Resource Analysis to Improve Recovery of Unconventional Oil and Gas

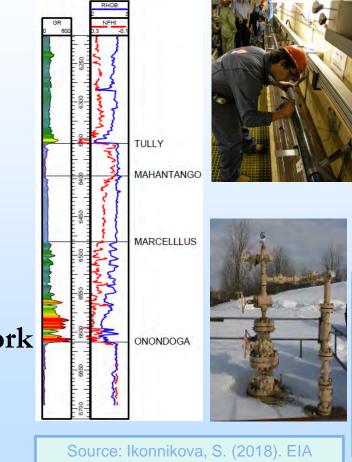
Don Remson Energy Systems Analysis Team

U.S. Department of Energy National Energy Technology Laboratory Mastering the Subsurface Through Technology Innovation, Partnerships and Collaboration: Carbon Storage and Oil and Natural Gas Technologies Review Meeting

August 13-16, 2018

Discussion Agenda

- Scope and Overview
- Pilot Project
 - Study Area
 - Data
 - Results and Findings
- Next Steps/Ongoing Work
- Questions/Discussions



Energy Forecasting Forum - April 2018



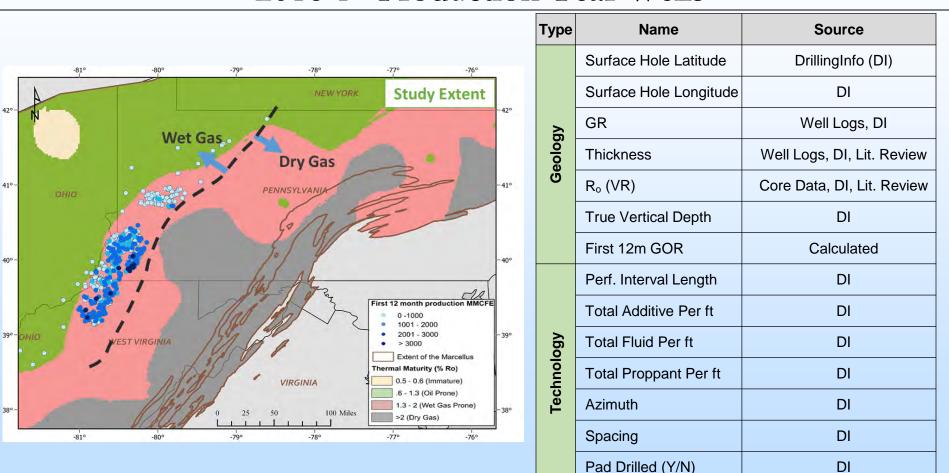
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Scope and Objectives

Detailed Analysis of Industry Performance in Marcellus Shale

- Evaluate region-specific industry performance data with the goal of identifying R&D needs conducive to improving the recovery of oil and gas in unconventional reservoirs.
 - Apply regression-style techniques to develop a model capable of predicting EUR based on available data parameters.
 - Test several machine learning regression algorithms and assess relevance in O&G applications.
 - Use sensitivity analysis or other means to quantify the relative contribution of each input parameter on productivity.
 - Identify most critical research needs and pass that information to fundamental researchers.

Pilot Evaluation – Western Marcellus Western Marcellus Shale – Wet Gas Region; 2007 Through 2016 1st Production Year Wells



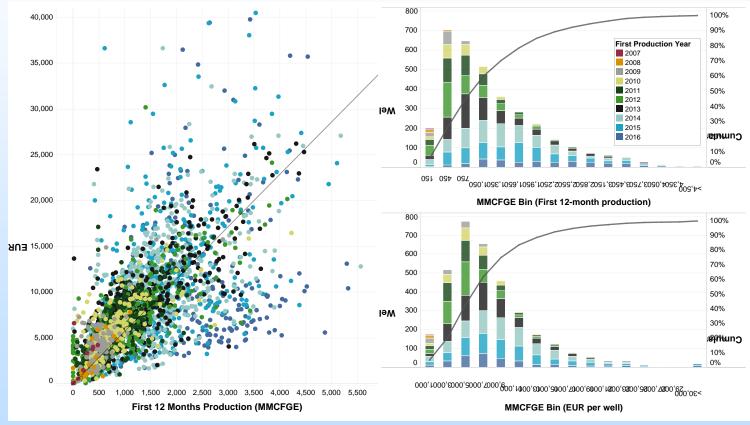
First 12m Production

Prod.

DI

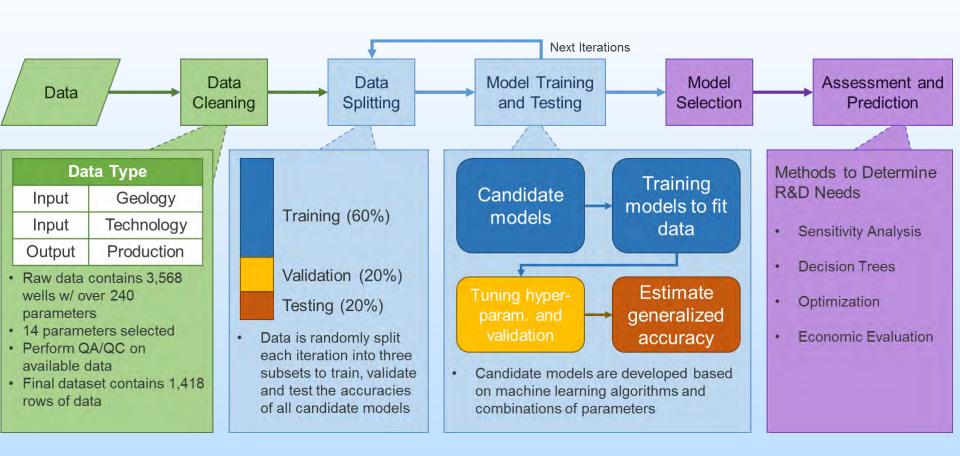
Justification for Use of 1st Year Production

