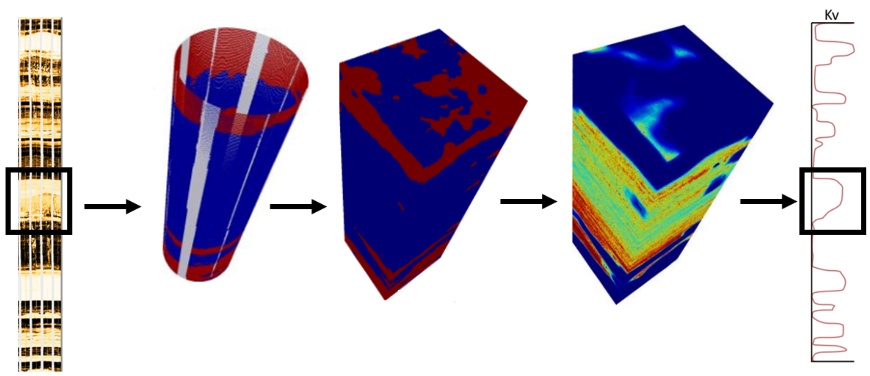
CCG Centre for Computational Geostatistics Solutions

Micro-modeling for Improved Permeability Estimates



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Prepared by Ryan M. Barnett

Summary

- Permeability data is freqently measured in a sparse manner that is unrepresentative of geology in the well bore. This leads to unrealistic permeability modeling of the subsurface, which leads in turn to inaccurate reservoir forecasting.
- Micromodeling utilizes core photos or microresisitivity logs to generate fine scale property models of the well bore that capture its geology. Flow simulation upscaling of these `micromodels' yields realistic permeability estimates that reflect the unique flow pathways and barriers that are observed in each well.
- The micromodeling workflow has been developed and refined in industry applications for nearly a decade. The workflow is fully automated so that entire resistivity logs or core image databases can be quickly processed, generating logs micromodeling derived permeability estimates.

1 The Setting

A critical property to model for virtually every petroleum project is permeability, K. Modeled K is a required input to flow simulation, which is necessary for reservoir forecasting. For example, consider the steam assisted gravity drainage (SAGD) (Denbina, 1998; Edmunds & Sugget, 1994) method that is used for the *insitu* production of bitumen in the Athabasca oil sands (Figure 1).

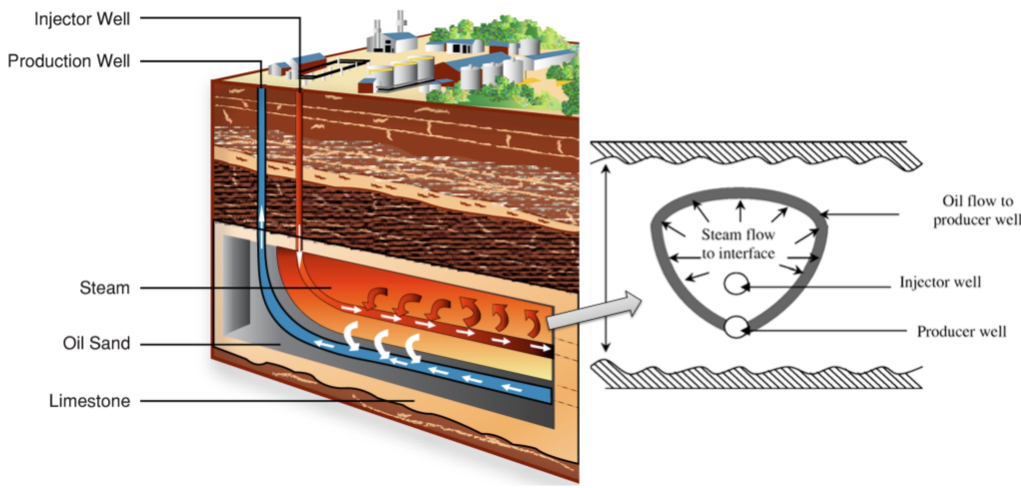

Figure 1: Schematic of the SAGD process, modified from Surmont (2016).

