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The Effect of Geologic Parameters and Uncertainties on Subsurface Flow: Deepwater Depositional Systems

William J. Milliken, Marjorie Levy, and Sebastien Strebelle, Chevron Energy Technology Company; and Ye Zhang University of Michigan

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Abstract

The application of reservoir simulation as a tool for reservoir development and management is widespread in the oil and gas industry. Moreover, it is recognized that the results of any reservoir simulation model are strongly influenced by the underlying geologic model. However, the direct relationship between geologic parameters and subsurface flow is obscure. In this paper we explore this relationship in a deepwater depositional system using data from two reservoir analogs: the shallow seismic dataset from the Mahakam Fan and outcrop data from the Brushy Canyon Formation of West Texas.

Shallow seismic data from the Mahakam Fan area shows a high-resolution deepwater channel-levee system consisting of 10 migrating channels. Using an experimental design framework and a series of three increasingly complex models, we investigated the effect of nine different geologic factors on several different measures of the flow behavior. Our results show that, as expected, different geologic factors influence different measures of the flow. Most significant is the clear effect that the proportion and organization of the different internal facies making up the channels have on the recovery factor and net oil production.

The Brushy Canyon outcrops used in this work represent sand-rich proximal deposits of a distributary lobe complex. Here we built models on a very small length scale to investigate the effects of sheet-like reservoir architecture as well as internal facies distribution of the sheets on subsurface flow. Again, an experimental design framework was employed, this time to examine the influence of 11 input variables. The proportion and organization of the internal lobe facies has a significant influence on the subsurface flow here but in these distributary lobe complexes other variables, including the stacking of the lobes, were also found to be important.

The models in this study address flow behavior in deepwater, sparse well environments. Using models from the simple to the complex, we found that several parameters incorporated in the complex models, and not in simple models, had a significant impact on the predicted flow.

Introduction

The use of reservoir modeling and simulation is common in the oil and gas industry. Indeed, virtually every major oil and gas reservoir is studied or managed using earth modeling and reservoir simulation. Nevertheless, the relationship between input geologic elements and subsurface flow is not generally obvious. The objective of this work is to examine this relationship in detail for deepwater depositional settings.

The link between geology and subsurface flow has been examined extensively in the literature. For example, Larue and co-workers[1-4] have looked at fluvial systems using both conceptual models and the Meren reservoir. They examined a large number of models in an effort to investigate the largest possible variety of geologic interpretations and found a very wide range of resulting behavior (200% variation in breakthrough time and a factor of two variation in oil recovery). They also established that less 'complex' models could be built and capture the full range of subsurface performance results in their study.

In another example, Jones and co-workers[5,6] looked at both low and high net-to-gross fluvial reservoirs. In their study of low net-to-gross reservoirs, the net-to-gross, stacking patterns, and channel dimensions were found to have a significant effect on the flow. For high net-to-gross reservoirs, they found permeability contrast was the most important.

In this study, we use the method of experimental designs and statistical analysis to examine the effects of different geologic factors (i.e., input parameters for the earth model) on subsurface flow behavior in deepwater reservoirs . The earth models are based on high-resolution shallow seismic data and outcrop studies. The models are built and simulated with a high degree of detail to allow a clearer understanding of the subsurface flow. To understand the subsurface flow, we look at several different flow measures including the saturation profiles in the models.

The terms ‘geologic elements’ and ‘geologic variables’ are chosen here to refer to the parameters describing and controlling the geologic model; these parameters are inputs to the earth models. Ideally, these are parameters that can be measured or inferred quantitatively based on available data. We are particularly interested in the effect of the distribution and organization of facies in the geologic model on the subsurface flow. As such, we examine the effect on flow of the parameters that describe and control facies distributions. However, we will examine a broad range of inputs (though certainly not exhaustive) including such things as the variogram correlation lengths, porosity/permeability transforms, and oil viscosity.

Subsurface flow measures

The performance metrics that control decisions in any reservoir depend upon the prevailing economic and political conditions. A proper evaluation of the flow results of any reservoir simulation must reflect those conditions. Just as performance metrics vary, there are various different measures that can be used to quantify subsurface flow. An effort to elucidate the effect of geologic parameters on subsurface flow can only be made when considering these various measures. It is quite possible that different input parameters are of principal significance to different measures of the flow.

There is a plethora of measures to evaluate and examine subsurface flow. These include the sweep efficiency curve, the ultimate recovery, the time to breakthrough of an injected fluid, the saturation profile at a particular time, etc. None of these measures are inherently better than the others. In any reservoir study, the measure (or measures) of interest is determined by the objectives and business drivers of that particular project.

In this study we chose to focus on three measures of subsurface flow: the Sweep Efficiency Curve, the Net Oil, and the Cumulative Recovery. The choice of these measures is not entirely arbitrary. Sweep Efficiency Curves, plots of fractional recovery of oil as a function of pore volumes injected, examine differences in model performance in a non-dimensional way; this choice removes some time and rate effects. Net Oil, or more specifically, net present oil or discounted oil, is a reflection of the time value of money and the fact that oil today is worth more than it is later in time. For Net Oil we use a discount factor of 10%/year. Cumulative oil, or ultimate recovery, or recovery factor after a certain time is a measure frequently used when the business driver is maximization of a resource. Each of these measures is imperfect but using more than one allows us to examine the different conclusions one may draw depending upon the objective of the project. In addition to the above mentioned measures we also look at the saturation distributions in the models.

In this study, the method of experimental designs is employed to choose models for construction and simulation. The various flow measures predicted by the experiments are then analyzed with statistical regression.[7-9] Because we are primarily interested in identifying the relative importance of various geologic factors on the selected subsurface flow measures, the Plackett-Burman screening design is used in most of our experiments. This methodology provides an efficient means to identify the parameters that have a first-order impact on flow.

The application of experimental designs relies on the appropriate choice of uncertainty variables and their ranges. Indeed, inaccurate conclusions may be drawn as a result of the use of inappropriate ranges for variables. In this study, we look at a broad range of geologic factors as model parameters. We choose ranges for these parameters after a careful review with a number of subject matter experts. After obtaining preliminary results, we review those ranges and in some cases change their values based on a better understanding of the problem.

This paper examines two depositional systems: the Mahakam Fan, a channelized system, and the Brushy Canyon, a deepwater sheet system; both systems are not actual reservoirs. Data for the Mahakam Fan are based on a high-resolution (shallow) seismic data set; the data for the Brushy Canyon are obtained from analyzing a large number of outcrops.

For the Mahakam models we also analyze the effects of the input geometric variables on the OOIP (Original Oil In Place). Many geologic parameters, for example the proportion of a particular facies, affect both the volume of oil in place and the subsurface flow; these effects cannot be separated.

In the next section we will describe the Mahakam Fan experiments followed by the Brushy Canyon. In each case, we describe the depositional system and the methods used to build the geologic models. Each model is simulated using streamline simulation; the details of the simulations will be described followed by the results.

Mahakam Fan

Geologic Description

In this first example, we look at the effects of geologic inputs on subsurface flow in the Pleistocene Mahakam Fan of the Kutei Basin. The sediments of the Mahakam Fan were deposited at the modern break of slope and consist of a sinuous, deepwater channel-levee system superimposed on an unconfined fan[11,12]. This system extends about 22 km into the basin and is about 22 km wide.

