

1 **A lithofacies approach for modeling non-Fickian solute transport in a**
2 **heterogeneous alluvial aquifer**

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5 Marco Bianchi¹, Chunmiao Zheng^{2,3}

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7 ¹ British Geological Survey, Environmental Science Centre, Keyworth, Nottingham,
8 United Kingdom.

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10 ² School of Environmental Science and Engineering, South University of Science and
11 Technology of China, Shenzhen, China.

12 ³ Department of Geological Sciences, University of Alabama, Tuscaloosa, AL, United
13 States.

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21 Corresponding Author:

22 Marco Bianchi, British Geological Survey, Environmental Science Centre, Keyworth,
23 Nottingham, NG12 5GG, United Kingdom. marcob@bgs.ac.uk. Tel. +44 (0)155 9363136

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25 **Key points:**

- 26 - Lithofacies are mapped as basis for 3D hydraulic conductivity distribution.
- 27 - Non-Fickian transport behavior emerges naturally from lithofacies distribution.
- 28 - Verifiable explanations are developed for the plume behavior at the MADE site.

29

30 **Abstract.** Stochastic realizations of lithofacies assemblage based on lithological data
31 from a relatively small number of boreholes were used to simulate solute transport at the
32 well-known Macrodispersion Experiment (MADE) site in Mississippi (USA). With sharp
33 vertical contrasts and lateral connectivity explicitly accounted for in the corresponding
34 hydraulic conductivity fields, experimental results from a large-scale tracer experiment
35 were adequately reproduced with a relatively simple model based on advection and local
36 dispersion. The geologically based model of physical heterogeneity shows that one well
37 interconnected lithofacies, with a significantly higher hydraulic conductivity and
38 accounting for 12% of the total aquifer volume, may be responsible for the observed non-
39 Fickian transport behavior indicated by the asymmetric shape of the plumes and by
40 variations of the dispersion rate in both space and time. This analysis provides a
41 lithological basis to the hypothesis that transport at MADE site is controlled by a network
42 of high-conductivity sediments embedded in a less permeable matrix. It also explains the
43 calibrated value of the ratio of mobile to total porosities used in previous modelling
44 studies based on the dual-domain mass transfer approach. The results of this study
45 underscore the importance of geologically plausible conceptualizations of the subsurface
46 for making accurate predictions of the fate and transport of contaminants in highly
47 heterogeneous aquifers. These conceptualizations may be developed through integration
48 of raw geological data with expert knowledge, interpretation and appropriate geostatistical
49 methods.

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51 **Keywords.** solute transport, heterogeneity, MADE site, lithofacies

52

53 **1 Introduction and background**

54 Despite significant theoretical, experimental and computational advances, modelling
55 of contaminant transport in heterogeneous aquifers is still challenging and subject of
56 continuing debate in the scientific community [e.g., *Hadley and Newell, 2014; Neuman,*
57 *2014; Molz, 2015*]. Yet, accurate simulations of the fate of contaminants are needed to
58 address an ever growing demand for clean groundwater resources and an increasing
59 interest in the use of the subsurface for the storage of nuclear waste, CO₂, and heat.

60 Transport of nonreactive solutes through porous media is traditionally modelled with
61 the advection–dispersion equation (ADE):

$$62 \quad \frac{\partial C}{\partial t} = \nabla \cdot (\mathbf{D} \nabla C) - \nabla \cdot (\mathbf{v} C) \quad (1)$$

63 where C is concentration, \mathbf{v} is the macroscopic advective velocity, and \mathbf{D} is the
64 hydrodynamic dispersion coefficient tensor. The latter is a function of the molecular
65 diffusion coefficient, \mathbf{v} , and fixed longitudinal (α_L), horizontal transverse (α_{TH}) and
66 vertical transverse (α_{TV}) dispersivities. Because the first term on the right hand side of
67 Equation (1) is analogous to Fick’s law of molecular diffusion, solute transport described
68 by the ADE is referred to as Fickian. However, tracer experiments at different scales very
69 often show “anomalous” or non-Fickian features indicated by non-Gaussian asymmetric
70 plumes, apparent loss of mass due to sequestration in relatively immobile zones, variations
71 of mean transport velocity, and increases in the dispersion rates (i.e., dispersivity) with
72 mean travel distance or in time [e.g., *Silliman et al., 1987; Adams and Gelhar, 1992;*

73 *Haggerty et al.*, 2001; *Levy and Berkowitz*, 2003; *Cortis and Berkowitz*, 2004; *Bromly and*
74 *Hinz*, 2004; *Bianchi et al.*, 2011a; *Cherubini et al.*, 2013].

75 For nonreactive tracers, non-Fickian transport is observed in aquifers characterized by
76 sharp contrasts in hydraulic conductivity (K) and by connectivity of high- K regions
77 [*Zheng and Gorelick*, 2003; *Klise et al.*, 2009; *Bianchi et al.*, 2011b; *Zhang et al.*, 2013],
78 which are commonly found in alluvial aquifers [e.g., *Fogg*, 1986; *Webb and Anderson*,
79 1996; *Fogg et al.*, 2000; *Labolle and Fogg*, 2001; *Baratelli et al.*, 2011; *Dell’Arciprete et*
80 *al.*, 2014]. The inability of the Fickian approach to describe transport in such
81 environments is explained by the fact that the travel distance required to reach asymptotic
82 or scale-independent conditions for macroscopic Fickian dispersion is larger than the
83 actual scale of the observed plumes [*Eggleston and Rojstacer*, 2000; *Berkowitz et al.*,
84 2006; *Neuman and Tartakovsky*, 2009; *Srinivasan et al.*, 2010; *Molz*, 2015]. In fact, a
85 scale-dependent (i.e., pre-asymptotic) behavior is observed for dispersivity, which is in
86 contrast with the fixed macroscopic dispersivity derived from the central spatial moments
87 of the plumes [e.g., *Adams and Gelhar*, 1992].

88 Field data collected at the research site in Columbus (Mississippi, USA), known as
89 the Macrodispersion Experiment (MADE) site, have been used over the last three decades
90 to investigate solute transport processes in alluvial aquifers. In particular, three large-scale
91 natural gradient tracer experiments were conducted at this site in the mid ‘80s and in the
92 ‘90s to test the applicability of the macrodispersion theory to explain solute transport in
93 heterogeneous porous media [*Boggs et al.*, 1992; *Boggs et al.*, 1993; *Boggs et al.*, 1995]. A
94 comprehensive list of references of the numerous studies concerning the geological and
95 hydrogeological characterization of the MADE site, as well as the results, interpretation,
96 and modelling of the tracer experiments, is given in the review paper by *Zheng et al.*
97 [2011]. Although the physical heterogeneity of the aquifer was initially characterized by

98 more than 2500 flowmeter K measurements [Rehfeldt et al., 1992], the application of the
99 macroscopic ADE failed to explain transport behavior observed during the three large-
100 scale experiments [Adams and Gelhar, 1992; Eggleston and Rojstaczer 1998a, 1998b;
101 Harvey and Gorelick, 2000; Feehley et al., 2000; Julian et al., 2001].

102 The failure of the macroscopic ADE to accurately describe the experimental data at
103 the MADE site has been the motivation for the application of alternative modelling
104 methods based on two approaches. The first approach is represented by non-Fickian
105 transport models including the dual domain mass transfer model [Harvey and Gorelick,
106 2000; Feehley et al., 2000; Guan et al., 2008; Llopis-Albert and Capilla, 2009], the
107 fractional advective-dispersive equation [Benson et al. 2001; Zhang and Benson, 2008],
108 and the continuous-time random walk [Berkowitz and Scher, 1998; Berkowitz et al., 2006].
109 These models were able to provide a reasonable interpretation of the anomalous features
110 of the observed plumes without an explicit representation of local-scale heterogeneity and
111 connectivity, although their effect on transport is taken into account through mathematical
112 formulations describing non-Fickian transport in time and space. A second approach,
113 namely the local-ADE approach [e.g., Fiori et al., 2013], considers an explicit
114 representation of small-scale heterogeneities based on the notion that if the velocity field
115 is sufficiently characterized, then transport can be effectively described by Equation (1)
116 considering advection, molecular diffusion, and local dispersion [e.g., Zheng and
117 Gorelick, 2003; Salamon et al., 2007; Zheng et al., 2011; Fiori et al., 2013].

