



Technical note: Quantification of flow field variability using intrinsic random function theory

Ching-Min Chang¹, Chuen-Fa Ni¹, Chi-Ping Lin², and I-Hsian Lee²

¹Graduate Institute of Applied Geology, National Central University, Taoyuan, Taiwan

²Center for Environmental Studies, National Central University, Taoyuan, Taiwan

Correspondence: Chuen-Fa Ni (nichuenfa@geo.ncu.edu.tw)





1	Abstract. Much of the stochastic analysis of flow field variability in heterogeneous
2	aquifers in the literature assumes that the parameters in the associated stochastic flow
3	equation are weakly (second order) stationary. On this basis, the spectral
4	representation approach can then be used to quantify the variability of the flow fields
5	given known covariance functions of the input parameters. However, the condition of
6	second-order stationarity is rarely encountered in nature and is difficult to verify using
7	the limited experimental data available. The purpose (or novelty) of this work,
8	therefore, is to develop a new framework for modeling the variability of the flow
9	fields that generalizes the stochastic theory that applies to stationary second-order
10	random input parameters to intrinsic (nonstationary) random input parameters. In this
11	work, the log hydraulic conductivity and log aquifer thickness are assumed to be
12	intrinsic random functions for flow through heterogeneous confined aquifers of
13	variable thickness. On this basis, semivariograms of depth-averaged hydraulic head
14	and integrated specific discharge fields are developed to characterize the variability of
15	flow fields. The application of the proposed stochastic theory to the case where the
16	variability of a random input parameter can be characterized by a linear
17	semivariogram model is provided.

18

19 **1 Introduction**





20

21	Much of the literature on solving the stochastic groundwater flow problem
22	assumes that the covariance functions of the random input parameters in the
23	corresponding stochastic differential equation for groundwater flow can be
24	characterized by spatial covariance functions. Based on these known covariance
25	functions of parameters, the variability of flow fields in heterogeneous aquifers
26	can then be represented by the covariances of hydraulic head and specific
27	discharge using the spectral representation approach (e.g., Dagan, 1989; Gelhar,
28	1993; Zhang, 2002; Rubin, 2003). It is important to recognize that the approach
29	is built on the assumption that the random processes of the input parameters are
30	second order stationary, so they can be represented by a covariance function.
31	The question arises: can the statistics of the flow field be determined if it is not
32	possible to identify the covariance function of the input parameter from the
33	available data or if the covariance functions of the parameter do not exist?
34	In many practical applications, the experimental variance of a random variable
35	(function) sampled from a field increases with the size of the field (e.g., Desbarats and
36	Bachu, 1994; Molz et al., 2004; Dell'Oca et al., 2020). This means that the data have an
37	almost unlimited scattering capacity and cannot be properly described by ascribing a
38	finite a priori variance to them. This implies that the second-order stationarity





39	hypothesis does not appear to be suitable and that the approach assuming spatial
40	variation of input parameters characterized by a spatial covariance function in the
41	treatment of stochastic models of groundwater flow is not appropriate.
42	But even if there is no finite a priori variance, the spatial increments of a random
43	function may still have a finite variance. Note that the random function that obeys the
44	intrinsic hypothesis (Matheron, 1965, 1971), i.e., the assumption that the increments of
45	the random function are weakly stationary, is called the intrinsic (nonstationary) random
46	function. In this case, the variability of a nonstationary random function can be
47	characterized by its semivariogram. This implies that it might be possible to determine
48	the characteristics of the random flow fields based on the known semivariogram of
49	the random input parameter from the field data for the case of a nonstationary process
50	of the input parameter. It is clear that the intrinsic hypothesis is weaker than the
51	second-order stationarity hypothesis.

According to Yaglom (1987) and Christakos (1992), an intrinsic function and its semivariogram admit a spectral representation. From these spectral representations, the associated stochastic groundwater flow equation can be solved in the wavenumber domain. Therefore, a spectral relationship between the wavenumber spectra of the input parameter fluctuations and the spectra of the output fluctuations can be obtained based on the solution of the stochastic





58	equation. This means that, given intrinsic semivariograms of the input parameters,
59	the variability of the flow fields can be characterized by the semivariograms of
60	the hydraulic head and the specific discharge fields using the spectral
61	representation approach. In other words, it is possible to establish stochastic
62	theories to characterize the variability of the flow fields without considering the
63	hypothesis of second-order stationarity for the random input parameters, which is
64	the goal of this study.

65 This work develops a general stochastic framework for quantifying the variability 66 of flow fields by semivariograms of depth-averaged hydraulic head and integrated specific discharge for essentially horizontal steady groundwater flow through a 67 68 heterogeneous confined aquifer of variable thickness. It is assumed that the random 69 input parameters appearing in the associated stochastic differential equation, such as 70 the log hydraulic conductivity and the log thickness of the confined aquifer, are 71 intrinsic random functions and therefore nonstationarity in the depth-averaged head 72 and integrated discharge. This work shows how to develop a stochastic modeling 73 framework for quantifying the variability of the flow fields given semivariograms of 74 the random input parameters, which, to our knowledge, has not been presented in the 75 literature before. An application of the proposed stochastic theories to the case where 76 the variability of a random input parameter can be characterized by a linear





- 77 semivariogram model is given.
- 78
- 79 2 Statement of the problem
- 80

81 In many practical situations, a variable measured on small samples over very short 82 distances may exhibit very large variations over those distances. To get around this 83 phenomenon, a variable is often measured as an average over a given volume or area 84 rather than at a point. This means that in reality the field data are never collected at a 85 single point, but always include support with finite dimensions, so that the 86 semivariogram over the sample support can no longer be considered a point 87 semivariogram (the theoretical semivariogram). Note that the theoretical 88 semivariogram $\gamma(h)$ defined at point x associated with a pointwise support can be 89 defined as

90
$$\gamma(\boldsymbol{\xi}) = \frac{1}{2} Var[Z(\boldsymbol{x} + \boldsymbol{\xi}) - Z(\boldsymbol{x})], \qquad (1)$$

91 In Eq. (1),
$$Z(\mathbf{x})$$
 is a random function.

It can be shown that the semivariogram of an intrinsic random function within a
volume ∀ is related to the point-theoretical semivariogram by the formula (e.g.,
Matheron, 1971; Journel and Huijbregts, 1978):