While deepwater depositional systems represent a very important oil-containing system today, there are few reservoirs that have been developed to sufficient maturity to make good candidates for investigating the interplay between geologic factors and subsurface flow. The Mahakam Fan does not contain hydrocarbons. However, because of its shallow location, the seismic data describing the Mahakam allows detailed identification of the individual channels in the system. With the channels identified, an examination of the effect of the internal channel structure and architecture on the subsurface flow can be undertaken. The Mahakam Fan thus provides an ideal data set for our analysis.

The models used in these experiments were built using Multi-Point Statistics (MPS). MPS is an innovative depositional facies modeling technique, developed by Chevron in collaboration with Stanford University. MPS uses 3D conceptual geological models as training images to integrate geological information into reservoir models. Replacing the traditional variogram with a training image allows MPS to capture complex spatial relationships between multiple facies, and to model non-linear shapes such as sinuous channels that conventional variogram-based modeling techniques typically fail to reproduce. In addition, because MPS is not an object-based, but still a pixel-based algorithm, MPS models can be constrained by very large numbers of wells as well as a 3D facies probability cube derived from seismic data or from reservoir facies deposition interpretation.[12,13]

For the Mahakam Fan three different 'groups' of models were built and tested; each group is described below. For each model the facies within the channel were simulated first using a new MPS training image tool. The porosity and permeability were populated on a facies by facies basis using, for porosity, Gaussian sequential simulation conditioned to an external histogram, and for permeability, co-located co-kriging. A deepwater Nigerian dataset was used to provide histogram input for porosity and permeability.

Three Groups of Models

Three different groups of models of increasing complexity were used in this study (see Figure 1). In the first case ('Group #1') the channels are modeled using a simple two-facies model (a reservoir/no-reservoir or RNR model). In this case the channel is filled with sand except in those locations occupied by a stochastically-distributed debris facies. In the second case ('Group #2') the internal architecture of the channel is modeled using five different facies: a massive sand channel axis, an interbedded sand-shale channel margin, a mudclast conglomerate on the bottom of the channel, surrounding silt drapes, and again the debris flow as in group #1. This second group of models is clearly much more complex than the first and incorporates the internal stratigraphic architecture of the channel.

The third group ('Group #3') of models adds an overlying abandonment facies to the channels and uses a much more reasonable shape for the channels. By examining the performance of each of these three sets of models, we can study both the influence of the different channel components on the subsurface flow and address the importance of including these internal facies components.

Figure 1: Three groups of models for the channels. Group #1 has only two facies: channel (yellow) and debris (gray). Group #2 has five facies comprising the channel: massive sand (yellow), interbedded sand (orange), mudclast conglomerate (red), silt drape (aqua) and debris flow (gray). Group #3 exhibits a more reasonable channel shape along with the addition of one new facies: an abandonment facies (green).

Simulation methodology

Limitations on simulation speed and memory requirements constrain most practical finite difference reservoir simulation models to a few hundred thousand cells (though the emergence of computer clusters and parallel simulation is changing that limitation). This limitation on cell number frequently requires that simulation models are built using rather large cells: typically hundreds of meters on a side and at least several feet thick.

One of the objectives of this study is to explore the effect of the internal architecture of the channels on the subsurface flow. In order to adequately resolve the channels and their internal facies distribution we used cells with an average areal dimension of about 80 feet and an average thickness of about 10 feet. These grid sizes, while small for simulation, are still a bit large given the dimensions of the channels. With these cell dimensions, the Mahakam Fan models are 398x198x44 for a total of 3.46 million cells; a bit large for finite difference simulation.

To resolve this dilemma, fluid flow simulation for each geologic model is performed using the FrontSim streamline simulator. Streamline simulators have advantages and disadvantages compared to finite difference simulators. The principal advantage of streamline simulation is that much larger models can be simulated in a relative short period of time without having to scaleup the models. This feature meets the needs of this project very well. Using streamline simulation we are able to eliminate the need for scaleup, maintain small cell sizes, and are thus able to focus attention on the relationship between geology and subsurface flow.

However, streamline simulators also have disadvantages. The most notable disadvantage is that streamline simulators do not perform particularly well in three-phase flow. As a result, the simulations performed for this study all assume two-phase flow with waterflood injection from Day 1. This protocol for the simulation results in the reservoir pressure remaining above the oil bubble point at all times. This scenario is not different from that employed in many deep water reservoirs.

Each model of the Mahakam Fan was simulated under a waterflood condition with three injectors and six producers all of which came on line at the start of simulation (the equivalent of pre-drilled wells). The number of wells was chosen to approximate the number that would be economic, given the OOIP of the models, in a deepwater offshore location (the well locations are shown in Figure 2). The wells were placed on both bottom hole pressure and rate constraints with well shut-in being undertaken when economic limits (100 STB/D oil or 95% water cut) were reached. The wells were completed over the entire reservoir interval and run for 30 years. The physical properties for the oil, water, and rock were taken from a deepwater GOM property and thus represent that encountered in real deepwater reservoirs.

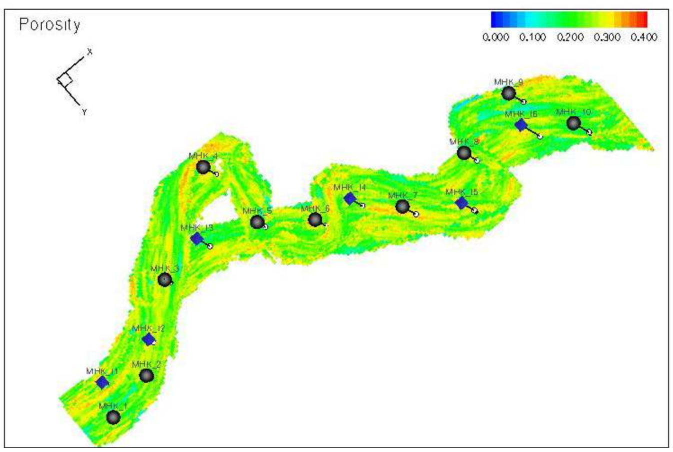


Figure 2: A top-down view of one of Mahakam Fan models. The circles indicate the locations of producers and the squares the locations of injectors.

Results for the Mahakam Fan

Group #1 Variables chosen for examination and range

For each group, a different (though related) set of uncertainty variables were chosen. For Group #1, the model consists of only two channel facies (the channel reservoir-quality sand and non-reservoir quality debris flow) plus a non-reservoir background facies. For this set of models four inputs were varied: the percentage of non-reservoir debris flow; the porosity-permeability histograms (a proxy for net-gross), the Kv/Kh ratio, and the degree of heterogeneity in the permeability (essentially the input permeability histogram).

Heterogeneity of the permeability has been linked to various measures of subsurface flow. There are numerous measures that can be used to quantify heterogeneity in a model each with their own pluses and minuses. For this study we use a Dykstra-Parsons (DP) coefficient.[14]

In this first group of models, the heterogeneity in the permeability histogram was increased or decreased using a simple algorithm that essentially increases (decreases) the higher permeability values and decreases (increases) the lower values resulting in a higher (lower) degree of heterogeneity as measured by the DP coefficient. This may not be the best way to vary the heterogeneity since it lacks any geologic underpinning. Indeed, the use of different populations of permeability with different characteristics is better. Moreover, heterogeneity of the permeability is affected by a variety of geologic inputs in addition to the permeability histogram (e.g., facies percentages and distributions). Thus, changing the heterogeneity in this ad hoc may be informative but is certainly limited in its application and generality.

