

Seismic Determination of Dolomitization and Associated Reservoir Quality Using Supervised Machine Learning Techniques: Lower-Middle Permian Carbonates of the Midland Basin*

Abidin Berk Caf¹ and John D. Pigott¹

Search and Discovery Article #42565 (2021)**

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Abstract

Extensive dolomitization is prevalent in platform and periplatform carbonates in the Lower-Middle Permian strata in the Midland and greater Permian basin. Early workers have found that the platform and shelf-top carbonates were dolomitized while slope and basinal carbonates were remained calcitic, proposing a Reflux Dolomitization Model as the possible diagenetic mechanism. More importantly, they underline that this dolomitization pattern controls the porosity and forms an updip seal. When applied to the Lower-Middle Permian dolomites in the Midland Basin, these studies are predominately conducted using well log, cores, and outcrops, and while exhibiting high resolution vertically, such determinations are laterally sparse, inhibiting regional mapping. This investigation employs Supervised Bayesian Classification and Probabilistic Neural Networks (PNN) on 3D seismic to create an estimation of the most probable distribution of dolomite and limestone within a subsurface 3D volume petrophysically constrained. Combining this lithologic information with porosity we then illuminate the diagenetic effects on a seismic scale. Workflow commences with deriving lithology classifications from well log cross-plots of Neutron Porosity and Acoustic Impedance to determine a priori proportions of lithologies, and Probability Density Functions (PDF) calculation for each lithology type. These probability distributions and a priori proportions are then applied to full seismic volumes of acoustic impedance and predicted NPHI volumes to create a lithology volume and their probabilities. Results suggest do support a regional Reflux Dolomitization Model, in which the porosity is increasing from shelf to slope while dolomitization is decreasing. However, when a seismic stratigraphic framework is employed, another possibility is that of an Oscillating Sea Level Drags Dolomitization Model. With the overprint of subsequent mixing zones during sea level change, porosity destroying dolomitization would be maximally concentrated in the updip region. However, more work is needed to better identify the most appropriate model of dolomitization in these Lower to Middle Permian strata. In any case, these results demonstrate that diagenesis and corresponding reservoir quality in these platforms and periplatform strata can be directly imaged and mapped on a seismic scale by quantitative seismic interpretation and supervised machine learning methods.

References Cited

- Mazullo, S.J., 1994, Dolomitization of periplatform carbonates (Lower Permian, Leonardian), Midland basin, Texas: Carbonates and Evaporites, v. 9, p. 95-112.
- Nieto, J., B. Batlai, and F. Delbecq, 2013, Seismic Lithology Prediction: A Montney Shale Gas Case Study: CSEG Recorder, v. 38/2, p. 35-42.
- Saller, A.H., and N. Henderson, 1998, Distribution of porosity and permeability in platform dolomites: Insight from the Permian of west Texas: AAPG Bulletin, v. 82/8, p. 1528–1550.
- Russell, B., D. Hampson, and B. Bankhead, 2006, An inversion primer: CSEG Recorder Special Edition, <https://csegrecorder.com/articles/view/an-inversion-primer> (web accessed October 18, 2020)
- Saller, A., and J. Dickson, 2011, Partial dolomitization of a Pennsylvanian limestone buildup by hydrothermal fluids and its effect on reservoir quality and performance: AAPG Bulletin, v. 95/10, p. 1745-1762.
- Saller, A., 2014, Late Pennsylvanian and Early Permian Sedimentation on the Central Basin Platform and Implications to the Wolfberry Deposition in the Western Midland Basin: AAPG 2014 Southwest Section Annual Convention, Midland, Texas, May 11-14, 2014.
- Verma, S., 2015, Seismic data conditioning for quantitative interpretation of unconventional reservoirs: Ph.D. dissertation, University of Oklahoma, Norman, Oklahoma.
- Xiao, Y., and G.D. Jones, 2015, Dolomitization, anhydrite cementation, and porosity evolution in a reflux system: Insights from reactive transport models: AAPG Bulletin, v. 89/5, p. 577–601.

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SCHOOL OF GEOSCIENCES
The UNIVERSITY of OKLAHOMA

Strategy

- Problem Definition
- Geologic Setting
- Methods
- Interpretation & Discussion
- Conclusions

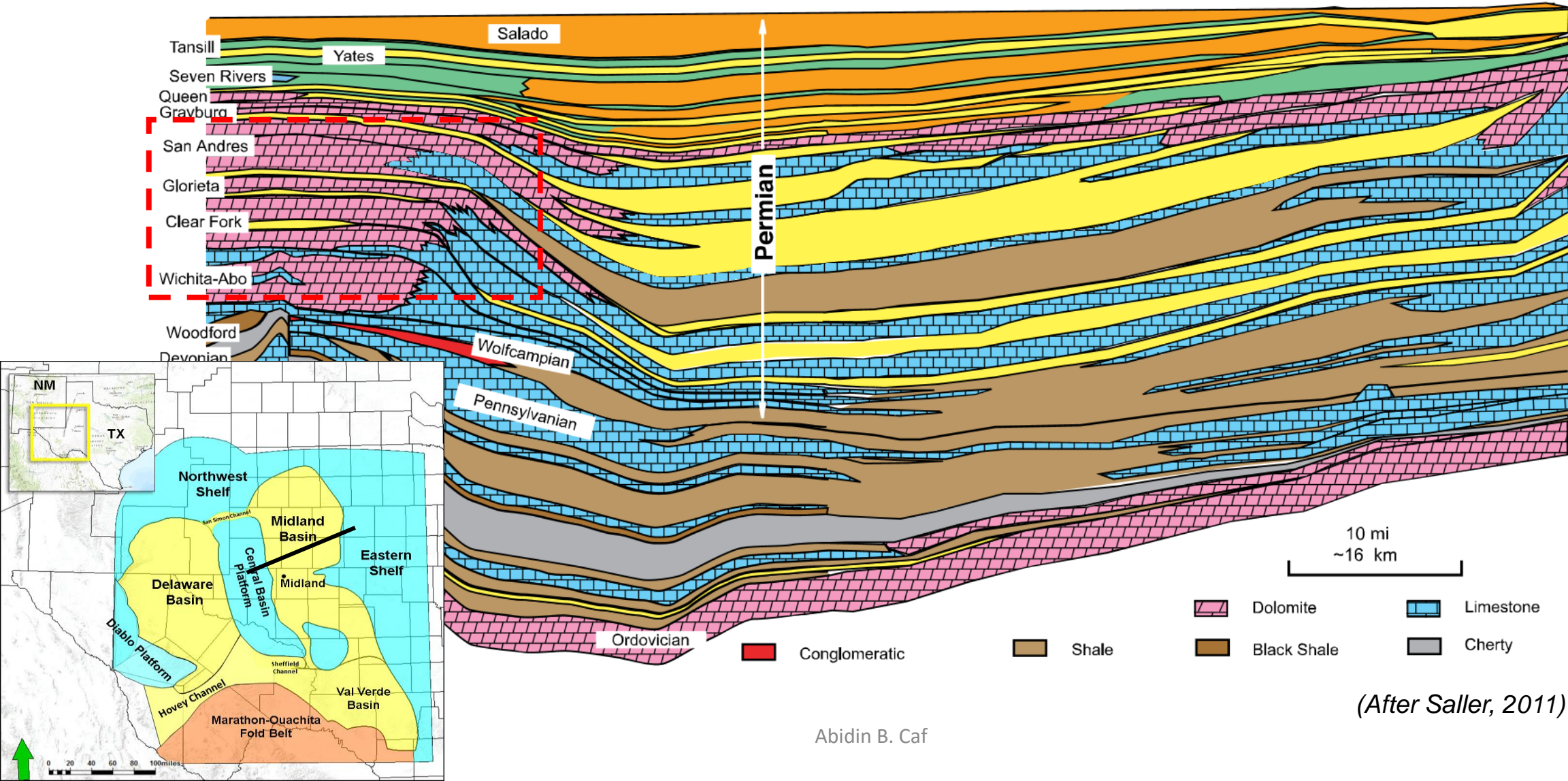
Problem Definition

- Extensive dolomitization is prevalent in platform and periplatform carbonates in the Lower- middle Permian strata in the Midland and greater Permian basin (Mazullo, 1994).
- The platform and shelf-top carbonates are usually dolomitized while slope and basinal carbonates remained calcitic (Saller et al., 1998, Mazullo et al., 1994).
- Reflux Dolomitization is the possible diagenetic mechanism. More importantly, this dolomitization pattern controls the porosity and forms updip seal.

Problem Definition

- There are numerous studies focused on Lower-Middle Permian dolomites in the Midland Basin, but they have been mostly conducted using well logs, core and outcrops. Though they exhibit high resolution vertically, they are laterally sparse.
- Aim of this study is to use Supervised Bayesian Classification and Probabilistic Neural Networks (PNN) to create estimation of the most probable distribution of dolomite, limestone and combine this lithology information with porosity to illuminate the diagenetic effect in the seismic scale.

Geologic Setting



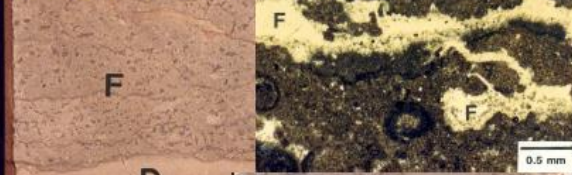
(After Saller, 2011)

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Geologic Setting-Diagenetic Model

PLATFORM INTERIOR

Fenestral Wackestones

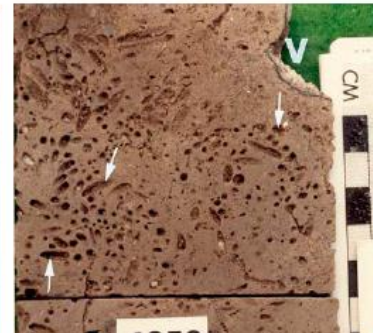
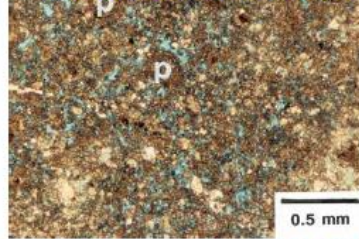


Nonporous Fusulinid Wackestone

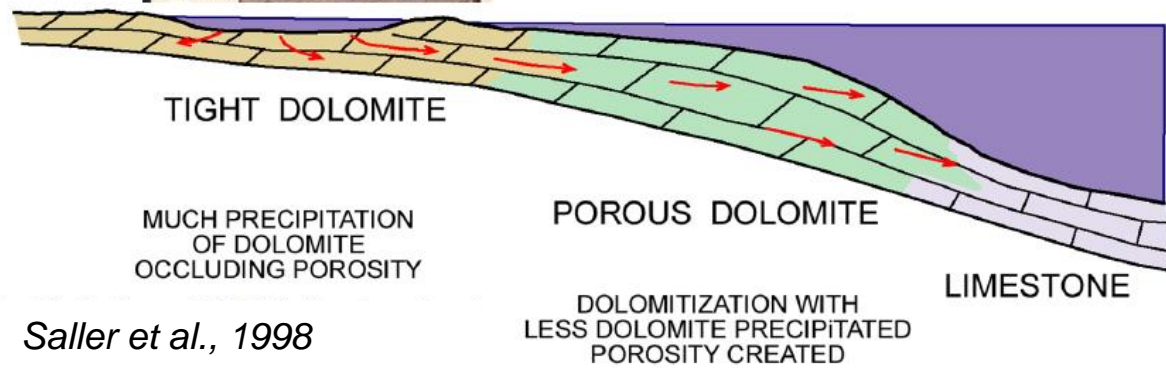
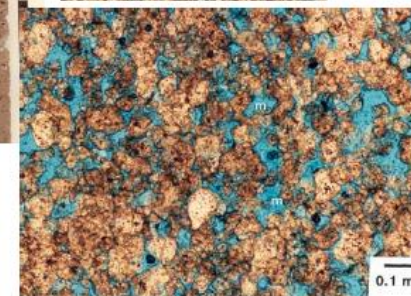