- Not a predicted value.
- Explicitly measured.
- Strongly correlated to predicted EUR.
- Better
 parameter for
 pilot-testing
 machine
 learning.



Machine Learning Framework

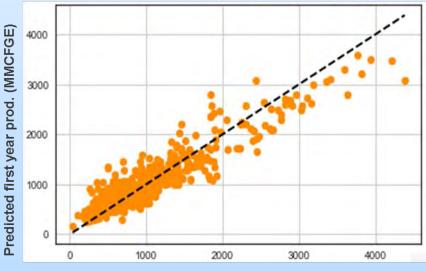
To Evaluate the Impact of Technology and Geology Parameters on Well Productivity



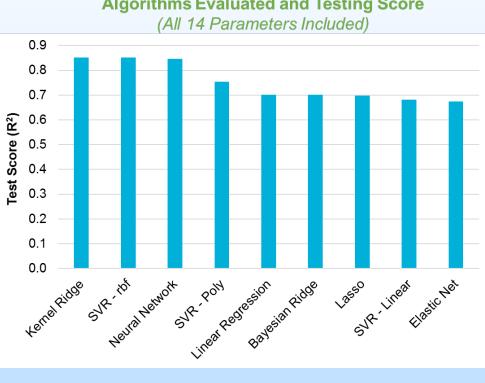
Modeling Training Results Overview Western Marcellus Predictive Model

- Nine algorithms with various parameter combinations (up to a total of 14) were tested in this study to compare model performance.
- Non-linear algorithms performed better, indicating complexity in predicting production.

Model performance (Kernel Ridge)

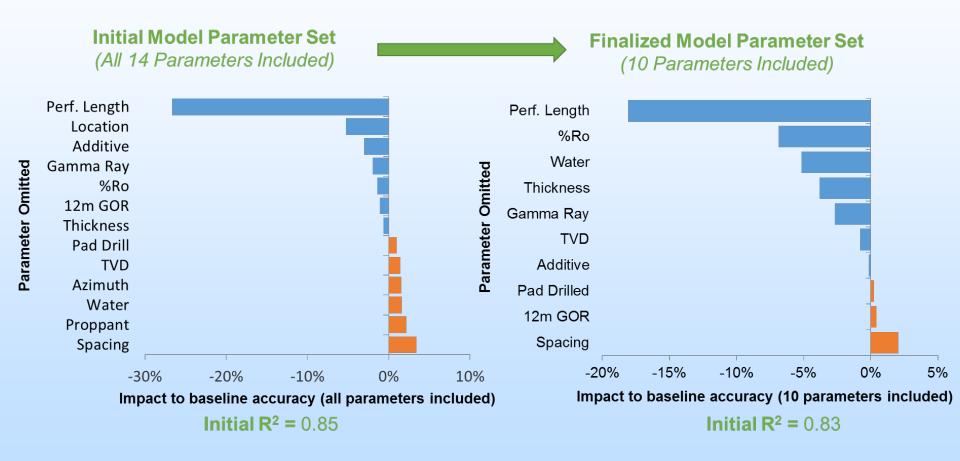


Actual first year prod. (MMCFGE)



Algorithms Evaluated and Testing Score

Assessing Parameter Impact on Accuracy R² Loss Evaluation on Down-Selected Parameter Set

