

Unconventional Multi-Variate Analysis: A Non-Linear Review of the Most Relevant Unconventional Plays in the U.S.*

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Search and Discovery Article #80428 (2014)**

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Abstract

Data is a powerful tool. It can be both overwhelming to the point of being ignored, and addictive, creating tendencies to overanalyze. In the fast-paced business world, successful leaders know the ability to make quick adjustments to workflows can make a huge difference to bottom lines. Data analysis is what identifies trends that seem to be working and that need to be changed.

It is no different in the oil and gas business, and many different industry specific software packages have been developed to try to handle the huge amounts of data that come in from daily operations. However, the key to success is in full scope integration of data from different fields of study. The use of the use multidisciplinary analytical methodologies has become a necessity in order to provide descriptive and predictive models to complement conventional geological, geophysical, and engineering analysis in unconventional resources plays.

The challenge is to unveil relationships and opportunities buried in mountains of geological, geophysical, and engineering data, collated at various scales: in depth as well as in time. This presentation will cover methodologies that can be used to integrate data collected in these various aspects, and review lessons learned from some of the most important unconventional shale plays in the U.S. such as: the Barnett Shale, Eagle Ford Shale, Haynesville Shale, and Utica Shale, in order to discover connections between the available input variables without explicit knowledge of the physical behaviors of the system.

References Cited

Browning, D.B., 2006, Investigating corrections between microseismic event data, seismic curvature, velocity anisotropy, and well production in the Barnett Shale, Fort Worth Basin, Texas: M.S. Thesis, University of Oklahoma, Norman, Oklahoma, 105 p.

Goodway, B., J. Varsek, C. Abaco, 2007, Anisotropic 3D amplitude variation with azimuth (AVAZ) methods to detect fracture prone zones in tight gas resource plays: CSPG, CSEG, CWLS Conference, p. 590-596.

Perez, R., 2013, Brittleness Estimation from Seismic Measurements in Unconventional Reservoirs: Application to the Barnett Shale: Ph.D. Dissertation, ConocoPhillips School of Geology and Geophysics: The University of Oklahoma.

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

Roth, M., 2013, An Analytic Approach to Sweetspot Mapping in the Eagle Ford Unconventional Play: Web Accessed November 11, 2014. <https://www.transforms.com/wp-content/uploads/2013/05/An-Analytic-Approach-to-Sweetspot-Mapping-in-the-Eagle-Ford-Unconventional-Play-2013-Geoconvention-Roth-Roth-Peebles.pdf>

Thompson, A., 2010, Induced fracture detection in the Barnett Shale, Ft. Worth Basin, Texas: M.S. Thesis, The University of Oklahoma, Norman, Oklahoma, 69 p.

Verma, S., A. Roy, R. Perez, R., and K.J. Marfurt, 2012, Mapping High Frackability and High TOC Zones in The Barnett Shale: Supervised Probabilistic Neural Network vs. Unsupervised Multi-Attribute Kohonen SOM: 2012 SEG Annual Meeting, 4-9 November, Las Vegas, Nevada.

UNCONVENTIONAL MULTI-VARIATE ANALYSIS:

*A non-linear review of
the most relevant
unconventional plays in
the U.S.*



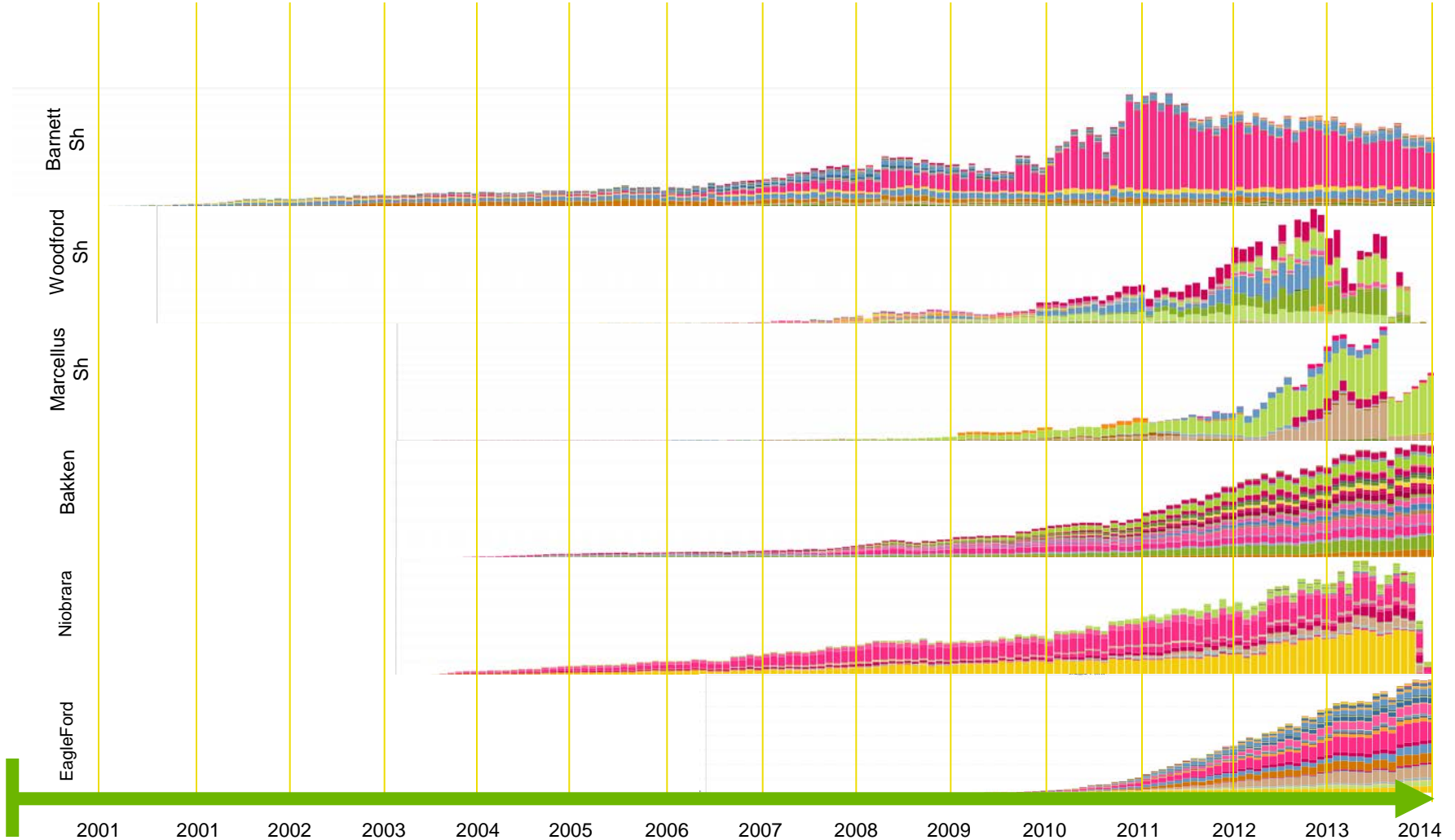
Roderick Perez Altamar, Ph.D.

November, 5th, 2014



PRODUCTION HISTORY

Timeline





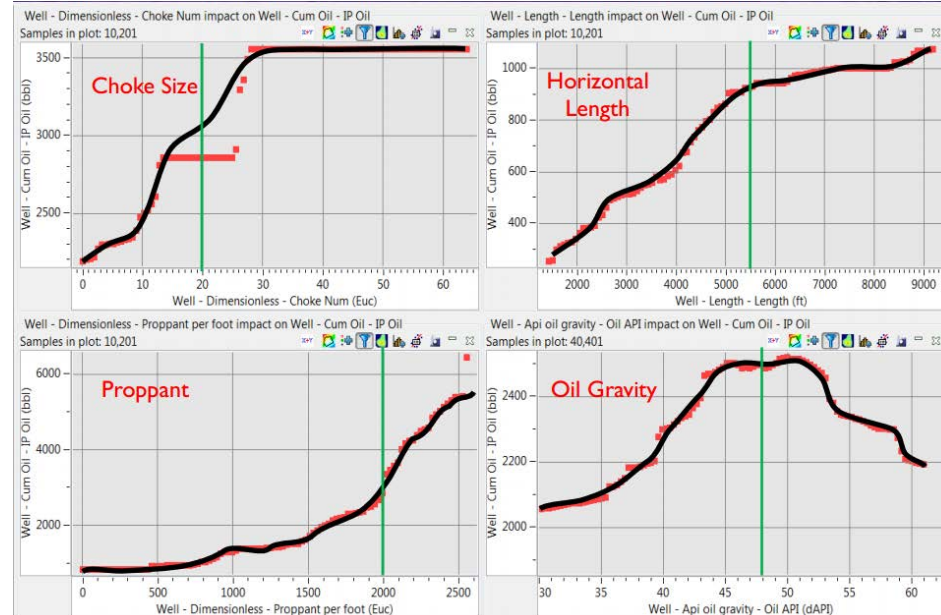
ANALYTICS

ANALYTICS



“The amount of data gathered from production activity has also increased due to placement of downhome sensors that relay information to the operator on a real-time basis.”

The Big Challenges of Big Data for Oil, Gas
by Karen Boman



Analytics is the discovery of meaningful patterns in data.

From Murray Roth - An Analytic Approach to Sweetspot Mapping in the Eagle Ford Unconventional Play

<https://www.transformsww.com/wp-content/uploads/2013/05/An-Analytic-Approach-to-Sweetspot-Mapping-in-the-Eagle-Ford-Unconventional-Play-2013-Geoconvention-Roth-Roth-Peebles.pdf>

(Unconventional) APPLICATION OF ANALYTICS

The data suggests that proximity to a natural gas well is correlated with lower housing prices.

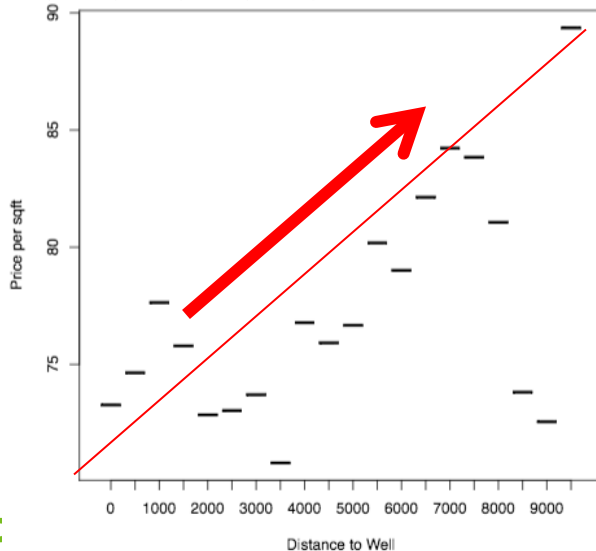
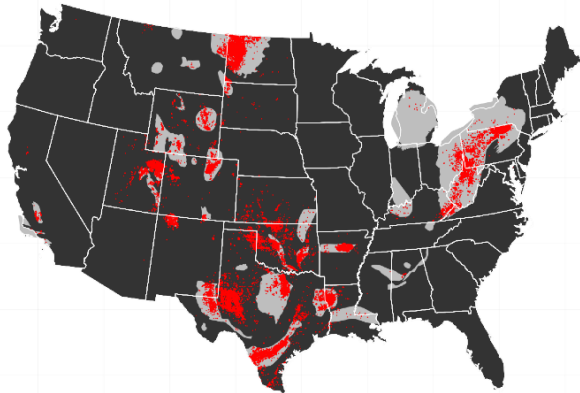


Table 1: Distance to Well and Property Price per Square Foot

	(1)	(2)	(3)	(4)
<i>10 km threshold</i>				
Distance to Well	0.014* (0.008)	0.014* (0.008)	0.014* (0.008)	0.012 (0.009)
bedrooms	-0.092*** (0.014)	-0.091*** (0.015)	-0.091*** (0.015)	-0.109*** (0.012)
baths	0.185*** (0.021)	0.181*** (0.020)	0.180*** (0.020)	0.098*** (0.020)
age	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.010*** (0.001)
Observations	29,207	29,207	29,207	29,207
Adjusted R ²	0.250	0.251	0.257	0.357
<i>20 km threshold</i>				
Distance to Well	0.009** (0.004)	0.009** (0.004)	0.009** (0.004)	0.010** (0.005)
bedrooms	-0.107*** (0.015)	-0.106*** (0.015)	-0.106*** (0.015)	-0.116*** (0.013)
baths	0.146*** (0.034)	0.143*** (0.033)	0.142*** (0.033)	0.085*** (0.021)
age	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.009*** (0.001)
Observations	44,423	44,423	44,423	44,423
Adjusted R ²	0.228	0.229	0.235	0.353
Fixed Effects	County	County & Year	County x Year	Census Tract & Year

Note: The dependent variable is the log of average price per square foot. Standard errors are clustered at the county level with stars indicating *** 0.01, ** 0.05, * 0.1.

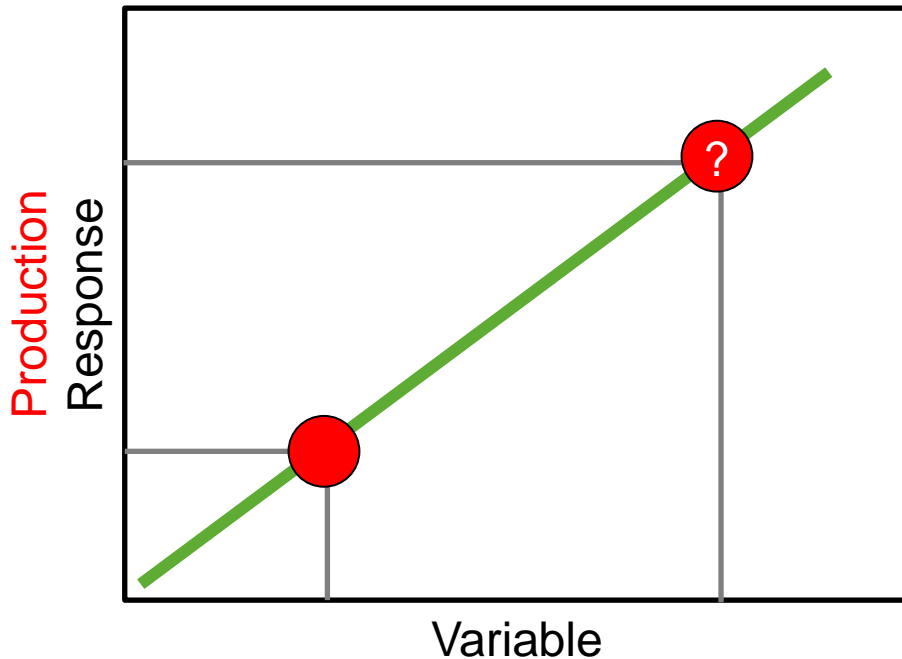
<http://freigeist.devmag.net/economics/808-fracking-and-house-prices-on-the-marcellus-shale.html>

CLUSTERING ANALYSIS ALGORITHMS & TECHNIQUES

- Classification
 - Fuzzy Logic
 - Supervised
 - Unsupervised
 - K-means
 - SOM
 - Hierarchical
- Regression
 - Linear
 - Principal Component Analysis
 - Non-Linear
 - Neural Networks

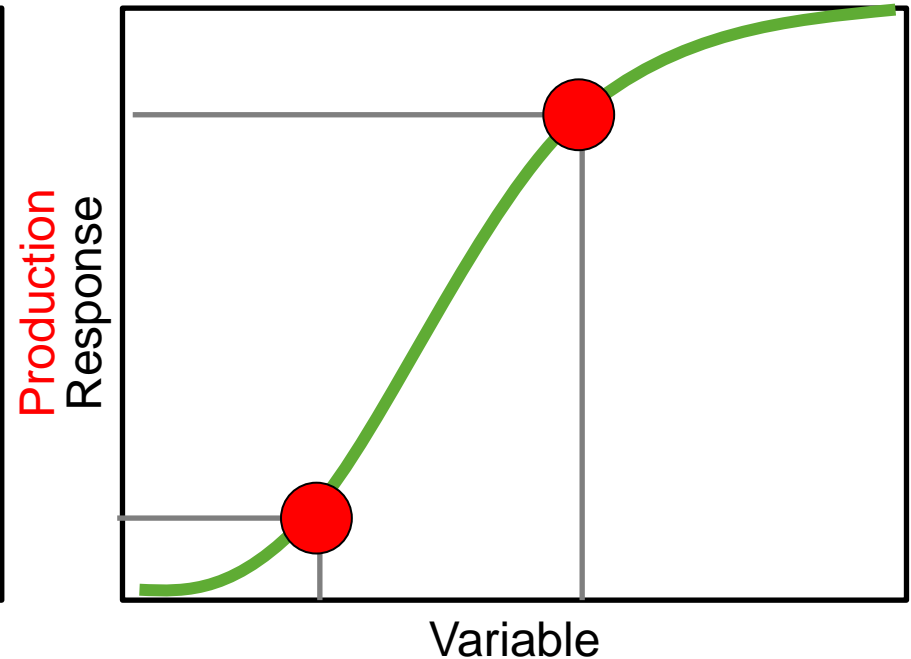
LINEAR vs. NON-LINEAR CORRELATION

LINEAR



Wellbore horizontal distance

NON-LINEAR

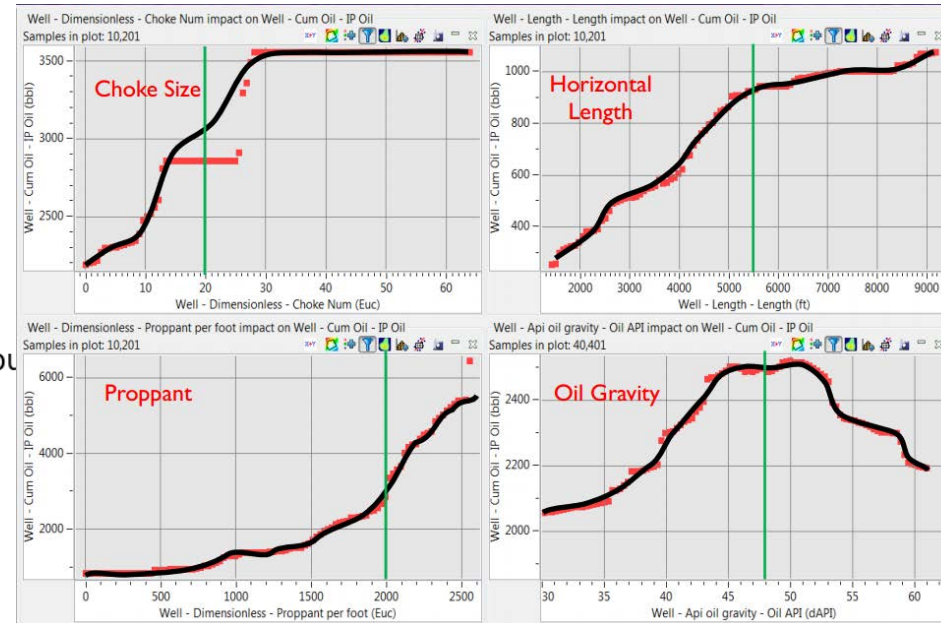
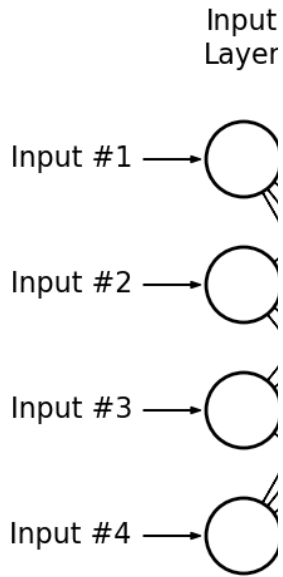


Wellbore horizontal distance

ANN vs. Non-Linear Regressions

ANN

Non-Linear Regression Modeling



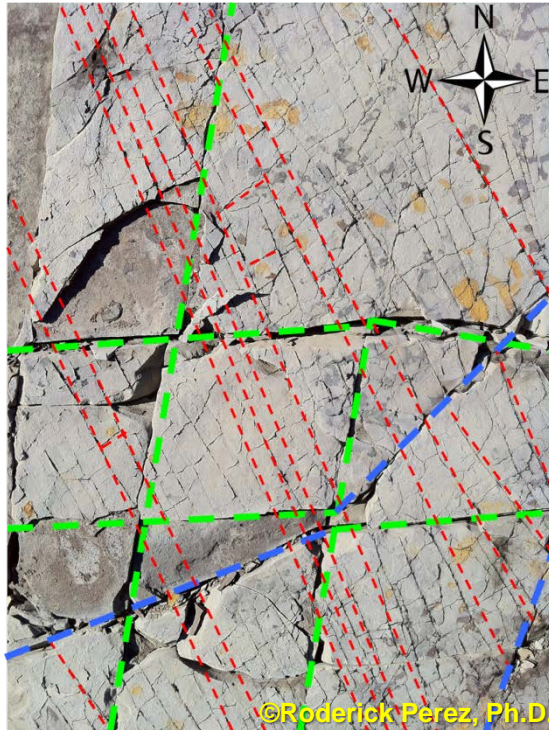
From Murray Roth - An Analytic Approach to Sweetspot Mapping in the Eagle Ford Unconventional Play

<https://www.transformsw.com/wp-content/uploads/2013/05/An-Analytic-Approach-to-Sweetspot-Mapping-in-the-Eagle-Ford-Unconventional-Play-2013-Geoconvention-Roth-Roth-Peebles.pdf>



BRITTLENESS

OBJECTIVE



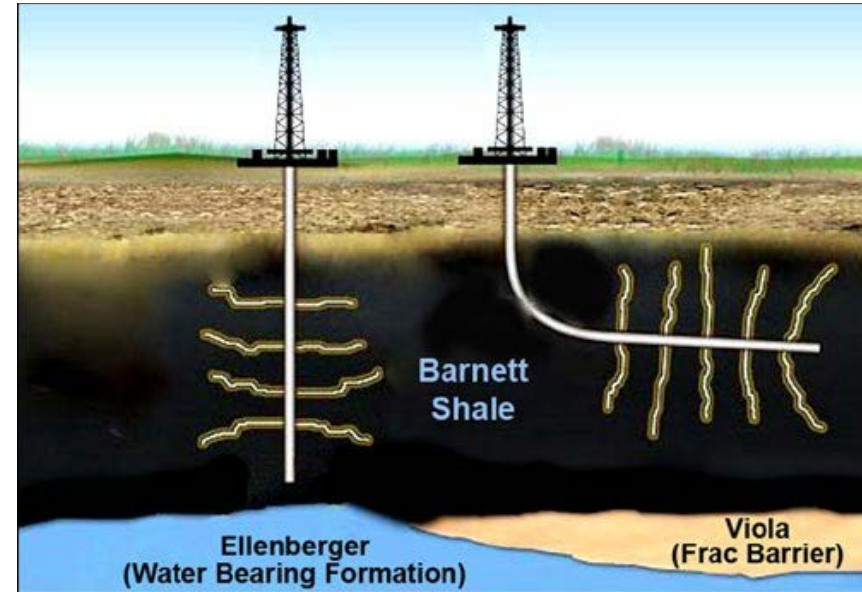
The figure shows the low permeability oil-saturated Woodford Shale, and relates the fracture size and length with a road speed limit, indicating that the higher the fracture size (the wider the road), the greater the permeability (or speed limit).

WOODFORD SHALE

Location: Ardmore, OK

Fracture set A	---		
Fracture set B	---		
Fracture set C	---		

inches



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 “brittle” is important in the development of a fracture fairway large enough to connect the highest amount of “rock volume” during the hydraulic – fracturing process.

WHAT IS BRITTLENESS?