95
$$\gamma_{\nu}(\boldsymbol{\xi}) = \frac{1}{\nu^{2}} \int_{\boldsymbol{\psi}} d\boldsymbol{x} \int_{\boldsymbol{\psi}} \gamma(\boldsymbol{\xi} + \boldsymbol{x} - \boldsymbol{x}') d\boldsymbol{x}' - \frac{1}{\nu^{2}} \int_{\boldsymbol{\psi}} d\boldsymbol{x} \int_{\boldsymbol{\psi}} \gamma(\boldsymbol{x} - \boldsymbol{x}') d\boldsymbol{x}', \qquad (2)$$





96	where $\gamma_{\nu}(x)$ is the transformed semivariogram and $\gamma(x)$ is the theoretical semivariogram
97	defined in Eq. (1). Matheron (1971) points out that Eq. (2) holds for any intrinsic
98	random function, even if the covariance function does not exist.
99	This work presents a stochastic analysis of flow through heterogeneous confined
100	aquifers of variable thickness (see Appendix A). The variability of the flow results
101	from the variation of the random input parameters, such as the log hudraulic
102	conductivity and the log thickness of the confined aquifer. In this work, the log
103	conductivity and log aquifer thickness are considered as spatially intrinsic random
104	functions whose semivariogram can be represented by Eq. (2). In addition, the
105	variation of depth-averaged hydraulic head and integrated specific discharge can be
106	described by the perturbation equations (A3) and (A4), respectively. The spectral
107	representation approach is used to develop the semivariograms of depth-averaged
108	hydraulic head and vertically integrated specific discharge to quantify the variability
109	of the flow fields.

110

111 **3** Theoretical developments of semivariograms of flow fields

112

113 Given the assumption that f and β in Eq. (A3) satisfy the intrinsic hypothesis, the intrinsic

114 random functions f and β each admit a spectral representation of the form (Yaglom, 1987;





115 Christakos, 1992),

116
$$f(x_1, x_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\exp[i(w_1 x_1 + w_2 x_2)] - 1}{i\sqrt{w_1^2 + w_2^2}} dZ_{sy}(w_1, w_2), \qquad (3a)$$

117
$$\beta(x_1, x_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\exp[i(w_1 x_1 + w_2 x_2)] - 1}{i\sqrt{w_1^2 + w_2^2}} dZ_{s\rho}(w_1, w_2), \qquad (3b)$$

118 where the w_i are the components of the wavenumber vector $\boldsymbol{w} (= (w_1, w_2))$ and $Sf(w_1, w_2)$ 119 and $Sp(w_1, w_2)$ are stationary spatial random processes with uncorrelated complex 120 Fourier increments $dZ_{sy}(w_1, w_2)$ and $dZ_{sp}(w_1, w_2)$, respectively. Due to the property of the 121 linearity of the driving forces in Eq. (A3), the depth-averaged head perturbation can 122 alternatively be decomposed into two parts as 123 $h(x_1, x_2) = h_f(x_1, x_2) + h_p(x_1, x_2)$, (4a) 124 where h_f represents the head fluctuation in response to the change in log hydraulic

where n_f represents the head fluctuation in response to the change in log hydraulic conductivity, while h_{β} represents the head fluctuation in response to the change in log thickness of the aquifer. Without any restrictions, each component of the depth-averaged head perturbation in Eq. (4a) can be expressed by Fourier-Stieltjes representations (Priestley, 1965) as follows:

129
$$h_{f}(x_{1}, x_{2}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Lambda_{f}(x_{1}, x_{2}; w_{1}, w_{2}) dZ_{Sf}(w_{1}, w_{2}), \qquad (4b)$$





130
$$h_{\beta}(x_1, x_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Lambda_{\beta}(x_1, x_2; w_1, w_2) dZ_{S\beta}(w_1, w_2).$$
 (4c)

- 131 In Eqs. (4b) and (4c), Λ_f and Λ_{β} are referred to as oscillatory functions (Priestley,
- 132 1965).
- 133 Introducing Eqs. (3)-(4) into Eq. (A3), the solution of Eq. (A3) is

134
$$h_{f}(x_{1}, x_{2}) = J \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}}{(w_{1}^{2} + w_{2}^{2})^{3/2}} \left\{ 1 - \exp[i(w_{1}x_{1} + w_{2}x_{2})] + i(w_{1}x_{1} + w_{2}x_{2}) \right\} dZ_{sy}(w_{1}, w_{2}), \quad (5a)$$

135
$$h_{\beta}(x_{1}, x_{2}) = 2J \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}}{(w_{1}^{2} + w_{2}^{2})^{3/2}} \left\{ 1 - \exp[i(w_{1}x_{1} + w_{2}x_{2})] + i(w_{1}x_{1} + w_{2}x_{2}) \right\} dZ_{S\beta}(w_{1}, w_{2}).$$
(5b)

136 That is,

137
$$h(x_1, x_2) = J \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_1}{(w_1^2 + w_2^2)^{3/2}} \left\{ 1 - \exp[i(w_1 x_1 + w_2 x_2)] + i(w_1 x_1 + w_2 x_2) \right\} dZ_{sy}(w_1, w_2)$$

138
$$+2J \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_1}{(w_1^2 + w_2^2)^{3/2}} \left\{ 1 - \exp[i(w_1x_1 + w_2x_2)] + i(w_1x_1 + w_2x_2) \right\} dZ_{S\beta}(w_1, w_2).$$
(5c)

139 The details of the development of this solution are given in Appendix B.

140 Furthermore, making use of the spectral representation Eq. (3) and Eq. (5) in Eq.

141 (A4), the perturbation for the integrated specific discharge in the direction of x_1 (mean

142 flow) is given by

143
$$q_1(x_1, x_2) = q_{f_1}(x_1, x_2) + q_{\beta_1}(x_1, x_2),$$
 (6a)





144 where

145
$$q_{f_1}(x_1, x_2) = e^{F+B} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\exp[i(w_1 x_1 + w_2 x_2)] - 1}{i\sqrt{w_1^2 + w_2^2}} \left(1 - \frac{w_1^2}{w^2}\right) dZ_{SF}(w_1, w_2), \quad (6b)$$

146
$$q_{\beta_{1}}(x_{1},x_{2}) = e^{F+B} J \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{\exp[i(w_{1}x_{1}+w_{2}x_{2})]-1}{i\sqrt{w_{1}^{2}+w_{2}^{2}}} \left(1-2\frac{w_{1}^{2}}{w^{2}}\right) dZ_{S\beta}(w_{1},w_{2}).$$
(6c)