The flow simulation of a SAGD reservoir is particularly dependent on vertical permeability, K_v, which is the primary control on the ability of: i) steam to rise from the injector well to form an efficient steam chamber, and ii) heated oil to flow down to the production well.

As K is typically measured using core plugs or well-test data, it sampled far more sparsely than other variables that are modeled and used as input to flow simulation (Boisvert et al., 2012; Crain, 2015). Well logs such as gamma ray, density and resistivity are exhaustively measured along the well bore before being used to derive variables that include ϕ, water saturation (S_w), shale volume (V_{sh}), etc. Given that much more data is available for the densely sampled variables, a typical modeling workflow will follow these steps:

1. Model densely sampled variables such as ϕ, S_w, V_{sh}, etc. using conventional algorithms such as sequential Gaussian simulation (SGS) (Deutsch & Journel, 1998; Isaaks, 1990);
2. Use colocated measurements to infer a distribution of K conditional to ϕ, $F(K|\phi)$;
3. Apply a cloud transformation (Bashore et al., 1994) to generate stochastic models of K, where Monte Carlo simulation is used to draw from $F(K|\phi)$ using modeled ϕ for conditioning.

This workflow attempts to capture the uncertainty of K while reproducing the measured ϕ-K relationship.

2 The Problem

There are potential consequences to the described approach, including:

1. There is often a great deal of uncertainty in the $F(K|\phi)$ distribution due to the sparse sampling of K. This is particularly problematic since modeled K is based entirely on $F(K|\phi)$ through the cloud transform.
2. Core plug data is often taken preferentially from homogeneous sandy intervals. This occurs since samples from heterogeneous sand-mud intervals often deteriorate prior to lab testing (Boisvert et al., 2012). Although this may be corrected if well test data is available for calibration, this is impossible in oil sands since the viscous bitumen is immobile under insitu pressure and temperature conditions.
3. Even when core plugs are taken in a reasonably unbiased manner, the resulting K often remains unrepresentative of the entire core interval. Geological elements that are observed at the core scale impart distinct flow properties that may be difficult to capture with core plugs.

Expanding on problem (3), consider the stratigraphic architecture of the Athabasca oil sands reservoir. A significant portion of the oil sands resource is hosted in inclined heterolithic stratification (IHS) (Thomas et al., 1998). IHS are formed by the lateral growth of tidal point bars, resulting in decimetre to metre-thick interbedded sets of sand and mud. Figure 3 presents a conceptual schematic of the IHS depositional environment [modified from Hassanpour (2013)]; of particular interest to this discussion is:

1. Point bar sand, which has good reservoir properties such as high ϕ and K. This is the first component of IHS.
2. Mud that is interpedded with point bar sand is the second component of IHS. These mud drapes have poor ϕ and K; they therefore represent major flow barriers.
3. Breccia that is composed of mud clasts within a sand matrix. This facies found at the base of IHS successions due to the erosion of older point bars.

Recalling that K_v is critical to the SAGD process, consider that IHS intervals are anticipated to perform very differently than breccia. As indicated by core photos of the facies in Figure 3, breccia often provides vertical pathways for oil to flow down (and steam to rise), whereas IHS mud drapes typically form continuous flow barriers. Note that flow barriers are indicated in photos by the white-grey mud, whereas flow pathways are indicated by black bitumen saturated sands.

Obvious geological differences between the two displayed cores are anticipated to yield differing flow properties. Unbiased core plugs within homogeneous sections of sand and mud are unlikely to capture these geological differences, however, leading to similar permeability measurements. This will lead in turn to inaccurate permeability models, flow simulation and reservoir forecasting. Biased core plug sampling only exacerbates this issue.

