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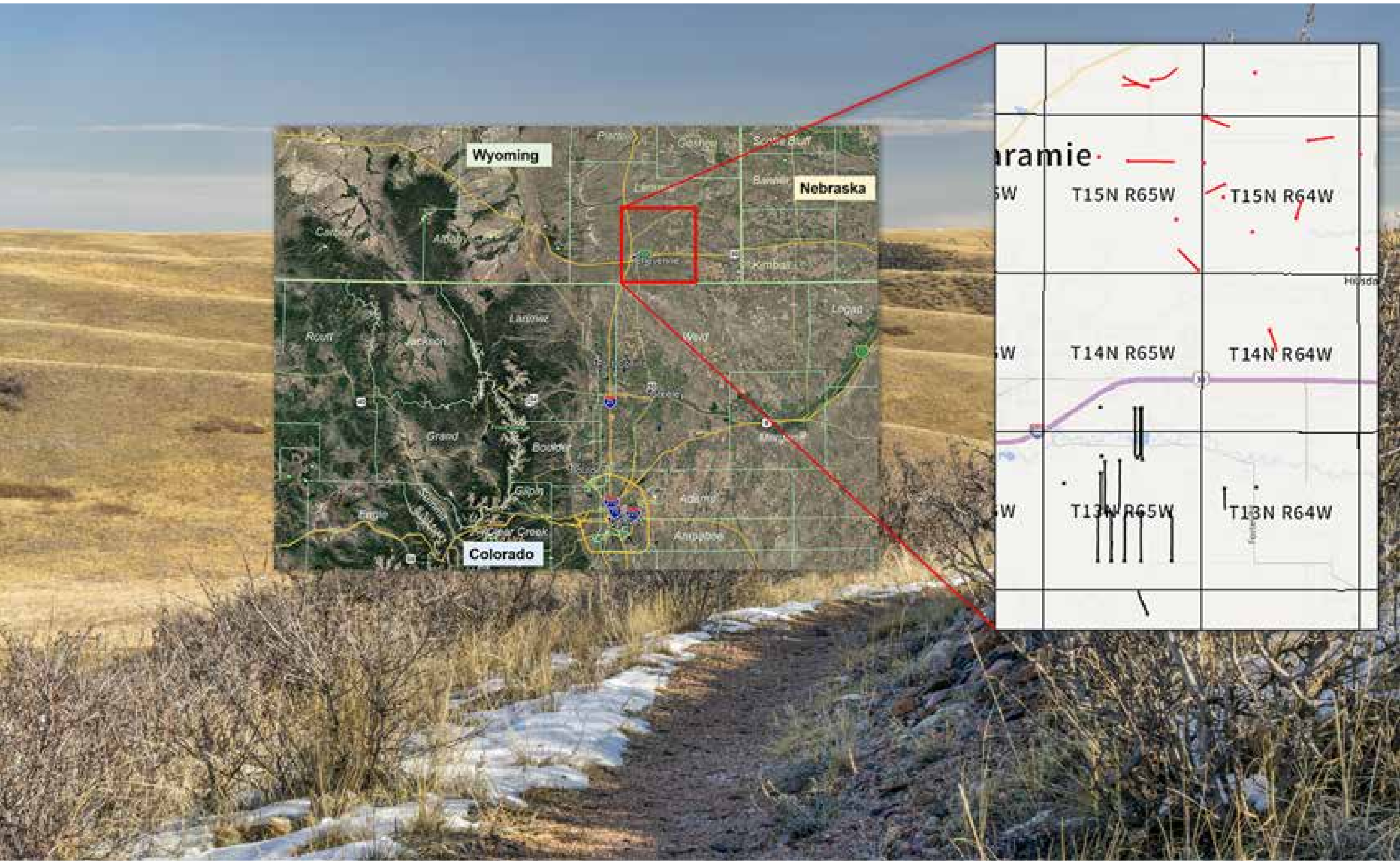

Northern Denver-Julesburg Basin Production Trends – A Multivariate Approach

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Enhanced Oil Recovery Institute

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Abstract

The northern Denver-Julesburg (DJ) Basin has seen a surge in activity in recent years, with many operators targeting the Codell and Niobrara formations. These horizontal wells have been drilled and completed using a variety of techniques. The learning curve for developing these unconventional plays is steep and costly. This paper utilizes multivariate analysis to compare the current drilling and completion practices and to analyze the main drivers behind cumulative oil production at different time intervals, while also considering the economics that are influencing the decision makers.

An extensive data-gathering effort was put in place to acquire and quality-check publicly available drilling, completion, and reservoir data in Laramie County, WY for horizontal Codell and Niobrara wells. Multivariate analysis iterations were conducted with various combinations of attributes to develop the highest correlation to the actual cumulative production or Estimated Ultimate Recovery (EUR). Having arrived at the final attributes that have the greatest impact on production, it is possible to present an optimized well design. Additionally, the completed model can be used to test hypothetical scenarios to determine their impact on production. In order to address the general economics of these wells, decline curve analysis was conducted to establish type curves. These type curves were then analyzed in an economic model for the purpose of comparing the return on investment (ROI) of different drilling and completion techniques.

This workflow provides a baseline for optimized drilling and completion design. For the Codell, the model indicates that the attributes of Proppant Volume, Horizontal Length, Gas-Oil Ratio (GOR), and Treatment Rate have the greatest influence on 6-, 12-, and 18-month cumulative oil production. This combination of attributes provides the highest correlation between the modeled cumulative and the observed cumulative production. By examining the individual attribute responses, the current best design in the Codell is a lateral length of at least 9,600 feet (ft), a job size of 12 million (MM) lbs, a treatment rate of at least 40 barrels per minute (bpm), and a GOR of 570 standard cubic feet per barrel (scf/bbl). The type curves from decline curve analysis provided predictive monthly production. The best EURs were obtained with the optimized design and yielded better overall economics when entered into the economic model.

For the Niobrara, a 9MM lb job size with a lateral length of 10,000 ft, a GOR of 900

scf/bbl, and a treatment rate between 40 and 45 bpm is optimal. Due to lack of available pricing data and the inability to generate valid type curves of production, an economic analysis could not be conducted for the Niobrara.

Introduction

It can be a daunting task to design and execute the ideal drilling and completion program. With so many unknowns, many operators simply use the methodology of what the "guy next door" is doing. But how do we know that the program chosen is optimal for the target reservoir? What are the economics saying?

The authors set forth to help answer these questions and to provide an optimized drilling and completion program based on current practices and a general view of economics. Although it can be challenging to capture all the various factors that are contributing to a well's productivity, the workflow evaluated herein provides a design that is based on observation trends derived from publicly available data. Hopefully, an operator's data can be examined in conjunction with the results provided by this work to offer a good starting point for well design.

The area of interest for this paper is the northern DJ Basin in Laramie County, WY and builds upon work published by the Wyoming State Geological Survey (WSGS) entitled, "Codell Sandstone Oil Production Trends, Northern Denver Basin, Laramie County, Wyoming, 2017." In the WSGS report, conclusions were made based on crossplots comparing single attributes to cumulative production. Before agreeing with such conclusions, and certainly before making any policy or economic decisions based on these conclusions, a more thorough investigation is warranted.

The methodology used in the WSGS report is a common one but is imperfect for a couple of reasons. Firstly, the WSGS included all Codell wells within Laramie County without regard to the geological stresses within the basin. As will be discussed later in this report, the minimum horizontal stress direction is east-west in most of Laramie County, which would normally suggest an optimal drilling azimuth oriented north-south. A stress anomaly exists within a portion of the study area, however, where the stress direction at Silo Field switches to more north-south, suggesting an east-west azimuth is preferable.

Secondly, merely looking at a single attribute versus production can lead to inaccurate conclusions due to the interrelationships of various engineering and geologic factors. For example, a significant number of the N-S wells used larger proppant volumes than those drilled E-W in the mature Silo Field. It is therefore uncertain whether the Azimuth or Proppant Volume attribute is the main contributing factor to production. This type of multivariate relationship is where multivariate statistical analysis (MVA) proves to be a useful and discerning tool.

MVA refers to the simultaneous statistical analysis of multiple variables. It can aid in determining the current best practices by examining the available data and their impact on production, as well as the interaction between the variables. MVA can be divided into two types: categorical data and continuous data. Categorical data analyses use classification algorithms (e.g. facies distributions), whereas continuous data can contain fractional data (i.e.

porosity, permeability, total proppant, etc.). Analyses of continuous data are the focus of this work and can help in understanding how variables relate to the particular variate for which a prediction is desired and to eliminate redundancies between variables. A more thorough discussion of the methods used for MVA is presented in the Methods section of this paper

Geology

This study examined horizontal wells in the Codell and Niobrara formations within Laramie County, WY (Figures 1 and 2). The Codell is a very-fine to fine-grained sandstone that ranges from 18 to 33 feet in thickness. Production occurs from two main facies: (1) a bioturbated sandstone with a porosity range of 8-13% and a permeability range of 0.008-0.05 millidarcies (md) and (2) a laminated sandstone with a porosity range of 8-15% and a permeability range of 0.01-0.10 md. The pay zone is low resistivity, exhibits low water cuts, and contains 15-25% clay with significant microporosity. The Niobrara in this area is an interbedded chalk/limestone, approximately 300 ft thick with 3 benches – A, B, and C. The B interval is the most targeted in Laramie County with 5-10% average porosity and <0.1md permeability in the lower B. The existence of natural fractures in these formations is a top geologic driver on well performance; while matrix porosity provides limited production potential (Sterling et al, 2016).

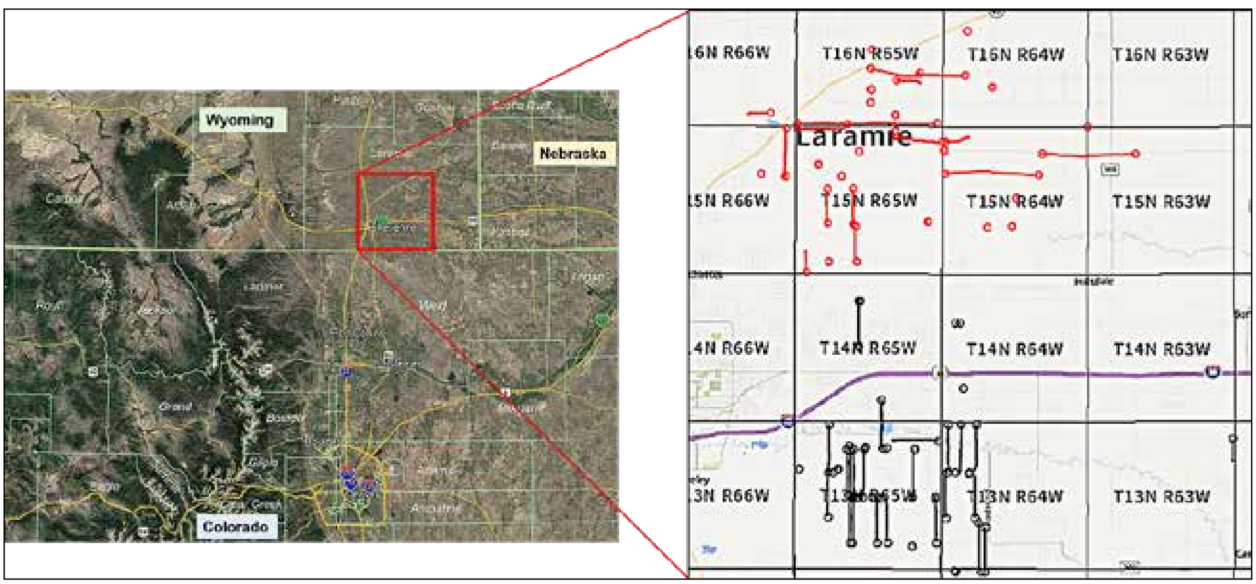


Figure 1: Codell Well locations. Wells in red are within Silo Field.

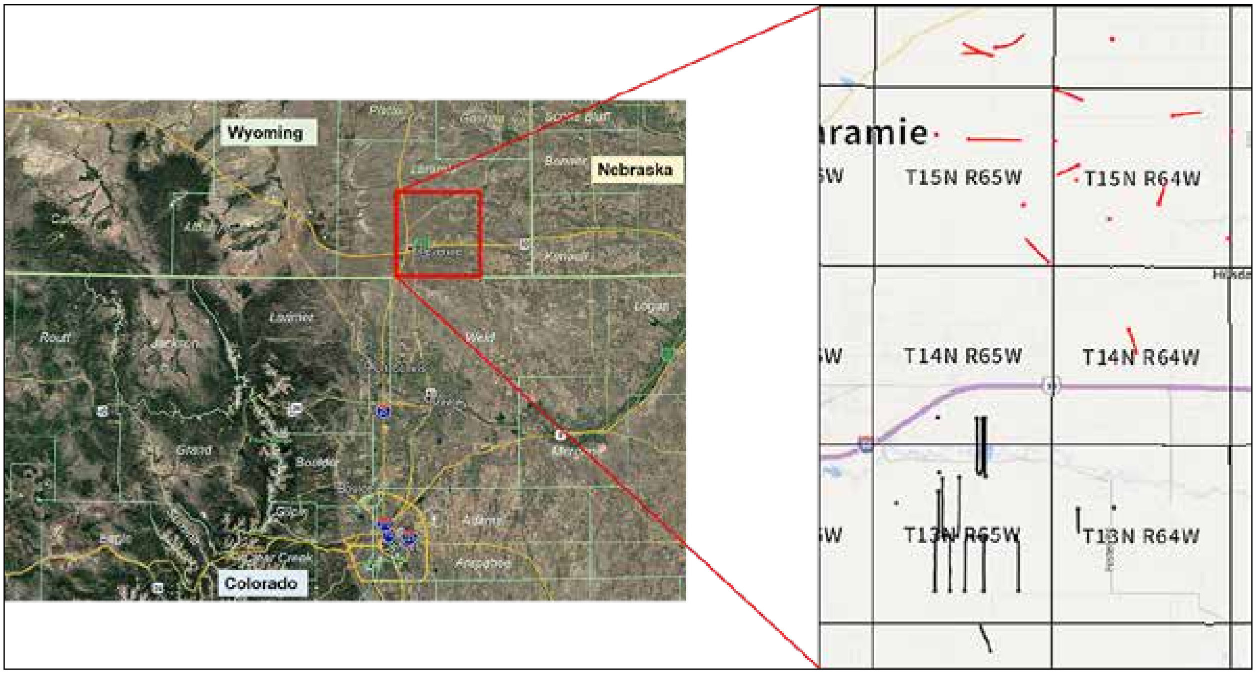


Figure 2: Niobrara Well locations. Wells in red are within Silo Field.

It is important to distinguish wells located within Silo Field due to the difference in stress regimes between that field and the rest of the basin. Outside of Silo Field, a dominant E-W natural fracture system exists yielding the need to drill N-S to capitalize on hydraulic fracture growth (Welker et al, 2013). Within Silo Field, the dominant natural fracture system is NW-SE (Figure 3), which requires operators to drill generally E-W to enhance hydraulic fracture treatments.