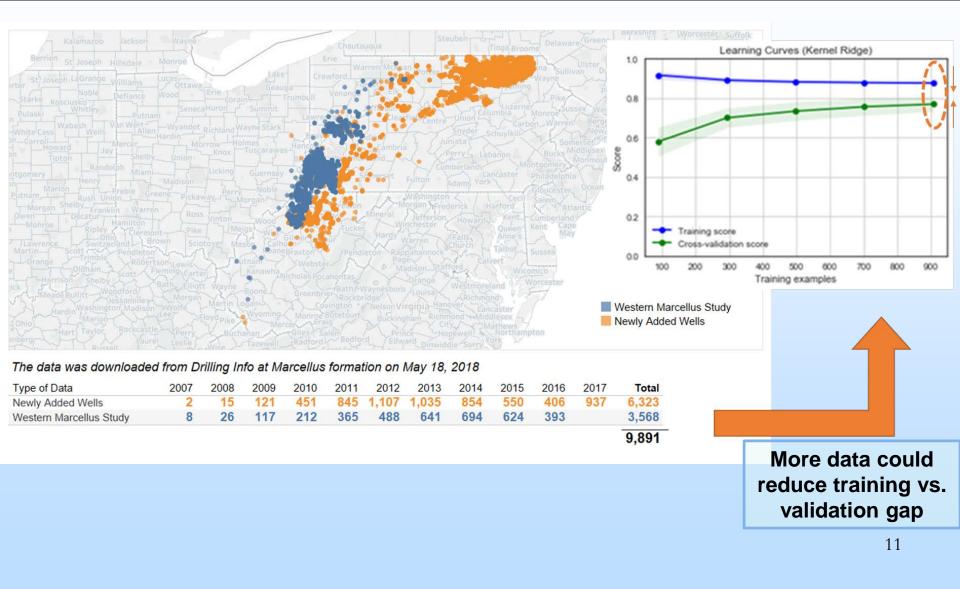


Pilot Study Conclusions

- Publicly available data can be used to develop reasonably performing regression models that can predict well productivity.
- Geology and technology parameters are needed in combination, in order to fully explain variance in well productivity.
- There is a need for expanded data sets, both in number of samples and in number of parameters in each sample.
- Early sensitivity analysis shows that there is room for optimization in all wells analyzed.

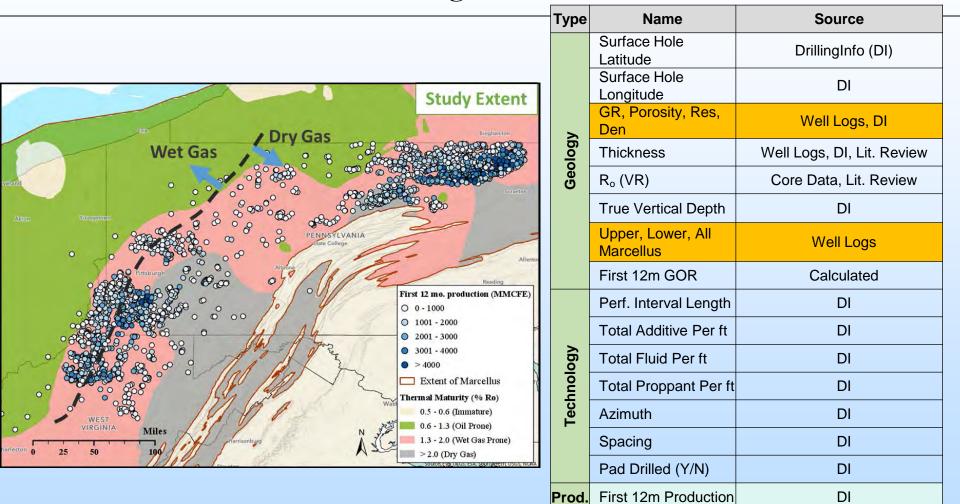
Next Steps/Ongoing Work

Expanded Study Area and Well Counts

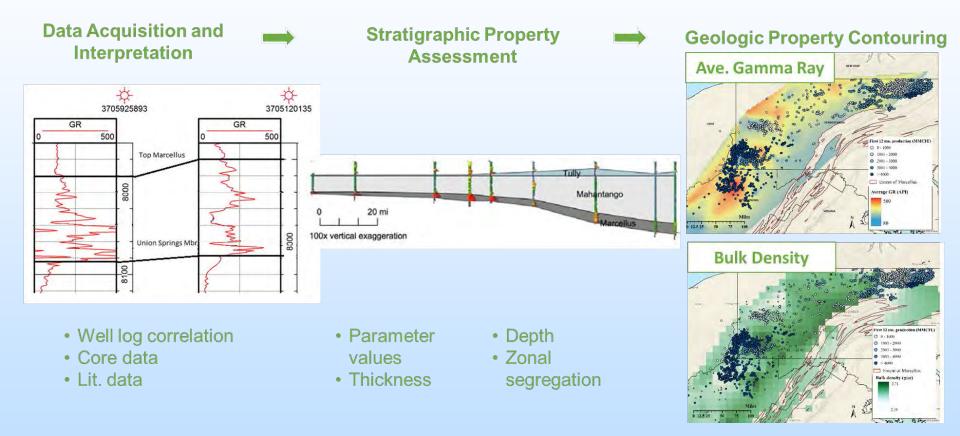


Expanded Evaluation – Marcellus Shale

Marcellus Shale – 2007 Through 2017 1st Production Year Wells

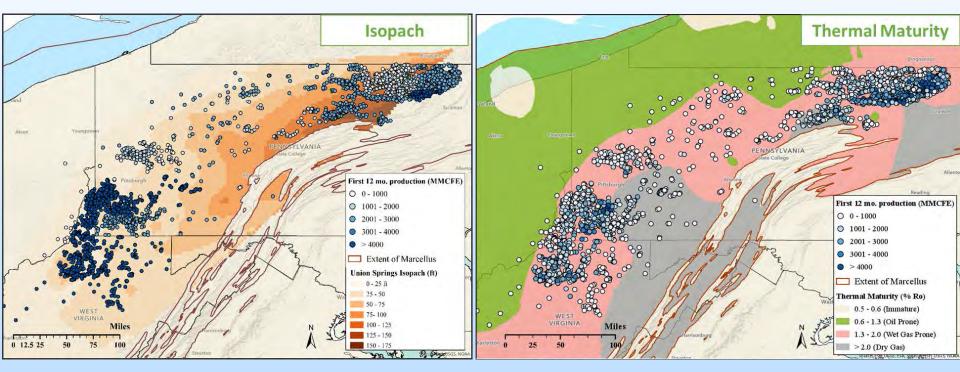


Expanding the Geologic Dataset

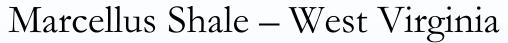


Preliminary – Geologic Assessment Isopach and Thermal Maturity

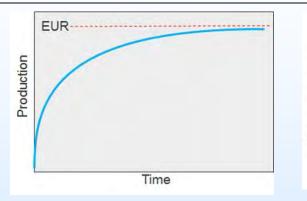
• Well log interpretation completed to assess geologic factors across play.

