

# First look at accelerating compositional models using CPU+GPU based systems

Hau Tran

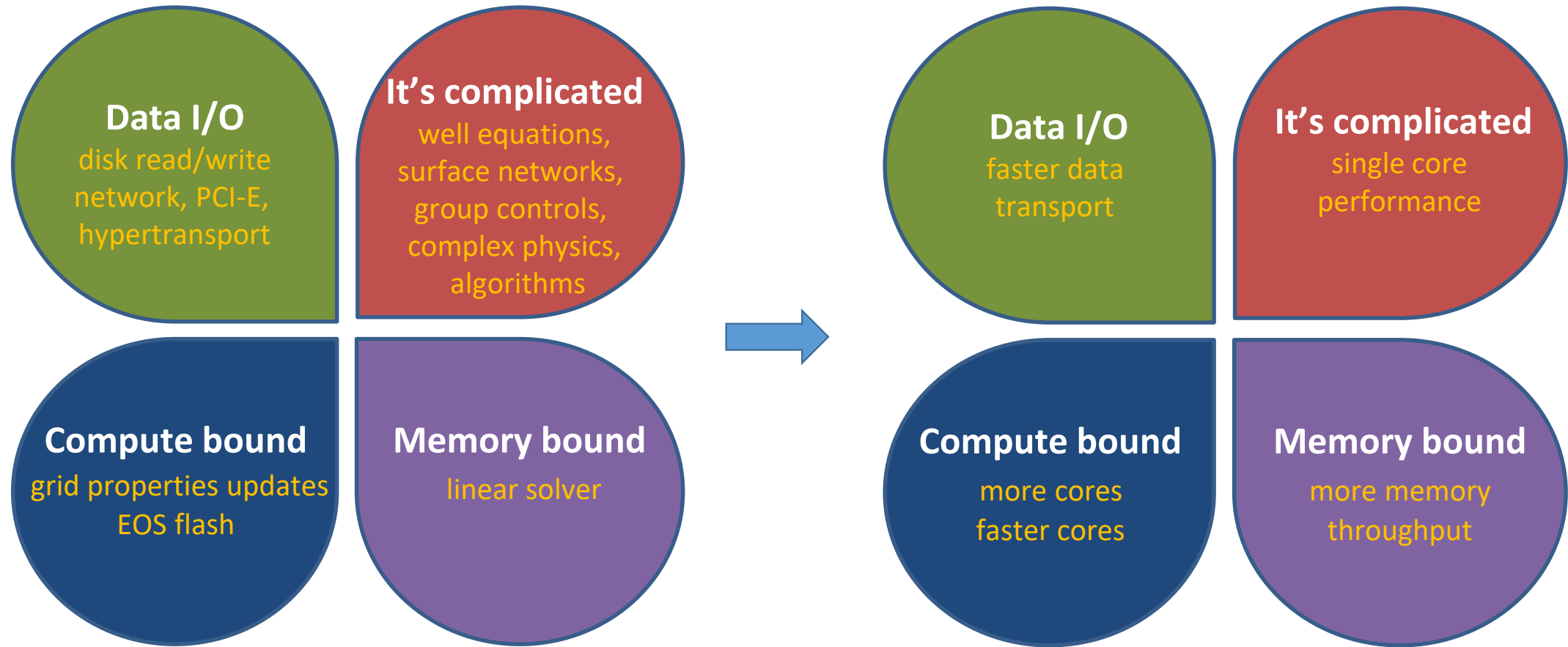
Rock Flow Dynamics



# Contents

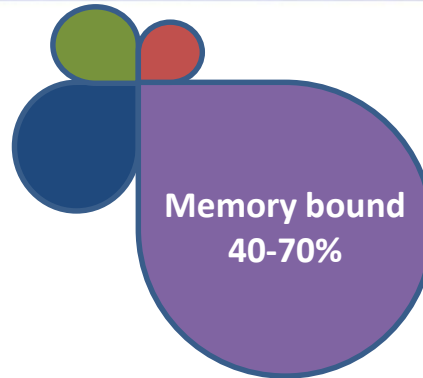
- What Affects Reservoir Simulation Performance?
- Why Do We Care about GPU?
- GPU for Linear Solver
- First Look at CPU+GPU for Compositional Models
- Next Platform for Reservoir Simulation

# What Affects Reservoir Simulation Performance?

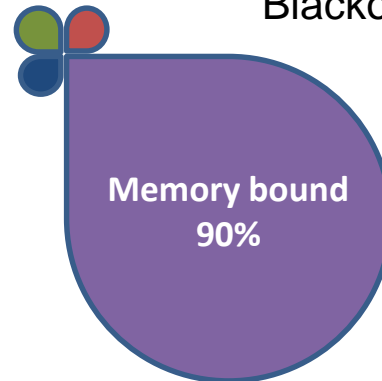


# Profiles for Different Physics Scenarios

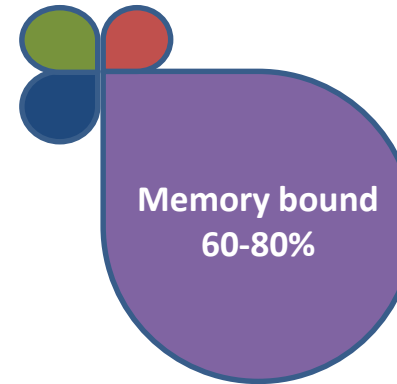
That's why reservoir simulations in general are often called "memory bound"!



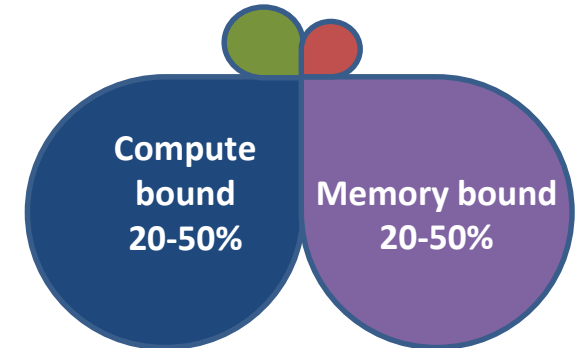
Blackoil models



SPE10



Shale models



Compositional models

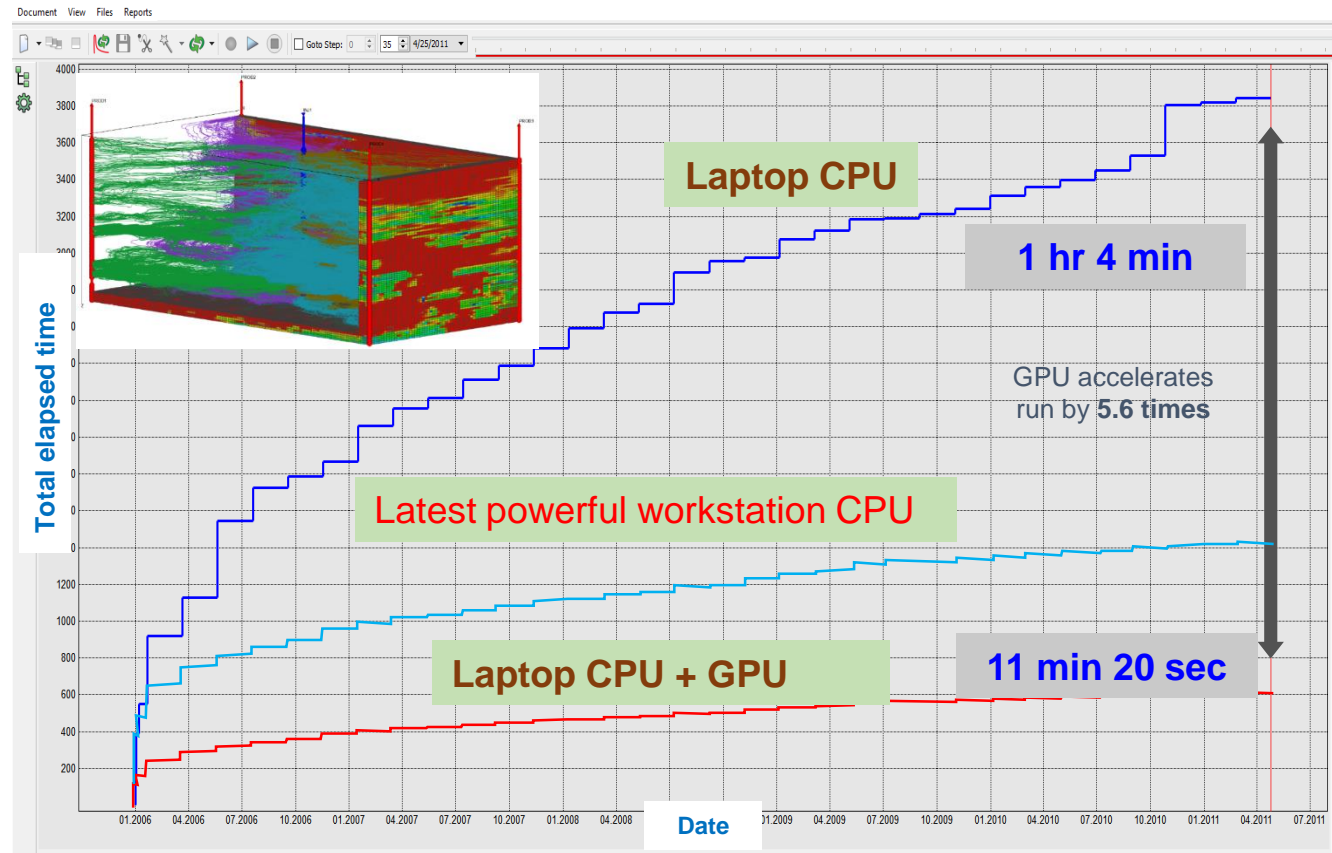
# CPU vs GPU – Peak Memory Bandwidth

Device	Cores	Clock	Memory	Size	Clock	Bandwidth	Price
CPU 1	16	2400MHz	DDR4	768GB	1866MHz	56GB/s	\$1340
CPU 2	28	2600MHz	DDR4	1.54TB	2400MHz	59GB/s	\$3500
GPU 1	2560	1607MHz	GDDR5X	8GB	10GHz	320GB/s	\$500
GPU 2	3584	1582MHz	GDDR5X	11GB	11GHz	484GB/s	\$700
GPU 3	3840	1560MHz	GDDR5X	24GB	9GHz	432GB/s	\$5500
GPU 4	3584	1328MHz	HBM2	16GB	715MHz	732GB/s	\$8900

To take advantage of 5 - 10 times higher GPU bandwidth for each model, the simulator has to employ all the available 2560 – 3584 cores!

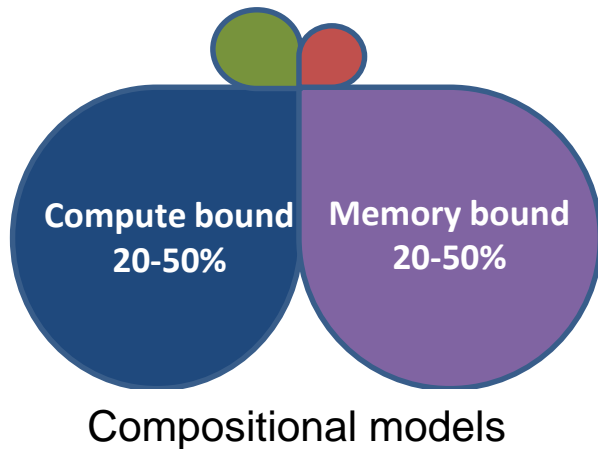
Moving linear solver to GPU, the rest on CPU

# SPE10 - Blackoil



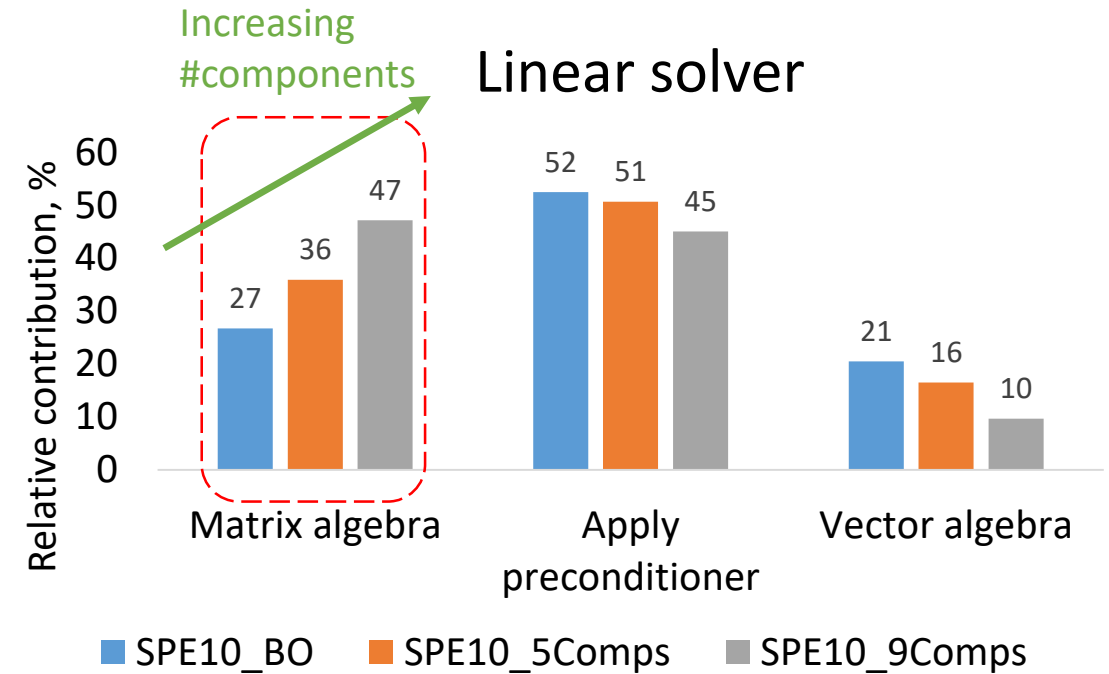
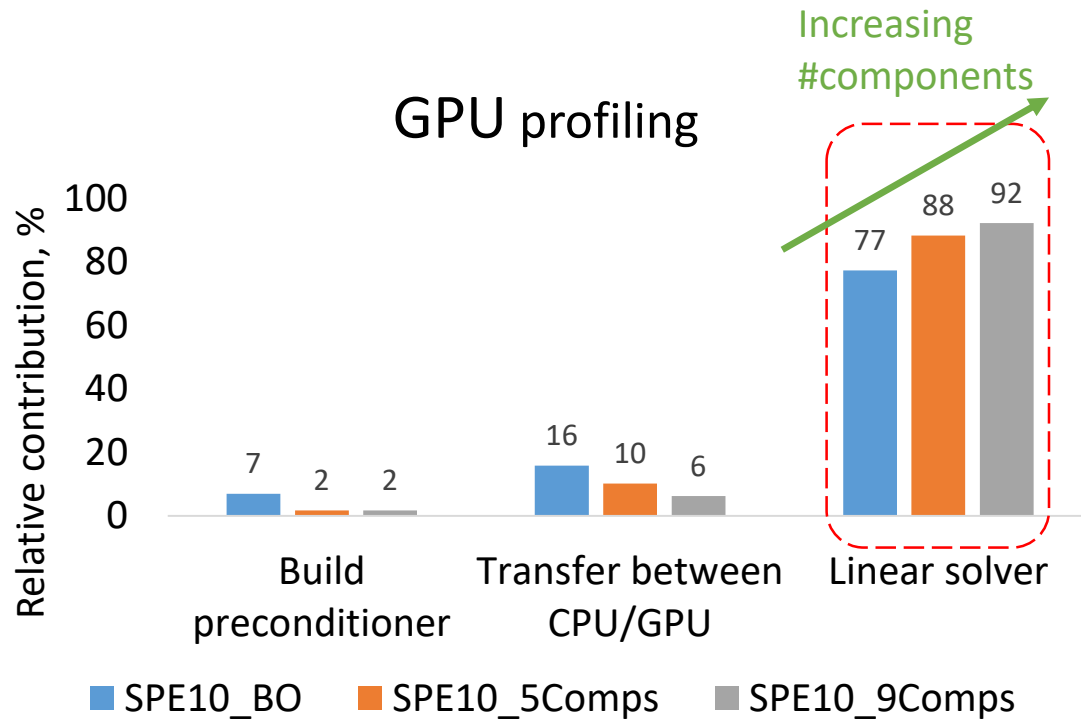
# Compositional Models on GPU

- GPU memory remains a challenge for multi-components (needs multiple GPUs)
- Old acceleration tricks (like AIM) are not as useful as for CPU



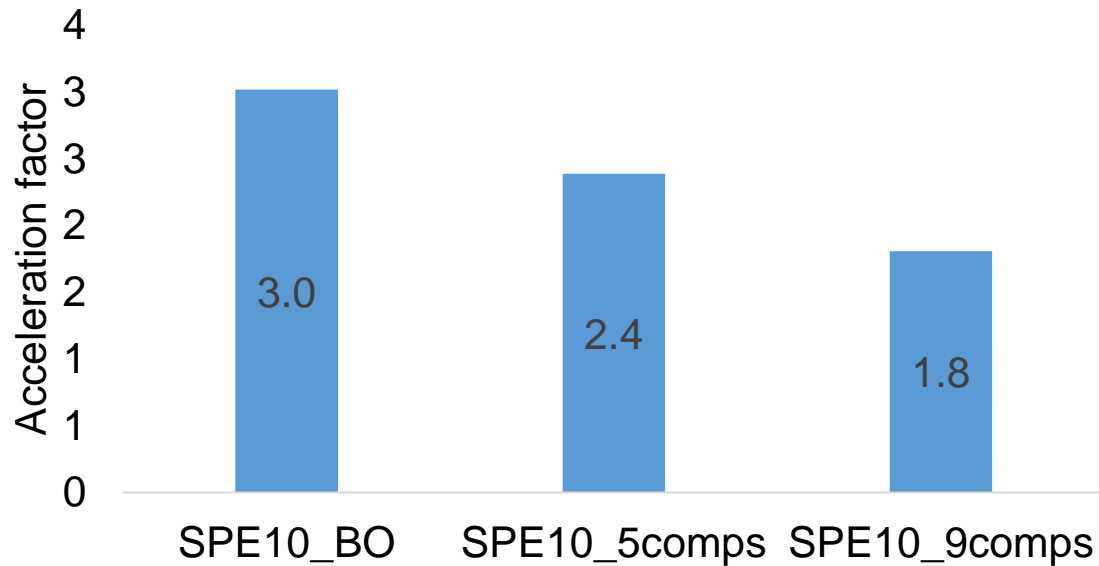
For this study, all the test cases were run on a workstation with dual **CPUs, 40 cores** and a **GPU GDDR5X 24GB**

# SPE10 – BO vs 5comps vs 9comps

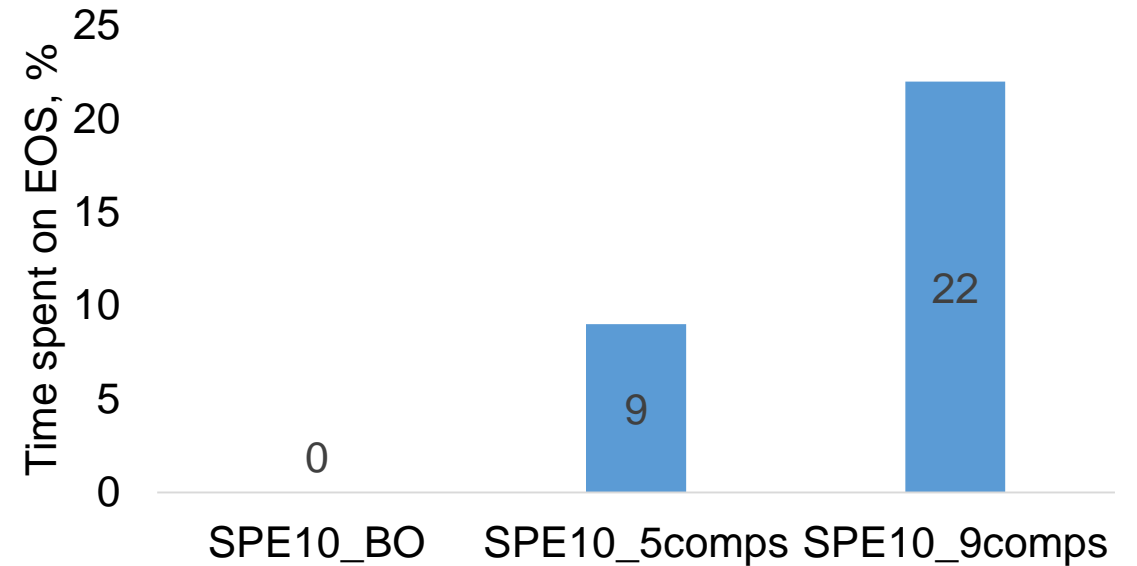


# SPE10 – BO vs 5comps vs 9comps

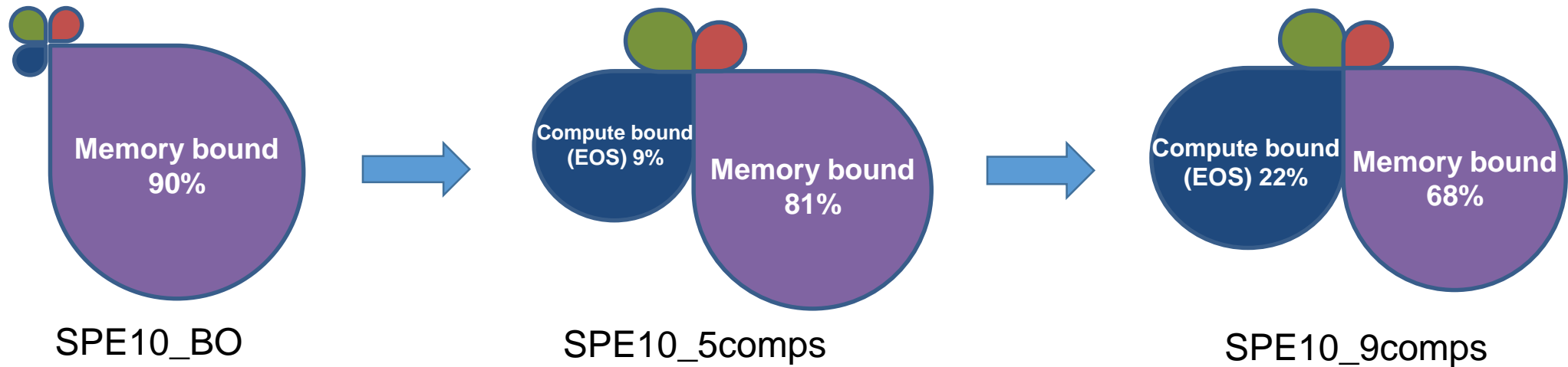
CPU+GPU vs CPU



CPU time spent on EOS



# SPE10 – from Blackoil to Compositional



# What did we learn?

- Acceleration factor for CPU+GPU vs CPU is seen from 1.2 to almost 6 times depending on model types and hardware (CPU and GPU)
- When discussed GPU acceleration vs CPU it is necessary to mention the hardware used for both CPU and GPU. The CPU/GPU balance is constantly changing , and things will look very different by the end of 2017
- The more powerful CPU is used the (relative) performance of a GPU card (plugged in to the same CPU) is reduced
- Benefits of moving EOS to GPU remains to be seen and needs further investigation

# What Next for Reservoir Simulation?

- We think that adding GPUs to the picture will change the way we run simulations, buy computing hardware in the future, **may bring 10X performance improvement**
- As we enter **2017** we clearly see ongoing violent “GPU wars”, as well as some indication of the upcoming “CPU wars”, between the CPU/GPU makers
- As much as we all are going to benefit from it, making the software to adopt to all these new platforms, the variety of technologies, many coding languages present a challenge: **C++, CUDA/Open CL for thousands of cores, vector processing AVX512 in new generation of CPUs**
- GPUs architecture life cycle is less than a year, small memory sizes remain an issue (compositional models!)

# Next Computing Platforms

In the last 15 years, 64-bit high performance computing had two periods of relative stability:

2003 – 2006 the domination of **one of** the two chip makers

2007 – 2017 a decade of the domination of **the other** chip maker

2018 – what platform is going to be better? what is optimal workstation/cluster node?

Going from  
dominant Dual  
CPU processors



Next generation of Dual CPUs + MCDRAM

New architecture of CPU

Dual CPUs + GPU (from different maker)

Dual CPUs + multiple GPUs (from different maker)

CPU + GPU (of the same maker)



# Thank you

# Questions?

# Probabilistic Uncertainty Quantification Using Advanced Proxy Methods and GPU-Based Reservoir Simulation

Reza Ghasemi

Nigel Goodwin



# Motivation

- The trend in industry has shifted from a single history match to probabilistic history match (ensemble of matches)
- Is a robust, valid, efficient probabilistic uncertainty quantification practical for large models a reality for today, or a research dream?
- We can't escape the need for flow simulations!
- Is there a better way to do this efficiently today? Maybe GPUs can help us?

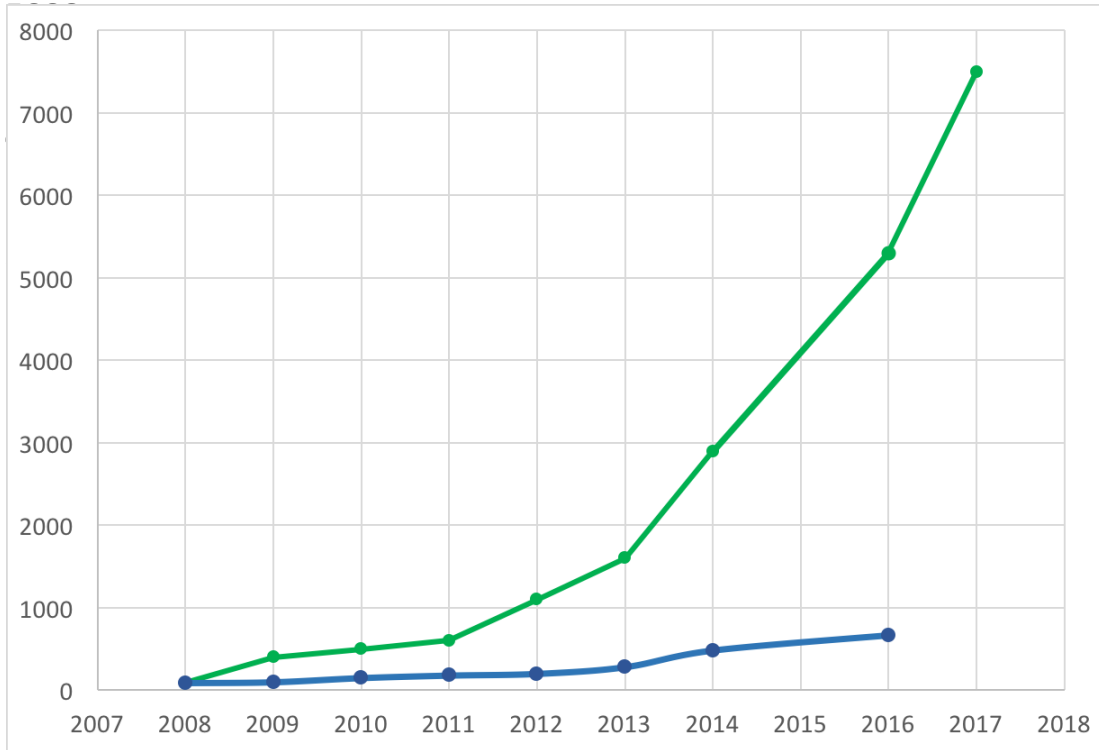
# Agenda

- GPU-based simulation
- Description of study
- What is valid, robust probabilistic forecasting?
- Proxy models – what are they?
- Markov Chain Monte Carlo methods – do they work?
- Why is our approach unique?
- Summary

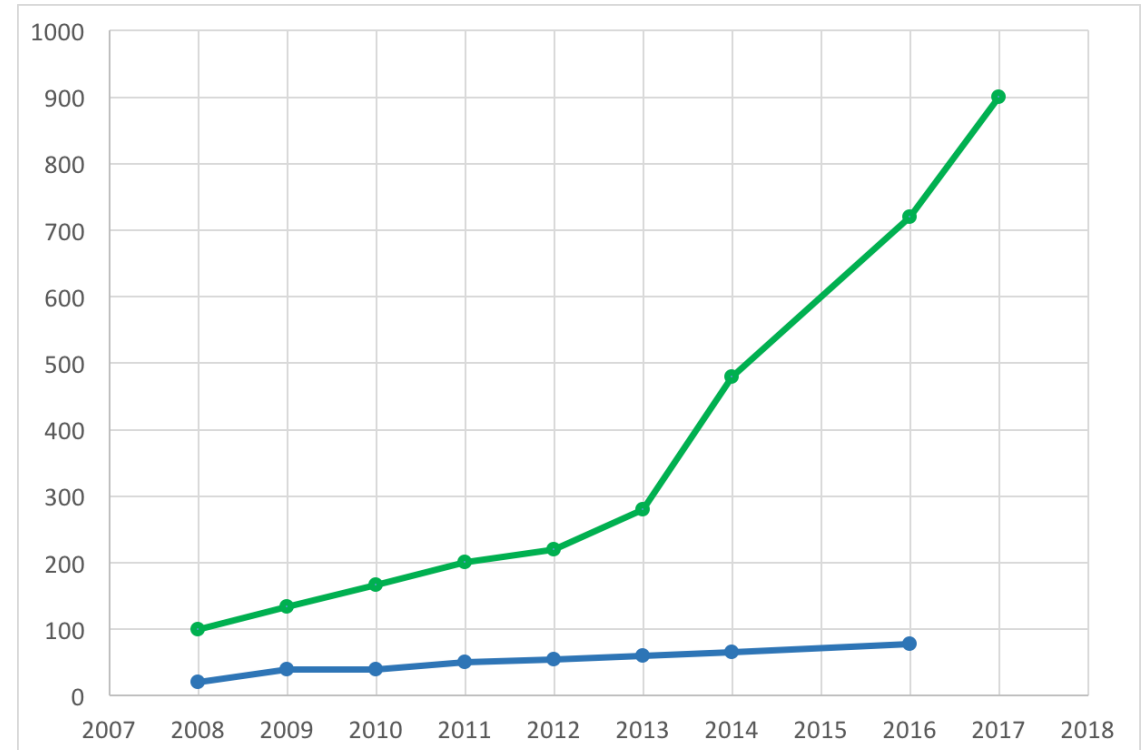
# Why GPU Matters?

**GPU** **CPU**

Peak Double Precision Flops (GFLOPs)

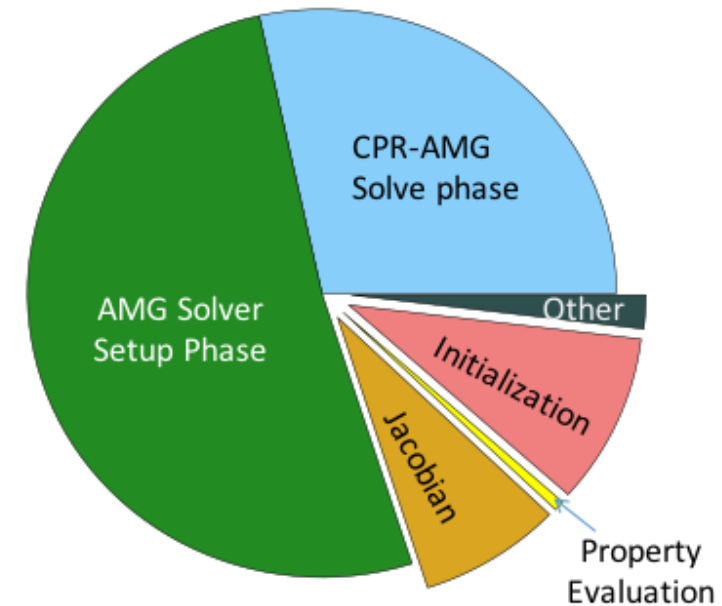


Peak Memory Bandwidth GB/s



# Challenges for Reservoir Simulation on GPU

- **Advanced solvers aren't easy on GPU**
  - Simple solvers/preconditioners are relatively straight-forward
  - Advanced solvers (e.g. AMG) important at large scale, require major redesign
- **Accelerating just the linear solver isn't enough**
  - Amdahl's Law: 10X on 70% is only 2.7X overall
  - CPU-GPU communication reduces this further
  - Overall performance gains are only marginal
- **Careful memory management is required**
  - 16 GB per GPU is enough, but no room for waste
  - Store too much → limits model size
  - Store too little → excessive communication



# The Emerging GPU Fat Node for HPC

**Work more productively with less hardware and maintenance**



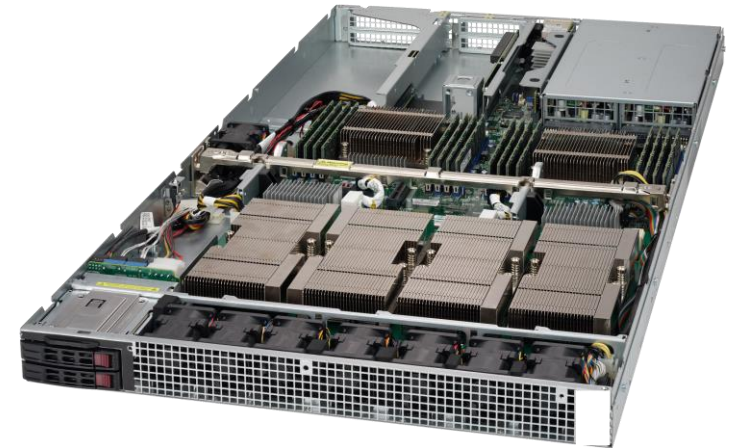
**Single K80 GPU**

**8M cells**



**Workstation**

**30M cells**



**Server Node**

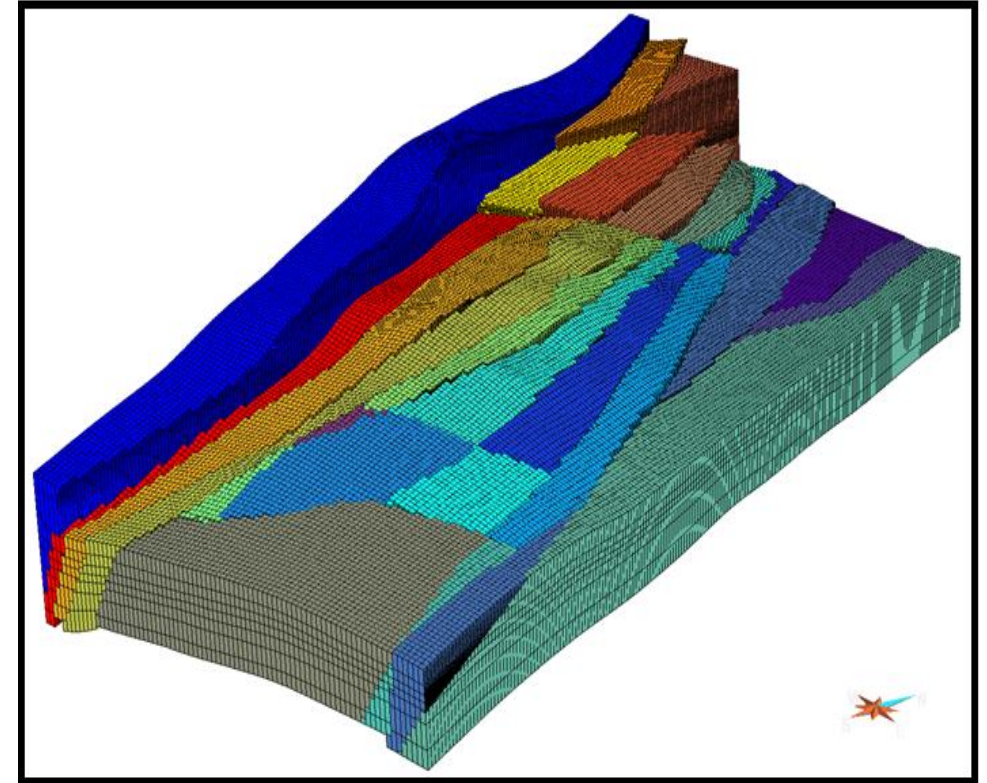
**60M cells**

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# Simulation Model

- 787 thousand active cells
- 308 possible compartments
  - 28 fault block multiplied by 11 zones
- 13 PVT regions
- 140 wells with over 30 years of history
- Averages 27% porosity
- Average 420 mD permeability



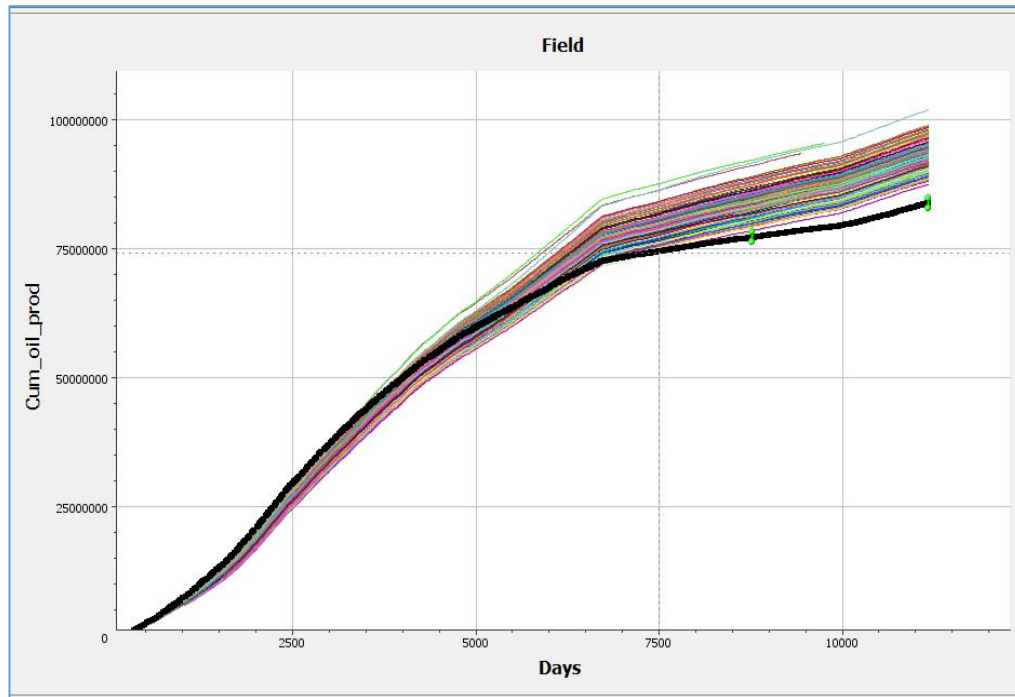
Major Fault Blocks

# Uncertainty parameters

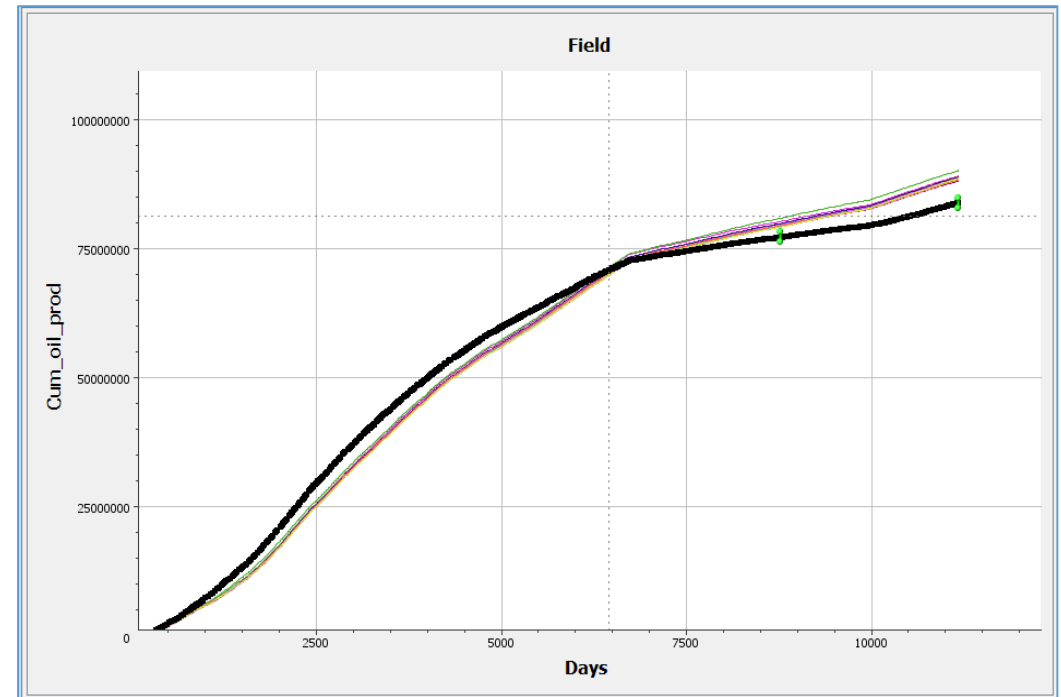
For this study, we focused on 145 modifiers

- 22 fault transmissibilities multipliers
  - ranged from 0.0 to 1.0
- 75 inter-regional transmissibilities multipliers
  - ranged from 0.0 to 1.0
- 48 regional horizontal and vertical permeability multipliers
  - range 0.2 to 5.0

# Field results

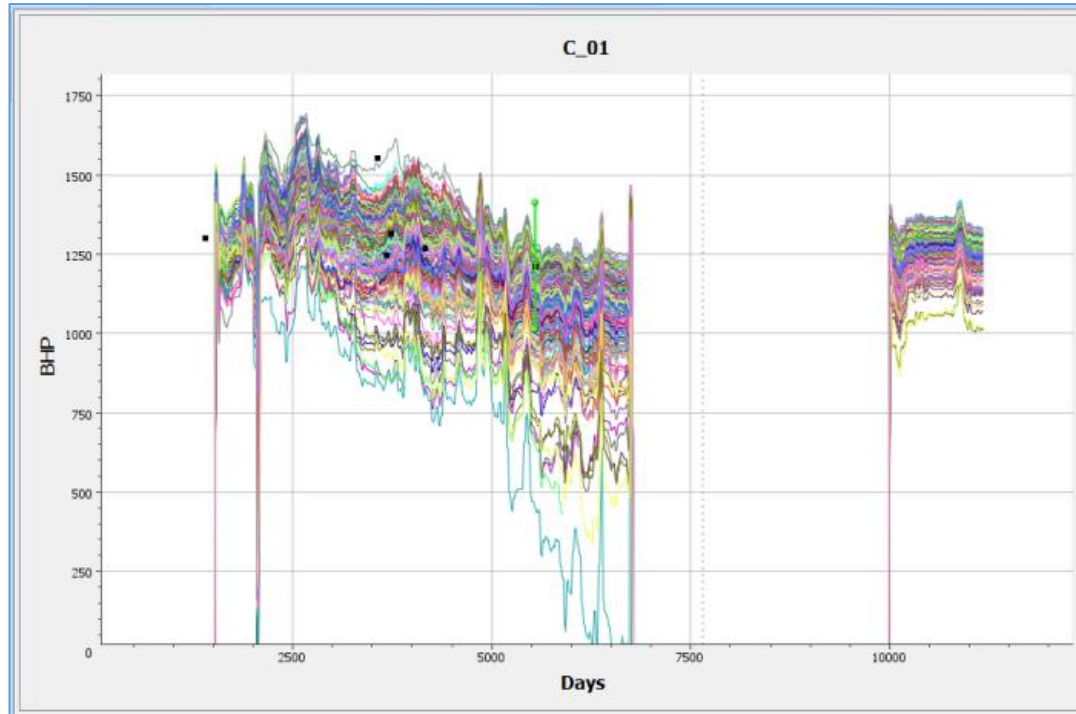


All simulation runs

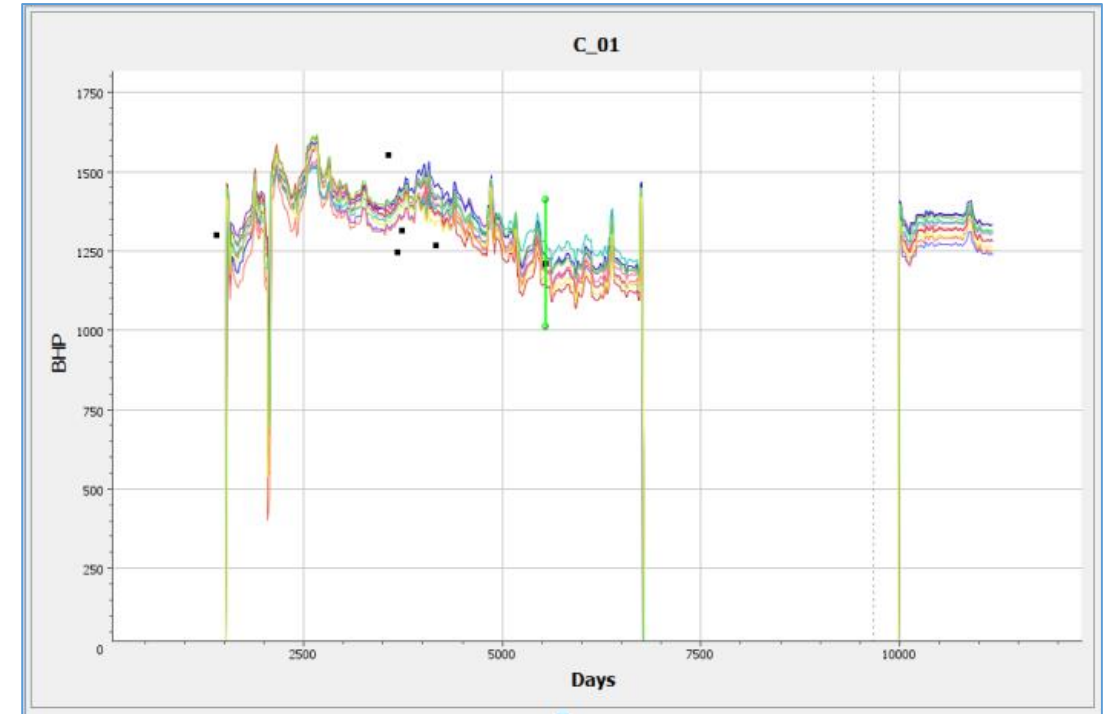


10 best simulation runs

# Individual well results

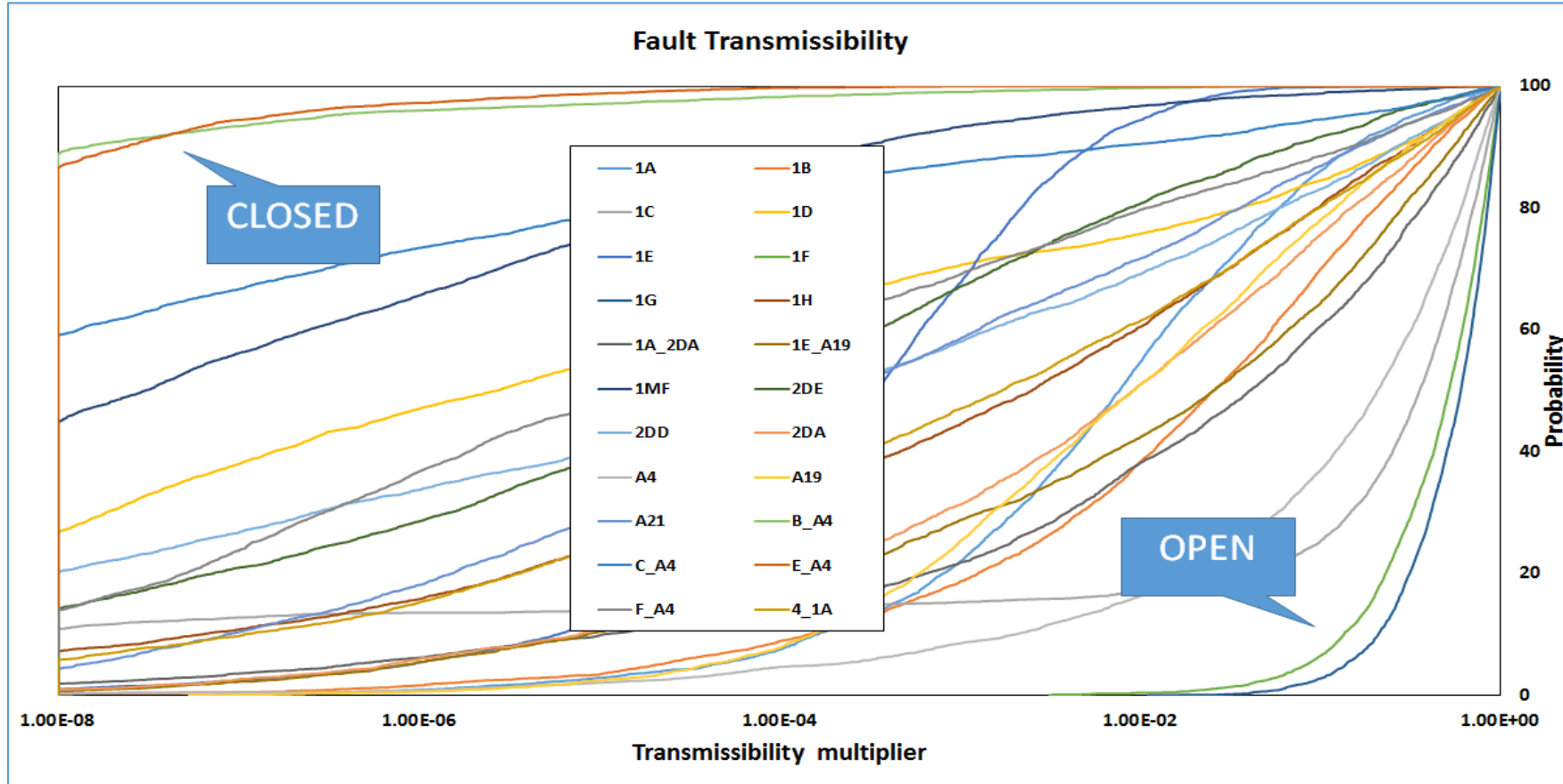


All simulation runs



10 best simulation runs

# Uncertainty in fault transmissibility modifier (S Curves)



# Runtime

- 145 variables for HM/prediction
- 7 minutes per simulation on one P100 GPU
  - CPU based industry standard simulator runs it in 340 minutes!
- Full probabilistic uncertainty after 225 simulation runs
- Total assisted history match can be done in order of hours vs days

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# History of history matching tools

- 1980's first generation
  - Early experimental design
- 1990's second generation
  - Early assisted history matching tools
  - Evolving genetic algorithms
  - Some adjoint local optimisation approaches
- 2000's third generation
  - Commercial and internal tools
  - Hundreds of history match studies
  - Typically 50+ modifiers

# What is the problem ?

- Good at history matching but poor at probabilistic forecasting
- Uncertainty methods have significant limitations
  - Over optimism on convergence behaviour
  - Under estimation of uncertainty
- Almost no validation, too much ‘trust me’
  - We don’t know if our P50 is really a P50 or P10
  - We don’t know if our ensemble is all above the P50
- Can we have a detailed model AND valid robust uncertainty forecasts?

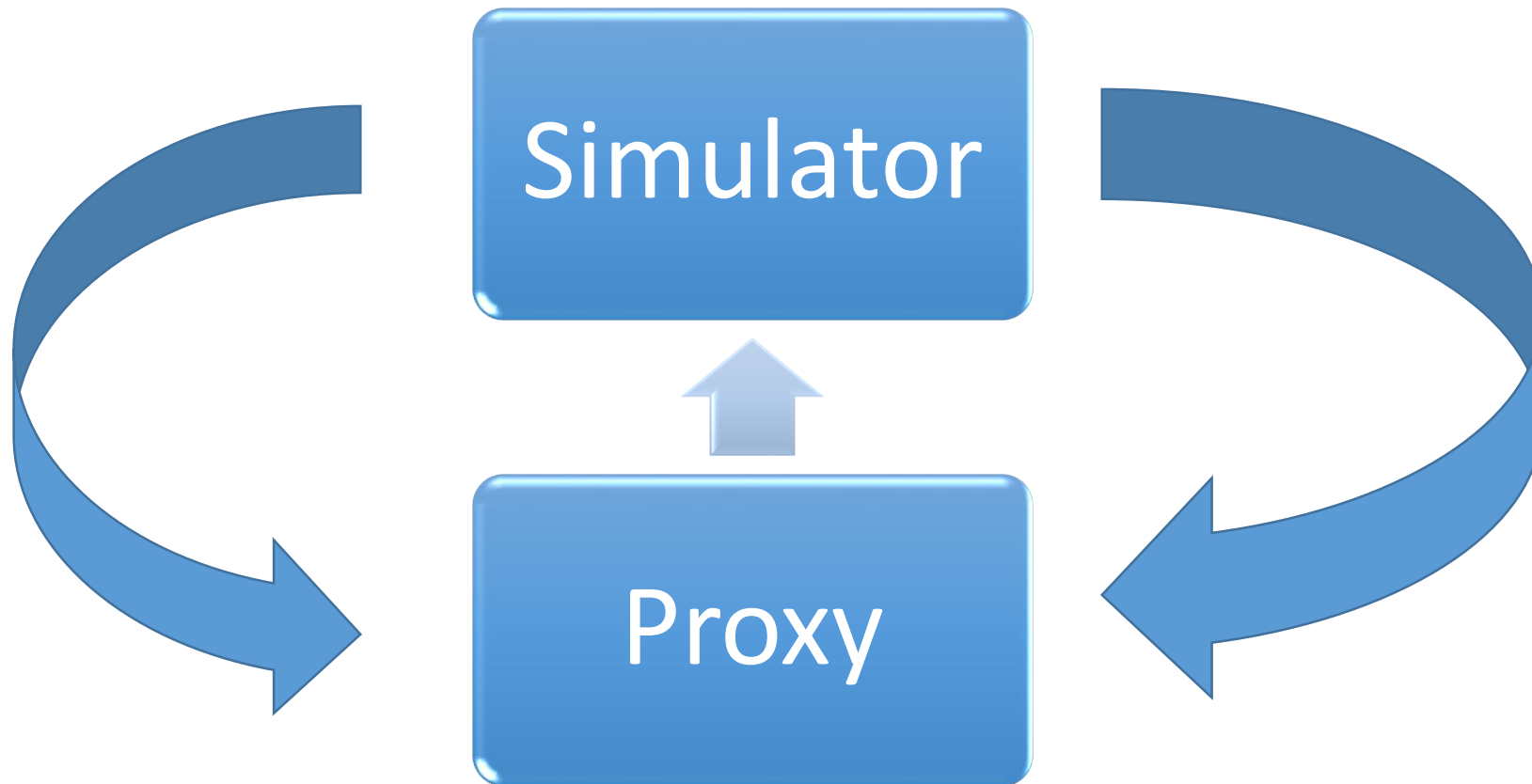
# Probabilistic forecasting

- An encapsulation of the team's beliefs about models, parameters and their ranges, quality of measurement data, and quality of simulation model, within a **probabilistic/Bayesian framework** which can generate **accurate and validated** probabilistic cumulative distribution curves (S curves) for quantities of interest at times of interest, which can then **be represented by a suitable set of simulation runs**.

