Mutual information analysis to approach nonlinearity in groundwater stochastic fields

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Abstract

In heterogeneous porous media, transmissivity can be regarded as a spatial stochastic variable. Transmissivity fluctuations induce stochasticity in the groundwater velocity field and transport features. In order to model subsurface phenomena, it is important to understand the relationships that exist between the variables that characterize flow and transport. Linear relationships are easier to deal with. Nevertheless, it is well known that flow and transport variables exhibit interdependences that become more and more nonlinear as the heterogeneity increases.

The aim of this work is to draw attention to the information contained in nonlinear linkages, and to show that it can be of great relevance with respect to the linear information content. Information theory tools are proposed to detect the presence of nonlinear components. By comparing the cross-covariance function and mutual information, the amount of linear linkage is compared with nonlinear linkage. In order to avoid analytical approximations, data from Monte Carlo simulations of heterogeneous transmissivity fields have been considered in the analysis. The obtained results show that the presence of nonlinear components can be relevant, even when the cross-covariance values are nil.

Key-Words

Nonlinearity, Mutual Information, Heterogeneous transmissivity fields, Groundwater stochastic fields

1. Introduction

Groundwater is the most relevant source of high quality fresh water. However, groundwater is vulnerable: overexploitation and pollution constitute an increasing threat. In order to manage this precious resource, studies are necessary to obtain a better understanding of flow and transport phenomena. Over the past few decades, the difficulty of obtaining detailed knowledge about the spatial distribution of aquifer parameters, and hydraulic conductivity in particular, has led to the development of stochastic approaches in order to resolve groundwater issues by means of numerical and analytical studies (e.g., Dagan 1989; Dagan and Neuman 1997; Rubin 2003). Hydraulic conductivity is modelled as a spatial random function with given statistical proprieties, which are inferred from field data analysis and, as a consequence, hydraulic heads, velocity components and solute trajectories also become stochastic variables.

In the past, a great deal of attention was paid to linear stochastic theory (e.g., Dagan 1984, 1989; Rubin 1991, 2003). In this case, the log-conductivity field is approximated by its first-order perturbation expansion and it is inserted into the continuity equation and Darcy's law. According to some hypotheses on the flow and the domain size, linear theory is able to provide analytical expressions for the first and second statistical moments of local variables (e.g. log-conductivity, head fluctuations, flow velocity components, whose values only depend on their location in the space) and transport variables (trajectory fluctuations, spatial moments of the plume) that depend on the entire transport process. The adoption of the first-order perturbation expression would limit the applicability of the linear theory to low levels of transmissivity heterogeneity, i.e., the log-conductivity variance should be less than one. Nevertheless, numerical and analytical studies (e.g., Bellin 1992; Hsu et al. 1996; Dagan et al. 2003) have shown that a linear theory can be applied to higher heterogeneity levels, because of the balance of higher-order terms. The increased range of applicability of the linear theory has drawn attention to the possibility of examining the properties of flow and transport, which had previously been investigated mainly through their statistical moments (e.g., Dagan 1984, 1989; Dagan and Neuman 1997; Rubin 2003).

Attention has also been paid to understanding the role of the higher-order terms that were omitted in linear theory approximations, and to the consequent nonlinear relationships between flow and transport variables (e.g., Dagan 1994; Hsu et al. 1996; Salandin and Fiorotto 1998). Hsu et al. (1996) developed second-order analytical expressions for fluid velocity covariance functions and for the covariance functions of trajectory fluctuations. They observed that the impact of second-order terms becomes appreciable in transport processes when the log-conductivity variance approaches two. Analyzing the frequency distributions of the velocity components and trajectory fluctuations and their values of the statistical moment, Salandin and Fiorotto (1998) clearly evidenced the effects of nonlinear terms in both flow and transport features.

As the effect of nonlinear terms increases with the heterogeneity level, several studies have been carried out on flow and transport in highly heterogeneous media (e.g., Dagan et al. 2003; Fiori et al. 2003; Jankovic et al. 2003; Gotovac et al. 2009; Meyer and Tchelepi 2010). These authors focused on the analysis of the probability density functions (pdfs) and the statistical moments of the characterizing quantities, such as the velocity components, trajectory fluctuations and travel time.

In this picture, the aim of the present work has been to draw attention to the nonlinear dependence that exists among some groundwater variables. Such a dependence can be relevant, even when the linear linkages are negligible, and it offers information that can be important in a number of problems, such as in conditioning techniques and inverse problems.

In order to shed light on the nonlinear linkages, cross-covariance functions have been analyzed and information theory tools (i.e., mutual information, Shannon 1948) have been applied. Mutual information tools capture nonlinear relationships, while cross-covariance functions only grasp the linear relationship

between variables. The analysis is performed by processing data obtained from Monte Carlo simulations. In this way, analytical expressions are not used for the covariance and cross-covariance functions, and the terms that are neglected in their derivation do not affect the analysis.

