Simultaneous use of hydrogeological and geophysical data for groundwater protection zone delineation by co-conditional stochastic simulations

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Protection zones, corresponding to particular isochrones, are foreseen in local regulations providing a time-related protection of groundwater sources or pumping wells. For example, in Walloon Region of Belgium, as in other regions, 'prevention zones' corresponding to the 1-day and 50-days isochrone contours must be delineated. In heterogeneous formations, numerical computational methods are often combined to geophysical and hydraulic tests data to obtain the most adequate perimeter. Recently, developments integrating conditioning procedures on hydraulic conductivity values (van Leeuwen et al., 2000), on head observations (Gomez-Hernandez et al., 1997; Vassolo et al., 1998; Feyen et al., 2001) and on additional data (Nunes and Ribeiro, 2000) have allowed to decrease prior uncertainty of hydraulic conductivity and therefore to reduce the uncertainty of the well protection zone.

A stochastic approach is used for an ideal fusion of hydraulic conductivity measurements with head observations and shallow electrical resistivity tomography results . For the purpose of the demonstration, a synthetic but realistic case was designed and the obtained results were presented and discussed previously (Rentier and Dassargues, 2002). Results discussed here are relative to a practical case study made of a pumping well in a gravel aquifer in the alluvial sediments of the river Meuse near the city of Dinant in Belgium. The 1-day and 50-days protection zones are calculated taking into account the uncertainty of the delineation.

