OMNIRA SOFTWARE

# Workflows to Minimize Uncertainty (and Risk) in Type Curve Development

Bertrand Groulx, Omnira Software


What about the uncertainty?
What uncertainty?

# Importance of Type Curves

*"Building type wells is arguably the most important exercise in decision making for unconventional resource plays. The type well and its associated uncertainty are often the largest drivers behind whether a project will be economic, or not. However, appropriately characterizing type well uncertainty is not trivial, and is often overlooked."*

SPE-201556-MS Miller, Dauncey and Gouveia

# Why should I care about uncertainty & risk?

- Market capital loss - investors do not react well to production guidance shortfalls
- Cashflow shortcomings
- Possible reserve write-downs

Impacts on stocks of companies that fell short of their production guidance

Reduced by 40% in 8 months

Reduced by 50% in 7 months

Reduced by 30% in 2 weeks

Reduced by 40% in 8 months

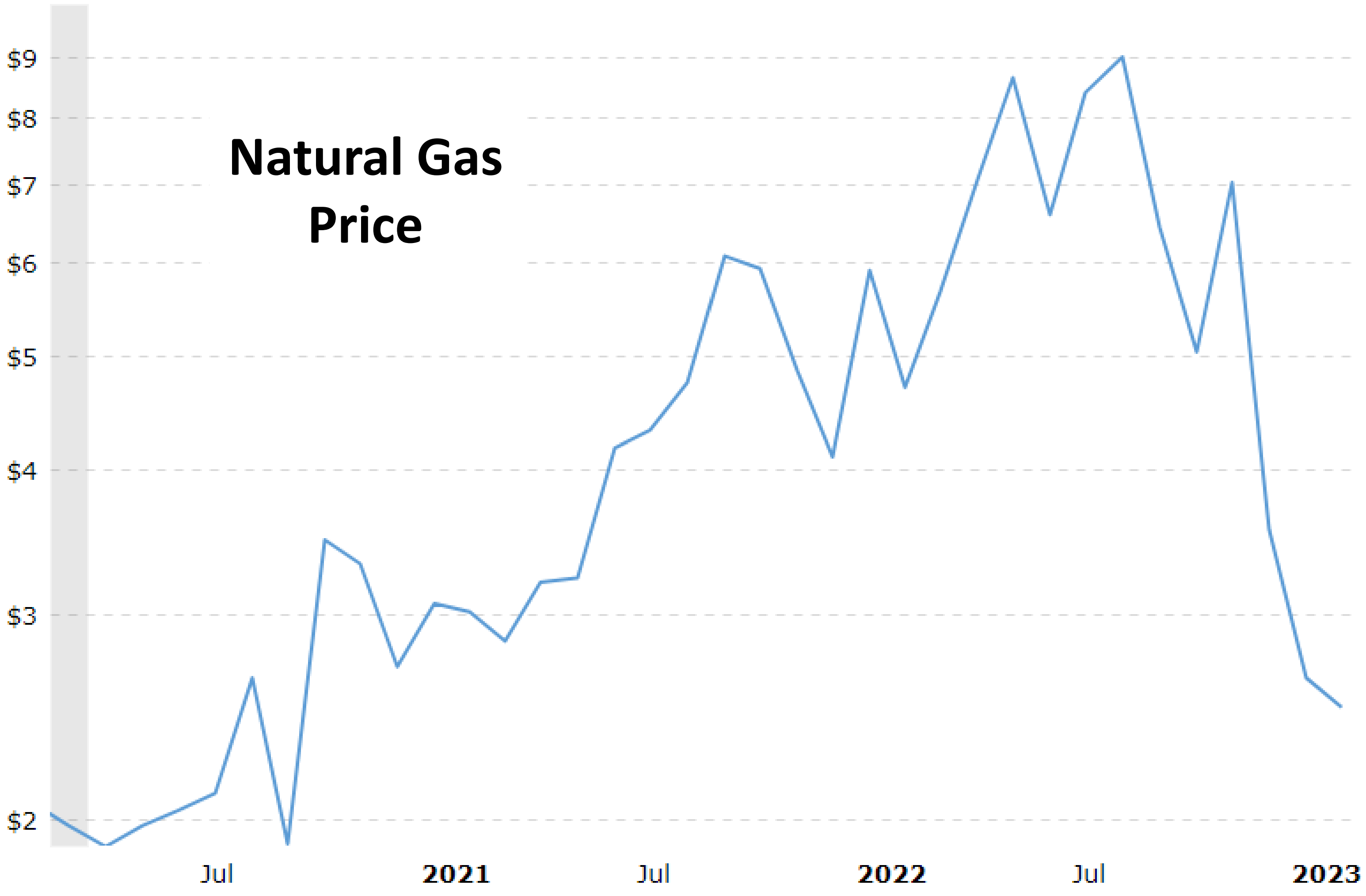
Reduced by 70% in 8 months

Reduced by 26% in 1 month

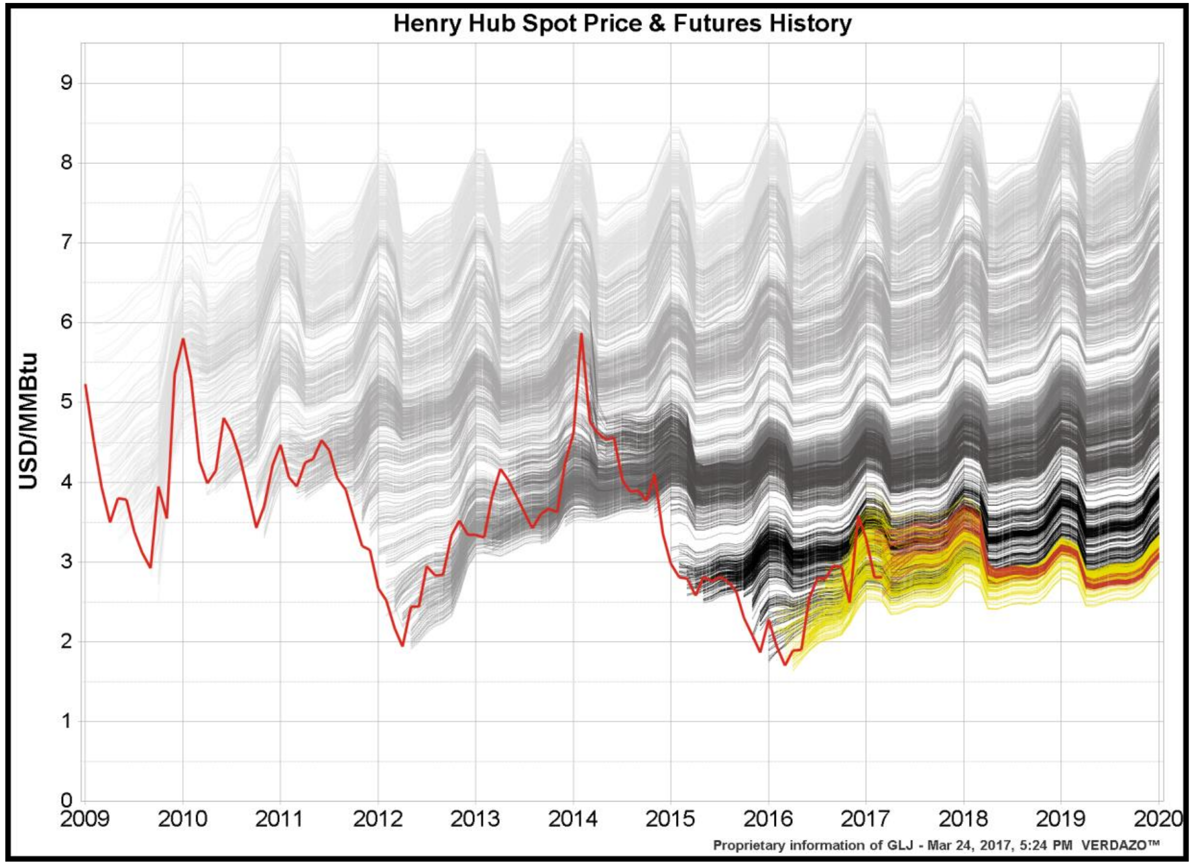
Reduced by 40% in 8 months

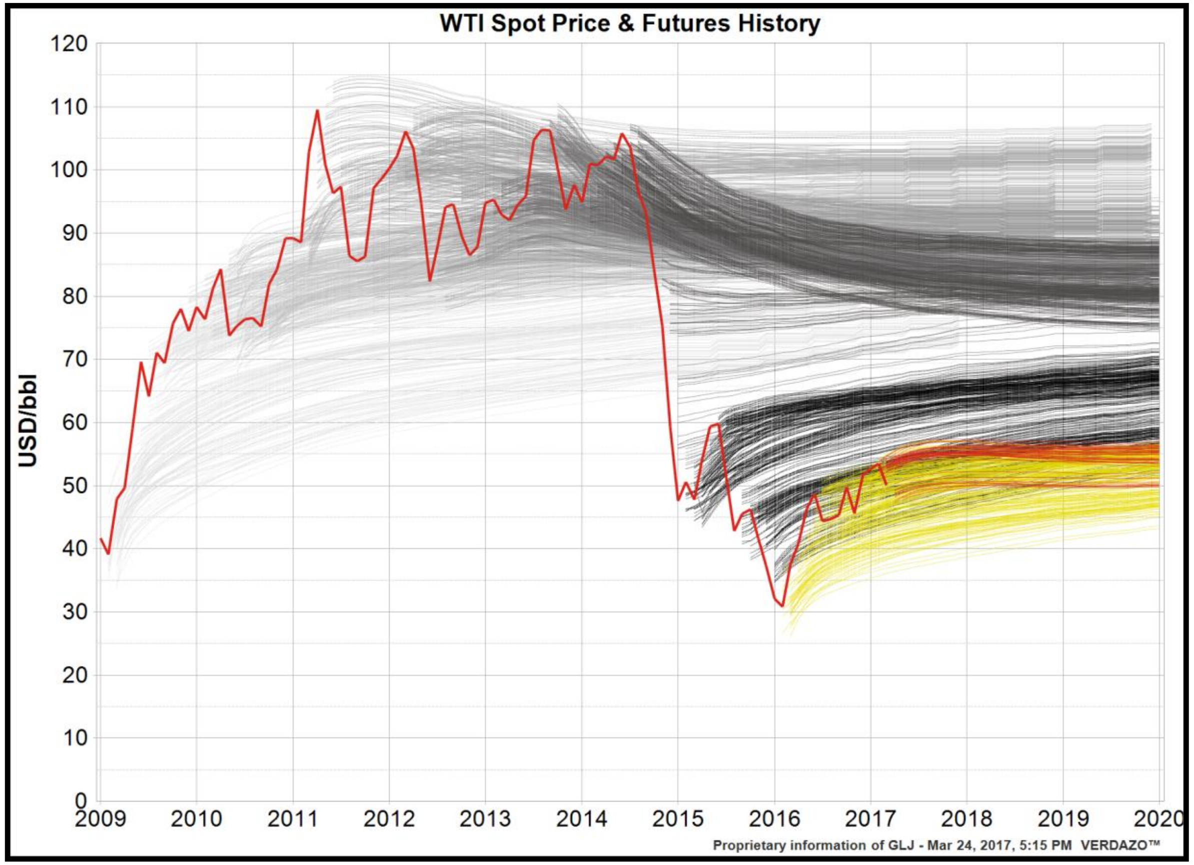
Reduced by 40% in 8 months

# Commodity Price uncertainty can punish even the best plans



# … and we're terrible at predicting Commodity Prices



# 7 Steps
# to
# Minimize Uncertainty & Risk

# 7 Steps to Minimize Uncertainty & Risk

1. Understanding Uncertainty
2. Improving the quality and quantity of data
3. Representativeness
4. Minimize the Addition of Uncertainty
5. Test Downside Scenarios using Aggregation
6. Monitor & Update Data
7. Decision Transparency

# Understanding Uncertainty

to inform value-based decision making

# Step #1

# My definitions (for the purpose of this presentation)

**Uncertainty** = Range of possible outcomes

- Provides the context to assess Risk

**Risk** = Threat of loss ($)

- Inherently value-focused

These should, ideally, always be considered together.

**Outcomes** = production or value outcomes

**Features** = input data

# How do you measure uncertainty?

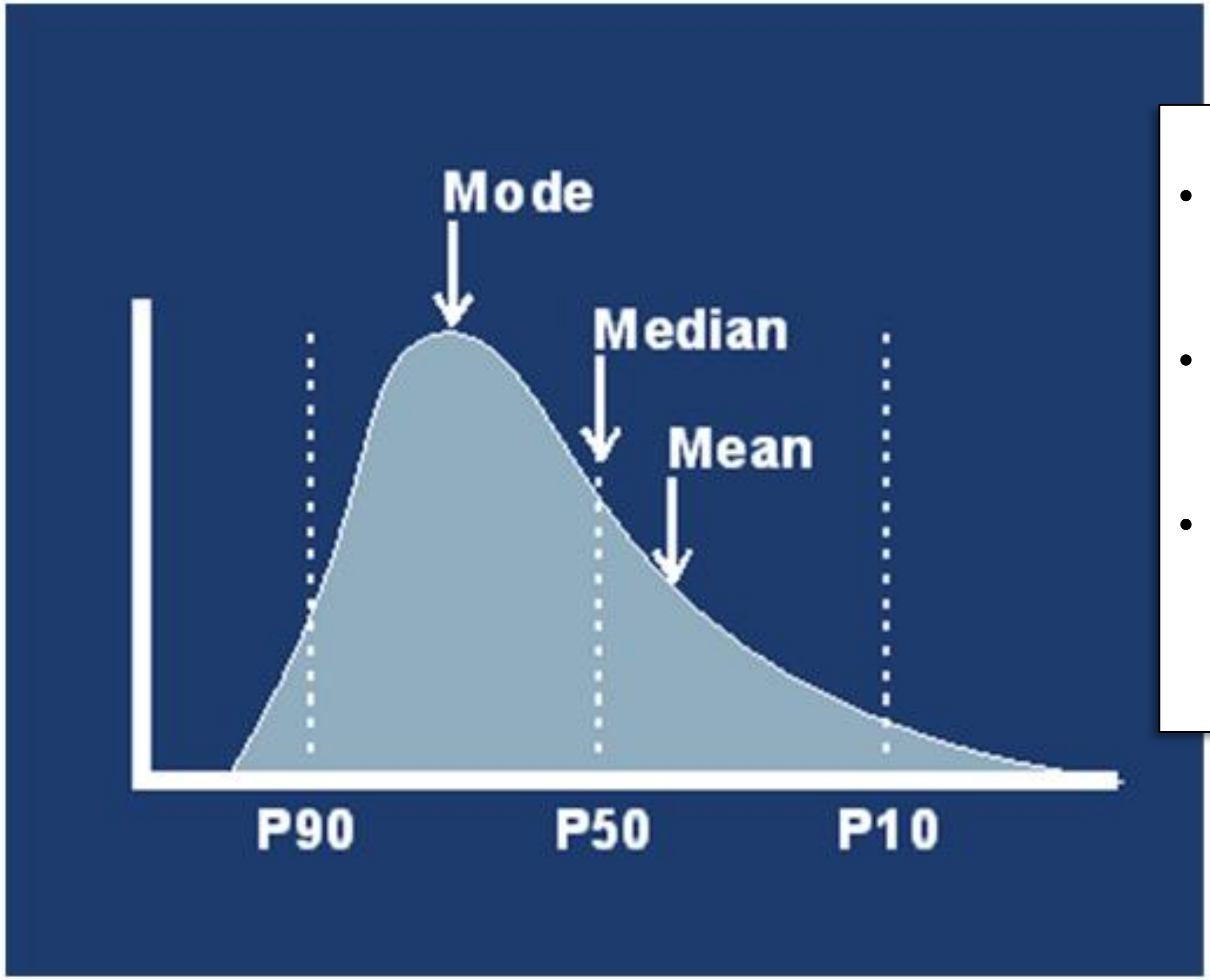
10-year-old → iioohhnoo = I don't know?

12-year-old → The question is absurd

Wife → With an uncertainty ruler!

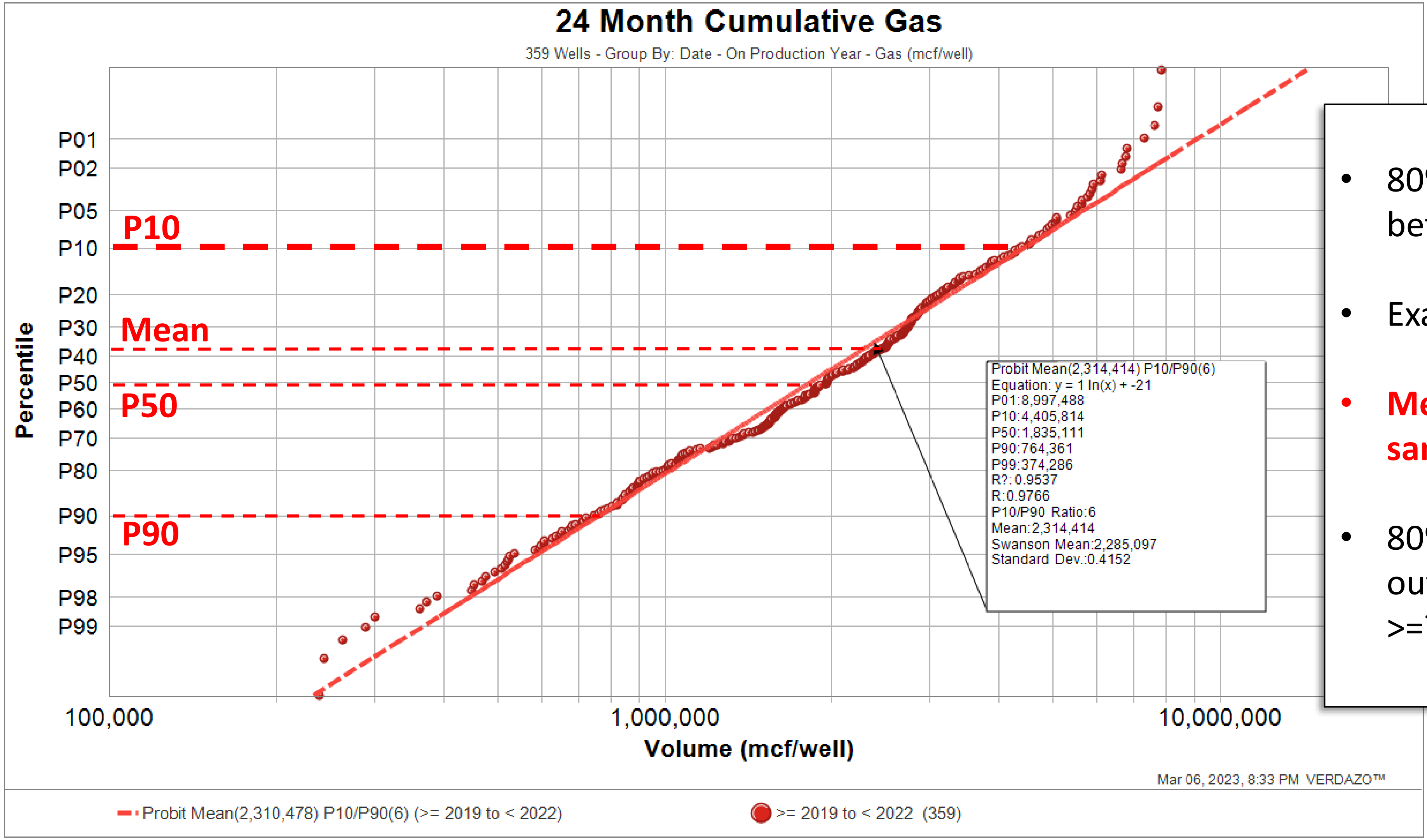
- While we can't measure uncertainty, we can use a proxy for it = P10:P90 ratio
- Communicates the range of outcomes with an 80% confidence interval
  (i.e. 80% of outcomes fall between the P10 and P90 values)

