An Assessment of the Impact of Geologic Heterogeneity on Predictions of Seawater Intrusion in Coastal Aquifers

Whitney J. Trainor[1], *R. Knight*[1] and *J. Caers*[2]
[1]Geophysics Department, Stanford University, Stanford, CA, USA
[2]Energy Resources Engineering, Stanford University, Stanford, CA, USA

INTRODUCTION

Coastal communities throughout the world are facing the threat of seawater intrusion due to extensive pumping of groundwater aquifers. A great need exists for water management strategies that can address these aquifer overdrafts. Effective groundwater management requires subsurface hydrogeologic models but also requires an assessment of the uncertainty of these models. How simple can the subsurface model be while still providing accurate predictions? The risks associated with poor predictions could justify the cost of collecting additional high quality data. The long-term goal of our research is to develop methodologies that quantify the value of information (VOI) derived from geophysical data for the benefit of water managers. The work presented in this paper represents an initial sensitivity analysis of the impact of geologic heterogeneity on predictions of the extent of seawater intrusion.

DECISION ANALYSIS METHOD

By developing a VOI methodology for geophysical data for water managers, we hope to build a tool that will address the question: 1) When are geophysical data worth the cost of acquiring? Modern decision theory has been developed to address questions of this nature. The general approach for this study is borrowed from a decision analysis procedure (Howard 1966). The reason for this approach is twofold. Firstly, decision analysis provides a probabilistic platform for engineers, scientists, managers and legal staff to communicate across expertise. And secondly, with decision analysis tools the “dollar value of uncertainty” can be assessed, thus providing a needed perspective on the cost of acquiring additional information.

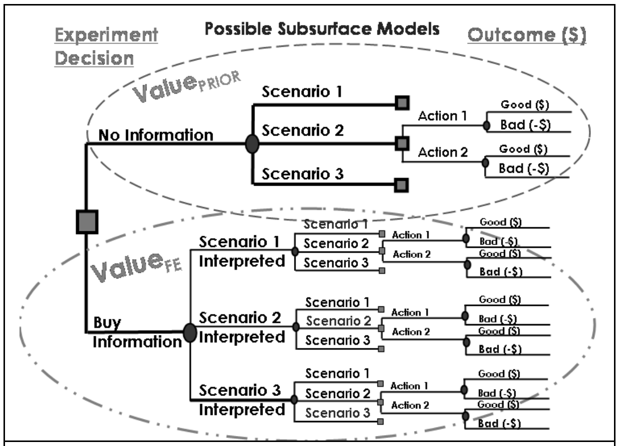

Figure 1. Decision Tree. Red: possibility nodes. Blue: decision node. Purple: Prior Value. Orange: Value with free experiment.

Decision analysis can be described in three phases: a sensitivity analysis, a probabilistic evaluation, and the postmortem analysis (Howard, 1966). In the sensitivity analysis, the decision, the profit function and the state variables all must be defined. The state variables are defined by testing which parameters affect the output (the profit function) the most. The uncertainty of each of these variables (that are deemed important in the sensitivity analysis) is evaluated in the stochastic phase. The postmortem phase evaluates whether the decision maker is comfortable with the level of uncertainty. Figure 1 demonstrates a decision tree, which is constructed using the information gathered in the first two phases. The blue square nodes of the tree represent the decisions to be made; red nodes represent the possibility nodes (some branches omitted due to space limitations). For our case, the key state variables are the possible scenarios of the subsurface. Therefore, in the stochastic phase, the probabilities gathered are assigned to each of the different subsurface scenarios. The purple dashed line encircles the information that was used to calculate the expected value of this decision without additional information.

Suppose the decision makers do not feel comfortable with the level of uncertainty regarding the outcomes of a decision and consequently decide to gather more information prior to making a decision. The bottom branches of Figure 1 (contained in the orange circle) demonstrate how interpreted geophysical information is treated as the additional information. The concept of the "value of information" (VOI) offers guidance on how the change in uncertainty should influence a decision. VOI is the expected gain in value after conditioning on the relevant new information, or the difference between the value after a free experiment (V_{FE}) and the value prior (V_{PRIOR}).

$$VOI = V_{FE} - V_{PRIOR}$$

Note that VOI is independent of the cost of information gathering (Eidsvik et al, 2007). If the VOI is greater than the cost of the experiment, then it is a sound decision to perform (purchase) the experiment.

SENSITIVITY ANALYSIS FOR A HYDROGEOLOGICAL PROBLEM

The goal of the first stage, the sensitivity analysis, is to determine which state variables affect the profit function the most. Modeling in subsequent stages will then focus on these variables. State variables and profit functions are straightforward for typical business problems. To demonstrate how a hydrogeologic problem can be framed in these terms, this study uses a hypothetical example of a coastal basin. In this example, we consider a scenario where the coastal aquifers are over-drafted due to a $250 million agricultural industry, which takes 90% of its water from the groundwater. This has resulted in seawater intrusion. We model a situation where the water managers have used artificial recharge to remediate some of the seawater intrusion. However, water managers question whether the costs of recharge are justified given the uncertainty of the heterogeneity of subsurface flow properties.

