Seismic Brittleness Index Volume Estimation from Well Logs in Unconventional Reservoirs*

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Search and Discovery Article #80381 (2014)**
Posted June 30, 2014

*Adapted from oral presentation given at 2014 AAPG Annual Convention and Exhibition, Houston, Texas, April 6-9, 2014

Abstract

Brittleness is a key rock property for effective reservoir stimulation in unconventional reservoirs. Differentiating brittle from ductile rocks is key to perform an efficient well location and completion. I calculate a brittleness index (BI) volume from surface seismic data calibrated by well logs in the Barnett Shale. Completion effectiveness is function of the interaction between multiple engineering variables (length of the horizontal wells, number of stages, number and size of the hydraulic fracture treatments in a multistage completion, volume of proppant placed, proppant concentration, total perforation length, and number of clusters) and the spatial variation between geological factors (permeability, porosity, maximum stress field, among others) in shale gas reservoirs. I correlate a BI log from a well with core descriptions and mineralogy log information with lithological (gamma ray) and geomechanically-related well logs building a non-linear relationship between these variables. Using prestack simultaneous inversion, I derived geomechanical seismic attributes and seismic volumes and I used them to predict lithology and geomechanical behavior in the reservoir. Additionally, I generated a pseudo gamma ray (GR) seismic cube using probabilistic neural network (PNN). I combined these seismic attributes using the non-linear relationship developed from well logs to generate a pseudo BI seismic cube. I propose a methodology to integrate well logs and seismic derived attributes using non-linear relationships to highlight and identify brittle zones in unconventional reservoirs. Finally, I correlated the resulting BI seismic volume with production and volume of proppant placed into the reservoir validating the effectiveness of this technique.

Selected References

Perez, R., 2013, Brittleness estimation from seismic measurements in unconventional reservoirs: Application to the Barnett Shale: Ph.D. Dissertation, The University of Oklahoma.

Perez. R., and K. Marfurt, 2014, Mineralogy-Based Brittleness Prediction from Surface Seismic Data: Application to the Barnett Shale: Interpretation (in press).

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Verma, S., A. Roy, R. Perez, and K. Marfurt, Finding high frackability and high TOC zones in Barnet shale with supervised: Probabilistic Neural Network and unsupervised: multi-attribute Kohonen SOM, SEG Abstract, 2012.

SEISMIC BRITTLENESS INDEX VOLUME ESTIMATION FROM WELL L,OGS IN UNCONVENTIONAL RESERVOIRS

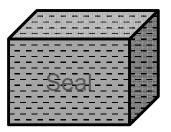
Roderick Perez A., Ph.D.

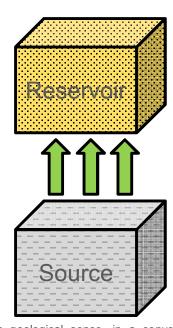
Houston, TX / 2014





INTRODUCTION



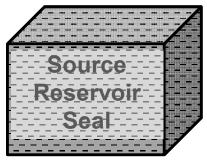


In a geological sense, in a conventional reservoir the hydrocarbon generated by a kerogen-rich rock migrates naturally and is stored by buoyant forces into the porous space of a reservoir rock, and subsequently is trapped by an impermeable seal. This geological definition of a petroleum system differentiates three rock types: source, reservoir and seal.



CONVENTIONAL* UNCONVENTIONAL*

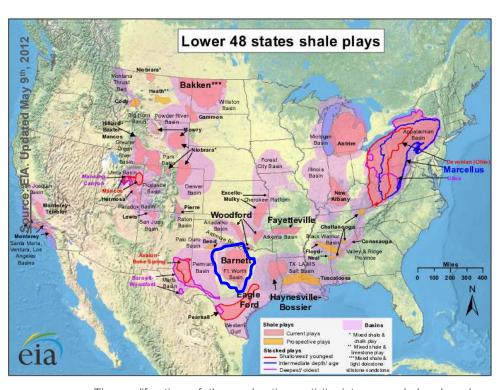
An unconventional reservoir is one where one single rock combines the previous rock characteristics, and the hydrocarbon storage in the rock pores (typically natural gas) does not flow naturally due to the low (> \$ 0.1 mD) rock permeability. Many of these lowpermeability rocks are shale and tight sandstone, but currently significant amounts of gas are also produced from low-permeability carbonates and coal bed methane.



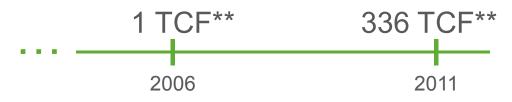
BARNETT SHALE:

Low permeability* (<0.1 mD) Low porosity* (6%) High TOC*

> *Average values corresponding to the Barnett Shale



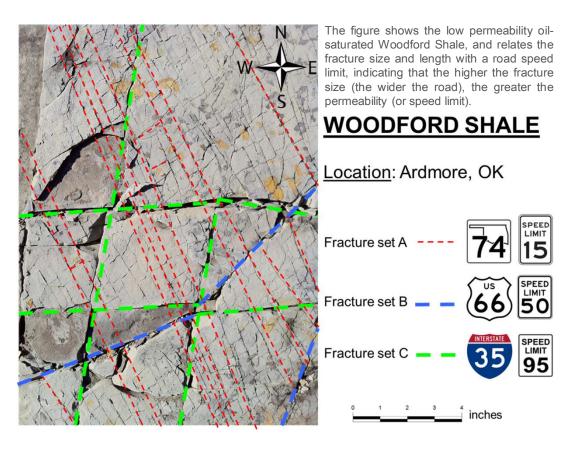
The proliferation of the exploration activity into new shale plays has increased the shale gas resources in the U.S. from 1 from 2006 to 336 TCF in August 2011. In this dissertation we will focus on the Barnett Shale, located in the Fort Worth Basin (Texas).

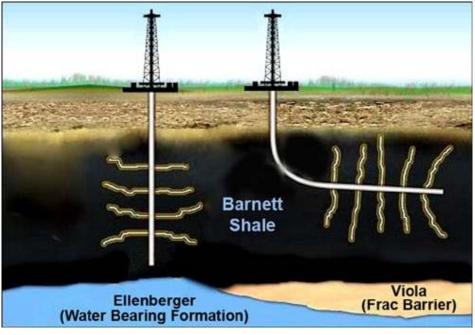


**Trillion cubic feet

*Geological

OBJECTIVE





Due to the low permeability, it is necessary apply enhanced recovery techniques, such as hydraulic fracture stimulation or steam injection to extract the gas molecules from the rock matrix and achieve gas production.

Finding areas in the shale play that are "<u>brittle</u>" is important in the development of a fracture fairway large enough to <u>connect</u> the highest amount of "<u>rock volume</u>" during the <u>hydraulic</u>—

<u>fracturing process</u>.



OUTLINE

- Introduction
- Objectives
- Review Brittleness Index (BI)
- BI estimation from logs
 - Linear correlation
 - Non linear correlation
- Seismic attributes
 - $\lambda \rho$, $\mu \rho$ (Geomechanical)
 - Pseudo GR (Geological)
- Conclusions



WHAT IS BRITTLENESS?

