currents. Within the experimental site, 13 vertical wells were drilled in a  
471 square of 50 m by 50 m in which full-diameter cores were obtained in borehole P6, P8 and P12  
472 (Figure 8b). The wells have a depth of 30m and are fully-penetrating wells, since they crosscut the  
473 whole late Burdigalian, down to the roof of the mid Burdigalian which presents a very low  
474 permeability. The hydraulic conductivity measured using 330 one-inch diameter cores plugged from  
475 the full-diameter cores spans four orders of magnitude ( $10^{-8}$  to  $10^{-4}$ ). The preliminary analysis of  
476 hydrodynamic response to pumping test and slug tests (Wang et al., 2019) showed a pretty high lateral  
477 heterogeneity of the hydraulic conductivity field. Besides, both the well logs and laboratory  
478 measurements on cores, showed that the spatial distribution of the hydraulic conductivity field is  
479 constrained by a multilayered system (Figure 8c).



480

481 **Figure 8:** Experimental site composed of a multilayered system. a) geo-localization map, b) well

482

pattern, c) log of P6 obtained from the core analysis.

#### 483 4.1. Flowmeter implementation and analysis

484 A series of spinner flowmeter tests are performed in the experimental site. The flowmeter tests are  
485 performed in each well. As described in the methodology, the flow log is obtained in a well subject to  
486 a pumping where the pump is positioned close to the surface. We also point out that the pump needs  
487 to remain under water and, depending on the generated drawdown, the investigated depth will be  
488 limited. To maximize the investigated depth, a small pumping flow rate was used. A series of  
489 flowmeter sweeps are performed inside a PVC with static water in order to realize the tool calibration  
490 of spin-velocity conversion. The log of flow rate can be obtained by taking into consideration the well  
491 diameter changes along the depth. An example of flowmeter measurements and interpretation for  
492 hydraulic conductivity distribution may be found in the supplementary material (Figure S3).

493 Considering that the total pumping flow rate comes under the pump, we can estimate the hydraulic  
494 conductivity log of the well as a function of the flow rate contribution of the different layers, once the  
495 effective hydraulic conductivity of the investigated depth of the aquifer is determined.

496 With the estimated hydraulic conductivity logs from the different wells, we fill the remaining space  
497 between them by interpolation, assuming that the distribution of the hydraulic properties in layers is  
498 continuous and correlated. A 3D hydraulic conductivity field is obtained.

#### 499 4.2. Pumping tests data

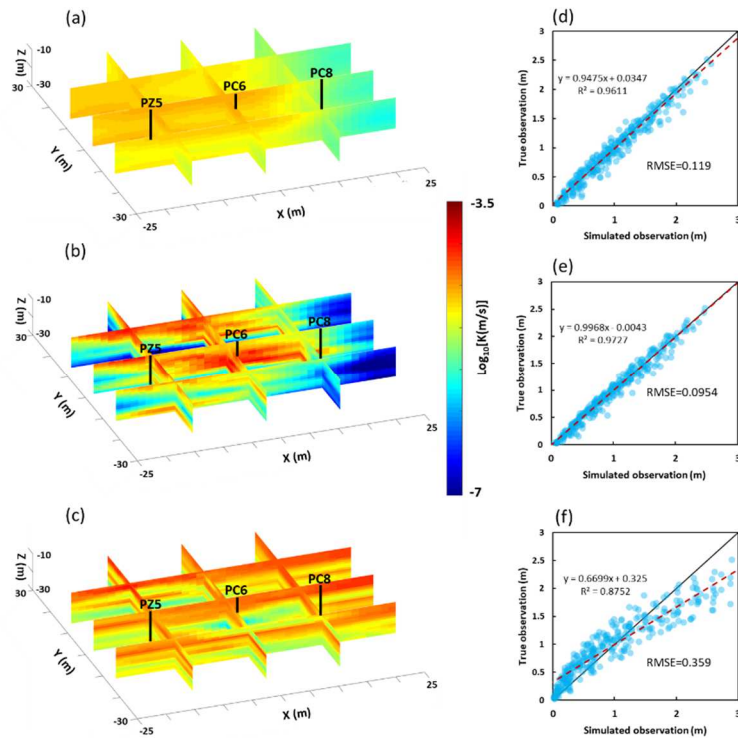
500 13 pumping tests were performed in our experimental site during summer 2016. During each test, the  
501 transient responses are measured in all the wells for all the tests. The pumping tests were long enough  
502 to reach a pseudo-steady state response. We randomly choose 5 cross hole pumping tests to use as  
503 observations for the following application. Different times from early and middle parts of the response  
504 were sampled and used as the HT observations. We didn't sample from late time to avoid any  
505 instability that may come from the biased modelling of the uncertain regional heterogeneity and  
506 boundary conditions. From the well test analysis, the estimated effective permeability and specific  
507 storage of the test site are  $K_{\text{eff}} = 1.34\text{e-}4 \text{ m}\cdot\text{s}^{-1}$  and  $S_s = 2.65\text{e-}5 \text{ m}^{-1}$ , which are used in the inversions.