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# Simulator and proxy models



# Simulator and proxy

Gaussian Process model

$$E(y(\mathbf{x})) = \underbrace{\mathbf{f}(\mathbf{x})^T \boldsymbol{\beta}}_{\text{Ensemble of linear regression models}} + \underbrace{(\mathbf{f}(\mathbf{x})^T \mathbf{Var}(\boldsymbol{\beta}) \mathbf{X}^T + \sigma^2 \boldsymbol{\phi}(\mathbf{x})^T)}_{\text{Gaussian Process model}} \boldsymbol{\phi}^{-1}(\mathbf{Y} - \mathbf{X} \boldsymbol{\beta})$$

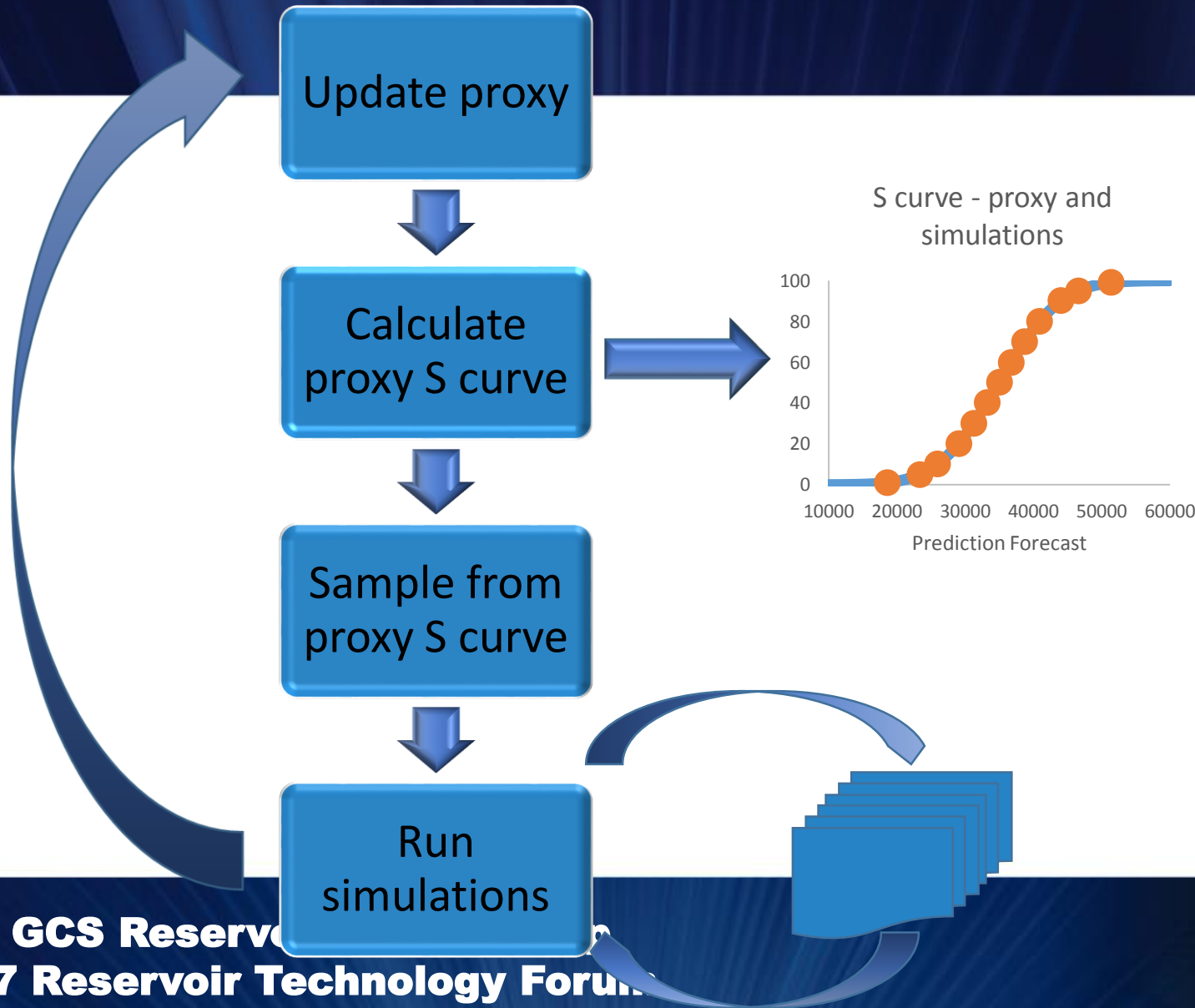
Ensemble of linear  
regression models

- Constructing the proxy model takes around a second
- Evaluating the proxy model takes around 0.025 milliseconds

# How can proxy models help us?

- We can sample tens of millions of times in Monte Carlo Markov Chain process to calculate valid probabilistic uncertainty
  - Completely impossible to perform MCMC directly with simulations
- An aid, not a replacement, for reservoir simulations

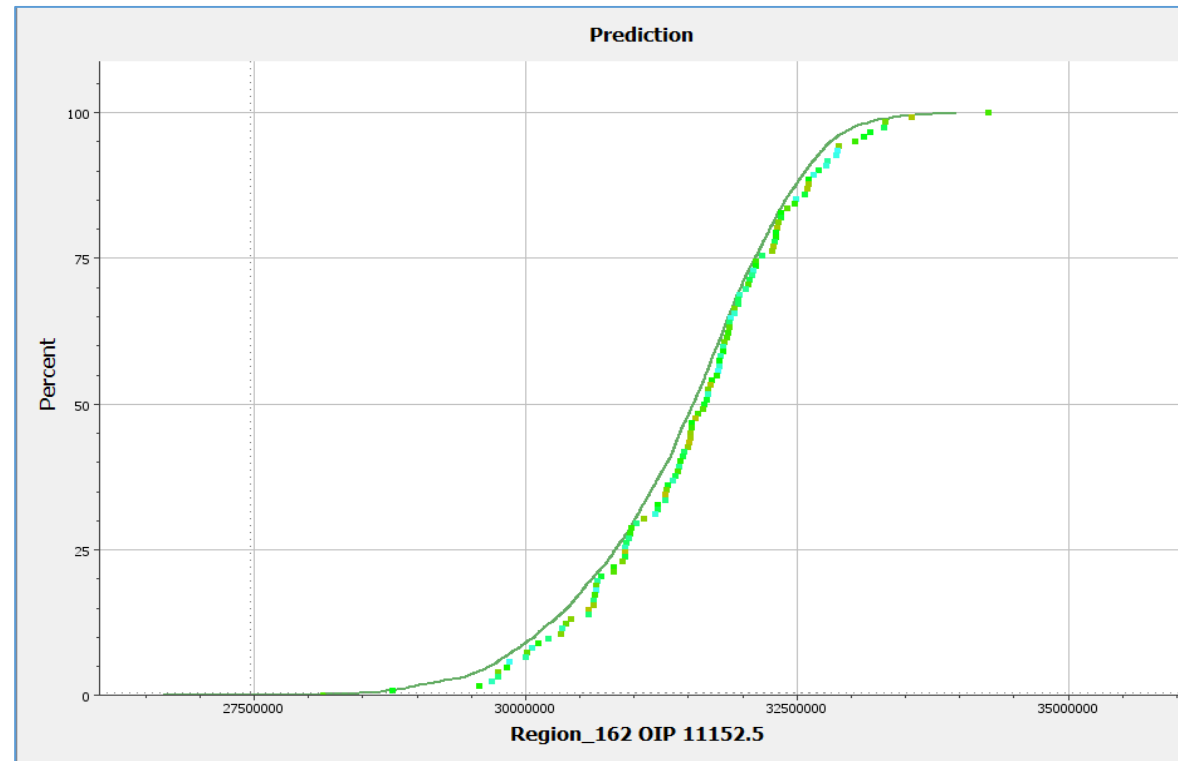
# Probabilistic Workflow



- S curve is created from proxy
- S curve from simulations is synergised
- Prediction is fully integrated with HM, no special workflow
- Easy to find P10, P50, P90 runs by inspection

# Synergy between Simulations and proxy

## Oil-in-place



S curve from proxy (smooth line) and from simulation runs (points)

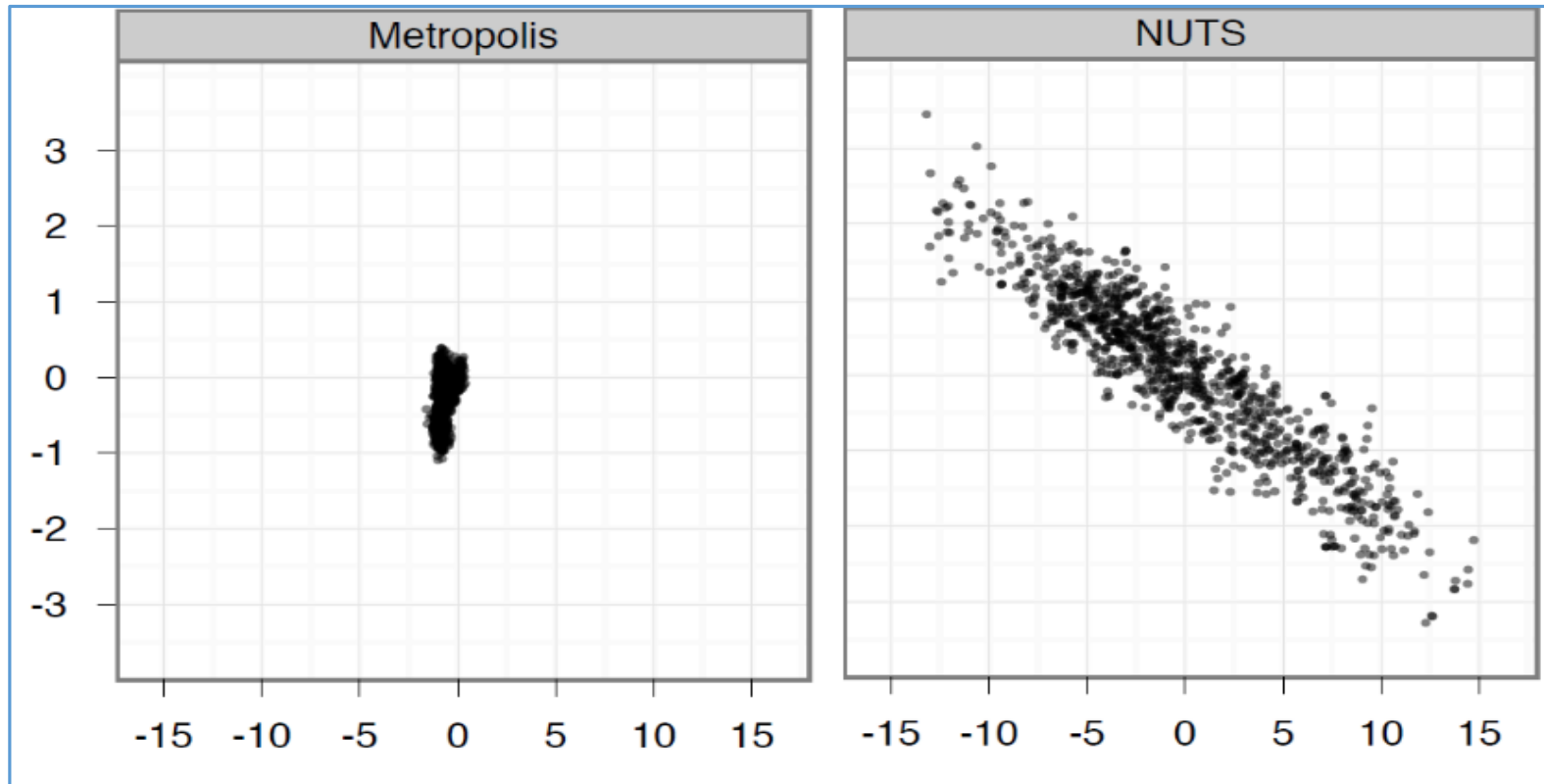
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# MCMC approaches

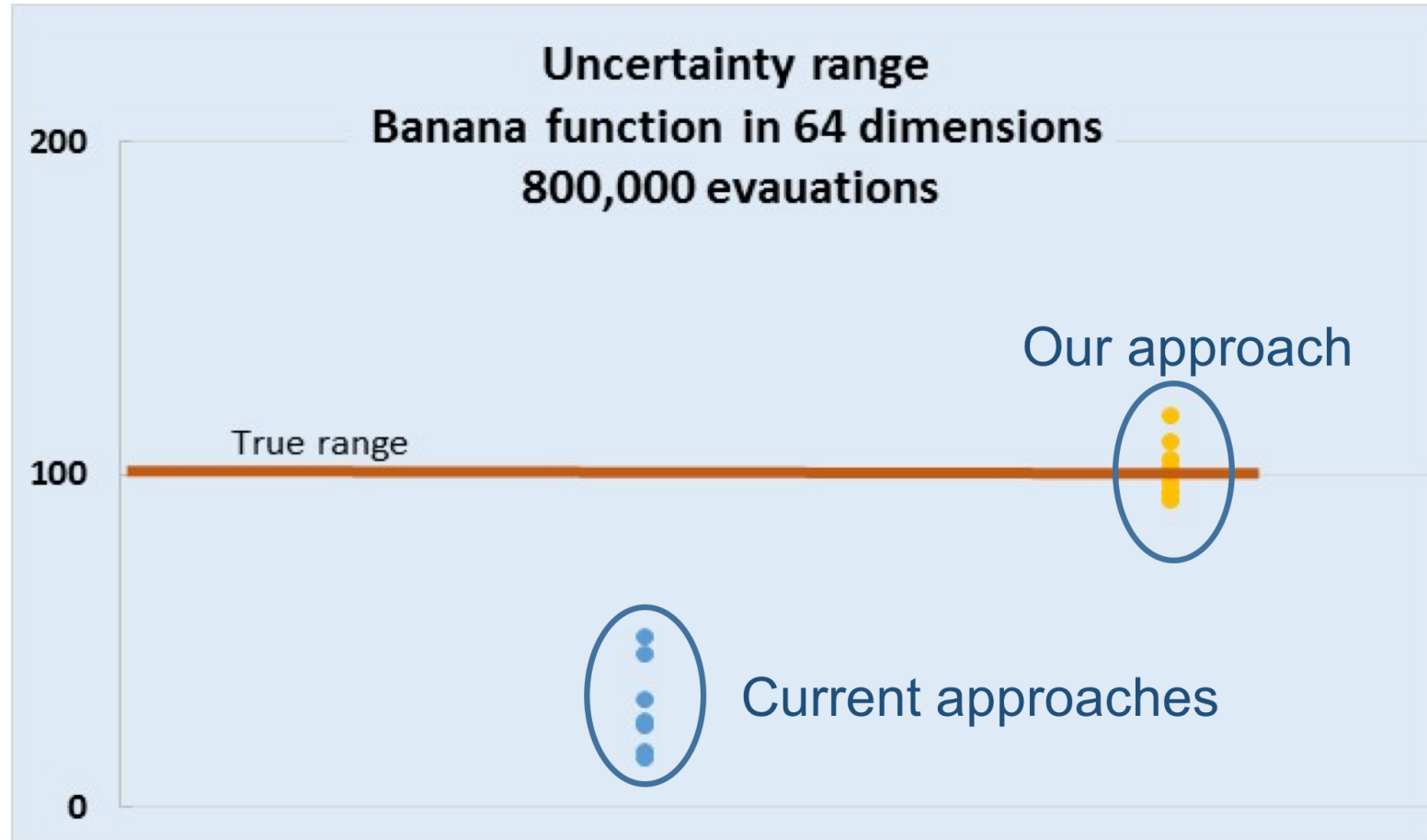
- Markov Chain Monte Carlo – the gold standard for uncertainty quantification for complex functions
  - Converges if you wait long enough
- Random Walk (RWM)
  - Fairly widely used in probabilistic forecasting
  - Can be grossly misleading for high dimensions
- Hamiltonian (NUTS) (2012)
  - Recent new method for high dimensions/complex problems
  - Requires derivatives

# Random Walk vs Hamiltonian



Samples generated by random walk (Metropolis) MCMC and NUTS (Hamiltonian) MCMC

# Validating Our Approach



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# Why our methods are valid and robust?

- The proxy S curve is valid and robust
- The ensemble of simulation runs conforms to the proxy S curve
- Ergo we have a valid and robust probabilistic ensemble of simulations
- The workflow does not depend critically on the accuracy of the proxy model

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# Summary

- Complex model
- 7 minutes per simulation
- Good HM 's emerge after 140 simulation runs
- Full probabilistic uncertainty after 225 simulation runs
- The first valid robust probabilistic uncertainty quantification approach

# Acknowledgement

- Huabing Wang and Jim Gilman, iReservoir
- Brian Lee, Memorial Resource Development Corp.

# Technical references

SPE 182637 Probabilistic Uncertainty Quantification of a Complex Field Using Advanced Proxy Based Methods and GPU-based Reservoir Simulation

N. Goodwin, SPE, Essence Products and Services Ltd,; K. Esler, M. Ghasemi, K. Mukundakrishnan, Stone Ridge Technology; H. Wang, J.R. Gilman, iReservoir.com, Inc.; B. Lee, Memorial Resource Development Corp.

SPE 173301 Bridging the Gap Between Deterministic and Probabilistic Uncertainty Quantification Using Advanced Proxy Based Methods

N. Goodwin, SPE, Essence Products and Services Ltd.

SPE-177427 Novel Workflow for the Development of a Flow Control Strategy with Consideration of Reservoir Uncertainties

Kousha Gohari, Heikki Jutila, Carlos Mascagnini and Andrey Gryaznov, Baker Hughes RDS; Nigel Goodwin, Essence Products and Services; Murray Howell and Peter J. Kidd, Baker Hughes; and Behrooz Bijani, Quadrant Energy Limited

# Thank you

# Questions?

## Speaker Introduction

- Education: UC Berkeley: Mechanical Engineering BS  
UC Berkeley: Mechanical Engineering, Masters  
Texas A&M U: Project Management, Masters  
Texas A&M U: Petroleum Engineering, PhD
- Experience: Professor & Faculty Senate  
PE in Alaska, California, & Texas  
PMP (Project Management Professional)  
Design, Construct, Start-up Mega-Projects (12 yrs)  
Reservoir Simulation (23 yrs)
- Expatriate: Lived & Worked on 5 of the 7 continents

Note taking optional. Slides available to attendees

Eric Laine (PhD, PE, PMP)  
Reservoir Simulation Engineer  
Laine & Associates, Inc.  
Established 1994

Why do 81% of O&G Executives believe  
Big Data is Critically important to success?

Because Published, Competitor's Success  
Means

My company is falling behind

90-day production is up by 250%

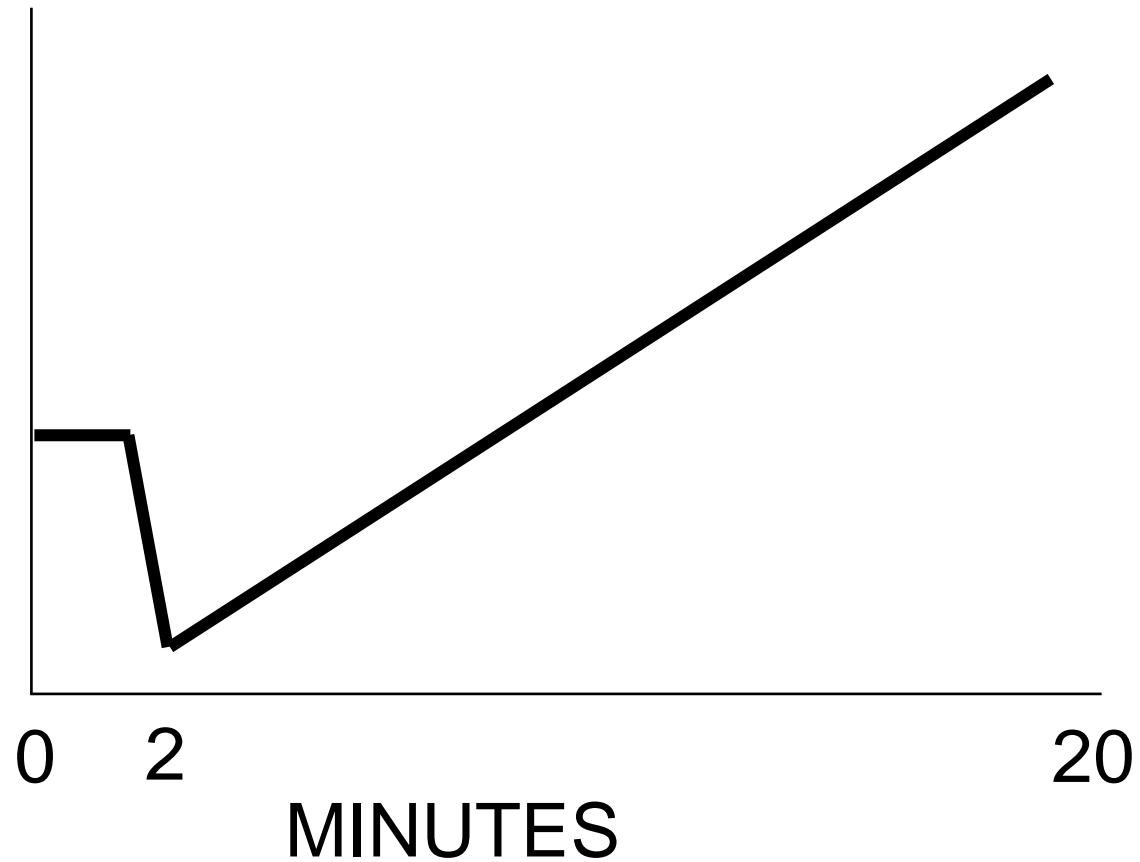
40% less cost to drill, complete & operate

10 minutes to update remaining reserves

Routine engineering tasks in minutes vs hours

# What To Expect Today

CONFIDENCE  
&  
KNOWLEDGE



IT projects

ZDNet, 2009

**38% successful**

62% either fail or perform poorly.

**50%** suffer 2 of 3 shortcomings

**80% over** planned time

**60% over** planned budget

30% short of planned functionality delivered

IT projects

Standish, 1995

16.2% successful

52.7% challenged

31.1% cancelled

## The “Black Box”

Do I need to trust it? (Yes)

Is it always right? (No)

Will I know if it's right? (Maybe)

Is it easy to understand? (No)

Who can help resolve the above?

# Education

	15-wk Certificate: Graduate Business Analytics	MBA Business Analytics	MBA Info & Operations Management	MS Applied Statistics & Data Analytics	MS Business Analytics	MS Data Science
Business Forecasting	100%	100%	100%	MS	100%	MS
Linear Programming and Optimization	100%					
Decision Analysis and Decision Trees	100%					
Project Planning Management	100%					
Simulation Models	100%					
Working with Data Science	100%					
Regression Analysis	100%					
Business Decision-Making Models & Strategy	100%	MBA	MBA	MS		MS
Visual and Social Analytics	100%					
Introduction to Data Mining	100%					
Classification and Prediction Mining	100%					
Clustering and Association Rule Mining	100%					
DATA 0001 Management Accounting I	100%	100%	100%			
DATA 0002 Management Accounting II	100%	100%	100%			
DATA 0003 Operations Management	100%	100%	100%			
DATA 0004 Big Data	100%	100%				
DATA 0005 Data Visualization	100%	100%			100%	100%
DATA 0006 Business Model Specialties	100%	100%	100%			
DATA 0007 Data Science Design for Business	100%	100%	100%		100%	100%
DATA 0008 Data Mining	100%	100%	100%		100%	100%
DATA 0009 Business Process Consulting	100%	100%	100%		100%	100%
DATA 0010 Business Management	100%	100%	100%		100%	100%
DATA 0011 Predictive Analytics & Research	100%	100%	100%		100%	100%
DATA 0012 Managing Service Operations	100%	100%	100%		100%	100%
DATA 0013 Project Management	100%	100%	100%		100%	100%
DATA 0014 Operations Management	100%	100%	100%		100%	100%
DATA 0015 Business Process Consulting	100%	100%	100%		100%	100%
DATA 0016 Inventory & Strategic Decisions	100%	100%	100%		100%	100%
DATA 0017 Green Data Analytics	100%	100%	100%		100%	100%
DATA 0018 Data Science	100%	100%	100%		100%	100%
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DATA 0081 Data Science	100%	100%	100%		100%	100%
DATA 0082 Data Science	100%	100%	100%		100%	100%
DATA 0083 Data Science	100%	100%	100%		100%	100%
DATA 0084 Data Science	100%	100%	100%		100%	100%
DATA 0085 Data Science	100%	100%	100%		100%	100%
DATA 0086 Data Science	100%	100%	100%		100%	100%
DATA 0087 Data Science	100%	100%	100%		100%	100%
DATA 0088 Data Science	100%	100%	100%		100%	100%
DATA 0089 Data Science	100%	100%	100%		100%	100%
DATA 0090 Data Science	100%	100%	100%		100%	100%
DATA 0091 Data Science	100%	100%	100%		100%	100%
DATA 0092 Data Science	100%	100%	100%		100%	100%
DATA 0093 Data Science	100%	100%	100%		100%	100%
DATA 0094 Data Science	100%	100%	100%		100%	100%
DATA 0095 Data Science	100%	100%	100%		100%	100%
DATA 0096 Data Science	100%	100%	100%		100%	100%
DATA 0097 Data Science	100%	100%	100%		100%	100%
DATA 0098 Data Science	100%	100%	100%		100%	100%
DATA 0099 Data Science	100%	100%	100%		100%	100%
DATA 0100 Data Science	100%	100%	100%		100%	100%

All 6 are at the same University

Is it a cat?

Unsupervised ML

1 billion neurons

10 million random pics

16,000 CPUs

3 training days

75% accuracy

Other Deep ML successes

Tumors in MRI scans

Chess & Go champions

Trains by playing itself



# How Much Data is Needed?

Enough data to Train & Test the Model

Unsupervised Machine Learning

Zettabytes ( $10^{21}$ ) of “clean” data

for 50 million neural nodes & weight factors

Contemporary data rate

4 TB / sec (reported)

126,144,000 TB / yr

0.126 ZB / yr (Is it “Clean”?)

Can I find the legacy data?

Mergers & Acquisitions

Bankruptcy

Right-Sized Organization

Office Moves

Catastrophes

Weeks-to-months

Could be it's own Data Analytics project

Substantial Subject Matter Expert Time

Is it relevant?

Is it accurate?

Is it too noisy (or is noise important)?

Is it complete enough?

Is it legible (or needs enhancement)?

Did it convert properly?

Are the SMEs adding bias?

All Humans (including SMEs) are biased

Biased SMEs train the Machine inappropriately

Try to imagine a secret ballot of this group

Did NASA fake the moon Landings?

Is global warming real?

Is my completion strategy the best?

Example: DOD uses ML to find hidden tanks

O&G Executive Beliefs about Data Analytics (81%)  
are Critically & Urgently Important  
will Quickly Improve Profitability  
will rival existing successes like:  
    travel industry (Airline reservations)  
    self-driving cars  
    routine activities (Manufacturing, Tax Preparation)  
will upscale to all our reservoirs (bridge uniqueness)  
will work equally well on 1 well & for portfolio  
AND  
will do so with rapidly changing requirements

## O&G Reality Check for Data Analytics

What if Executive expectations are too high?

Airlines: Decades of DA = Bloody passenger

Social Media are struggling with Fake News

Self driving cars seem to work well, mostly

My Form 1040 software < \$100

Reservoir Simulation software

Costs > \$100,000, &

10 years to reach commercial quality

Is EUR like assembly-line welds?

Changing requirements costs time and money

## Early Warning Signs of Project Failure

Individual disciplines are trained to sub-optimize

Project Manager herds cats to global optimization

One bad apple can spoil the barrel

Busy expert sends inexperienced/uninformed sub

This will be the initial oil rate

Test results extrapolated. Why did pumps fail?

This will be the capital cost

It will work better if we change “this”

This will be the completion date

Otherwise the project won't be sanctioned

## GOOD NEWS

There are ways to improve the odds of success

## Unsupervised (Deep) Machine Learning

How infants learn language

Find patterns in the gibberish

## Supervised (SME, rule-based) Machine Learning

How student learn language

Spelling, Punctuation, & Grammar

## What do we want from Data Analytics?

Description: How did it turn out?

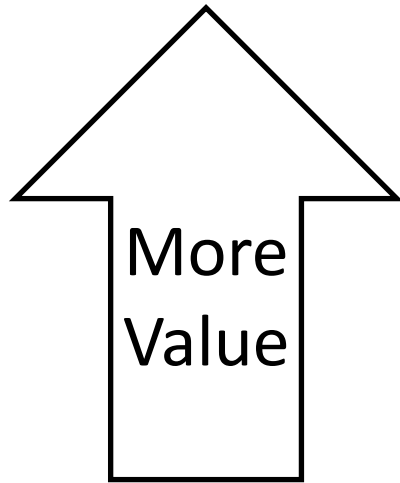
Diagnosis: Why did it turn out that way?

Prediction: How will it turn out in the future?

Prescription: What can we do better?

# Definitions

Keep It Simple Sister vs Top Down vs Both



			Prescribe
		Predict	
	Diagnose		
Describe			



Appreciate the Skills

Communication

Teamwork

Leadership

Organization

Technology



Project Success

4 of the 5 are **soft** disciplines

# Proper Pre-Project Planning Promotes Perfect Projects

## Rocket Scientists Make Mid-Course Maneuvers Successive Approximation

If 100% Probability of Success

Start using results after analyzing 40% of the data  
Analyze more data

If 50% Probability of Success

Start after analyzing 30% of the data  
Analyze more data

Maybe Pareto's Law (80-20) Applies

If 80% Probability of Success

Start using results after analyzing 20% of the data

BEYOND Deep ML  
It's irritated  
It's a kitten  
It's 2-to-4 months



CONCLUSION

My job is safe (probably, with life-long learning)

## Hardware

Specialized: Super & GPU computers

Higher Ops-to-I/O ratio

Better Scaling

Better Memory & Processor Utilization

Cluster of standard servers (x86)

Standard servers (x86) \$2,500-to-15,000

CPU with 12 cores

64-to-128 MB RAM

12 HDs, 2-to-3 TB each

The Cloud

Rent vs buy (maybe for pilot project)

Security?

## Security of Confidential Information

Authentication Protocols

Virtual Private Networks (VPN)

No Internet Connections (Air Gap)

Data Analytics can look for irregularities

Free (open source) Software  
Data Management Choices  
Analytic Calculation Choices

Paid software  
Commodity versions  
Custom versions

“68% of projects do NOT have an effective project sponsor to provide clear direction or help address problems.” KPMG

Coincidentally, **32%** of IT projects **succeed**  
ZDNet, 2009

Executive Champion

Executive Sponsor

Executive Project Initiator

The Project's Godfather

The More Senior The Better

Successful projects have:

- Executive Champion (The Godfather)

- Leadership (An Experienced Project Manager)

- Organization (An Experienced Scheduler)

- Quick & Flexible (Effective Change Management)

- Teamwork (Function Smoothly with All Disciplines)

### Executive Champion Responsibilities

- Leads writing Project Charter (i.e., Definition)

- Contract with Champion, Stakeholders, & Team

- Align with Corporate Mission & Vision

- Motivation, Benefits, & Business Case

- Define preliminary Roles & Responsibilities

- Define in-scope and out-of-scope

- Identify all Stakeholders (Primary & Others)

- Define Authorities: PM's, Budget, Reporting

- Define Allocation Authority for Scarce Resources

- Define Executive-level organization chart

### Project Manager

- Mostly “Soft” skills (aka Leadership)

- Reports to Executive Champion

- Substantial prior PM experience

  - Superior communication skills

  - Superior leadership skills

- Unlimited responsibility & finite authority

- Keeps the Team focused. (Herd the cats.)

- Team-member evaluations (hopefully).

- Timely team membership adjustments

- Brings refreshments to (short, rare) meetings

### Project Scheduler & Progress Documenter

Mostly “Hard” skills (organization)

Schedule: Create (& Update)

Progress: monitor & report (Earned Value)

Document Changes (Change Management)

Predict realistic end dates & costs

Identify member over commitment (8 hr/day)

“Soft” duties

Work closely with discipline leaders

Collect ideas to meet deadline & budget

## Hardware Specialists (MS #1)

- How much Memory

- Clusters vs Central Iron vs The Cloud

- How many Cores

## Algorithms Specialists (MS #2)

- Supervised Machine Learning

- Unsupervised Machine Learning

## Database Specialists (MS #3)

- Scalability (1 well to all Nations)

- Physical Storage

- External Access (user's dashboard)

- Rules of Manipulation

## Where to Start?

Thoughtfully pick team members

- Insist on experienced team members

- Each member has a known time commitment

- Team members must participate in person

- No substitutes allowed

  - Uninformed increases chance of failure

  - Inexperience increases chance of failure

Get help evaluating prospective DA team members

- Many Data-Analytics vendors have experience

- Few of them have actually done an O&G project

In-house IT/IS may not have enough DA experience

- Outside DA experts threaten in-house IT & IS

Embrace Teamwork

Have an Executive Champion (Godfather)

Read the Project Charter

Have a complete team of committed SMEs

Watch for the Early Warning signs

Improve your people “Soft” skills

Help the Project Manager herd the cats

Questions?

Start of Additional Information

There are more slides; just keep reading

## Facts

- O&G industry believes in Big Data

- Competition is using Big Data

- Big Data people are learning about O&G

- Big Data is NOT new to O&G

  - Classmate programmed AI in the late 1980s

  - I developed pattern recognition in the late 1980s

  - Both were relatively simple

## Conclusions

- Big Data continues to get better

- Not new, merely bigger

- It's time to learn to use bigger data

## Big Data

- Grows as time passes

  - Storage increases (cumulative)

  - Variety increases (new technology)

  - Rate increases

- Includes soft & hard “rules”

  - Soft: Targeted ads

  - Hard: Programed trading (stocks)

  - Hard: Symptoms of equipment failure

  - Hard: Kick detection

  - Hard: Fracture recommendations

  - Hard: EOR analysis (need future data)

**Not part of engineering school**

PMI, 2015

## **“Projects Completed in the Last Year:**

64% successfully met original goals/business objectives

62% were supported by active project sponsors

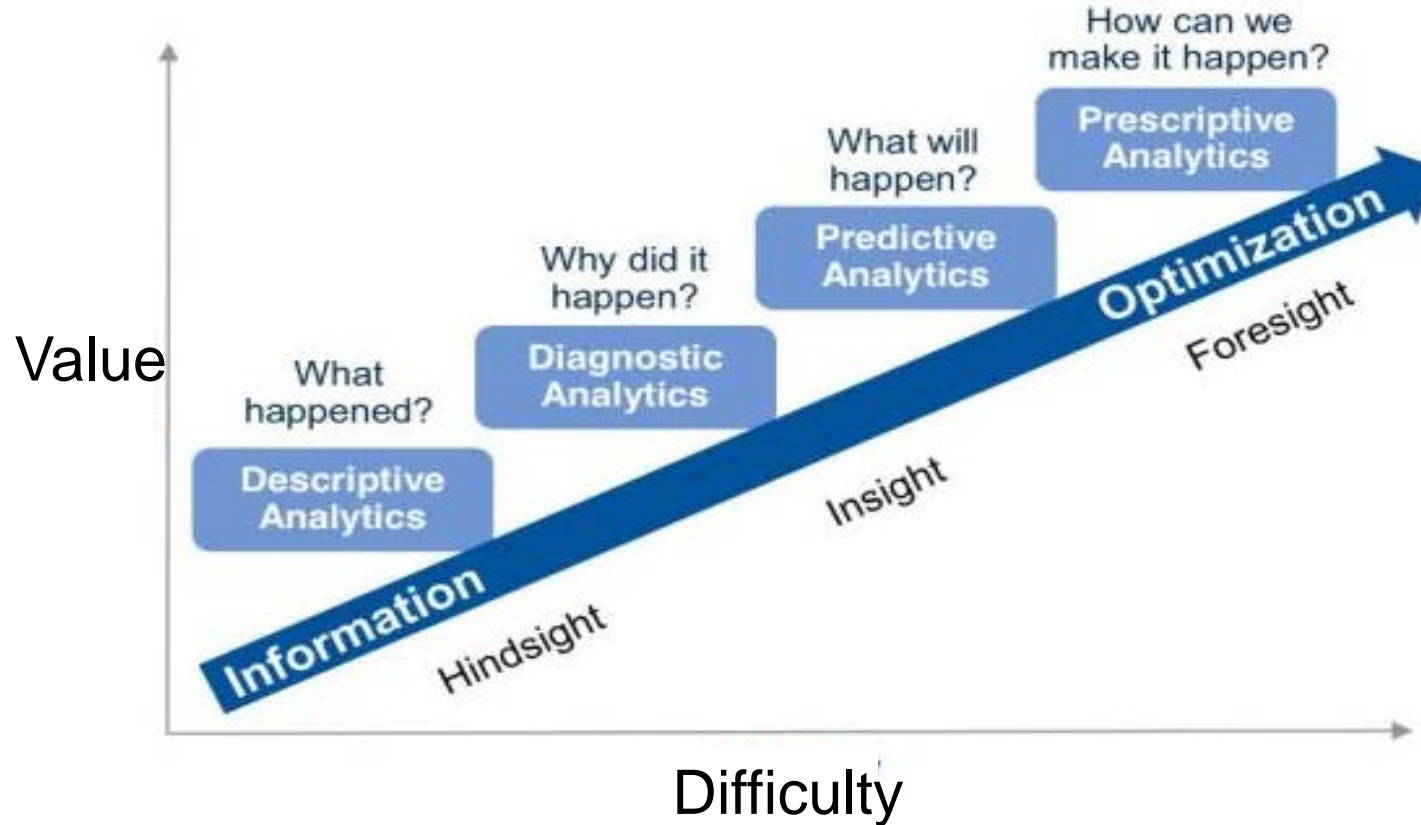
55% finished within budget

50% finished on time

44% experienced scope creep

15% were considered failures”

# Definitions



# Definitions

Clean Data: Complete, Accurate, Precise, Consistent

Taxonomy: the Science of Classification

Neural Network: Artificial Brain

Fuzzy Logic: Vague Logic; Gives Relative Answers

Supervised Machine Learning: student & teacher

Unsupervised Machine Learning: SiFi has arrived

Deep Machine Learning

With Physics

Without Physics (data driven)

Semi-supervised Machine Learning:

Artificial Intelligence: all of the above

Clean Data is the opposite of Unclean Data

Examples of Unclean Data

- Hard to read text (faded paper report)

- Production allocation

  - Among wells with a common header

  - From commingled reservoirs

- Rock properties based on limited data

  - Few electric logs

  - Fewer cores

- Subjective reports (biased conclusions)

- Production versus Time (with good instruments)

- Pressure versus Time (with good instruments)

Taxonomy is the science of classification

- A category scheme

- Identifying, describing, & naming categories

- A system of categories

- A file system

- A taxonomy has size (the number of categories)

- Fewer categories may be better

Example

- Hydraulic fractures

  - Fracture diagnostic techniques

  - Fracture mechanics

  - Fracture propagation models

  - Fracture treatment design

Fuzzy Logic (FL) is a subset of Artificial Intelligence (AI)

- Fuzzy Logic uses uncertain input

- NOT probabilistic logic

- Fuzzy Logic is inherently vague

- Relative issues: better, faster, more, less

- Fuzzy Logic is generalized logic

- Uses rules from Subject Matter Experts (SMEs)

- Fuzzy Logic is NON-binary

- Maybe is an acceptable answer

  - 0.23 is unlikely

  - 0.77 is likely

- Fuzzy may use words (spoken semantics)

Fuzzy Logic is compatible with Neural Networks

IEEE Standard 1855-2016: Fuzzy Markup Language  
Based on eXtensible Markup Language (XML)

May run on a single CPU

Examples

- Earthquake predictions

- Self-driving cars & trucks

- Genetic algorithms (assisted history matching)

- Initial production rate for a completion method**

Machine Learning (ML) is a subset of Artificial Intelligence (AI)

Machine Learning uses algorithms to:

- Sort through data

- Learn from the patterns, and

- Make a determination or prediction

Early Machine Learning (aka computer vision) used hard-coded subroutines to recognize shapes.

Now, the machine is “trained” using large amounts of data and (soft-coded) algorithms that have the ability to learn how to perform the task.

Supervised Machine Learning (SML) is more common

- Abundance of known relationships

  - Examples

    - Answers to odd problems in my math books

    - Library of known dynamometer cards

    - Effective recruiting & retention (HR Dept)

- Experts provide data sets that are “clean”

- An algorithm learns to map  $y = f(x)$

- SML subdivisions

  - Classification

  - Regression

## Supervised Machine Learning (SML)

### SML subdivisions

#### Classification

The output is a category

A color

Yes or No

#### Regression

The output is a real number

Dollars

Barrels per day

### Example Algorithms

Random forest (for clustering)

Linear regression

Unsupervised Machine Learning (USML)  
aka Deep Machine Learning (DML)

An algorithm looks for patterns given inputs

Find multiple  $y_i = f_j(x_k)$  given ONLY  $x_i$

Looking for unknown relationships

The algorithm teaches itself.

No teachers

No supervision

No answers known in advance

SME's evaluate and establish trust in the black box

USML subdivisions

Clustered

Associated

Unsupervised Machine Learning (USML = DML)

USML subdivisions

Clustered

Looking for inherent groups

Groups of points on a plot

“n-1” inputs plotted in n-space

Associated

Learning a rule describes a pattern

Given  $x_i$  inputs, plot to find groups of points

Algorithms

K-means (for clustering)

Apriori algorithm (for Association)

## Semi-Supervised Machine Learning (SSML)

An algorithm looks for patterns in  $x_i$   
Experts provide some “clean” data sets  
Few known relationships

Find multiple  $y_i = f_k(x_i)$  given  
Many many  $x_i$  needed  
Few  $y_i$  known in advance

SSML options

SML with SMEs' best guesses for training  
USML jump-started with partial training

# Definitions

Artificial Neural Networks (NN) are a subset of Artificial Intelligence (AI)

Artificial Neural Networks mimic the behavior of Natural Neural Networks (human brains)

Early Neural Networks used hard-coded subroutines to recognize shapes (with limited success).

Contemporary Neural Networks utilize parallel processing (multiple Graphical Processing Units, GPUs) to solve relatively challenging problems

Neural Networks subdivide the problem with layers of connected neurons.

The neural connections are weighted, and the final answer is based on the weights

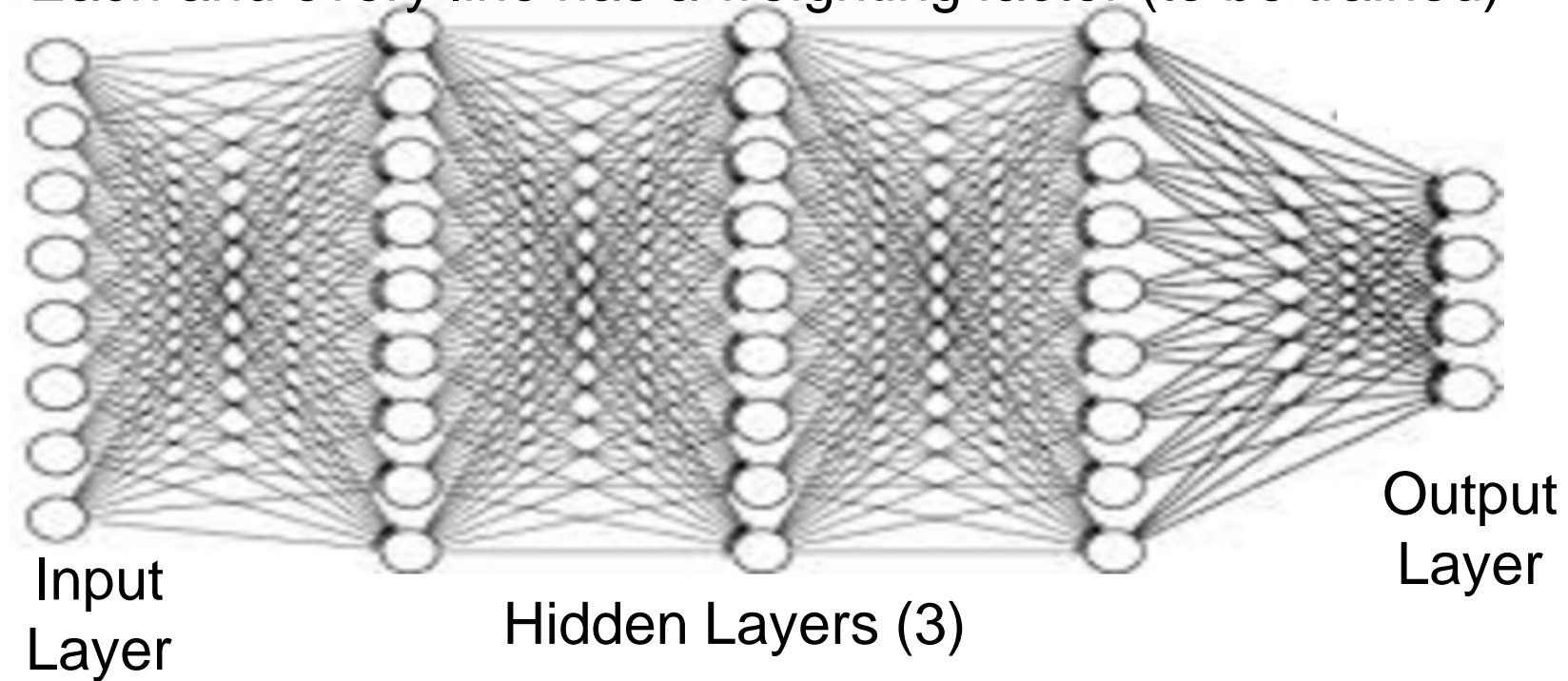
Training is the process of adjusting the weights

Training requires “significant” quantities of clean (accurately identified) correct & incorrect data.

Deep Learning required more connections and more clean data for Training

# Definitions

Each and every line has a weighting factor (to be trained)



**Imagine 10s of millions of weighting factors needed for  
Unsupervised, Deep, Machine Learning (USDML)**

# Acquired Bias

We are immersed in too much data

We do the best we can

We seek to logically & rationally use the data

We correlate our experiences

Our experiences are incomplete

We create rules of thumb

Our rules of thumb may be flawed

## WARNING

We may be tempted to pre-determine solutions

## CONCLUSIONS

Acting on intuition may be flawed

Our gut instincts may be flawed

Our educated guesses may be flawed

## Slow

- Paper (if you can find it)

  - Scan text (optical character recognition)

    - Log headers 4 times

      - Horizontal

      - Vertical

      - Sideways

      - Upside down

## Fast

- Electronic – prerecorded

## Faster yet

- Electronic - real time

  - TB / second

Faster yet

Electronic - real time

3 TB / second (really) (assume for a field)

31,536,000 sec / yr

94,608,000 TB / yr / field

1,000 fields

94,608,000,000 TB / yr

94,608,000 petabytes / yr

94,608 exabytes / yr

94.6 zettabytes / yr

0.946 yottabytes / yr (long live Yoda)

# Most Common Causes of Project Failure:

PMI, 2015

Changing priorities within organization – 40%

Inaccurate requirements – 38%

Change in project objectives – 35%

Undefined risks/opportunities – 30%

Poor communication – 30%

Undefined project goals – 30%

Inadequate sponsor support – 29%

Inadequate cost estimates – 29%

Inaccurate task time estimate – 27%

Resource dependency – 25%

Poor change management – 25%

Inadequate resource forecasting – 23%

Inexperienced project manager – 20%

Limited resources – 20%

Procrastination within team – 13%

Task dependency – 11%

# Team Members

Engineering is (only) one part of the puzzle

Executive-Suite Champion

Project Manager

Project Scheduler

Purchasing & Expediting

Database specialist (the right kind)

Analytics Software (the right kind)

Analytics Hardware (appropriate)

AND

Geol, Geophys, & Petrophys

Engineers (& Technicians)

# Team Members

## Project Scheduler & Progress Reporter

- Mostly “Hard” skills (aka Organization)

- Works closely with all disciplines

- Earned-Value & Scheduling experience

  - Superior communication skills

  - Superior organizational skills

- Collects progress from other team members

  - Reports progress

  - Predicts Expectation of Completion:

    - On-time

    - Within-budget

    - Fit-for-purpose

  - Change management records

Technical Team (secunded to PM)

Data-analytics specialists for:

DA Software

DA database architecture

DA hardware

Information Technology (traditional)

Purchasing, Expediting, etc.

Typical support staff (safety, admin, etc.)

Geo-scientists (all branches)

Engineers (all branches)

## O&G Reality Check for Data Analytics

Executive expectations are high

May rival other industry challenges

Overbooked reservations

Bloody passenger

No room at the Inn

Fake news; alternative facts

EURs versus millions of assembly line welds

Form 1040 versus Seismic & Simulation software

RFQ & RFP versus rapidly changing job needs

Assimilating lessons learned versus budget & schedule

Change management versus Scope Creep

## Leverage the Better Tool

### Human

- Learning Languages

- Infer New Concept w/ Little Data

- Quality Checking Machine Learning Output

### Machine Learning

- Infer New Concept from Big Data

- Work Faster

- Routine or Repetitious

## CONCLUSION

- Synergy is Productive

## Supervised Machine Learning

Successive layers learn to recognize:

- The pole

- The octagon

- The red color

- Text

- The individual letters

- And so on



The output may be a highly-educated guess.

- Maybe 85% correct

- Maybe 15% it's really a kite stuck in a tree

Expect success rate to improve with more training

Remove mystery with end users on development team

Black-Box is a mystery

Default rules provided

Temptation to use defaults

Pro: Easy to use

Pro: No need for SME's

Con: May not be the right rules for my data

Con: Wasted time (if discovered in time)

Con: Failed development (if NOT discovered in time)

Description

Hydraulic Fracture Outcome

Diagnostic

The Good & Bad of a Completion

Predictive

Production Forecast

Prescription

How to better complete THIS well

# Competition's Answers

## One Competitor's Successes means

My company is falling behind

90-day production now 350% (after Data Analytics)

40% less cost to drill, complete & operate

10 min to calculate company's remaining reserves

Minutes versus hours to do routine engineering tasks

“They” did that with Machine Learning

Extensive inter-disciplinary communication

New vocabulary. Life-long learning

Will this improve share holder's wealth?

Optimize the Global (not the individual discipline)

It's about the money (not the engineering)

## Considerations

- Ability to:

  - Scale up later

  - Analyze data fast enough

  - Ability to analyze all the data

- Availability

- Flexibility

- Cost

  - Pilot on The Cloud

  - Proof of concept

  - Non-competitive data

## Team Member Issues

- Skillful communication required

  - Data Analytics SMEs unfamiliar with O&G

  - IT SMEs unfamiliar with Data Analytics

  - Technical SMEs unfamiliar with DA & IT

  - Purchasing unfamiliar with special orders

- Vocabulary unique to each discipline

  - Learning curves

  - Cross training

- New ways of thinking

  - Local vs Regional vs International scales

  - New hardware configurations

Embrace the value of all disciplines

Executive Champion

Project Management, Scheduling & Progress Reporting

Stock Analysts & Shareholders & Media

Data-Analytics: Algorithms, Hardware, & Databases

Existing Information Technology & Systems

Health Safety Security & Environment

Regulators

Non-Government Organization

Purchasing, Expediting, etc.

Admin Services & Facilities Management

Geo-Scientists & Technicians

Engineers & Technicians

## Stock Analysts

- Know about the high profile of Data-Analytics

- Tend to ignore need for long-haul results

- Tend to focus on day-trading audience

- May seek naive team members for “the scoop”

- Competitive edge may require secrecy & confidentiality

## Shareholders

- Corporation’s fiduciary responsibility is to shareholders

- Shareholders prefer good news (dividends & share value)

- It’s about the money (not the engineering)

## Media

- Official press releases

- Public opinion

# Summary – General Duties

## Data-Analytics

### Hardware Specialists

- How much Memory

- How many Cores

- Clusters vs Central Iron vs The Cloud

### Algorithms Specialists

- Fuzzy Logic

- Supervised Machine Learning

- Unsupervised Deep Machine Learning

### Database Specialists

- Scalability (1 well to all Nations)

- Architecture

  - Physical Storage

  - External Access (user's dashboard)

  - Rules of Manipulation

# Where to Start?

Look for early success

Start modestly.

Executive, Project Manager, technical SME input  
prepare a professional Project Charter

3 TB of data is a small project

2 weeks to clean & convert data

2 weeks for SMEs to prepare training data

2 weeks initial supervised learning

2 weeks verifying results & adjusting algorithms

Already well understood

Existing Information Technology & Systems

Health Safety Security & Environment

Regulators

Non-Government Organization

Purchasing, Expediting, etc.

Admin Services & Facilities Management

Geo-Scientists & Technicians

Engineers & Technicians

Paper (Legacy)

Electronic (Newer)

Streaming (Real Time)

Electric logs

Mud logs

Tables

Charts & Graphs

Photographs

Movies

Text

Speech

## Data Preparation – A Choice?

- Take the time to convert all of it, or
- Convert just enough to get started

## Scan Legacy Data

- Optical character recognition (OCR)

- Digitize log traces

- How many font orientations on log headers? (4)

## Convert Electronic Data to the Proper Format

## Stream New Data in Proper Format

- Consider sampling data (if rate is too fast)

Intentionally blank

# ***Reservoir Engineering Aspects and Forecasting of Well Performance in Unconventional Resources***

**Tom BLASINGAME  
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College Station, TX 77843-3116 (USA)  
+1.979.845.2292 — [t-blasingame@tamu.edu](mailto:t-blasingame@tamu.edu)**

## Brief Biography — Tom Blasingame

### ● "Who am I"

- Professor, Texas A&M U.
- B.S., M.S., & Ph.D. from Texas A&M U.

