

On the Link Between Contaminant Source Release Conditions and Plume Prediction Uncertainty

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Abstract

The initial width of contaminant plumes is known to have a key influence on expected plume development, dispersion and travel time statistics. In past studies, initial plume width has been perceived identical to the geometric width of a contaminant source or injection volume. A recent study on optimal sampling layouts (Nowak et al., 2010) showed that a significant portion of uncertainty in predicting plume migration stems from the uncertain total hydraulic flux through the source area. This result points towards a missing link between source geometry and plume statistics, which we denote as the effective source width. We define the *effective* source width by the ratio between the actual and expected hydraulic flux times the *geometric* source width. The actual hydraulic flux through the source area is given by individual realizations while the expected one represents the mean over the ensemble. It is a stochastic quantity that may strongly differ from the actual geometric source width for geometrically small sources, and becomes identical only at the limit of wide sources (approaching ergodicity). We derive its stochastic ensemble moments in order to explore the dependency on source scale. We show that, if the effective source width is known rather than the geometric width, predictions of plume development can greatly increase in predictive power. This is illustrated on plume statistics such as the distribution of plume length, average width, transverse dispersion, total mass flux and overall concentration variance. The analysis is limited to 2D depth-averaged systems, but implications hold for 3D cases.

Keywords: Stochastic Hydrogeology, Heterogeneous porous media, Stream function statistics, Contaminant dispersion, Conditioning

1. Introduction

Stochastic description of contaminant transport is a necessity since full characterization of natural porous media, such as aquifers, is an unfeasible task. Many past studies have provided powerful tools to predict contaminant transport, based on the ensemble behavior of the plume's spatial and temporal moments (for an extensive review see Rubin, 2003). In these studies, the initial width of a plume (e.g., the dimension of the contaminant source) is directly related to fundamental characteristics such as plume ergodicity and is a key parameter in predictions of plume development, dispersion, dilution and mixing (e.g., Rubin et al., 1994; Andricevic and Cvetkovic, 1998; Dentz et al., 2000).

Up to date, the initial plume width has been perceived as identical to the width of a source or of an injection volume (e.g., Dentz et al., 2000; Fiorotto and Caroni, 2002; Schwede et al., 2008). A recent study by Nowak et al. (2010) has identified optimal sampling strategies for minimum variance prediction of contaminant concentrations at environmentally sensitive locations located downgradient of the source. In their resulting optimal designs, the largest number of samples is spent in order to investigate certain hydraulic phenomena directly at the source location rather than transport phenomena further down-gradient. The authors proposed that the major source of uncertainty addressed by these optimal sampling schemes is the total volumetric water flux passing through the source area.

The importance of focused volumetric water flux in the spreading of contaminants in saturated porous media is shown in Werth et al. (2006) and Valocchi and Nakshatrala (2009). These authors showed, through numerical and analytical approaches, how the convergence of streamlines within some given zone can enhance the transverse mixing of the plume. When flow is focused within a high permeability zone, streamlines converge and then diverge again. While the streamlines are closer together, a higher diffusive transfer of solute mass is facilitated, contributing to lateral plume dilution. The opposite occurs when flow is blocked by a low-permeability zone. Experimental evidence was also shown in Rahman et al. (2005) and recently by Rolle et al. (2009), where the squeezing of contaminant plumes in high permeability inclusions was investigated. Based on their experimental observations, Rahman

35 et al. (2005) defined a source equivalent width which is a function of the vol-
36 umetric injection rate (in similar fashion to the asymptotic catchment zone
37 width of a pumping well which is defined by the ratio between background
38 flow and pumping rate). Recently, Valocchi and Nakshatrala (2009) showed
39 the sensitivity of transversal spreading on the contaminant source location.
40 They illustrated how spreading is enhanced if the source is located within
41 high- or low-permeability zones. In this paper, we will show that the effects
42 of streamline convergence/divergence are much more relevant if it occurs at
43 the contaminant source location, because it influences the entire transport
44 regime (mass flux, plume width, etc.) farther downstream. Strong field evi-
45 dence for the relevance of local field hydraulic conditions at the source zone
46 may be found in Frind et al. (1999), where the plume leaving a DNAPL source
47 was unexpectedly thin and could almost not be detected.

48 The above evidence and discussion indicates that there is a missing link
49 between a given source geometry and the resulting width of a plume. The
50 basic idea of the current work is to differentiate between the actual geometric
51 width of the source zone and its effective width, related by what we denote
52 as the source efficiency. We define source efficiency as the ratio of actual (in
53 each realization) versus the expected (ensemble mean) hydraulic flux pass-
54 ing through the geometric area of the source. In real situations, the actual
55 hydraulic flux through the source can be obtained by collecting head and
56 hydraulic conductivity measurements around the source area. Consequently,
57 this data could be used to condition simulations, see Ch. 3 of Rubin (2003).
58 The effective source width is an uncertain quantity that results from the
59 stochastic nature of total discharge through the cross-sectional area where
60 the contaminant source is located. Hence, its theoretical statistical moments
61 can be derived from the integral statistics of specific discharge within the
62 source volume.

63 The results by Nowak et al. (2010) indicate that effective source width is
64 a key parameter in the prediction of contaminant transport. In their work
65 on concentration probability functions, Schwede et al. (2008) conceptualized
66 the uncertainty of flow rate in the source, but approximated it by point-
67 scale velocity statistics. However, velocity at a single point has different
68 statistics than the integral discharge over the cross-sectional area of a non-
69 point source. Hence, further efforts are necessary to investigate the properties
70 of source hydraulics. We hypothesize that, if the effective source width at a
71 given site was known, predictions of contaminant plume development (i.e.,
72 total mass flux, plume length, width, dispersion, dilution and concentration

73 variance) would increase in predictive power. The aim of the current work
 74 is to support this hypothesis through the use of closed-formed analytical
 75 expressions for effective source width derived from the governing equations
 76 of flow. We verify its validity with high-resolution numerical Monte-Carlo
 77 flow and transport simulations of characteristic plume statistics depending
 78 on the effective source width in a 2D depth-averaged setting.

79 Section 2 introduces the concept of effective source width along with
 80 its mathematical formulation. We also define a parameter denoted source
 81 efficiency η , which according to our definition, absorbs all randomness of ef-
 82 fective source width. Section 3 derives of the statistical moments of source
 83 efficiency. The effects, significance and implications of the results with re-
 84 spect to plume prediction and its spatial moments are illustrated in Section
 85 4. Finally, conclusions are given in Section 5.

86 2. The Concept of Effective Source Width

87 2.1. Mathematical Formulation

88 In the following, we will differentiate between the geometric width of the
 89 source zone (w_{sz}) and its effective width (w_{eff}). We consider an incompress-
 90 ible, fully saturated, two-dimensional steady-state flow within a confined,
 91 depth-averaged aquifer. Let $\mathbf{x} = (x_1, x_2)$ represent the cartesian coordinate
 92 system with velocity field \mathbf{v} satisfying Darcy's Law. The mean flow is taken
 93 along the direction x_1 . Consider a contaminant line source (width equal to
 94 w_{sz}) perpendicular to the direction of mean flow with fixed concentration c_o
 95 (other release conditions are discussed in Section 4.5). The effective source
 96 width, w_{eff} , is defined with the aid of the continuity equation:

$$w_{eff} = w_{sz} \frac{Q_{sz}}{\langle Q_{sz} \rangle}, \quad (1)$$

97 where Q_{sz} is the volumetric water flux passing through the source zone:

$$Q_{sz} = \int_{w_{sz}} q_1(x_1, x_2) b dx_2. \quad (2)$$

98 Here, b denotes aquifer depth, $q_1(x_1, x_2)$ the specific discharge passing through
 99 the source zone and $\langle \cdot \rangle$ the ensemble expectation. Taking the geometric
 100 source width as a given quantity in equation (1), the randomness lies in the
 101 source efficiency denoted as η :