# P10:P90 ratio proxy for uncertainty (80% confidence)



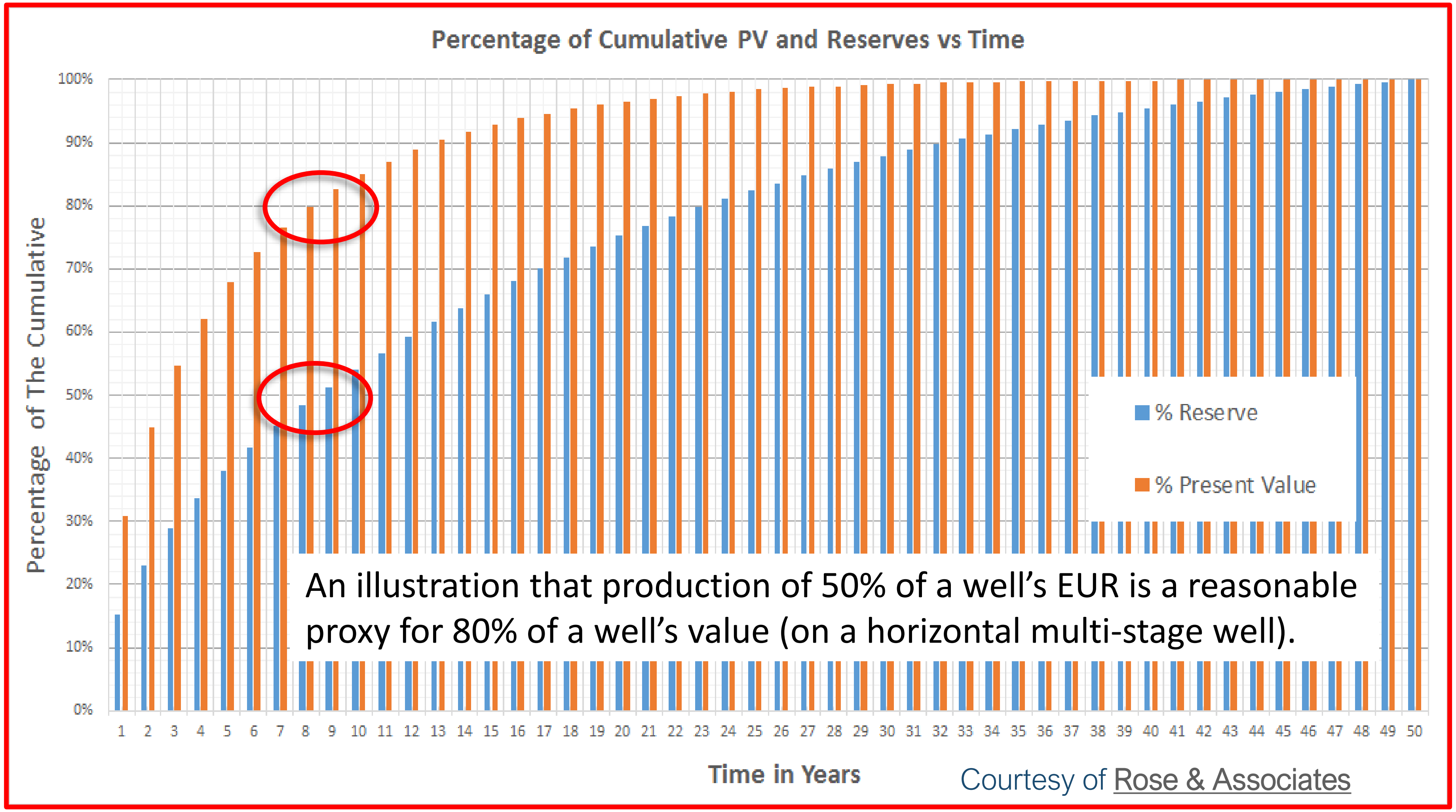

- P10:P90 ratio is an expression of the range of possible outcomes
- This is a proxy used to “measure” (estimate) uncertainty
- The higher the P10:P90 ratio, the further the Mean is from the Median (P50) = a lower likelihood of achieving the Mean or more

# Example Probit Plot

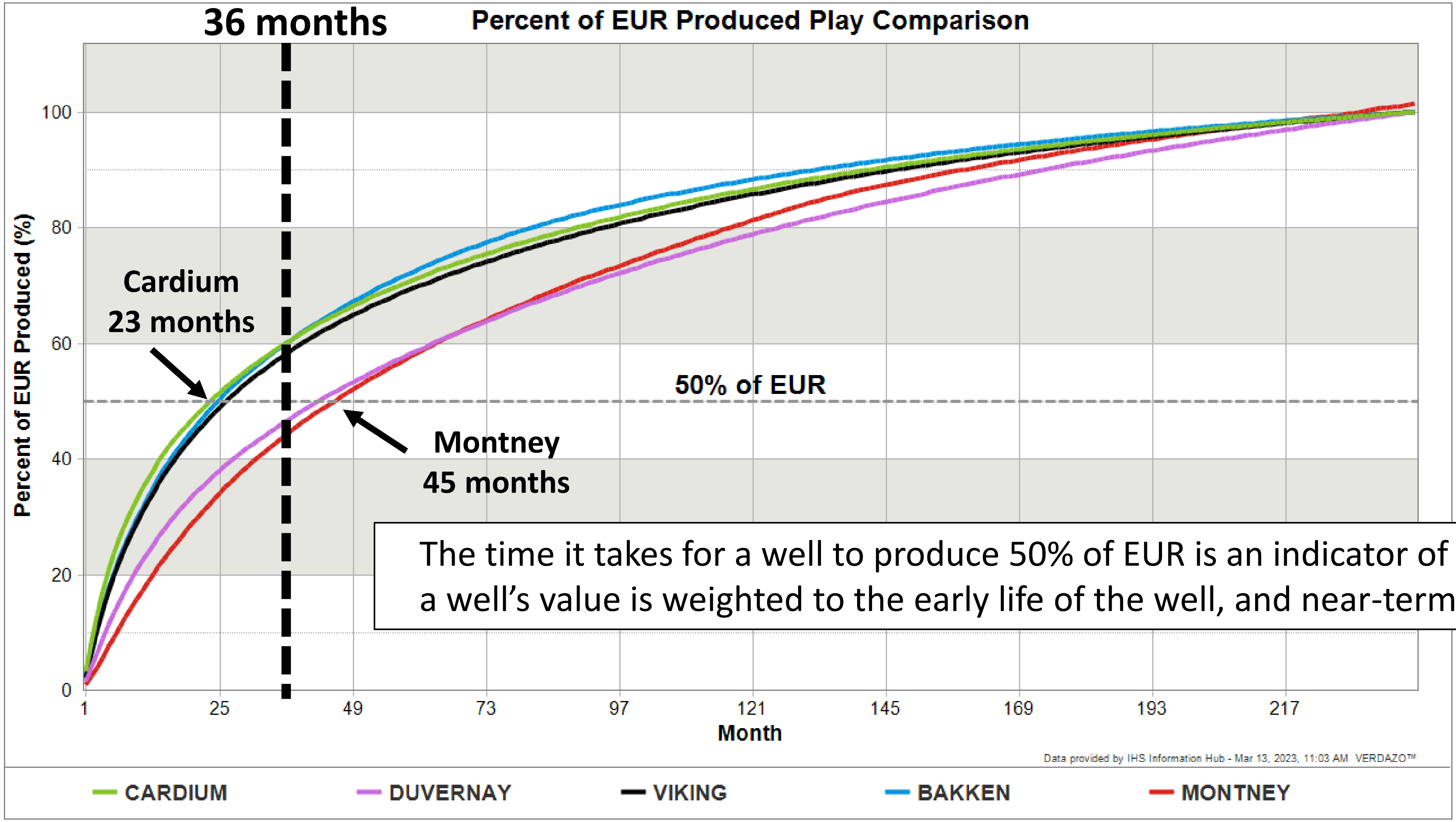



- 80% probability that outcomes fall between the P90 and P10 values
- Example: P10:P90 ratio = 6
- **Mean is at P37 = 63% chance of sampling below the mean**
- 80% confidence independent outcomes will fall between >=764,361 & <=4,405,814

# Value focus = 50% EUR as a Proxy for 80% Value



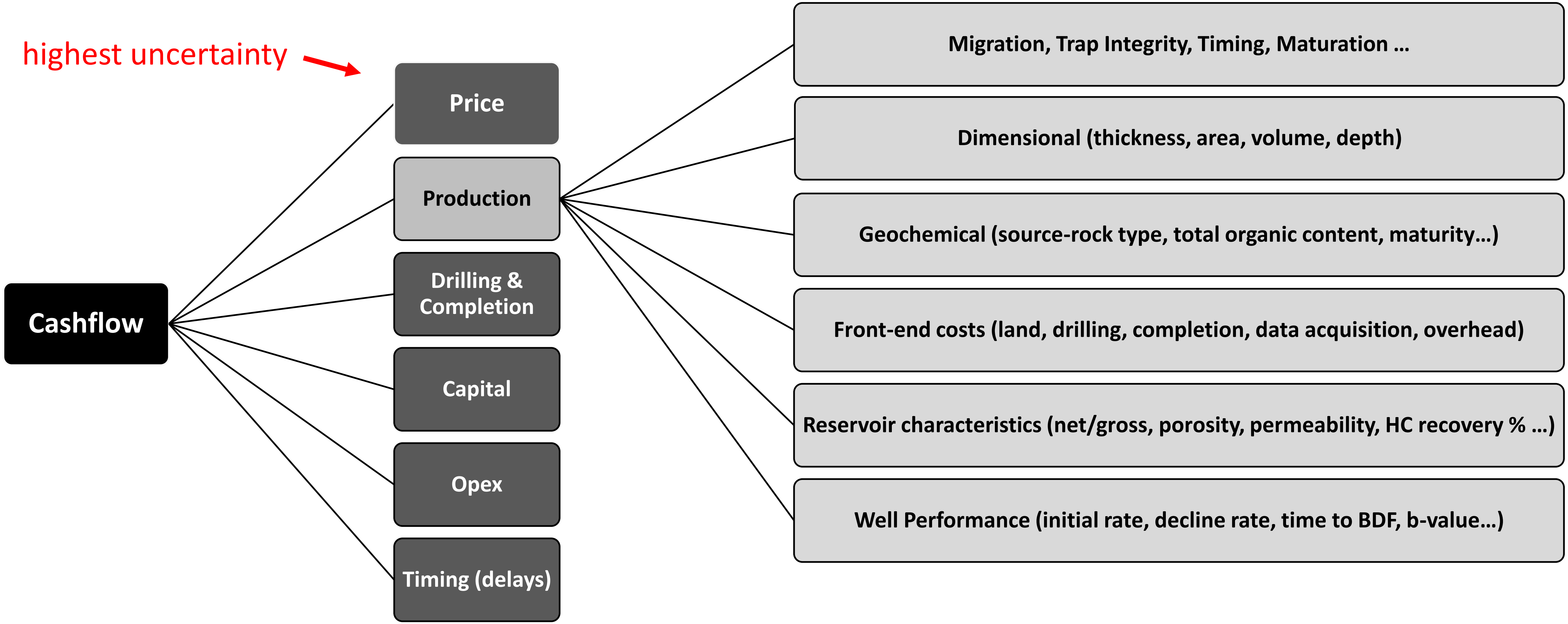
# 50% EUR Comparison Across Plays




The time it takes for a well to produce 50% of EUR is an indicator of how much a well's value is weighted to the early life of the well, and near-term prices.

# Uncertainties that Affect Value

Optimistic estimates become exposed when prices fall



# Cognitive Biases Can Contribute Uncertainty

Confirmation    Social Proof    Anchoring

Survivorship    Availability

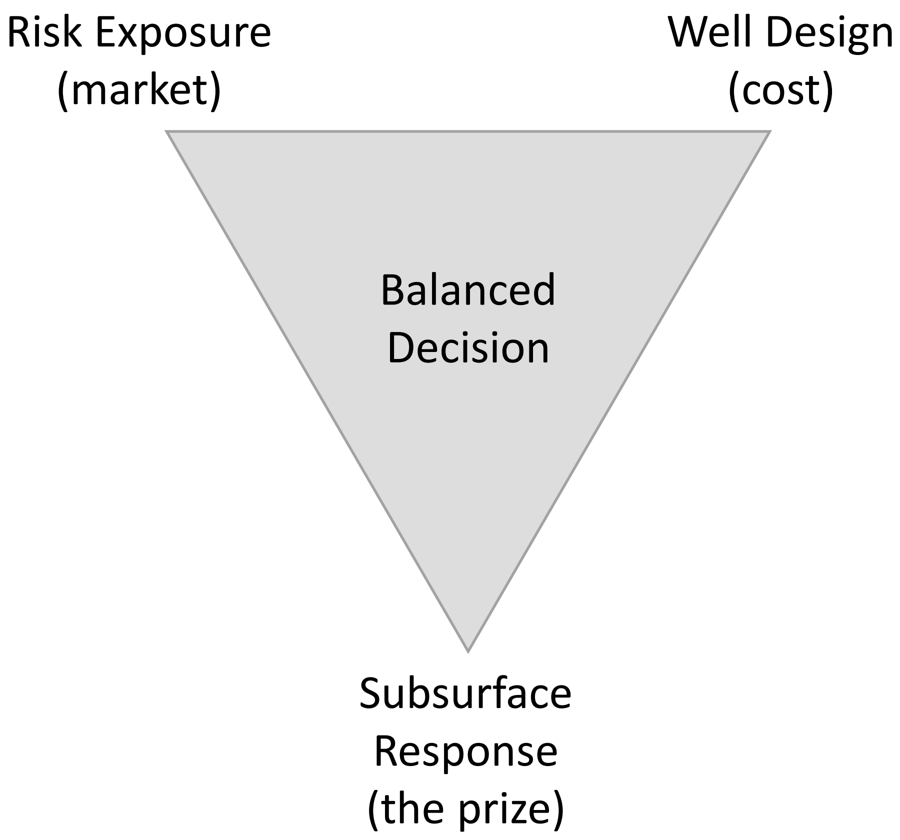
Conservatism    Clustering    Recency

Salience    Overconfidence

Ostrich    Bandwagon

HiPPO = Highest Paid Person's Opinion

# Primary Risk & Uncertainty Elements That Drive Decisions




- Available funds
- Size of the prize
- Threat & magnitude of loss

# Improving the quality and quantity of data

# Step #2

# Ask Chat GPT

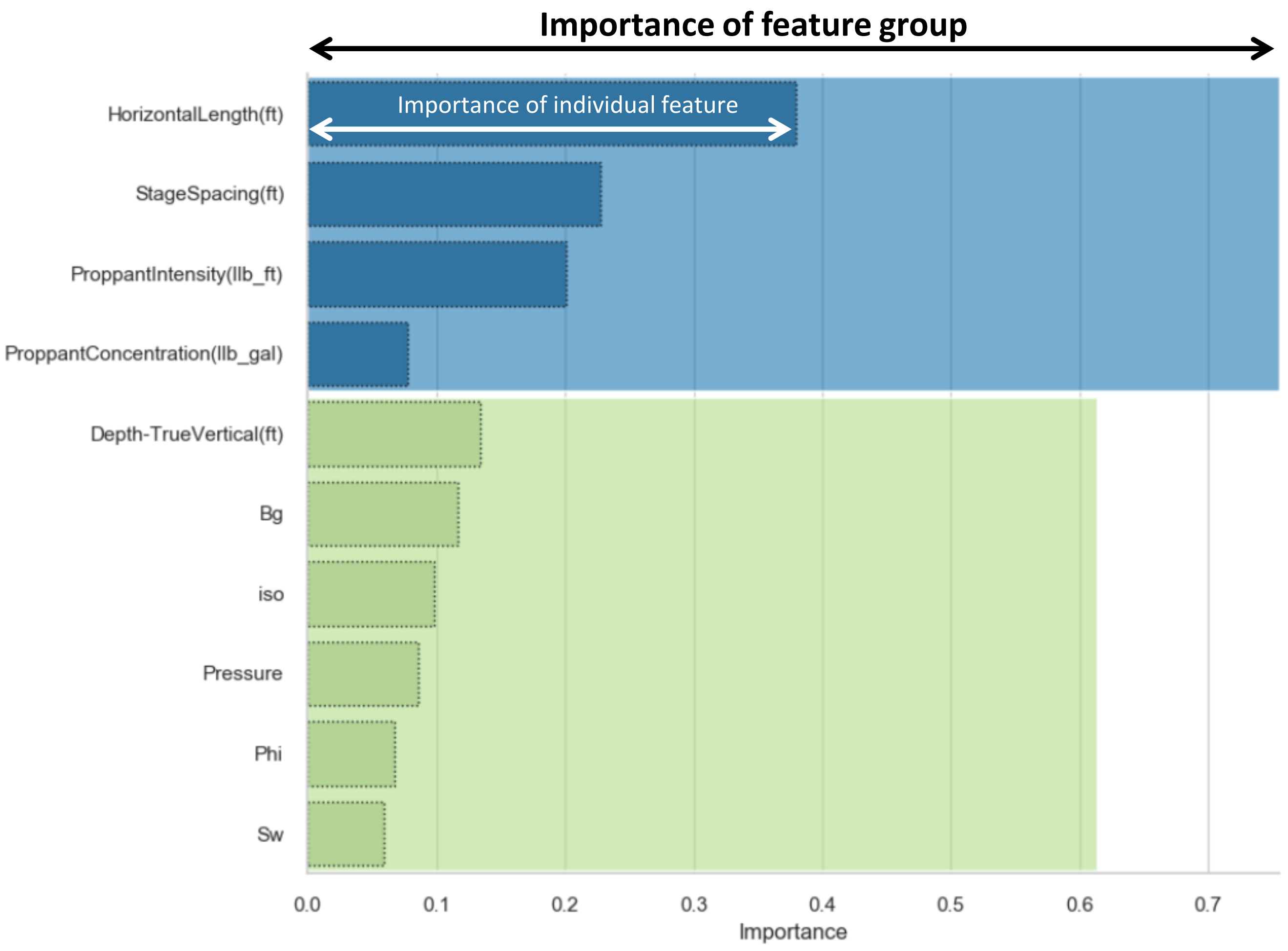
## How can I reduce uncertainty in production forecasts?

Reducing uncertainty in production forecasts is an important goal for petroleum companies, as it can help to improve planning and decision-making. Here are some strategies that can help to reduce uncertainty in production forecasts:

1. Improve data quality: Accurate production forecasting relies on high-quality data. This includes data on reservoir characteristics, production history, and well performance. **By improving the quality and quantity of data, you can reduce uncertainty** in your production forecasts.
2. Use multiple methods: There are different methods that can be used to forecast production, including analytical models, numerical simulations, and machine learning algorithms. By using multiple methods and comparing the results, you can get a better understanding of the uncertainty in your forecasts and identify areas where further data or analysis is needed.
3. Incorporate uncertainty analysis: Uncertainty analysis can help you to quantify the level of uncertainty in your production forecasts. This can be done by using techniques such as Monte Carlo simulation, which involves running multiple simulations with different input parameters to generate a range of possible outcomes. By incorporating uncertainty analysis into your forecasting process, you can better understand the range of possible outcomes and develop more realistic production forecasts.
4. Monitor and update forecasts: Production forecasts are not static and can change over time as new data becomes available or conditions change. By monitoring production closely and updating your forecasts regularly, you can reduce uncertainty and improve the accuracy of your predictions.
5. Engage experts: Engaging experts in the field, such as geologists, reservoir engineers, and production analysts, can help to identify key factors that may impact production forecasts and provide insights into how to reduce uncertainty. Collaboration with experts in the field is an important step towards a more accurate production forecast.