#### 508 4.3. Hydraulic tomography

509 The dimensions of the inverted domain are length=50 m, width=50 m and height=20 m; the  
510 dimensions of the buffer area are length=200 m, width=200 m and height=20 m. The outer boundaries

511 are set to constant hydraulic head  $h_0=25$  m while the upper and lower boundaries (top and bottom) are  
512 set to no flow condition. The initial condition is set to a constant hydraulic head  $h_0=25$  m in the whole  
513 domain. A covariance matrix is constructed using the hydraulic conductivity field. In fact, a nested  
514 covariance function for multiscale heterogeneity is used in order to perform the inversion. It allows to  
515 incorporate geological information to constrain the results (Zha et al. 2017). The nested covariance  
516 matrix constructed based on flowmeter data interpolation can be found in Figure S5. The statistical  
517 parameter used for the generating the covariance is provided in Table S2. Different facies are  
518 determined and, in each facies, a correlation is defined. The main objective is not to perfectly  
519 reproduce the drawdown responses, but to obtain a more realistic hydraulic property distribution with  
520 a good fitting of the observed drawdowns. The initial guess is constructed from flowmeter interpreted  
521 hydraulic conductivity field. A similar interpolation method as adopted in the synthetic inversion is  
522 used to interpolate the flowmeter data. The covariance matrix is built accordingly to flowmeter results;  
523 layers information is prioritized. The covariance is a result of a sum of different covariance matrices,  
524 one defines the layers, another represents the variance and correlation length inside each layer and the  
525 last one defines the variance and the correlation length of the whole domain.

526 For the experimental field case, we performed two inversion runs, the first one by a classical  
527 hydraulic tomography approach and we used only observation from the pumping tests, while in the  
528 second run, flowmeter interpretations were used to initialize the parameter and the covariance matrix.  
529 Figure 7 shows the inverted hydraulic conductivity for both cases; Figure 7a corresponds to the  
530 inverted hydraulic conductivity field with classical hydraulic tomography while Figure 7b  
531 corresponds to the inverted hydraulic conductivity field with hydraulic tomography conditioned by  
532 flowmeter data; Figures 7c and 7d are scatter plots of observations (hydraulic head measurements)  
533 data fitting obtained using respectively results from Figure 7a and 7b.



534

535 **Figure 9:** Inverted hydraulic conductivity map and observation data fitting results from hydraulic  
 536 tomography of real-case experimental site. a) inverted hydraulic conductivity map obtained from  
 537 classical HT, b) inverted hydraulic conductivity map obtained from HT conditioned by flowmeter data,  
 538 c) hydraulic conductivity map obtained from flowmeter interpretation, d) data fitting for classical HT  
 539 results, e) data fitting for HT conditioned by flowmeter data, f) data fitting for flowmeter  
 540 interpretation.