### ● Counts: (May 2017)

- 13 Ph.D. Graduates
- 62 M.S. (thesis)/33 M.Eng. (report) Graduates
- Over 140 Technical Articles

### ● Recognition:

- SPE Distinguished Member (2000)
- SPE Distinguished Service Award (2005)
- SPE Distinguished Lecturer (2005-2006)
- SPE Uren Award (2006)
- SPE Lucas Medal (2012)
- SPE DeGolyer Distinguished Service Medal (2013)
- SPE Distinguished Achievement Award for PETE Faculty (2014)
- SPE Honorary Member (2015)
- SPE Technical Director for Reservoir Description and Dynamics (2015-2018 )

### ● Research Interests: 2017

- |  |                                    |
|--|------------------------------------|
| ■ Time-Rate Analysis (Models & Diagnostics)                      | <i>[unconventional reservoirs]</i> |
| ■ Correlation of Production Metrics/Completion Parameters        | <i>[unconventional reservoirs]</i> |
| ■ Early-Time "Flowback" Analysis/Interpretation                  | <i>[unconventional reservoirs]</i> |
| ■ Interpretation/Analysis of Time-Rate-Pressure Performance      | <i>[unconventional reservoirs]</i> |
| ■ Mechanistic Well Performance Behavior                          | <i>[unconventional reservoirs]</i> |
| ■ Parametric/Non-Parametric Correlation of Well Performance Data | <i>[various applications]</i>      |
| ■ Explicit Relations for Wellbore Storage                        | <i>[various applications]</i>      |



[2012]



[2016]  
(Saudi Arabia  
visa photo)

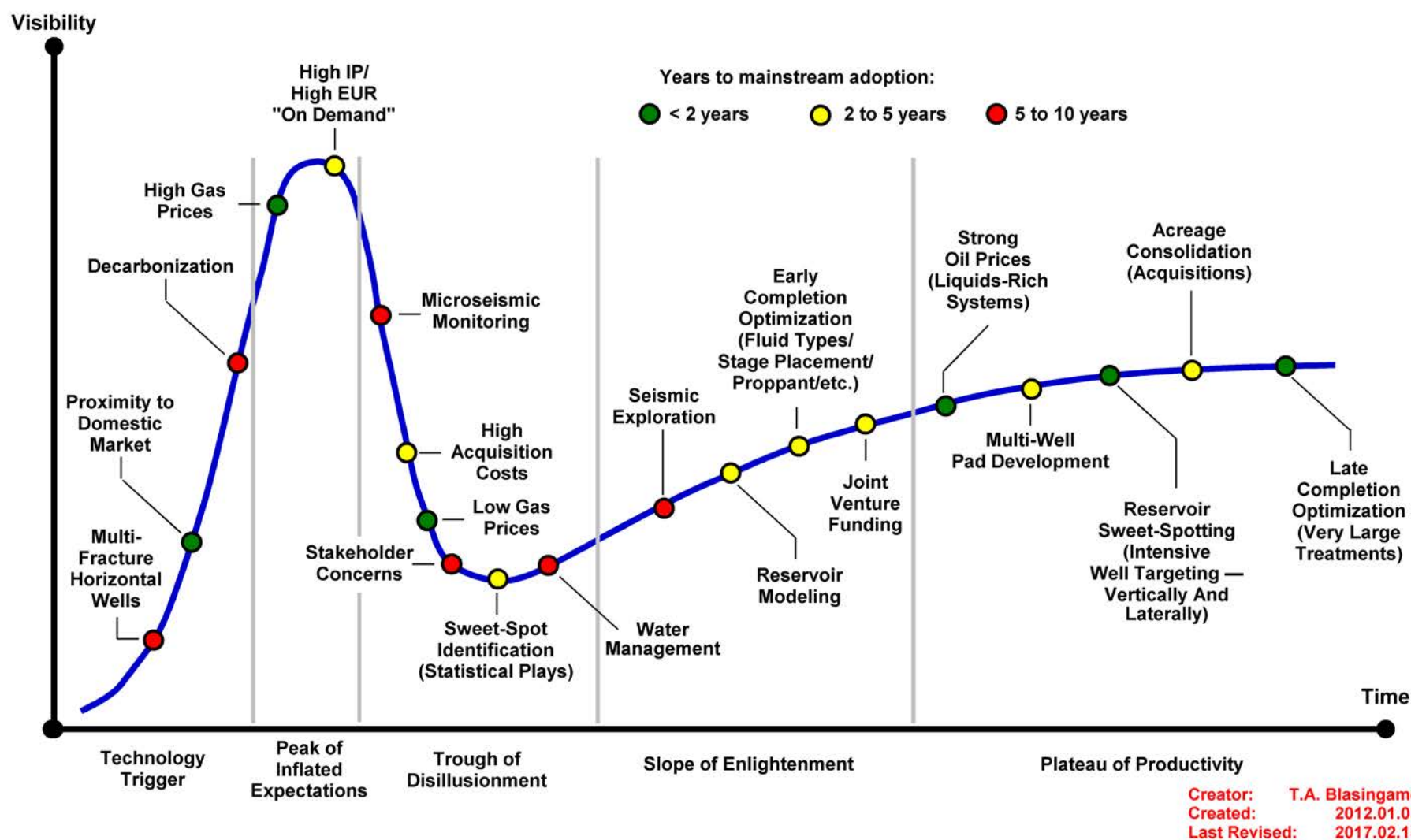


[self image]



[how others  
see me]

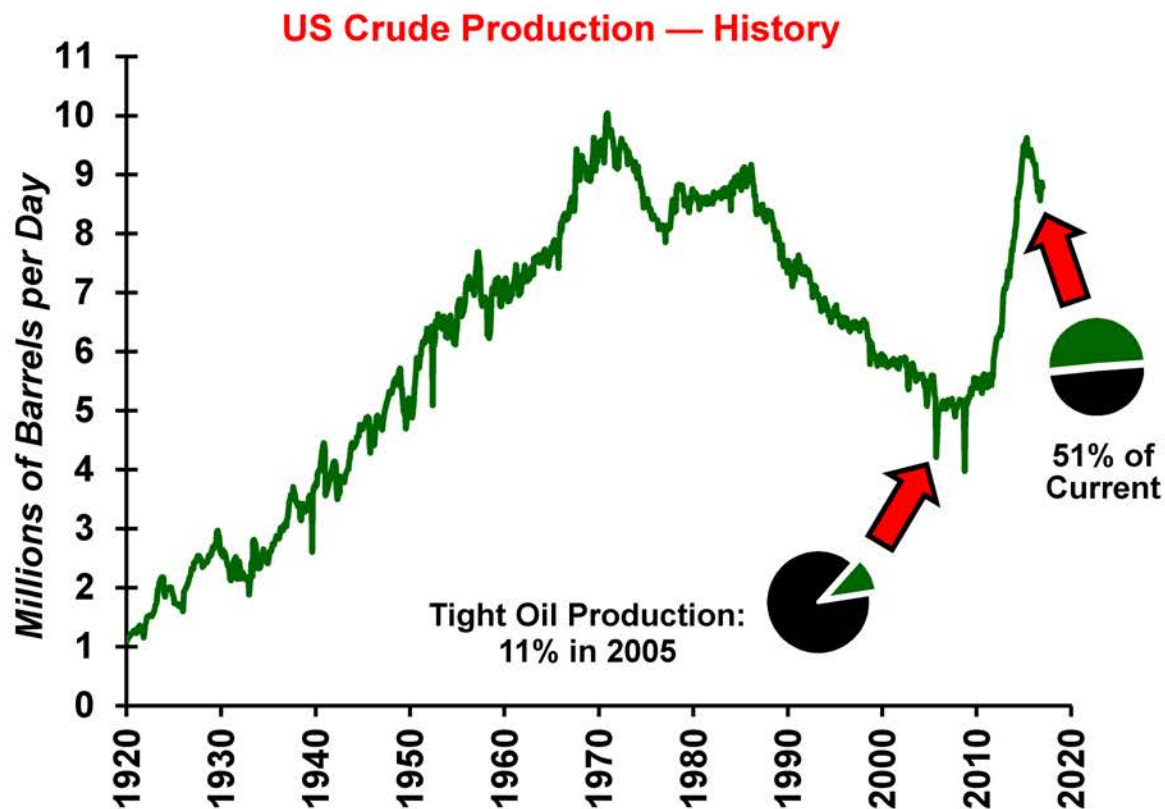
## Start-Up — "Progression Cycle" for Unconventional Resources



### Discussion:

- "Progression Cycle" plots are often used to illustrate "product" development.
- There is (almost) always a "hype" point for a new technology, then reality sets in.
- The perception early on in unconventional development is that IP correlates with EUR.
- Unconventional gas was the starting point, liquids-rich systems are the value multiplier.

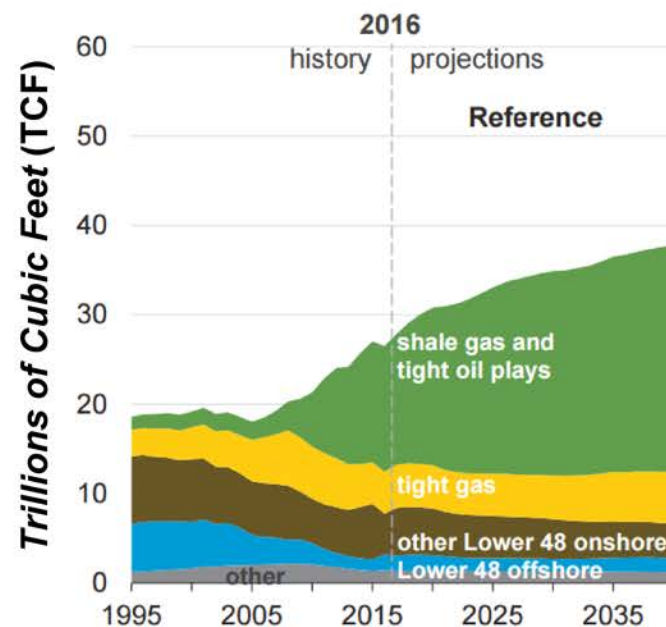
## Start-Up — "Technology Impact" — Significant Gains in Oil and Natural Gas Production



Source: US Energy Information Agency  
Last Revised: 2017.02.28

Original Concept/Content From:  
Mike WEAVER, Anadarko Petroleum Corp.

## US Natural Gas Production — History

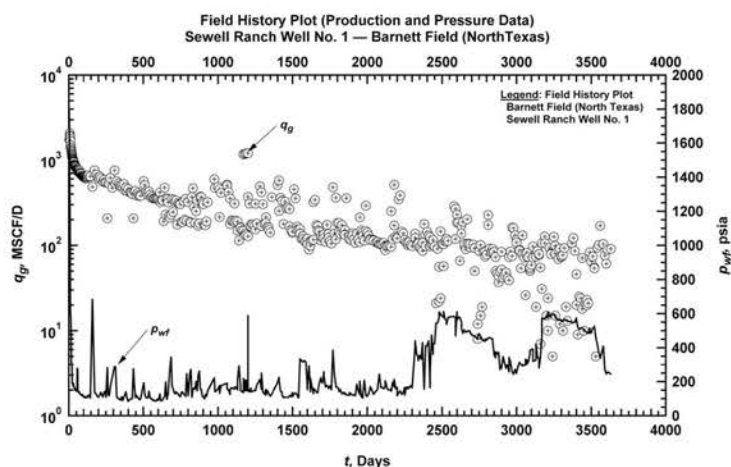


Source: US Energy Information Agency  
Publication: Annual Energy Outlook 2017  
Last Revised: 2017.01.05

## Discussion:

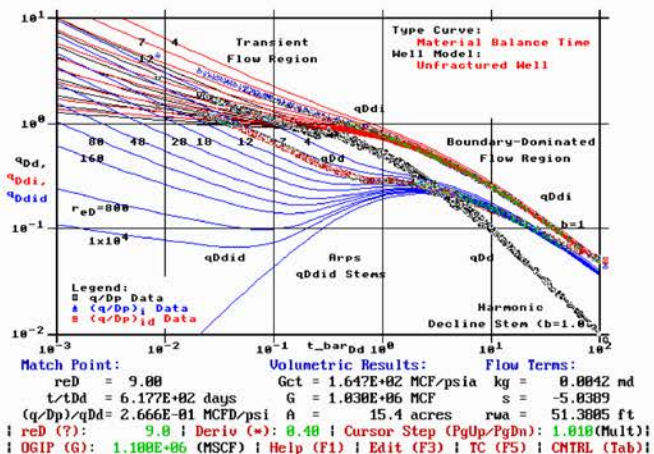
- Stimulation technology has been the primary enabler for development of unconventional.
- Unconventional resources have global ramifications on supply and production.
- Significant increases in production can be achieved from tight formations in a very short time.
- US has cut net energy imports by 2/3 in 10 years, potential to be net exporter by 2026(?).

## Start-Up — Barnett Shale — 1990s: Vertical Wells

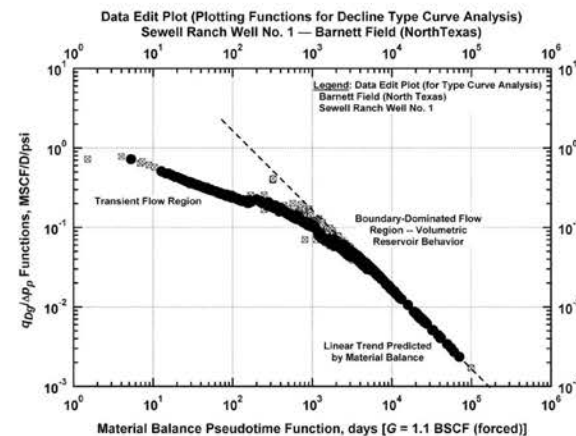


a. "History Plot" — Gas rate and computed bottomhole pressures.

Well Id: Sewell Ranch Inc. #1  
Analyst: Dept. of Petroleum Engineering, TAMU

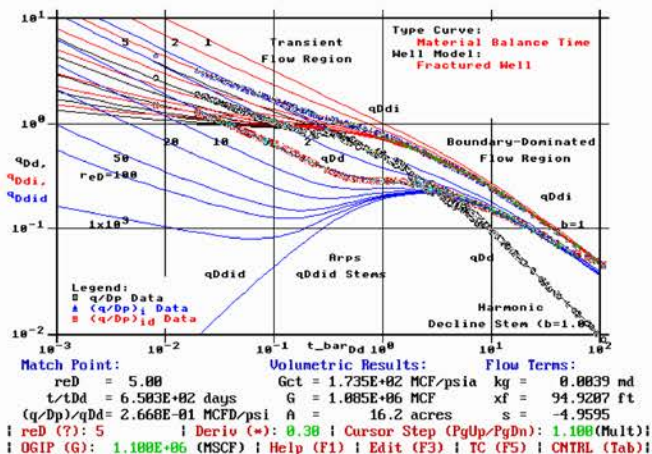


c. "WPA Plot" — (original RTA) Unfractured well model.



b. "Edit Plot" — Gas productivity Index and gas material balance pseudotime, edited data are shown as open symbols (circa 1998).

Well Id: Sewell Ranch Inc. #1  
Analyst: Dept. of Petroleum Engineering, TAMU



d. "WPA Plot" — (original RTA) Fractured well model (infinite conductivity case).

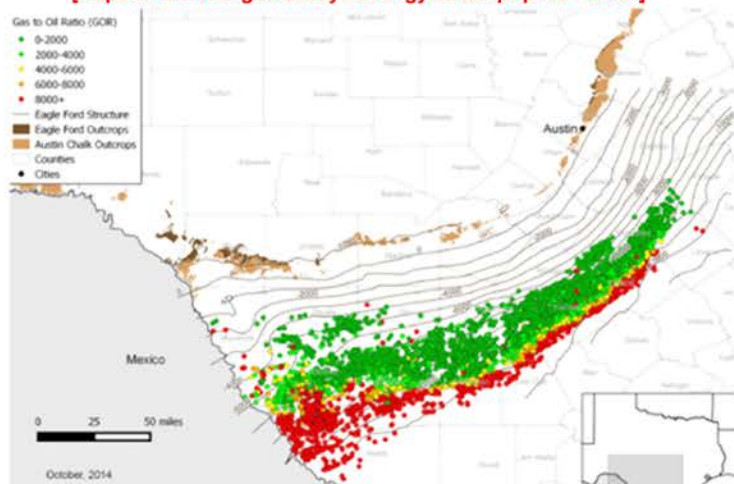
Creator: T.A. Blasingame  
Created: ~1998.04.01

## Discussion:

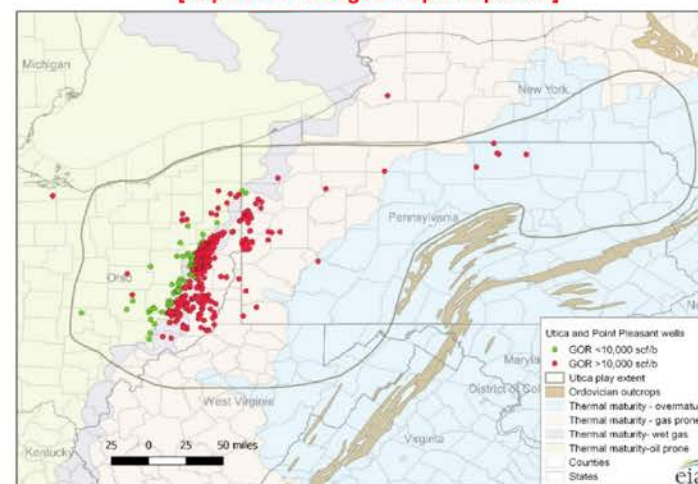
- Barnett Shale example case (surface rates/computed bottomhole pressures, vertical well).
- "Data Edit" plot is actually a diagnostic plot (note trends).
- WPA (RTA) type curve matches for an unfractured well and a fractured well.
- This was the starting point for "modern" unconventional oil and gas development.

## Start-Up — Liquids Rich Plays — Major Activities

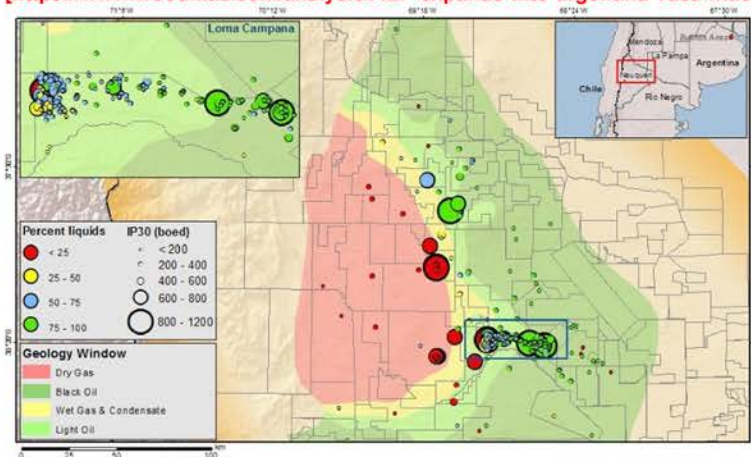
Initial Gas-to-Oil Ratios — Eagle Ford Shale (Jan 2010 - Jun 2014)  
[<https://www.eia.gov/todayinenergy/detail.php?id=19651>]



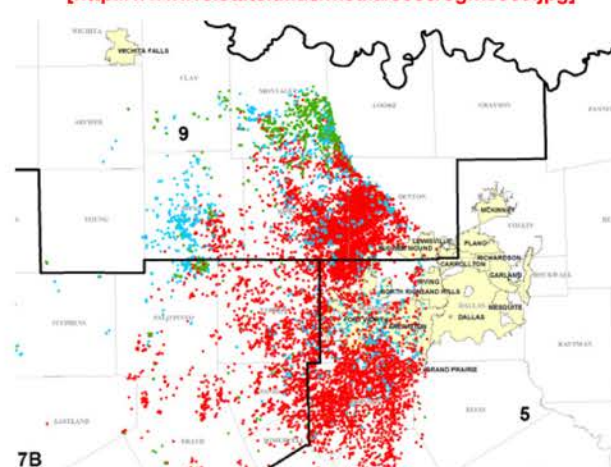
Initial Gas-to-Oil Ratio — Utica/Point Pleasant Shale (Jun 2016)  
[<https://www.eia.gov/maps/maps.htm>]



Initial Gas-to-Oil Ratio — Vaca Muerta Shale (Jan 2016)  
[<https://www.woodmac.com/analysis/AEP-expands-into-argentina-vaca-muerta>]



Oil and Gas Wells — Barnett Shale (Sep 2013)  
[<http://www.rrc.state.tx.us/media/8983/ogm0069.jpg>]



## Discussion:

- Sampling of major plays — GOR/number of oil/gas wells (indicates oil or gas preference).
- Eagle Ford (TX) is most cited "liquids-rich" play; Vaca Muerta (AR) is Eagle Ford analog.
- Barnett Shale is primarily a gas play, most often used for comparative studies.
- Where is/are the next major plays/developments? (And why? And when?)

## ***Objectives — Things that need attention, but will not be completely covered here...***

### ● **Reservoir Characterization:**

- ***Geology:*** *Defining unconventional/shale reservoir systems*
- **Geophysics:** Defining the role of seismic and microseismic data
- ***Petrophysics:*** *Correlating porosity and permeability concepts*
- **Flow Behavior:** Scaling effects related to Darcy and Knudsen flow behavior
- **Phase Behavior:** Characterizing PVT for "liquids-rich" shale reservoirs

### ● **Well Completions/Field Development/Operations:**

- ***Stimulation:*** *Identifying current/expected practices, strategies, optimization*
- ***Data:*** *Collecting, analyzing, and interpreting well performance data*
- ***Production:*** *Liquid-loading, role of artificial lift, field practices/operations*
- **Development:** Field development, well spacing/placement, performance expectations

### ● **Reservoir Performance:**

- ***Diagnostics:*** *Identifying well performance characteristics/flow regimes*
- ***RTA:*** *Time-rate-pressure analysis for production data and flow diagnostics*
- **PTA:** Practical aspects of time-pressure analysis
- ***Modeling:*** *Modeling aspects for unconventional*
- **Reserves:** Utilization of time-rate (decline curve) models
- ***Parameters:*** *Estimating reservoir/completion parameters using well performance*
- **Forecasting:** Forecasting for various production, completion, development
- ***Workflow:*** *Providing a workflow(s) to help quantify well performance uncertainty*

Petrophysics — Tight Gas Basins (circa 1980s)

Comparison of Properties for Conventional and Tight Gas Reservoirs

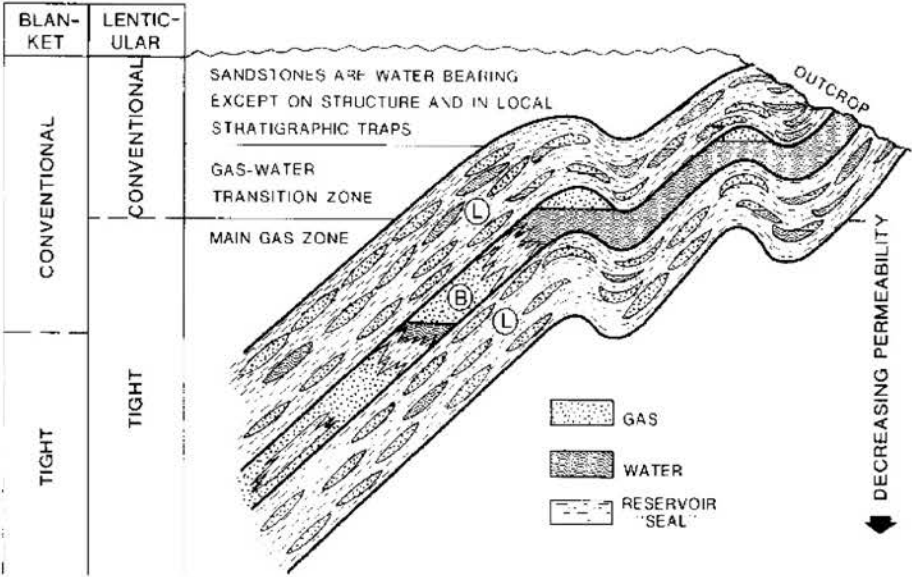
	Conventional Gas Sandstone	Tight Gas Blanket and Lenticular Sandstone (LP Reservoir)	Tight Gas Blanket Siltstone, Silty Shale (HP Reservoir)	Tight Gas Blanket Chalk (HP Reservoir)
Porosity (%)	14-25 +	3-12 +	10-30 + in individual siltstone laminations	<25-45
Porosity Type	Primary (intergranular), some secondary	Common secondary (microvug), some intergranular	Dominantly primary, some secondary	Primary
Porosity Communication	Good to excellent short pore throats	Poor, relatively long, sheet or ribbonlike capillary system	Good, short pore throats, but gas flow impeded by clays, small size of pores, and high $S_w$	Excellent, but gas flow impeded by size of pores and high $S_w$
Relative Clay Content in Pores	Low	High to moderate	Low to high	Low
Geophysical Well-Log Interpretation	Generally reliable in low-clay-content reservoirs	Inaccurate; true porosity difficult to determine	Generally unreliable owing to very thin porous laminations and high water saturation	Fair, some problems with deep mud filtrate invasion
Water Saturation (%)	25-50	45-70 +	40-90 approximate	30-70 approximate
In-Situ Permeability to Gas (md)	1.0-500 +	0.1-0.0005	<0.1	1.0- <0.1, mostly <0.1
Capillary Pressure	Low	Relatively high	Moderate	Moderate to high
Reservoir Rock Composition	Abundant quartz, minor feldspar and rock fragments	Quartz (60-90%), common rock fragments and some detrital feldspar and mica; may have carbonate cement	Quartz, feldspar, rock fragments, and clay; may have carbonate cement	Silt-size calcium carbonate microfossils, minor clay and quartz
Grain Density (g/cm <sup>3</sup> )	2.65	2.65-2.74 + ; average 2.68-2.71 in siltstone	Unknown; probably 2.65-2.70	2.71
Reservoir Pressure	Usually normal to underpressured	May be underpressured or overpressured	Underpressured	Underpressured
Recovery of Gas in Place (%)	75-90	<15-50 estimated low for individual reservoirs	Unknown; probably low	30-50 +

a. Comparative data for conventional and tight gas reservoirs in the U.S. (circa 1980's). Note that "tight" is defined as  $k < 0.1$  md.

Spencer, C.W.: "Review of Characteristics of Low-Permeability Gas Reservoirs in Western United States," Bull., AAPG (1989) 73, 613-629.

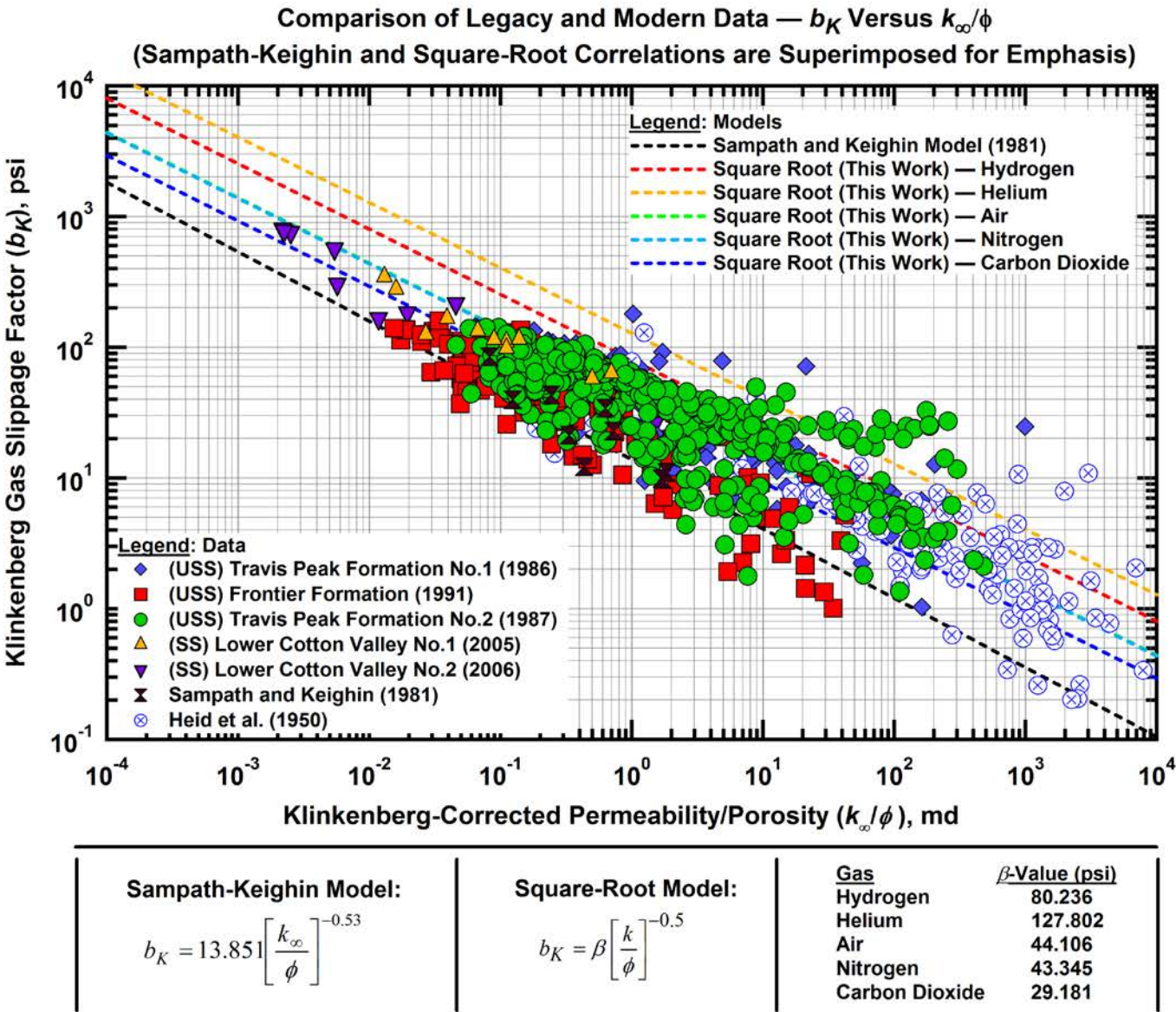


b. Tight gas reservoir basins and areas in western United States (circa 1980).



c. Cross section showing general distribution of gas and water in conventional and tight lenticular and blanket sandstone reservoirs.

Petrophysics — Correlation of Klinkenberg Correction Factor (Tight Gas) (circa 1980s)



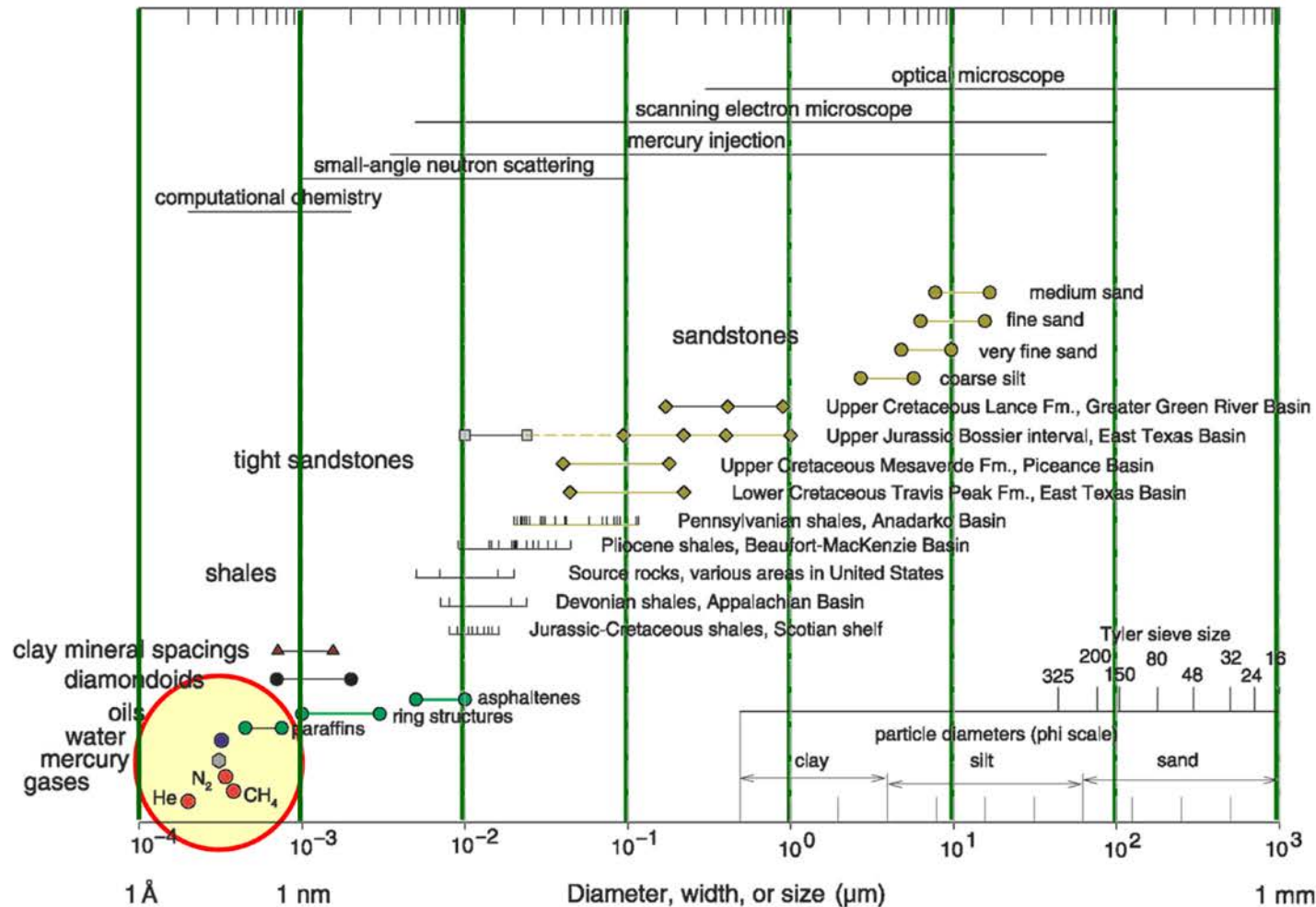
Discussion: Sampath-Keighin

- The square-root model seems to give better results.
- The Sampath-Keighin Model matches mainly their data.

Florence, F. A., Rushing, J., Newsham, K. E., & Blasingame, T. A. (2007, January 1). Improved Permeability Prediction Relations for Low Permeability Sands. Society of Petroleum Engineers. doi:10.2118/107954-MS (<http://dx.doi.org/10.2118/107954-MS>)

## Petrophysics — Very Small Spaces (circa 2010)

← Each green line is x10 SMALLER scale.



**Figure 2.** Sizes of molecules and pore throats in siliclastic rocks on a logarithmic scale covering seven orders of magnitude. Measurement methods are shown at the top of the graph, and scales used for solid particles are shown at the lower right. The symbols show pore-throat sizes for four sandstones, four tight sandstones, and five shales. Ranges of clay mineral spacings, diamondoids, and three oils, and molecular diameters of water, mercury, and three gases are also shown. The sources of data and measurement methods for each sample set are discussed in the text.

Nelson, P. H., 2009, Pore-throat sizes in sandstones, tight sandstones, and shales: AAPG Bulletin, v. 93, p. 329–430, doi:10.1306/10240808059.

### Perspectives:

- The concept of pores and pore throats begins to break down at these scales.
- The flow path can be as small as 10-20 molecular diameters (or less).

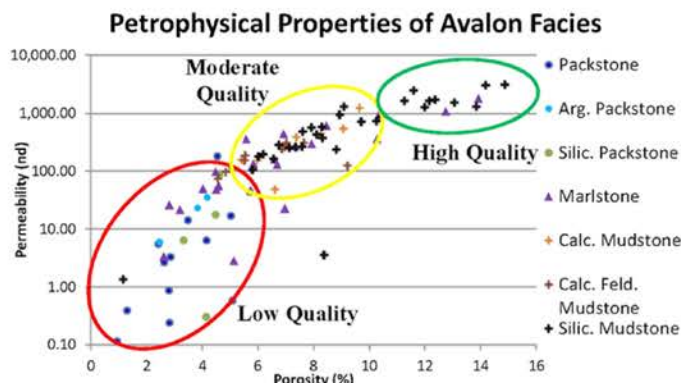
### Issues:

- How do the fluids move?
  - Darcy flow?
  - Dispersion (gases)?
  - Knudsen flow?
- How are the fluids stored?
  - In the organic matter?
  - Adsorbed?
  - Another mechanism?

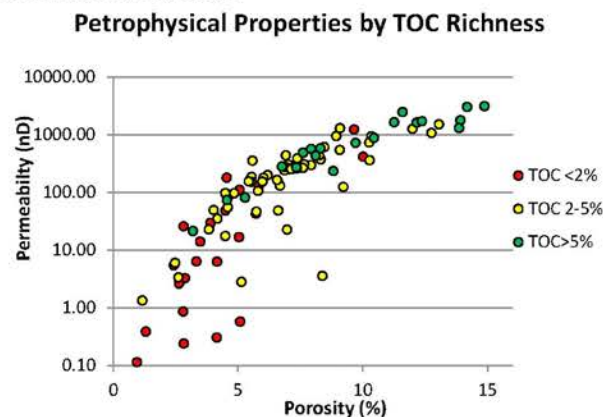
### Question(s):

- How small are pores in shales?
  - Note that the size of the pores is on the order of 10-20 times the diameter of the fluid molecule.
  - What about "confinement" issues — i.e., bubblepoint suppression of black/volatile oils.

## Petrophysics — Reservoir Characterization (Petrophysics) (circa 2015)



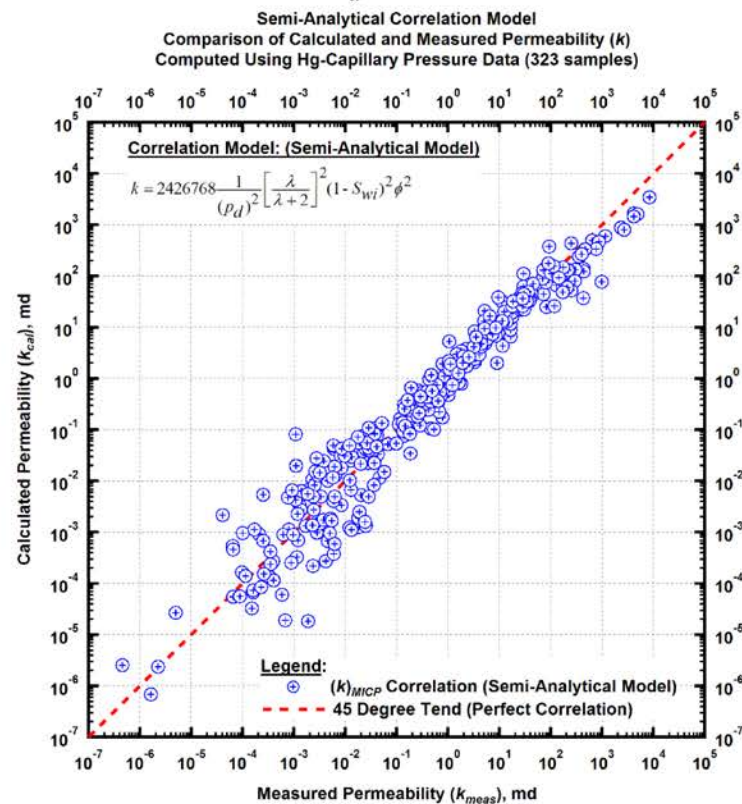
a. Plot showing petrophysical properties of Avalon facies. Plot illustrates that carbonate facies show lower porosities and permeabilities than mudstone facies and that permeability increases with increased porosity. Petrophysical properties are from Gas Research Institute (GRI) analysis of core. Permeability values shown are absolute.



b. Plot showing petrophysical properties of Avalon deposits. Plot illustrates that deposits with low total organic carbon (TOC) have lower porosity/permeability values than those with high TOC and that permeability increases with increased porosity. Petrophysical properties are from Gas Research Institute (GRI) analysis of core. Permeability values shown are absolute.

**Huet Model**  
(coefficients forced to 2)

$$k = 2426768 \frac{1}{p_d^2} \left[ \frac{\lambda}{\lambda + 2} \right]^2 (1 - S_{wi})^2 \phi^2$$



c. Permeability correlation based on capillary pressure — "Huet" model, all coefficients forced to 2.

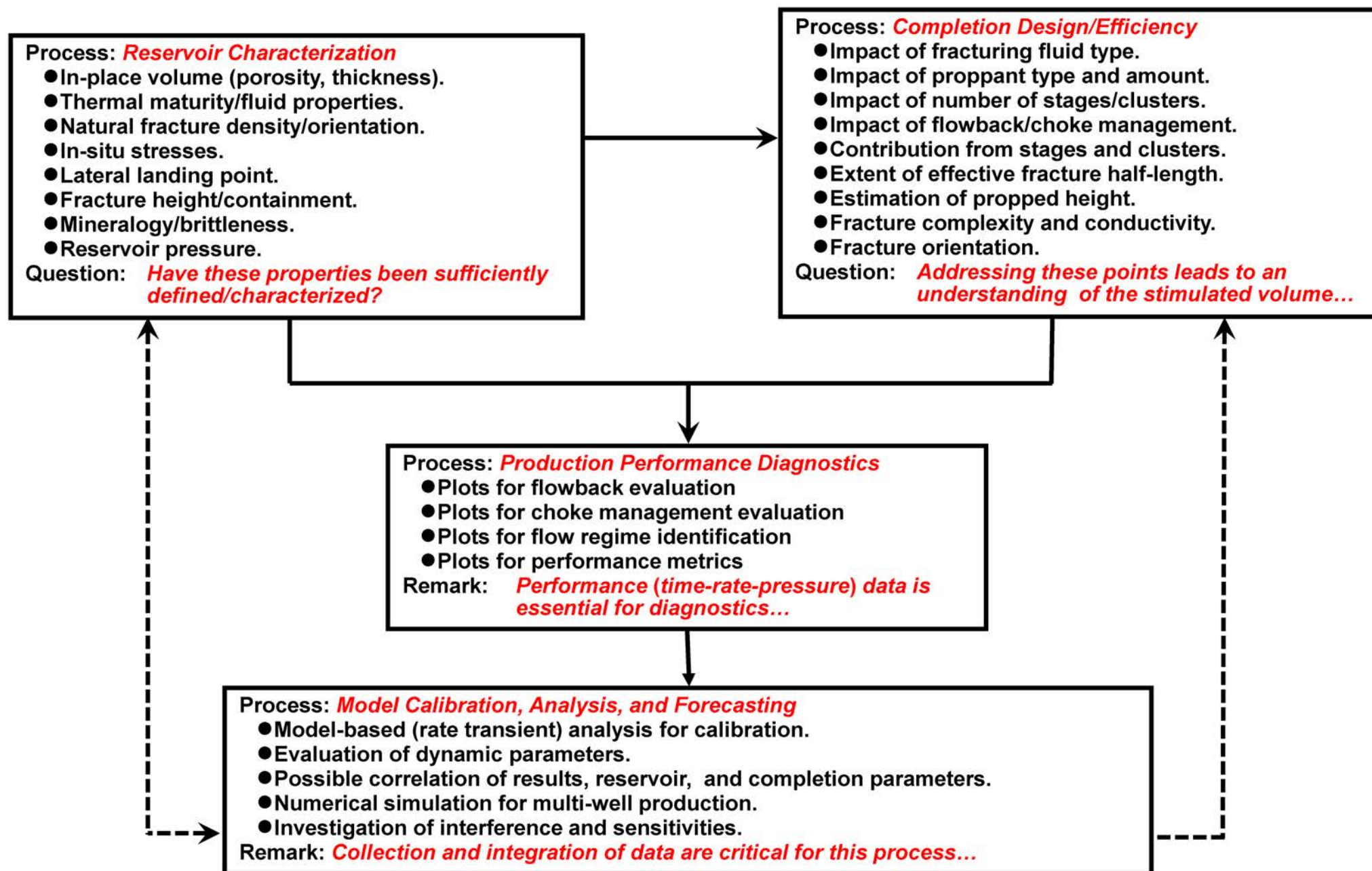
Stoltz, D.J.: Reservoir Character of the Avalon Shale (Bone Spring Formation) of the Delaware Basin, West Texas and Southeast New Mexico: Effect of Carbonate-rich Sediment Gravity Flows, Ph.D. Dissertation, U. Kansas (2014).

Apisaksirikul, S., & Blasingame, T. A. (2016, August 1). The Development and Application of a New Semi-Analytical Model to Estimate Permeability from Mercury Injection Capillary Pressure. Unconventional Resources Technology Conference.

### Discussion: *Where We Are — Reservoir Characterization (Petrophysics)*

- We can measure (steady-state methods) or infer permeability (GRI method).
- Note that Stoltz shows  $\log[k] = f(\phi)$  for both deposition and TOC.
- We have a good predictor of permeability from MICP, we but need more nano-Darcy cases.
- The major value of this type of work may be to correlate geology and well performance.

## Process-Based Workflow — Optimal Evaluation and Development



Creator:  
Created:

D. Ilk  
2017.02.21

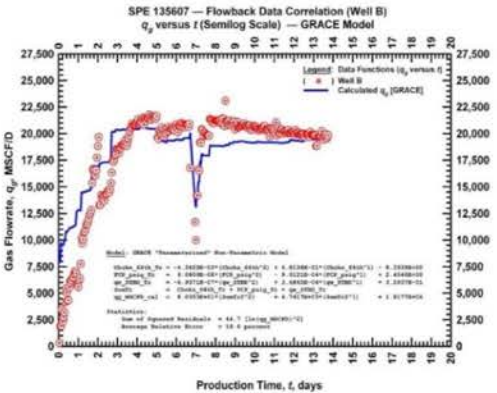
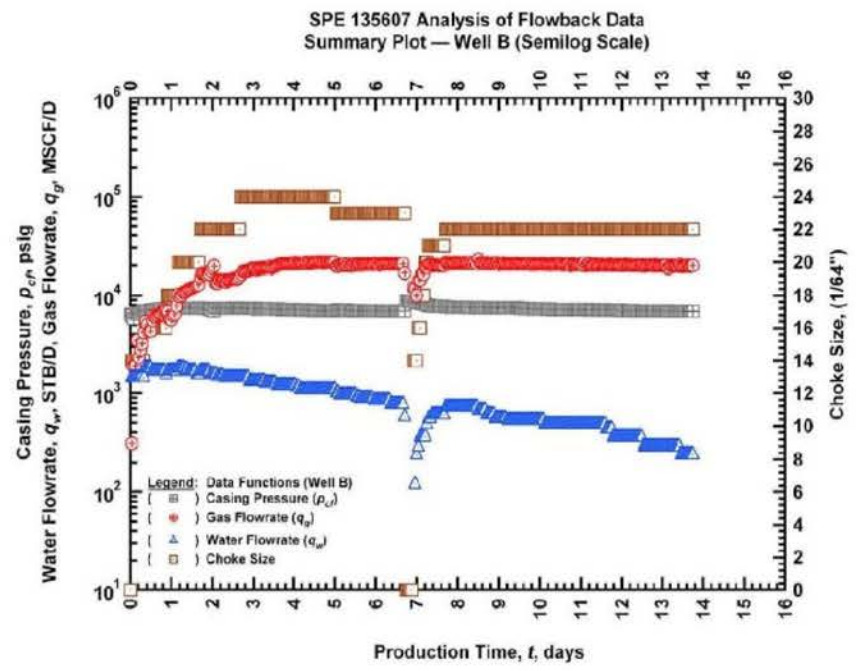
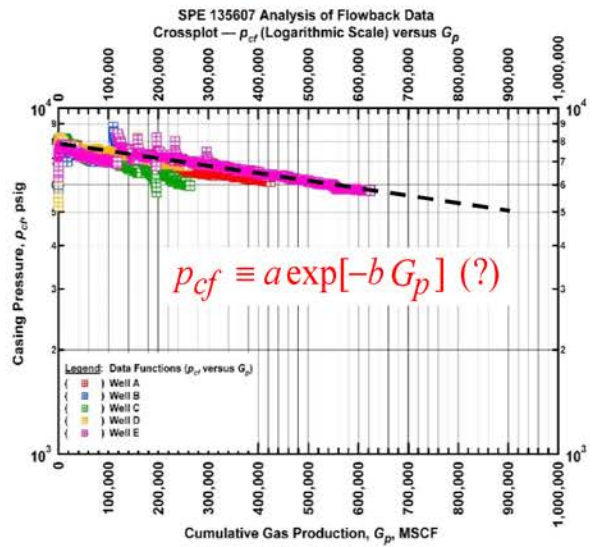
Review of Flowback Data

Objectives of Flowback Data Analysis:

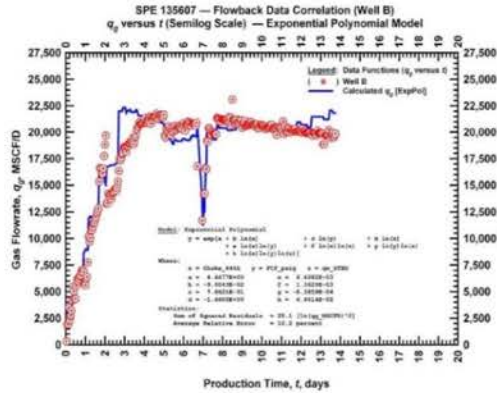
- Provide a unique visualization of flowback data.
- Provide a correlative and integrated analysis of these data.
- Provide an interpretation of specific data features.
- Provide guidelines for flowback testing. (i.e., choke management).

Process:

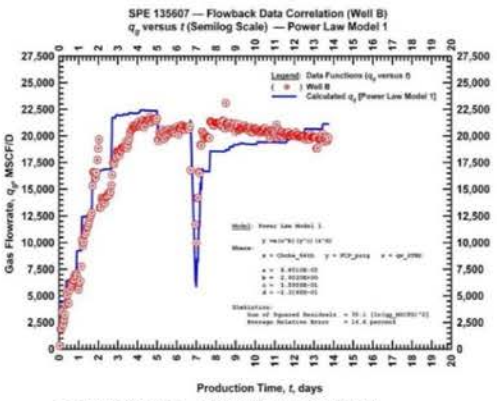
- Collection/quality control of well performance/completion data.
- Construct/calibrate a base well/reservoir model.
- Construct specialized plots to identify features (i.e., unloading).
- Correlate flowback data by empirical and non-parametric models.



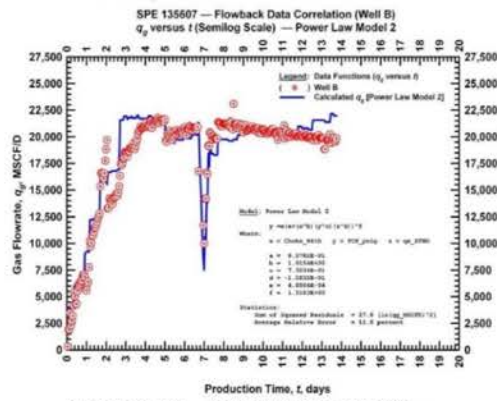
a. Correlation Plot — Well B: GRACE correlation, based on non-parametric correlation of multiple variables (each variable is scaled and correlated).



b. Correlation Plot — Well B: "Exponential Polynomial" — typically the most "flexible" relation. Performance is statistically the best.



c. Correlation Plot — Well B: "Power Law Model 1" — most simple model attempted, average correlation.



d. Correlation Plot — Well B: "Power Law Model 2" — very good correlation, relatively simple model.

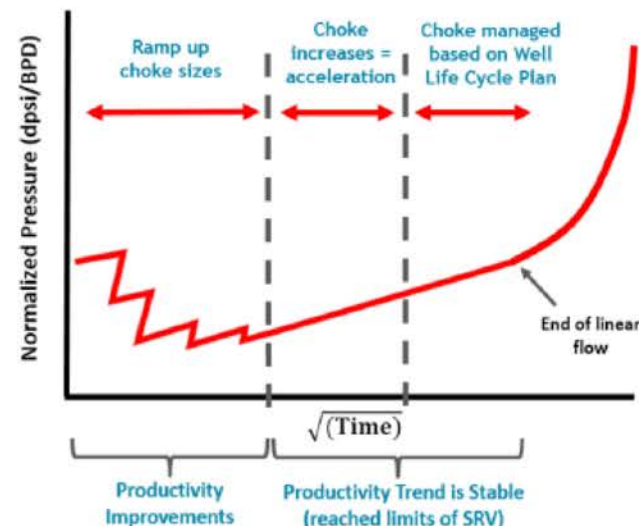
## Optimal Drawdown Management

### Choke Management:

- Essentially empirical (*i.e.*, trial and error).
- Operators tend to be conservative (at least initially).
- Gas wells are often easier (just water, no oil issues).
- "Set it and forget it" is the standard in the industry.

### Practices:

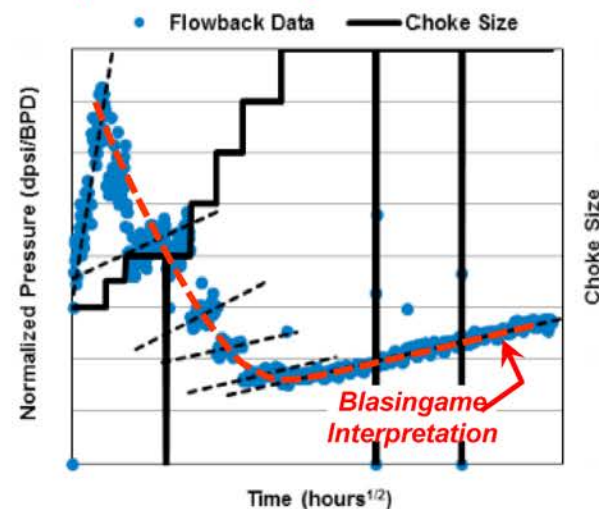
- Start at 10-14 64th (inches) (depending on fluids, well length, etc.)
- Make a 2/64th (inch) change every 12 hr (sometimes every 6 hr).
- **Dashboard:** (what to watch)
  - Total fluid rate (volume management)
  - Oil rate (look for increases in oil rates with each choke change).
  - Gas rate in oil-gas systems (look for excessive gas production).
  - Wellbore pressure decline (watch for excessive pressure drop).
  - Productivity Index or Reciprocal Productivity Index plots.



### Choke Management Plots:

- **Deen-Daal-Tucker Concept:**
  - Reciprocal Productivity Index plots.
  - Each choke changes is seen to "improve" productivity.
  - Final linear trend ( $x$ -axis =  $\text{SQRT}[t]$ ) is reservoir signature.
- **Blasingame Comments:**
  - Early-time "Improvement" w/ increasing choke is a function of:
    - "Decreasing" skin effects.
    - Wellbore unloading effects (wellbore storage effects).
    - A combination of both effects.
  - Aggressive choke management can improve time to unload.
  - Any/all choke management schemes must be tested/updated.

**Example Plot**  
Reciprocal Productivity Index and Choke Size



Deen, T., Daal, J., & Tucker, J. (2015, September 28). Maximizing Well Deliverability in the Eagle Ford Shale Through Flowback Operations. Society of Petroleum Engineers. doi:10.2118/174831-MS (<http://dx.doi.org/10.2118/174831-MS>).