The first group of models is very simple having only two facies. The variables that were investigated and their values used in the geologic model building and reservoir simulation are shown in Table 1 along with the results for OOIP and recovery after 30 years of production. The results in Table 1 show a significant two-fold variation in both OOIP and recovery after 30 years.

RUN	Debris Flow	ϕ–k	Kv/Kh	DP	OOIP (MMSTB)	Rf
1	20%	Low	0.01	High	4.98	31.3%
2	20%	High	0.01	Low	7.03	48.0%
3	20%	High	μ=0.17	Low	7.03	46.0%
4	40%	High	μ=0.17	High	5.30	44.4%
5	20%	Low	μ=0.17	High	4.98	32.1%
6	40%	High	0.01	High	5.30	45.8%
7	40%	Low	μ=0.17	Low	3.75	26.1%
8	40%	Low	0.01	Low	3.75	26.4%

Table 1: Plackett-Burman Experimental Design Table for the simulations done in Group #1. For the Kv/Kh ratio, a constant value of 0.01 was used for the low value while a variable Kv/Kh was used for the high value; the mean for the high Kv/Kh ratio was 0.17. The ϕ-k transform acts as a proxy for the net-to-gross (NTG) ratio.

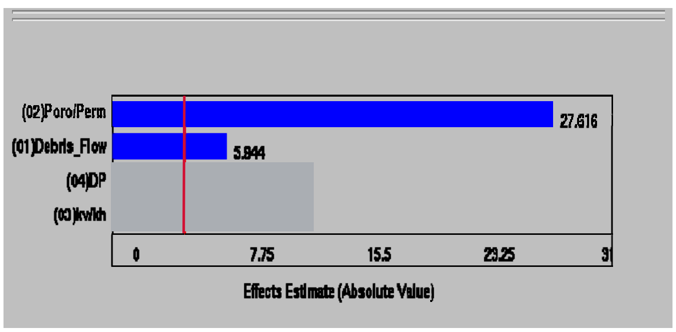


Figure 3: A Pareto chart showing the relative effects of the 4 variables in Group #1 on the original oil in place (OOIP). Not surprisingly, the heterogeneity (DP) and Kv/Kh ratio have no effect on the OOIP.

In Figures 3 and 4, we show the Pareto charts for the OOIP and recovery factor after 30 years for the Group #1 experiments. A Pareto chart shows the relative importance of the input variables on the output parameter. The Kv/Kh ratio and the permeability heterogeneity have no effect on the OOIP as expected. The red line in the figure demarcates the statistical significance at the 95% confidence level. Given that Table 1 shows an almost two-fold variation in OOIP it is not surprising that both the porosity-permeability level and the amount of debris flow have a statistically significant impact on these parameters as both parameters have directly effect on the pore volume in the model.

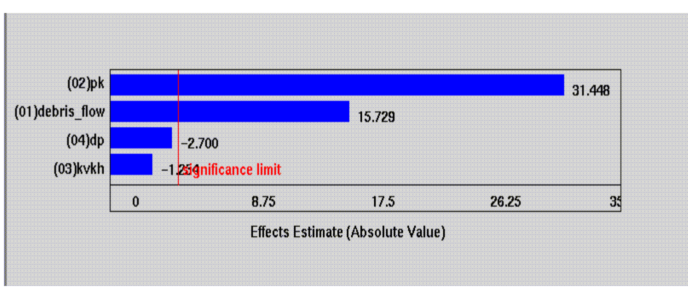


Figure 4: A Pareto chart showing the relative effects of the 4 variables in Group #1 on the recovery factor after 30 years of production. Here we see that the porosity-permeability (pK) level and the amount of debris flow have the most influence on the recovery factor as they did on OOIP in Figure 3.

The Pareto chart for the recovery factor shows a result that is less intuitive than that for the OOIP. Here we find that two of our input variables fall below the statistical significance level. This is somewhat surprising as the variables examined in this first group were chosen because they were expected to exert a significant influence on the results. It is possible that the ranges chosen for the heterogeneity and the Kv/Kh ratios were too small to see any effect. We will examine these variables in more detail in the Group #2 and #3 experiments.

Group #2

Group #2 models differ significantly from those of Group #1. Instead of a simple RNR facies model we now employ five facies to describe the internal channel architecture. The debris flow is still stochastically distributed in the channels but the remaining four facies have very definite organization (see Figure 1). These models provide a more realistic description of the internal stratigraphic architecture of deepwater channels.

RUN	Silt Drape	MS Proportion	Debris	k Transform	Variogram
1	High	50%	40%	High	Low
2	High	95%	40%	Low	High
3	High	95%	20%	Low	Low
4	Low	95%	20%	High	Low
5	High	50%	20%	High	High
6	Low	95%	40%	High	High
7	Low	50%	20%	Low	High
8	Low	50%	40%	Low	Low
CP	-	60%	30%	-	-

Table2: Experimental design table for the Group #2 experiments. For this set of runs five variables were chosen for examination.

For Group #2, five input variables are examined; they are summarized in Table 2 and the stratigraphic variables are displayed in Figure 5. The first three variables reflect the stratigraphic architecture. The first one is the silt drapes. The low case has a silt fringe on the margins as well as silt along the base of each channel, the base case (center run) has just a silt fringe on the side margins, and the high case has no silt drapes at all. The second variable is the proportion of massive sand, which ranged from a low of 50% to a high of 95%. The third variable is the amount of debris flow and it ranged from a low case of 40% to a high case of 20%. In addition, we varied the permeability by either increasing or decreasing the transform. The last variable was the variogram correlation length for the distribution of porosity and permeability, which ranged from much less than well spacing in the low case to and much greater than well spacing in the high case.

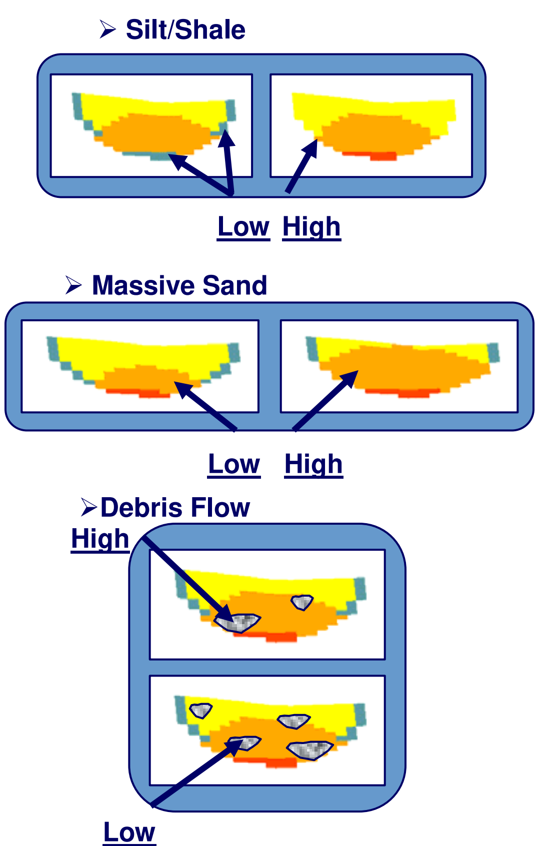


Figure 5: This figure shows the difference in stratigraphic elements in the Group #2 models between the 'high' or +1 case and the 'low' or -1 case. The facies colors are the same in this figure as in Figure 1.