POROUS PLATFORM MARGIN

Porous Peloid Wackest-Packstone



Porous Fusulinid Wackestone-Packstone



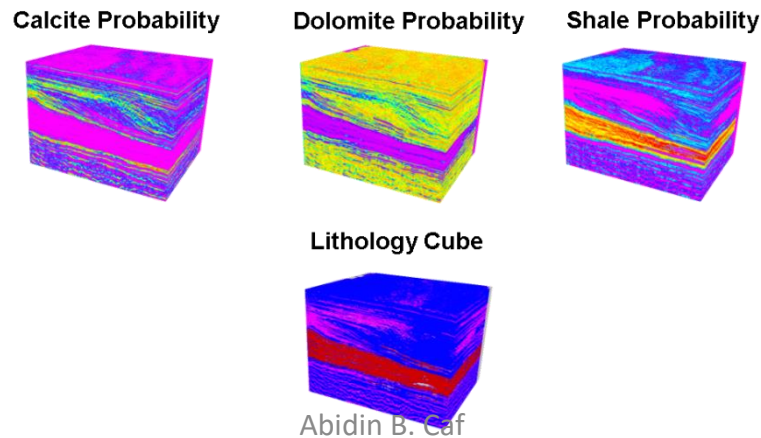
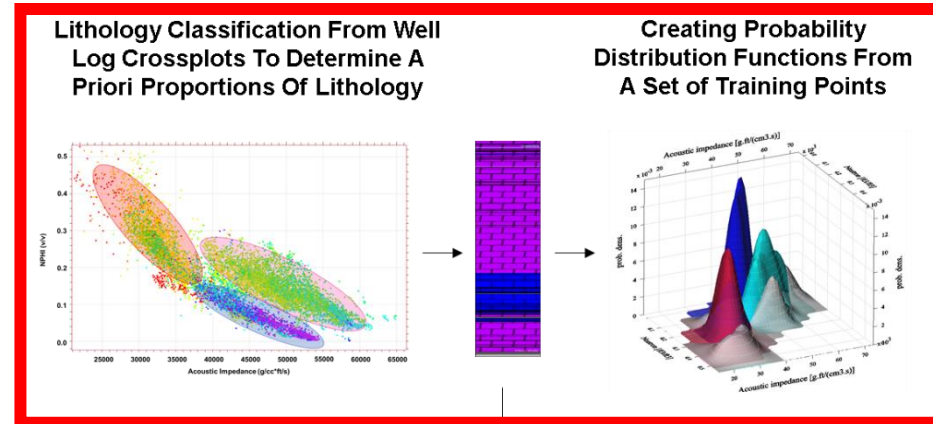
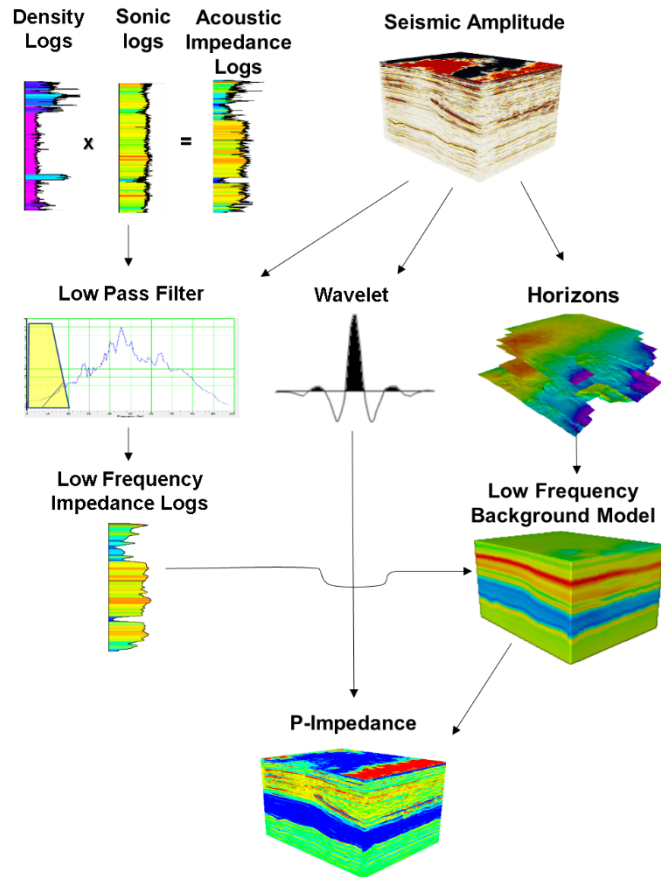
Saller et al., 1998

- Dolomitization is most likely related to evaporated seawater (supersaturated) formed in lagoons.
- This evaporated seawater is dense. Therefore, it seeps downward and dolomitizes.
- Most of the precipitation occurs on the platform and margin.

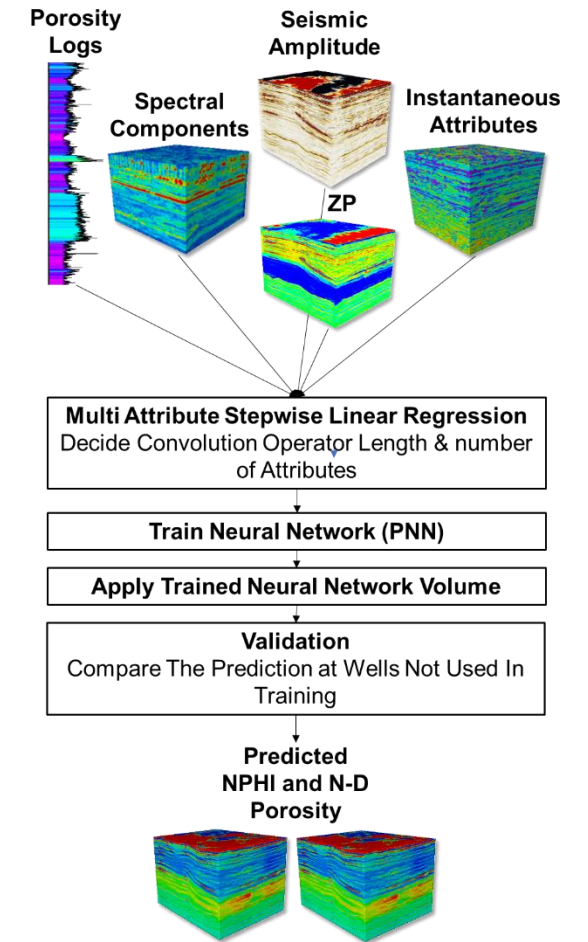
Methods

Supervised Bayesian Classification

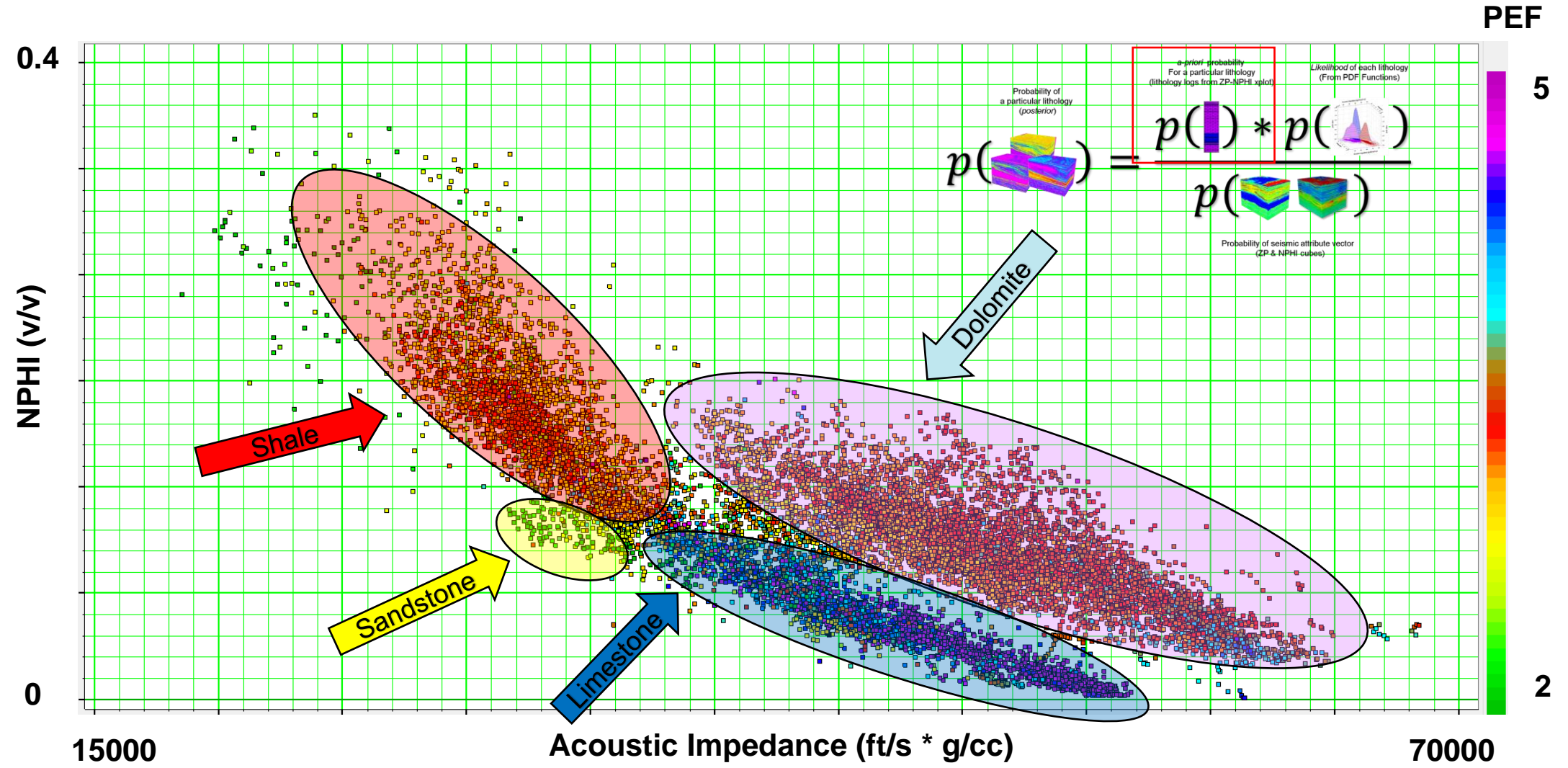
Post- Stack Inversion



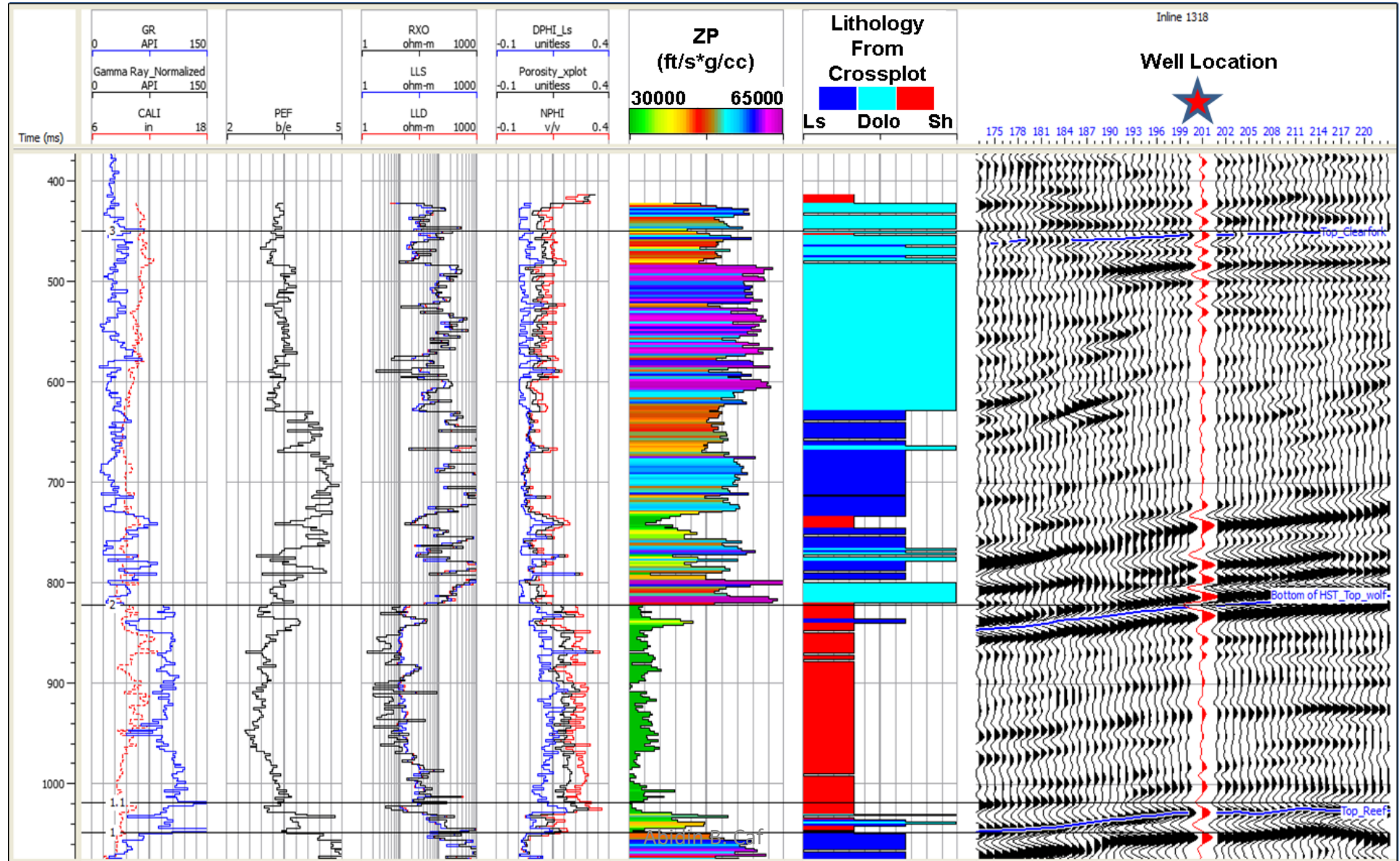
Probabilistic Neural Network (PNN)