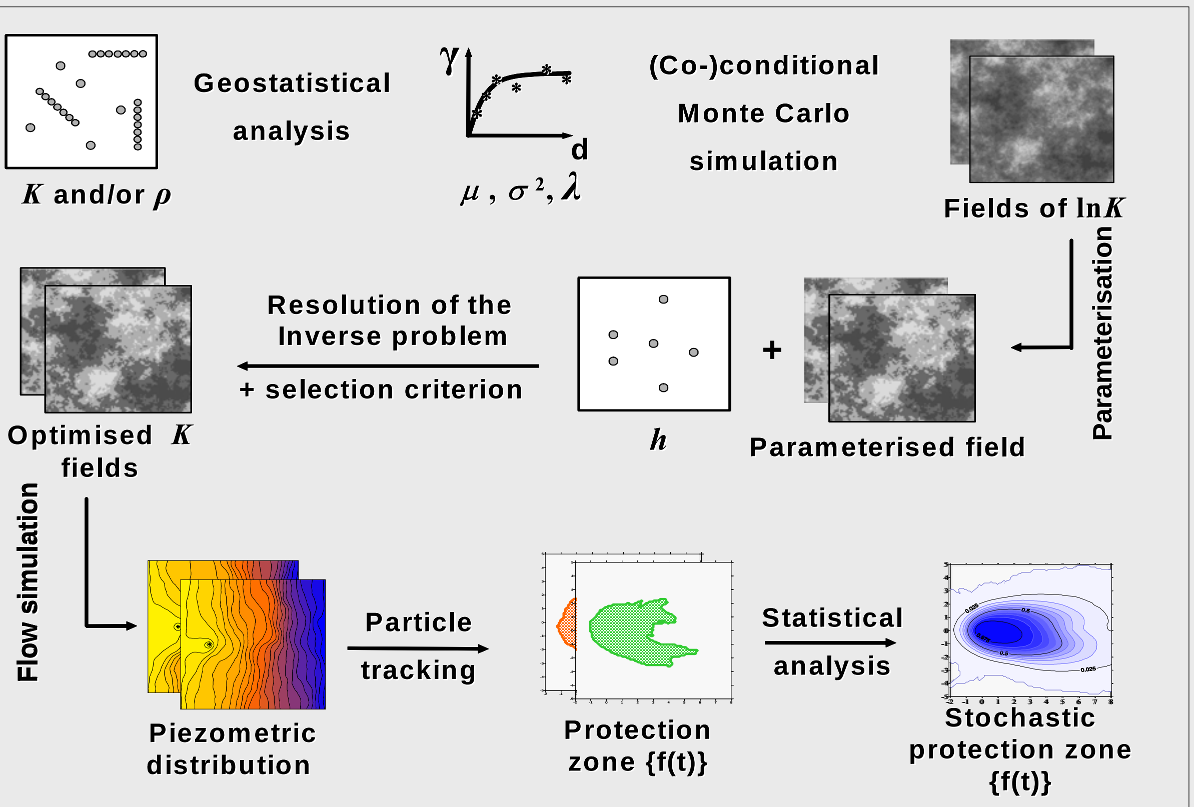
Methodology

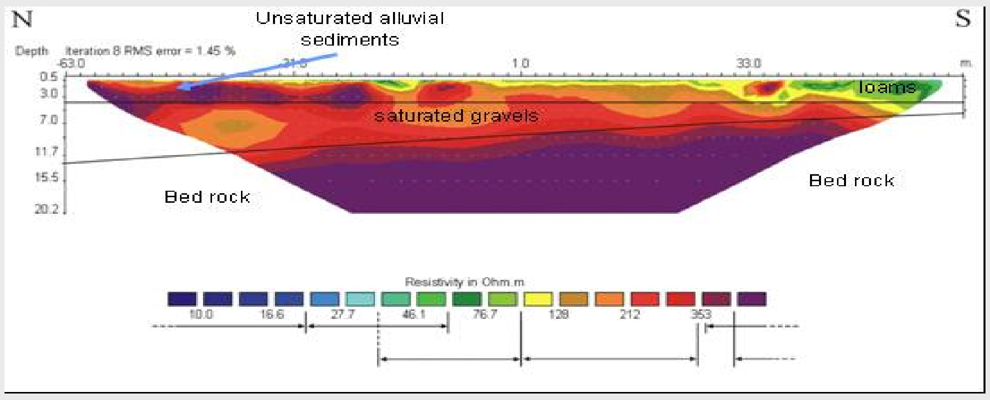
The stochastic methodology developed by Varljen & Shafer (1991) is applied but additional steps are added in order to condition on the other data like geophysical data and piezometric heads.

First, stochastic simulations of equiprobable hydraulic conductivity fields are generated and subsequently conditioned on the hydraulic conductivity measurements by a kriging technique.

Geophysical data are directly integrated in the generation process by co-conditioning the stochastic simulation on both hydraulic conductivity measurements and electrical resistivity values by a cokriging technique. In each cell of a 2D horizontal groundwater model, an equivalent value of electrical resistivity *(ρ)* of the gravels is used.

Another additional conditioning can also be obtained by calibrating the groundwater flow on head measurements (inverse modelling) for each simulated medium generated previously. For this particular step, resolution of the inverse problem requires usually a zonation of the domain and a parameterisation: reducing the number of adjustable parameters. Therefore a zonation is performed that consists, based on specified threshold values, in dividing the hydraulic conductivity variation interval in classes of uniform value, representing the adjustable parameters. The threshold values are defined by determining the best hydraulic conductivity data combination that minimizes the variability within each class (Rentier and Dassargues, 2002).