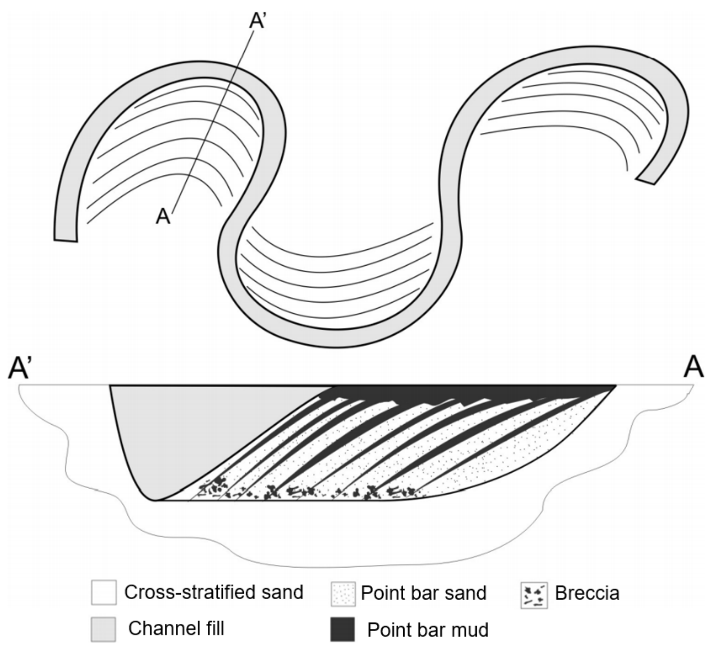

Figure 2: Architectural Elements of an estuarine system.

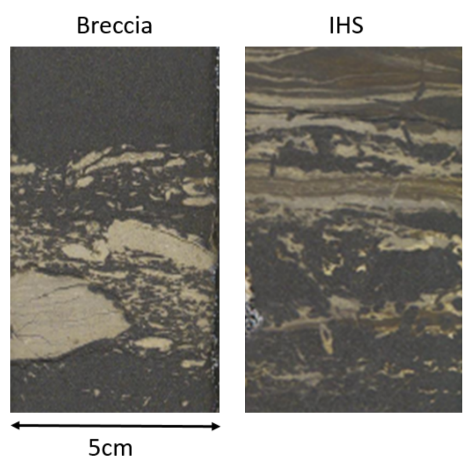

Figure 3: Oil sands core displaying breccia (left) and IHS (right) facies.

3 The Solution

To address the described issue, the CCG has developed and refined a method that is termed micro-modeling (Boisvert et al., 2012; Manchuk & Deutsch, 2014; Niven & Deutsch, 2009). Micromodeling uses high resolution images of the well geology, which is frequently available as core photographs or micro-resistivity images such as the Schlumberger Fullbore Formation MicroImager (FMI) logs (Schlumberger, 2013). The micromodeling workflow is summarized in Figure 4, where:

1. Each pixel (typically 0.5 to 2 square mm in width) of the FMI or core image is assigned a binary value that indicates whether it is sand (0) or mud (1). This assignment is based on thresholding the resistivity or color of the image, leading to sand and mud proportions that are calibrated to match measured well log properties such as V_{sh}. The indicator data is then transformed to 3D coordinates in preparation of micromodel conditioning.
2. The indicactor data is used to simulate a model of sand and mud that encapsulates the well bore. This simulation is performed at the resolution of the image data, and uses common geostatistical algorithms such as sequential indicator simulation (SIS) (Alabert, 1987; Deutsch, 2005) or multiple point statistics (MPS) (Strebelle, 2002).
3. Within the modeled sand and mud, use SGS to simulate continuous properties that are necessary for flow simulation, such as ϕ, V_{sh}, S_w, K_h and K_v.
4. Flow simulate to calculate the upscaled permeability at the well bore scale.