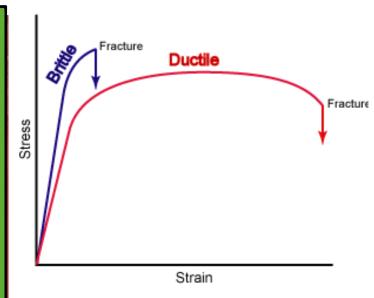
BRITTLE

BRITTLENESS is the measurement of stored energy before failure, and is function of:

- Rock strength
- lithology
- texture
- effective stress
- temperature
- fluid type
- diagenesis
- TOC

BRITTLENESS INDEX (BI) is the most widely used parameter for the quantification of rock brittleness.

$$BI = \frac{\sigma_c}{\sigma_t}.$$



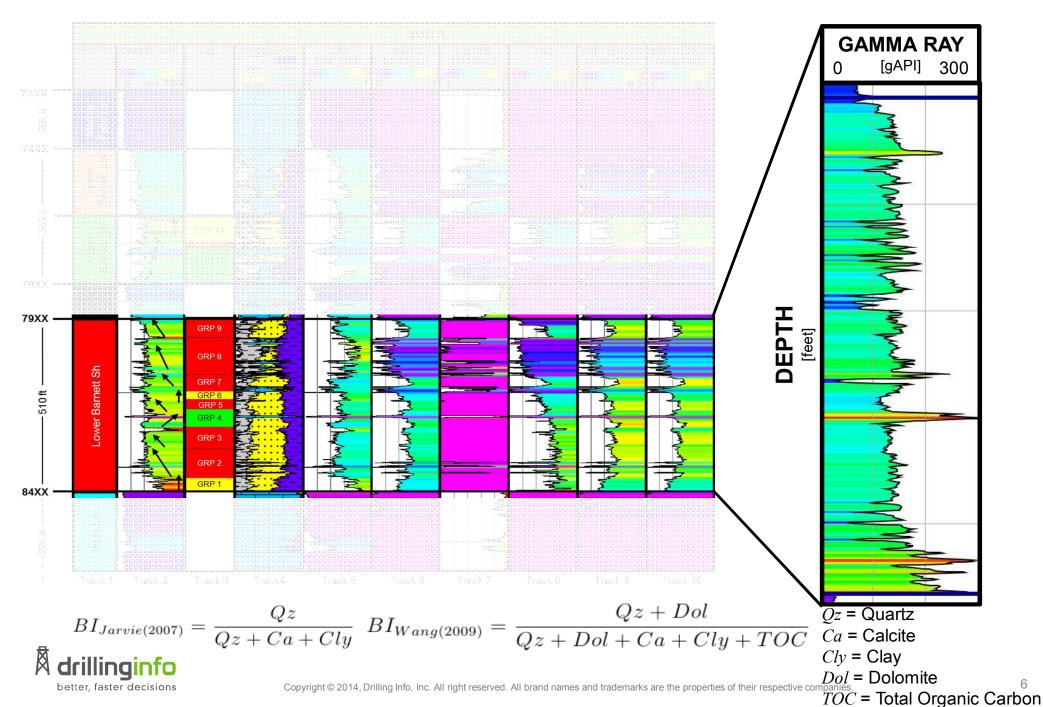
Higher the magnitude of the BI, the more brittle the rock is

DUCTILE

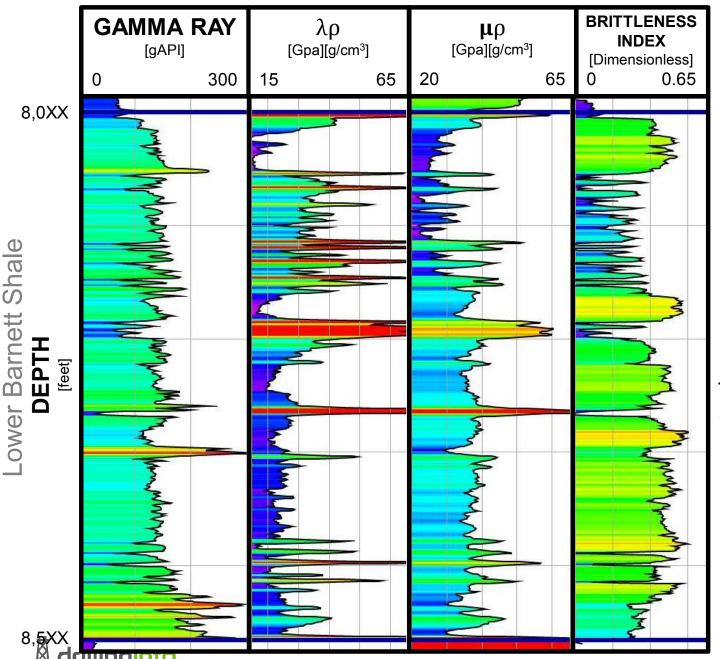




BRITTLENESS INDEX FROM LOGS



BRITTLENESS INDEX FROM LOGS



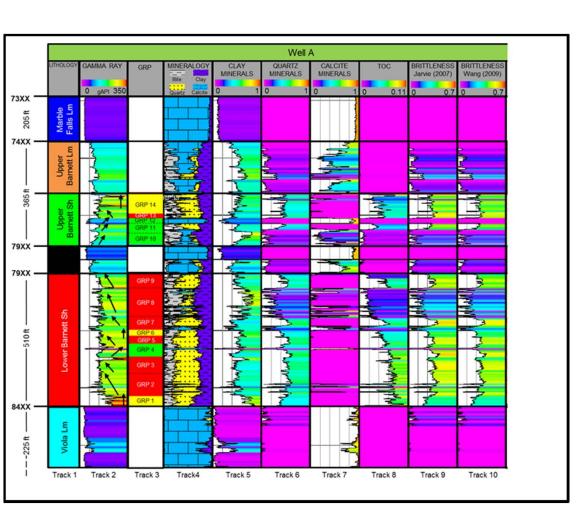
better, faster decisions

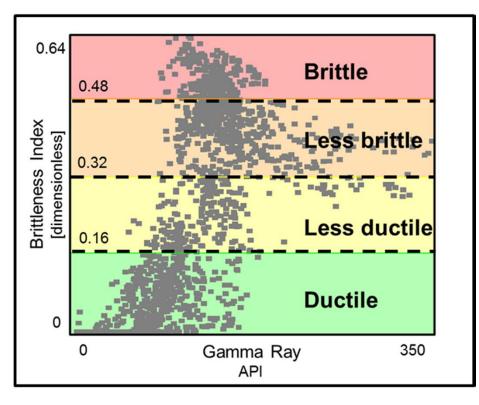
 $f_{BI}(\lambda\rho,\mu\rho,GR)$

Brittleness Index:

$$BI_{Wang(2009)} = \frac{Qz + Dol}{Qz + Dol + Ca + Cly + TOC}$$

BRITTLENESS INDEX (Mineralogy)





$$BI_{Jarvie(2007)} = \frac{Qz}{Qz + Ca + Cly}$$

$$BI_{Jarvie(2007)} = \frac{Qz}{Qz + Ca + Cly} BI_{Wang(2009)} = \frac{Qz + Dol}{Qz + Dol + Ca + Cly + TOC}$$

Qz = Quartz Ca = Calcite Clv = Clay

Dol = Dolomite*TOC* = Total Organic Carbon

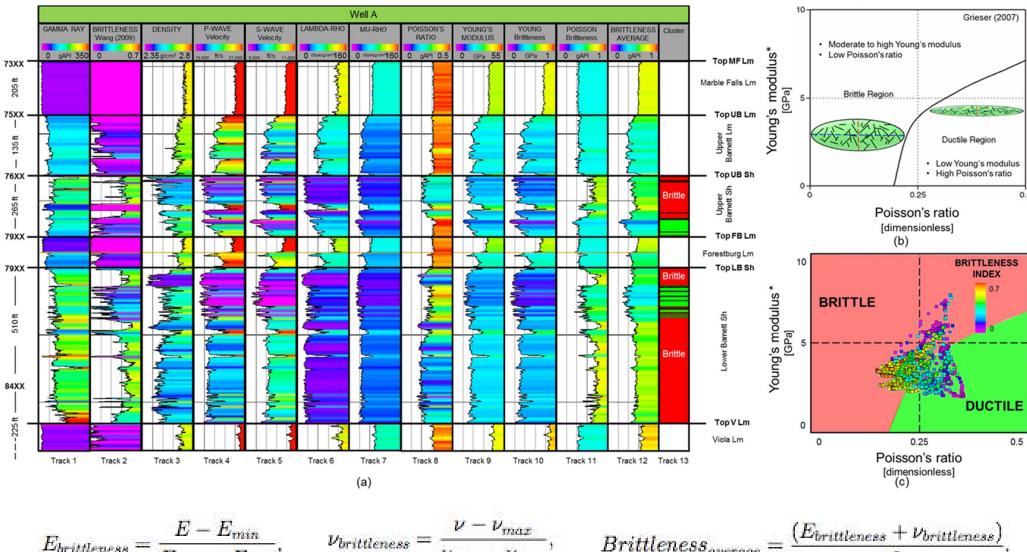


BRITTLENESS INDEX (Mineralogy)

