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1	An inve	erse approach integrating flowmeter and pumping test data for three-dimensional
2	aquifer characterization	
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10	Highlights	
11	1.	Coupling flowmeter and pumping test data for low-cost 3D aquifer characterizations
12	2.	3D hydraulic conductivity distribution is assessed from an inverse approach
13	3.	The effectiveness of integrating the two datasets is studied with 3D synthetic models

#### 14 Abstract

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

2

#### 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., Liu et al., 2007, Illman et al., 2007, Illman et al., 2010, Zhao et al., 2016, Zhao and Illman 2017) and 55 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).

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

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

Flowmeter surveys characterize the vertical inflow profile of a given well (Paillet et al. 1998, Molz et al. 1994, Zlotnik and Zurbuchen 2003, Williams and Paillet. 2002, Day-Lewis et al. 2011). They are a widely used approach to determine vertical profiles of hydraulic conductivities at well locations. Complex geological medias are often layered systems and flowmeter analysis has shown its efficiency to detect the main layers contributing to the total pumped flux (Day-Lewis et al. 2011, Paillet and 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

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

#### 126 2.1 Groundwater flow model

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

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

131 with

132

$$|h|_{t=0} = h_0, h|_{\omega} = h_0,$$
 (2)

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

### 137 2.2 Flowmeter analysis

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

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

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

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

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

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

168 
$$Qcum(b) = \int_{z0}^{b} Q(z)dz = Q_p = \sum_i \Delta Q_i = \alpha \sum_i \Delta z_i K_i = \alpha K_{avg}b .$$
 (5)

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

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

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



174 *Figure 2*: Flowmeter setup scheme with an interpretation example. Qcum is the cumulative flow rate
175 and Krel is the interpreted relative permeability from flow log.

#### 176 2.2 Principal component geostatistical approach

In order to optimize the hydraulic conductivity field in the model we use the principal component
geostatistical approach (PCGA) (Kitanidis and Lee 2014). The observation equation that links the *m*unknown hydraulic conductivities, stored in a vector s, to the observation data (hydraulic heads)
stored in a matrix y is (Kitanidis 1995):

181 
$$y = h(s) + v,$$
 (8)

182 where h() is the forward model, v is the observation error with a random normal distribution with 183 mean 0 and variance **R**, which is usually the error measurement multiplied by the identity matrix. The 184 prior probability of *s* is a Gaussian distribution with mean  $X\beta$  generalized by a covariance matrix *Q*. 185 X is a *m*-vector of ones and  $\beta$  represents the mean hydraulic conductivity value. The posterior 186 probability density function (objective function **L**) of *s* and  $\beta$  is given by:

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

188 The optimization of the hydraulic conductivity values is obtained by minimizing this objective189 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 Q. The 198 covariance matrix can be rewritten with its decomposed form as:

$$Q = V S V^T, (10)$$

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

$$Q_k = V_k S_k V_k^T, \tag{11}$$

205 where

 $Q_k \approx Q, \qquad (12)$ 

207 It can be also written as a sum:

208 
$$\boldsymbol{Q}_{k} = \boldsymbol{V}_{k}\boldsymbol{S}_{k}\boldsymbol{V}_{k}^{T} = \sum_{i=1}^{k} \boldsymbol{\xi}_{i}\boldsymbol{\xi}_{i}^{T}, \qquad (13)$$

209 where

$$\xi_i = \sqrt{\lambda_i} V_i. \tag{14}$$

210

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

215 
$$\bar{s} = X\bar{\beta} + QH^T\bar{\xi},$$
 (15)

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

218 
$$\begin{bmatrix} HQH^T + R & HX \\ (HX)^T & 0 \end{bmatrix} \begin{bmatrix} \overline{\xi} \\ \overline{\beta} \end{bmatrix} = \begin{bmatrix} y - h(\overline{s}) + H\overline{s} \\ 0 \end{bmatrix}.$$
 (16)

219 The minimized objective function L can also be written as:

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

In PCGA, the sensitivity matrix H is not fully calculated and an alternative way to approximate it isproposed.