In Figure 6, the effect of the different variables on the recovery factor after 30 years is shown. The most significant factors on recovery are the amount of massive sand and the amount of debris flow present. This is not surprising given that these two are the two most extreme facies, i.e., best reservoir facies and non-reservoir facies.

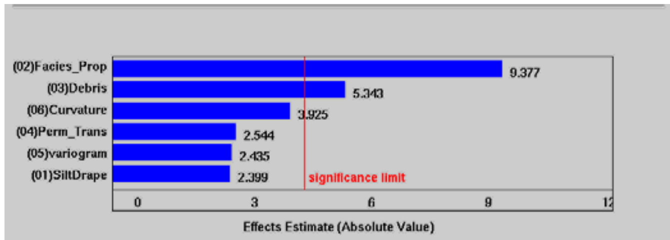


Figure 6: The Pareto chart for the recovery factor after 30 years of simulation for Group #2. We see that the two parameters that are above the 95% significance threshold are the percentage of massive sand in the channel (Facies_prop) and the percentage of debris flow (Debris).

What is surprising in Figure 6 is that the silt drapes, which are also non-reservoir, did not have a significant impact on the results. Obviously, if the silt drapes are completely continuous (i.e., separating each channel into a separate reservoir unit) there would be compartmentalization and some impact on the subsurface flow. But, with the limited amounts of silt drapes in these models, the impact is minimal. We also find that the variogram range and the permeability transform have a very limited impact on the results.

Group #3

Group #3 is the final and most realistic set of models built for the Mahakam Fan. In this group, the channels are given a more realistic sigmoidal shape and an additional facies, the abandonment facies, is included in the channels. In this group, we examined eight different parameters including the channel stacking arrangement.

In Figure 7, we present a plot of cumulative oil as a function of time. This plot shows, dramatically, that there are very large differences in the predicted oil production in these simulations. The difference between the model with the highest oil recovery and that with the lowest oil recovery is 3300%! Even if we remove the lowest curve, which may be unrealistic because it contains low values for all of the input geologic variables, the range of oil recovery is still 375%.

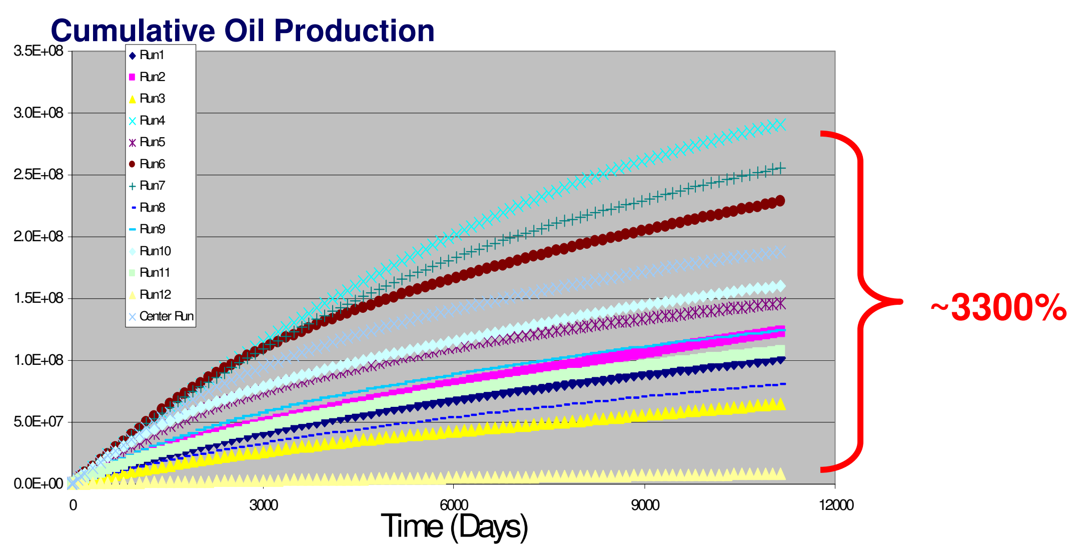


Figure 7: A plot of cumulative oil recovery for the models in Group #3.

The differences among the models in Figure 7 are due to several factors. There is a difference of almost a factor of five in the OOIP of the models. There is also a difference in the average permeabilities in the models and a difference in the average permeabilities of each of the facies in the models. For these reasons, some people might argue that the differences in recovery in Figure 7 overstate the effect of the input geology on the subsurface flow. We believe that these different observations (average permeability, OOIP, cumulative oil recovery, etc.) all depend on the same underlying geologic input. It is the basic input about which we have the most knowledge and that input is driving all of the effects in concert.

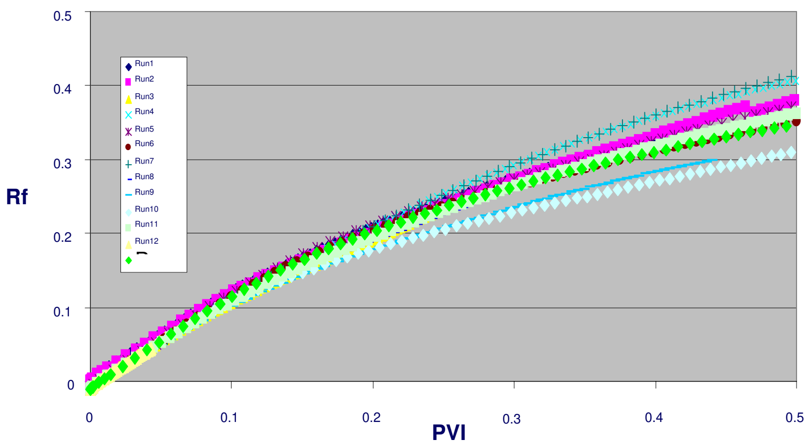


Figure 8: Sweep Efficiency Curves for Group #3, i.e., Recovery Factor (Rf) v. Pore Volume Injected (PVI)

A sweep efficiency plot, a plot of the recovery factor of oil (Rf) as a function of pore volume injected (PVI), is a way of separating the effects of pore volume variation (and OOIP) and permeability in the results. Pore volume variations and variations in the average permeability tend to control the time scale of the production.

In Figure 8 we examine the sweep efficiency curve for the models in Group #3. The variation between the models in this figure is substantially smaller than that seen in Figure 7. Still, the sweep efficiency curves show a 32% variability in the sweep after 0.5 PV injected. While this variation is much smaller than that seen for the cumulative oil production, an examination of the Pareto chart for recovery factor (Figure 9) shows that there are still statistically significant differences in results. In particular, the presence and amount of two of the reservoir facies, the silt drapes and massive sand facies, have the strongest influence on the sweep efficiency.

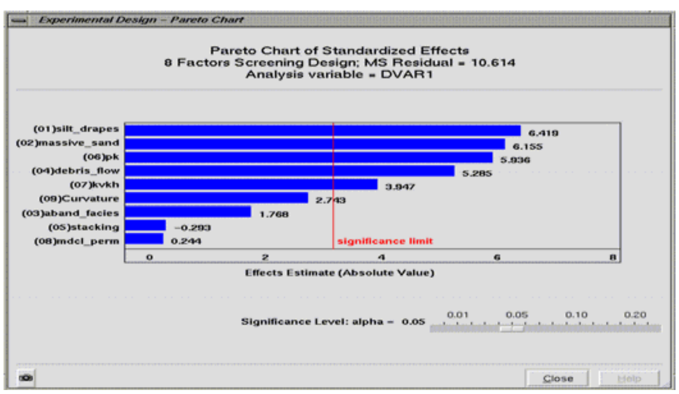


Figure 9: Pareto chart for the recovery factor after 1 PV injected for Group #3. The proportion of facies (massive sand, silt drape, and debris flow) has the largest impact on the recovery factor.