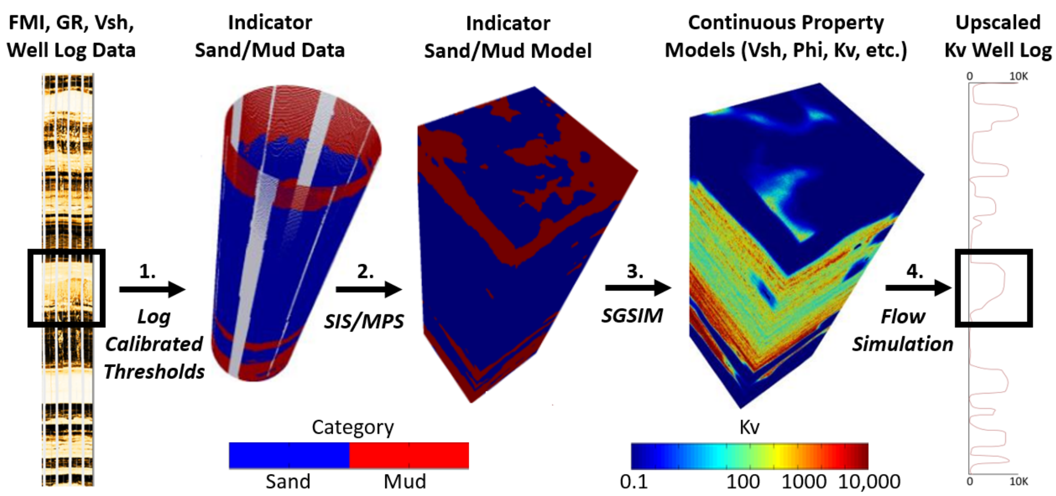

Figure 4: Overview of the micro-modeling process.

The micromodeling workflow has been developed and refined in industry applications for nearly a decade. The workflow is fully automated so that entire FMI or core image databases can be quickly processed, generating logs of micromodeling derived K_h and K_v. Practitioner time is only required for the initial setup, supervision of the workflow and validation of results. Following this workflow, permeability values can be modeled across the subsurface using the same approach as other densely sampled variables such as ϕ and V_{sh}. This leads in improved flow simulation and reservoir forecasting.

4 Distinct Permeability for Distinct Geology

The micromodeling workflow is demonstrated in greater detail using two different oil sands facies. These facies illustrate that the structure of geological elements are captured by micromodeling and transferred to realistic permeability estimates. As this data is taken from a SAGD project, the distinct K_v of each facies is critical to reservoir forecasting.

Categorical Assignment

An FMI image and core photo is displayed for intervals containing IHS and breccia facies in Figure 5 and Figure 6 respectively. The FMI is used as modeling data in this particular exercise, whereas the core photos are only presented for visual aid. Sand appears as light yellow to white in the FMI and black in the core photo (due to bitumen saturation). Conversely, mud appears brown-black in the FMI and grey in the core photo (lack of porosity prevents bitumen saturation).

The n pixels that comprise the FMI intervals are assigned a binary indicator value, m_i of 0 (sand) or 1 (mud) based on a threshold resistivity t:

$$m_i = \begin{cases} 0 \text{ if } r_i \geq t \text{ (Sand)} \\ 1 \text{ if } r_i < t \text{ (Mud)} \end{cases}$$

where r_i is the resistivity value of the i^{th} pixel. The value of t can be determined in several ways, although it is often calibrated to yield a sand-mud ratio that matches the average V_{sh} of the interval according to:

$$t = \arg\min \left(\left| \overline{V_{sh}} - 1/n \sum_{i=1}^{n} m_i \right| \right)$$

Note that the V_{sh} log of both the IHS and breccia intervals is represented by the yellow-grey (sand-mud) log that appears beside the FMI. Visual inspection of the vertical sand-mud (blue-red) proportions in the indicator data shows that it corresponds with the V_{sh} log that underlies its calibration.