## Artificial Lift Applications in Unconventionals

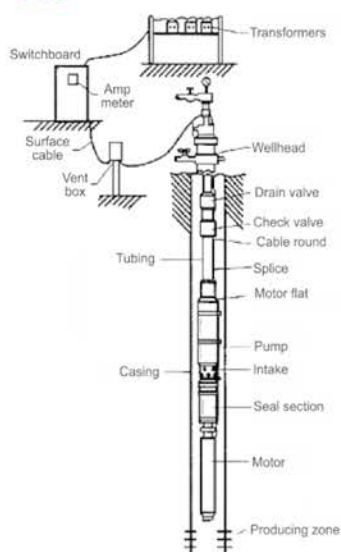
### Types of Artificial Lift Used in Unconventionals:

- Electric Submersible Pump (ESP)
- Gas Lift
- Jet Pump
- Plunger Lift
- Progressive Cavity Pump (PCP)
- Rod Pump

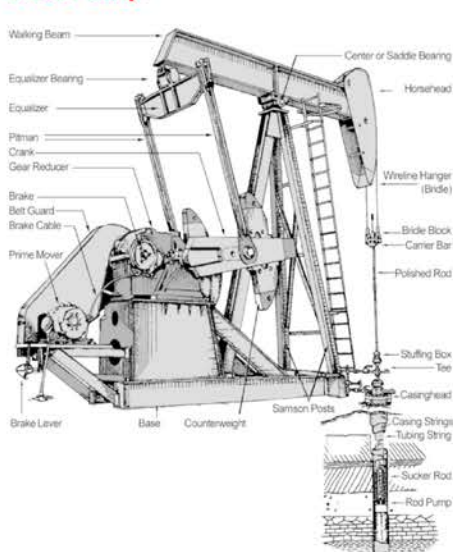
### What is best for your operations?

- **Electric Submersible Pump** — ESPs have been used to "kick-off" wells with high water volume. ESPs are typically not the most economic artificial lift solutions, but are effective at moving large volumes of liquids.
- **Gas Lift** — This is probably the most popular artificial lift option for unconventional. Gas lift is efficient and effective, and typically requires very low maintenance.
- **Jet Pump** — Jet pumps have been shown to have very good performance, but these were "one-off" types of installations and required a great deal of monitoring and had very high installation costs.
- **Plunger Lift** — Plunger lift is a very popular artificial lift option, particularly in liquids-rich plays such as the Eagle Ford and the Niobrara shales.
- **Progressive Cavity Pump** — Probably the least used artificial lift method for unconventional reservoirs due to the relatively shallow depth of operation.
- **Rod Pump** — Sucker rod pumps are generally the "terminal" artificial lift method due to the relatively low lifting volumes (hundreds of barrels/day) and high capital costs (usually on the order of > USD 200,000).

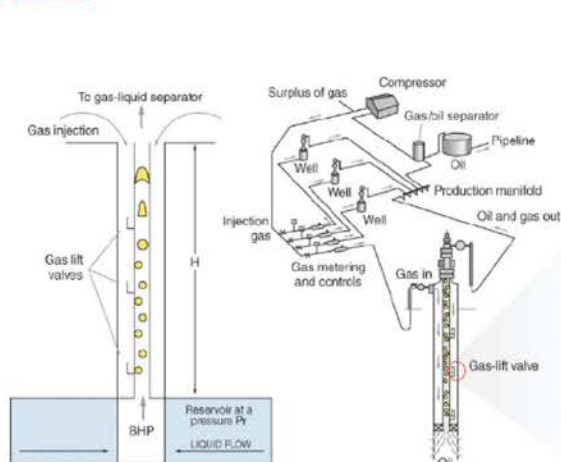
ESP



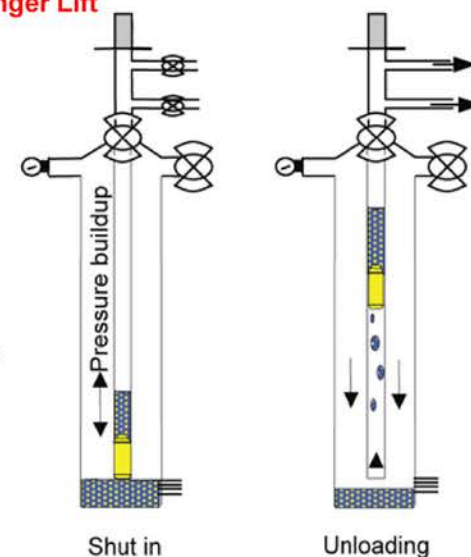
Rod Pump



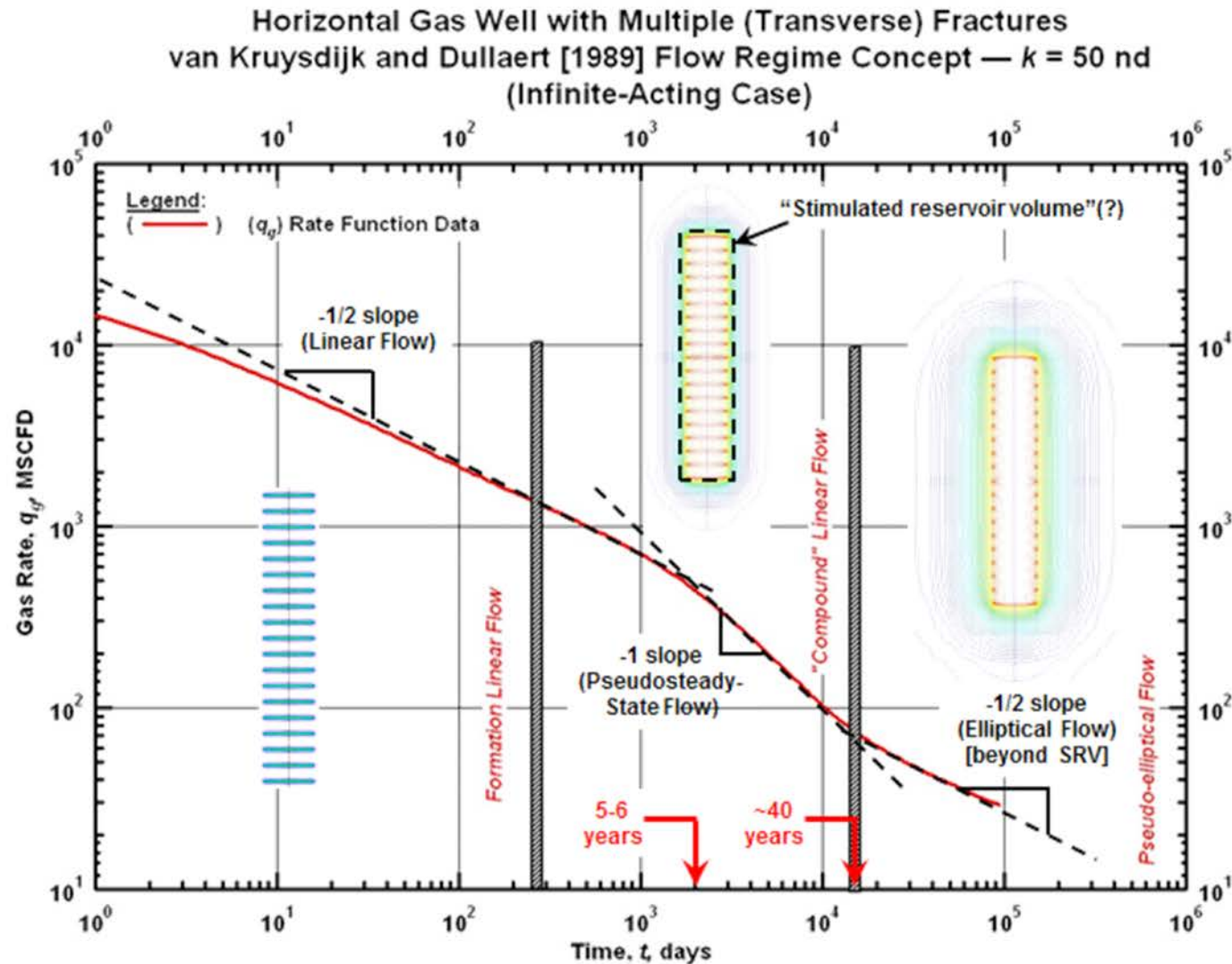
Gas Lift



Plunger Lift



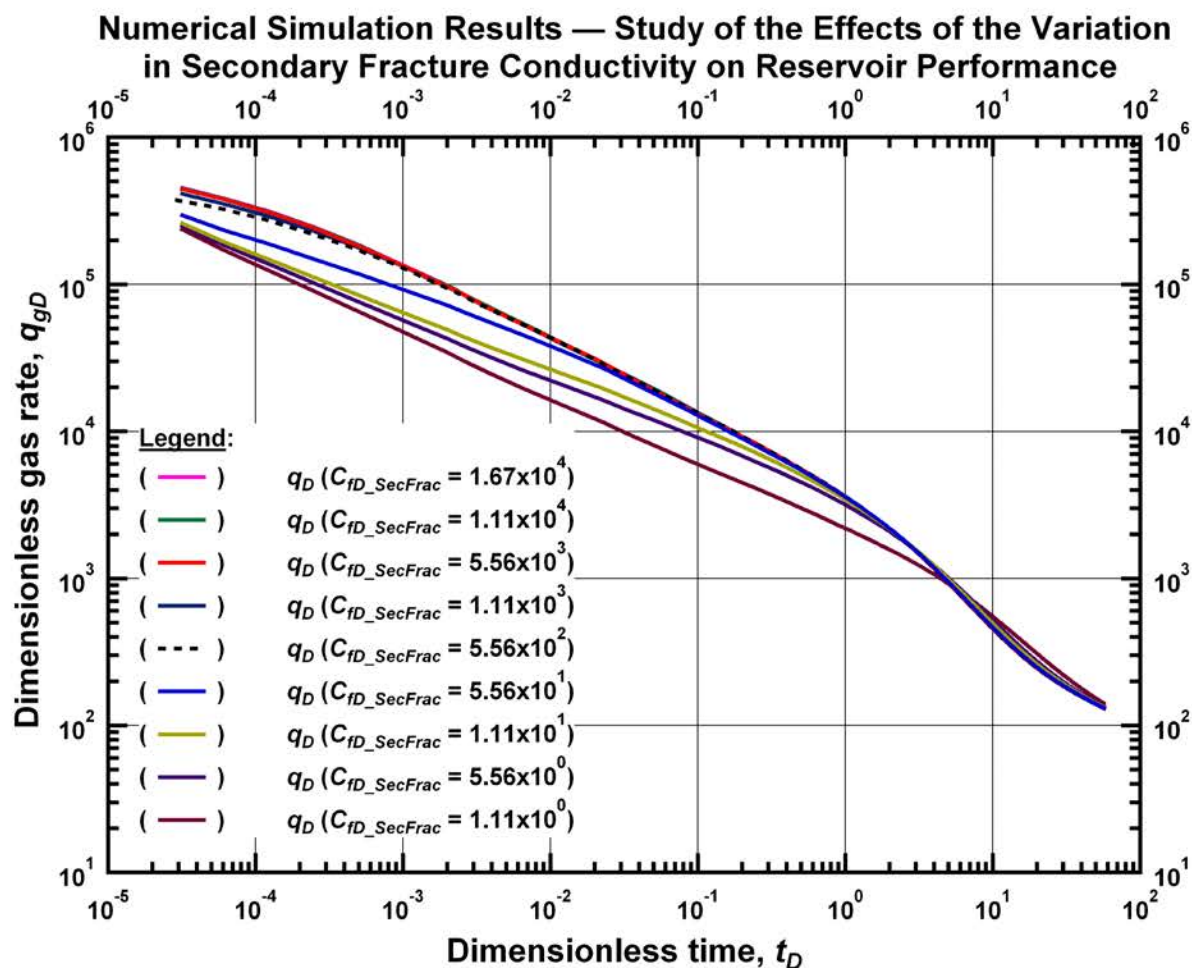
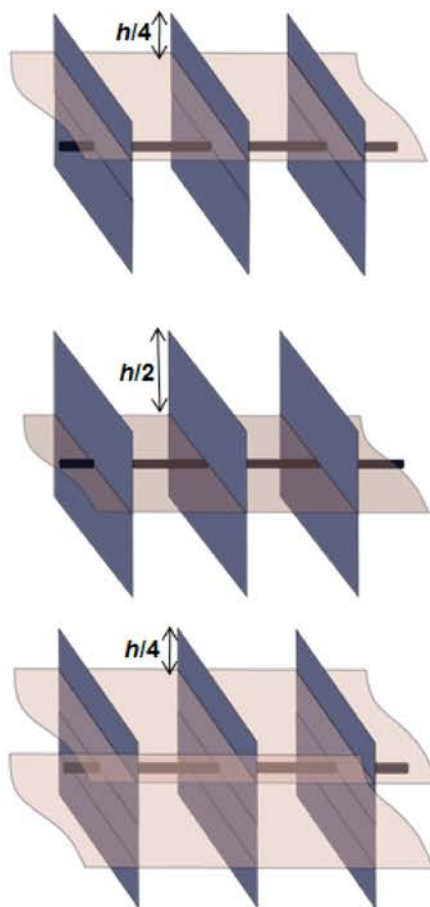
## Rate Transient Analysis (RTA) — Multi-Fracture Horizontal Well (MFHW) Model



### Discussion:

- The Multi-Fracture Horizontal Well (MFHW) model is the "master" solution for unconventional.
- All flow regimes are modeled, but not often observed.
- Diagnostics can be obscured by clean-up and liquid-loading.

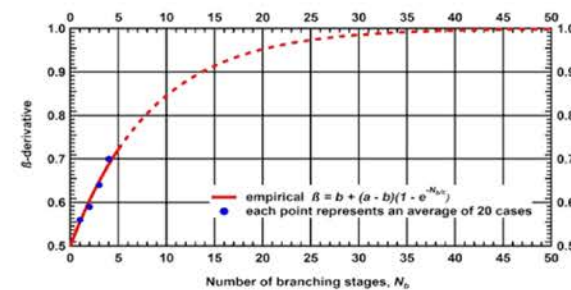
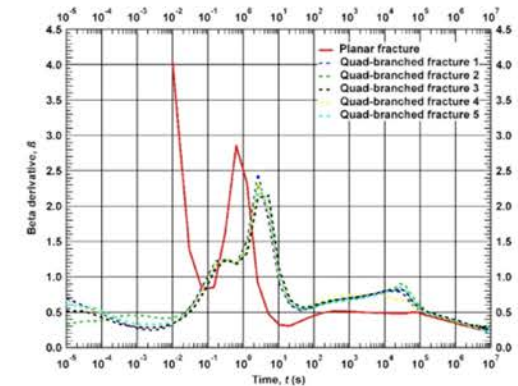
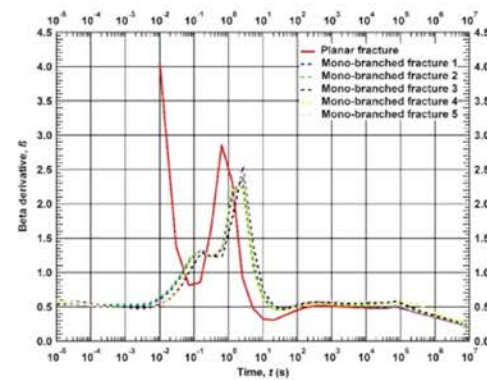
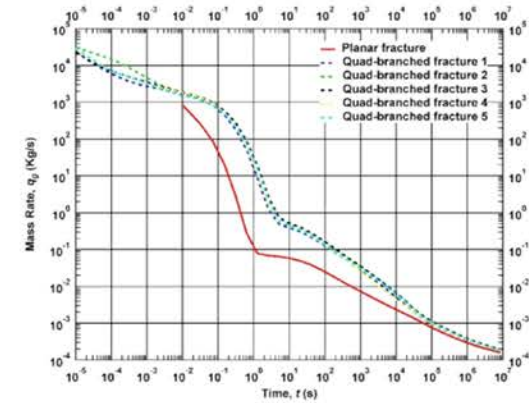
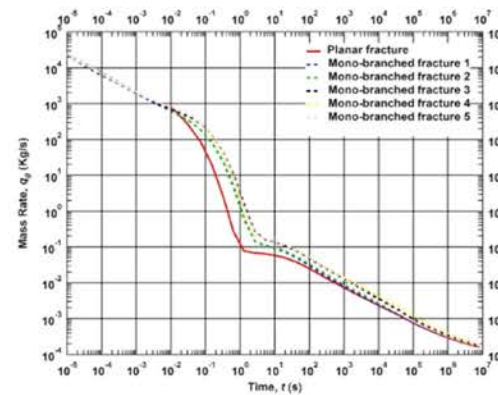
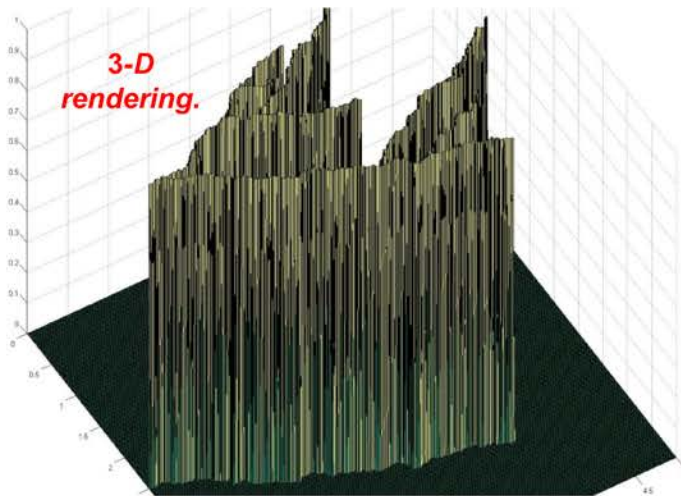
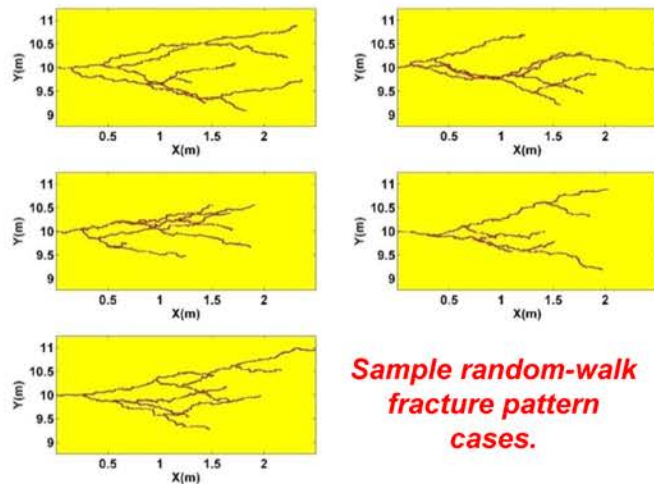
## Rate Transient Analysis (RTA) Concept Models — Olorode (SPE 152482)



### Discussion:

- Reduction from linear flow (half-slope) for  $C_{fD\_SecFrac} < 10$ .
- Model trends are also observed in field data.
- Secondary fracture concept may be useful in optimizing fracture design.

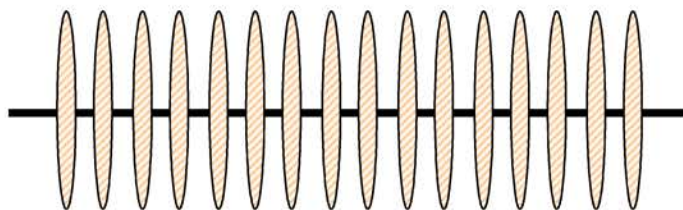
## Rate Transient Analysis (RTA) Concept Models — Mhiri (TAMU 2014)



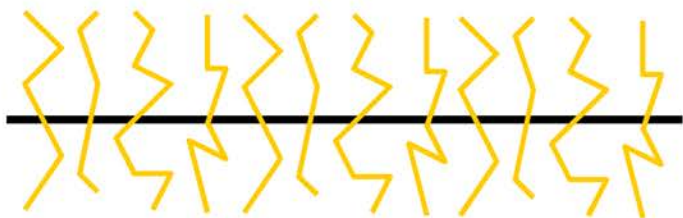
### Discussion:

- After a random number steps, the fractures may bifurcate (split).
- $\beta$ -derivative of the mass flowrate is the diagnostic function.
- $\beta$ -derivative is 0.55 (mono-branch) and 0.70 (quad-branch) for the cases.

## Practical Aspects — Stimulation



**Individual Fractures from Individual Perforation Clusters**



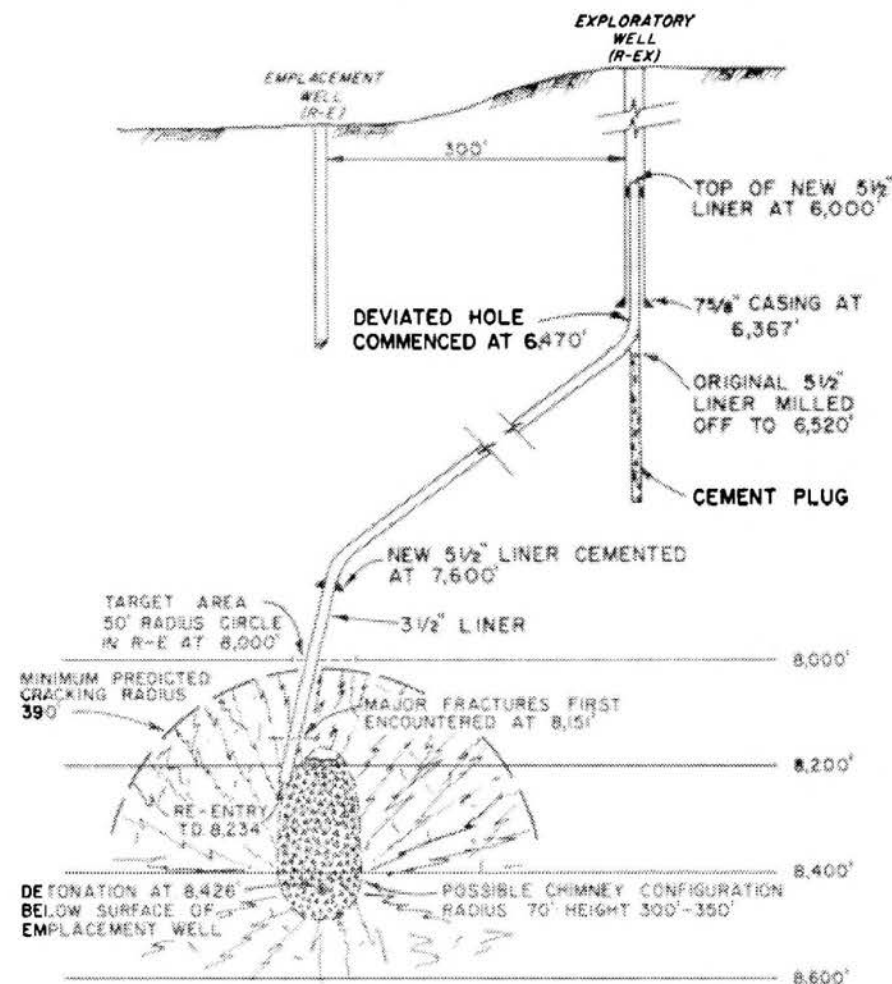
**Complex Fractures from Individual Perforation Clusters**

## Discussion:

- **SRV (Stimulated Reservoir Volume)**
  - Build Complexity → Slickwater
  - Build Conductivity → Hybrid/Gel
- **Future Stimulation Challenges:**
  - "Rubble-ize" the reservoir?
  - "Pulverize" the reservoir?
  - Do this with little or no water?

**"You only produce from what you fracture ..."**  
Anonymous

### SCHEMATIC DIAGRAM OF RE-ENTRY WELL



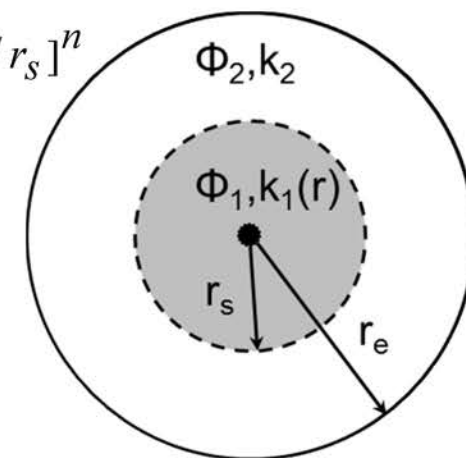
**Project Rulison (1971)**  
**Stimulation using Atomic Weapons**

## Rate Transient Analysis (RTA) Concept Models — Broussard (TAMU 2013)

### Geometry: (radial composite system)

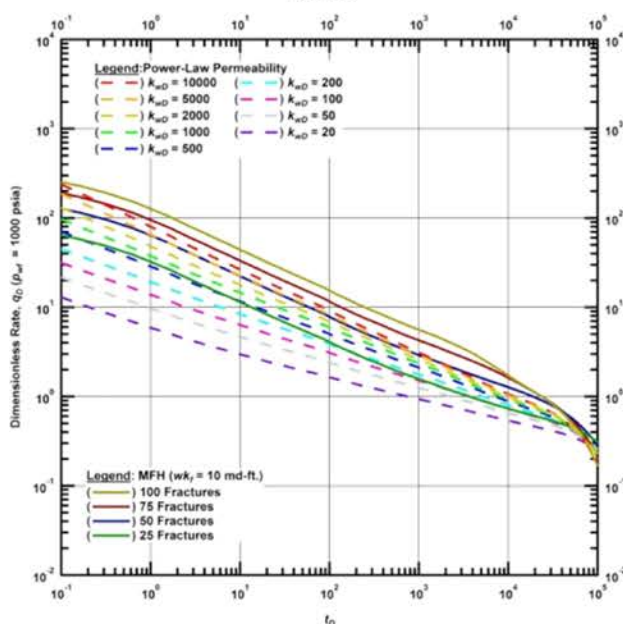
- Composite, cylinder consists of two regions:
  - Inner region is stimulated ( $k$  = power-law function).
  - Outer region is unstimulated and homogeneous.
- Horizontal well centered in a cylindrical volume.
- Wellbore spans the entire length of the reservoir.
- Radial flow only.

$$k_r(r) = k_o[r/r_s]^n$$



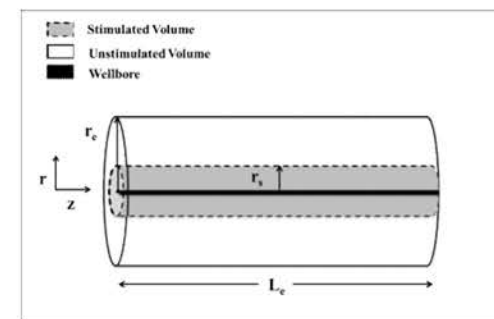
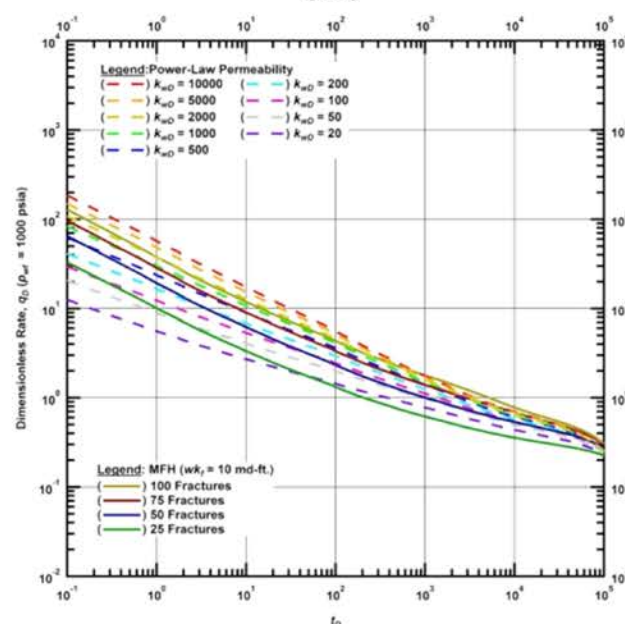
$$x_f = r_s = 50 \text{ ft}, wk_f = 10 \text{ md-ft}$$

Simulated MFH ( $x_f = 50$  ft.) Comparison  
With Power-Law Permeability Cases ( $r_s = 50$  ft.)  
 $q_D$  vs.  $t_D$

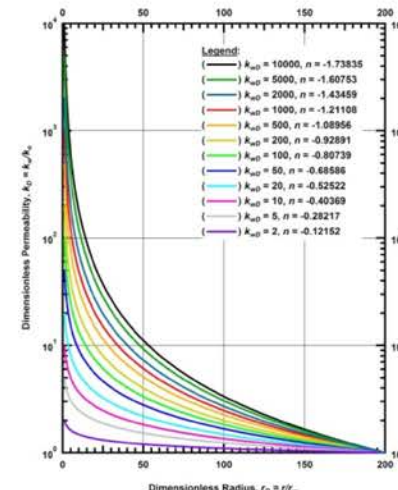


$$x_f = r_s = 25 \text{ ft}, wk_f = 10 \text{ md-ft}$$

Simulated MFH ( $x_f = 25$  ft.) Comparison  
With Power-Law Permeability Cases ( $r_s = 25$  ft.)  
 $q_D$  vs.  $t_D$



Power-Law Permeability Distribution (Dimensionless)  
 $r_{sD} = 200, r_{eD} = 400$

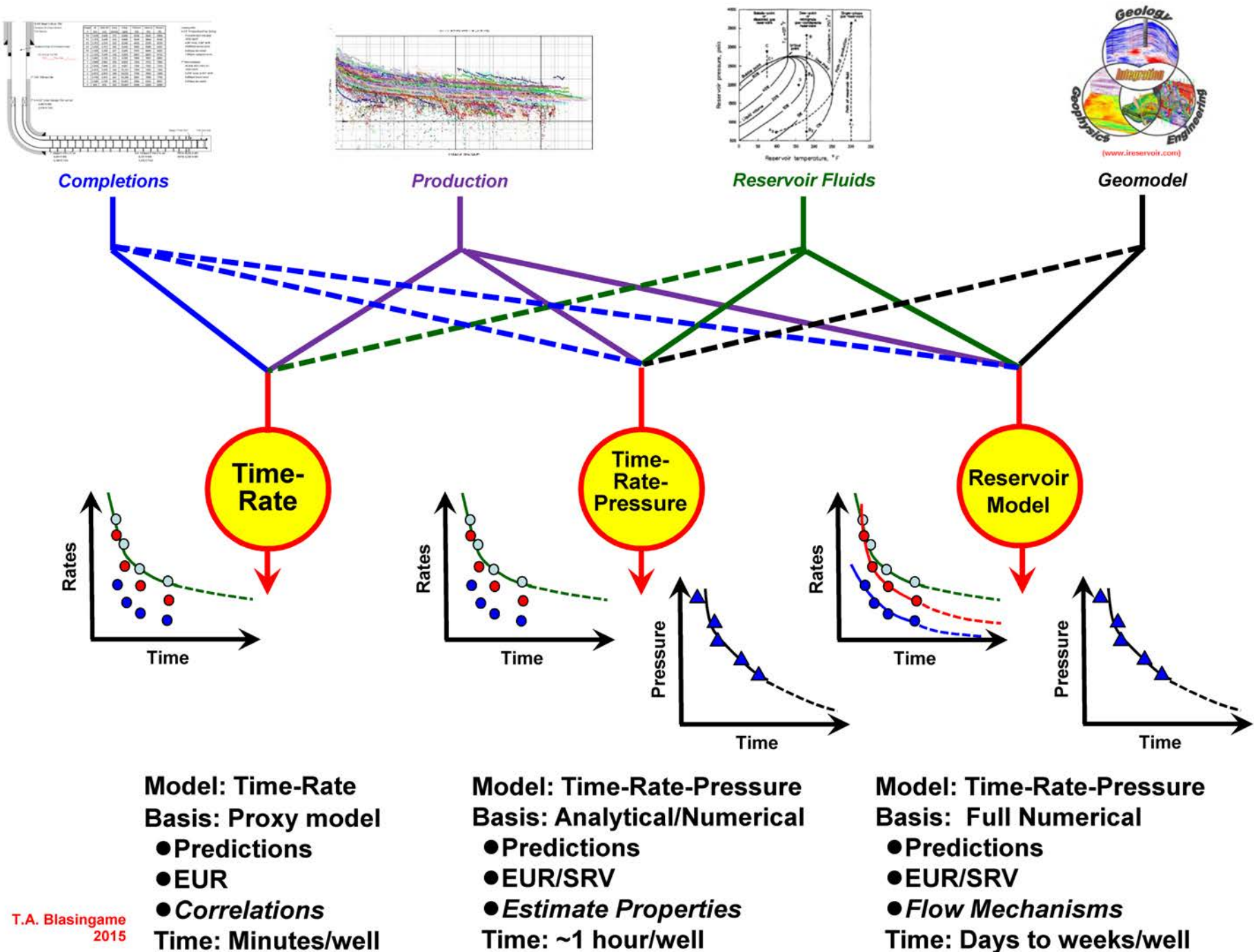


Performance of radial composite system very similar  
to that for a multi-fracture horizontal well solution.

## ***Correlation of Production Metrics and Completion Parameters***

- **Play A: (Segregated Liquids-Rich System)**
  - **Fluid type (spatial location)**
  - **Total number of perforation clusters**
  - **Total proppant**
  - **Barrels of water**
- **Play B: (Dry Shale Gas)**
  - **Total number of perforation clusters**
  - **Total proppant**
  - **Well target zone (up dip/down dip)**
- **Play C: (Complex Liquids-Rich System)**
  - **API Gravity**
  - **Lateral Length**
  - **Initial Pressure**
  - **Total Proppant**
  - **Barrels of water**
  - **Petrophysical Parameters ( $TOC$ ,  $V_{shale}$ , etc.)**
  - **Proppant/Stage**

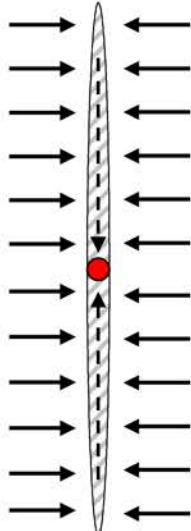
Work Path — Analysis of Well Performance



Creator: T.A. Blasingame  
Created: 2015

## Time-Rate Behavior — (Formation) Linear Flow — Theory ( $q/\Delta p$ form)

### Solution for a Single Fracture: (transient linear flow)



$$p_D = \sqrt{\pi t D_{xf}}$$

*Solving for flowrate divided by pressure drop, we have ...*

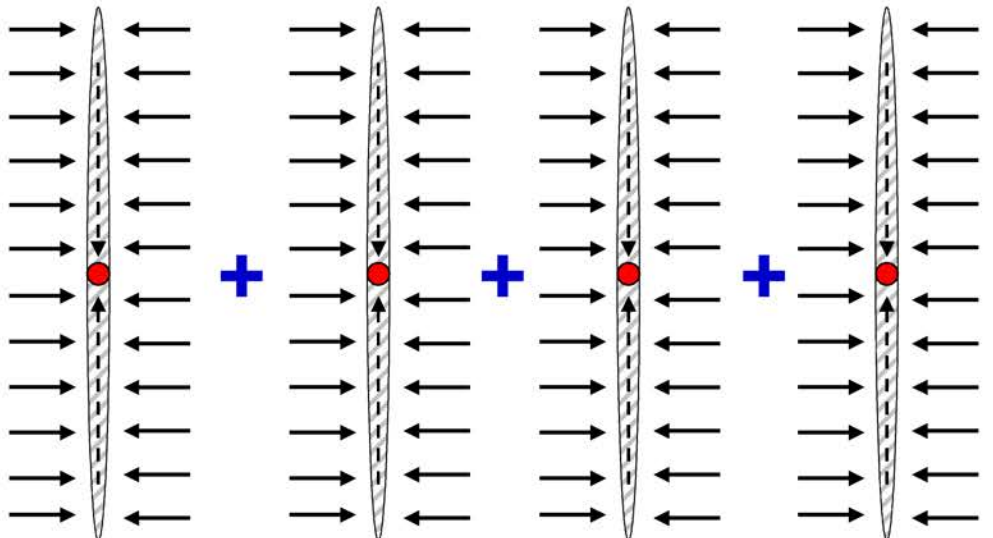
$$\frac{q}{(p_i - p_{wf})} = \frac{1}{8.128494} \frac{1}{B} \sqrt{\frac{\phi c_t}{\mu}} \sqrt{k} A_{xf} \frac{1}{\sqrt{t}} \quad (\text{time in days})$$

$$\frac{q}{(p_i - p_{wf})} = C A_{xf} \frac{1}{\sqrt{t}} \quad \left[ C = \frac{1}{8.128494} \frac{1}{B} \sqrt{\frac{\phi c_t}{\mu}} \sqrt{k} \right]$$

#### Note:

*These solutions are only valid for transient linear flow [i.e., the case of non-interfering pressure distributions (due to the fractures)].*

### Additive Fractures: (transient linear flow)



$$\frac{q_{\text{tot}}}{(p_i - p_{wf})} = C [A_{xf,1} + A_{xf,2} + A_{xf,3} + A_{xf,4} + \dots + A_{xf,n}] \frac{1}{\sqrt{t}}$$

$$\frac{q_{\text{tot}}}{(p_i - p_{wf})} = C (A_{xf})_{\text{tot}} \frac{1}{\sqrt{t}}$$

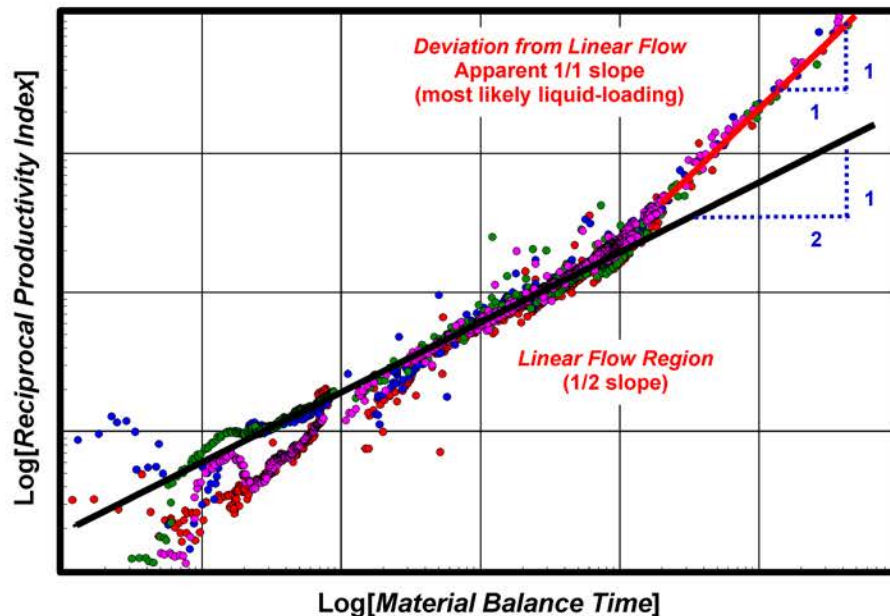
## Time-Rate Behavior — (Formation) Linear Flow — $\Delta p/q$ versus SQRT[t] Plot

- Formation Linear Flow: ( $t = t$  or  $t_{mb}$  (material balance time))
  - Log-log diagnostic plot:  $\log[\Delta p/q]$  versus  $\log[t]$  (slope = -1:2)
  - "Traditional" plot:  $\Delta p/q$  versus SQRT[t] (straight-line portion)
  - **Extrapolation of rate using a linear flow model will over-predict EUR...**

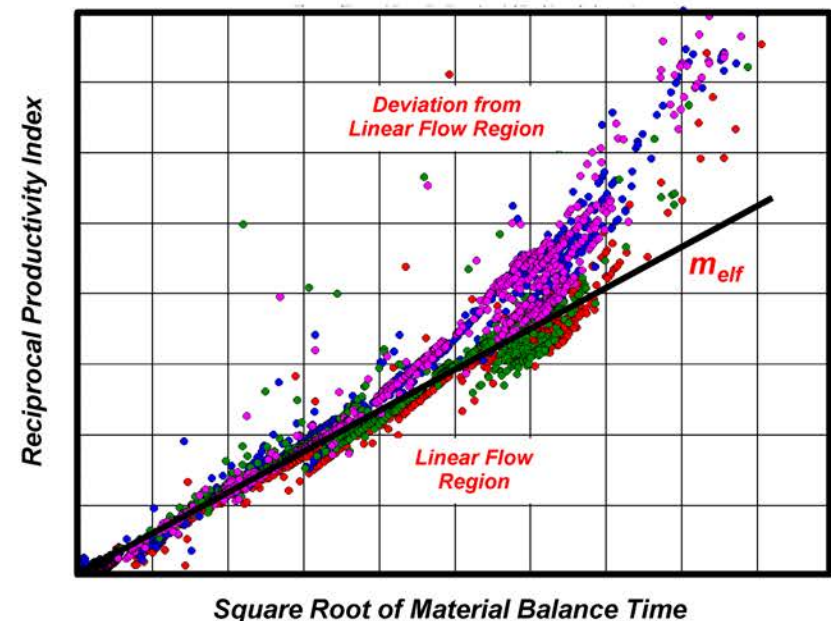
● Governing Relation: 
$$\frac{(p_i - p_{wf})}{q} = m_{elf} \sqrt{t}$$

Where  $m_{elf}$  is the slope of the straight - line trend on a plot of  $\frac{(p_i - p_{wf})}{q}$  vs  $\sqrt{t}$

Solving for the  $\sqrt{k} A_{xf,tot}$  term, 
$$\sqrt{k} A_{xf,tot} = 8.128494 B \sqrt{\frac{\mu}{\phi c_t} \frac{1}{m_{elf}}}$$



a. (Log-log plot): Reciprocal productivity index versus material balance time, multiple wells.

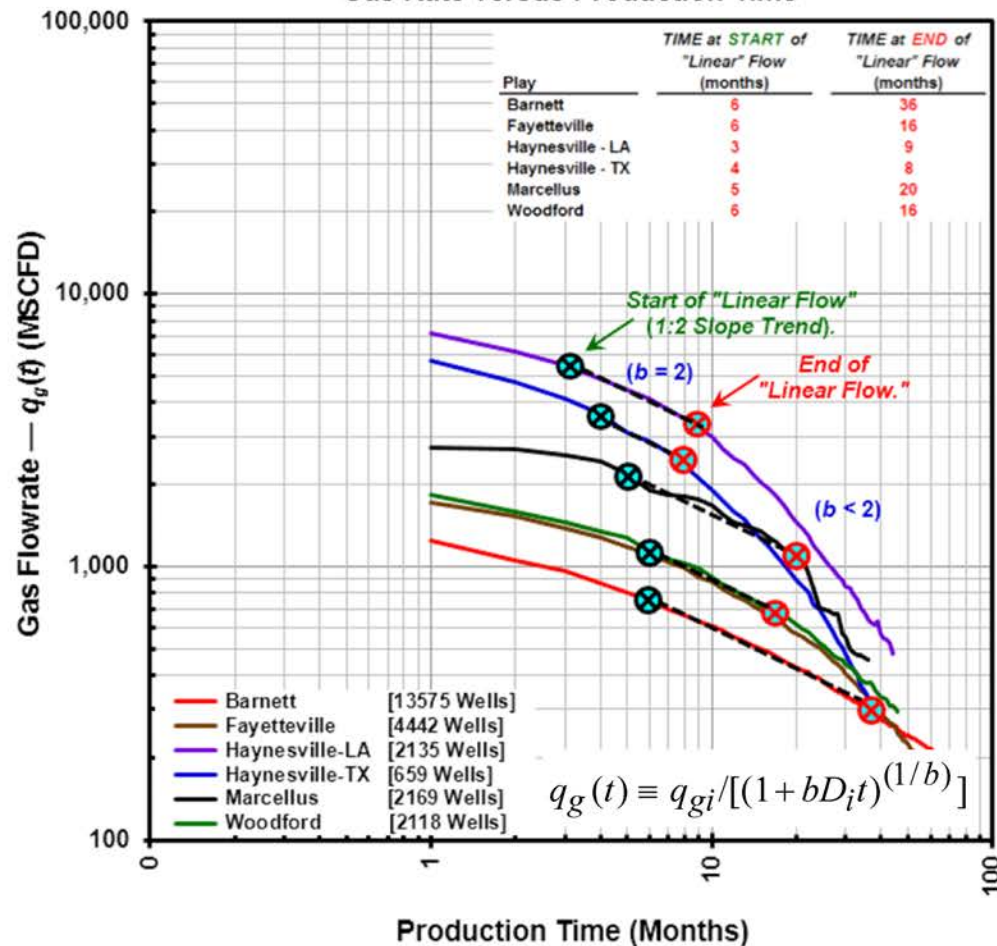


b. (Square root plot): Reciprocal productivity index versus square root of material balance time, multiple wells.

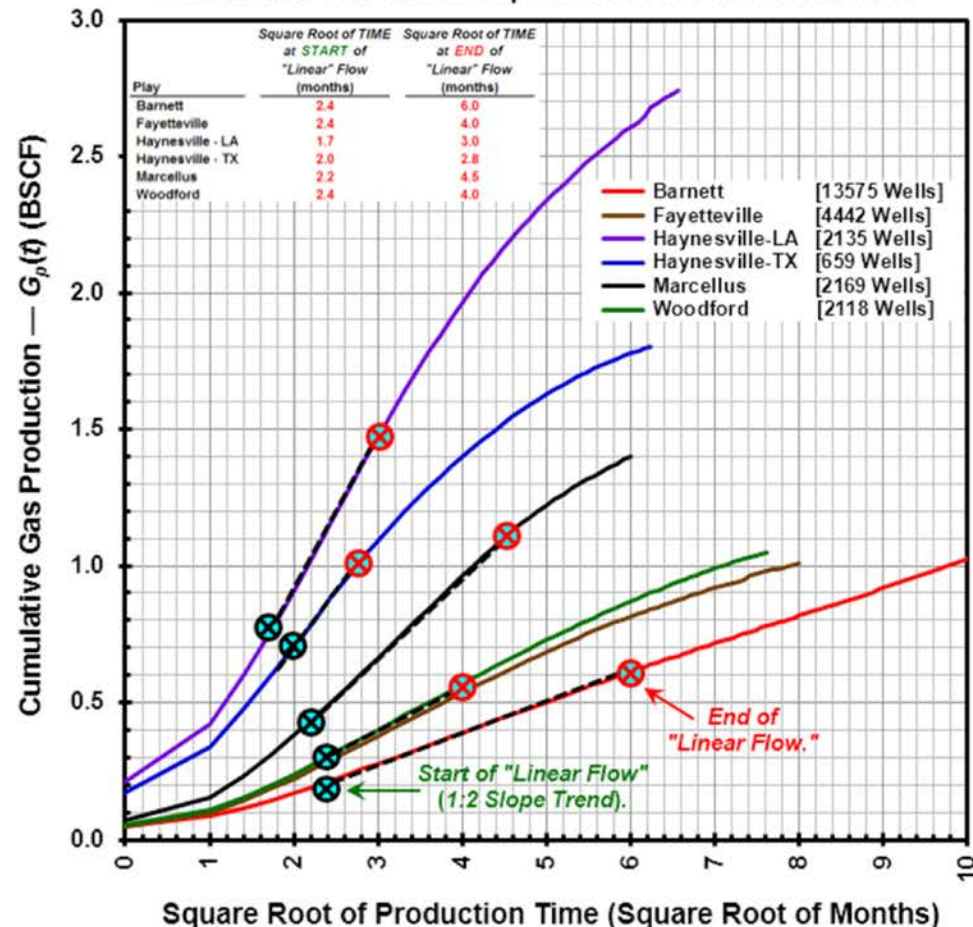
## Rate-Time Analysis — Start and End of Linear Flow (Gas Shales)

**Data taken from publicly available sources — Horizontal Shale (Dry) Gas Wells ONLY**

**P50 Horizontal Well  
Gas Rate versus Production Time**



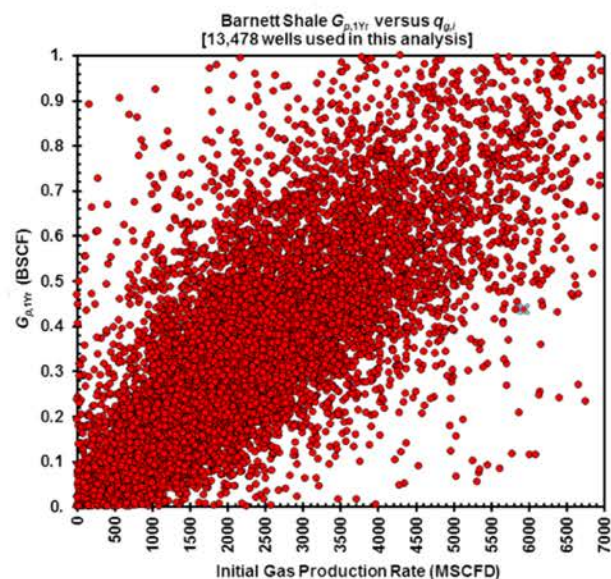
**P50 Horizontal Well  
Cumulative Gas versus Square Root of Production Time**



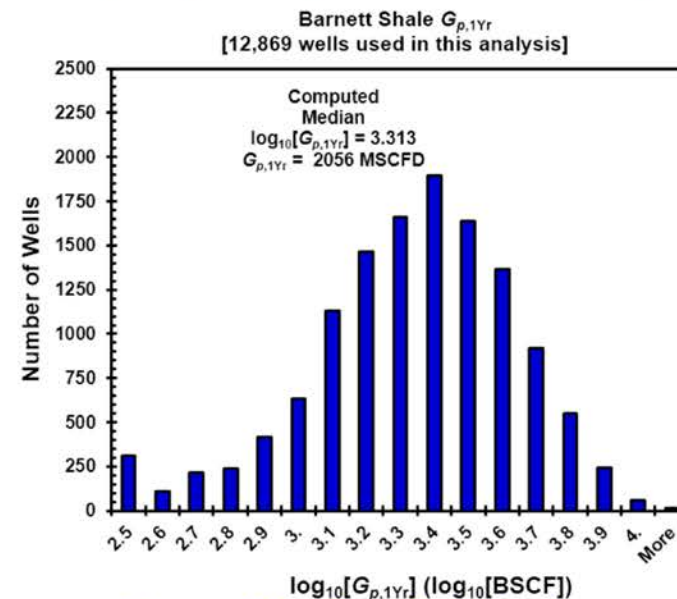
Heckman, T.L., et al (2013): Best Practices for Reserves Estimation in Unconventional Reservoirs — Present and Future Considerations, Keynote presentation presented at the 2013 SPE Unconventional Resources Conference, The Woodlands, TX (USA), 10-12 April 2013.

### Discussion:

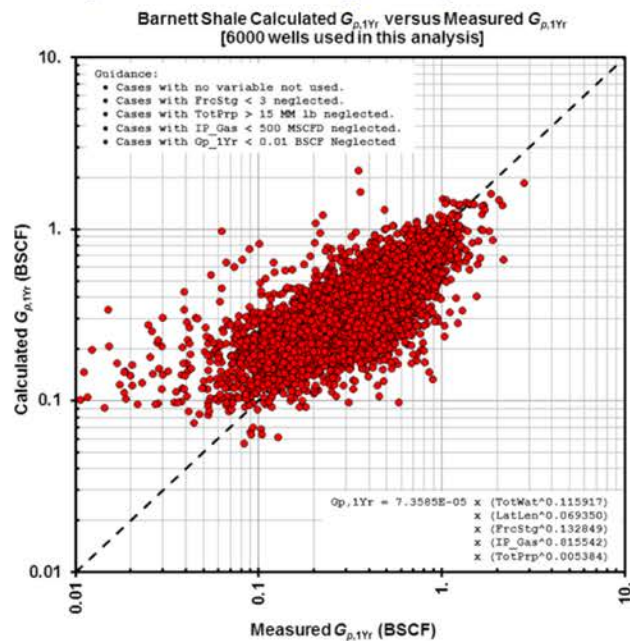
- START of "Linear Flow" (~3-6 months).
- END of "Linear Flow" (~9-36 months).
- "Linear Flow" is represented by linear trends on these plots ( $b=2$  for log-log plot).
- Square root time plot used to show linear portion of trend ( $G_p(t)$  vs.  $SQRT(t)$  is most clear).

**(Sort of) "Big Data" Analysis — Barnett Shale Example (Data prior to Mar 2013)**

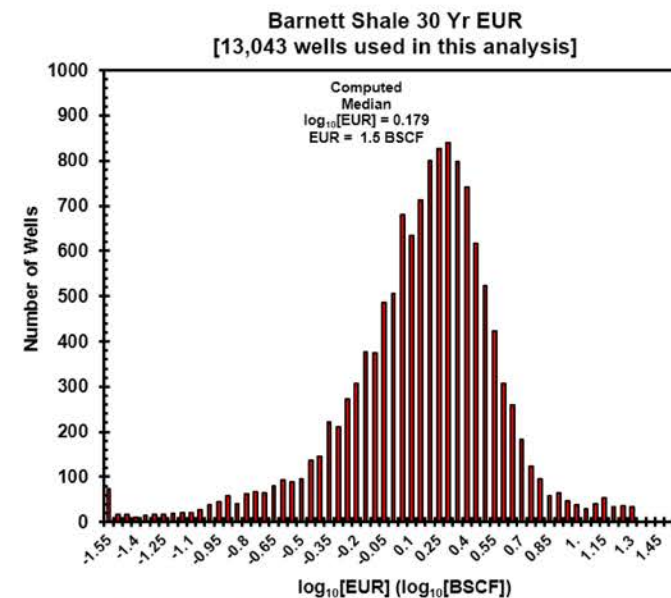
Correlation of  $G_{p,1Yr}$  vs. Initial Gas Production  
(Barnett Shale horizontal gas wells).



Histogram of  $G_{p,1Yr}$  (Barnett Shale horizontal gas wells).



Correlation of  $G_{p,1Yr}$  using Initial Gas Production and various completion parameters (Barnett Shale horizontal gas wells).

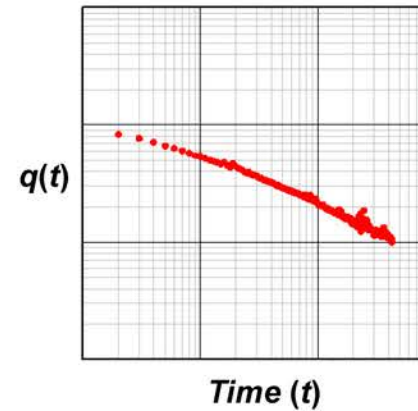


Histogram of  $EUR_{30Yr}$  (Barnett Shale horizontal gas wells).