In order to estimate HQ and HQH<sup>T</sup>, **k** forward runs are needed to be solved in additional to the forward run of the actual best estimate, the forward models are used to calculate  $\eta$  defined as follows:

225 
$$\eta_i = H\xi_i \approx \frac{1}{\delta} [h(s + \delta\xi_i) - h(s)], \qquad (18)$$

226  $\delta$  is the finite difference interval from the Taylor series expansion (Kitanidis and Lee, 2014). Then 227 HQ and HQH<sup>T</sup> are defined as:

228 
$$HQ \approx HQ_k = H\sum_{i=1}^k \xi_i \xi_i^T = \sum_{i=1}^k (H\xi_i) \xi_i^T = \sum_{i=1}^k \eta_i \xi_i^T,$$
(19)

229 
$$HQH^T \approx HQ_kH^T = H[\sum_{i=1}^k \xi_i \xi_i^T]H^T = \sum_{i=1}^k (H\xi_i)(H\xi_i)^T = \sum_{i=1}^k \eta_i \eta_i^T.$$
 (20)

230 In order to estimate **HX**, one (columns of **X**) forward run is needed, following:

231 
$$HX_i \approx \frac{1}{\delta} [h(\bar{s} + \delta X_i) - h(\bar{s})].$$
 (21)

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

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

In total, each iteration requires k+3 forward runs; 1 forward run of the actual best estimate, 1 forward
run to estimate H\$\overline{s}\$, 1 forward run to estimate H\$\overline{X}\$ and \$\overline{k}\$ forward models to estimate H\$\overline{Q}\$ and \$\overline{H}\$\overline{G}\$.
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 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

distinguished from flowmeter data, we try to incorporate the vertical information into the inversionprocess and constrain its convergence path.

254 **3.** Va

# 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 specific storage is assumed constant and a value of  $S_s = 10^{-4} \text{ m}^{-1}$  was used. 276

The wells are modeled explicitly with a radius of  $r_w=0.1$  m. We attribute to wells a high hydraulic conductivity (K=1 m.s<sup>-1</sup>) and a low specific storage (10<sup>-10</sup> 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.

The simulated vertical velocity curves are converted into hydraulic conductivity distributions following the procedure described as follows (An example of the manipulation is provided in the 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  $\Delta z_i$

- Step4: Hydraulic conductivity profile is obtained in each well.

The hydraulic conductivity profiles are then interpolated using a triangular-base bilinear interpolation to obtain a hydraulic conductivity map for areas within between the wells. For the rest of the inversion 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

into the initial covariance matrix for HT. The interface between different facies or zones may exhibit
an abrupt change of hydraulic properties. On the other hand, the variability inside a particular facies or
zone (compared to its large-scale mean) can be described by a zero mean and a small-scale covariance
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 to initialize both the parameter and the covariance matrix which was updated during inversioniterations.

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).



Figure 3: Two-dimensional validation case – results of HT using different prior information. a) true
hydraulic conductivity, d) interpreted hydraulic conductivity from flowmeter tests, b, c, e and f are
inverted hydraulic conductivities using different prior models. K<sub>i</sub> and Q<sub>i</sub> correspond to the initial
hydraulic conductivity and initial covariance matrix respectively, g) is the constructed facies from
flowmeter analyses to use in order to construct the nested covariance.

346

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

flowmeter data are integrated, the inverted hydraulic conductivities represent the true model better (R<sup>2</sup> 359 360 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

Figure 4: Scatterplots of true hydraulic conductivity versus estimated hydraulic conductivity for the
different cases of the two-dimensional synthetic case. c) scatter plot of true K versus interpreted K
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** 

We extend the approach to a three-dimensional synthetic case and try to show if flowmeter data can provide the vertical information for a 3D aquifer characterization instead of packer tests. Similar to the simplified two-dimensional case, we use a three-dimensional random field generator (Rass et al. 2019) to generate a three-dimensional synthetic hydraulic conductivity map using the following parameters (Correlation function: exponential, standard deviation = 1.5,  $L_x=100$  m,  $L_y=100$  m and  $L_z=$  5 m). Such parameters provide a hydraulic conductivity map that is representative of a multilayered system. The dimensions of the inverted domain are length=70 m, width=70 m and height=30 m; the lateral dimensions of the buffer area are length=700 m and width=700 m; the buffer was not extended in the vertical direction. The outer boundaries are set to constant zero hydraulic head while the upper and lower boundaries (top and bottom) are set to no flow condition. The initial condition is set to zero hydraulic head in the whole domain. The specific storage is assumed constant and a value of S<sub>s</sub> = 10<sup>-4</sup> m<sup>-1</sup> 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.