Information theory tools have been largely used in other fields, such as economics, biology, mathematics and geophysics (e.g., Islam and Sivakumar, 2002; Pluim et al, 2003; Leydesdorff et al., 2006; Donges et al., 2009; Kinney and Atwal, 2014). Information theory has already been used to deal with groundwater problems: for example, Woodbury and Ulrych (1993, 1996, 2000) successfully applied the principle of minimum relative entropy to forward probabilistic modelling and to recover the release history of a groundwater contaminant, while Kitanidis (1994) proposed the dilution index which is an adaptation of the entropy expression. Mishra et al. (2009) proposed the use of mutual information analysis as a global sensitivity analysis technique, instead of stepwise regression analysis. Gotovac et al. (2010) have recently applied the maximum entropy principle to obtain the complete characterization of the travel time pdf (probability density function). Zeng and Wu (2012) also applied mutual information to detect the most important uncertainty factors in groundwater levels for a specific case study. However, mutual information has never been adopted to detect the role of nonlinear components in groundwater transport processes.

2. Methods

The Bravis-Pearson index, ρ, is known as the linear correlation coefficient or Pearson correlation coefficient. It is a measure of the linear dependence of two random variables. Given two variables x and y, and assuming that N couples of (x_i, y_i), data are available, the linear correlation coefficient is defined as

$$\rho = \frac{Cov(x,y)}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 \sum_{i=1}^{N}\left(y_i - \bar{y}\right)^2}}, \tag{1}$$

where $Cov(x,y)$ is the covariance between x and y, σ_x and σ_y are the standard deviations of x and y, respectively, and $\bar{x}$ and $\bar{y}$ are the mean values.

Considering the Schwarz inequality $|Cov(x,y)| \leq \sigma_x \sigma_y$, it follows that $|\rho| \leq 1$: if $|\rho|=1$, a perfect linear relationship exists between x and y and the variables are fully correlated; instead, if $|\rho|=0$, the variables are not correlated. It is well known that a nil value of the linear correlation coefficient does not mean that the variables are independent of each other: in fact, there can be a nonlinear relationship that has not been captured by the linear correlation coefficient.

Entropy is a measure of the uncertainty of a system (Shannon, 1948). If x is a discrete random variable with pdf $p(x)$ and N data of x are available, its entropy is

$$H(x) = -\sum_{i=1}^{N} p\left(x_i\right) \ln p\left(x_i\right) \tag{2}$$

and if two random variables are considered, x and y with joint pdf $p(x,y)$, their joint entropy is given by

$$H(x,y) = -\sum_{j=1}^{N}\sum_{i=1}^{N} p\left(x_i, y_j\right) \ln p\left(x_i, y_j\right). \tag{3}$$

Considering that *x* and *y* can be dependent on each other, mutual entropy is defined. Mutual entropy between *x* and *y* represents the reduction in uncertainty of *y* as a result of the information on *x* (and *vice versa)*, and it is expressed as follows:

$$I(x,y) = H(x) + H(y) - H(x,y) = \sum_{i=1}^{N}\sum_{j=1}^{N} p\left(x_i, y_j\right) \ln \frac{p\left(x_i, y_j\right)}{p\left(x_i\right) p\left(y_j\right)}, \tag{4}$$

where it can be verified that $I(x,y) \geq 0$.

In mutual information analysis, two indicators are used to measure the dependence of two variables, the $\mathscr{U}$ uncertainty coefficient (Theil, 1972) and the *R* coefficient (Granger and Lin, 1994), namely

$$\mathscr{U}(x,y) = 2\frac{I(x,y)}{H(x)H(y)} \quad (0 \leq U \leq 1), \tag{5}$$

$$R(x,y) = \left\{1 - \exp\left[-2I(x,y)\right]\right\}^{1/2} \quad (0 \leq R \leq 1). \tag{6}$$

The $\mathscr{U}$ measure lies between 0 and 1: when the uncertainty coefficient is zero, it means that *x* and *y* are not dependent on each other; if its value is unitary, the knowledge of *x* is able to completely predict *y*, and the opposite is also true, i.e., a one-to one relationship exists between *x* and *y*. Similarly, if *R* is zero, *x* and *y* are independent, while *R* is equal to one when there is an exact (linear or nonlinear) dependence relationship between *x* and *y*.

It can also be verified (Cover and Thomas, 1991) that when the bivariate distribution $p(x,y)$ of *x* and *y* is Gaussian then

$$R(x,y) = \left|\rho(x,y)\right|. \tag{7}$$

Property (7) makes use of the *R* indicator particularly interesting to investigate the linear/nonlinear relationship between two variables when one variable has a Gaussian pdf and the other one is presumed to be linearly related to the first one. In this case, if the *R* and ρ values are identical, the relationship is purely linear, otherwise their displacement is a proxy of nonlinear terms in the relationship between the variables. Variables that deviate from Gaussianity are also considered in the present manuscript. In order to compare *R* and $|\rho|$, we selected cases where either at least one variable is Gaussian or the correlation coefficient is almost nil. In the first case, as only one of the two variables is Gaussian, R-$|\rho|$ being different from zero implies that the other variable is not a pure linear function of *x*. In the second case, an approximately zero value of $|\rho|$ entails that the whole dependence embedded in *R* can be ascribed to nonlinear dependencies, regardless of the pdf of the variables.

It can also be observed that both *R* and $|\rho|$ varies from 0 and 1, and typical values of *R*=0.6-0.7 mark a strong association between the variables (e.g., Mishra et al. 2009), while $|\rho|$=0.6-0.7 means an important correlation (i.e., linear dependence). In the same way, *R*=0.2-0.3 marks a weak association between

variables, while $|\rho|$=0.2-0.3 means a weak correlation (i.e., linear dependence). Therefore, R-$|\rho|$ seems to be significant when it is greater than 0.3-0.4, namely when R and $|\rho|$ clearly describe a different degree of association.

