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Multivariate Analysis Using Advanced Probabilistic Techniques for Completion Optimization

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Agenda

1) Introduction (Multivariate Analysis)
2) Objective & Purpose of this Study
3) Hybrid Visual Approach
4) Parallel Coordinates Distribution Patterns
5) Input Optimization Distributions
6) Workflow
7) Studies
8) Conclusions

Introduction: Multivariate Analysis

Multivariate Analysis has evolved to include tools, techniques, technologies and workflows that include:

- **Regression analysis** (i.e. “black box” tools) provides predictive outcomes, often with limited supporting evidence, or supporting evidence that is difficult to understand.
- **Visual tools** that effectively communicate correlations/relationships on less complex data, but fail in increasingly complex data.
- **Correlation analysis** proves difficult on complex data as the correlations tend to be weak and vary over the full range of values.
- **Statistical methods** are unique in their ability to provide insights into non-continuous correlations where upper and lower thresholds exist, but are less effective at providing deterministic measures of an input’s effect on an outcome.

... but all of these are not without their dangers (see Multivariate Analysis: Completion Optimization’s Silver Bullet?)

Objective

- We looked outside oil & gas for visual multivariate analysis techniques that could be combined with the strengths of statistical techniques and deliver accessible, transparent insights.
- Our objective was to provide a visual methodology that could:
    - identify patterns of behavior.
    - fuel discovery through targeted investigations.
    - cultivate an understanding of a completion input parameter's impact on production performance.

Purpose of this Study

To develop a scalable and repeatable visual analysis approach that:

1) Uses statistical techniques that are readily accessible to a broad audience.
2) Offers data-driven statistical insights with visual nuances that can inform completion modelling first principles and advanced regression analysis.
3) Is suitable for small to very large datasets.
4) Is effective even when all inputs are not available for all wells.

Workflow

1) Selection of a performance measure set
2) Analogue well selection
3) Selection of numerical completion design input parameters
4) Parallel Coordinates Distributions (PCD): input parameter impact analysis
5) Evaluation of analogue fitness and subset selection
6) Input Optimization Distributions (IOD): input optimization process

Parallel Coordinates

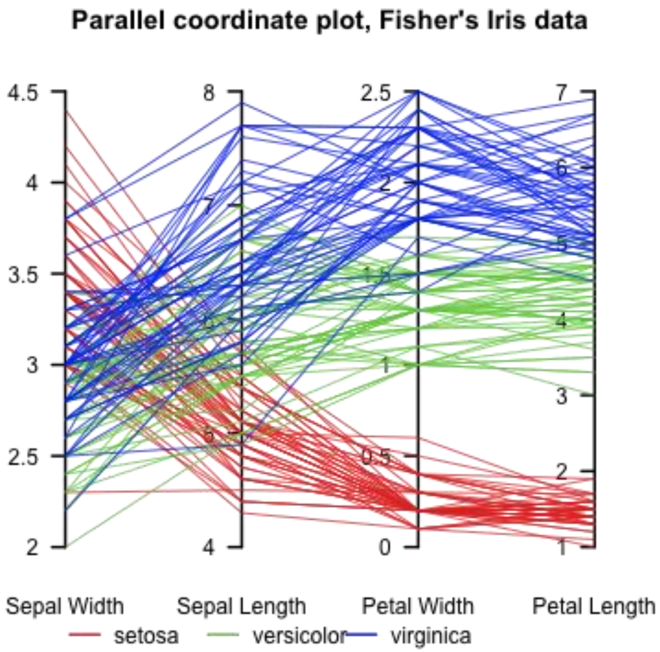


Figure 1

- **Parallel Coordinates** are a common way of visualizing high-dimensional geometry and analyzing multivariate data.
- Earliest documented uses in the late 1800's.
- Important applications are in collision avoidance algorithms (1987), process control, and more recently in intrusion detection.

Source: [Wikipedia]

Parallel Coordinates applied to Completion Analysis

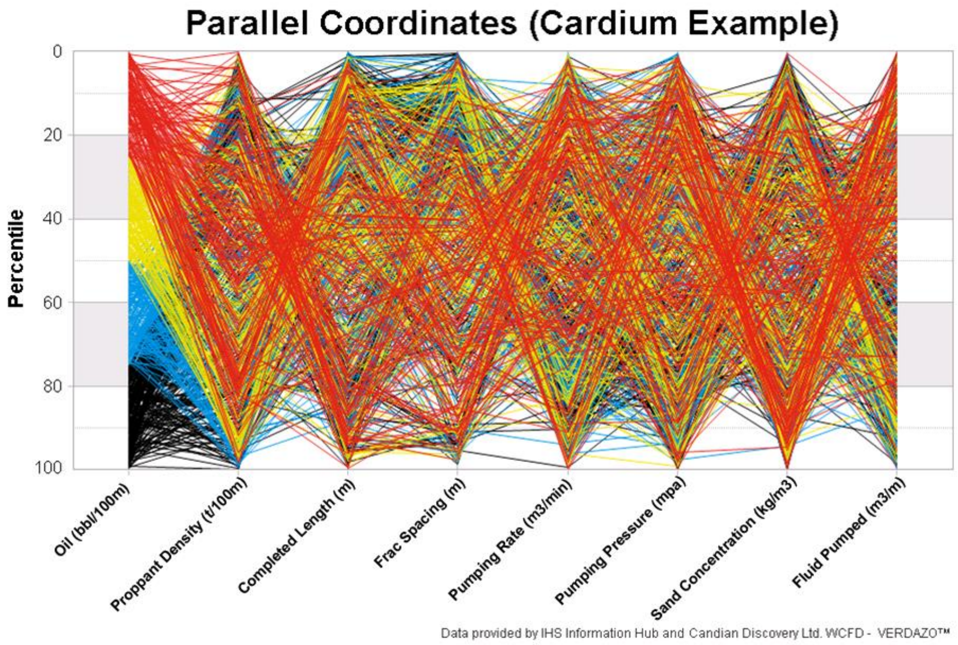
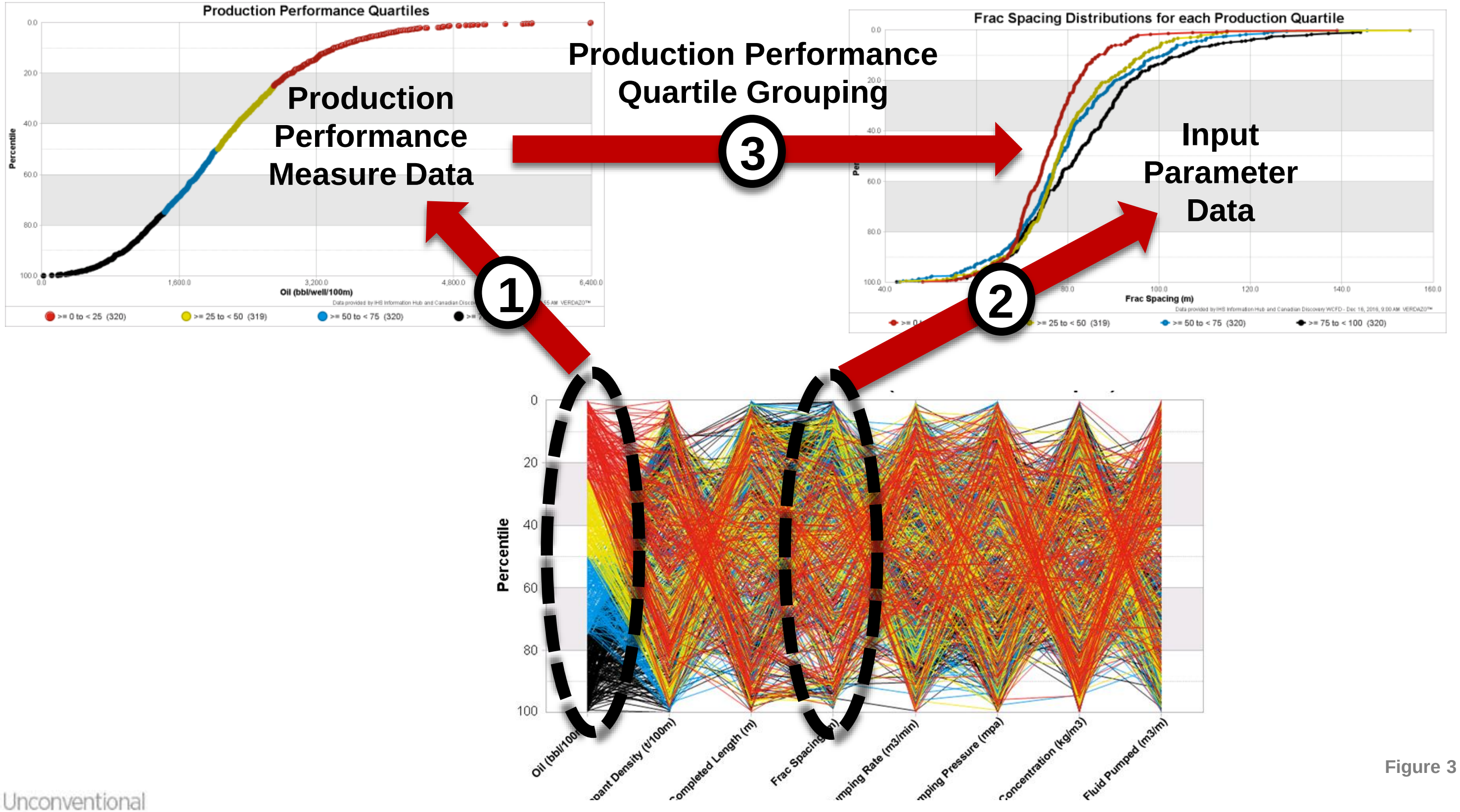


Figure 2

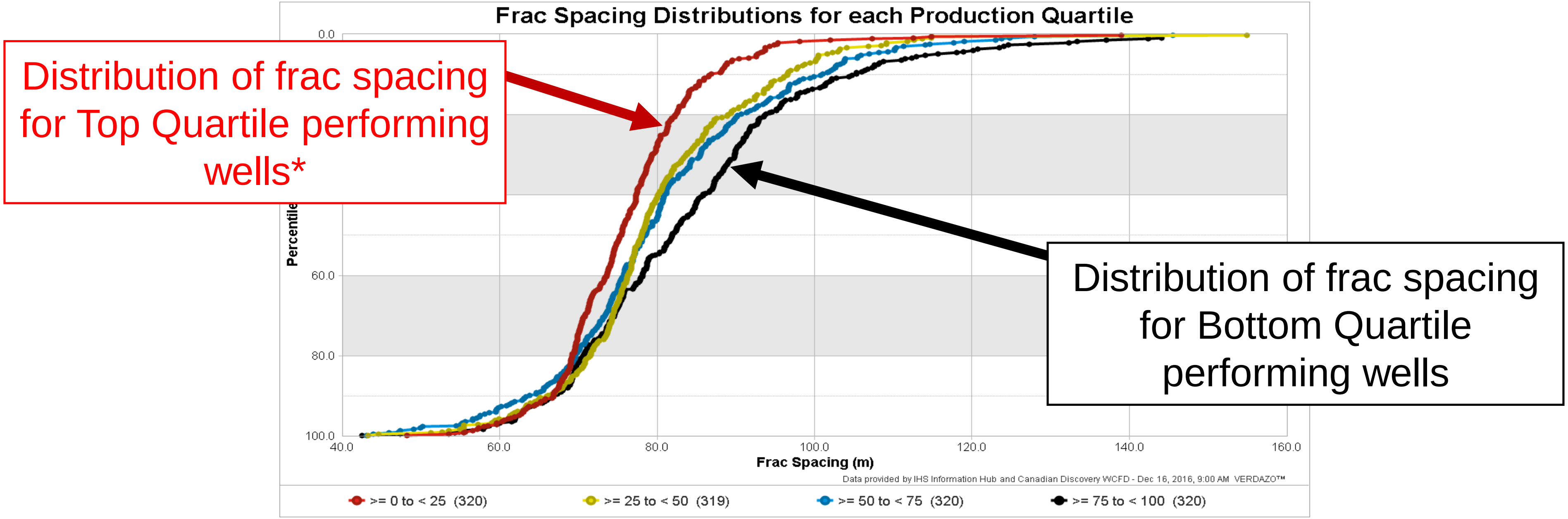
- Applying the same “brushing technique” to more complex data leads to “over-plotting”.
- This does not yield any discernable insights or obvious relationships.