LITHOFACIES			Average TOC (wt%)	Average silica (SiO ₂) %	0.64	0.48	High Toc Tocittle
In situ phosphatic deposit	1	\ ⊟↑	6	10 - 15			
Siliceous, non calcareous mudstone	richness	r oxygen	4.5	30	Index less]	0.00	e e b tile
Siliceous, calcareous mudstone	0.000	water	3.5	-	_	0.32	
Calcareous laminae	organic	bottom	3.5	-	Brittleness Inde [dimensionless]		Less ductile
Micritic / limy mudstone	.⊑	.⊑	1.2	10	P.	0.16	
Reworked shelly deposit	ncrease	Decrease	2.6	2 - 10			Low TOC:ile
Silty shelly (wavy) interlaminated deposit	=	Dec	-	20	0		Ducine
			Sir	igh (2008)		0	Gamma Ray 350 API



BRITTLENESS AVERAGE (Elastic parameters)



$$E_{brittleness} = rac{E - E_{min}}{E_{max} - E_{min}},$$

$$u_{brittleness} = \frac{\nu - \nu_{max}}{\nu_{min} - \nu_{max}}$$

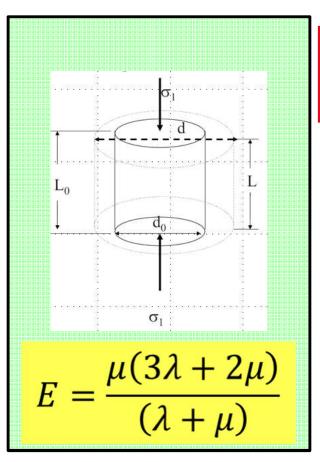
$$Brittleness_{average} = \frac{(E_{brittleness} + \nu_{brittleness})}{2}$$

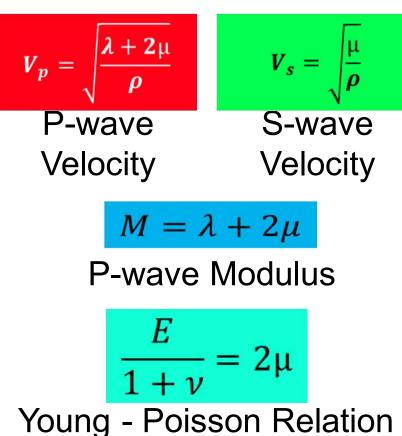


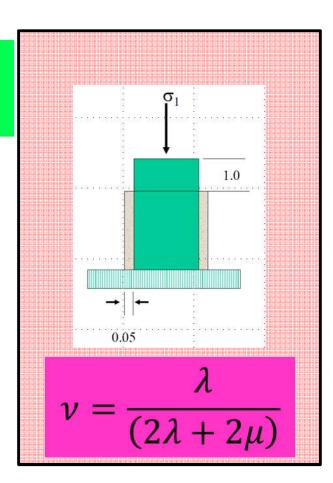
ROCK PHYSICS REVIEW

Young's Modulus

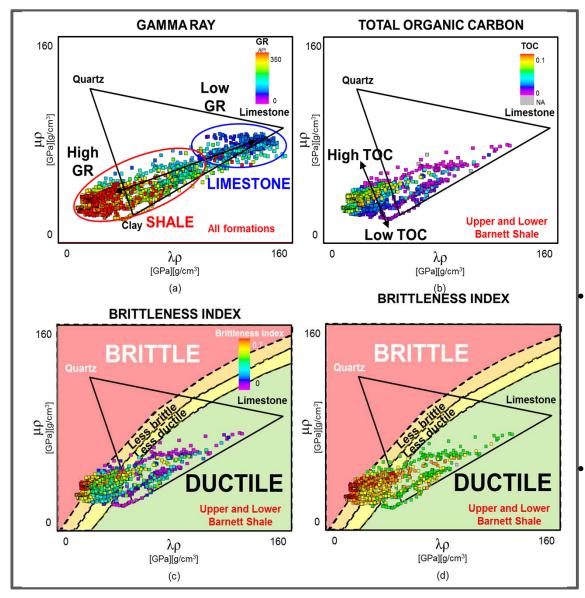
Poisson's ratio





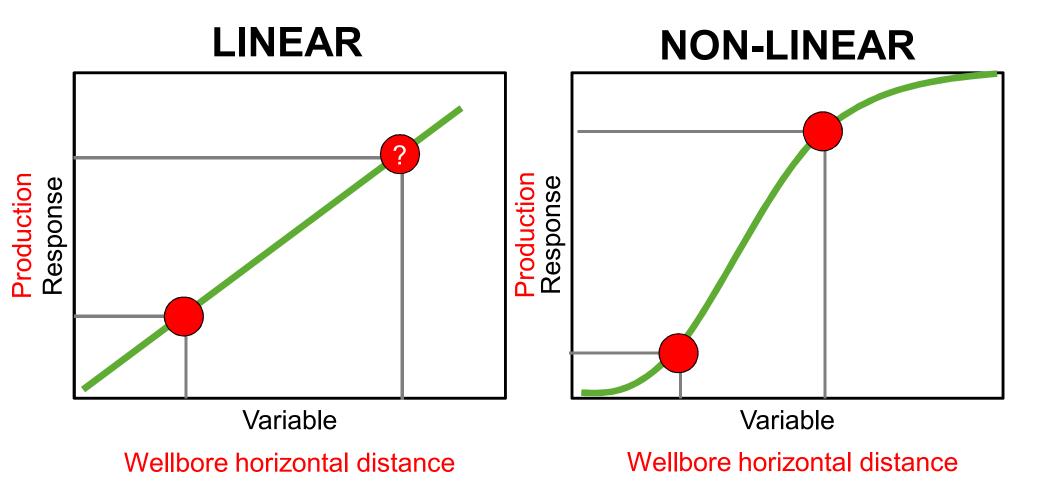


CALIBRATION GEOLOGIC AND GEOMECHANICAL PARAMTERS



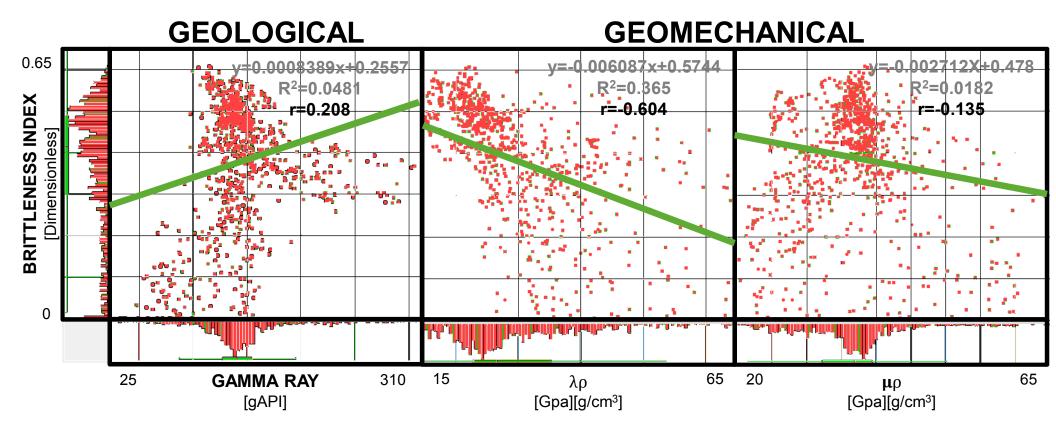
Perez, 2013, Brittleness estimation from seismic measurements in Unconventional reservoirs: Application to the Barnett Shale: Ph.D. Dissertation, The University of Oklahoma. Perez, R. and K. Marfurt, 2014, Mineralogy-Based Brittleness Prediction from Surface Seismic Data: Application to the Barnett Shale (Manuscript ID: INT-2013-0161)