149
$$\gamma_h(\boldsymbol{x}, \boldsymbol{y}) = \gamma_{h_f}(\boldsymbol{x}, \boldsymbol{y}) + \gamma_{h_f}(\boldsymbol{x}, \boldsymbol{y}),$$
 (7a)

150 where
$$\mathbf{x} = (x_1, x_2), \mathbf{y} = (y_1, y_2)$$
, and

151
$$\gamma_{\mu}(\mathbf{x}, \mathbf{y}) = \Xi_1(\mathbf{x} - \mathbf{y}) + r_1 \Xi_2(\mathbf{x}, \mathbf{y}) + r_2 \Xi_3(\mathbf{x}, \mathbf{y}),$$
 (7b)

152
$$\gamma_{h_s}(\boldsymbol{x},\boldsymbol{y}) = 4 \Big[\Omega_1(\boldsymbol{x}-\boldsymbol{y}) + r_1 \Omega_2(\boldsymbol{x},\boldsymbol{y}) + r_2 \Omega_3(\boldsymbol{x},\boldsymbol{y}) \Big],$$
(7c)

153 $r_1 = x_1 - y_1$, $r_2 = x_2 - y_2$. The expressions for $\Xi_1 - \Xi_3$ and $\Omega_1 - \Omega_3$ in Eq. (7) are given in the

154 Appendix C. Note that the random process of the spectral representation according to

155 Eq. (5) and the semivariogram according to Eq. (7) is called an intrinsic random

156 function of order 1 (Matheron, 1973).

157 Similarly, the application of Eq. (6) in Eq. (1) yields the semivariogram of the

158 integrated specific discharge in the mean flow direction of the form

159
$$\gamma_q(\mathbf{x}, \mathbf{y}) = \gamma_{q_f}(\mathbf{x} - \mathbf{y}) + \gamma_{q_f}(\mathbf{x} - \mathbf{y}),$$
 (8a)

160 where





161
$$\gamma_{q_{f}}(\boldsymbol{x}-\boldsymbol{y}) = e^{2(F+B)} J \int \int \int \frac{1-\cos(w_{1}r_{1})\cos(w_{2}r_{2})}{w_{1}^{2}+w_{2}^{2}} \left(1-\frac{w_{1}^{2}}{w_{1}^{2}+w_{2}^{2}}\right)^{2} S_{sf}(w_{1},w_{2})dw_{1}dw_{2}, \quad (8b)$$

162
$$\gamma_{q_{\mu}}(\boldsymbol{x}-\boldsymbol{y}) = e^{2(F+B)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1 - \cos(w_{1}r_{1})\cos(w_{2}r_{2})}{w_{1}^{2} + w_{2}^{2}} \left(1 - 2\frac{w_{1}^{2}}{w_{1}^{2} + w_{2}^{2}}\right)^{2} S_{s\beta}(w_{1}, w_{2}) dw_{1} dw_{2}.$$
(8c)

From Eqs. (6) and (8), it can be seen that the random process for the integrated discharge in the mean flow direction is an intrinsic random process (or an intrinsic random function of order 0, Matheron, 1973).

166 To evaluate Eqs. (7) and (8), which are used to quantify the variability of flow 167 fields, the spectral density functions S_{sy} and S_{sp} must be determined. It can be shown 168 that when the intrinsic random function has a spectral representation as in Eq. (3), the 169 semivariograms of the intrinsic functions f and β are related to the covariance 170 functions of the stationary processes Sf and $S\beta$ by

171
$$\frac{\partial^2}{\partial r_1^2} \gamma_f(\mathbf{x} - \mathbf{y}) + \frac{\partial^2}{\partial r_2^2} \gamma_f(\mathbf{x} - \mathbf{y}) = C_f(\mathbf{x} - \mathbf{y}), \qquad (9a)$$

172
$$\frac{\partial^2}{\partial r_1^2} \gamma_{\beta}(\mathbf{x} - \mathbf{y}) + \frac{\partial^2}{\partial r_2^2} \gamma_{\beta}(\mathbf{x} - \mathbf{y}) = C_{\beta}(\mathbf{x} - \mathbf{y}), \qquad (9b)$$

173 where γ_f and γ_{β} are semivariograms of f and β functions, respectively, and C_f and C_{β} are 174 covariance functions of *Sf* and *S* β processes, respectively. The spectral density functions of 175 the fluctuations of f and β are then obtained by the inverse Fourier transform of C_f and 176 C_{β} respectively, i.e.,





177
$$S_{Sf}(w_1, w_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp[w_1 \xi_1 + w_2 \xi_2] C_f(\xi_1, \xi_2) d\xi_1 d\xi_2, \qquad (10a)$$

178
$$S_{s\beta}(w_1, w_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp[w_1 \xi_1 + w_2 \xi_2] C_{\beta}(\xi_1, \xi_2) d\xi_1 d\xi_2.$$
(10b)

179 Equations (7) and (8), together with Eqs. (2), (9), and (10), provide the necessary

180 framework for quantifying the variability of the flow fields. The results can be181 obtained for specific input parameter models. This line of research will be pursued in

- 182 the next section.
- 183

184 **4** Application

185

186 **4.1 The linear intrinsic semivariogram**

187

188 If a volume \forall is taken as a straight segment of length L and the point-theoretical

189 semivariogram of an input parameter in Eq. (2) is considered to be described by a

- 190 linear model (e.g., Journel and Huijbregts, 1978; Bardossy, 1997; Usowicz and Lipiec,
- 191 2021), i.e.,

$$192 \quad \gamma(\xi) = \alpha |\xi|, \tag{11}$$

193 then the transformed semivariogram in Eq. (2) can be written as





194
$$\gamma_{L}(\boldsymbol{\xi}) = \frac{\alpha}{L^{2}} \int_{L} dx \int_{L} |\boldsymbol{\xi} + x - x'| dx' - \frac{\alpha}{L^{2}} \int_{L} dx \int_{L} |x - x'| dx'.$$
 (12)

195 Note that the semivariogram of a second order stationary random function is 196 necessarily bounded, while the semivariogram of an intrinsic random function is not. 197 The integration of Eq. (12) can be performed using the Cauchy algorithm (e.g., 198 Matheron, 1971) 199 $\gamma_L(\xi) = \frac{\alpha}{L^2} \int_{-L}^{L} (L - |x|) |\xi + x| dx - \frac{\alpha}{L^2} \int_{-L}^{L} (L - |x|) |x| dx$

$$200 \qquad = \alpha(\left|\xi\right| - \frac{L}{3}) \qquad |\xi| \ge L. \tag{13}$$

The details of this development are given in Appendix D. This result agrees with that of Journel and Huijbregts (1978) obtained by a different integrating approach. Note that γ_L in Eq. (13) reaches -L/3 when ξ approaches zero, and that this negative value is called the "pseudo-negative nugget effect" (Journel and Huijbregts, 1978) due to regularization.