# Subsurface Data is as important as Completion Data

...and harder to come by




**Completion = Controllable**

**Subsurface = Non-controllable**

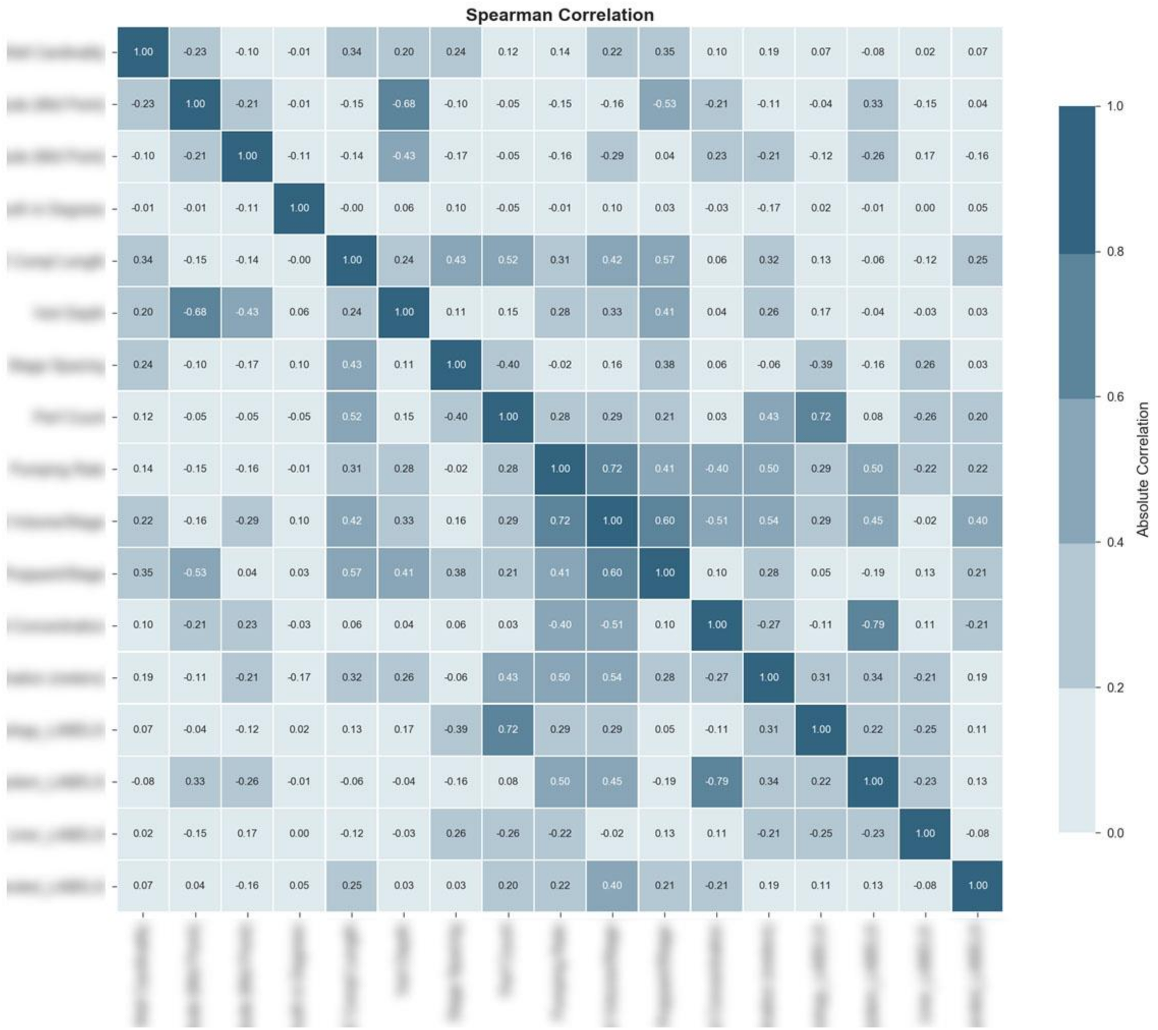
(but selectable… you can choose where you drill your well)

Using ML in multiple plays we consistently see that completions & geoscience data contribute (near) equally to production predictions.

# Subsurface Data = #1 opportunity for more, & better, data

- Biggest data opportunity to reduce uncertainty & improve predictability
- Data is rarely centralized and maintained as a single “source of truth”
- Inconsistent cut-offs and nomenclature across multiple geologists working on a single play
- Rarely is there a formalized process to “Look Back” at results and test/recalibrate/update subsurface data in a centralized location

# Feature Interdependence (Correlation) – A Challenge




1) It's hard to understand and separate the effects of two or more features that are correlated
2) It's harder to intelligently select which features to include in a model

# Reduce Redundancy With Feature Engineering

**Highly Correlated = Redundancy**

- Length
- Total Proppant
- Total Fluid

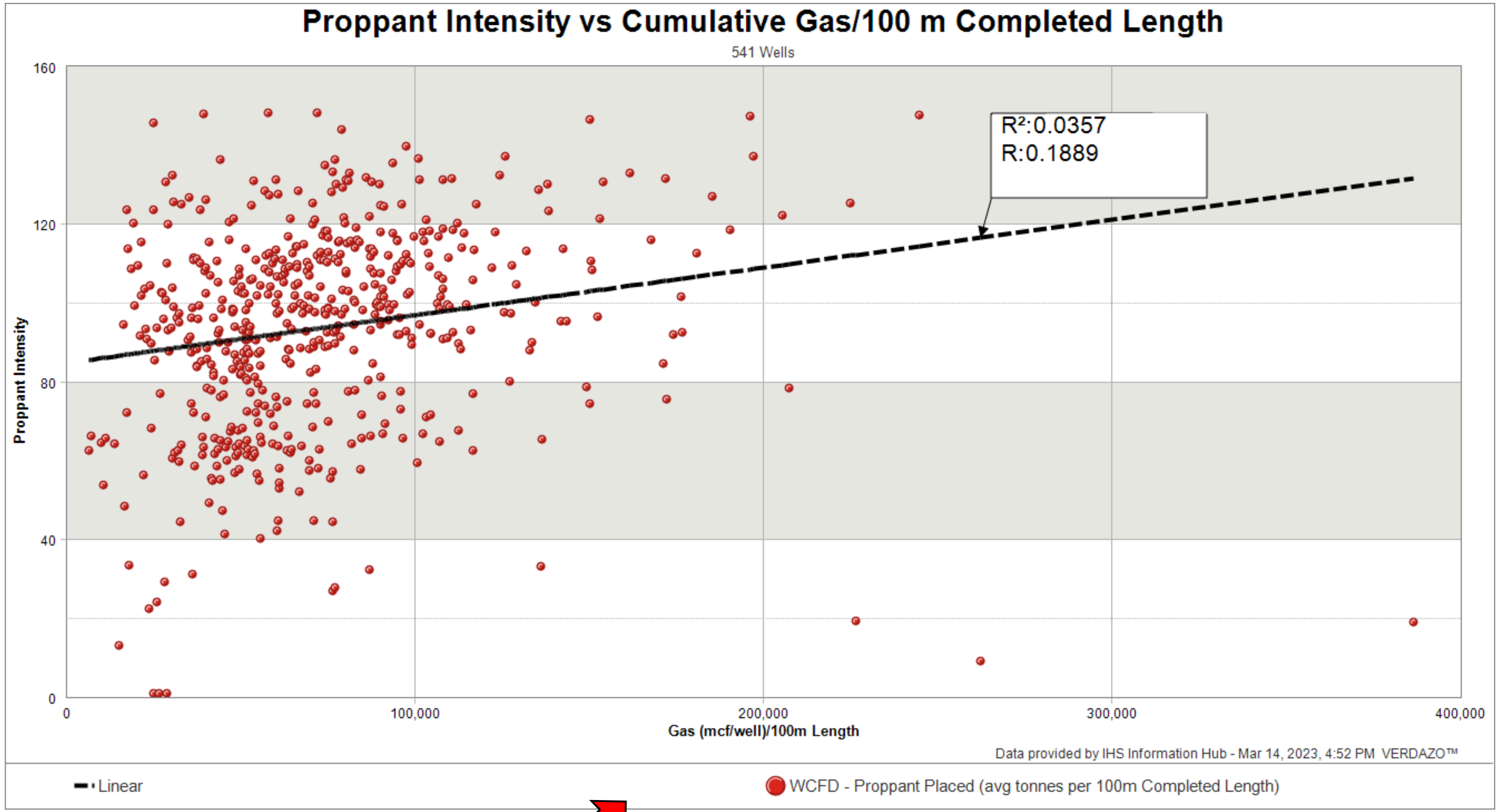
**Feature Engineering (New Information)**

- Length
- Proppant Intensity (lbs/foot)
- Proppant Concentration (lbs/gallon)

# Don't rely on correlations as a measure of importance

**Bin the data using a well design feature, (or geological feature)**

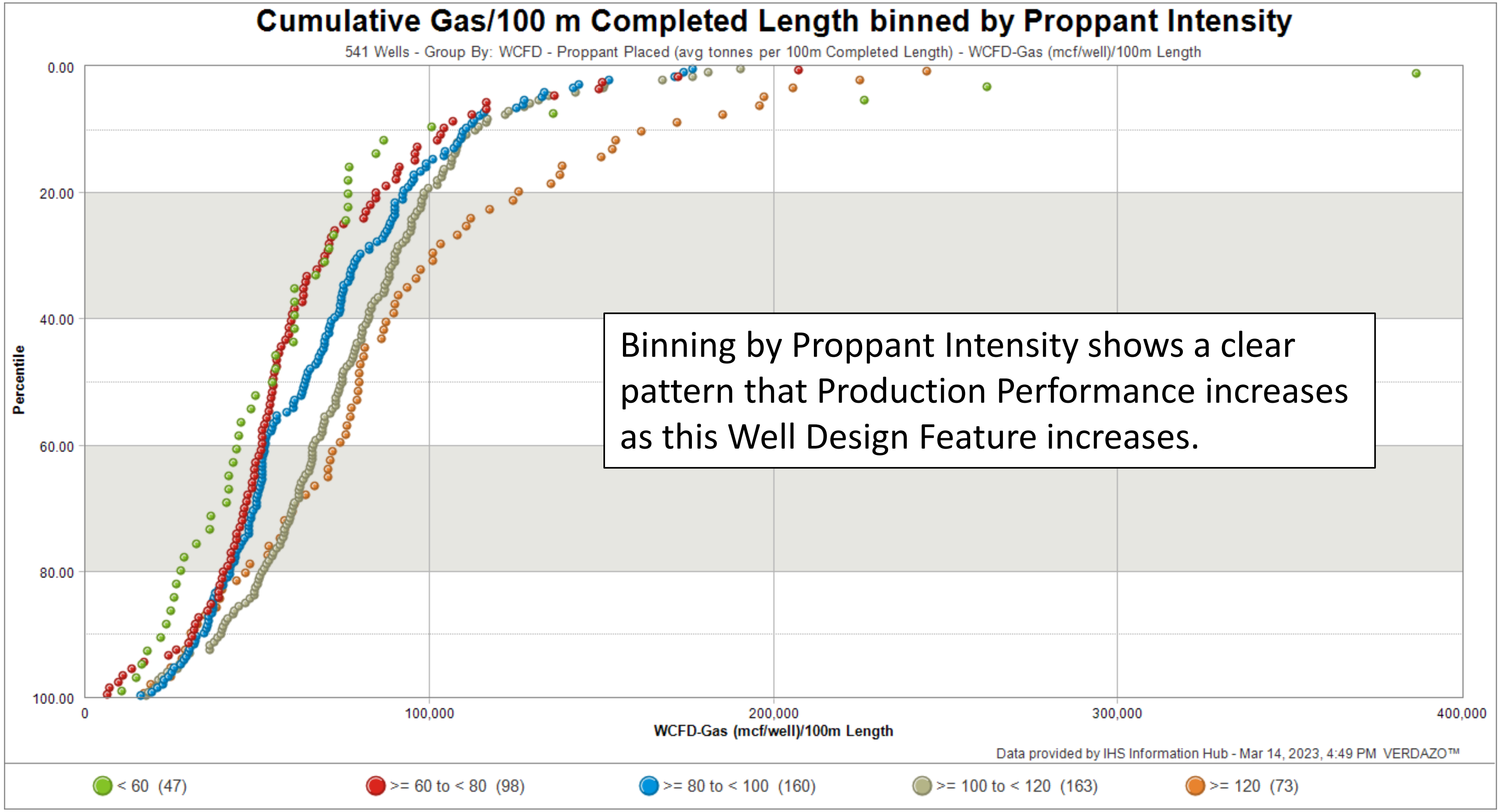
Well Design Feature




**Plot percentile of the production measure**

# Binned Cumulative Probability Plots Can Convey Clear Trends

Same data as previous slide



# Representativeness (Analogue Selection)

finding the balance between Sample Size & Relevance

# Step #3

# Analogue Selection

- Analogue wells should have a similarity on which a comparison may be based and represent the range of possible outcomes (i.e. don't just select the best wells).

- Selecting wells with similar characteristics may reduce the range of uncertainty in your type-well curve.

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- Common criteria for selecting similar wells include:

  1) **Geology**
  2) **Reservoir**
  3) **Well Design**
  4) **Well Density**
  5) **Operational Design**

# Is "Representativeness" even possible?

For example, analogs should have the same or similar:

1. Geology – lithology, principal mineralogy, clay content, total organic carbon (TOC), etc.
2. Depth, temperature and pressure
3. Fluid composition and properties
4. Reservoir drive mechanism
5. Spacing – distance between wells
6. Completion design – lateral length, fracture stimulation design (stages, fluid type and volume, and proppant)
7. Time-frame
8. Operating conditions – flowing wells producing at similar separator conditions


SPE-175527-MS Validating Analog Production Type Curves for Resource Plays (McLane & Gouveia)

# Analogue Selection Dilemma

**Statistical Power**
(sample size)

**Representativeness**
(analogue-ness)

**Sometimes we have to sacrifice representativeness for sample size**

# <u>Analogue Selection Process</u>

Build an understanding before limiting selection

1) Start with the largest reasonable dataset that your subsurface data will allow (the biggest constraint)

2) Dimensionally normalize production to length (e.g. Volume/100 m)

3) Test subsurface features & well design features for "<u>impact</u>" → statistical multivariate analysis

4) Only use "<u>**impactful**</u>" features from Step 3 to limit your <u>Subsurface Feature analogue selection</u> (many papers refer to this as a "geodomain")

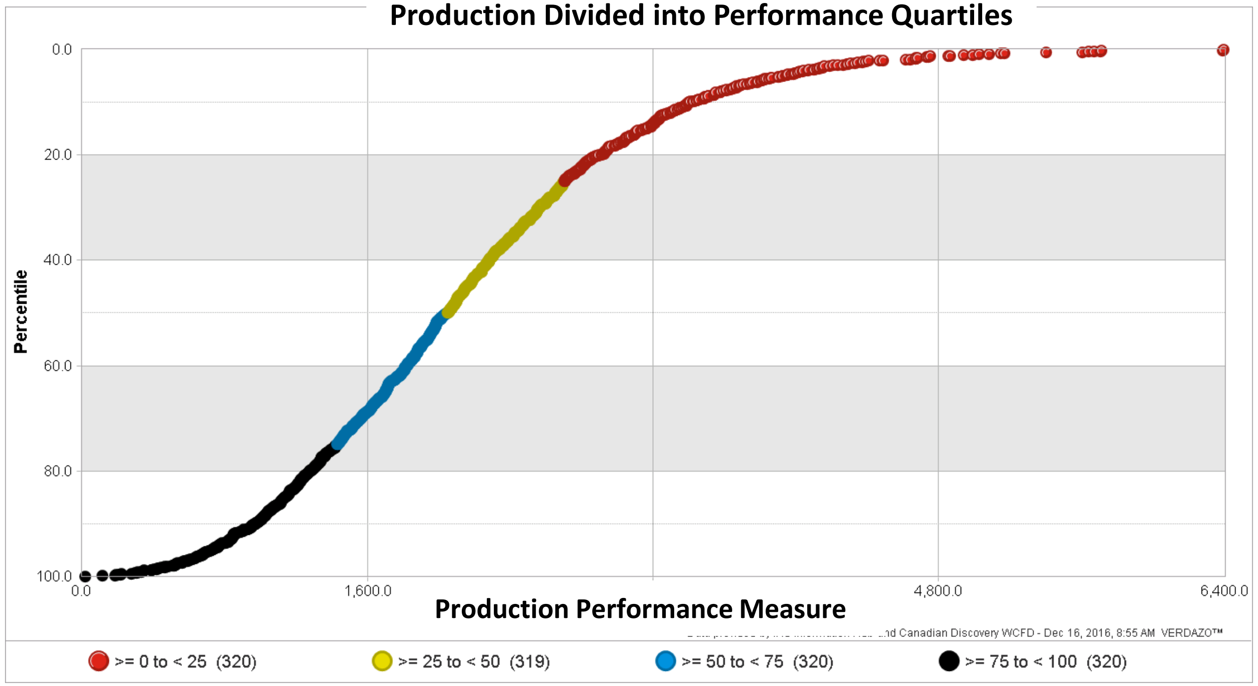
5) Only use "<u>**impactful**</u>" features from Step 3 to limit your <u>Well Design Feature analogue selection</u>.

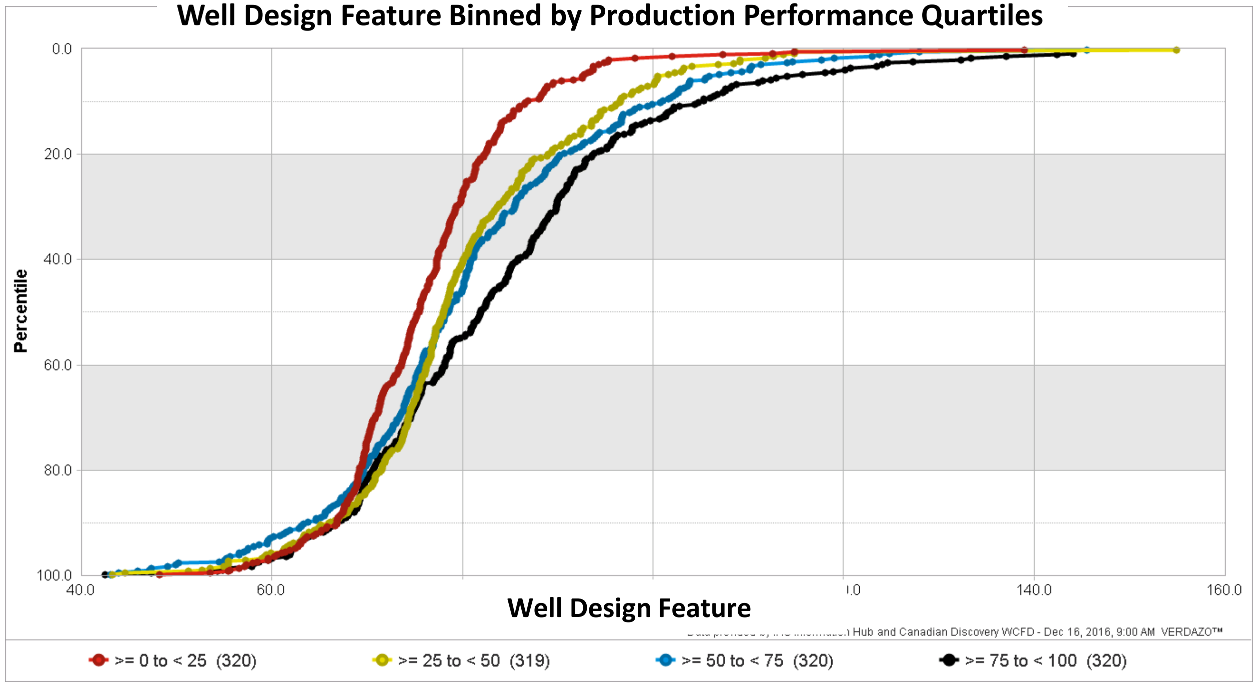
6) Reduce uncertainty by choosing geodomains & well designs that exhibit more consistent results (i.e. lower P10:P90 ratios)