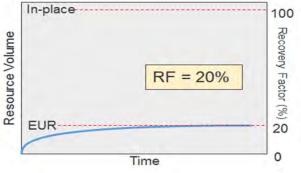


Recovery Factor (RF) Assessment

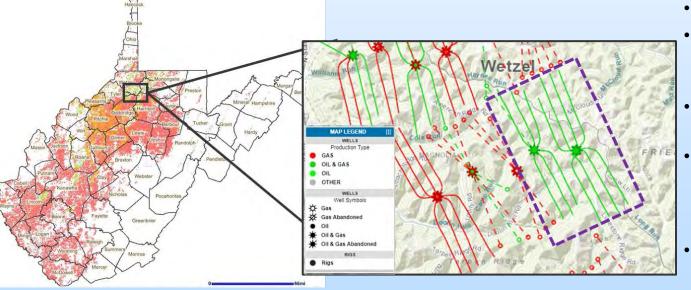


• RF is the ratio of the EUR of a specific entity (i.e., well, lease area, or play) divided by the total in-place resource.





- Acquire OGIP data.
 - Evaluate RF for areas totally developed or nearly developed.
- Use info to inform the regression analysis if possible.
- Analyze the data parameters to determine their individual impact on well productivity (EUR) and RF.
- Collaboration with the West Virginia Geologic Survey.



Desired data sets

- Only partial understanding can be attained from publicly-available data/information alone.
 - State reporting requirements strongly influence data availability and quality across plays
- Expanded datasets would enable for refined models, and enable better determination of parameters influencing production.

• Desired datasets:

- Well logs (i.e. .las files)
- Completion-related information (i.e. stage count, total perforations, and pressures)
- Additive type, proppant size and type
- Well orientation (toe-up vs. toe down; % in zone)
- Well spacing
- Pre-stimulation pay-zone pore pressures
- Geochemical and geophysical data
- Natural fracture extent
- Others...

Acknowledgements

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Proposal Portfolio Lead

Mission Execution and Strategic Analysis (contractors)

Derek Vikara Chung Yan Shih Anna Wendt ShangMin Lin Aranya Venkatesh

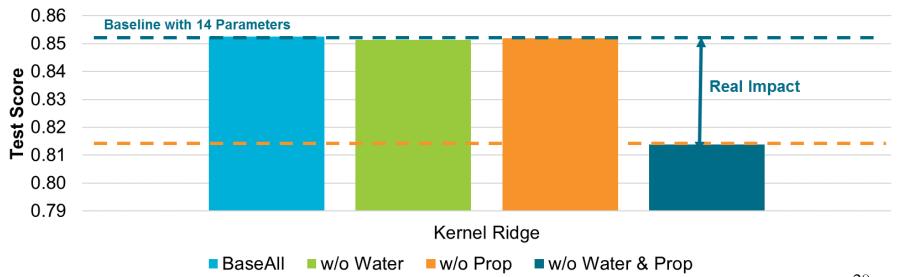
Questions ?

Backup Slides

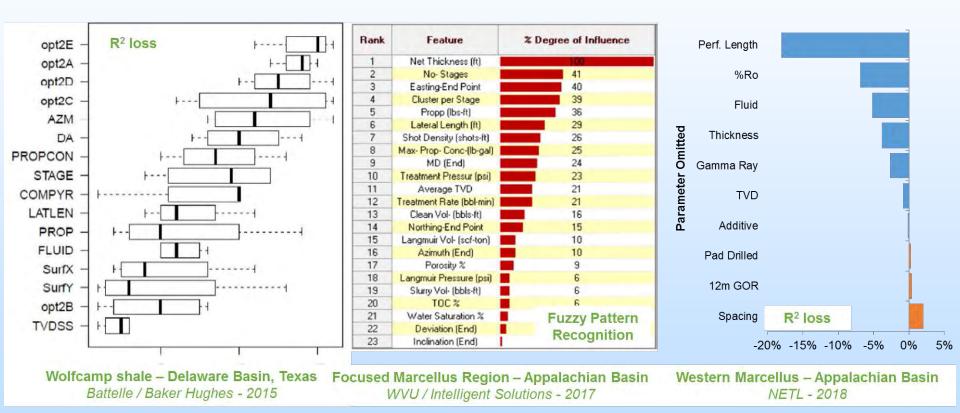
Impact of Correlated Parameters on Accuracy

Water and Proppant Correlation

- Volumes of water and proppant injected were found to be strongly correlated.
- Should either of the two parameters be excluded in model training, the other compensates, suggesting that neither parameter has importance.
- But, when both parameters are removed, the test scores drop considerably.