In this study, it is assumed that the variograms of the input parameters depend only on the magnitude of the distance between the two points and not on its direction. The spatial variability of the input parameters (such as the log conductivity and log thickness of the aquifer) can be characterized by the following semivariograms

210
$$\gamma_{L_f}(\xi_1,\xi_2) = \alpha_f(|\boldsymbol{\xi}| - \frac{L}{3}) \quad |\boldsymbol{\xi}| \ge L,$$
 (14a)

211
$$\gamma_{L_{\beta}}(\xi_1,\xi_2) = \alpha_{\beta}(|\xi| - \frac{L}{3}) \quad |\xi| \ge L,$$
 (14b)

212 which represent the extension of Eq. (13) to two dimensions. In Eq. (14), $|\xi| =$





- 213 $(\xi_1^2 + \xi_2^2)^{1/2}$.
- 214 The covariance functions of Sf and $S\beta$ processes are determined from substituting Eq.
- 215 (14) into Eq. (9), respectively,

216
$$C_f(\xi_1,\xi_2) = \frac{\partial^2}{\partial \xi_1^2} \gamma_{L_f}(\xi_1,\xi_2) + \frac{\partial^2}{\partial \xi_2^2} \gamma_{L_f}(\xi_1,\xi_2) = \frac{\alpha_f}{\sqrt{\xi_1^2 + \xi_2^2}},$$
 (15a)

217
$$C_{\beta}(\xi_{1},\xi_{2}) = \frac{\partial^{2}}{\partial\xi_{1}^{2}} \gamma_{L_{\beta}}(\xi_{1},\xi_{2}) + \frac{\partial^{2}}{\partial\xi_{2}^{2}} \gamma_{L_{\beta}}(\xi_{1},\xi_{2}) = \frac{\alpha_{\beta}}{\sqrt{\xi_{1}^{2} + \xi_{2}^{2}}}.$$
 (15b)

- 218 From Eqs. (10) and (15), the corresponding spectral density functions of f and β are
- 219 obtained, respectively, as follows:

00 or

220
$$S_{Sf}(w_1, w_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \exp[w_1\xi_1 + w_2\xi_2] \frac{\alpha_f}{\sqrt{\xi_1^2 + \xi_2^2}} d\xi_1 d\xi_2 = \frac{\alpha_f}{2\pi} \frac{1}{\sqrt{w_1^2 + w_2^2}}, \quad (16a)$$

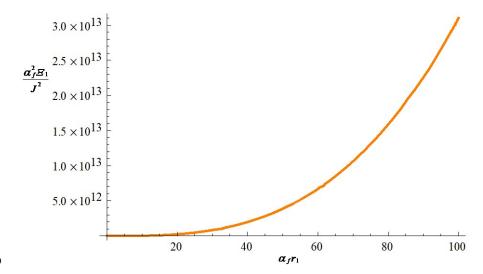
221
$$S_{S\beta}(w_1, w_2) = \frac{1}{(2\pi)^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp[w_1 \xi_1 + w_2 \xi_2] \frac{\alpha_\beta}{\sqrt{\xi_1^2 + \xi_2^2}} d\xi_1 d\xi_2 = \frac{\alpha_\beta}{2\pi} \frac{1}{\sqrt{w_1^2 + w_2^2}}.$$
 (16b)

The semivariogram of depth-averaged hydraulic head used to quantify the variability of the head field can then be obtained by substituting Eq. (16) into Eq. (7) and integrating over the wavenumber range. Note that the first term on the right-hand side of Eq. (7b) or Eq. (7c), $\Xi_i(x-y)$ or $4\Omega_i(x-y)$, is called the generalized covariance function by Matheron (1973). Figure 1 shows the numerical integration result for the generalized covariance function of depth-averaged hydraulic head Ξ_i , i.e., the component of γ_{h_i} that reflects the effect of variation in hydraulic conductivity fields,





229	using Eq. (16a) in Eq. (C1). The unbounded increase in the generalized covariance
230	function Ξ_i with separation distance suggests that there is no finite depth-averaged head
231	variance. This implies that the variation in depth-averaged hydraulic head does not
232	satisfy the second-order stationarity hypothesis. Quantifying the variability in
233	depth-averaged head using the assumption of second-order stationarity for the input
234	parameter can lead to a significant underestimation of head variability for the case of
235	intrinsic random log-conductivity fields. It can also be shown that similar conclusions
236	can be drawn from the term $4\Omega_i(x-y)$ in Eq. (7c), the component of $\gamma_{h_{\beta}}$ reflecting the
237	effect of variation in the log-aquifer thickness fields, for the case of intrinsic random
238	log-aquifer thickness fields.



239

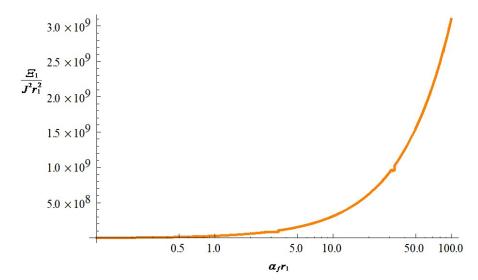
Figure 1. The generalized covariance function of depth-averaged hydraulic head (the component of γ_{h_j} that reflects the effect of variation in the log hydraulic conductivity fields) as a function of separation distance in the mean flow direction, where $r_1 = x_1 - y_1$.