We construct a nested covariance using the interpreted flowmeter map as described for the twodimensional case. In the inverse problem, a structured grid is used to discretize the model domain. For the three-dimensional cases, the number of grid blocks in x, y and z directions are nx = 20, ny = 20, nz = 8 respectively (See Figure R3). For PCGA setup, we use a truncation number of k=30 for a number of unknowns n=20\*20\*8, R=0.001\*Id where Id is the identity matrix and  $\delta$ =0.0001 for the finite difference interval. The specific storage was kept constant (S<sub>s</sub> = 10<sup>-4</sup> m<sup>-1</sup>) in the inversion and we focus on the characterization of K fields.

Figure 5 shows the results of the three-dimensional validation case. Figure 5c corresponds to the generated, considered true, hydraulic conductivity field. Figure 5a is the inverted hydraulic conductivity field using a classical hydraulic tomography that used same covariance information as in 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).





*Figure 5:* Three-dimensional validation case - results of HT using different prior information; b)
interpreted hydraulic conductivity from flowmeter tests, c) true hydraulic conductivity, a, d and e are
inverted hydraulic conductivities using different prior models. K<sub>i</sub> and Q<sub>i</sub> correspond to the initial
hydraulic conductivity and initial covariance matrix respectively.

These results obtained with the 3D synthetic case are similar to the ones obtained with the 2D synthetic case, and thus confirm that adding flowmeter information allows improving the hydraulic permeability field. This conclusion is consistent with the fact that flux, in addition to hydraulic head measurements, enhance K values estimate (Yeh et al. (2011, 2015a, 2015b), Mao et al. (2013a, 2013b), Tso et al. 2016).

To better evaluate the quality of the estimated hydraulic conductivity field, we simulate a transient pumping test in well P6 (see Figure 5c) using this inverted hydraulic conductivity map and compare the simulated drawdowns to the simulated drawdowns obtained with the true hydraulic conductivity field (see Figure 6).



Figure 6: Hydraulic head response to simulated pumping tests in the new added well P6. Solid red,
dotted and dashed black curves correspond to the simulated drawdowns using respectively the true
conductivity, the hydraulic conductivity map obtained from hydraulic tomography and the hydraulic
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.

We also show a scatter plot of true hydraulic conductivity and estimated hydraulic conductivity inFigure 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 hydraulic conductivity is overestimated by the interpolation of flowmeter profiles. When the 455 456 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.





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 permeability. The hydraulic conductivity measured using 330 one-inch diameter cores plugged from 474 the full-diameter cores spans four orders of magnitude  $(10^{-8} \text{ to } 10^{-4})$ . The preliminary analysis of 475 476 hydrodynamic response to pumping test and slug tests (Wang et al., 2019) showed a pretty high lateral heterogeneity of the hydraulic conductivity field. Besides, both the well logs and laboratory 477 478 measurements on cores, showed that the spatial distribution of the hydraulic conductivity field is 479 constrained by a multilayered system (Figure 8c).





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.

With the estimated hydraulic conductivity logs from the different wells, we fill the remaining space
between them by interpolation, assuming that the distribution of the hydraulic properties in layers is
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 storage of the test site are  $K_{\text{eff}} = 1.34\text{e-4} \text{ m.s}^{-1}$  and  $Ss = 2.65\text{e-5} \text{ m}^{-1}$ , which are used in the inversions. 507

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<sub>0</sub>=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.





Figure 9: Inverted hydraulic conductivity map and observation data fitting results from hydraulic
tomography of real-case experimental site. a) inverted hydraulic conductivity map obtained from
classical HT, b) inverted hydraulic conductivity map obtained from HT conditioned by flowmeter data,
c) hydraulic conductivity map obtained from flowmeter interpretation, d) data fitting for classical HT
results, e) data fitting for HT conditioned by flowmeter data, f) data fitting for flowmeter
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 parameter can be updated to derive the residual covariance, the continuous updating of residual
covariance allows to correctly address the uncertainty and enhance convergence of the inverse
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<sub>s</sub>. 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.

