Production Forecasting: Improved Understanding of Why Sparse Data, Static and Dynamic Reservoir Modeling Limitations, and Human Bias Leads to Optimistic Recovery Forecasts*

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Search and Discovery Article #42442 (2019)**
Posted September 23, 2019

*Adapted from oral presentation given at AAPG 2019 Annual Convention & Exhibition, San Antonio, Texas, May 19-22, 2019

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Abstract

Reservoir production forecasts used to sanction project approvals are typically optimistic, sometimes significantly optimistic. Nandurdikar and Wallace's 2011 SPE paper, which was based on a large number of project lookbacks, noted that the production shortfall for projects that were found to have reservoir-related "issues" such as optimistic OOIP or more than expected reservoir compartmentalization or heterogeneity typically produced only about 55% of the volumes projected at time of project sanction. A portion of the forecast optimism, perhaps 15-25%, may be explained by the impact of sparse data, particularly in the early phases of development when the number of wells is limited. The typical parameters used to build reservoir models may contribute 20-40% of the forecast optimism particularly if relatively coarse grids and/or significant horizontal and/or vertical upscaling is done prior to dynamic modeling. Well location optimization workflows may contribute 10-25% of the observed forecast optimism. Human biases such as the real or perceived need to move a project forward, likely contribute 30-40% to the observed forecast optimism. Mitigation of most of the mentioned sources that contribute to the observed production forecast optimism may be mitigated through better understanding of the impact of static and dynamic modeling parameters on the resulting forecast. For example: (1) Use the smallest possible grid cell size when building the initial geological model; (2) limit the amount that the geological model is upscaled as the dynamic model is constructed; and (3) consider the potential bias introduced as a result of the location of delineation/appraisal wells. Finally, the use of truly independent peer reviews may significantly reduce the impact of human bias, particularly in cases where there may be a "management-induced" bias to advance or approve a particular project. Note that the observations reported above are based on a large number of projects, particularly early development and mature fields undergoing waterflooding or steamflooding to maintain or improve production volumes.

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Selected References

Meddaugh, W. Scott, 2006. Reservoir Modeling for Mature Fields – Impact of Workflow and Up-scaling on Fluid Flow Response, SPE 99833 (Vienna).

Meddaugh, W. Scott, Meddaugh, Andrew J., 2018. Geological Heterogeneity in Geological Models - A Review of the Impact of Available Data, Modeling Parameters, and Modeling Workflow on Primary Recovery, Waterflooding, and Steamflooding Projects (SPE Paper 191527, SPE Annual Technical Conference, Dallas, September 2018)

Nandurdikar, N and L. Wallace, 2011. Failure to Produce: An Investigation of Deficiencies in Production Attainment, SPE 145437, Denver.

Obi, E., N. Eberle, A. Fil, and H. Cao, 2014, Giga Cell Compositional Simulation: International Petroleum Technology Conference, doi:10.2523/IPTC-17648-MS



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Key Terms

- Forecast Quantitative description of the oil, gas, and water production from a reservoir as a function of a defined development plan.
- Model Numerical, often grid-based representation of the subsurface properties such as porosity, permeability, and saturation.
- Optimistic Forecast Actual hydrocarbon production of a given project is less than that forecast at the time the project received financial sanction (approval)



Are Production Forecasts Optimistic?

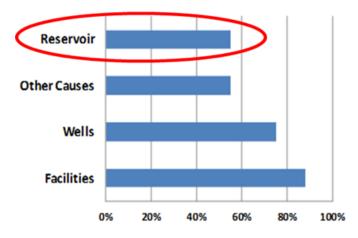




Are Production Forecasts Optimistic - Yes

- For example, Nandurdikar and Wallace reported in 2011 based on an Independent Project Analysis Inc. (IPA) study, that major capital projects were delivering, on average, only 75% of production forecast at the time of financial sanction.
- Major reasons for optimistic forecasts:
 - Optimistic subsurface assumptions
 - Failure of internal assurance/review processes
 - Lack of accountability for production volumes including project decision look-backs

Functional Area Impact on Production Forecast Attainment



Production Forecast Attainment

Note that projects impacted by reservoir "issues" achieve only about 55% of the forecast production volumes

*Failure to Produce: An Investigation of Deficiencies in Production Attainment (Nandurdikar and Wallace, 2011, SPE 145437)



Why Are Production Forecasts Optimistic?