Hybrid Approach: Parallel Coordinates Distribution (PCD)



Parallel Coordinates Distribution (PCD) Chart

(Shows distributions of Input Values for each Production Performance Quartile)



*Note: the production performance measure used here is 12 month cumulative oil per 100m completed length.

Purpose of Parallel Coordinates Distribution (PCD) Chart

- Identify the inputs that warrant optimization investigation (i.e. to focus your efforts where it counts the most)
- Identify patterns that illustrate the concepts of thresholds and correlation windows.
- Use patterns to determine target values used in the binning of Input Optimization Distribution charts (discussed later in this presentation).
- Identify peculiarities in the patterns that may suggest the analogue is not well defined and subsets should be investigated.

PCD Chart Patterns: Clear Performance Pattern

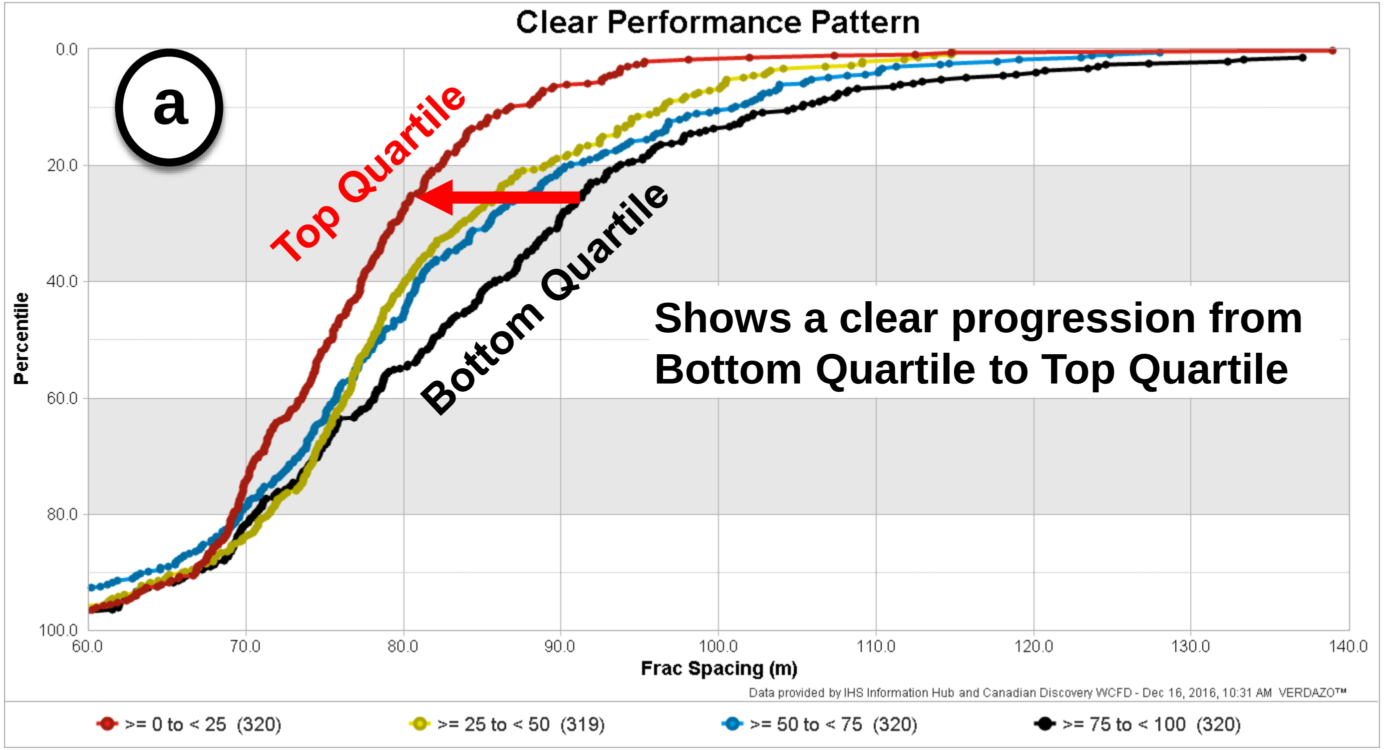
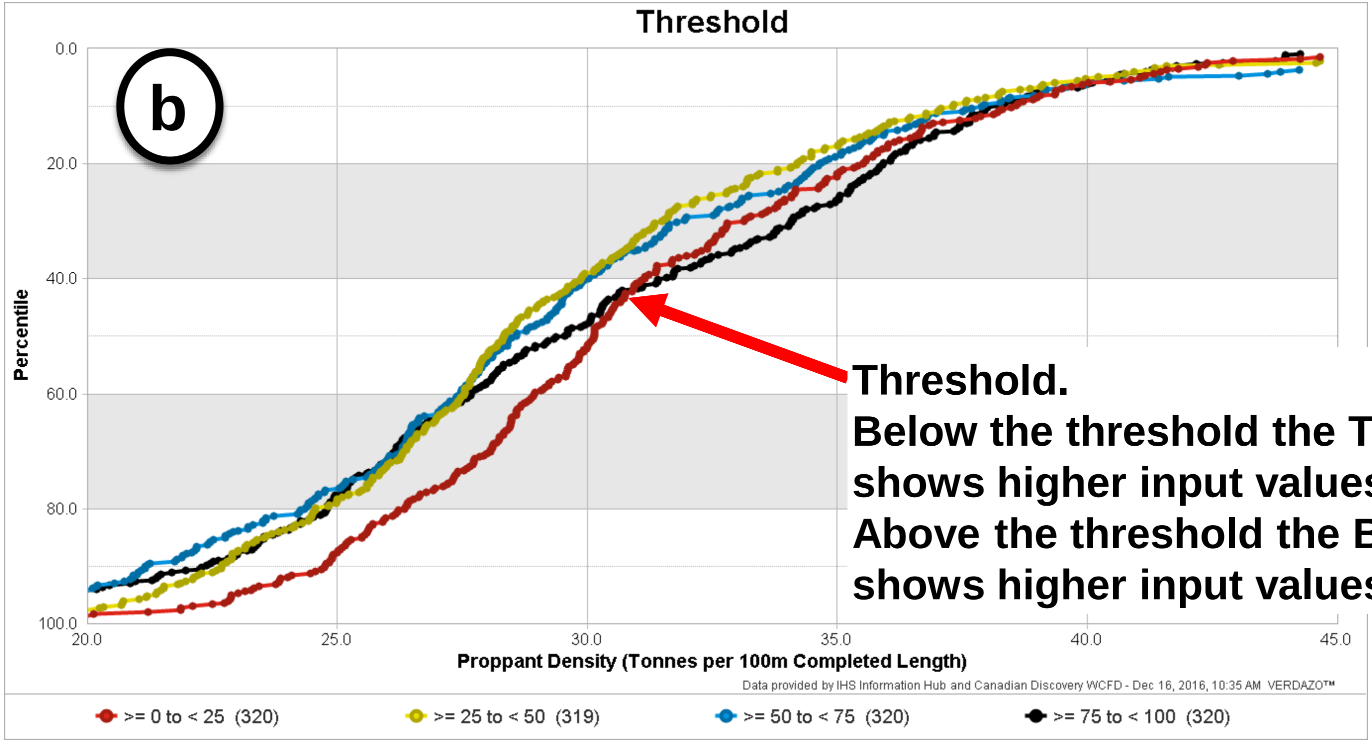


Figure 4

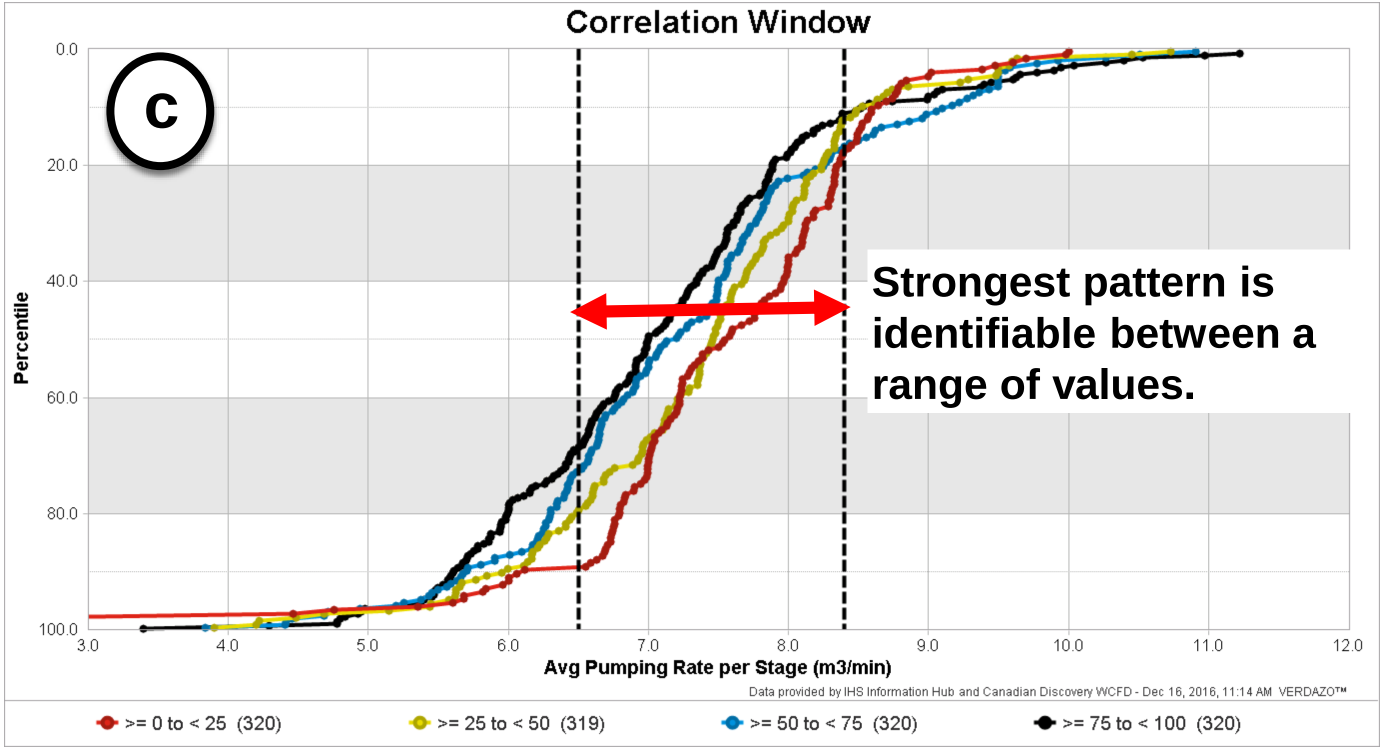
PCD Chart Patterns: Threshold



Threshold.
Below the threshold the Top Quartile shows higher input values.
Above the threshold the Bottom Quartile shows higher input values.