## Modified-Hyperbolic Relation (Early Hyperbolic/Late Exponential)

### Time-Rate Relation:

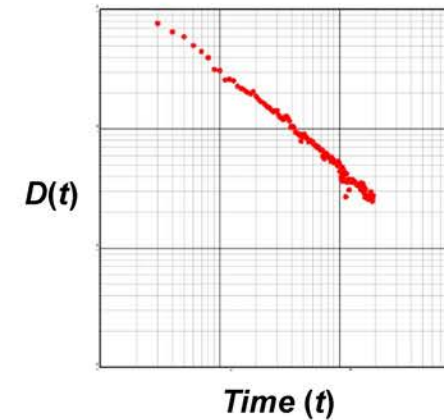
$$q(t) \equiv \begin{cases} \frac{q_{i,hyp}}{(1 + bD_i t)^{1/b}} & (t < t_{lim}) \\ q_{lim} \exp[-D_{lim}(t - t_{lim})] & (t > t_{lim}) \end{cases}$$



### Terminal Decline "Switch:"

$$q_{lim} = q_{i,hyp} \left[ \frac{D_{lim}}{D_i} \right]^{(1/b)}$$

$$t_{lim} = \frac{1}{bD_i} \left[ \left[ \frac{q_{i,hyp}}{q_{lim}} \right]^b - 1 \right]$$

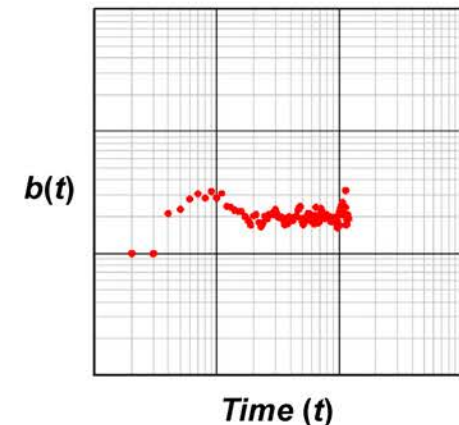


### $D(t)$ Relation:

$$D(t) \equiv -\frac{1}{q} \frac{dq}{dt} = \frac{D_i}{1 + bD_i t}$$

### Arps " $b$ -factor:"

$$b(t) \equiv \frac{d}{dt} \left[ \frac{1}{D(t)} \right] = b = \text{constant}$$



**Time-Rate Relations – Comments**

**Models:**

- Arps Rate Functions [ ...  $D(t)$  and  $b(t)$  definitions]
- Exponential Relation [ ... can be derived, but result is approximate]
- Hyperbolic Relation [ ... semi-analytical/(gas) boundary-dominated flow]
- Modified-Hyperbolic Relation [ ... early hyperbolic/late exponential]
- Power-Law Exponential Relation [ ... based on power-law  $D(t)$  behavior]
- Stretched Exponential Relation [ ... historical statistical function]
- Duong Relation [ ... empirical power-law  $\log[q(t)/Q(t)]$  vs.  $\log[f]$  behavior]
- Future Relations? [ ... still just  $q(t) = f(t)$ ]

**Diagnostic Decline Curve Analysis:**

- The " $qDb$ " plot is the essential component.
- If the model and data do not agree (on the  $qDb$  plot), rethink the model.
- The Duong model is an over-estimator and has non-physical behavior.
- The Modified-Hyperbolic relation is the "currency" of reserves analysis.

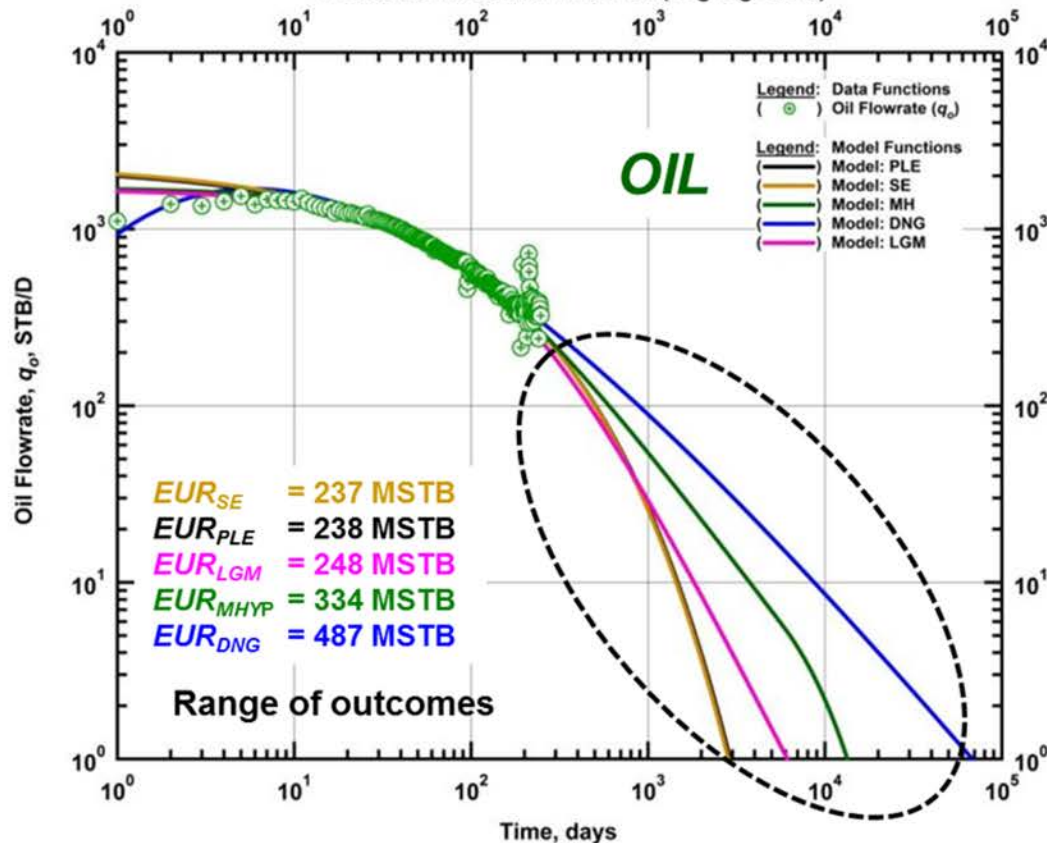
**Time-Rate Relations – Time Required for a Match/Extrapolation (Various Sources)**

**Reference:**

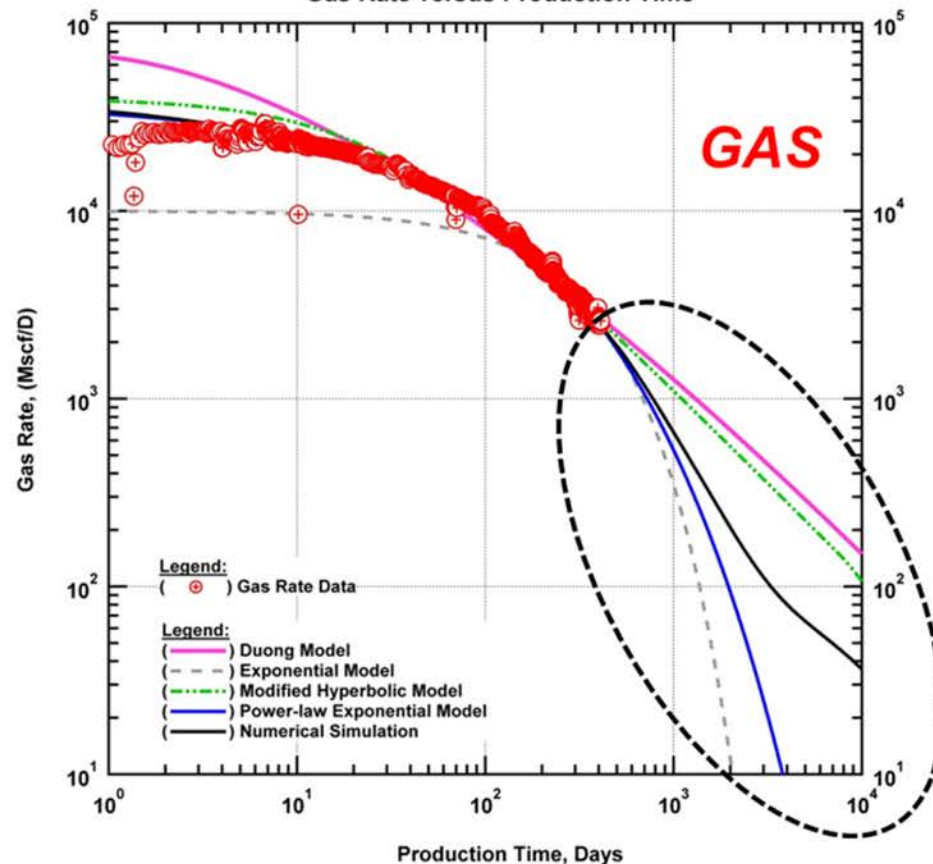
	Number of Months Used in Matching
Mishra (SPE 161092, 2010)	50-180
Hategan (CSUG, 2011)	>36
Clark (UTexas MS Thesis, 2011)	50-90
Johanson (CSM MS Thesis, 2013)	72 (average)
Patzek et al (PNAS, 2013)	>36
Berman (2014)	24-36
Ali and Sheng (2015)	72 (average)
Shahamat (2015)	86-526
Joshi (2015)	30-40 (basis)

## Production Forecasting — Example Comparison of Models

Rate-Time Models: Eagle Ford Shale Oil Well (Oil Rates)  
Production Rate and Time Plot (Log-log Scale)



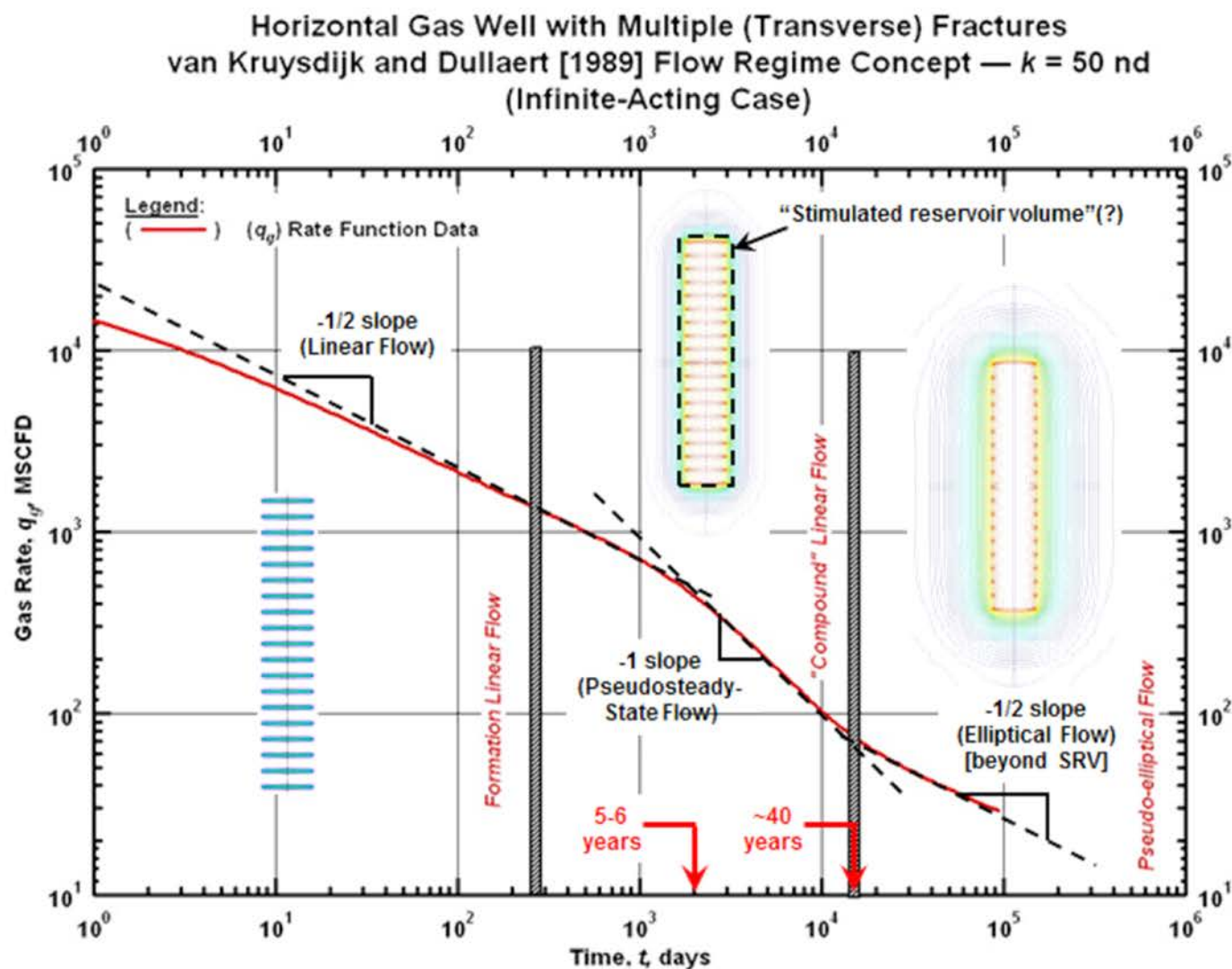
Production Forecast Plot  
Decline Curve Relations and Numerical Model  
Gas Rate versus Production Time



### Discussion:

- Each decline curve analysis (DCA) model is **EMPIRICAL** (no direct link with theory).
- Each model has some sort of tie to a specific flow regime or other characteristic behavior.
- Implicitly, each model assumes that the well is produced at a constant bottomhole pressure.
- Can time-rate analysis truly represent well performance? (someone has to ask...)

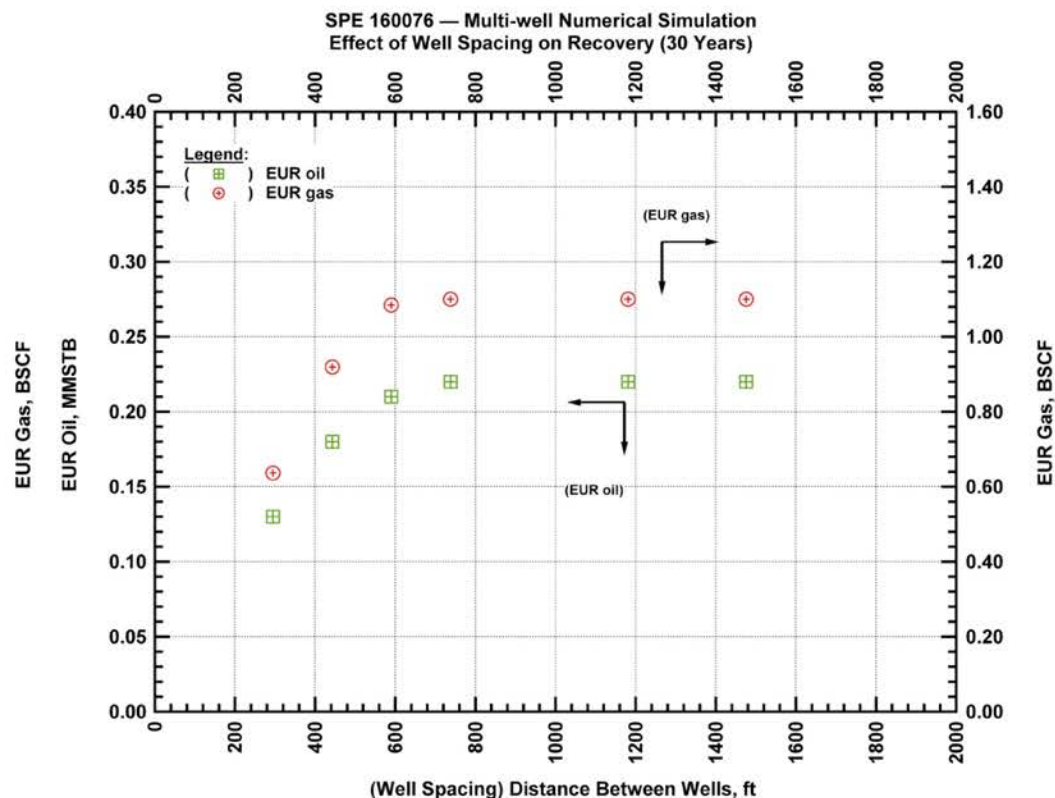
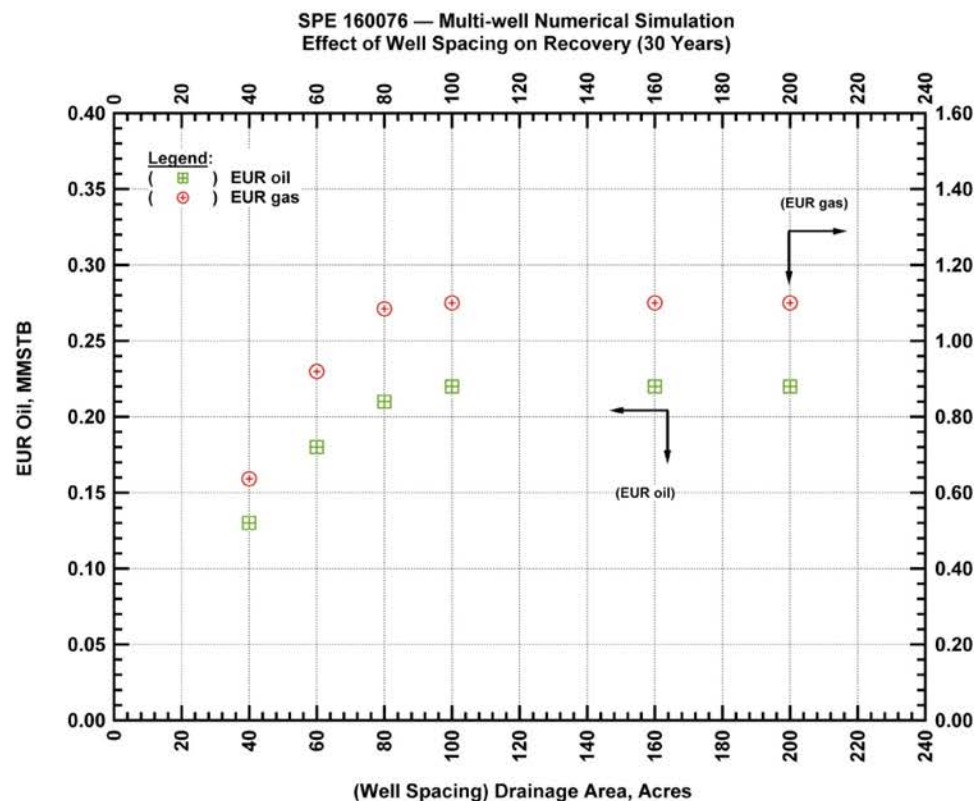
## Production Forecasting — Horizontal Well with Multiple Fractures



### Discussion:

- The MFHW model is the "master" solution for unconventional wells.
- All flow regimes are modeled, but not often observed.
- Diagnostics can be obscured by clean-up and liquid-loading.
- Note the very significant time involved for observing a particular flow regime ( $k = 50$  nd).

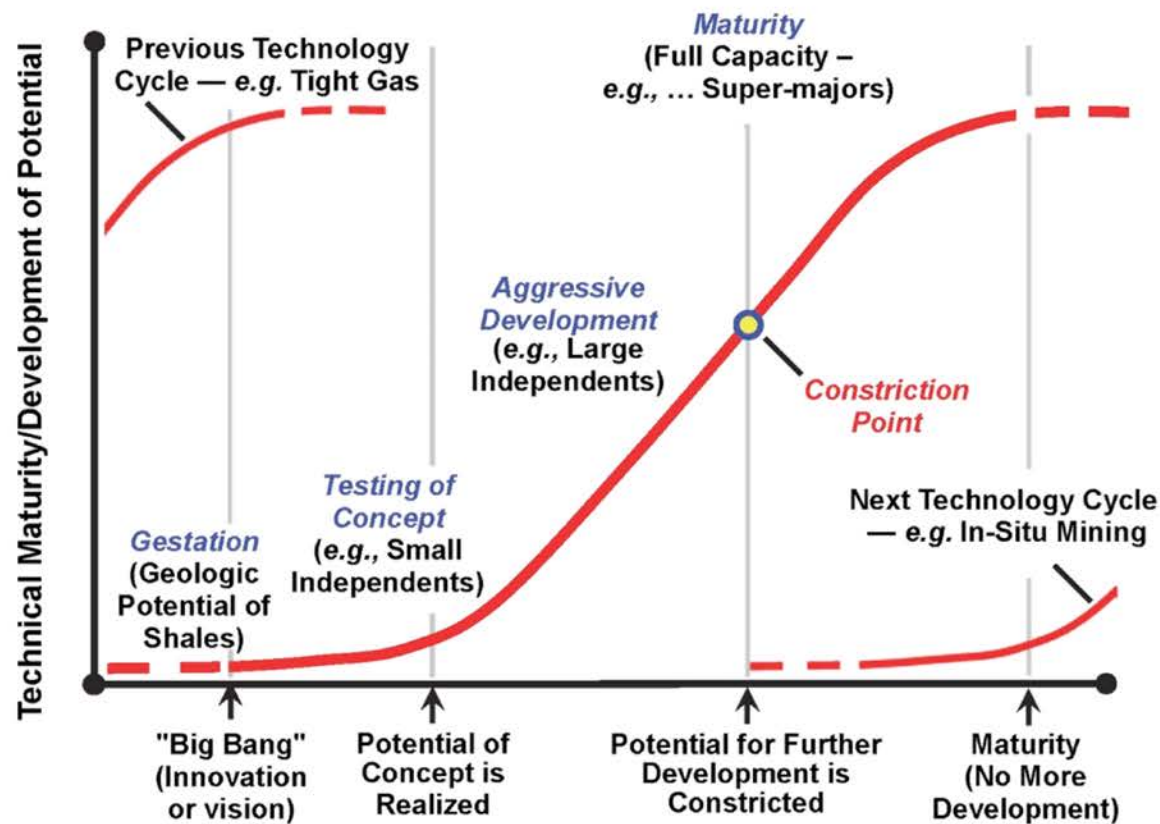
## Eagle Ford Shale Example — Multi-Well Numerical Simulation Model (SPE 160076)



### Discussion:

- EUR degradation for well spacing for < 100 acres.
- For this case, the model sees no EUR degradation for well spacing > 100 acres.
- EUR values are estimated at 30 years of production.
- For this model configuration, 100 acres well spacing corresponds to 738 ft distance between wells.

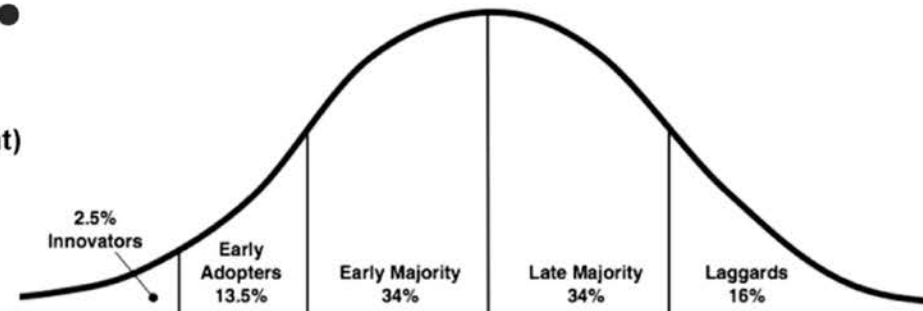
## What's Next? — "Technology Maturity" for Unconventional Resources



Creator: T.A. Blasingame  
Created: 2012.01.03  
Last Revised: 2017.05.15

### Diffusion of Innovation: (Rogers, 1962)

- **Innovators (2.5%)** – Innovators are willing to take risks, youngest in age, are very social and have closest contact to scientific sources and interaction with other innovators. Risk tolerance has them adopting technologies which may ultimately fail.
- **Early Adopters (13.5%)** – Early adopters have the highest degree of opinion leadership among the other adopter categories. Early adopters are also typically younger in age, have more financial lucidity, advanced education, and are more socially forward than late adopters.
- **Early Majority (34%)** – Individuals in the Early Majority category tend to be slower in the adoption process, contact with early adopters, and seldom hold positions of opinion leadership in a system.
- **Late Majority (34%)** – Individuals in the Late Majority category will adopt an innovation after the average member of the society. Late Majority are typically skeptical about an innovation, and very little opinion leadership.
- **Laggards (16%)** – Laggard are the last to adopt an innovation. Unlike some of the previous categories, individuals in this category show little to no opinion leadership. These individuals typically have an aversion to change-agents and tend to be focused on "traditions."



Rogers, Everett M. (1962). Diffusion of innovations (1st ed.). New York: Free Press of Glencoe.

### Discussion:

- Graphic explains "Technology Maturity" for unconventional resources.
- The maximum "value" occurs as the potential is realized (*i.e.*, very early).
- The "constriction point" implies too many players/less innovation/value.

## What's Next? — "Expect the Unexpected" ...

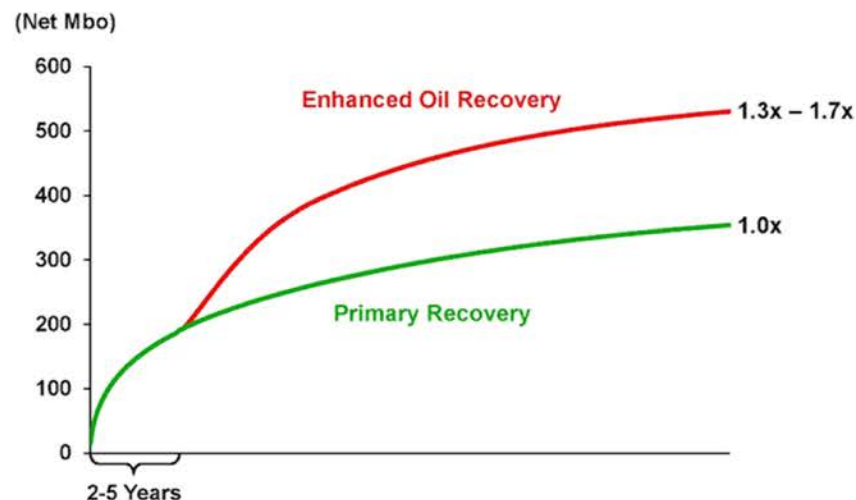
### Possible "Next-Step Technologies:"

- **Waterless Stimulation...**
  - EM Pulse?
  - Explosives?
- **Improved Recovery...**
  - Thermal?
  - Lean gas injection?
  - In-situ recovery enhancement?
- **In-Situ Mining...**
  - Extremely tight spacing?
  - Very accurate well targeting?
  - Multi-lateral wells?
  - Revert to vertical wells?
- **Engineering...**
  - Near-well productivity assessment?
  - Near-critical PVT characterization?
  - Inter-well flow characterization?
- **Petrophysics...**
  - Flow-scale permeability?
- **Geophysics...**
  - Inversion for shale properties?
  - Correlate TOC to attributes?

### EOG Resources Eagle Ford Enhanced Oil Recovery

- Four Gas Injection Pilot Projects with 15 Producing Wells
  - One Additional Project Planned for 2016 with 32 Wells
  - Geologically and Geographically Diverse
  - EOR Incremental Production in 2016 ≈ 1,000 Net Bopd

### EOG Resources Eagle Ford Enhanced Oil Recovery Cumulative Oil Production per Well



Helms, Jr., L.W. (EOG Resources)  
J.P. Morgan Inaugural Energy Equity Investor Conference  
(Wednesday, June 29, 2016)

### Discussion:

- Enhancements in well stimulation will happen (but will be "evolutionary, not revolutionary").
- Improved recovery efforts for tight oil will focus on lean/wet gas injection and thermal recovery.
- Reservoir characterization and reservoir engineering aspects will be critical as well.
- "Data Analytics" will help, but to interpret and reduce uncertainty, predictions remain trial/error.

# ***Reservoir Engineering Aspects and Forecasting of Well Performance in Unconventional Resources***

## ***End of Presentation***

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# Scoping and Forecasting Cyclic Natural Gas Injection in the Eagle Ford

Authors:

Carlos Pereira, Mahmood Ahmadi, Carolina Mayoral

**MI3** Petroleum Engineering

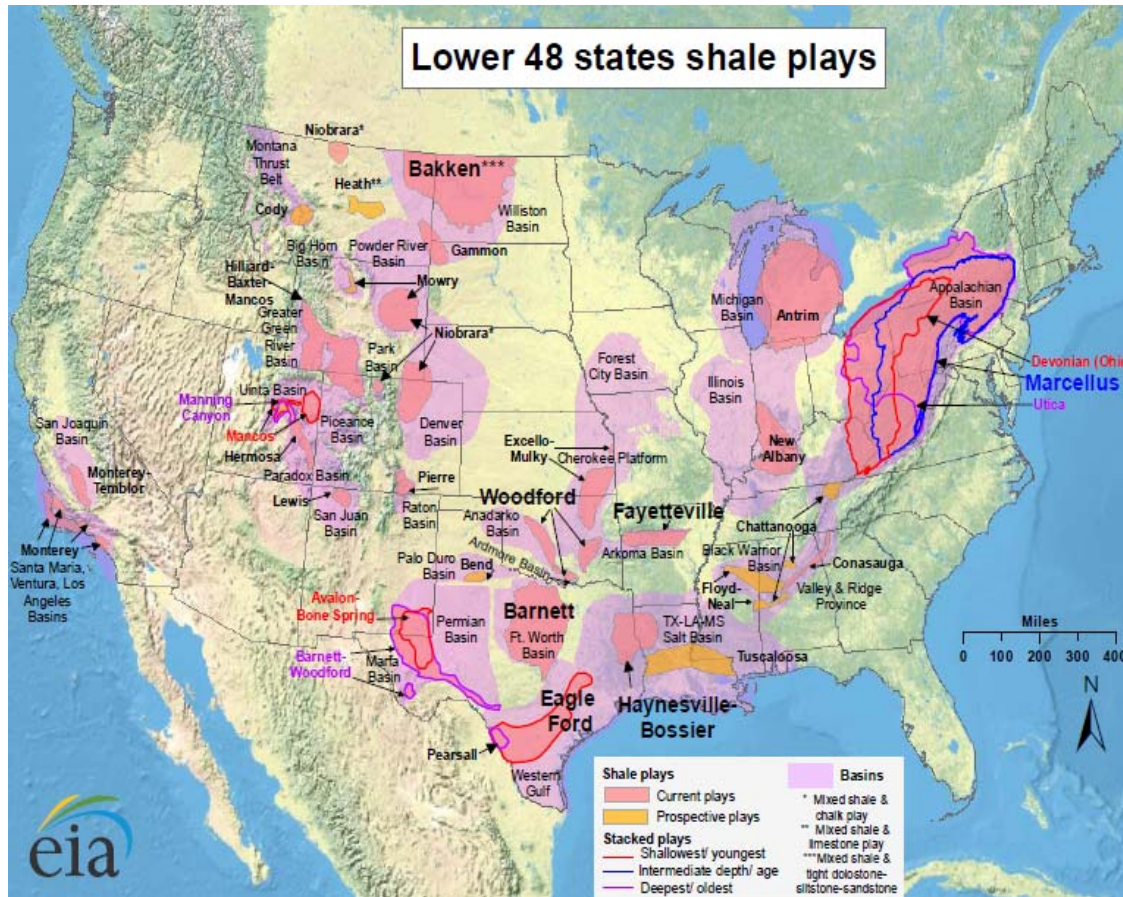
2017 Reservoir Technology Forum – The Woodlands, TX

SPE GCS Reservoir Study Group  
2017 Reservoir Technology Forum



# Vision

## Big Prize = Big Challenges



### Lower 48 states

- Technically recoverable ~50-70 Bbbl
- Unconventional OOIP ~500-700 Bbbl
- Resources left behind ~450-600 Bbbl
- IOR/EOR methods could help extract some of the product left behind



### Eagle Ford

- Large number of wells stagnant at low recovery and low oil rates
- Black oil, volatile, condensate systems
- Natural gas supply at low cost
- Opportunity for cyclic natural gas injection

Identification > Scoping > Evaluation > Forecasting > Economic justification > Implementation > Monitoring > Expansion

# EOR in unconventional reservoirs

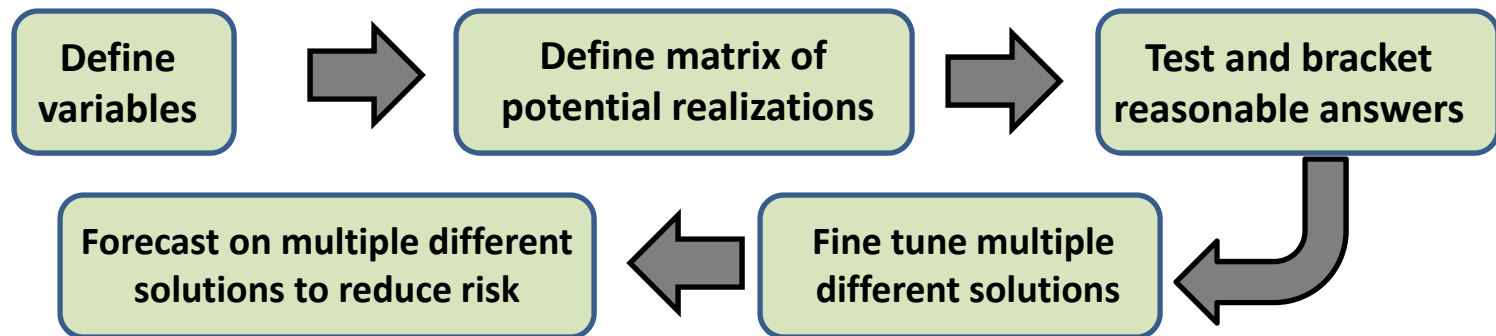
## Cyclic Natural Gas Injection (CNGI) - Challenges

- Large capital deployment with very little upside potential beyond primary recovery (single digit) – Look for ways to extend and improve the economic life of those assets.
- No significant commercial applications yet - Few pilots
- Lack of analogs and industry expertise, early part of the learning curve
- Difference between conductivity of the fractures and the conductivity of the matrix is the biggest challenge. Most of the fluid is stored in the ultra low conductivity system and low amounts are stored in the ultra high conductivity system (fractures)
- Complex phase behavior, fluid property changes, interfacial tension, Kr changes, Pc changes.
- Natural gas utilization / Compression cost / Operational pressure / Volume and rate constrains
- When and how to apply to see benefits and reduce cost

# CNGI Evaluation - Methodology

**Start with a wide range – End with few diverse cases**

- The conventional deterministic multidisciplinary approach could lead to erroneous interpretations, models, and inaccurate forecast due to the number of unknowns and the wide range of values for the same variable.
- It is important to consider all possible reasonable ranges in key variables to identify probable numerical solutions. Start by selecting at least 3 wells for each fluid window: pessimistic, AVG, optimistic.



# What we know?

We know what we know and what we do not know

## Reasonable certainty

- Depth
- Pressure
- Temperature
- Porosity
- TOC
- Isotherm
- Thickness and net pay
- Fluid properties
- Wellbore length
- # Frac Stages
- Sw
- Geomechanical properties
- PVT
- Production history
- Completion history



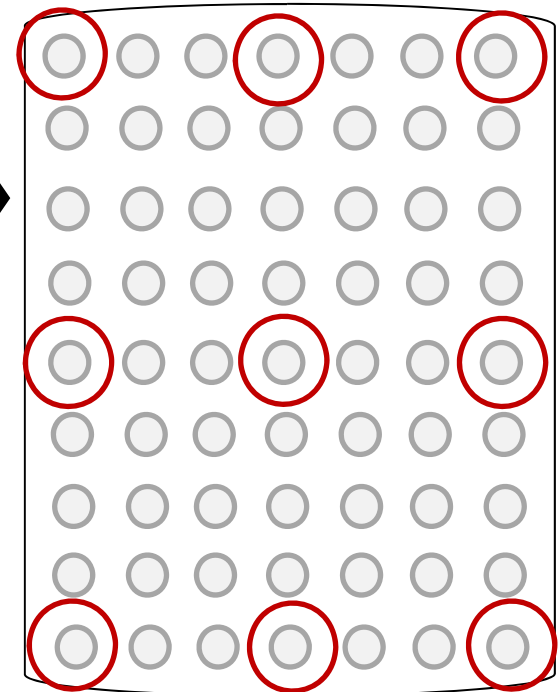
## Reasonable uncertainty

- Matrix permeability
- Fracture penetration
- Fracture permeability
- Fracture density vs.  $X_f$
- Effective wellbore length
- $K_r$ ,  $P_c$
- Many unmeasured or uncertain parameters.



Many likely realizations

Find a reasonable domain with reasonable answers



# Modeling shale reservoir

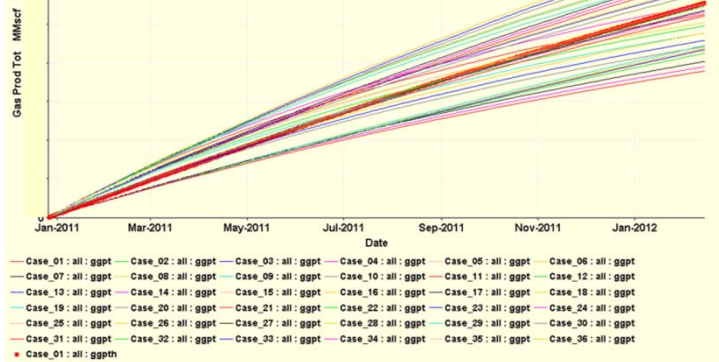
## Scoping and Forecasting Approach

### Parametric study

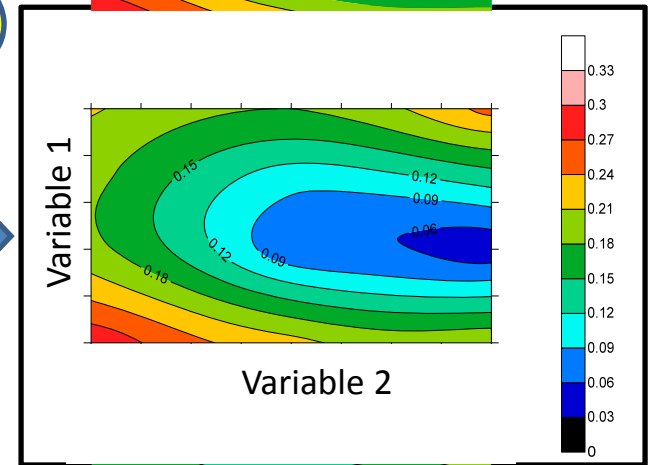
Identify likely range of variables

1

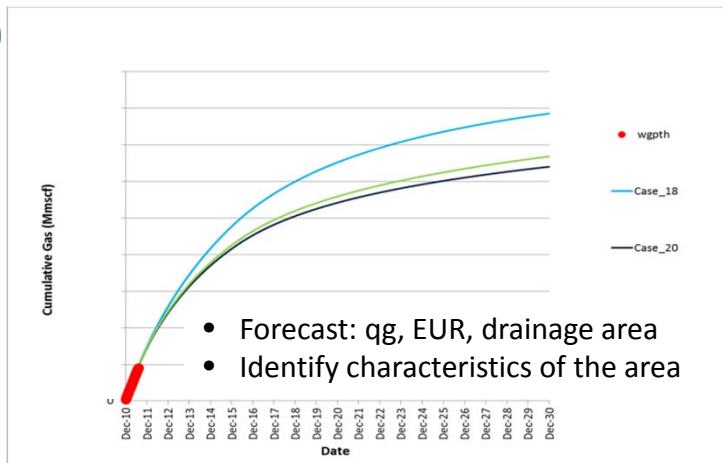
- Define variables, unknowns, ranges
- Construct 3-D Models, simulate and screen



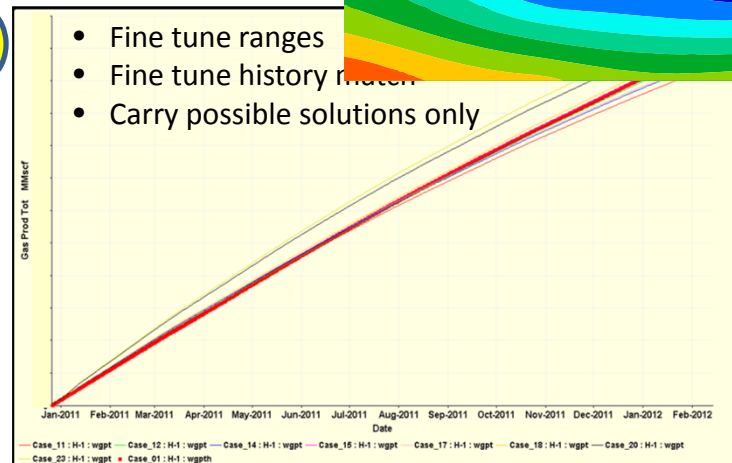
2



4



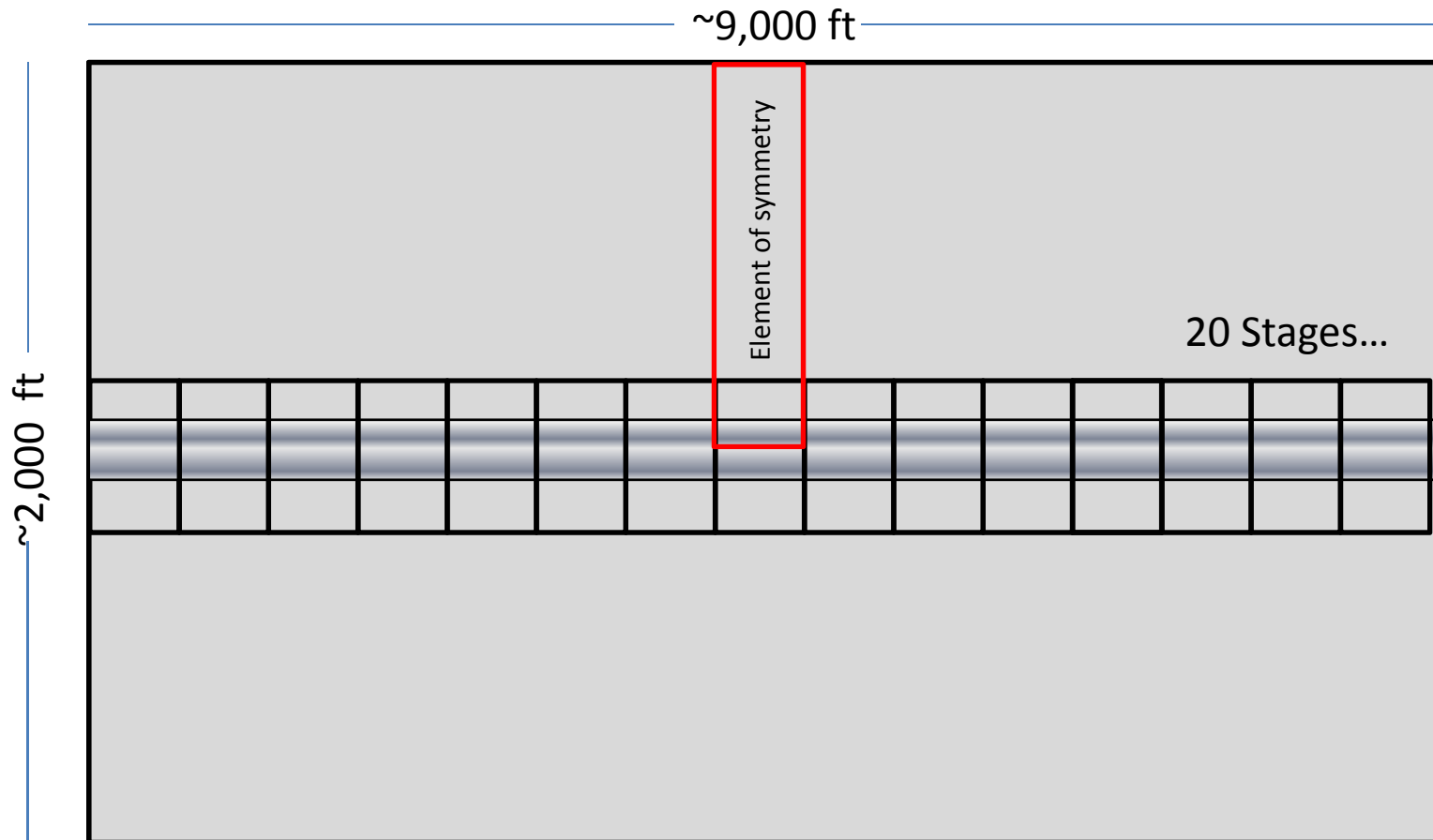
3



# Confidential Well

## Schematic Representation – Element of symmetry

Top view of an horizontal well



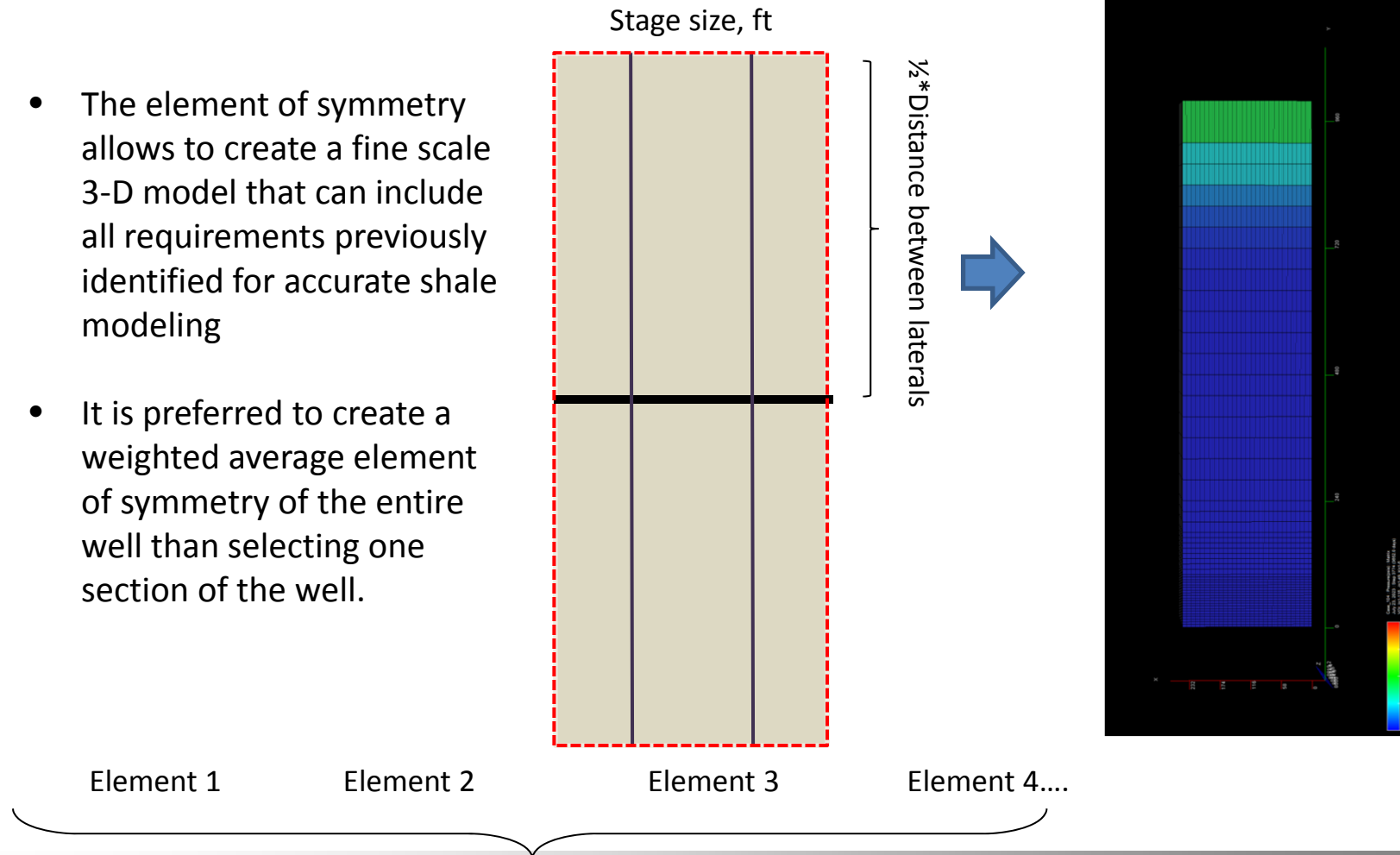
Not to scale

# Methodology

## Model Description – Element of Symmetry

Dual-porosity / Dual-permeability 3-D compositional models

- The element of symmetry allows to create a fine scale 3-D model that can include all requirements previously identified for accurate shale modeling
- It is preferred to create a weighted average element of symmetry of the entire well than selecting one section of the well.



