Abstract

Accurate quantification of the geometric and hydraulic (K) properties of fracture zones (FZs) and their connectivity is crucial to the management of groundwater resources. The widely used porosity medium approach is inadequate to predict fracture transport processes due to the averaging of the sharp K contrast between the matrix and the FZs. Geophysics provide a viable opportunity for high-resolution imaging of spatially continuous properties of fractured systems.

Traditional geophysical imaging strategies, however, produce smoothed-out fracture features. A recently developed Markov random field (MRF)-based stochastic imaging produces geologically realistic sharp lithologic contrast. This strategy infers site-specific statistics from hydrogeophysical measurements and applies the calibrated statistics for reconstruction.

We present here the first field-scale application of the algorithm. We demonstrate the strategy with field-scale pumping tests and 2D cross-borehole electrical resistivity experiments. We show, from joint inversion of the hydrogeophysical measurements, that the strategy is able to accurately delineate non-smooth FZs and their connectivity with fairly good correlations with FZs identified from optical borehole images from the two wells.

Introduction

Application of hydrogeophysical inverse modeling is becoming increasingly indispensable in groundwater resource management. Fig. 1 presents a flow chart for the motivation for this research.

Field Experiments

The field experiments were performed at the University at Buffalo Environmental Geophysics Imaging Site (UBEGIS). The pumping test experiments were performed in two wells, Well 1 and Well 2.

Joint Inversion with Data Unconditioned GD Parameters

• The data-conditioned parameters were identified, their edges were poorly resolved.
• The standard deviation plot (Fig. 6) indicates that while data are well-resolved and FZs in and 2.0–22.0 m depths were identified, their edges were poorly resolved.
• There seems to be low FZ intensity from about 0–12 m with two main identified fractures in the area connecting the two wells.
• There appears to be a higher FZ intensity in well 2 compared to those in well 1, which corroborates the two fractures observed in well 2 in contrast to those associated with well 1 (Fig. 3).

Conclusion

• The preliminary results of the first field application of the MRF-based stochastic joint inversion to identify FZ and connectivity seem promising, with estimation of geologically realistic sharp matrix and FZ boundaries.
• While the data-unconditioned GD parameters poorly resolve FZ and connectivity, the performance of the data-conditioned GD parameters improved significantly with higher certainty associated with estimated FZs that are also identified in the OBIs.
• There is mis- or non-identification of some of the FZs identified in the OBIs, which is plausibly attributable to the inability of the 2D FZ model to fully explain the actual 3D pumping test response.

Future Research Direction

• Development of a 3D version of the algorithm.
• Development of a site-specific petrophysical model that accounts for surface conduction (high shale) to convert the updated K model directly into a resistivity model for the joint inversion.

Model Validation with Optical Borehole Images (OBIs)

A correlation of the estimated and OBI identified FZs (Fig. 9) reveal that, while not all the OBI identified FZs were estimated, estimated FZs that are also identified in the OBIs seem well resolved (Figs. 8 and 9).

Fig. 1: Motivation for the proposed work.

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Application of MRF-based Stochastic Joint Inversion of Transient Hydraulic Head and Electrical Resistivity Measurements to Identify 2D Fracture Zone Connectivity
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Gibs Energy Estimation

Potential Gibbs energy (Eq. 2) serves as a guide to searching for the minimal solution. The smaller the Gibbs energy the higher the likelihood and vice versa [Derin and Elliot, 1987].

\[ E = \sum_{i} \phi \left( k_{i} (u_{i}, k_{i}) \right) \]

where \( k_{i} \) is the centroid pixel value, \( k_{i} \) are the neighboring pixel positions, \( \phi \) is an indicator function that assesses how the pixels interest in a clique (Fig. 2), and the voronoi contains the GD parameters (spatial statistics) of the various clique configurations (Fig. 2).

Fig. 2: A 2D order neighborhood system and all possible clique configurations. The \( u_{i} \) and \( u_{i} \) represent the parameters of a Gibbs distribution (GD), which contains spatial statistics, like size, orientation, and clustering.

Fig. 3: shows the flow chart of the estimation algorithm, which involves a two-step simulation process. The Representative Hydraulic Conductivity (K) and Resistivity Values for Rock Matrix and Fracture Facies (Fig. 4) are generated on the basis of actual 3D pumping test response.

Fig. 4: Flow chart for modeling algorithm.

Modeling Methodology

Fig. 6: Pumping test and cross-borehole electrical resistivity setup.

Fig. 7: Sampling path of the OBI parameter estimation.

Fig. 8: Identities of fracture zone based on OBI and model replicates with OBI confined GD parameters.

Fig. 9: Estimated K field vs. OBI. OBI identified fracture zone (FZ) in the top right and the identified fracture zone (FZ) in the top right corner and features from about 9.5 m to 12 m in depths seem fairly resolved, the FZ identified in the OBIs were mostly poorly estimated.

Fig. 10: Estimated Mean K Field.

Results & Discussions

Motivation of Proposed Work

...led to the development of a new stochastic joint inversion approach based on the Markov Random Field (MRF) model, which has been shown to provide improved resolution and accuracy compared to traditional methods. The proposed workflow aims to optimize the recovery of fracture zones with OBIs...