LINEAR vs. NON-LINEAR CORRELATION





LINEAR CORRELATION



	Brittlene	GR (Gam	Lambda	Mu_Rho
Brittleness	1.0	0.208	-0.604	-0.135
GR (Gamm	0.208	1.0	-0.259	-0.343
Lambda_R	-0.604	-0.259	1.0	0.603
Mu_Rho (P	-0.135	-0.343	0.603	1.0

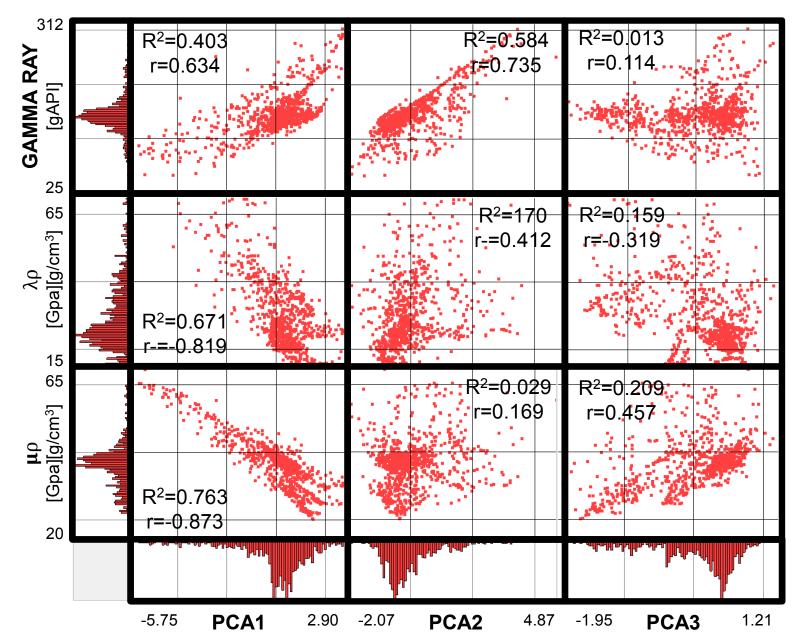
	Brittlene	GR (Gam	Lambda	Mu_Rho
Brittleness	1.0	0.015	-0.732	-0.036
GR (Gamm	0.015	1.0	-0.142	-0.34
Lambda_R	-0.732	-0.142	1.0	0.419
Mu_Rho (P	-0.036	-0.34	0.419	1.0