118 A recent application of the local-ADE approach at the MADE site is the study by
119 Dogan et al. [2014], in which flowmeter measurements and additional high-resolution K
120 data, collected with the direct-push injection logger [DPIL; Liu et al., 2009; Bohling et al.,
121 2012], were used to generate extremely detailed representations of the K field
122 [Meerschaert et al., 2013] in a sector of the MADE site aquifer. This sector is about 1/6 of

123 the total extension of the domain investigated by the three large-scale tracer experiments.
124 Transport simulations based on nine stochastic realizations of the K field showed a good
125 agreement with experimental data collected during the first tracer test (MADE-1). Results
126 from this work are significant because they provide strong confirmation that the local
127 ADE approach can predict solute transport in very heterogeneous porous media such as
128 the MADE site aquifer. However, the computational effort (on a grid of $0.25\text{ m} \times 0.25\text{ m}$
129 $\times 0.05\text{ m}$, which amounts to approximately 111 million nodes for the entire MADE site
130 domain of $120\text{ m} \times 290\text{ m} \times 10\text{ m}$) and the amount of data used for generating the K field
131 realizations (more than 5,500 measurements) were very substantial and not usually
132 attainable.

133 Thus, in this work we test the hypothesis that we can explain the characteristics of the
134 observed transport behavior at the MADE site with a much simpler local ADE-based
135 model, without relying on exceedingly fine grid spacing or thousands of K data points.
136 Differently from all the previous studies at the MADE site, we considered lithological data
137 rather than K measurements (either from flowmeter or DPIL) to generate geologically
138 consistent realizations of the spatial assemblage of five lithofacies, identified from a
139 relatively small set of aquifer samples. These realizations were then used as basis for the K
140 fields in transport simulations of the MADE-2 experiment. The agreement between
141 simulated and experimental data provides an unprecedented lithological explanation for
142 the observed non-Fickian transport behavior at the MADE site, while also demonstrating
143 that this behavior can be adequately simulated by a local ADE-based model without an
144 extraordinarily high-resolution characterization of the K field.

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146

147 2 Data

148 Lithological data consist of 411 aquifer samples collected from 38 boreholes covering
149 the total thickness of the aquifer (about 11 m on average). Location of these boreholes is
150 shown in Figure 1, while lithological descriptions and the results of grain-size analyses
151 performed on a subset of 214 soil samples from 29 boreholes are presented in a
152 preliminary hydrogeological characterization study of the MADE site [Boggs *et al.*, 1990].
153 Aquifer sampling was conducted using a hollow stem auger and split core barrel samplers
154 [Boggs *et al.*, 1990; 1992] and samples were generally collected at 1.5 meter intervals.
155 The majority of the boreholes are located in the southern sector of the site, with only 6
156 boreholes located within the boundary of the network of multilevel sampling wells used to
157 monitor concentrations during the tracer experiments.

158 Grain size data consist of percentages of gravel (diameter of soil grains greater than
159 4.76 mm), sand (diameter between 0.074 mm and 4.76 mm) and fines (diameter smaller
160 than 0.074 mm). Values of the 10th (d_{10}), 25th (d_{25}), and 60th (d_{60}) percentiles of the
161 cumulative grain size distribution are also available. Most of the aquifer at the MADE site
162 consists of bimodal mixtures of gravel and sand with a low percentage of fines (less than
163 5% on average). In general, mixtures of gravel, sand and fines are more predominant in
164 the most superficial part of the aquifer (up to 4 m of depth). Gravel content decreases with
165 depth (less than 25% on average), and it is particularly low toward the bottom boundary of
166 the aquifer represented by low-permeable marine deposits of the Eutaw formation. This
167 deeper portion of the aquifer consists mostly of well sorted sand with fines content
168 ranging from 1% up to 22%. Additional details on the vertical variability of gravel, sand,
169 and fines content are provided by Boggs *et al.* [1990, 1992].

170

171 3 Methods

172 3.1 Lithofacies identification

173 Aquifer samples were classified into five lithofacies on the basis of the relative
174 content of gravel (G), sand (S) and fines (f), as well as of values of d_{10} , d_{25} and of the
175 uniformity coefficient ($U = d_{60} / d_{10}$). The criteria used for the identification of these
176 lithofacies and key parameters are summarized in Table 1.

177 Lithofacies HCG (“highly conductive gravel”) and GS (“gravel with sand”), which
178 represent the 12% and the 18% of the samples respectively, consist of poorly sorted sandy
179 gravels (gravel content > 50%) with minor fines (< 5%). The two lithofacies are
180 distinguishable on the basis of the d_{10} (> 0.25 mm for HCG) and d_{25} values (> 1.0 mm for
181 HCG). The two threshold values of 0.25 mm and 1.0 mm were chosen to be corresponding
182 to the smallest grain sizes to define “medium sands” and “very coarse sands” according to
183 the widely used soil classification by *Krumbein* [1934]. Grain size in HCG is also
184 relatively more uniform than in GS ($U = 30$ vs. 41). In particular, HCG represents coarse
185 gravelly sediments, as shown by the values of the d_{60} with values ranging between 6.4 mm
186 and 19.7 mm. Lithofacies SGf (“sand, gravel and fines”) consists of mixtures of gravel,
187 sand and fines in various proportions. In general, sand content is higher than that of
188 gravel, although some samples have gravel content up to 70%. The content of fines is
189 higher than 5% in all samples. This lithofacies is the most represented in the aquifer
190 samples (35%). Lithofacies SG (“sand and gravel”) consists of moderately sorted gravelly
191 sands and represents the 14% of the samples. On average, SG has moderately high sand
192 content (about 65%), minimal fines (< 3% average), and d_{10} values similar to those in GS,
193 albeit with more uniformity in the grain-size distribution ($U=16$). Lithofacies S (“sand”)
194 consists of well sorted sand (sand content > 85%; average $U = 2.6$) with an average d_{10}
195 values similar to that in SGf (0.14 mm and 0.12 mm, respectively).

196

197 3.2 Stochastic simulation of lithofacies assemblage

198 Spatial continuity of the identified lithofacies was initially assessed along cross-
199 sections intercepting the boreholes to identify transition trends and estimate lateral and
200 vertical extensions. In a second stage, transition probabilities between lithofacies were
201 calculated and modelled with a three-dimensional Markov chain in a conditional
202 simulation framework [Carle, 1999]. The transition probability approach introduced by
203 Carle and Fogg [1996, 1997] has been used to produce geologically consistent
204 representations of subsurface heterogeneity by preserving the connectivity of lithofacies
205 and juxtapositional tendencies [e.g., Carle et al., 1998; Weissmann and Fogg, 1999; Ritzi,
206 2000; Ritzi et al., 2004; Lee et al., 2007; Dai et al., 2007; Ye and Khaleel, 2008; Bianchi et
207 al., 2011b]. Differently from traditional variogram-based geostatistical methods, with this
208 approach the spatial structure of the data is represented by transition probabilities, which
209 are defined in terms of the following conditional probability:

$$210 \quad t_{i,k}(\mathbf{h}) = \Pr \{k(\mathbf{x} + \mathbf{h}) | i(\mathbf{x})\} \quad (2)$$

211 where $t_{i,k}$ is the transition probability from lithofacies i to lithofacies k , and \mathbf{x} and \mathbf{h} are the
212 spatial location and lag distance vectors. Because, from Equation (2), the occurrence of
213 lithofacies k at location $\mathbf{x} + \mathbf{h}$ is only dependent on the occurrence of lithofacies i at
214 location \mathbf{x} , three-dimensional continuous-lag Markov Chain models can be developed to
215 model discrete transition probabilities observed in the data. In this work, the fitting of a
216 3D Markov chain to the transition probabilities measured in the borehole data was
217 performed by adjusting embedded transition probabilities and mean length and thickness
218 values of lithofacies (Figure 2). Because of the relatively small number of boreholes, the
219 estimation of mean length values from the plots of auto-transition probabilities in the
220 horizontal direction is characterized by a certain degree of uncertainty. Therefore, in order

221 to apply a more objective criterion for the estimation of the spatial correlation of the
222 lithofacies in the horizontal direction, we have chosen to apply an early lag data approach
223 [Carle and Fogg, 1997] in which the lag-one transition probability was used to compute
224 the Markov chain model. This fit also produces probabilistic estimates of the mean length
225 for each lithofacies (Figure 2a). We also tested the sensitivity of the transport modelling
226 results with respect to this choice, especially regarding variations of the mean length of
227 lithofacies HCG. The results of this sensitivity analysis will be discussed later. The
228 calibrated Markov chain model also assumes isotropic behavior in the horizontal plane
229 and lithofacies SGf as the background category. Volumetric proportions of the lithofacies,
230 represented by the sill of the transiograms in the model, are also assumed equal to the
231 proportions exhibited by the borehole data. Modeled transition probabilities and values of
232 mean length and thickness for each lithofacies (Table 1) are reasonable and consistent
233 with the spatial continuity assessed in the cross-sections. The mean lengths of the
234 lithofacies inferred from the transition probability analysis is of the order of tens of
235 meters, while thicknesses are in the order of a meter indicating higher variability along the
236 vertical direction as in shown by previous investigations [e.g., Rehfeldt *et al.*, 1992;
237 Bohling *et al.*, 2012]

238

239 3.3 Flow and transport simulations

240 A three-dimensional stochastic flow and transport model was implemented to
241 simulate the second large scale tracer experiment (MADE-2; Boggs *et al.*, 1993). The
242 block-centered numerical grid, with a total size of 120 m × 290 m × 10 m (Figure 1), has a
243 resolution of 2 m in the horizontal plane and 0.5 m in the vertical direction. The total
244 number of cells of the numerical grid is about 1.82×10^4 , which is about 18 times less than

245 the number of cells in the model by *Dogan et al.* [2014], even though the latter considers a
246 smaller domain.