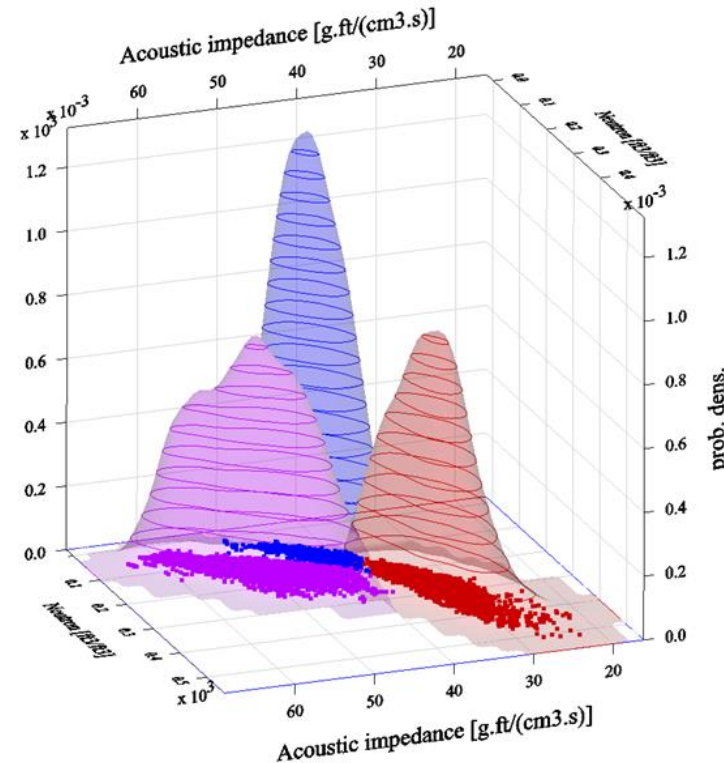
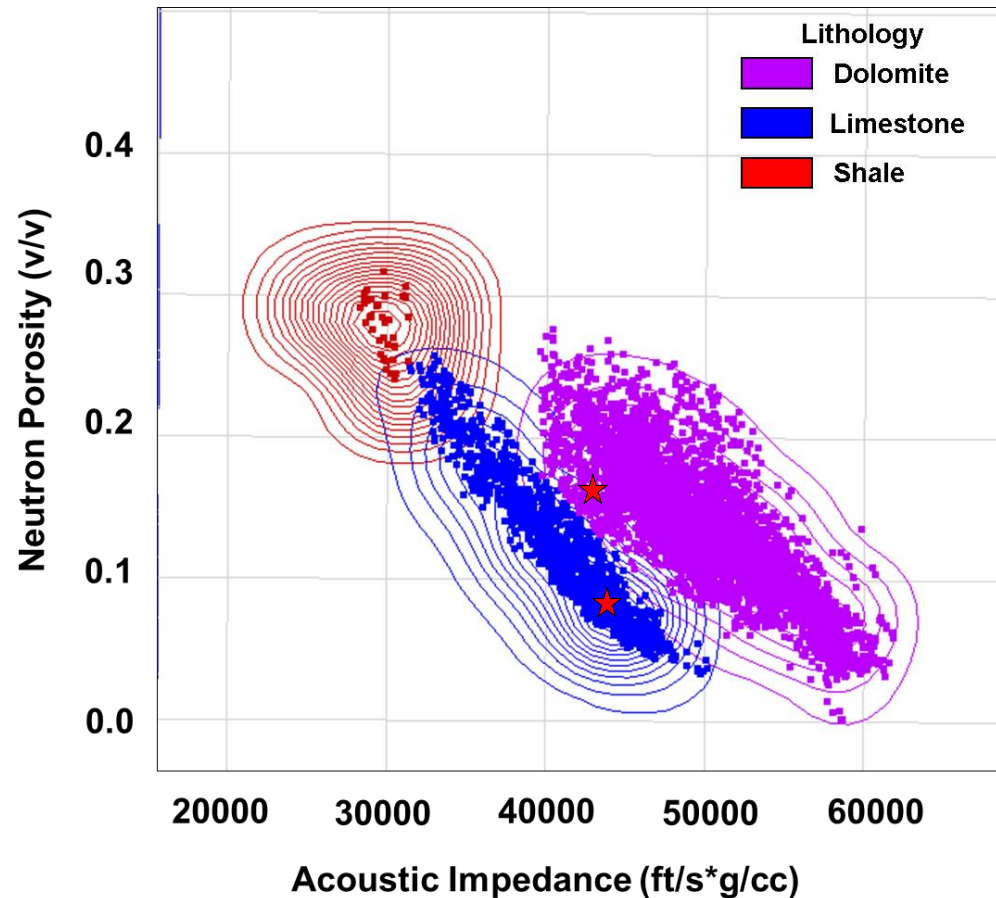
Supervised Bayesian Classification- Creating Lithology logs



Supervised Bayesian Classification- QC' ing Lithology logs



Supervised Bayesian Classification-PDF's



Probability of a particular lithology (posterior)

$$p(\text{Lithology}) = \frac{p(\text{Lithology}) * p(\text{Likelihood of each lithology})}{p(\text{Probability of seismic attribute vector (ZP & NPHI cubes)})}$$

a-priori probability
For a particular lithology
(lithology logs from ZP-NPHI xplot)

Likelihood of each lithology
(From PDF Functions)

The cross plot is convolved with a smooth kernel function:

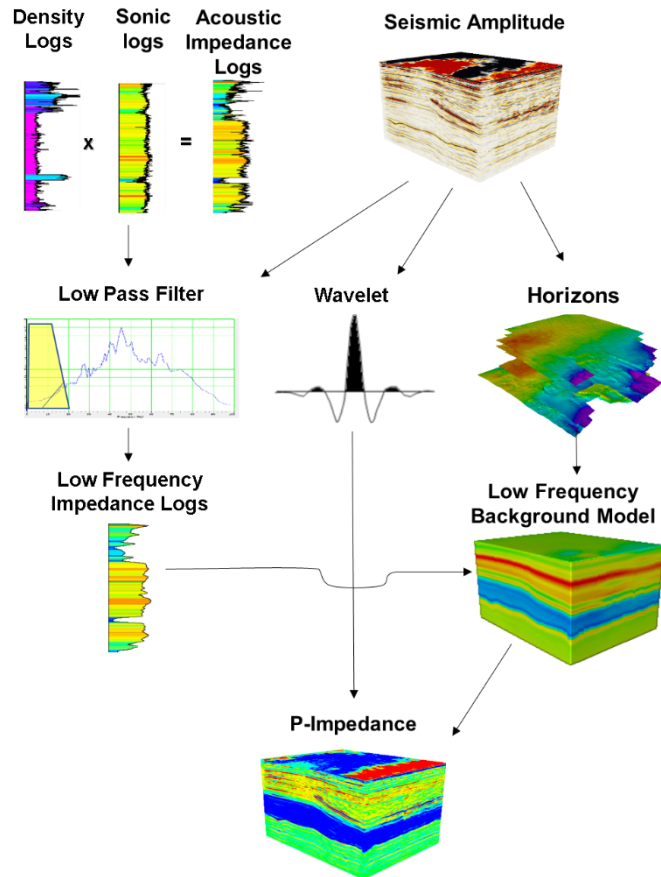
x_i (e.g., Zp)

(Nieto, 2013)

- PDFs are built by convolving the data point in the cross-plot with an operator (it is called kernel function)
- This provides the likelihood of each lithology for the given point in our cross-plot space

Methods

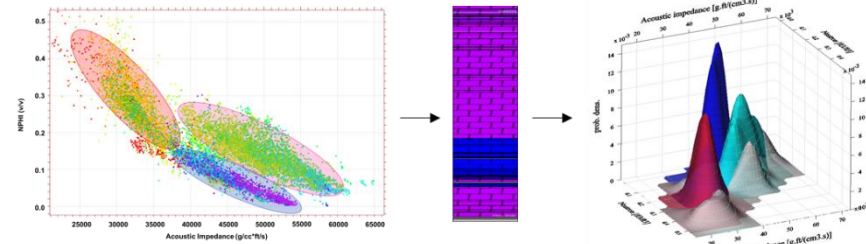
Post- Stack Inversion



Supervised Bayesian Classification

Lithology Classification From Well Log Crossplots To Determine A Priori Proportions Of Lithology

Creating Probability Distribution Functions From A Set of Training Points

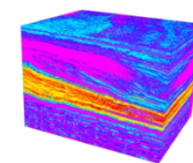
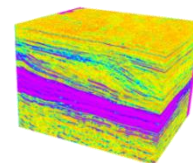
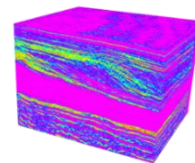


QC & Apply Probability Distribution Functions And A Priori Proportions To Full Seismic Volumes To Generate Probability Volumes And Most Probable Facies