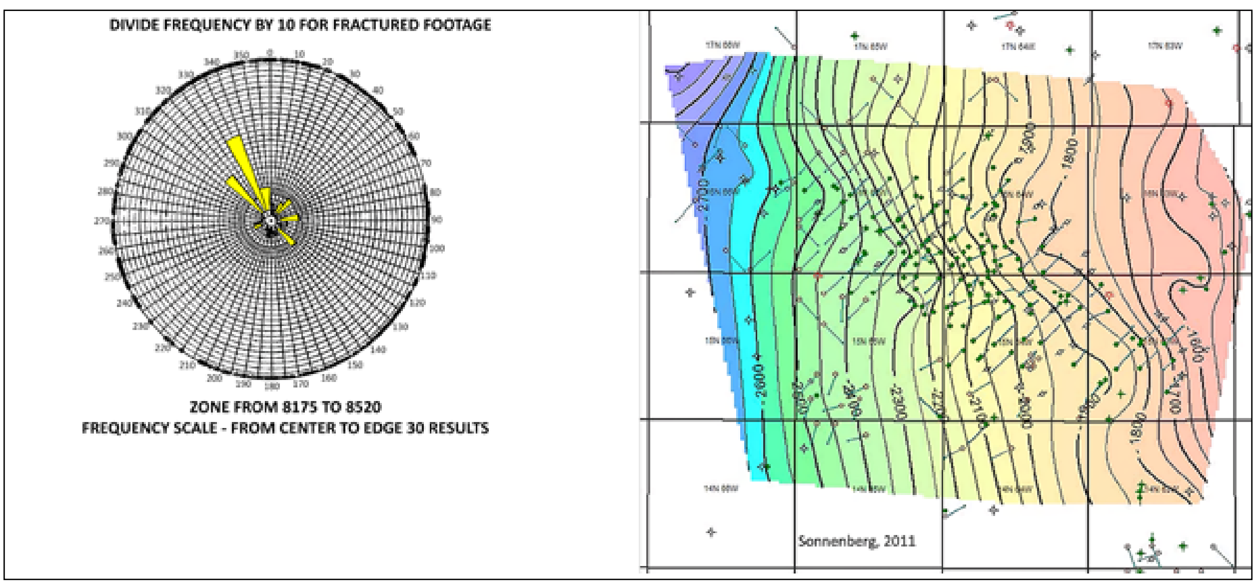


Figure 3: Natural Fracture Network within Silo Field modified from Sonnenberg, 2011.

Methods for using Multivariate Analysis

There are several software programs that can perform multivariate analyses. The program that was selected to conduct this work is Drilling Info's (DI) Transform, which integrates geological, geophysical, and engineering data. A variety of analyses can be conducted within Transform, but this paper will focus on MVA. Transform uses a proprietary multi-variate analytics engine with a variety of algorithms.

There are three algorithms for classifying how the data are to be processed in the program: unsupervised, supervised, and hierarchical. Two algorithms exist for property prediction: linear and non-linear regression. Since completely linear relationships between variables are not expected, non-linear regression was chosen to analyze the dataset.

Non-linear regression is a type of regression analysis where the observed data are modeled with a function that combines the model parameters nonlinearly and is dependent on one or more independent variables. Non-linear regression models are mostly parametric, using a nonlinear equation to define the model. With non-linear regression, each attribute (Lateral Length, Proppant Volume, etc.) is a single value per well. Once a "response" attribute (e.g. cumulative oil production, EUR, etc.) is chosen, then the other attributes are used to predict (model) the response attribute. The combination of attributes that most closely models the response attribute (i.e. similar to history matching) is selected as the final model. By closely examining the individual attribute plots that are generated in the modeling, an optimized design can be obtained. The non-linear regression algorithm will determine what relationship, or combination of relationships, makes the most sense with each input variable and the response variable.

The four available trends for the model to match are: linear, positive or negative monotonic, periodic, or higher order. The type of trend the model selects will be data dependent (e.g. azimuth will have a periodic trend due to equal relationships between north-south and east-west). The response variable will typically be cumulative oil or gas production at varying time intervals or EUR. The response variable, however, can be any value that an investigator is attempting to predict. An example of input variables that can be included in the MVA are noted in Table 1.

When beginning this type of analysis, a large number of input variables can be selected. Each variable will undergo an outlier analysis. The tails of the distribution of an attribute are examined, and the data that exceed a modeled limit are identified. The user sets the threshold that will define the tail limits to be examined and any values that exceed this threshold will be tagged as an outlier. This analysis is based on cumulative probability distribution and population probability distribution functions. A table is generated where the user can decide if these are true outliers or if they should remain in the dataset.

Once the outliers have been identified, a multicollinearity analysis can commence. This analysis is crucial for identifying attributes that are too closely related to one another and may have a negative impact on the MVA results. For example, Proppant Per Foot and Total Proppant will not be included in the same analysis, because they are too closely correlated. A correlation table is generated with the attributes that the user elects to include in the analysis. The relationships are then examined not only from predictor variables to response variable but also between predictor variables, thereby providing an analysis of their "relationship" or their multicollinearity.

Example of Input Variables
Total Proppant Volume
GOR
Frac Stage Length
Number of Stages
Treatment Rate
Frac Fluid Type
Perforated Length
Proppant per Foot
Frac Treatment Volume
Wellbore Azimuth
Proppant Size
WOR
Temperature
Log Properties
Reservoir Pressure
Core Properties
Liner Completion Type
Total Slurry
Proppant Type
Horizontal Length

Table 1: Example of Possible Input Variables

Data Gathering and Quality Check

Constructing a thorough, accurate, and statistically significant dataset is the most important part of any analysis and is normally the most time-consuming; this study proved no exception. There are little public data available in tabular form for the study area, thus requiring the extraction of information from various locations to populate the Enhanced Oil Recovery Institute (EORI) database, which was used for this analysis. Data obtained from DI, the Wyoming State Geological Survey (WSGS), and the Wyoming Oil and Gas Conservation Commission (WOGCC) were extracted and then quality-checked (QC'd). The EORI downloaded and transcribed Form 3 completion data from the WOGCC for each well to create a completion database. Only wells that had reported completion data were included in the analysis. In order to have a representative dataset with newer completion techniques, only wells completed after 2013 were included. This selection criteria yielded a total of 81 Codell wells and 43 Niobrara wells.

As long as there is a statistically significant data type, then any attribute that can be expressed as a single value per well can be used. Existential variables, such as depletion, localized geologic anomalies, well maintenance, etc., cannot be expressed as a single attribute per well, so these variables must also be considered when evaluating the results of an MVA analysis.

There are some very useful tools within Transform that allow for the calculation of well spacing, porpoising, dog-leg severity, and percent in zone. Unfortunately, only about half of the wells considered in the data set contained survey data, so these attributes could not be incorporated into the analysis. The EORI is also in the process of compiling temperature data and average log data across the zone of interest to help incorporate more geologic data into the MVA, which will be presented after further analysis. Operator engagement resulting in increased data availability will greatly improve the dataset and allow more key attributes to be displayed and discussed.

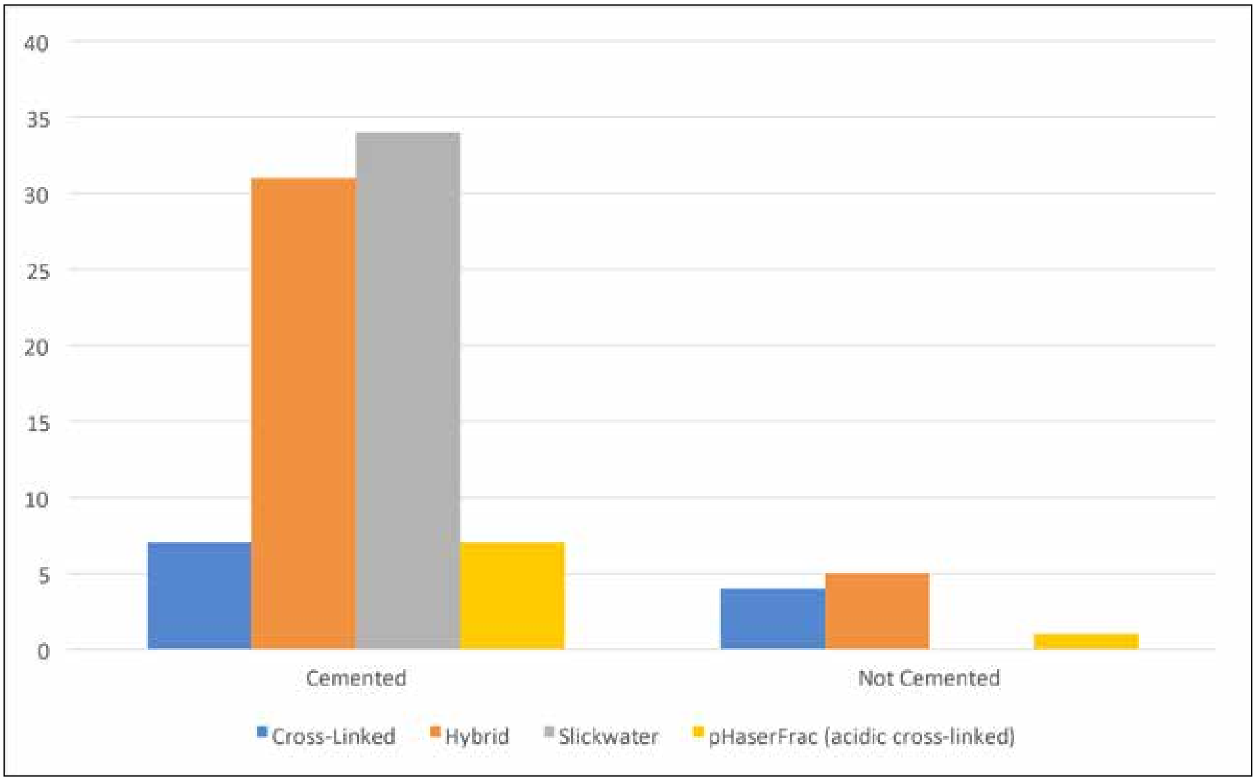


Figure 4: Production String Completion Type and Treatment Fluid Pumped

Once all the available data were gathered, they were QC'd, both by manual inspection and through graphing. Crossplots and bar graphs provide a visualization tool to identify outliers and general trends before starting any MVA. The Codell well dataset is discussed first, as it provides a higher level of detail than the Niobrara dataset. Figures 4-8 show some examples of the data QC that was conducted.

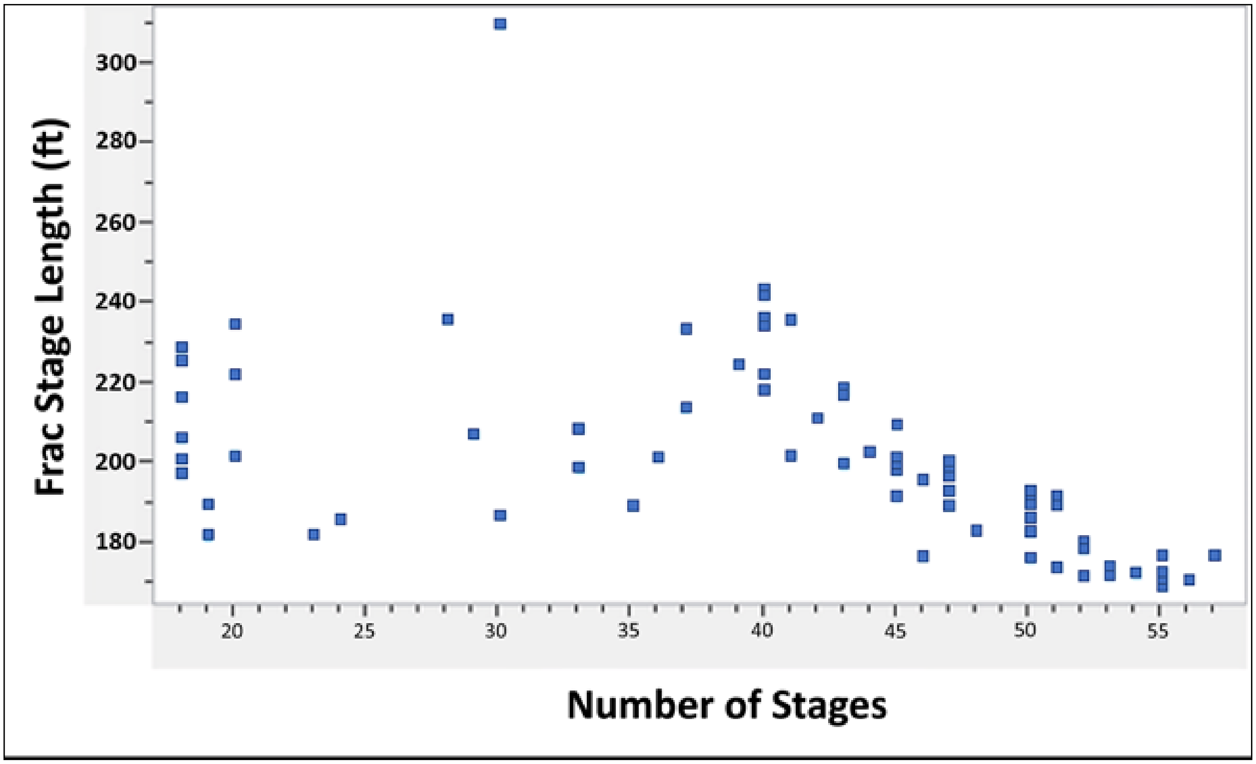


Figure 5: Codell Induced Fracture (Frac) Stage Length Versus Number of Stages

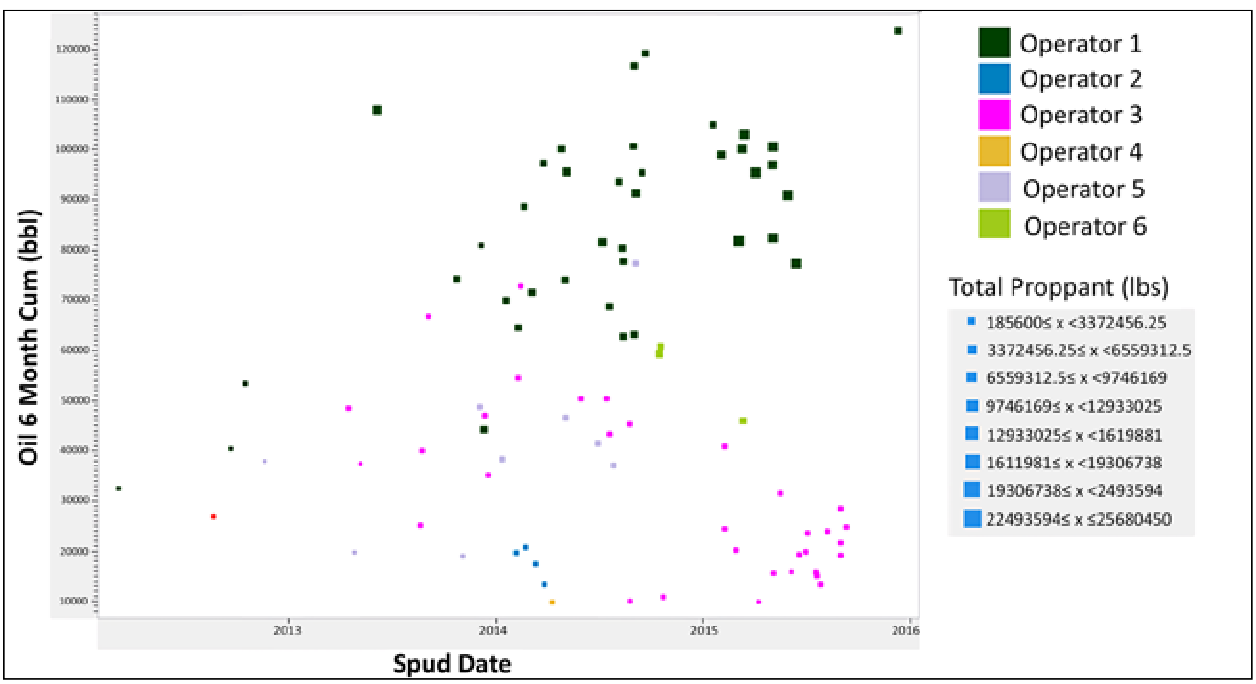


Figure 6: Codell Oil 6-Month Cum Versus Spud Date; Colored by Operator and Sized by Total Proppant