Discussion of the Mahakam Fan Results

Figures 4, 6, and 9 each demonstrates the significance of the proportion of different facies on the subsurface flow in these channels. It is logical to ask the question, is the flow principally affected by the amount of each facies or is the organizational structure of the facies within the channel also important (of course these two effects cannot be easily separated). Figure 10 shows clearly that the organization of the facies and not just the facies proportions has a significant impact on the flow.

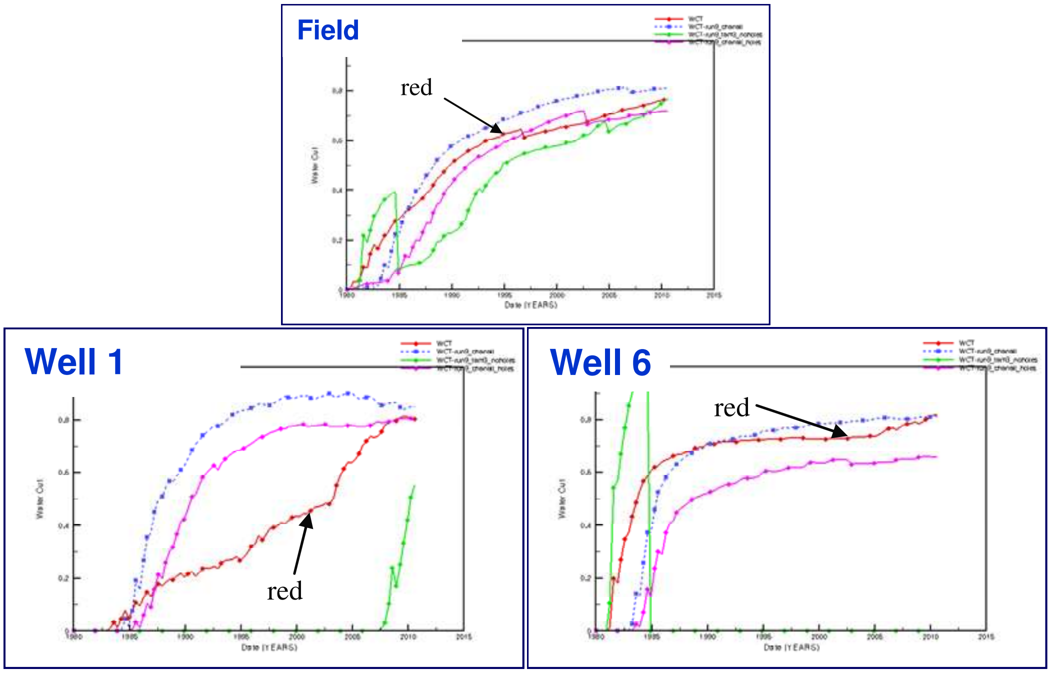


Figure 10: This figure displays the water cut for the field and two wells in the model over time. In these figures, the red line denotes a model with full stratigraphic architecture including silt drapes with erosional holes. The green line has the same full architecture but the silt drapes have no erosional holes. The blue curve has the same distribution of porosity and permeability as the red and green curves, but its distribution is not dictated by any internal facies organization, nor does it have any silt drapes. The pink line is similar to the blue line, but it has silt drapes with erosional holes.

In Figure 10 we have compared the water cut for the entire model (Field) and two individual wells (Well 1 and Well 6) for a couple of different special experiments. The red line denotes one of the models that we ran as part of the experiments in Group #3. The model has internal stratigraphic architecture with five different facies. One of those facies is the silt drape surrounding the channels. In our Group #3 models the silt drapes all have erosional holes. The green curve is equivalent to the red curve except that there are no erosional holes in the silt drapes. Clearly the predicted water cut is very different as expected.

The pink curve in Figure 10 is analogous to the red curve in that it denotes a model with the same average porosity and permeability and has silt drapes with erosional holes. However, the model denoted by the pink curve has no internal facies organization; that is, the permeability and porosity are simply populated using SGS techniques. If the internal facies architecture is not important to the subsurface flow, then the red curve and pink curve should be fairly similar. Clearly, Figure 10 shows they are not similar.

Lastly, we have the blue curve which denotes a model that is analogous to the pink except that now the silt drapes with erosional holes have been omitted. Again we see a significant change in the water cut performance. Figure 10 shows unequivocally that, at least for these models, the internal facies organization is important to predicting the subsurface flow.

The Mahakam dataset affords an excellent opportunity to look at the subsurface flow in channel systems. Previous studies using synthetically generated channels[1,2,3] have found that the effect of channel width/thickness ratio, sinuosity, and stacking pattern have a weak effect on subsurface flow especially sweep efficiency. Our results in Group #3 corroborate this result. However, we also see significant effects of other variables on the subsurface flow.

Brushy Canyon

Geologic Description

In the second part of this paper, we examined models built using the high-resolution stratigraphy of outcrops of the Permian Lower Brushy Canyon Formation. These deposits are interpreted as proximal basin-floor deposits, comprising small distributary lobes and branching channel networks in a relatively unconfined fan.[15] The area modeled in this study was 2.3 km by 1.6 km, and comprised 20 m of stratigraphy.

Similar to the Mahakam Fan dataset, the Brushy Canyon dataset is ideal for this study. First, it is a well established sheet system with a number of outcroppings that have been characterized extensively. This allows not only the incorporation of the observed facies architecture into the models but also allows testing of the results to variations in architecture observed in the system. However, like the Mahakam, the Brushy is not a reservoir thus there is no production data for comparison with our results.

For the Brushy Canyon formation, we built one 'group' of models. These models are all characterized using the same four facies: an axial sand facies that represents the best reservoir facies; a marginal tractive deposit that consists of interbedded sand and silt and is of mixed reservoir quality; a marginal grunge facies surrounding the lobe that is a non-reservoir facies comprising predominantly silt with minimal amounts of sand; and a background interlobe facies. In these experiments we vary the parameters to describe the relative proportions of each facies, the dimensions and orientations of the lobes, and their stacking patterns. Figure 11 shows some examples of the lobe shapes and their internal facies distributions.

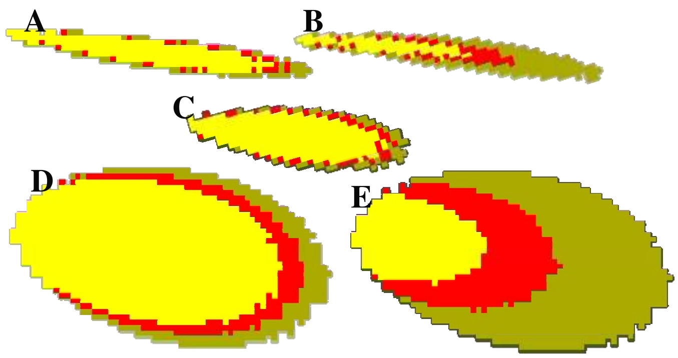


Figure 11: Examples of lobe shapes and facies distributions within the lobes. A and B are thin lobes, C is a bit wider, while D and E are very much wider. A, C, and D are dominated by axial sand facies whereas B and E are dominated by marginal grunge facies.