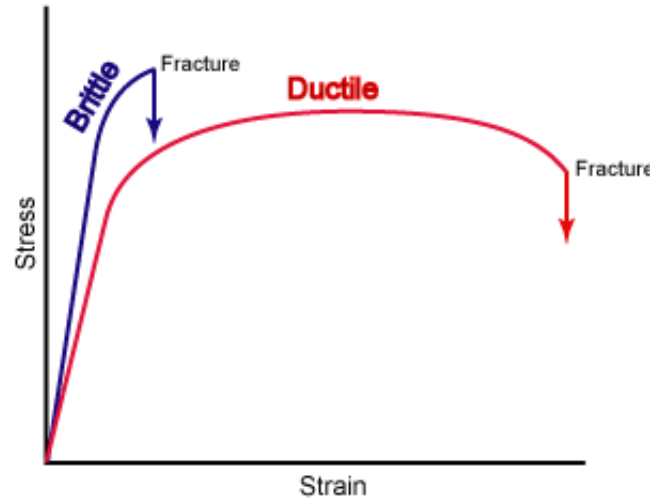
BRITTLE

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



HOW DO TO QUANTIFY BRITTLENESS???

MINERALOGY

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

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

BRITTLENESS

Mineralogy

Young's modulus & Poisson's ratio

GEOLOGY

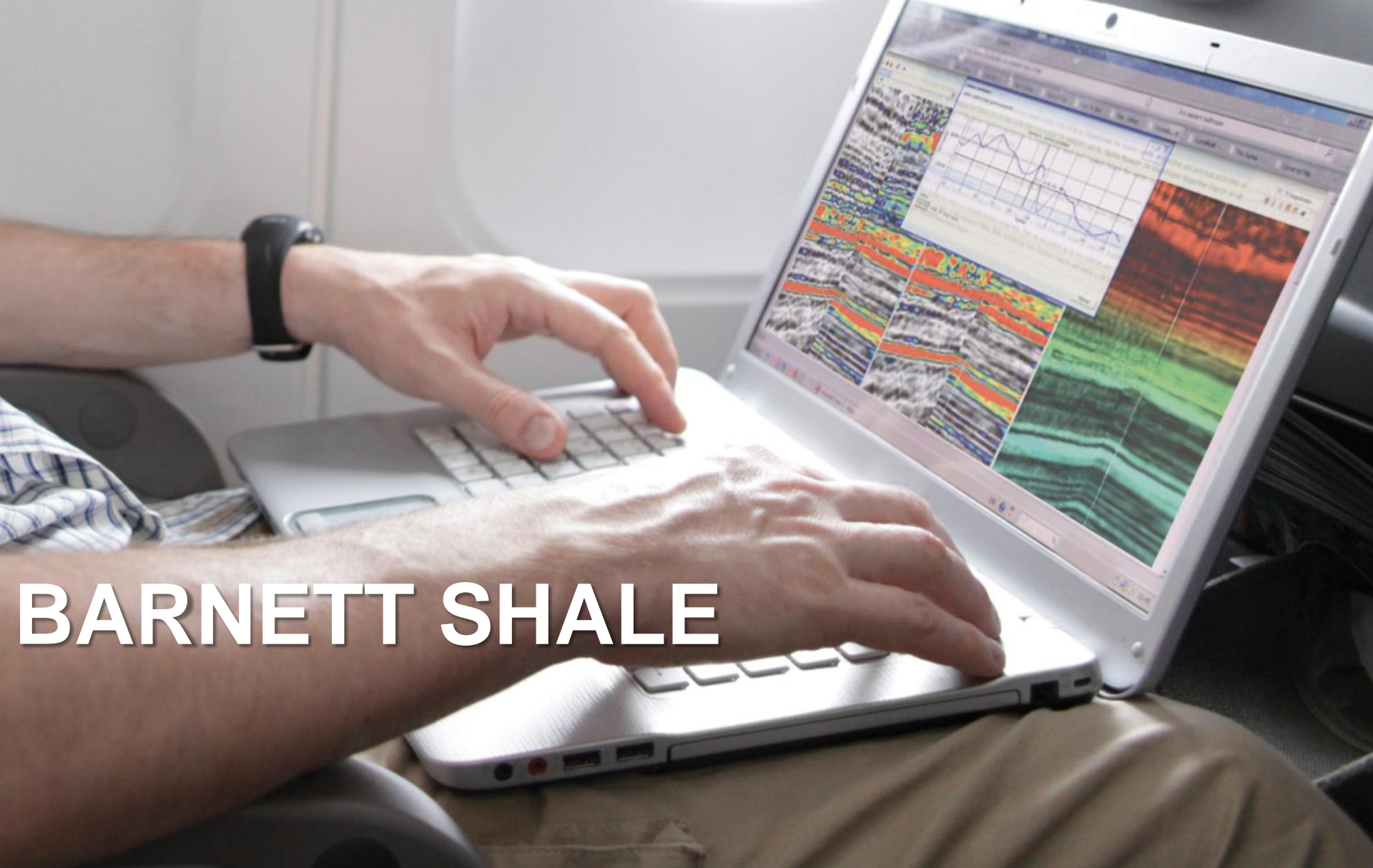
GEOMECHANICAL

ELASTIC PARAMETERS

$$E_{brittleness} = \frac{E - E_{min}}{E_{maz} - E_{min}},$$

$$\nu_{brittleness} = \frac{\nu - \nu_{maz}}{\nu_{min} - \nu_{maz}},$$

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



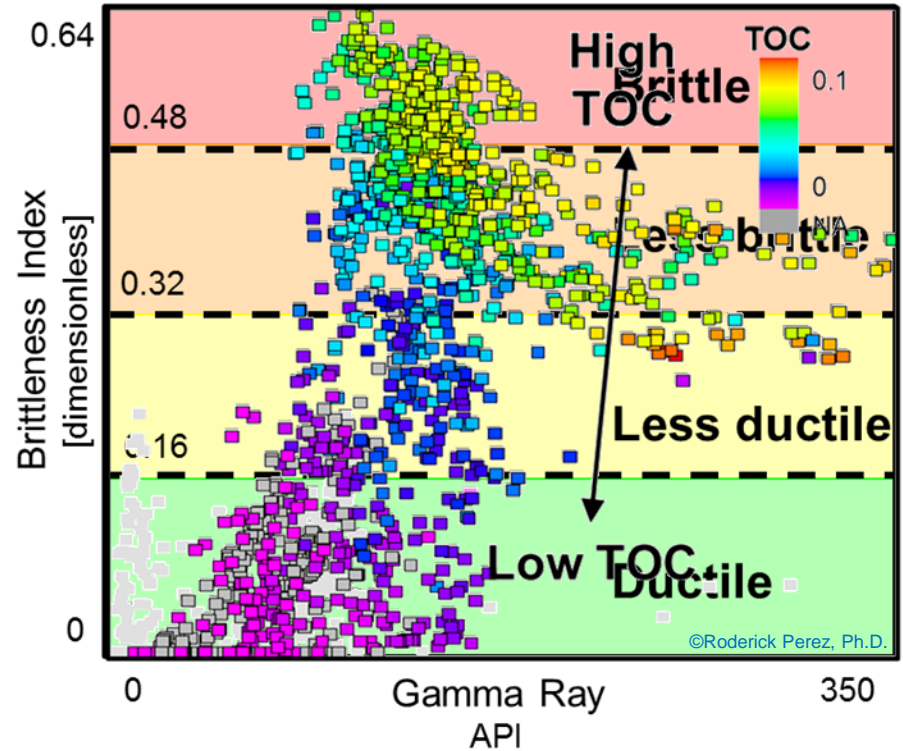
BARNETT SHALE

BRITTLENESS INDEX (Mineralogy)

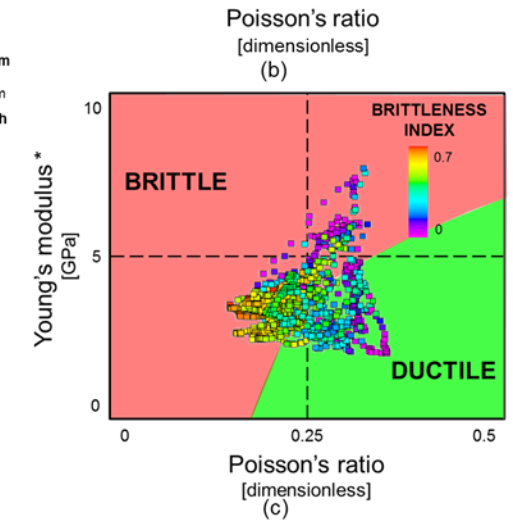
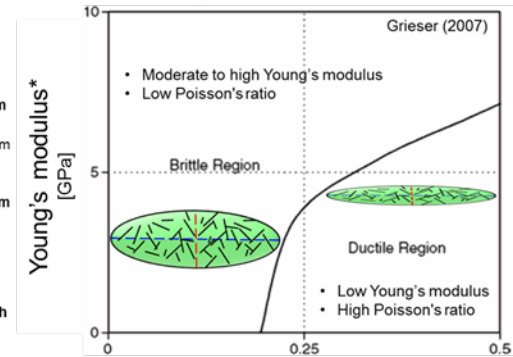
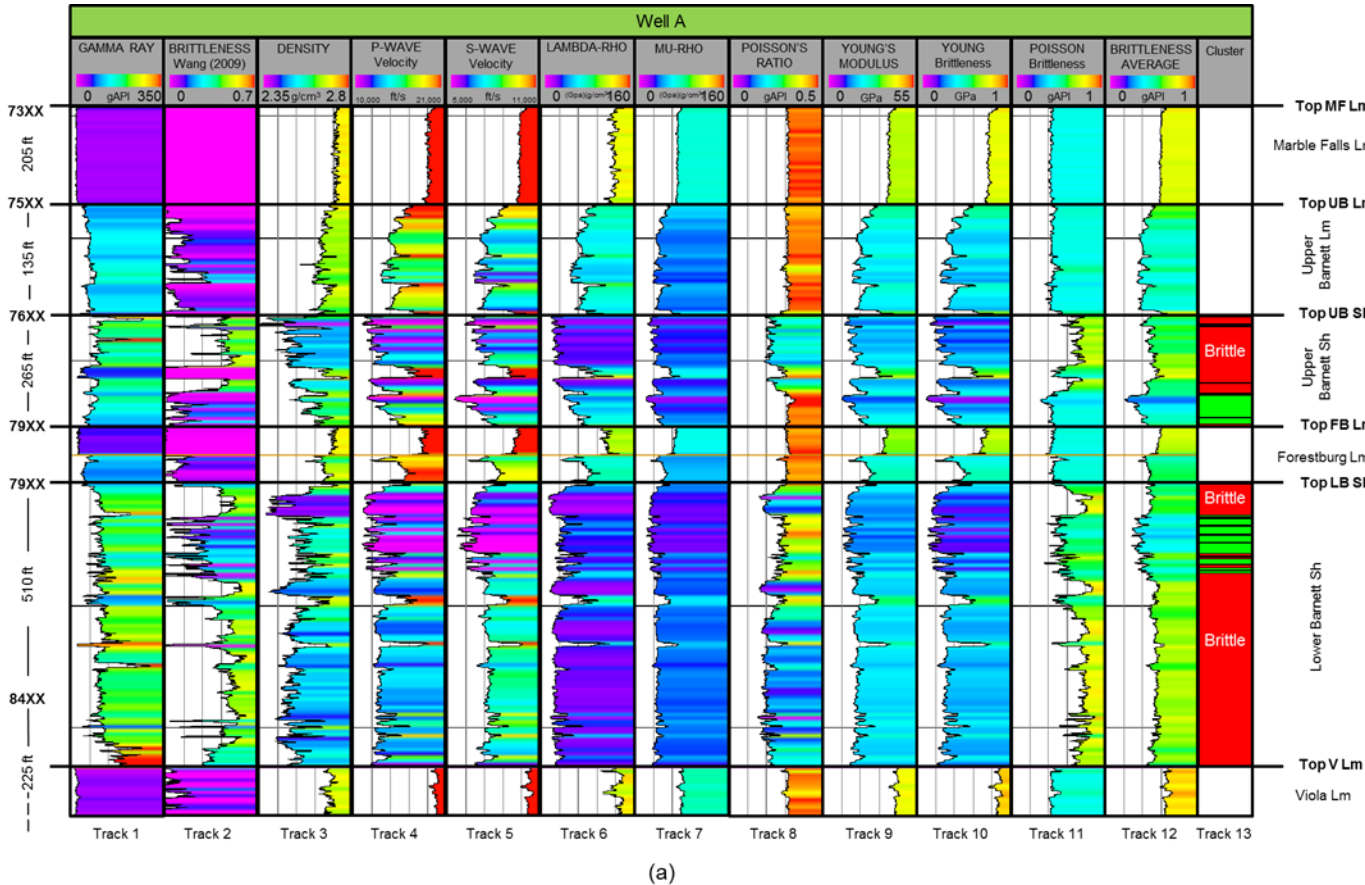
LITHOFACIES	Average TOC (wt%)	Average silica (SiO ₂) %
<i>In situ</i> phosphatic deposit	6	10 - 15
Siliceous, non calcareous mudstone	4.5	30
Siliceous, calcareous mudstone	3.5	-
Calcareous laminae	3.5	-
Micritic / limy mudstone	1.2	10
Reworked shelly deposit	2.6	2 - 10
Silty shelly (wavy) interlaminated deposit	-	20

Increase in organic richness
 Decrease in bottom water oxygen

Singh (2008)



BRITTLINESS AVERAGE (Elastic parameters)

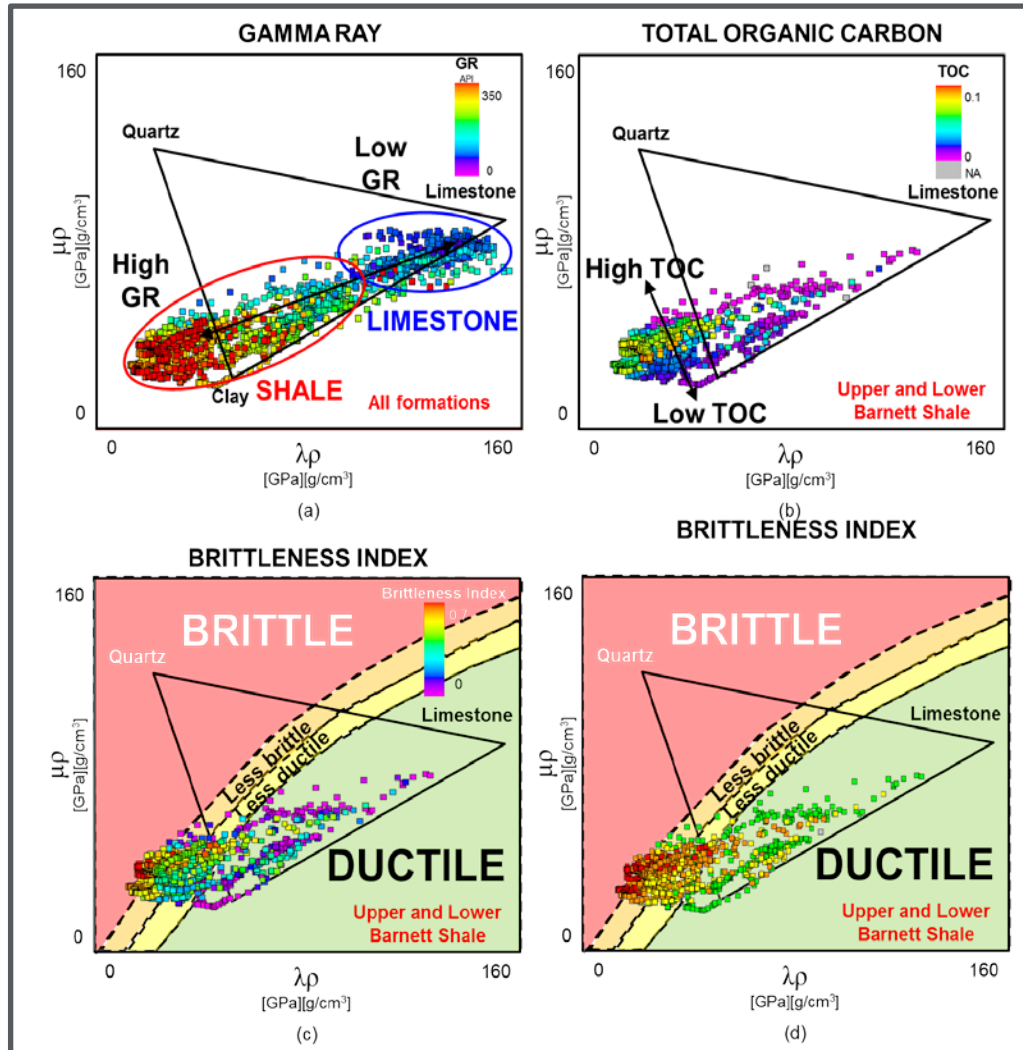


$$E_{brittleness} = \frac{E - E_{min}}{E_{max} - E_{min}}$$

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

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

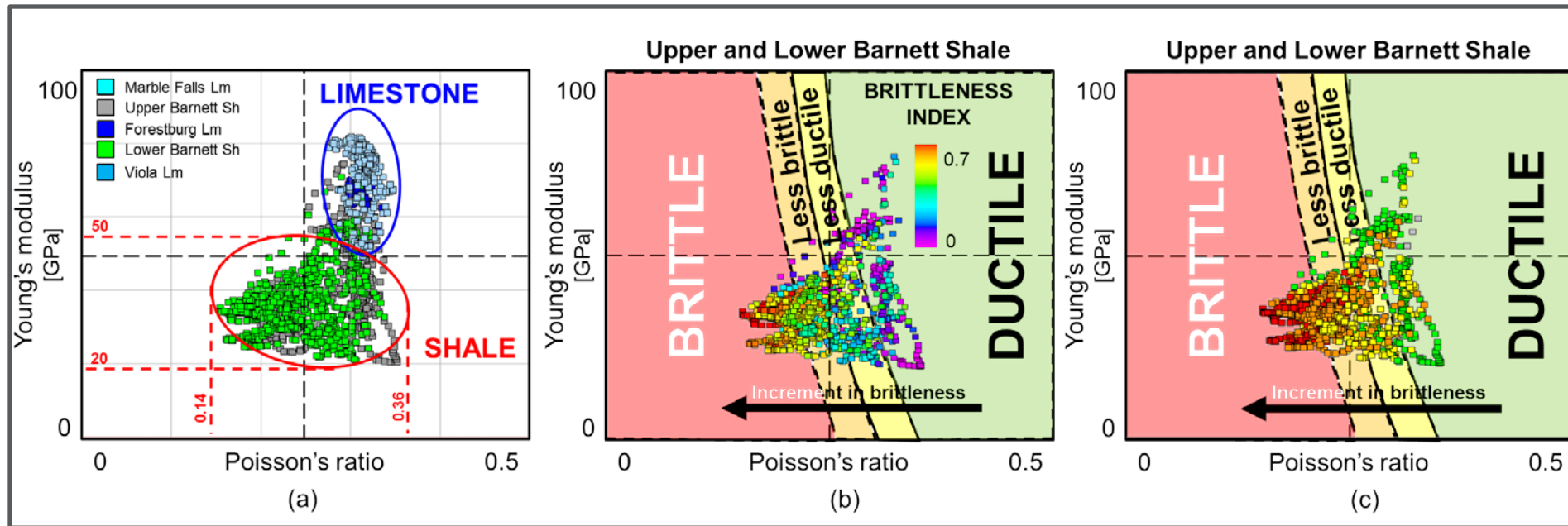
CALIBRATION GEOLOGIC AND GEOMECHANICAL PARAMETERS



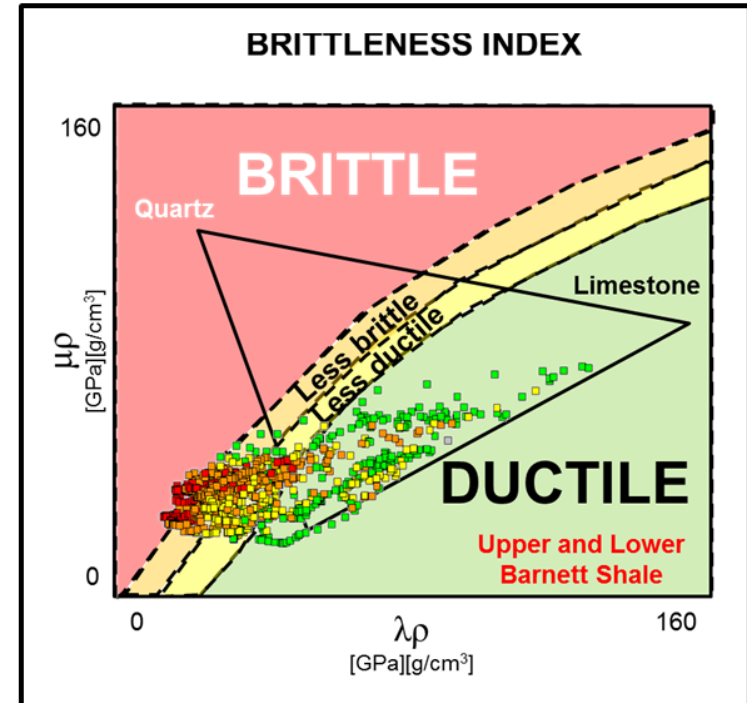
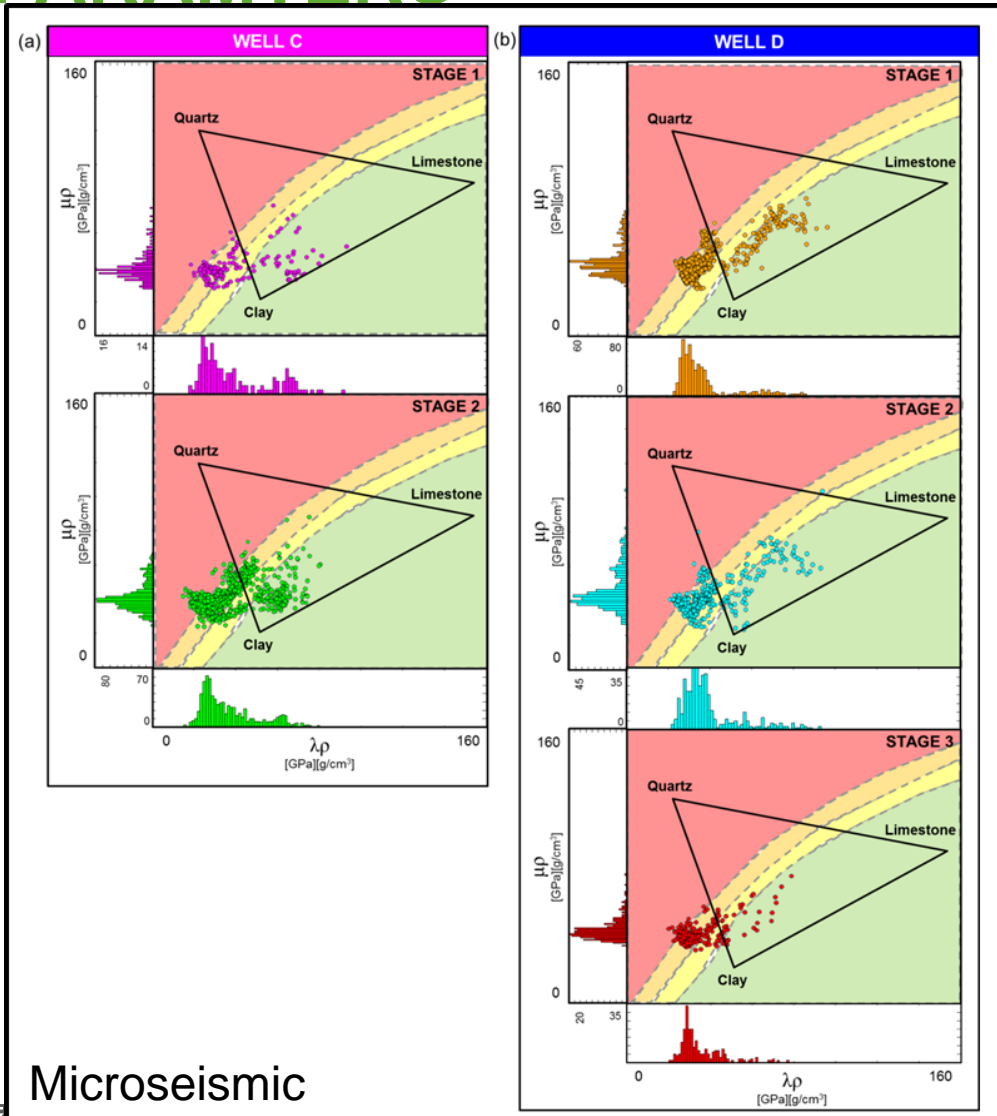
Well log