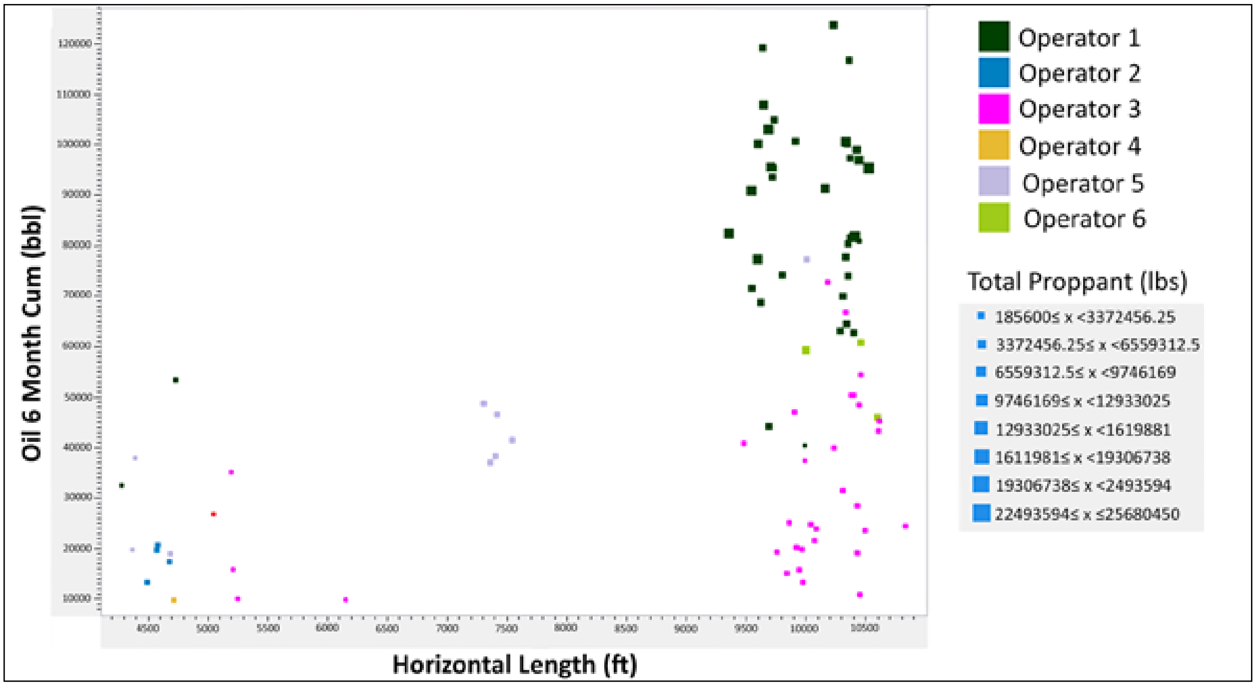


Figure 7: Codell 6-Month Cum Versus Horizontal Length; Colored by Operator and Sized by Total Proppant

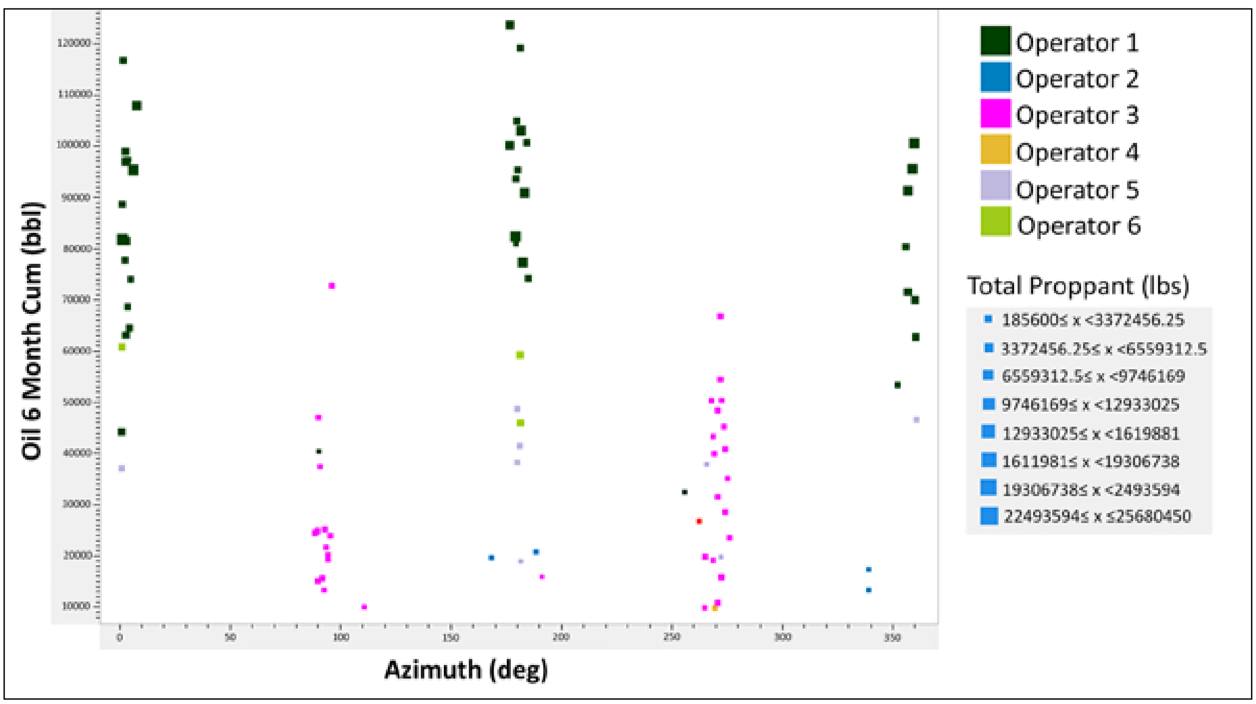


Figure 8: Codell Oil 6-Month Cum Versus Azimuth; Colored by Operator and Sized by Total Proppant

The figures above provide a general notion of current completion practices. Most of the wells are ~10,000 ft cemented laterals with 40-plus induced fracture (frac) stages, utilizing a slickwater or hybrid fracturing fluid system. This hybrid system comprises slickwater in pad and low proppant concentration stages, followed by a crosslinked gel in the higher proppant concentration stages. The 6-month cumulative production crossplots show some interesting trends that warrant further discussion. The analysis indicates that Azimuth, Proppant Volume, and Horizontal Length are impacting production, but it is unclear how much of an impact each variable has on production. For example, laterals drilled N-S or S-N exhibit better production than those that have been drilled E-W or W-E; however, a majority of the N-S/S-N wells also have larger proppant volumes than those wells drilled E-W/W-E. There are some observed differences between operator performance since a majority of the wells in the study area are owned by operators 1 and 3, and a stark difference can be seen between the 6-month cumulative production between the two. Although useful for general trends and quality control, it is difficult to draw any definitive conclusions solely from crossplots. A multivariate approach becomes useful in these instances by determining how impactful each input variable is on the response variable.

Codell Six-Month Cumulative Production Multivariate Analysis

Correlation Table

Once the data have been QC'd, and general drilling and completion trends have been determined, the MVA can begin. For the initial MVA analysis, cumulative 6-month oil production was selected as the response variable and numerous variables were considered as input variables. Arriving at the final set of input attributes is an iterative process. Not only do the attributes need to be impactful on the response variable, but they also cannot be too closely correlated to each other. Variables that are too similar will skew the results of the analysis (e.g. the need for multicollinearity analysis). Each step of the workflow needs to be examined to verify that the results are logical. Initially, wells within Silo Field were separated from those outside of Silo Field due to the stress anomaly; however, there were not enough wells in these two separate datasets to be individually statistically significant. For this reason, the wells were combined for the MVA work.

Other Variables Considered in Analysis
Frac Stage Length
Number of Stages
Frac Fluid Type
Perforated Length
Proppant per Foot
Frac Treatment Volume
Well Spacing
Percent in Zone
Toe Up/Down
Wellbore Azimuth
Liner Completion Type
Total Slurry
Proppant Type

Table 2: Variables Considered but Not Used in Final Model

By comparing different combinations of attributes, it is possible to determine those variables that maximize R squared (R^2) of the actual and measured cumulative production and minimize correlation between input attributes. As previously described, an outlier analysis and multicollinearity analysis were performed to arrive at the final set of attributes. Table 2 displays additional variables that were tested in the iterative process but not included in the final analysis.

The variables are displayed in a correlation table to better understand their relationship to the response variable and to other input variables. Figure 9 illustrates the standard correlation coefficient (Pearson's r) table and the rank correlation coefficient (Spearman's rho). By examining the values in these tables, the user can get an indication of the way the variables interact and if any variable should be excluded. If an attribute has a high-standard-correlation-coefficient (Hs) and a high-rank-correlation-coefficient (Hr), then a linear relationship exists between the variables. An example of this sort of relationship is a comparison of sonic and porosity values.

Standard correlation coefficient

	Oil6MonthCum	WGSTotalProppant	HorizontalLength	GOR3Months	EORI_Treatment_Rate
Oil6MonthCum	1.0	0.763	0.491	0.14	0.582
WGSTotalProppant	0.763	1.0	0.452	0.16	0.703
HorizontalLength	0.491	0.452	1.0	0.06	0.152
GOR3Months	0.14	0.16	0.06	1.0	0.112
EORI_Treatment_Rate	0.582	0.703	0.152	0.112	1.0

Rank correlation coefficient

	Oil6MonthCum	WGSTotalProppant	HorizontalLength	GOR3Months	EORI_Treatment_Rate
Oil6MonthCum	1.0	0.788	0.299	0.197	0.653
WGSTotalProppant	0.788	1.0	0.291	0.271	0.673
HorizontalLength	0.299	0.291	1.0	0.032	-0.005
GOR3Months	0.197	0.271	0.032	1.0	0.267
EORI_Treatment_Rate	0.653	0.673	-0.005	0.267	1.0

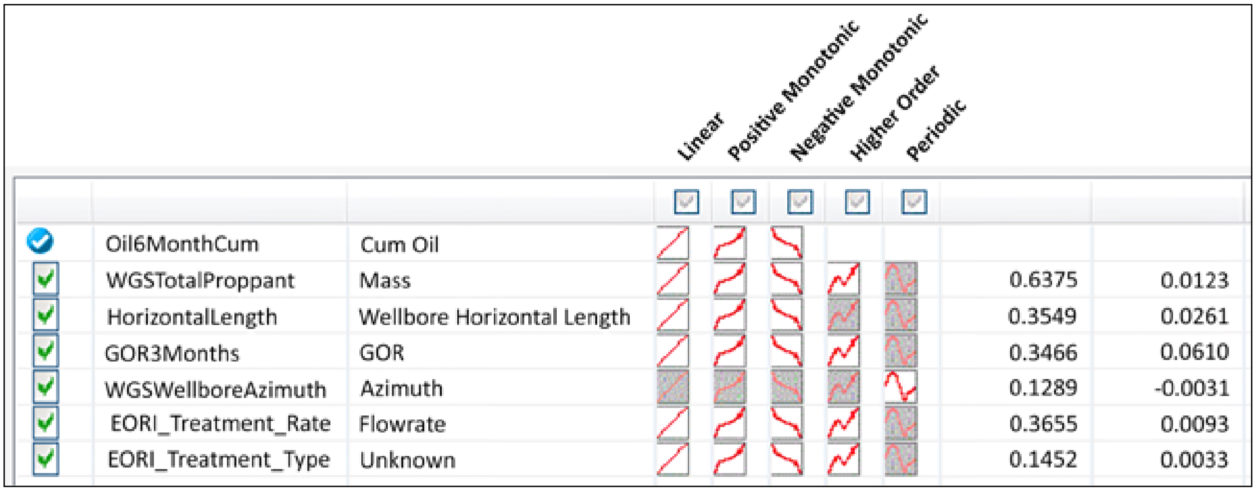
Figure 9: Correlation Tables for Final Set of Attributes

A low-standard-correlation-coefficient (Ls) and a Hr indicates a nonlinear relationship between the variables. This relationship is common with the variables being examined and shows that nonlinear regression should be exercised. For example, a correlation would not be anticipated between GOR and lateral length.

Hs and low-rank-correlation-coefficient (Lr) demonstrates outliers and shows that the outlier analysis should be revisited. Ls and Lr each indicate that there is no clear relationship between the variables. Some of the main takeaways from these correlation tables are the linear relationship between Total Proppant and Oil 6-Month Cum indicated by the Hs and Hr. Additionally, the tables reveal a linear relationship between Treatment Rate and Oil 6-Month Cum. A majority of the other variables have Ls and Lr, which is logical, since one would not expect a relationship between variables such as Horizontal Length and GOR.

MVA Model

Before the model with the final attributes is presented, it is important to examine an iteration example to demonstrate the process of arriving at the final attributes. Figure 10 displays the MVA model for one of many iterations.



			Linear	Positive Monotonic	Negative Monotonic	Higher Order	Periodic		
	Oil6MonthCum	Cum Oil							
	WGSTotalProppant	Mass						0.6375	0.0123
	HorizontalLength	Wellbore Horizontal Length						0.3549	0.0261
	GOR3Months	GOR						0.3466	0.0610
	WGSWellboreAzimuth	Azimuth						0.1289	-0.0031
	EORI_Treatment_Rate	Flowrate						0.3655	0.0093
	EORI_Treatment_Type	Unknown						0.1452	0.0033

Figure 10: Iteration Example for the MVA Model

The blue check mark in the upper left of Figure 10 signifies the response variable and each green checked attribute will be used as an input variable in the model. The small graphs depict the transformations that the model will be using in the run. If the graph is white, then Transform used that option in the algorithm, as opposed to a gray box indicating that the respective transformation was not used. Each input attribute is examined to determine which transformation or combination of transformations gives the best match to the response attribute. The available transformations are linear, positive monotonic, negative monotonic, higher order, and periodic. Certain transformations were ignored due to the variable type. Because of its sinusoidal nature, Azimuth uses a periodic transformation. Similarly, Horizontal Length does not include higher order and periodic transformations because this type of relationship with production is not logical.

The significance and sensitivity are calculated as a result from the MVA. Significance is the ratio of the range of transforms of a variable to the range of transforms of the response variable. Sensitivity reflects how much the correlation is dependent on a particular variable. The higher the sensitivity and the significance, the more impactful the attribute is to the response variable. A variable that has a negative sensitivity is detrimental to the analysis and should be removed from the model. Negative sensitivity decreases the R^2 of the model, thus making it less robust. In this example, azimuth has a negative sensitivity, due to the fact the sample set has wells located in two different stress regimes that require different azimuths to optimize recovery. The program recognized this fact and highlighted the problem.

Figure 11 illustrates the final attributes that equated to a modeled 6-month cum that had the highest R^2 when plotted against the actual 6-month cum values. All of the attributes have high significance and relatively high sensitivity. The actual values for sensitivity are not so important; what is important is the magnitude of differences between them. The attributes are sorted from most impactful to least impactful. As can be seen, Total Proppant is impacting 6-month oil cum the most;

its significance values are about double the significance of other attribute values. It is important to examine the individual attribute response both to make sure the trends are logical and to arrive at what is providing high production for each attribute.

Use	Variable	Property Type						Significance	Sensitivity
	Oil6MonthCum	Cum Oil							
	WGSTotalProppant	Mass						0.6290	0.0540
	HorizontalLength	Wellbore Horizontal Length						0.3714	0.0362
	GOR3Months	GOR						0.3448	0.0493
	EORI_Treatment_Rate	Flowrate						0.2675	0.0275

Figure 11: Final Attributes for the MVA Model

Individual Attribute Response

Non-linear regression is defined in Equation 1 below. The sum of all the individual attribute transformations equates to the transformed 6-month oil cum and the resulting 6-month cum. Figure 12 illustrates how the model calculates the 6-month cum for each well. In this example, the sum of the following transformations for each attribute (using the Transformed attribute values displayed on the y-axes in Figure 13), results in the transformed 6-month oil cum. For example, if individual transformation values were summed for a select well: 0.2 + 0.1 + 0.2 + 0.1 = 0.6, then this transformed cum directly correlates to the modeled cum of 78,612 barrels of oil (BO).