- 1. Underlying geological models may not adequately model reservoir heterogeneity due to model parameter choices.
- 2. Original or remaining hydrocarbon in place too high
 - Sparse and/or non-representative data that is often biased towards better reservoir quality
 - Inadequate or improperly used analog data and/or uncertainty assessment workflows
- 3. Reservoir simulation models that are inadequate due to grid size, up-scaling, and/or the use of well location optimization workflows.
- 4. Human Biases
 - Technical team "sourced" bias
 - Management "sourced" bias

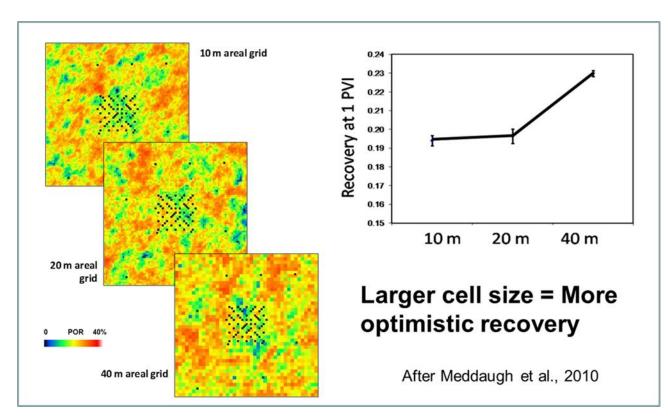


Impact of Model Grid Size

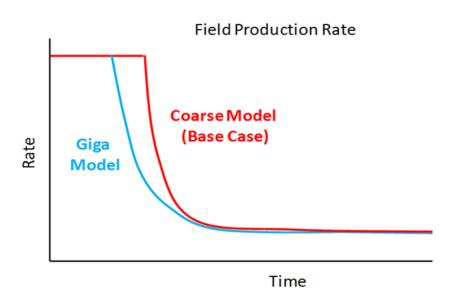
- Geological models typically now have tens to hundreds of million of model cells.
- Reservoir simulation models typically have only a million or so model cells due to run-time "limits".
- Consequently, geological models are generally up-scaled.
- An impact of up-scaling may be the loss of "geology", particularly permeability contrasts (e.g. barriers/baffles, thief zones).



Impact of Model Grid Size On Forecast Recovery



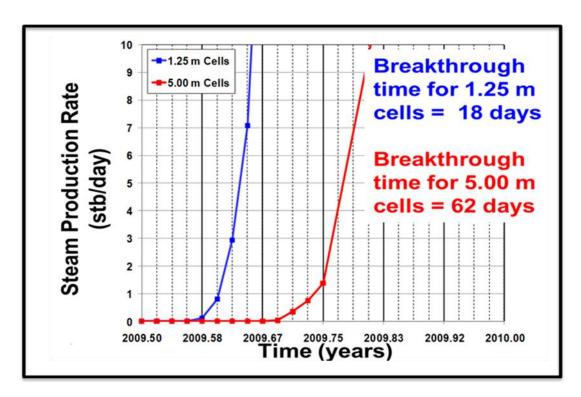
Larger model cell size = More optimistic recovery



Coarse Model forecast 10-15% more oil than a Giga-Cell Reservoir Model (After Obi et al.,2014)



Impact of Model Grid Size On Breakthrough Time



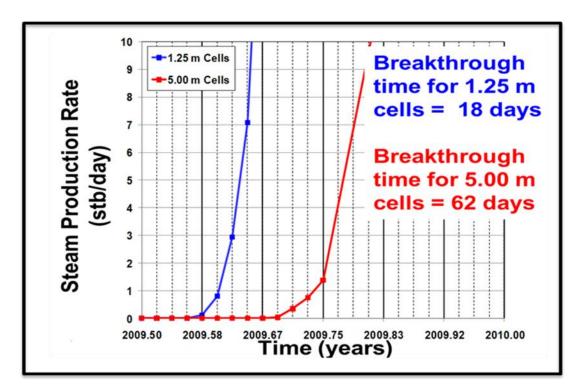
Larger model cell size = Slower Steam Breakthrough