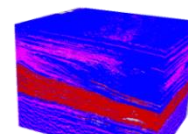
Calcite Probability

Dolomite Probability

Shale Probability

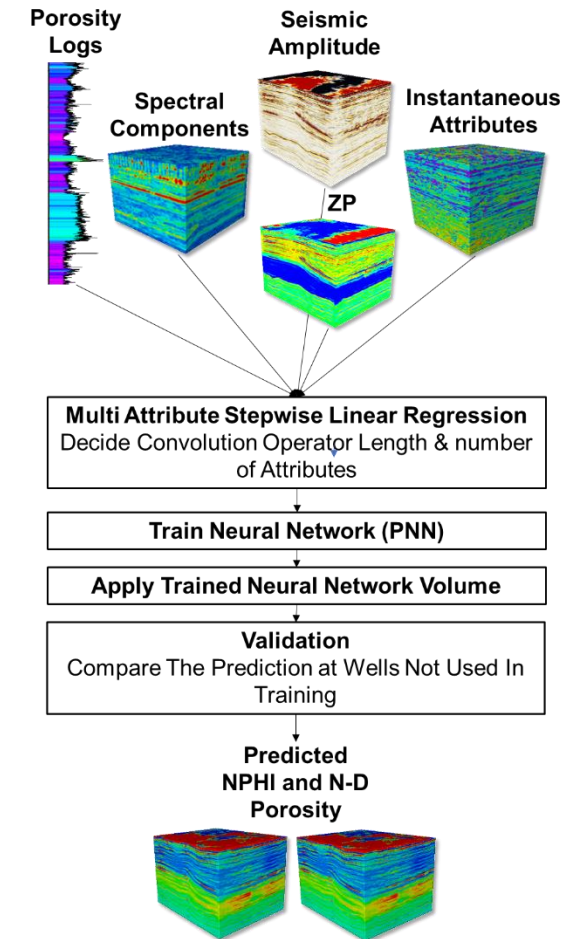


Lithology Cube

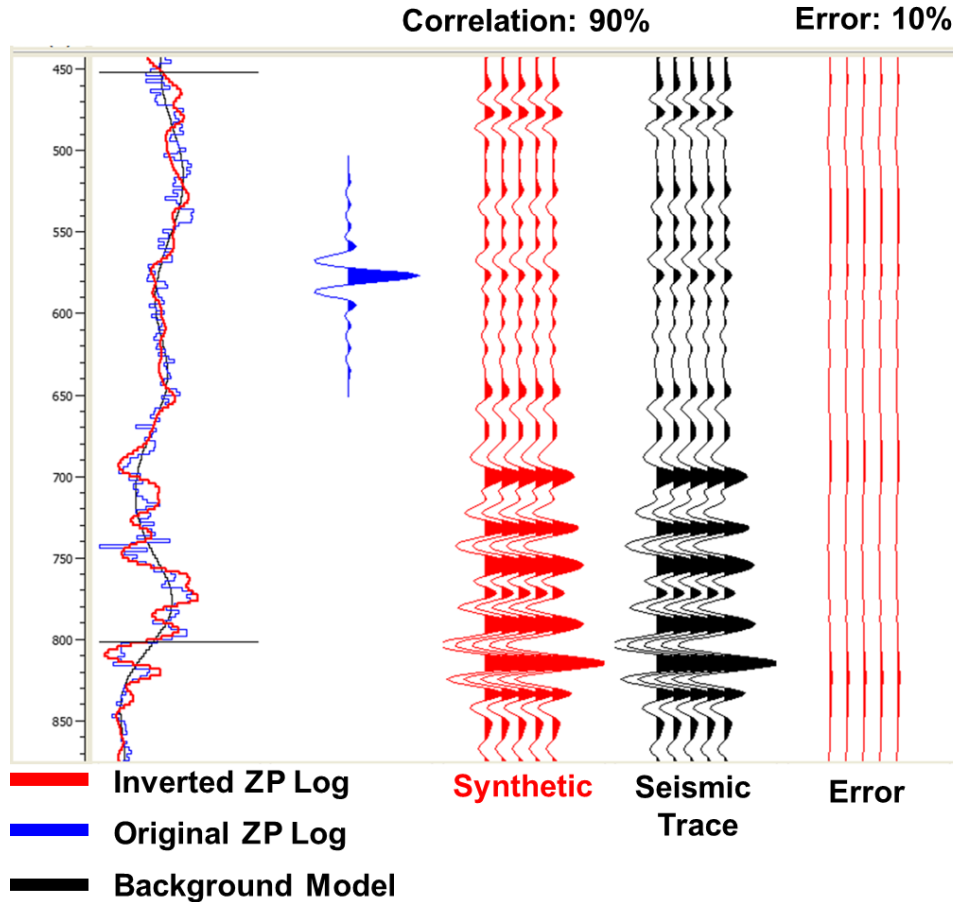


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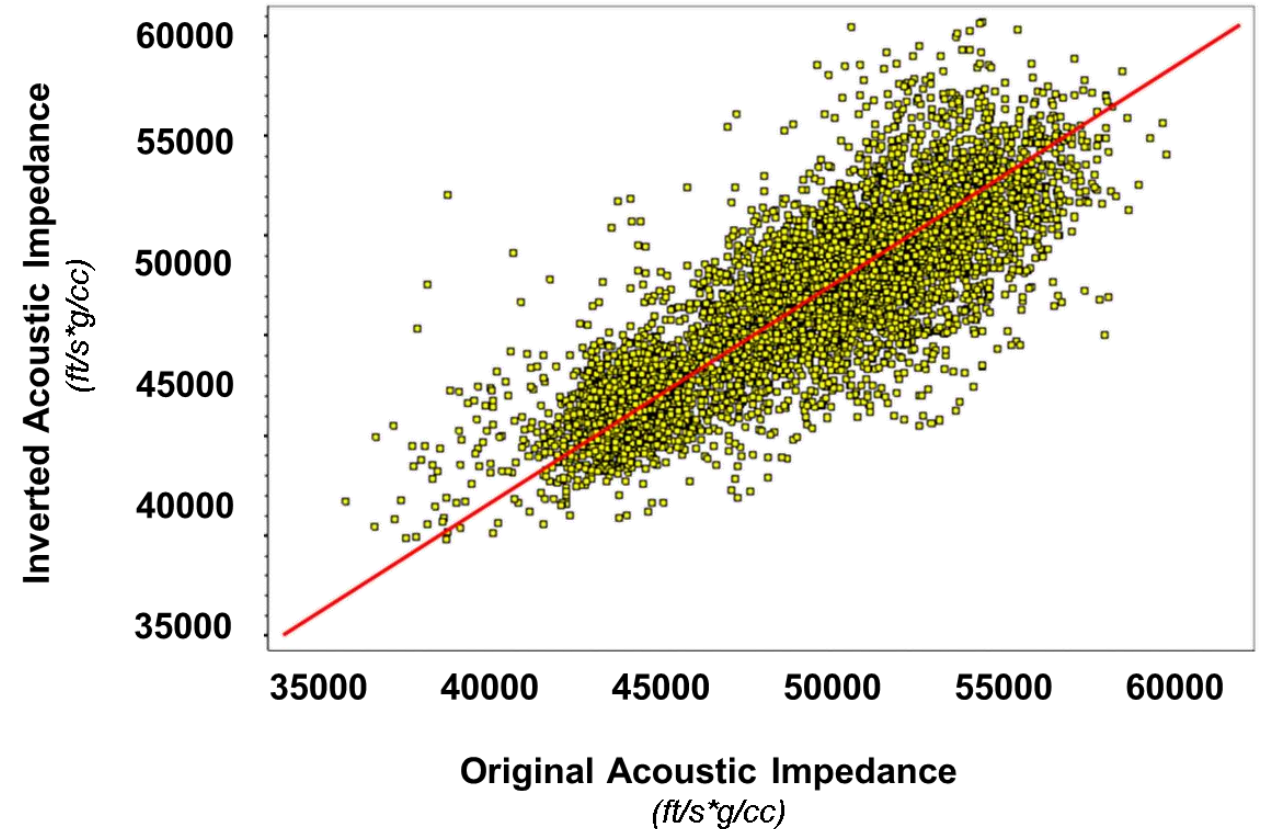
Probabilistic Neural Network (PNN)



Post Stack Inversion - QC



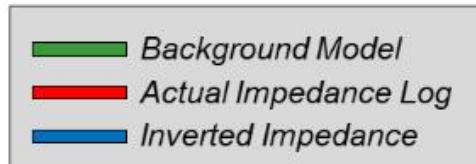
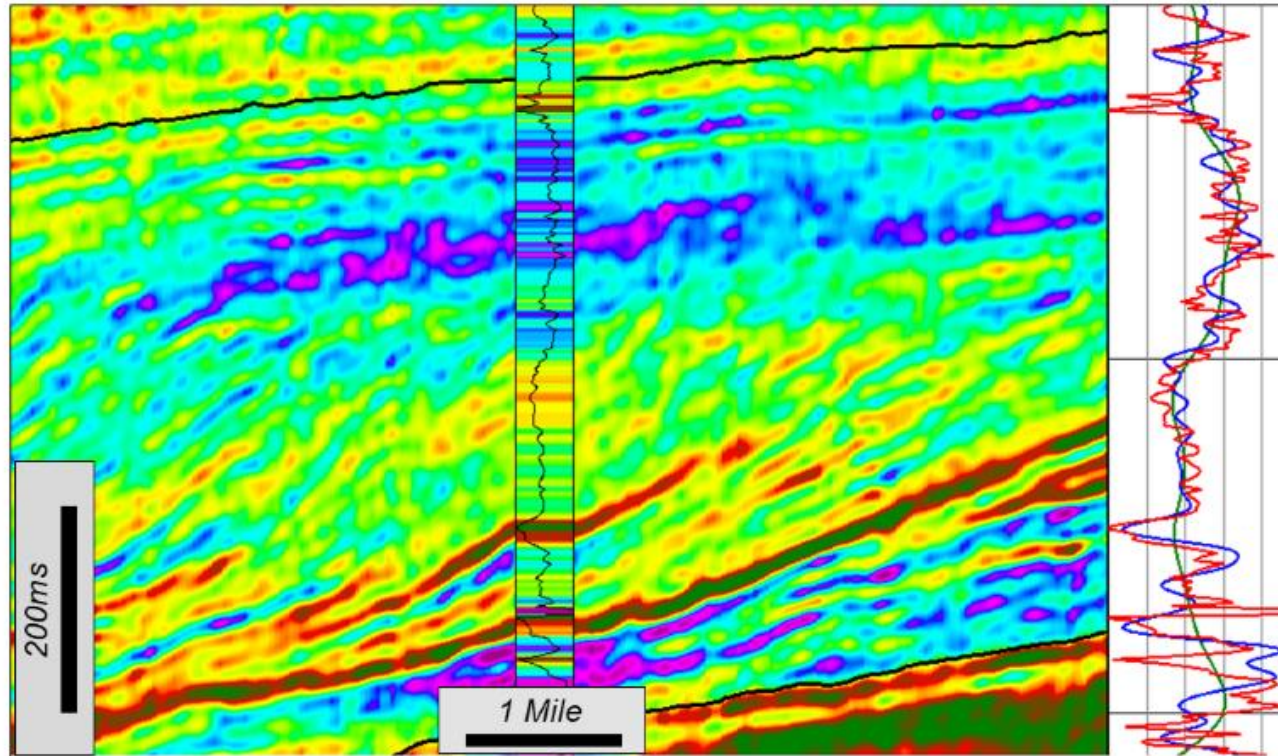
- Post-Stack Inversion QC on the Well #1. Correlation is 90%.



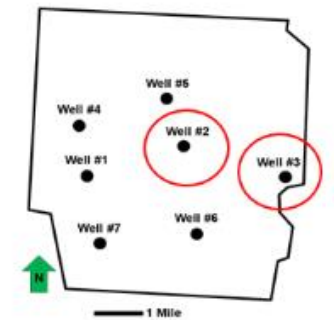
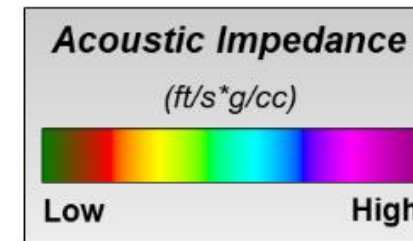
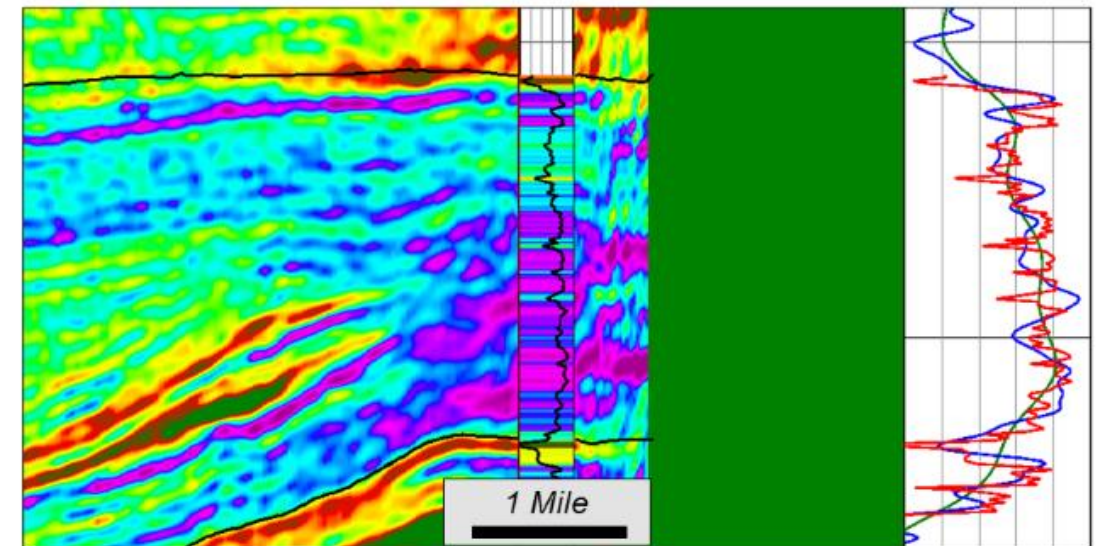
- Cross-plot between inverted ZP vs. Original Well log ZP

Post Stack Inversion - Result

Well #2



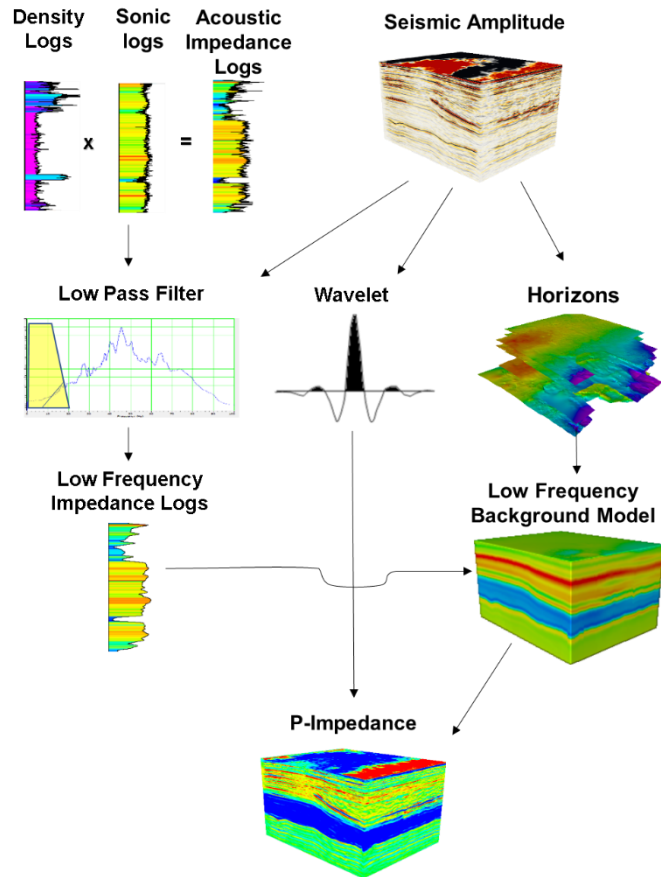
Well #3



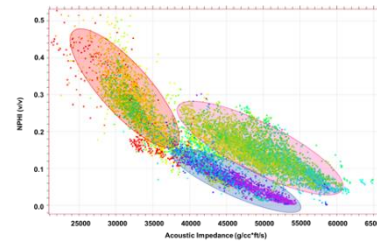
Methods

Supervised Bayesian Classification

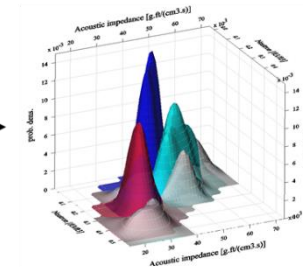
Post- Stack Inversion



Lithology Classification From Well Log Crossplots To Determine A Priori Proportions Of Lithology

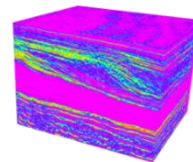


Creating Probability Distribution Functions From A Set of Training Points

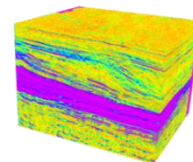


QC & Apply Probability Distribution Functions And A Priori Proportions To Full Seismic Volumes To Generate Probability Volumes And Most Probable Facies

