Geophysical Research Abstracts, Vol. 7, 07754, 2005
SRef-ID: 1607-7962/gra/EGU05-A-07754

REGULARIZATION AND MODEL-REDUCTION FOR INVERSE GROUNDWATER MODELLING

C.B.M. te Stroet (1), J.R. Valstrar (1), P.T.M. Vermeulen (2)

(1)Netherlands Institute of Applied Geosciences TNO, (2) Delft University of Technology, c.testroet@nitg.tno.nl

Inverse methods in groundwater flow and transport have been studied for some decades. There are two aspects that are distinguishing the different methods: 1.) the parameterization used, and 2.) the objective function that has to be minimised. Both aspects are dealing with regularization, i.e. making the problem (more) identifiable. Originally, the unknown parameter field (e.g. transmissivity) was zoned or seen as a constant unknown variable. With the development of geostatistics also geostatistical inverse methods became available that were able to condition random fields (RF). For transport problems parameterization as a RF can be important because of the direct influence of heterogeneity on flowlines.

Two methods that use a RF, and that will be explained in this presentation, are the Self Calibrating Method and the Representer method. The Representer method uses the cross-covariance between the RF and the dependent variable at a measurement location as a parameterization (the cross-covariance 'represents' the information that

is available in a measurement about the parameter at a certain location of the RF). It can be shown mathematically to be the optimal parameterization. In the objective function of the Representer method, not only deviations from the prior estimates and the measured heads/concentrations are penalised, but also a deviation from the model

equation (model error). It will be shown that the use of model error, although seldomly used, is also an important form of regularization.

During the last years very large scale models with a small grid size have to be calibrated. Our approach to solve the regularization problem then is then based on model reduction. First an ensemble of forward model simulations is generated in order to

approximately determine the covariance matrix of the model variability. By selecting a limited number of leading eigenvectors (EOF's) of this matrix a model sub space can be defined. By projecting the original model onto this sub space, an approximate linear reduced model is obtained. This projection requires as many forward model simulations as the dimension of the reduced space. Once this approximate linear reduced model is available, the adjoint of this model is available too and the minimization problem can be solved completely in reduced space with negligible computational costs. If necessary, the procedure can be repeated a number of times by generating new ensemble members close to the most recent estimate of the control function.

To explain the working of the different methods a simple hypothetical flow example is used to show the role of prior information, model error and the Monte Carlo approach vs. direct estimation of uncertainty. The applicability of the methods is further illustrated by some results of real-world studies.