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

The data fitting in both inversions is relatively similar (RMSE = 0.0912 for HT using pumping tests data and RMSE = 0.0874 for HT using pumping tests and flowmeter data). However, the prediction of transient drawdowns becomes significantly better using K estimate obtained with the incorporation of flux measurements data. For further validation, we sampled hydraulic conductivity values from 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 kg m<sup>-3</sup>, 583 water viscosity  $\mu$ =0.001 kg m<sup>-1</sup> s<sup>-1</sup> and gravity acceleration g=9.81 m s<sup>-2</sup>) of plugs on the cored wells 584 as well as the flowmeter interpreted hydraulic conductivity.



585

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

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

#### 2 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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# 635 References

- Berg, S. J., and W. A. Illman (2011), Three-dimensional transient hydraulic tomography in a highly
  heterogeneous glaciofluvial aquifer-aquitard system, Water Resour. Res., 47, W10507,
  doi:10.1029/2011WR010616.
- Bohling, G. C., Butler Jr., J. J., Zhan, X., and Knoll, M. D. (2007), A field assessment of the value of
  steady shape hydraulic tomography for characterization of aquifer heterogeneities, Water Resour.
  Res., 43, W05430, doi:10.1029/2006WR004932.
- Bohling, G. C., Zhan, X., Butler, J. J., and Zheng, L., Steady shape analysis of tomographic pumping
  tests for characterization of aquifer heterogeneities, Water Resour. Res., 38(12), 1324,
  doi:10.1029/2001WR001176, 2002.
- Bohling, G.C. and Butler, J.J., Jr. (2010), Inherent Limitations of Hydraulic Tomography.
  Groundwater, 48: 809-824. https://doi.org/10.1111/j.1745-6584.2010.00757.x
- 647 Brauchler, R., R. Hu, L. Hu, S. Jimenez, P. Bayer, P. Dietrich, and T. Ptak (2013), Rapid field
- 648 application of hydraulic tomography for resolving aquifer heterogeneity in unconsolidated sediments,
- 649 Water Resour. Res., 49, 2013–2024, doi:10.1002/wrcr.20181.
- 650 Brauchler, R., R. Hu, P. Dietrich, and M. Sauter (2011), A field assessment of high-resolution aquifer
- 651 characterization based on hydraulic travel time and hydraulic attenuation tomography, Water Resour.
- 652 Res., 47, W03503, doi:10.1029/2010WR009635.

- Butler, J. J., McElwee, C. D., and Bohling, G. C. (1999), Pumping tests in networks of multilevel
  sampling wells: Motivation and methodology, Water Resour. Res., 35(11), 3553–3560,
  doi:10.1029/1999WR900231.
- 656 Cardiff, M., Barrash, W., and Kitanidis, P. K. (2012), A field proof-of-concept of aquifer imaging
  657 using 3-D transient hydraulic tomography with modular, temporarily-emplaced equipment, Water
  658 Resour. Res., 48, W05531, doi:10.1029/2011WR011704.
- Cardiff, M., W. Barrash, P. K. Kitanidis, B. Malama, A. Revil, S. Straface, and E. Rizzo (2009), A
  potential-based inversion of unconfined steadystate hydraulic tomography, Ground Water, 47(2),
  259–270, doi:10.1111/j.1745-6584.2008.00541.x
- 662 Chen, J.S., S. Hubbard, and Y. Rubin. 2001. Estimating thehydraulic conductivity at the South Oyster
  663 Site from geo-physical tomographic data using Bayesian techniquesbased on the normal linear
  664 regression model. Water Re-sources Research 37, no. 6: 1603–1613
- 665 COMSOL AB (2018), Subsurface Flow Module User's Guide, COMSOL Multiphysics v. 5.4,
  666 COMSOL AB, Stockholm, Sweden
- 667 Cooper, H. H., and Jacob, C. E. (1946), A generalized graphical method for evaluating formation
  668 constants and summarizing well-field history, Eos Trans. AGU, 27(4), 526–534,
  669 doi:10.1029/TR027i004p00526
- Day-Lewis, F.D., Johnson, C.D., Paillet, F.L. and Halford, K.J. (2011), A Computer Program for
  Flow-Log Analysis of Single Holes (FLASH). Groundwater, 49: 926-931.
  https://doi.org/10.1111/j.1745-6584.2011.00798.x
- De Clercq T., A. Jardani, P. Fischer, L. Thanberger, T.M. Vu, D. Pitaval, J.-M. Côme, P. Begassat.
  2020. The use of electrical resistivity tomograms as a parameterization for the hydraulic
  characterization of a contaminated aquifer. Journal of Hydrology 587: 124986.