Equation 1: Non-linear Regression Equation

Non-linear regression $\theta(\Upsilon) = \alpha + \sum_{i=1}^{p} \phi_i (X_i) + \epsilon$

$$\text{where } \theta \text{ is a function of the response variable}, \Upsilon, \text{and}$$
$$\phi_i \text{ are functions of the predicators } X_i, i = 1, \ldots, p$$

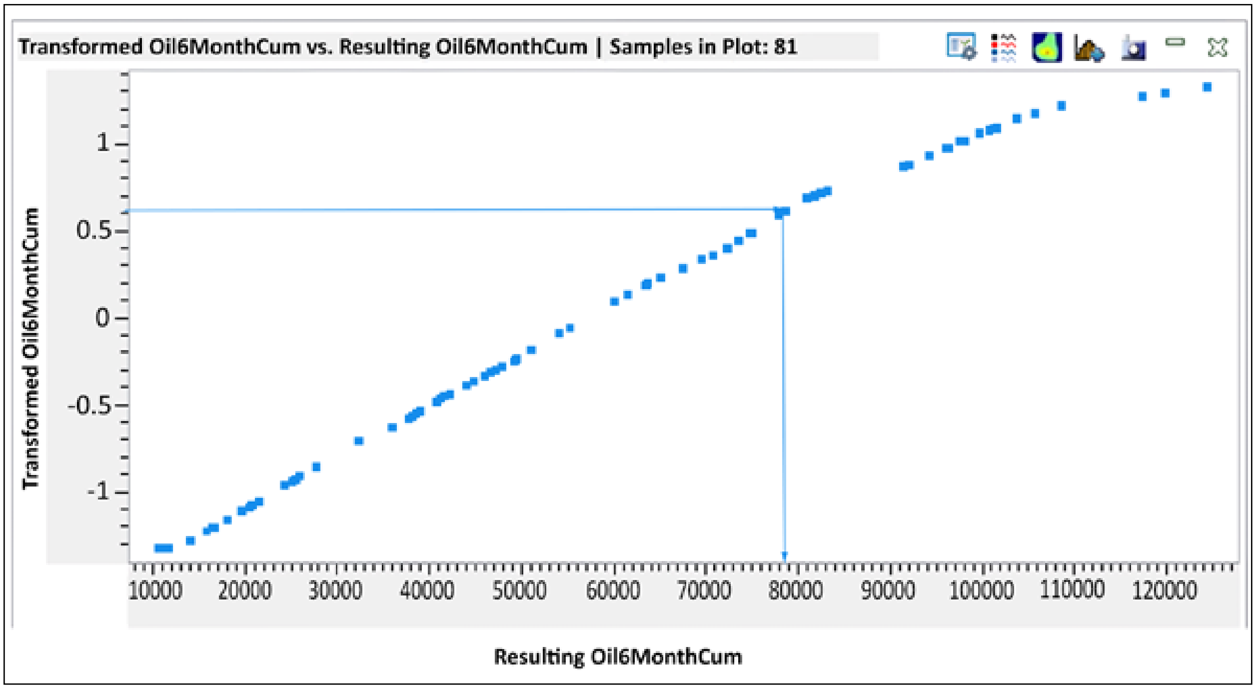


Figure 12: Transformed Oil 6-Month Cum Versus Modeled Oil 6-Month Cum

Figure 13 illustrates the individual attribute responses. These responses are closely analyzed with each model run in order to help determine best practices. The Total Proppant transformation shows that more proppant yields higher production; however, there is a significant slope change around 12MM lbs of proppant. This proppant volume is a reasonable starting point for operators to maximize 6-month cum. For Horizontal Length, laterals around 10,200 ft are yielding the best production. A GOR around 570 scf/bbl is ideal, and a minimum fracture treatment rate of 40 bpm should be used.

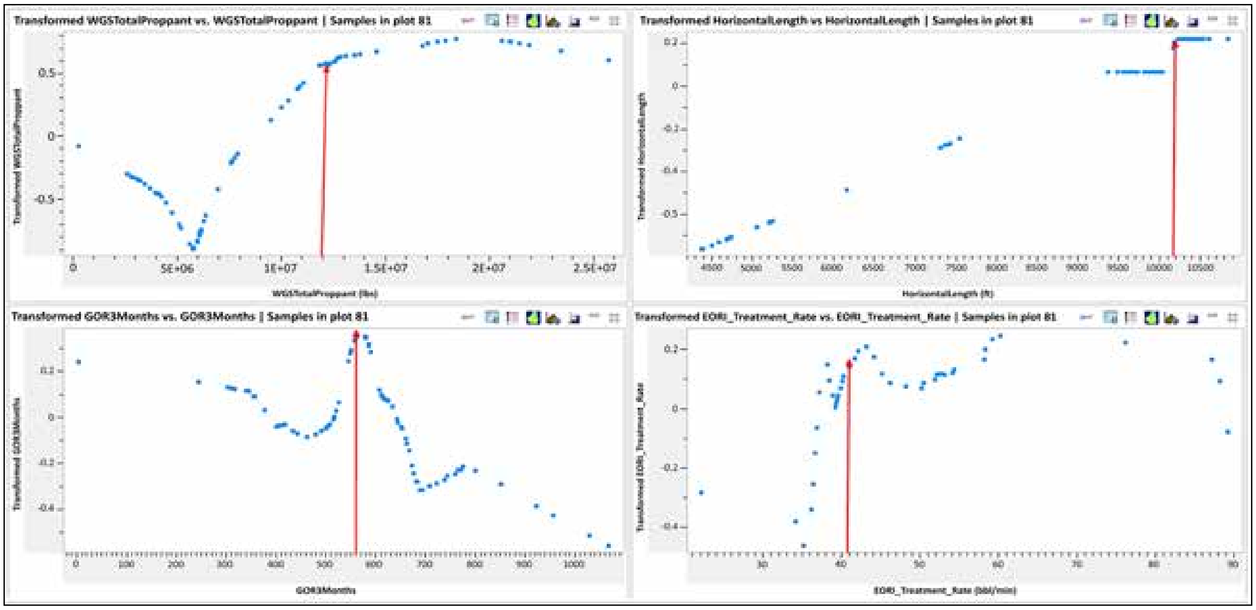


Figure 13: 6-Month Cum Predictor Attribute Individual Transformations

Now that each of the individual transformations have been examined, it is time to look at the validity of the model as a whole. The modeled 6-month cum for each well is compared to the actual 6-month cum. The higher the correlation between the modeled and the actual production, the higher the confidence in the results. Figure 14 illustrates the modeled versus actual production numbers based on the final predictor attributes shown in Figure 11.

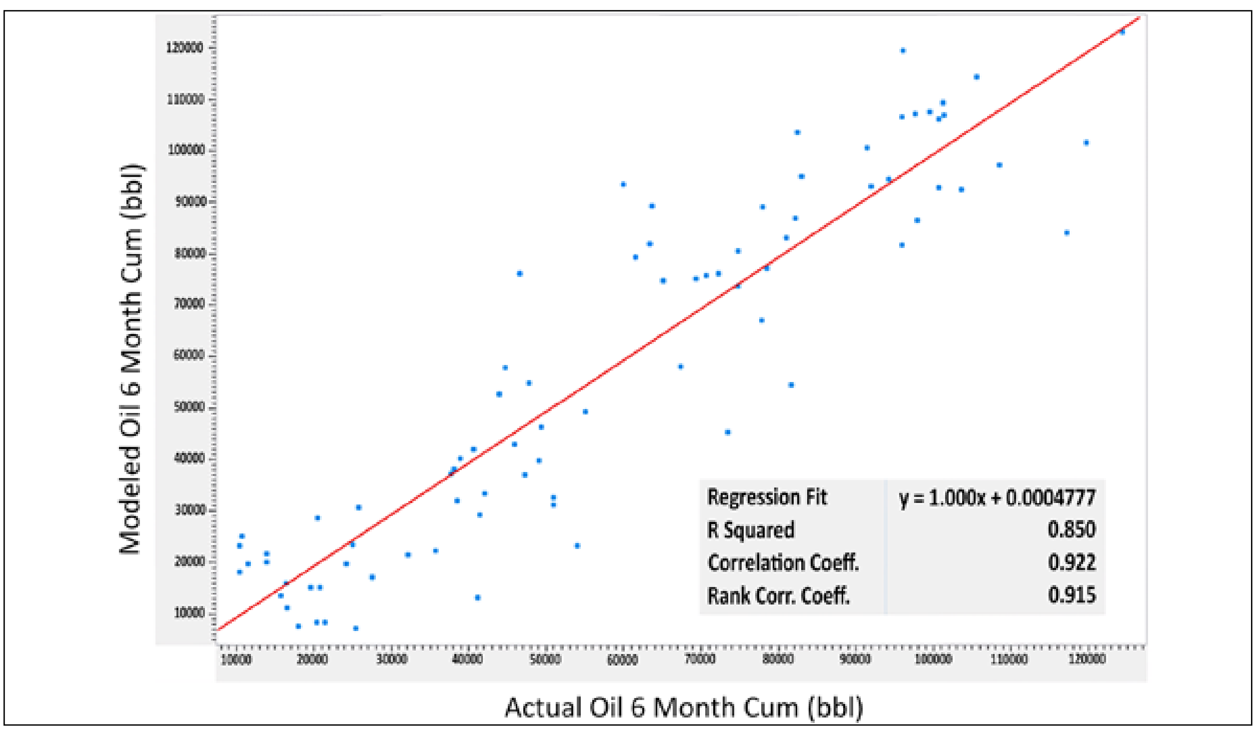


Figure 14: Modeled Versus Actual 6-Month Cumulative Oil Production

The final MVA model is yielding a high R^2, Correlation Coefficient, and Rank Correlation Coefficient. The higher these numbers, the better the model is at replicating the actual production numbers (i.e. similar to history matching).

Hypothetical Scenarios

One of the benefits of MVA is that once a model has been finalized, an equation is created that can be used to model hypothetical scenarios. As an example, since Total Proppant is the most significant factor affecting production in this study, a hypothetical case was prepared to see what might happen if every well would have used the optimal proppant volume of 12MM lbs, with all of the other attributes remaining at their original values. Figures 15-17 examine the same variables as did Figures 6-8 but using 12MM lbs as the constant proppant volume to calculate 6-month cum production.

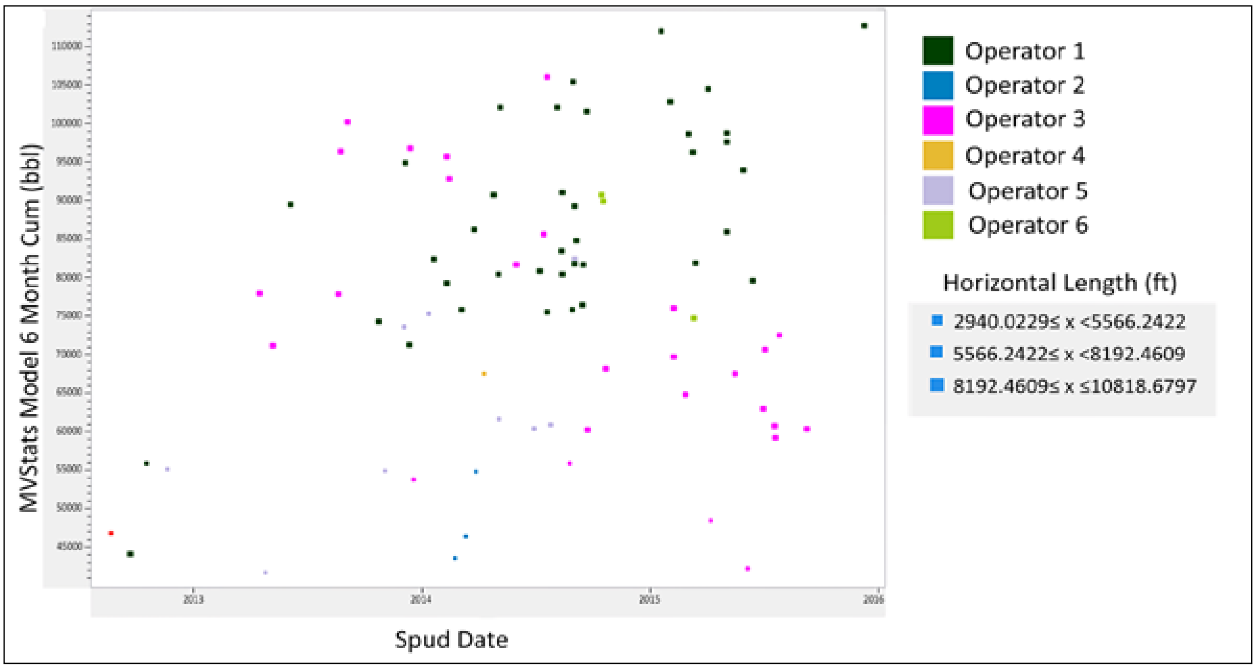


Figure 15: 12MM lbs Proppant Volume Normalized Modeled 6-Month Cum Versus Spud Date

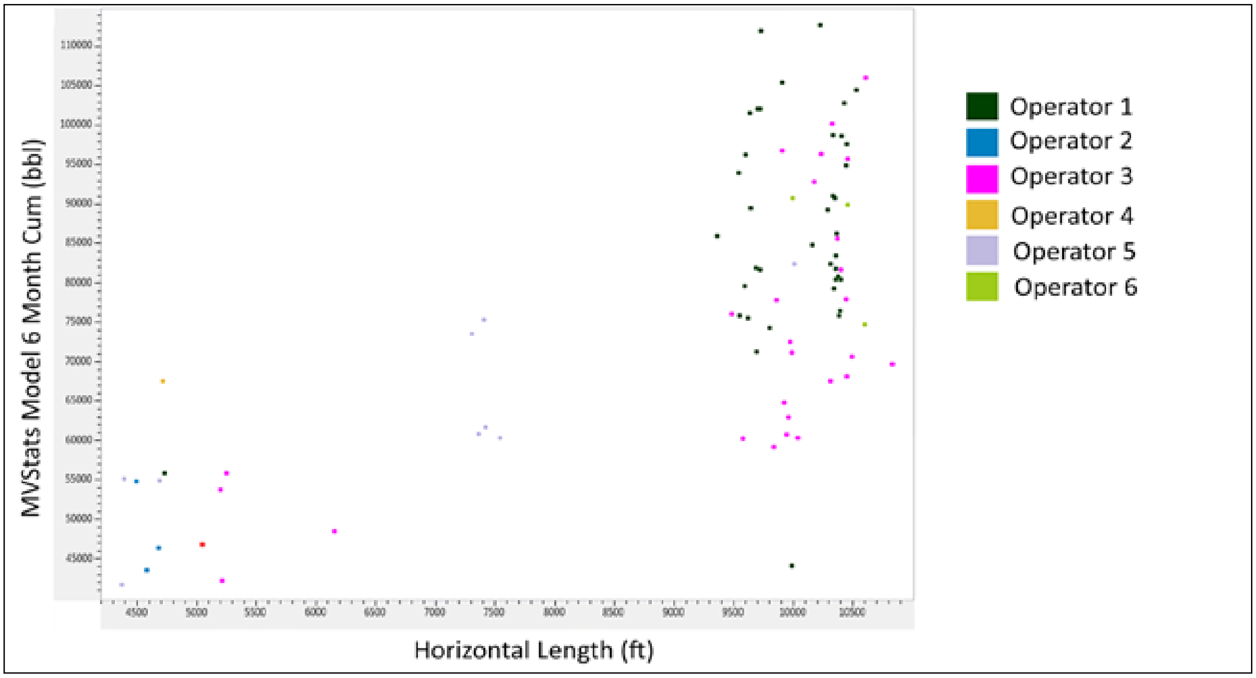


Figure 16: 12MM lbs Proppant Volume Normalized Modeled 6-Month Cum Versus Horizontal Length