- 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)

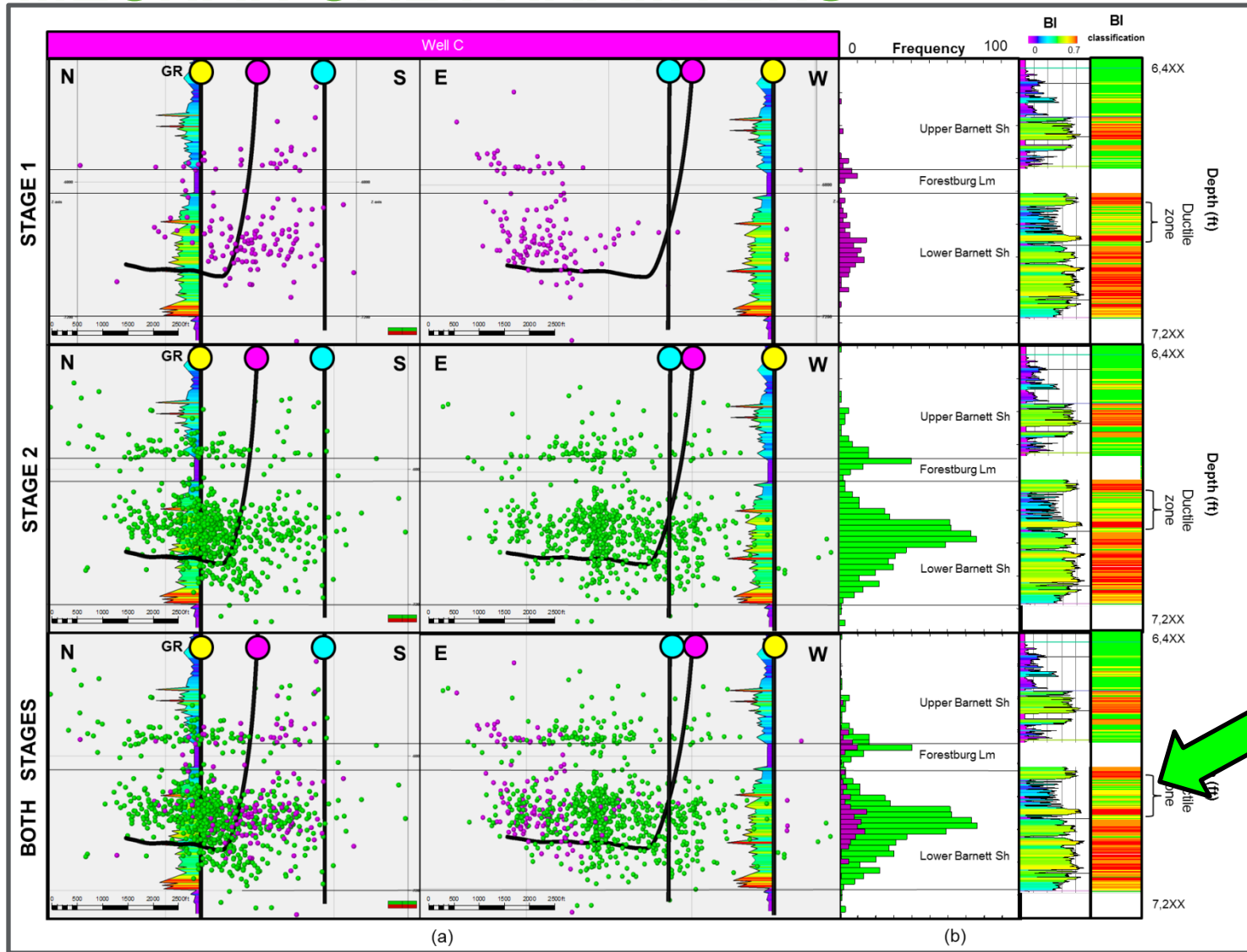
CALIBRATION OF BRITTLINESS TO ELASTIC ROCK PROPERTIES VIA MINERALOGY LOGS



CALIBRATION GEOLOGIC AND GEOMECHANICAL PARAMETERS



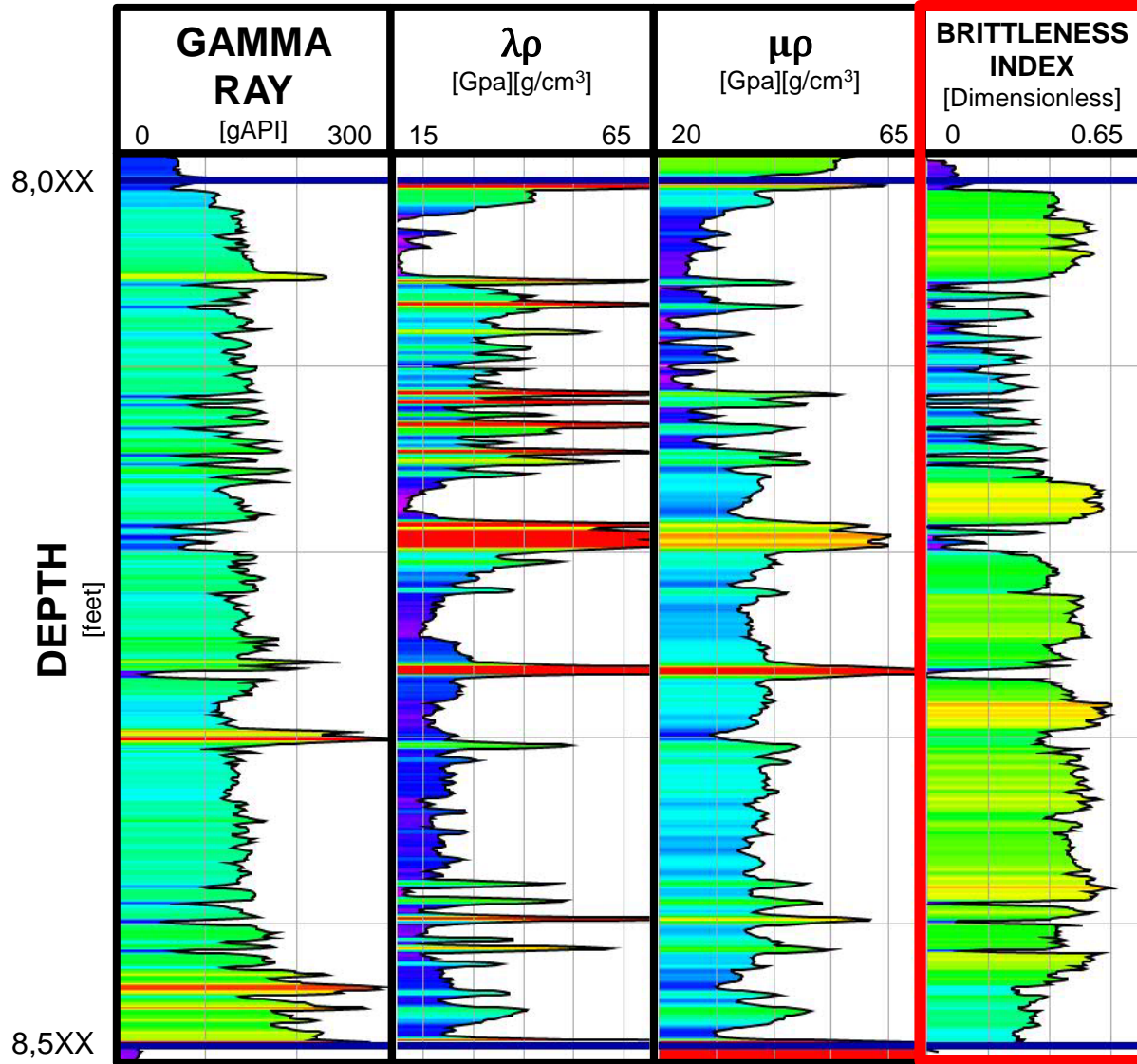
CALIBRATION GEOLOGIC AND GEOMECHANICAL PARAMETERS





STATISTICAL ANALYSIS

BRITTLINESS INDEX FROM LOGS



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

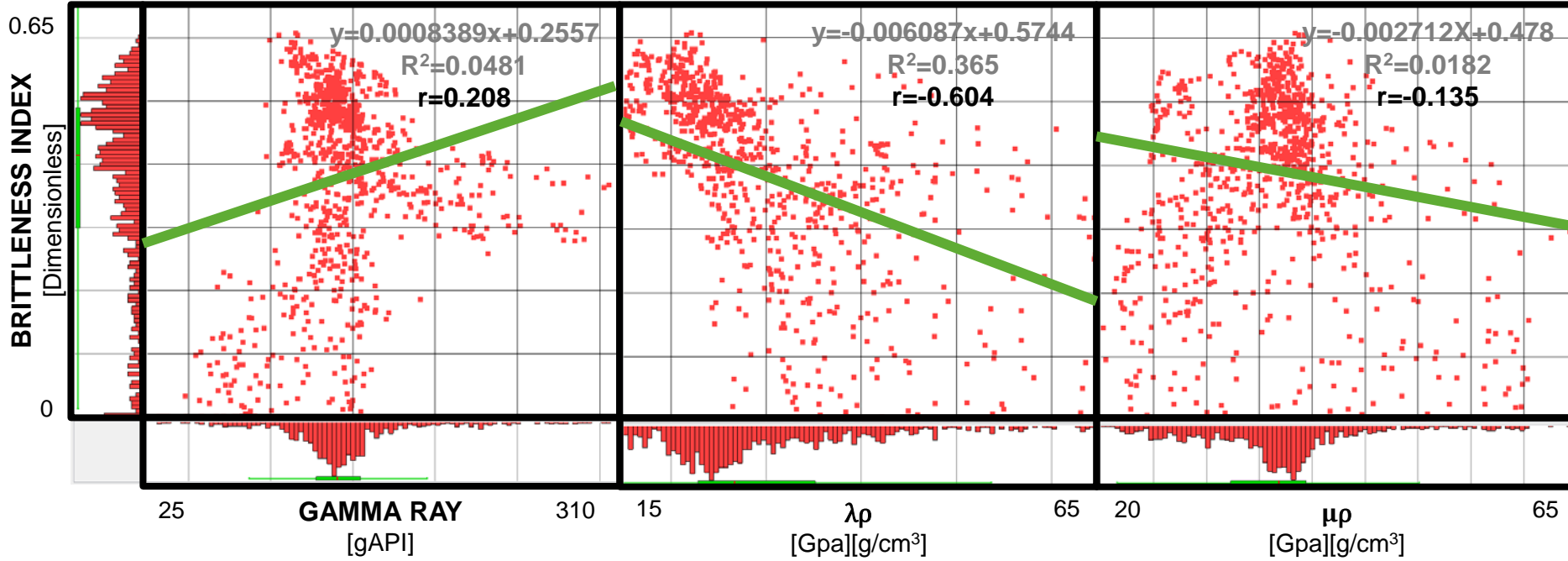
Brittleness Index:

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

LINEAR CORRELATION

GEOLOGICAL

GEOMECHANICAL



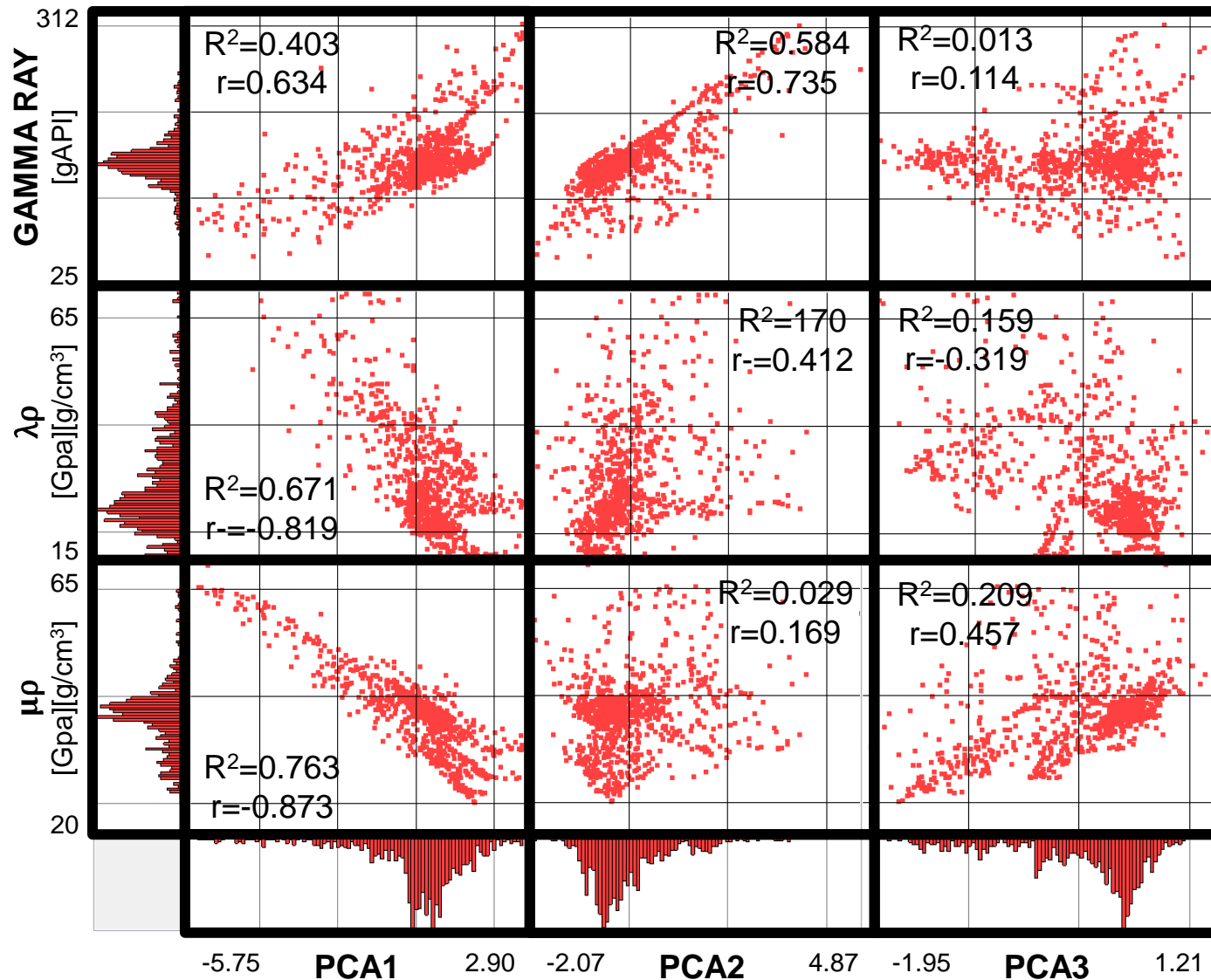
	Brittlene...	GR (Gam...	Lambda_...	Mu_Rho ...
Brittleness_...	1.0	0.208	-0.604	-0.135
GR (Gamm...	0.208	1.0	-0.259	-0.343
Lambda_R...	-0.604	-0.259	1.0	0.603
Mu_Rho (P...	-0.135	-0.343	0.603	1.0

Correlation coefficient

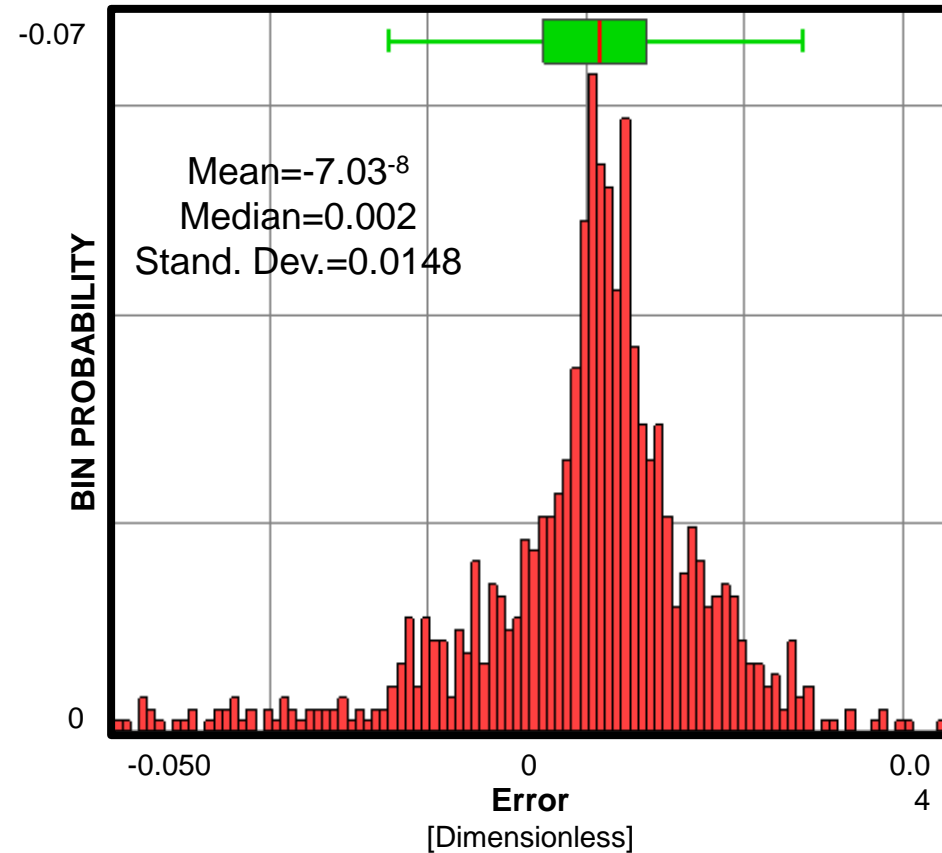
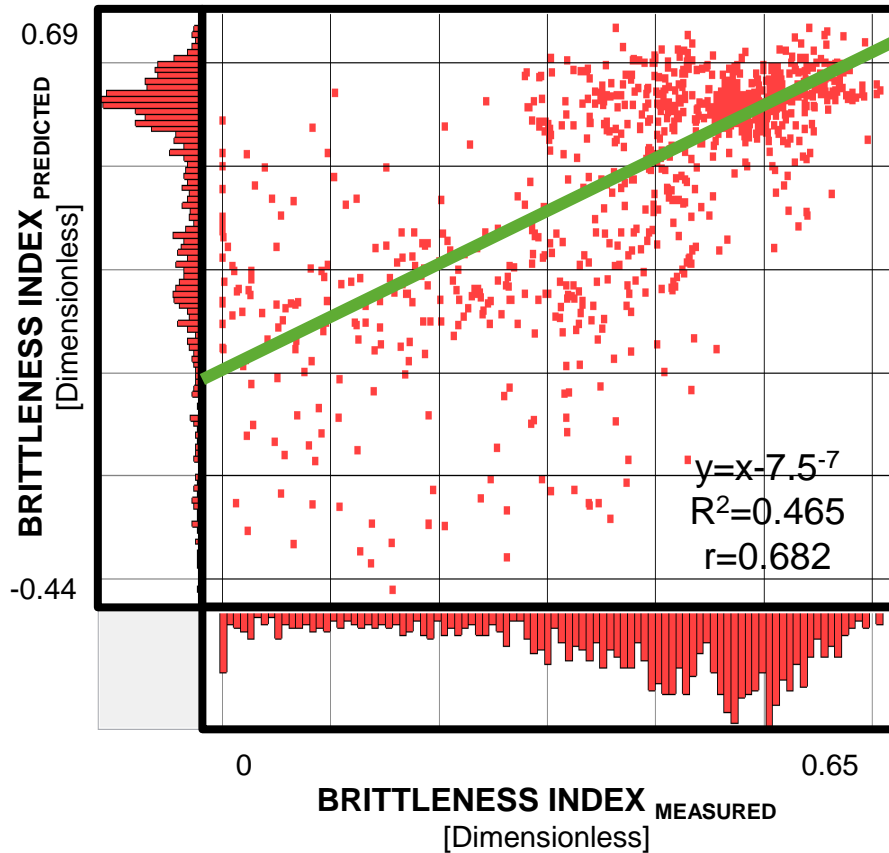
	Brittlene...	GR (Gam...	Lambda_...	Mu_Rho ...
Brittleness_...	1.0	0.015	-0.732	-0.036
GR (Gamm...	0.015	1.0	-0.142	-0.34
Lambda_R...	-0.732	-0.142	1.0	0.419
Mu_Rho (P...	-0.036	-0.34	0.419	1.0

Rank

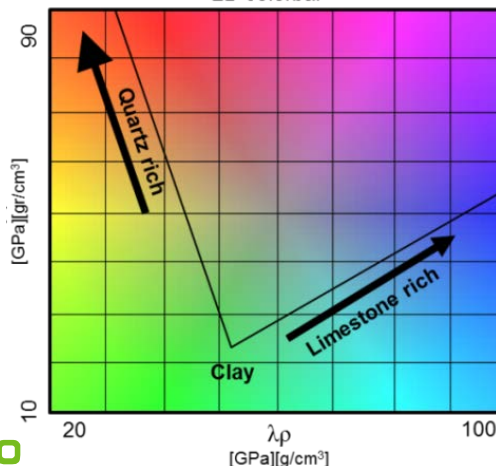
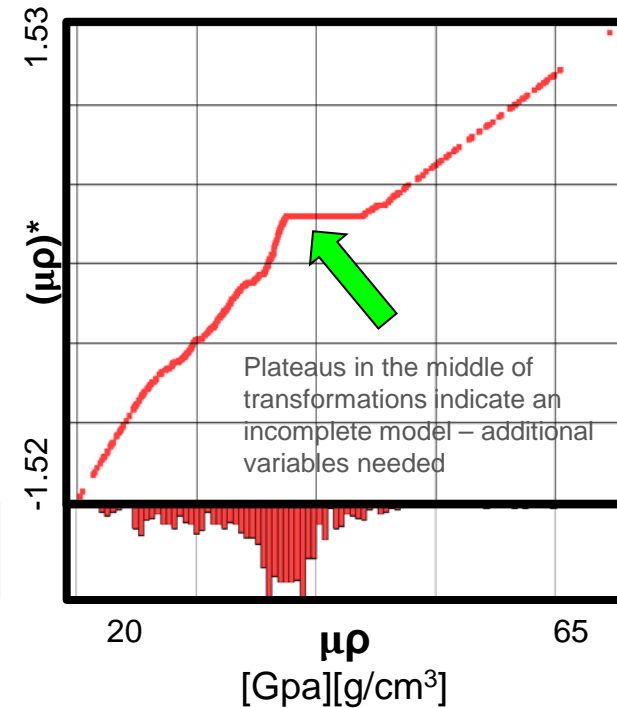
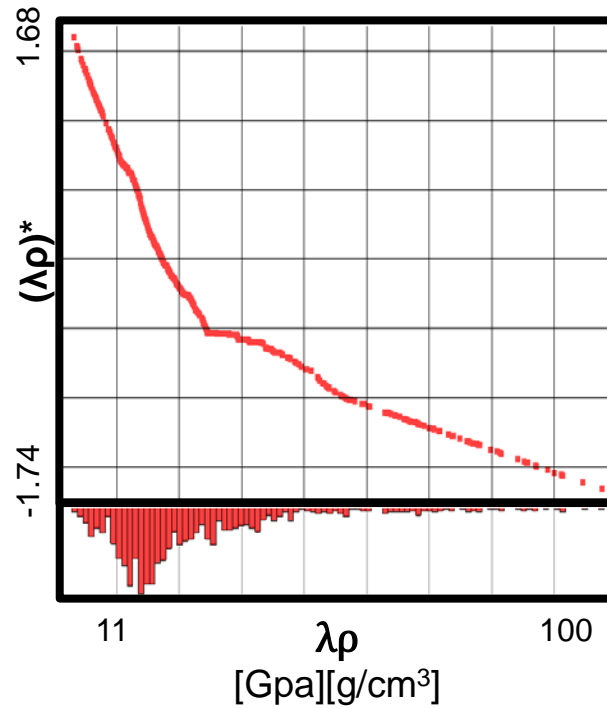
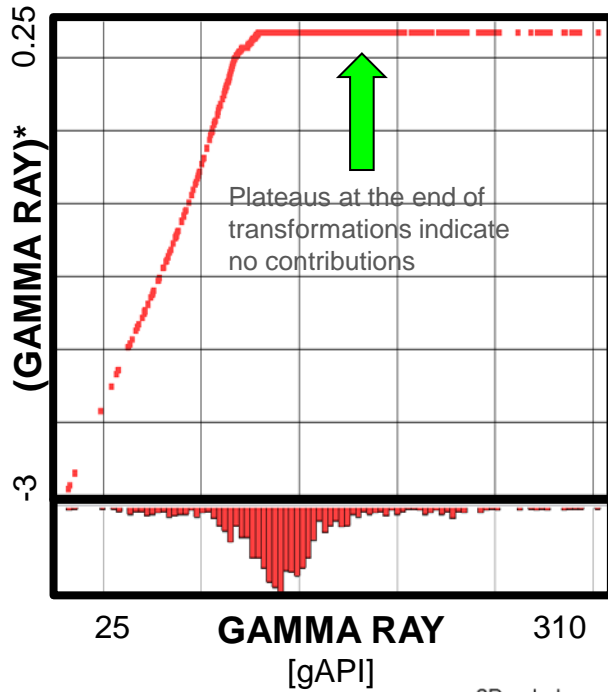
PRINCIPAL COMPONENT ANALYSIS