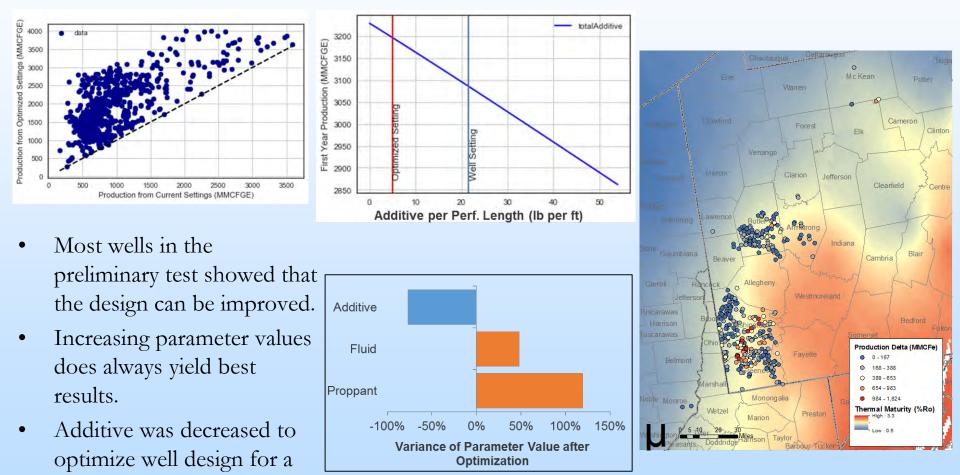


Variation in Parameter Impact on Accuracy Comparison of Different Studies Predicting Production



Optimization of Well Design

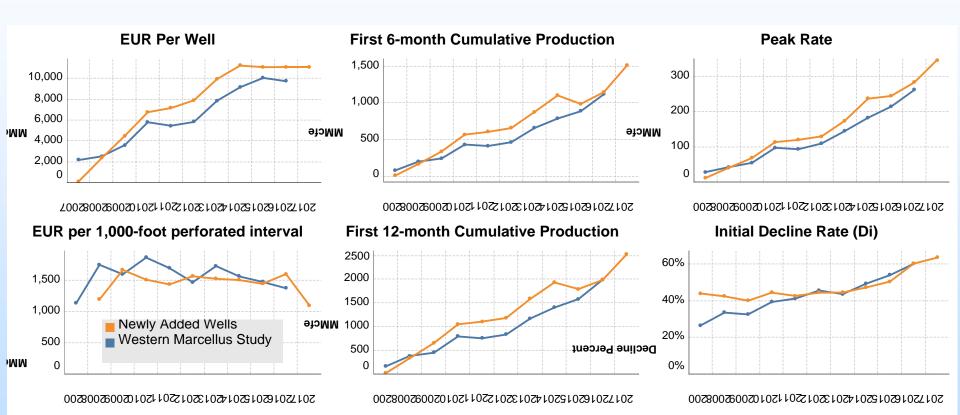
Modifying Additive, Fluids, and Proppant per Perforated Interval Length



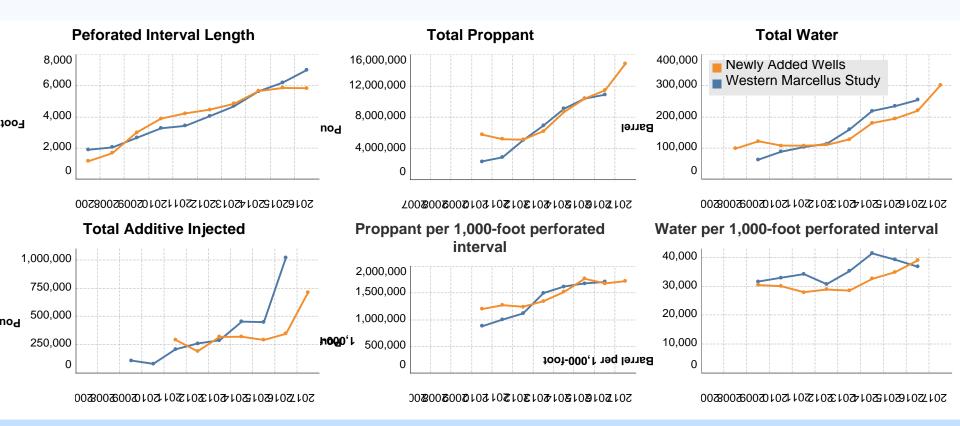
case-study well.

Production Performance Summary

Marcellus Shale – All Wells (2007 – 2017)



Well Completion/Design Summary Marcellus Shale – All Wells (2007 – 2017)



Recovery Factor (RF) Assessment

- RF is a concept not readily applied to UOG.
- EUR is a function of the marriage of technology and geology.
 - Technology changes with time (future >>> past).
 - Geology changes with location (core >>> margins).
 - Assessments can get EUR very wrong for either (both) reasons.
- In-place volumes subject to great uncertainty.
- RF is better with gas. Also better with depth/pressure.
- RF is likely better than we think in core areas and worse than we think at the margins.
- Minor improvements in RF can be directly translated into immense and tangible economic and national security benefits.