Figure 4

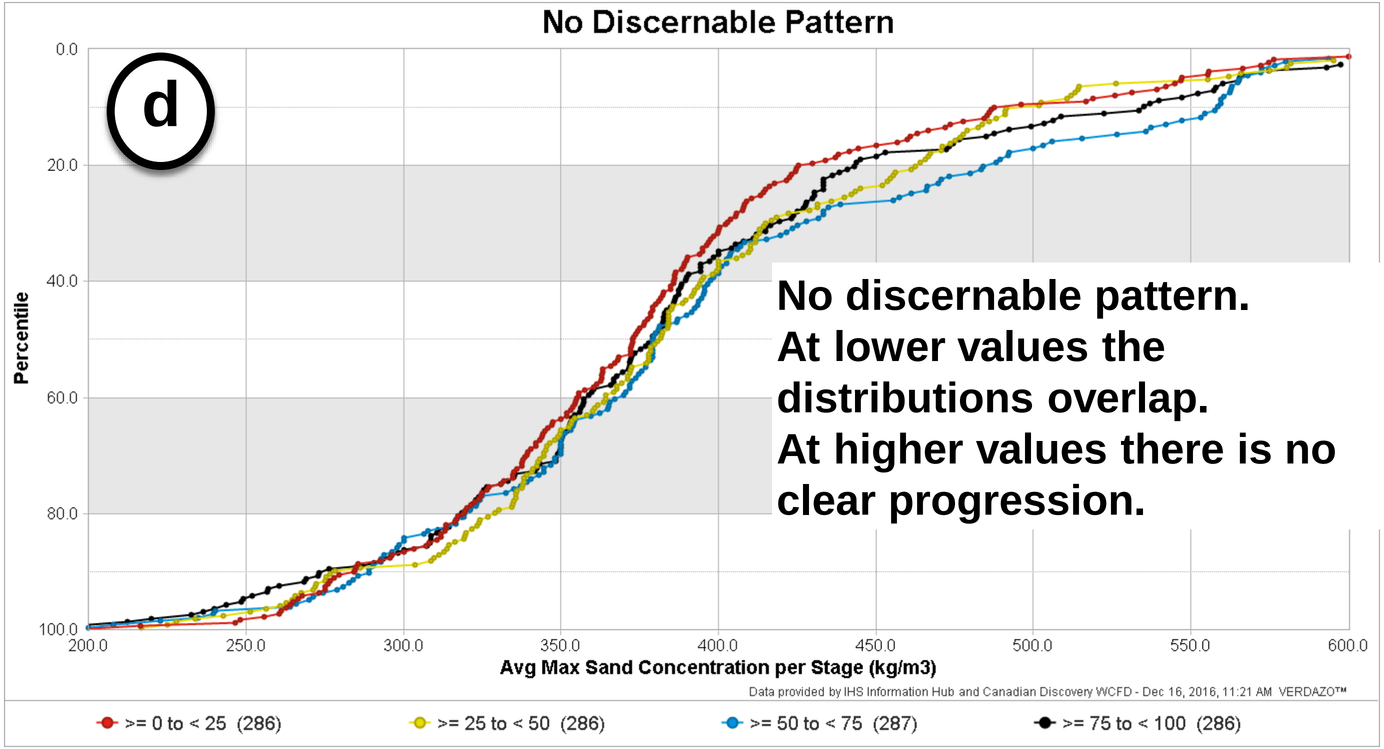
PCD Chart Patterns: Correlation Window



Strongest pattern is identifiable between a range of values.

Figure 4

PCD Chart Patterns: No Discernable Pattern



No discernable pattern.
At lower values the distributions overlap.
At higher values there is no clear progression.

Figure 4

PCD Matrix

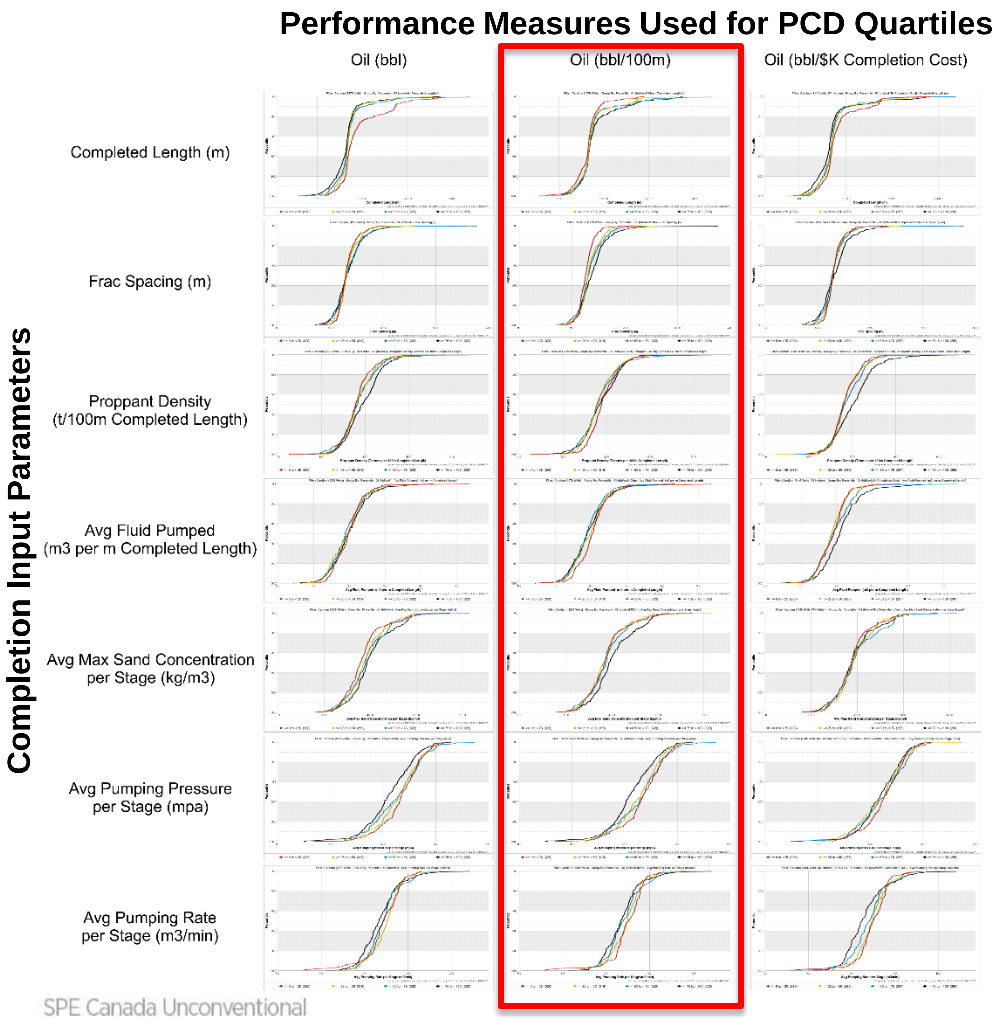


Figure 5

- Columns = Production Performance Measures
- Rows = Inputs
- Used to identify which inputs have the greatest impact on production performance and warrant further optimization analysis
- 12 month cumulative production/100m was the performance measure most effective at producing discernable patterns

Identifiable Patterns in Small Datasets

(note similar threshold values in each dataset)

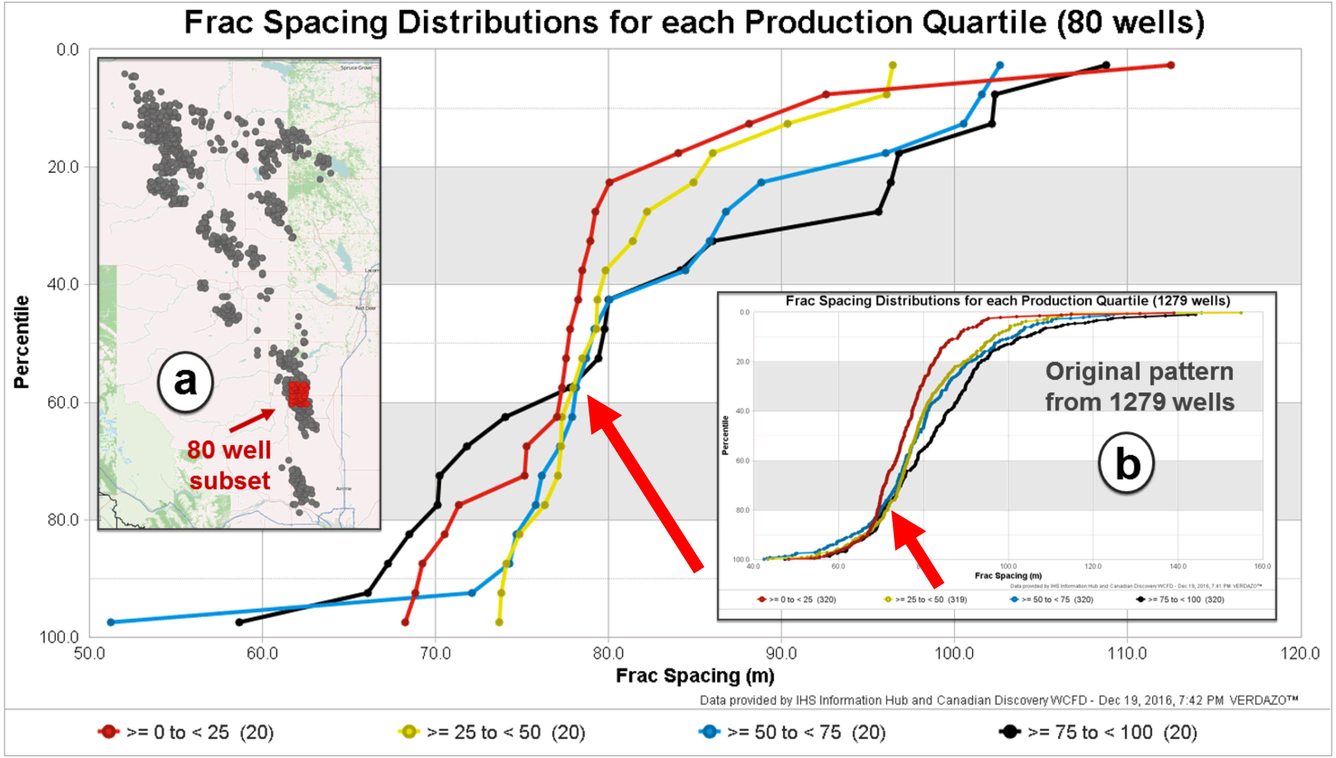


Figure 6

Important PCD Considerations

1) Dimensionally normalized performance measures show patterns more clearly

2) Length is the easiest parameter to correct for (e.g. production/100m)

3) Patterns can still be seen in sample sets as small as 80 wells

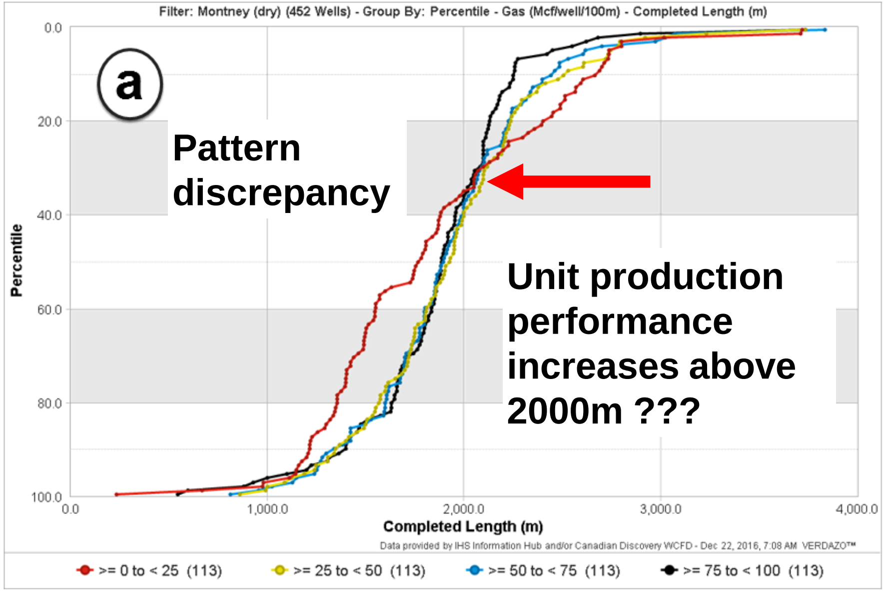
4) Consider that uncertainty of the mean (and of how representative the distribution is) increases as the sample size get smaller