From Meddaugh at al., 2012

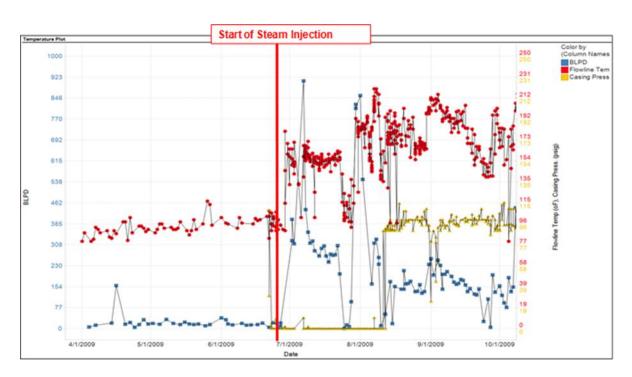




Impact of Model Grid Size On Breakthrough Time



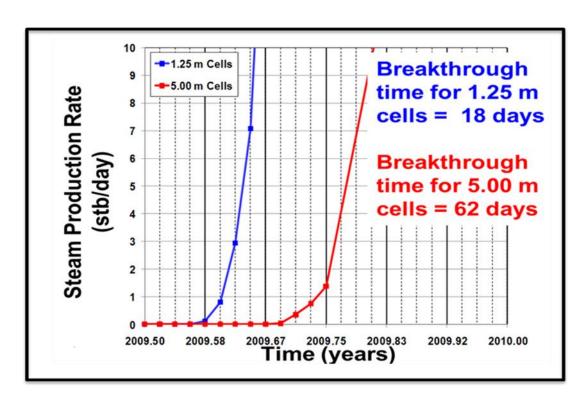
Larger model cell size = Slower Steam Breakthrough



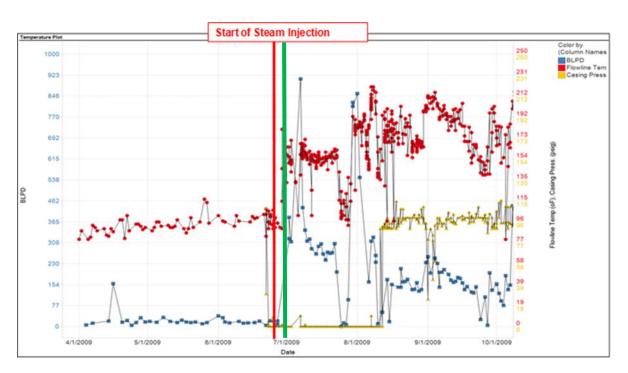
Field Data – Wafra First Eocene Pilot



Impact of Model Grid Size On Breakthrough Time



Larger model cell size = Slower Steam Breakthrough

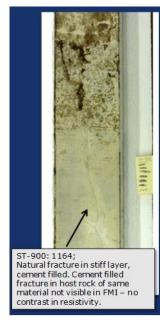


Field Data – Wafra First Eocene Pilot Hot Water at Producing Well in about Four Days

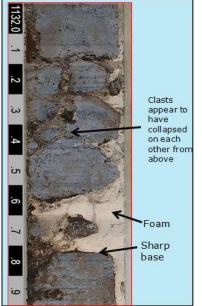


Possible Reasons for Rapid Well Response to Steam Injection

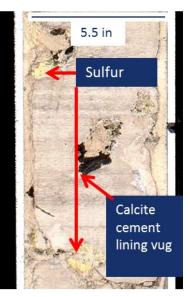
- High permeability pathways
 - Fractures
 - Karst zones
 - Stratigraphy or diagenesisrelated (connected vugs)



Small Fractures in Core



Small Karst Zone in Core



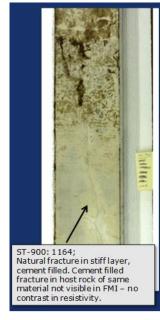
Open and Filled Vugs in Core



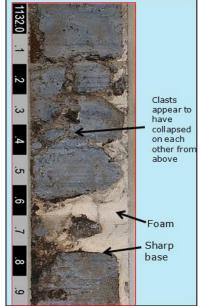


Possible Reasons for Rapid Well Response to Steam Injection

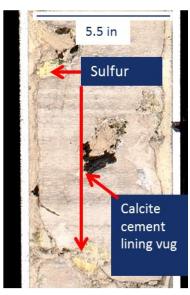
- High permeability pathways
 - Fractures
 - Karst zones
 - Stratigraphy or diagenesisrelated (connected vugs)
 - Connected very high permeability "paths" not due to any of the above