The key state variables in this study are the parameters that control seawater intrusion and artificial recharge: heterogeneity parameters such as the type of geologic depositional system present, the clay (flow-barrier) percentage, and clay spatial distribution. The two interpreted geologic depositional settings are fluvial and estuarine. Figure 2 displays the two different training images (TI) that were used to represent these depositional patterns and were used in the multiple-point geostatistical algorithm SNESIM (Strebelle, 2002) to generate subsurface models of clay and sand distribution (Figure 3). Thirty-six different facies realizations were generated and populated with permeability values ($1\text{x}10^3$mD for clay and $1\text{x}10^5$mD for sand).

In this study, reservoir flow simulation is a function that transforms the state variables of clay location and proportion into profit. Under the same pumping conditions, flow simulation is performed on each permeability model with the seawater modeled as a pressure-dependent boundary condition.

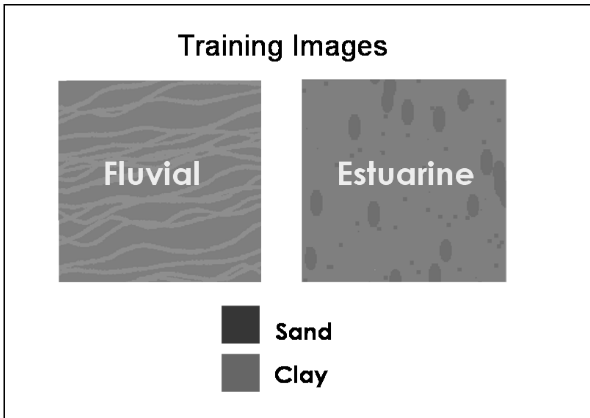

Figure 2. Training Images used in SNESIM algorithm

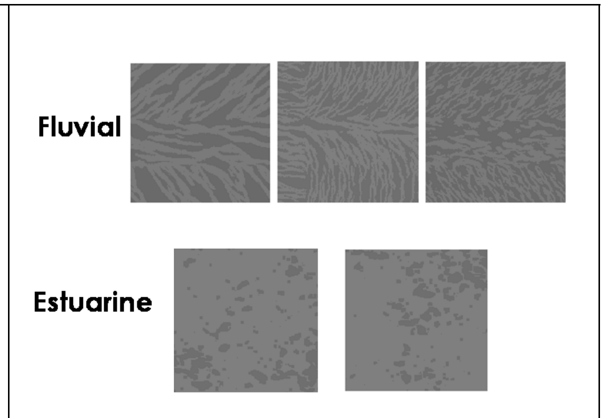

Figure 3. Example Realizations

SENSITIVITY ANALYSIS RESULTS

As described, the goal of the sensitivity analysis is to identify which state variables impact the profit function the most. The tornado charts, shown in Figures 4-6, display the input (either the TI or the channel connectivity) on the left and the output (the salt produced at the pumping wells) on the right. The salt produced at the well represents the revenue potential for each model. Figure 4 shows all models with 12% clay. The variance in the salt production for the models with 12% clay is almost 5 times greater for the fluvial models than the estuarine models. Variance is almost twice as great in models with 25% clay.

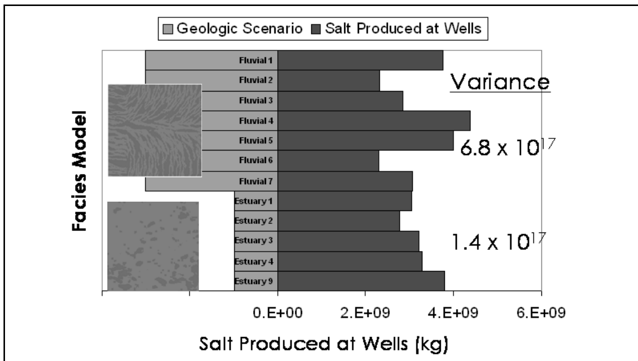

Figure 4. All models with 12% clay, top group from fluvial TI, bottom from Estuarine TI

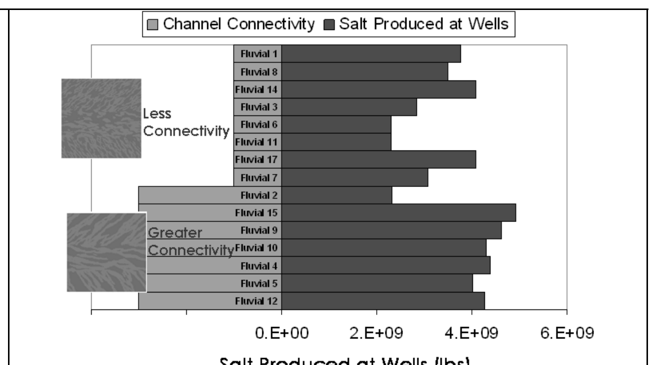

Figure 5. All Fluvial Models

Figure 5 shows the salt production results for all fluvial models, with the top group having less channel connectivity.