Workflow

1) Selection of a performance measure set
2) Analogue well selection
3) Selection of numerical completion design input parameters
4) Parallel Coordinates Distributions (PCD): input parameter impact analysis
5) Evaluation of analogue fitness and subset selection
6) Input Optimization Distributions (IOD): input optimization process

Evaluation of analogue fitness and subset selection

Full Dataset



Subset (extreme proppant density wells excluded)

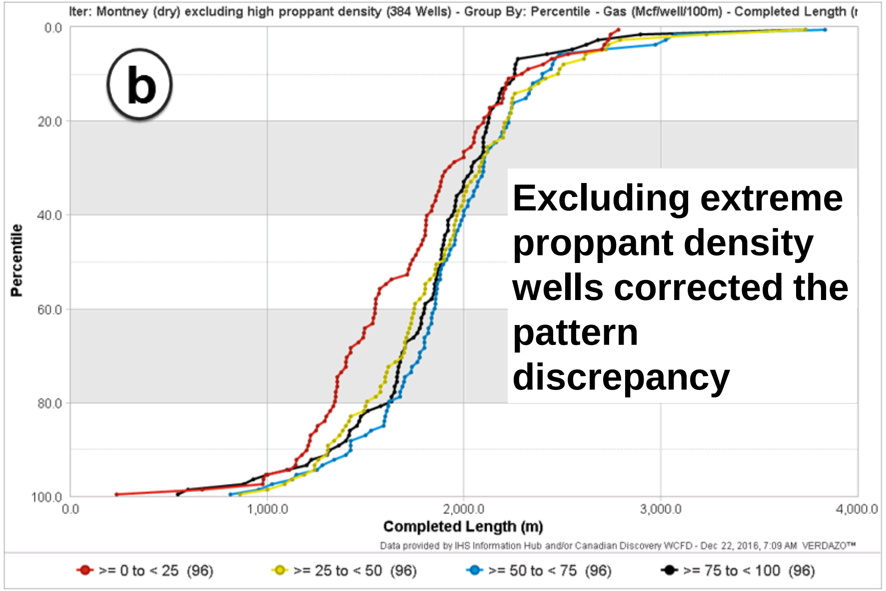


Figure B-3

Workflow

1) Selection of a performance measure set
2) Analogue well selection
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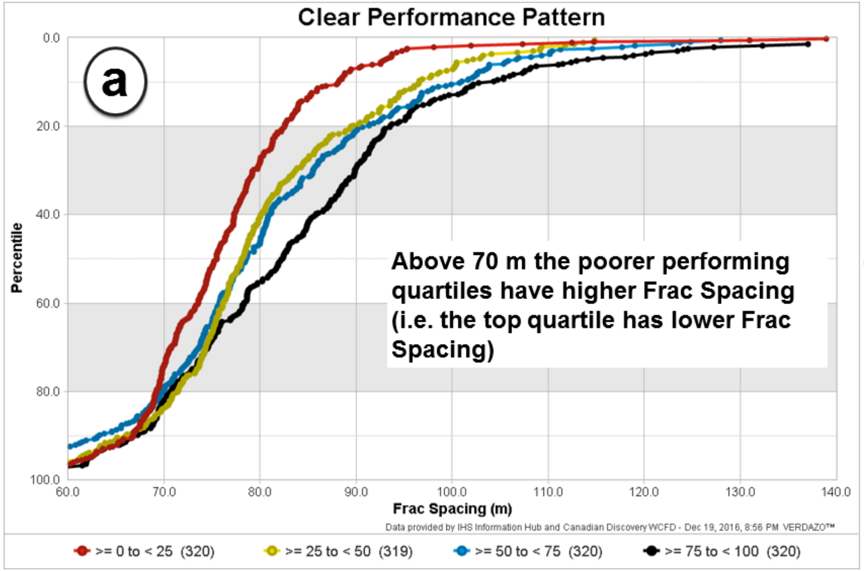
6) Input Optimization Distributions (IOD): input optimization process

Input Optimization Distribution (IOD) Chart

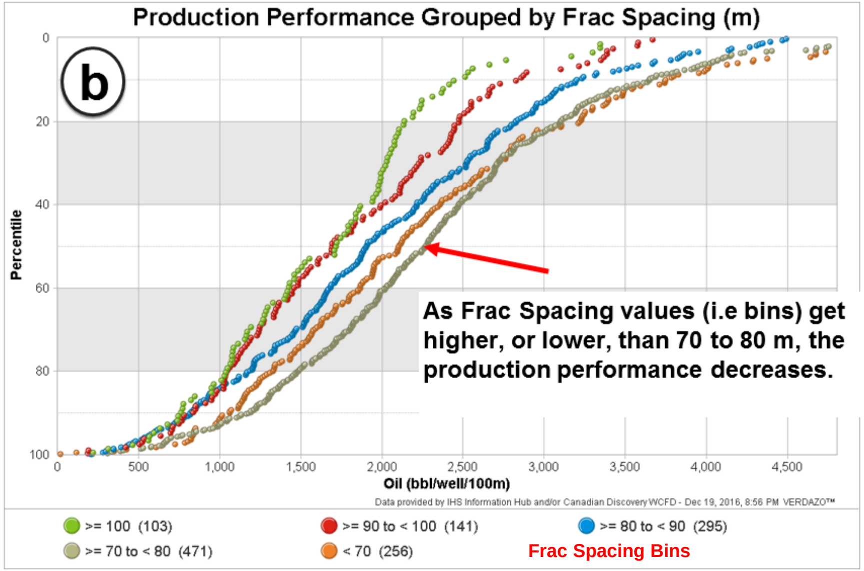
- Motive is to identify the optimal Input Parameter value.
- Distribution of a Production Performance measure binned by an Input Parameter.
- Use the insights from the PCD patterns to identify:
  a) bottom threshold bin value.
  b) bin size (to highlight a particular threshold value).
  c) top threshold value.
  d) adjusting all of the above to get reasonable well counts in each bin and a visually manageable number of bins.
- Isolate specific bins of interest in an analogue subset, and use smaller bin values to draw more detailed conclusions.