247 The K fields in the numerical simulations are directly linked to the spatial
248 distribution of the identified lithofacies. These were generated according to the following
249 procedure. In a first step, K values for each sample were estimated with the Kozeny-
250 Carman empirical formula [e.g., *Riva et al.*, 2010]:

$$251 \quad K = 8.3 \times 10^{-3} \frac{g\theta^3}{\nu(1-\theta)^2} d_e^2 \quad (3)$$

252 where g is gravity (9.81 m²/s), ν is the kinematic coefficient of viscosity of water (1.002
253 m²/s at 20 °C), d_e is a representative grain diameter, and θ is porosity. Porosity was
254 estimated according to the empirical formula of *Vucovic and Soro* (1992) :

$$255 \quad \theta = 0.255(1 + 0.83^U) \quad (4)$$

256 Porosity values for each lithofacies (Table 1) and the average of all the samples (0.307)
257 are similar to measurements in collected aquifer samples (*Boggs et al.*, 1990; *Boggs et al.*,
258 1992). Although there are different interpretations for d_e in the literature [e.g., *Koltermann*
259 *and Gorelick*, 1995], here it was assumed to be corresponding to d_{10} for lithofacies GS,
260 SG, SGf and S. There is in fact experimental evidence showing the reliability of this
261 assumption in medium to coarse gravelly sands [*Odong*, 2007] and in well to moderately
262 sorted sand/gravel mixtures [e.g., *Barahona-Palomo et al.*, 2011]. The average between
263 d_{10} and d_{25} was chosen instead for lithofacies HCG because of lower sand content and
264 significantly coarser grain size (Table 1). With this choice, estimated K values for the
265 HCG samples are also more comparable with previous K estimates [*Boggs et al.*, 1990;
266 *Eggleston and Rojstaczer*, 1998b] based on a different empirical formula, which was
267 developed specifically for gravel and sand mixtures [*Seiler*, 1973]. In the subsequent
268 discussion, we will test the effect of this assumption on simulated transport behavior. In a

269 second step, descriptive statistics of the log transformed K estimates were computed for
270 the five lithofacies (Table 1). As expected given the coarsest grain size, statistical analysis
271 of the estimated K values for each lithofacies (Figure 3) indicates that HCG is
272 significantly the most conductive lithofacies, with a mean K value that is about 1.5 to 2
273 orders of magnitude higher than the mean values of the other lithofacies. Next, three-
274 dimensional conditional realizations of the spatial assemblage of lithofacies were
275 generated according to the calculated transition probabilities and fitted Markov chain
276 model [Carle *et al.*, 1998; Carle, 1999]. In the transport model domain the realizations are
277 conditioned to the lithofacies identified in the samples from 6 boreholes (Figure 1). In the
278 final step, an appropriate K value was assigned to each cell of the numerical grid of
279 transport simulations according to the simulated distribution of lithofacies. This value was
280 randomly generated from the truncated lognormal distribution, with mean and standard
281 deviation equal to the corresponding values for each lithofacies. One standard deviation
282 below and above the mean were considered as truncation thresholds to avoid excessive
283 overlapping among different lithofacies and preserve the lithological structure on the
284 generated K fields.

285 Groundwater flow was simulated in three stress periods of the duration of 2, 158 and
286 168 days using MODFLOW-2005 [Harbaugh, 2005]. The duration of the first stress
287 period was chosen to represent the tritium injection. During the MADE-2 experiment, a
288 total of 9.3 m³ of a solution containing tritium was injected for approximately 48 hours
289 through a linear array of five injection wells, spaced 1 m apart, and centered on the origin
290 of the Cartesian coordinates system in Figure 1 (Boggs *et al.* 1993). The injection wells
291 were screened at a depth interval between 57.5 m and 58.1 m a.s.l. The injection procedure
292 in the model was simplified such that only two cells of the numerical grid were considered
293 for the injection. However, the location of these cells and the total injected tritium mass

294 (0.5387 Ci) are consistent with the experimental conditions. The remaining stress periods
295 were chosen to represent two distinct climatic periods observed over the 328 days of the
296 experiment, which are clearly shown by significant water table fluctuations registered by
297 the groundwater level monitoring network [Boggs *et al.*, 1993; Stauffer *et al.*, 1994; Guan
298 *et al.*, 2008]. Accordingly, average values of groundwater levels measured at different
299 wells during these two climatic periods were used to define specified-head boundary
300 conditions at $Y = -20$ m and $Y = 270$ m, while no-flow boundary conditions were
301 imposed at $X = -50$ m, $X = 70$ m and $Z = 52$ m. Despite the possible importance of
302 transient flow conditions on transport at the MADE site [Llopis-Albert and Capilla, 2009],
303 flow was assumed steady state in all stress periods. The ratio between vertical and
304 horizontal K assumed in the model (0.13) is based on the results of a pumping test
305 conducted at the MADE site [Boggs *et al.*, 1990].

306 Transport simulations based on Equation (1) were performed with MT3DMS
307 [Zheng, 2010] with the advection component solved with the total-variation-diminishing
308 (TVD) scheme to minimize numerical dispersion given the relative coarseness of the grid
309 and avoid mass balance inconsistencies. A Courant number of 0.75 was used for all
310 transport simulations. Porosity values were assigned to the grid according to the
311 lithofacies distribution. These correspond to the average of the values estimated with
312 Equation 4 for each lithofacies (Table 1). Other input parameters include a molecular
313 diffusion coefficient for tritium of 1.16×10^{-9} m²/s [Salomon *et al.*, 2007], α_L equal to 1 m
314 [Feehley *et al.*, 2000; Llopis-Albert and Capilla, 2009], and values of α_{TH} and α_V of one
315 and two orders of magnitude lower than α_L .

316 The accuracy of the implemented model was tested by comparing simulated and
317 observed 1-D longitudinal mass distributions at 27, 132, 224, and 328 days after the

318 injection. These times correspond to the first four “snapshots” of the MADE-2 experiment
 319 [*Boggs et al.*, 1993]. For the calculation of experimental mass distributions, the mass
 320 along each monitoring well was integrated vertically and then interpolated in 2-D over the
 321 same grid used for flow and transport simulations. Observed and simulated mass
 322 distributions for each snapshot were then obtained by integrating the fraction of total
 323 recovered mass in 30 equally spaced zones of 10 m width along the general flow direction
 324 (y axis).

325 The mean longitudinal displacement (\bar{y}) and the longitudinal variance of the
 326 observed and simulated 1-D mass profiles (σ_{yy}^2) were also calculated on the basis of the
 327 central spatial moments according to the following equations (e.g., *Adams and Gelhar*,
 328 1992):

$$329 \quad \bar{y} = M_1 / M_0 \quad (5)$$

330 and

$$331 \quad \sigma_{yy}^2 = M_2 / M_0 - M_1^2 / M_0 \quad (6)$$

332 The generic spatial moment M_i for the observed and simulated longitudinal mass profiles
 333 was calculated with the following equation:

$$334 \quad M_i = \sum_{p=1}^N m_p y^i \quad (7)$$

335 where m_p is the fraction of recovered mass at the point p of coordinates y , and N is the total
 336 number of points. Note that since tritium mass was normalized with the total recovered
 337 mass, the zero-th moment M_0 is equal to 1 for both observed and simulated mass profiles.