LINEAR REGRESSION RESULTS

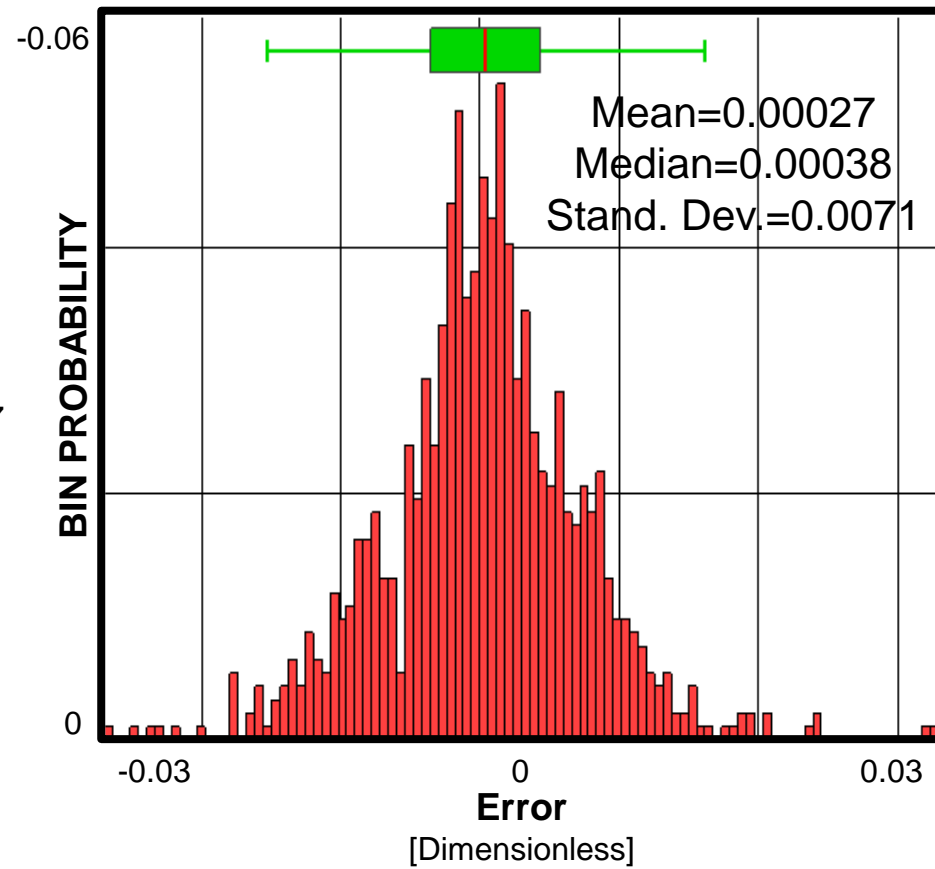
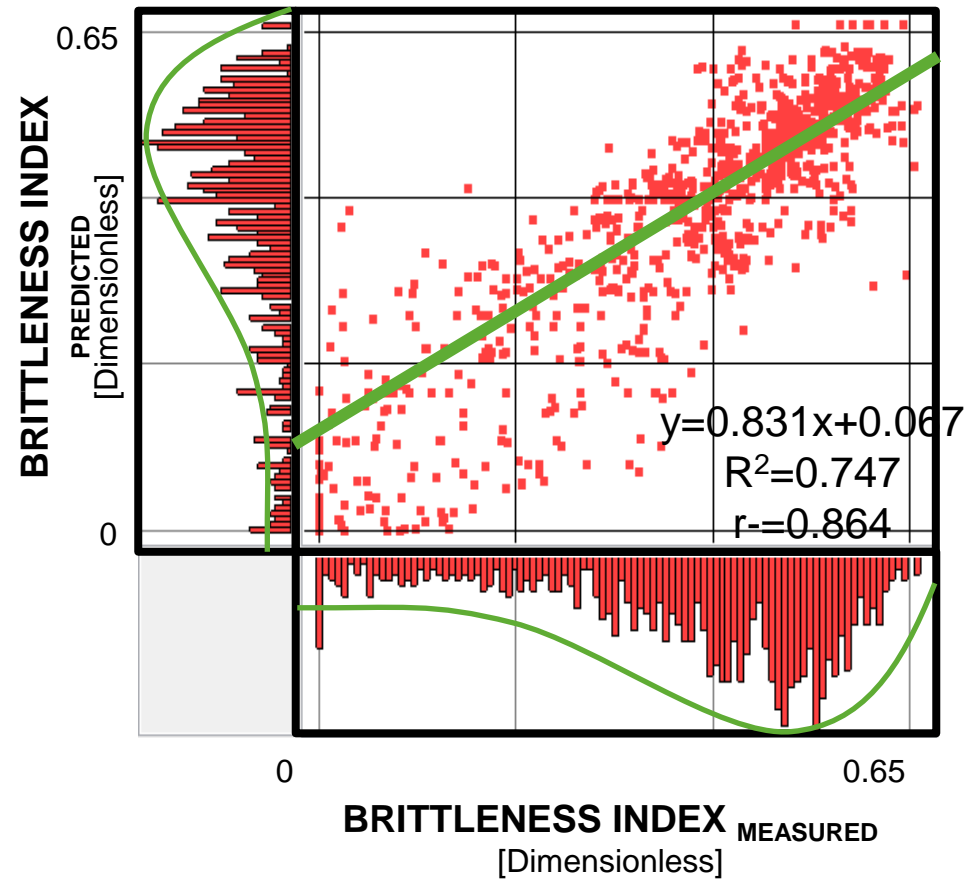


NON-LINEAR REGRESSION RESULTS

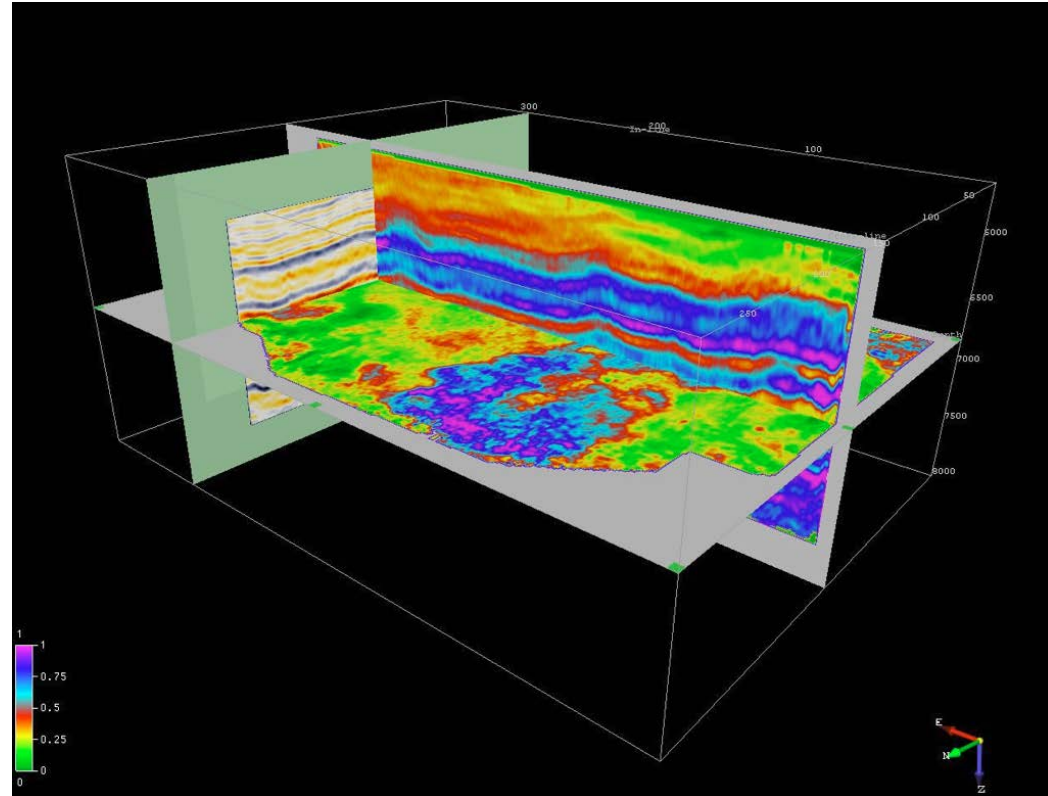
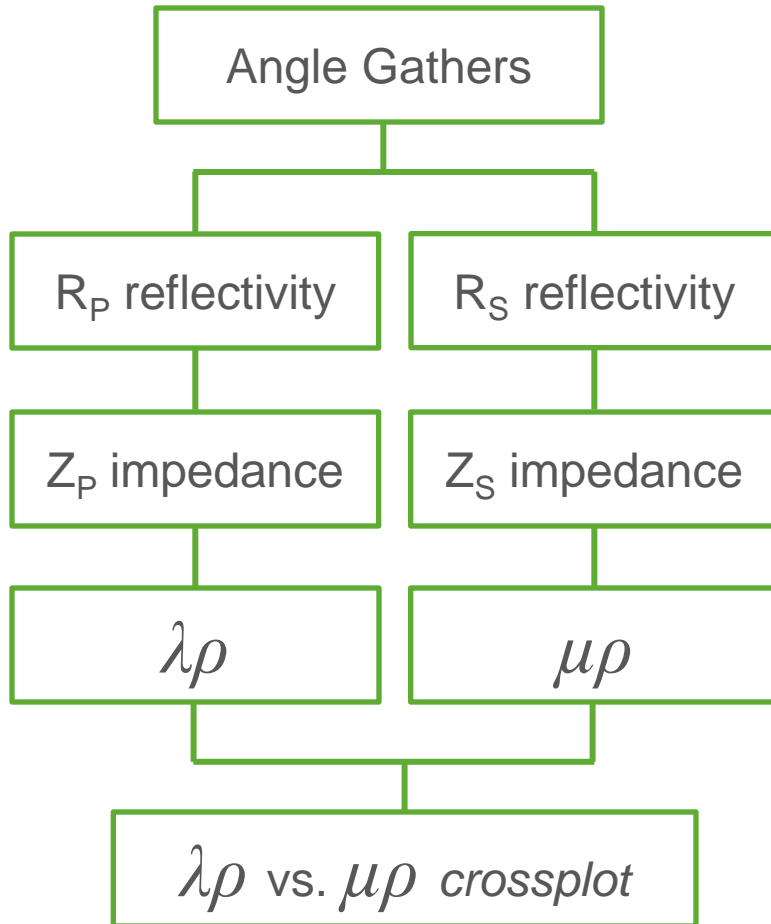


- Perez, R., 2013, Brittleness estimation from seismic measurements in unconventional reservoirs: Application to the Barnett Shale: Ph.D. Dissertation, The University of Oklahoma
- Perez, R., and K. Marfurt, 2014, Mineralogy-Based Brittleness Prediction from Surface Seismic Data: Application to the Barnett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

NON-LINEAR REGRESSION RESULTS



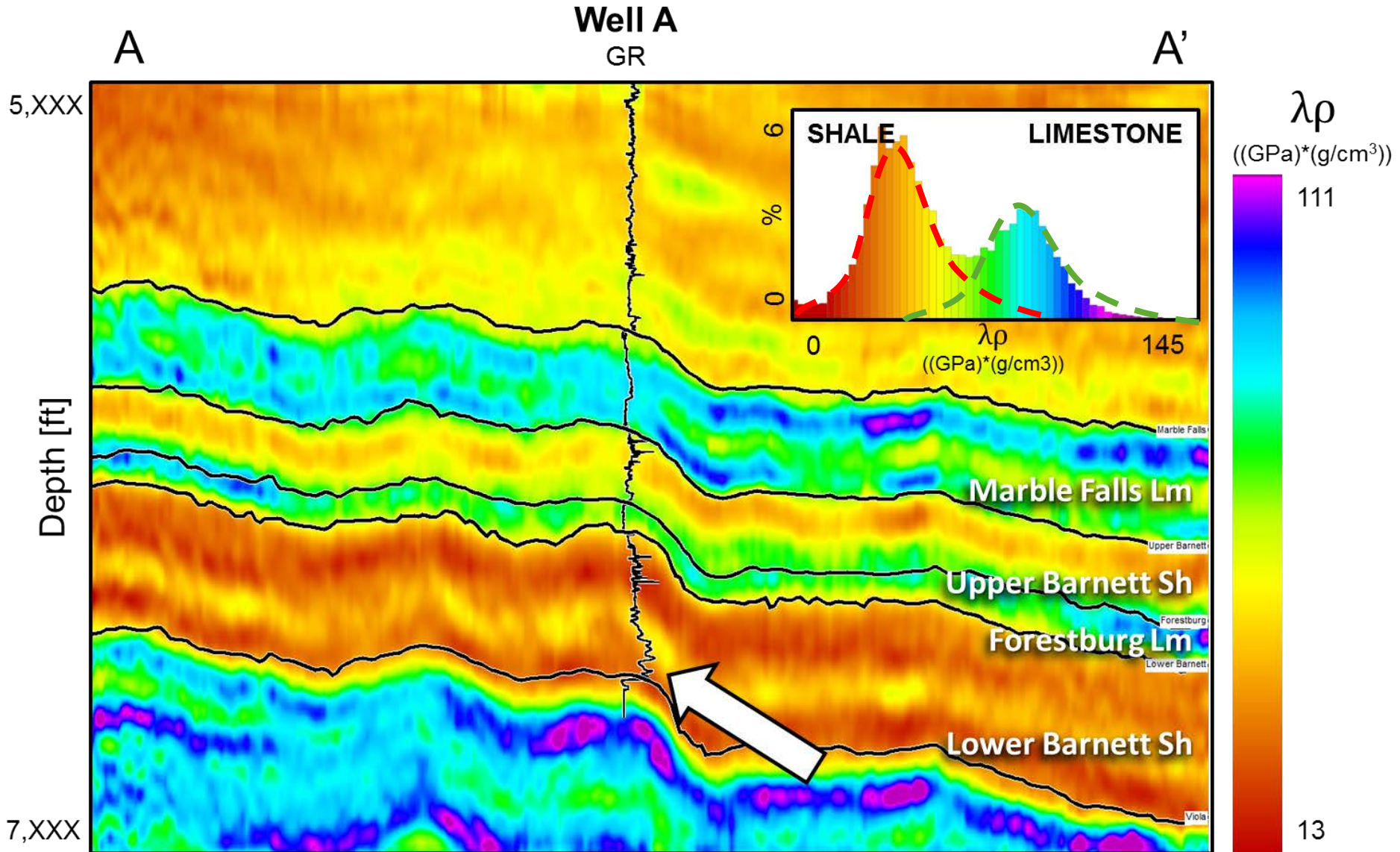
SEISMIC PROCESSING



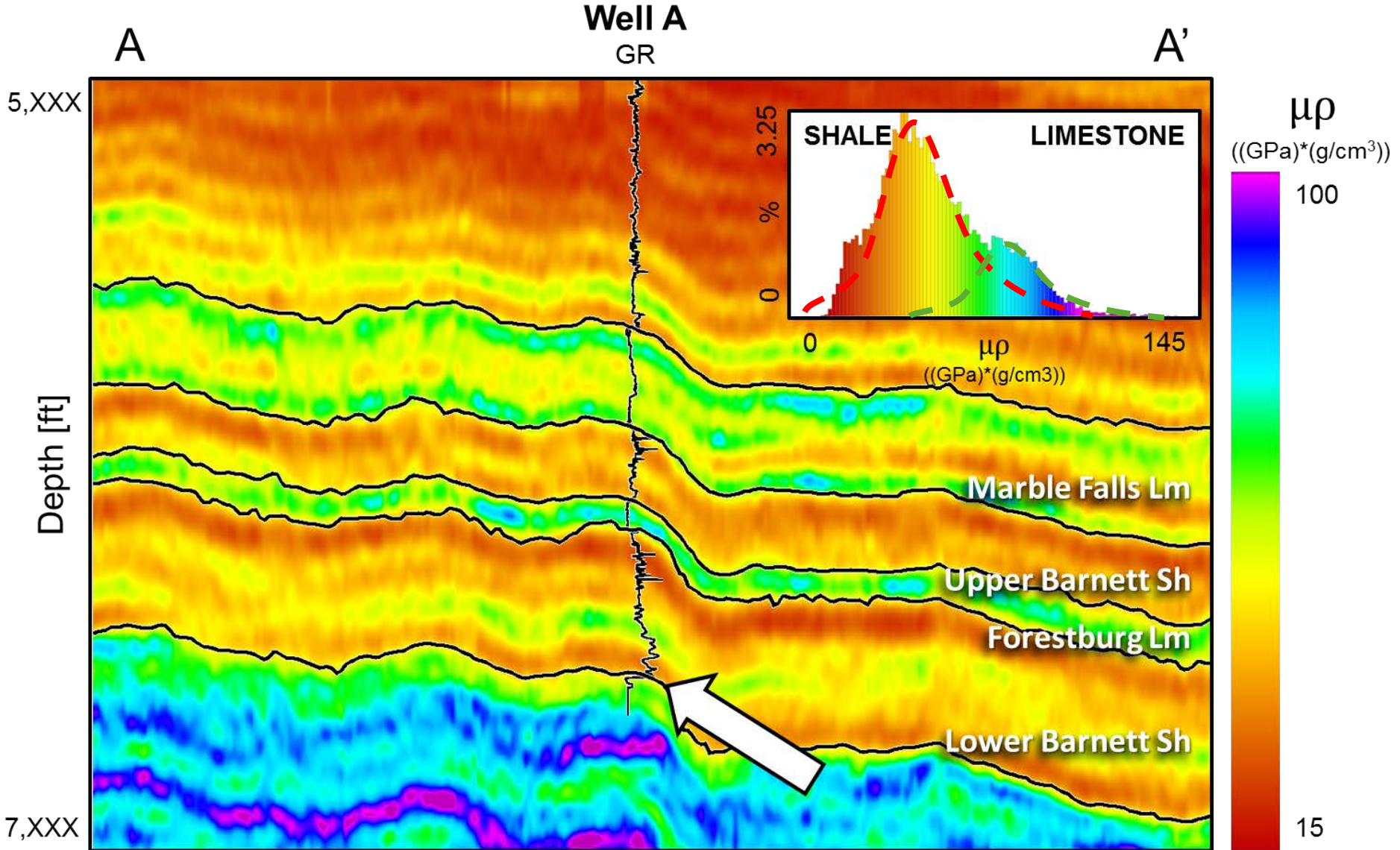
$$\lambda\rho = (\rho V_P)^2 - 2(\rho V_S)^2. \quad \mu\rho = (\rho V_S)^2$$

Goodway (2007)