3. Problem statement

In this work, flow and transport phenomena have been considered through heterogeneous porous media. A simple flow scheme is proposed, where the source of non-linearity is easily controlled by the log-transmissivity heterogeneity level. Two-dimensional confined aquifers, without recharging, are considered: the boundary conditions are constant in time and produce a flow that develops in the $\{x_1, x_2\}$ plane (see Fig. 1): the beds of the confined aquifer are plane and parallel (the thickness, B, of the aquifer is constant), one of the principal anisotropy directions, x_3, is orthogonal to the confining beds and the hydraulic head gradient in the $\{x_1, x_2\}$ plane does not depend on x_3 (e.g., de Marsily 1981). Heterogeneity is due to spatial variations of transmissivity, while the effective porosity is considered to be constant.

The approach to the problem is stochastic: transmissivity is a spatial random function with statistical features that are inferred from the data. The aquifer is considered a realization of an ensemble of statistically equivalent aquifers.

The velocity field and the hydraulic head field are related to the transmissivity field through Darcy's law and the continuity equation

$$U_i(\mathbf{x}) = \frac{1}{nB}\sum_{j=1}^{2}\left(T_{ij}(\mathbf{x})J_j(\mathbf{x})\right) \quad i=1,2\,, \tag{8}$$

$$\nabla\cdot\left(\mathbf{T}\nabla H\right)=0\,, \tag{9}$$

where U_i is the seepage velocity component (i=1,2), n is the effective porosity, $\boldsymbol{J}(\mathbf{x})$ is the hydraulic head gradient, T_{ij} is the point value of the transmissivity tensor $\mathbf{T}$ and H is the hydraulic head.

Because of the stochasticity of transmissivity, the velocity components and hydraulic heads are also stochastic. In each realization, the value of a variable at a given point is characterized by a fluctuation value: $v_i(\mathbf{x})=U_i(\mathbf{x})-\langle U_i(\mathbf{x})\rangle$, where $v_i(\mathbf{x})$ is the velocity component fluctuation in direction i (i=1,2), $U_i(\mathbf{x})$ is the velocity value at location $\mathbf{x}$ and the symbol < > denotes the ensemble mean operator; similarly, $h(\mathbf{x})=H(\mathbf{x})-\langle H(\mathbf{x})\rangle$ is the hydraulic head fluctuation.

Transport processes are affected by the stochasticity of the flow field. Considering the motion of a particle released into an aquifer at time t=0 in $\mathbf{x_0}$=(0,0), its location at time t — given by $\mathbf{X}(t)=\int_0^t \mathbf{U}\left(\mathbf{X}(t)\right)dt$ — is stochastic: the ensemble mean location has coordinates $\langle X_1(t)\rangle$ and $\langle X_2(t)\rangle$, along the x_1 and x_2 axes, respectively, and the trajectory fluctuations are given in each realization by $X'_1(t)= X_1(t)-\langle X_1(t)\rangle$ and $X'_2(t)= X_2(t)-\langle X_2(t)\rangle$.

In this work, in order to take advantage of eq.(7) and to detect nonlinearity, the log-transmissivity field, $Y(\mathbf{x})=\ln(T(\mathbf{x}))$, is assumed to be a stationary second order field with a multivariate normal (MVN) distribution, according to classic stochastic approaches (e.g., Delhomme 1979; Dagan 1984). As Y has an MVN pdf, if the flow and transport variables are linearly related to Y, they also have an MVN pdf and the bivariate distribution of these variables is normal: in this case, eq.(7) is verified and $R=|\rho|$. Instead, the non-equality between R and ρ values points out the presence of nonlinear terms in the relationships between the considered variables. The impact of nonlinear terms increases as the difference between R and ρ increases.

The numerical data processed in this work were obtained by means of Monte Carlo simulations of the transmissivity field. The numerical approach is the same as the one that was used in previous works (e.g., Butera et al. 2009; Butera and Soffia 2017). A brief description of the Monte Carlo set up is presented hereafter.

Two-dimensional heterogeneous transmissivity fields in the $\{x_1, x_2\}$ plane, which model confined aquifers with horizontal flow, were generated through the Fast Fourier Transform method (Gutjahr 1989). The log-transmissivity field, $Y(\mathbf{x})=\ln(T(\mathbf{x}))$, is assumed (i) to be a stationary second order field, (ii) to have an MVN pdf and (iii) to be characterized by an exponential covariance function $C_Y(\mathbf{x},\mathbf{x}')=\sigma_Y^2\exp(-r/\ell_Y)$, where $r=|\mathbf{x}-\mathbf{x}'|$ and ℓ_Y is the correlation length of log-transmissivity.

Since the impact of the nonlinear terms increases as the transmissivity field variance increases, two heterogeneity levels were considered — σ^2_Y=0.16 and σ^2_Y =2 — to reproduce weakly and mildly heterogeneous aquifers. The generated transmissivity fields had a square shape with a size equal to 42ℓ_Y and were subdivided into 252x252 blocks with a side size equal to ℓ_Y/6; a value of transmissivity was assigned to each block. If the ensemble mean of the velocity values is computed, the flow is uniform, it evolves along direction x_1 and it is obtained by assigning an impervious boundary condition to the northern and southern sides and fixed head values to the western and eastern sides (Fig.1).