338

339 4 Results and discussion

340 The ensemble mean and median of 1-D longitudinal mass distributions from 500
341 Monte Carlo realizations of the model are shown in Figure 4a-d. The interquartile range is
342 also reported to provide a description of the variability of the simulated results. In general,
343 the model is accurate in reproducing the mass accumulation near the injection site and the
344 spreading to the far field. The model tends to overestimate the position of the edge of the
345 plume in the first two snapshots, even though the mismatch is limited to fractions of
346 recovered mass below 0.01. At later times (224 and 328 days), the model does not match
347 the relative peak of mass observed between 160 m and 200 m from the injection site. This
348 peak is most probably the effect of transient variations in the flow field during the
349 experiment as suggested by fluctuations in the water table of up to 30% of the saturated
350 thickness, which were observed during later stages of the MADE-2 test [Stauffer *et al.*,
351 1994; Llopis-Albert and Capilla, 2009]. These variations were not considered in the
352 presented model. A better match between observed and simulated mass profiles could also
353 be probably achieved with calibration of some of the model input parameters (e.g.,
354 porosity and K values of the lithofacies, boundary conditions). However, a calibration
355 procedure not only is beyond the scope of the present work, but also would reduce the
356 predictability of our lithofacies approach and compromise the insight about its
357 transferability to other sites. Notwithstanding these simplifications, the implemented
358 transport model is able to capture the overall characteristics of the MADE-2 plume with
359 reasonable accuracy, especially considering the limited number of hard conditioning
360 points used in the stochastic realizations of subsurface heterogeneity.

361 Reasonable accuracy is further confirmed by comparisons between observed and
362 simulated central moments (Figure 5a-c). The percentage error between the observed
363 longitudinal displacement and the ensemble mean of the simulated values is between 11%

364 and 51%. The highest discrepancy is calculated for the displacement at 132 days, because
365 simulated plumes tend to advance too rapidly (9.2 m vs. 13.9 m). The error between
366 observed and simulated displacement at 224 and 328 is around 25%, but this discrepancy
367 is strongly influenced by the relative peak of mass observed at later times and by the
368 extremely rapid movement of the center of mass observed between 132 and 224 days. One
369 important aspect regarding the proposed model shown in Figures 5b and 5c is that the
370 second central moment representing the longitudinal variance of the plume grows at
371 different rates in both time and space. This characteristic and the asymmetric shape of the
372 simulated mass distributions are indicative of non-Fickian transport behavior.

373 From the comparison between the spatial distributions of the identified lithofacies
374 (Figure 6a), the corresponding K fields (Figure 6b), and the location of the plume front at
375 different times (Figure 6c), it is evident that the asymmetric shape of the plume and the
376 rapid movement of the edge are controlled by the location and the lateral continuity of the
377 highly conductive lithofacies HCG. Given the dimension of the simulated domain in the
378 longitudinal direction (145 cells) and its mean length (30 m = 15 cells), the percolation
379 threshold for lithofacies HCG is expected to be around 0.14, according to *Harter* [2005].
380 Because the percolation threshold corresponds to the critical volumetric fraction for which
381 there is occurrence of one cluster of cells spanning the entire domain, the estimated
382 volumetric fraction of 0.12 for lithofacies HCG indicates that this lithofacies defines an
383 interconnected network of high- K values that almost fully percolate the MADE site
384 aquifer. This result provides a further confirmation of the hypothesis advanced by several
385 previous studies [e.g., *Fogg*, 1986; *Fogg et al.*, 2000; *Labolle and Fogg*, 2001; *Zheng and*
386 *Gorelick*, 2003; *Zheng et al.*, 2011; *Moltz*, 2015] that the “anomalous” transport behavior
387 observed in heterogeneous alluvial aquifers is mostly the effect of connectivity of high- K
388 sediments. This connectivity enhances fast advective transport of a fraction of mass along

389 preferential flow-paths, while a larger fraction travels in a relatively less permeable
390 matrix. In the matrix, the role of diffusive transport is more significant especially in
391 directions perpendicular to the main flow. When high- K zones connectivity is taken into
392 account, faster than expected breakthrough times and late-time tailing of contaminants
393 concentrations, which are commonly observed in contaminated aquifer sites, can be
394 successfully predicted [*Labolle and Fogg, 2001*].

395 The influence of lithofacies HCG on the velocity field and consequently on advective
396 transport is also shown by the analysis of the frequency distributions of the generated K
397 fields (Figure 7). These are clearly bimodal, with the majority of the $\log_{10}(K)$ values
398 clustered around a value of about 0.75 m/d, and a smaller set of values around the average
399 value for lithofacies HCG (Table 1). Comparisons between the distribution for the
400 generated K fields and the distributions of K data previously collected at the MADE site
401 with two different methods [*Rehfeldt et al., 1992; Bohling et al., 2012*] indicate similarity
402 between the modal value of the K estimates for lithofacies GS, SGf, SG and S and average
403 value of the flowmeter measurements. The K estimates for lithofacies HCG are also
404 comparable to the upper tails of the distributions of both the flowmeter and the DPIL data.
405 However, the three K data sets differ in terms of sample variances, and the correlation
406 between corresponding values at different depths in boreholes located within a 3.5 m
407 radius is generally poor. A discussion of the possible causes for the mismatch between the
408 flowmeter data and the DPIL data is presented by *Bohling et al.* [2012], while mismatches
409 between the K estimates based on grain-size analysis and flowmeter data have been also
410 observed in other alluvial aquifers [*Barahona-Palomo et al., 2011; Guting et al., 2015*].
411 As for these other aquifers, the lack of correlation between types of K data for the MADE
412 site aquifer is most likely explained by the difference in the support scale associated with

413 each method, which ranges from a few centimeters for DPIL, to about 1.5 decimeters for
414 the flowmeter measurements, up to several decimeters for the grain-size estimates.

415 Our interpretation may also provide a geological explanation for the success of the
416 dual-domain mass transfer rate approach (DDM) in reproducing the experimental data at
417 this site [Harvey and Gorelick, 2000; Feehley et al., 2000; Guan et al., 2008; Bianchi et
418 al., 2011a]. This approach simulates transport in two distinct but overlapping mobile and
419 immobile domains, each characterized by a certain porosity value, and the total porosity of
420 the system is given by the sum of the mobile and immobile porosities. A mass transfer rate
421 coefficient controls the exchange of solute mass between the two domains. According to
422 the dual-domain conceptualization, pore space in the mobile domain is filled with water
423 that can actually move through the porous structure and solute transport is mainly due to
424 advection. On the other hand, pores in the immobile domain are filled with stagnant water
425 and molecular diffusion is the main transport process. This separation into two mobile and
426 immobile domains is therefore particularly suitable for reproducing transport when
427 interconnected high- K sediments (i.e., the mobile domain) are embedded in a relatively
428 lower permeable matrix (i.e., the immobile domain).

429 Because our results suggest that the lithofacies HCG can be considered the mobile
430 domain through which fast advective transport occurs, it is very noteworthy that the
431 volumetric fraction estimated from the borehole data (0.12) corresponds to the calibrated
432 value of the ratio between mobile and total porosities ($1/8 = 0.125$) of dual-domain
433 models, which were able to fit the observed plume spreading at the MADE site [Zheng et
434 al., 2011 and references therein]. As a confirmation, we implemented a DDM model
435 (single-rate) based on a homogenous field with K equal to the ensemble mean of the
436 equivalent K values for a subset of realizations of the K field. For each realization, the
437 equivalent K was estimated by applying Darcy's law between the two specified-head

438 boundaries of the simulated domain in Figure 1, and by assuming a preservation of the
439 total discharge. This approach is similar to that used by *Liu et al.* [2007] to test the
440 applicability of the DDM to represent transport in binary K fields characterized by
441 decimeter-scale highly conductive channels. The model also assumes a mobile to total
442 porosity ratio equal to the volumetric fraction of HCG. Comparisons between observed
443 and simulated plumes show that we can match the observed the transport behavior with
444 adequate accuracy by a simple calibration of the mass transfer rate coefficient (Figure 8
445 and Figure 5d). As in the model proposed by *Guan et al.* [2008], calibrated values for this
446 parameter indicate that the single-rate mass transfer coefficient is scale-dependent and
447 decreases with time.

448 Results shown in Figure 4a-d are based on the input parameters of Table 1. Because
449 of the uncertainty associated with some of these parameters and the dominant influence of
450 lithofacies HCG on the simulated transport behavior, we also analyzed the sensitivity of
451 the results with respect to changes of K and mean length for this lithofacies. The results
452 for the snapshot at 328 days are shown in Figure 4e. When lithofacies HCG is ignored in
453 the generation of the K fields and its K value is assumed equal to that of lithofacies GS,
454 the mass distribution showed very limited spreading and a symmetric shape. A similar
455 result was obtained in a scenario in which the K of lithofacies HCG is estimated by
456 considering the d_{10} as the value for d_e in Equation 2. The model is also sensitive with
457 respect to changes of the mean length of lithofacies HCG. However, even when the mean
458 length is assumed to be one half of the value in Table 1, we still observe a significantly
459 asymmetric mass distribution although the leading edge of the plume is about 40 m
460 shorter. This result indicates that even if a small range of mean length values would fit the
461 estimated auto-transition probabilities equally well for lithofacies HCG (Figure 2a), the
462 main conclusion regarding its role on controlling non-Fickian transport is still valid.