CONCLUSIONS AND FUTURE WORK

After performing the sensitivity analysis, it was found that the profit function was most sensitive to the fluvial training image, clay percentage and channel locations. Channel identification is critical in locating the preferential flow paths for seawater intrusion. Therefore, it will be these variables that will be included in the next stage, the stochastic phase, in the decision analysis framework.

Recall the expression for VOI: $VOI=V_{FE}-V_{prior}$. The prior value calculation reveals value without data. The posterior value is calculated using data. To initiate the stochastic phase, another set of multiple, equi-probable permeability realizations are used to represent the prior value. This time we consider the maximum value of four actions on each realization. Three of the actions will perform artificial recharge at 3 different locations. The last flow simulation will be performed without artificial recharge. The value of one flow result will be evaluated at time = 40 years:

$$V_{FE} = R \times \sum_{i=1}^{N} \phi_i (s_{fresh_i}) - C$$

where R is the revenue for the area of crop that could be grown by groundwater in gridblock *i* (if below a salinity threshold), N is the total number of gridblocks, ϕ_i is the porosity, and s_{fresh_i} represents the saturation of fresh water at gridblock *i*.

Location of preferential flowpaths is the key subsurface uncertainty that will determine the value of the subsurface model after a 40 year simulation. We will consider the use of airborne EM data to obtain information on lithology (clay or sand). Figure 6 displays the workflow for calculating flow models conditioned to geophysical data.

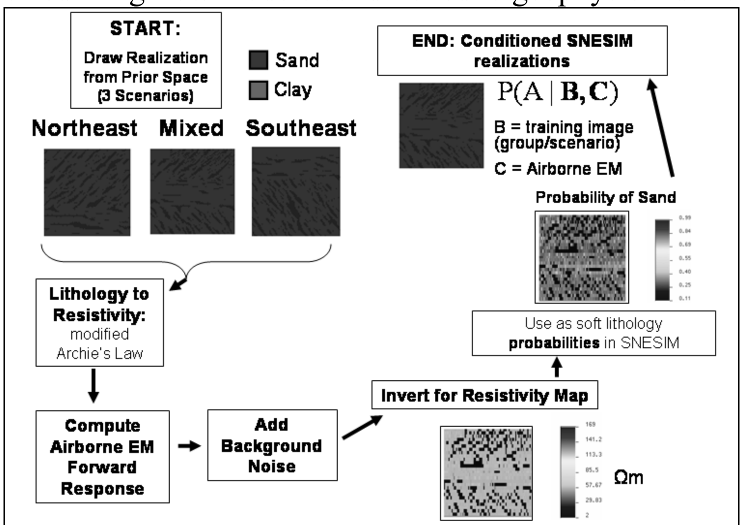

Figure 6. Workflow for conditioning lithology models to EM data

SNESIM realizations will use the inverted geophysical models as a soft probability for sand or clay locations. These SNESIM conditioned models are used to calculate $V_{FE.}$ Flow simulations will be performed using these models to find the maximum value of all 4 actions (described above), allowing us to calculated the total value with the free experiment. In the final step, the value of information will be calculated: VOI = $V_{FE} - V_{prior}$.

ACKOWLEDGMENTS

The authors would like to acknowledge the support of Schlumberger Water Services and the affiliates of Stanford Center for Reservoir Forecasting. Discussions with Tapan Mukerji and Debarun Bhattacharjya contributed to this work.

REFERENCES

Eidsvik, J., Bhattacharjya, D., and Mukerji, T. [2007] Estimating the value of information in spatial decision making for reservoir development, *Society of Exploration Geophysics Annual Meeting*, Expanded Abstracts, 26, pp. 1367-1371.

Howard, R.A. [1966] Decision analysis: applied decision theory, *Proceedings of the Fourth International Conference on Operational Research*, Wiley-Interscience, pp. 55-71.

Strebelle, S. [2002] Conditional simulation of complex geological structures using multiple-point statistics. *Mathematical Geology*, V. 34, No. 1, 1-26.

Contact Information: Whitney J. Trainor, Geophysics Dept., Stanford University, 397 Panama Mall, Stanford, CA 94305 USA, Phone: 650-575-8661; Fax: 650-725-7344, Email: wtrainor@stanford.edu