- Fienen, M.N., P.K. Kitanidis, D. Watson, and P. Jardine. 2004. An application of Bayesian inverse
  methods to vertical de-convolution of hydraulic conductivity in a heterogeneousaquifer at Oak Ridge
  National Laboratory. MathematicalGeology 36, no. 1: 101–126.
- Fischer P., Jardani A., Jourde H., Hydraulic tomography in coupled discrete-continuum concept to
  image hydraulic properties of a fractured and karstified aquifer (Lez aquifer, France) Adv. Water
  Resour., 137 (2020), p. 103523, 10.1016/j.advwatres.2020.103523
- 682 Gottlieb, J., and P. Dietrich. 1995. Identification of the permeability distribution in soil by hydraulic
  683 tomography. InverseProblems 11, no. 2: 353–360.
- Hubbard S.S., Rubin Y. (2005) Introduction to Hydrogeophysics. In: Rubin Y., Hubbard S.S. (eds)
- Hydrogeophysics. Water Science and Technology Library, vol 50. Springer, Dordrecht.
  https://doi.org/10.1007/1-4020-3102-5\_1
- Illman, W. A., Zhu, J., Craig, A. J., and Yin, D. (2010), Comparison of aquifer characterization
  approaches through steady state groundwater model validation: A controlled laboratory sandbox
  study, Water Resour. Res., 46, W04502, doi:10.1029/2009WR007745.
- Illman, W.A., X. Liu, and A. Craig. 2007. Steady-state hydraulictomography in a laboratory aquifer
  with deterministic het-erogeneity: Multi-method and multiscale validation of hydraulic conductivity
  tomograms, Journal of Hydrology341, no. 3–4: 222–234
- Javandel, I., and P.A. Witherspoon. 1969. A method of analyzing transient fluid flow in multilayeredaquifer. WaterResources Research 5, no. 4: 856–869.
- Kabala, Z. J. (1994), Measuring distributions of hydraulic conductivity and specific storativity by the
- 696 double flowmeter test, Water Resour. Res., 30(3), 685–690, doi:10.1029/93WR03104
- Kitanidis, P. K., and Lee, J. (2014), Principal Component Geostatistical Approach for large
  dimensional inverse problems, Water Resour. Res., 50, 5428–5443, doi:10.1002/2013WR014630.

- Kitanidis, P.K. 1995. Quasi-linear geostatistical theory for inversing. Water Resources Research 31,
  no. 10: 2411–2419.
- Klepikova, M. V., Le Borgne, T., Bour, O., and de Dreuzy, J.-R. (2013), Inverse modeling of flow
  tomography experiments in fractured media, Water Resour. Res., 49, 7255–7265,
  doi:10.1002/2013WR013722.
- Li, W., Englert, A., Cirpka, O.A. and Vereecken, H. (2008), Three-Dimensional Geostatistical
  Inversion of Flowmeter and Pumping Test Data. Groundwater, 46: 193-201.
  https://doi.org/10.1111/j.1745-6584.2007.00419.x
- Liu, S., T.-C. J. Yeh, and R. Gardiner (2002), Effectiveness of hydraulic tomography: Sandbox
  experiments, Water Resour. Res., 38(4), 1034, doi:10.1029/2001WR000338
- Liu, X., Illman, W. A., Craig, A. J., Zhu, J., and Yeh, T.-C. J. (2007), Laboratory sandbox validation
  of transient hydraulic tomography, Water Resour. Res., 43, W05404, doi:10.1029/2006WR005144.
- Mao, D., T.-C. J. Yeh, L. Wan, C.-H. Lee, K.-C. Hsu, J.-C. Wen, and W. Lu (2013a), Crosscorrelation analysis and information content of observed heads during pumping in unconfined
  aquifers, Water Resour. Res., 49, 713–731, doi:10.1002/wrcr.20066.
- Mao, D., T.-C. J. Yeh, L. Wan, K.-C. Hsu, C.-H. Lee, and J.-C. Wen (2013b), Necessary conditions
  for inverse modeling of flow through variably saturated porous media, Adv. Water Resour., 52, 50–61,
  doi:10.1016/j.advwatres.2012.08.001.
- 717 Molz, F. J., Morin, R. H., Hess, A. E., Melville, J. G., and Güven, O. (1989), The Impeller Meter for
- 718 measuring aquifer permeability variations: Evaluation and comparison with other tests, Water Resour.
- 719 Res., 25(7), 1677–1683, doi:10.1029/WR025i007p01677.
- Molz, F.J., G.K. Boman, S.C. Young, and W.R. Waldrop. 1994. Borehole flowmeters: Field
  application and data analysis. Journal of Hydrology 163, no. 4: 347–371.