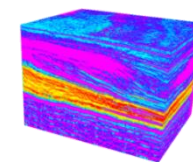
Calcite Probability



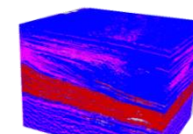
Dolomite Probability



Shale Probability

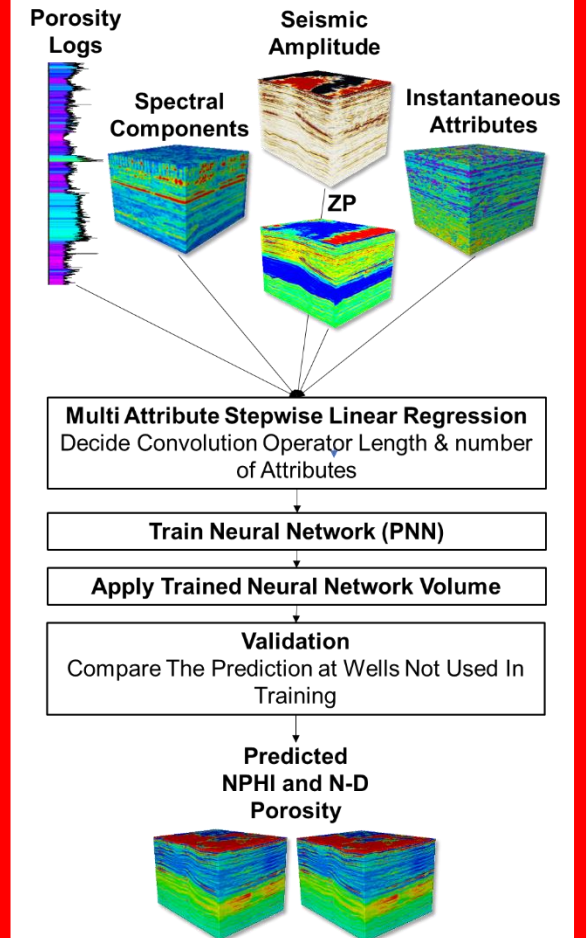


Lithology Cube

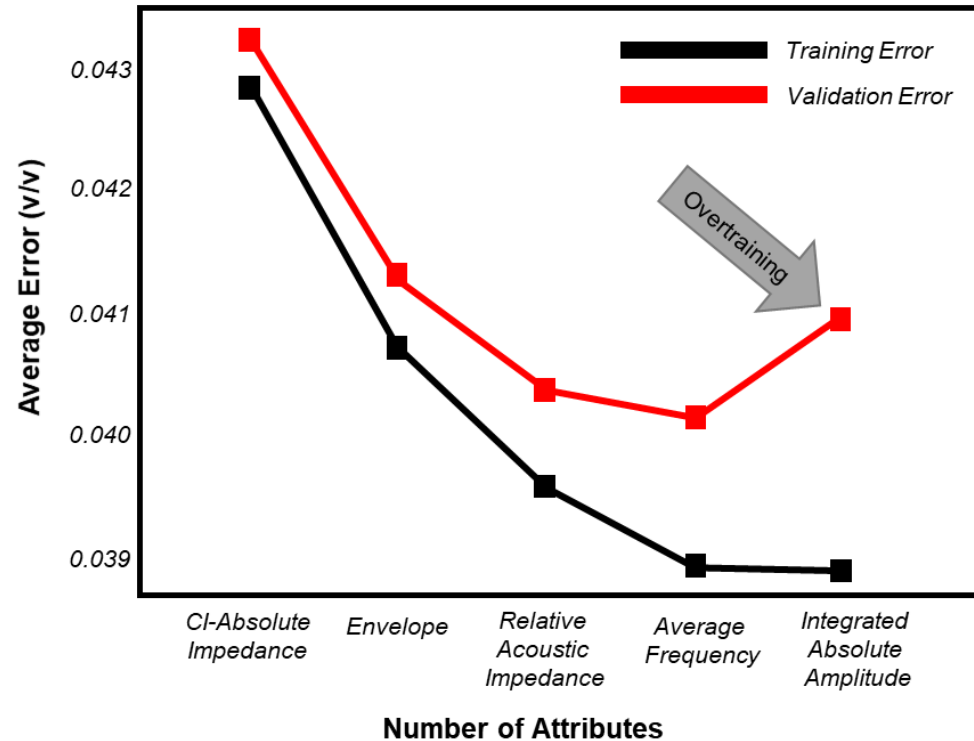


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Probabilistic Neural Network (PNN)



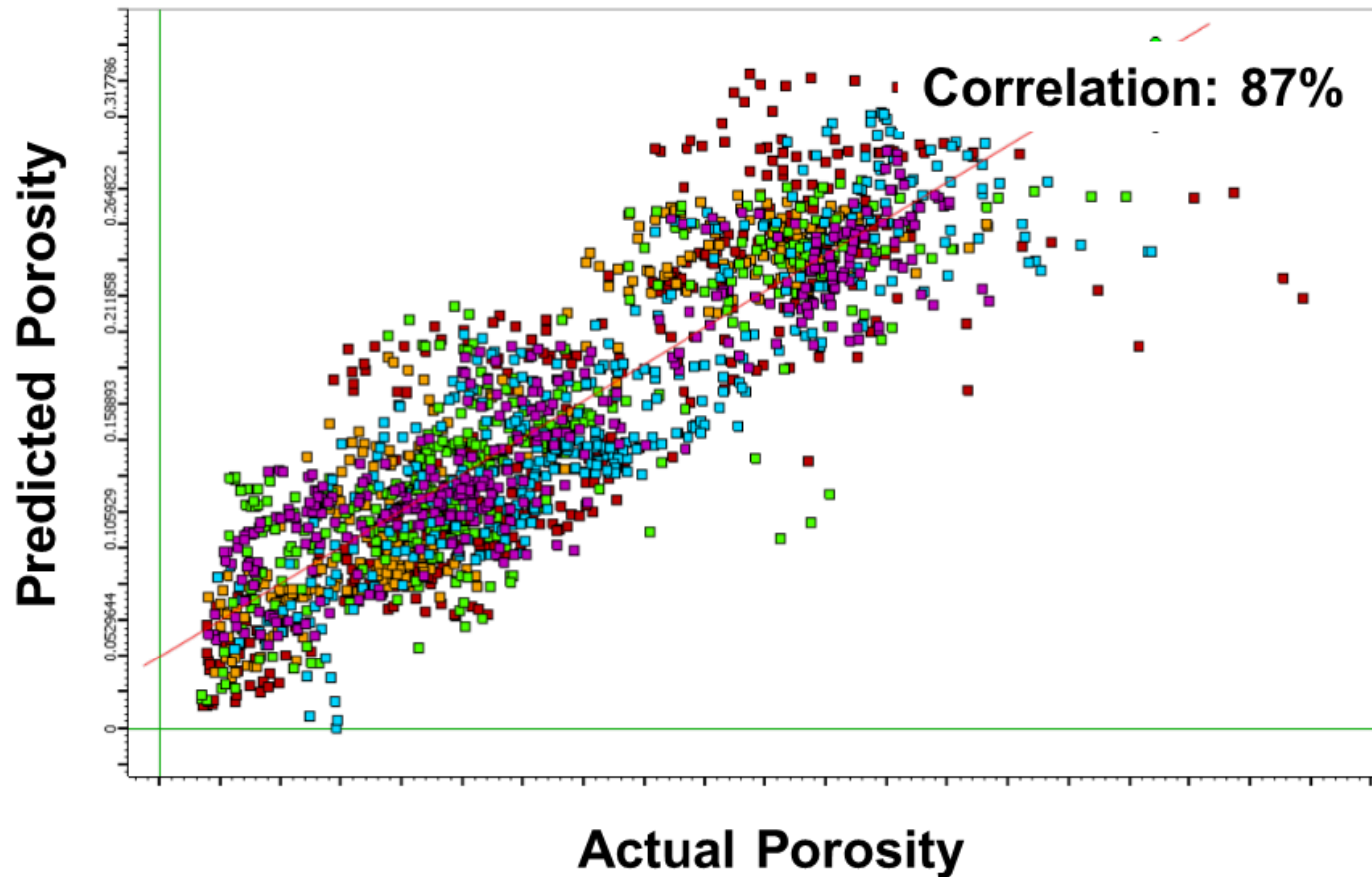
PNN for NPHI Volume Estimation - Training



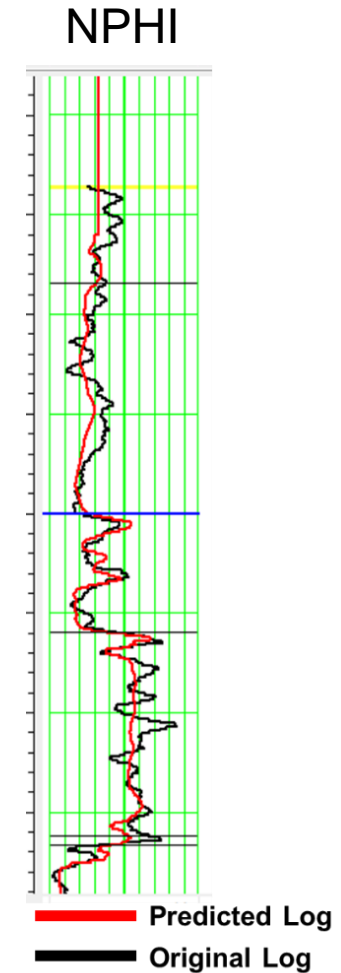
Target	Final Attribute	Training Error (v/v)	Validation Error (v/v)
Neutron Porosity	Colored Inversion-Absolute Impedance	0.046053	0.047575
Neutron Porosity	Envelope	0.040881	0.042741
Neutron Porosity	Relative Acoustic Impedance	0.039697	0.042486
Neutron Porosity	Average Frequency	0.039299	0.042381

- Selection of optimum number of attributes is crucial for having the minimum validation error. Adding more attributes can cause “Overtraining”
- Next step is to train the Probabilistic Neural Network (PNN) with the given the set of attributes. This process tries to produce non-linear regression between set of attributes and the target log

PNN for NPHI Volume Estimation - Validation

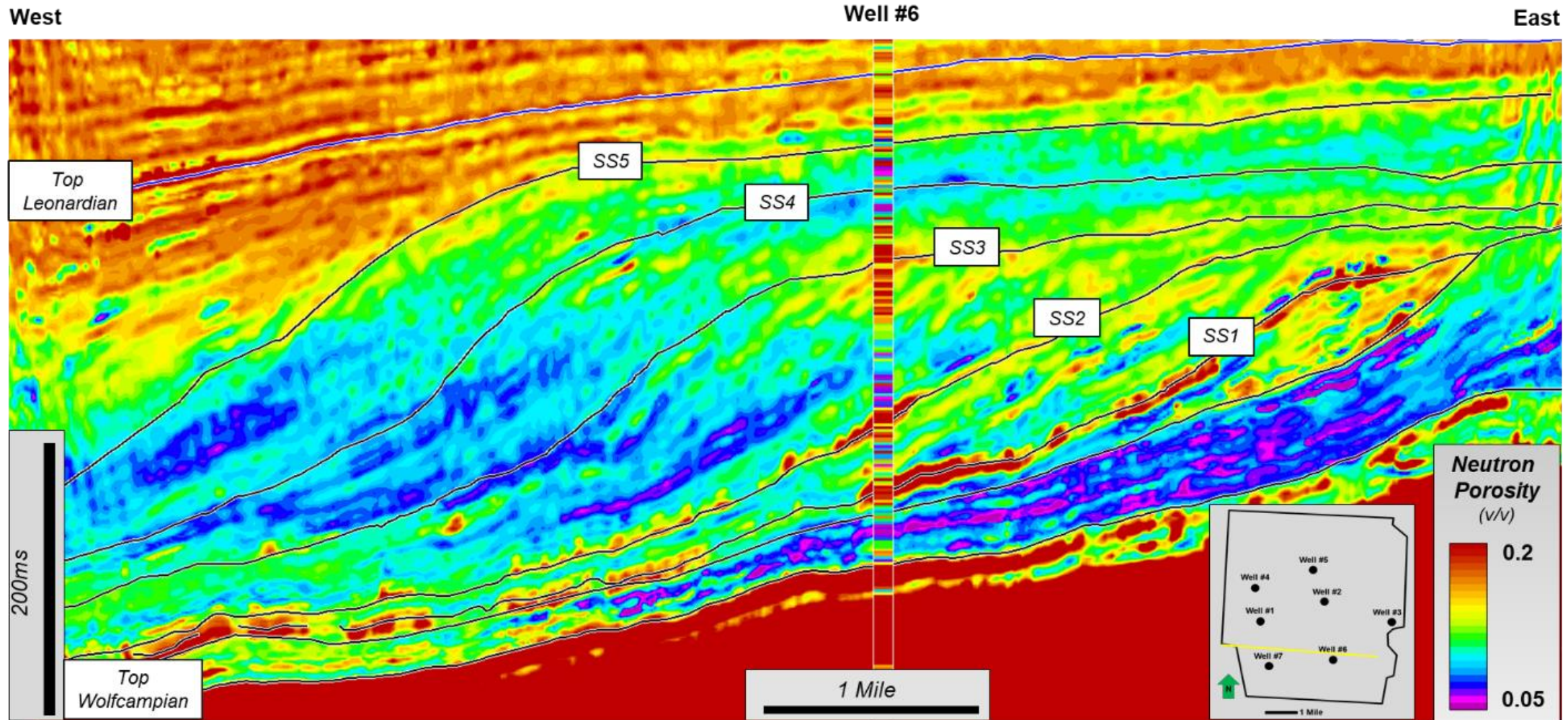


- Cross-plot of predicted and actual porosity shows 87% correlation .