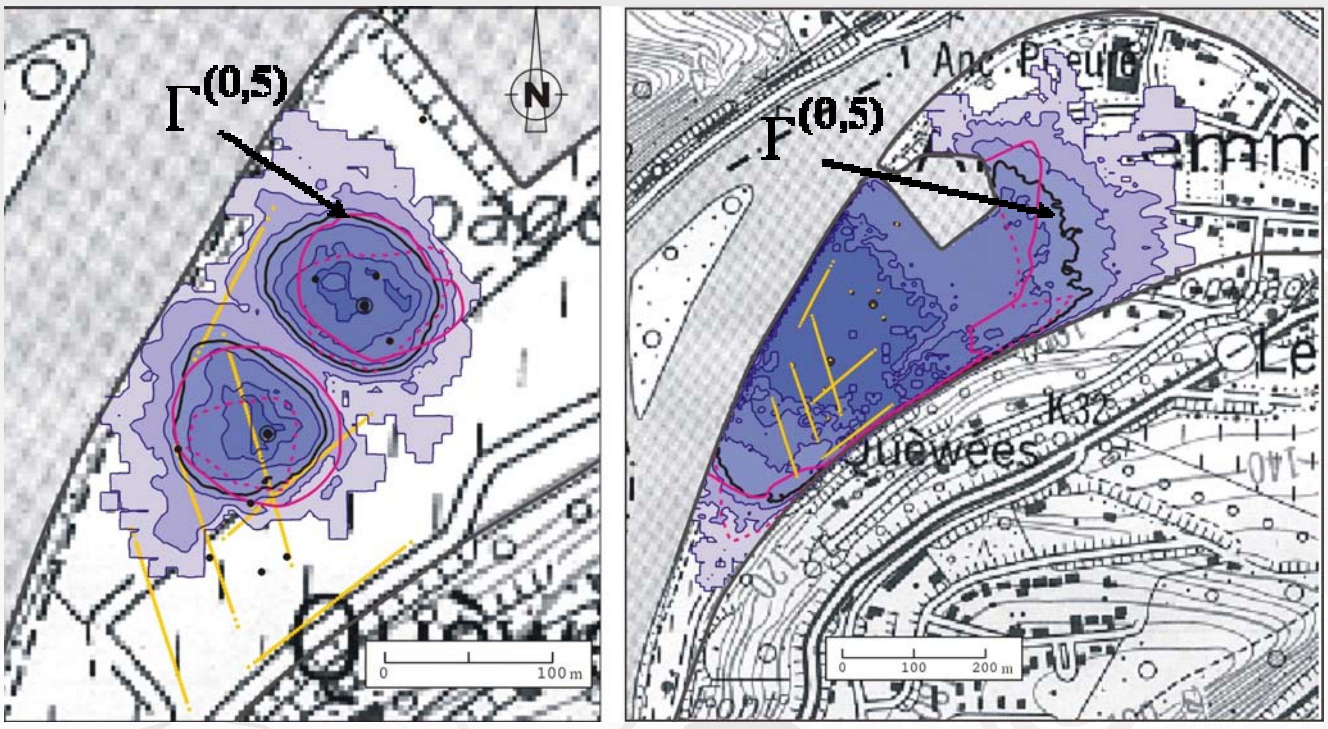
Then, the inverse procedure is applied to optimize the value of hydraulic conductivity in each class. Rentier (2003) has shown that provided the rejection of realisations not respecting the prior relative order KCi < KC(i+1), the spatial structure of the optimised remaining equiprobable media is not drastically disturbed by these parameterisation and inverse procedures.

Groundwater flow and a particle tracking process are then computed for each remaining realization. The ensemble of obtained capture zones is then treated statistically to infer the capture zone probability distribution (CaPD). This CaPD gives the spatial distribution of the probability that a conservative tracer particle released at a particular location is captured by the well within a specified time span (van Leeuwen, 2000), in this particular case, 1 day or 50 days.

Results and conclusions

Results for to the well capture zones corresponding to 1 day and 50 days are given for the practical case study located in the alluvial plain of the River Meuse. Location of the isoline Γ(0.5) for which 50% probability of capture is obtained can easily be compared to results from previous deterministic studies.

Advances in the delimitation of protection zones are made by fusion of direct and indirect available data through the use of conditional and co-conditional stochastic simulations. Introduction of additional available data decreases the prior uncertainty of the parameters and, in consequence, reduces the uncertainty of the well capture zone probability distribution (CaPD). This observation was demonstrated previously (Rentier and Dassargues, 2002). Since geophysical data and head observations are easier to collect on the field then hydraulic conductivity measurements, they are generally more abundant. Here, the methodology has been fruitfully tested on a real application to quantify the uncertainty in the location and extent of the well capture zones …when little or no information is available about the hydraulic properties. Conditioning on geophysical data and on head observations (through parameterisation and inverse procedures) allows to decrease the uncertainty of the delineated perimeters.



Spatial distribution of well capture zones of 24 hours (on the left) and 50 days (on the right). Isoline Γ(0.5) is compared to other contours from previous deterministic studies. CaPD values are given by the blue ranges from 95% (dark blue) to 5% (light blue).

From the presented case study, it is clear that including all available geological/hydrogeological/geophysical data in a conditional stochastic modelling procedure is advantageous for solving practical problems in geological media of high or low heterogeneity.

However, the co-conditional stochastic simulation methods, described here, assume that the geostatistical properties of each data-set are known from calculated (co-)variances and/or (co-)variograms. If these statistics are also unknown or partly unknown, a Bayesian framework can be used.