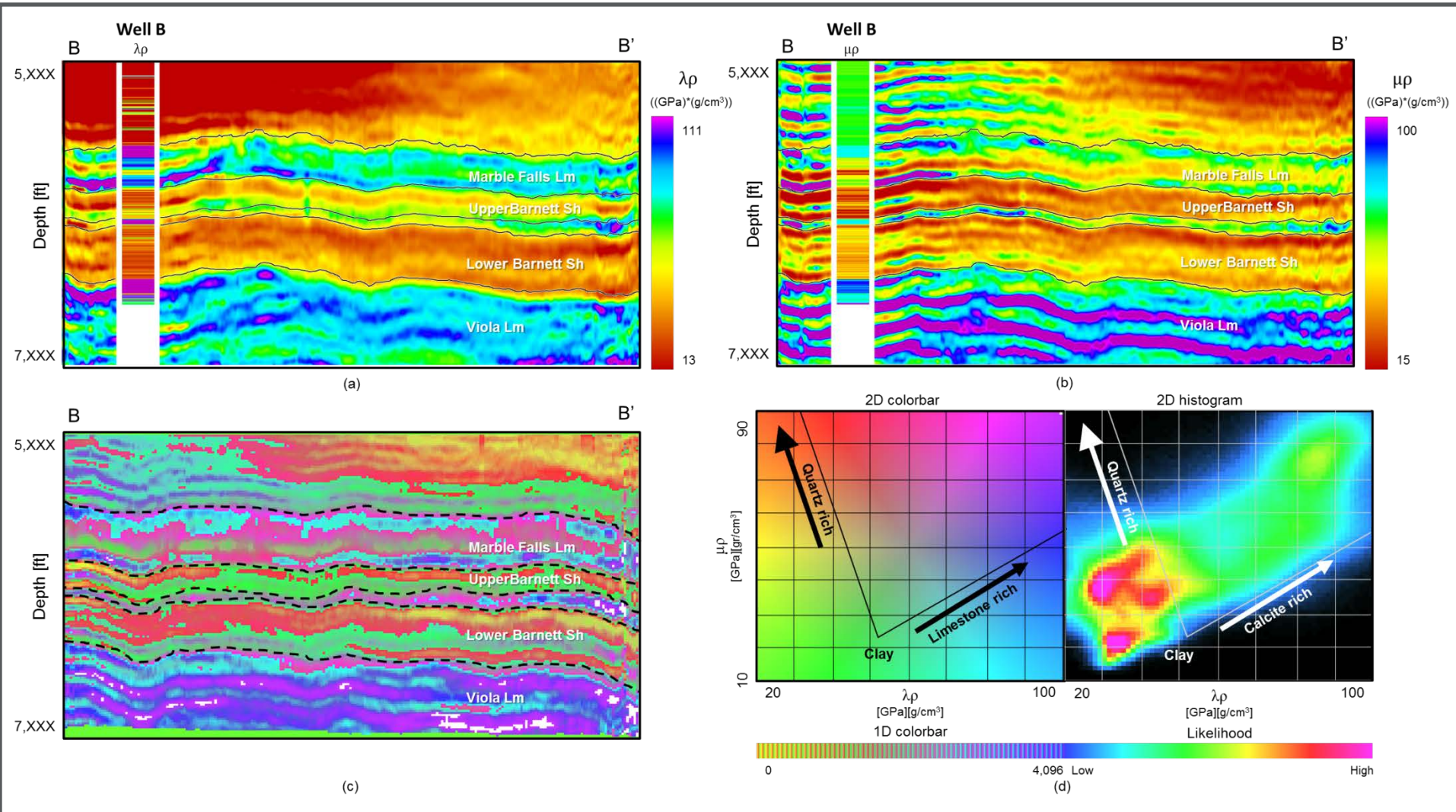
SEISMIC ATTRIBUTES



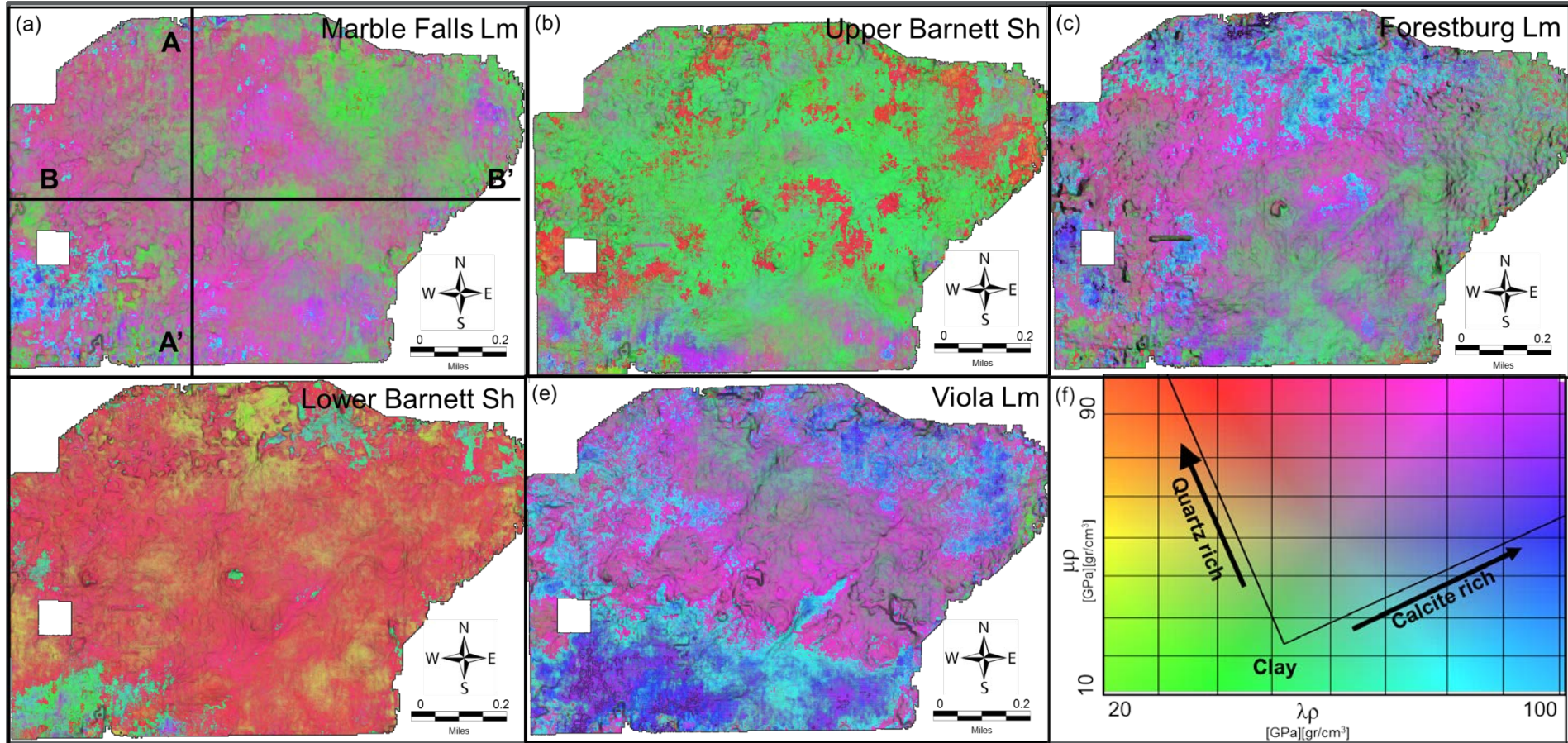
SEISMIC ATTRIBUTES



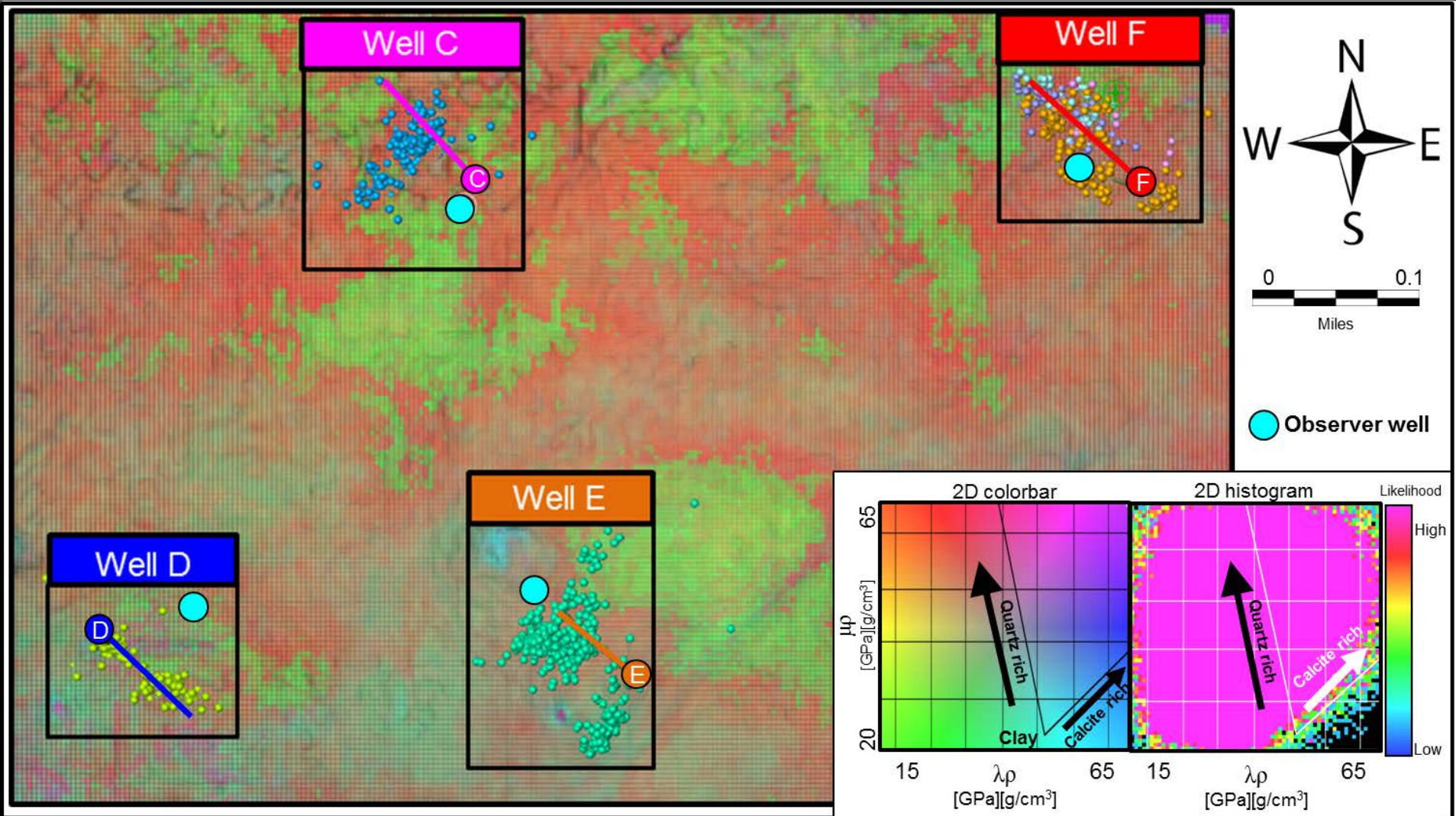
SEISMIC ATTRIBUTES – 2D colorbar visualization



SEISMIC ATTRIBUTES – 2D colorbar visualization

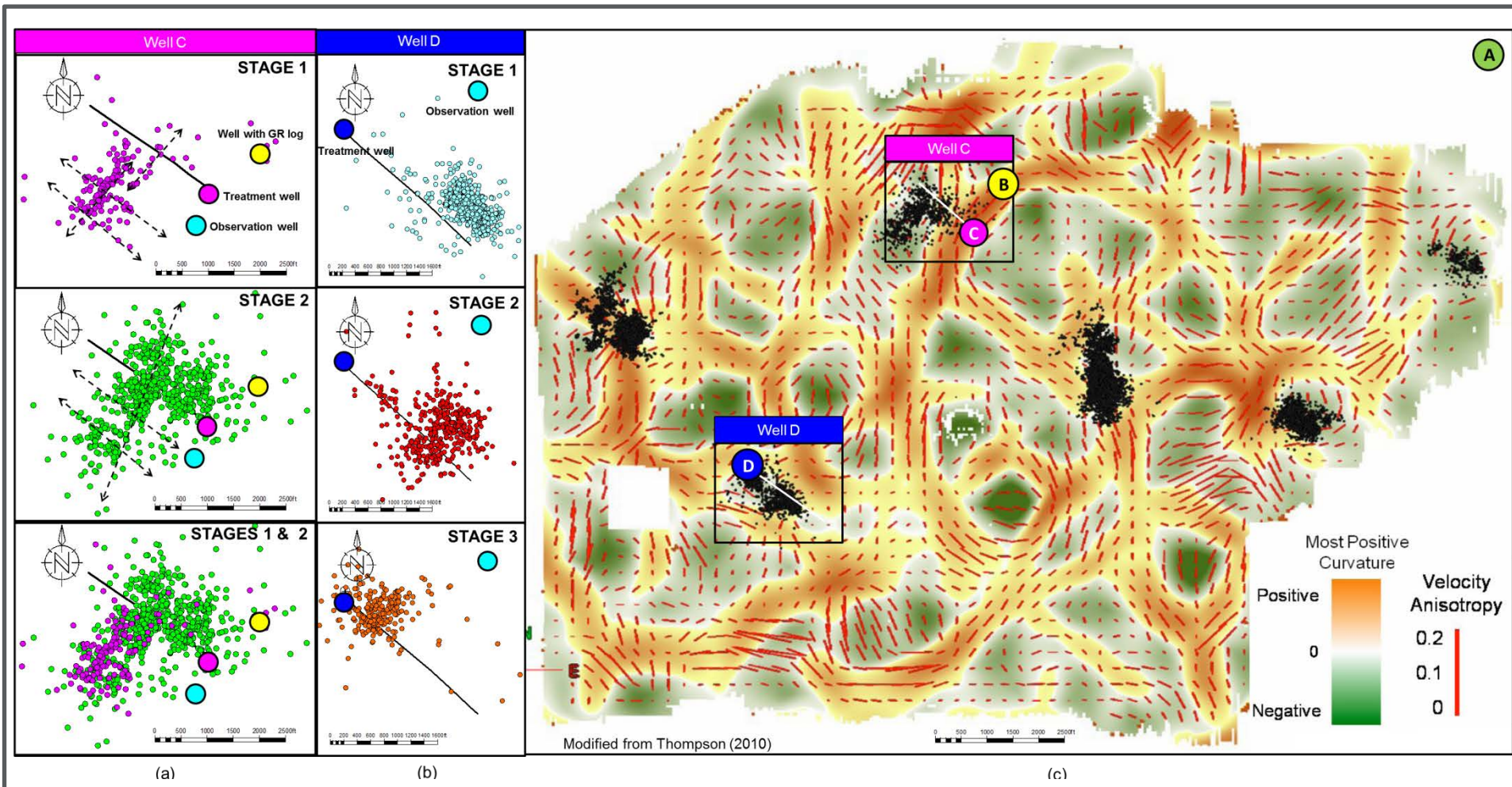


SEISMIC ATTRIBUTES + Microseismic



Microseismic events trend towards quartz rich areas, avoiding clay rich zones (green).

SEISMIC ATTRIBUTES + Microseismic

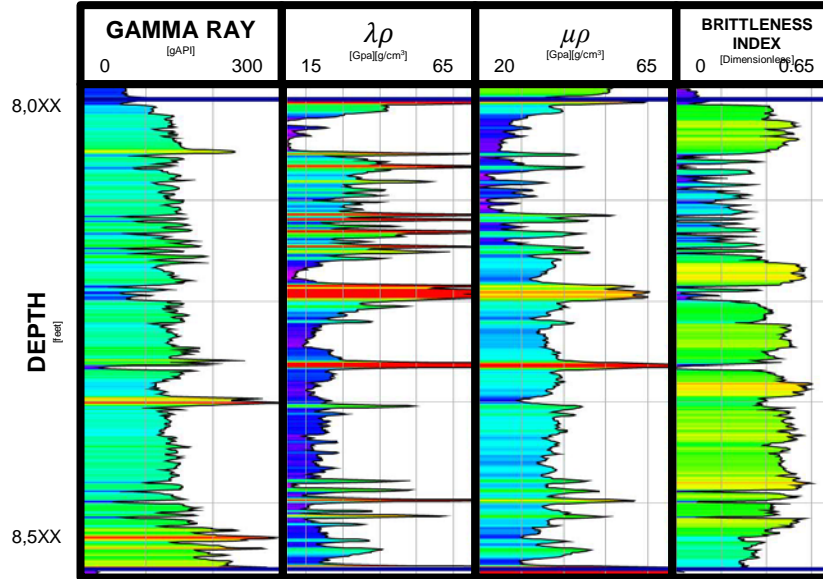


Microseismic events trend towards negative curvature values (green) avoiding the most positive curvature zones (orange) and follow the velocity anisotropy trend, previously described by Thompson (2010) and Browning (2006).



NON-LINEAR REGRESSION ANALYSIS

WORKFLOW SUMMARY

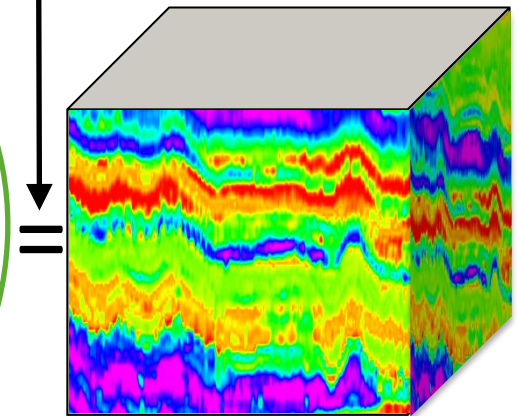
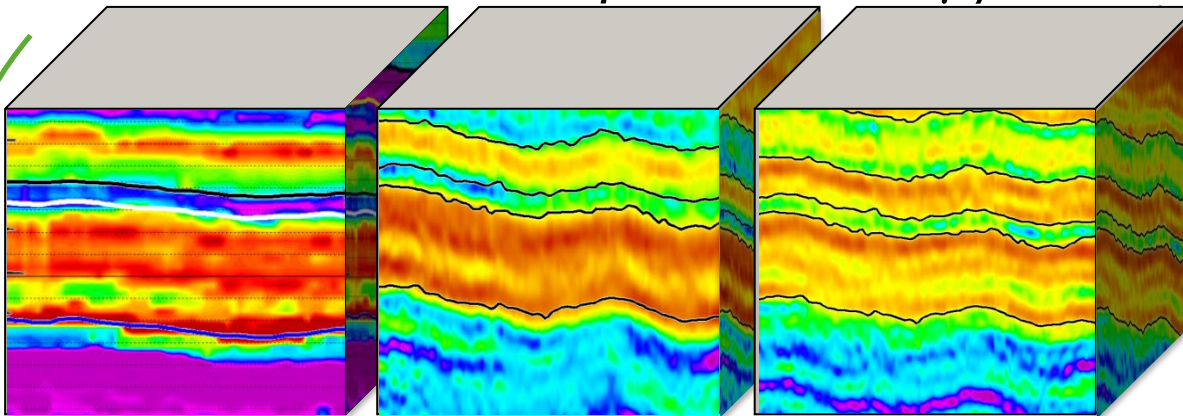


$$f_{BI}(\lambda\rho, \mu\rho, GR)$$

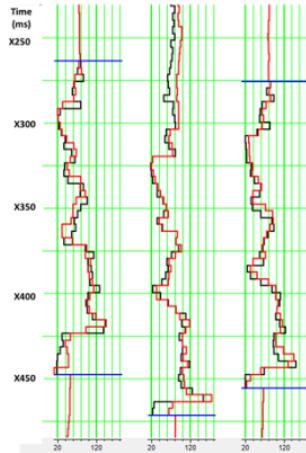
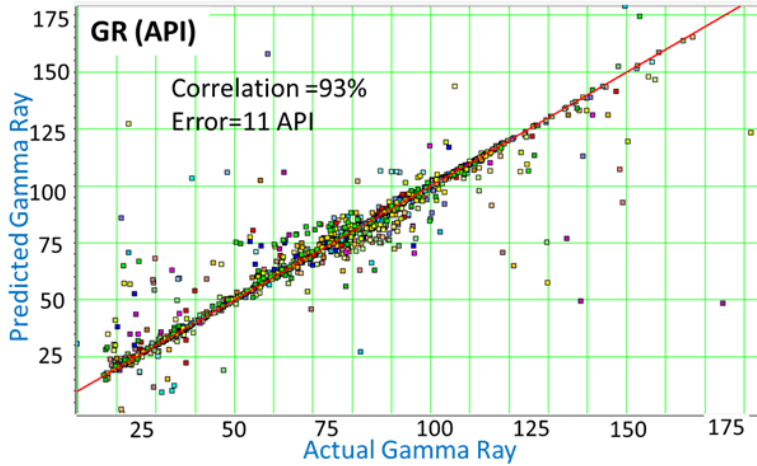
Gamma Ray

 $\lambda\rho$ $\mu\rho$

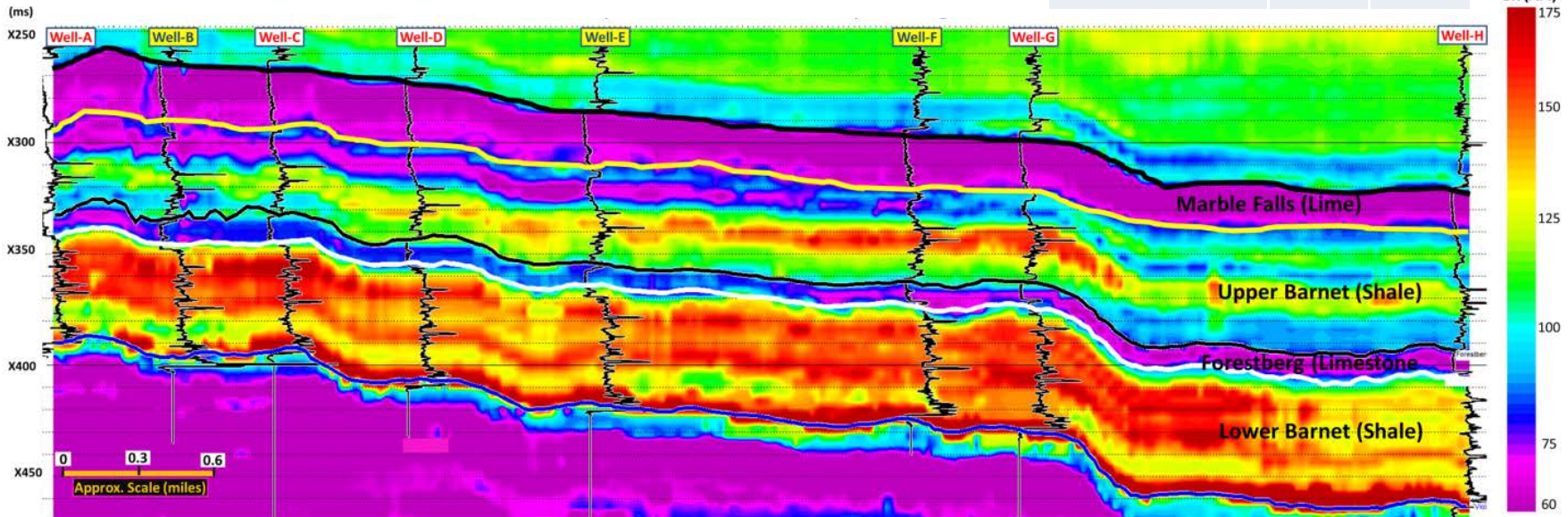
Brittleness Index



GR SEISMIC VOLUME

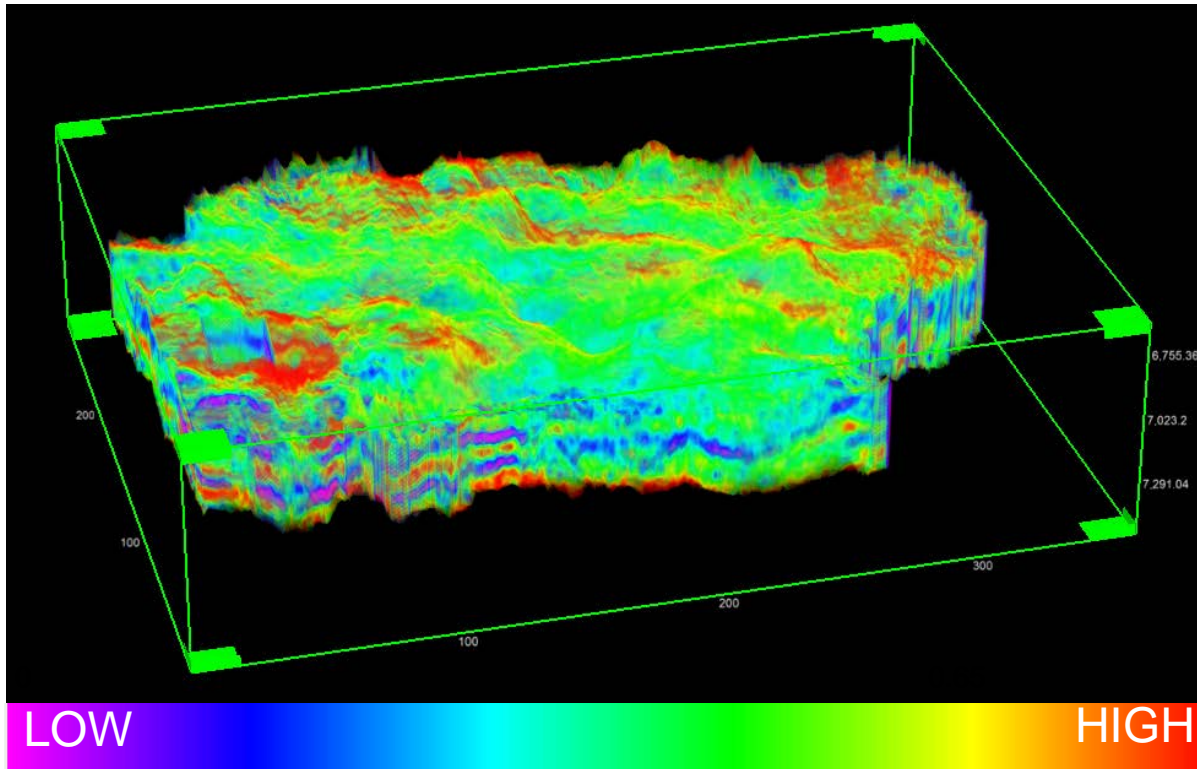


Final Attribute Operat. length: 9	Train. Error	Valid. Error
(Zp)**2	22.15	22.48
RAI	20.57	21.00
Sweetness	19.98	22.55
(Quadrature)**2	19.47	20.20
1/Zs	19.16	20.10
Vs/Vp	18.51	19.46
Coherent Energy	18.20	19.27
Spectral Mag_20Hz	18.10	19.34

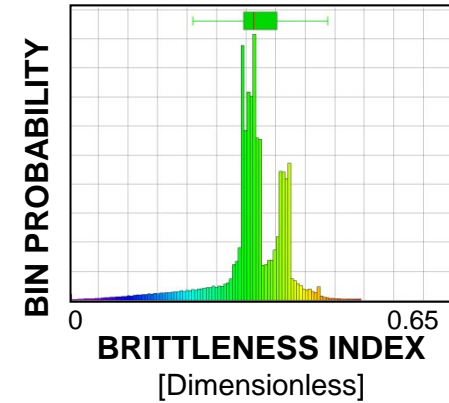


Verma, S., Roy, A., Perez, R., and Marfurt, Finding high frackability and high TOC zones in Barnett shale with supervised: Probabilistic Neural Network and unsupervised: multi-attribute Kohonen SOM, SEG Abstract, 2012.