Small Fractures in Core



Small Karst Zone in Core

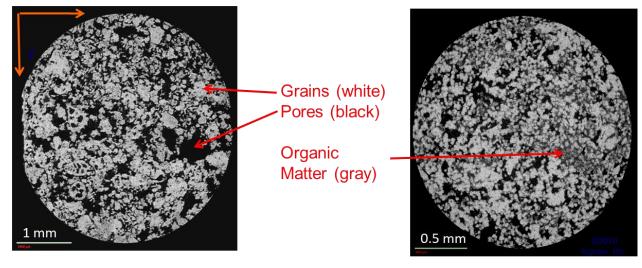


Open and Filled Vugs in Core



Possible Reasons for Rapid Well Response to Steam Injection

- High permeability pathways
 - Fractures
 - Karst zones
 - Stratigraphy or diagenesisrelated (connected vugs)
 - Connected very high permeability "paths" not due to any of the above



Preliminary Permeability Values

X-Perm = 6700mD Y-Perm = 6100mD Z-Perm = 6900mD

Preliminary Permeability Values

X-Perm = 720mD Y-Perm = 710mD Z-Perm = 790mD

Porosity of Both Samples is About 35%



How Well is Reservoir Heterogeneity Captured in Reservoir Models?

- 1. Model Grid Size and Number of Cells
- 2. Spatial Continuity as modeled by the semivariogram for point-based methods or the geometry of objects in object-based algorithms
- 3. Stratigraphy Detail and Continuity





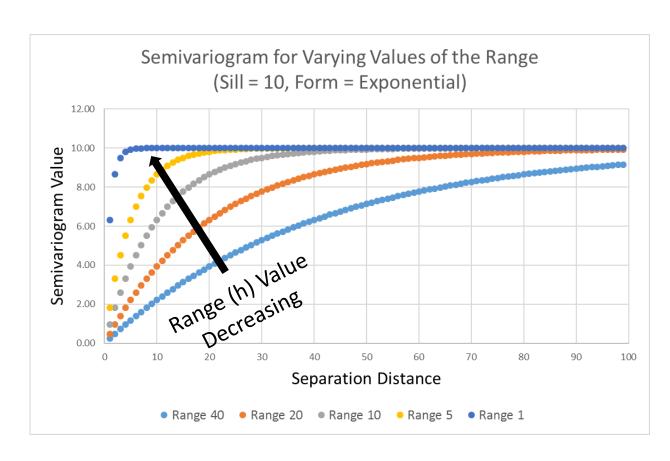
How Well is Reservoir Heterogeneity Captured in Reservoir Models?

- 1. Model Grid Size and Number of Cells More is Better
- Spatial Continuity as modeled by the Semivariogram for pointbased methods or the geometry of objects in object-based algorithms
- 3. Stratigraphy Detail and Continuity



Semivariogram Basics

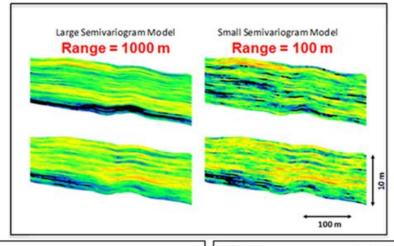
- Semivariogram (γ) Measure of spatial continuity or heterogeneity
- Range parameter (h) Increases as the spatial continuity of the property of interest (e.g. porosity) increases
 - Small h = More Heterogeneity
 - Large h = Less Heterogeneity



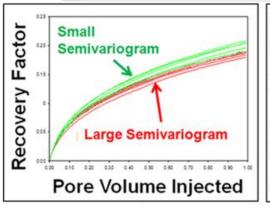


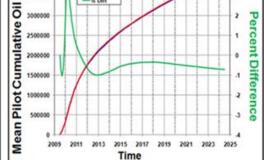
Impact of Semivariogram

- Top Cross sections through models generated with 1000m range and 100m range
- Bottom Comparison of forecast recovery for waterflood and steamflood. Note very small difference for waterflood and essentially no difference for steamflood