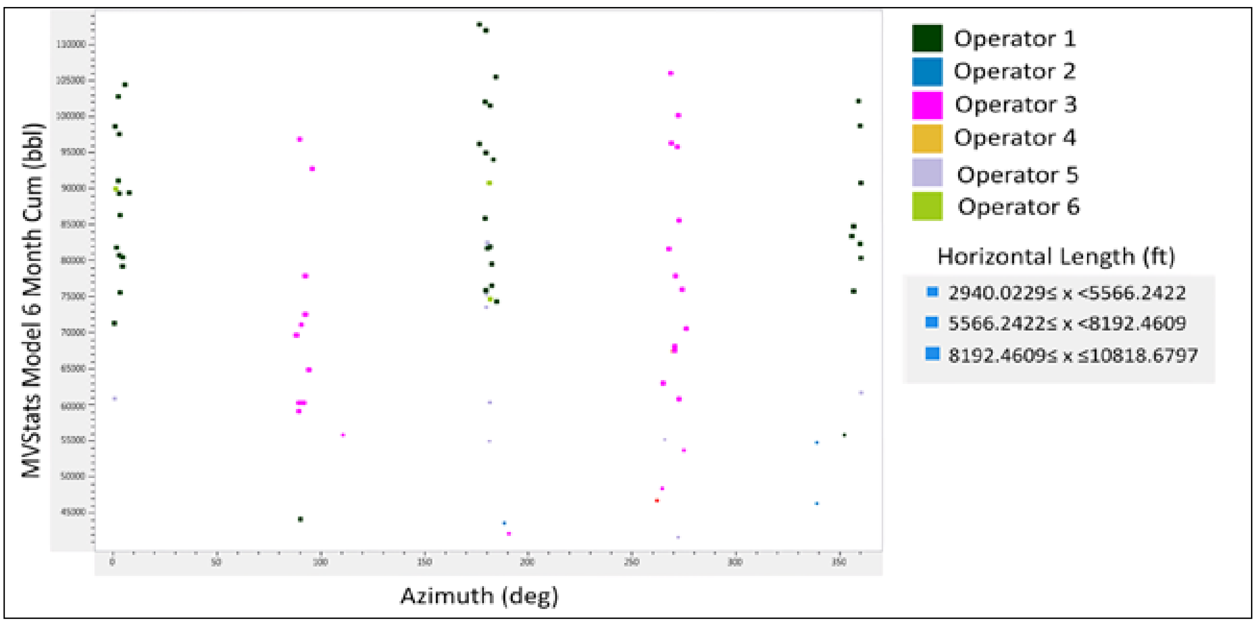


Figure 17: 12MM lbs Proppant Volume Normalized Modeled 6-Month Cum Versus Azimuth

According to this model, if every operator would have pumped 12MM lbs of proppant, then the discrepancies that were apparent between operators drilling long laterals are eliminated. Figure 15 turns into more of a shotgun pattern, showing no significant discrepancies between different operators and their 6-month cums, and in Figure 16, an advantage in drilling direction is not evident. This is not to say that every operator should be pumping 12MM lbs due to specific field/well issues, but based on this model, pumping 12MM lbs of proppant is providing the best 6-month cums. For instance, operators in Silo must deal with the possibility of communication to depleted zones from pre-existing wellbores, so a large proppant volume frac could be detrimental to their field development.

By simply looking at crossplots, one would assume that Azimuth would have been a major factor on production; however, when Proppant Volume is normalized, there is no clear winner in terms of Azimuth in this particular study. This observation makes sense based on the different stress states between wells within Silo Field and those outside of Silo Field. Operators are drilling in the correct direction in each scenario, validating that Azimuth becomes a non-contributing attribute for this study.

Codell 12-Month Cumulative Production Multivariate Analysis

Now that the contributing factors to 6-month cum production have been determined, similar analyses were performed for a 12-month period. All of the attributes were re-examined to see if there were any different factors impacting production at twelve months. After numerous iterations, the final set of attributes ended up being the same as those for six months. The 12-month results are in shown in Figure 18.

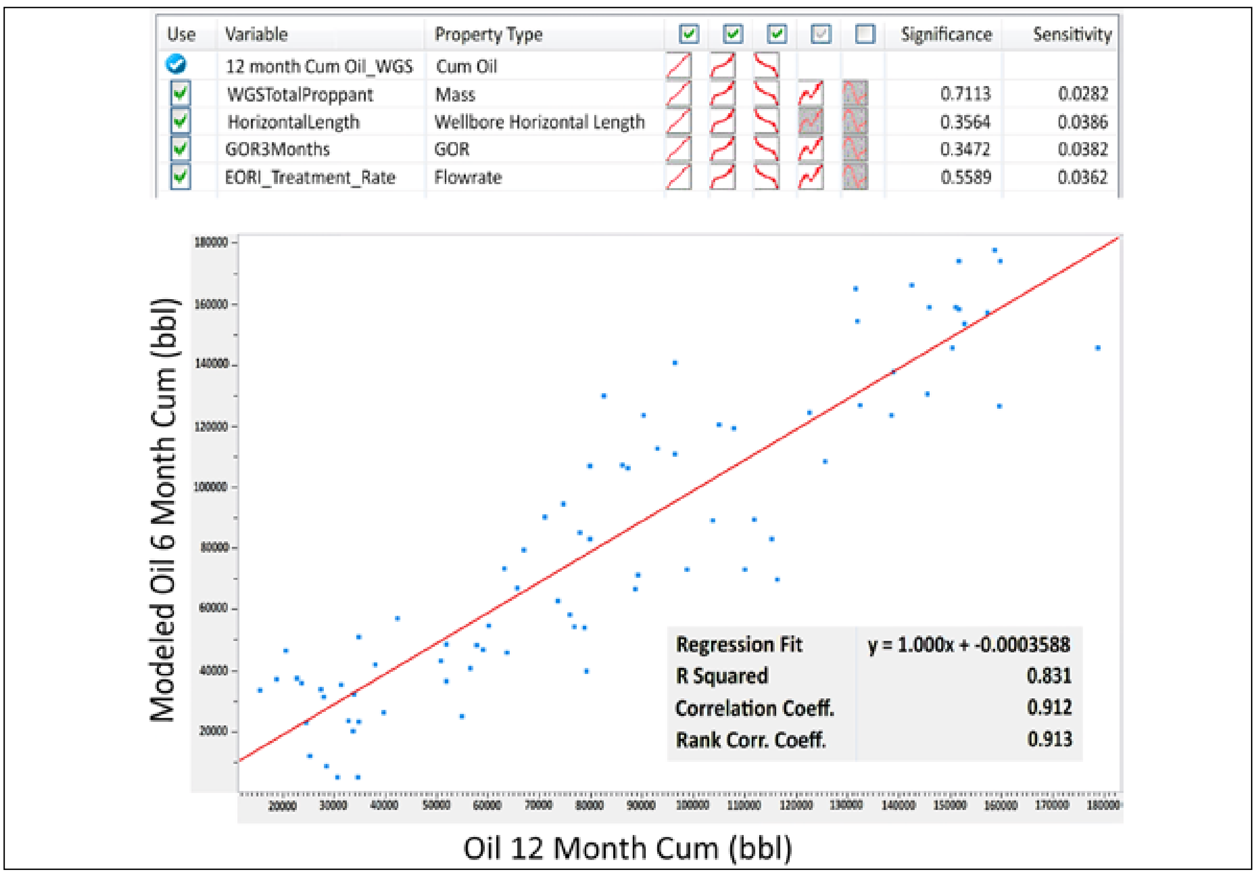


Figure 18: 12-Month Cumulative Production MVA Model

Total Proppant Volume is still the most impactful variable and its significance has increased from the 6-month cum model. Treatment Rate has increased to the second most impactful variable, while GOR and Horizontal Length are very similar. The R^2 and correlation coefficients are all still high, giving confidence in the model results. Figure 19 displays the individual attribute responses for the 12-month cum model. There is still a slope change around 12MM lbs of proppant; however, it is not as stark. Proppant volumes greater than 12MM lbs are positively impacting production more at 12 months compared to 6 months. The other attributes are fairly similar to what was seen from the transformations at 6 months.

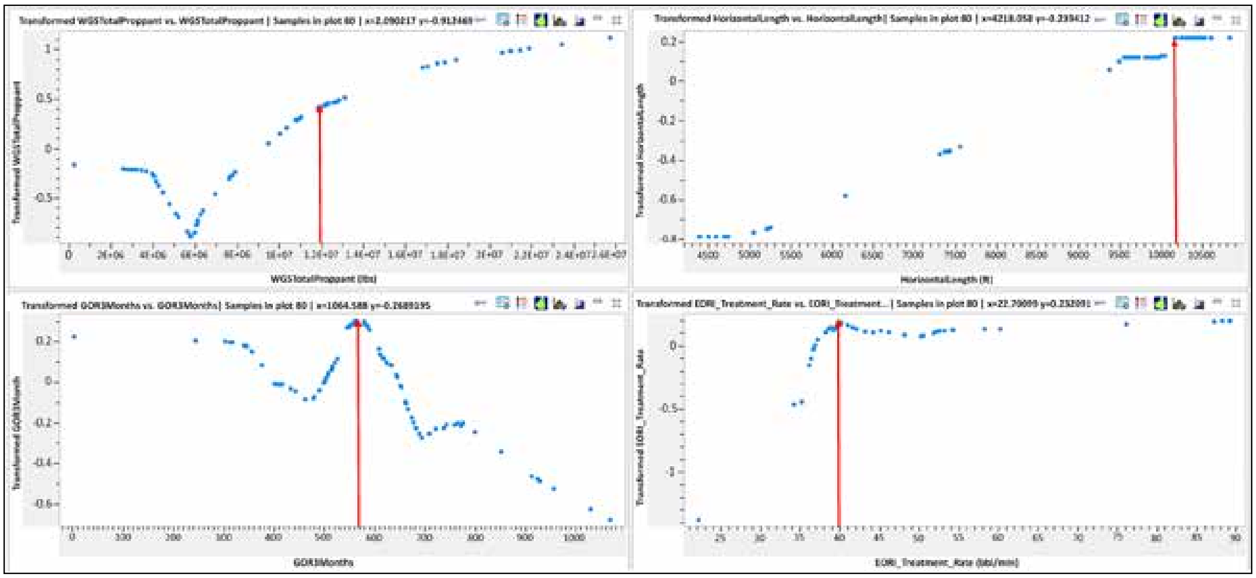


Figure 19: 12-Month Cumulative Production Predictor Attribute Individual Transformations

Codell 18-Month Cumulative Production Multivariate Analysis

The next analysis involved an 18-month cum. The number of available wells decreased to 60. As with the previous 6- and 12-month models, all of the attributes were considered in this analysis, but as in the case with the 12-month cum analysis, the final set of attributes is the same as at 6 months. Figure 20 displays the results from the 18-month cum MVA model.

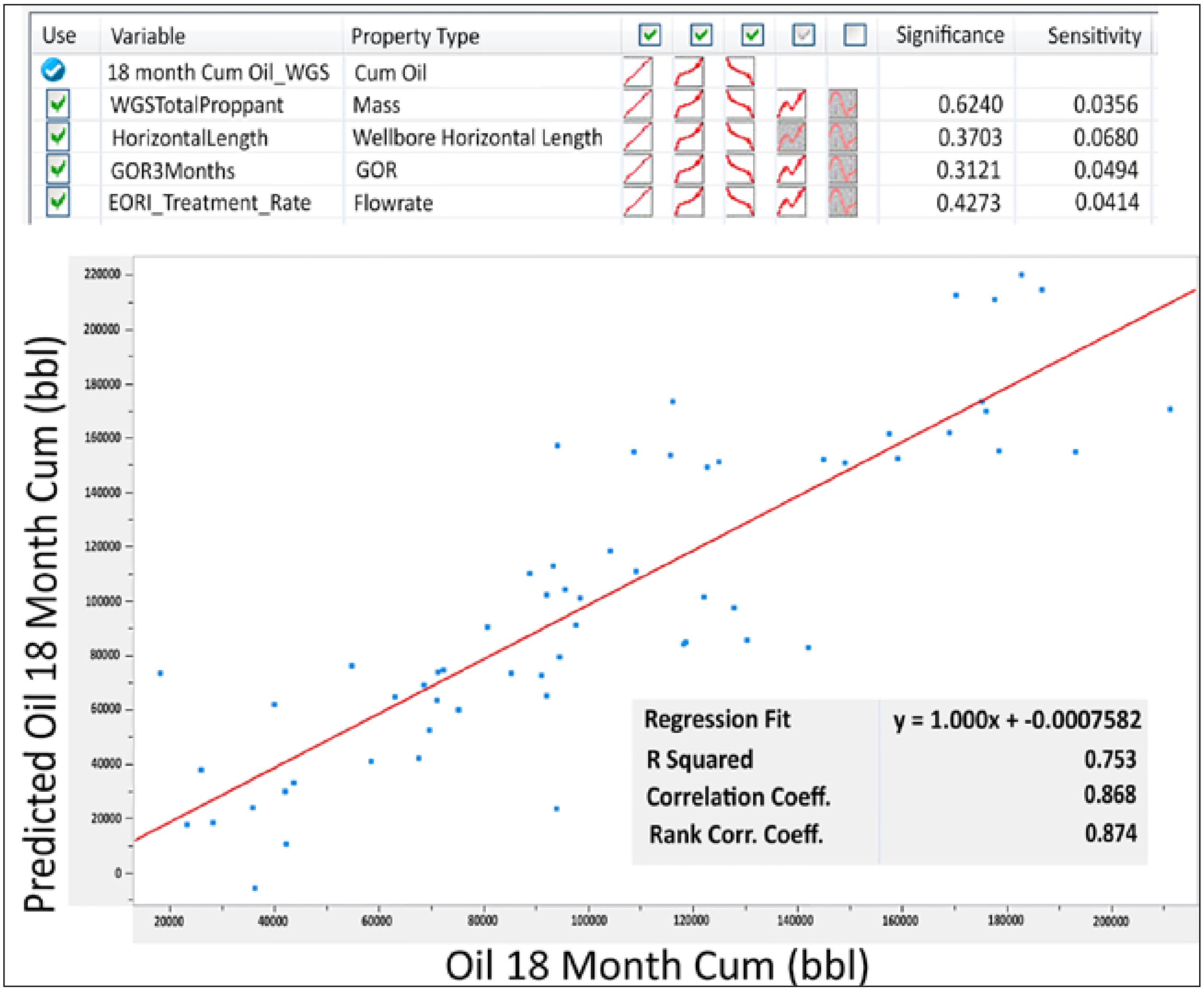


Figure 20: 18-Month Cumulative Production MVA Model

Even with the reduction in available wells (to 60), there is a good match between the model and actual production data. Although the R^2 and correlation coefficients are lower than with the previous two models, they are still reasonable. Total Proppant is once again the most impactful variable, followed by Treatment Rate, Horizontal Length, and GOR. Figure 21 illustrates the individual attribute response at 18 months. A more prominent slope change at 12MM lbs on the Total Proppant transformation plot is again apparent at 18 months, and the step change present at 6- and 12-months for Horizontal Length has vanished. At 18 months, it is apparent that lateral lengths over 9,600 ft are not providing any increase in production.