Correlation coefficient

Rank

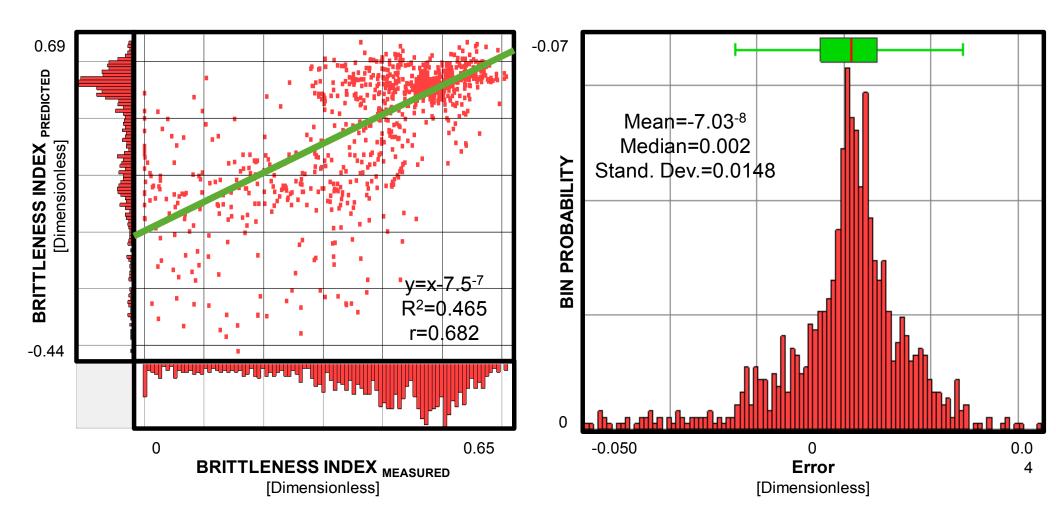


PRINCIPAL COMPONENT ANALYSIS





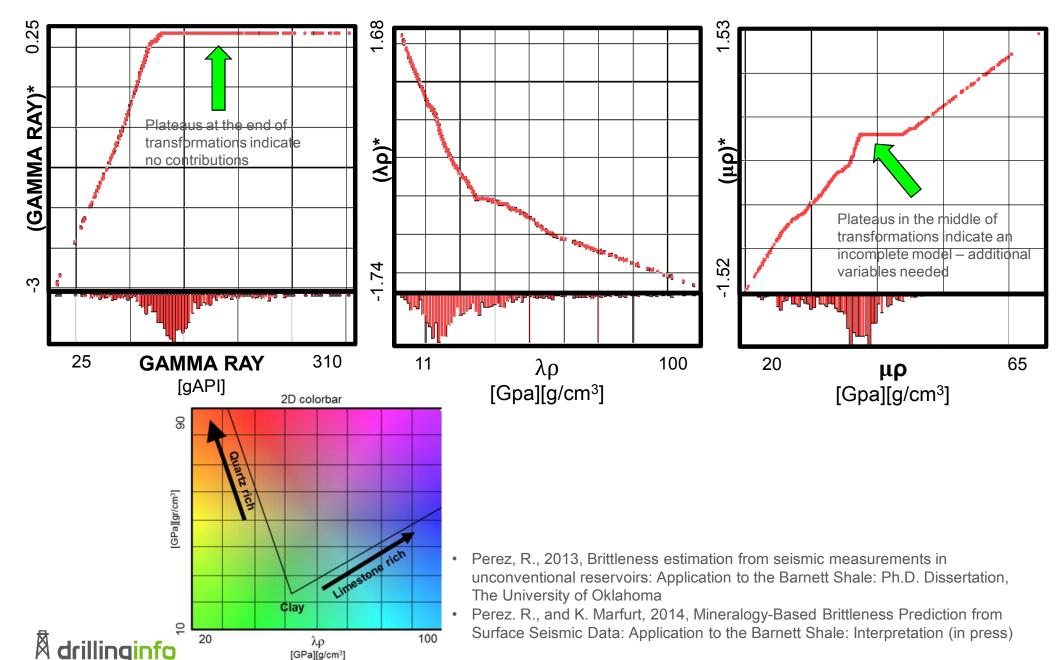
LINEAR REGRESSION RESULTS



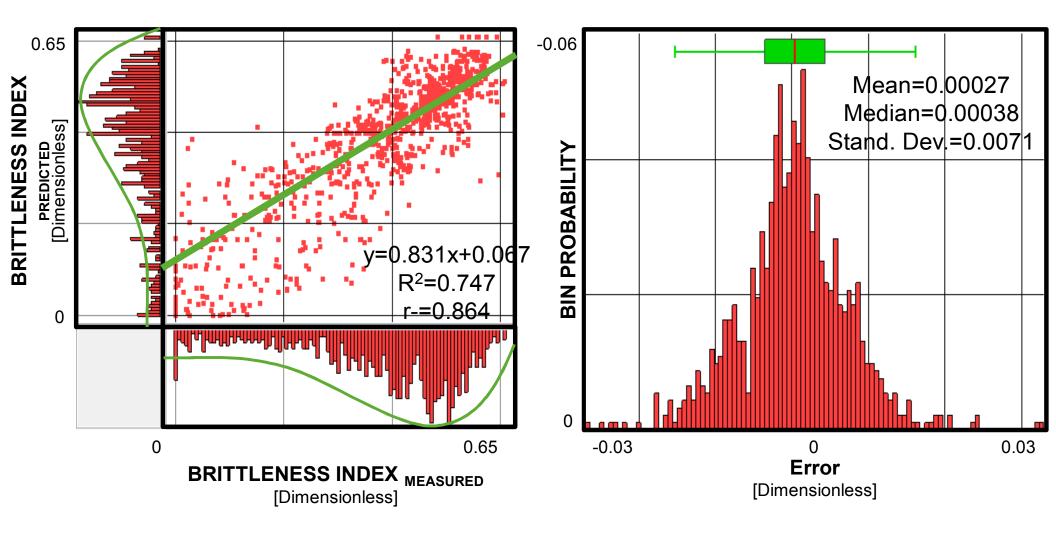


NON-LINEAR REGRESSION RESULTS

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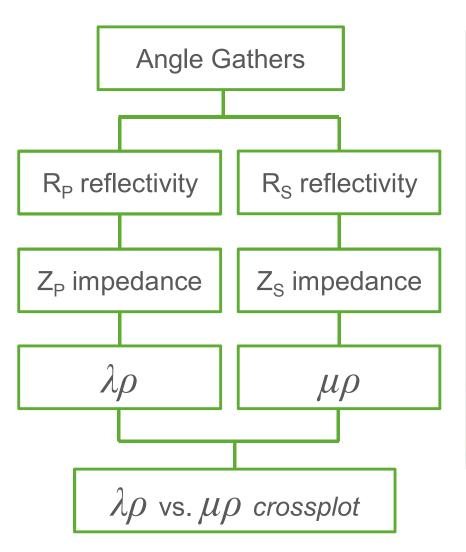


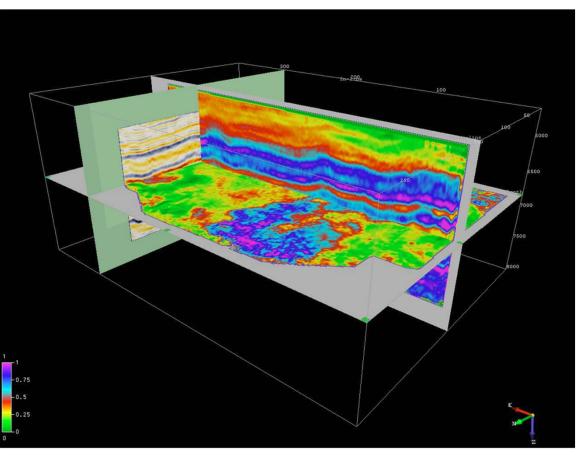
NON-LINEAR REGRESSION RESULTS





SEISMIC PROCESSING





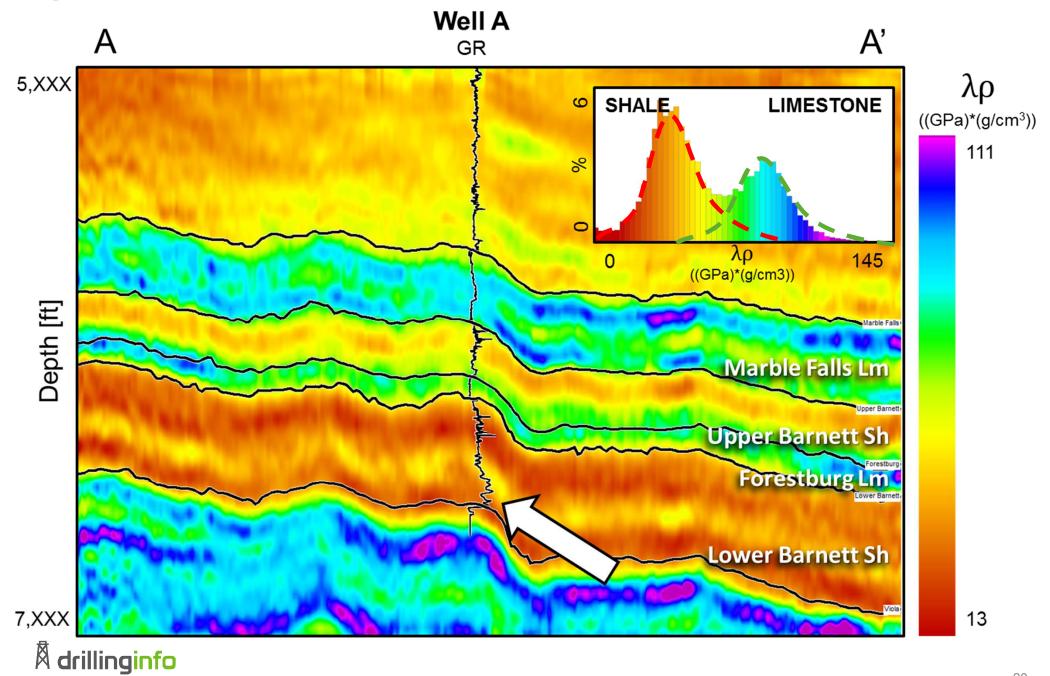
$$\lambda \rho = (\rho V_P)^2 - 2(\rho V_S)^2$$
. $\mu \rho = (\rho V_S)^2$

Goodway (2007)