$$\eta = \frac{Q_{sz}}{\langle Q_{sz} \rangle}. \quad (3)$$

102 For an unbounded two-dimensional aquifer with uniform-in-the-average
103 flow, $\langle Q_{sz} \rangle$ is given by:

$$\langle Q_{sz} \rangle = JT_G w_{sz}, \quad (4)$$

104 where J is the mean hydraulic gradient in the x_1 direction and T_G is the
105 geometric mean of transmissivity. Equation (4) applies because T_G is the
106 effective transmissivity for infinite, two-dimensional aquifers (for a quick refer-
107 ence, see Ch. 5 of Rubin, 2003). In addition, we can express Q_{sz} in terms
108 of the stream function values that bound the edges of the geometrical source
109 (namely, ψ_s and ψ_i , see Bear, 1972). The subscripts “s” and “i” corresponds to
110 the superior and inferior streamlines bounding the contaminant source area.
111 The relationship between the Darcy flux and stream function can be found
112 in Bear (1972) and is reproduced for completeness in Appendix A. Now we
113 can re-write equation (3) as follows:

$$\eta = \frac{\psi_s - \psi_i}{JT_G w_{sz}}. \quad (5)$$

114 The stochastic moments of η will follow in section 3 as well as its verification
115 with Monte-Carlo simulations.

116 2.2. Illustrative Example

117 In order to establish the importance of source efficiency for predicting
118 contaminant concentrations, we first demonstrate, visually, its general im-
119 pact on transport problems by performing a Monte-Carlo transport analysis
120 with 20,000 realizations. The physical-mathematical formulation, boundary
121 conditions and numerical implementation details are provided in Appendix
122 A with parameter values given in Table 1. For each realization, we com-
123 puted the total volumetric flux passing through the source zone to obtain
124 the respective source efficiency η and the effective source width w_{eff} . From
125 that ensemble, we extracted two subsets, one with effective source width
126 $w_{eff} > 3/2 w_{sz}$ and another with $w_{eff} < 1/2 w_{sz}$ (in terms of source effi-
127 ciency: $\eta > 3/2$ or $\eta < 1/2$). The respective concentration mean and variance
128 fields of the total Monte Carlo set and extracted subsets are shown in Fig-
129 ures 1.a-c and 2.a-c.

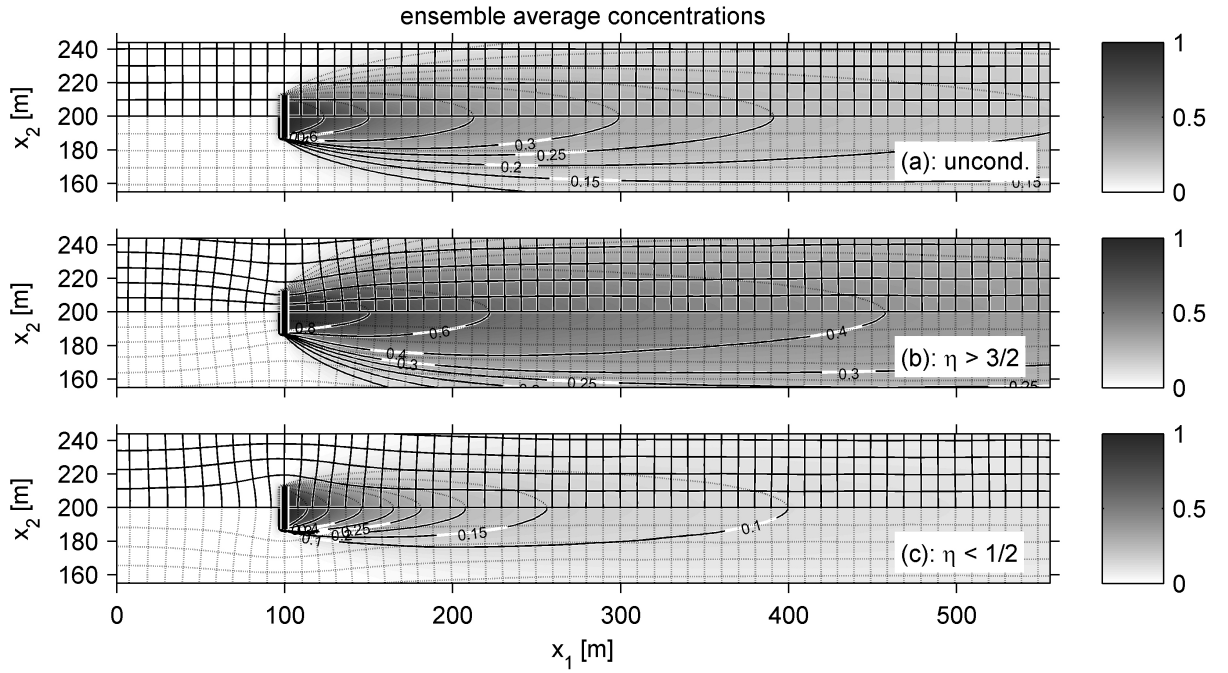


Figure 1: Impact of effective source width, see equations (1) and (3), on ensemble mean concentration (base case scenario). Simulation results for an isotropic exponential covariance model and parameters summarized in Table 1: (a) Concentration mean of the unconditional simulation. (b) Concentration mean of all realizations with source efficiency larger than $3/2$. (c) Same for source efficiency smaller than $1/2$. For parameter values, refer to Table 1. The black bar in the figure denotes the contaminant source. Contours in the upper half represents streamlines. Contours in the lower half represents isolines of mean concentration.

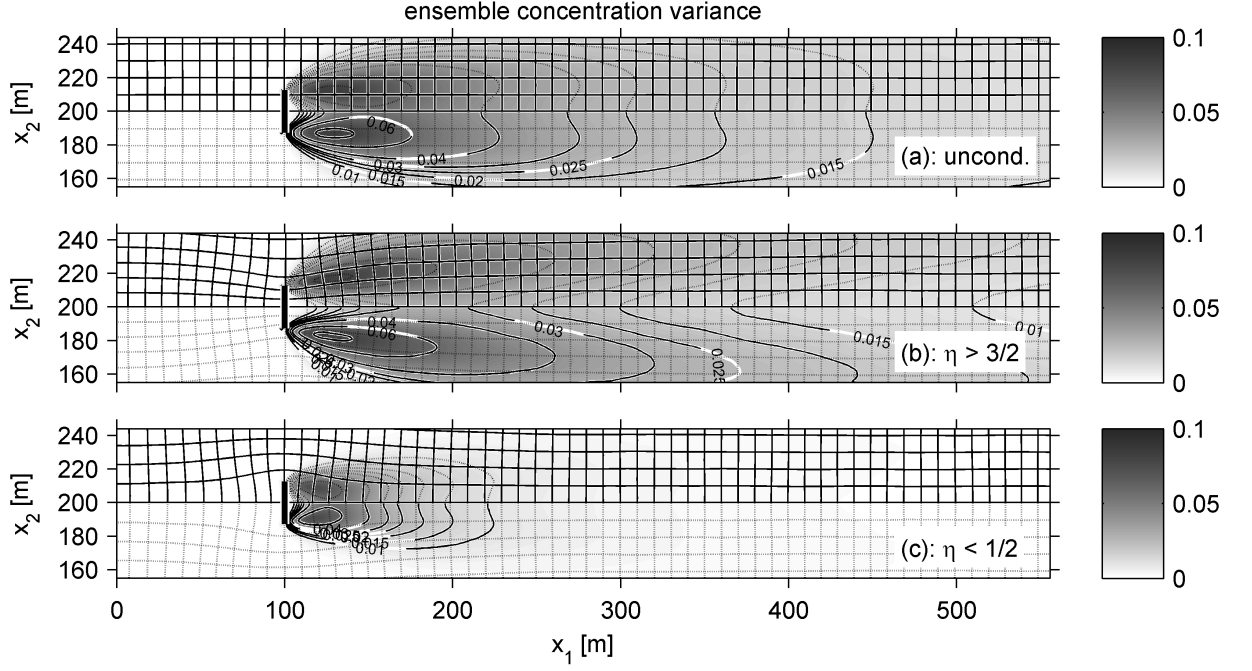


Figure 2: Same as in Figure 1 but for concentration variance. For parameter values, refer to Table 1.