IOD applied to a PCD with a Clear Performance Pattern

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart

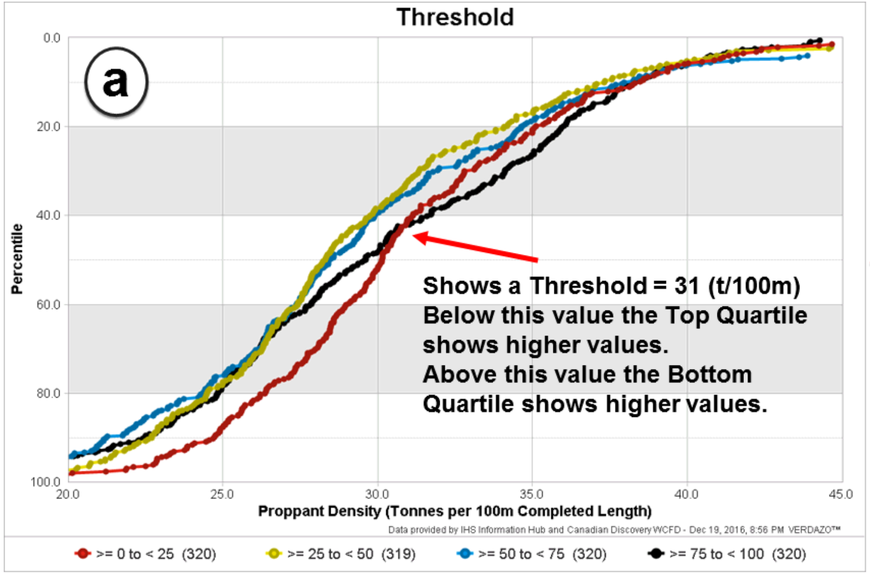


Note: colours on each chart represent different groupings

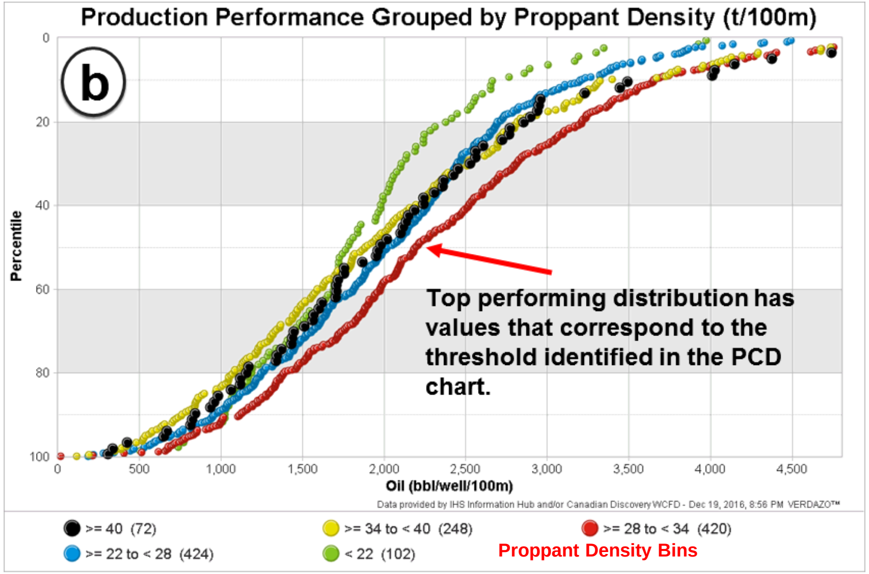
Figure 7

IOD applied to a PCD with a Threshold Pattern

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart

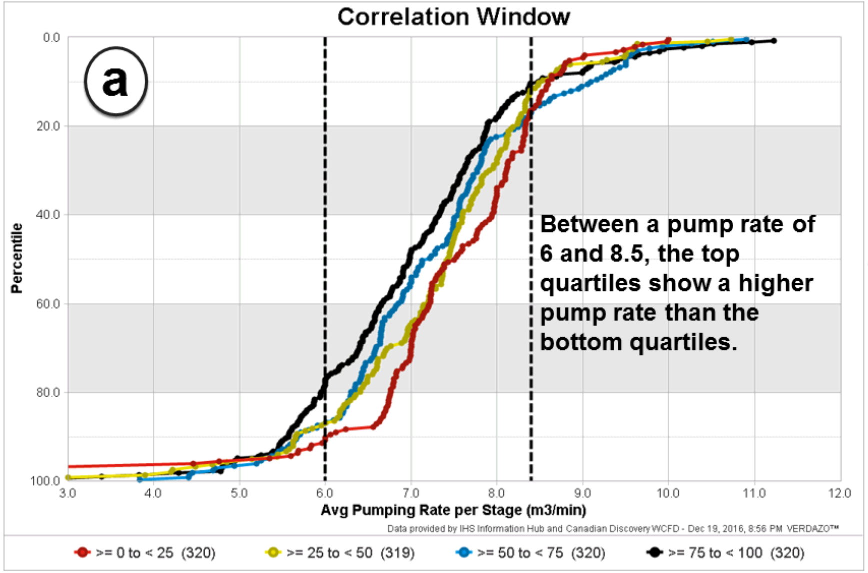


Note: colours on each chart represent different groupings

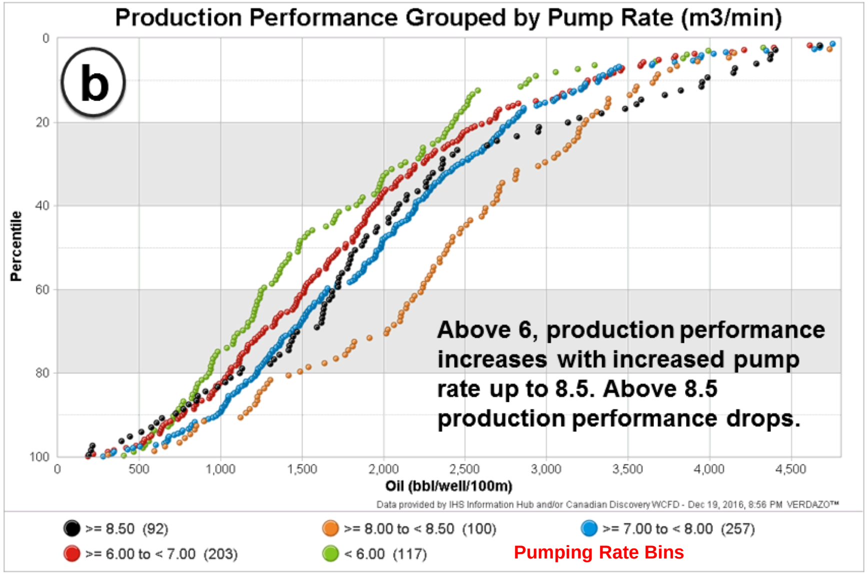
Figure 8

IOD applied to a PCD with a Correlation Window

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart

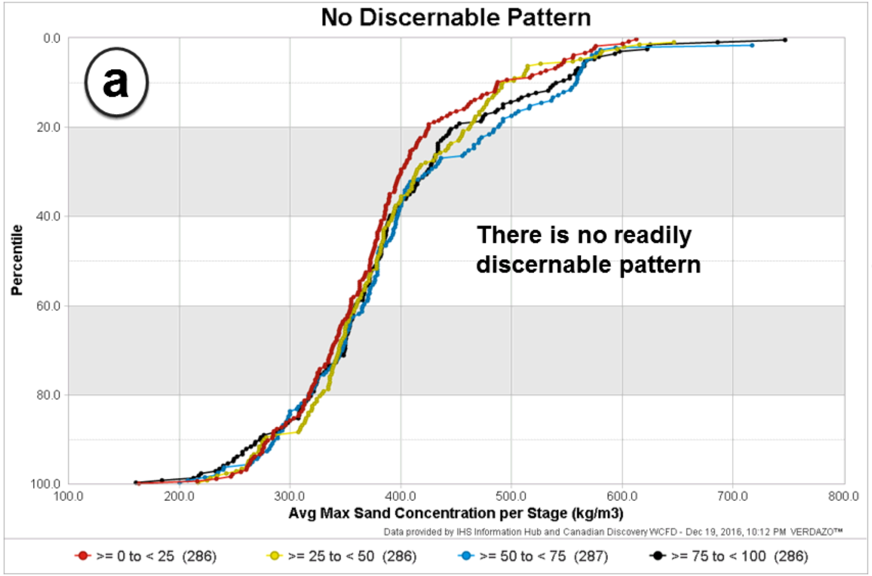


Note: colours on each chart represent different groupings

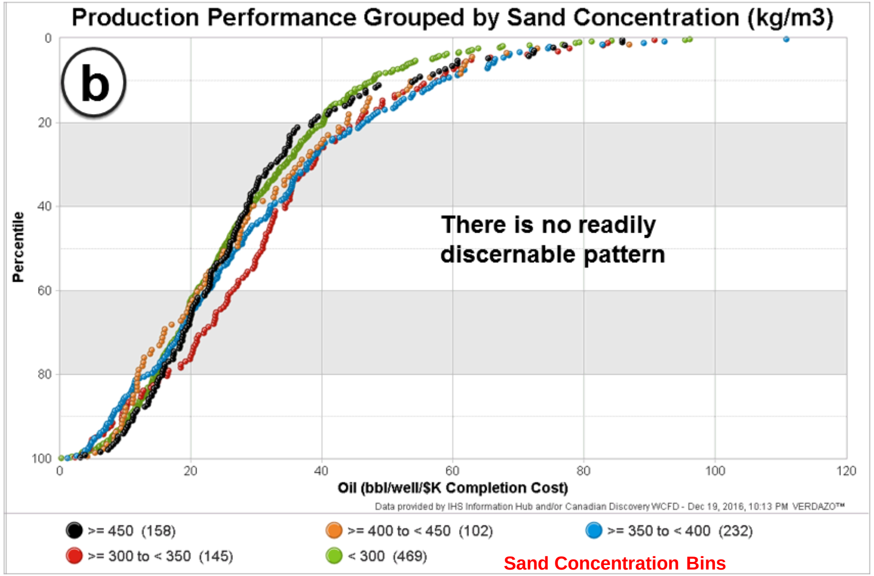
Figure 9

IOD applied to a PCD with No Discernable Pattern

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart



Note: colours on each chart represent different groupings

Figure 10

Studies

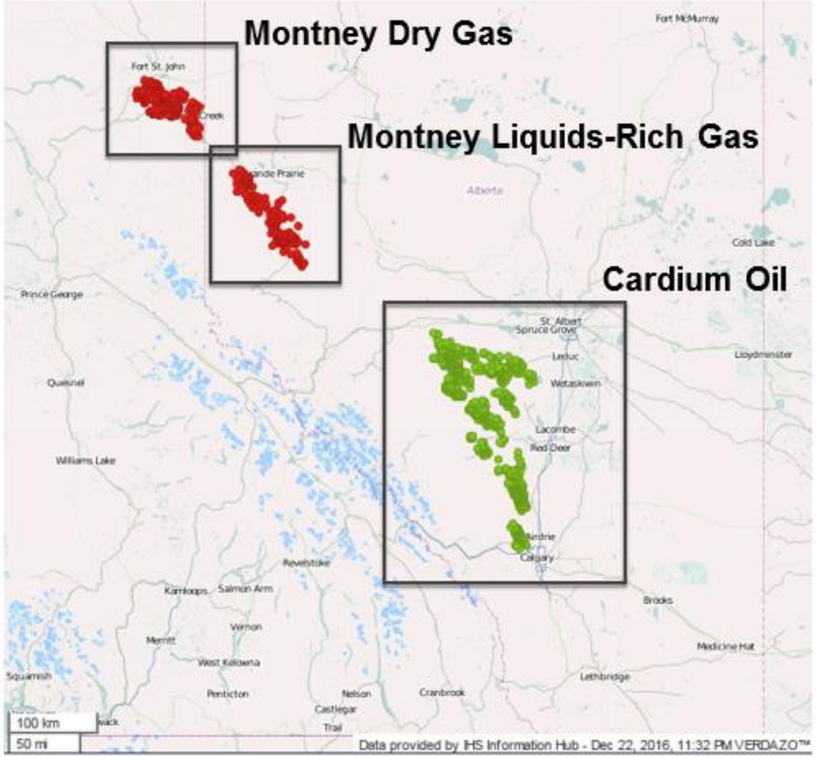


Figure 11

- Datasets range from 236 wells to 1279 wells
- Studies were performed to illustrate concepts
- A more rigorous analysis should incorporate geological information to refine analogue subsets

Workflow

1) Selection of a performance measure set
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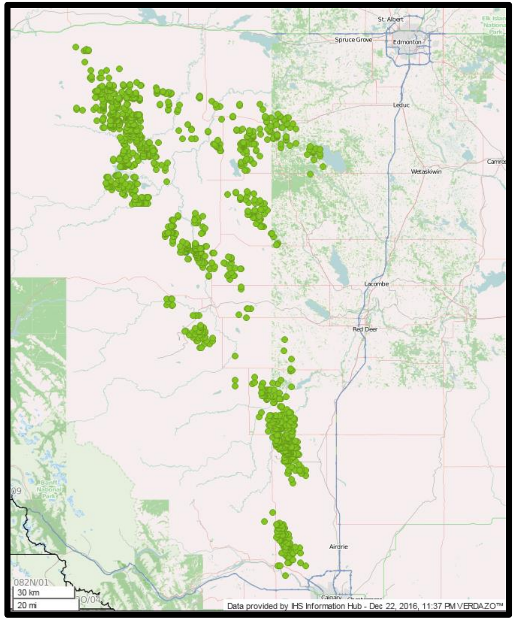
Cardium Oil Study Area



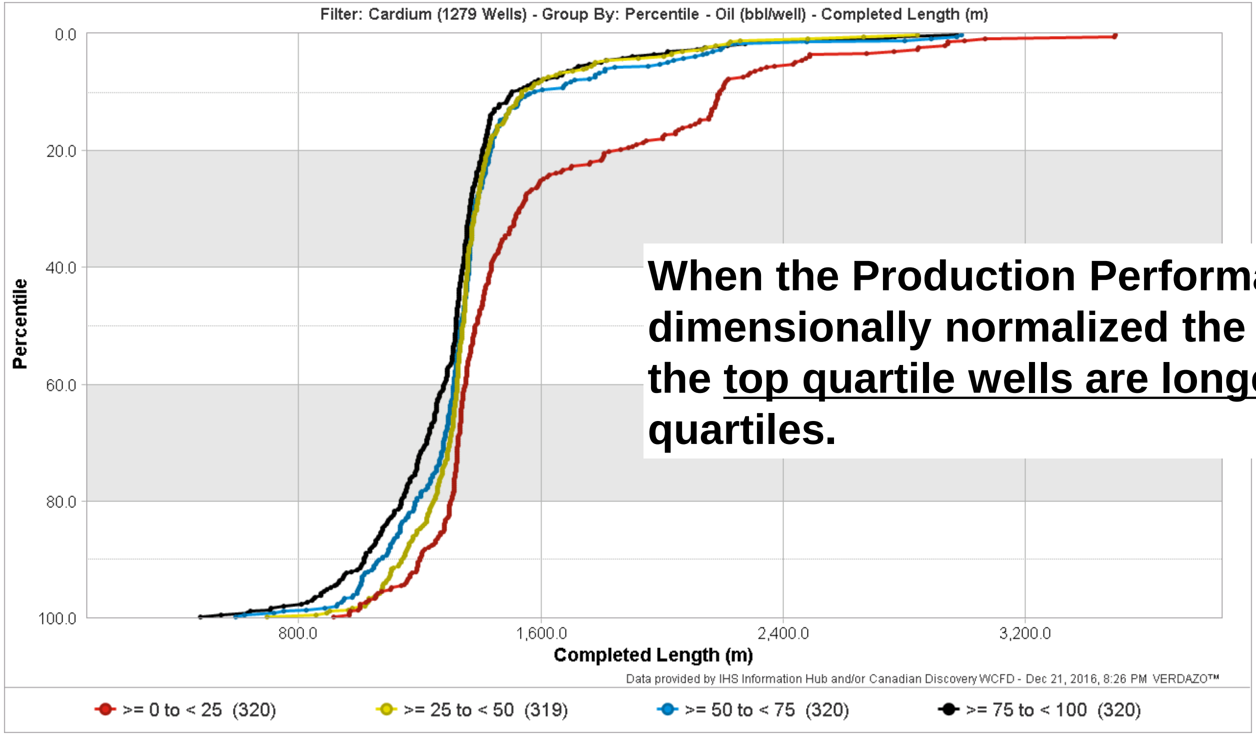
<u>1279 wells within the study area:</u>

- Formation = Cardium Oil
- Primary Product = Oil
- Open Hole
- Base Fluid = Slickwater
- Horizontal
- Production Year >2010
- Frac information available
- > 12 months of production

Figure A-1

- Tighter Frac Spacing improves unit production performance until Frac Spacing drops below a threshold of ~70 m (see slide 23).
- Increasing Proppant Density improves unit production performance until the upper threshold of ~31 t/100m is reached (see slide 24).
- As Pump Rates increase from 6 m^3/min, unit production performance increases up to an upper threshold of ~8.5 m^3/min (see slide 25).