# Simulation Cases - Screening Phase

## Matrix Permeability 5nD

Case	1	2	3	4	5	6	7	8	9	10	11	12
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	13	14	15	16	17	18	19	20	21	22	23	24
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	25	26	27	28	29	30	31	32	33	34	35	36
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	37	38	39	40	41	42	43	44	45	46	47	48
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5

# Simulation Cases - Screening Phase

## Matrix Permeability 50 nD

Case	49	50	51	52	53	54	55	56	57	58	59	60
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	61	62	63	64	65	66	67	68	69	70	71	72
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	73	74	75	76	77	78	79	80	81	82	83	84
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	85	86	87	88	89	90	91	92	93	94	95	96
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50

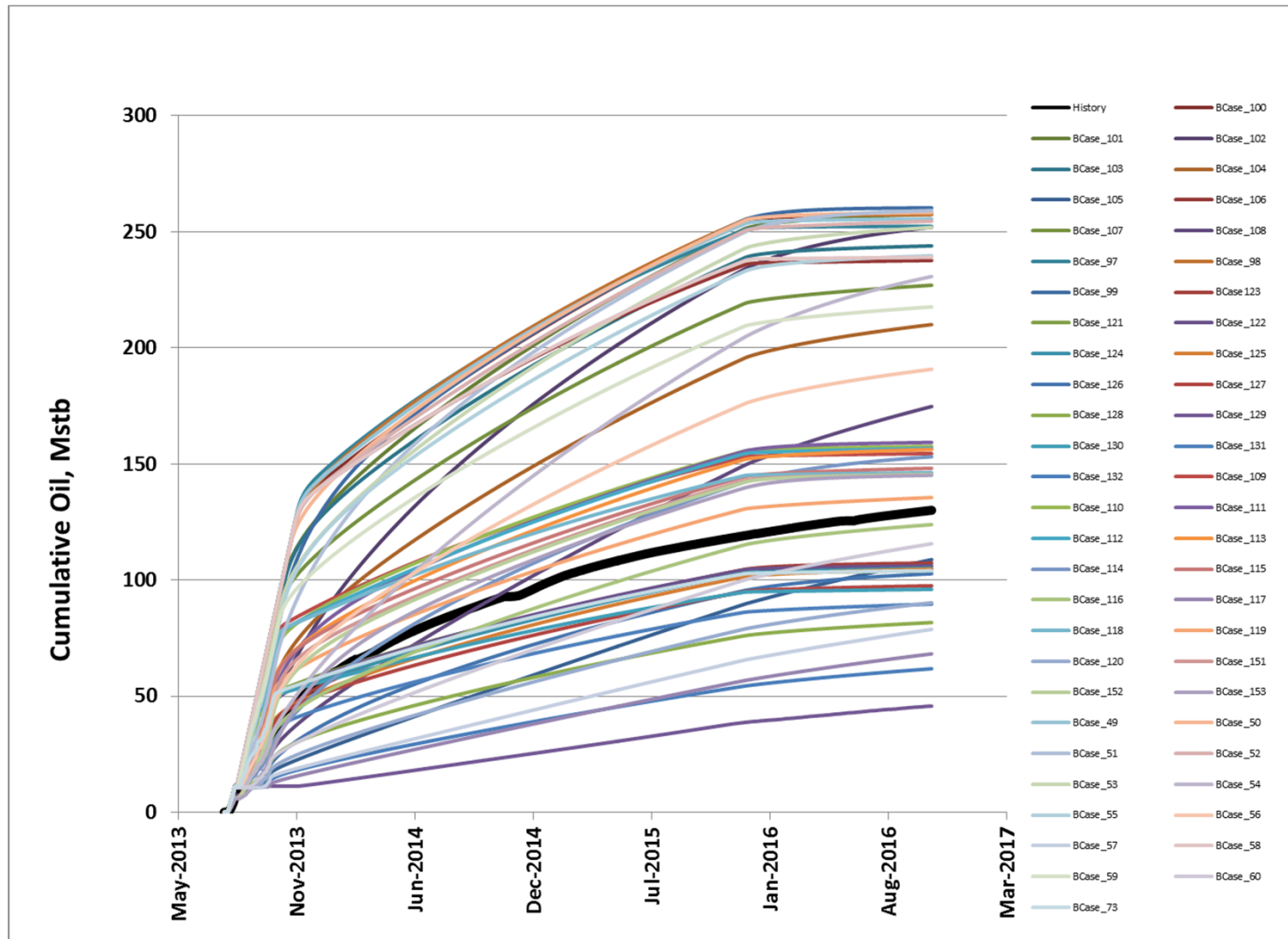
# Simulation Cases - Screening Phase

## Matrix Permeability 100 nD

Case	97	98	99	100	101	102	103	104	105	106	107	108
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	109	110	111	112	113	114	115	116	117	118	119	120
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	121	122	123	124	125	126	127	128	129	130	131	132
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	133	134	135	136	137	138	139	140	141	142	143	144
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100

# Simulation Cases - Screening Phase

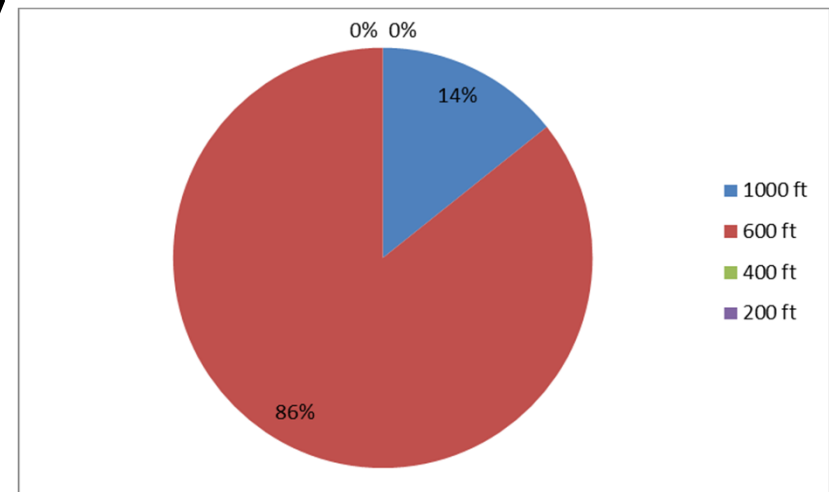
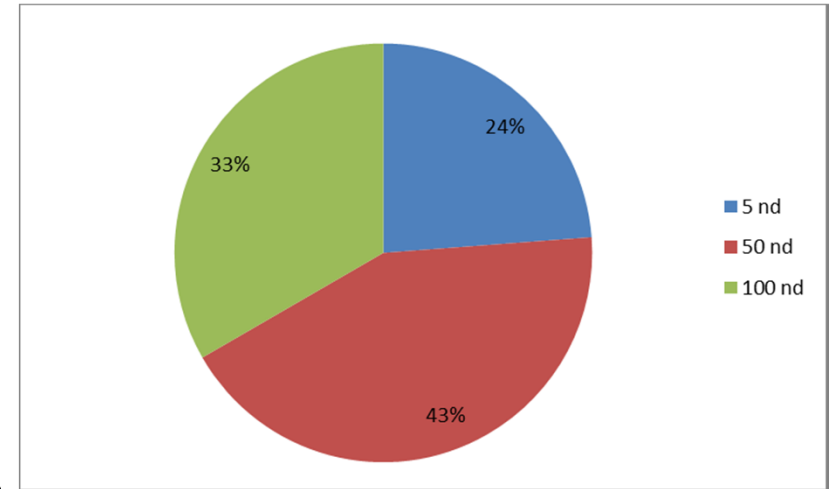
## History Matching Results



# Results – Screening Phase

## History Matching

Case	1	2	3	4	5	6	7	8	9	10	11	12
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	13	14	15	16	17	18	19	20	21	22	23	24
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	25	26	27	28	29	30	31	32	33	34	35	36
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	37	38	39	40	41	42	43	44	45	46	47	48
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	5	5	5	5	5	5	5	5	5	5	5	5
Case	49	50	51	52	53	54	55	56	57	58	59	60
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	61	62	63	64	65	66	67	68	69	70	71	72
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	73	74	75	76	77	78	79	80	81	82	83	84
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	85	86	87	88	89	90	91	92	93	94	95	96
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	50	50	50	50	50	50	50	50	50	50	50	50
Case	97	98	99	100	101	102	103	104	105	106	107	108
Xf	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	109	110	111	112	113	114	115	116	117	118	119	120
Xf	600	600	600	600	600	600	600	600	600	600	600	600
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	121	122	123	124	125	126	127	128	129	130	131	132
Xf	400	400	400	400	400	400	400	400	400	400	400	400
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100
Case	133	134	135	136	137	138	139	140	141	142	143	144
Xf	200	200	200	200	200	200	200	200	200	200	200	200
Fracture density function	F1o	F1a	F1p	F2o	F2a	F2p	F3o	F3a	F3p	F4o	F4a	F4p
Km	100	100	100	100	100	100	100	100	100	100	100	100



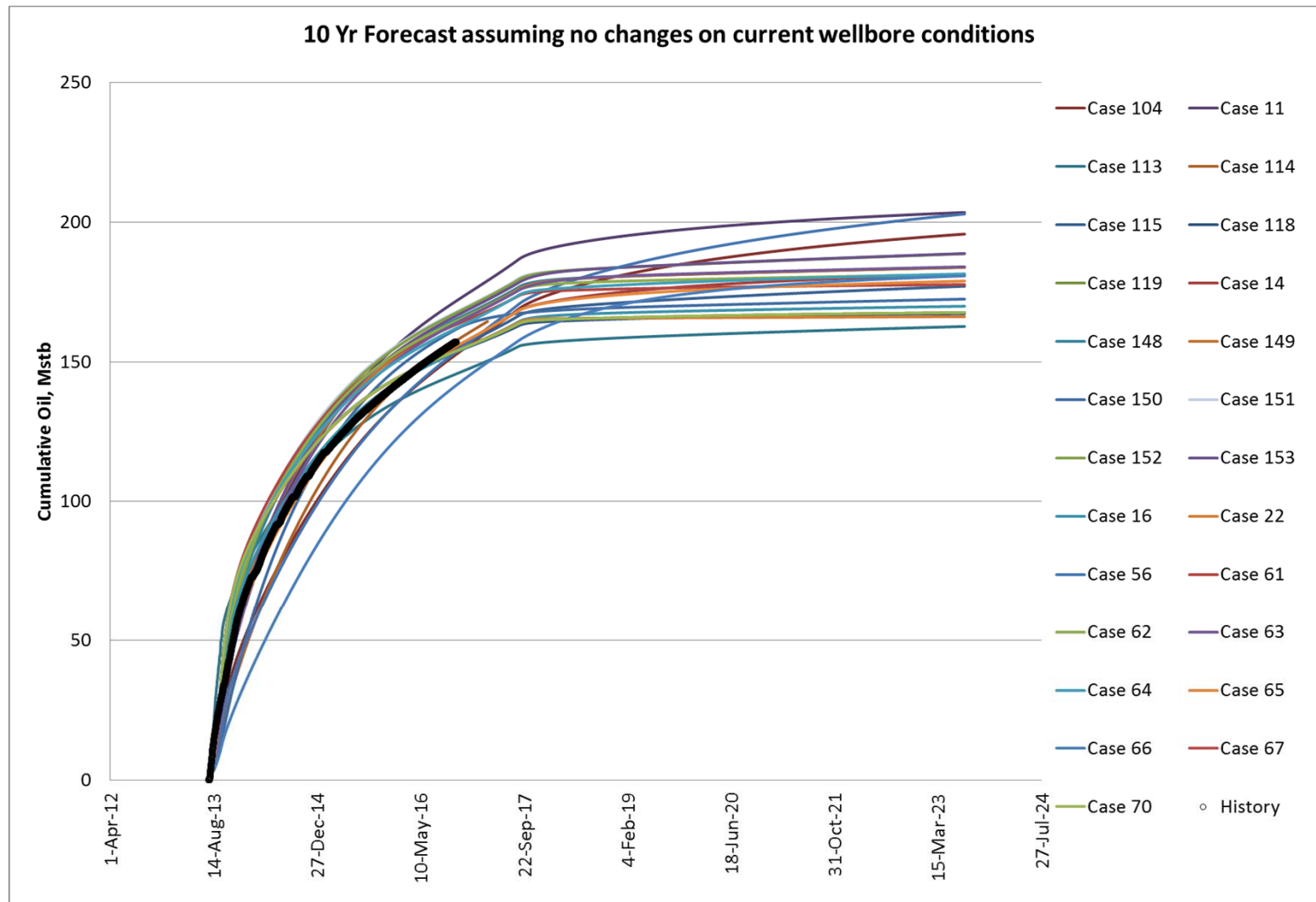
# Results – Screening Phase

## History matching

- The results of the screening phase suggest that the effective fracture half length ( $X_f$ ) is at least 600 ft.
- Despite of using high fracture density and high matrix permeability values, no case using  $X_f$  of 400 ft or less was close to the actual results
- 86% of all cases with a reasonable match confirmed micro-seismic studies suggesting  $X_f$  close to 600 ft.
- Average matrix K it is likely to be around 50 nd, but a few 5nd and 100 nd cases provided a good match
- MI3 took all best history matching cases to the forecast mode:
  - Base case
  - Cyclic natural gas injection (few very different cases)

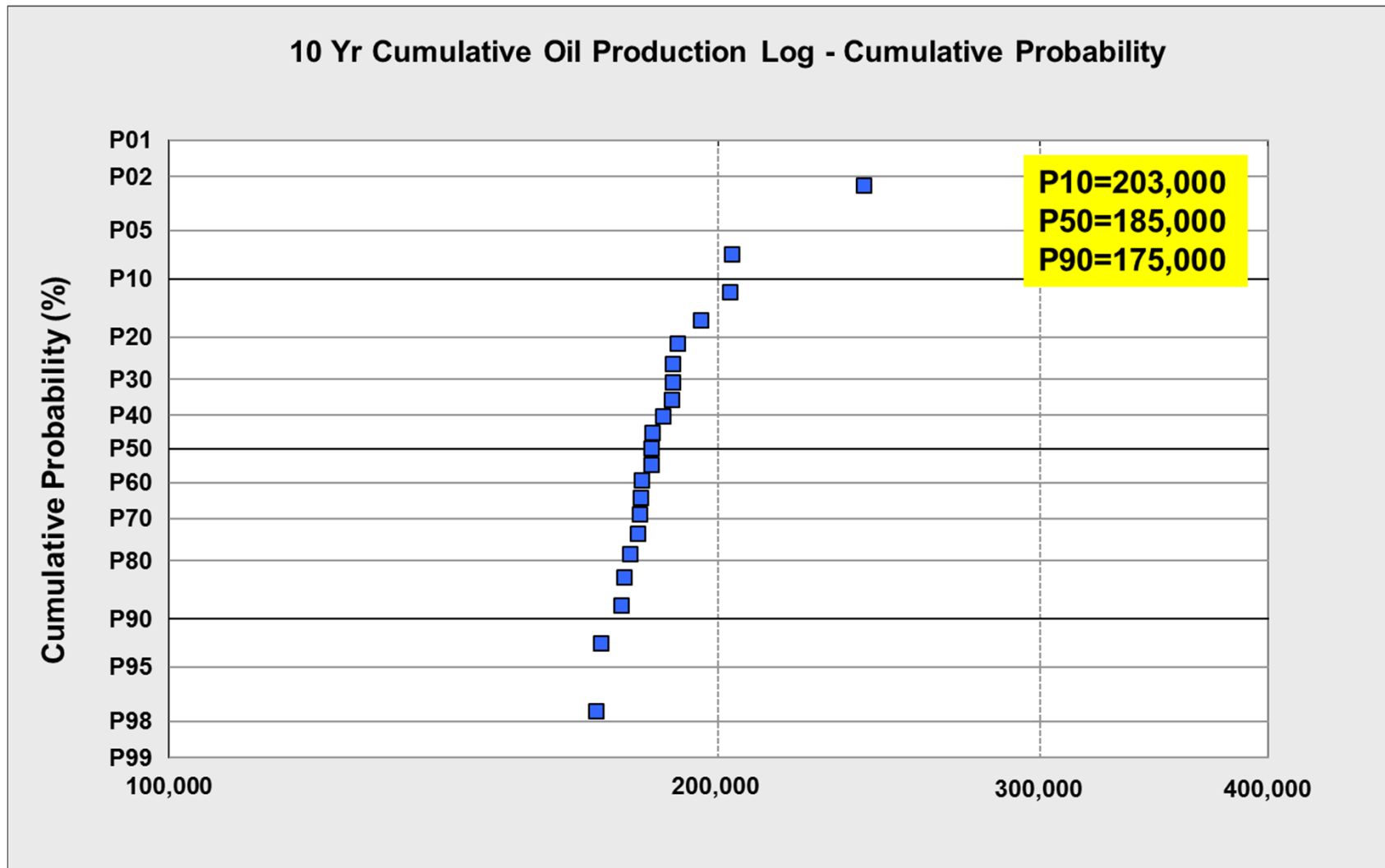
# 10 Yr Forecast (Base Case)

## Primary Recovery Forecast– No future changes



# 10 Yr Forecast (Base Case)

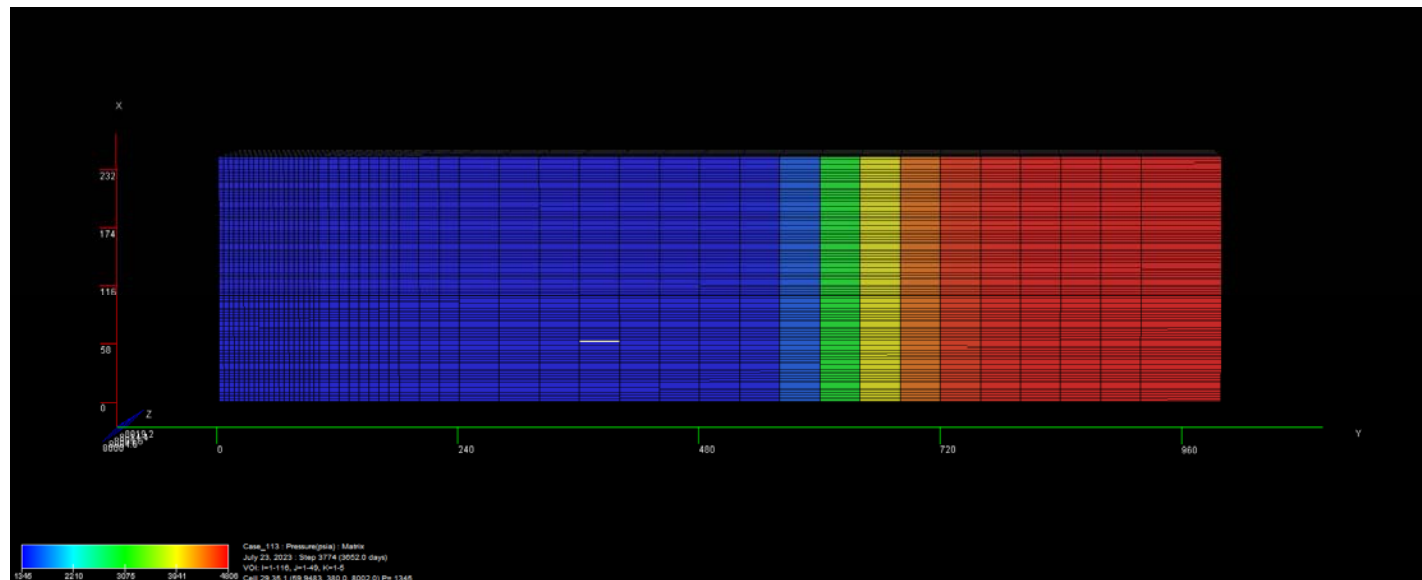
## Base Case – Primary Recovery



# 10 Yr Forecast (Base Case)

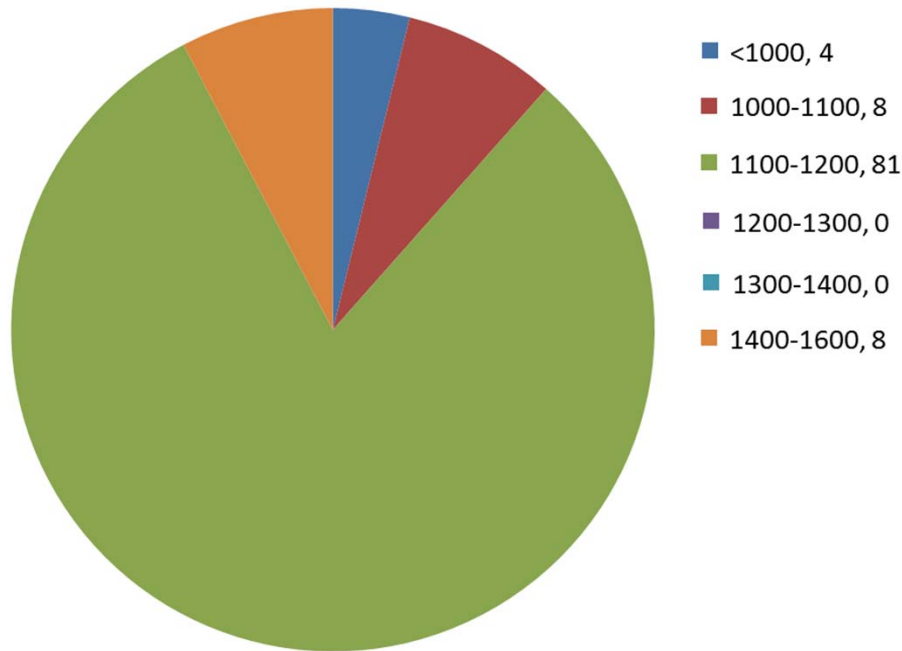
## Base Case (No gas injection) – Drainage area

Case 113 (1,200 ft)



# 10 Yr Forecast (Base Case)

## No gas Injection – Drainage area



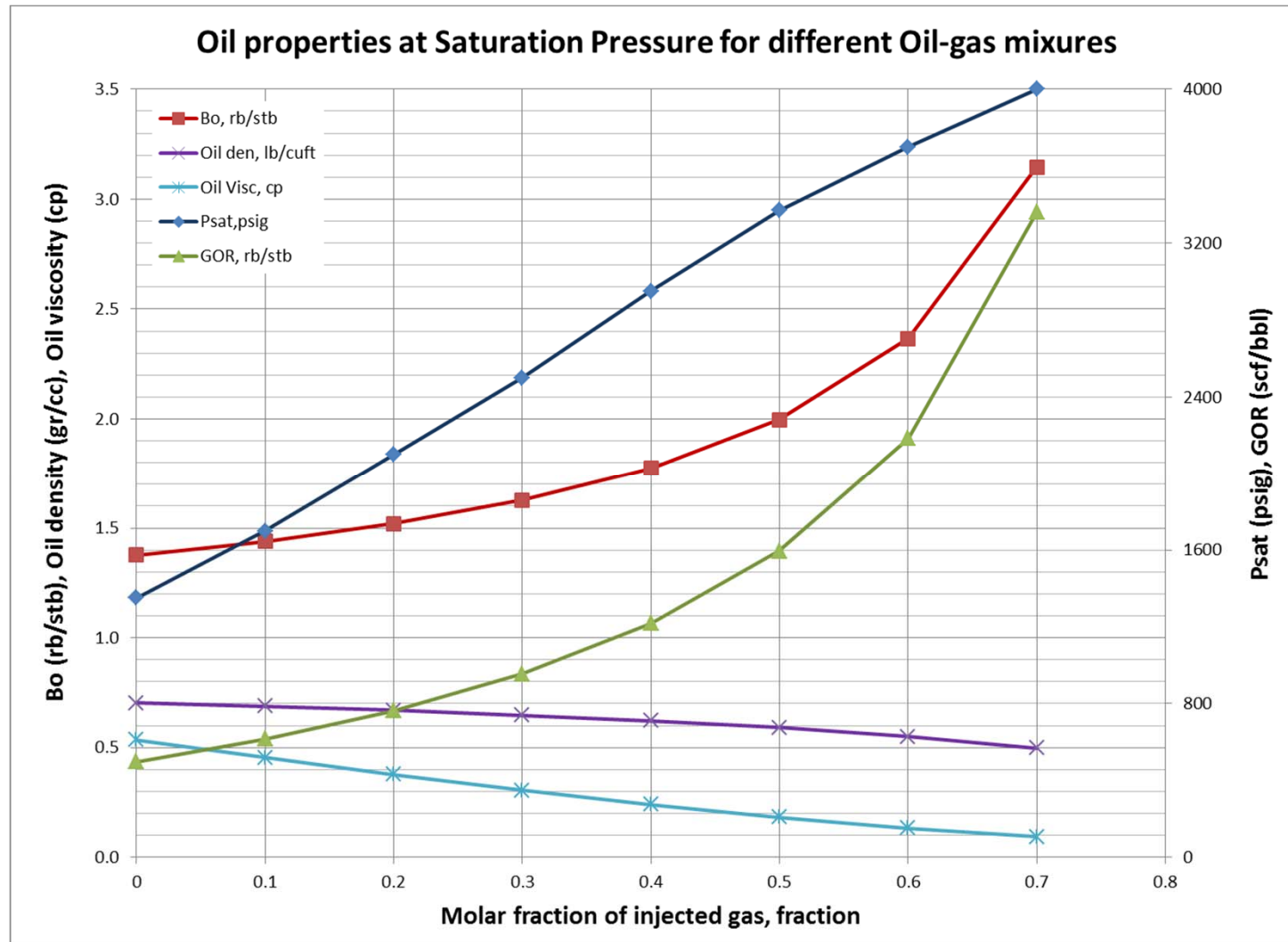
- 81% of simulation cases suggest that perpendicular drainage from the horizontal well is between 1,100 ft and 1,200 feet
- Only 8%, suggest the perpendicular drainage from the horizontal well could be between 1,400 ft and 1,600 ft.
- Depending on the area and wells, these results will change. Multiple simulations of multiple wells across the acreage will yield to a more representative result and better planning
- Assuming that most of the wells behave like this well, It is recommended a maximum well spacing between wells of 1,600 ft, and a minimum of 1,200 ft

# Forecast - EOR

## Natural Gas Cyclic Injection

# Simulated Effect of Gas Injection

## Estimated PVT changes in the oil (Example case)



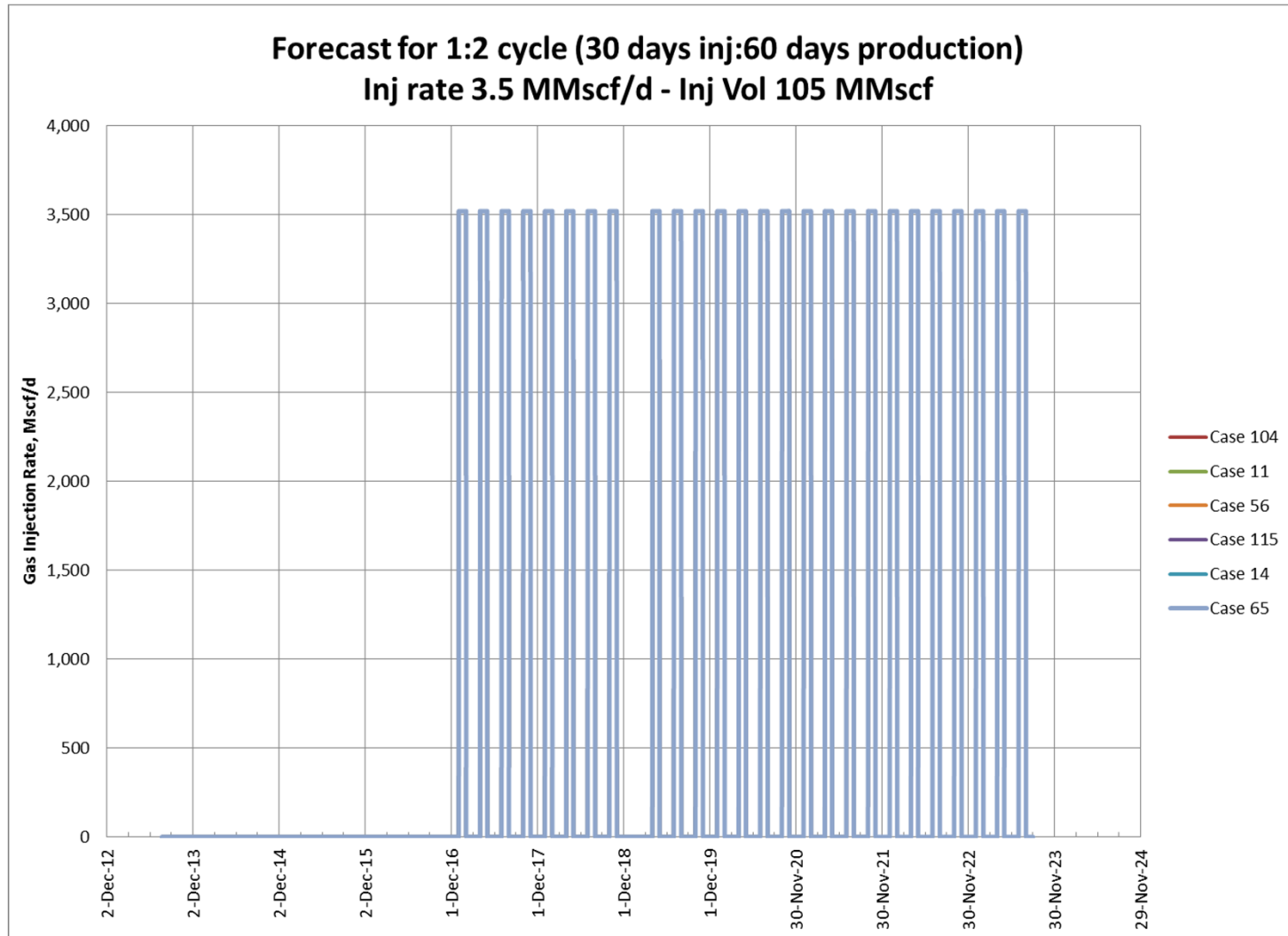
# Cyclic Natural Gas Injection

## Key assumptions – Forecast (Example Case)

- Cycle 1:2 (Inj:Prod)
- Injection
  - Inject at least 3.5 MMscf/d
  - Max. BHP injection=7,000 psi (Below frac pressure)
  - Min. Volume of gas per injection cycle= 105 MMscf/d
- Production
  - Hold production max. 300 bbl/d
  - Min. 1350 psi (FBHP)
  - Max. 60 days production cycle

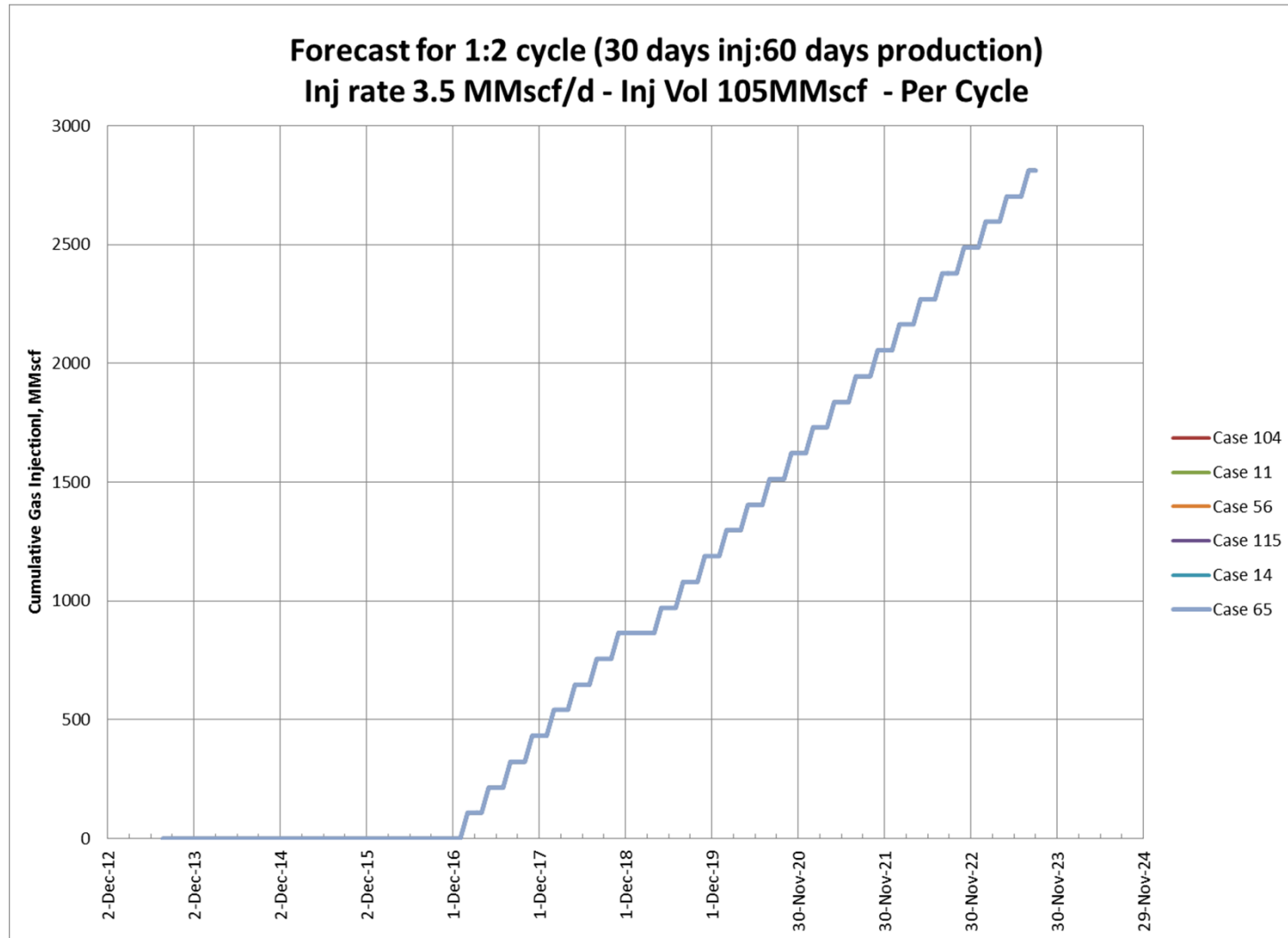
# Cyclic Natural Gas Injection

## Natural Gas Injection rate



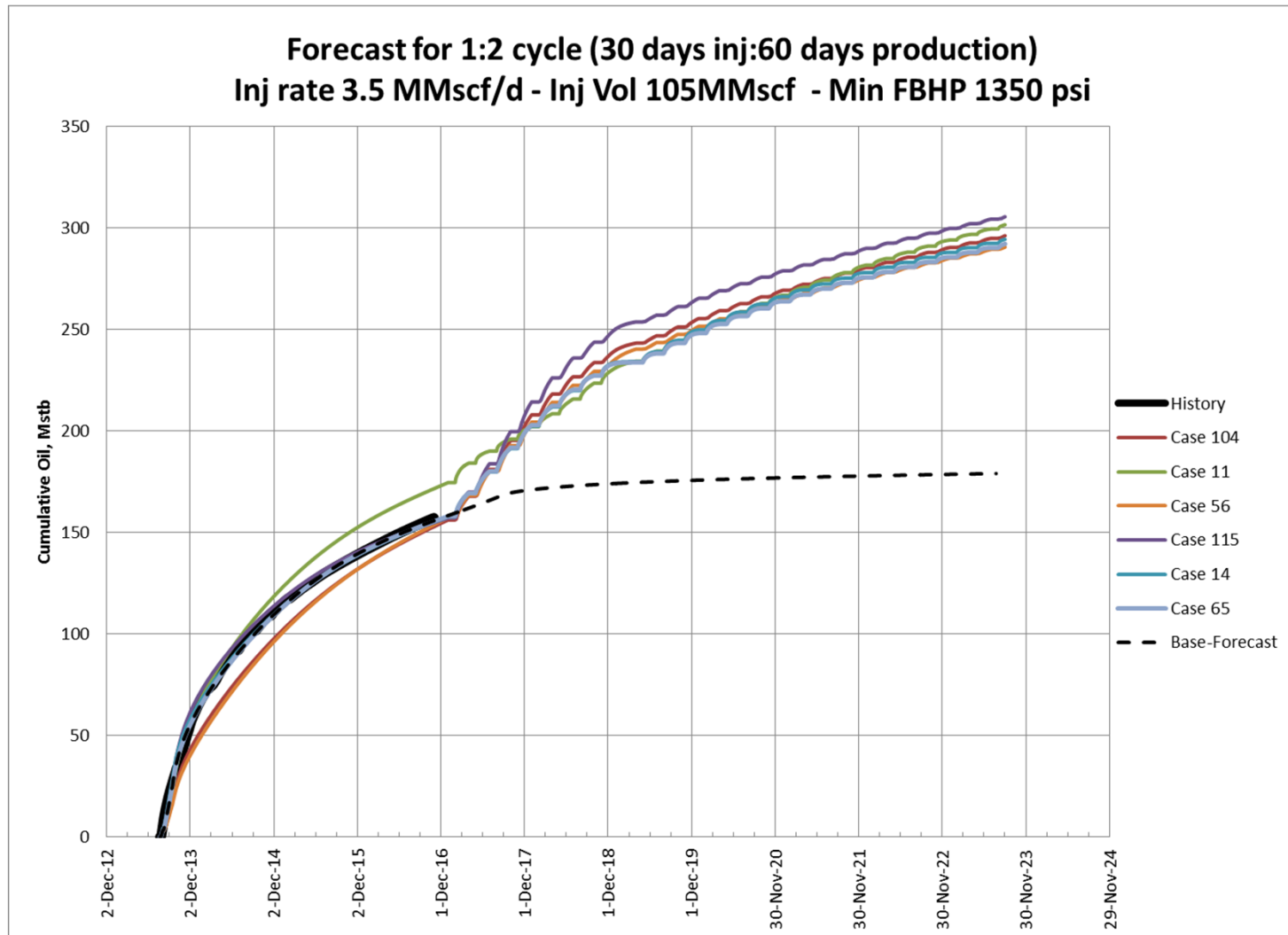
# Cyclic Natural Gas Injection

## Cumulative Gas Injection



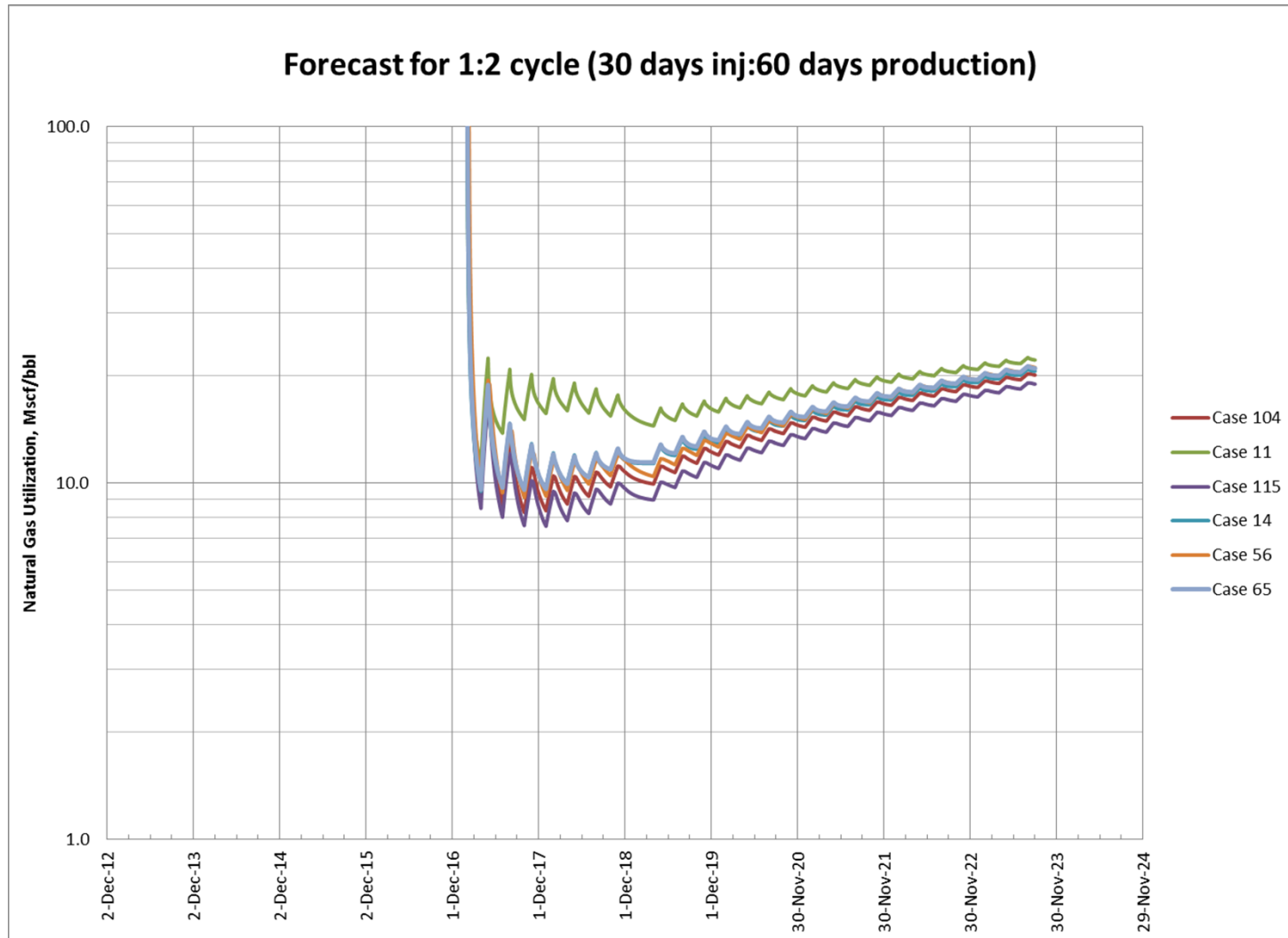
# Cyclic Natural Gas Injection

## Cumulative Oil



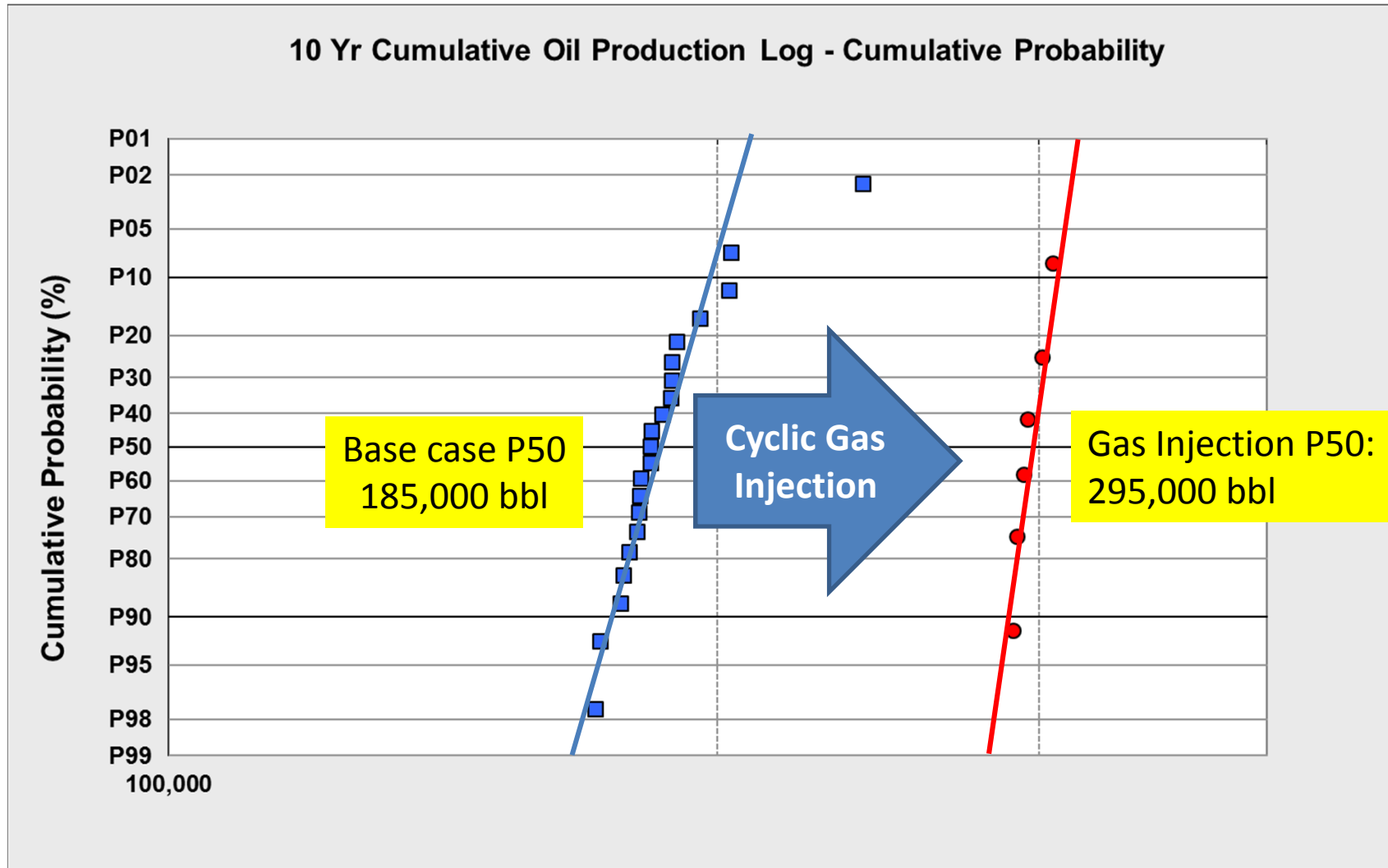
# Cyclic Natural Gas Injection

## Natural Gas Utilization



# Cyclic Natural Gas Injection

## Incremental Recovery – 10 yr period



# Recommendations

1. Divide the acreage in regions that cover different reservoir and fluid systems. identify representative pessimistic, average and optimistic wells for each region.
2. Quantify and qualify your data, define uncertainties and ranges.
3. Generate a matrix of probable cases
4. Create a weighted average elements of symmetry using dual-porosity/dual-permeability compositional model
5. Test some of the potential solutions starting with the extremes and the center of your matrix, find the likely space of reasonable matches for the historical data
6. Fine tune the history match, and carry all the cases that differ the most from each other to the forecast mode
7. Run the base case forecast without gas injection
8. Define key assumptions for the cyclic natural gas injection
9. Forecast under the same constrains
10. Plot incremental recoveries in Cum Probability Chart (Log scale)
11. Base on the results, rank and delineate the area candidate for cyclic natural gas injection, define expectations
12. Take a representative case to run more sensitivities

# Questions and Comments

# Integration of Improved Asymmetric Frac Design Using Strain Derived From Geomechanical Modeling in Reservoir Simulation

SPE-182729-MS

Sandra Vargas-Silva

Oza, S., Paryani, M., FracGeo, Moody, D., Venepalli, K., Erdle, J., CMG, Ouenes, A., FracGeo

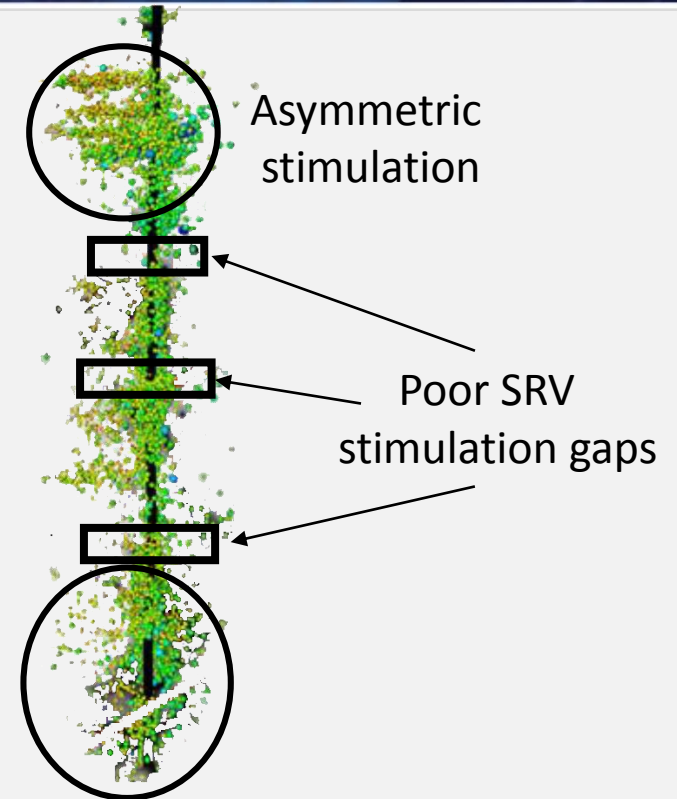


# Outline

- The challenge
  - The current approach
- Integrating Geoscience and Geomechanics with Engineering modeling
  - MPM
  - Fracture mechanics
  - Input data for MPM
  - MPM Results
- Deriving enhanced permeability from Strain
  - Volumetric approach
- Fracture geometry and conductivity from Hydraulic Frac Design
- Migration of results to simulation and parameterization
  - Single-frac per stage solution
  - Multi-frac per stage solution
- Results
  - Comparing different approaches
- highlights - Workflow
- Conclusions

# The Challenge

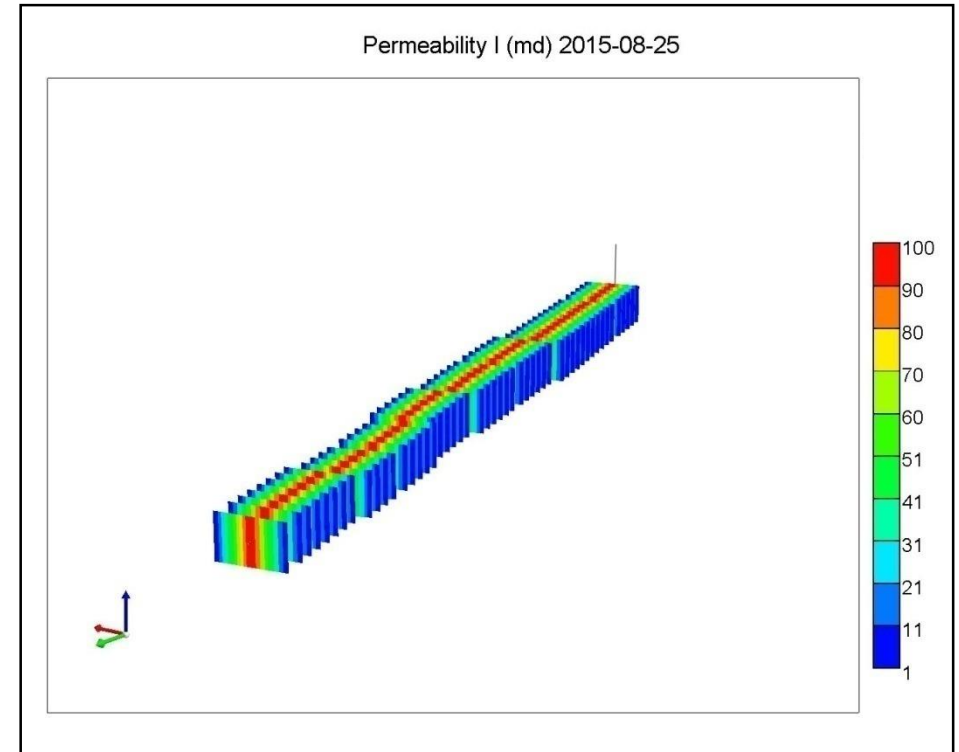
- Realistic representation of heterogeneous conductivity distribution of the propped volume and its interaction with natural fractures
  - Reasonable depletion patterns to optimize development plans:
    - Well spacing
    - Stacking
  - Improve performance forecasting



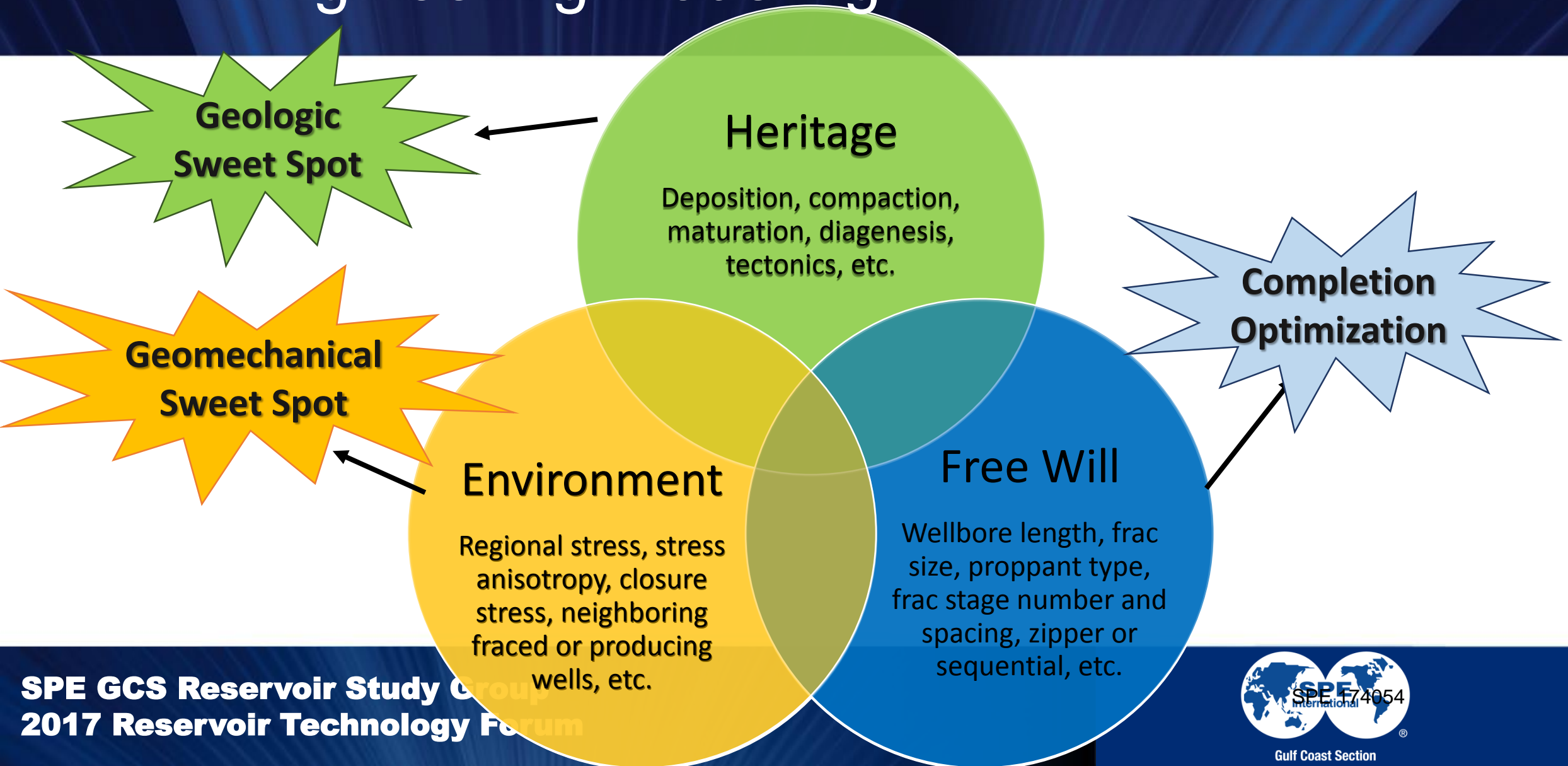
Microseismicity @ Wolfcamp well as shown by White et al. URTEC 1934166, 2014

# Current approach

- Hydraulic fractures are represented by symmetrical explicit fracture planes
- There is no differentiation from stage to stage
- Conductivity within fracture plane is considered either constant or linearly distributed from center to tip
- Interaction with natural fractures is not taken into consideration



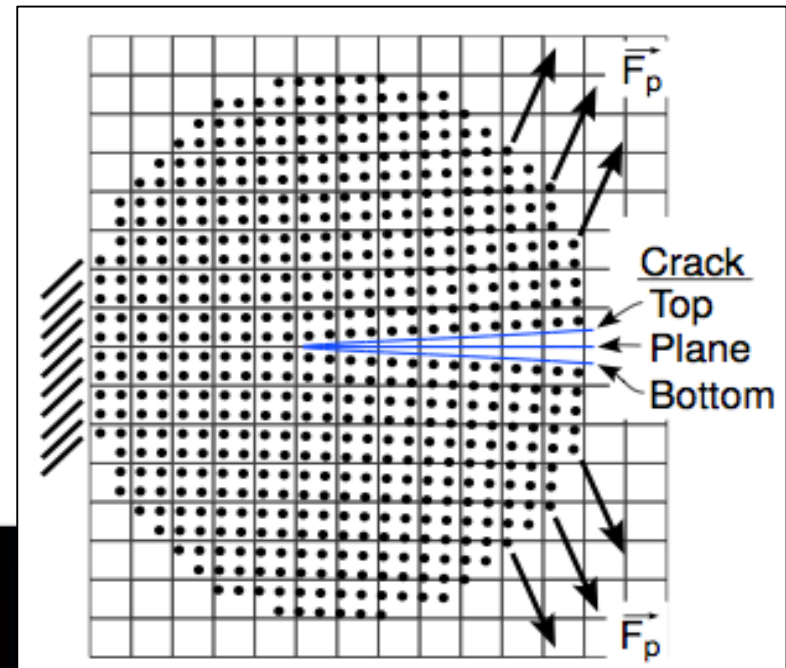
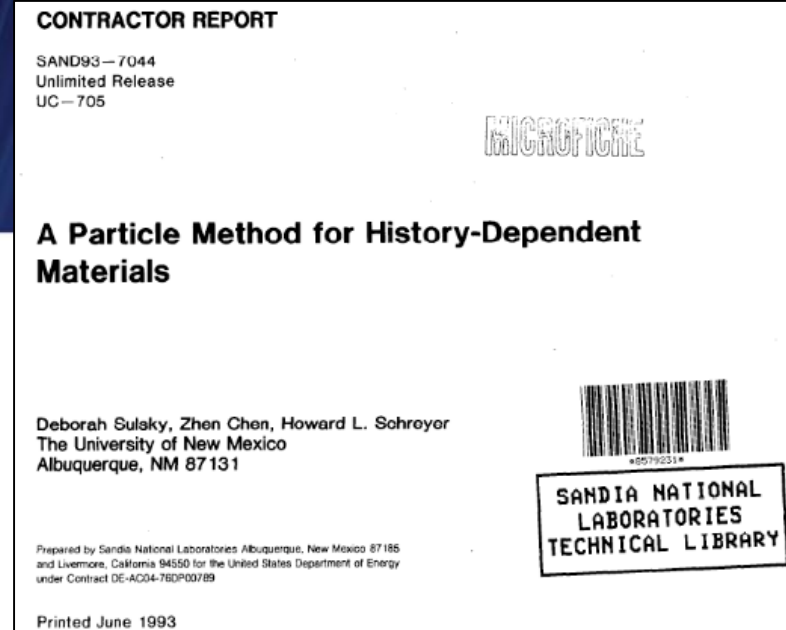
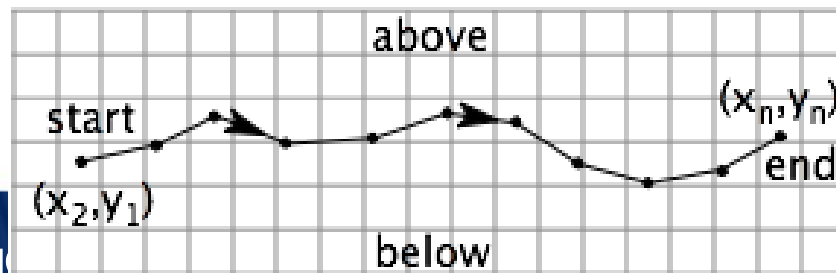
# Integrating Geoscience and Geomechanics with Engineering Modeling





# Material Point Method (MPM)

- Powerful tool developed for solid dynamics problems at Sandia National Laboratory (Sulsky, Chen & Schreyer, 1994)
- Meshless method: discretization into points, called particles
- At each time step, particles' information are extrapolated to the background grid to solve the equations of motion
- CRAMP is MPM extended to handle explicit fractures (Nairn, 2003)

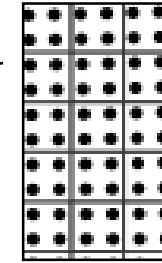
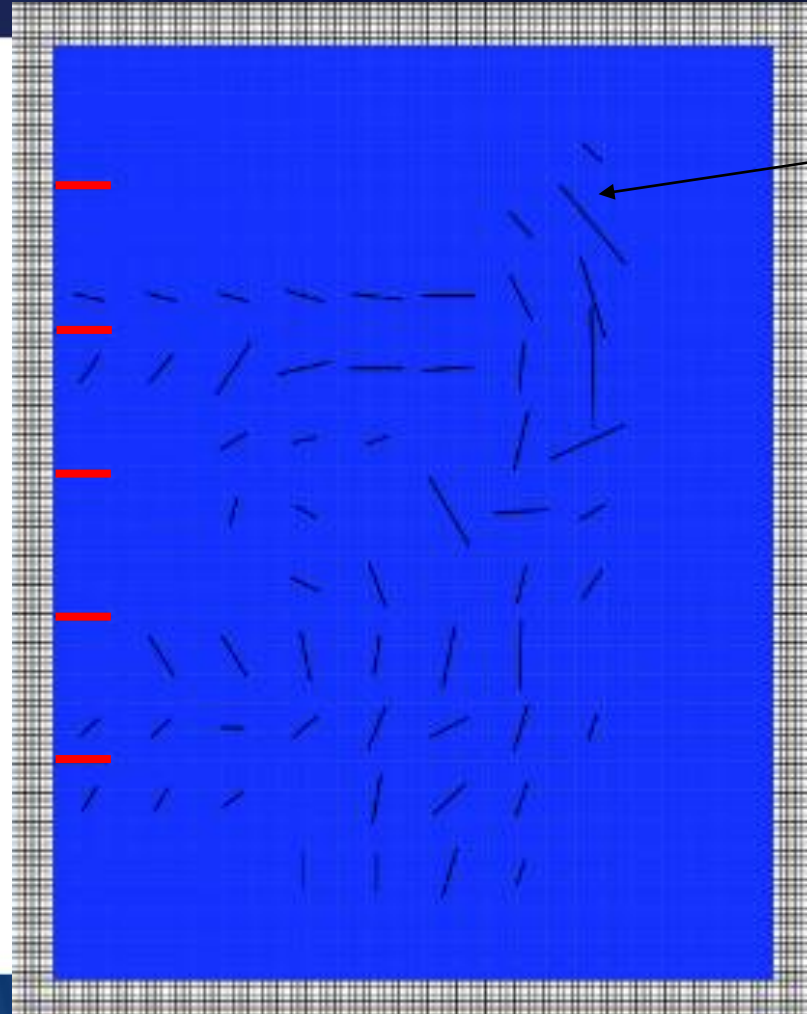