Parameters Used in Simulation	
Domain Size $L \times W$	2500 m \times 400 m
Grid Size: $(\Delta x_1, \Delta x_2)$	(2, 0.5)
Dispersivities: $(\alpha_{11}, \alpha_{22})$	(2.5, 0.25)
Geostatistical Correlation Length: λ	10 m
Variance of Y : σ_Y^2	2
Geometric Mean for Conductivity: K	0.0004 m/s
Head Gradient: ∇h	0.0008
Source Width: w_{sz}	25 m
Molecular Diffusion: D_m	10^{-9} m ² /s
Geostatistical Covariance Function C_Y	Isotropic Exponential
Effective Porosity n_e	0.35

Table 1: Parameter values used in simulation

130 The concentration mean of the unfiltered ensemble, as shown in Figure
 131 1.a, follows the classical macro-dispersive transport equation with travel-
 132 time dependent dispersion coefficients (e.g., Gelhar and Axness, 1983; Dagan,
 133 1988). The result in Figure 1.b depicts the statistics with sources situated in
 134 areas of high volumetric flow rate. It illustrates the mean of all realizations
 135 that have an effective source width of $w_{eff} > 3/2 w_{sz}$ (or $\eta > 3/2$). On
 136 average, the realizations with $w_{eff} > 3/2 w_{sz}$, as shown in Figure 1.b, have a
 137 higher transmissivity in the source zone than the global mean. Before pass-
 138 ing through the source zone, the streamlines are squeezed, to diverge again
 139 downstream of the source. Hence, the average plume is wider than would
 140 be expected from the geometric source width regardless of source efficiency,
 141 see Figure 1.a. Sources placed within high-volumetric flux zones will emit a
 142 larger total contaminant flux \dot{m} . This is because, in the advection-dominated
 143 case, the total mass flux is directly proportional to the total volumetric flux
 144 through the source:

$$\dot{m} = c_o Q_{sz}. \quad (6)$$

145 In addition, known from previous studies, a wider plume is less prone
 146 to ensemble dispersion (for a review on this matter, see Rubin, 2003), since
 147 the uncertainty in transverse position relates to the plume width. It is also
 148 less prone to dilution of the peak concentration along the centerline, since
 149 transverse effective dispersion (Dentz et al., 2000) takes more time to reach
 150 and diminish the peak concentration at the plume's center. Combined, this
 151 leads to an overall longer persistence of high concentrations along the plume's
 152 centerline in Figure 1.b.

153 The opposite case is illustrated in Figure 1.c ($w_{eff} < 1/2 w_{sz}$ or $\eta < 1/2$):
 154 In this case, the resulting plumes are more narrow on-the-average, are more
 155 affected by ensemble dispersion and dilution, emits a smaller total flux and
 156 are shorter on average. Given this illustrative example, we conclude that
 157 effective source width is a singular and highly significant parameter that
 158 controls (1) actual plume width, (2) contaminant dispersion and dilution,
 159 (3) the total mass flux leaving the source and (4) plume length.

160 Figure 2 depicts the concentration variance field for the unconditional and
 161 conditional simulations. The results show how the behavior of the streamlines
 162 at the source location also affect the bimodal characteristics of the concen-
 163 tration variance: Source efficiency influences the magnitude and persistence
 164 of the two peaks of high concentration variance at the fringe of the plume

165 throughout the domain. This characteristic of the concentration variance at
 166 the plume's fringes (especially at early travel distance) is of importance when
 167 quantifying uncertainty in transport (and risk assessment) and has been sub-
 168 ject of study in the past (see works by Rubin, 1991; Kapoor and Kitanidis,
 169 1997; Fiori and Dagan, 2000; Fiorotto and Caroni, 2002) and recently by
 170 Dentz et al. (2009b) and Dentz et al. (2009a). More details of the Monte
 171 Carlo analysis are shown and discussed in subsequent sections.

172 3. Stochastic Moments of Source Efficiency

173 3.1. Analytical Development

174 From equation (5), the source efficiency η results from the stochastic na-
 175 ture of total discharge Q_{sz} (defined in terms of the bounding stream function
 176 values) through a finite cross-sectional area of extent w_{sz} perpendicular to
 177 the mean flow.

178 In two-dimensional (depth-averaged) aquifers, the statistics of the bound-
 179 ing stream function values offer a mathematically straightforward way to ob-
 180 tain analytical first-order approximations to the first and second stochastic
 181 moment of effective source width. As shown in Appendix B, the mathemat-
 182 ical development is straightforward, since well-known methods used for the
 183 stochastic groundwater flow equation can be transferred to the corresponding
 184 streamline equation.

185 Since w_{eff} is proportional to η , we now focus on the stochastic moments
 186 of η . We start by taking the expected value of η :

$$\langle \eta \rangle = \left\langle \frac{Q_{sz}}{JT_G w_{sz}} \right\rangle = 1. \quad (7)$$

187 It follows that, of course, the geometric source width is the best estimate
 188 of initial plume width in absence of site-specific data. The variance of η is
 189 expressed as:

$$\begin{aligned} \sigma_\eta^2 &= \frac{1}{J^2 T_G^2 W_{sz}^2} Var [\psi_s - \psi_i] \\ &= \frac{2}{J^2 T_G^2 w_{sz}^2} \Gamma_{\psi_s \psi_i}, \end{aligned} \quad (8)$$

190 where $\Gamma_{\psi_s \psi_i}$ is the stream function variogram value for the bounding values ψ_s
 191 and ψ_i . The stream function variogram $\Gamma_{\psi_s \psi_i}$ is evaluated at the longitudinal

192 and transversal lag-distances r_1 and r_2 such that $\Gamma_{\psi_s\psi_i} \equiv \Gamma_{\psi}(0, w_{sz})$. A
 193 formal derivation for the stream function variogram, along with the necessary
 194 assumptions that includes statistical and temporal stationarity, is given in
 195 Appendix B and leads to:

$$\Gamma_{\psi}(r_1, r_2) = T_G^2 \Gamma_h(r_2, r_1), \quad (9)$$

196 where Γ_h corresponds to the hydraulic head variogram. Equation (9) reflects
 197 a rotation of Γ_h by ninety degrees with a scaling factor given by T_G^2 . For the
 198 given lag distances (dictated by w_{sz}), this leads to:

$$\sigma_{\eta}^2 = \frac{2}{J^2 w_{sz}^2} \Gamma_h(w_{sz}, 0). \quad (10)$$

199 After replacing Γ_{ψ} by the head variogram Γ_h , we can draw on existing
 200 analytical solutions. In our case, we will use (for demonstration) the first-
 201 order approximation given by Dagan (1985a, 1989), derived for the isotropic
 202 exponential covariance model. Figure (3) illustrates how the variance of η
 203 decays with increasing values of w_{sz} . Equation (10) quantifies to what degree
 204 small sources are more affected by the uncertainty in w_{eff} than wide sources.
 205 It indicates the transition to ergodic hydraulic conditions within the source
 206 cross-sectional area (rather than ergodic plume width), where effective and
 207 geometric source width become almost identical (when the variance becomes
 208 negligible), to be around 100 transverse integral scales.

209 3.2. Verification by Monte-Carlo Simulation

210 Dagan (1985a) found that first-order approximations for hydraulic head
 211 covariances are quite accurate even for higher variances of log-conductivity
 212 σ_Y^2 . Since our solution is based on the head variogram, we also expect it
 213 to be robust even for high values of σ_Y^2 . For comparison and verification
 214 purposes, we performed an accompanying numerical evaluation by Monte-
 215 Carlo analysis of the streamline equation. The results are taken from 20,000
 216 realizations in a domain sized $100\lambda \times 100\lambda$, at a grid spacing of 10 elements
 217 per λ , thus easily satisfying the requirement given by Bellin et al. (1992) and
 218 Rubin et al. (1999) to adequately resolve heterogeneity on numerical grids.
 219 Results were obtained for different values of σ_Y^2 in order to detect the range of
 220 validity in σ_Y^2 . The volumetric fluxes were evaluated at hypothetical source
 221 zones with varying width, placed in the center of the domain to minimize
 222 boundary influences.