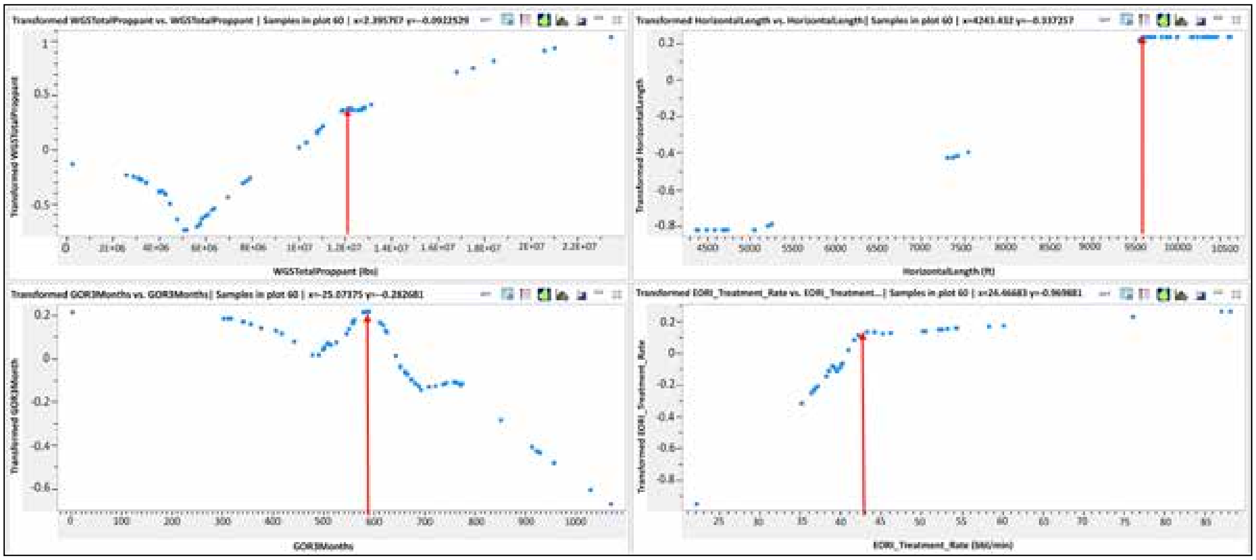


Figure 21: 18-Month Cumulative Production Predictor Attribute Individual Transformations

An additional analysis was attempted with EUR values calculated by DI as the response variable; however, the current dataset (e.g. number of wells) was insufficient to arrive at a statistically significant set of values. This shortcoming is something that the EORI will continue to pursue with operator engagement and increased data.

Codell Economic Analysis

In order to determine the most cost-effective amount of proppant to use during a frac treatment, type curves were generated for varying proppant volumes. The initial crossplots (Figures 6-8) show that a majority of the wells are owned by Operator 1 and Operator 3; therefore, the economic analysis will focus on these two operators. Operator 1 pumped high-volume fracs of up to 20MM lbs of proppant with their average being 12MM lbs. Operator 3 pumped 6MM lbs of proppant on average. This proppant range provides a good spectrum for current Codell frac jobs in Laramie County.

Decline Curve Analysis

Transform contains an internal decline curve analysis (DCA) tool that generates type curves based on normalized production data. There are five available models for the program to autofit the data: Arps, Stretched Exponential Production Model (SEPD), Duong, Power Law, and Logistic Growth. For these types of wells, the models that were selected were Arps, SEPD, and Power Law, because they accurately model horizontal wells with multiple frac stages. Segmentation analysis, using up to three segments, could be utilized for curve matching. The maximum allowable months in EUR was set at 600 and the minimum monthly production was 180 BO. The 12MM lb type curve is shown in Figure 22, with the top graph being the DCA of the type curve generated from the eight production curves shown in the lower graph. The best fit was obtained with two segments both using the Arps Model. The details of the analysis are contained in Figure 22.

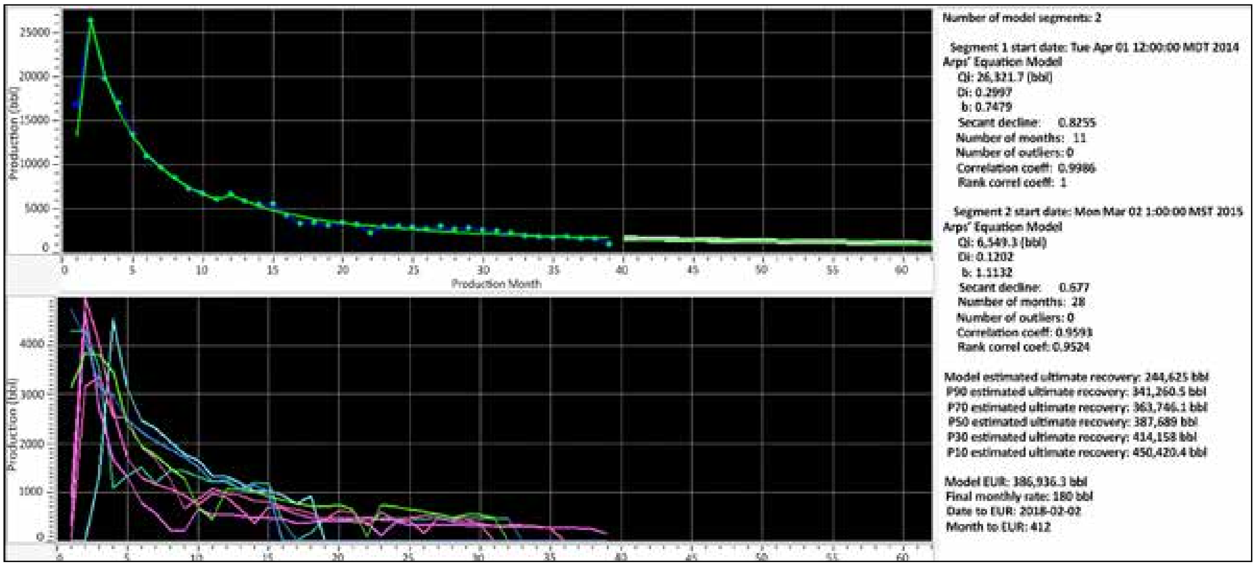


Figure 22: 12MM Lb Proppant Volume Oil Type Curve

Next, the large proppant volume type curve was generated for the 20MM lbs jobs using the same input parameters. The analysis is divided into two segments, both using the Power Law Model. This type curve is based on only two production curves with limited production data. This analysis will continue to be refined as more data become available. Figure 23 displays the results.

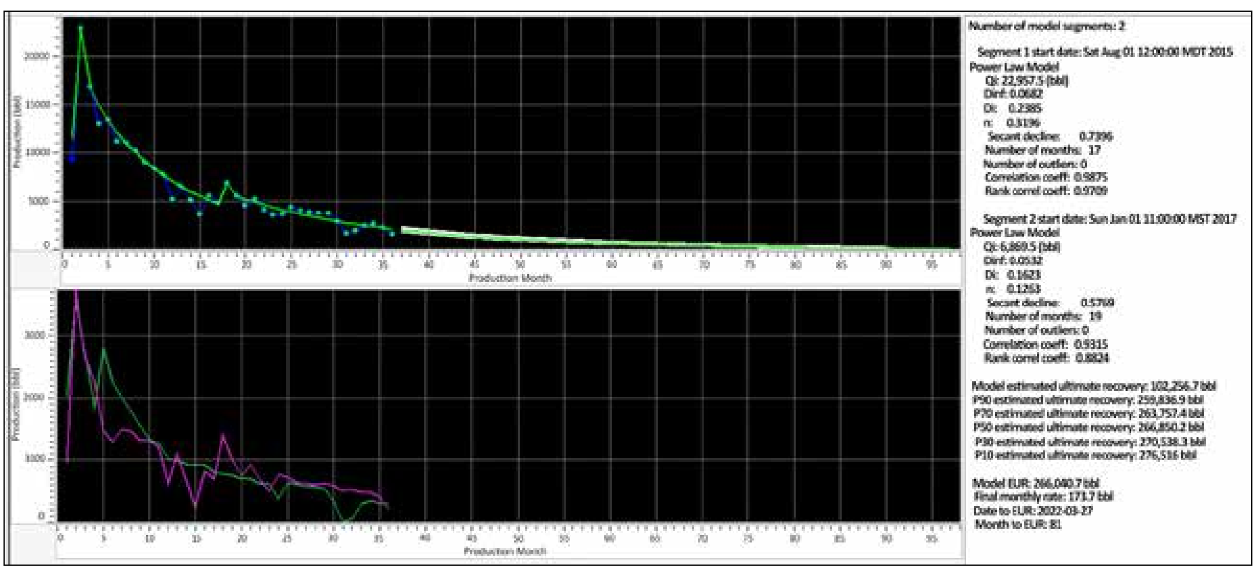


Figure 23: 20MM Lb Proppant Volume Oil Type Curve

The type curve for the 6MM lb job volume was based on seven individualized production curves and utilized the same input parameters as in the previous cases. As indicated in Figure 24, this type curve is broken into two segments with the first portion of the decline following a SEPD Model and the second being best fit by an Arps model. The individual production curves show that a majority of the wells used in this analysis experience an increase in production around a similar time, coinciding with the application of artificial lift.

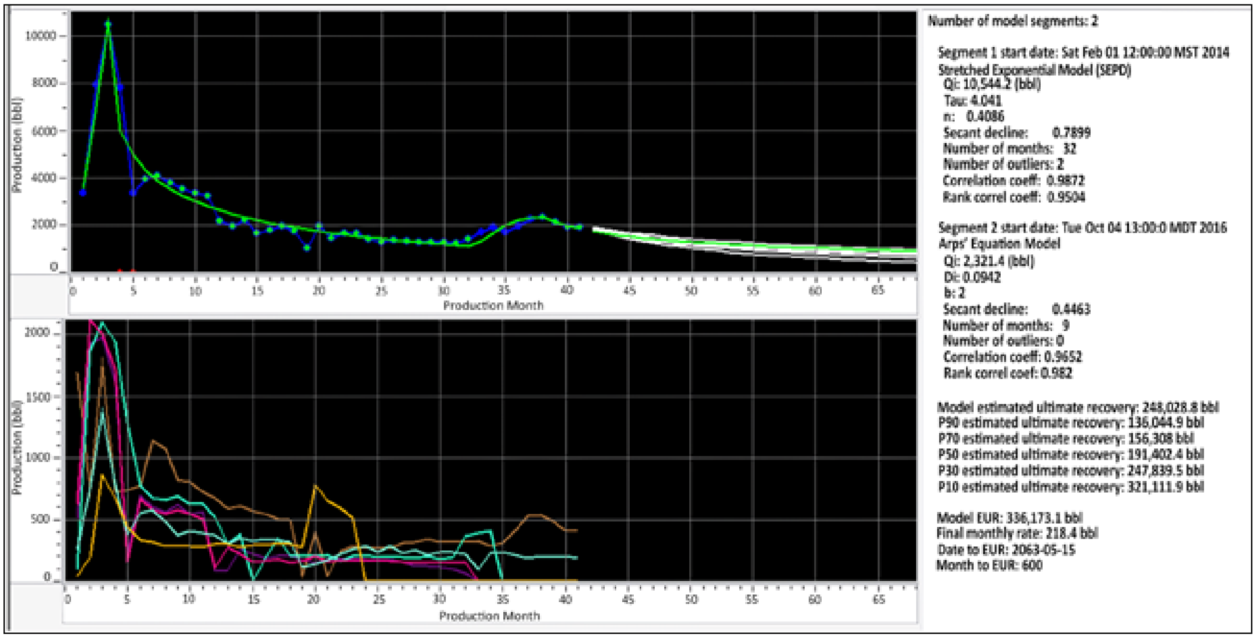


Figure 24: 6MM Lb Proppant Volume Oil Type Curve

The 12MM lb type curve yields the best EUR at 386,939 BO, followed by the 6MM lb type curve at 336,173 BO and the 20MM lb volume at 266,041 BO. Once again, the EUR for the 20MM lb job is likely to change with additional data from increased production time.

Economic Model

With the type curves in place, an economic model could be applied to examine the profitability of the different proppant volumes. This model was created by Dr. Ben Cook, Sr. Energy Economist with the EORI. For oil and gas prices, a stochastic pricing scenario was selected for calculating the economic indicators using different type curves (Figure 25). Drilling and completion costs for these operators were collected from force-pool Authorization for Expenditure (AFE) numbers that were presented to the WOGCC. Figure 26 illustrates the

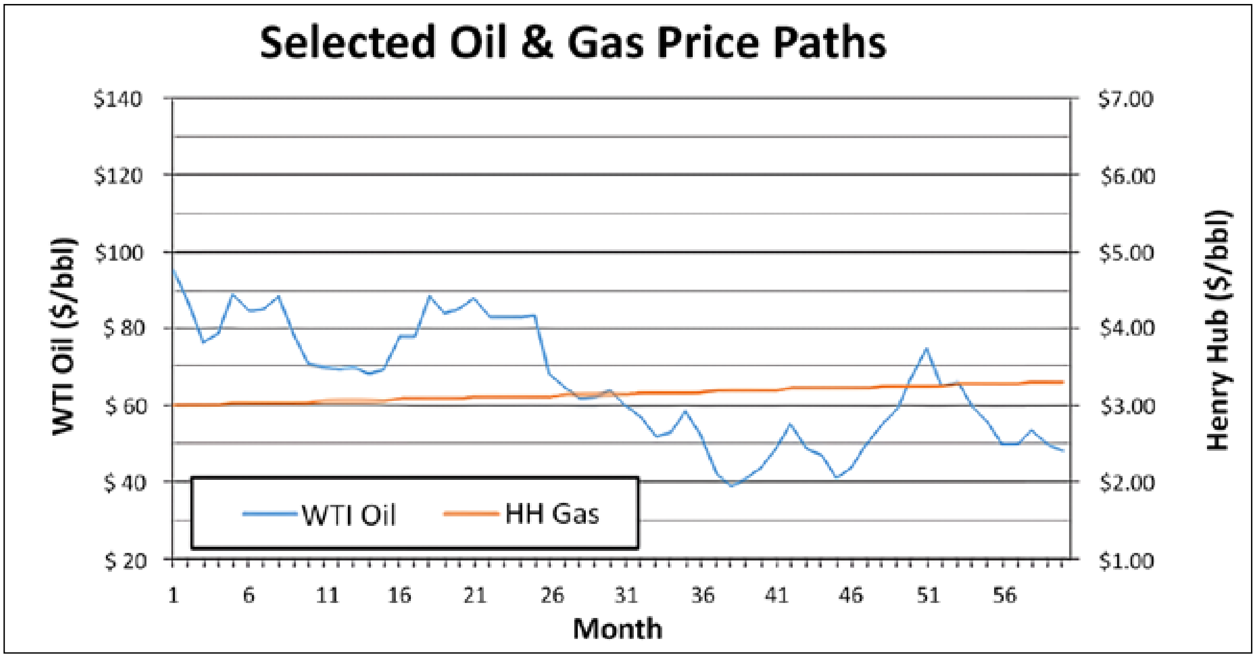


Figure 25: Stochastic Oil and Gas Pricing

breakout of completion cost per pounds of proppant pumped by operator. Operator 1 has seen a continuing decrease in completion costs while Operator 3 has seen costs remain stable. The different pricing environments by operators were considered in the economic analysis by looking at the economic indicators in terms of all the type curves and both Operator 1 and Operator 3 pricing. The results from this analysis are shown in Table 3. All three proppant volume type curves show favorable economics using Operator 1 pricing, although the 12MM lb Type Curve is superior. With Operator 3 pricing, the 12MM lb Type Curve is the only economic option. The economic analysis has helped to validate the use of a 12MM lb proppant volume, even in a higher price environment. As previously stated, other factors must be considered (e.g. communication with existing wells, depletion, different economics), but this proppant volume is yielding the best performance within this dataset.