Hydraulic heads, $H(\mathbf{x})$, were computed at the nodes of the transmissivity blocks, and eq. (9) was solved by means of the Galerkin finite element method. In order to avoid boundary effects, the external frame (with 6ℓ width) was no longer considered in the subsequent analysis of the local and transport variables. The transport simulation considered an instantaneous release of the solute from a point source: the particle trajectory was computed in the 0τ - 21τ interval, using the particle tracking method, where $\tau=t\langle U_1\rangle/\ell_Y$ is the dimensionless time and $\langle U_1\rangle$ is the ensemble mean velocity, which is uniform in space. In each realization, a particle was released into $\mathbf{x_0}$=(0,0), using the coordinate systems shown in Fig.1.

A total of 1500 realizations were performed for the smaller log-transmissivity variance and 3000 for the higher . The number of simulations was chosen to ensure the convergence of the second moments of both the velocity and trajectory components. The time step used in the particle tracking procedure is the

minimum between $\Delta\tau_1$ and $\Delta\tau_2$, where $\Delta\tau_1$=0.2*Δx/v1max (Δx is the grid side size, which is equal to ℓ_Y/6, and v1max is the maximum velocity value along direction 1 in the simulation) and $\Delta\tau_2=\tau-\tau_{rec}$ (τ_{rec} is the recording time).

Standard routines that implement eq. (1) were used to compute the linear correlation coefficients. Different estimators were applied to evaluate the mutual entropy from a data series (e.g., see Papana and Kugiumtzis 2008) and tested. The tests, which are not reported here, considered both noised linear series and noised nonlinear series; the latter were obtained using Henon and Mackey-Glass models. Four different estimators were implemented: the histogram method — i.e., eq. (4) was computed from the empirical $p(x)$ and $p(x,y)$, and the results were affected to a great extent by the choice of the binning — and those based on the k nearestneighbours, that is, the Kozachenko and Leonenko (1987) estimator and the Kraskov et al. (2004) estimator. The tests considered time series with up to 4000 elements and with a normal bivariate distribution: therefore, R was expected to be equal to $|\rho|$. The histogram method and the Kozachenko and Leonenko method gave the worst performances, as they resulted to be affected to a great extent by the series' number of the elements. The two algorithms proposed by Kraskov et al. (2004), which compute mutual entropy without using eq.(4), were found to be equivalent and produced better results when the free parameter was set equal to three. Accordingly, the second algorithm (i.e. I^2) proposed by Kraskov was used in the subsequent computations.

The R parameter was found to be very sensitive to I fluctuations (numerical error) close to zero. In order to smooth the spurious fluctuations of the R parameter in Figs. 2-4, a moving average was applied in some cases, paying attention not to affect the trend of the data. The size of the moving average window is specified in the figure captions.

4. Results and Discussion

The results obtained after processing the data of the Monte Carlo experiments are reported hereafter. The analysis considers both local variables (log-transmissivity, velocity and hydraulic head), whose fluctuations constitute spatial random functions, and non-local variables (i.e., trajectories), whose fluctuations at a given time are the result of a path through the heterogeneous field.

The behaviour of the absolute value of the linear correlation coefficient and parameter R is compared in Fig.2, which refers to the following local variables: $Y(\mathbf{x})$ (log-transmissivity), $v_1(\mathbf{x})$ (fluctuation of the longitudinal velocity component), $v_2(\mathbf{x})$ (fluctuation of the transversal velocity component) and $h(\mathbf{x})$ (hydraulic head fluctuation). The Y values in all the frames in Fig. 2 were measured in $\mathbf{x_0}$=(0,0), while the other variables were sampled at $\mathbf{x_i}=(x_i,0)$ locations, along the longitudinal axis and passing through the origin of the reference system (see Fig. 1).

Figs 2a and 2b refer to the relationship between log-transmissivity and hydraulic head for two heterogeneity levels. A good agreement between R and $|\rho|$ can be noted for both of the heterogeneity

levels. This agreement denotes the absence of significant nonlinear linkages between these variables, that is, up to σ^2_Y=2.0. *R* is below the correlation coefficient at some points; this is a numerical artefact that occurs for small *R* values, due to its high sensitivity to small errors in the computation of *I*. Figs 2c and 2d show the relationship between log-transmissivity and the longitudinal velocity component. A good agreement between *R* and $|\rho|$ can be noted for the smaller heterogeneity variance (Fig. 2c), which excludes the presence of important nonlinear relationships between those variables, while the agreement is not so good in Fig. 2d when *Y* and v_1 are at the same location, thus indicating that nonlinearity occurs.

Figs 2e and 2f are more interesting. It can be seen that while the correlation function is close to zero for almost every point, the *R* curve has a peak at zero, that is, when $Y(\mathbf{x})$ and $v_2(\mathbf{x})$ are measured at the same location, or at a short distance aligned along the flow direction, the dependence between the variables is fully nonlinear. This fact shows that, although the correlation function is zero, transversal velocity components depend on the *Y* fluctuations, which modify the flow field around it: the dependence is weak for σ^2_Y=0.16 (*R*=0.28), but is quite important for σ^2_Y=2.0 (*R*=0.59). It is worth noting that the nonlinear relationship denoted by *R* cannot be captured by higher-order analytical covariance functions, which could resemble the numerical covariance values.