# Inputs to the MPM dynamic geomechanical model

$\sigma_1$

## Fractures

- Equivalent Fracture Model (EFM)
- Hydraulic Fractures



## Rock Mechanical Properties

- Young's Modulus
- Poisson's Ratio
- Density
- Pore pressure

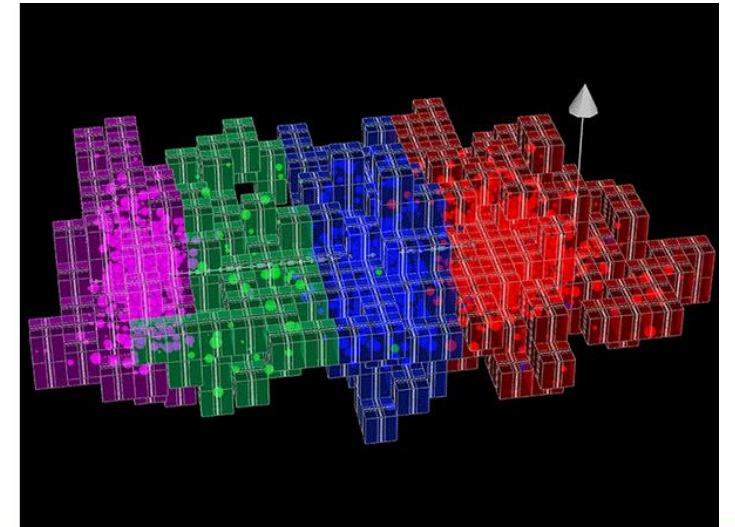
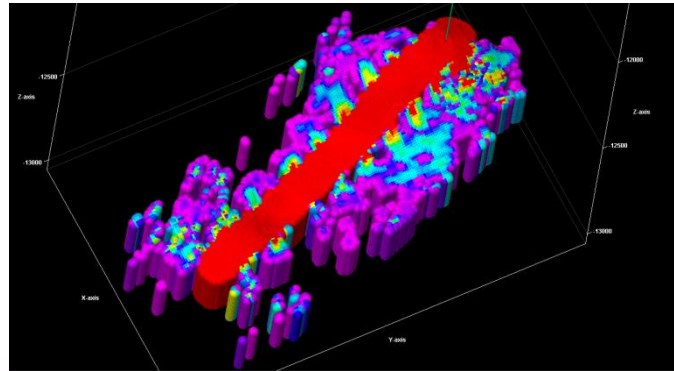
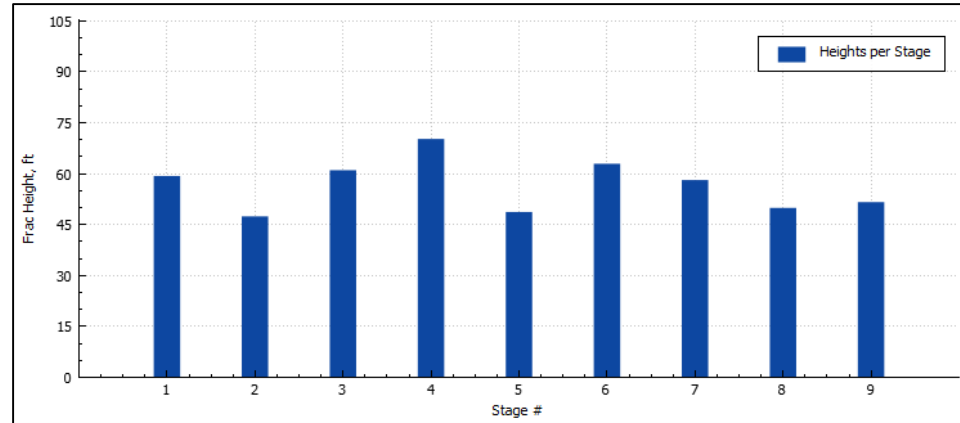
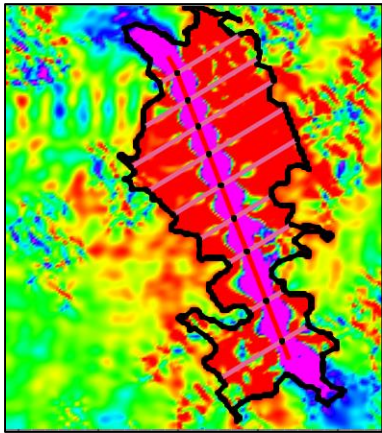


$\sigma_1$

## Regional Stress

- Orientation
- Magnitude
- Anisotropy

# Enhance Perm derived from Strain: volumetric approach



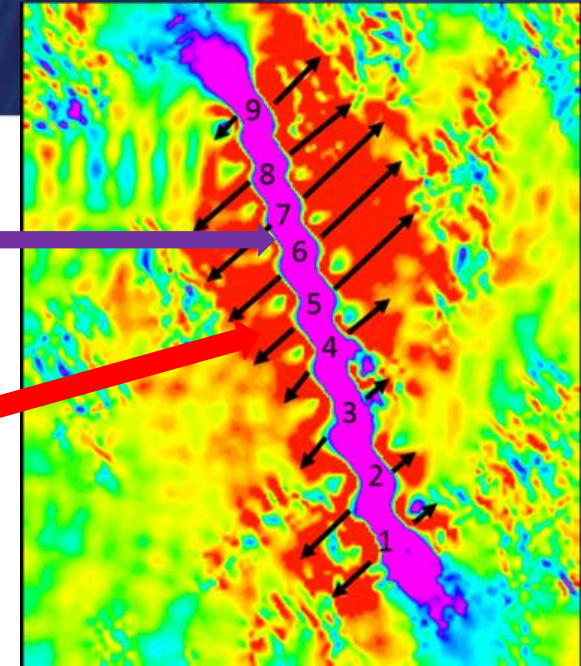
# Enhance Perm derived from Strain: volumetric approach

$$K_{\text{near}} = C1 \cdot \left[ \left( \frac{STR(r)}{r} \right)^3 \right]$$

In the vicinity of the well

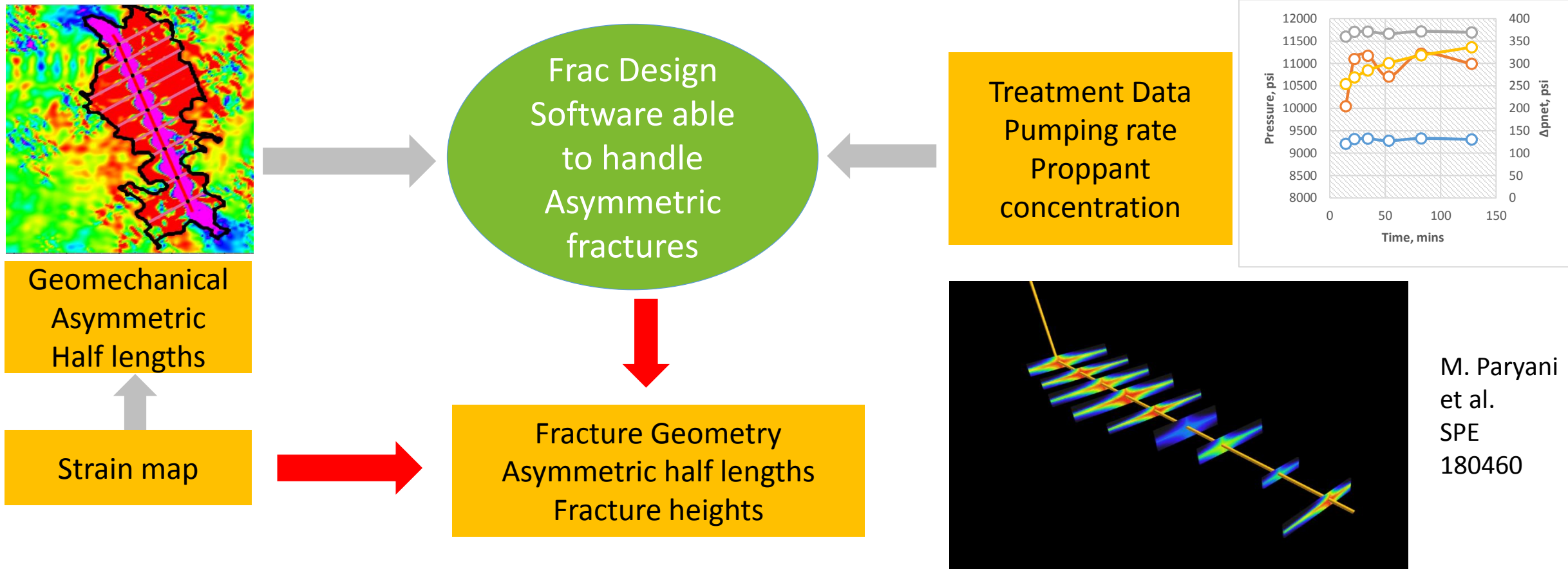
$$K_{\text{SRV}} = C2 \cdot \left[ \left( \frac{STR(r)}{r} \right)^2 \right]$$

Inside SRV region

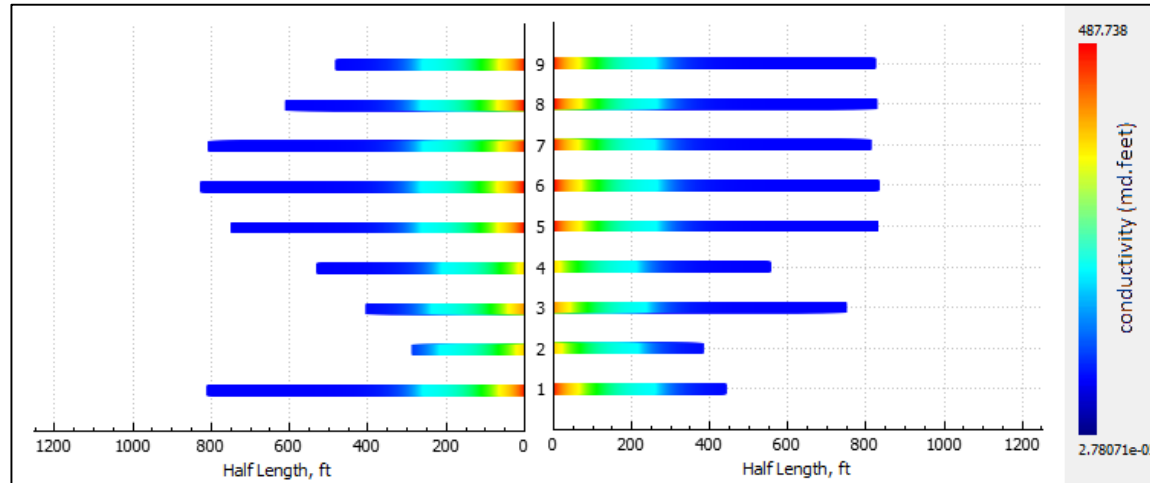
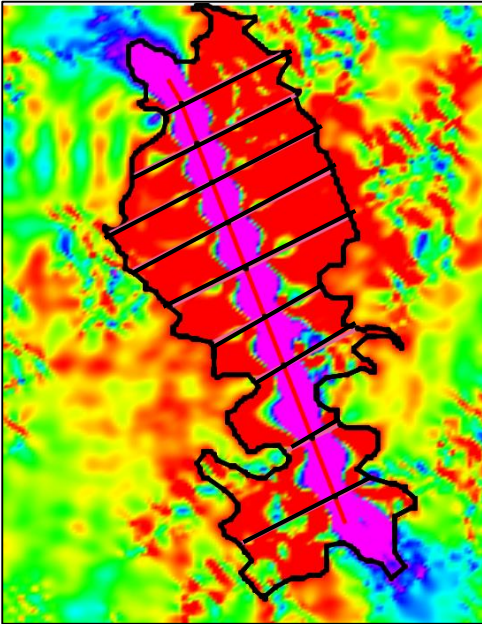


- $K_{\text{near}}$  is the permeability in the vicinity of the wellbore
- $K_{\text{SRV}}$  is the permeability inside the SRV region as delimited by the strain half lengths
- $STR$ : is the normalized volumetric strain
- $r$ : is the normalized distance from the wellbore that cannot exceed the variable half lengths
- $C1$  and  $C2$  are two calibration constants which need to be estimated during history matching. These 2 unknowns can be estimated initially by using pressure transient analysis if available.

# Enhance Perm derived from Strain: Hydraulic Fracture Design



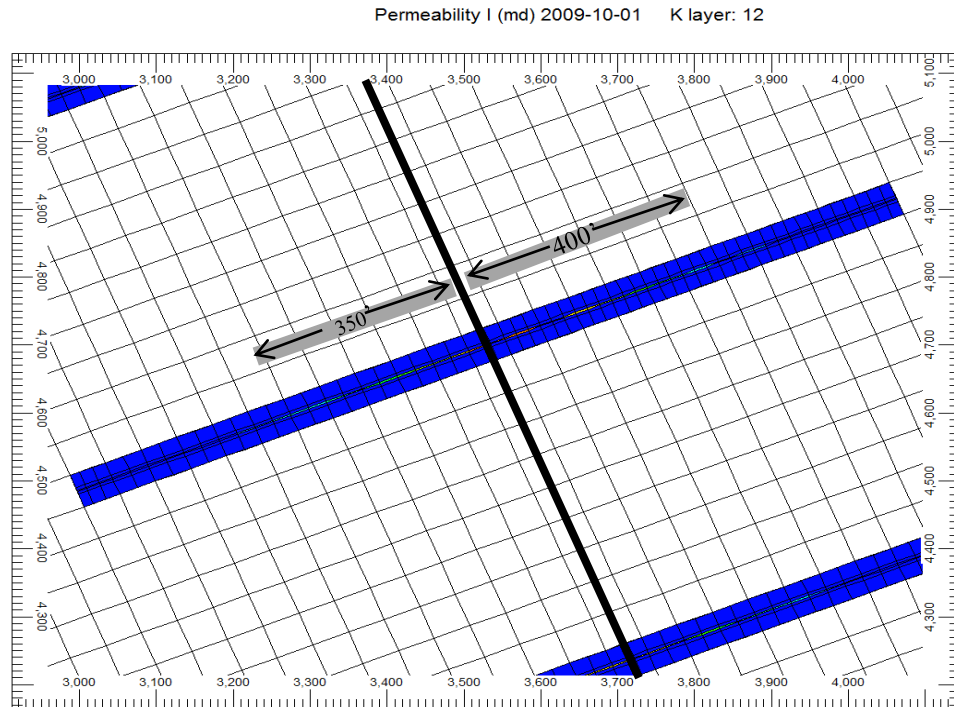
# Migration to dynamic simulation



	A	B	C	D	E	F	G	H
1	3D Output							
2	Length Unit	Feet						
3	Block Size.ft	10	10	5				
4	Azimuth Max	63						
5	MD.FT	TVD.FT	Height.FT	HOffset.FT	Width.FT	KfWf.md*ft	Cp.lb/ft2	
6								
7	16870.9	12884.3	-29.65	-812.033	0.101425	1.640E-05	0.0001459	
8	16870.9	12884.3	-29.65	-800	0.101425	2.100E-05	0.0001648	
9	16870.9	12884.3	-29.65	-790	0.101425	2.570E-05	0.0001825	
10	16870.9	12884.3	-29.65	-780	0.101425	3.150E-05	0.000202	
11	16870.9	12884.3	-29.65	-770	0.101425	3.860E-05	0.0002237	
12	16870.9	12884.3	-29.65	-760	0.101425	4.730E-05	0.0002477	
13	16870.9	12884.3	-29.65	-750	0.101425	5.800E-05	0.0002742	
14	16870.9	12884.3	-29.65	-740	0.101425	7.110E-05	0.0003036	

Gulf Coast Section

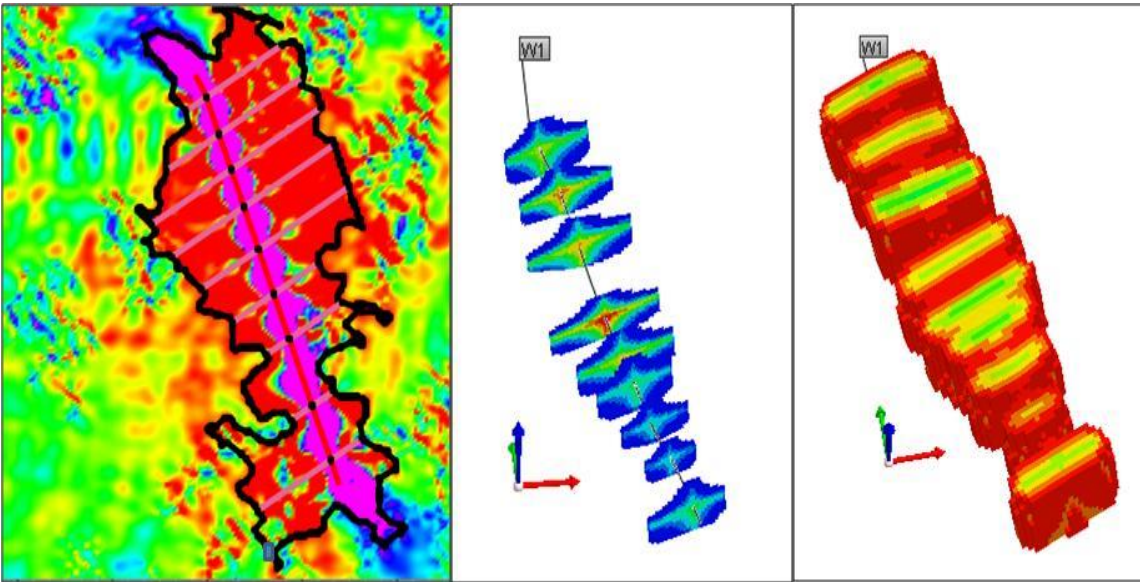
# Parameterization



LGR around a fracture plane, center cell represents actual frac plane and adjacent blue cells represent transition zone.

Asymmetrical conductivity distribution can be observed in the fracture plane

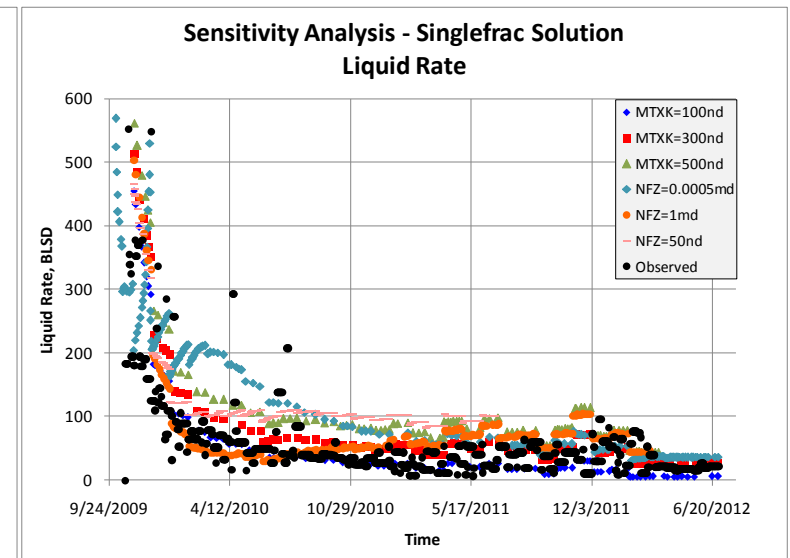
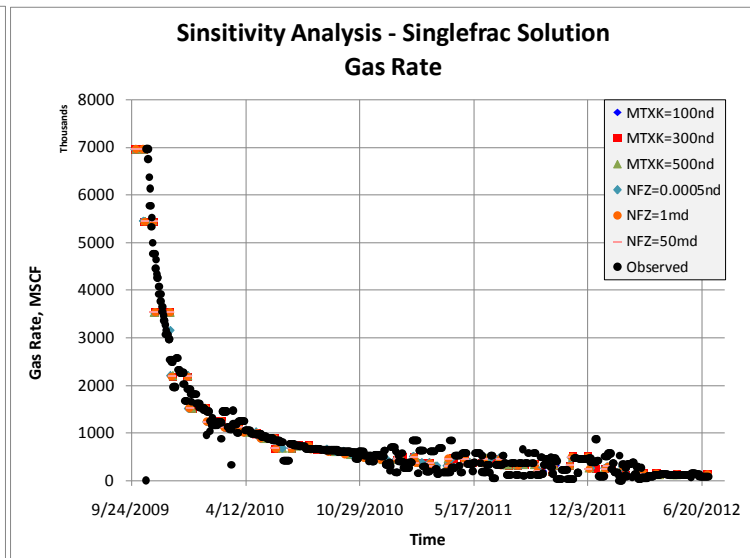
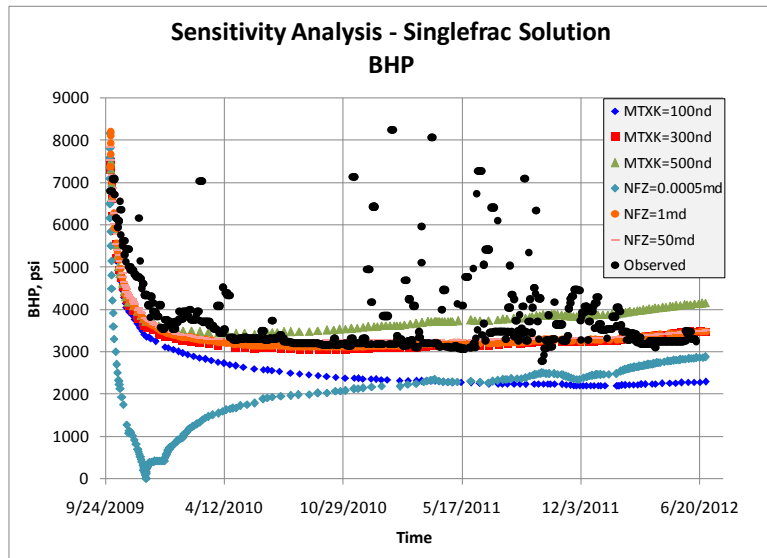
# Single-frac per stage solution



## Assumptions

- 9 Stages, single-frac per stage
- Fractures are modeled explicitly, using LGR.
- Asymmetric geometry and conductivity are sampled in simulation grid.
- Transition zone from matrix to hydraulic fracture is incorporated to avoid flow restriction due to high contrast of conductivity from matrix to hydraulic fractures.

# Single-frac per stage solution: history match

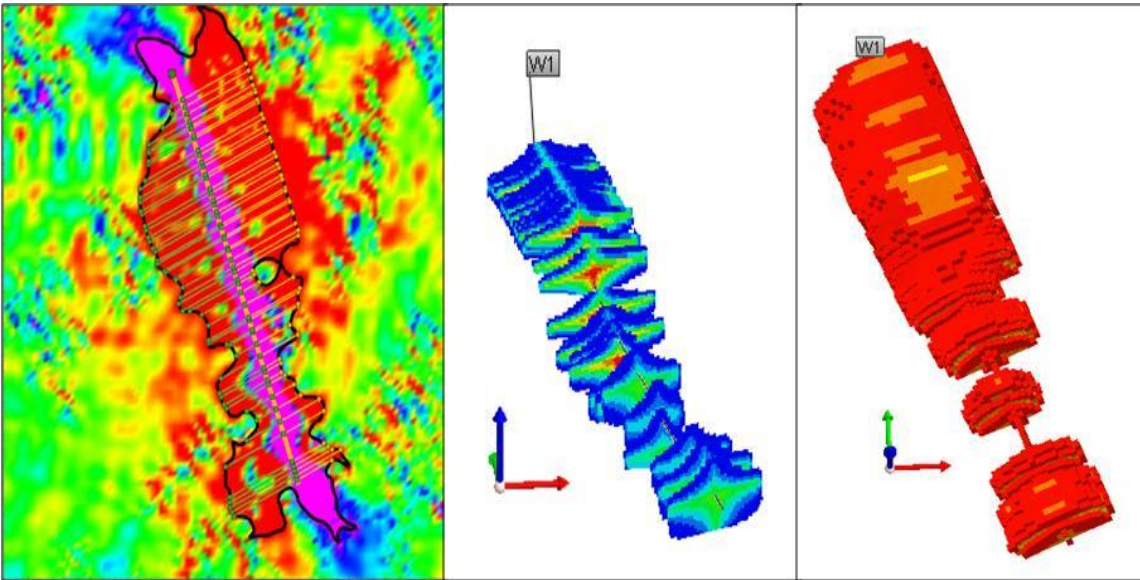


Best Solution: MTXK 50nd, NFZ 1md

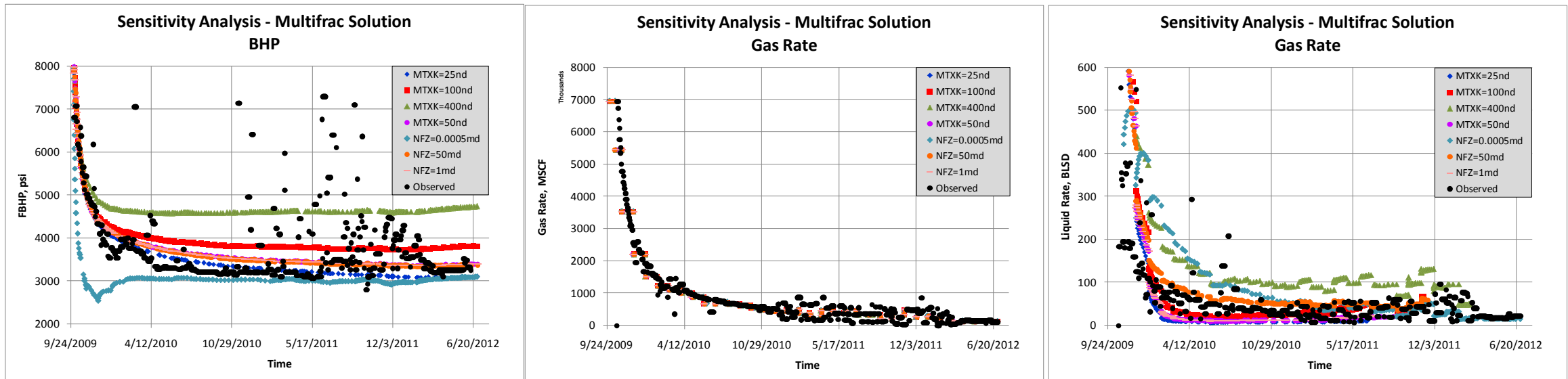
# Multi-frac per stage solution

## Assumptions

- 9 Stages, multi-frac per stage, total of 35.
- Fractures are modeled explicitly, using LGR.
- Asymmetric geometry and conductivity are sampled in simulation grid.
- Transition zone from matrix to hydraulic fracture is still required to avoid flow restriction due to high contrast of conductivity from matrix to hydraulic fractures.

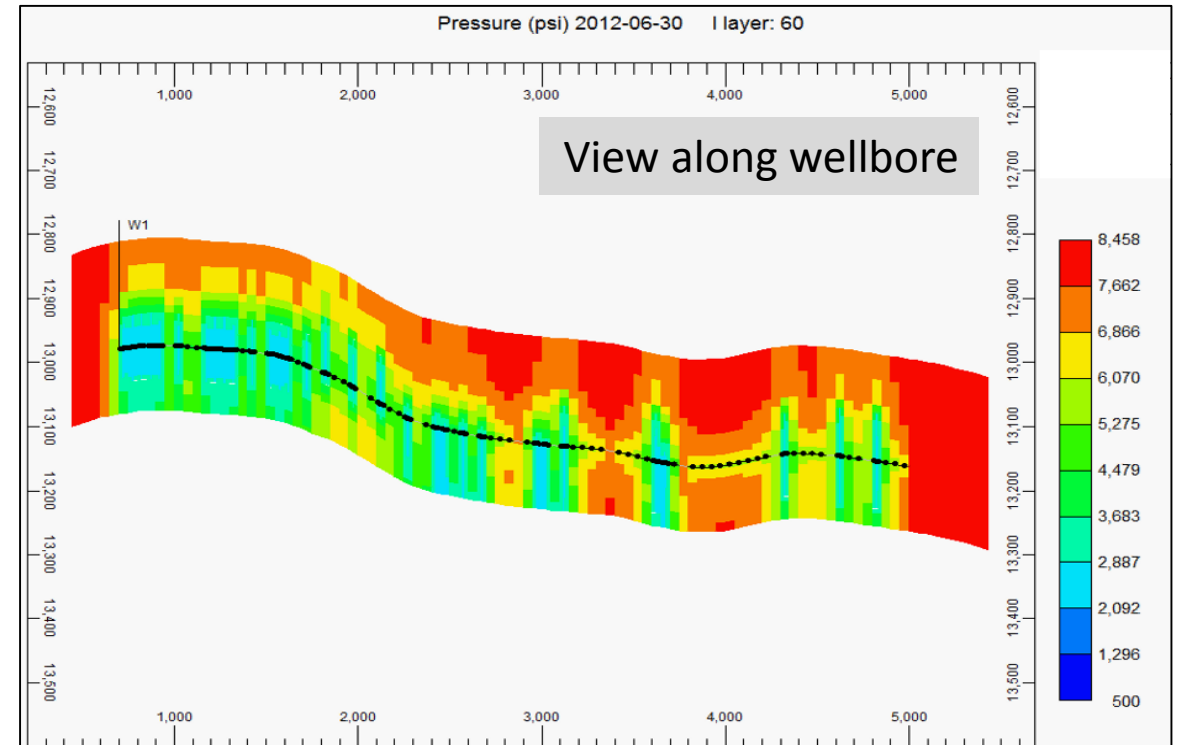
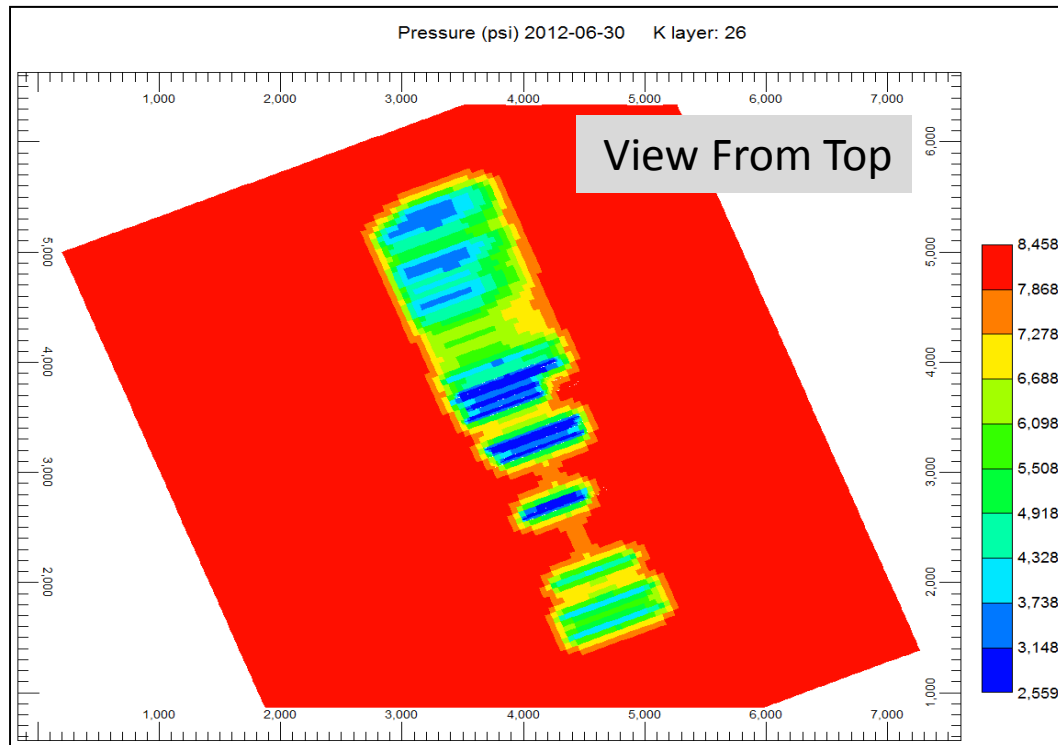


# Multi-frac per stage solution: history match



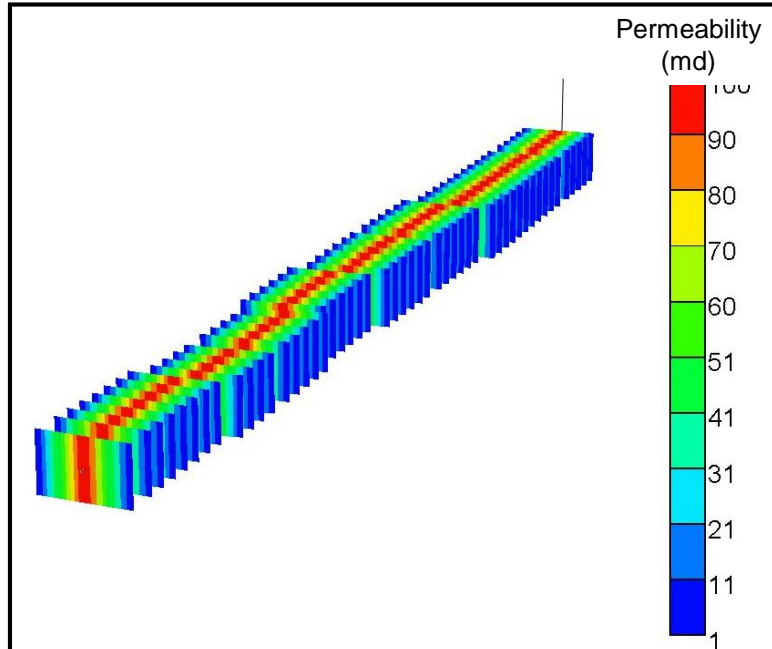
Summary of sensitivity simulation results for multi frac solution

# Results: Realistic depletion patterns

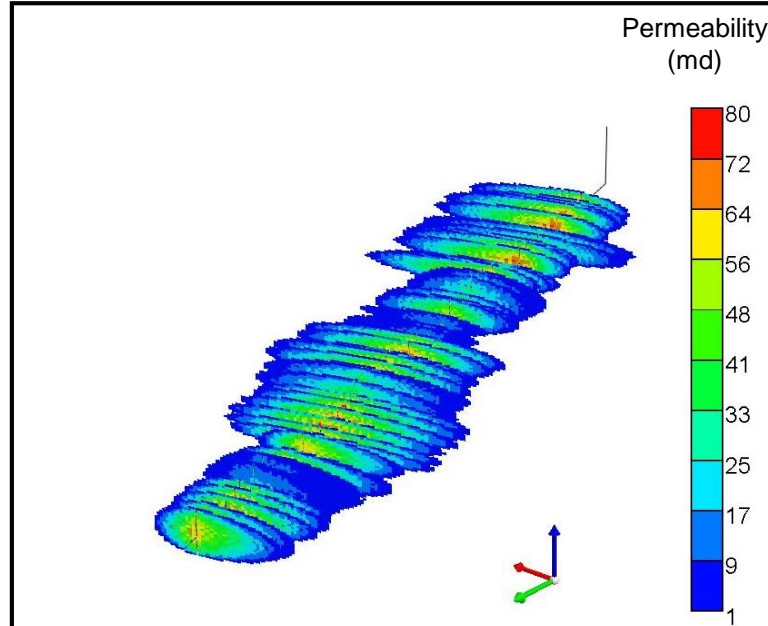


Asymmetrical distribution of conductivity dominates flow in the horizontal and vertical direction. Depletion patterns correlate to strain.

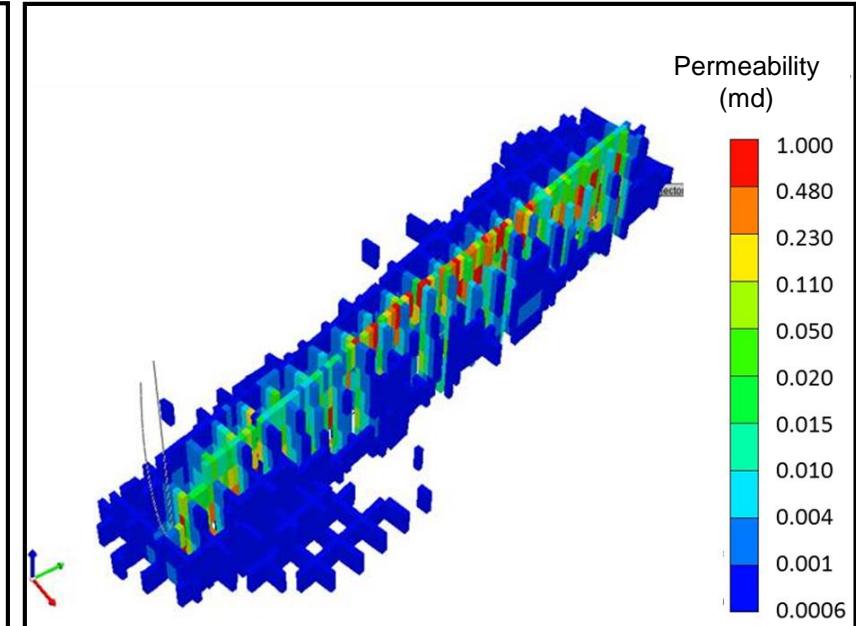
# Results: Comparing different approaches



Case 1  
Symmetric Bi-wing  
fracture planes

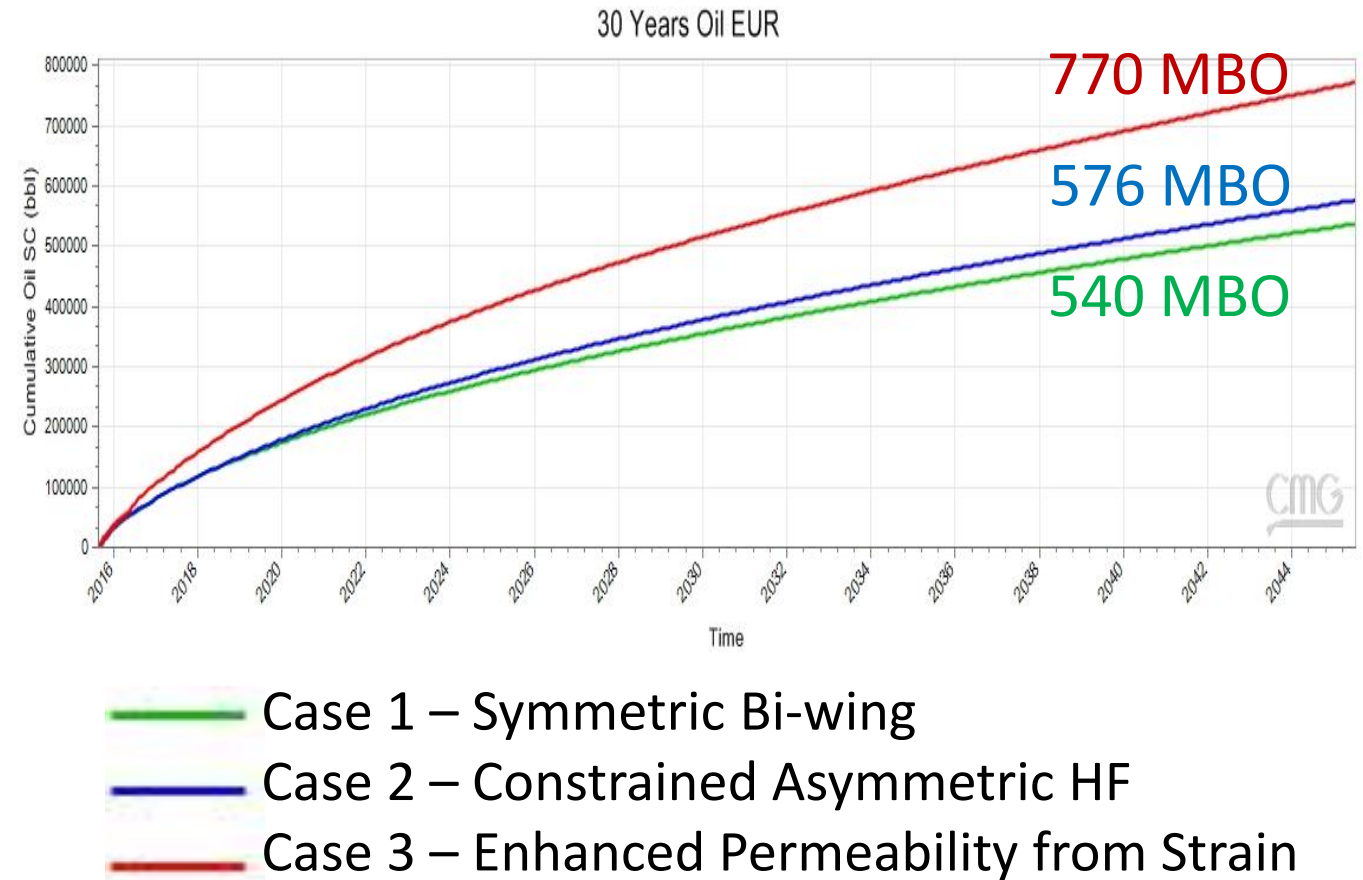
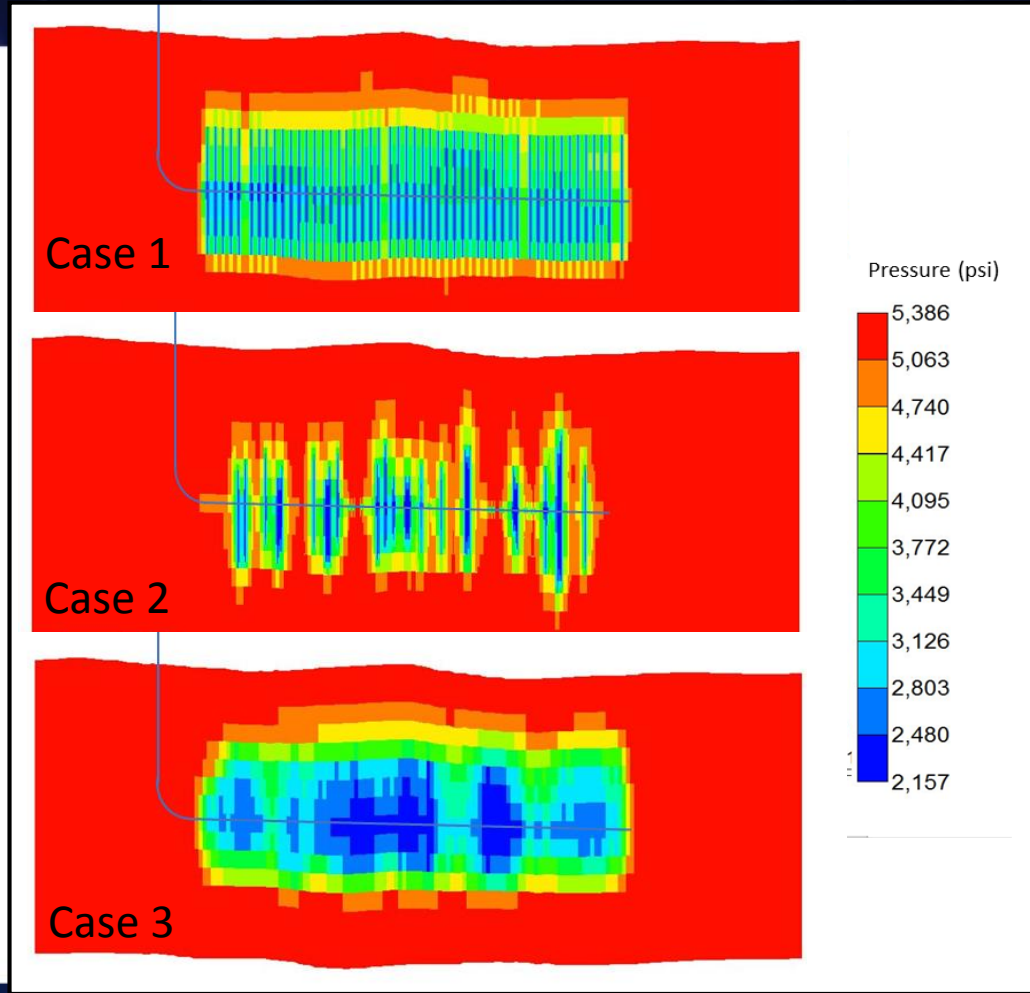


Case 2  
Constrained Asymmetric  
fracture planes



Case 3  
Enhanced Permeability from  
**Volumetric Strain**

# Results: Comparing different approaches



# Highlights - Workflow

- Workflow covers the entire spectrum from seismic inversion to reservoir simulation ensuring that all the necessary information is transferred to the next step in the modeling process
- Asymmetric behavior of hydraulic fractures is captured in the geomechanical modeling where the three major factors causing stress gradients are considered: variable elastic properties, natural fractures and pressure depletion
- Geologic and Geomechanical constraints are imposed on the hydraulic fracture model and reservoir simulation which reduce uncertainty and minimize the problem of non-unique solutions.

# Conclusions

- Using the derived geometry and conductivity distribution, allows the numerical simulation work to be not only constrained by the geomechanical heterogeneity of the reservoir, but also, by the fracture design and treatment data, providing more sources of validation.
- Suitable solution to successfully space and stack child wells from depleted parent wells, but also applicable to non-developed areas.
- Unconstrained hydraulic fractures create significant uncertainty in the reservoir simulation results
  - More variables to the parameterization: sensitivity analysis.
  - Overestimation/underestimation of EURs
  - Unrealistic pressure depletion profiles which are inconsistent with field surveillance data

## Acknowledgements

The authors would like to acknowledge the collaboration efforts by Computer modeling Group.



# Making Partnerships Work in a Low-Price Environment

Geoff Walker

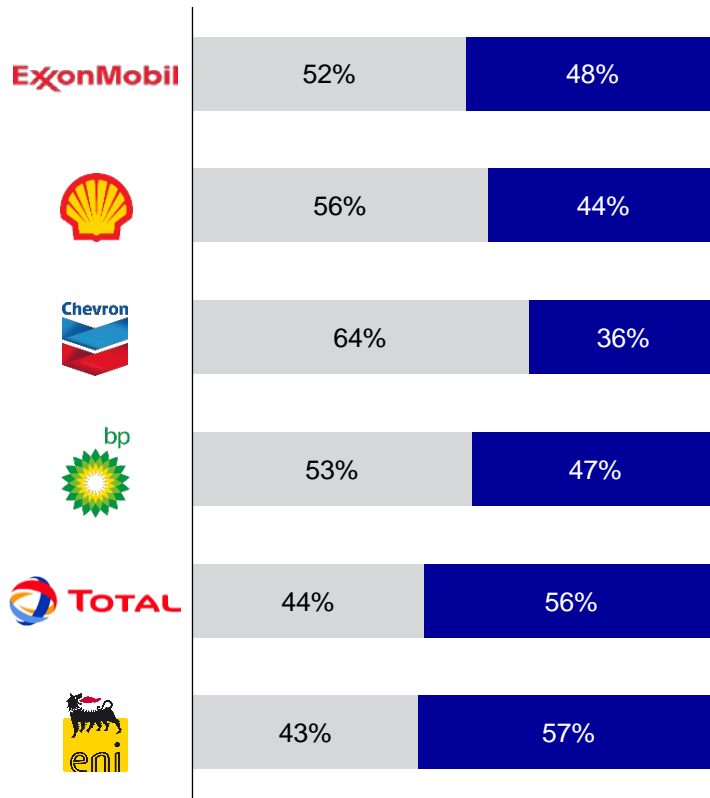
Water Street Partners



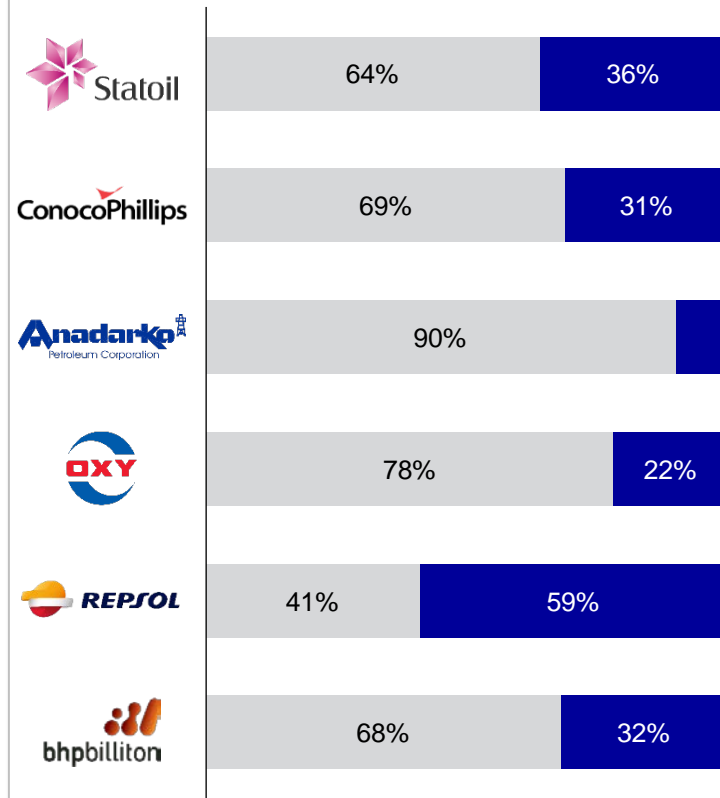
# Partnerships are everywhere in upstream

 Operated  
 Non-Operated

## Supermajors<sup>1</sup>



## Large Independents<sup>1</sup>



Source: Rystad Energy UCUBE database  
– 2015 average production data

# Partnerships have been in the news for the wrong reasons

## HSE Risk: Macondo



- \$9 billion (50%) drop in company market capitalization after incident
- \$4 billion payment to BP for share of costs
- \$160M fine from US government as co-owner



## Deemed Operator Risk: Buncefield



- JV was designated Operator of terminal with largest UK explosion since WWII
- Total held liable as actual Operator due to level of involvement
- Total held solely liable for £750M



## JV Performance Surprise Risk: Jasmine Field

BG GROUP



- 12-month delay in first production announced to market, resulting in 13% share price drop
- Delay was unexpected and not previously signaled by Operator



## HSE and Reputational Risk: Samarco



- Independent JV OPCO HSE event caused 19 deaths
- Shareholders liable for \$55BN+ of damages and JV Directors criminally prosecuted



# A set of factors are driving changes in the ways companies are approaching their partnerships

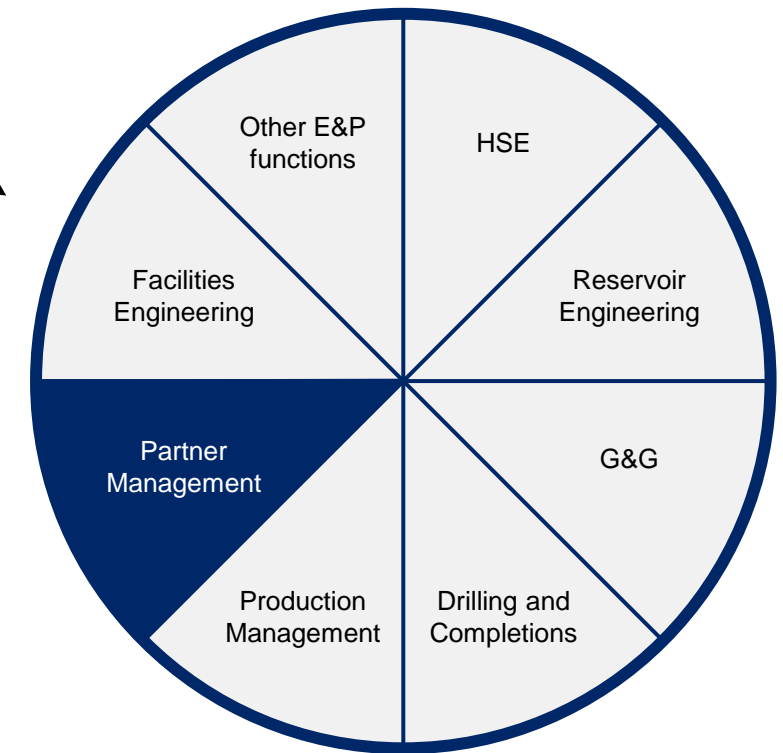
- 1 Risk exposure, esp in NOJVs
- 2 Lower for longer / cost pressure
- 3 Shifting regulatory environment
- 4 New players in upstream (e.g PE)
- 5 Old players in new markets (NOCs)
- 6 Divestiture targets
- 7 More mixed operator models
- 8 Others...

# Companies are rethinking their approach to partner management

Non-Operated Assets Teams – Illustrative



Operated Assets Teams – Illustrative



## JV Management

- Role of JV Management depends first and foremost on the company's position in the venture – op vs. non-op
- Non-op asset teams are defined by Partner Management – arranged around a core "Non-Operated Asset Management" function
- Operated asset teams are not arranged around this function but instead supported by a "Partner Management" function

# Most companies in the industry have a long way to go on the journey to partner management excellence

“How do we exercise influence in this asset where we have extremely **limited contractual rights**? Our guys don’t really understand how to do that.”



“Our non-operating partners are such a drag... If only they would stroke me a check and let us get on with it, our lives would be so much easier. How can I make them behave differently?”



“Historically, we have made it hard on Asset Managers. We throw engineers into the role, don’t given them much support or guidance in how they interact with their stakeholders, and expect them to just figure it out. **We need to change this if we are going to be great influencers.**”



“When I look at **ExxonMobil**, they seem to have enormous impact as a non-operator – and do it without a lot of resources. How do we replicate that?”

Thank you

Questions?

# Volumes and Value, a Banking Reservoir Engineer's Perspective

Stephen R. Gardner  
BBVA Compass

# Disclaimer

The following opinion does not represent the opinions of BBVA and are based on my observations for US domestic Reserve Based Loans (RBL).

# Which one is a better representative of the current value?

1. SEC
2. PRMS
3. 3<sup>rd</sup> Party Reserve Report



# SEC Reserve Report

- Fixed cost and the average of the previous 12 month prices
- SEC Revision effective January 1, 2010 –
- Page 1 – “The revisions are intended to provide investors with a more meaningful and comprehensive understanding of oil and gas reserves, which should help investors evaluate the relative value of oil and gas companies.”
- Page 13 – “The objective of reserves estimation is to provide the public with comparable information about volumes, not fair value, of a company’s reserves available to enable investors to compare the business prospects of different companies.”