# Statistical Multivariate Analysis Approach

## Parallel Coordinates Distribution (PCD)

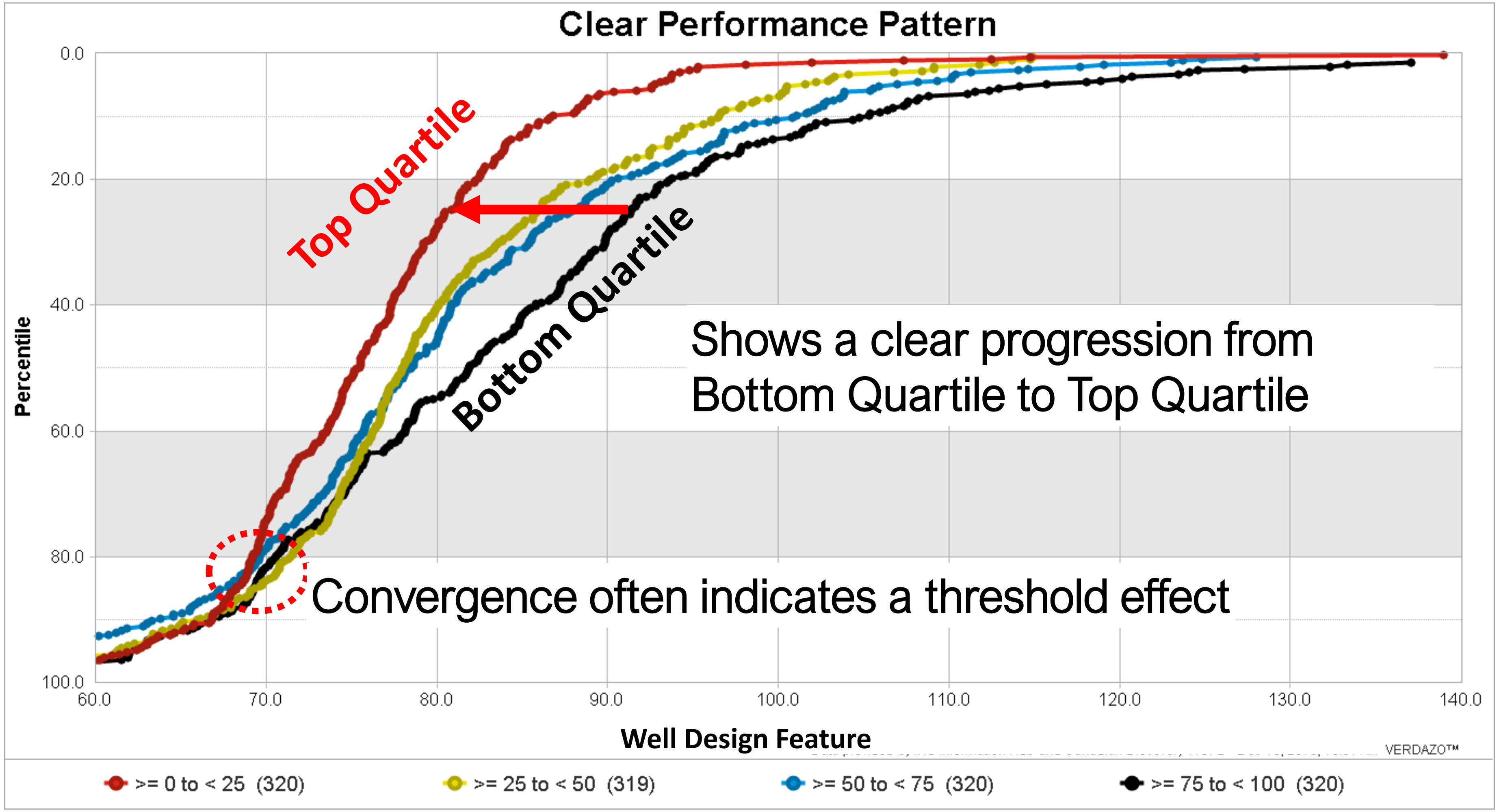
**Production Performance Quartiles** → **Production Performance Quartile Grouping** → **Feature Data**




SPE-185077-MS • Multivariate Analysis Using Advanced Probabilistic Techniques for Completion Optimization • B. Groulx

# Parallel Coordinates Distribution (PCD) Chart : Clear Performance Pattern

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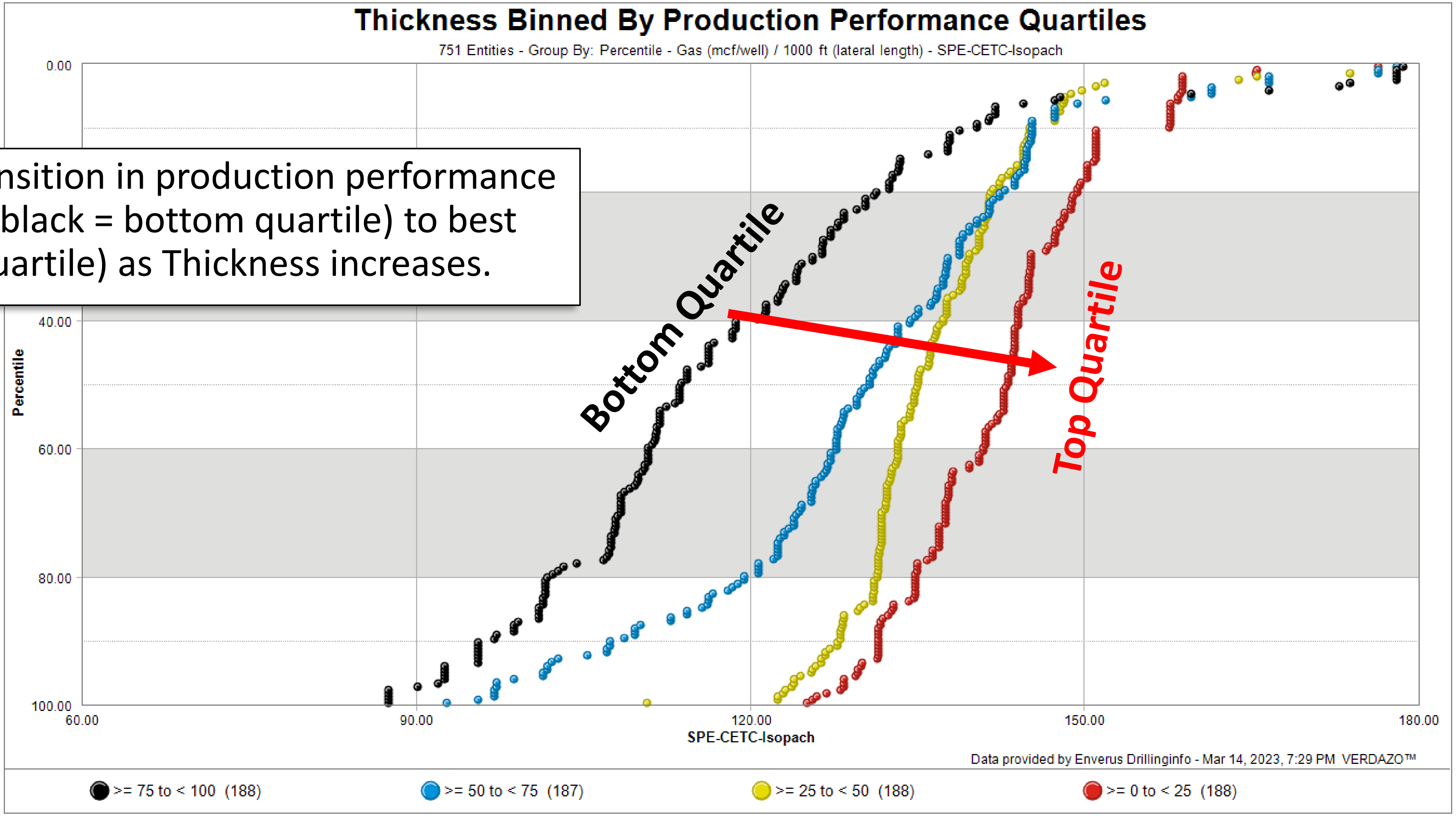
# Use Parallel Coordinates Distributions on Subsurface Features Too

Note the clear transition in production performance from worst wells (black = bottom quartile) to best wells (red = top quartile) as Thickness increases.



# Example: Setting up Geodomain Analogue Datasets

**NAMES ASSIGNED TO GEODOMAINS**

| | | Depth <6000 | 6000-7000 | 7000-8000 | >8000 |
|---|---|---|---|---|---|
| Thickness | <100 | 1a | 1b | 1c | 1d |
| | 100-125 | 2a | 2b | 2c | 2d |
| | 125-150 | 3a | 3b | 3c | 3d |
| | >150 | 4a | 4b | 4c | 4d |

- Geodomain attributes are used to identify wells in each domain, named for easy selection, comparison and analysis.
- Depth (as a proxy for pressure) and Thickness were identified as the most impactful subsurface features.
- Impactful Well Design features were used to further limit the Geodomain Analogue datasets
- **WELL COUNTS** and **P10:P90 Values** for each Well Design constrained Geodomain are shown below.

**WELL COUNTS**

| | | Depth <6000 | 6000-7000 | 7000-8000 | >8000 |
|---|---|---|---|---|---|
| Thickness | <100 | 55 | 7 | 6 | 3 |
| | 100-125 | 96 | 105 | 61 | 134 |
| | 125-150 | 16 | 395 | 374 | 234 |
| | >150 | 7 | 21 | 126 | 11 |

**P10:P90 Values**

| | | Depth <6000 | 6000-7000 | 7000-8000 | >8000 |
|---|---|---|---|---|---|
| Thickness | <100 | 3.1 | | | |
| | 100-125 | 2.1 | 2.51 | 2.83 | 2.97 |
| | 125-150 | | 3.99 | 4.01 | 3.68 |
| | >150 | | 2.55 | 4.44 | 5.14 |

# Minimize the Addition of Uncertainty

# Step #4

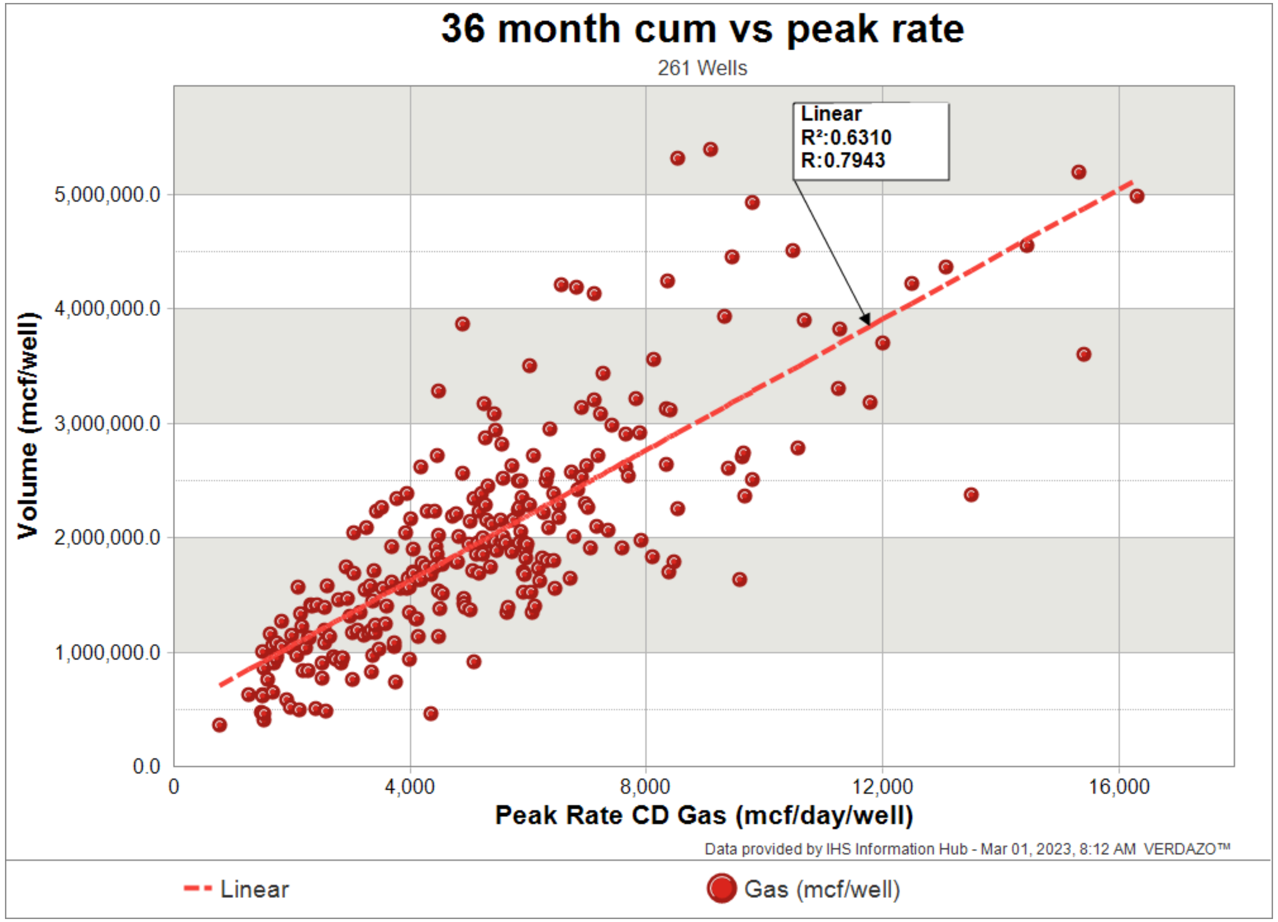
# What would you rather be?

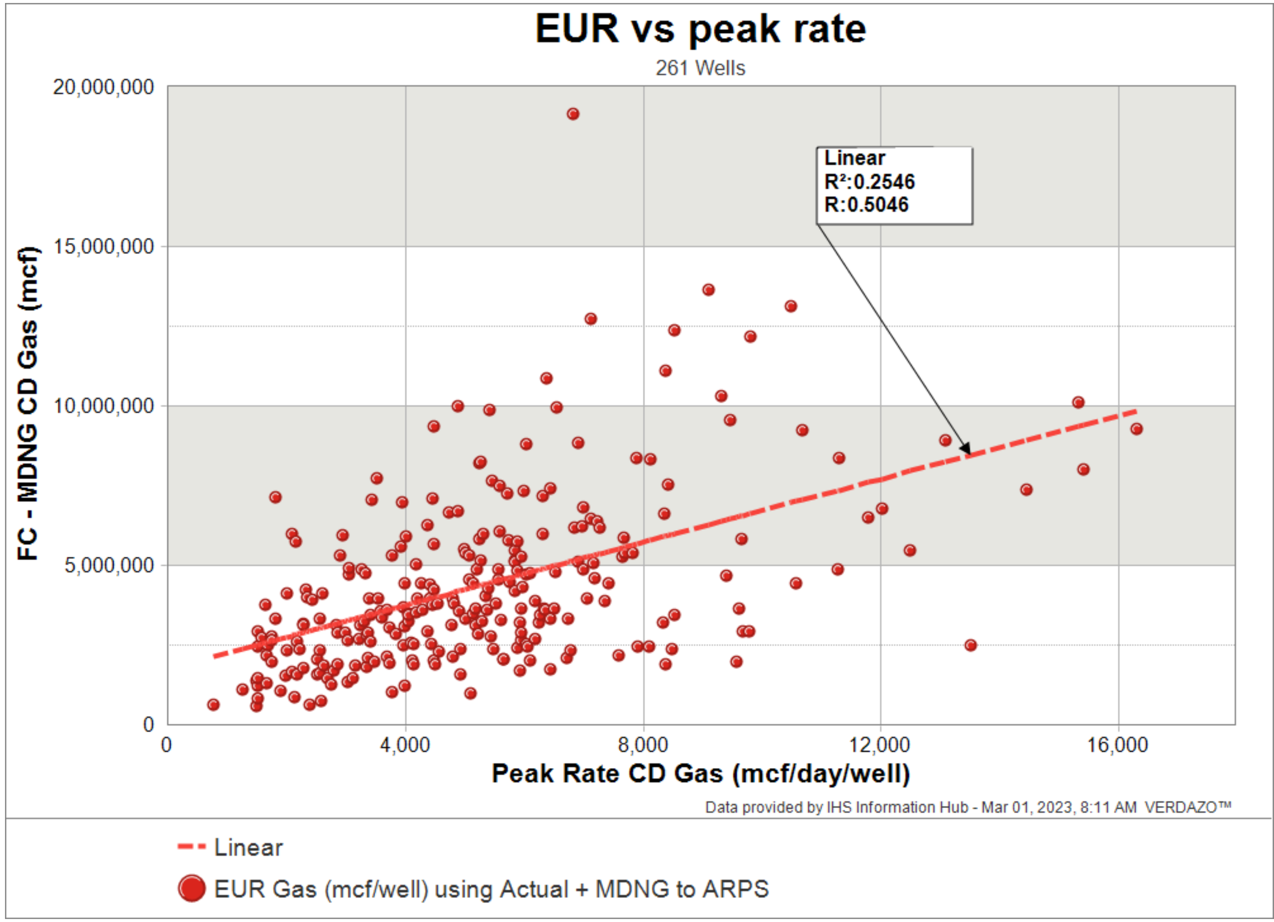
## Vaguely Correct
- Quickly
- Inexpensively

## Precisely Wrong
- Slowly
- Expensively

- Increasing industry trend to sacrifice accuracy for speed.
- More options, more scenarios = faster assessments & more focused decisions
- Shorter value-focused approach better reflects near-term price sensitivities

# Less Uncertainty in Shorter Forecasts



# 3-year discounted cashflow better reflects near term risk-exposure

**1) 3yr DCF = discounted cashflow using a 3-year production forecast**

- Fast & arguably good enough for screening options & estimating risk-exposure
- Less data is forecasted = more data in the type curve will be based on production history
- Introduces uncertainty & risk to a broader, & less technical, audience

**2) EUR DCF = Full EUR type curve & run discounted economics using Monte Carlo simulation**

- Modeling all input uncertainties is more resource intensive, complex & robust.
- More data is forecasted = widening effect on Trumpet Curve bands (discussed later)

Check out SPE-185053-MS Building Type Wells for Appraisal of Unconventional Resource Plays (Miller, Frechette & Kellett)

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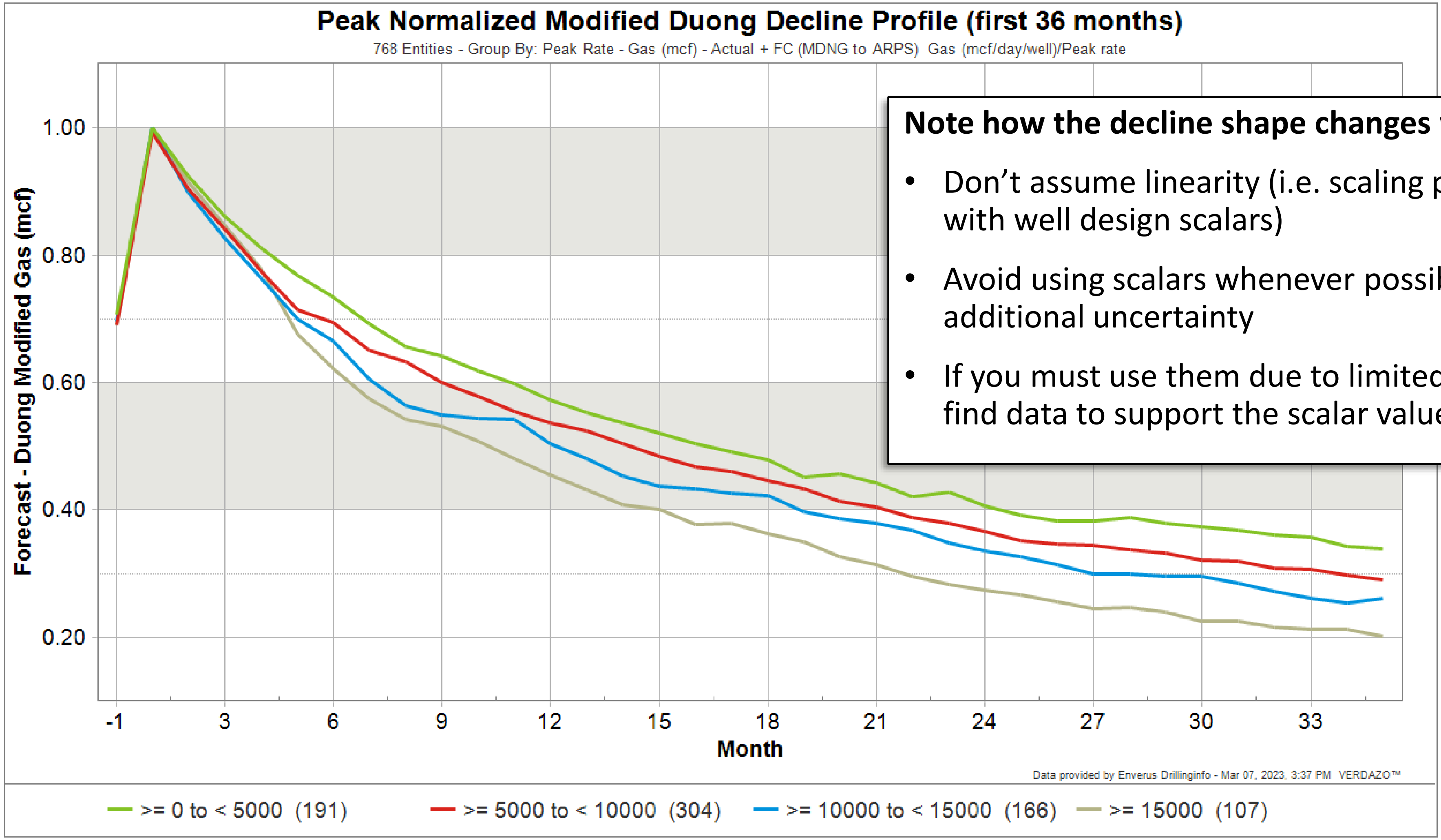
**Suggested approach:**

a) Run several options at different price scenarios using 3yr DCF to identify candidate options within your risk tolerance.
b) Then run EUR DCF on those candidate options for a fuller understanding of possible production & value outcomes.