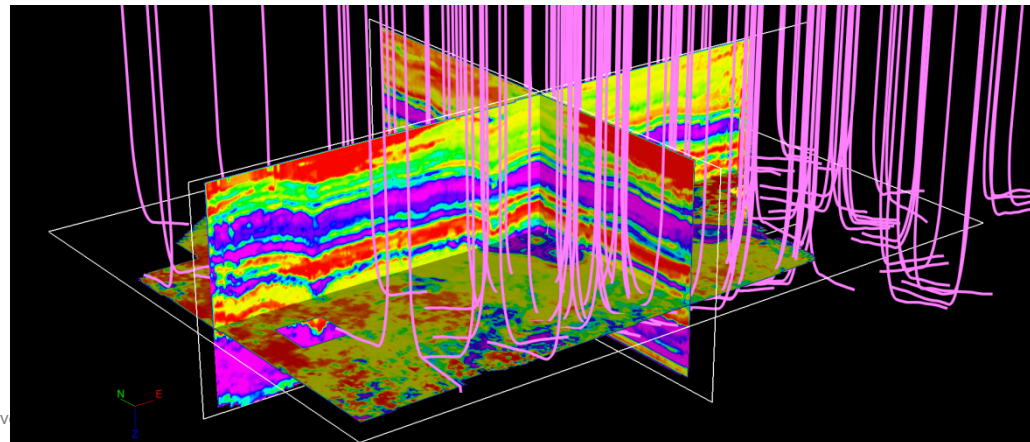
BRITTLENESS INDEX VOLUME



BRITTLENESS INDEX
[Dimensionless]



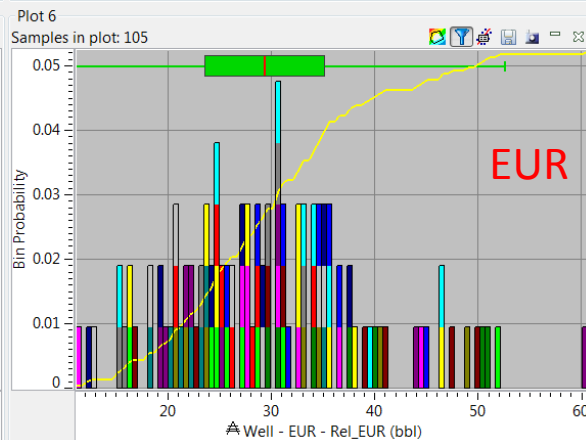
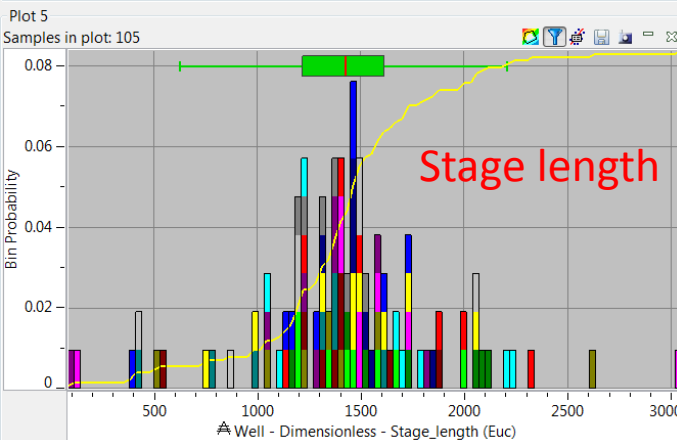
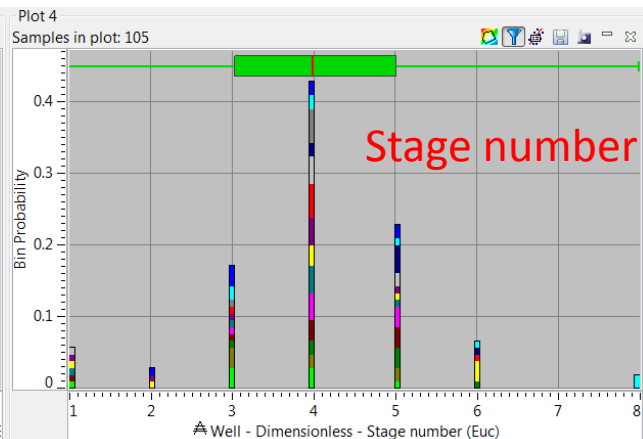
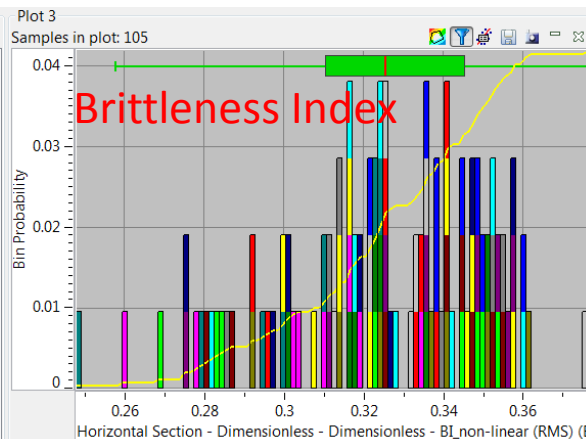
Num Points	1823034
Minimum	0.00
Maximum	0.494
Mean	0.310
Mean Absolute	0.310
Median	0.313
Std Deviation	0.0636
Skewness	-1.67
Kurtosis	4.67
25th %	0.296
75th %	0.353



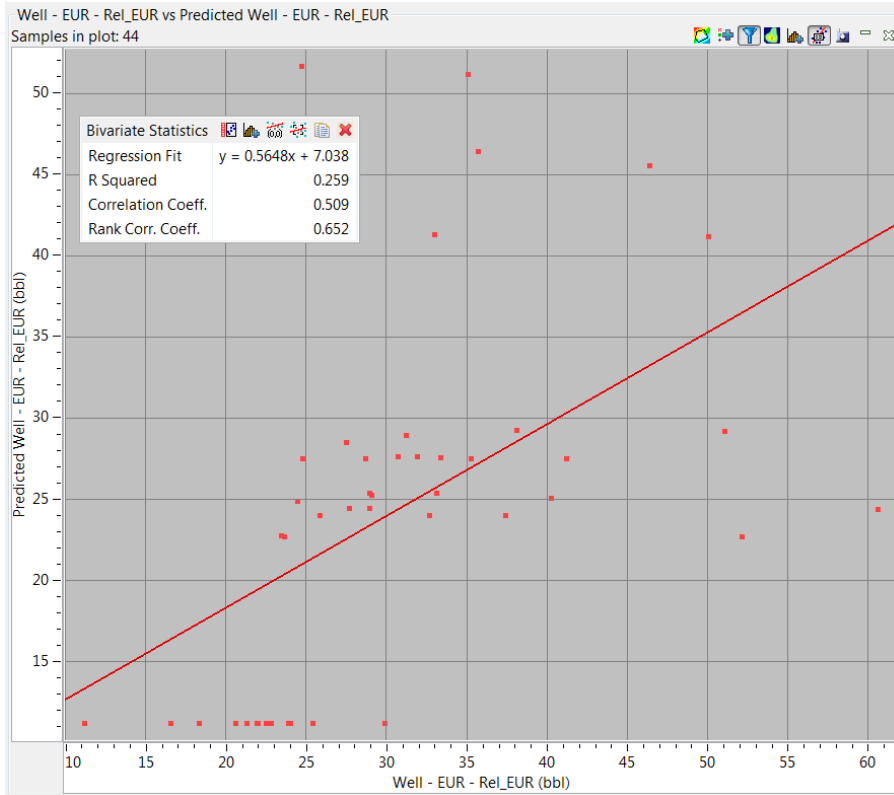
BRITTLENESS INDEX VOLUME + ENGINEERING VARIABLES

Plot 2
Data Correlations (44)

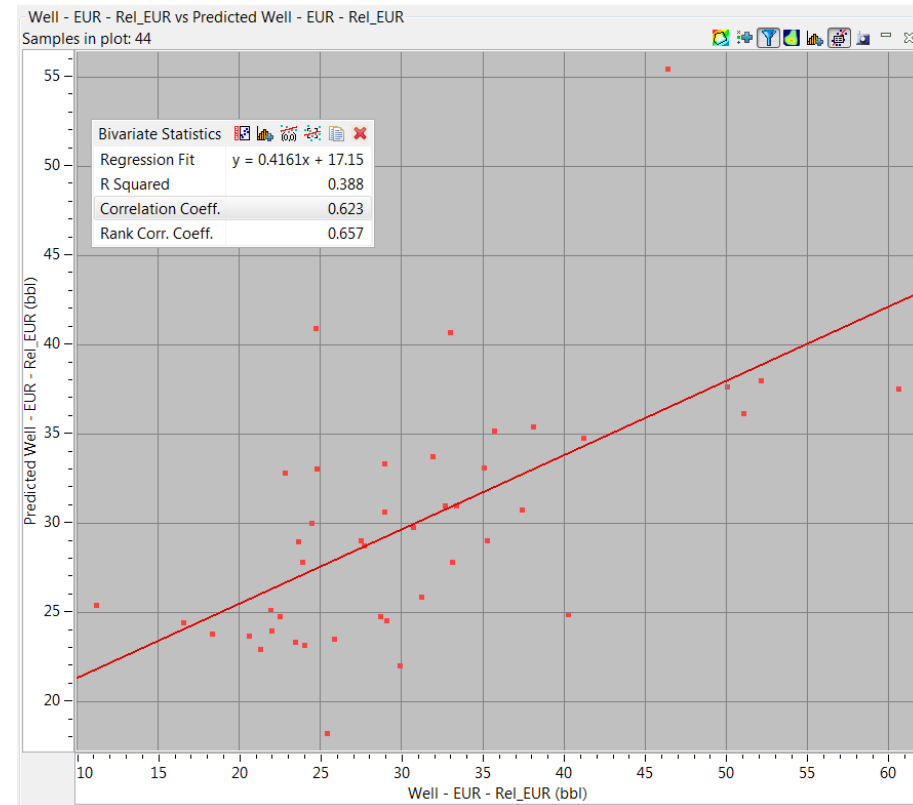
	Well - Dim...	Well - Dim...	Well - Dim...	Well - EUR...	Horizontal ...
Well - Dimen...	1.0	0.297	-0.7	-0.001	-0.02
Well - Dimen...	0.297	1.0	0.394	0.281	-0.389
Well - Dimen...	-0.7	0.394	1.0	0.145	-0.207
Well - EUR - ...	-0.001	0.281	0.145	1.0	0.06
Horizontal Se...	-0.02	-0.389	-0.207	0.06	1.0



BRITTLENESS INDEX VOLUME + ENGINEERING VARIABLES

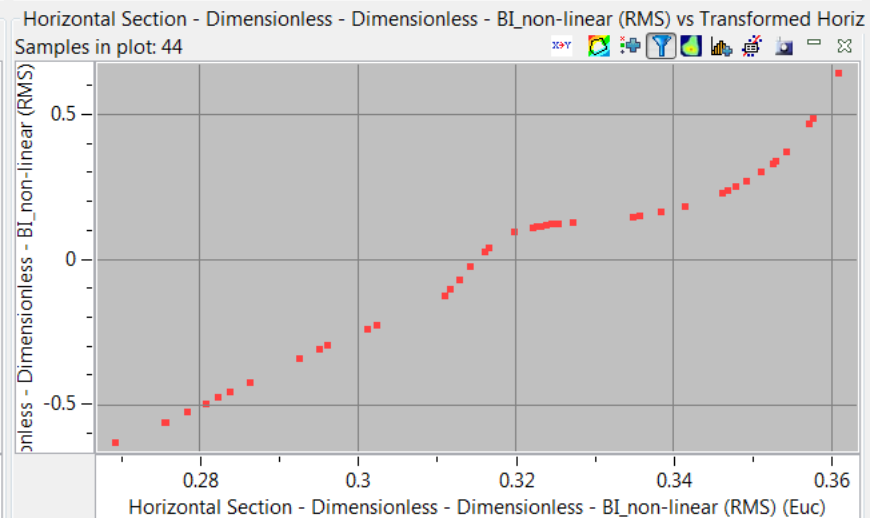
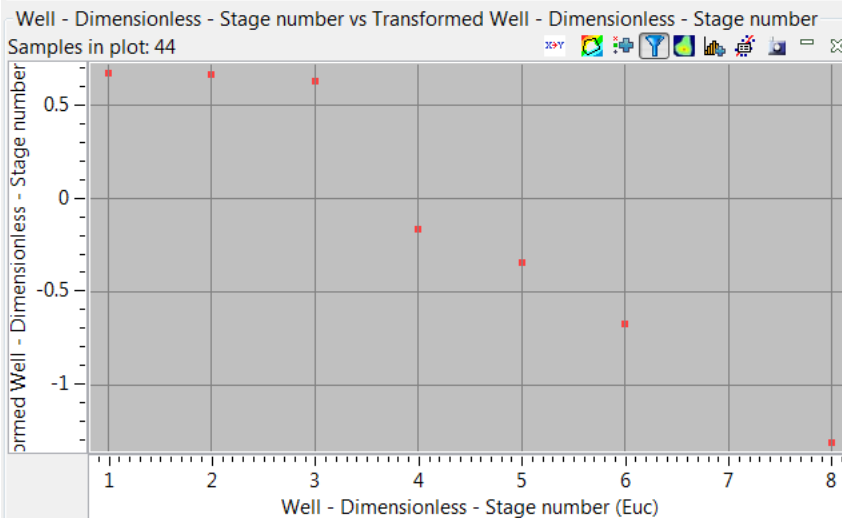
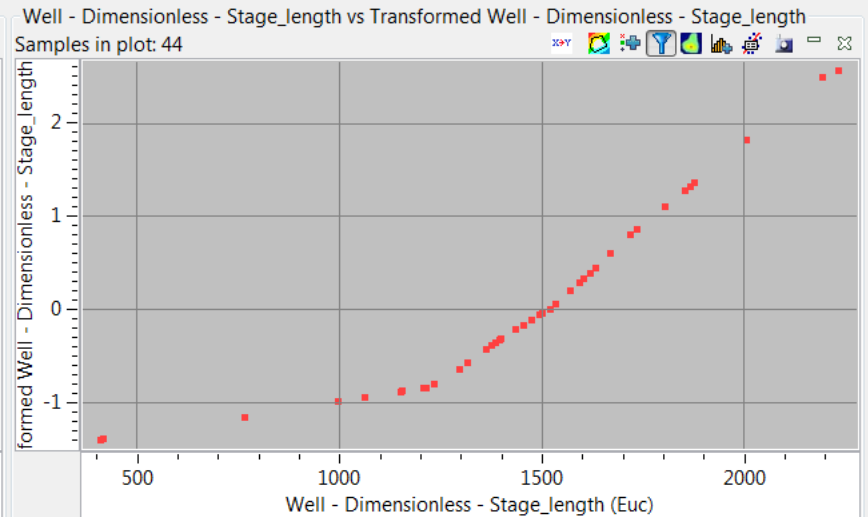
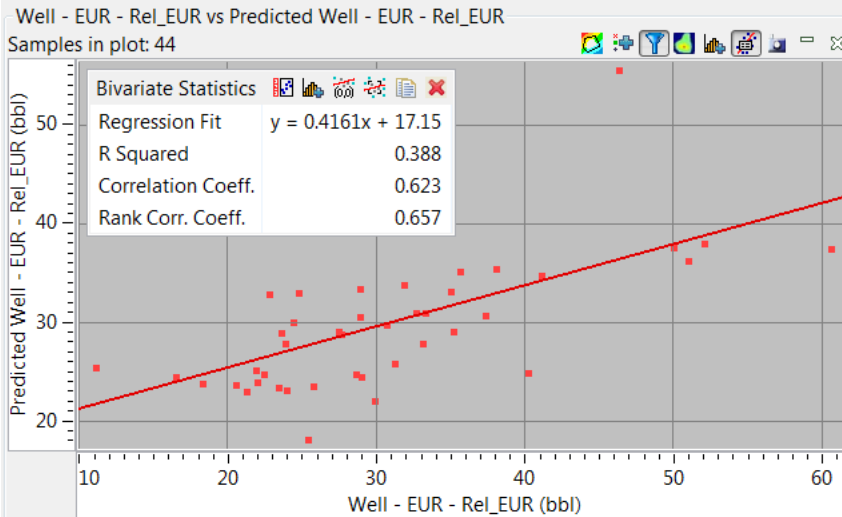


Engineering variables

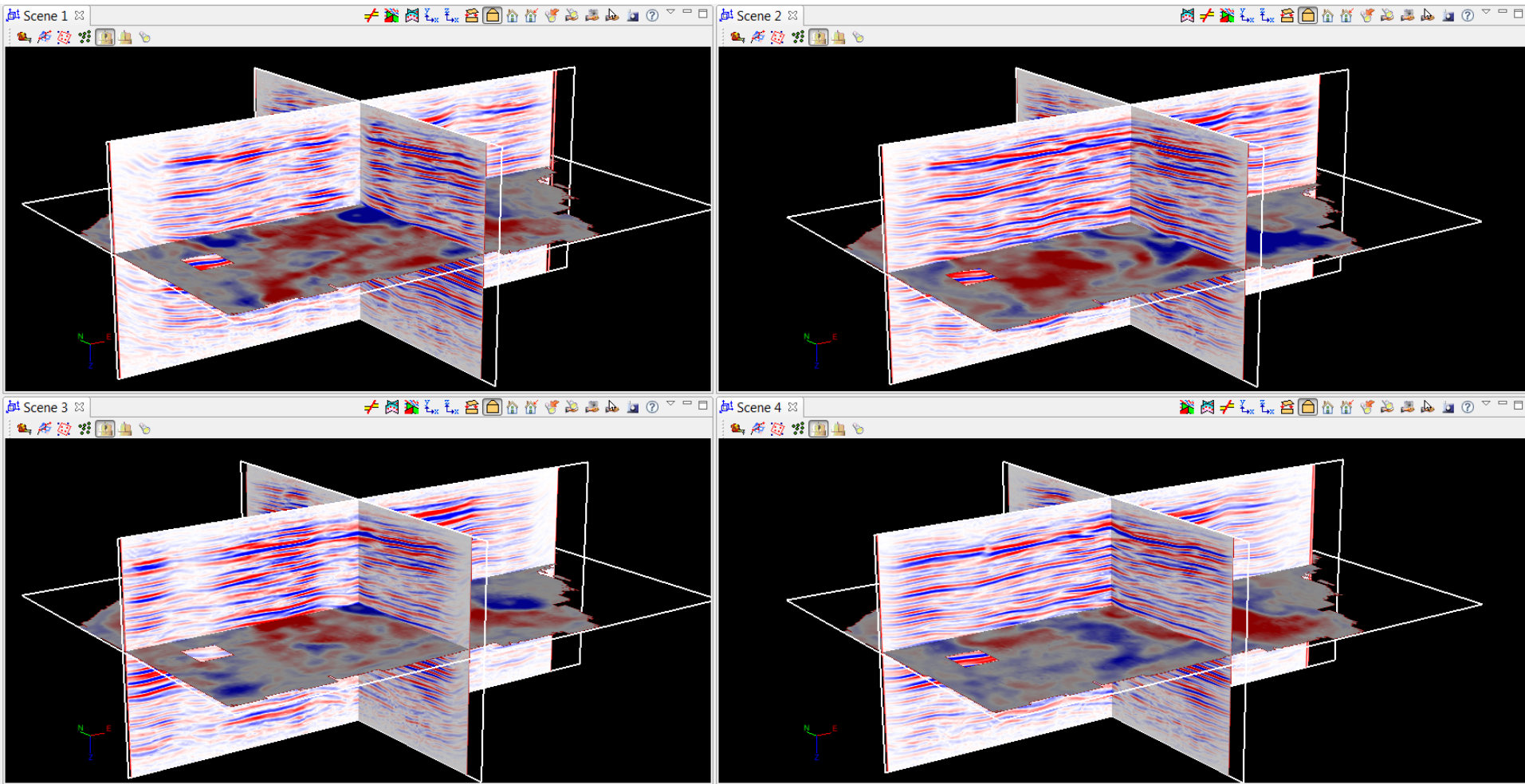


Engineering variables + BI

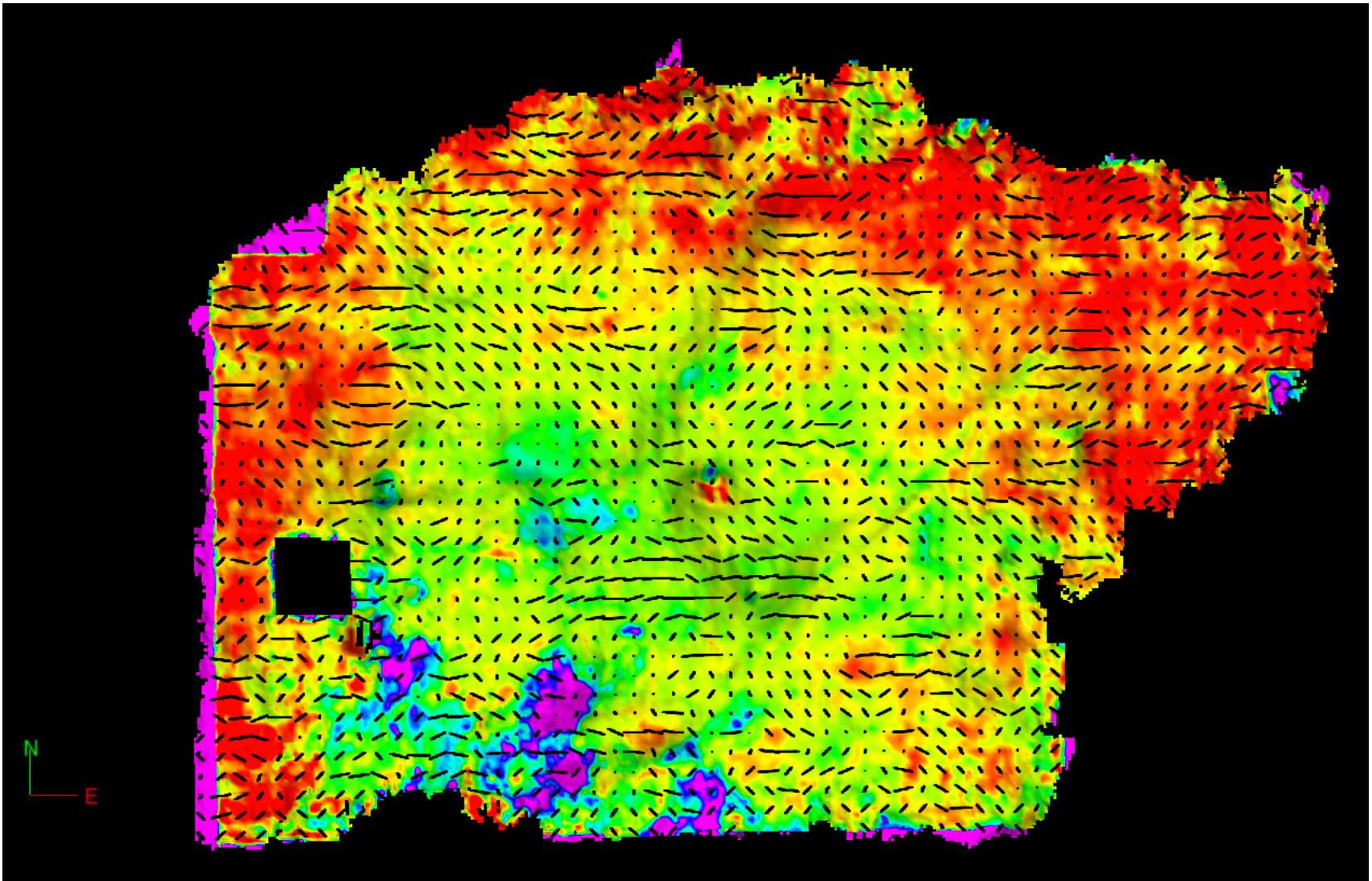
BRITTLENESS INDEX VOLUME + ENGINEERING VARIABLES