# PRMS

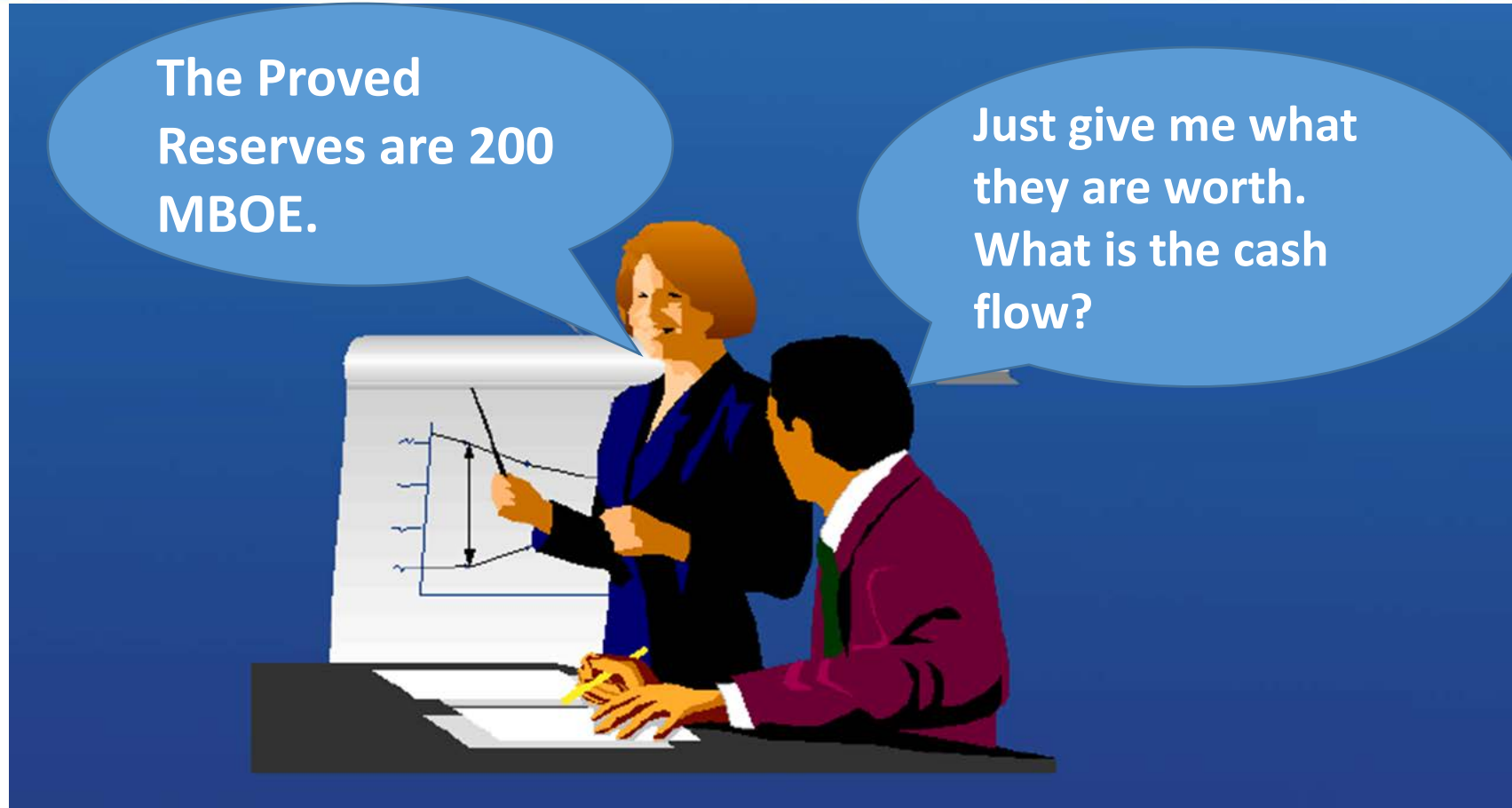
- SPE has been at the forefront of leadership in developing common standards for petroleum reserves and resources definitions.
- SPE's initial involvement in establishing petroleum reserves definitions began in 1962 following a plea from US banks and other investors for a consistent set of reserves definitions, that could be both understood and relied upon by the industry in financial transactions, where petroleum reserves served as collateral.
- Focused primarily on estimated recoverable sales quantities

# 3<sup>rd</sup> Party Quotes from Reserve Report

Estimates of oil, condensate, and gas reserves, future net revenue, and contingent resources should be regarded only as estimates that may change as further production history and additional information become available. Not only are such estimates based on that information which is currently available, but such estimates are also subject to the uncertainties inherent in the application of judgmental factors in interpreting such information.

The estimated reserves presented in this report, as of July 1, 2016, are related to hydrocarbon prices based on escalated price parameters. As a result of both economic and political forces, there is significant uncertainty regarding the forecasting of future hydrocarbon prices. The recoverable reserves and the income attributable thereto have a direct relationship to the hydrocarbon prices actually received; therefore, volumes of reserves actually recovered and amounts of income actually received may differ significantly from the estimated quantities presented in this report. The results of this study are summarized as follows.

# The Real Challenge





# Bank

## Reserve-Based Loan (RBL)

- The RBL typically is a revolving facility secured by lower-risk proved reserves
- Governed by a borrowing base determined by a valuation of those reserves.
- Most RBLs have a term of three to five years
- Redeterminations typically occur semiannually

# Three C's of Banking

1. Connection
2. Costs
3. Consistency

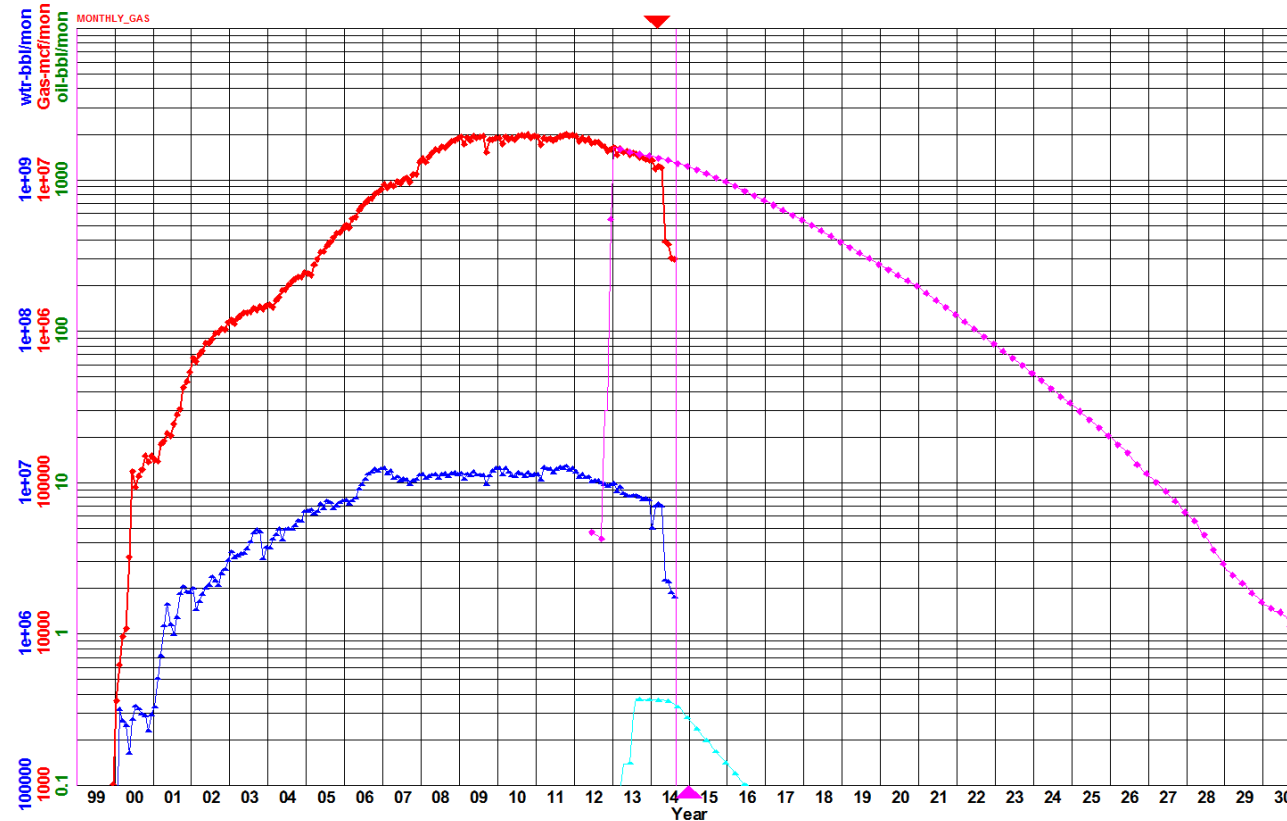


# Connection

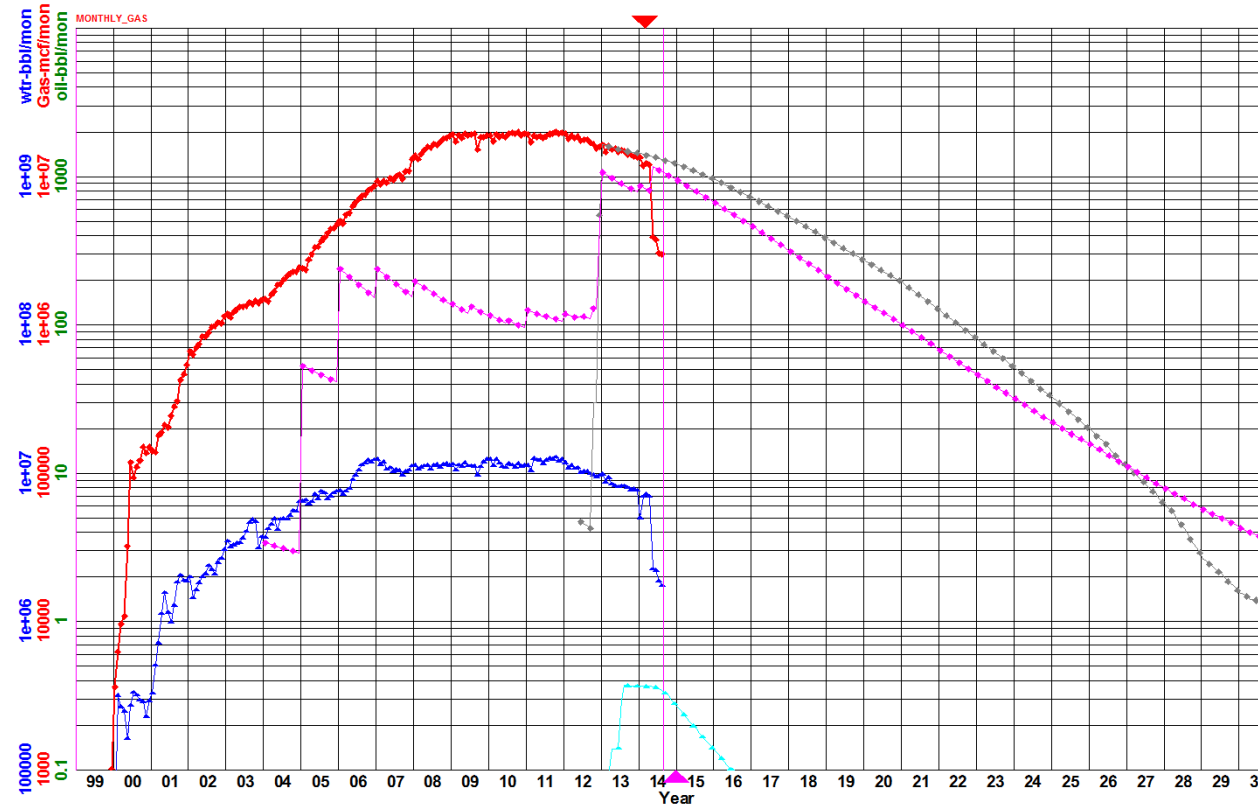
## Historical production and the forecast rates tie

- Increasing production rates are not included in the PDP category
- Forecast on plateau should be given a high amount of scrutiny
- An established production history in order for reserves to be classified as PDP
- Evaluate wells individually as opposed to forecasting a number of wells in aggregate

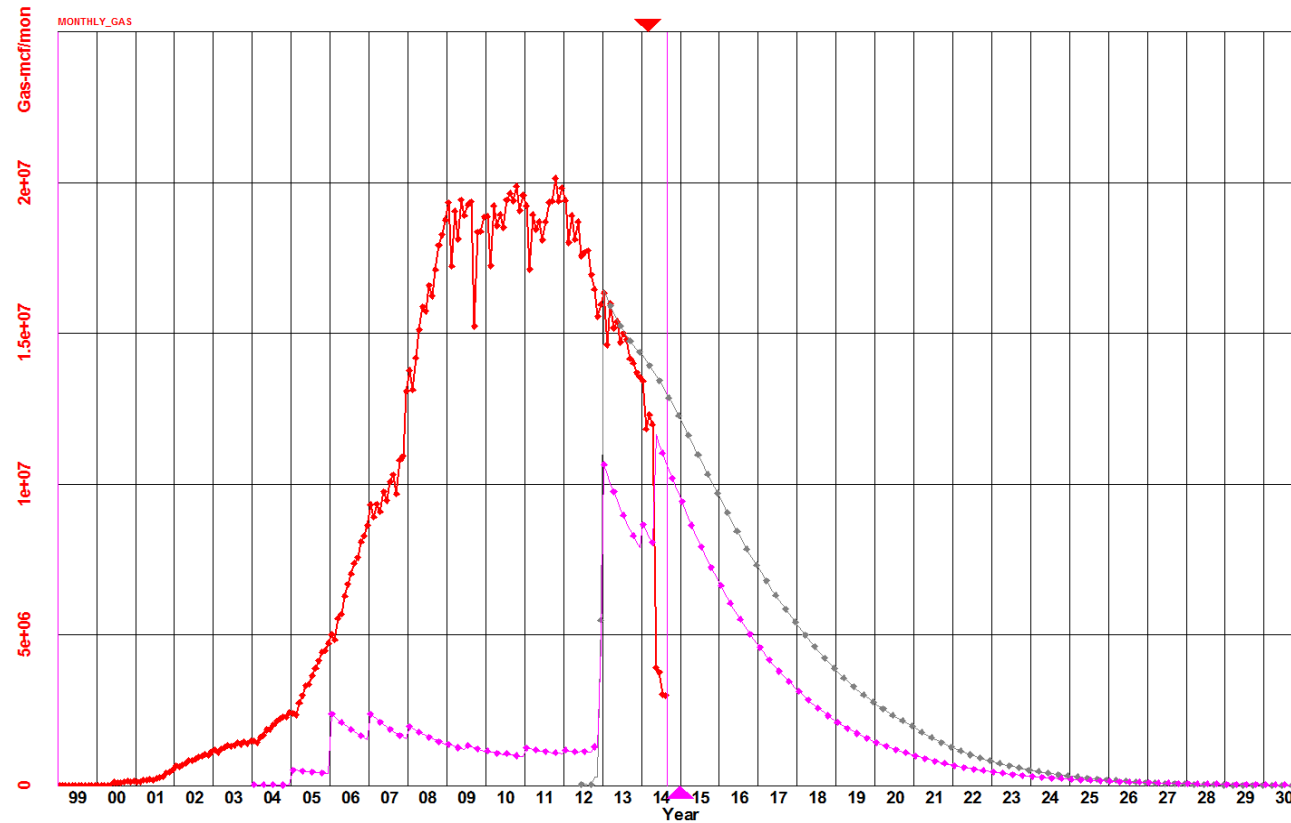
# Sum Plot of PDP Historical Production with Forecast



# Sum Plot of PDP Historical Production with Revised Forecast

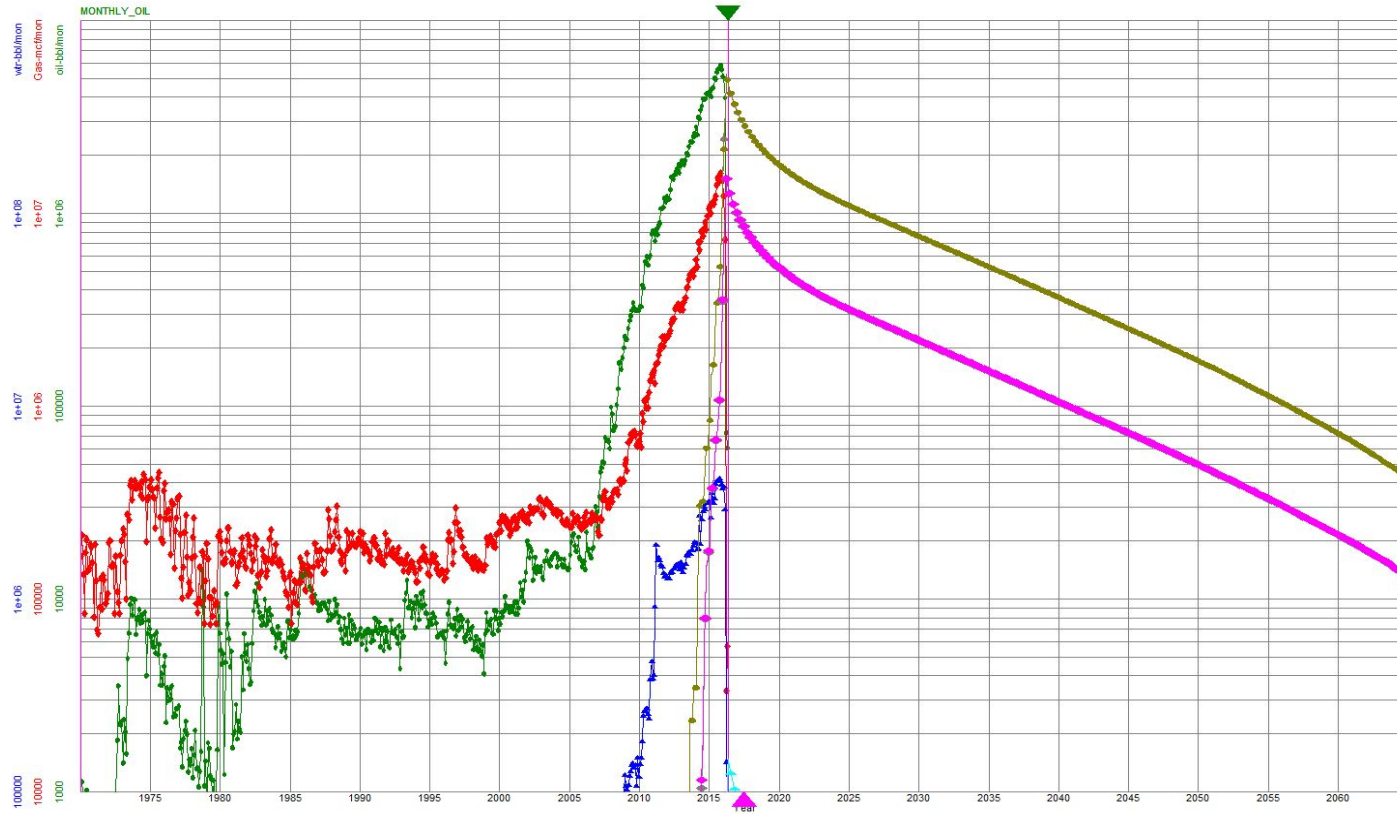


# PDP Forecast & Historical Production – Cartesian Plot



**31 % reduction in Volume**  
**38 % reduction in Value**  
**36 % reduction in PV9**

# PDP Summed Historical Production with Forecast



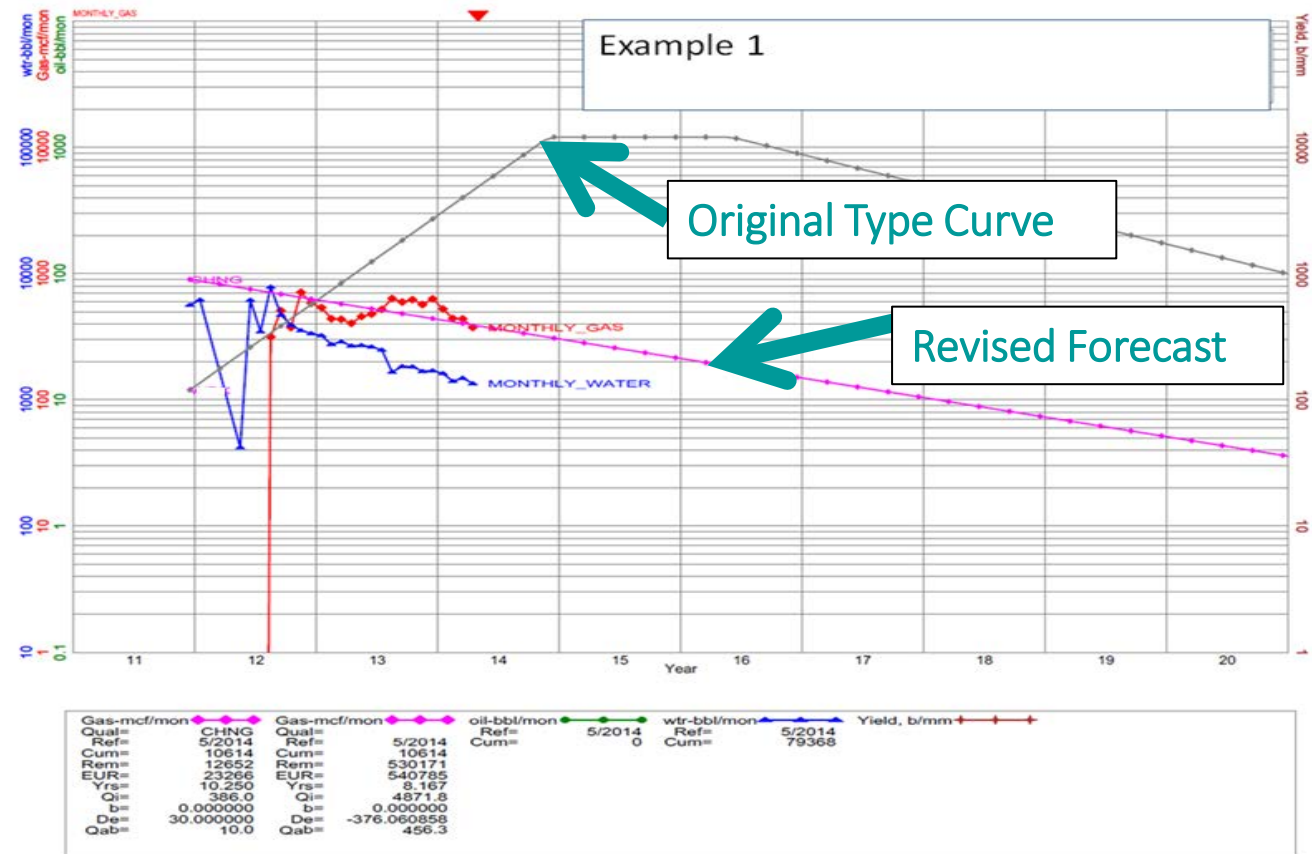
**0.4 % reduction in Volume**  
**2.9 % reduction in Value**  
**2.5 % reduction in PV9**

# Observed Reserve Reporting

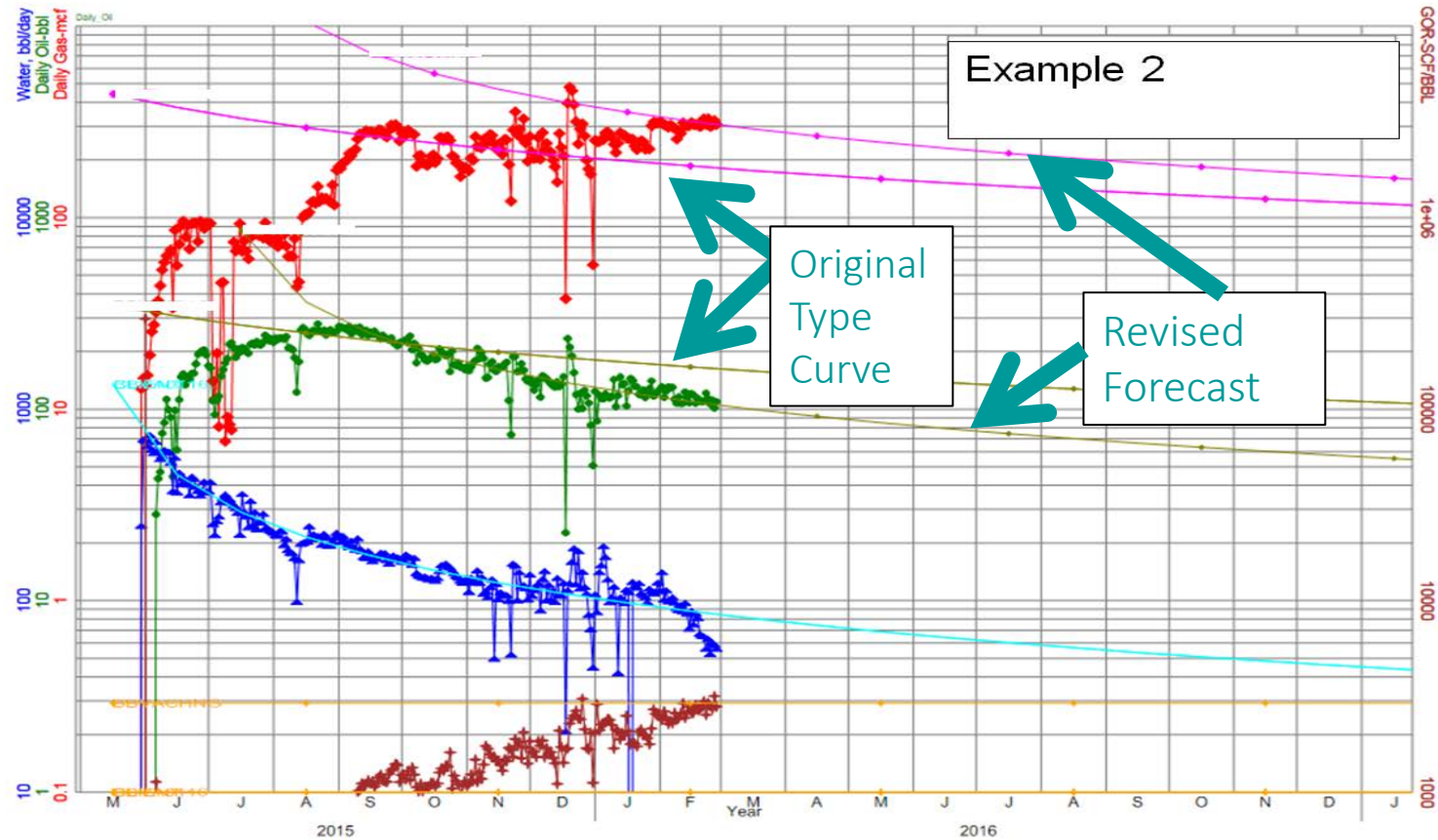
- Reliance on Type curves for forecasting
- Not updating to current production trend
- A desire for a particular outcome motivated by current situation



# Example 1

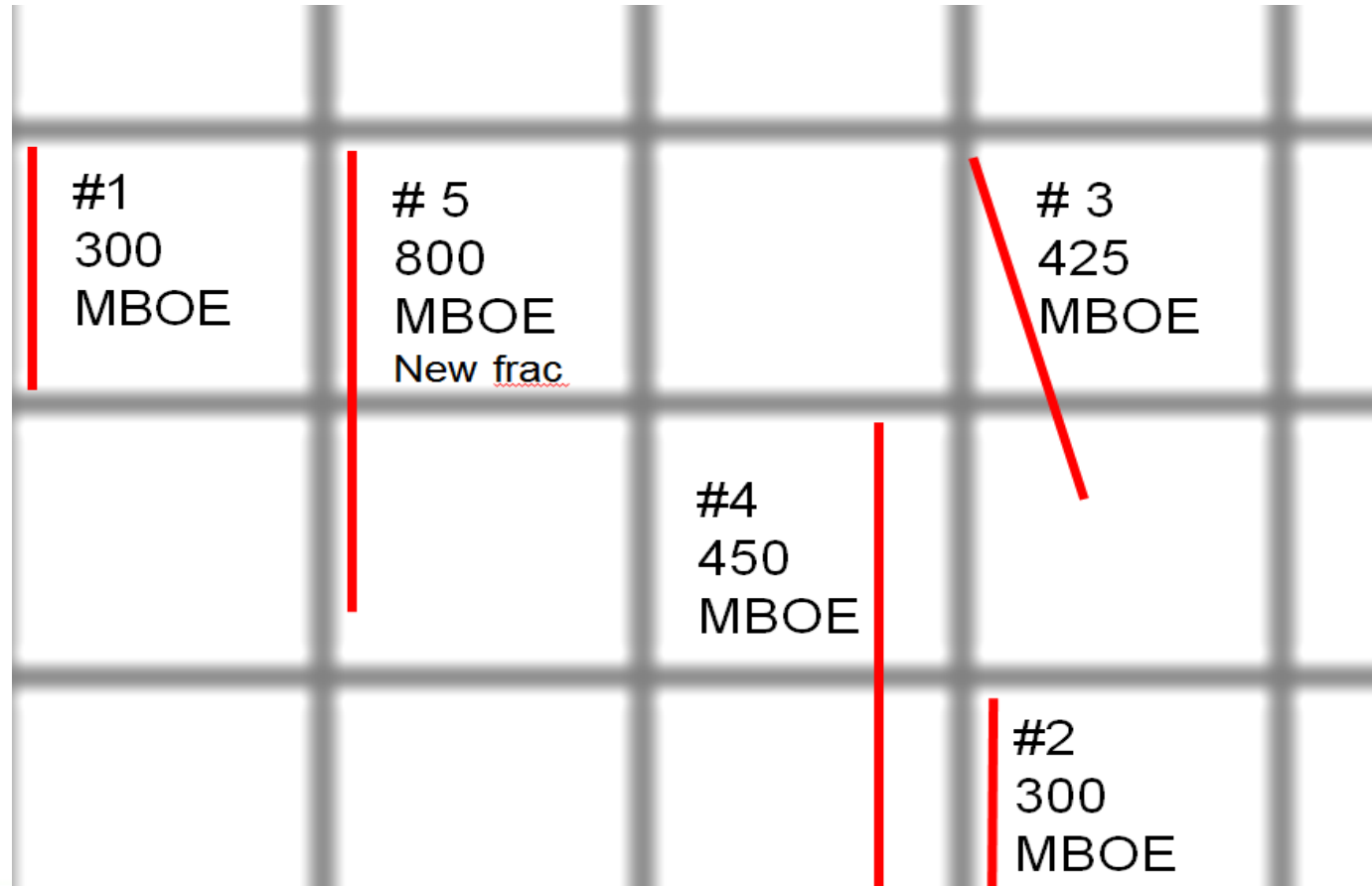


# Example 2



# New area with 5 new wells

## Longest production is 1 year from wells #1 & #2 with 3 months for newest well #5



20 PUD's are booked at results from well #5 based on anticipated PUD lateral length, new frac design & earth model

Do the historical production and the forecast rates tie?

# Costs

- Product Prices
- Operating Costs
- Capital
- Timing

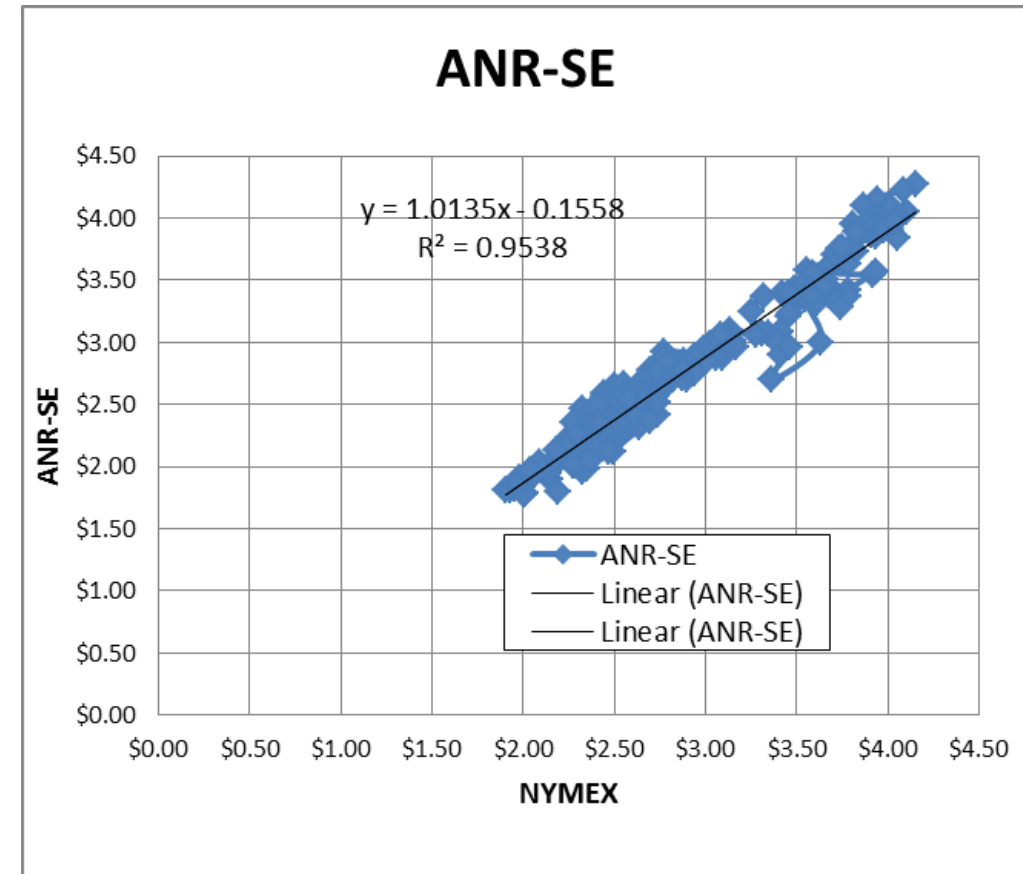


Establishing current economic conditions should include relevant historical petroleum prices and associated costs and may involve an averaging period that is consistent with the purpose of the reserve estimate, appropriate contract obligations, corporate procedures, and government regulations involved in reporting the reserves.

# Product Pricing



**Price differentials are calculated sales point, or by field if a common field price is received based on historical**



# Product Pricing



## Each Bank sets Energy Product Pricing

	2017	2018	2019	2020	2021	2022	Cap	LOE Esc (%)	Discount Rate (%)
<b>Oil Prices (\$/BBL) - WTI</b>									
<b>Low</b>	\$41.00	\$44.00	\$46.00	\$49.00	\$50.00	\$50.00	\$50.00	0.00%	7%
<b>Median</b>	\$46.00	\$48.00	\$50.00	\$51.00	\$52.50	\$54.00	\$57.75	0.00%	9%
<b>Mean</b>	\$46.97	\$49.12	\$50.78	\$52.49	\$53.69	\$54.81	\$60.06	0.10%	9%
<b>High</b>	\$55.72	\$56.36	\$61.00	\$66.00	\$69.00	\$70.00	\$85.00	2.00%	10%

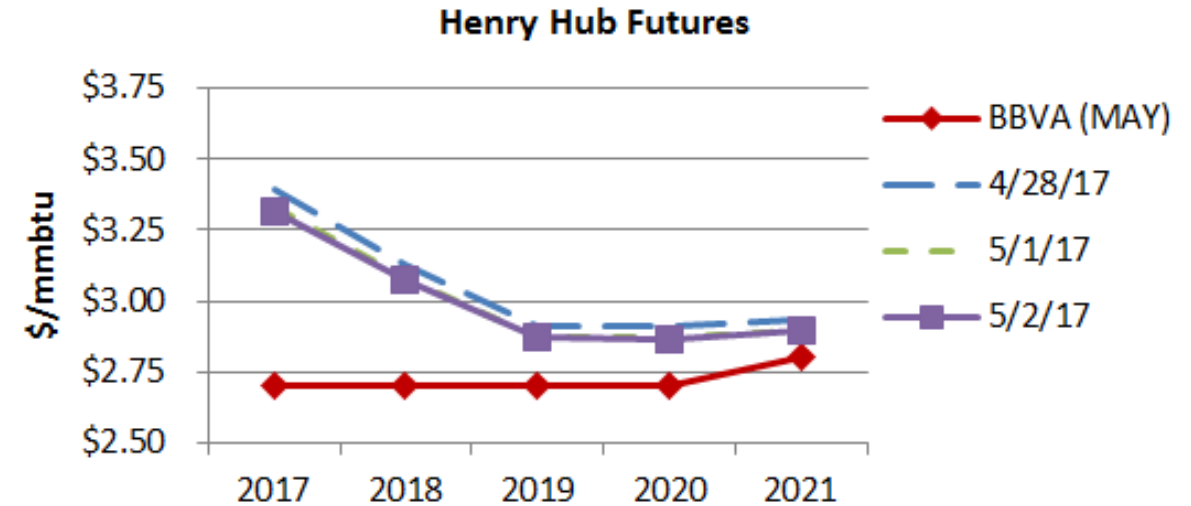
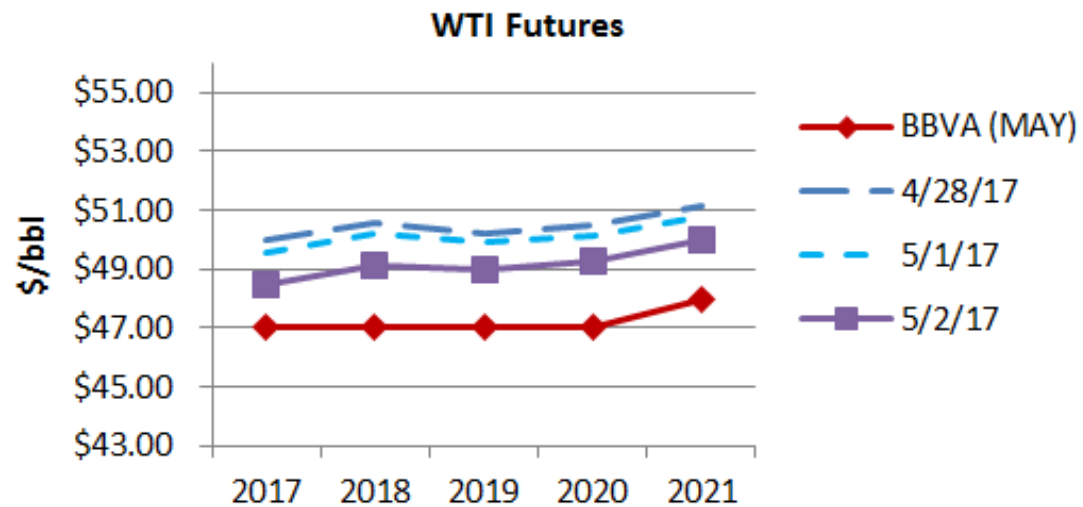
<b>Gas Prices (\$/MMBtu) - Henry Hub</b>									
<b>Low</b>	\$2.40	\$2.50	\$2.60	\$2.65	\$2.75	\$2.75	\$2.75	0.00%	7%
<b>Median</b>	\$2.83	\$2.75	\$2.78	\$2.80	\$2.92	\$3.00	\$3.63	0.00%	9%
<b>Mean</b>	\$2.84	\$2.79	\$2.82	\$2.87	\$2.96	\$3.04	\$3.64	0.00%	9%
<b>High</b>	\$3.54	\$3.15	\$3.40	\$3.50	\$3.60	\$3.70	\$6.00	0.00%	10%

Range	Advance	Reserve Categories
Rate (%)		

<b>low</b>	55%	PDP
<b>High</b>	70%	PDP
	Varies	Total Proved
<b>low</b>	55%	Total Proved
<b>High</b>	70%	Total Proved

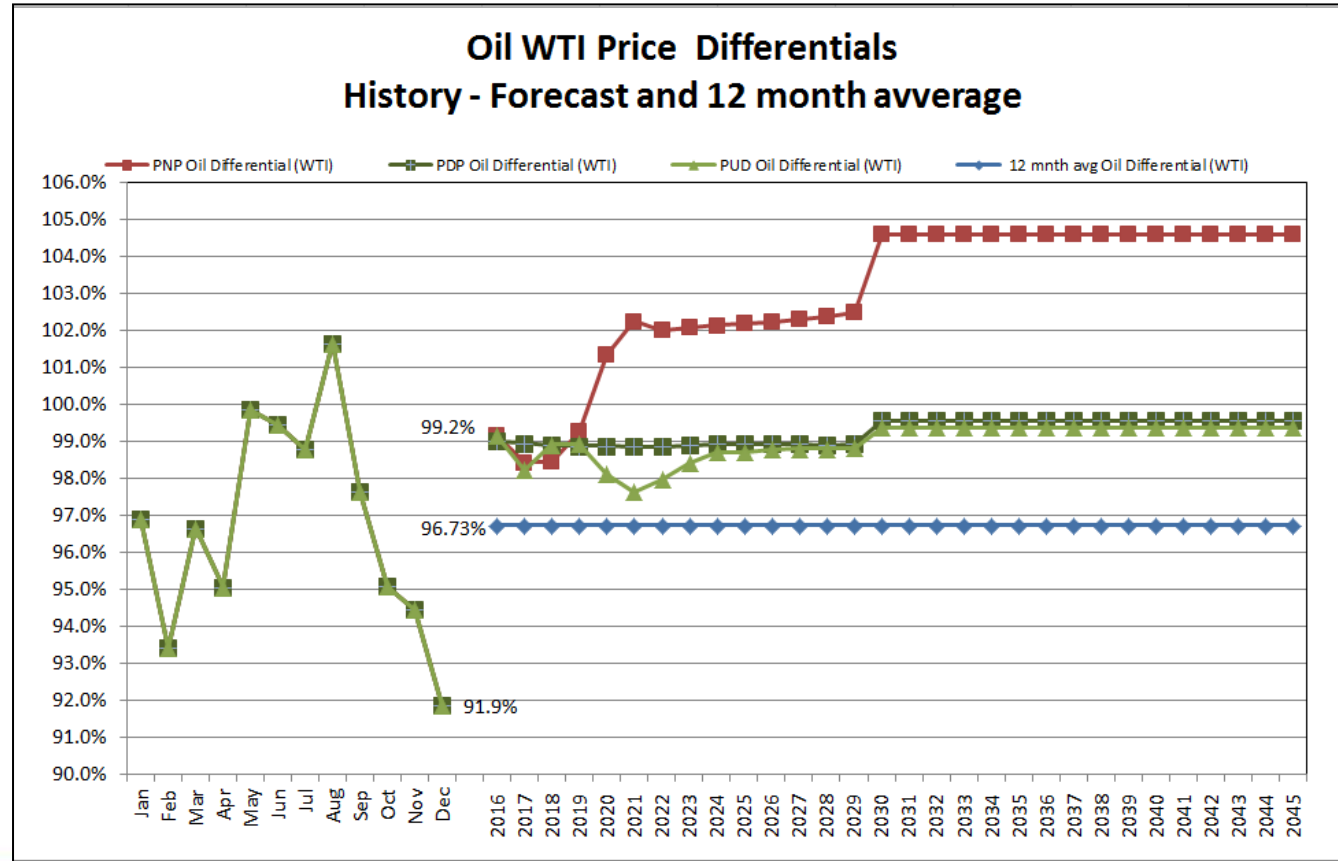
Macquarie Capital Energy Lender Price Survey, Q1/17 - 34 respondents

# Current Future Contracts



# Oil WTI Price Differentials

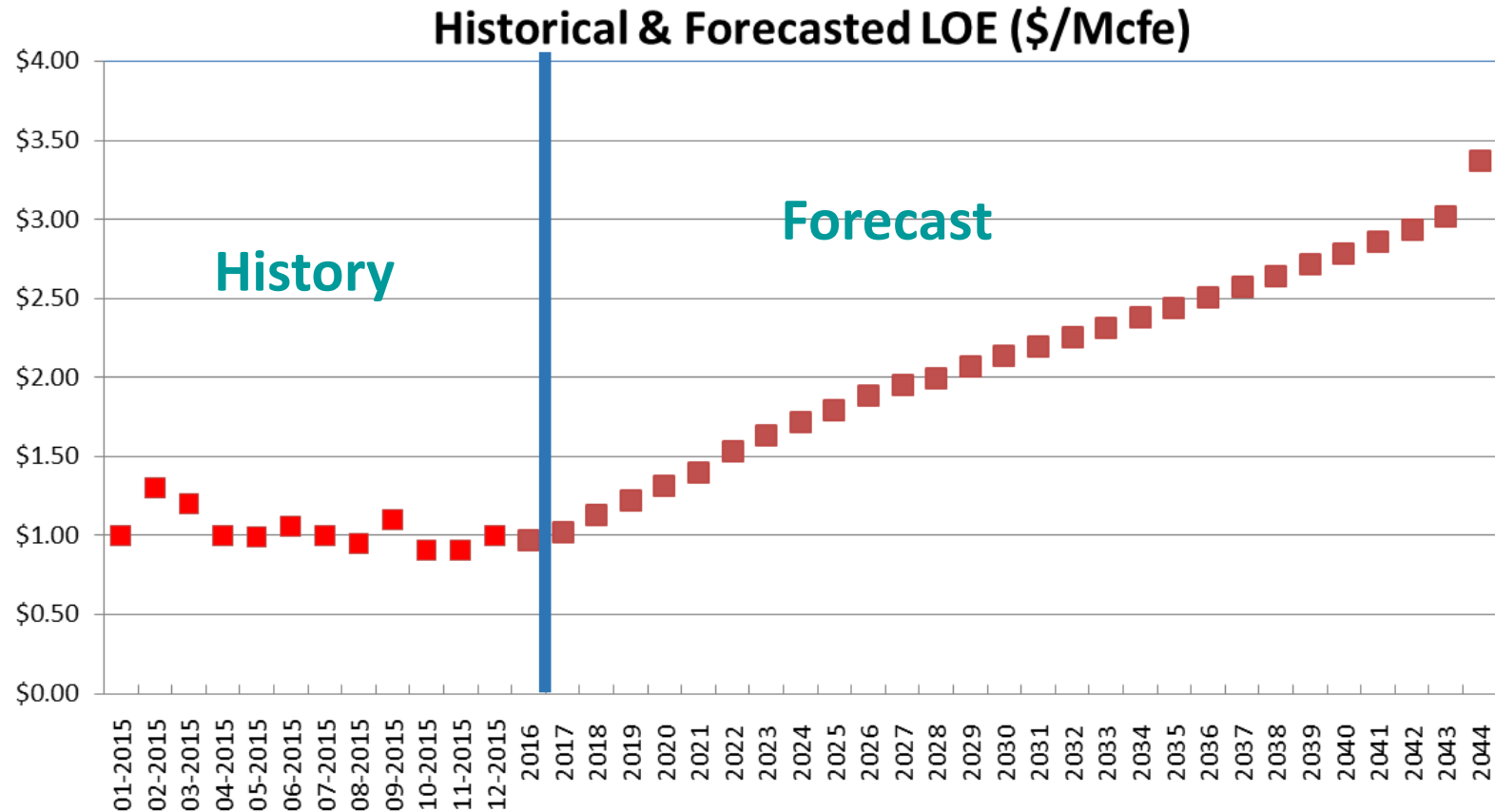
## History – Forecast and 12 month average



# Lease Operating Expenses (LOE)

- **Lease Operating Expenses are calculated based on historical data provided by the borrower - LOS , 10 K or 10 Q**
- **The LOE projected is compared to historical values**
  - **Marginal or uneconomic wells that are below the economic limit are a common source of the discrepancy**
  - **Other reasons could include past work overs and recent acquisitions**
  - **Non-recurring expenses may be excluded from LOE**
- **LOE must tie within a tolerance of the forecasted LOE or LOE is increased to historical level**

# LOE tied to Forecast (PDP)



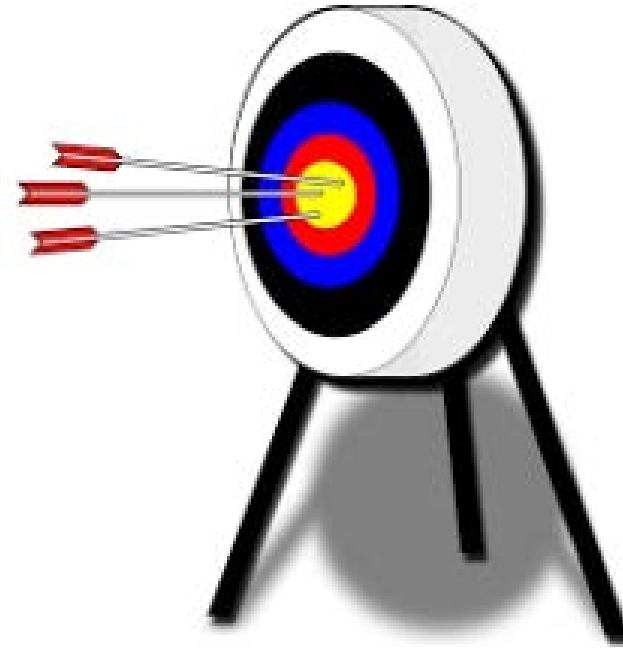
# Consistency Matters

**Changing how you calculate Reserves on a regular basis is not good for forecasting, and does not give credibility to the Reserves you report**



# Consistency Matters

- **PDP – Produced what you forecasted**
- **Costs – Tie to historical**
- **PUD – conversion/ results/ costs**



# What is value?

**The bank  
reservoir  
engineer's goal  
is the  
assessment of  
the value and  
Assets Cash  
Flow.**



# The Real Challenge



# Future Net Revenue

**Revenue** - Sum of the estimated productive life of a proved area based on the economic limits and cash flow of the producing asset

- certain price
- cost parameters
- estimated royalties
- production costs
- development costs
- production and ad valorem taxes
- other income - Hedges
- future capex
- well abandonment



# Determining value of the borrowing base

Roll forward value 6 months

**PDP + Hedges  $\geq$  75 % of total value**

**PDNP risked @ 25 %**

**PUD Risked @ 50 %**

**= Total Risked Discounted Value**

**\* 65 % = Borrowing Base / cash flow**

**Banks limit the contribution of undeveloped - PDNP and PUD**

Range	Advance	Reserve Categories
Rate (%)		

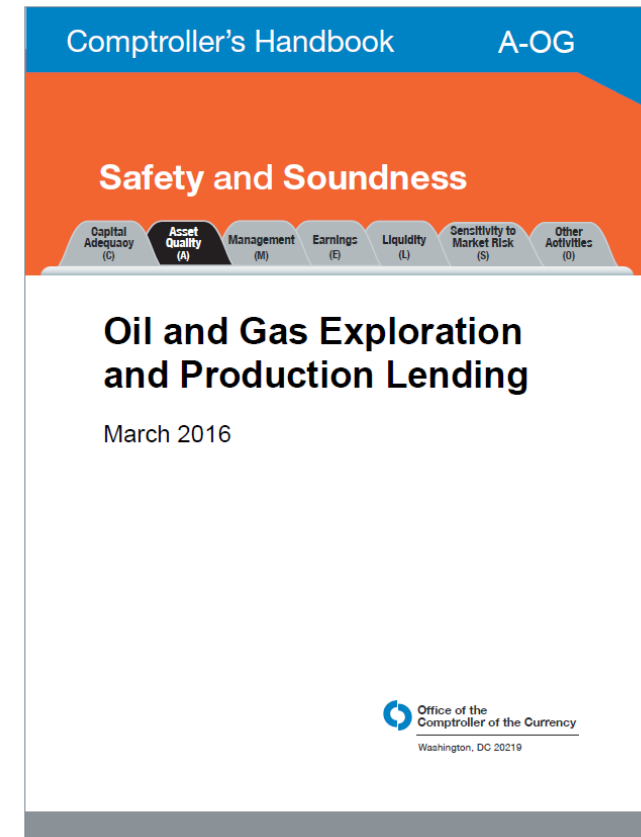
low	55%	PDP
High	70%	PDP
	Varies	Total Proved
low	55%	Total Proved
High	70%	Total Proved

Macquarie Capital Energy  
Lender Price Survey, Q1/17 -  
34 respondents

# OCC – Office of the Comptroller of the Currency

- Asset Diversity
- Repayment of RBL
- Repayment of Total Secured Debt
- Collateral Coverage
- Liquidity
- Leverage Ratio
- Susceptibility to Price Changes
- Total Debt Coverage

<https://www.occ.gov/publications/publications-by-type/comptrollers-handbook/pub-ch-og.pdf>



# OCC Guidelines

## RBL Loan Classification Summary

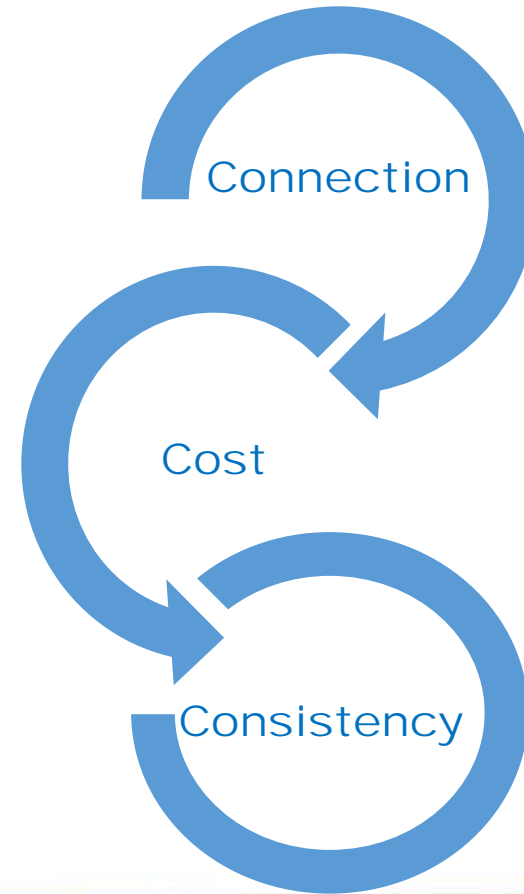
Calculated from the NYMEX unrisked total cash flows

RBL Loan Rating					
Test	Pass	Criticized	Classified		
		Special Mention	Substandard	Doubtful	Loss
Repayment RBL	< .60 Reserve Life	.60 - .75 Reserve Life	> .75 Reserve Life		
Repayment Total Secured	< .75 Reserve Life	.75 - .90 Reserve Life	> .90 Reserve Life		
Funded Debt / EBITDAX	< 3.5 X	3.5 - 4.0 X	> 4.0 X		
Funded Debt / Capital	< .50	.50 - .60	> .60		
Committed Debt / Total Reserves	< .65	.65 - .75	> .75		
			Debt <100% Risked Reserves	Incremental Debt Above Substandard < 100% <u>Unrisked</u> Reserves	Remaining Debt > 100 % <u>Unrisked</u> Reserves

# CONCLUSION

**Repayment of the loan with interest – This is the best possible case**

**The Bank Reservoir Engineer's goal is the assessment of the value from the standpoint of protecting the bank's interest and realizing the full value of the clients' assets.**



# Thank you

# Questions?