Paillet, F. L. (1998), Flow modeling and permeability estimation using borehole flow logs in
heterogeneous fractured formations, Water Resour. Res., 34(5), 997–1010, doi:10.1029/98WR00268.

Paillet, F.L. and Reese, R.S. (2000), Integrating Borehole Logs and Aquifer Tests in Aquifer
Characterization. Groundwater, 38: 713-725. https://doi.org/10.1111/j.1745-6584.2000.tb02707.x

- Paul Constantine (2021). Random Field Simulation
  (https://www.mathworks.com/matlabcentral/fileexchange/27613-random-field-simulation), MATLAB
  Central File Exchange. Retrieved July 19, 2021.
- Räss, L., Kolyukhin, D., Minakov, A. (2019). Efficient parallel random field generator for large 3-D
  geophysical problems. Computers & Geosciences 131, 158-169
- Rehfeldt, K. R., J. M. Boggs, and L. W. Gelhar (1992), Field study of dispersion in a heterogeneous
  aquifer: 3. Geostatistical analysis of hydraulic conductivity, Water Resour. Res., 28(12), 3309–3324,
  doi:10.1029/92WR01758.
- Roubinet D., Irving J., Day-Lewis F.D., Development of a new semi-analytical model for crossborehole flow experiments in fractured media Adv. Water Res., 76 (2015), pp. 97-108,
  10.1016/j.advwatres.2014.12.002
- Soueid Ahmed, A., Zhou, J. Jardani, A., Revil, A., Dupont, J.P., Image-guided inversion in steadystate hydraulic tomography Adv. Water Resour., 82 (2015), pp. 83-97,
  10.1016/j.advwatres.2015.04.001.
- Tamayo-Mas, M. Bianchi, M. Mansour Impact of model complexity and multi-scale data integration
  on the estimation of hydrogeological parameters in a dual-porosity aquifer Hydrogeol. J., 26 (6)
  (2018), pp. 1917-1933, 10.1007/s10040-018-1745-y
- Theis, C. V. (1935), The relation between the lowering of the Piezometric surface and the rate and
  duration of discharge of a well using ground-water storage, Eos Trans. AGU, 16(2), 519–524,
  doi:10.1029/TR016i002p00519.

- Tso, M., C.-H., Zha, Y., J. Yeh, T.-C., and Wen, J.-C. (2016), The relative importance of head, flux,
  and prior information in hydraulic tomography analysis, Water Resour. Res., 52, 3–20,
  doi:10.1002/2015WR017191.
- 749 Wang, X., Jourde, H., Aliouache, M., Massonnat, G., Characterization of horizontal transmissivity 750 anisotropy using cross-hole slug tests, J. Hydrol., 564 (2018),pp. 89-98, 751 10.1016/j.jhydrol.2018.06.068
- Wen, J.-C., Chen, J.-L., Yeh, T.-C.J., Wang, Y.-L., Huang, S.-Y., Tian, Z. and Yu, C.-Y. (2020),
  Redundant and Nonredundant Information for Model Calibration or Hydraulic Tomography.
  Groundwater, 58: 79-92. https://doi.org/10.1111/gwat.12879
- Williams, J., and F. Paillet (2002), Using flowmeter pulse tests to define hydraulic connections in the
  subsurface: A fractured shale example, J. Hydrol., 265, 100–117.
- Yeh, T.-C., M. Jin, and S. Hanna, An iterative stochastic inverse method: Conditional effective
  transmissivity and hydraulic head fields, Water Resour. Res., 32(1), 85-92, 1996
- Yeh, T.-C. J., and Liu, S. (2000), Hydraulic tomography: Development of a new aquifer test
  method, Water Resour. Res., 36(8), 2095–2105, doi:10.1029/2000WR900114.
- 761 Yeh, T.-C. J., D. Mao, L. Wan, C.-H. Lee, J.-C. Wen, and K.-C. Hsu (2011), Well Definedness, Scale
- 762 Consistency, and Resolution Issues in Groundwater Model Parameter Identification, Dep. of Hydrol.763 and Water Resour., Univ. of Ariz., Tucson.
- Yeh, T.-C. J., D. Mao, L. Wan, C.-H. Lee, J.-C. Wen, and K.-C. Hsu (2015b), Well definedness, scale
- 765 consistency, and resolution issues in groundwater model parameter identification, Water Sci. Eng.,
- 766 8(3), 175–194, doi:10.1016/j.wse.2015.08.002.
- Yeh, T.-C. J., R. Khaleel, and K. C. Carroll (2015a), Flow Through Heterogeneous Geologic Media,
  Cambridge Univ. Press, Cambridge, U. K.