The difference between *R* and $|\rho|$ shown in Figs. 2 denotes that even when the log-transmissivity field has been generated with a Gaussian pdf, the velocity components and hydraulic head appear to deviate from a Gaussian distribution. This fact is in agreement with the results of numerical analyses (e.g., Bellin et al. 1992, Salandin and Fiorotto 1998). The behaviour of the *R* parameter and the behaviour of the linear correlation coefficient are shown in Figs 3 and 4, considering the trajectory fluctuations (the non-local variable) and a local variable. Fig. 3 shows the relationship between the log-transmissivity fluctuations at $\mathbf{x}_0$=(0,0) (i.e. the solute injection point) and the trajectory fluctuations at a given time. The results for the largest heterogeneity level are shown only up to τ=8.4, because some particles exit from the numerical domain for larger times, and the trajectory statistics cannot be computed, as only the slower particles would be considered. The use of mutual-information-based tools for a higher heterogeneity level allows us to capture the presence and the importance of nonlinear relationships compared to linear ones. In fact, considering both X_1(t) and X_2(t), there is a rough agreement between *R* and $|\rho|$ for the lower heterogeneity level (Figs. 3a and 3c), while the *R* parameter is clearly above $|\rho|$ for the higher heterogeneity level (Figs. 3b and 3d). This is much more evident in Fig. 3d, which considers *Y*(0,0) and $X_2(\tau)$: although the correlation value is almost nil, *R* varies from 0.46 to 0.18, thus showing a moderate association between the variables for early travel times.

The presence of nonlinear terms is also evident in Fig 4, where selected cases are shown in order to depict the role of nonlinear dependences between velocity and trajectory fluctuation. Figs. 4a and 4b illustrate the behaviour of *R* and $|\rho|$ for v_2(0,0) and $X_1(\tau)$, while Figs. 4c and 4d show the behavior of *R* for v_1(0,0) and $X_2(\tau)$. In these cases, the correlation coefficient is almost nil, thus denoting the absence of any significant

linear relationships between the variables, while *R* is not nil, that is, all the relationships between the variables are nonlinear. The *R* value decreases with time, as expected, and it shows that there is a good association between the variables at an early time for the higher heterogeneity level, which is not captured by the correlation coefficient. The results shown in Fig. 4 suggest that nonlinearity plays a key role in the relationship between velocity and trajectory components, when different directions (v_1-X_2; v_2-X_1) are considered. These nonlinear dependences contain important information that can be useful to both understand the phenomena and to solve, for instance, conditioning and inverse problems.

5. Conclusions

In this work, information theory tools have been applied to draw attention to the presence of non-negligible nonlinear terms in the relationships between the flow and transport variables that take place in heterogeneous porous formations. The analysis was aimed at pointing out the nonlinear interdependence that exists between variables, and its weight with respect to the linear interdependence. Multi-Gaussian transmissivity fields were considered to take advantage of the relationship that exists between the mutual information *R* parameter and the correlation coefficient $|\rho|$ for normal bivariate distributions: in this case, linear and nonlinear contributions can clearly be identified. In order to protect the analysis from analytical approximation effects, numerical data from Monte Carlo experiments were used.

The obtained results show that nonlinear components can be relevant for mildly heterogeneous aquifers (σ^2_Y=2) and that the use of covariance/cross-covariance functions can be somewhat limiting to investigate the relationships that exist between groundwater variables and to manage field data. Nonlinear relationships are less important in weakly heterogeneous aquifers (σ^2_Y=0.16), but they show that, in some cases, variables with nil correlation coefficients are not independent.

The unsuitability of the covariance/cross-covariance functions to address nonlinearity can be extended to non-Gaussian transmissivity fields (Gomez-Hernandez and Wen 1998, Riva et al. 2017); however, in this case, a direct comparison of the mutual information *R* parameter and the correlation coefficient $|\rho|$ cannot be made.

According to the Authors, mutual information-based tools could be applied extensively in groundwater analyses in order to shed light on the nonlinear relationships that exist among groundwater variables. Such tools could improve the understanding of the subsurface flow and of transport phenomena and their forecasting, and could thus be used to support other statistical approaches, e.g. geostatistical methods that are based on covariance functions and which can only be applied in the case of linear relationships between variables.

Future developments of the research could include the impact of small deviations from Gaussianity on the *R*-$|\rho|$ metric, the effect of molecular diffusion, the role of the covariance structure of nonlinear dependence,

other nonlinearity sources (e.g., more complex flow fields), and methods to incorporate the information contained in nonlinear relationships in model developments and parameterizations.