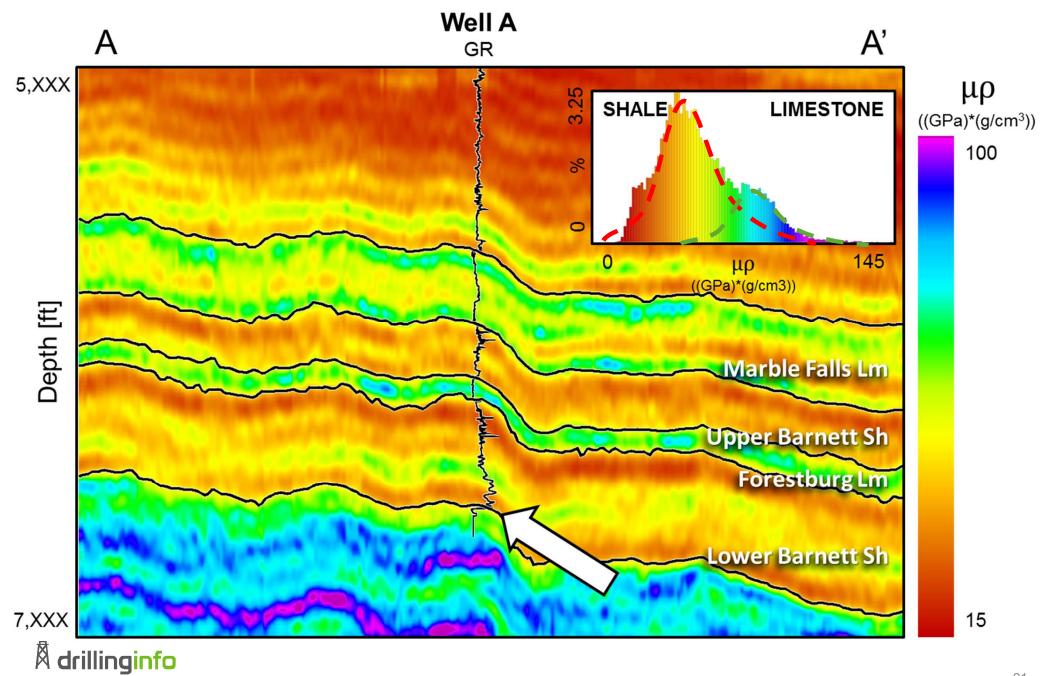
$\lambda \rho$ SLICE

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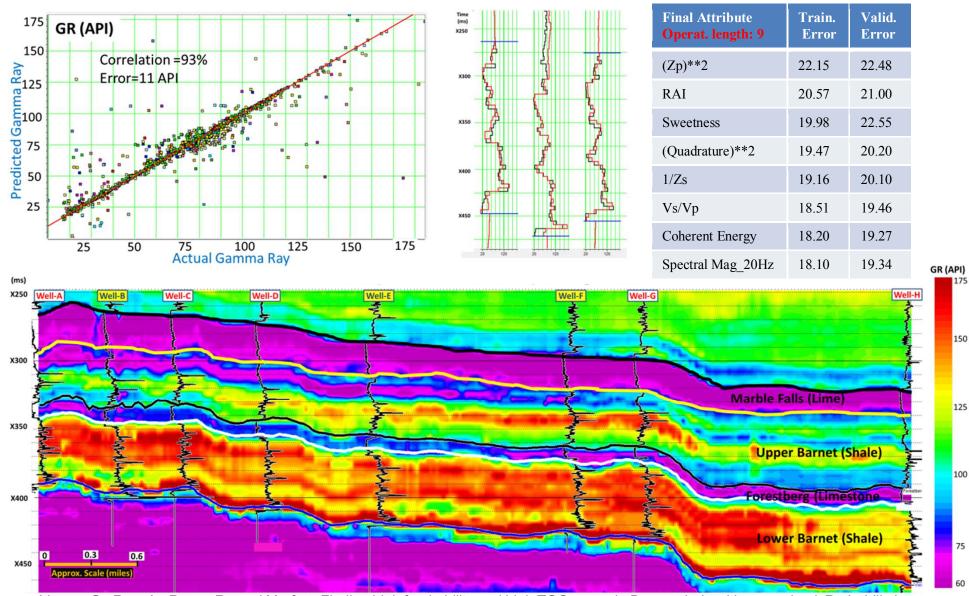


μρ SEISMIC SLICE

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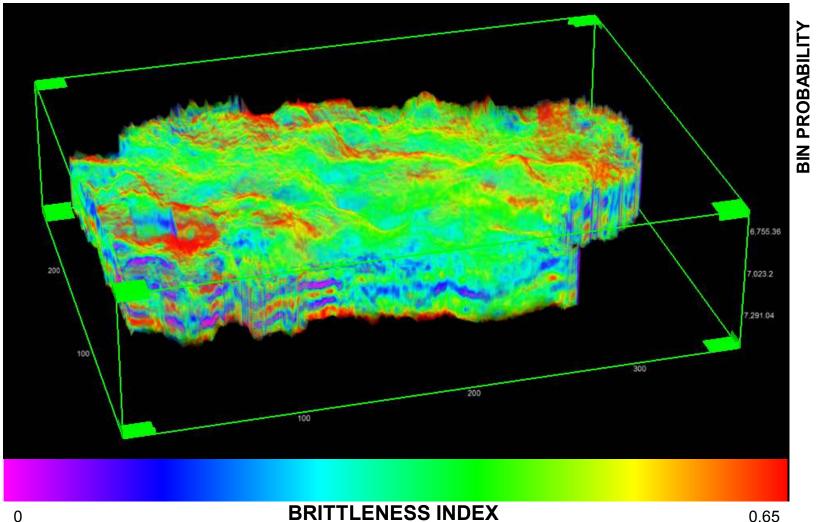
GR SEISMIC VOLUME

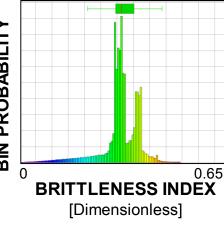


Verma, S., Roy, A., Perez, R., and Marfurt, Finding high frackability and high TOC zones in Barnet shale with supervised: Probabilistic Neural Network and unsupervised: multi-attribute Kohonen SOM, SEG Abstract, 2012.



BRITTLENESS INDEX SEISMIC VOLUME



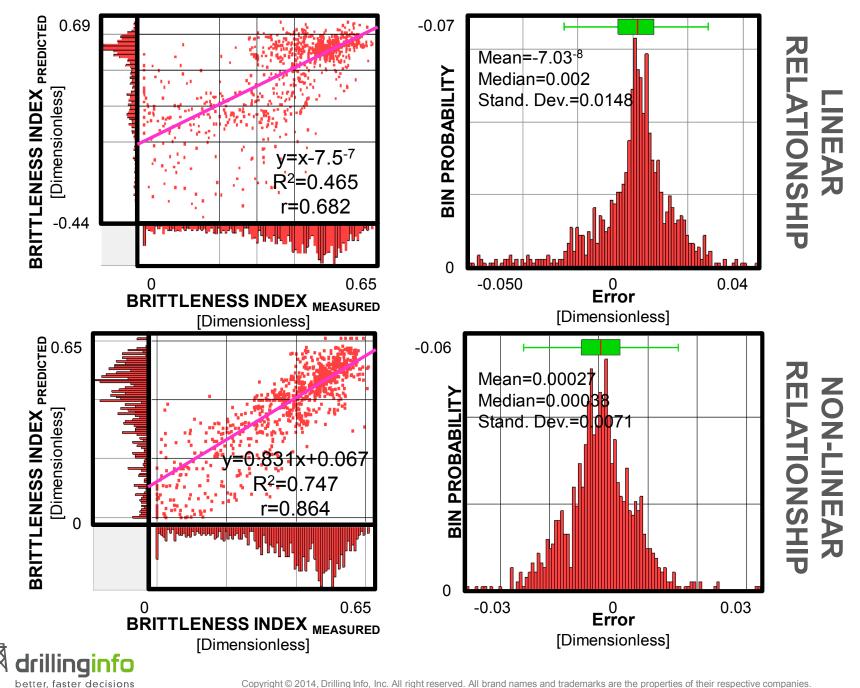


1823034
0.00
0.494
0.310
0.310
0.313
0.0636
-1.67
4.67
0.296
0.353

BRITTLENESS INDEX [Dimensionless]