Figure 2 depicts the behavior of the generalized covariance function Ξ_1 as a function of parameter α_r for a given separation distance r_1 . A larger α_r increases the variability of the log conductivity fields, resulting in a larger Ξ_1 and thus a larger semivariogram γ_{hr} . It can also be shown that the larger the parameter α_{μ} , the larger the variability of the generalized covariance function $4\Omega_1$. It can therefore be concluded that the variability of the depth-averaged hydraulic head caused by the variation of the log hydraulic conductivity and log aquifer thickness is larger for larger parameters α_r





251

Figure 2. The generalized covariance function of depth-averaged hydraulic head (the component of γ_{h_r} that reflects the effect of variation in the log hydraulic conductivity fields) as a function of parameter α_r in the mean flow direction, where $r_1 = x_1 - y_1$.

The numerical integration results for the components of the semivariogram of the integrated specific discharge in the mean flow direction, γ_{q_f} and γ_{q_g} , obtained by





257	substituting Eq. (16) into Eq. (8), are shown in Figs. (3a) and (3b). The unlimited
258	increase of the integrated discharge semivariogram with the separation distance
259	shown in Fig. 3 indicates that the variation of the integrated discharge process is
260	nonstationary. This is the result of the nonstationary process of the depth-averaged
261	hydraulic head caused by the intrinsic random log-conductivity and log-aquifer
262	thickness fields. The figure also shows that there is an increase in the semivariogram
263	of the integrated specific discharge in the mean flow direction with parameters α_{f} and
264	α_{β} for a given separation distance. Larger α_{f} and α_{β} cause greater variability in the
265	depth-averaged pressure fields and thus greater variability in the integrated specific
266	discharge fields.

267

268 4.2 The exponential semivariogram

269

It is important to note that the stationary variables always satisfy the intrinsic hypothesis, while the opposite is not always true, since the intrinsic variable can be nonstationary. The stochastic theory developed here to quantify the variability of the flow fields remains valid for any second order stationary random variable. For example, if the point theoretic semivariogram of an input parameter is chosen as $\gamma(\xi) = \mu (1 - \exp[-\frac{|\xi|}{\lambda}]),$ (17)





- 276 the transformed semivariogram over a segment of length L can then be calculated
- using Eq. (2) and the Cauchy algorithm (e.g., Matheron, 1971) as follows:

278
$$\gamma_{L}(\boldsymbol{\xi}) = \frac{\mu}{L^{2}} \int_{-L}^{L} (L - |x|) (1 - \exp[-\frac{|\boldsymbol{\xi} + x|}{\lambda}]) dx - \frac{\mu}{L^{2}} \int_{-L}^{L} (L - |x|) (1 - \exp[-\frac{|x|}{\lambda}]) dx, \qquad (18)$$

279 This results in

280
$$\gamma_{L}(\xi) = \mu \frac{\lambda^{2}}{L^{2}} \left\{ 2\exp[-\frac{|\xi|}{\lambda}] - \exp[-\frac{|\xi| + L}{\lambda}] - \exp[-\frac{|\xi| - L}{\lambda}] + 2\left(-1 + \exp[-\frac{L}{\lambda}] + \frac{L}{\lambda}\right) \right\} \quad |\xi| \ge L.$$
(19)

- 281 For the development of Eq. (19), the reader is referred to Appendix E.
- Extending Eq. (19) to two dimensions and substituting it into Eq. (9), the covariance functions of the random input parameters (f and β) can then be expressed,
- 284 respectively, as

285
$$C_{f}(\xi_{1},\xi_{2}) = \mu_{f} \frac{(\exp[\frac{L}{\lambda_{f}}] - 1)^{2}}{L^{2}} \frac{\lambda_{f} - \sqrt{\xi_{1}^{2} + \xi_{2}^{2}}}{\sqrt{\xi_{1}^{2} + \xi_{2}^{2}}} \exp[-\frac{\sqrt{\xi_{1}^{2} + \xi_{2}^{2}} + L}{\lambda_{f}}], \qquad (20a)$$

286
$$C_{\beta}(\xi_{1},\xi_{2}) = \mu_{\beta} \frac{(\exp[\frac{L}{\lambda_{\beta}}] - 1)^{2}}{L^{2}} \frac{\lambda_{\beta} - \sqrt{\xi_{1}^{2} + \xi_{2}^{2}}}{\sqrt{\xi_{1}^{2} + \xi_{2}^{2}}} \exp[-\frac{\sqrt{\xi_{1}^{2} + \xi_{2}^{2}} + L}{\lambda_{\beta}}].$$
 (20b)

287 Using Eq. (20) in Eq. (10), it follows that the spectral density functions of the

288 fluctuations of f and β each have the form

T

289
$$S_{sy}(w_1, w_2) = \frac{\mu_f}{2\pi} \frac{(\exp[\frac{L}{\lambda_f}] - 1)^2}{(\frac{L}{\lambda_f})^2} \frac{\lambda_f^2(w_1^2 + w_2^2)}{[1 + \lambda_f^2(w_1^2 + w_2^2)]^2},$$
(21a)

290
$$S_{S\beta}(w_1, w_2) = \frac{\mu_{\beta}}{2\pi} \frac{\left(\exp\left[\frac{L}{\lambda_{\beta}}\right] - 1\right)^2}{\left(\frac{L}{\lambda_{\beta}}\right)^2} \frac{\lambda_{\beta}^2(w_1^2 + w_2^2)}{\left[1 + \lambda_{\beta}^2(w_1^2 + w_2^2)\right]^2}.$$
 (21b)

291





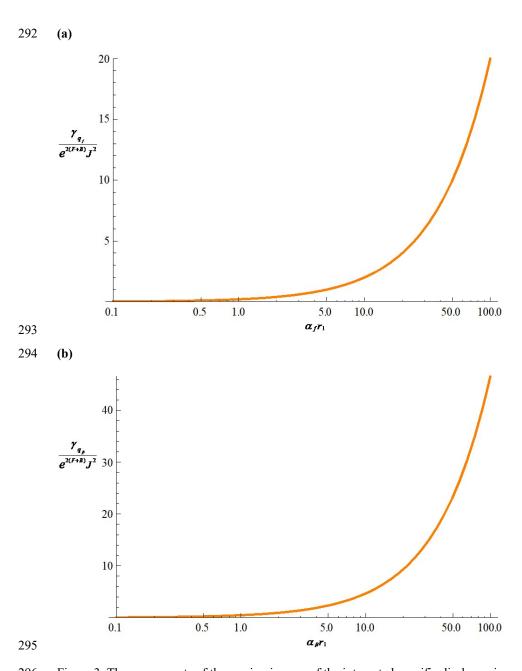


Figure 3. The components of the semivariogram of the integrated specific discharge in the mean flow direction, (a) $\gamma_{q,\rho}$ reflecting the effect of variation in the log hydraulic conductivity fields, and (b) $\gamma_{q,\rho}$ reflecting the effect of variation in the log aquifer thickness fields, as a function of parameters α_f and α_{ρ} and separation distance.