223 The numerical results are included in Figure 3 as a gray-scale series of
 224 lines. The agreement between the analytical and numerical curves for the
 225 limiting case of $\sigma_Y^2 \rightarrow 0$ is perfect ($\sigma_Y^2 = 0.0001$, results not shown here).
 226 Overall, the analytical solution is very robust even at values of $\sigma_Y^2 > 1$.
 227 The deviations with increasing σ_Y^2 are conform with recent head and velocity
 228 statistics published in the literature: A higher variance of η for small geomet-
 229 rical width coincides with the fact that the local variance of specific discharge
 230 scales more than linearly with σ_Y^2 (e.g., Englert et al., 2006; Nowak et al.,
 231 2008). Englert et al. (2006) demonstrated that the transverse correlation of
 232 specific discharge degenerates with increasing variance of conductivity. This
 233 effect explains why the high variance curves again approach our analytical
 234 solution with increasing geometric source width. The sudden drop to zero
 235 close to 100 integral scales is an artifact of the bounded numerical domain
 236 used in our Monte-Carlo analysis. The analytical result for the variance of
 237 source efficiency reaches an asymptotic value of zero only for $w_{sz} \rightarrow \infty$.

238 The results in Figure 3 lead to another fundamental question: Over what
 239 range of source width does the source efficiency remain the dominant ex-
 240 planatory variable for solute transport prediction? In other words: Over
 241 what range of w_{sz} does η display correlation with downstream plume char-
 242 acteristics? Similar to the ergodicity of large domains for the effective flow
 243 problem, we expect its impact to fade with increasing geometric width of the
 244 source. This question will be pursued in Section 4.3.

245 3.3. Empirical Probability Density Function for η

246 In absence of higher-order moments, the maximum entropy assumption
 247 would be that η follows a Gaussian distribution (Jaynes, 1982; Singh, 1997).
 248 This contradicts with the fact that source efficiency should mostly be non-
 249 negative for physical reasons: Negativity would occur only if flow is reversed
 250 due to high contrasts in Y (see Englert et al., 2006; Nowak et al., 2008).
 251 Therefore, a Gaussian distribution can only be assumed for small variances,
 252 where the lower bound at $\eta = 0$ does not yet have a significant influence on
 253 the shape of the distribution. The suggestive distribution for η at hand is the
 254 log-normal one, accounting for non-negativity. From the above Monte-Carlo
 255 analysis for $\sigma_Y^2 = 1$, we evaluated an empirical probability density function
 256 (PDF) using a Gaussian Kernel estimate technique with Kernel width equal
 257 to 2.56×10^{-4} (Parzen, 1962; Wasserman, 2004). At the same time, we used
 258 our analytical first-order results for the mean and variance of η and fitted a
 259 log-normal distribution to these two moments. Figure 4 shows good visual

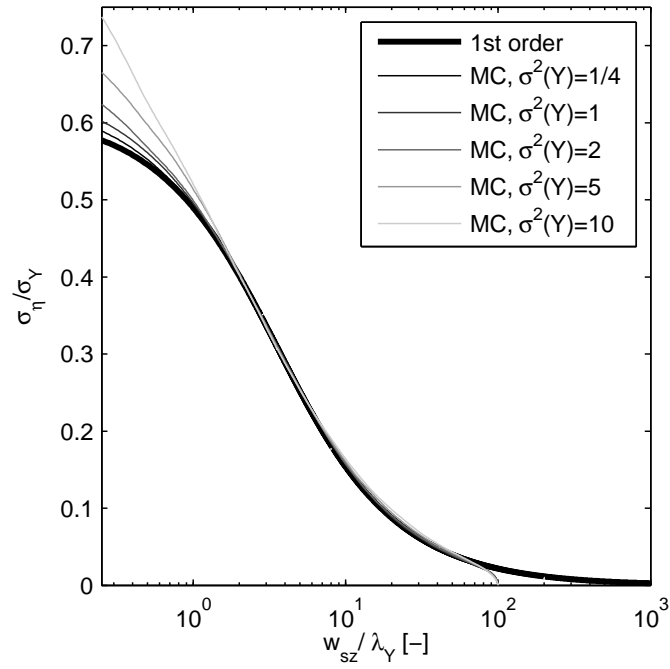


Figure 3: Dependence of source efficiency standard deviation on normalized geometric source width, comparison of analytical first-order expression and results from Monte-Carlo analysis. For parameter values, refer to Table 1.

260 agreement between the two. For quantitative analysis, we also computed
 261 the empirical cumulative distribution function (CDF) from the same Monte-
 262 Carlo analysis and evaluated the difference between the empirical CDF and
 263 the moment-based log-normal CDF obtained by moment-matching with our
 264 analytical first-order moments. The typical maximum difference, measured
 265 as in a Kolmogorov-Smirnov test, is in the order of 5%. When repeating the
 266 same analysis with a log-normal CDF fitted to the moments obtained from
 267 the Monte-Carlo analysis, the maximum difference is in the order of 2% over
 268 the entire range of w_{sz} . In conclusion, we recommend to approximate η as a
 269 log-normal quantity.

270 4. Effects, Significance and Implications

271 4.1. Relation to Plume Length

272 In many practical applications, hydrogeologists are interested in predict-
 273 ing the extension of a given contamination in order to meet with environmen-
 274 tal regulations, for instance risk assessment. In this subsection, we wish to
 275 illustrate how source efficiency can be used to better estimate the extent of a
 276 concentration isoline as a measure for plume length (denoted by L_P). Figure
 277 5 shows the dependency of L_P on η for different dimensionless concentrations
 278 ($c/c_o = 0.1, 0.2, 0.4$ and 0.8) as a scatter plot. Results were obtained from
 279 the Monte-Carlo simulation presented in Section 2.2.

280 By fixing a value for η , we can predict the length of the plume defined
 281 by a given isoline (for example, $c/c_o = 0.1$). Larger values of η imply a larger
 282 extent of the plume (as already shown in Figure 1). The results shown
 283 here are limited to a steady-state release condition. However, with increased
 284 computational power, one may obtain similar plots for the transient regime.
 285 We observe that all fitted curves have the same slope of 2 in log-log scale,
 286 implying a quadratic law. In order to make this point clear, consider an
 287 idealized situation, similar to the physical scenario used to obtain Figure
 288 5, of a steady-state release within a 2D setting with uniform longitudinal
 289 velocity U and transversal dispersion D_{22} . Recalling the analytical solution
 290 from Domenico and Palciauskas (1982) (which neglects longitudinal disper-
 291 sion D_{11}) and substituting the effective source width *in lieu* of the actual
 292 geometrical source width we have:

$$\frac{c}{c_o} = \operatorname{erf} \left[\frac{\eta w_{sz}}{\sqrt{\frac{x}{U} D_{22}}} \right]. \quad (11)$$