463

464 **5 Conclusions**

465 Site-scale transport behavior observed during one of the MADE site experiments
466 (MADE-2) was effectively reproduced with a relatively simple, local ADE-based model.
467 The physical aquifer heterogeneity in the transport model was conceptualized and
468 represented by 3-D realizations of the spatial distribution of lithofacies identified from
469 aquifer samples collected from 39 boreholes, mostly located outside the domain used for
470 transport simulations. The lithofacies approach appears to have provided an unprecedented
471 explanation to “anomalous” plume-scale behavior at the MADE site that has motivated a
472 long line of studies over the past 30 years. Furthermore, results suggest that such behavior
473 can be reproduced with a model based on a much smaller set of aquifer property data than
474 previously thought possible.

475 In particular, this analysis shows that some of the non-Fickian features of the
476 observed plume can be explained by a highly permeable lithofacies with limited (less than
477 1 m) vertical extent and moderate (>10 m) horizontal correlation. The presence of a
478 network of well interconnected highly permeable sediments embedded in a less permeable
479 matrix has been previously suggested for the MADE site [*Harvey and Gorelick, 2000*;
480 *Zheng and Gorelick, 2003*] and tested in small sectors of the investigated domain [*Liu et*
481 *al., 2010*; *Ronayne et al., 2011*; *Bianchi et al., 2011a, 2011b*], but never assessed at the
482 scale of the large scale tracer experiments. In the context of about three decades of
483 research work at the MADE site, the identification of the most conductive lithofacies
484 (HCG) from borehole lithological data is a significant result providing a previously
485 elusive, simple explanation for the observed non-Fickian transport behavior from a
486 geological perspective.

487 The proposed model of physical heterogeneity for the MADE site aquifer seems also
488 to provide a lithological basis for the success of dual-domain mass transfer rate approach
489 in reproducing non-Fickian transport behavior at this site [Zheng *et al.*, 2011]. In this
490 respect, this work can also be seen as a first successful attempt to infer the ratio between
491 mobile to total porosities, which is at the basis of dual-domain conceptualization, from
492 grain-size analysis data and volumetric fractions of lithofacies.

493 Even though this study is focused on a particular alluvial aquifer, the impact of the
494 results is broader because they show that if the geological structure – here represented by
495 the spatial distribution of the lithofacies – is properly represented in the 3-D hydraulic
496 conductivity field, then solute transport in heterogeneous aquifers can be accurately
497 simulated with local ADE-based models without relying on exceedingly fine grid spacing
498 or high-resolution K data. The incorporation of the geological structure in the physical
499 model of heterogeneity also provides verifiable explanations for the observed plume
500 behavior. Therefore, this work underscores the importance of geologically based
501 representations of the subsurface, which can be developed through integration of raw
502 geological data (e.g., borehole logs, aquifer analog descriptions, geophysical surveys) with
503 expert knowledge, interpretation and appropriate geostatistical methods.

504

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512 found in the referenced report *Boggs et al.* [1990]. Tracer data used in this study are
513 available in the referenced report *Boggs et al.* [1993].

514

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731

732 **LIST OF TABLES**

733

734 Table1. Criteria used for lithofacies identification and representative parameters.

	Highly conductive gravel (HCG)	Gravel with sand (GS)	Sand gravel and fines (SGf)	Sand and gravel (SG)	Well sorted sand (S)
Identification criteria	G > 50% f < 5% d ₁₀ > 0.25 mm d ₂₅ > 1 mm	G > 50% f < 5%	f > 5%	S > 50% f < 5%	S > 85% U < 3
G* [%]	64.6	56.2	40.8	32.2	3.1
S* [%]	32.0	40.7	51.7	64.9	90.2
f* [%]	3.4	3.1	7.5	2.9	6.7
d ₁₀ * [mm]	0.62	0.22	0.14	0.21	0.12
d ₂₅ * [mm]	2.7	0.72	0.45	0.36	0.16
d ₆₀ * [mm]	12.4	8.73	5.56	3.3	0.28
U*	30.4	41.0	38.3	15.6	2.6
Proportions [%]	12	18	35	14	21
Mean length [m]	30	31	39	25	35
Mean thickness [m]	1.0	0.5	0.9	0.4	1.7
Mean Log ₁₀ (K) [m/d]	2.482	0.830	0.402	0.889	0.752
Variance Log ₁₀ (K)	0.589	0.210	0.343	0.228	0.165
Mean θ	0.265	0.257	0.259	0.298	0.415