300	Finally, substituting Eq. (21) into Eqs. (7) and (8), the semivariograms of
301	depth-averaged head and the semivariogram of integrated specific discharge in the
302	mean flow direction can now be evaluated.
303	The practical advantage of using the general stochastic modeling framework
304	developed here with the intrinsic hypothesis is a wider range of possible
305	semivariogram models compared to the cases with second-order stationarity. The
306	condition of second-order stationarity is rarely encountered in nature (e.g., Wu and Hu,
307	2004) and is difficult to verify using the limited experimental data available. It is
308	under these conditions that the presented stochastic approach has the greatest utility of
309	quantification of the flow field variability.

310

Conclusions 311 5

312

313 In this work, a general stochastic methodology is developed for quantifying the 314 variability of flow fields in heterogeneous confined aquifers of variable thickness. The 315 stochastic theories developed here, namely the semivariograms of depth-averaged 316 hydraulic head and integrated specific discharge used to characterize flow field variability, can address the effects of nonstationarity due to variations in parameters 317 318 and output. The proposed stochastic theories generalize existing stochastic theory,





319	which applies to second order stationary random input parameters, to nonstationary
320	random input parameters. Stationarity in the spatial variation of soil properties is very
321	rarely encountered in nature. The stochastic theories developed here improve the
322	quantification of flow field variability in natural confined aquifers.
323	The results show that the introduction of intrinsic random input parameters leads
324	to a nonstationary process of depth-averaged hydraulic head fluctuations (an intrinsic
325	random function of order 1) and a nonstationary process of integrated specific
326	discharge fluctuations (an intrinsic random function of order 0). Application of the
327	stochastic theories developed here to the case where the variability of a random input
328	parameter can be characterized by a linear semivariogram model shows that larger
329	parameters α_{f} and α_{ρ} increase the variability of the depth-averaged head and thus the
330	variability of the integrated discharge in the mean flow direction.
331	
332	Appendix A: A steady flow through a heterogeneous confined aquifer
333	of variable thickness
334	
335	According to Chang et al. (2021), an essentially horizontal, steady groundwater flow

through a heterogeneous confined aquifer of variable thickness can be represented asfollows:

21





$$338 \qquad \frac{\partial^2}{\partial x_i^2} \tilde{h}(x_1, x_2) + \left[\frac{\partial}{\partial x_i} \ln K(x_1, x_2) + 2\frac{\partial}{\partial x_i} \ln b(x_1, x_2)\right] \frac{\partial}{\partial x_i} \tilde{h}(x_1, x_2) = 0 \qquad i = 1, 2,$$
(A1)

which is the vertically integrated form of the continuity equation. In Eq. (A1), $\tilde{h}(x_1,x_2)$ is the depth-averaged hydraulic head, $K(x_1,x_2)$ is the hydraulic conductivity and $b(x_1,x_2)$ is the aquifer's thickness. From Eq. (A1), it can be seen that the variations in hydraulic conductivity and aquifer thickness that occur affect the depth-averaged hydraulic head. If the log conductivity and log thickness in Eq. (A1) are treated as stochastic (random) variables, Eq. (A1) can be considered as a stochastic partial differential equation with a stochastic output \tilde{h} .

346 Similarly, integrating the equation for specific discharge along the x_3 -axis and 347 applying Leibniz's rule leads to the vertically integrated specific discharge in the x_i 348 direction as follows:

349
$$Q_{x_i}(x_1, x_2) = -K(x_1, x_2)b(x_1, x_2)\frac{\partial}{\partial x_i}\tilde{h}(x_1, x_2)$$
(A2)

Under the influence of a uniform mean hydraulic gradient, the perturbation equations for the depth-average hydraulic head and integrated specific discharge associated with Eqs. (A1) and (A2) are given, respectively, by

353
$$\frac{\partial^2}{\partial x_i^2} h(x_1, x_2) = J\left[\frac{\partial}{\partial x_1} f(x_1, x_2) + 2\frac{\partial}{\partial x_1} \beta(x_1, x_2)\right] \quad i = 1, 2,$$
(A3)

354
$$q_i(x_1, x_2) = e^{F_{+B}} J \{ [f(x_1, x_2) + \beta(x_1, x_2)] \delta_{1i} - \frac{\partial}{\partial x_i} h(x_1, x_2) \} \qquad i = 1, 2.$$
(A4)

355 In Eqs. (A3) and (A4), h and q_i are the fluctuations of depth-average head and 356 integrated discharge, respectively, J is the constant mean hydraulic gradient, F and B





- 357 are the mean log conductivity and mean aquifer thickness, respectively, and f and β
- 358 are the fluctuations of log conductivity and log aquifer thickness, respectively. A
- detailed development of Eqs. (A3) and (A4) can be found in Chang et al. (2021).
- 360

361 Appendix B: Derivation of Eq. (5)

- 362
- 363 Since equation (A3) is linear, it can alternatively be divided into two parts as follows:

364
$$\frac{\partial^2}{\partial x_1^2} h_f(x_1, x_2) + \frac{\partial^2}{\partial x_2^2} h_f(x_1, x_2) = J \frac{\partial}{\partial x_1} f(x_1, x_2), \qquad (B1a)$$

$$365 \qquad \frac{\partial^2}{\partial x_1^2} h_{\beta}(x_1, x_2) + \frac{\partial^2}{\partial x_2^2} h_{\beta}(x_1, x_2) = 2J \frac{\partial}{\partial x_1} \beta(x_1, x_2). \tag{B1b}$$

366 Applying Eqs. (3a) and (4b) into Eq. (B1a), it follows that

367
$$\frac{\partial^2}{\partial x_1^2} \Lambda_f(x_1, x_2; w_1, w_2) + \frac{\partial^2}{\partial x_2^2} \Lambda_f(x_1, x_2; w_1, w_2) = J \frac{w_1}{\sqrt{w_1^2 + w_2^2}} \exp[i(w_1 x_1 + w_2 x_2)], \quad (B2)$$