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Figures

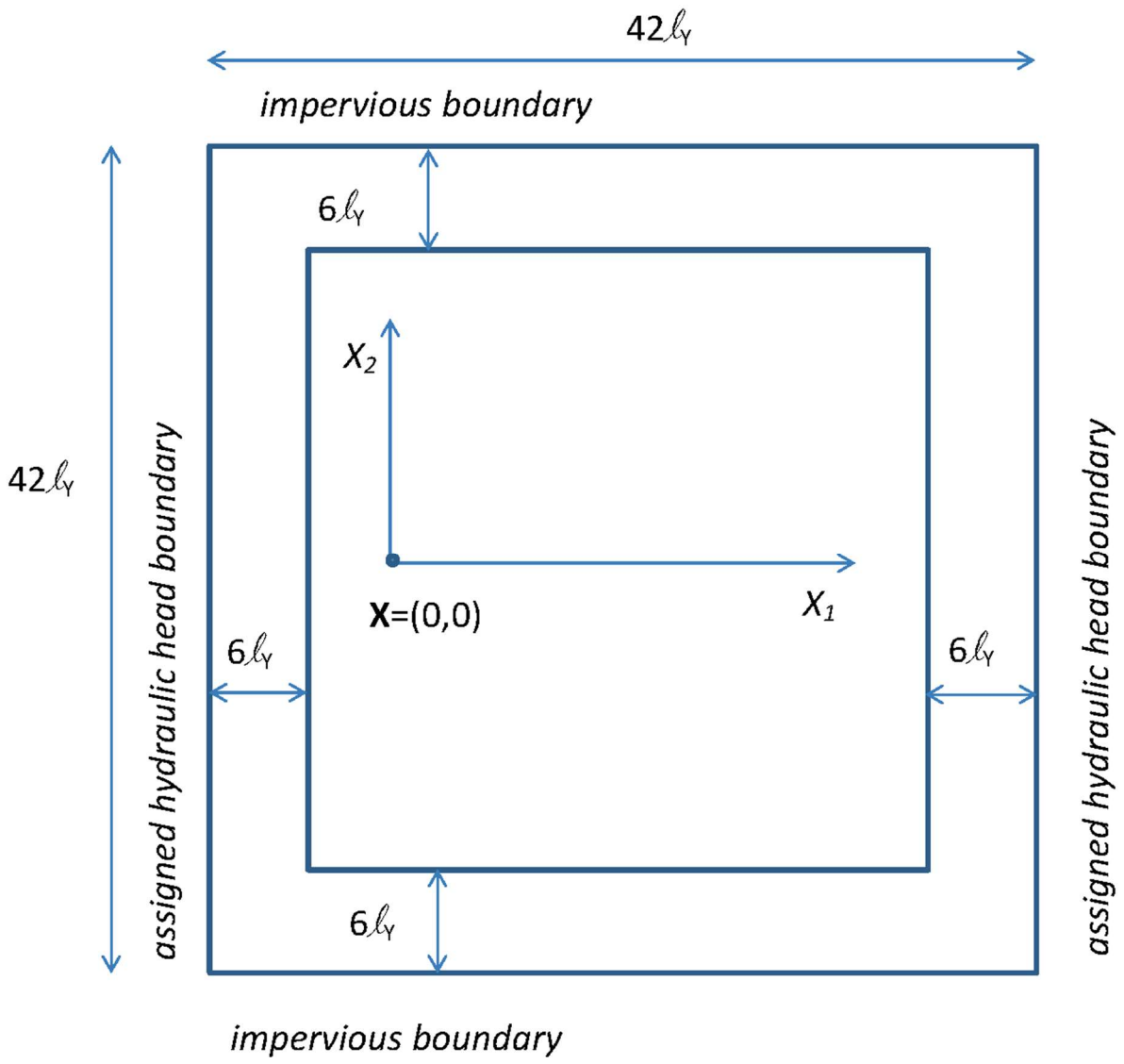

Fig.1. Sketch of the numerical domain.