541 **5. Discussion**

542 Incorporating flowmeter data into hydraulic tomography allows to obtain a better K estimate in the  
 543 synthetic validation cases. For the 2D validation case, the results (see Figure 3) show that initializing  
 544 the parameter and the covariance matrix with flowmeter interpretation data provides better K  
 545 estimates. The initial parameter value can play an important role on converging to a different K  
 546 estimate solution. Such an effect can be observed on the inverted hydraulic conductivity when  
 547 flowmeter estimate was used to initialize the parameter (Figure 3c). On the other hand, the initial  
 548 covariance matrix can also contain layers' information by correlating the cells that belong to the same  
 549 layer. However, the correlation constraint can be strong on the K estimate especially when the  
 550 covariance remains unchanged and equal to the initial (Figure 3e). The covariance of unknown

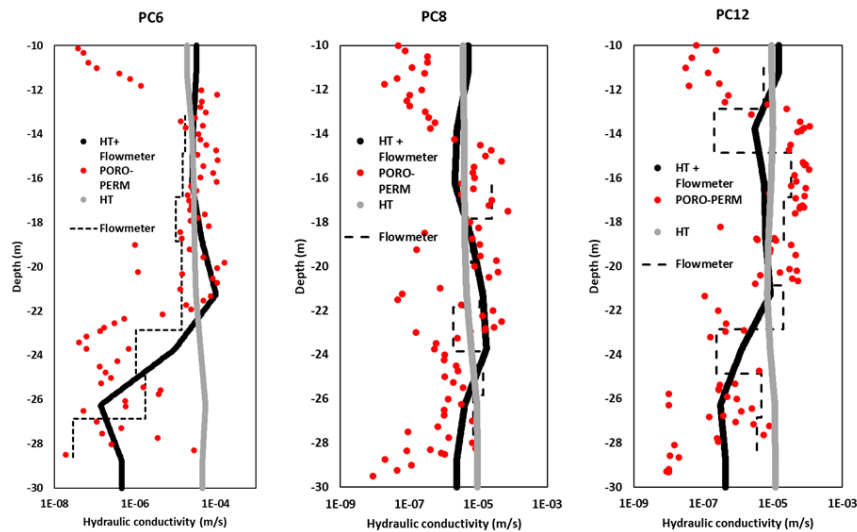
551 parameter can be updated to derive the residual covariance, the continuous updating of residual  
552 covariance allows to correctly address the uncertainty and enhance convergence of the inverse  
553 solution (Zha et al. 2018) which can be confirmed with the results in Figure 3f.

554 The approach of integrating flowmeter data was also tested using synthetic case in three dimensions  
555 and results (see Figure 5) are in total agreement with the 2D case observations. For this case, we also  
556 showed the quality of the result by simulating drawdown curves in a prediction well (which was not  
557 included in observation wells) using the inverted hydraulic conductivity field and compared them with  
558 the true observed drawdown (see Figure 6). It clearly shows how flowmeter data adds a non-  
559 redundant vertical profile information and, thus, enhance considerably the K estimates. In the present  
560 study, we focused on reconstructing K distributions by keeping  $S_s$  as a constant. Although previous  
561 studies have shown that the selection of  $S_s$  value may impact the K estimates (Castagna et al., 2011;  
562 Zhao et al., 2021), our interpretation of field site single-hole and cross-hole pumping tests did not  
563 indicate a strong variation of  $S_s$ . For this reason, we think the treatment is reasonable. However, in the  
564 future, we attempt to perform a full inversion to simultaneously estimate the spatial distribution of  
565 both K and  $S_s$ . These would require more pumping test data points to be sampled and used in the  
566 inversion as the inclusion of  $S_s$  distribution would double the number of unknown parameters, which  
567 increases drastically the underdetermined-ness of the inversion problem.

568 Figure 9 summarizes the results of the approach applied to a real field case. The two inverted  
569 hydraulic conductivity fields are totally different from each other while their data fitting are quite  
570 similar. K estimates obtained from HT conditioned by flowmeter data exhibits a multilayered system  
571 with more geological realism comparing to K estimates obtained from classical HT without any  
572 additional profile information. The same layering system has been observed in other measurements  
573 (core analysis, logs, permeameter measurements, etc.).