(Meddaugh et al., 2012)

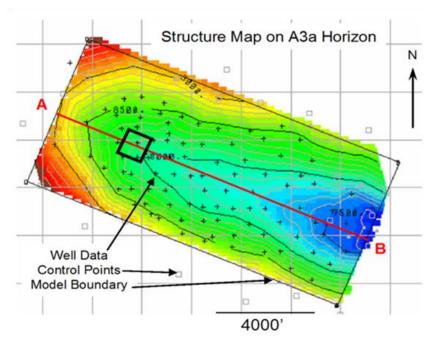




Waterflood

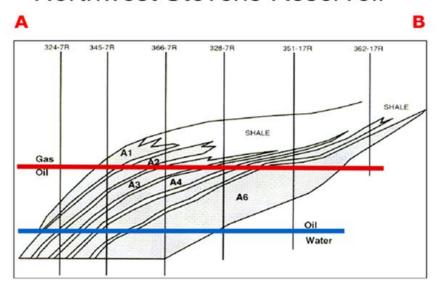
Steamflood





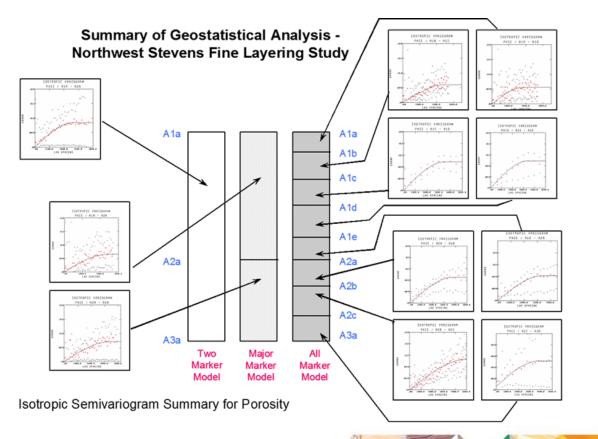
Black square on west side of structure map shows the study area.

Northwest Stevens Reservoir



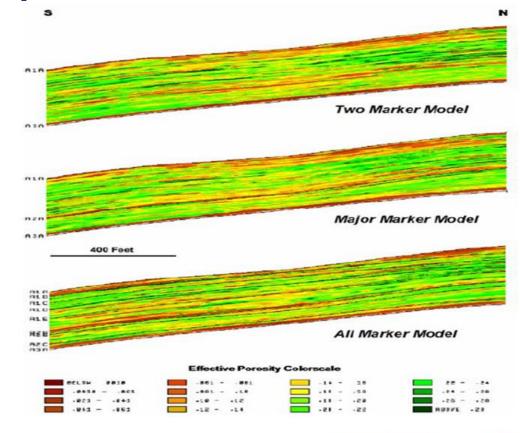


- Cases studied:
 - Two marker (top, bottom only)
 - Three "major" markers
 - Nine "detailed" markers





- Cases studied:
 - Two marker (top, bottom only)
 - Three "major" markers
 - Nine "detailed" markers





- Summary of fluid flow results obtained from twenty realizations for each of the three levels of stratigraphic detail shown at right
- Note that there is little difference in recovery or breakthrough time for the three cases

Summary of Flow Simulation Results for the Three Levels of Correlation Detail, A1 and A2 Sands, NWS Reservoir, Elk Hills, California.

Correlation Detail Case	Water Break- Through (Days)	Range of Water Break- Through (Days)	Cumulative Production through 5 Years (Mbbl)	Range of Cumulative Production through 5 Years (Mbbl)
Two Marker	1091±66	1003-1230	388 ± 10.4	373-407
Major Marker	1106±64	981-1212	387 ± 7.6	373-399
All Marker	1063±98	842-1250	381 ± 11.6	365-404

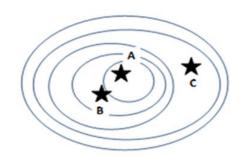




Impact of Sparse Data – Simple Case

- Forecast, as a function of well drilling order is shown in table at bottom. Forecast is based on a data set consisting of 18 analog reservoirs.
 - 1. One well forecast recovery range is 27-51%
 - 2. Two well forecast recovery range is 34-46%
 - 3. Three well forecast is 40%
- Impact of sparse data on forecast may be large; about 10-15 RFUs in this "very simple" example. (From Meddaugh, 2015)