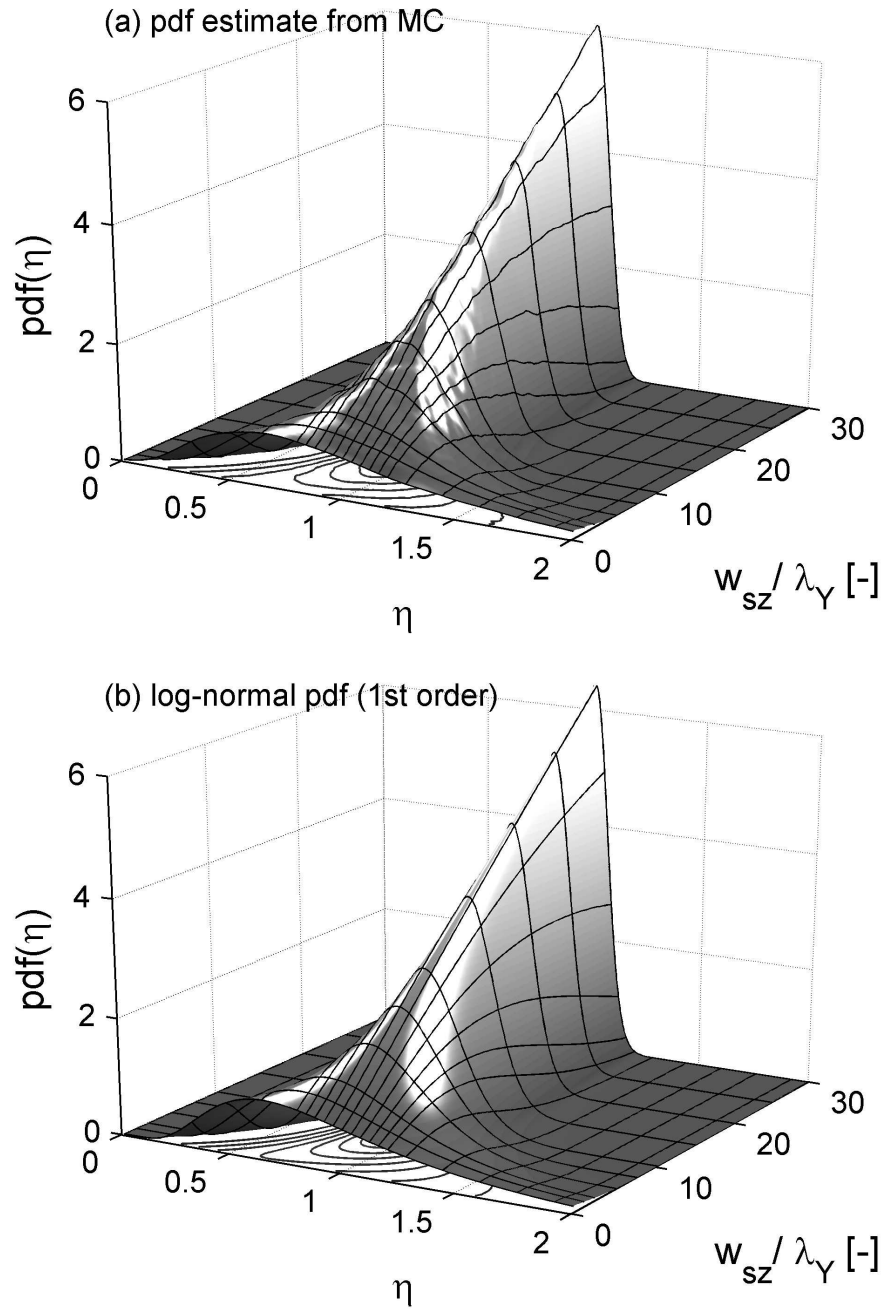


Figure 4: Probability density of source efficiency η and its dependency on geometric source width w_{sz} : (a) estimate from MC analysis with 20,000 realizations and (b) log-normal PDF fitted to the first-order expressions of the mean and variance. The high-valued distribution tail for small w_{sz}/λ is cut-off for better visibility of the overall behavior. For parameter values, refer to Table 1.

293 Further manipulation of Equation (11) and inserting $x \equiv L_P$ leads to the
 294 expression found in Rahman et al. (2005), who substituted the source width
 295 with the injection rate divided by ambient flow. Adapted for our work, the
 296 expression given in Rahman et al. (2005) reads:

$$L_P = \frac{U}{D_{22}} \left[\frac{\eta w_{sz}}{4 \operatorname{erf}^{-1} \left(\frac{c}{c_o} \right)} \right]^2. \quad (12)$$

297 The above result shows, theoretically, the quadratic law between L_P and
 298 η for the physical case analyzed in this work (with a slope equal to 2 when
 299 applying the logarithm). As for the statistical distribution of L_P , Monte-
 300 Carlo results again suggest a skewed distribution (not shown here), which is
 301 confirmed by the scaling with η^2 in Equation (12). In fact, one may re-write
 302 the above equation as $L_p = A\eta^2$ where A accounts for all the other parameters
 303 present in Equation (12). By transformation of variables, we can obtain a
 304 PDF f_L for L_p from the assumed log-normal PDF f_η of source efficiency η
 305 with our analytical first-order moments (see Section 3.3):

$$f_L(L_p) = \frac{1}{2\sqrt{AL_p}} f_\eta(\sqrt{L_p/A}). \quad (13)$$

306 Figure 6 displays the comparison between Equation (13) and the empirical
 307 PDF of L_p obtained from numerical Monte Carlo simulations for $c/c_o = 0.2$.
 308 The Monte Carlo results show a larger variance of L_p because effective source
 309 width is not the only source of uncertainty.

310 Equation (12) also implies that the significance of η as a explanatory vari-
 311 able for L_P vanishes with increasing w_{sz} , because its variance decreases with
 312 w_{sz} as indicated by equation (12) and other sources of uncertainty down-
 313 stream of the source start to dominate.

314 4.2. Plume Spatial Moments

315 Here, we quantify some of the aspects observed in Figures 1 and 2. Fig-
 316 ures 7.a-b shows how the spatial moments of the plume depend on the source
 317 efficiency under the parameter values provided in Table 1. Results are ob-
 318 tained through numerical Monte-Carlo simulations. Here, we analyze the
 319 mass flux $m_{o,flux}$, relative transversal dispersivity $\alpha_{t,eff}$ and the macroscopic

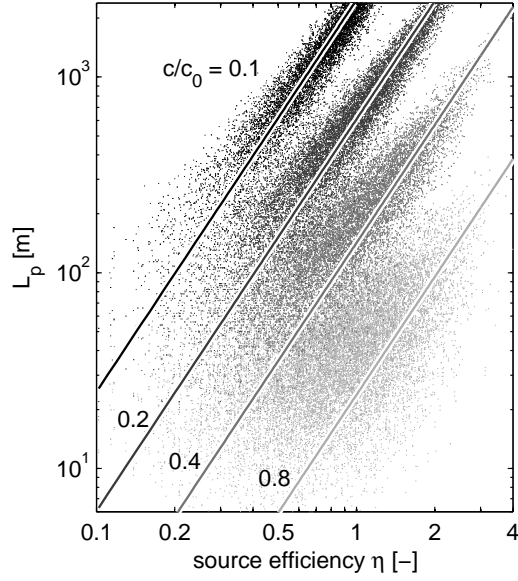


Figure 5: Plume length (L_P) versus source efficiency obtained through numerical Monte Carlo simulations. Results conditional on $c/c_0 = 0.1, 0.2, 0.3$ and 0.5 with simulation parameter values in Table 1.

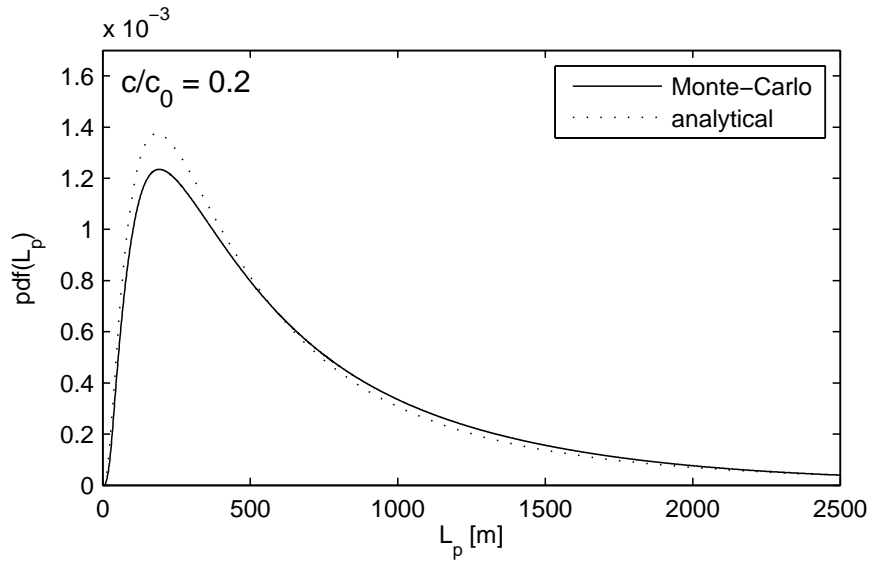


Figure 6: Probability density function for plume length (L_P). Comparison between analytical solution (Eq. 13) and numerical Monte Carlo simulation. Results for $c/c_0 = 0.2$ with simulation parameter values in Table 1.