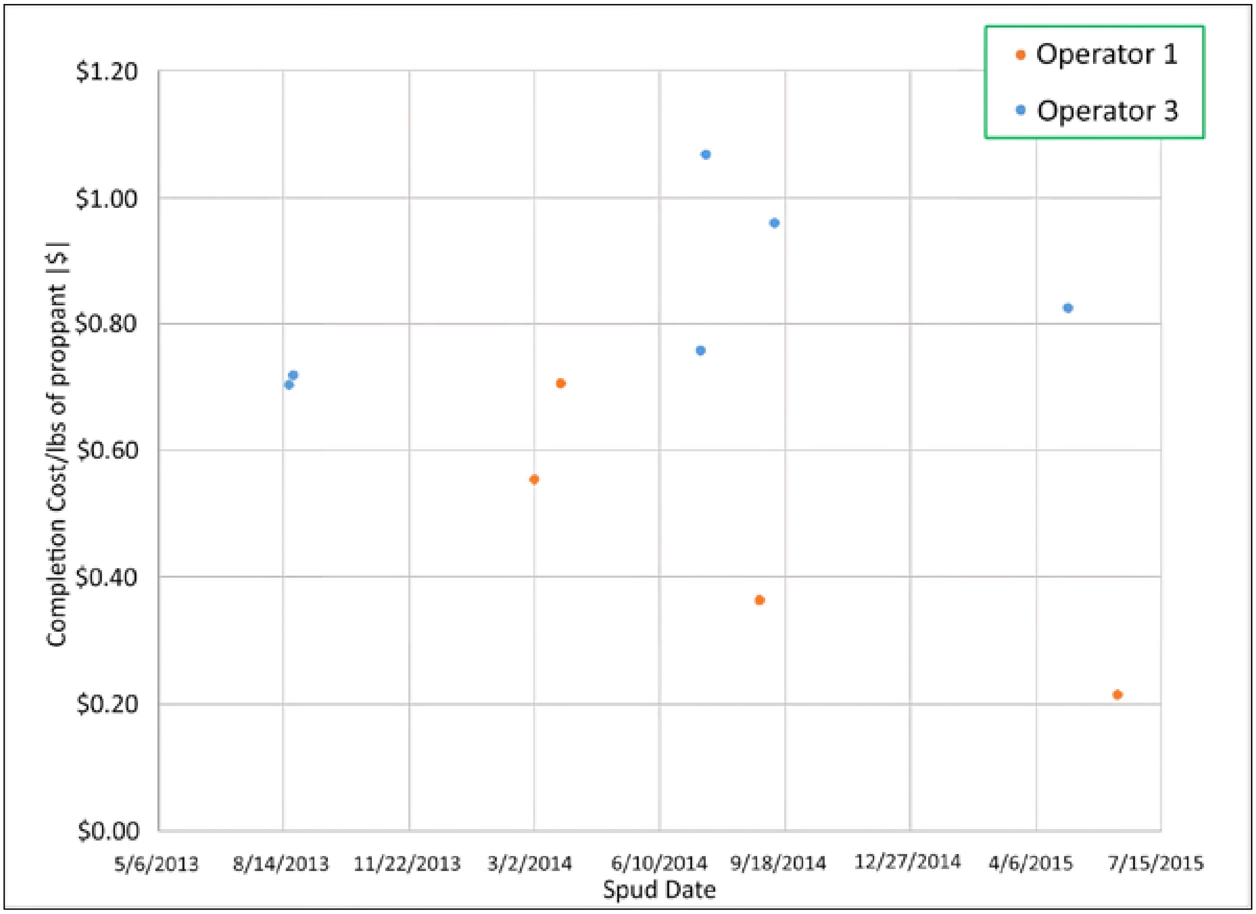


Figure 26: Completion Costs/Lbs of Proppant Versus Spud Date: Colored by Operator

	Operator 1 Pricing			Operator 3 Pricing		
Scenario Selection	6MM lb Type Curve	12MM lb Type Curve	20MM lb Type Curve	6MM lb Type Curve	12MM lb Type Curve	20MM lb Type Curve
NPV10	$0.12	$3.05	$1.63	($3.25)	($0.37)	($5.92)
NPV15	($0.25)	$2.58	$1.25	($3.62)	($0.84)	($6.29)
NPV20	($0.53)	$2.17	$0.90	($3.90)	($1.26)	($6.64)
IRR	11.5%	60.0%	34.7%	-7.0%	6.6%	-38.9%
PP (Months)	46.10	11.10	16.74	< -100%	46.35	< -100%
PP (Years)	3.84	0.93	1.40	< -100%	3.86	< -100%

Table 3: Results of Economic Model

Niobrara Analysis

A similar workflow was carried out with the 43 Niobrara wells. The Niobrara in this area is not as prolific as in other parts of the DJ Basin, and therefore this is a smaller dataset than the Codell. Subsequently, the same analyses cannot be conducted due to a lack of statistical relevance.

Crossplots

Figures 27-29 display the raw data to give an idea of the current practices.

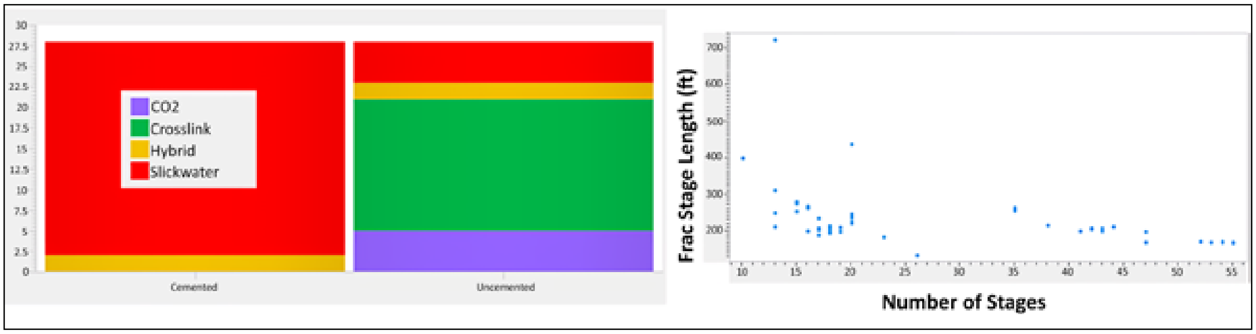


Figure 27: Fluid Treatment Type and Production Liner Completion Type and Frac Stage Length Versus Number of Stages

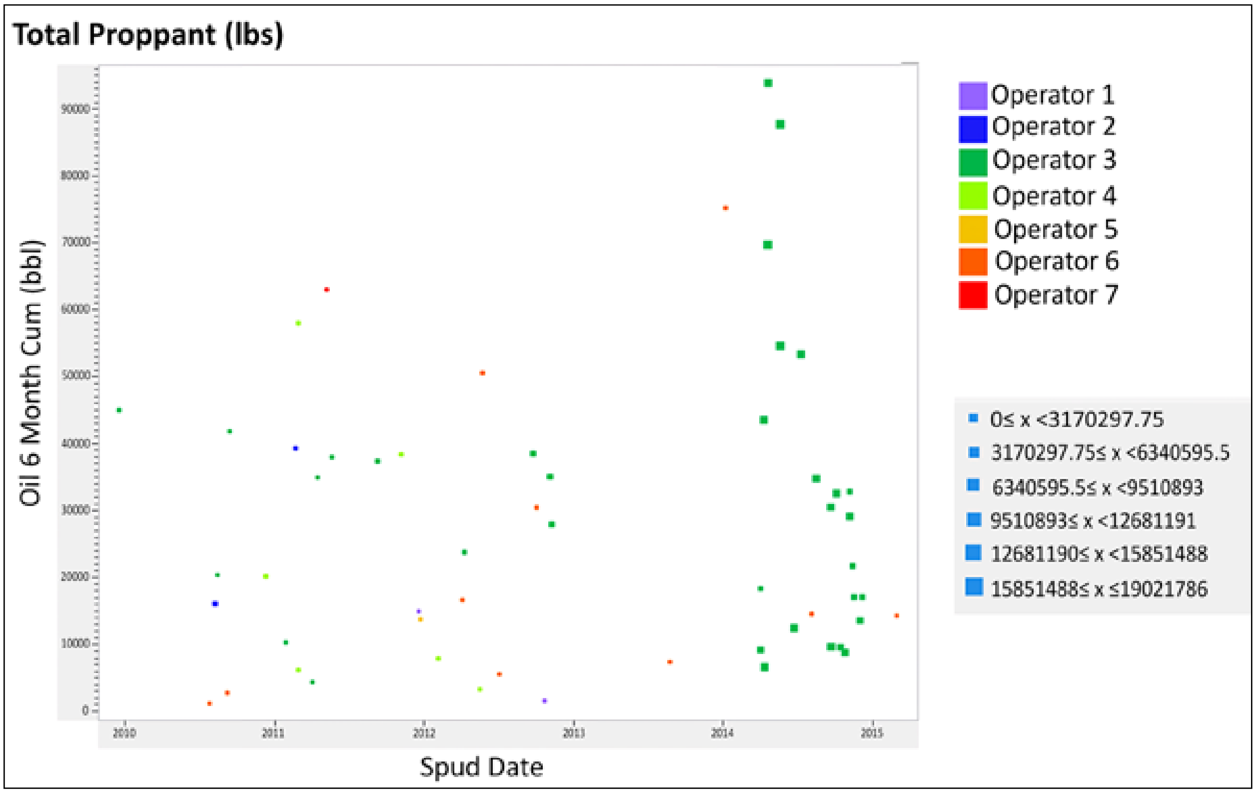


Figure 28: Oil 6-Month Cum Versus Spud Date: Colored by Operator and sized by Total Proppant

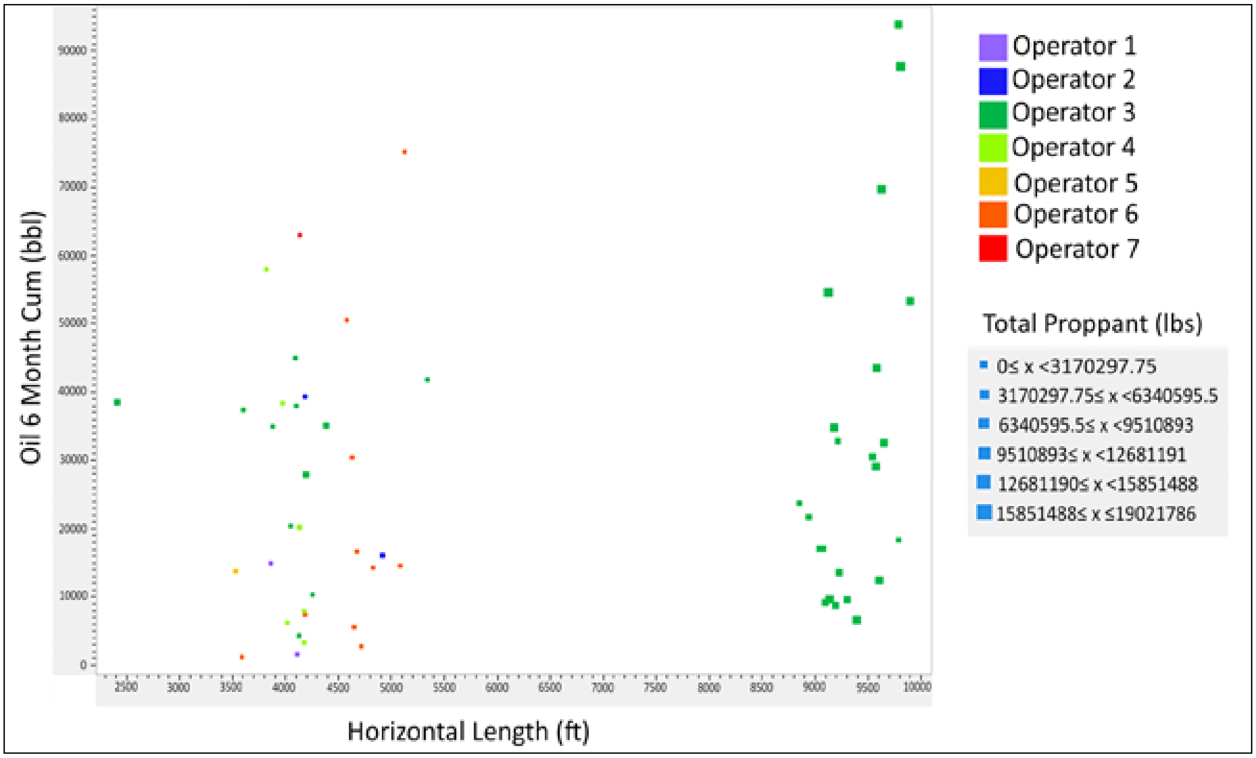


Figure 29: Oil 6-Month Cum Versus Horizontal Length: Colored by Operator and sized by Total Proppant

Examining the above figures, more variability is present than observed with the Codell wells. These characteristics can be explained by looking at Figure 28; a majority of these wells were completed circa 2014, before the big shift towards cemented liners with slickwater fluid systems. It is also interesting to note that only one operator (i.e. Operator 1) has drilled long laterals (9,000 ft or longer). This same operator is also the only one to pump any high proppant volumes.

6-Month Oil Multivariate Analysis

The same workflow was employed with the Niobrara analysis as with the Codell; however, not as much detail will be shown for this analysis since the procedures have been explained in the previous section. Figure 30 displays the final attributes that were selected after numerous iterations, and Figure 31 displays the individual attribute responses. The predictor attributes are again displayed from most impactful to least impactful from top to bottom. Just as was the case with the Codell, Total Proppant is the most impactful variable on production; Lateral Length, Azimuth, GOR, and Treatment Rate follow. The optimized amount of proppant for this dataset is just under 9MM lbs. Lateral Length is harder to interpret due to the fact that there are not many long laterals, and there is not a major difference in the length of those long laterals. The data indicate that for the lengths noted, the longer the lateral, the better the 6-month cum. Azimuth is showing a slight advantage to N-S, but not S-N. This discrepancy could be attributed to the small dataset. A GOR of ~900 scf/bbl is ideal, as is a treatment rate around 43 bpm. Figure 32 illustrates the MVA predicted 6-month cum versus the actual 6-month cum. The fit that was achieved in the Niobrara has a high R^2 and high correlation coefficients, but the confidence level is lower than in the Codell due to the smaller dataset.

Use	Variable	Property Type	Significance	Sensitivity
	6 Month Cum Oil	Cum Oil		
	EORI_Total Proppant	Total Proppant	0.5894	0.1421
	EORI_Lateral Length	Length	0.4605	0.1006
	Wellbore Azimuth	Azimuth	0.3427	0.0638
	GOR Cumulative Gas Oil	GOR	0.2635	0.0406
	EORI_Treatment Rate	Slurry Flow Rate	0.1781	0.0240