Table 1 - Well Properties for the "Test" Reservoir					
Well	Net Avg. Porosity %	Net Avg. Perm md	Net Pay feet		
Α	27	320	61		
В	22	300	55		
С	15	260	35		

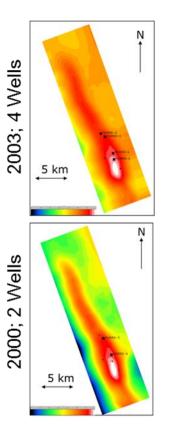


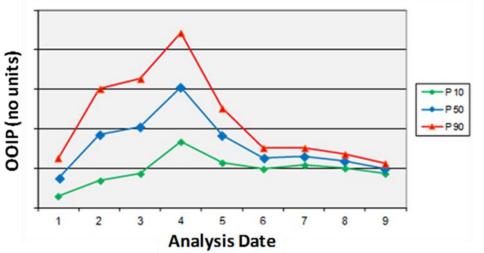
	"Test" Reservoir Forecast				
Drilling Order	1 Well	2 Wells	3 Wells		
ABC	41.7	46.2	39.8		
BAC	50.6	46.2	39.8		
CBA	27.0	38.8	39.8		
ACB	41.7	34.3	39.8		
BCA	50.6	38.8	39.8		



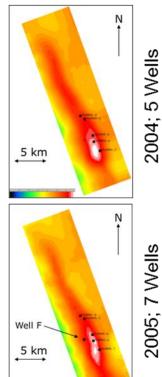
Impact of Sparse Data – Real Case

Variation of OOIP
 as a Function of
 "Time" for the
 Humma Marrat
 Reservoir





Summary of an actual reservoir change in estimated OOIP over time based on information from Meddaugh et al. (2009). Note that the early and significant rise in OOIP reflected sparse data obtained from mostly favorable locations (high on structure). Only after a series of "true" delineation wells after Analysis Date "4" did the OOIP uncertainty as shown by the spread of the P10 and P90 curves significantly decrease. As noted by Meddaugh (2009), the early, post-discovery wells were drilled as "safe producers" rather than delineation wells.





Impact of Human Bias – A "Synthetic" Case

- Evaluation of Potential Technical Team or Management "Induced" Bias to Move a Project Towards or Away from Project Sanction
- An "experiment" was done
 (Gilbert et al, 2015; Meddaugh
 2015) in which a group of student
 volunteers were given specific
 instructions (next slide) and an
 "exhaustive" analog data set with
 18 reservoirs with known
 reservoir properties and ultimate
 recoveries (shown at right)

S	ynthetic	Analog	Data Se	t				
	Porosity	Perm	Net Pay	Recovery				
Reservoir	(%)	(md)	(feet)	(%)				
1	26.0	293	45	47				
2	22.5	299	55	38				
3	25.7	418	65	42		0.0		
4	22.0	586	105	45		. 2		
5	21.3	230	45	37				
6	22.6	283	50	45		/* ·		
7	22.2	500	90	45	•/			 Forecast Re
8	16.4	151	35	30				ronecasene
9	24.6	431	70	48				- Linear (For
10	18.7	389	110	47				Recovery)
11	21.1	364	70	44				y = 0.7785x + 8.4
12	15.3	222	55	22				R2 = 0.7785
13	19.8	129	25	25	20	40	60	
14	18.1	140	30	30	Actual R	lecovery		
15	18.9	203	25	30				
16	19.5	190	40	42				
17	19.2	240	50	37				
18	14.3	215	60	31				



Impact of Human Bias – A "Synthetic" Case

The "Experiment" Set-Up

Pro-Project Bias

"Your management has decided that it needs to move forward on the project for the sake of their job as well as yours (cutbacks are coming and bonuses are planned for those staff retained!). You need this project to go forward. Therefore, management has "requested" the highest possible recovery forecast that can be defended using a minimum of eight of the 18 analog reservoirs. There will be no peer review of the analog data base used to support your analysis."