- Validation of the Neural Network result at the "blind well"

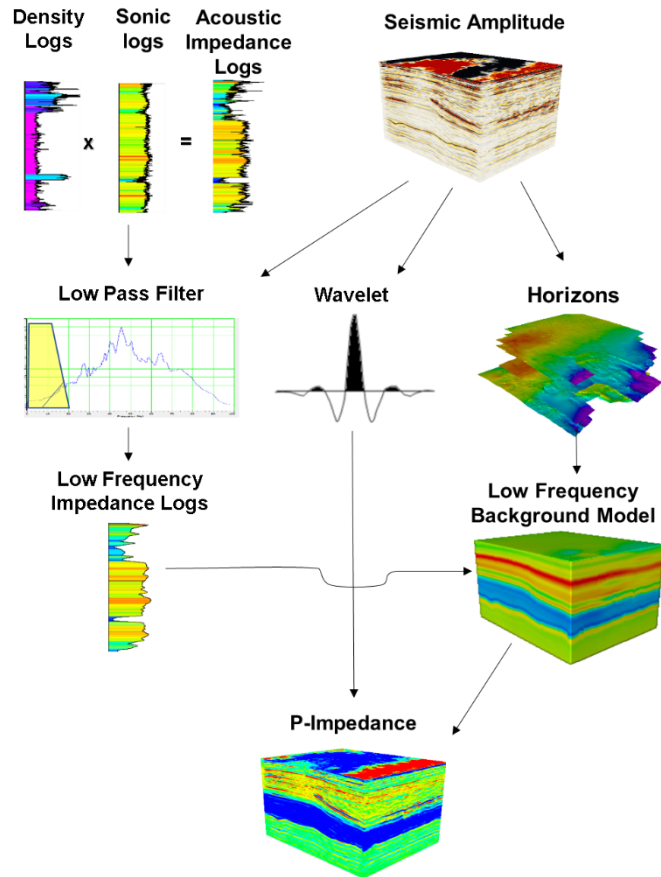
PNN for NPHI Volume Estimation - Results



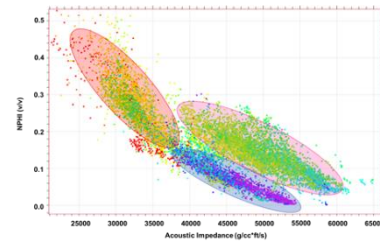
Methods

Supervised Bayesian Classification

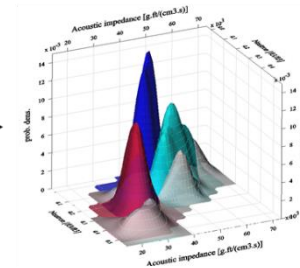
Post- Stack Inversion



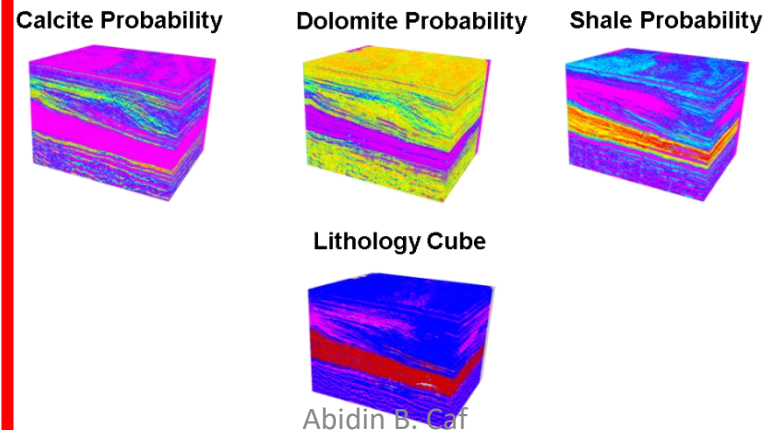
Lithology Classification From Well Log Crossplots To Determine A Priori Proportions Of Lithology



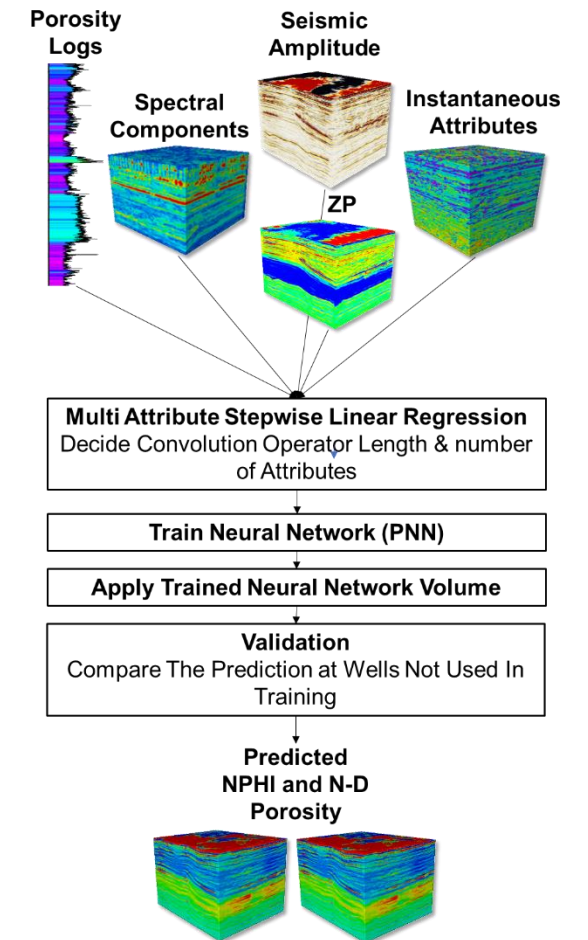
Creating Probability Distribution Functions From A Set of Training Points



QC & Apply Probability Distribution Functions And A Priori Proportions To Full Seismic Volumes To Generate Probability Volumes And Most Probable Facies

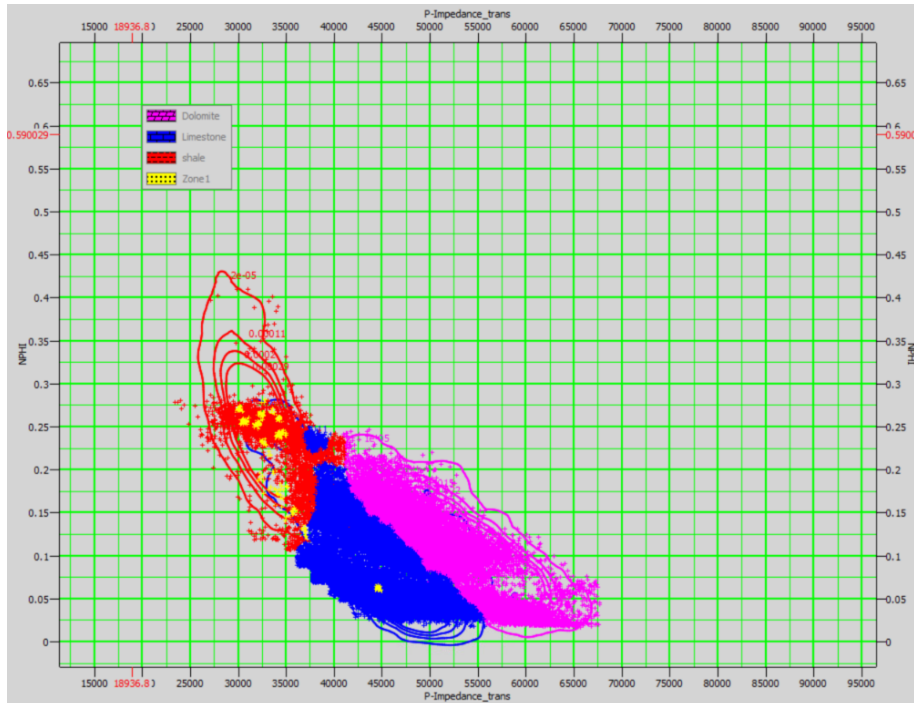


Probabilistic Neural Network (PNN)



Supervised Bayesian Classification - QC & Application

Seismic volume PDF's overlapped on well log PDF's



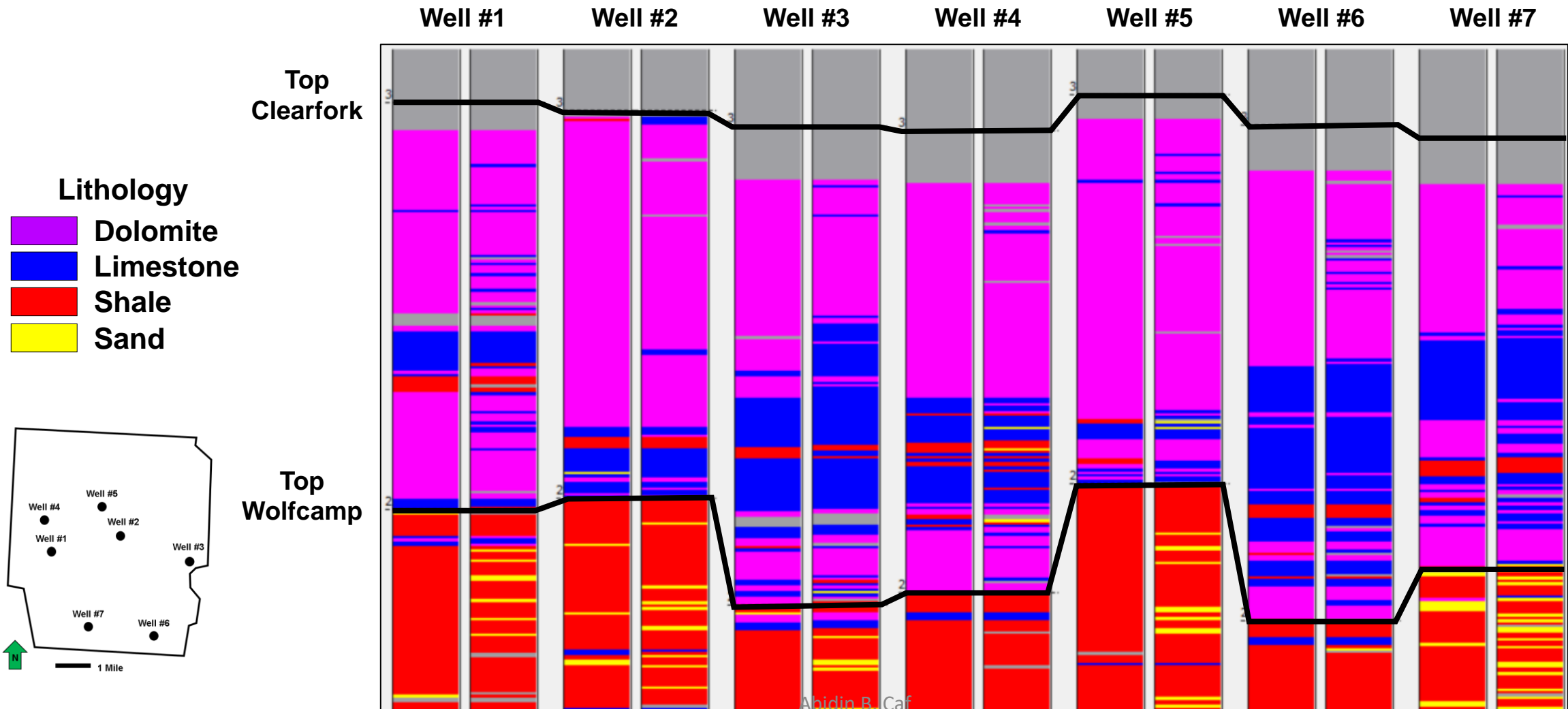
Confusion Matrix

		Classified Log			
Litho-Log		Dolomite	Limestone	Shale	Sand
	Dolomite	87.53%	12.47%	0.00%	0.00%
	Limestone	7.12%	86.89%	4.49%	1.50%
	Shale	0.13%	1.04%	85.45%	13.38%
	Sand	0.00%	3.33%	80.00%	16.7%

- Confusion matrix shows the match between the lithology from well logs and the predicted lithology
- It provides a key QC for the prediction of the lithology by answering the question, “How often we correctly classify limestone as limestone (86.89%) or misclassify the limestone as dolomite? (7.12%)
- Note that sand is poorly predicted and often misclassified as shale (80.00%)

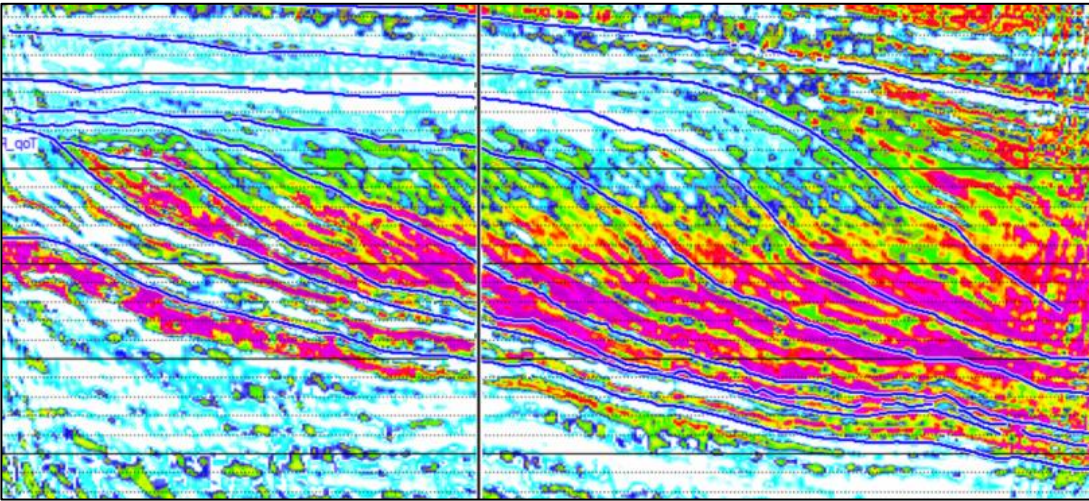
Supervised Bayesian Classification - QC & Application

Lithology logs (left) vs. estimated lithologies extracted from well locations (right)