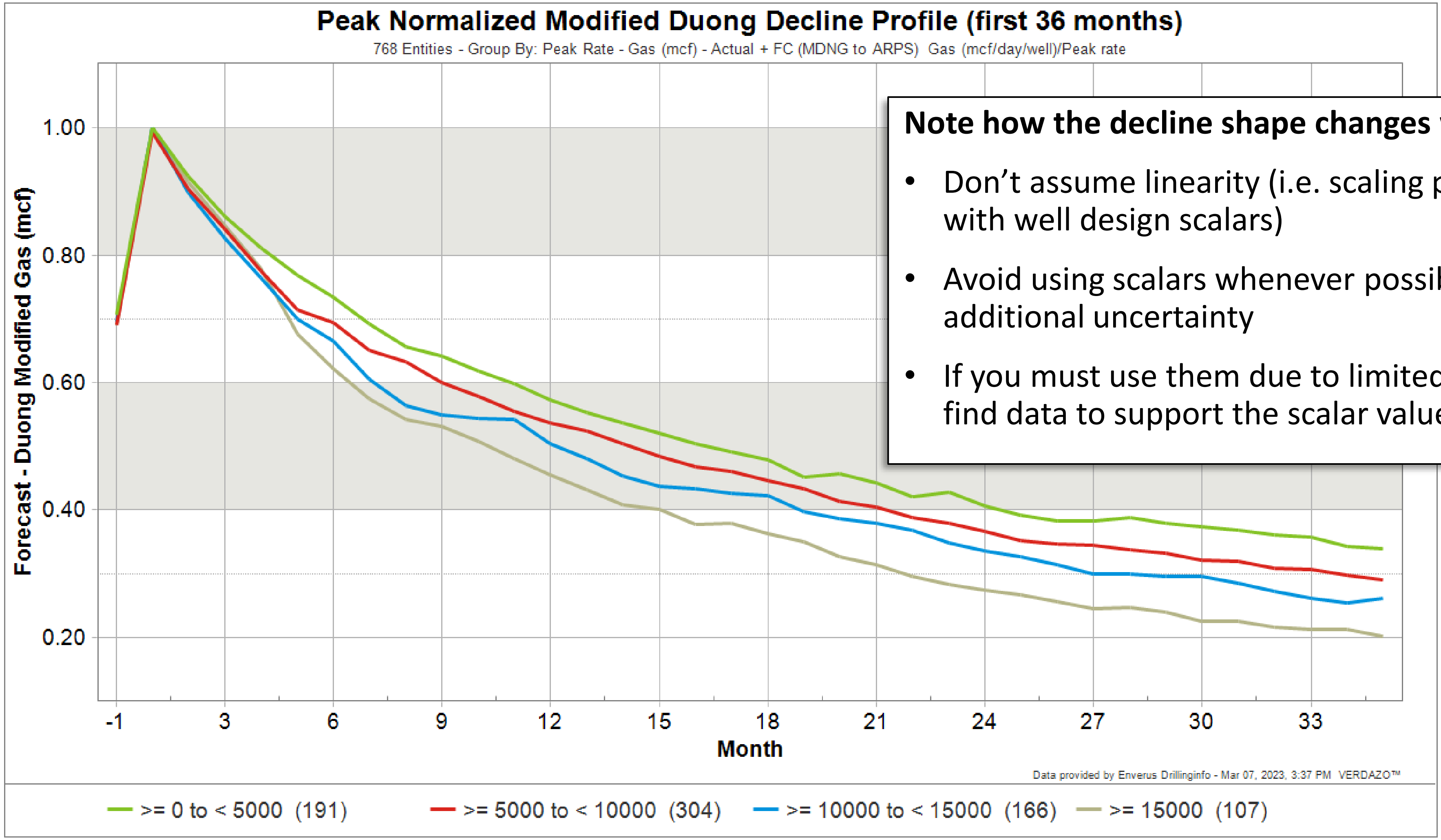
# Assumptions of Linearity = More Uncertainty




**Note how the decline shape changes with peak rate.**

- Don't assume linearity (i.e. scaling production type curves with well design scalars)
- Avoid using scalars whenever possible… scalars introduce additional uncertainty
- If you must use them due to limited analogue well counts, find data to support the scalar value used

# Assumptions of Linearity = More Uncertainty

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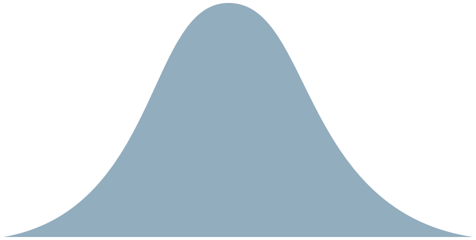
# Test Downside Scenarios using Aggregation

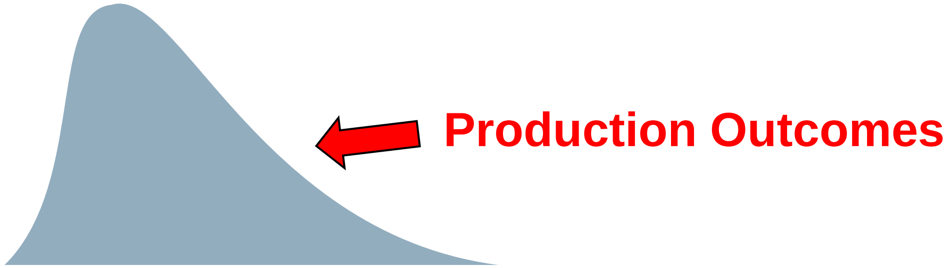
to help protect against risk-exposure

# Step #5

# Central Limit Theorem

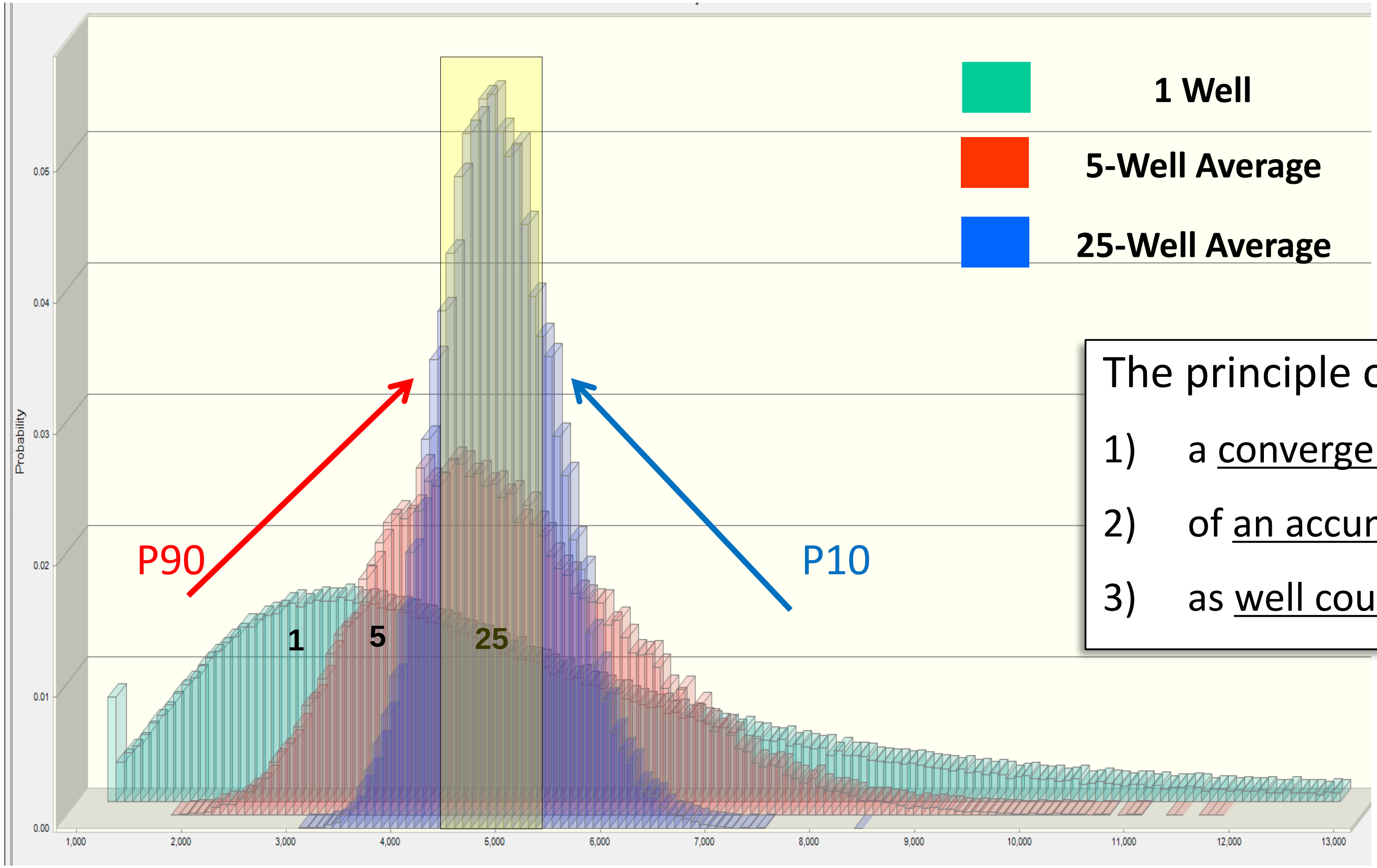


**SUM** of independent random variables yields a **NORMAL DISTRIBUTION**




**PRODUCT** of independent random variables yields a **LOGNORMAL DISTRIBUTION**

# Aggregation 101



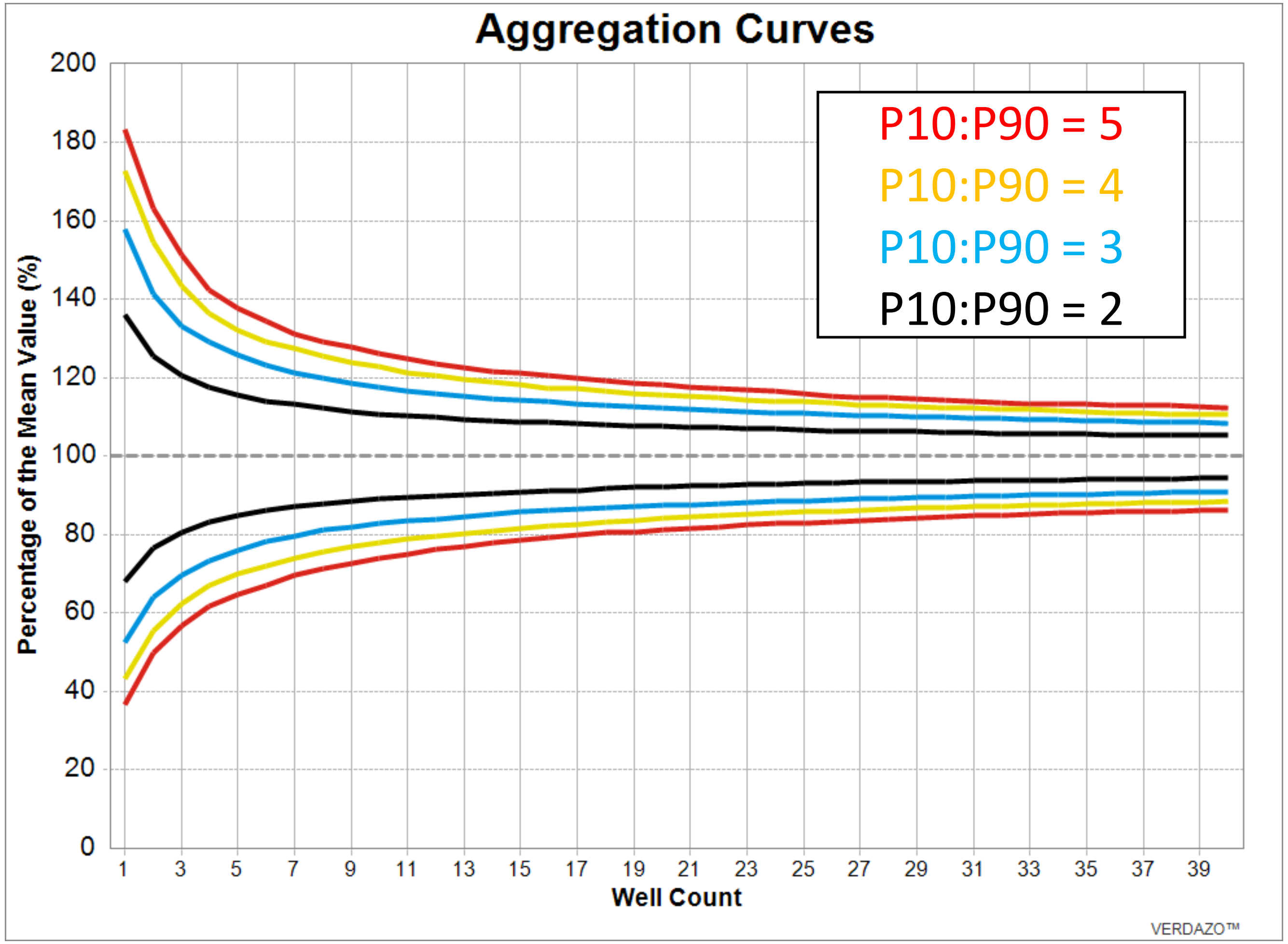

EUR – MMSCF

The principle of aggregation can be thought of as:

1) a convergence towards the mean
2) of an accumulating average
3) as well count increases

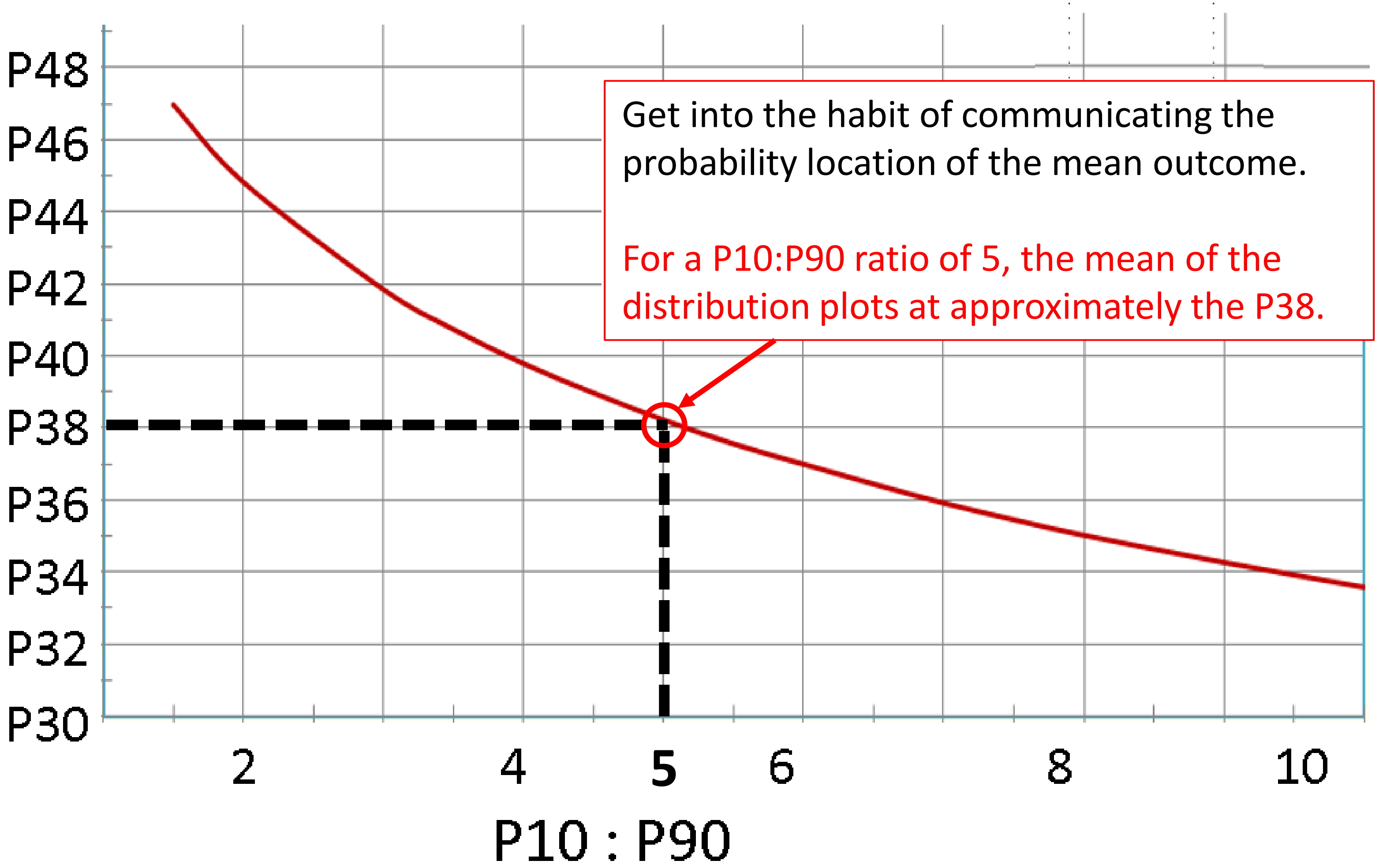
**SPE-175527-MS Figure 9 - Aggregating EURs with a P10:P90 ratio of 4**
**Validating Analog Production Type Curves for Resource Plays (**Mark McLane, and Jim Gouveia)

# Aggregation (Trumpet) Curves




- Trumpet plots show the P10 and P90 probability bounds (i.e. the 80% probability bounds)
- Y-axis is the variability in outcomes expressed as a percentage of the Mean of your dataset for a given well count (X-axis)
- The 80% probability bands get wider as the P10:P90 ratio of your dataset increases
- The 80% probability bands (of the accumulated mean) converge as well count (X-axis) increases

# Percentile Location of the Mean vs P10:P90 Ratio

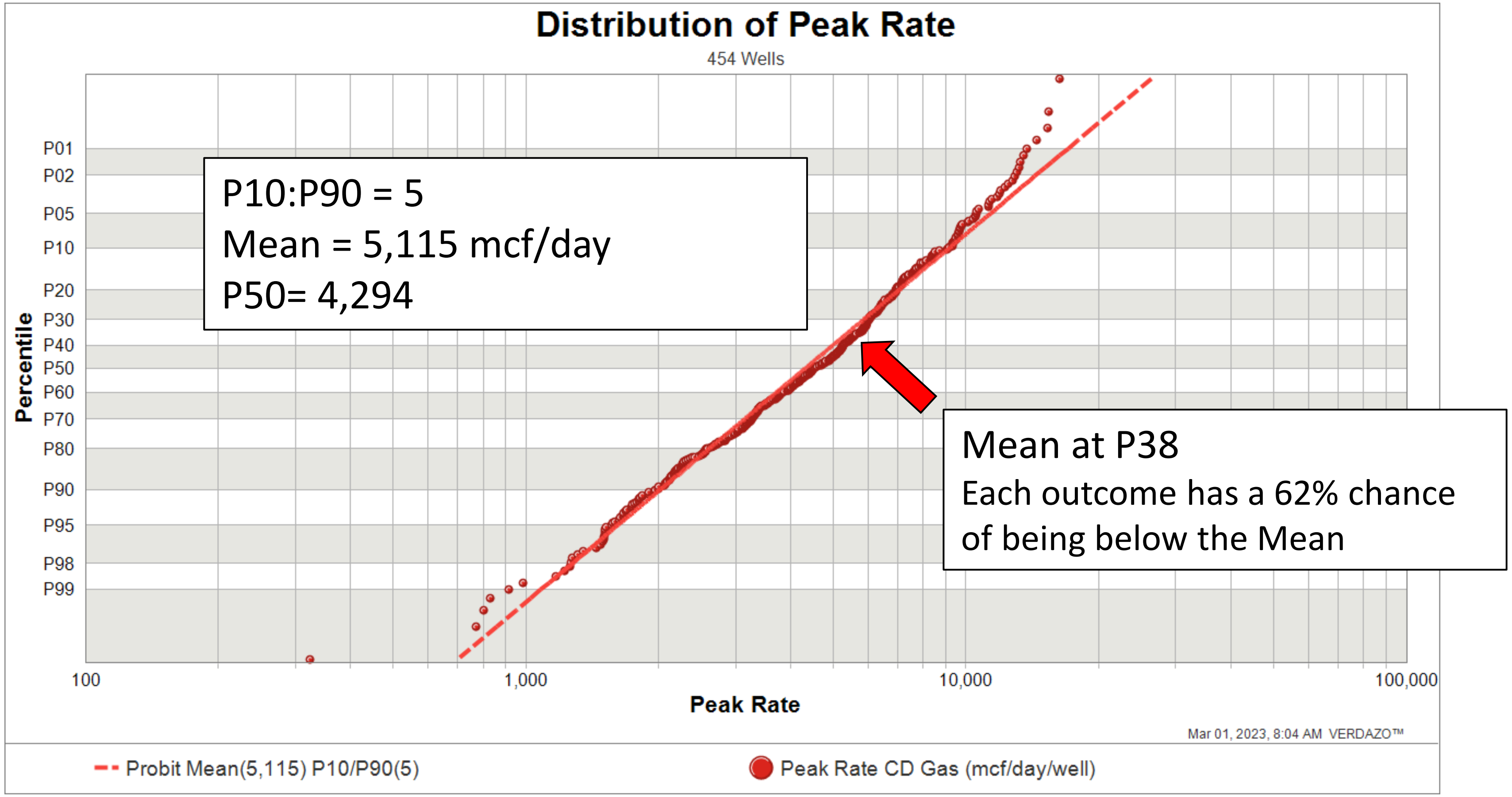



Get into the habit of communicating the probability location of the mean outcome.