Plays	Barnett	Fayetteville	Havnesville	Marcellus	
Gas-in-place ¹ , bcf/sq. mile	50	30	77	18	
Year-end Output, bcfd	5.31	2.87	3.87	10.90	
Cumulative Production, tcf	14.7	4.2	8.5	6.7	
Reserves(EUR) ² , tcf	20	9	12	140	
Recovery Factor, %	6.1	11.2	1.7	9.3	
Production Potential ³ , bcfd	5.64(2011)	2.88(2012)	7.0(2011)	24	
Peak Well-Productivity, Mcfd/well	438 (2008)	833 (2010)	3,382 (2010)		
Present Well-Productivity, Mcfd/well	303	610	1,195	1,050	
Year-end Producing Wells	17,494	4,704	3,238	10,369	
Current 180-day Well IPs, MMcfd	1.9	2.1	9.5	4.9	
Well-Productivity Decline Rate, %/year	7	10	35		
Well EUR, bcf/well	2.2	3.0	3.5	1.6	
Well-Productivity by 2020, Mcfd/well	190	306	102		

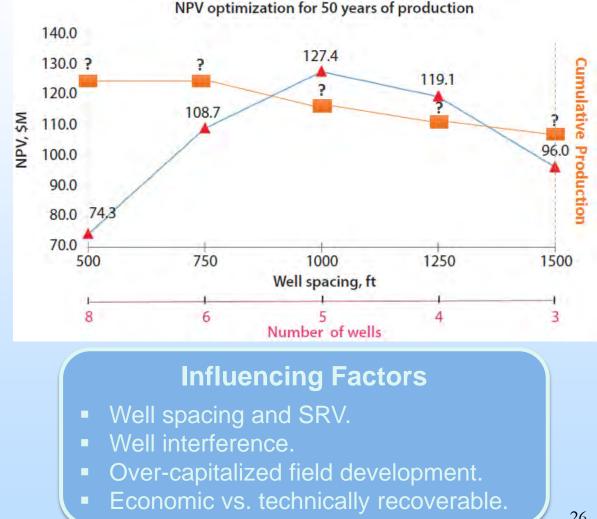
Sandrea and Sandrea, OGJ, 2014

Basin	Formation/Play	Age	Oil In-Place (MBbls/Mi ²)	Oil Recovery (MBbls/Mi ²)	Oil Recovery Efficiency (%)	
	Bakken ND Core	Mississippian-Devonian	12,245	1,025	8.4%	
	Bakken ND Ext.	Mississippian-Devonian	9,599	736	7.7%	
Williston	Bakken MT	Mississippian-Devonian	10,958	422	3.9%	
	Three Forks ND	Devonian	9,859	810	8.2%	
	Three Forks MT	Devonian	10,415	376	3.6%	
Maverick	Eagle Ford Play #3A	Late Cretaceous	22,455	1,827	8,1%	
	Eagle Ford Play #3B	Late Cretaceous	25,738	2,328	9.0%	
	Eagle Ford Play #4A	Late Cretaceous	45,350	1,895	4.2%	
	Eagle Ford Play #4B	Late Cretaceous	34,505	2,007	5.8%	
Ft. Worth	Barnett Combo - Core	Mississippian	25,262	377	1.5%	
	Barnett Combo - Ext.	Mississippian	13,750	251	1.8%	
	Del. Avalon/BS (NM)	Permian	34,976	648	1.9%	
· · · · · · · · · · · · · · · · · · ·	Del. Avalon/BS (TX)	Permian	27,354	580	2.1%	
	Del. Wolfcamp (TX Core)	Permian-Pennsylvanian	35,390	1,193	3.4%	
	Del. Wolfcamp (TX Ext.)	Permian-Pennsylvanian	27,683	372	1.3%	
Permian	Del. Wolfcamp (NM Ext.)	Permian-Pennsylvanian	21,485	506	2.4%	
	Midl, Wolfcamp Core	Permian-Pennsylvanian	53,304	1,012	1.9%	
	Midl. Wolfcamp Ext.	Permian-Pennsylvanian	46,767	756	1.6%	
	Midl. Cline Shale	Pennsylvanian	32,148	892	2.8%	

25

Shale Well Production Economic Model

- Well spacing/design typically based on spacing patterns that yield the highest NPV.
- Coupling data-driven predictive model with cash flow model enables economic evaluation of well/pad/lease optimization.
- Enables comparison of improving recovery (DOE mission) vs. maximizing profitability/NPV (Industry mission).