Anti-Project Bias

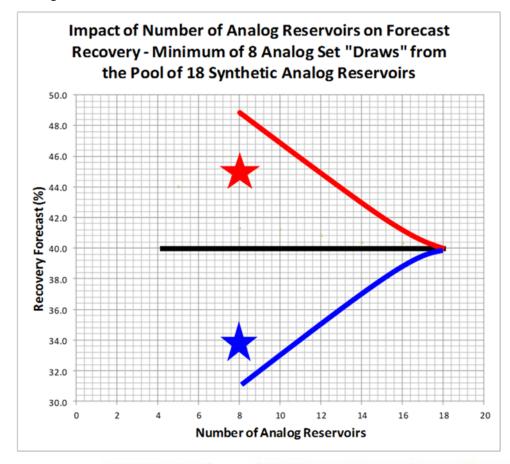
"Your local management has decided that it needs to cancel this dubious project even though the company owner believes it to be a very good project. Thus, you need help your local manager to cancel this dubious project. Therefore, local management has "requested" the lowest possible recovery forecast that can be defended using a minimum of eight of the 18 analog reservoirs. There will be no peer review of the analog data base used to support your analysis."





Impact of Human Bias – A "Synthetic" Case

- The Recovery Forecast "Experiment" Results:
 - Most Optimistic Student Forecast (45% of OOIP) with Applied "Project Forward" Bias Shown by Red Star
 - Most Pessimistic Student Forecast (33.5% of OOIP) with Applied "Project Termination" Bias Shown by Blue Star
 - Conclusion Human Bias Impact Can Be Quite Large; Easily 5-10 or more RFUs





Summary of Potential Recovery Forecast Bias Sources, Impact, and Direction

Bias Source	Magnitude in Recovery Factor Units (RFUs)	Direction of Bias – Optimistic, Pessimistic, or Either
Reservoir Modeling	Small, less than 5 RFU.	Either
Parameters		
Vertical Upscaling	Small, less than 5 RFU.	Optimistic
Horizontal Upscaling, Areal Cell Size	Small to Large, likely between 5-15 RFUs	Optimistic
Well Location Optimization	Large, likely between 5 -15 RFU. May tend to be larger for strongly anisotropic reservoirs (e.g. channelized)	Optimistic though additional study is much needed.
Sparse Data	Large, likely between 10-15 RFUs	Either; will be optimistic if early wells sample higher quality reservoir volume as is the "usual" case
Human Decision Bias	Moderate, at least 5-10 RFUs; maybe higher (up to 15 RFUs)	Either; will almost certainly be optimistic given the typical "need" to move projects towards sanction



Key Message

- Human, workflow, and software choices drive forecasts towards significant optimism
- Many of the optimism "sources" may be mitigated by:
 - Better use of statistics and analogs
 - Wider knowledge of the impact of modeling parameters and well optimization (not discussed in this talk) on forecasts
 - Enhanced use of management-independent peer teams and assurance processes to reduce human-induced optimism in forecasts
- Bottom line
 - Better forecasts = Better use of capital and improved company financial performance



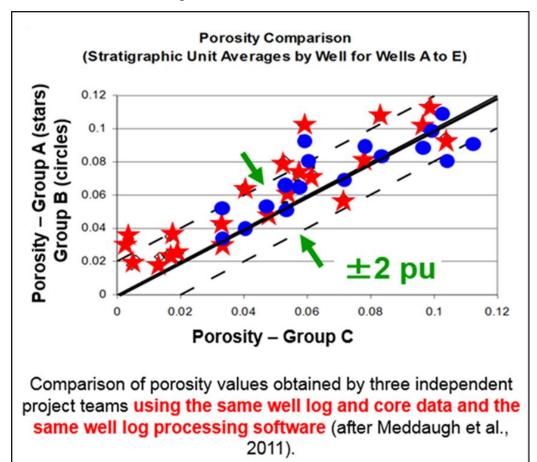
Better Practices

- Incorporate larger range of uncertainty respect the potential impact of sparse data as well as the potential "non-randomness" of sparse data
- Use models with small areal grid block (cell) sizes larger number of smaller cells is much better!
- Increased use of actual reservoir lookbacks to assess impact of sparse data on in-place volumes and forecasts
- Increased use of external peer reviews to reduce project team and management bias





A Closing Thought or Question – How Well Do We Really "Know" Our Data?





Thank You