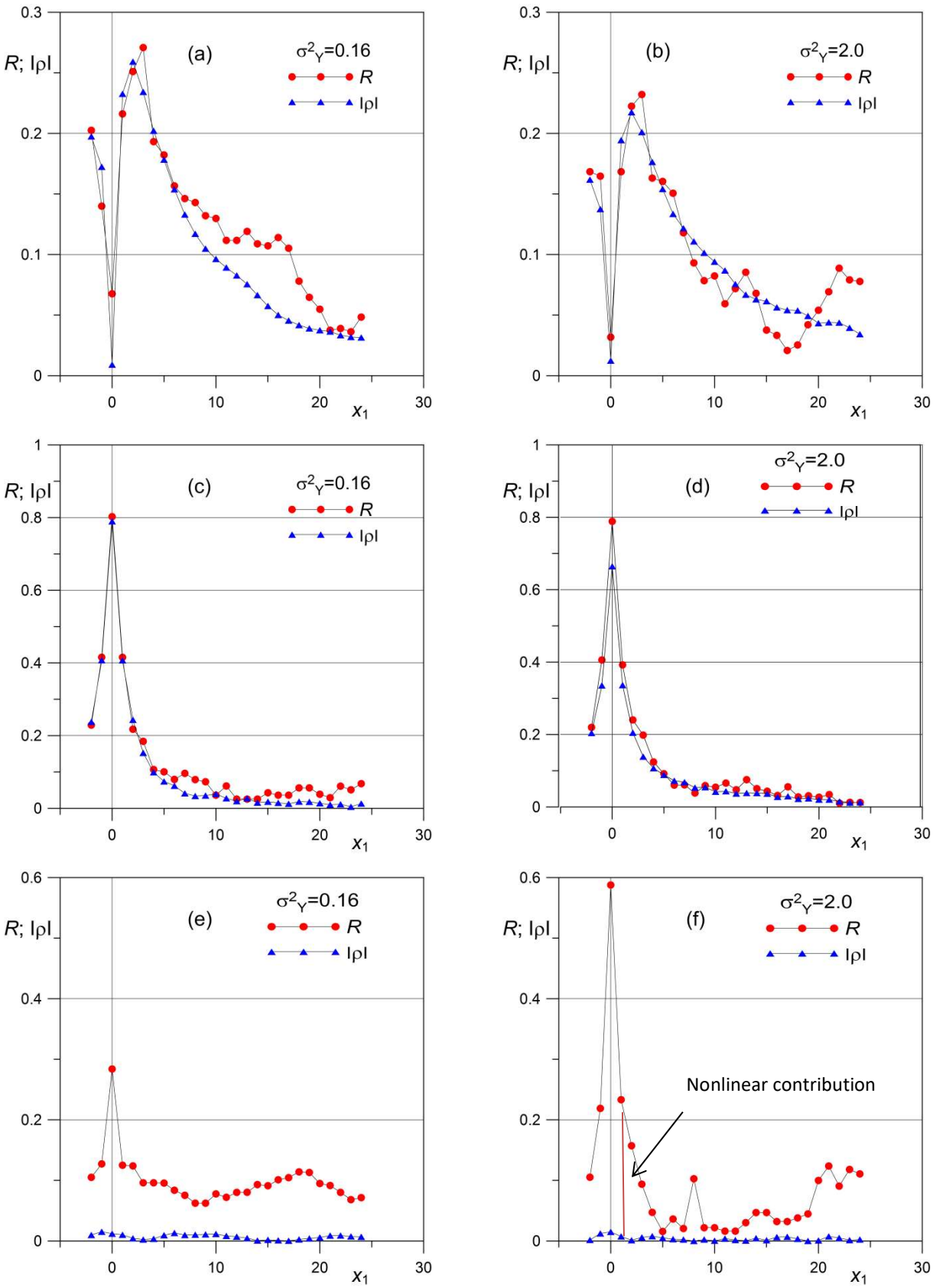

Fig. 2. R (circle) and $|\rho|$ (triangles) versus x_1, for different couples of variables. a) $Y(0,0)$-$H(x_1)$, σ^2_Y=0.16; b) $Y(0,0)$-$H_1(t)$, σ^2_Y=2.0; c) $Y(0,0)$-$v_1(x_1)$, σ^2_Y=0.16; d) $Y(0,0)$- $v_1(x_1)$, σ^2_Y=2.0; c) $Y(0,0)$- $v_2(x_1)$, σ^2_Y=0.16; d) $Y(0,0)$- $v_2(x_1)$, σ^2_Y=2.0 . The moving average window in the (a-b) panels is over five points for R<0.18 and x_1>0, while no moving average is applied to the (c-f) panels.