- Yeh, T.-C., Mas-Pla, J., Williams, T. M., and McCarthy, J. F. (1995), Observation and ThreeDimensional Simulation of Chloride Plumes in a Sandy Aquifer Under Forced-Gradient Conditions,
  Water Resour. Res., 31(9), 2141–2157, doi:10.1029/95WR01947.
- Zha, Y., T.-C. J. Yeh, D. Mao, J. Yang, and W. Lu (2014), Usefulness of flux measurements during
- 773 hydraulic tomographic survey for mapping hydraulic conductivity distribution in a fractured medium,
- Adv. Water Resour., 71, 162–176, doi:10.1016/j.advwatres.2014.06.008.
- Zha, Y., Yeh, T.-C. J., Illman, W. A., Zeng, W., Zhang, Y., Sun, F., et al. (2018). A reduced-order
  successive linear estimator for geostatistical inversion and its application in hydraulic tomography.
  Water Resources Research, 54, 1616–1632. https://doi.org/10.1002/2017WR021884
- Zha, Y., Yeh, T.-C.J., Illman, W.A., Tanaka, T., Bruines, P., Onoe, H., Saegusa, H., Mao, D.,
  Takeuchi, S. and Wen, J.-C. (2016), An Application of Hydraulic Tomography to a Large-Scale
  Fractured Granite Site, Mizunami, Japan. Groundwater, 54: 793-804.
  https://doi.org/10.1111/gwat.12421
- Zha, Y., Yeh, T.-C. J., Illman, W. A., Onoe, H., Mok, C. M. W., Wen, J.-C., Huang, S.-Y., and Wang,
  W. (2017), Incorporating geologic information into hydraulic tomography: A general framework
  based on geostatistical approach, Water Resour. Res., 53, 2850–2876, doi:10.1002/2016WR019185.
- Zhao, Z., and W. A. Illman (2017), On the Importance of Geological Data for Three-dimensional
  Steady-State Hydraulic Tomography Analysis at a Highly Heterogeneous Aquifer-Aquitard System. J.
  Hydrol., 544, 640–657
- Zhao,Z.,Illman,W.A.,Berg,S.J.,2016.On the importance of geological data for hy-draulic tomography
  analysis: laboratory sandbox study. J.Hydrol.https://doi.org/10.1016/j.jhydrol.2016.08.061
- Zheng, C. and Gorelick, S.M. (2003), Analysis of Solute Transport in Flow Fields Influenced by
  Preferential Flowpaths at the Decimeter Scale. Groundwater, 41: 142-155.
  https://doi.org/10.1111/j.1745-6584.2003.tb02578.x

- 793 Zhu, J., and T.-C. J. Yeh (2006), Analysis of hydraulic tomography using temporal moments of
- drawdown recovery data, Water Resour. Res., 42, W02403, doi:10.1029/2005WR004309
- 795 Zhu, J., and Yeh, T.-C. J. (2005), Characterization of aquifer heterogeneity using transient hydraulic
- 796 tomography, Water Resour. Res., 41, W07028, doi:10.1029/2004WR003790.
- 797 Zlotnik, V.A., and B.R. Zurbuchen. 2003. Estimation of hydraulic conductivity from borehole
- flowmeter tests consideringhead losses. Journal of Hydrology 281, no. 1–2: 115–128.