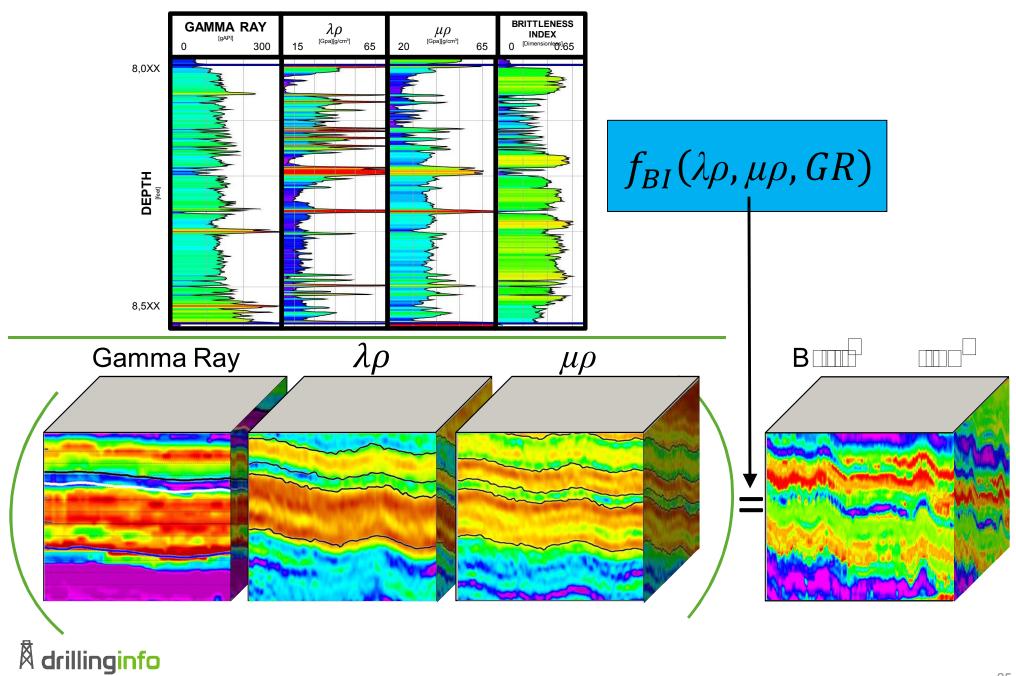


SUMMARY



SUMMARY

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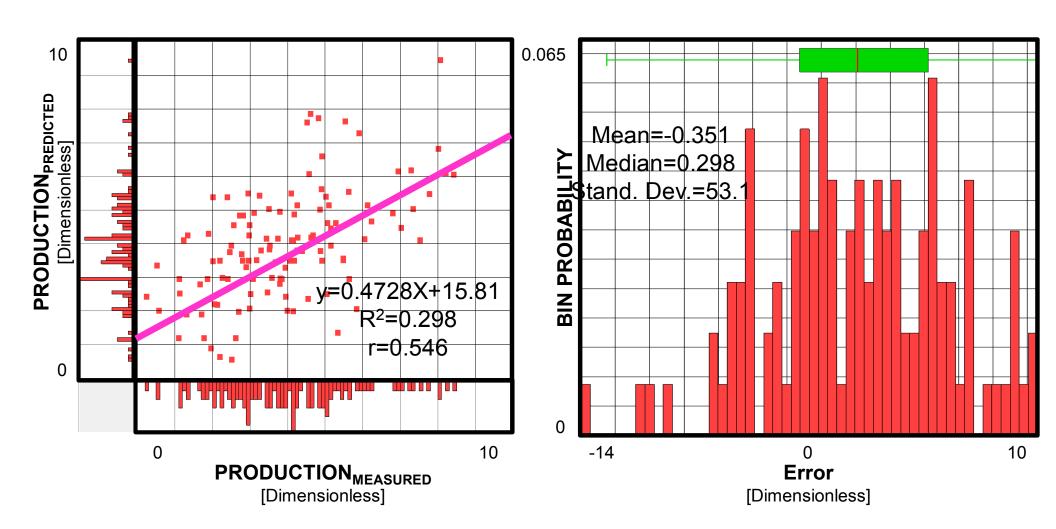


CORRELATION TO PRODUCTION

- **RESPONSE**: Relative EUR
- VARIABLES:

Engineering variables-

- Horizontal length
- Azimuth
- Number of stages
- Total stage length

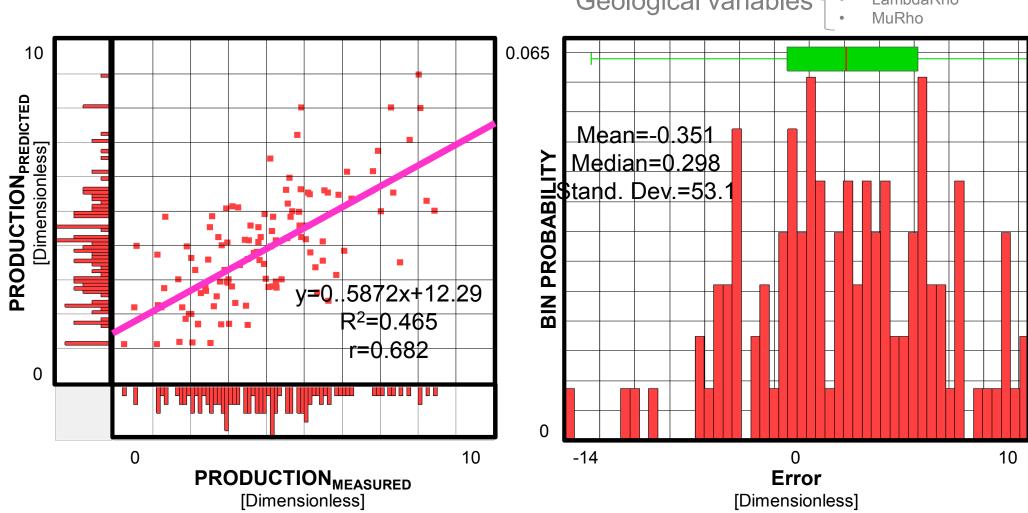




CORRELATION TO PRODUCTION

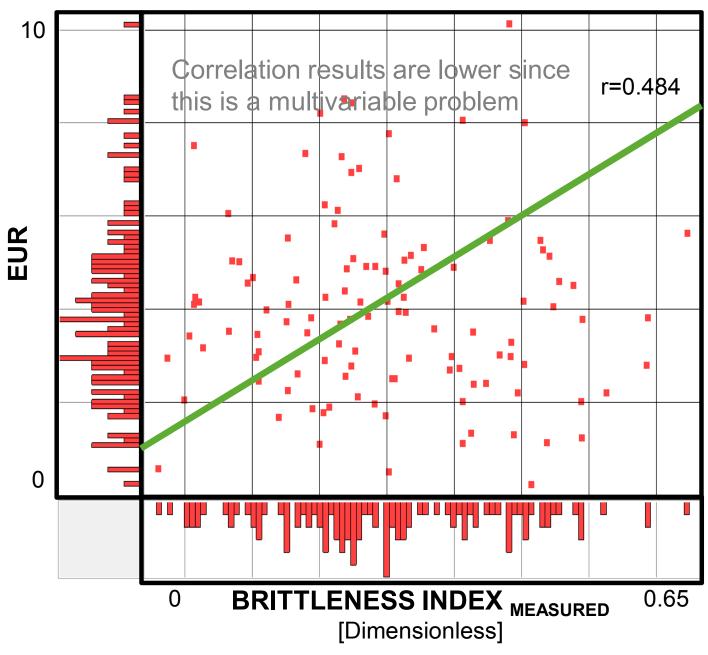
- **RESPONSE:** Relative EUR
- **VARIABLES:**
 - Horizontal length
 - Azimuth
 - Number of stages
 - Total stage length
 - GR
- Geological variables LambdaRho