368 which is known as Poisson's equation and has a particular solution in the form

369
$$\Lambda_{f}(x_{1}, x_{2}; w_{1}, w_{2}) = J \frac{w_{1}}{\sqrt{w_{1}^{2} + w_{2}^{2}}} \frac{1 - \exp[i(w_{1}x_{1} + w_{2}x_{2})] + i(w_{1}x_{1} + w_{2}x_{2})}{w_{1}^{2} + w_{2}^{2}}.$$
 (B3)

370 Similarly, using Eqs. (3b) and (4c), Eq. (B1b) can be written as follows:

371
$$\frac{\partial^2}{\partial x_1^2} \Lambda_{\beta}(x_1, x_2; w_1, w_2) + \frac{\partial^2}{\partial x_2^2} \Lambda_{\beta}(x_1, x_2; w_1, w_2) = 2J \frac{w_1}{\sqrt{w_1^2 + w_2^2}} \exp[i(w_1 x_1 + w_2 x_2)], \quad (B4)$$

and accordingly,





373
$$\Lambda_{\beta}(x_1, x_2; w_1, w_2) = 2J \frac{w_1}{\sqrt{w_1^2 + w_2^2}} \frac{1 - \exp[i(w_1 x_1 + w_2 x_2)] + i(w_1 x_1 + w_2 x_2)}{w_1^2 + w_2^2}.$$
 (B5)

- 374 Finally, substituting Eqs. (B4) and (B5) into Eq. (4), Eq. (5) is obtained.
- 375

376 Appendix C: Expressions for the functions in Eq. (7)

377

378
$$\Xi_{1}(\boldsymbol{x}-\boldsymbol{y}) = J^{2} \int_{-\infty}^{\infty} \frac{w_{1}^{2}}{(w_{1}^{2}+w_{2}^{2})^{3}} \Big[1 - \cos(w_{1}r_{1})\cos(w_{2}r_{2}) + \frac{1}{2} (w_{1}r_{1}^{2}+w_{2}r_{2}^{2}) \Big] S_{sy}(w_{1},w_{2}) dw_{1}dw_{2}, (C1)$$

379
$$\Xi_{2}(\boldsymbol{x},\boldsymbol{y}) = J^{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}^{3}}{(w_{1}^{2} + w_{2}^{2})^{3}} \left[-\sin(w_{1}x_{1})\cos(w_{2}x_{2}) + \sin(w_{1}y_{1})\cos(w_{2}y_{2}) \right] S_{sy}(w_{1},w_{2}) dw_{1}dw_{2}, (C2)$$

380
$$\Xi_{3}(\mathbf{x},\mathbf{y}) = J^{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}^{2} w_{2}}{(w_{1}^{2} + w_{2}^{2})^{3}} \Big[-\cos(w_{1}x_{1})\sin(w_{2}x_{2}) + \cos(w_{1}y_{1})\sin(w_{2}y_{2}) \Big] S_{sy}(w_{1},w_{2}) dw_{1} dw_{2}, (C3)$$

381
$$\Omega_{1}(\boldsymbol{x}-\boldsymbol{y}) = J^{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}^{2}}{(w_{1}^{2}+w_{2}^{2})^{3}} \left[1-\cos(w_{1}r_{1})\cos(w_{2}r_{2})+\frac{1}{2}(w_{1}^{2}r_{1}^{2}+w_{2}^{2}r_{2}^{2})\right] S_{S\beta}(w_{1},w_{2})dw_{1}dw_{2}, (C4)$$

382
$$\Omega_{2}(\boldsymbol{x},\boldsymbol{y}) = J^{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}^{3}}{(w_{1}^{2} + w_{2}^{2})^{3}} \left[-\sin(w_{1}x_{1})\cos(w_{2}x_{2}) + \sin(w_{1}y_{1})\cos(w_{2}y_{2}) \right] S_{S\beta}(w_{1},w_{2}) dw_{1}dw_{2}, (C5)$$

383
$$\mathcal{Q}_{3}(\boldsymbol{x},\boldsymbol{y}) = J^{2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{w_{1}^{2} w_{2}}{(w_{1}^{2} + w_{2}^{2})^{3}} \Big[-\cos(w_{1}x_{1})\sin(w_{2}x_{2}) + \cos(w_{1}y_{1})\sin(w_{2}y_{2}) \Big] S_{s\beta}(w_{1},w_{2}) dw_{1}dw_{2}, (C6)$$

384 $r_1 = x_1 - y_1$, $r_2 = x_2 - y_2$, and $S_{s\beta}$ are the spectral density functions of the stationary

385 processes of *Sf* and *S* β , respectively.





386

387 Appendix D: Derivation of Eq. (13)

388

389 The condition for Eq. (13) that the absolute value of $\boldsymbol{\xi}$ is greater than or equal to $L(|\boldsymbol{\xi}|$

390 $\geq L$) means that $\xi \geq L$ or $\xi \leq -L$. For $\xi \geq L$, the integrand of the integral Eq. (13) can be

391 expressed as

$$392 \qquad \gamma_{L}(\boldsymbol{\xi}) = \frac{\alpha}{L^{2}} \int_{-L}^{0} (L+x)(|\boldsymbol{\xi}|+x)dx + \frac{\alpha}{L^{2}} \int_{0}^{L} (L-x)(|\boldsymbol{\xi}|+x)dx - \frac{\alpha}{L^{2}} \int_{-L}^{0} (L+|x|)(-x)dx - \frac{\alpha}{L^{2}} \int_{0}^{L} (L-x)xdx$$

393
$$= \alpha(|\xi| - \frac{L}{3}).$$
 (D1)

394 For $\xi \leq -L$, the integrand of the integral Eq. (13) can be expressed as

$$395 \qquad \gamma_{L}(\boldsymbol{\xi}) = \frac{\alpha}{L^{2}} \int_{-L}^{0} (L+x)(|\boldsymbol{\xi}|-x)dx + \frac{\alpha}{L^{2}} \int_{0}^{L} (L-x)(|\boldsymbol{\xi}|-x)dx - \frac{\alpha}{L^{2}} \int_{-L}^{0} (L+|x|)(-x)dx - \frac{\alpha}{L^{2}} \int_{0}^{L} (L-x)xdx$$
$$396 \qquad = \alpha(|\boldsymbol{\xi}| - \frac{L}{3}). \tag{D2}$$