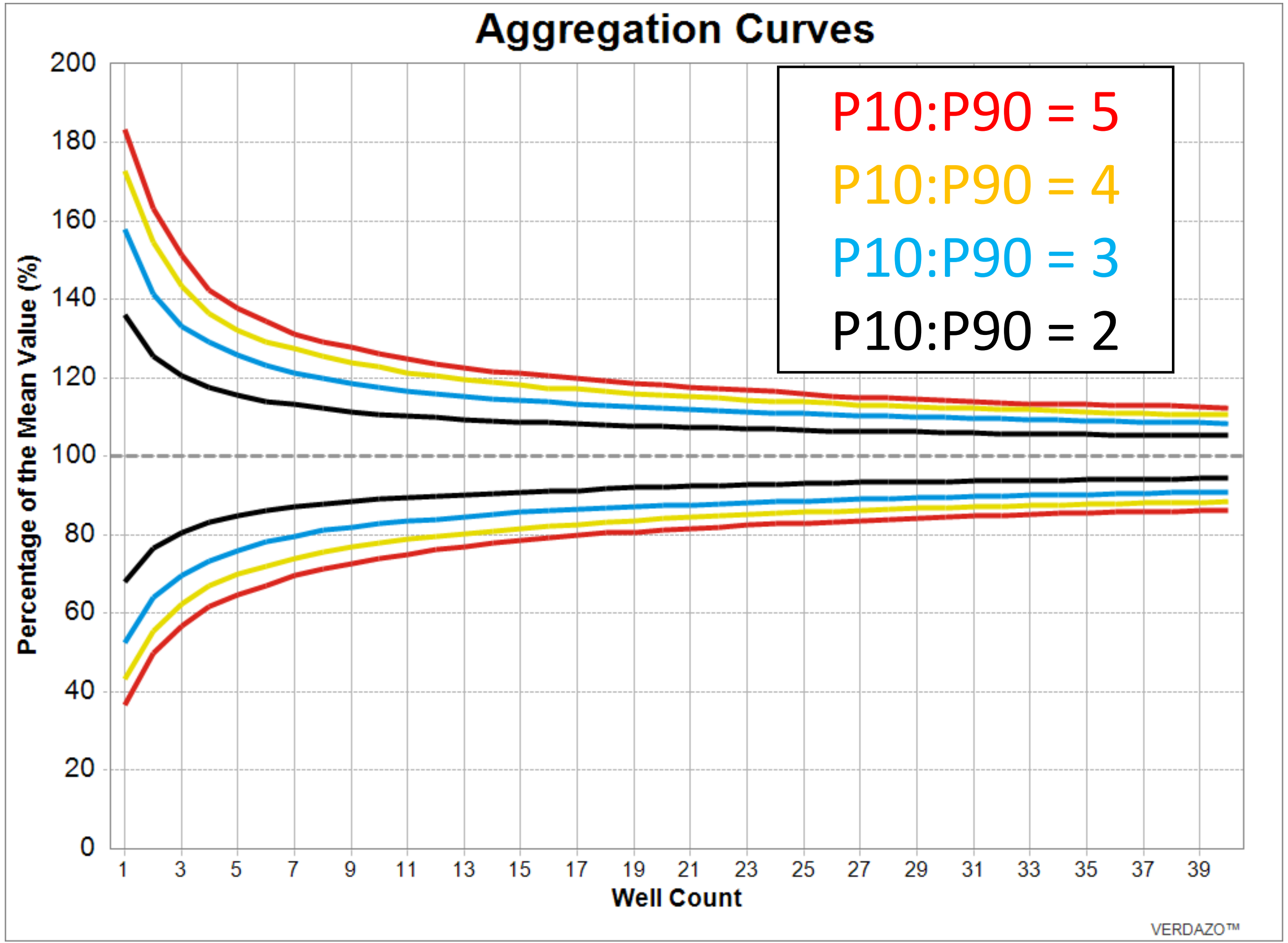
For a P10:P90 ratio of 5, the mean of the distribution plots at approximately the P38.

# Example: Distribution of Peak Rate P10:P90 = 5

Each well has a 62% chance of being less than the mean



# Aggregation Downside Mean Workflow



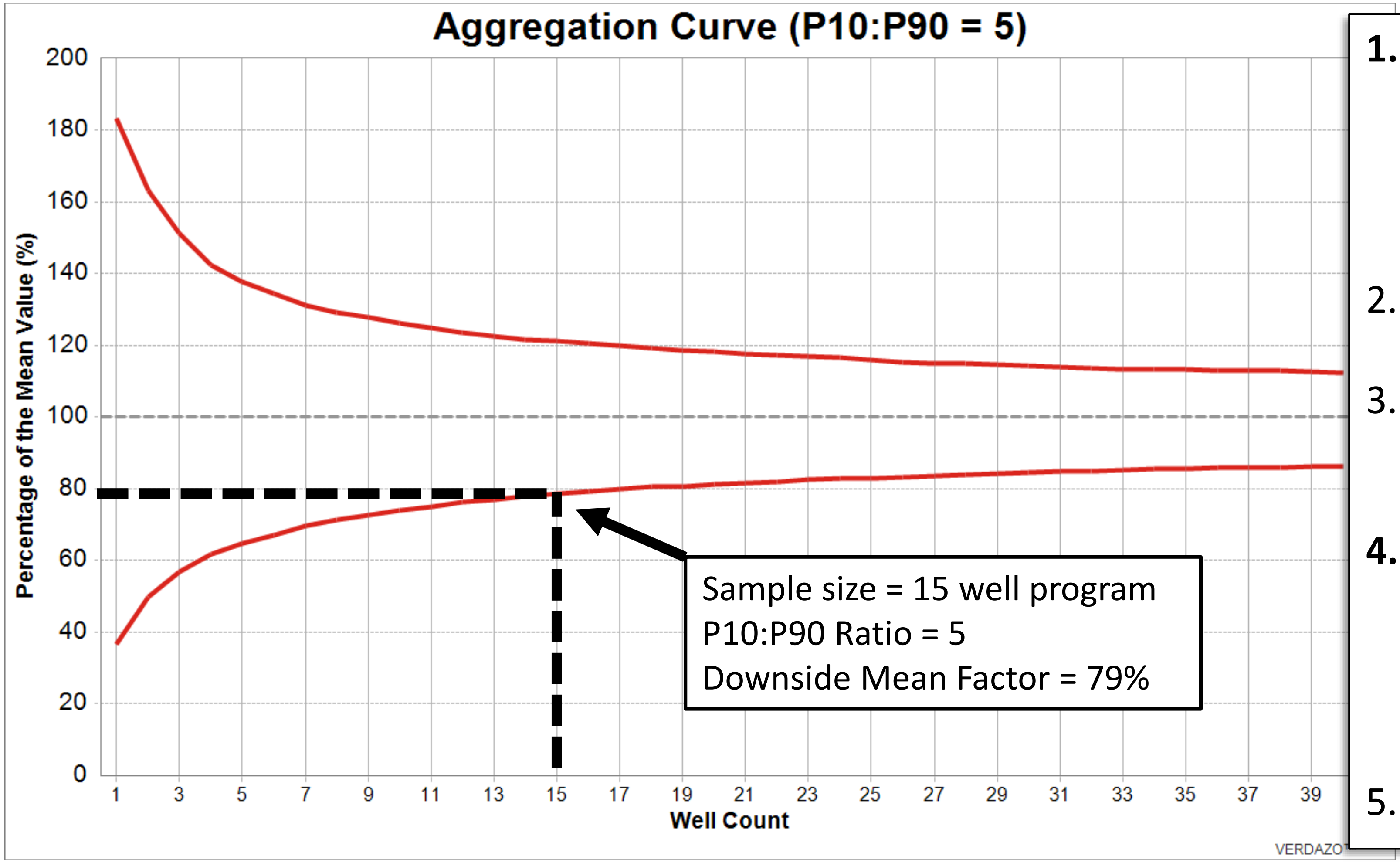

1. I have a known reliable analogue **Mean** and P10:P90 ratio (based on a statistically significant analogue sample set).

2. Downside (Program Arithmetic) Mean is the mean that you have a 90% chance of achieving or exceeding given the **number of wells you're drilling**.

3. Find the count of wells to be drilled on the X-axis for the P10:P90 ratio Trumpet Curves of your sample set and determine the **Downside Mean Factor** on the Y-axis.

4. Multiply your analogue Mean by the Percentage on the Y-axis to get your **Downside Mean**.

# Example: 15 well program with P10:P90 = 5




1. **<u>Mean</u>** of my data set = Peak Rate of 5,115 mcf/day, with a **P10:90 = 5**. Each independent outcome has a 62% chance of being less than the mean.

2. I'm drilling **<u>15 wells</u>**.

3. Locate the **<u>Downside Mean Factor</u>** = 79%

4. **Calculate the <u>Downside Mean</u>**
   = 5,115 x 79% = 4,041 mcf/day (90% chance of the accumulated mean of 15 wells being >= this value)

5. Test Downside Mean for **risk-exposure**

# Forecasting Introduces More Uncertainty

Widening Effect due to Model Bias results from:

- Higher correlation between individual results
- Uncertainty of decline parameters

(check out SPE-201556-MS Appropriately Characterizing Uncertainty in Estimated Ultimate Recovery for Unconventional Type Wells)

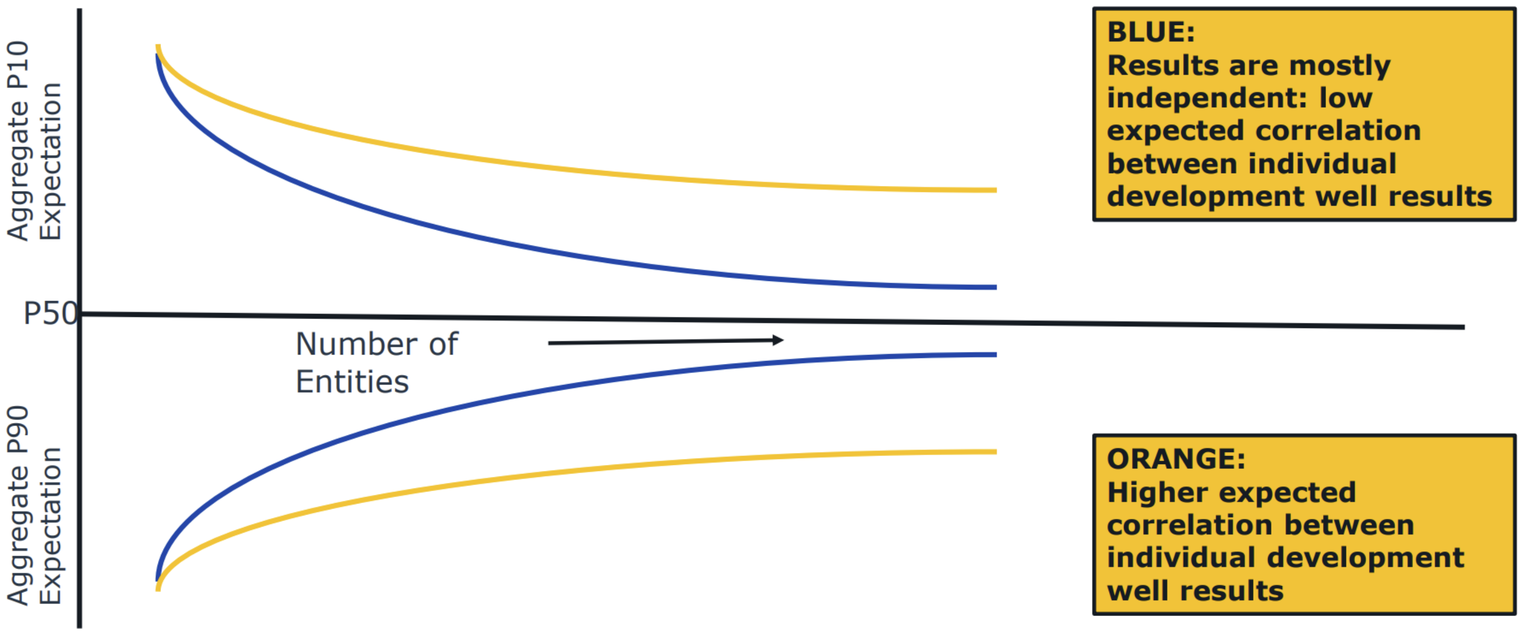



Image courtesy of Tyler Schlosser

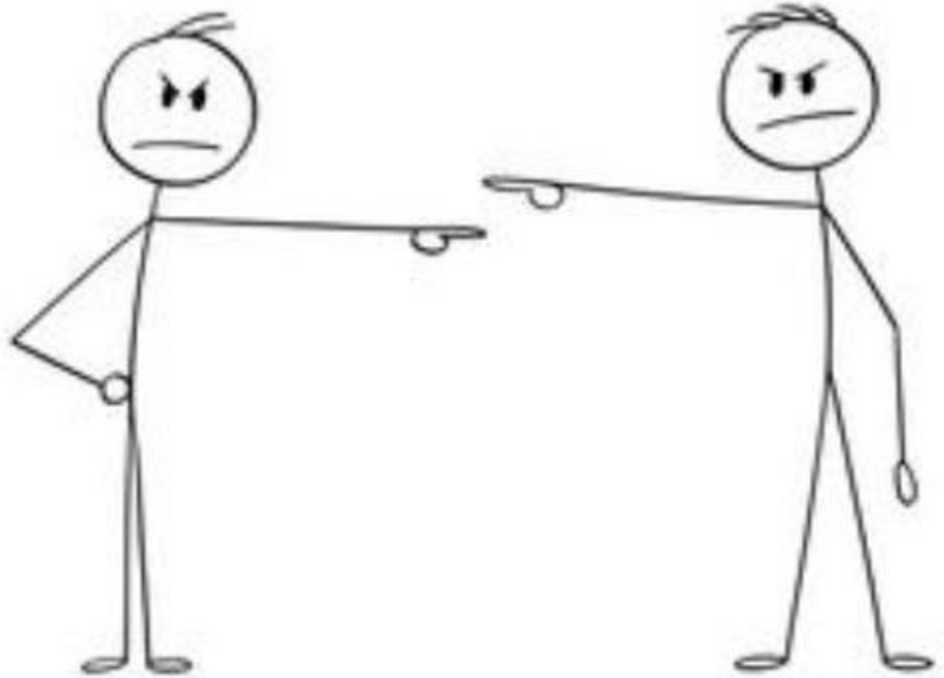
# Monitor & Update Data

data quality refinement

# Step #6

# Data Quality Refinement

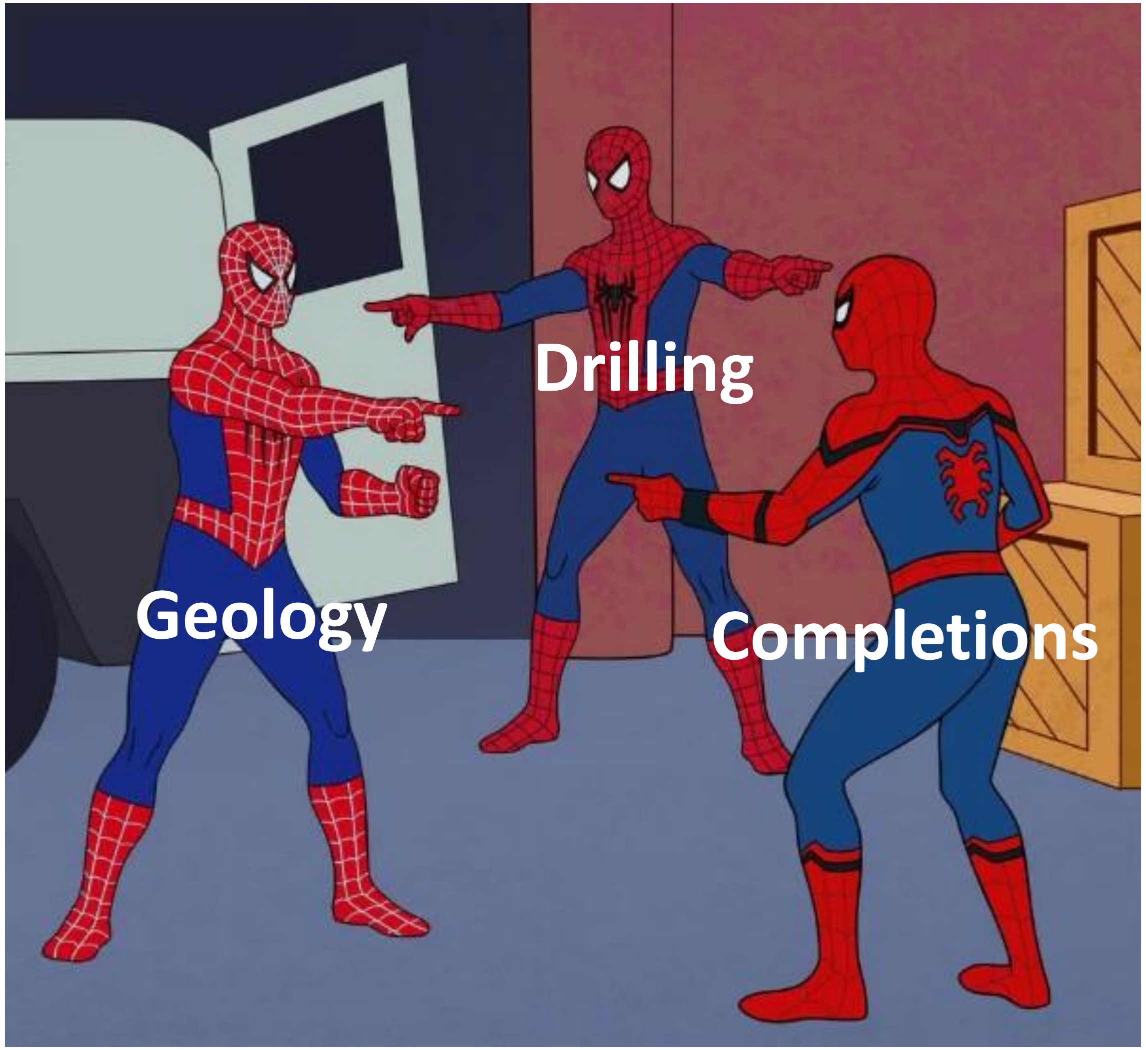
(collaboration & peer reviews)