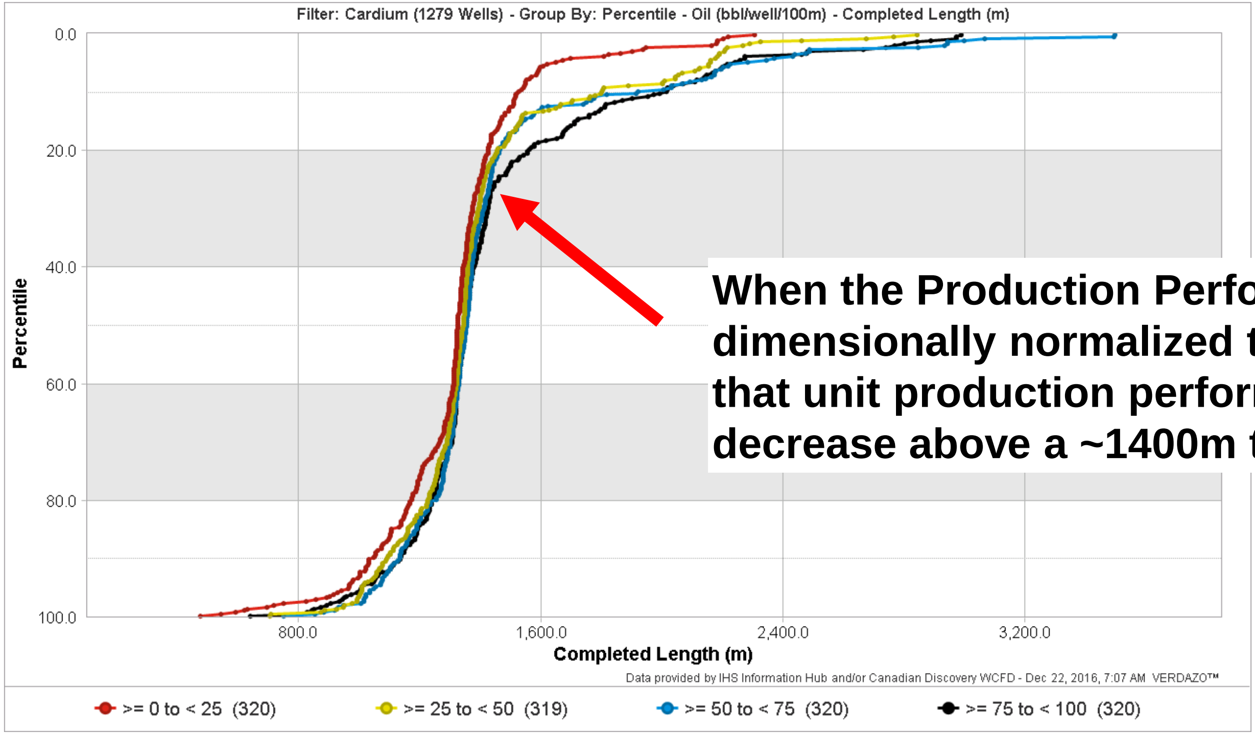
Cardium Oil PCD Chart for 12 Month Cumulative Oil (bbl)



When the Production Performance measure <u>is not</u> dimensionally normalized the main insight is that the <u>top quartile wells are longer</u> than the other quartiles.

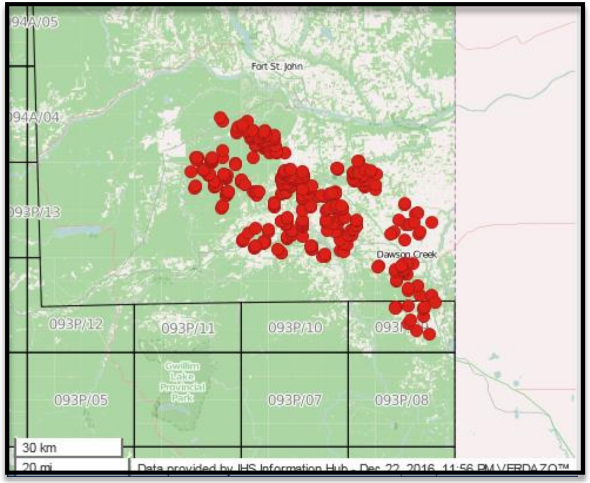
Figure A-2

Cardium Oil PCD Chart for 12 Month Cumulative Oil (bbl/100m)



When the Production Performance measure <u>is</u> dimensionally normalized the main insight is that unit production performance begins to decrease above a ~1400m threshold.

Figure A-3



452 wells within the study area:

- Formation = Montney
- Primary Product = Gas
- Cased
- Base Fluid = Slickwater
- Horizontal
- Production Year >2009
- Frac information available
- > 12 months of production

Figure B-1

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Montney Dry Gas Study Area

- Demonstrated a contradictory PCD pattern on Completed Length that required investigating an analogue subset selection (to separate out extreme proppant density wells).
- Reduction in unit production performance above upper threshold of ~ 2000m completed length.
- Dramatic increase in unit production performance with higher Proppant Density (t/100m) with no upper threshold.

Montney Dry Gas PCD Chart for 12 Month Cumulative Gas (Mcf)

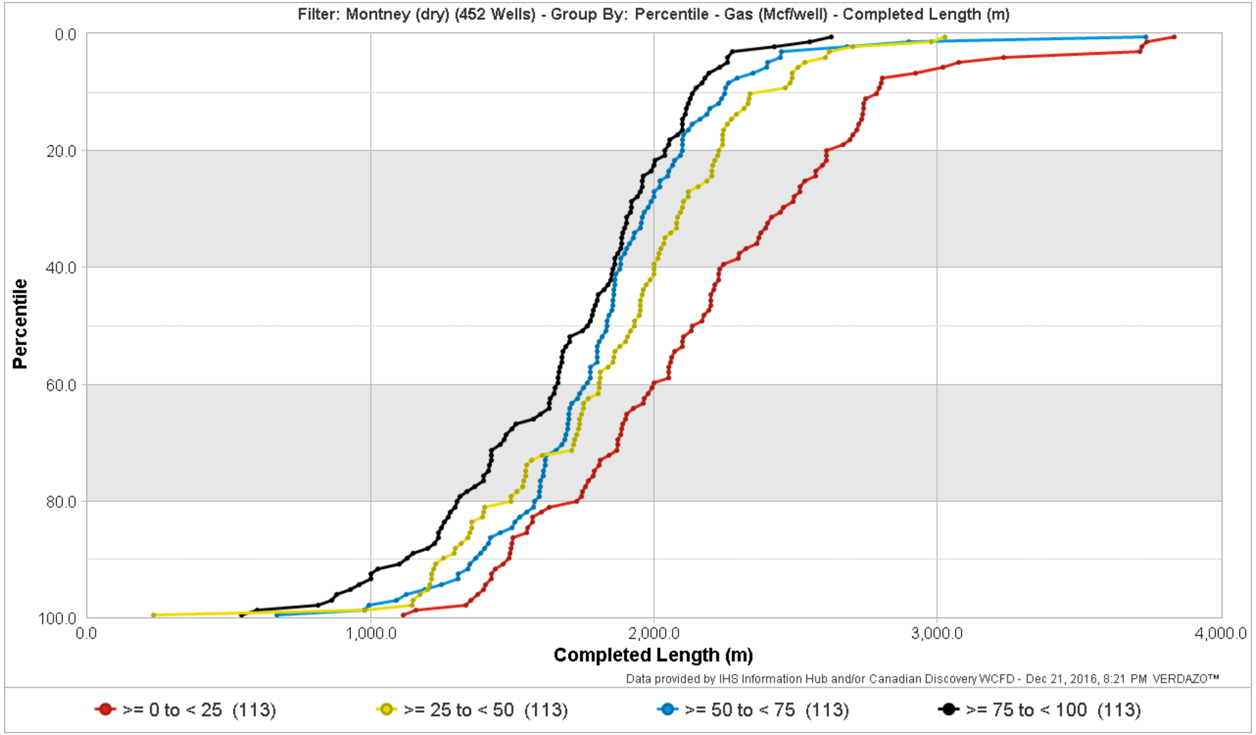
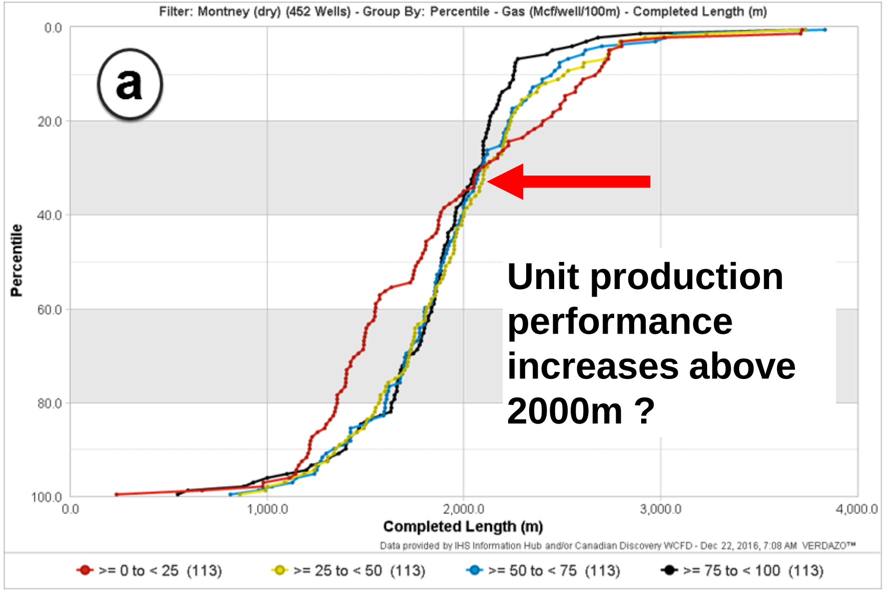


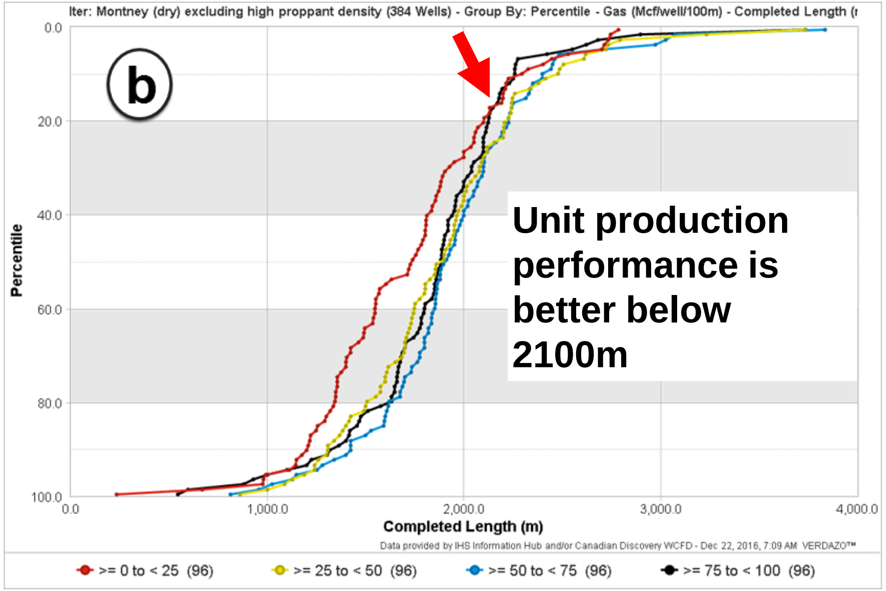
Figure B-2

Montney Dry Gas → Analogue Subset Selection

Full Dataset



Subset (extreme proppant density wells excluded)