Figure 30: 6-Month Cumulative Oil Final Attributes

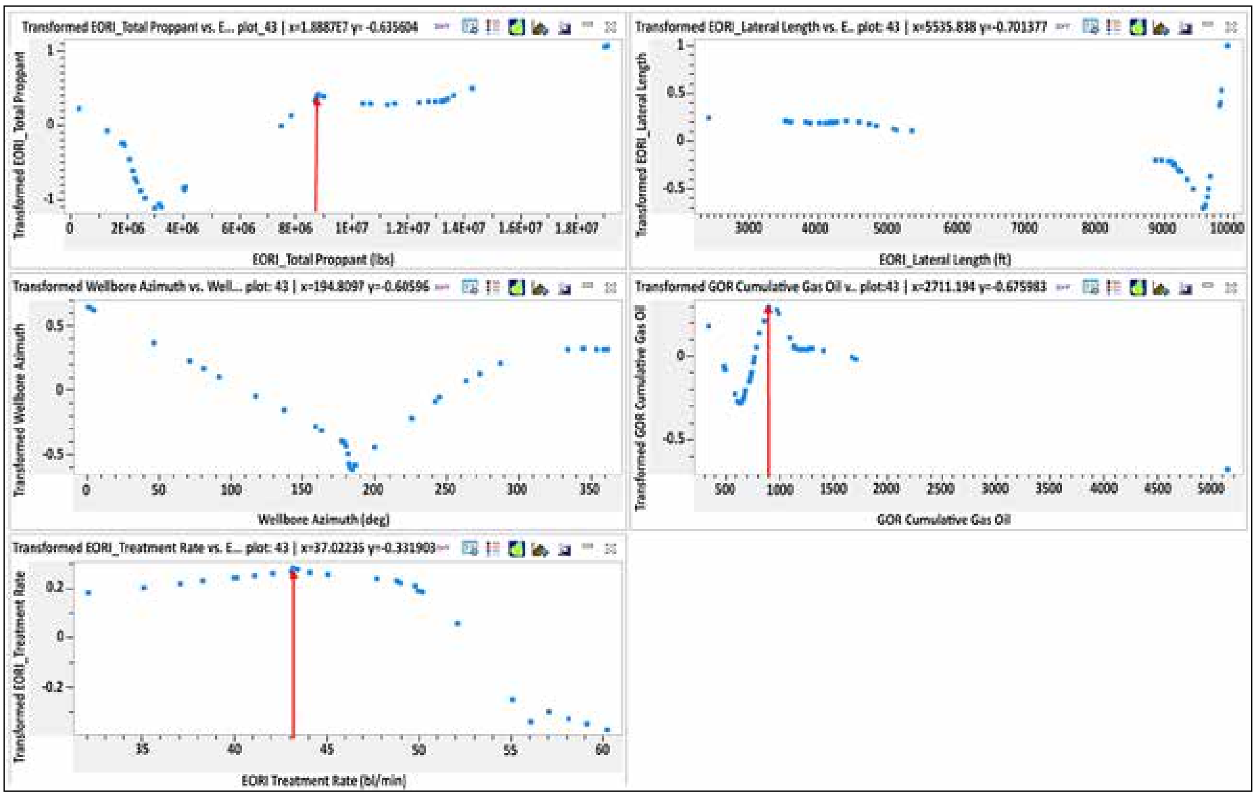


Figure 31: 6-Month Oil Cumulative Predictor Individual Attribute Response

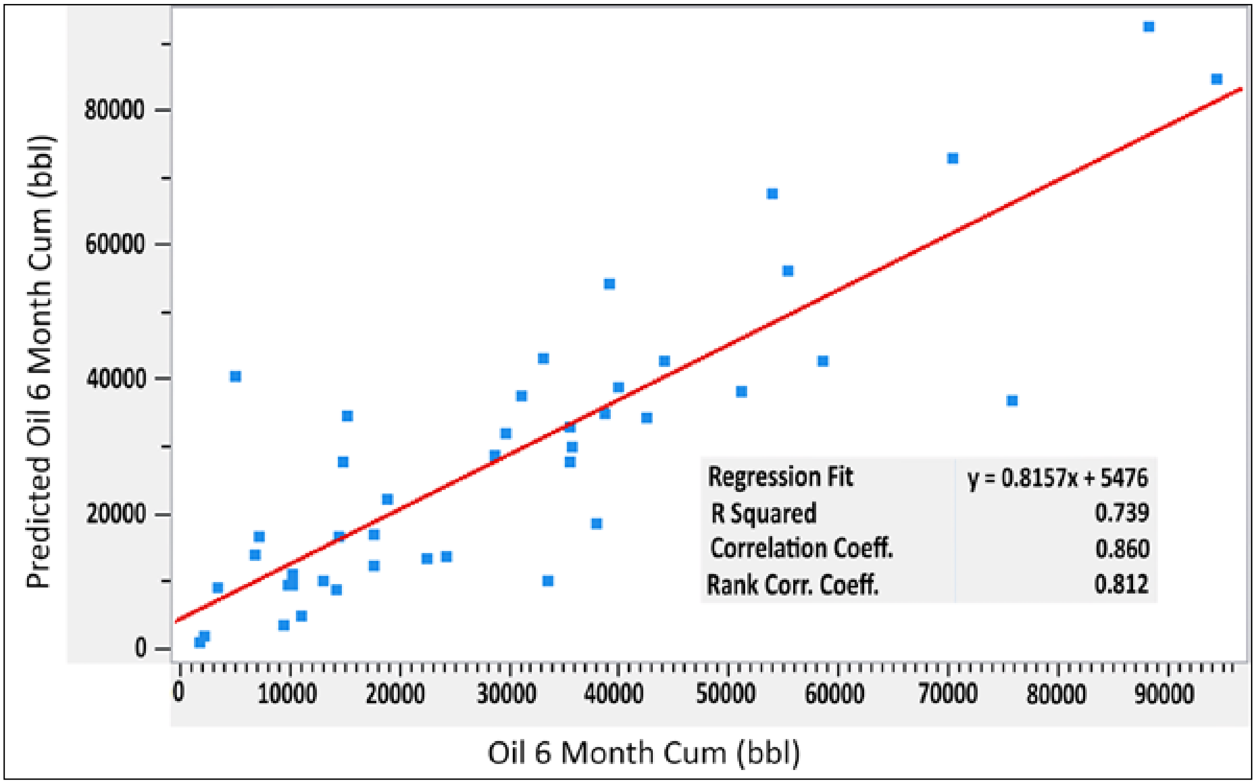


Figure 32: Predicted Oil 6-Month Cumulative Production Versus Actual Oil 6-Month Cumulative Production

Additional analyses were attempted with 12-month cum and 18-month cum but a number of wells are missing these production values, thus making these analyses statistically questionable. All of the wells did have an EUR value, so an MVA model was generated with EUR as the response variable.

EUR Multivariate Analysis

Figure 33 displays the final attributes used in the MVA model. Combinations of all of the attributes were tried in order to achieve the best match. The same variables that were impactful at 6 months cumulative production were the most impactful with the EURs. Figure 34 displays the individual attribute responses. Total Proppant is still the most impactful variable with a slope change around 9MM lbs; however, larger proppant volumes are positively impacting EUR more so than at 6 months. Lateral Length is a close second with the longer the lateral, the higher the EUR, followed by GOR with an optimal value of 900 scf/bbl. The ideal treatment rate is between 40 and 45 bpm. Azimuth indicates that, for this sample set, wells being drilled N-S (outside of Silo Field) and E-W (inside of Silo Field) are both yielding good results.

Overall there is a strong correlation between modeled EUR and actual calculated EUR (Figure 35) but there are some outliers that do not fit the trend.

Use	Variable	Property Type						Significance	Sensitivity
	Nio EUR	EUR							
	EORI_Total Proppant	Total Proppant						0.5406	0.0789
	EORI_Lateral Length	Length						0.5322	0.0746
	GOR Cumulative Gas Oil	GOR						0.4236	0.0820
	EORI_Treatment Rate	Slurry Flow Rate						0.2645	0.1119
	Wellbore Azimuth	Azimuth						0.1225	0.0445

Figure 33: Predicted Oil 6-Month Cumulative Production Versus Actual Oil 6-Month Cumulative Production

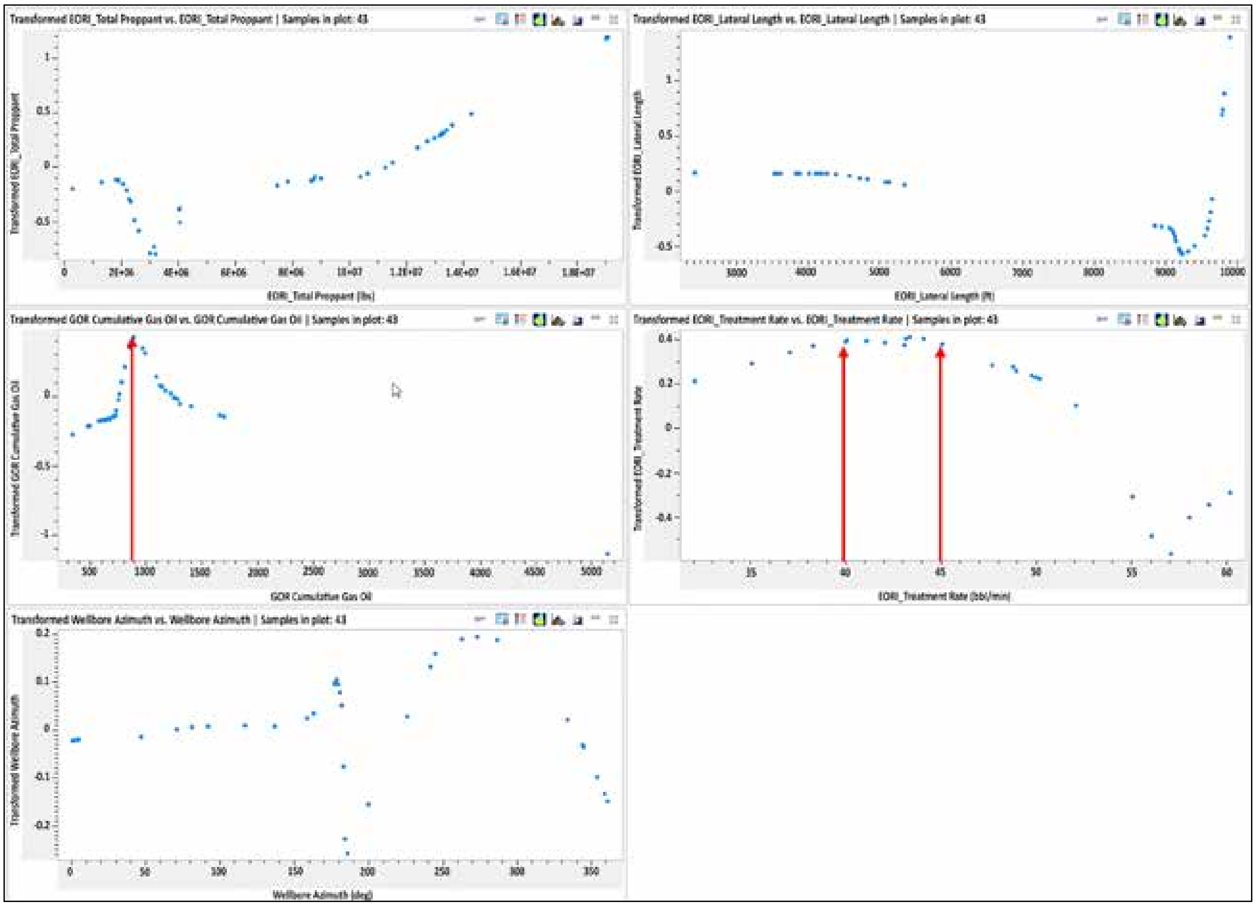


Figure 34: Predictor Individual Attribute Responses

With the Niobrara, it appears that operators tried a variety of techniques with varying degrees of success. In the Codell, operators seemed to have refined their choices to a few methods that were working for them in terms of job size, lateral length, etc. This difference makes it challenging to generate type curves and conduct an economic analysis; additionally, the force pool numbers are limited for the well designs that are most closely mimicking the optimized design. Therefore, generation of type curves and a subsequent economic analysis was not conducted in the Niobrara. If interest in the Niobrara increases, and additional operator data are available, the EORI will revisit this analysis.

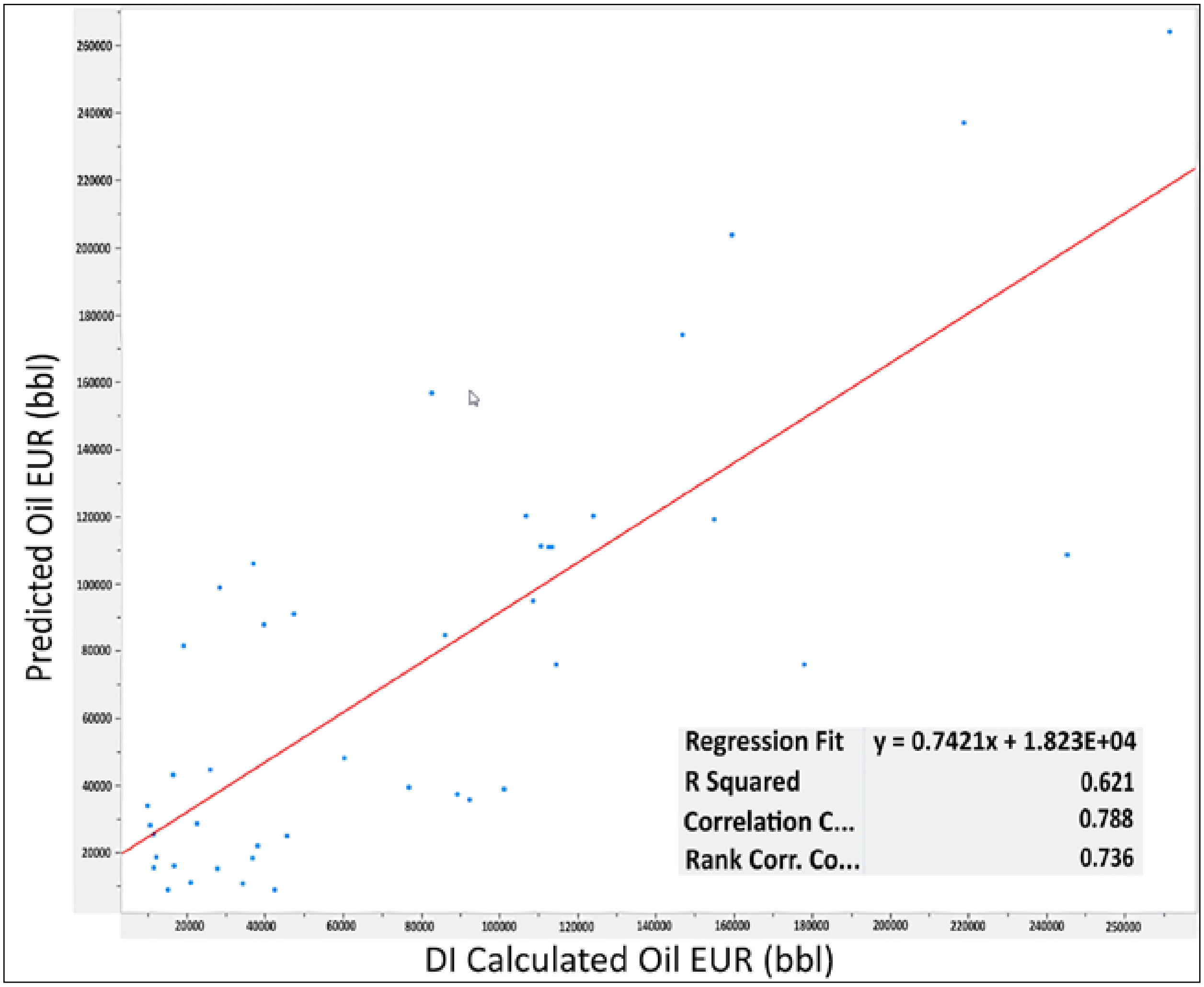


Figure 35: Predicted Oil EUR Versus DI Oil EUR

Conclusions

This multivariate work provides operators with a starting point for determining how to optimize their drilling and completion designs. In the Codell, optimal well performance can be achieved by approximating:

- a lateral length of at least 9,600 ft,
- a total proppant volume of 12MM lbs,
- a frac treatment rate of at least 40 bpm, and
- drilling in an area with a GOR of 570 scf/bbl.

The economic model supports this proppant volume and the 12MM lb type curve has the best economic indicators in both a high and low completion cost environment.

For the Niobrara, optimal well performance can be realized by approximating:

- a lateral length of 10,000 ft,
- a total proppant volume of 9MM lbs,

- a treatment rate of 40-45 bpm, and
- drilling in an area with a GOR of 900 scf/bbl.

Looking at production from a multivariate approach allows operators to determine which factors have had the greatest impact on maximizing production. Simple crossplots are not sufficient to determine best practices due to the number of variables that must be addressed and weighed simultaneously. The results drawn from the WSGS report (Toner, 2017) should be scrutinized due to their lack of a multivariate approach.

The EORI is committed to refining and continuing this effort in the Northern DJ Basin and other basins throughout the state. Additional data gathered through operator engagement will be highly beneficial to the analyses. Please reach out to the EORI (www.eoriwyoming.org) with any questions, suggestions, or willingness to share data. Specialized analyses can be conducted to include proprietary data on a case-by-case basis.

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Glossary of Terms

Authorization for Expenditure (AFE) - A budgetary document, prepared by an operator, to capture the costs associated with drilling, completing, producing and, eventually, abandoning a well.

Barrels per minute (bpm) - A common measurement for hydraulic fracture treatment rate.

Estimated Ultimate Recovery (EUR) - The total amount of hydrocarbons predicted throughout the lifetime of well until it reaches its economic limit as determined by the operator. This is normally obtained by decline curve analysis.

Gas Oil Ratio (GOR) - The ratio of the amount of gas produced to the oil produced at standard conditions

Return on Investment (ROI) - A measure of the gain or loss generated by an investment relative to the amount of money spent. ROI = Net Profit / Cost of Investment x 100

Stochastic - randomly determined; having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely.

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