**Geologist** **Completion Engineer**

# Data Quality Refinement

(collaboration & peer reviews)



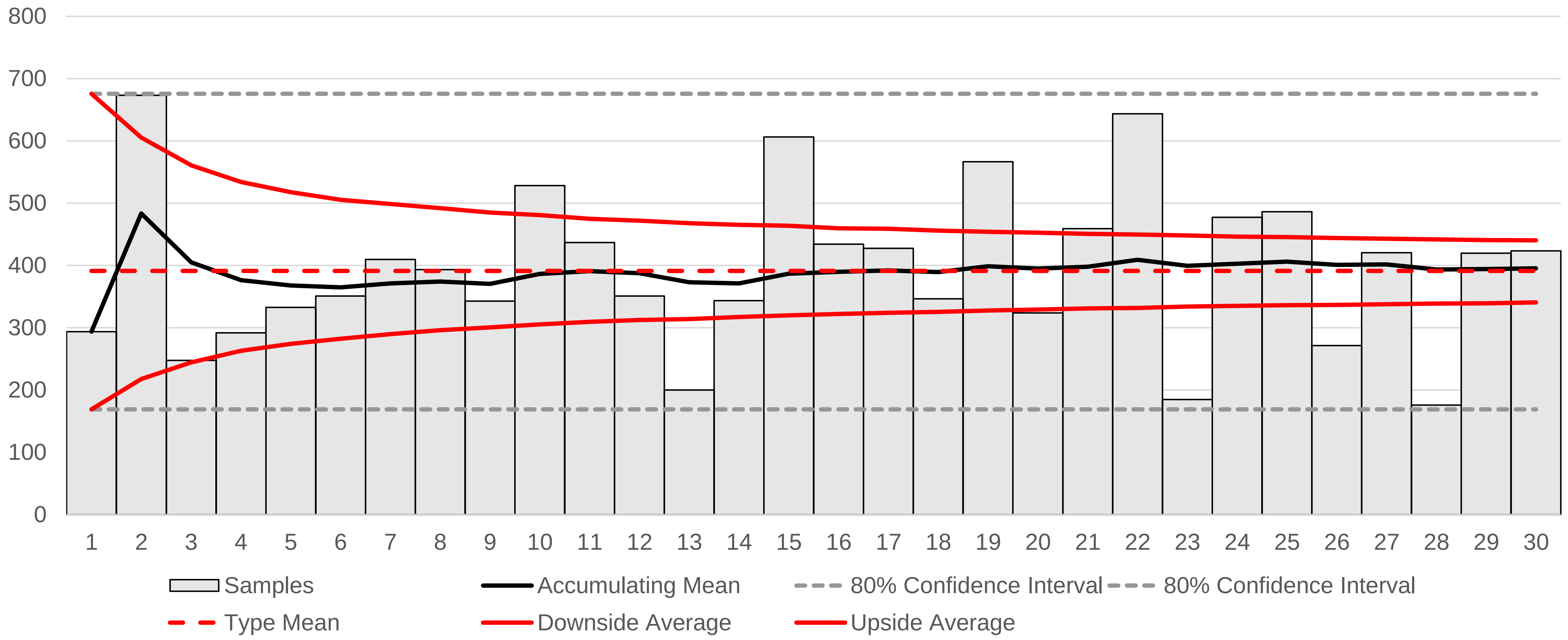
# Sequential accumulation plots for performance tracking

1) Show the accumulating mean values of well production outcomes in the context of the Trumpet plots

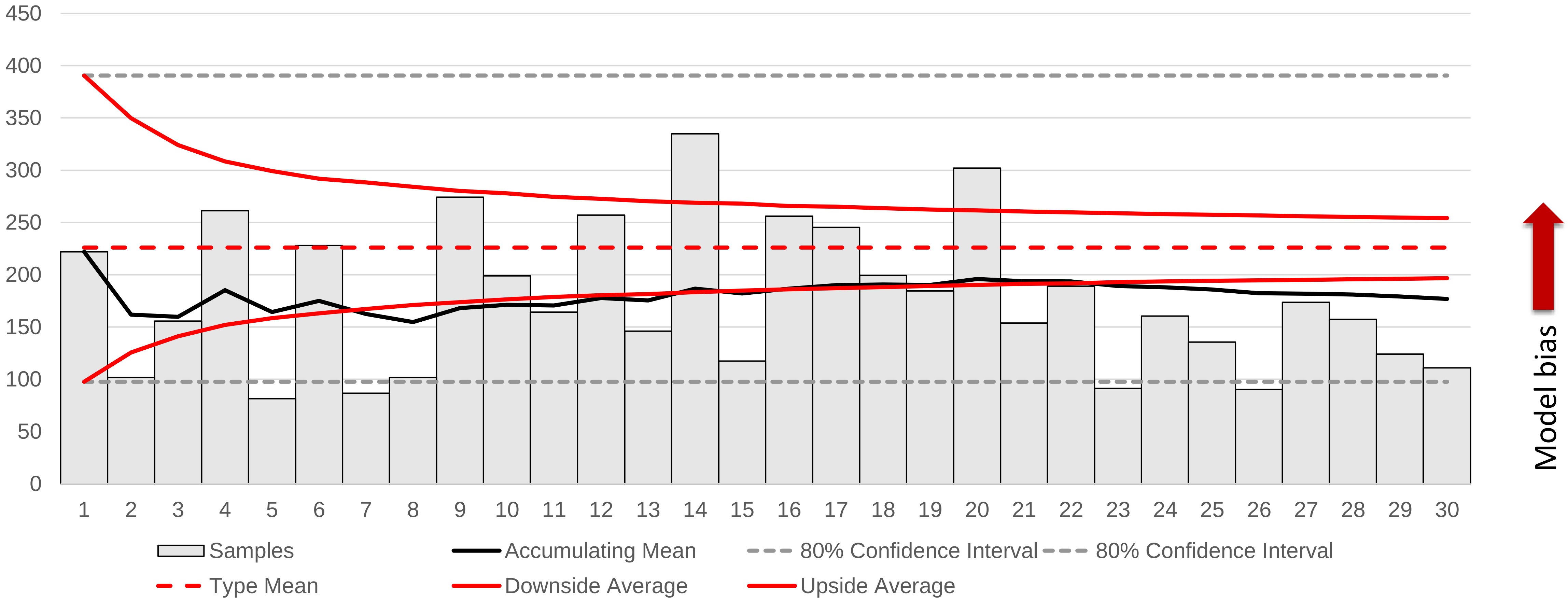
2) Most use an **early production measure** (how well does this correlate to long term production?)

3) Reveals how a program is tracking as well-count increases sequentially

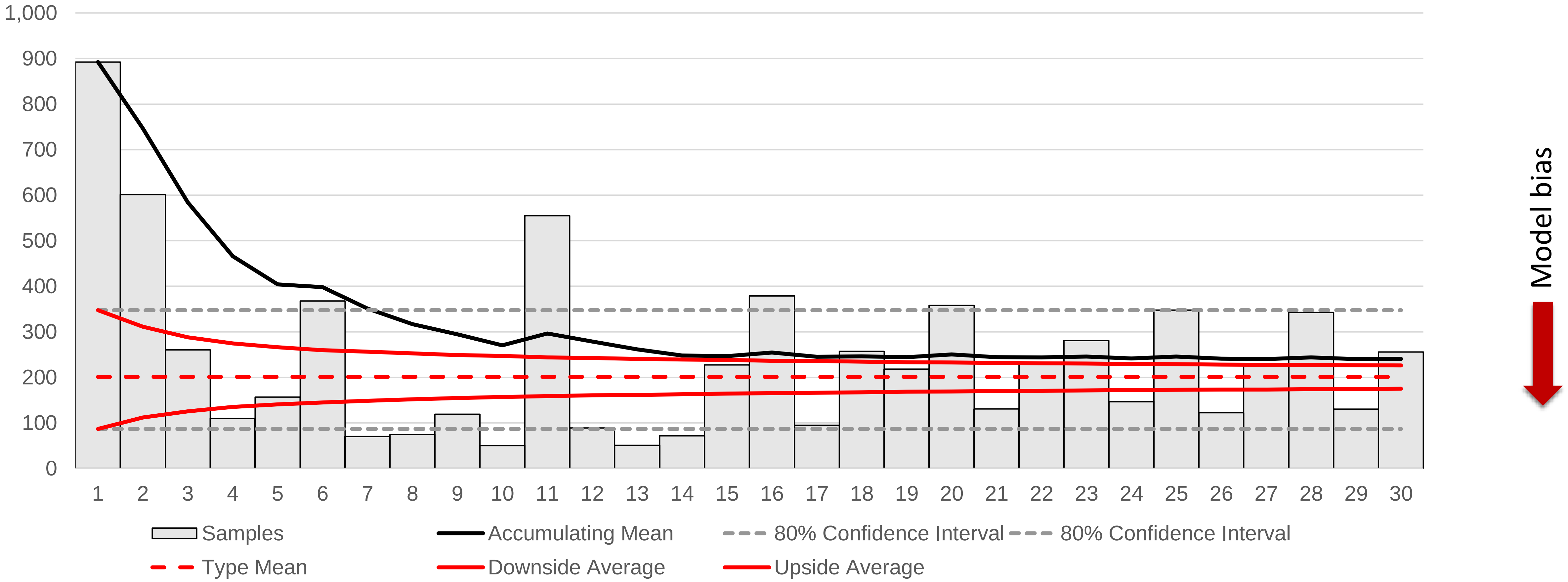
# Sequential Accumulation (good)



# Sequential Accumulation (not so good)



# Sequential Accumulation (better than expected)



# But wait! → This was early production focused

- These Sequential Accumulation plots allowed us to monitor how a program was tracking to expectations & established uncertainty for an early production performance measure.
- What are my best early production measures to use? (see next slide)
- How can I track forecasted production (and value) with limited early production data? (see Peak-Normalized Type Curve slides…)

# Early Production Correlations to EUR

I'll be using Peak in the example coming up

## Analysis of Production Measure Correlations to EUR for 4 Plays

| | | Montney (Gas) | | | | Cardium (Oil) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Data Set 1 | | Data Set 2 | | Data Set 1 | | Data Set 2 | |
| | | Correlation % | Well Count | Correlation % | Well Count | Correlation % | Well Count | Correlation % | Well Count |
| | PD Rate (month 1) | 10.6 | 585 | 18.9 | 227 | 33.8 | 1592 | 37.7 | 769 |
| | PD Rate (month 1-2) | 21.0 | 584 | 29.9 | 226 | 42.3 | 1592 | 49.9 | 769 |
| | PD Rate (month 1-3) | 31.2 | 583 | 36.7 | 225 | 48.1 | 1592 | 58.0 | 769 |
| | Peak | 60.0 | 585 | 50.6 | 227 | 53.5 | 1592 | 67.0 | 769 |
| | IP30 | 32.6 | 585 | 39.3 | 227 | 44.4 | 1574 | 56.2 | 769 |
| | IP60 | 42.7 | 585 | 45.2 | 227 | 54.8 | 1573 | 68.6 | 769 |
| | IP90 | 49.2 | 585 | 49.9 | 227 | 60.8 | 1573 | 74.2 | 769 |
| | IP180 | 60.8 | 576 | 62.0 | 227 | 70.0 | 1561 | 80.7 | 769 |
| | IP365 | 72.4 | 576 | 74.9 | 227 | 79.9 | 1561 | 86.1 | 769 |
| Condensed Data | 3 Month Cum | 23.2 | 585 | 19.4 | 227 | 46.9 | 1592 | 60.2 | 769 |
| Condensed Data | 6 Month Cum | 49.3 | 585 | 45.1 | 227 | 65.4 | 1592 | 76.6 | 769 |
| Condensed Data | 12 Month Cum | 67.1 | 523 | 67.0 | 227 | 77.6 | 1524 | 84.8 | 769 |
| Condensed Data | 18 Month Cum | 75.4 | 473 | 76.1 | 227 | 82.9 | 1357 | 88.7 | 769 |
| Condensed Data | 24 Month Cum | 79.7 | 377 | 81.6 | 227 | 86.7 | 1233 | 91.1 | 769 |
| Condensed Data | 30 Month Cum | 83.5 | 287 | 85.1 | 227 | 90.3 | 966 | 92.8 | 769 |
| Condensed Data | 36 Month Cum | 87.5 | 227 | 87.5 | 227 | 94.1 | 769 | 94.1 | 769 |
| Non-condensed Data | 3 Month Cum | 16.4 | 585 | 8.9 | 227 | 43.8 | 1592 | 57.1 | 769 |
| Non-condensed Data | 6 Month Cum | 40.3 | 585 | 30.5 | 227 | 63.8 | 1592 | 74.0 | 769 |
| Non-condensed Data | 12 Month Cum | 59.5 | 523 | 56.2 | 227 | 77.3 | 1524 | 84.5 | 769 |
| Non-condensed Data | 18 Month Cum | 71.5 | 473 | 70.5 | 227 | 82.9 | 1357 | 88.6 | 769 |
| Non-condensed Data | 24 Month Cum | 77.5 | 377 | 78.4 | 227 | 86.7 | 1233 | 91.0 | 769 |
| Non-condensed Data | 30 Month Cum | 82.0 | 287 | 83.5 | 227 | 90.2 | 966 | 92.7 | 769 |
| Non-condensed Data | 36 Month Cum | 86.4 | 227 | 86.4 | 227 | 94.1 | 769 | 94.1 | 769 |

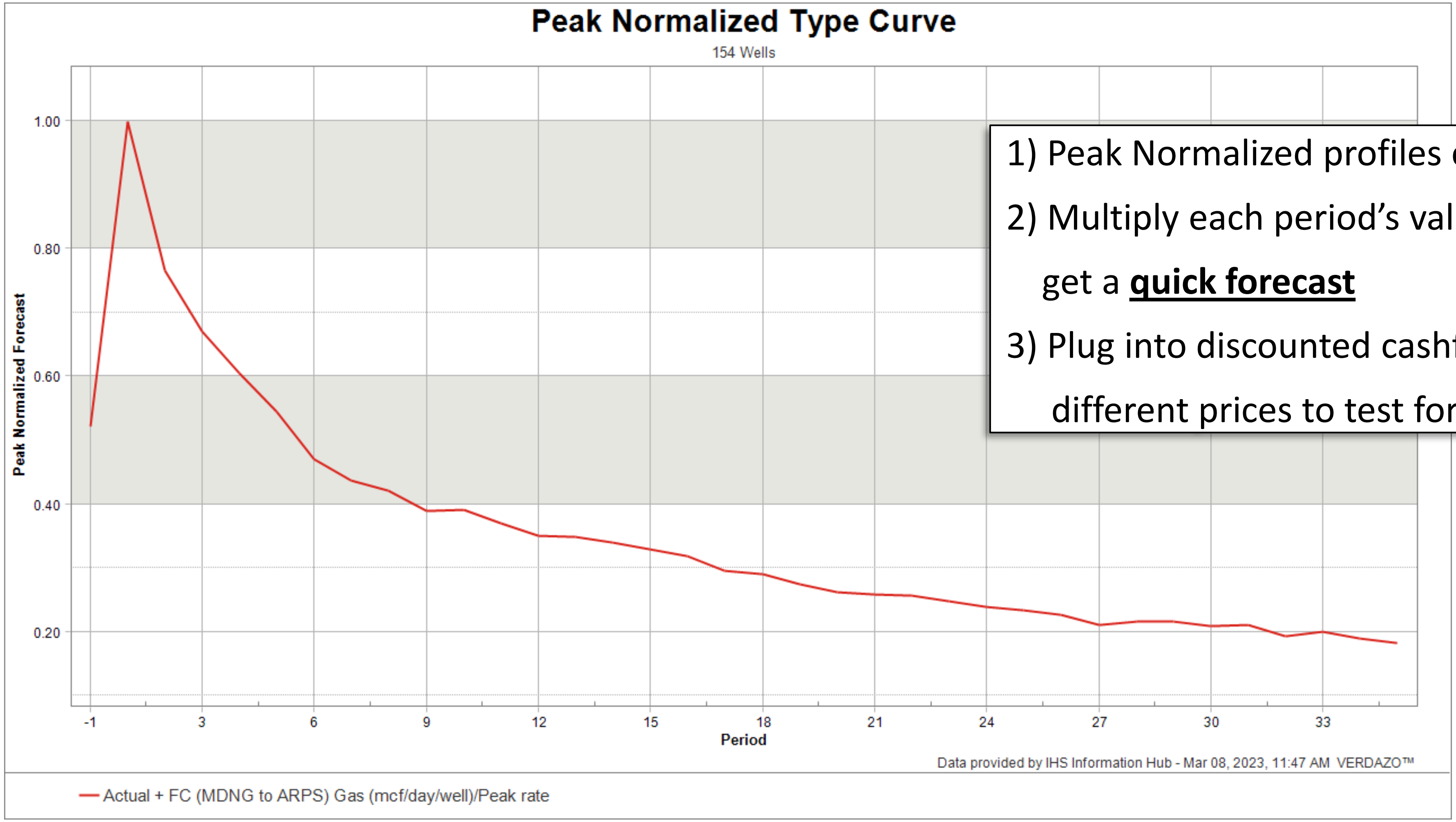
| | | Viking (Oil) | | | | Bakken (Oil) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Data Set 1 | | Data Set 2 | | Data Set 1 | | Data Set 2 | |
| | | Correlation % | Well Count | Correlation % | Well Count | Correlation % | Well Count | Correlation % | Well Count |
| | PD Rate (month 1) | 21.8 | 3098 | 19.5 | 818 | 30.1 | 1387 | 30.0 | 991 |
| | PD Rate (month 1-2) | 28.6 | 3098 | 35.3 | 818 | 39.5 | 1387 | 38.9 | 991 |
| | PD Rate (month 1-3) | 33.4 | 3098 | 45.2 | 818 | 46.4 | 1387 | 45.1 | 991 |
| | Peak | 40.1 | 3098 | 65.1 | 818 | 61.3 | 1387 | 65.5 | 991 |
| | IP30 | 30.9 | 2999 | 52.3 | 818 | 44.8 | 1387 | 45.7 | 991 |
| | IP60 | 38.5 | 2999 | 59.7 | 818 | 51.3 | 1387 | 51.4 | 991 |
| | IP90 | 43.5 | 2999 | 64.0 | 818 | 56.5 | 1387 | 56.1 | 991 |
| | IP180 | 53.4 | 2994 | 71.0 | 818 | 66.6 | 1387 | 66.8 | 991 |
| | IP365 | 69.1 | 2994 | 79.0 | 818 | 77.5 | 1387 | 78.8 | 991 |
| Condensed Data | 3 Month Cum | 36.4 | 3098 | 58.9 | 818 | 52.2 | 1387 | 52.2 | 991 |
| Condensed Data | 6 Month Cum | 65.4 | 3098 | 70.0 | 818 | 65.0 | 1387 | 64.6 | 991 |
| Condensed Data | 12 Month Cum | 67.8 | 2563 | 77.9 | 818 | 76.5 | 1357 | 77.1 | 991 |
| Condensed Data | 18 Month Cum | 79.4 | 2002 | 82.4 | 818 | 82.3 | 1249 | 84.0 | 991 |
| Condensed Data | 24 Month Cum | 84.2 | 1551 | 85.3 | 818 | 88.6 | 1184 | 88.3 | 991 |
| Condensed Data | 30 Month Cum | 87.4 | 1125 | 87.5 | 818 | 91.1 | 1067 | 90.9 | 991 |
| Condensed Data | 36 Month Cum | 89.7 | 818 | 89.7 | 818 | 92.6 | 991 | 92.6 | 991 |
| Non-condensed Data | 3 Month Cum | 35.5 | 3098 | 56.1 | 818 | 51.6 | 1387 | 52.0 | 991 |
| Non-condensed Data | 6 Month Cum | 49.1 | 3098 | 64.6 | 818 | 63.8 | 1387 | 63.5 | 991 |
| Non-condensed Data | 12 Month Cum | 67.3 | 2563 | 76.9 | 818 | 76.2 | 1357 | 76.7 | 991 |
| Non-condensed Data | 18 Month Cum | 79.3 | 2002 | 82.3 | 818 | 82.1 | 1249 | 83.7 | 991 |
| Non-condensed Data | 24 Month Cum | 84.2 | 1551 | 85.3 | 818 | 88.4 | 1184 | 88.0 | 991 |
| Non-condensed Data | 30 Month Cum | 87.5 | 1125 | 87.6 | 818 | 90.9 | 1067 | 90.7 | 991 |
| Non-condensed Data | 36 Month Cum | 89.8 | 818 | 89.8 | 818 | 92.4 | 991 | 92.4 | 991 |