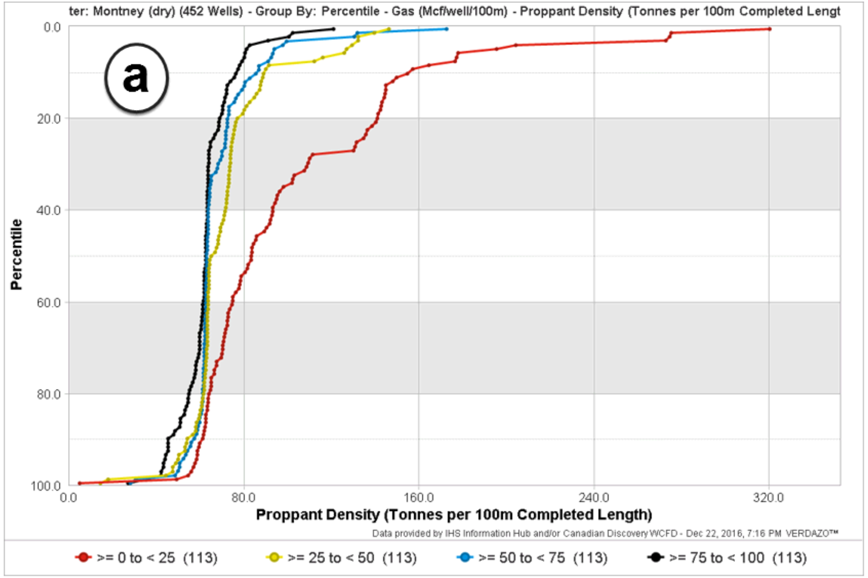


Note: colours on each chart represent different groupings

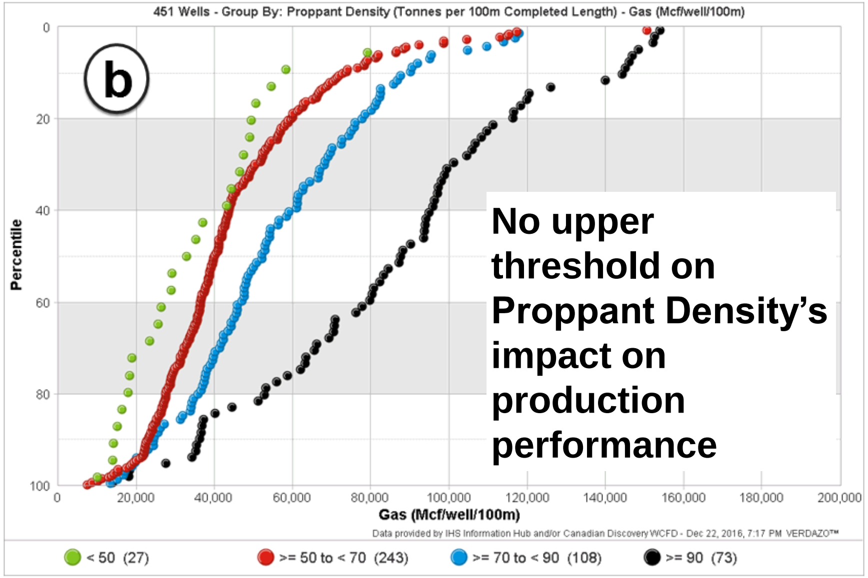
Figure B-3

Montney Dry Gas IOD Chart of Proppant Density

Parallel Coordinate Distribution (PCD) Chart

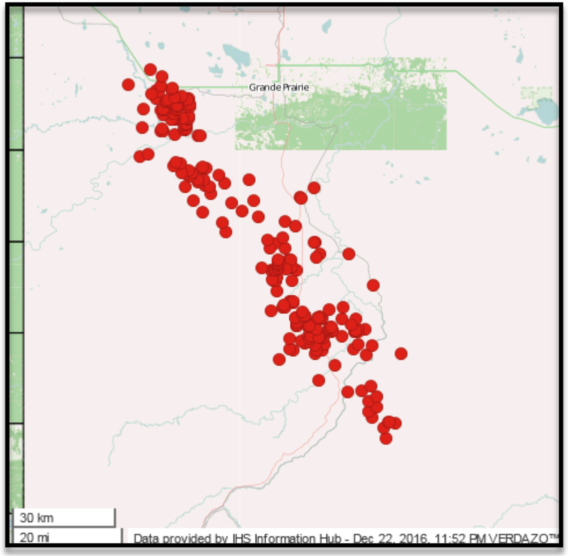


Input Optimization Distribution (IOD) Chart



Note: colours on each chart represent different groupings

Figure B-4



Montney Liquids-Rich Gas Study Area

- Increased Completed Length shows a reduction in unit production performance (mcf/100m) across the entire range of values
- Proppant Density shows a reduction of unit production performance above ~105 t/100m
- Higher Pumping Rates show an increase in unit production performance with no upper threshold

236 wells within the study area:

- Formation = Montney
- Primary Product = Gas
- Open
- Base Fluid Group = Water
- Horizontal
- Production Year >2008
- Frac information available
- > 12 months of production

Figure C-1

Montney Liquids-Rich Gas PCD Chart for 12 Month Gas (Mcf/100m)

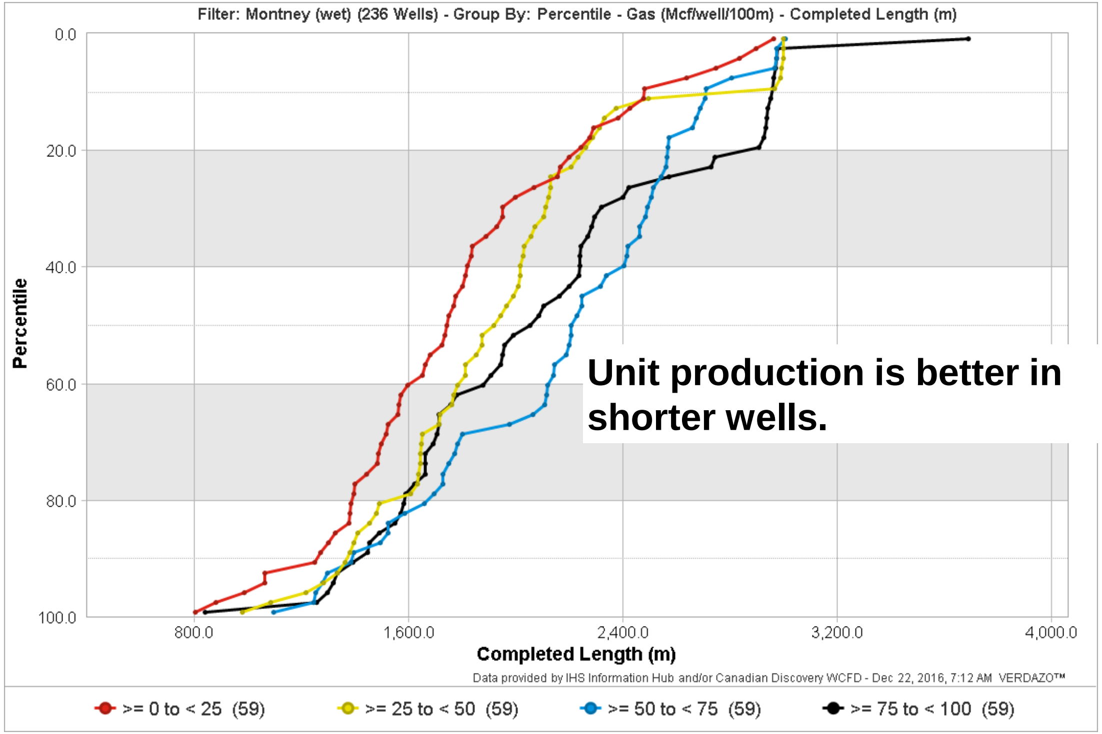
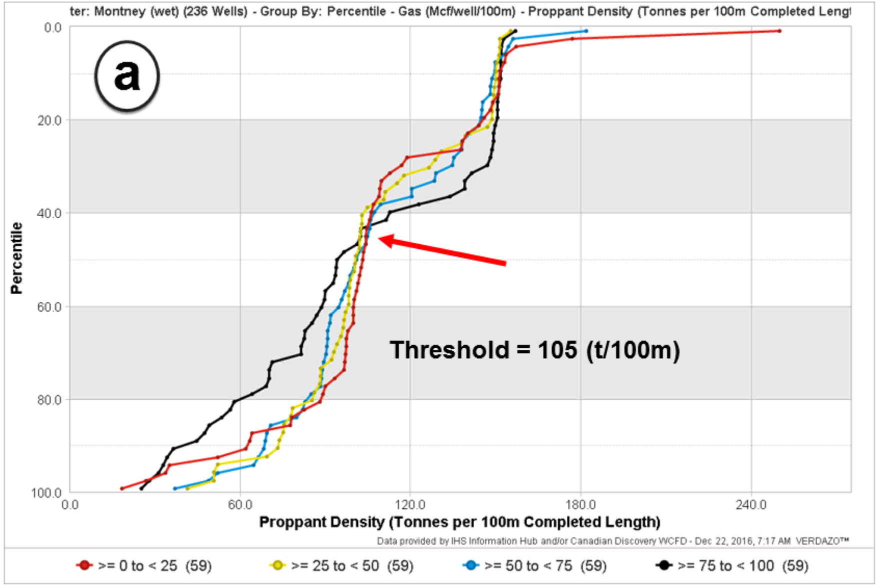