Engineering variables-



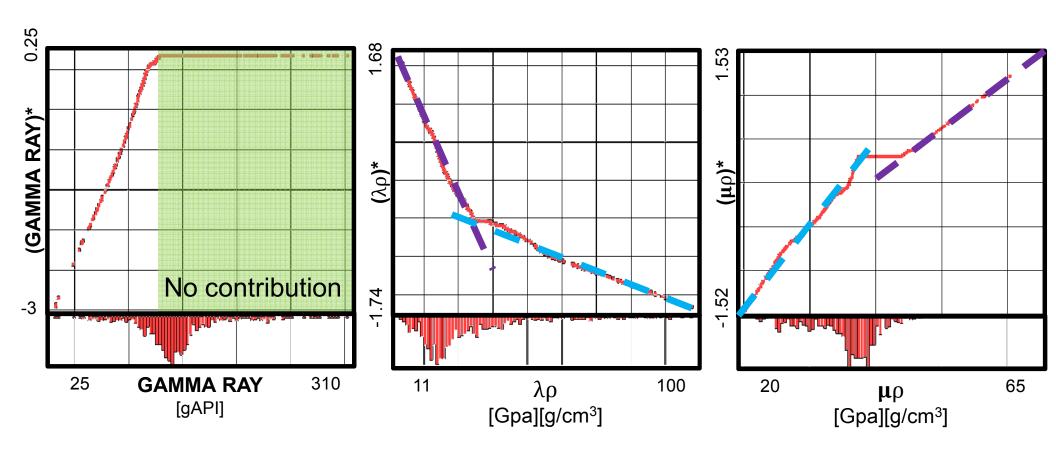


CORRELATION TO PRODUCTION



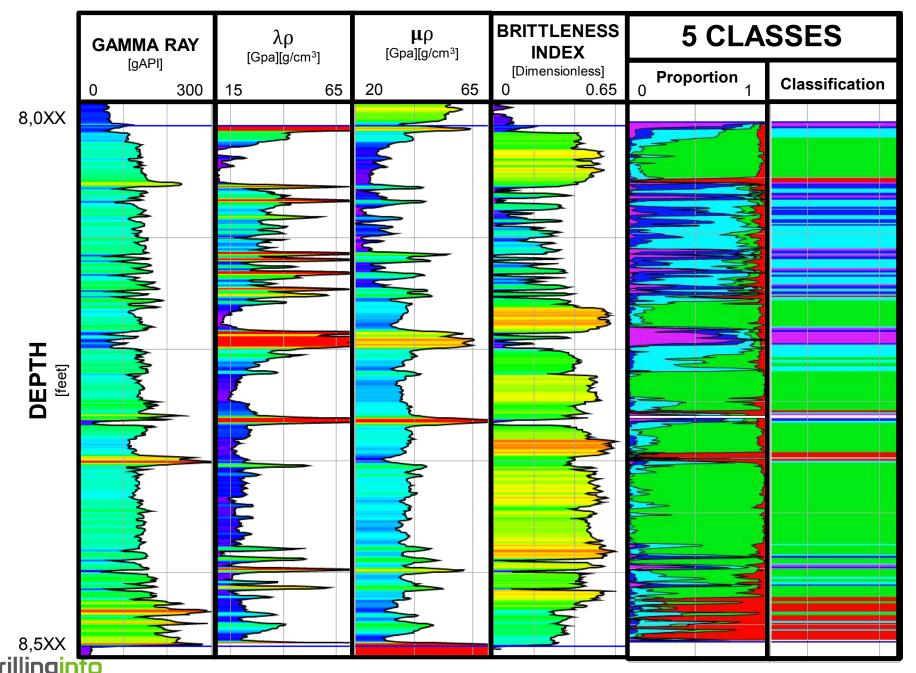


REFINING NON-LINEAR REGRESSION RESULTS Facies Dependent Brittleness



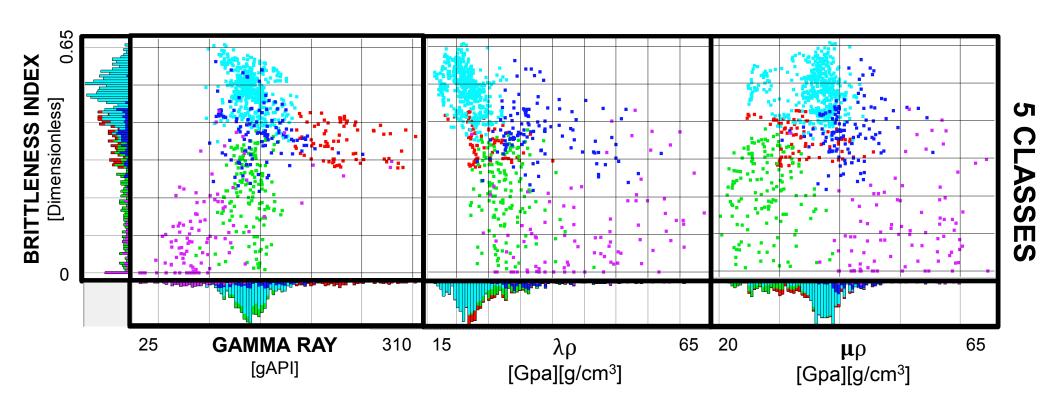


REFINING NON-LINEAR REGRESSION RESULTS



better, faster decisions

REFINING NON-LINEAR REGRESSION RESULTS Facies Dependent Brittleness





INTRODUCTION

After removing possible outliers using a non-parametric approach based upon distribution smoothing and degree of rejection (alpha).

Variable	Sensitivity
GR	0.02
λρ	0.83
μρ	0.14

Retained	Sensitivity
1	0.402
2	0.427
3	0.682

Total

100%

Eigenvalue solution

	Eigenvalue	Variance	Cumulative
PCA1	1.836238	0.612079	0.612079
PCA2	0.78276	0.26092	0.873
PCA3	0.381001	0.127	1

Component Loading solution

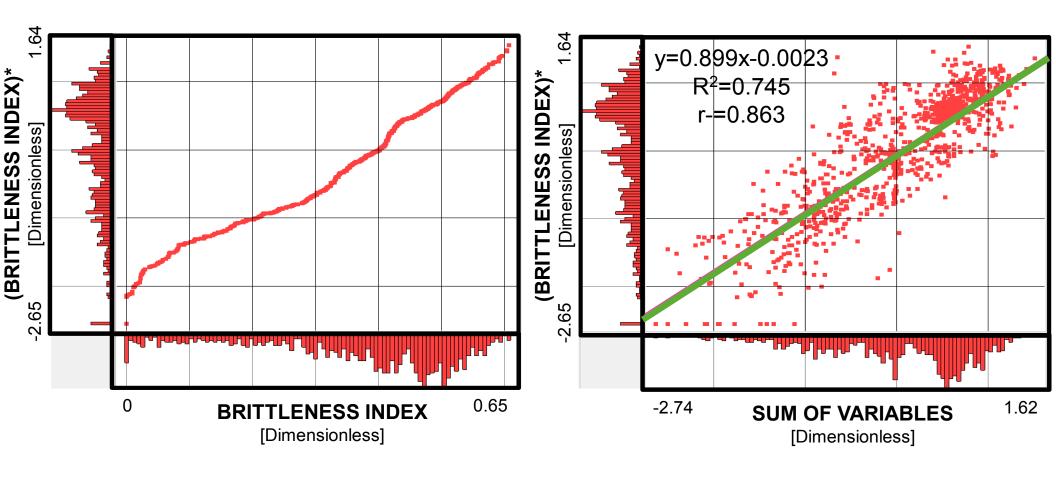
Variable	PCA1	PCA2	PCA3
GR (Gam	0.4682	0.864121	0.184616
Lambda	-0.604558	0.46564	-0.646289
Mu_Rho (-0.644437	0.190981	0.740424

Correlation matrix

Variable	PCA1	PCA2	PCA3
GR (Gamma R	0.634447	0.76452	0.113955
Lambda_Rho (-0.819229	0.411972	-0.398927
Mu_Rho (Pres	-0.873257	0.168967	0.457026



NON-LINEAR REGRESSION RESULTS





CONCLUSIONS

- In order to generate a brittleness index seismic volume was necessary select a combination of geological and geomechanical seismic attributes
- Non-linear relationships shows better results than the linear methods to calibrate results with seismic data
- Refining BI results by facies definitions is necessary to correlated to geological results from core descriptions



ACKNOWLEDGEMENTS

I would like to thank Devon Energy for providing the seismic and well data, and financial support to complete this project, along with DrillingInfo for providing software licenses of Transform EssentialTM, and production data. Additionally, we thank the industry sponsors of the Attribute Assisted Seismic Processing and Interpretation (AASPI) Consortium at the University of Oklahoma for their ongoing financial support.