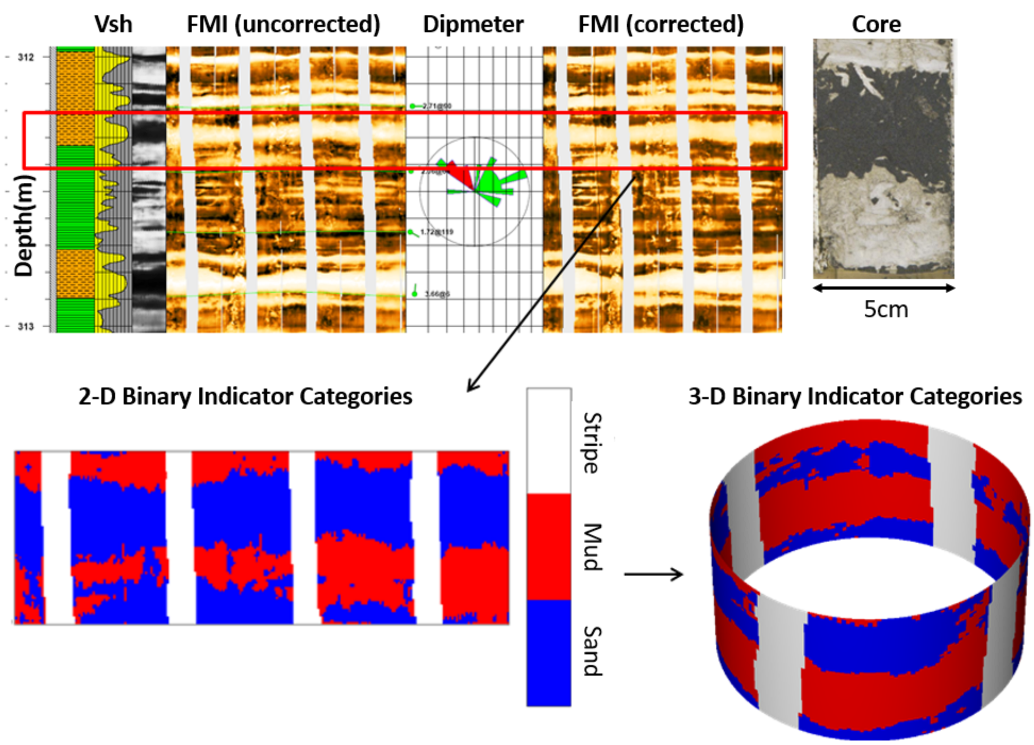

Figure 5: Assignment of sand and mud categories for an IHS interval.

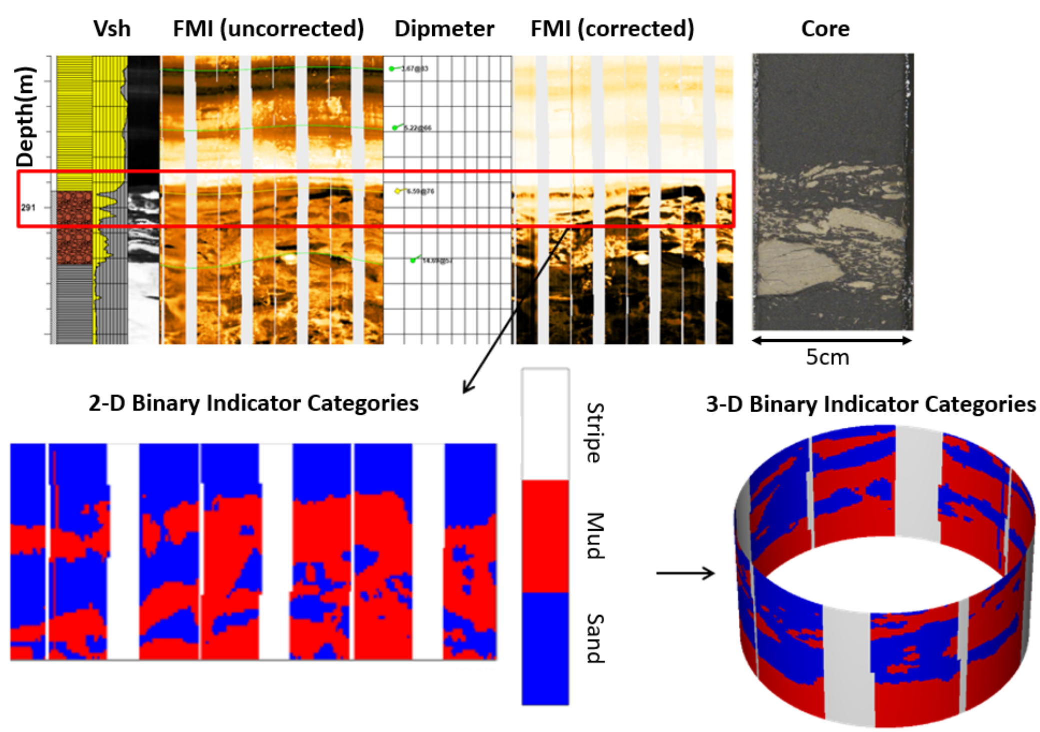

Figure 6: Assignment of sand and mud categories for a breccia interval.