Our objective in this study is to link geologic parameters with their effects on subsurface flow particularly the effects of facies organization and stacking pattern. The sheet system here has facies variations on a considerably smaller length scale than that of the Mahakam channels. Consequently the cell size used for the Brushy Canyon models is quite small: 20 feet areally by half an inch vertically! Obviously, this scale is much too small for any practical reservoir simulation study but it allows us to build sheet models with a reasonable distribution of internal facies and to study the effect of the facies modeling on the flow.

Simulation methodology

As in the first part of this paper, we used streamline simulation (FrontSim) for the subsurface flow modeling in these experiments. These models have dimensions of 114x81x400 for a total of 3.7 million cells, but, because the dimensions of these cells are much smaller than the ones used in the Mahakam models, the hydrocarbon pore volume is correspondingly smaller. For this reason we use only four wells in the simulations: two injectors and two producers. This number of wells is consistent with the number of wells that are likely to be economic in a deepwater reservoir with this amount of oil in place.

The physical property data (PVT, relative permeability, etc) used in the simulations is taken from a deepwater Gulf of Mexico field as was the case with the Mahakam models. The models are run with all wells on injection and production starting from time zero (the equivalent of having pre-drilled wells). The wells are completed from the top of the reservoir to the bottom. Figure 12 shows a top down view of one model. All simulations were run for 30 years using both rate and pressure constraints with economic limits for the wells set at 100 STB/D and 95% water cut. An examination of the sensitivity of the results to well number and location (not included here) indicated that the conclusions drawn here are not particularly sensitive to the well locations or number.

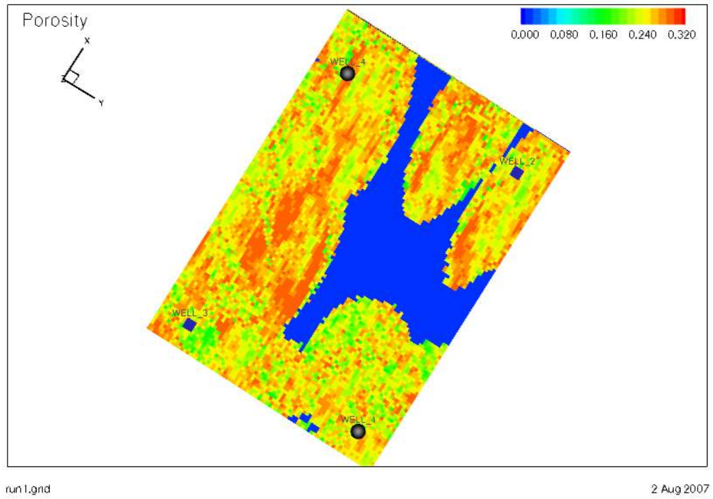


Figure 12: A top down look at one of the models used for the Brushy Canyon modeling. In the figure, the circles are producers and the squares are injectors.

Two Experimental Designs

For the Brushy Canyon models, we performed two separate experimental designs. In the first part, we used a Plackett-Burman (PB) screening design to identify the key variables. In this part, we include both the geologic variables that describe the lobe complex and several 'engineering' variables. In this way, we compare the relative importance of these two different types of parameters. In the second part, we use a three-layer D-optimal design to examine, in more detail, the variables that were identified as important in the first part of the study. The D-optimal design also allows us to examine the combined effects of some variables.

For the initial PB screening runs, a set of 8 geologic input variables was examined: the proportion of sand lobes, the lobe (bed set) dimensions, the degree of lobe amalgamation, the lobe offset stacking distance, the azimuth map, the relative proportion of internal lobe facies, the porosity/permeability distributions, and the Kv/Kh ratio. In addition we included two 'engineering' parameters in the analysis: fluid viscosity and relative permeability. Figures 13 and 14 describe the geologic variables used in the experiments and their ranges.

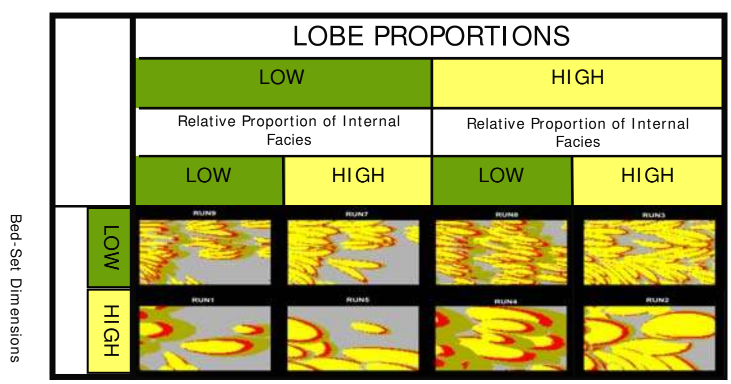


Figure 13: This figure shows the ranges and shapes used for the Brushy Canyon models. In the figure the yellow is axial sand facies, red is marginal tractive facies, olive is marginal grunge facies, and gray is interlobe siltstone.

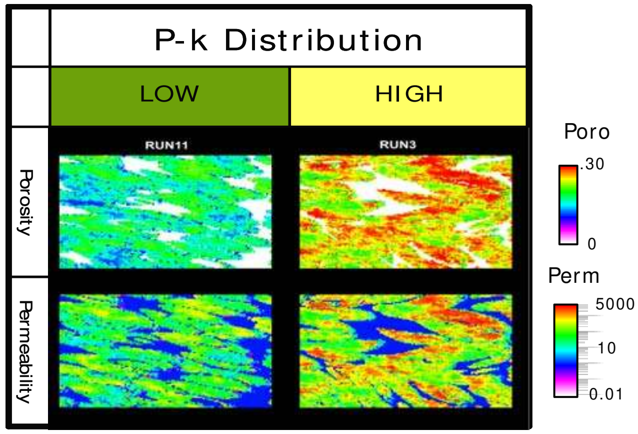


Figure 14: Permeability and porosity distributions (high and low) used in the Brushy Canyon models.

Results

Simulation Results

A sweep efficiency curve for these experiments is shown in Figure 15. The recovery factor after 0.5 PVI injected varies between 37% and 56%, an appreciably wide range. While Figures 13 and 14 show obvious visual differences in the input geology, Figure 15 shows that these differences translate into significant differences into the subsurface flow performance.

In Figure 16, we show saturation distributions in several cross-sections from the highest and lowest recovery models at a time mid way through the simulation. The map view cross section (bottom two figures) show similar sweep patterns and little bypassed oil. However the vertical cross sections, especially the middle figures) show a much greater difference in sweep pattern

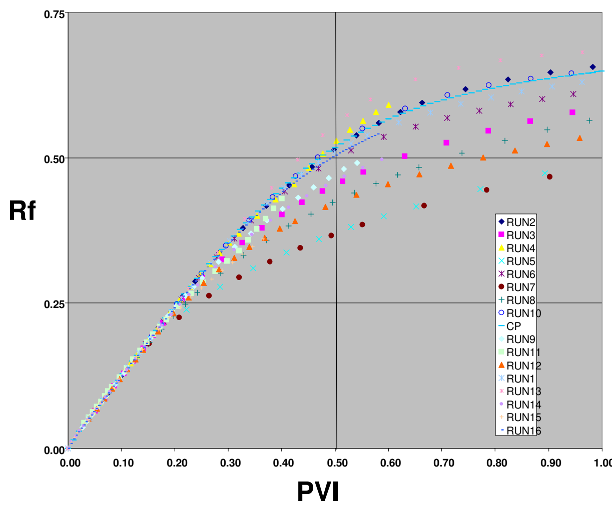


Figure 15: A sweep efficiency plot for the Placket-Burman runs. Rf is the recovery factor; PVI is pore volumes injected.