735

736 G: gravel content;

737 S: sand content;

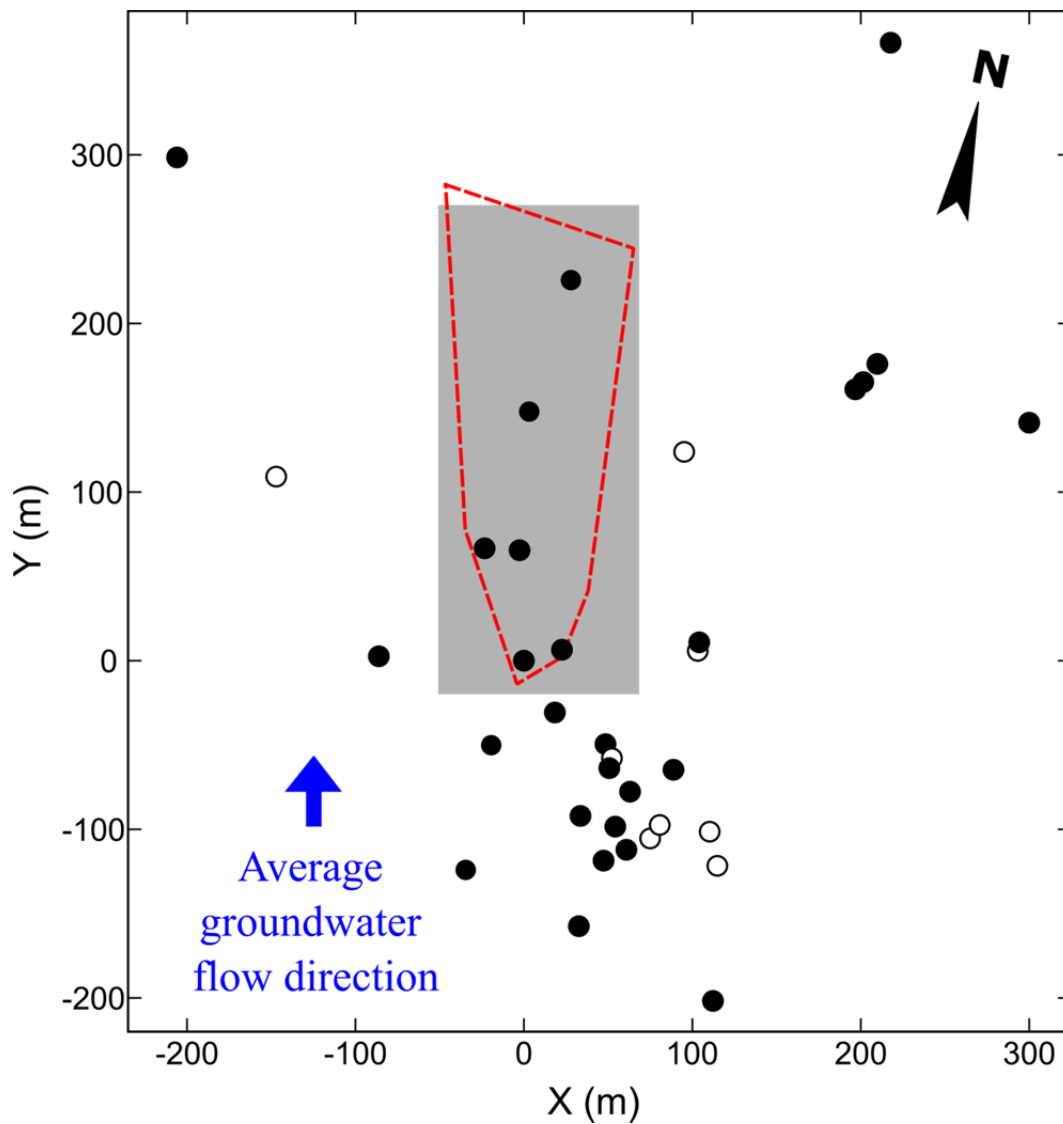
738 f: fines content

739 * average value

740

741 LIST OF FIGURES

742



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744

745 Figure 1. Map of boreholes used for lithological characterization of the MADE site. Black

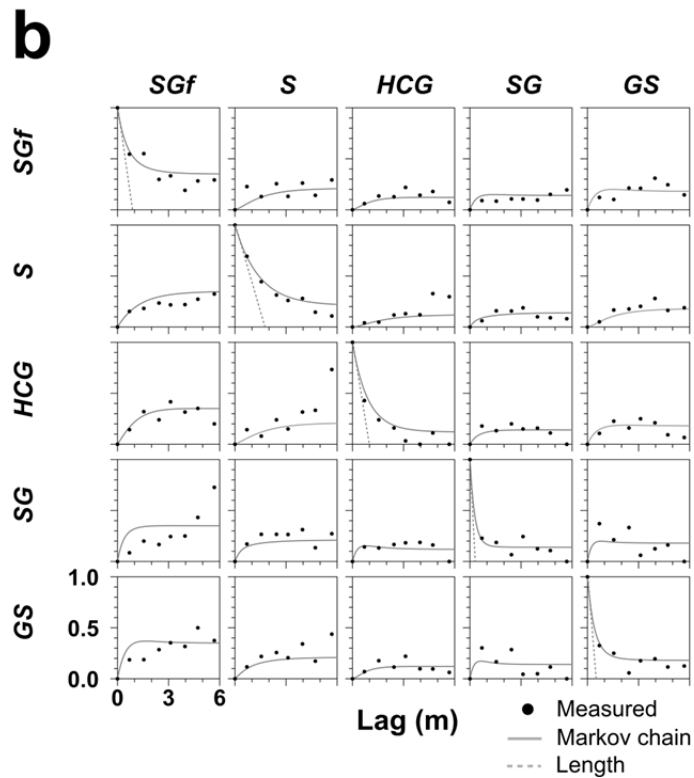
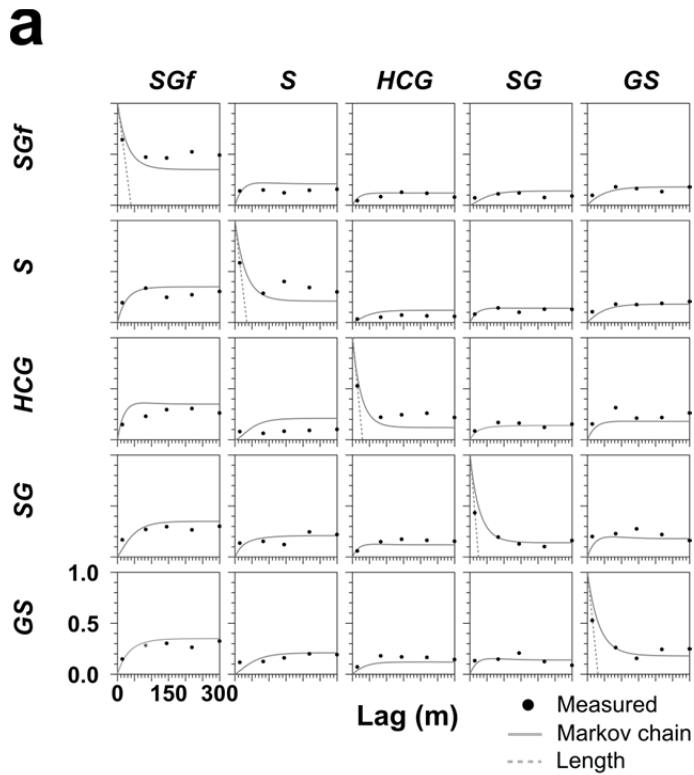
746 circles indicate boreholes with grain size data in Appendix A in *Boggs et al.* [1990].

747 Boreholes with only lithological description are indicated by open circles. The grey

748 shaded area indicates the extension of the domain used for flow and transport modelling.

749 The red dashed line indicates the boundary of the network of multilevel sampling wells

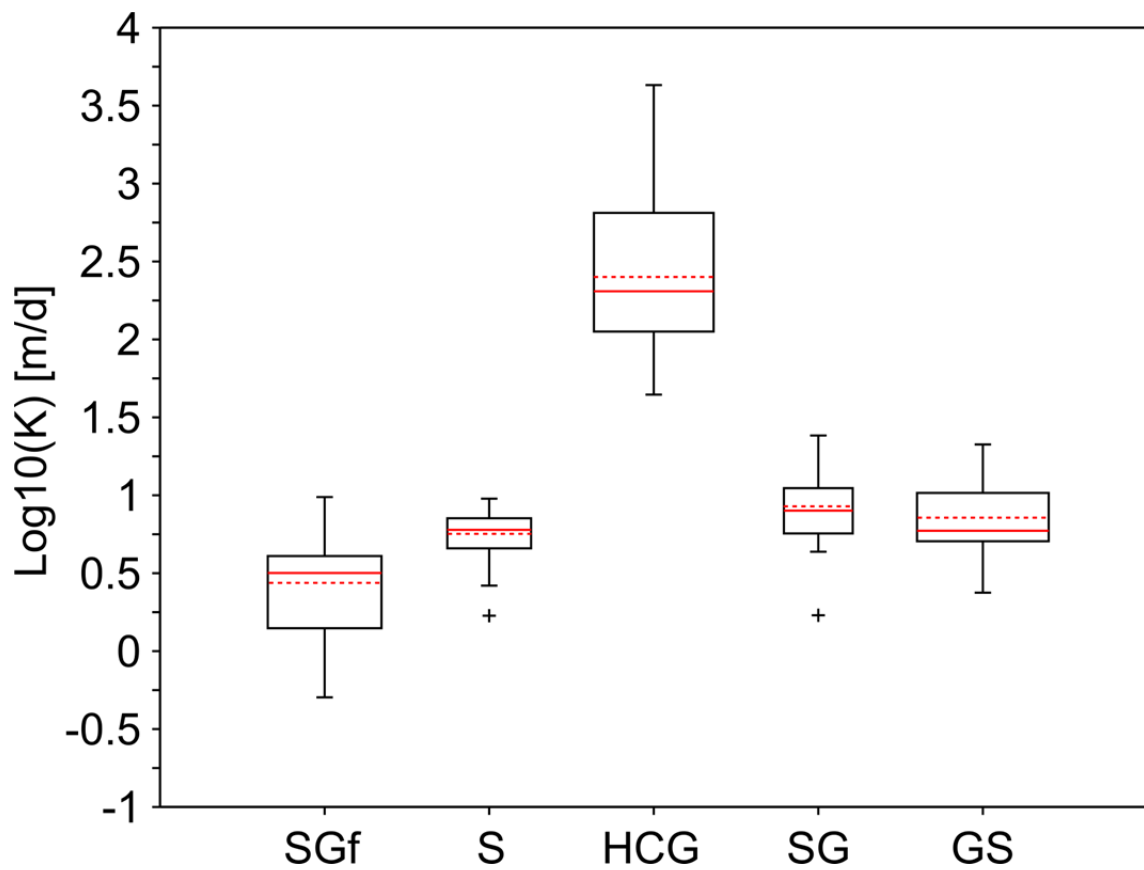
750 used during the large-scale tracer tests.