Modeling and Flow Simulation

SIS is performed to generate the categorical models, where the target sand-mud proportions are based on the conditioning data. The categorical models should also reproduce the specific spatial structure of the data. This is accomplished by using variogram models that are fit to each interval. Experimental variograms are easily calculated using the dense and regularly spaced data that is available for each interval. The relatively continuous nature of sand and mud at this extremely fine scale leads to variogram shapes that can be reliably modeled by auto-fitting software (Deutsch, 2015; Larrondo et al., 2003). The automatic calculation and modeling of variograms is essential to automation of the micromodeling workflow. Similar measures are taken for workflows that use MPS in place of SIS.

SGS is performed next to model continuous properties that are required for subsequent flow simulation upscaling. This includes ϕ, V_{sh}, K_h and K_v, where the targeted histogram and variogram of each variable is based on their measured global properties in sand and mud. For example, micro-scale mud laminations in IHS sands lead to an average K_h-K_v ratio of ~0.8 (for this particular dataset).These laminations are largely absent from breccia sands, leading to its average K_h-K_v of ~1.0. For reasons that have been discussed, K data is not available for this dataset due to biased core plug sampling. Constant K_h and K_v values of 0.1 milli-Darcies (mD) are assigned to mud pixels as a result; this is considered a reasonable approximation.

Key modeling results are displayed for the IHS and breccia facies in Figure 7 and Figure 8 respectively. Note that only model cells with greater than 0.1 mD are displayed for the K_v models. This highlights the flow barriers that are expected to have a large impact on upscaled K_h and in particular, K_v. A 2D slice of the K_v model is provided for the breccia facies to more clearly display the vertical flow paths that still exist between the mud clasts. Flow simulation upscaling leads to the displayed permeability of each micromodel.

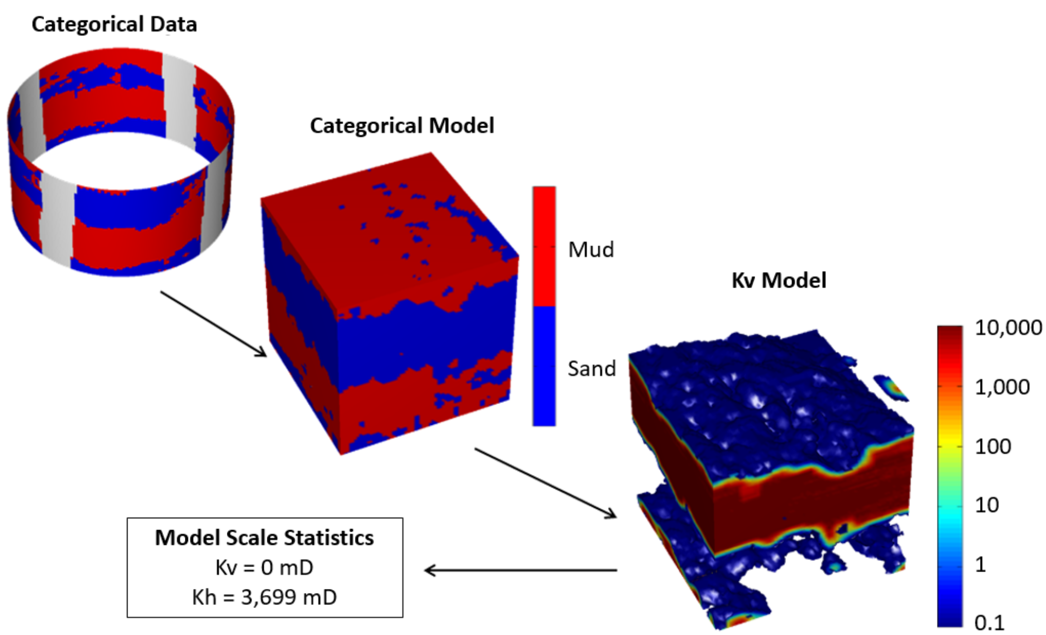

Figure 7: Micromodels and upscaled statistics for an IHS interval.