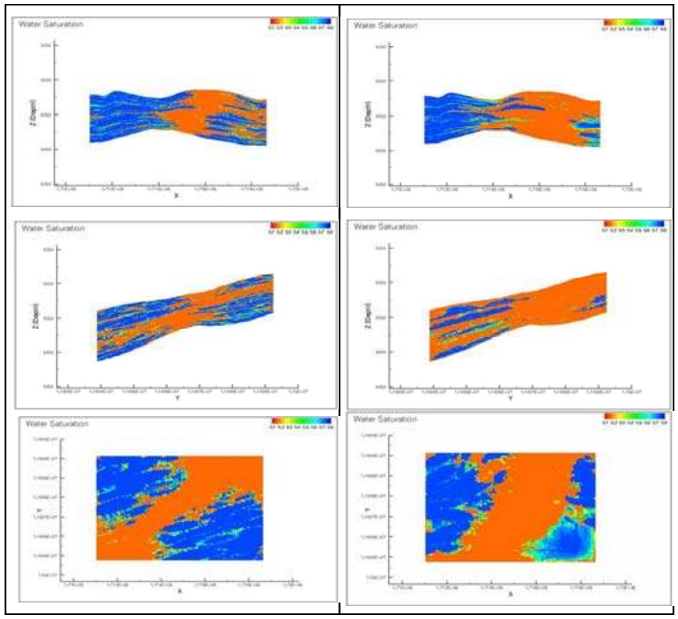
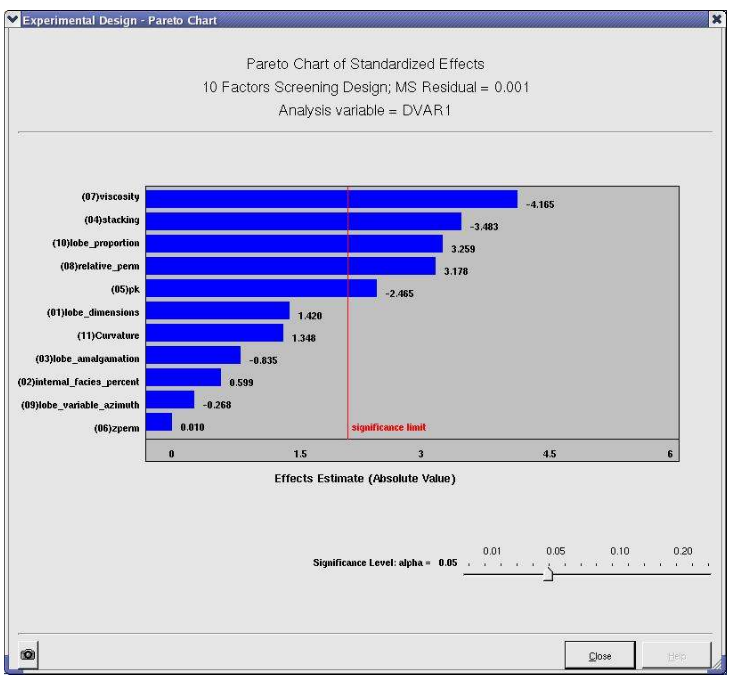


Figure 16: Saturation plots for the highest (left) and lowest (right) recovery cases in the PB design. The top plots are cross sections in the x-direction, the middle figures are cross sections in the y-direction, and the bottom figures are map-view cross sections. Each cross section is taken roughly through the middle of the model.

In Figure 17, we present the Pareto charts for the PB experiments for recovery factor (top) at the end of simulation (a proxy for cumulative recovery) and Net Oil (bottom). For both measures, five variables fall above the line that indicates statistical significance at the 95% level. Among the geologic parameters we see that the sheet stacking pattern, the proportion of lobe facies and the permeability-porosity level are the key variables. For Net Oil, these variables plus the relative proportion of internal facies are important. In addition to these geologic factors, the viscosity and relative permeability have influence above the statistically significant level for both flow measures. This finding emphasizes the importance of including both geologic and engineering parameters in screening analysis.



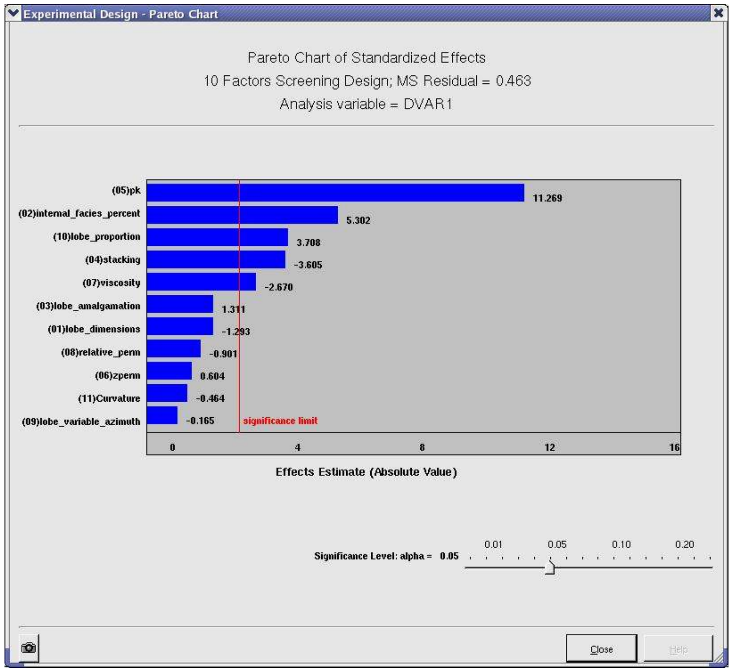


Figure 17: Pareto charts of the recovery factor (top) at the end of simulation time (30 years) and Net Oil (bottom).

Based on the results of the Plackett-Burman analysis, a three-level D-optimal design was used to investigate these results in more detail. For this three-level design, we chose to look at the effect of only five variables: the internal facies proportion, the porosity-permeability level, the lobe proportion, the Kv/Kh ratio, and the stacking pattern. We chose not to carry the uncertainty in viscosity and relative permeability into the D-optimal analysis for two reasons. First, the focus of this study is on the relationship of geologic factors and subsurface flow. Second, in the case of the viscosity we believe that in the PB analysis the range used for the uncertainty in the viscosity was probably much too large.

The relative importance of all the variables examined in this study, both geologic variables and engineering variables, depends upon the range chosen for the variables. In Figure 17, the viscosity is identified as a significant factor. But, upon further consideration of the viscosity range used, we concluded that such a range was unreasonably broad. We initially chose a range that reflected the range in viscosities observed in a set of deepwater reservoirs. This range was about an order of magnitude. However, the uncertainty in the viscosity in any individual field is considerably smaller and more appropriate to use in the PB design. To compare the relative importance of different variables it is essential that the uncertainty ranges used are appropriate for a given (specific) reservoir.

A Pareto chart for the recovery factor for the D-optimal design is shown in Figure 18. Here two key observations are made. First, this chart emphasizes the complex and non-linear nature of detailed earth modeling and reservoir simulation. Indeed, three of the four most significant variables are non-linear interactions between the key variables from the screening design. Second, the proportion of internal facies appears as the single most important variable.