574 The data fitting in both inversions is relatively similar (RMSE = 0.0912 for HT using pumping tests  
575 data and RMSE = 0.0874 for HT using pumping tests and flowmeter data). However, the prediction of  
576 transient drawdowns becomes significantly better using K estimate obtained with the incorporation of  
577 flux measurements data. For further validation, we sampled hydraulic conductivity values from  
578 inversion results and we compared them to some available permeameter measurements at the same

579 locations. Within the 13 wells available in the experimental site, three (PC6, PC8 and PC12) were  
 580 cored. Cores allowed to obtain a permeability log from laboratory permeameter measurements along  
 581 the wells. Figure 8 shows a comparison of extracted conductivity from THT results and laboratory  
 582 permeability measurements (converted into hydraulic conductivity using water density  $\rho=1000 \text{ kg m}^{-3}$ ,  
 583 water viscosity  $\mu=0.001 \text{ kg m}^{-1} \text{ s}^{-1}$  and gravity acceleration  $g=9.81 \text{ m s}^{-2}$ ) of plugs on the cored wells  
 584 as well as the flowmeter interpreted hydraulic conductivity.



585

586 **Figure 10:** Hydraulic conductivity profiles for wells PC6, PC8 and PC12 of the experimental site.  
 587 Red dots are laboratory measurements. Grey solid line is extracted from THT results. Black solid line  
 588 is extracted from THT integrating flowmeter analysis data results. Dashed line is from flowmeter  
 589 interpretation.

590 Figure 10 strengthen the fact that flowmeter data enhance HT results, especially in the vertical profiles  
 591 of the hydraulic conductivity estimates. Flowmeter conditioning data allows the K estimate to get  
 592 closer to the measured permeability from the plugs of the cored wells. Hydraulic conductivity  
 593 profiles in the wells obtained from transient hydraulic tomography (Figure 10, grey solid line), show  
 594 that normal pumping tests do not contain vertical information about the aquifer's hydraulic properties;  
 595 the hydraulic conductivity profiles are similar to a result of a 2D THT extruded into the third  
 596 dimension (depth averaged values).

597 Our work is in agreement with other previous works in terms of how flux measurements enhance  
598 hydraulic tomography results. The work of Li et al. (2008) showed that inverting both steady state  
599 hydraulic head measurements and flux measurements data leads to better hydraulic conductivity  
600 estimates. They used both data in the inverse process as conditioning observations. However, in this  
601 work, only transient hydraulic head measurements are used to condition the inversion and flowmeter  
602 tests data are used to initialize the prior inputs of the inversion. Our results show that incorporating  
603 flowmeter data in the initial parameter and the prior covariance matrix may be sufficient to enhance  
604 considerably the K estimates. Zha et al. (2014) and Tso et al. (2016) also worked on combining flux  
605 measurements with pumping tests data. Zha et al. (2014) inverted synthetic case in 2D by using  
606 normal pumping tests and used lateral fluxes as an additional data to strengthen the result and Tso et  
607 al. (2016) extended it to 3D by using the same observation datasets. They both showed that flux data  
608 improves estimates resolution of HT analysis. The difference between the two studies is the  
609 dimension and the fact that Zha et al. (2014) used it to characterize a discrete fracture network while  
610 Tso et al. (2016) investigated a porous media instead. However, both studies were not tested on any  
611 real case study.

## 612 **6. Summary and conclusions**

613 In this study, we performed a transient hydraulic tomography of cross-hole pumping tests by  
614 integrating flowmeter data in prior inputs on an experimental site and managed a 3D imaging of the  
615 aquifer system that was coherent with geological observations and existing permeability  
616 measurements. We used flowmeter data as source of the vertical information additional to pumping  
617 tests that provides the lateral information. In order to incorporate the vertical data into hydraulic  
618 tomography, flowmeter tests are interpreted separately to obtain a prior K estimate which was used to  
619 initialize the parameter and the covariance matrix. While, the pumping tests observations were used to  
620 condition the inversion convergence process. Using different initial parameters and initial covariance  
621 matrices showed that the prior inputs of the inversion are important and can modify the result  
622 considerably. Also, the non-packer pumping tests do not contain vertical information: the inverted  
623 hydraulic conductivity using only pumping tests was generally constant along the vertical profile. The

624 integration of vertical hydrogeological information obtained from flowmeter surveys and horizontal  
625 information from cross-hole pumping tests allow a 3D transient hydraulic tomographic (THT)  
626 characterization of sedimentary layered rocks. Flowmeter data are a non-redundant information and  
627 different data other than flowmeter could also be used to better define the variations of vertical  
628 hydraulic conductivity such as laboratory measurements on cored wells or classical logs that are able  
629 to be converted into relative conductivity profiles.



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