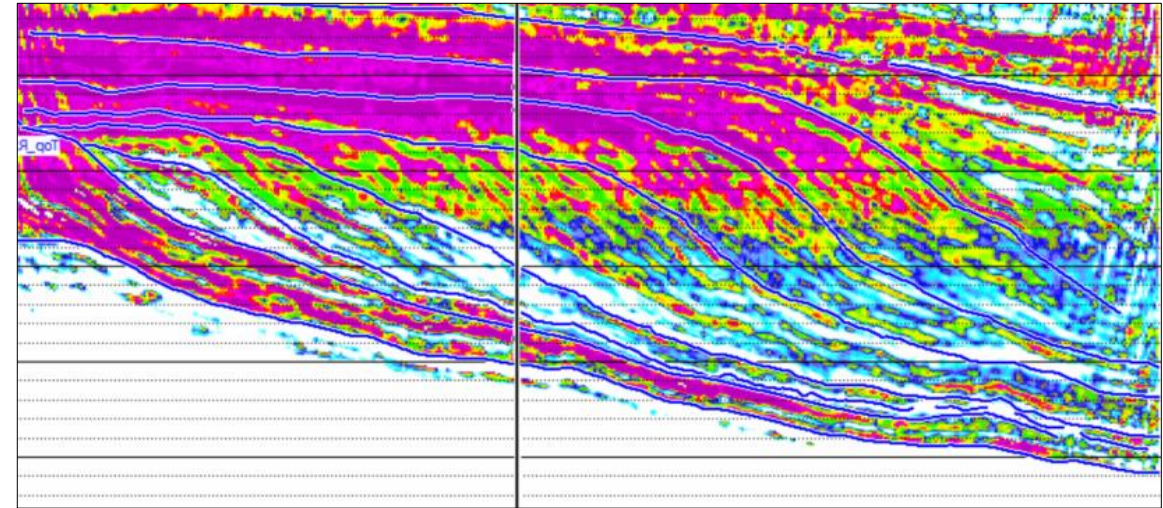


Supervised Bayesian Classification - Results

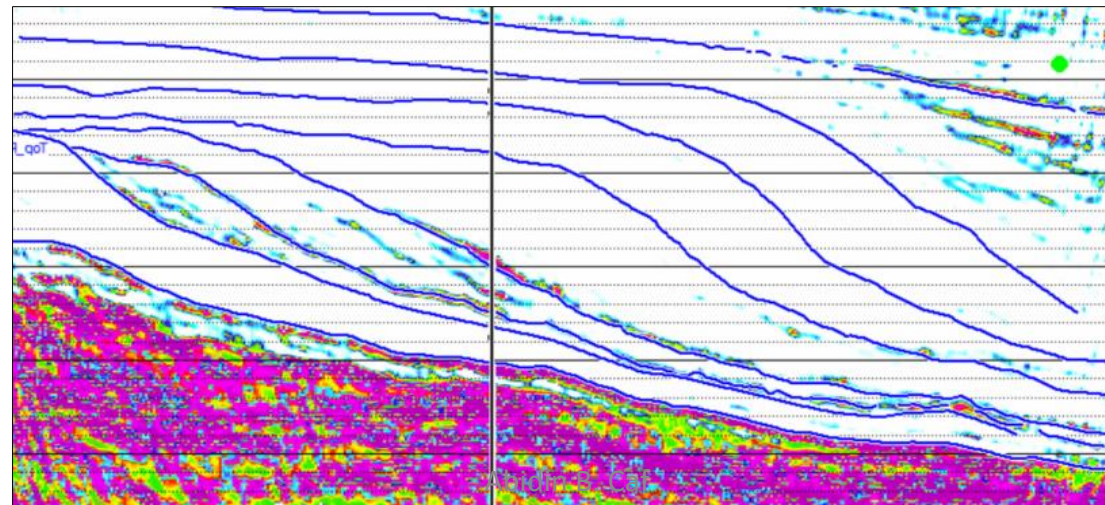
Probability of Limestone



Probability of Dolomite



Probability of Shale

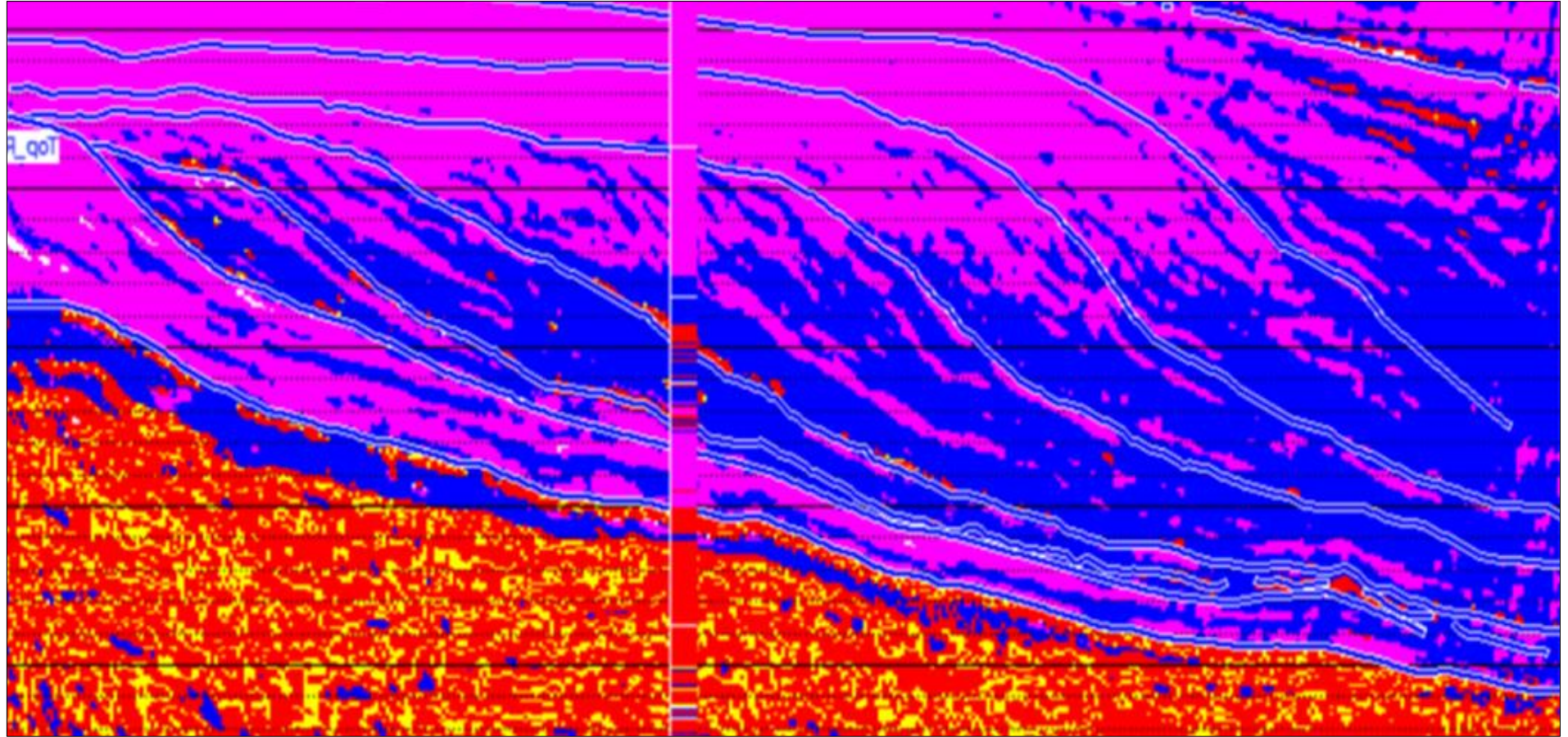


Probability (%)



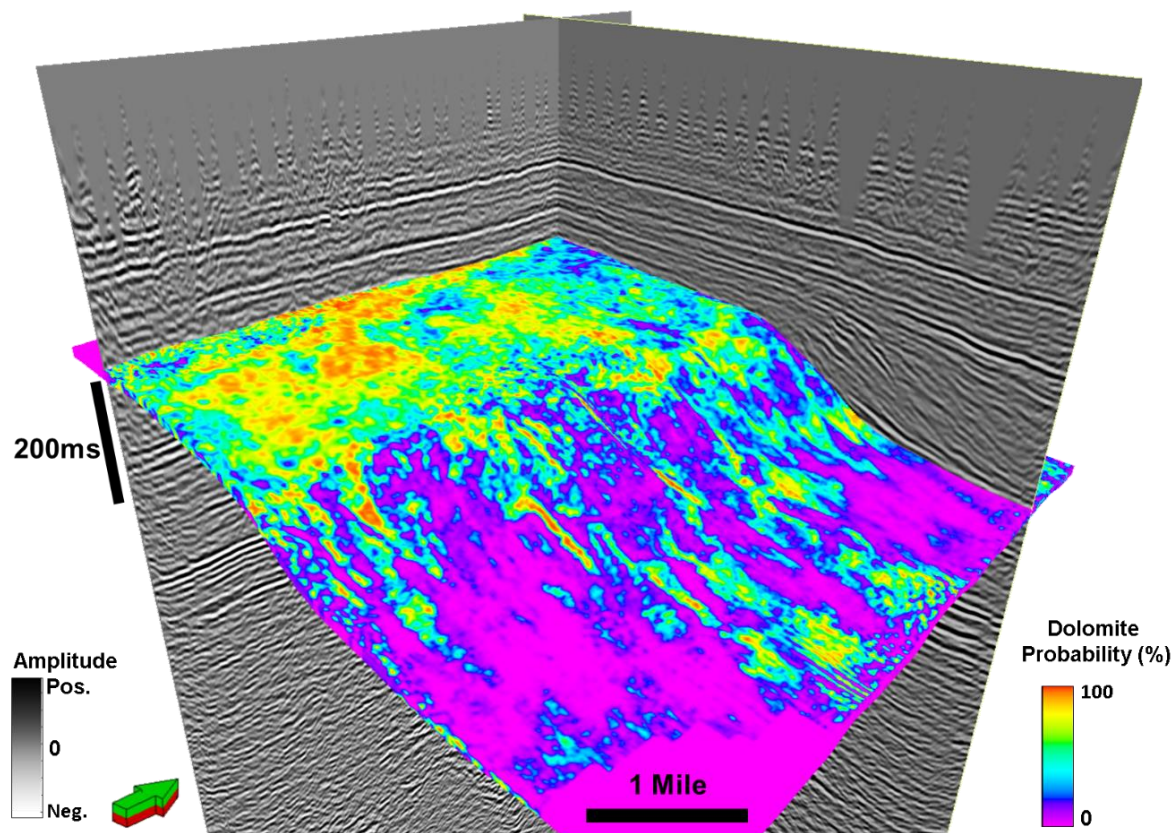
Supervised Bayesian Classification - Results

Most Probable Lithology



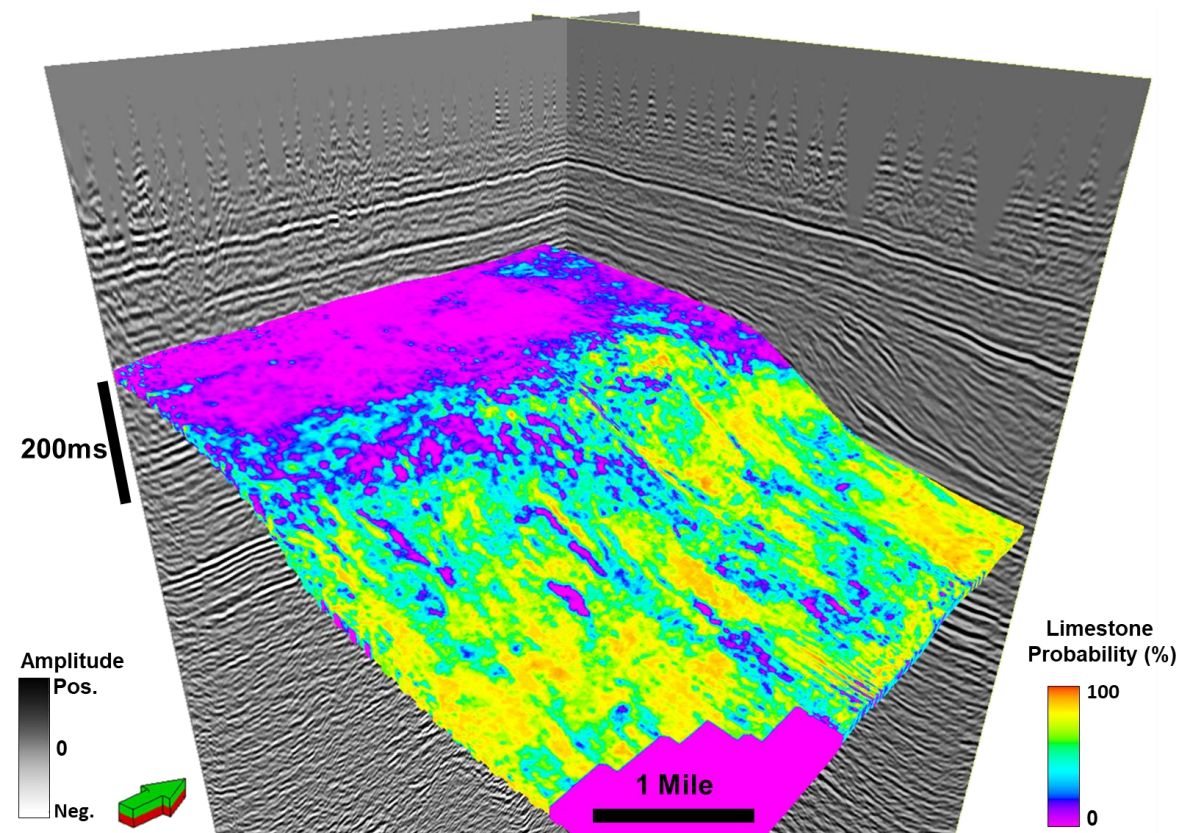
Interpretation and Discussion

Dolomite Probability



- Dolomite Probability extracted on the Middle Clearfork interval. Note the decreasing dolomite probability from shelf to slope.