751

752 Figure 2. Lateral (a) and vertical (b) transition probabilities and fitted Markov chain

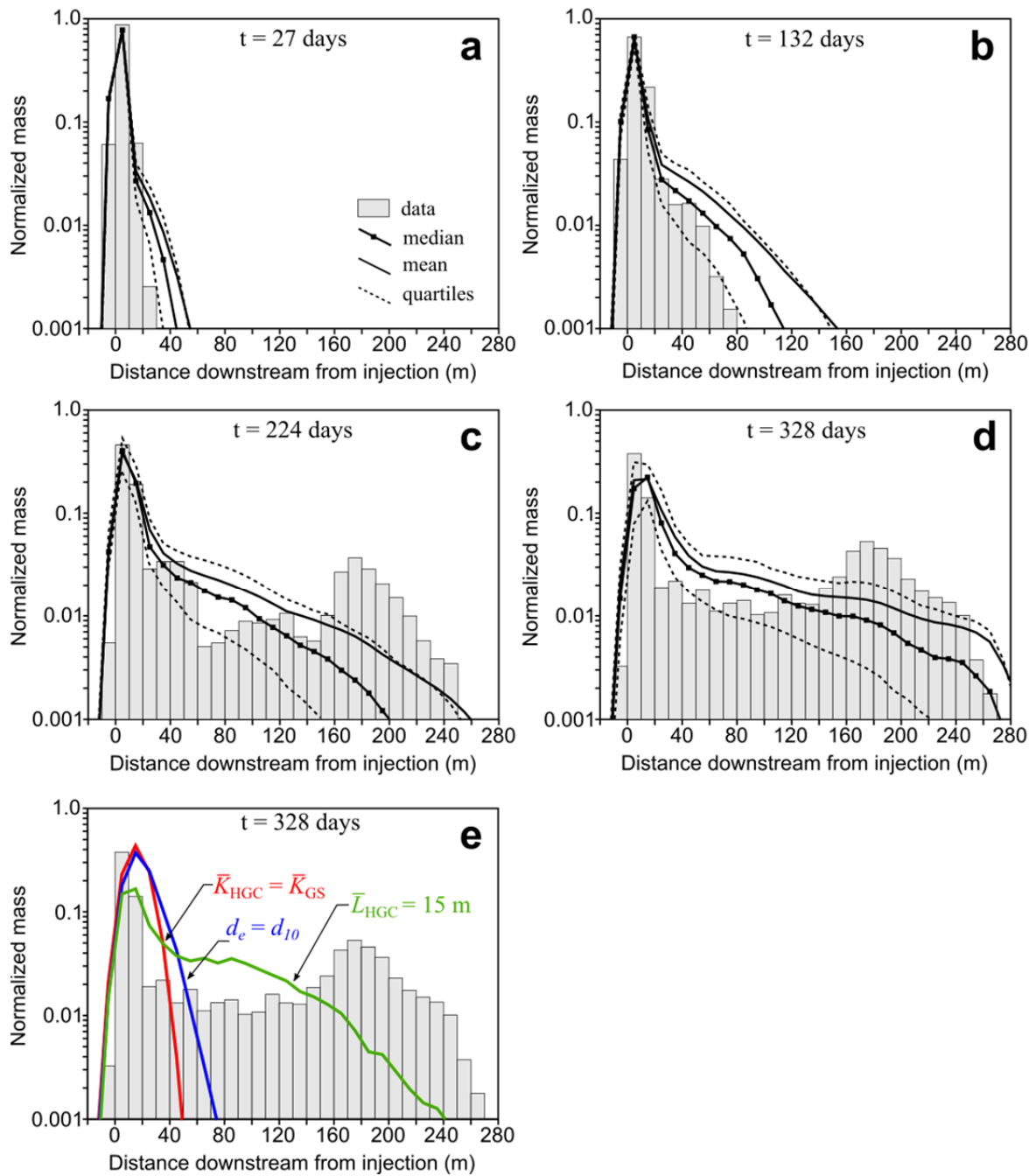
753 model.



754

755

756 Figure 3. Box plots of the estimated log-transformed hydraulic conductivity (K) values for
 757 each lithofacies showing median, interquartile range and extreme values (crosses). Red
 758 dashed lines indicate mean values.



759

760

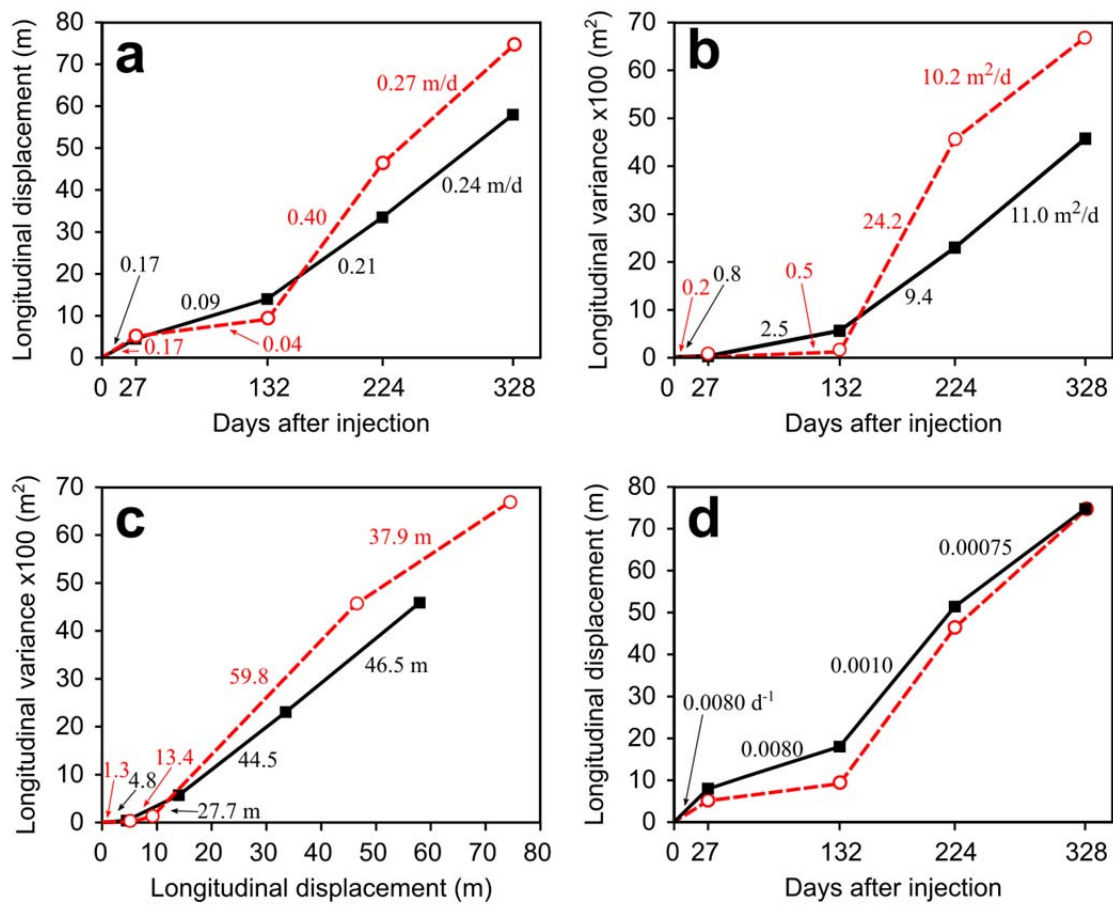
761 Figure 4. (a-d) Observed and simulated longitudinal mass distributions of the tritium

762 plume. Simulated distributions were obtained with input parameters in Table 1. (e) Mass

763 distribution at 328 days for simulations considering different mean K and mean length for

764 lithofacies HCG. The scenario assuming a mean K value for HGC equal to that for

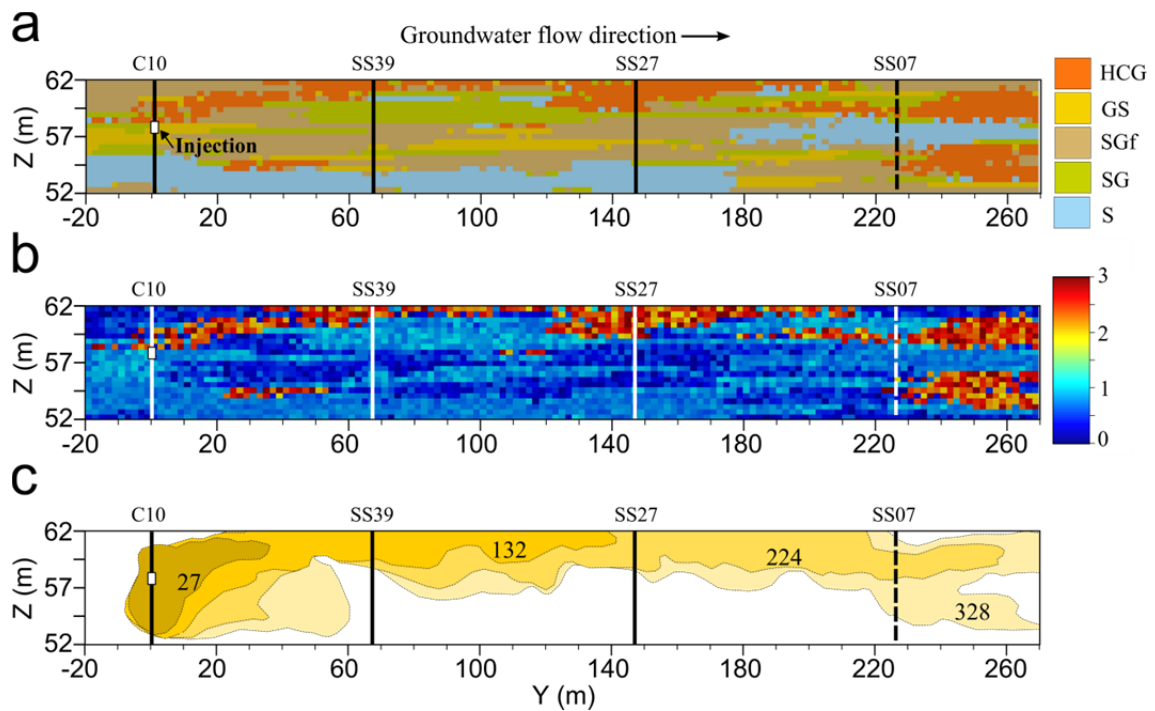
765 lithofacies GS is shown red. The scenario assuming d_e as d_{10} for K estimations is shown in
766 blue. The scenario assuming a mean length (\bar{L}) of 15 m is shown in green.
767