397

398 Appendix E: Derivation of Eq. (19)

399

400 Analogous to Eq. (13), the integral of Eq. (18) under the condition $|\xi| \ge L$ can be

401 evaluated separately as the integration of Eq. (18) under the condition $\xi \ge L$ and that

- 402 under the condition $\xi \leq -L$.
- 403 For $\boldsymbol{\xi} \ge L$,





404
$$\gamma_{L}(\xi) = \frac{\mu}{L^{2}} \int_{-L}^{0} (L+x)(1-\exp[-\frac{|\xi|+x}{\lambda}])dx + \frac{\mu}{L^{2}} \int_{0}^{L} (L-x)(1-\exp[-\frac{|\xi|+x}{\lambda}])dx$$

405
$$-\frac{\mu}{L^2} \int_{-L}^{0} (L+x)(1-\exp[\frac{x}{\lambda}])dx - \frac{\mu}{L^2} \int_{0}^{L} (L-x)(1-\exp[-\frac{x}{\lambda}])dx$$

406
$$= \mu \frac{\lambda^2}{L^2} \left\{ 2\exp[-\frac{|\xi|}{\lambda}] - \exp[-\frac{|\xi| + L}{\lambda}] - \exp[-\frac{|\xi| - L}{\lambda}] + 2\left(-1 + \exp[-\frac{L}{\lambda}] + \frac{L}{\lambda}\right) \right\}.$$
 (E1)

407 For $\boldsymbol{\xi} \leq -L$,

$$408 \qquad \gamma_{L}(\xi) = \frac{\mu}{L^{2}} \int_{-L}^{0} (L+x) (1 - \exp[-\frac{|\xi| - x}{\lambda}]) dx + \frac{\mu}{L^{2}} \int_{0}^{L} (L-x) (1 - \exp[-\frac{|\xi| - x}{\lambda}]) dx$$

409
$$-\frac{\mu}{L^2} \int_{-L}^{0} (L+x)(1-\exp[\frac{x}{\lambda}]) dx - \frac{\mu}{L^2} \int_{0}^{L} (L-x)(1-\exp[-\frac{x}{\lambda}]) dx$$

410
$$= \frac{\mu^2}{L^2} \left\{ 2\exp\left[-\frac{\left|\xi\right|}{\lambda}\right] - \exp\left[-\frac{\left|\xi\right| + L}{\lambda}\right] - \exp\left[-\frac{\left|\xi\right| - L}{\lambda}\right] + 2\left(-1 + \exp\left[-\frac{L}{\lambda}\right] + \frac{L}{\lambda}\right) \right\}.$$
 (E2)

411

412 Data availability. No data was used for the research described in the article.

- 413
- 414 Author contributions. C-MC: Conceptualization, Methodology, Formal analysis,
- 415 Writing original draft preparation, Writing review & editing.
- 416 C-FN: Conceptualization, Methodology, Formal analysis, Writing original draft
- 417 preparation, Writing review & editing, Supervision, Funding acquisition.

418 C-PL: Conceptualization, Methodology, Formal analysis, Writing - original draft
419 preparation, Writing - review & editing.

420 I-HL: Conceptualization, Methodology, Formal analysis, Writing - original draft

- 421 preparation, Writing review & editing.
- 422

423 Competing interests. The authors declare that they have no conflict of interest.





424	
425	Acknowledgements. Research leading to this paper has been partially supported by the
426	grant from the Taiwan Ministry of Science and Technology under the grants MOST
427	110-2123-M-008-001-, MOST 110-2621-M-008-003-, and MOST
428	110-2811-M-008-533.
429	
430	References
431	
432	Bardossy, A.: Introduction to Geostatistics, Institute of Hydraulic Engineering,
433	University of Stuttgart, 1997.
434	Chang, C-M, Ni, C-F, Li, W-C, Lin, C-P, and Lee, I-H: Stochastic analysis of the
435	variability of groundwater flow fields in heterogeneous confined aquifers of
436	variable thickness, Stoch. Environ. Res. Risk Assess.,
437	https://doi.org/10.1007/s00477-021-02125-7, 2021.
438	Christakos, G.: Random Field Models in Earth Sciences, Academic, San Diego, 1992.
439	Dagan, G.: Flow and Transport in Porous Formations, Springer, New York, 1989.
440	Dell'Oca, A., Guadagnini, A., and Riva, M.: Interpretation of multi-scale permeability
441	data through an information theory perspective, Hydrol. Earth Syst. Sci., 24,
442	3097-3109, 2020.





- 443 Gelhar, L.W.: Stochastic Subsurface Hydrology, Prentice Hall, Englewood Cliffs,
- 444 New Jersey.
- 445 Journel, A. G. and Huijbregts, C. J.: Mining Geostatistics, Academic Press, New York,
- 446 1978.
- 447 Matheron, G.: Les variables regionalisees et leur estimation, Masson, Paris, 1965.
- 448 Matheron, G.: The theory of regionalized variables and its applications, Les Cahiers
- du Centre de Morphologie Mathematique in Fontainebleu, Paris, 1971.
- 450 Molz, F. J., Rajaram, H., and Lu, S. L.: Stochastic fractal-based models of
- 451 heterogeneity in subsurface hydrology: Origins, applications, limitations, and
- 452 future research questions, Rev. Geophys., 42, RG1002, 2004.
- 453 Priestley, M. B.: Evolutionary spectra and non-stationary processes, J. R. Stat. Soc. Ser.
- 454 B., 27(2), 204-237, 1965.
- Rubin, Y.: Applied Stochastic Hydrogeology, Oxford University Press, New York,
 2003.
- 457 Usowicz, B. and Lipiec, J.: Spatial variability of saturated hydraulic conductivity and
- 458 its links with other soil properties at the regional scale, Sci. Rep., 11, 1-12, 2021.
- 459 Wu, J. and Hu, B.: Stochastic study of solute flux in nonstationary flow field
- 460 conditioning on measured data, Developments in Water Science, 55(1), 705-716,
- 461 2004.





462	Yaglom, A. M.: Correlation Theory of Stationary and Related Random Functions, Vol.
463	I: Basic Results, Springer Series in Statistics, Springer, New York, 1987.
464	Zhang, D.: Stochastic Methods for Flow in Porous Media: Coping with Uncertainties,
465	Academic Press, San Diego, 2002.
466	