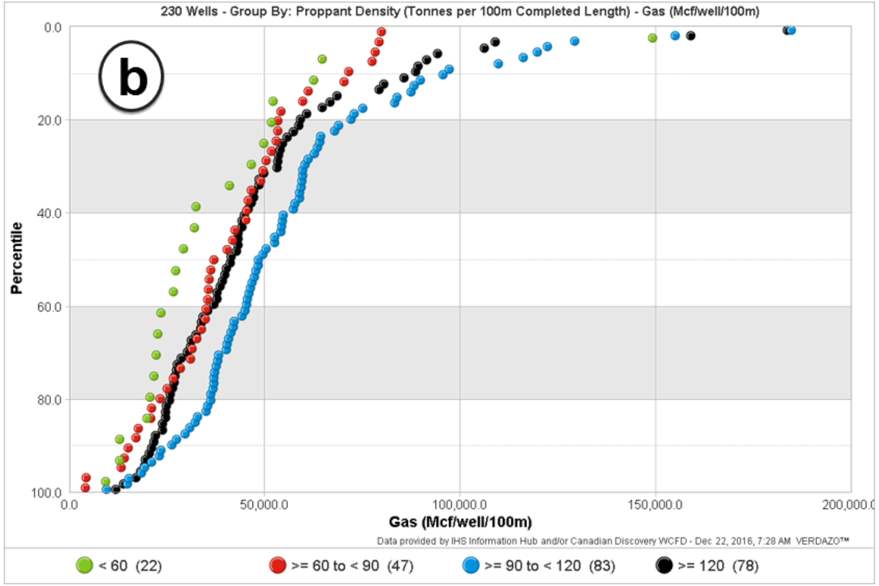
Figure C-3

Montney Liquids-Rich Gas IOD Chart of Proppant Density

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart

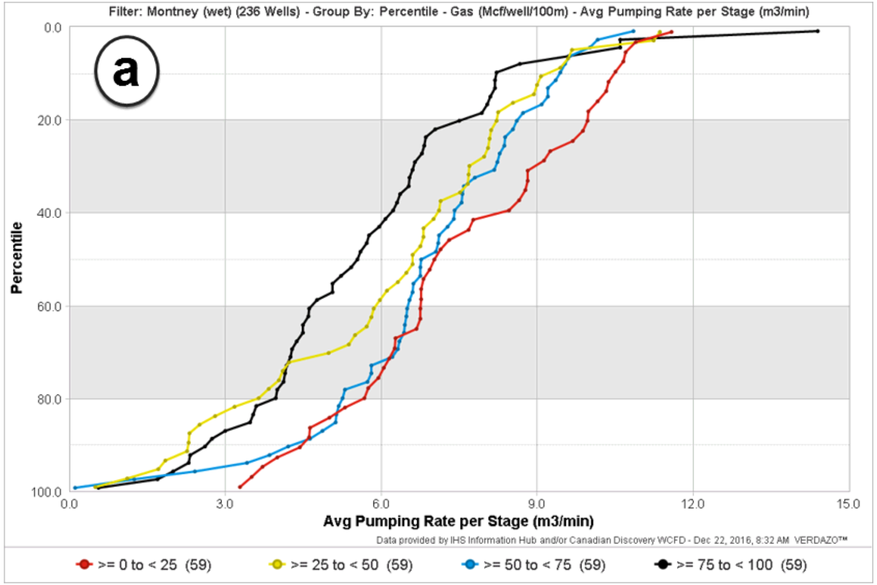


Note: colours on each chart represent different groupings

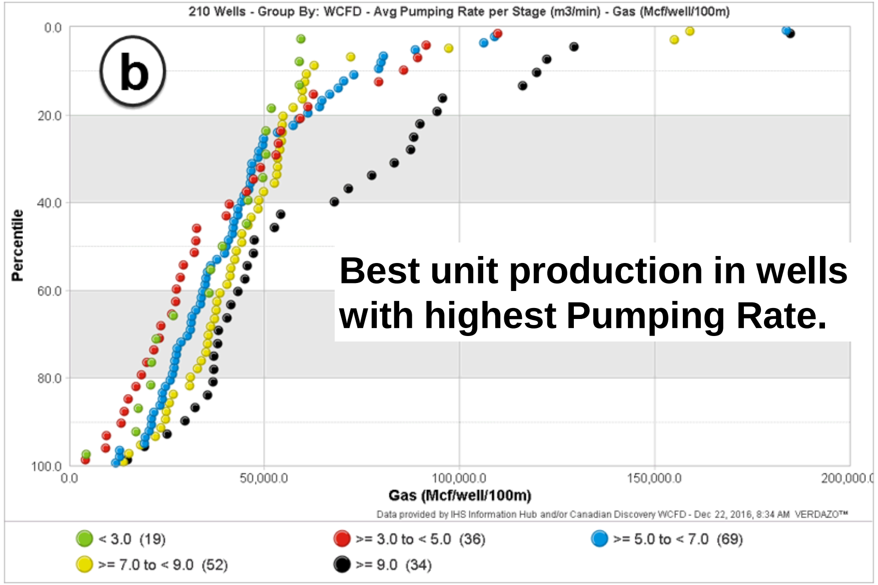
Figure C-4

Montney Liquids-Rich Gas IOD Chart of Pumping Rate

Parallel Coordinate Distribution (PCD) Chart



Input Optimization Distribution (IOD) Chart



Note: colours on each chart represent different groupings

Figure C-5

Conclusions Part 1

- The PCD and IOD visual analysis methodology is suitable for testing any input's impact on any performance measure.
- PCD Patterns were identifiable in all study areas, suggesting this methodology is suitable for all play types.
- Where rate restriction practices are being used it is recommended that cumulative production (for >= 12 months) be used (i.e. IP90 or other near-term performance measures could yield misleading results).
- Patterns are better defined when performance measures and inputs use dimensional normalization.
- Lateral length is the easiest, and most effective, input parameter to correct for.

Conclusions Part 2

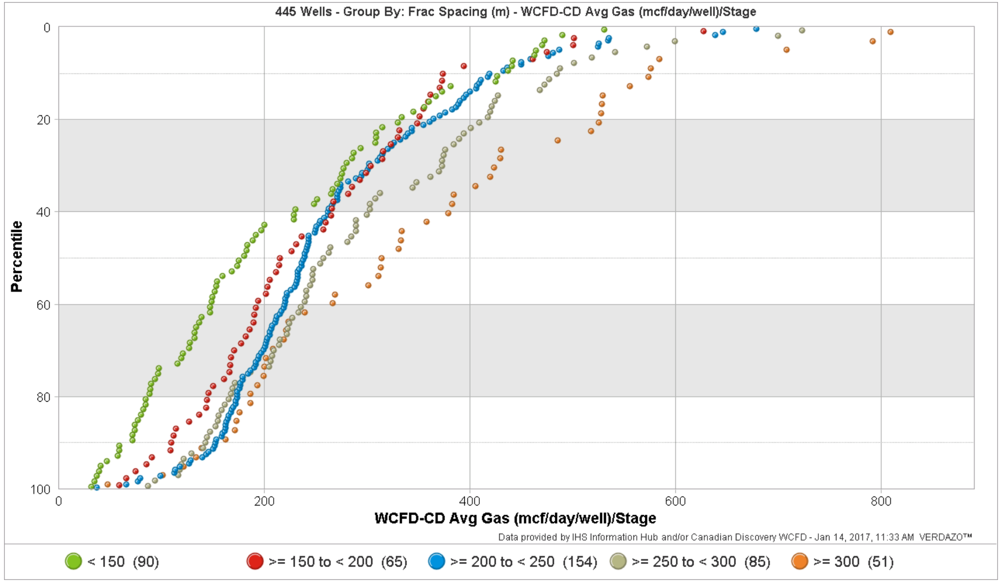
- Inputs require enough statistical variability to see PCD Patterns (observations indicate that P10:P90 of input parameter values need to be >1.6)
- This approach is effective at communicating nuances in the data, such as thresholds and correlation windows.
- Specific threshold values and correlation window ranges can be valuable inputs to other regression techniques or modelling efforts.
- The approach is scalable, accommodating datasets containing greater than 1000 wells down to as few as 80 wells.
- Inexplicable patterns are an effective way of identifying the need for analogue review and subset selection.

Acknowledgements / Thank You / Questions

The authors wish to acknowledge:

- IHS Markit's Canadian Information Hub for production data.
- Canadian Discovery Ltd.'s Well Completion and Frac Database (now owned by geoLOGIC Systems) for completion data.
- Verdazo Analytics Inc. and Rose and Associates for their support.

Supporting slide for anticipated question:



“Why did you not use production/stage as your performance measure?”

Stages work collectively as a system, not independently. As you increase stage spacing you increase the degree to which the stimulated rock volumes for each stage overlap (as evidenced in this image).

Optimal production for a well occurs when the amount of overlap for a collection of stages produces the highest production levels. The maximum production/stage will not deliver optimal well production unless the stages do not interfere with one another.

Supporting slide for anticipated question:

“Why did you choose 12 month cumulative production as your production performance measure instead of EUR?”

The next slide (from the blog How useful are IP30, IP60, IP90 … initial production measures?) shows the correlations of different production performance measures to EUR.

12 month cumulative production:

- is the minimum number of months required to ensure a strong correlation to EUR
- has enough production to matter, while short enough to include as many recent wells as possible
- is accessible to anyone doing analysis → whereas the only practical way to use EUR would be to rely on auto-forecasting methods which are not readily available to everyone

4 Play Analysis of the Correlation of Production Measures to EUR using VISAGE

		Montney (Gas)				Cardium (Oil)				Viking (Oil)				Bakken (Oil)			
		Data Set 1		Data Set 2		Data Set 1		Data Set 2		Data Set 1		Data Set 2		Data Set 1		Data Set 2	
		Correlation %	Well Count	Correlation %	Well Count	Correlation %	Well Count	Correlation %	Well Count	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	21.8	3098	19.5	818	30.1	1387	30.0	991
	PD Rate (month 1-2)	21.0	584	29.9	226	42.3	1592	49.9	769	28.6	3098	35.3	818	39.5	1387	38.9	991
	PD Rate (month 1-3)	31.2	583	36.7	225	48.1	1592	58.0	769	33.4	3098	45.2	818	46.4	1387	45.1	991
	Peak	60.0	585	50.6	227	53.5	1592	67.0	769	40.1	3098	65.1	818	61.3	1387	65.5	991
	IP30	32.6	585	39.3	227	44.4	1574	56.2	769	30.9	2999	52.3	818	44.8	1387	45.7	991
	IP60	42.7	585	45.2	227	54.8	1573	68.6	769	38.5	2999	59.7	818	51.3	1387	51.4	991
	IP90	49.2	585	49.9	227	60.8	1573	74.2	769	43.5	2999	64.0	818	56.5	1387	56.1	991
	IP180	60.8	576	62.0	227	70.0	1561	80.7	769	53.4	2994	71.0	818	66.6	1387	66.8	991
	IP365	72.4	576	74.9	227	79.9	1561	86.1	769	69.1	2994	79.0	818	77.5	1387	78.8	991
Condensed Data	3 Month Cum	23.2	585	19.4	227	46.9	1592	60.2	769	36.4	3098	58.9	818	52.2	1387	52.2	991
	6 Month Cum	49.3	585	45.1	227	65.4	1592	76.6	769	65.4	3098	70.0	818	65.0	1387	64.6	991
	12 Month Cum	67.1	523	67.0	227	77.6	1524	84.8	769	67.8	2563	77.9	818	76.5	1357	77.1	991
	18 Month Cum	75.4	473	76.1	227	82.9	1357	88.7	769	79.4	2002	82.4	818	82.3	1249	84.0	991
	24 Month Cum	79.7	377	81.6	227	86.7	1233	91.1	769	84.2	1551	85.3	818	88.6	1184	88.3	991
	30 Month Cum	83.5	287	85.1	227	90.3	966	92.8	769	87.4	1125	87.5	818	91.1	1067	90.9	991
	36 Month Cum	87.5	227	87.5	227	94.1	769	94.1	769	89.7	818	89.7	818	92.6	991	92.6	991
Non-condensed Data	3 Month Cum	16.4	585	8.9	227	43.8	1592	57.1	769	35.5	3098	56.1	818	51.6	1387	52.0	991
	6 Month Cum	40.3	585	30.5	227	63.8	1592	74.0	769	49.1	3098	64.6	818	63.8	1387	63.5	991
	12 Month Cum	59.5	523	56.2	227	77.3	1524	84.5	769	67.3	2563	76.9	818	76.2	1357	76.7	991
	18 Month Cum	71.5	473	70.5	227	82.9	1357	88.6	769	79.3	2002	82.3	818	82.1	1249	83.7	991
	24 Month Cum	77.5	377	78.4	227	86.7	1233	91.0	769	84.2	1551	85.3	818	88.4	1184	88.0	991
	30 Month Cum	82.0	287	83.5	227	90.2	966	92.7	769	87.5	1125	87.6	818	90.9	1067	90.7	991
	36 Month Cum	86.4	227	86.4	227	94.1	769	94.1	769	89.8	818	89.8	818	92.4	991	92.4	991

Legend	
86.4	Green = Correlation between 70% and 100%
59.5	Yellow = Correlation between 50% and 70%
40.3	Red = Correlation between 30% and 50%
16.4	Grey = Correlation between 0% and 30%

Data Set 1 = wells with >80% correlation on Modified Duong fits for both "a" and "m" and >6 months production after peak

Data Set 2 = subset of Data Set 1 where all wells have >=36 months production

Note: Sample sets include only horizontal wells.

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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