Parameter Overview by Well Vintage

Average Values

	Unit	Well First Production Year							Percentage			
Parameter		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Change Min to Max
Perforated lateral length	foot	2,712	2,258	2,821	3,313	3,441	4,090	4,712	5,555	6,098	6,612	193%
Water used for hydraulic fracturing	bbl/1,000 foot perforated	NA	NA	27,824	34,573	33,317	29,529	35,939	41,853	39,685	42,983	54%
Proppant used for hydraulic fracturing	pound/foot perforated	NA	NA	1,251	444	672	1,127	1,521	1,733	1,711	1,975	345%
Additive used for hydraulic fracturing	pound/foot perforated	15	25	72	58	63	81	61	99	66	143	850%
Well azimuth trajectory*	degree	139	139	128	132	131	137	139	140	138	140	10%
Well spacing	foot	601	2,709	1,617	1,360	1,083	1,251	1,283	1,167	1,313	1,328	351%
GOR cumulative at 12 months	mcf/bbl	4,445	2,401	2,870	3,793	4,397	3,773	3,763	3,650	4,729	7,272	203%
True vertical depth	foot	7,088	6,799	7,528	7,868	7,768	7,435	7,469	7,494	7,588	7,804	16%
Thickness	foot	30	29	28	28	29	29	28	29	29	29	7%
Gamma ray	API	261	259	268	268	271	265	270	276	271	273	7%
Thermal maturity	% R ₀	1.5305	1.5304	1.6007	1.6373	1.6305	1.5708	1.5894	1.5964	1.6238	1.6555	8%

Predictive Models for 12-mo Productivity

Comparative Analysis

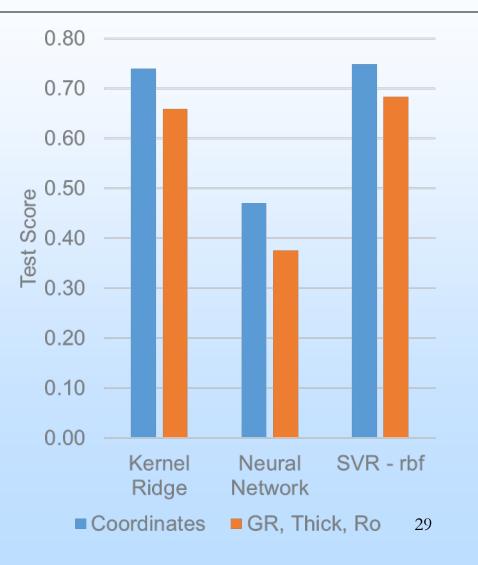
		Team KeyLogic	MIT [1]	BEG UT Austin [2, 3]
Technology		Perforated Lateral Length, Proppant, Fluid (Water), Pad Drilled, WellSpacing	Lateral Length, Fluid (Water), Proppant	WellLocation, Lateral Length, Proppant, Fluid (Water)
Geology		Thickness, VR, Gamma Ray, Depth, Location	Location	OGIP, Thickness, Porosity, Gravity, Pressure
Algorithm		Kernel Ridge	Regression-Kriging Tree Regression, Random F Model Based Recursive Partitioni	
Prediction		12 Month Cumulative Gas	12 Month Cumulative Gas	12 Month Cumulative Gas, EUR
Scores	MASE	0.28 (Lower the Better)	0.62	
	R²	0.83 (Higher the Better)		0.68-0.72 [3]
Key Tał	ke Aways	 Using a comprehensive geology data set instead of location data (latitude and longitude) will provide more accurate production outlooks Initial results suggested that well completion designs can still be optimized to improve the overall production 	RK modelling can be used to develop supply curves for different economic scenarios or optimize design parameters at different well locations To prevent overly optimistic potential well production projections, the chosen modeling method must consider the influence of location	 Lateral length does not significantly affect recovery factor Completion type and well spacing were revealed to be the most significant factors affecting productivity Recovery factor can be increased in the low to mid productivity range

- Montgomery and O'Sullivan, Spatial variability of tight oil well productivity and the impact of technology, *Applied Energy* 195 (2017)
 Ikonnikova, S., Vankov, E., Gülen, G., Browning, J., "Understanding Shale Resource Production: What are the Key Variables?" presented at SPE/IAEE Hydrocarbon Economics and Evaluation Symposium, Houston, Texas, United States, 2016.
- [3] Ikonnikova, S., Vankov, E., Smye, K., Browning, J., Gülen, G., Tinker, S., McDaid, G., Scanlon, B., "Evolution of Shale Oil and Gas Drilling Technology and its Implications," *Bureau of Economic Geology (BEG), The University of Texas at Austin*, Houston, Texas, United States, 2018 (Draft).

Geology

Differences Between Coordinates and Geology (gamma ray, thickness, R_o)

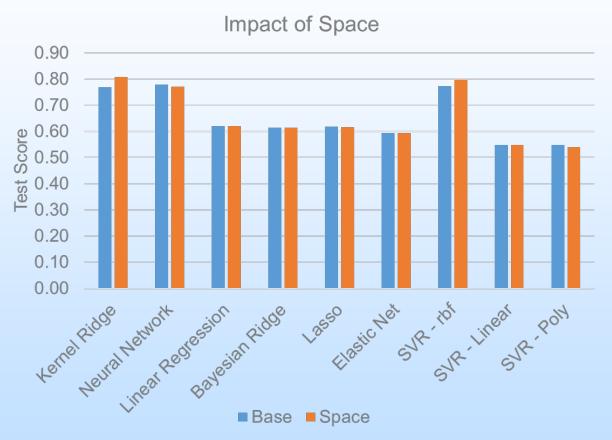
- Algorithms trained exclusively with either (1) spatial coordinates, or (2) GR, thickness, and R_o.
- Production varies spatially, likely due to changes in geologic quality.
 - Most studies use coordinates (lat/long) as a proxy for geology.
 - For this study, the geologic assessment enabled extrapolation of geologic parameters to entire study area.
 - Extrapolation imposes less certainty than explicit well-specific measurements.
- Results indicate that geologic parameters acquired (despite extrapolation) have similar test score trend as using coordinates.