AZIMUTHAL VOLUMES



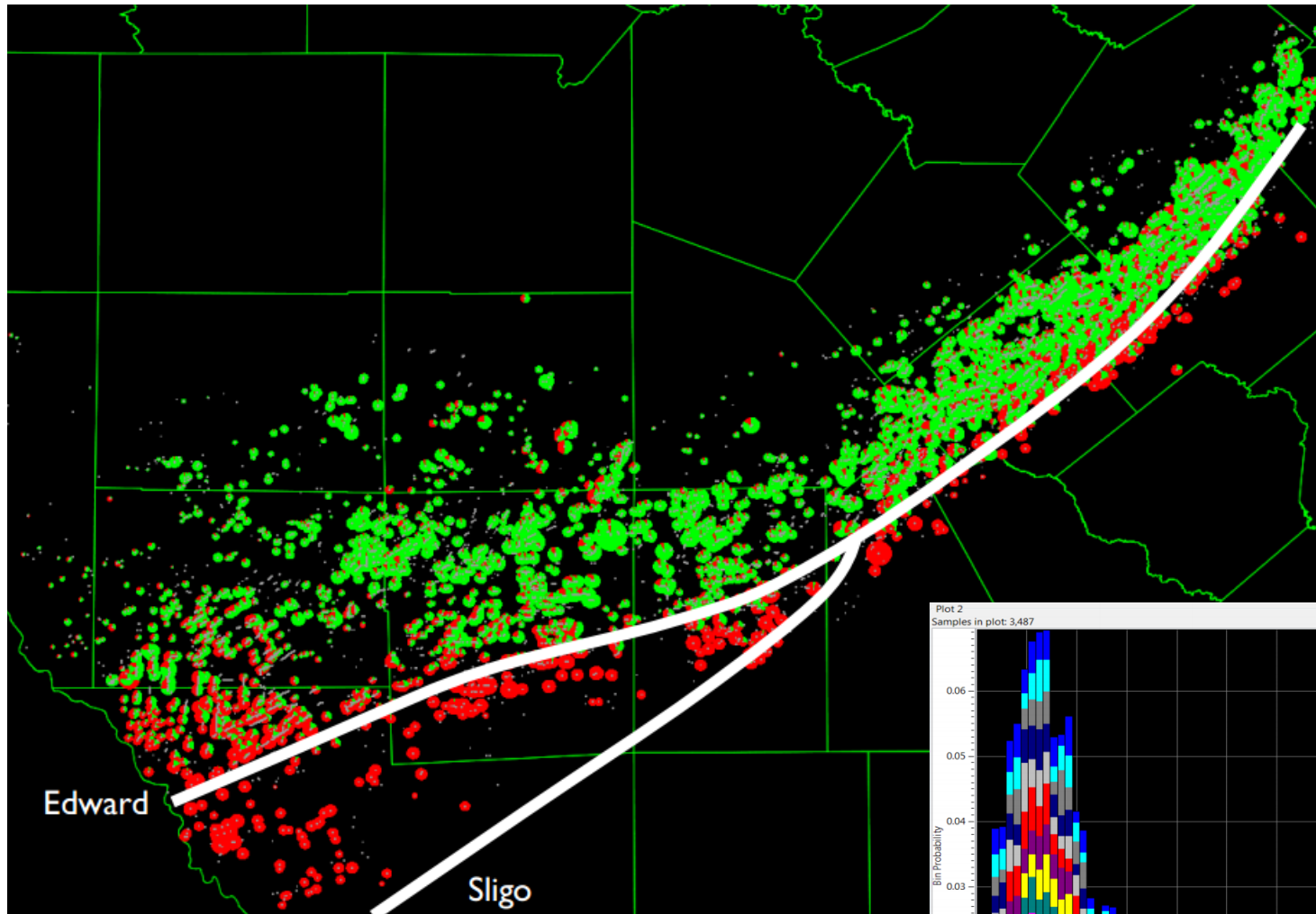
ANISOTROPY DIRECTION & INTENSITY + BI



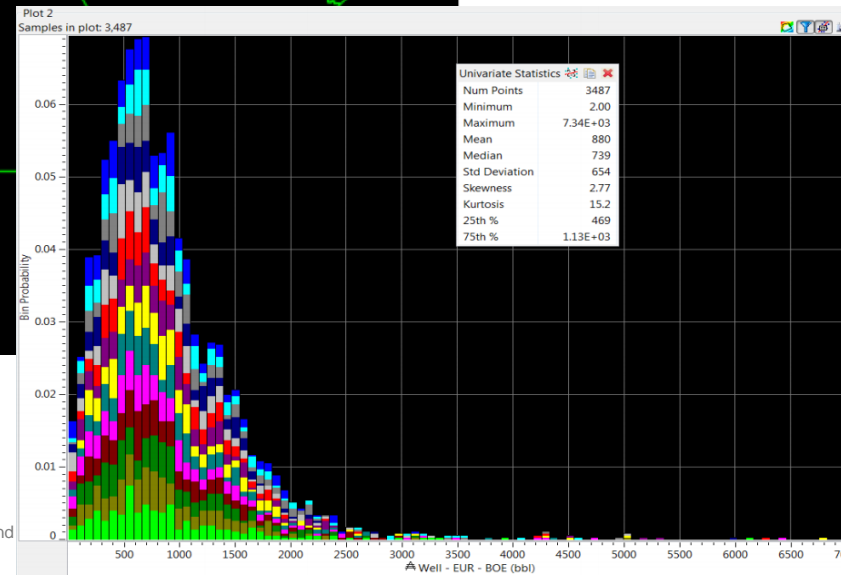


EAGLEFORD

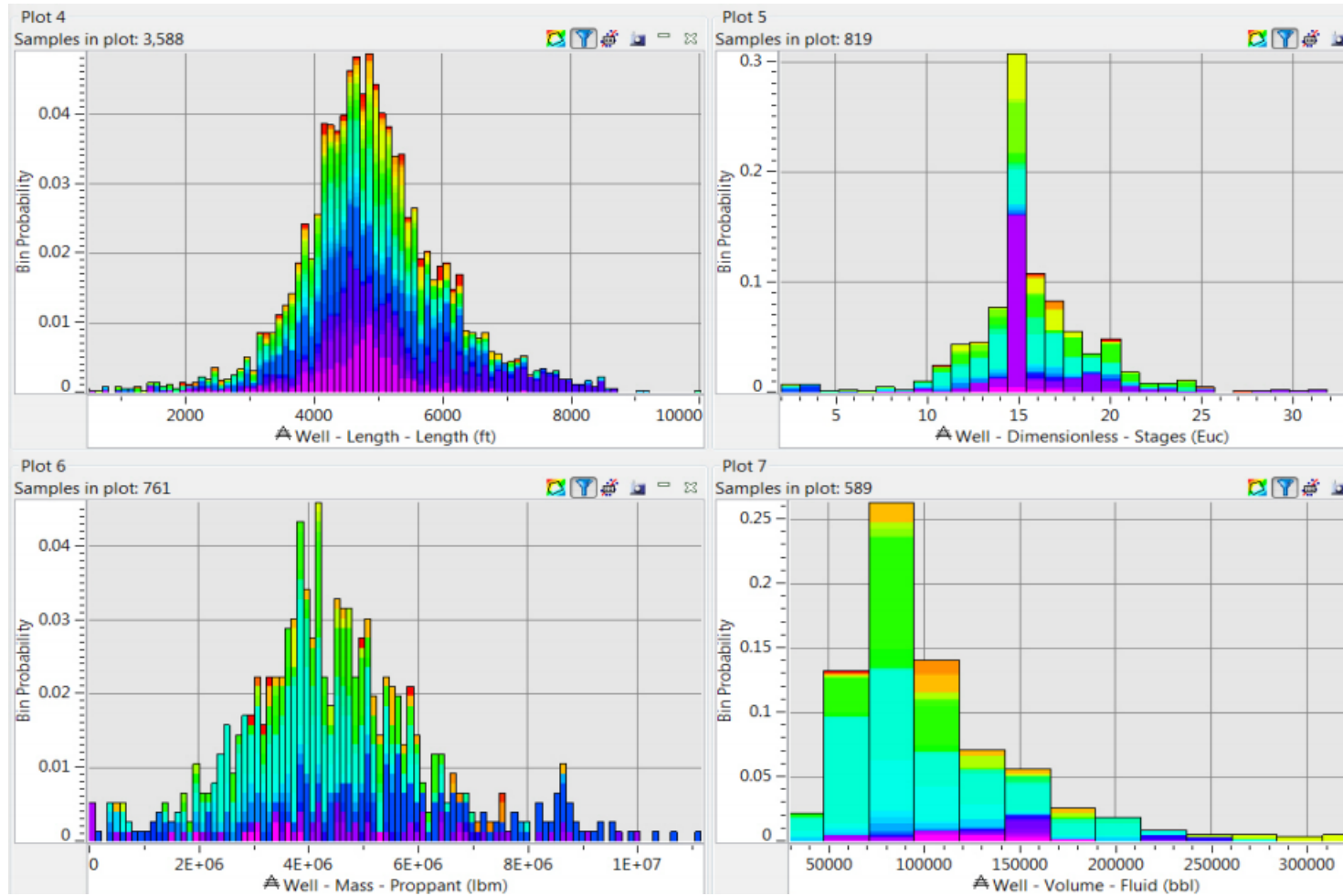
EF OIL/GAS/CONDENSATE PRODUCTION



From Murray Roth



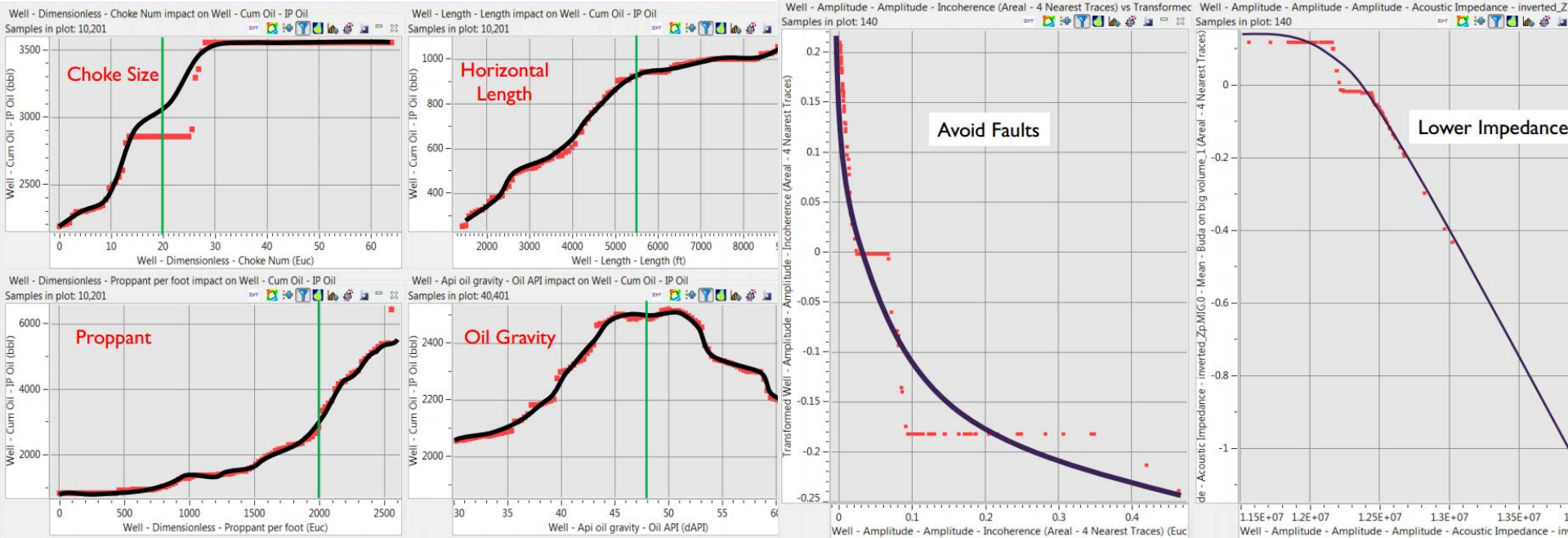
EF DRILLING AND COMPLETION DATA



From Murray Roth

EF DRILLING AND COMPLETION DATA

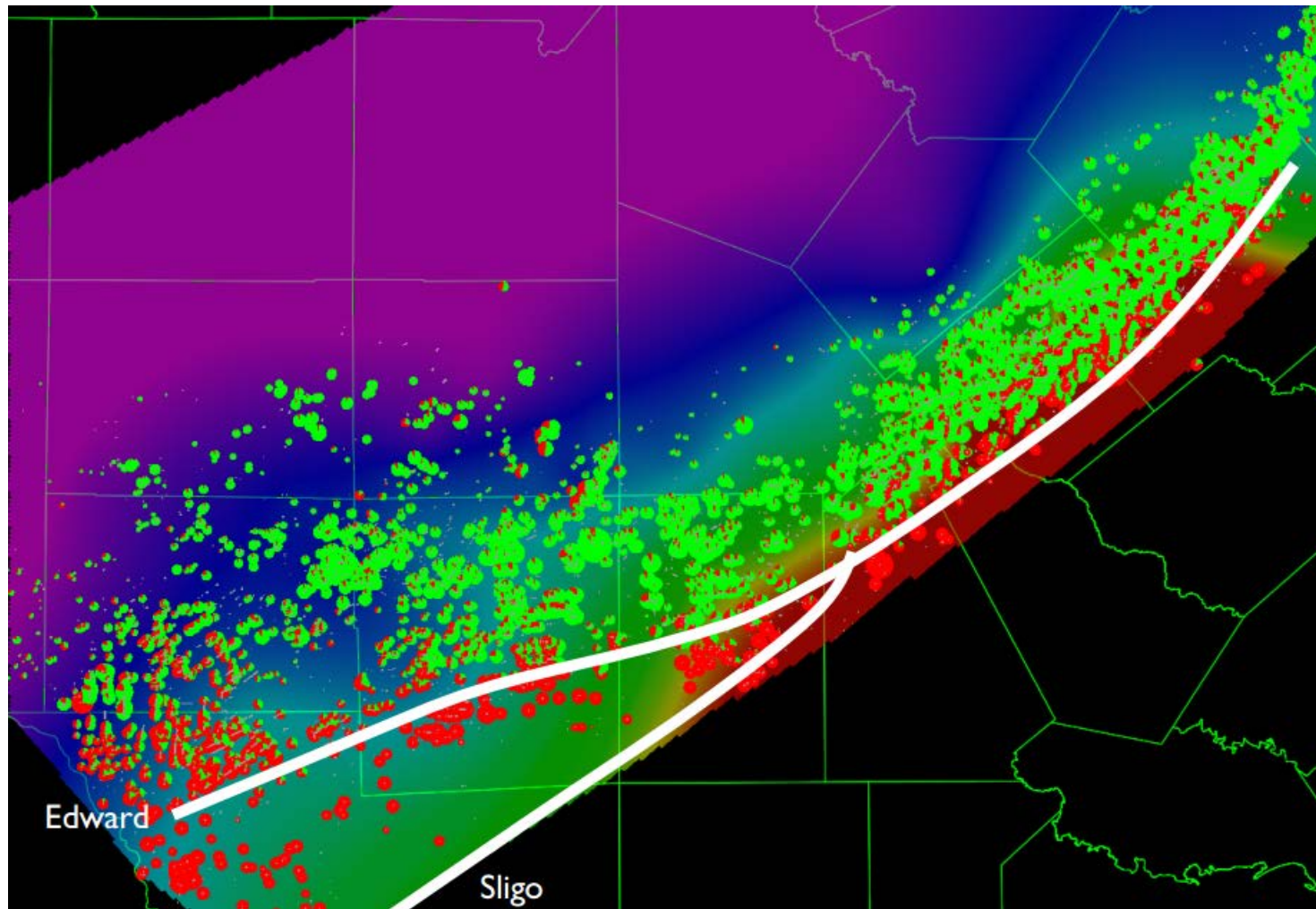
From Murray Roth



Engineering variables

G&G variables

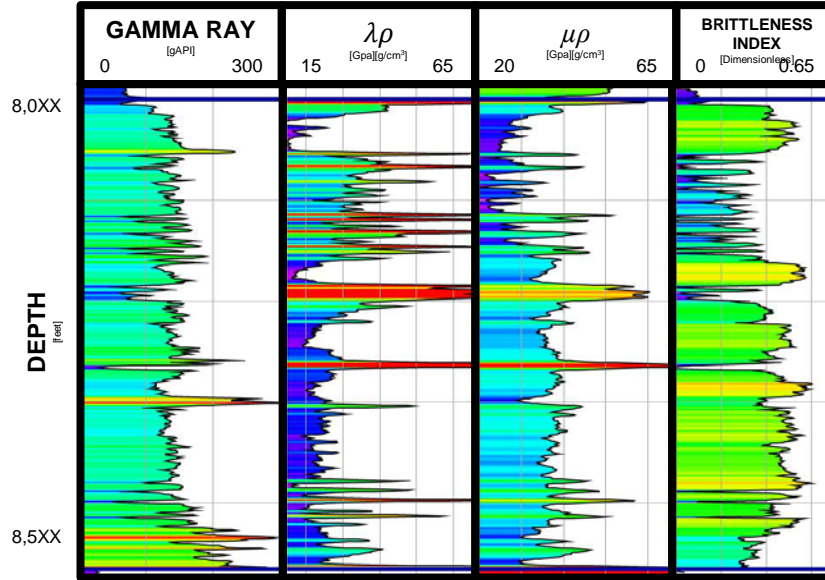
SWEEPSPOT MAP





SUMMARY

WORKFLOW SUMMARY

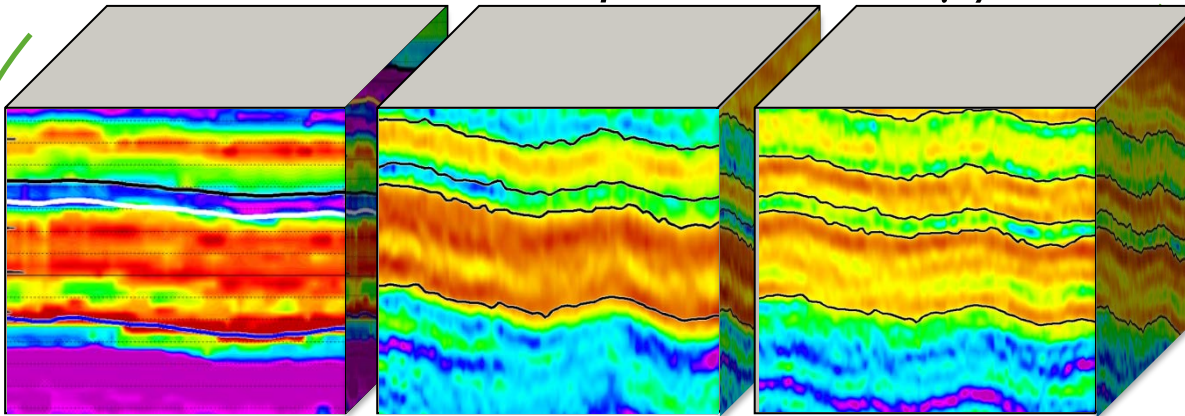


$$f_{BI}(\lambda\rho, \mu\rho, GR)$$

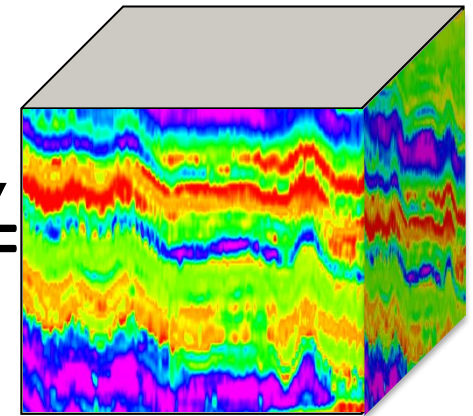
Gamma Ray

 $\lambda\rho$ $\mu\rho$

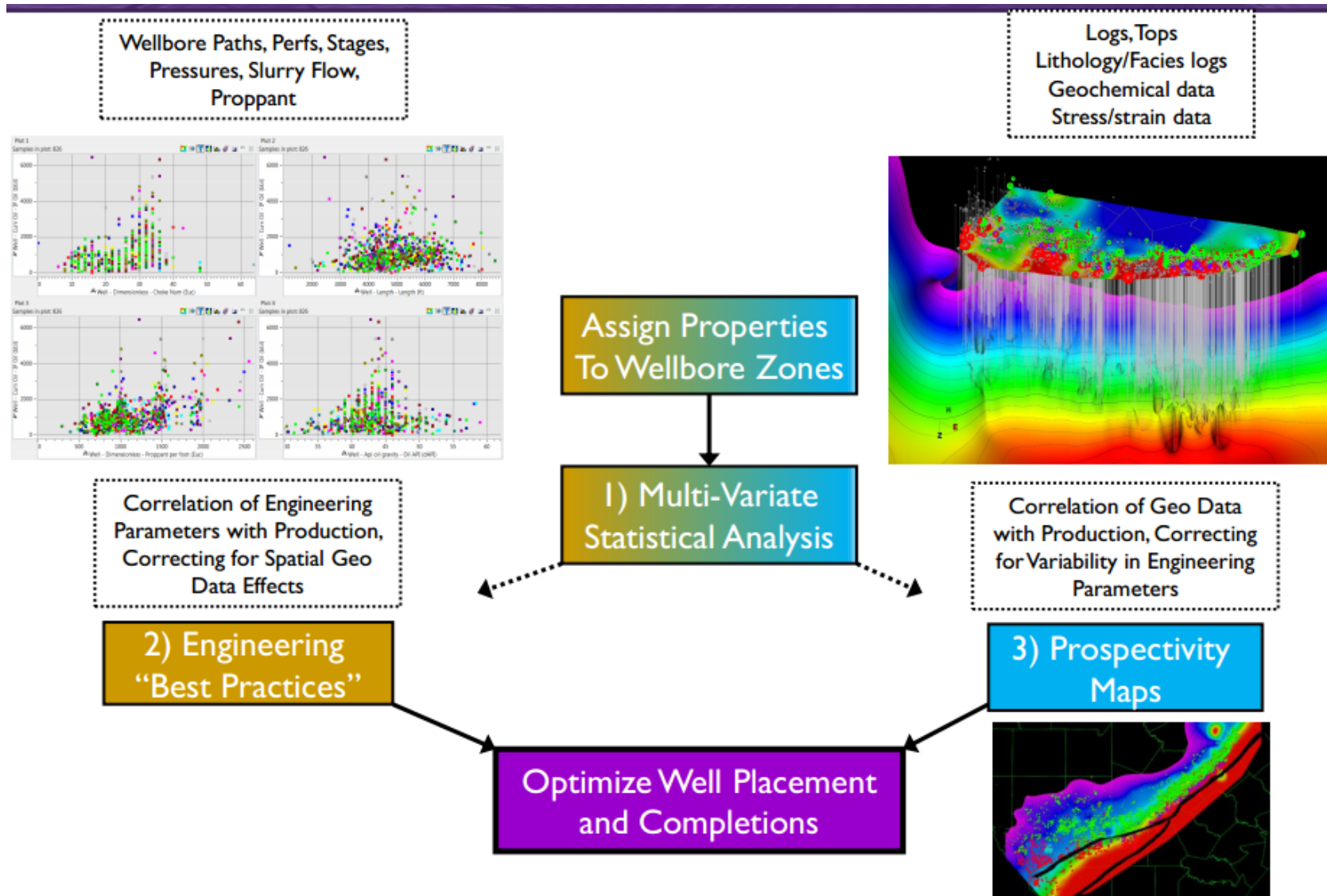
Brittleness Index



=



ANALYTIC WORKFLOW



THANK YOU

Questions & Open Discussion

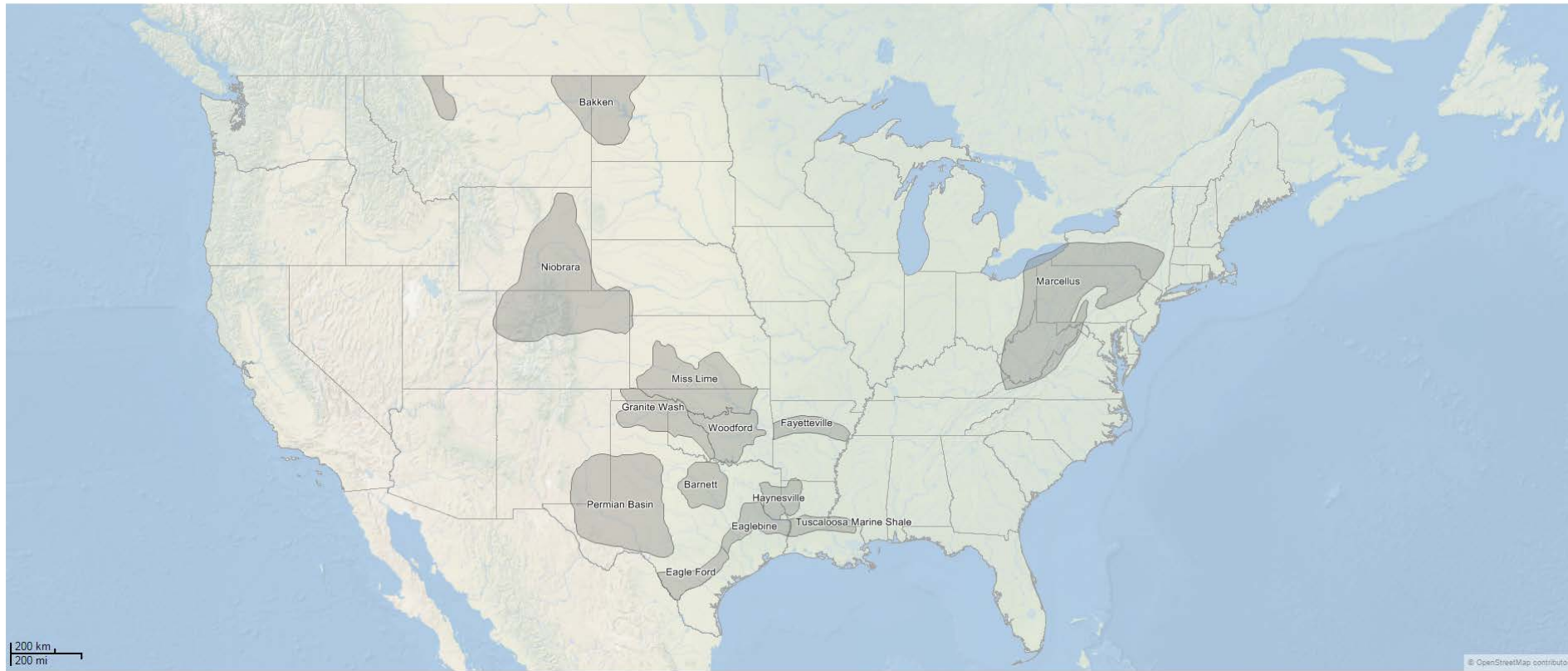




MAJOR UNCONVENTIONAL U.S. BASINS

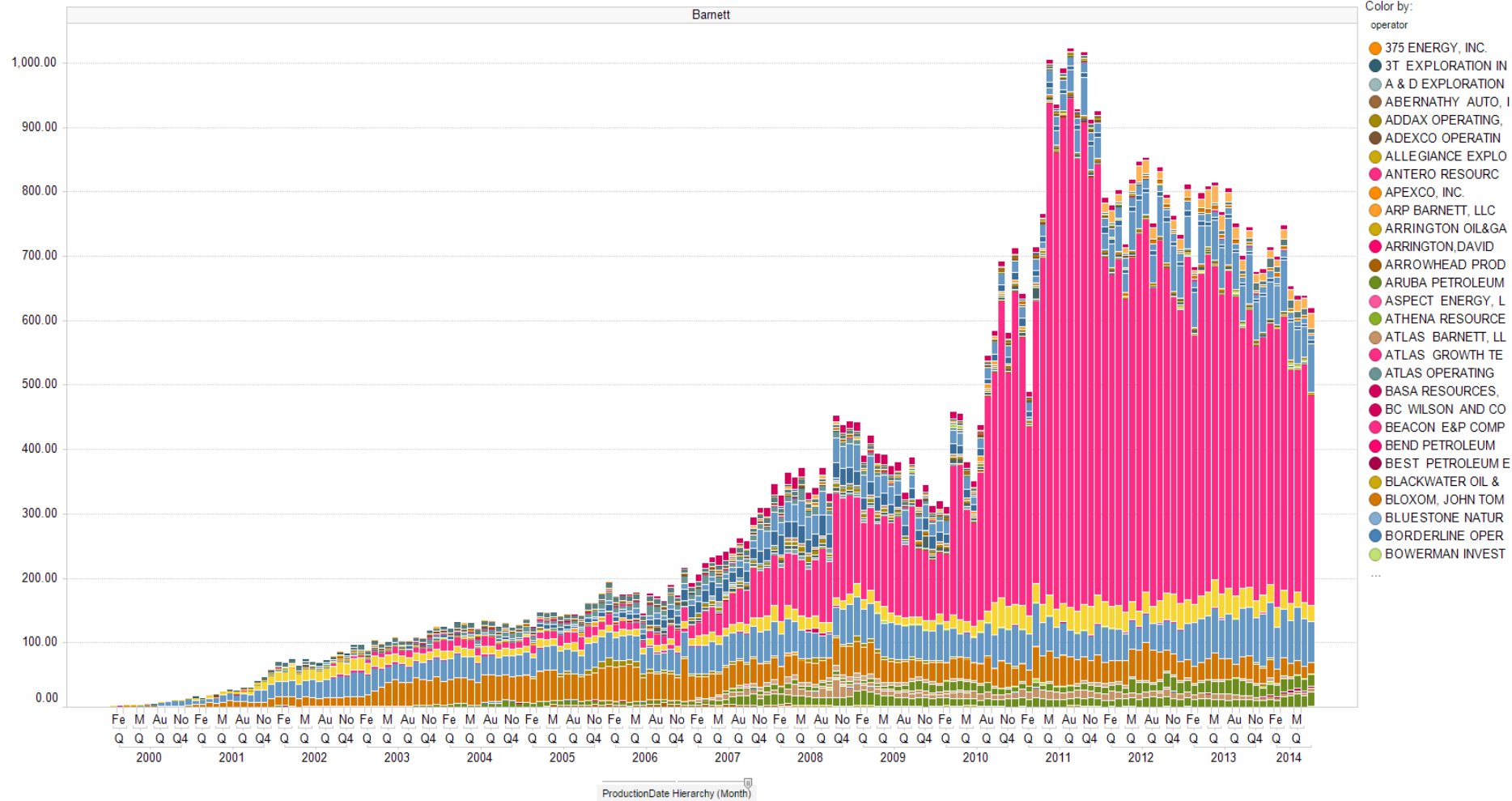


Select Resource Play. Data Table Updated: 10/27/2014.



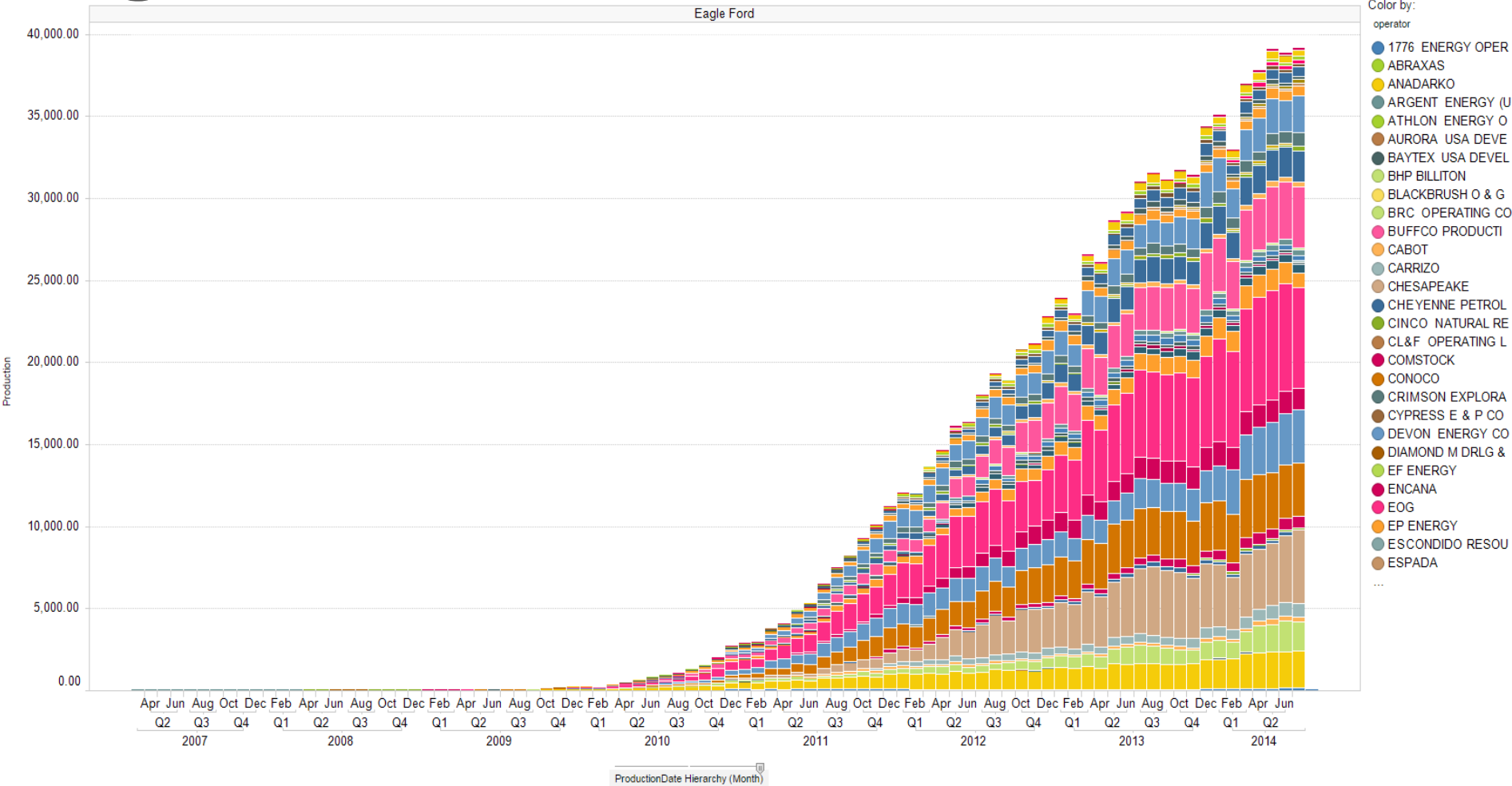
PRODUCTION HISTORY

Barnett Shale



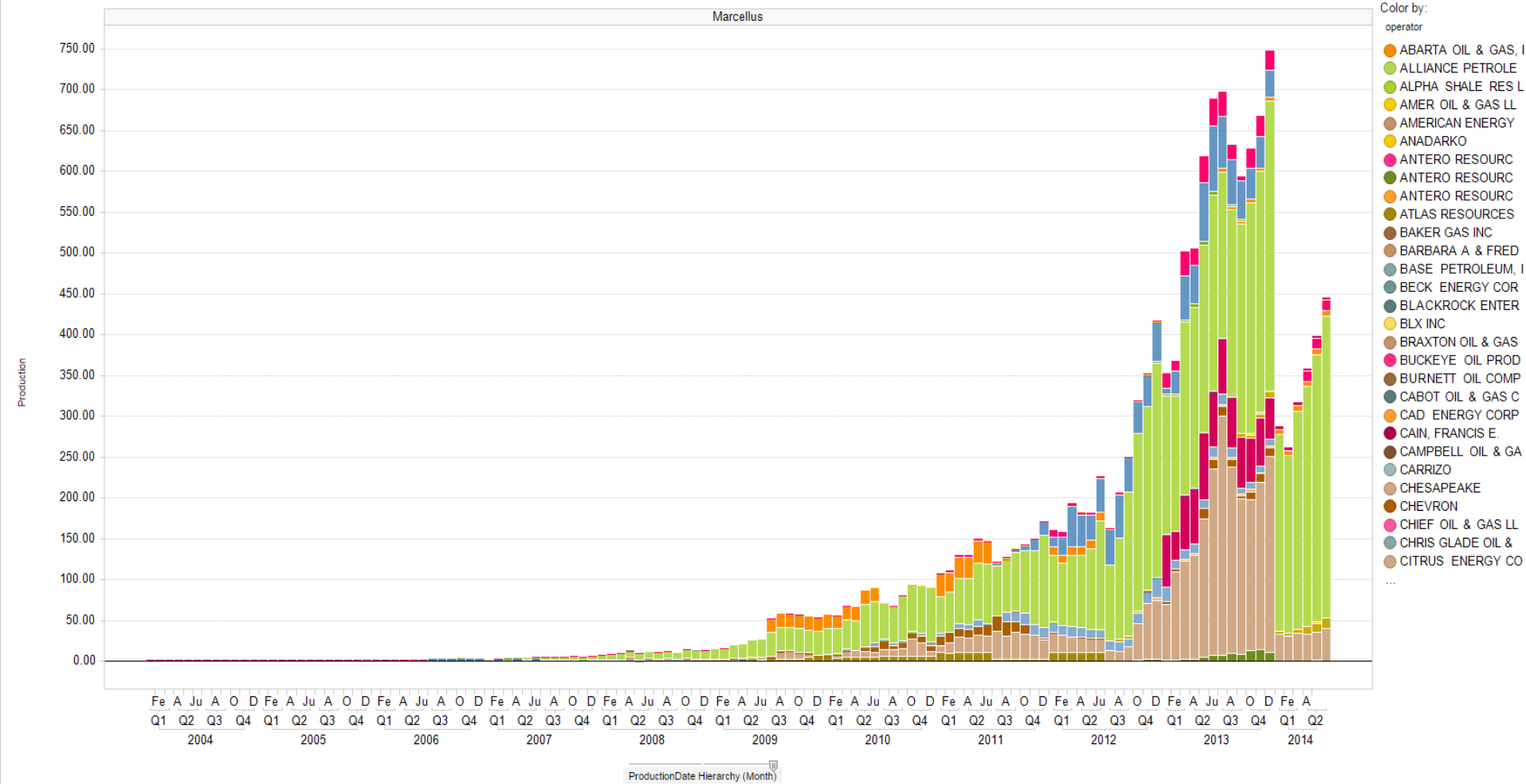
PRODUCTION HISTORY

EagleFord



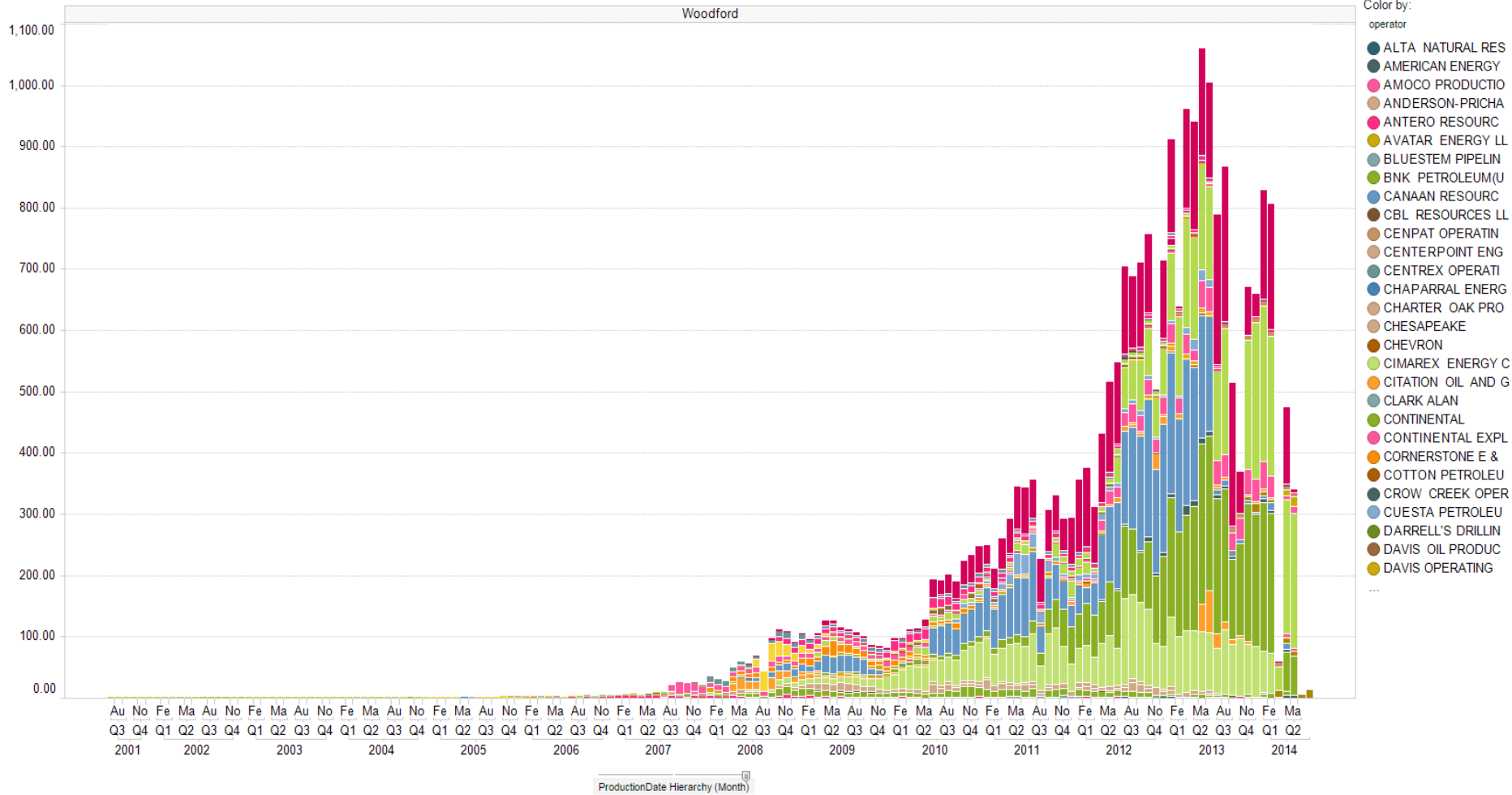