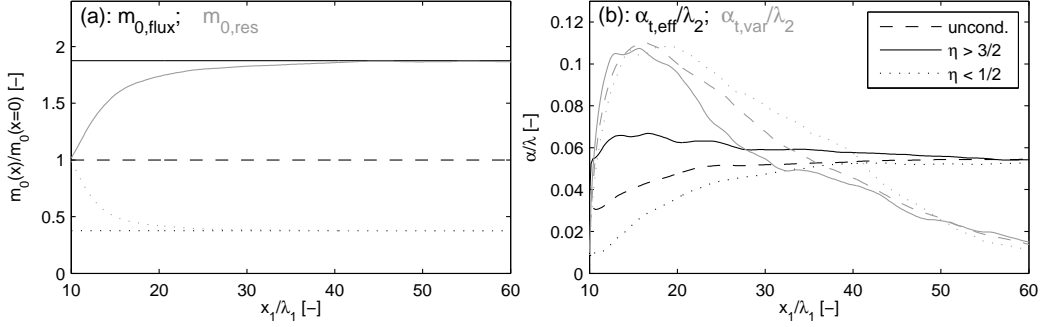


Figure 7: Plume spatial moments (conditional and unconditional) as a function of the normalized longitudinal distance x_1/λ_1 . Dashed curve denotes unconditional simulations. Pointed and solid curves corresponds to simulations conditioned on $\eta > 3/2$ and $\eta < 1/2$. Notice that in the current scenario we have $\lambda_1 = \lambda_2 = \lambda$. For parameter values, refer to Table 1.

320 transversal dispersivity $\alpha_{t,var}$ of meandering. The later is solely due to the
 321 variance of the transverse centroid position of the plume, i.e., it quantifies
 322 meandering. The sum of $\alpha_{t,eff}$ and $\alpha_{t,var}$ yields the classical macrodispersivity.
 323 The following equations were used to estimate the above-mentioned
 324 quantities:

$$m_{o,flux}(x_1) = \int_A [\mathbf{q}(\mathbf{x})c(\mathbf{x})] \cdot \mathbf{n}dA; \quad (14)$$

$$\alpha_{t,eff}(x_1) = \frac{1}{2Um_{o,res}} \frac{\partial}{\partial x_1} [\langle m_{22,c}(x_1) \rangle]; \quad (15)$$

$$\alpha_{t,var}(x_1) = \frac{1}{2Um_{o,res}} \frac{\partial}{\partial x_1} [\langle m_2(x_1) \rangle], \quad (16)$$

325 where $m_{22,c}$ denotes the second central spatial moment (around individual
 326 plume centroids in individual realizations), $m_2/m_{o,res}$ is the plume's centroid
 327 position in x_2 , and $m_{o,res}$ is the total resident mass integrated over x_2 (Rubin,
 328 2003). U is the mean velocity in the longitudinal direction and A is the cross-
 329 sectional area.

330 For Figure 7.a, we observe how the amount of resident mass (at the cross
 331 section of the domain perpendicular to the mean flow direction) increases
 332 with travel distance for $\eta > 3/2$. This is due to divergence of streamlines
 333 after the source location, leading to a wider plume on average. Evidently,

334 the opposite occurs when streamlines converge ($\eta < 1/2$) after the source
 335 zone (see eq. 6). The constant curves in Figure 7.a display the mass flux
 336 throughout the longitudinal distance.

337 Figure 7.b displays some characteristics of the dispersive behavior of the
 338 plume conditional (and unconditional) on the flow regime at the contami-
 339 nant source. For instance, Figure 7.b depicts the plume's relative transversal
 340 dispersivity $\alpha_{t,eff}$ (see Andricevic and Cvetkovic, 1998), or *effective disper-*
 341 *sion* as termed in Dentz et al. (2000). The curves account for the plume
 342 spread without meandering, while the remaining curves for $\alpha_{t,var}$ represent
 343 the macroscopic transversal dispersion due to the sole variance of the plume's
 344 transversal centroid position. For $\eta > 3/2$, the focusing of streamlines at the
 345 source lead to higher $\alpha_{t,eff}$ since the streamlines are squeezed. For $\eta < 1/2$,
 346 $\alpha_{t,eff}$ is less pronounced. As expected, the unconditional curve lies in be-
 347 tween the conditional cases. To measure the intensity of plume meandering
 348 conditional on η , we refer again to Figure 7.b ($\alpha_{t,var}$ curves): It can be seen
 349 that larger η implies wider plumes, thus less prone to the effect of meander-
 350 ing. The opposite behavior is observed for smaller η .

351 In all plots in Figure 7, a characteristic distance can be observed in which
 352 the local effect of conditioning fades away. Eventually, after this characteris-
 353 tic distance, the curves become parallel except for the artifact of Monte-Carlo
 354 simulation. However, the global inferred effect on plume statistics prevails
 355 for all travel distances.

356 4.3. Significance

357 The power of source efficiency as explanatory variable for concentra-
 358 tion can be visualized by mapping their Pearson's correlation coefficient
 359 $r = r[c(\mathbf{x}), \eta]$ throughout the domain. The corresponding map, obtained from
 360 our Monte-Carlo transport simulation, is shown in Figure 8. Correlations of
 361 η with logconductivity and hydraulic heads are given Figure 8.a-b. The cor-
 362 relation of η with concentration (see Figure 8.c-e) is always positive, because
 363 a higher source efficiency leads to a larger total mass flux and wider plume
 364 emitted by the source. The correlation is highest, about 0.9, along the plume
 365 center line: The effective source width dictates the persistence of high con-
 366 centrations along the plume's center line, see Figure 5. Correlations of about
 367 0.5 prevail throughout most regions of the plume. Only locations outside
 368 the plume fringes show almost no correlation. In those regions, only extreme
 369 transverse (secondary) flow effects, not linked to the hydraulic circumstances
 370 at the source, can have an effect.

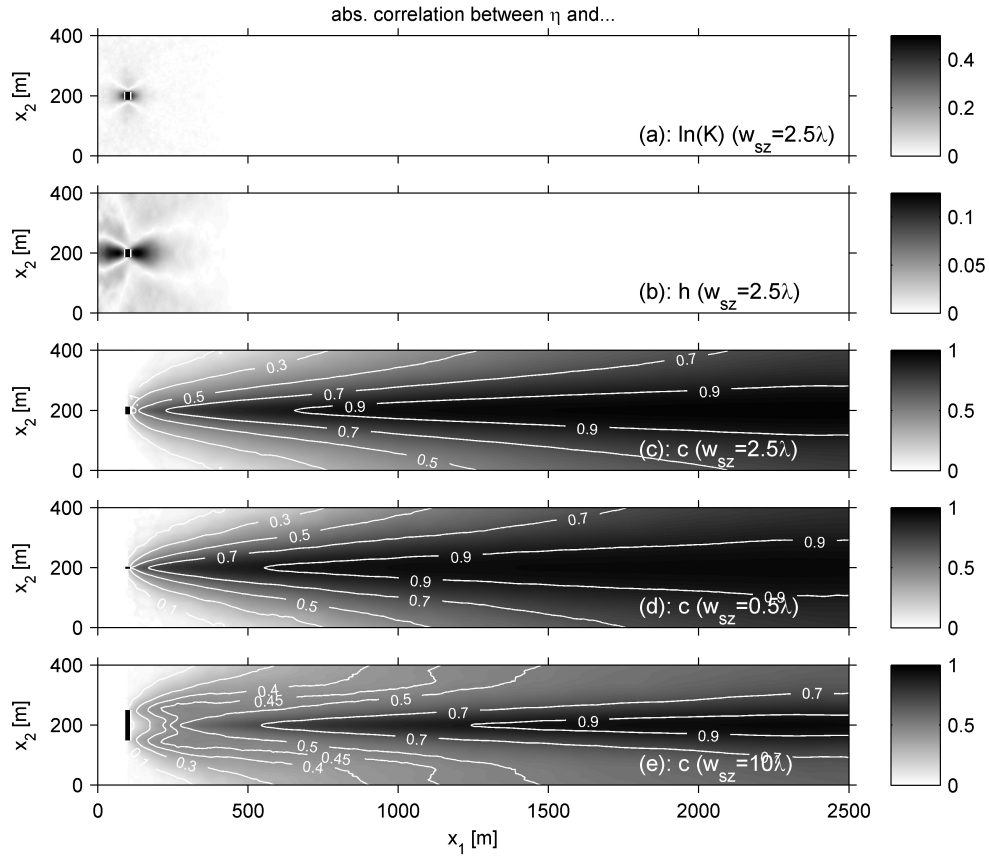


Figure 8: Correlations (absolute values) of (a) $Y = \ln T$, (b) heads and (c)-(e) concentration with source efficiency η . Correlations between η and concentrations are obtained for (c) $w_{sz}=2.5 \lambda$, (d) $w_{sz}=0.5 \lambda$, and (e) $w_{sz}=10 \lambda$ (as depicted in the plots). Numerical result from Monte-Carlo analysis with 20,000 realizations. For parameter values, refer to Table 1.