**Legend**

| | | |
|---|---|---|
| 86.4 | Green = Correlation between 70% and 100% | **Data Set 1** = wells with >80% correlation on Modified Duong fits for both "a" and "m" and >6 months production after peak |
| 59.5 | Yellow = Correlation between 50% and 70% | **Data Set 2** = subset of Data Set 1 where all wells have >=36 months production |
| 40.3 | Red = Correlation between 30% and 50% | |
| 16.4 | Grey = Correlation between 0% and 30% | Note: Sample sets include only horizontal wells. www.visageinfo.com |

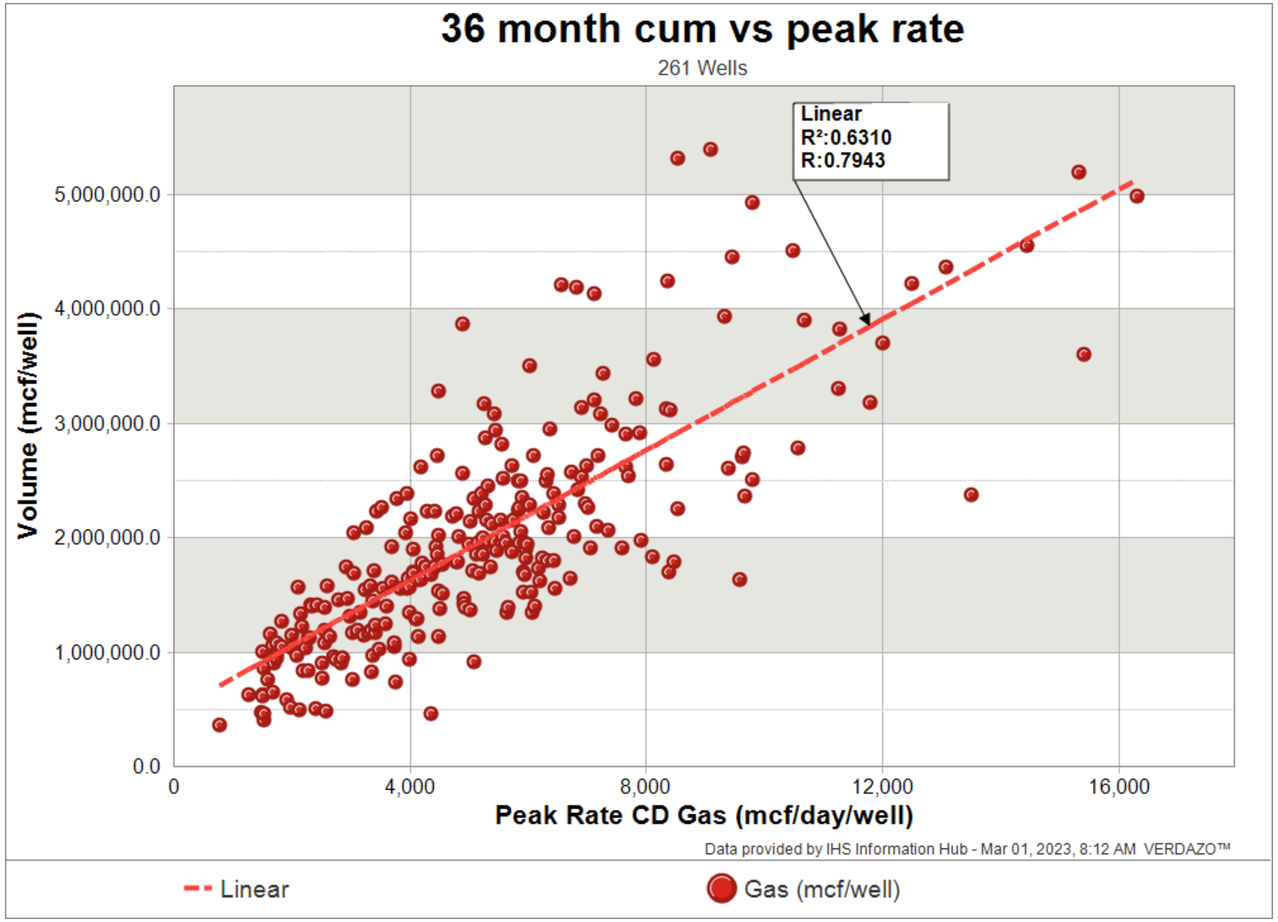
EUR calculation based on 240 month forecast using Modified Duong auto-forecast up to boundary dominated flow BDF), then transitioning to Arps for remainder of forecast.
Gas wells (Montney) used 60 months to BDF and a ***b*** value of 0.5 for Arps
Oil wells (Cardium, Viking and Bakken) used 48 months to BDF and a ***b*** value of 0.5 for Arps

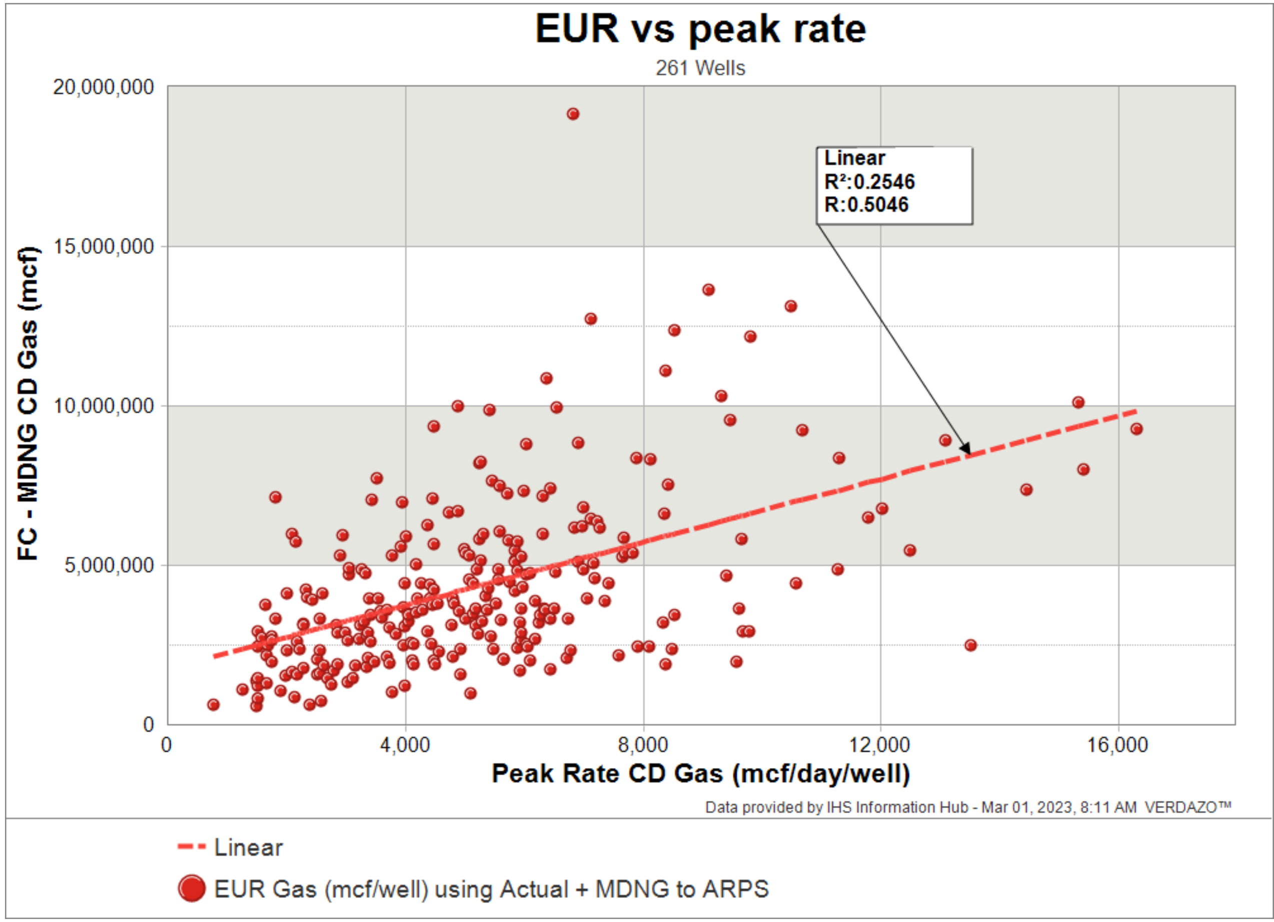
# Peak Normalized 36 Month Type Curve




1) Peak Normalized profiles convey decline shape.
2) Multiply each period's value by the Peak Rate to get a ***quick forecast***
3) Plug into discounted cashflow calculation at different prices to test for risk-exposure

# Less Uncertainty in Shorter Forecasts



# Decision Transparency

Show your work

# Step #7

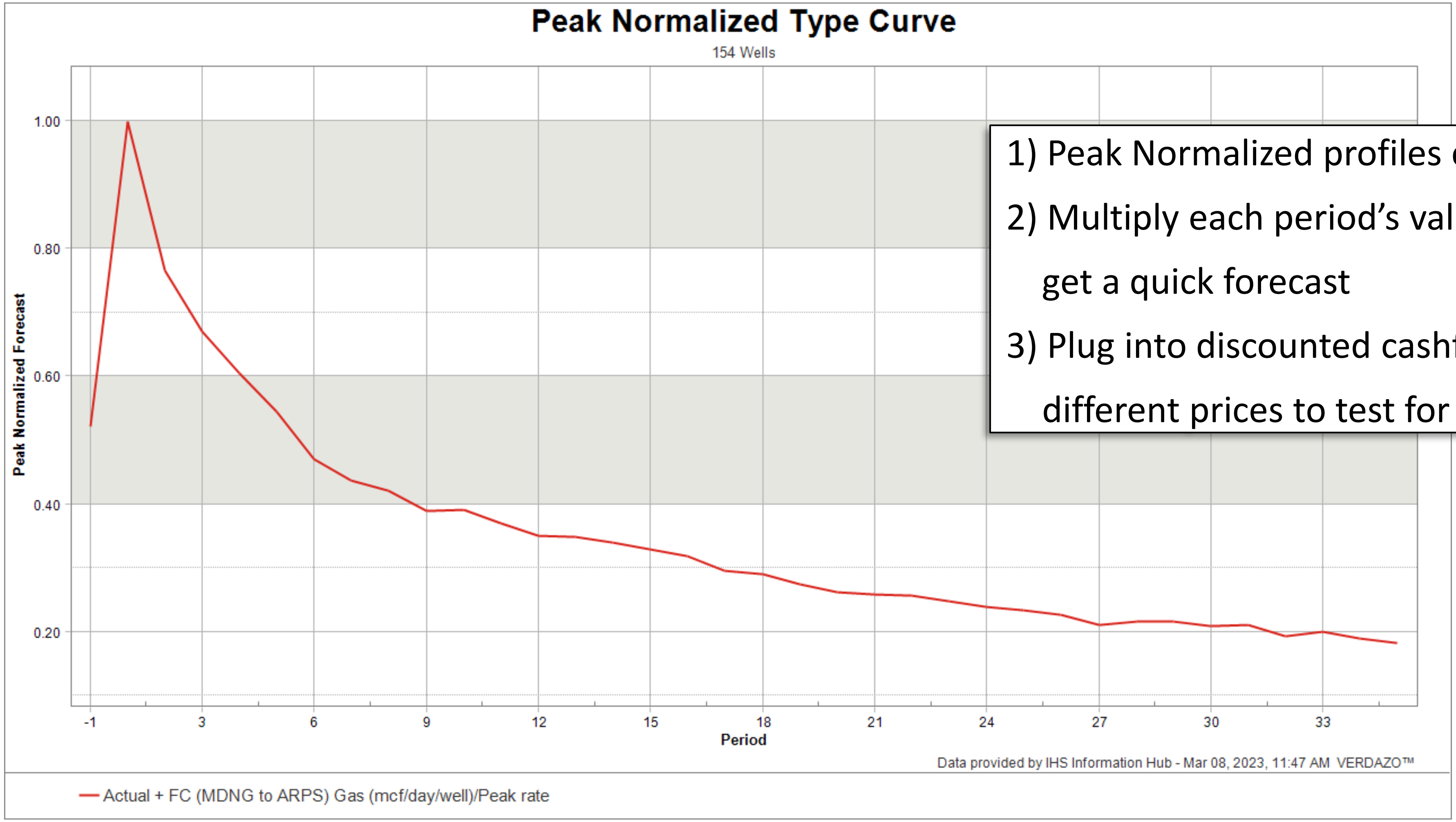
# Example: Decision Transparency in Risk Assessment

1) We have an analogue dataset with similar subsurface features
2) We have identified two well design options to assess
3) We have mean Peak values & P10:P90 ratios from each well design option's analogue set
4) Determine downside factors for each option based on program well count
5) We have a Peak Normalized type curve for 36 months
6) Calculate volume forecast (scale type curve to Peak and Downside Peak values of each option)
7) Test 36-month cashflow against different prices to assess risk-exposure

# Agile Risk Assessment Using Downside Mean

| | | Completion Option 1 | Completion Option 2 | |
|---|---|---|---|---|
| | Length | 1,400 | 1,400 | |
| | Proppant | 85 | 115 | 35% more proppant |
| | Frac Spacing | 50 | 50 | |
| | Cost ($ million) | 3.0 | 3.7 | $700K capital increase (23%) |
| | Operating Cost ($/mcf) | 1 | 1 | |
| | Peak (mcf/day) | **5,500** | **6,000** | 10% production increase |
| | Analogue Sample Size | 60 | 94 | |
| | P10:P90 | 3 | 5 | Note different P10:P90 |
| 12 well program | Downside Factor | 0.84 | 0.75 | |
| | Downside Peak | **4,620** | **4,500** | |

# Peak Normalized 36 Month Type Curve




1) Peak Normalized profiles convey decline shape.
2) Multiply each period's value by the Peak Rate to get a quick forecast
3) Plug into discounted cashflow calculation at different prices to test for risk-exposure

# Agile Risk Assessment Using Downside Mean

| Gas Price ($) | | Completion Option 1 | Completion Option 2 |
|---|---|---|---|
| | | 3 yr NPV10 $Million | |
| 2.00 | using peak rate | -1.14 | -1.68 |
| 2.00 | using downside peak rate | -1.44 | -2.18 |
| 3.00 | using peak rate | 0.71 | 0.35 |
| 3.00 | using downside peak rate | 0.12 | -0.66 |
| 4.00 | using peak rate | 2.56 | 2.37 |
| 4.00 | using downside peak rate | 1.68 | 0.85 |
| 5.00 | using peak rate | 4.42 | 4.39 |
| 5.00 | using downside peak rate | 3.23 | 2.37 |
| 6.00 | using peak rate | 6.27 | 6.42 |
| 6.00 | using downside peak rate | 4.79 | 3.89 |

While Option 2 yields 10% more production, it is more risk-exposed at prices below $4/mcf and has a lower downside discounted cashflow even at $6/mcf.

Option 1: Capital = 12 * $3 million = $36 million

Option 2: Capital = 12 * $3.7 million = $44.4 million

# Would your decision be different using a 20 year forecast?

| Gas Price ($) | | Completion Option 1 — 3 yr NPV10 $Million | Completion Option 2 — 3 yr NPV10 $Million | Completion Option 1 — 20 yr NPV10 $Million | Completion Option 2 — 20 yr NPV10 $Million |
|---|---|---|---|---|---|
| 2.00 | using peak rate | -1.14 | -1.68 | -0.17 | -0.62 |
| 2.00 | using downside peak rate | -1.44 | -2.18 | -0.63 | -1.39 |
| 3.00 | using peak rate | 0.71 | 0.35 | 2.65 | 2.47 |
| 3.00 | using downside peak rate | 0.12 | -0.66 | 1.75 | 0.93 |
| 4.00 | using peak rate | 2.56 | 2.37 | 5.48 | 5.55 |
| 4.00 | using downside peak rate | 1.68 | 0.85 | 4.13 | 3.24 |
| 5.00 | using peak rate | 4.42 | 4.39 | 8.31 | 8.63 |
| 5.00 | using downside peak rate | 3.23 | 2.37 | 6.5 | 5.55 |
| 6.00 | using peak rate | 6.27 | 6.42 | 11.13 | 11.72 |
| 6.00 | using downside peak rate | 4.79 | 3.89 | 8.87 | 7.86 |

| | bcf | |
|---|---|---|
| EUR using peak | 4.1 | 4.5 |
| EUR using downside peak rate | 3.4 | 3.4 |

While 3 yr NPV10 Option 2 yields 10% more production, it is more risk-exposed at prices below $4/mcf and has a lower downside discounted cashflow even at $6/mcf.

Option 1: Capital = 12 * $3 million = $36 million

Option 2: Capital = 12 * $3.7 million = $44.4 million

# Summary

What did we accomplish today?

1) Pragmatic way to measure uncertainty
2) Optimized analogue selection that is focused on impactful-features to reduce uncertainty
3) How to measure downside potential of production outcomes using Aggregation Curves
4) Benefits of using near-term, higher-confidence, production forecasts for value-driven decisions
5) An example of an Agile Risk Assessment process in action

# Conclusions

1) Including uncertainty & risk in decision making doesn't have to be a lot of extra work

2) Fast, less accurate, approaches can be an easy way to test scenarios for risk exposure

3) This supports devoting a stronger focus on options that warrant more robust assessments

# Including Uncertainty & Risk Analysis in Decision Making

1) **Don’t overwork the problem → keep it as simple as you can**
2) It doesn’t replace good engineers & geoscientists
3) It doesn’t eliminate risk → it helps you understand and manage it
4) It doesn’t replace good judgment → check assumptions & results for reasonability
5) Asset Teams must understand it → this requires staff “buy-in” and training
6) Success depends on management commitment

# References

## Papers

- SPE-201556-MS Appropriately Characterizing Uncertainty in Estimated Ultimate Recovery for Unconventional Type Wells (Miller, Dauncey & Gouveia)
- SPE-175527-MS Validating Analog Production Type Curves for Resource Plays (McLane & Gouveia)
- SPE-195811-MS Applying Decision Trees to Improve Decision Quality in Unconventional Resource Development (Miller & Gouveia)
- SPE-185053-MS Building Type Wells for Appraisal of Unconventional Resource Plays (Miller, Frechette & Kellett)
- SPE-185077-MS Multivariate Analysis Using Advanced Probabilistic Techniques for Completion Optimization (Groulx, Gouveia & Chenery)

## Presentations & Blogs

- Multivariate Analysis Using Advanced Probabilistic Techniques for Completion Optimization
- Understanding Type Curve Complexities and Analytic Techniques
- Uncertainty Considerations for Development Planning Type Curves
- IP90 and the Datasaurus: The dangers of summary statistics
- How useful are IP30, IP60, IP90 … initial production measures?

# 7 Steps to Minimize Uncertainty & Risk

1. Understanding Uncertainty
2. Improving the quality and quantity of data
3. Representativeness
4. Minimize the Addition of Uncertainty
5. Test Downside Scenarios using Aggregation
6. Monitor & Update Data
7. Decision Transparency

**Thank You!**

# Appendix: additional slides for reference

# Additional cautions & considerations

- Caution: assumptions of linearity in scalars
- Caution: inadequate consideration of operational (downtime) reality
- Consider: using broader analogue selection brackets to increase sample size (improves statistical power)

OMNIRA SOFTWARE

# Workflows to Minimize Uncertainty (and Risk) in Type Curve Development

**Bertrand Groulx, Omnira Software**