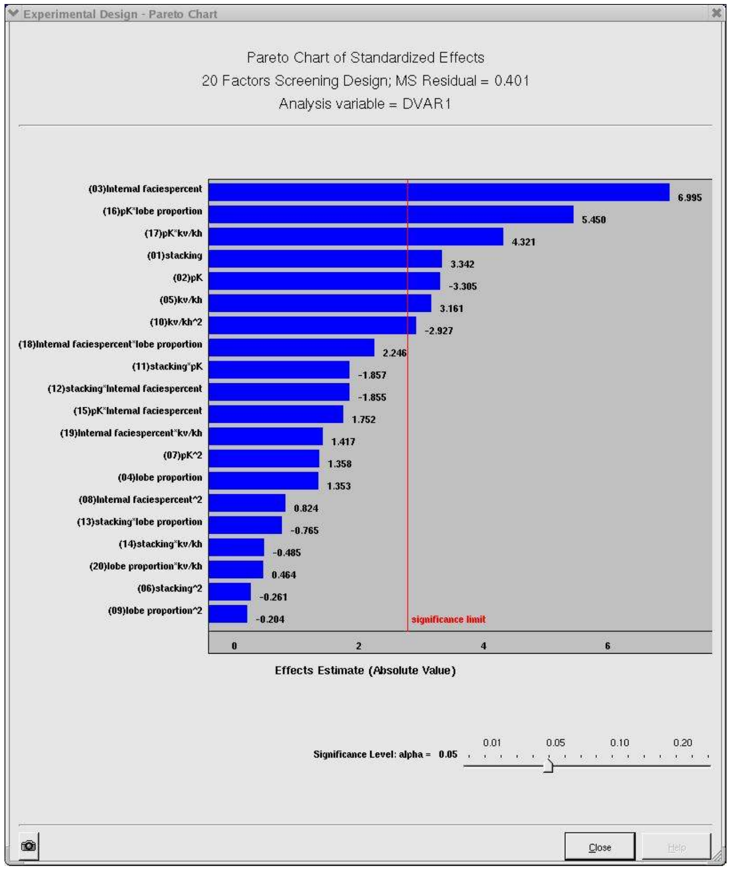


Figure 18: Pareto charts of the recovery factor after 30 years time. Note that the single most important variable is the proportion of internal facies.

Conclusions

The overall objective of this investigation is to understand the relationship between geologic variables and subsurface flow. The results for both the Mahakam Fan and the Brushy Canyon models are very consistent in elucidating this relationship: there is no simple relationship between any one input variable and one subsurface flow measure.

Beyond this basic statement, there are several other conclusions that may be drawn from our analysis. First, the dependence of any particular measure of the flow (e.g., the recovery factor after 1 PVI or the cumulative oil produced) depends upon the measure of interest. While some input variables are found to be of lesser importance for most or all subsurface flow measures we investigated, the most important and significant inputs varied. This fact emphasizes the need to understand what measures of subsurface flow are important to a particular study before deciding on the type of model to build (some might refer to this as fit-for-purpose modeling).

Second, in deepwater reservoirs there appears to be clear value in accurate facies modeling. This is shown to be particularly true for the measures of subsurface flow that we examined in this study: cumulative production, sweep efficiency, and net oil. It is important to remember that it is not just the proportion of facies present that is found to be important but also their organization and architecture.

We attempted to look for relationships among other parameters that might characterize geologic models with respect to their subsurface flow capability. In particular, we looked for relationships between our flow measures and the model heterogeneity and connectivity. However, we did not find any relationship; this point is consistent with our first conclusion.

Finally, it is important to remember that these results are for only one depositional setting and are based on outcrop and shallow seismic analogs. The conclusions cannot be extended to deepwater reservoirs without care or extended to other depositional settings without a thorough examination and review of the differences from this deepwater setting.

References

1. Friedmann, F., Chawathe, A., and Larue, D.K., “Assessing Uncertainty in Channelized Reservoirs Using Experimental Designs”, SPE 71622 presented at the SPE ATCE New Orleans, LA (2001).
2. Jian, F.X., Larue, D.K., Castellini, A., and Toldi, J, “reservoir Modeling Methods And Characterization Parameters For A Shoreface Reservoir: What Is Important For Fluid Flow Performance?, SPE 77428, presented at the SPE STCE San Antonio, TX (September 2002).

3. Castellini, A., Chawathe, A., Larue, D., Landa, J.L., Jian, F.X., Toldi, J.L., and Chian M.C., "What is Relevant to Flow? A Comprehensive Study Using a Shallow Marine Reservoir", SPE 79669, presented at SPE Reservoir Simulation Symposium Houston, TX (2003).
4. Larue, D.K., and Lagarre, H., "Flow units, connectivity, and reservoir characterization in a wave-dominated deltaic reservoir: Meren reservoir, Nigeria", AAPG Bulletin, v.88(3) pp. 303-324, (2004).
5. Jones, A., Doyle, J., Jacobsen, T., and Kjonsvik, D., "which Sub-seismic Heterogeneities Influence Waterflood Performance? A Case Study of a Low Net-to-gross Fluvial Reservoir" In De Hann, H.J., (ed.) *New Development in Improved Oil Recovery*, Geological Society Special Publication **No.84** pp5-18, (1995).
6. Jones, A., Verly, G.W., and Williams, J.K., "What Reservoir Characterization Is Required For Predicting Waterflood Performance in High Net-to-gross Fluvial Environment?" *North Sea Oil and Gas Reservoirs* – III, Norwegian Institute of Technology, pp. 223-232, (1994).
7. Montgomery, D.C., *Design and Analysis of Experiments*, Fifth Edition, John Wiley & Sons, New York, NY. (2000).
8. Berthouex, P.M. and L.C. Brown, *Statistics for Environmental Engineers*, 2nd edition, CRC Press, (2002)
9. Box, G.E.P., Hunter, J.S., and Hunter, H.W., *Statistics for Experimenters: Design, Innovation, and Discovery*, 2nd Edition, Wiley, (2005).
10. Saller, A., Lin, R., and Dunham, J., "Leaves in turbidite sands: The main source of oil and gas in the deep-water Kutei Basin, Indonesia", AAPG bulletin, v.90, no.10 , pp. 1585-1608 (October 2006).
11. Posamentier, H.W, Meizarwin, P.S.W., and Plawman, T., "Deep-water depositional systems – Ultra-deep Makassar Strait Indonesia", in P. Weimer, Slatt, R.M., Coleman, J., Rosen, C., Nelson, H., Bouma, A. H., Styzen, M.J., and Lawrence, D.T., eds., *Deep-water reservoirs of the world: SEPM Gulf Coast Section 20th annual Research Conference*, p. 806-816, (2000).
12. Strebelle, S. "Sequential Simulation Drawing Structures from Training Images", Ph.D. thesis, Department of Geological and Environmental Sciences, Stanford University, Stanford (2000).
13. Strebelle, S. "Conditional Simulation of Complex Geological Structures Using Multiple-Point Statistics", Math. Geol. **34**(1), (2002).
14. Dykstra, H. and Parsons, R.L., "The Predictin of Waterflood Performance with Variation in Permeability Profile", *Prod. Monthly* **15**, pp.9-12 (1950).
15. Gardner, M.H. and Borer, J.M., "Submarine Channel Architecture along a Slope to Basin Profile, Permian Brushy Canyon Formation, West Texas (68)" In: *Fine-Grained Turbidite Systems*, AAPG Memoir 72/SEPM Special Publication , pp. 195-215 (2000).