768

769

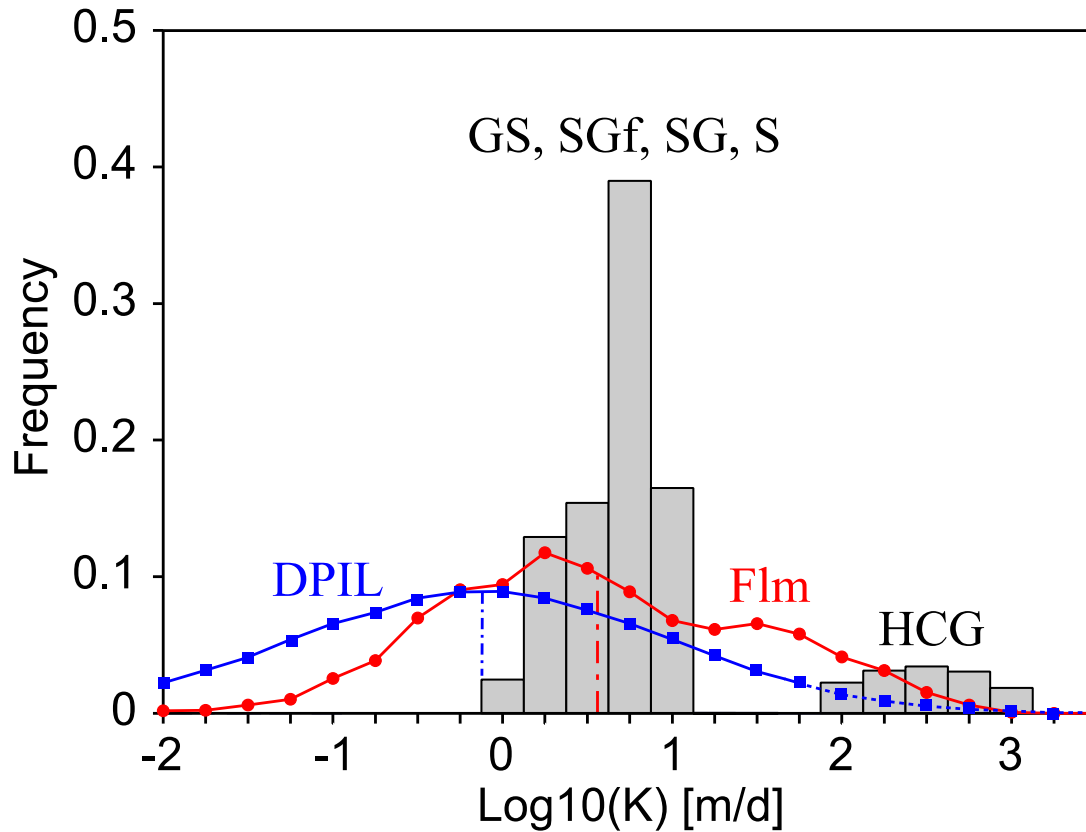
770 Figure 5. First and second central spatial moments evolution for the observed (in red) and
 771 simulated (in black) plumes. Simulated points in a-c represent mean values of the Monte
 772 Carlo realizations. (a) Values indicate the estimated mean plume velocity. (b) Values
 773 indicate one half of the growth rate of the longitudinal variance with time (c) Values
 774 indicate one half of growth rate of the longitudinal variance with the mean travel distance.
 775 Under the assumption of a uniform flow field these values correspond to the macroscopic
 776 longitudinal dispersivity. (d) Longitudinal displacement of a dual-domain single rate mass
 777 transfer model (DDM) in which the ratio of mobile to total porosity is equal to the
 778 volumetric fraction of HCG. Values indicate calibrated values for the mass transfer rate
 779 coefficient (see text for explanation).



780

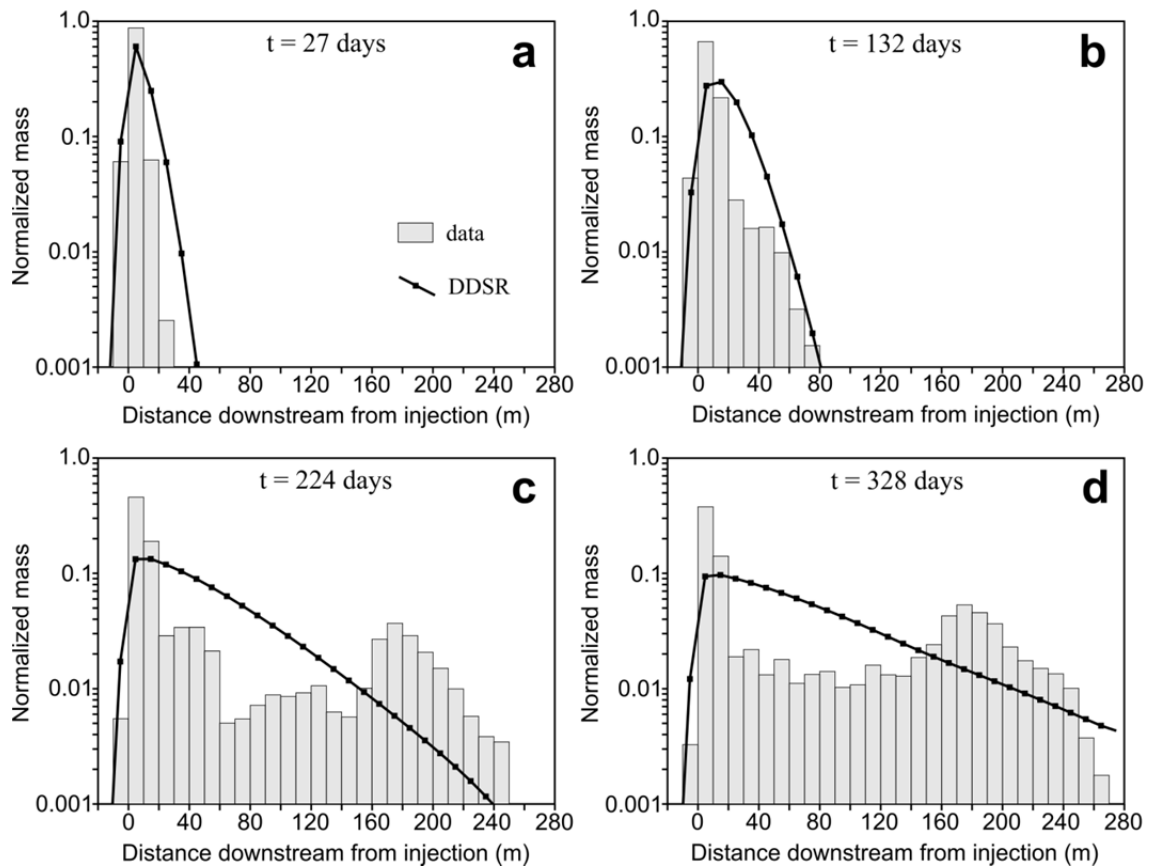
781

782 Figure 6. (a) One equally probable realization of the simulated spatial distribution of
 783 lithofacies shown in a cross section oriented parallel to the main flow direction and
 784 crossing through the injection site and three boreholes. Location of borehole SS07 is
 785 projected. (b) Corresponding $\log_{10}(K)$ field [m/d]. (c) Evolution of the simulated plume
 786 front ($C = 2\text{pCi/ml}$) with time.



787

788 Figure 7. Example of frequency distribution of the generated K fields. The distributions of
 789 the K measurements using the impeller flowmeter (Flm) and direct-push injection logger
 790 (DPIL) are also shown. The vertical dash-dot lines indicate the mean of the two
 791 distributions. Flowmeter measurements data from *Rehfeldt et al.* [1992]. The DPIL data
 792 distribution was estimated by assuming a lognormal distribution with a geometric mean of
 793 8.9×10^{-6} m/s and a variance of natural log-transformed K values of 6.6 [Table 1 in *Bowling*
 794 *et al.*, 2012]. The upper limit of the DPIL instrument is about 60 m/d [*Bowling et al.*,
 795 2012; *Dogan et al.*, 2014].



796

797

798 Figure 8. Observed and simulated longitudinal mass distributions of the tritium plume.

799 Simulated profiles were calculated with a dual-domain single rate mass transfer model in

800 which the ratio of mobile to total porosity is equal to the volumetric fraction of HCG.

801 Values for the mass transfer rate coefficient (see Figure 5d) were estimated by calibration

802 with a trial-and-error approach.