371 The area with high correlation mostly coincides with the area of high
 372 expected concentrations, stressing the potential of effective source width to
 373 effectively reduce the coefficient of variation of concentration within wide
 374 areas of the plume. The fact that source efficiency controls the large-time
 375 persistence of peak (high) concentrations along the plume's center line, with
 376 high correlations found especially at large distances, unambiguously under-
 377 lines the surprising importance of near-source sampling for far field prediction
 378 shown in Nowak et al. (2010). In addition, Figure 8.c-e illustrates how the
 379 correlation map changes according to w_{sz} . Results are plotted for $w_{sz}=0.5\lambda$,
 380 2.5λ and 10λ . Wider source width leads to a down-gradient shift of the
 381 iso-lines present in the correlation map (for instance, see the 0.9 isoline for
 382 $w_{sz}=0.5\lambda$ and $w_{sz}=10\lambda$). This result is in agreement with the physical
 383 insight given in Equation (10), summarized in Figure 3: As w_{sz} increases,
 384 thus approaching ergodicity in the sense that the volume average of the spe-
 385 cific discharge equals the ensemble average (thus making the total discharge
 386 Q_{sz} through the source a deterministic quantity), the explanatory strength
 387 of source efficiency for downstream plume characteristics becomes less pro-
 388 nounced. However, its significance prevails for longer travel distances.

389 4.4. Implications for Site Investigation

390 Nowak et al. (2010) have identified optimal sampling strategies for min-
 391 imum variance prediction of contaminant concentrations at an environmen-
 392 tally sensitive location located downgradient of the source. Their results
 393 showed that large portion of the samples were located around the source
 394 zone and that the uncertainty in plume prediction was reduced by sampling
 395 hydraulic conductivities and heads near the source. They hypothesized that
 396 the major source of uncertainty addressed by these optimal sampling schemes
 397 is the total volumetric water flux passing through the source area. This hy-
 398 pothesis is confirmed theoretically and numerically in the current work.

399 The correlations depicted in Figure 8.a-b confirm that hydraulic conduc-
 400 tivities and head measurements are informative for the effective source width,
 401 and hence for far-field prediction. In other words, a small set of measure-
 402 ments (heads and conductivities) located around the source helps to identify
 403 the actual value of effective source width and improve prediction power as
 404 discussed in the previous sections.

405 4.5. *Alternative Release Conditions*

406 The results shown in this work are under the assumption of a line source
407 with fixed concentration c_o . Relevant physical scenarios leading to the results
408 shown here may be, for example, a fast dissolution process (e.g., of a DNAPL
409 contamination with finely dispersed residual saturation) that installs solubil-
410 ity limit. However, other scenarios can occur such as: (I) Fixed mass flux
411 release of a contaminant (e.g., a leaking tank with instance dissolution) or (II)
412 a slow kinetic dissolution process (e.g., diffusion of remaining contaminant
413 out of low-conductivity regions after an incompleter source remediation).

414 In both cases, all considerations in plume width and dispersion hold be-
415 cause they are linked to the geometrical characteristics of the contaminant
416 source. Equation (6) can apply, in the re-arranged form $c_f = \dot{m}/Q_{sz}$, to case
417 (I). Here, c_f denotes the flux-averaged concentration determined from a fixed
418 mass flux \dot{m} . In this scenario, η will be connected with the uncertainty of
419 the concentration leaving the source since $Q_{sz} = \eta \langle Q_{sz} \rangle$ (see Equation 3).
420 Therefore, in that case, the statistics of concentrations are linked with the
421 statistics of η .

422 In case (II), the flux-averaged concentration leaving the source will depend
423 on the resident time of water flowing through the source (τ_{sz}). In this case,
424 one may assume $\eta \propto \langle \tau_{sz} \rangle / \tau_{sz}$, where $\langle \tau_{sz} \rangle$ denotes the ensemble expectation
425 of residence time within the source area.

426 In summary, even under other contaminant and release conditions, similar
427 effects, as discussed in previous sections, will still lead to the same importance
428 of source hydraulics for downstream plume predictions.

429 5. **Summary of Conclusions**

430 In this paper, we have shown that better understanding of the flow regime
431 through the source zone can provide better contaminant predictions. We for-
432 mally introduced the concept of the effective source width w_{eff} and source
433 efficiency η , and we illustrated and analyzed how knowledge of these quanti-
434 ties can better help quantify contaminant transport. We define the effective
435 source width via the actual, rather than the expected, hydraulic flux through
436 the source area and source efficiency as a factor that absorbs all randomness
437 of the effective source width. In the current work, we highlight the following
438 points:

- 439 1. An analytical solution for the statistics of η was formally derived up
440 to first-order. The solution was succesfully compared with numerical

- 441 Monte-Carlo simulations. We showed how the variance of η decreases
442 with the geometrical source width and reaches ergodicity when w_{sz} is
443 equal to approximately 100 transversal integral scales. The obtained
444 closed-form solution proved robust for values of σ_Y^2 far above unity.
- 445 2. The PDF shape for η was computed numerically and we showed that
446 it can reasonably well approximated by a log-normal distribution.
 - 447 3. It was shown that (and how) source zone release conditions impact
448 the concentration mean and variance fields. In particular attention, we
449 point out its role in defining the bimodal behavior of the concentration
450 variance with strong implications in risk assessment.
 - 451 4. The relationship between η and plume length L_P was also addressed.
452 For the physical scenario analyzed, L_P scales with η^2 . Therefore, effec-
453 tive source width can be used to better predict the extent of contami-
454 nation at a prescribed concentration level within the field. This shows
455 how η can be used in applications that are of interest in risk assessment,
456 for example, determining maximum contaminant levels (MCL) or for
457 driving sampling campaigns within a health risk-driven approach as
458 highlighted in de Barros and Rubin (2008) and de Barros et al. (2009).
 - 459 5. The impact of conditioning plume spatial moments on source charac-
460 teristics is also investigated. We quantified how both mass fluxes and
461 relative dispersion increases and centroid variance decreases with in-
462 creasing source efficiency η .

463 In summary, local hydraulic conditions in the area of contaminant release
464 have a strong impact on plume characteristics. As shown throughout this
465 work, knowing the hydraulics near the contaminant source is of high im-
466 portance even for far-field predictions of contaminant transport, e.g., when
467 dealing with practical problems, such as estimating human health risk due to
468 groundwater contamination. Moreover, the current paper provides a simple
469 approach to increase the predictive power of existing analytical solutions.
470 As an outlook of future work, the analytical solution, as well as the results
471 given here, could be particularly useful to quantify the additional dilution
472 effects due to inclusions of high- (or low-) permeability materials at later
473 travel distances. This would help to theoretically underline the results pub-
474 lished by Rolle et al. (2009), where the impact of inclusions on dilution of
475 contaminants was shown experimentally.

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482 **Appendix A. Flow and Transport Formulation**

483 In our illustrations, we limit the solute transport problem to a steady-
 484 state continuous line source in a depth-integrated, divergence-free 2D, ground-
 485 water flow at steady-state within a domain $\Omega = L \times W$ (length \times width,
 486 respectively). The domain boundary $\partial\Omega$ is divided into two parts: $\partial\Omega_i$ with
 487 prescribed head \hat{h} and the remaining parts $\partial\Omega \setminus \partial\Omega_i$ with prescribed flux (\hat{q}):

$$\begin{aligned} \nabla \cdot [T(\mathbf{x}) \nabla h] &= 0, \quad \forall \mathbf{x} \in \Omega & \text{(A.1)} \\ h &= \hat{h}, \quad \forall \mathbf{x} \in \partial\Omega_i \\ -\mathbf{n} \cdot [T(\mathbf{x}) \nabla h] &= \hat{q}, \quad \forall \mathbf{x} \in \partial\Omega \setminus \partial\Omega_i, \end{aligned}$$

488 where $T(\mathbf{x}) [L^2/t]$ is the locally isotropic, spatially heterogeneous transmis-
 489 sivity and $h [L]$ is hydraulic head. We can relate each component of the the
 490 Darcy flux $\mathbf{q} [L/t]$ with the stream function by using the following expressions
 491 (Batchelor, 2000; Bear, 1972):

$$\begin{aligned} q_1 &= -\frac{\partial\psi}{\partial x_2} \\ q_2 &= \frac{\partial\psi}{\partial x_1}, \end{aligned} \quad \text{(A.2)}$$

492 where isolines of stream functions and hydraulic heads are always orthogonal
 493 to each other, forming a potential flow net, in absence of sources and sinks.