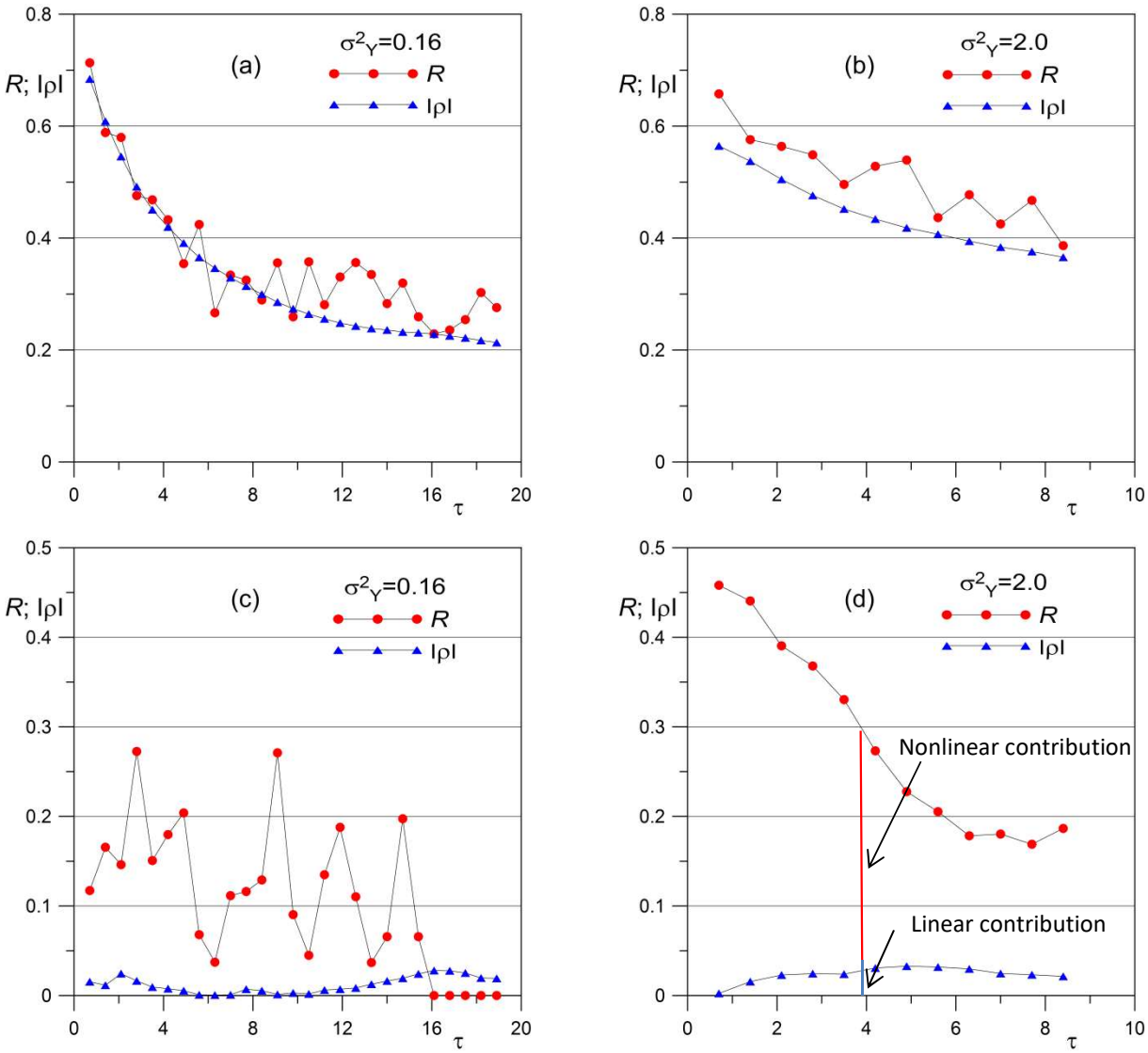

Fig. 3. *R* (circle) and $|\rho|$ (triangles) behaviour versus τ, for different couples of variables. a) $Y(0,0)$-$X_1(t)$, σ^2_Y=0.16; b) $Y(0,0)$-$X_1(t)$, σ^2_Y=2.0; c) $Y(0,0)$-$X_2(t)$, σ^2_Y=0.16; d) $Y(0,0)$-$X_2(t)$, σ^2_Y=2.0. The moving average window is over three points for R<0.25 in the (a,c) panels, while no moving average is applied to the (b,d) panels.

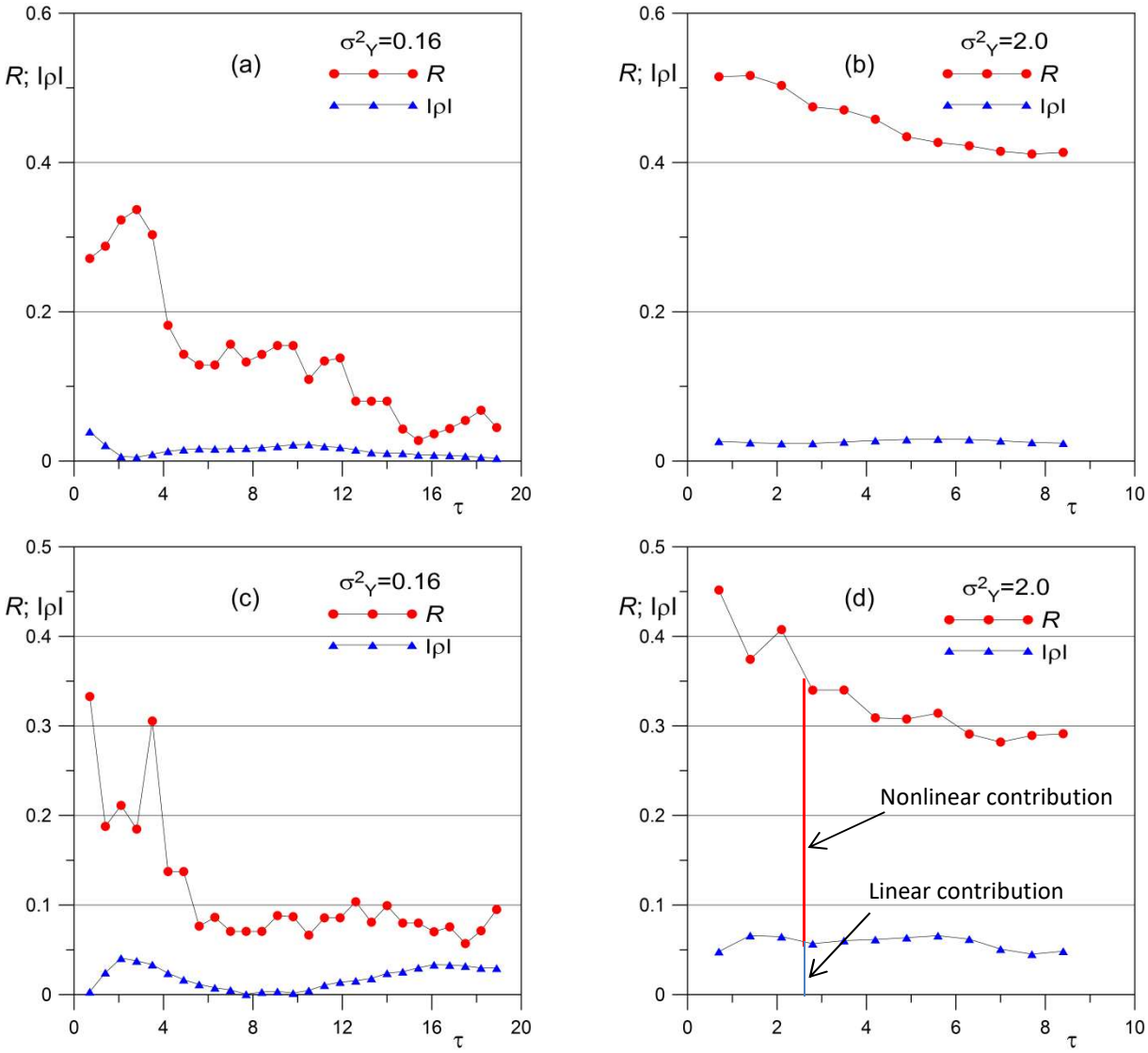

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Figure captions

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