Effect of Spacing

"Distance to Nearest Well" and "Pad Drill"

- Accuracy remains after removing both spacing related parameters.
 - It is known that wells can interfere when drilling too close to each other.
- Possible conclusions:
 - Noisy data about well spacing (i.e., not accurately reflecting well spacing).
 - Wells in the dataset are at spacings that are not causing interference or "frac hits."
- R&D Pursuit: Evaluation of optimal spacing in Marcellus to maximize production and improve RF.
 - Parent/Child well impacts.



Note: This baseline does not include coordinates and azimuth

Desired Datasets

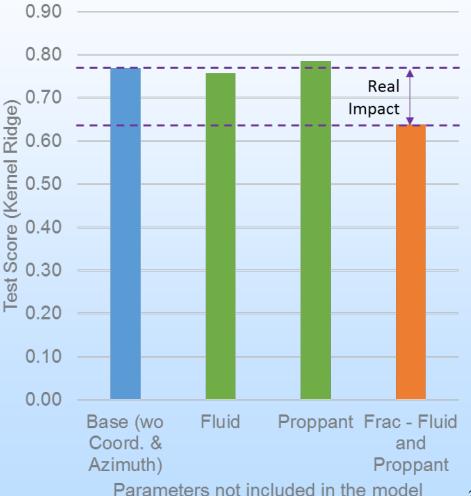
- Only partial understanding can be attained from publicly available data/information alone.
 - State reporting requirements strongly influence data availability and quality across plays.
- Expanded datasets would enable for refined models, and enable better determination of parameters influencing production.
- Desired datasets:
 - Well logs (i.e., .las files)
 - Completion-related information (i.e. stage count, total perforations, and pressures)
 - Additive type, proppant size and type
 - Well orientation (toe-up vs. toe down; % in zone)
 - Pre-stimulation pay-zone pore pressures
 - Lateral trajectory data
 - Geochemical and geophysical data
 - Natural fracture extent
 - Others...

Methods to Determining R&D Needs

Parameter Impact Assessment

Requires Various Approaches to Extract Actual Parametric Impact

- Removing Fluid or Proppant alone does not show significant impact to the overall accuracy.
- However, removing both parameters shows the real impact of fracture fluid and proppant.
- This problem is non-linear and certain parameters are likely collinear and/or have high degree interaction.
- Simple one-at-a-time sensitivity tests not suitable for identifying the parameter importance.
 - Monte-Carlo variance-based approach.
 - Sobol total index approach
 - Decision tree analysis.

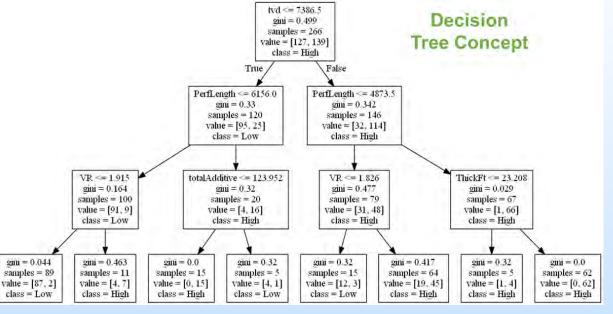


Decision Tree Analysis

Exploration of Parameters that Contribute to "Extreme" Well Performance

- Dataset with low and high performing wells.
 - <25th percentile (low) and >75th percentile (high).
- Used key features to "classify" wells.
- Preliminary results show that:

TVD	Perf. length	Thickness	VR		Well quality
Low	Low		Low		Low
High	High	High		-	High



- All left branches at each node = True, all right branches at each node = False.
- gini is a 'score' for each node (zero when all cases in a node are classified into a single category).
- Value represents number of samples classified into each category [Low, High].

Literature Review

Machine Learning for Unconventional Oil and Gas Applications

Study	Region	Methods	ta used	Key parameters/ findings		
Zhou et al	West Virginia	Multiple linear regression, principal components analysis and k-means	acture fluid, proppant, true vertical depth gth (LL), stages, treatment rate, therma ckness	Stages, lateral length		
Izadi et al	Bakken	Multiple linear regression, boosted tree models	ll location, LL, azimuth, stages, fracturir e and volumes	Well location, proppant quantity		
Schuetter et al	Wolfcamp shale	R ² -loss for model selection, decision trees	Latitude and longitude, TVD, LL, proppant quantity and concentration, stages		TVD, proppant quantity, LL	
Montgomery and O'Sullivan	Williston Basin	Multiple linear regression, fixed- effects regression, kriging	Latitude and longitude, LL, water, proppant volumes		Location data,	
Mohaghegh et al	Marcellus	Neural networks, Monte Carlo simulation, optimization	TVD, thickness, porosity, TOC, LL , clusters per stage, clean volume, proppant quantity per ft LL		Net thickness, well spacing, LL,	
Mishra et al	Literature review	Decision trees, gradient boosting machine, support vector machine, neural networks, kriging	cross-validation typically not been do most studies analyze only a handful o these studies typically ignore records they do not typically evaluate relative	of regression models with missing data poir	nts	