PRODUCTION HISTORY

Marcellus



PRODUCTION HISTORY

Woodford



A close-up photograph of a person's hands typing on a silver laptop. The laptop screen displays a complex software interface with multiple panels. On the left, there's a vertical stack of colorful geological cross-sections. In the center, a line graph shows data trends over time. On the right, there's a large heatmap or contour plot with a color gradient from green to red. The person is wearing a black wristband on their left wrist and a plaid shirt. The background is a plain, light-colored wall.

PRODUCTION SCENARIO ANALYSIS

PRODUCTION SCENARIO ANALYSIS

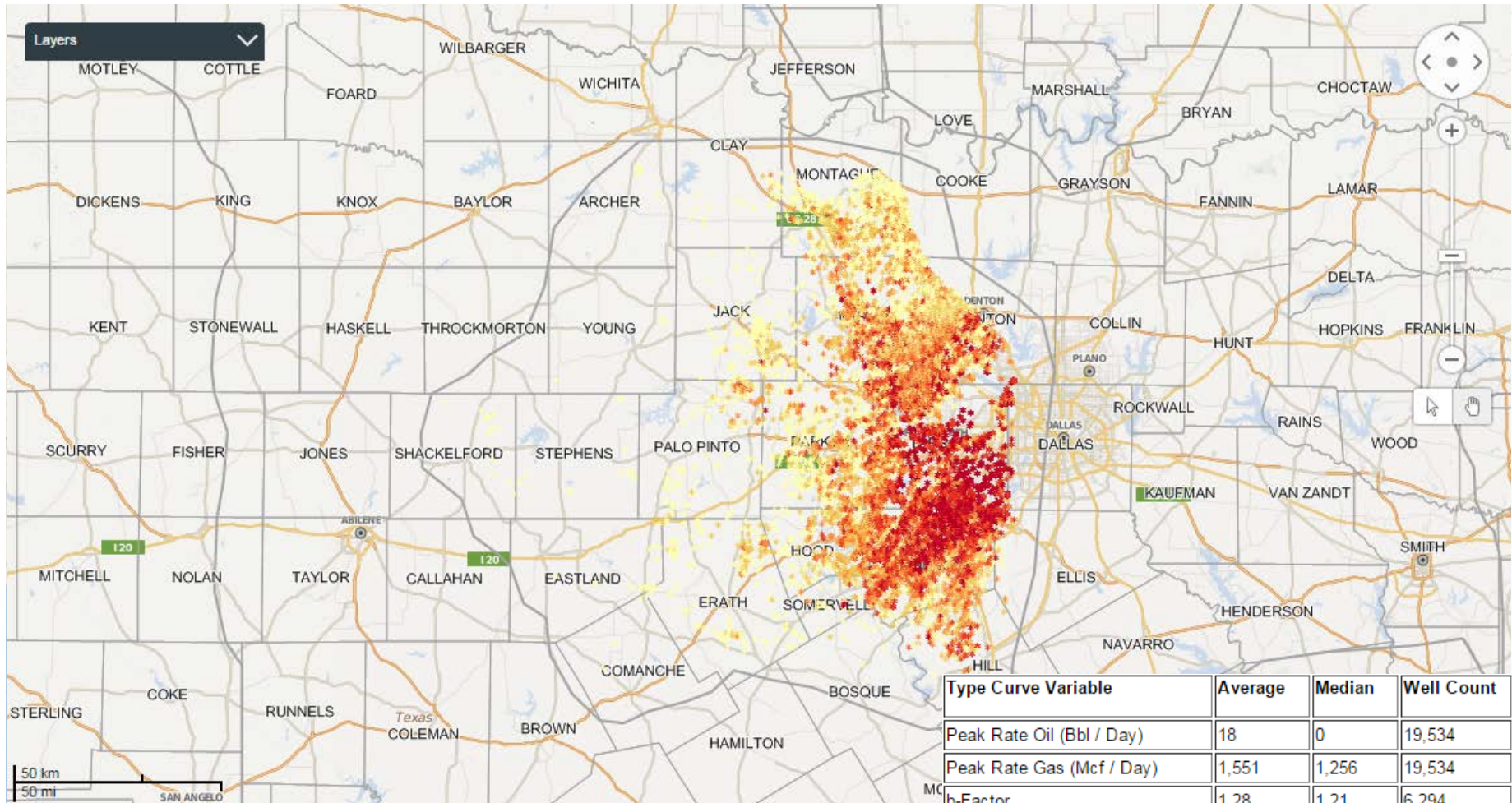
Workflow



PRODUCTION SCENARIO ANALYSIS

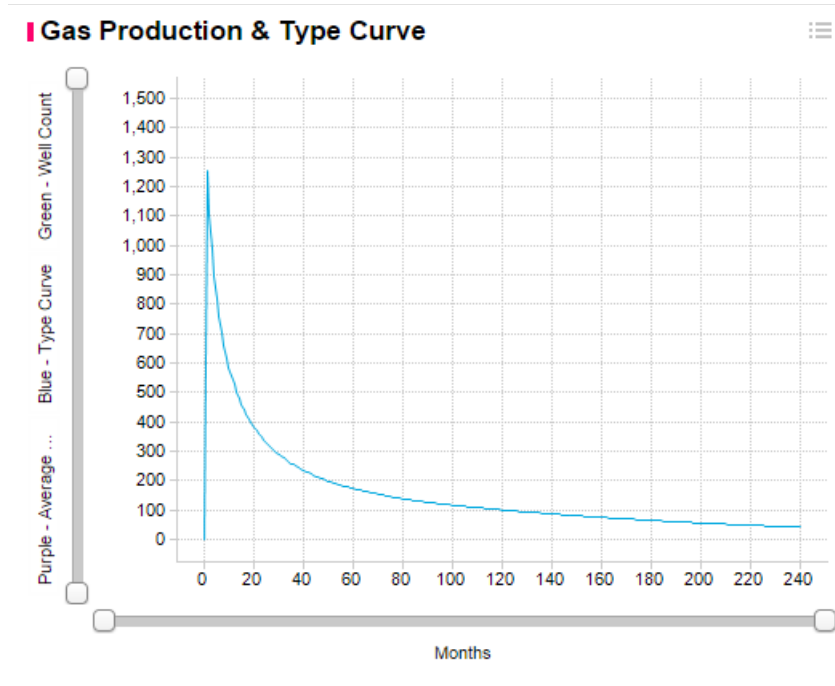
Barnett Shale

Peak Monthly Rate Gas (Mcf)



PRODUCTION SCENARIO ANALYSIS

Barnett Shale



Type Curve Variable	Average	Median	Well Count	Value
Peak Rate Oil (Bbl / Day)	18	0	19,534	<input type="text" value="0"/>
Peak Rate Gas (Mcf / Day)	1,551	1,256	19,534	<input type="text" value="1,256"/>
b-Factor	1.28	1.21	6,294	<input type="text" value="1.21"/>
Effective Annual Secant Decline (Desi) (%)	60 %	61 %	6,294	<input type="text" value="60 %"/>