494 The corresponding governing equation for the stream function ψ and
 495 boundary conditions are given as (Bear, 1972):

$$\begin{aligned} \nabla \cdot \left[\frac{1}{T} \nabla \psi \right] &= 0, \quad \forall \mathbf{x} \in \Omega & \text{(A.3)} \\ \mathbf{n} \cdot \nabla \psi &= 0, \quad \forall \mathbf{x} \in \partial\Omega_i \\ \psi &= \hat{\psi}, \quad \forall \mathbf{x} \in \partial\Omega \setminus \partial\Omega_i, \end{aligned}$$

496 with $\hat{\psi}$ being a boundary fixed value for the stream function (determined by
 497 integration over \hat{q}). Steady-state concentration is given by:

$$\mathbf{v} \cdot \nabla c - \nabla \cdot (\mathbf{D}_d \nabla c) = 0, \quad \forall \mathbf{x} \in \Omega, \quad (\text{A.4})$$

498 where $c [M/L^3]$ is concentration, $\mathbf{v} = \mathbf{q}/n_e [L/t]$ is velocity, $n_e [-]$ is porosity,
 499 and $\mathbf{D}_d [L^2/t]$ is the local-scale dispersion tensor. Uncontaminated ground-
 500 water with $c = 0$ enters at $x_1 = 0$, and the outflow boundary at $x_1 = L$ is
 501 unrestricted. The lateral boundaries are closed. We solved these equations
 502 using the same numerical implementation as in Nowak et al. (2008).

503 **Appendix B. Relation between Stream Function Statistics and** 504 **Head Statistics**

505 In order to derive the stream function statistics, we make use of the head
 506 correlation structure expressed here in terms of the head variogram Γ_h . A
 507 first-order approximation to Γ_h has been provided by Dagan (1985b, 1989).
 508 Assumptions in the derivation were unbounded domain, mildly heterogeneous
 509 porous media, absence of sources and sinks, and geostatistical stationarity.
 510 Much less attention has been given to stream function statistics with a few
 511 exceptions such as Cirpka et al. (2004), who used linear error propagation and
 512 adjoint-state sensitivities to obtain the variance of stream function differences
 513 in the hydraulic design of a funnel-and-gate system.

514 Our starting point is equation (A.3), which is formally identical to the
 515 groundwater flow equation. To obtain the stream function variogram, we
 516 follow the same formal steps taken by Dagan (1985b) for the head variogram
 517 and provided in more detail in Dagan (1989) and Rubin (2003). Let $Y = \ln T$
 518 such that $Y(\mathbf{x}) = \langle Y \rangle + Y'(\mathbf{x})$. Substituting these expressions in equation
 519 (A.3) and using $1/T = \exp(-Y) = \exp(-Y')/T_G$, we have:

$$\begin{aligned} \nabla \cdot \left[e^{-\langle Y \rangle} e^{-Y'} \nabla \psi \right] &= 0; \\ \Leftrightarrow \nabla^2 \psi - \nabla \psi \cdot \nabla Y' &= 0. \end{aligned} \quad (\text{B.1})$$

520 By expanding the stream function into a polynomial of conductivity fluc-
 521 tuations Y' , we obtain:

$$\nabla^2(\psi_o + \psi_1 + \dots) - \nabla(\psi_o + \psi_1 + \dots) \cdot \nabla Y' = 0. \quad (\text{B.2})$$

522 Solving the equation for each *order* separately yields:

$$\begin{aligned} (n = 0) : \quad & \nabla^2 \psi_o = 0; \\ (n = 1) : \quad & \nabla^2 \psi_1 = \nabla \psi_o \cdot \nabla Y', \end{aligned} \quad (\text{B.3})$$

523 where the solution of ($n = 0$) for uniform-in-the-average flow must satisfy:

$$-\frac{\partial \psi_o}{\partial x_i} = \gamma_i. \quad (\text{B.4})$$

524 Due to their orthogonality (see Batchelor, 2000), heads and stream functions
525 are coupled as:

$$\begin{aligned} -T_G \frac{\partial h}{\partial x_1} &= \frac{\partial \psi}{\partial x_2} = -\gamma_2; \\ -T_G \frac{\partial h}{\partial x_2} &= -\frac{\partial \psi}{\partial x_1} = \gamma_1, \end{aligned} \quad (\text{B.5})$$

526 which implies:

$$\begin{aligned} \gamma_1 &= J_2 T_G \\ \gamma_2 &= -J_1 T_G \\ \gamma &= \sqrt{\gamma_1^2 + \gamma_2^2} = T_G J, \end{aligned} \quad (\text{B.6})$$

527 with $J = \sqrt{J_1^2 + J_2^2}$. There are two differences between the stream function
528 formulation and the pressure head formulation: (1) comparing the right-hand
529 side in equation (B.3) for $n = 1$ to Equation 3d of Dagan (1985b), we observe
530 that they have opposite signs due to the appearance of T^{-1} in the stream
531 function equation; and (2) the solution for $n = 0$ contains a gradient of γ_i
532 instead of J_i . Now we duplicate the first-order equation ($n = 1$) for space
533 coordinates \mathbf{x} and \mathbf{y} . Multiplying these two equations leads to:

$$\nabla_x^2 \nabla_y^2 \psi_1(\mathbf{x}) \psi_1(\mathbf{y}) = \sum_{i=1}^d \sum_{j=1}^d \gamma_i \gamma_j \frac{\partial Y'(\mathbf{x})}{\partial x_i} \frac{\partial Y'(\mathbf{y})}{\partial y_j}, \quad (\text{B.7})$$

534 where d is the physical dimension. Taking the expected value yields the
 535 generating equation for the stream function covariance:

$$\nabla_x^2 \nabla_y^2 C_\psi(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^d \sum_{j=1}^d \gamma_i \gamma_j \frac{\partial}{\partial x_i} \frac{\partial}{\partial y_j} C_Y(\mathbf{x}, \mathbf{y}). \quad (\text{B.8})$$

536 The opposite sign has vanished now and the generating equation is iden-
 537 tical to that for the head covariance, except that $\gamma_i \neq J_i$. This allows to
 538 use the analytical solutions derived for the head variogram with substituted
 539 coefficients (γ_i), thus leading to a rotation by ninety degrees and scaling by
 540 T_G^2 .

541 For the isotropic exponential covariance model, $C_Y(\mathbf{r}) = \sigma_Y^2 \exp[\mathbf{r}/\lambda]$
 542 with variance σ_Y^2 and correlation length λ , the first-order head variogram for
 543 lag distances r along the mean flow direction is (see Dagan, 1985b):

$$\Gamma_h(r, 0) = \sigma_Y^2 \lambda^2 J^2 \frac{1}{2} \zeta(r), \quad (\text{B.9})$$

544 with:

$$\zeta(r) = \frac{1}{2} + \frac{e^{-r/\lambda} \left[\left(\frac{r}{\lambda}\right)^2 + 3 \left(\frac{r}{\lambda}\right) + 3 \right] - 3}{\left(\frac{r}{\lambda}\right)^2} - Ei\left(-\frac{r}{\lambda}\right) + \left(\frac{r}{\lambda}\right) + e^{-r/\lambda} - 0.4228. \quad (\text{B.10})$$

545 Due to rotation and scaling, we arrive at the stream function variogram
 546 for transverse lag distances as:

$$\Gamma_\psi(0, r) = T_G^2 \Gamma_h = \sigma_Y^2 \lambda^2 J^2 T_G^2 \frac{1}{2} \zeta(r). \quad (\text{B.11})$$

547 In summary, the required assumptions necessary for the derivation of
 548 equation (9) are: (i) unbounded domain, (ii) uniform-in-the-average steady-
 549 state flow, (iii) mildly heterogeneous porous media ($\sigma_Y^2 \lesssim 1$) with absence of
 550 sources and sinks, (iv) 2D depth-averaged, and (iv) statistical stationarity.

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