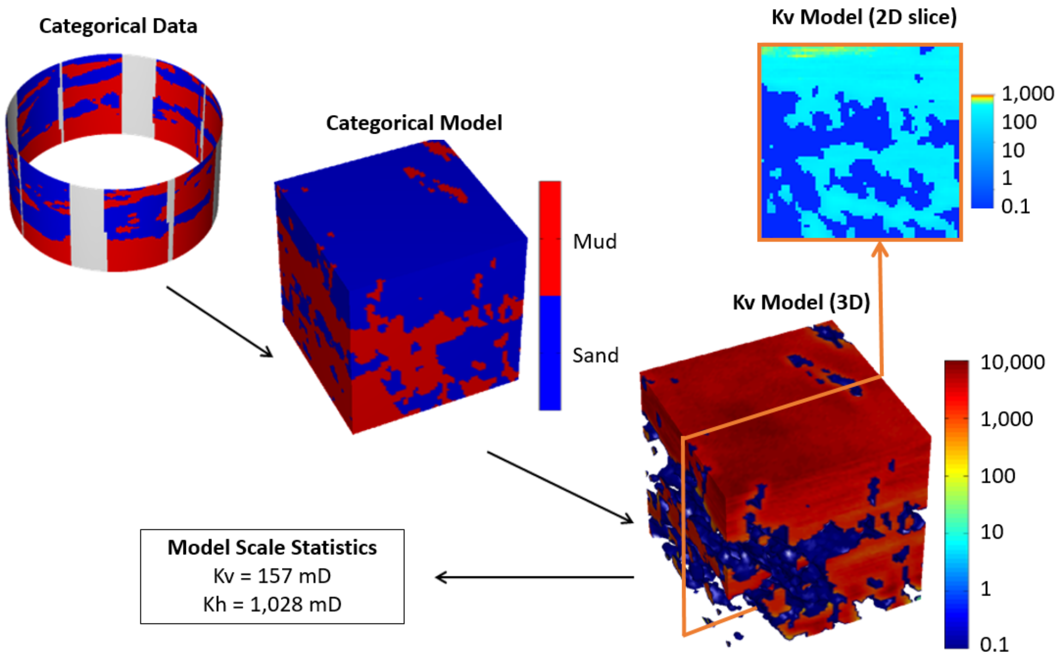

Figure 8: Micromodels and upscaled statistics for a breccia interval.

Discussion

As the mud layers of the IHS interval are relatively thick and continuous, they are interpretted to be representative of aerially extensive point bar mud drapes that were schematically illustrated in an earlier figure. These mud layers represent major flow barriers that would reduce K_v and consequently, the performance of the SAGD process.

The breccia interval consists of mud clasts that form discontinuous flow barriers relative to the IHS mud drapes. As a result, the K_v of breccia is much higher than that of IHS. Both of the selected intervals have similar proportions of sand and mud that could potentially measure similarly according to core plug analysis. The micromodeling workflow, however, has captured the geological differences between the two intervals, leading to markedly different K_v estimates. Subsequent modeling and flow simulation of SAGD reservoirs would therefore be more accurate with micromodeling derived permeability estimates.

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Who We Are

The CCG was launched by Professor Clayton V. Deutsch with the vision of becoming a leader in the education of geostatisticians and the delivery of geostatistical tools for modeling heterogeneity and uncertainty. The main objective of the CCG is to support the mutual needs of industry and academia in research and education. The benefits to industry include the opportunity to influence geostatistical research and education, interaction with students as potential employees, early access to publications and access to faculty members for discussions and presentations. The CCG provides a mechanism for industry to contribute to and sustain geostatistical research and teaching, which is of long term interest to many companies.

Contact Us

For more information regarding the demonstrated Solution or to discuss another problem that your project presents, please contact Professor Clayton V. Deutsch at: <cdeutsch@ualberta.ca>
Or drop by our offices at:

Centre for Computational Geostatistics
6-247 Donadeo Innovation Centre For Engineering
9211-116 Street, University of Alberta
Edmonton, Alberta, Canada T6G 1H9

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