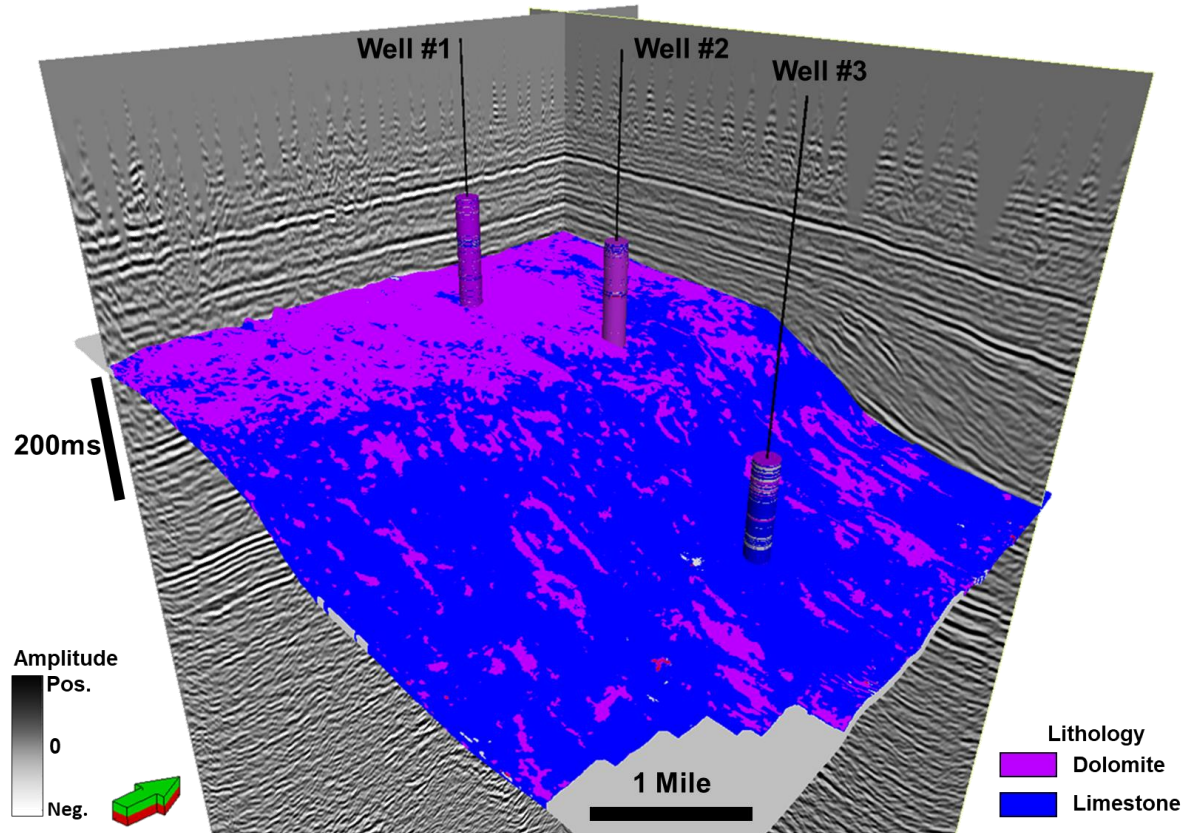
Limestone Probability



- Limestone Probability extracted on the Middle Clearfork interval. Note the Increasing Limestone probability from shelf to slope.

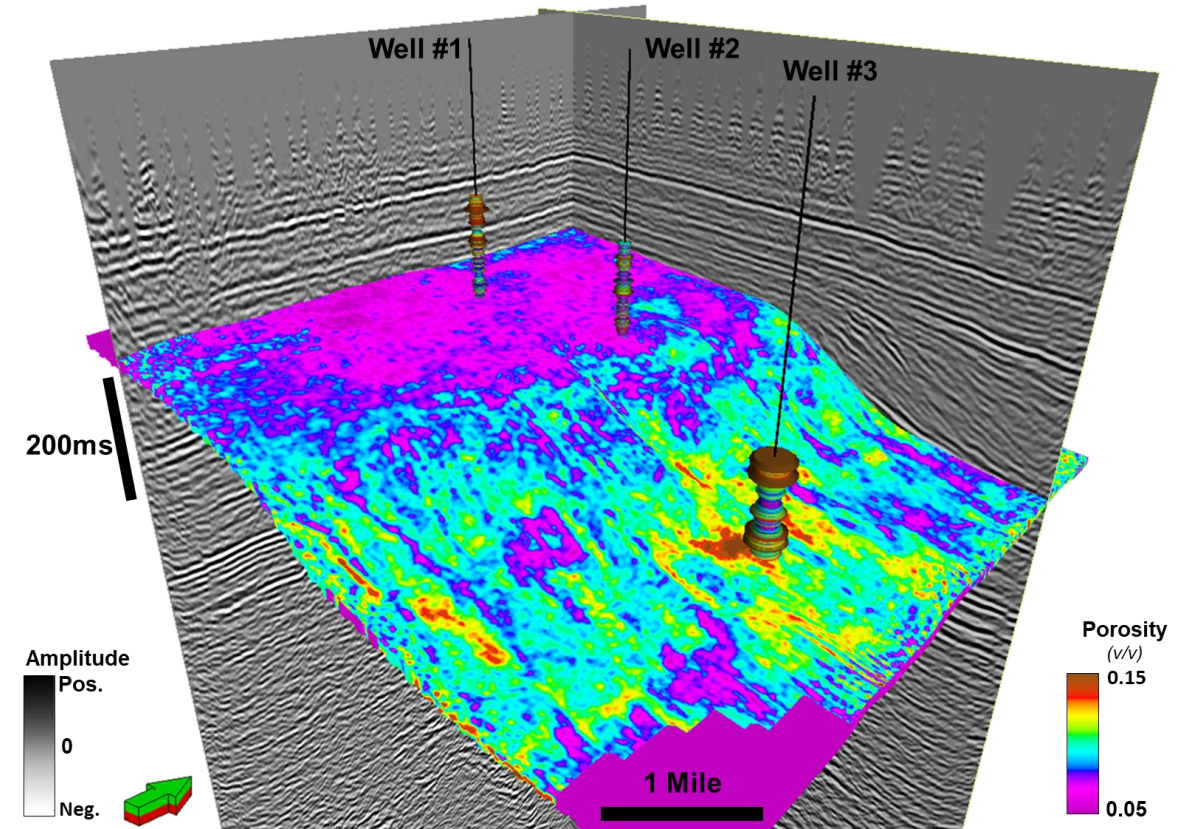
Interpretation and Discussion

Predicted lithology



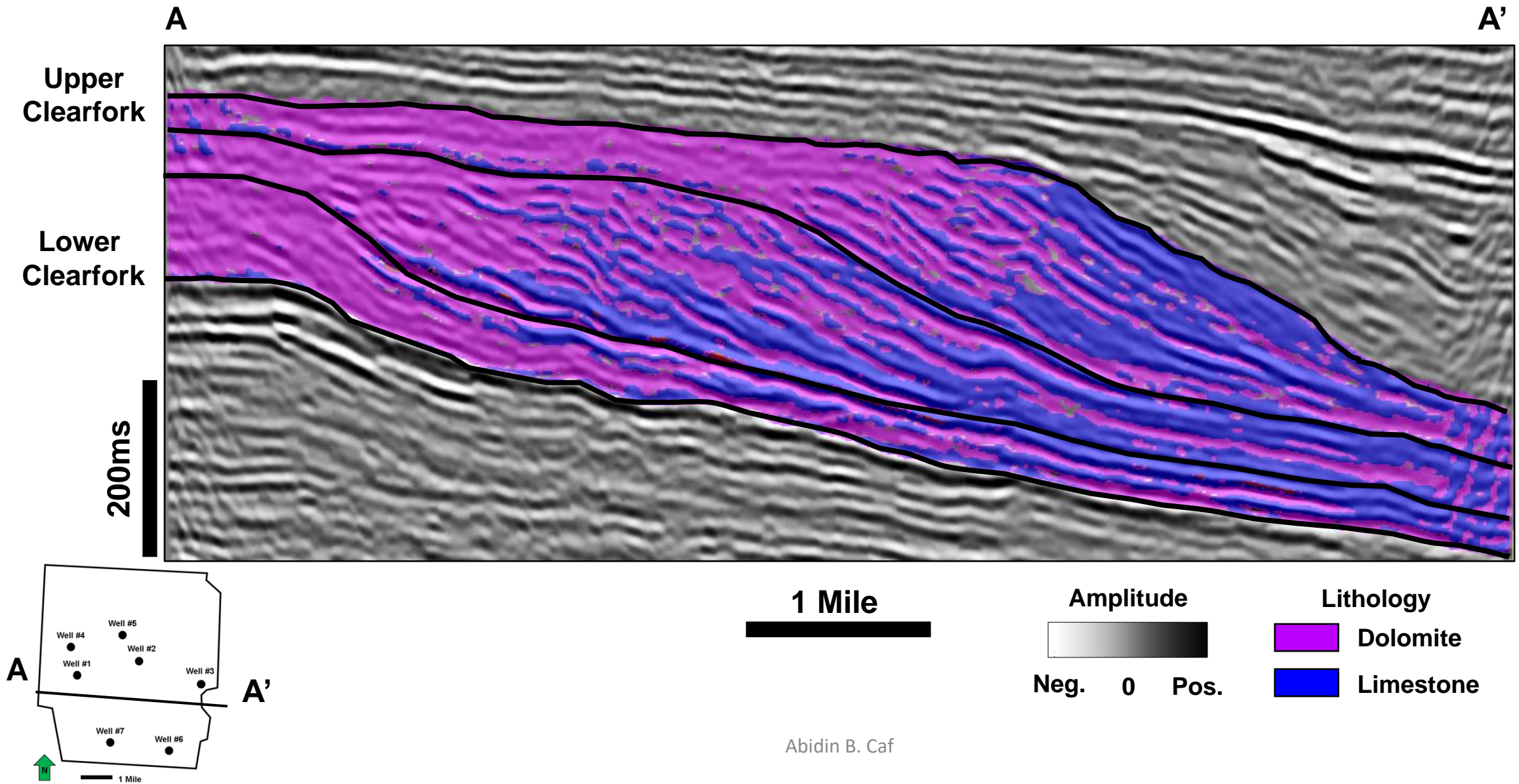
- Predicted lithology extracted from the Middle Clearfork Interval. Platform is dolomitized, while shelf and slope are remained calcitic.

Total Porosity

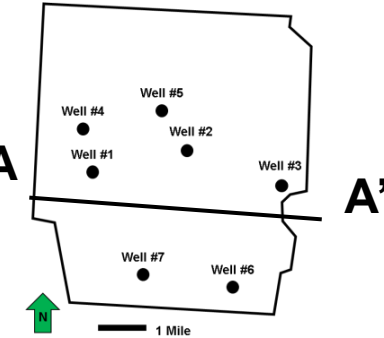
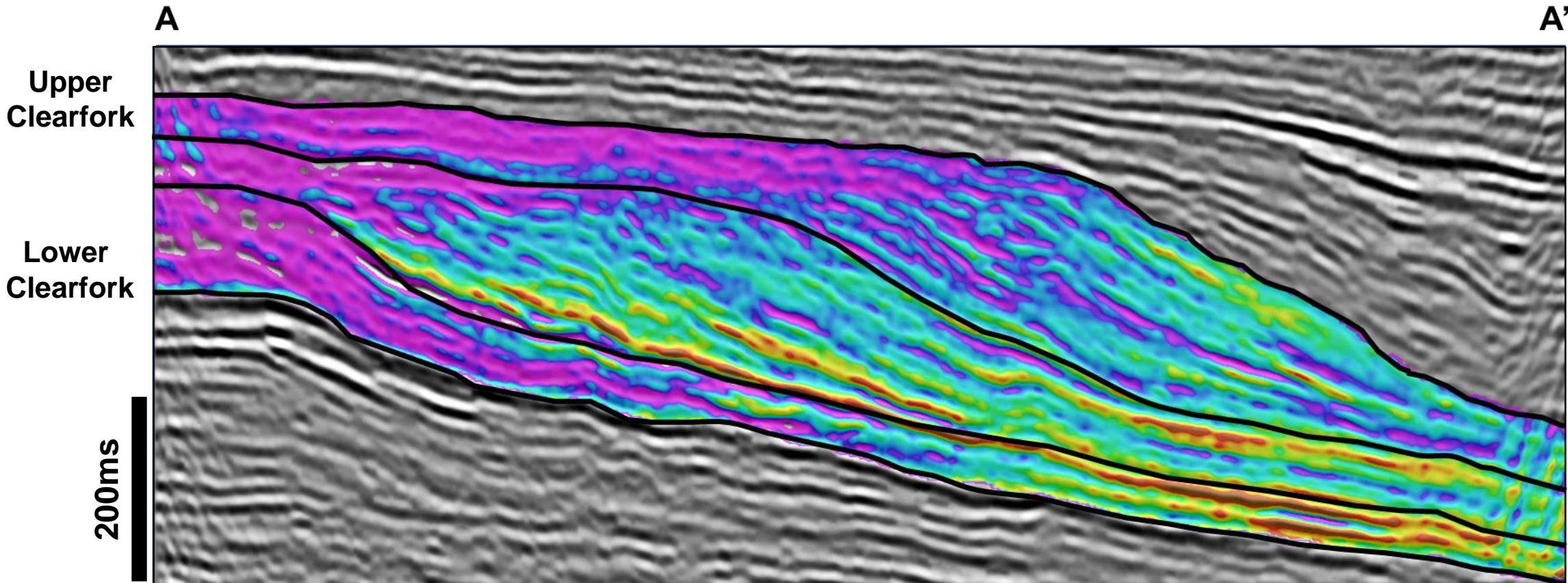


- Predicted total porosity extracted on the Middle Clearfork interval. Porosity increases from shelf to slope.

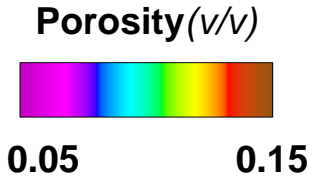
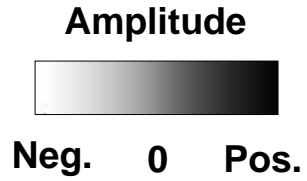
Interpretation and Discussion



Interpretation and Discussion

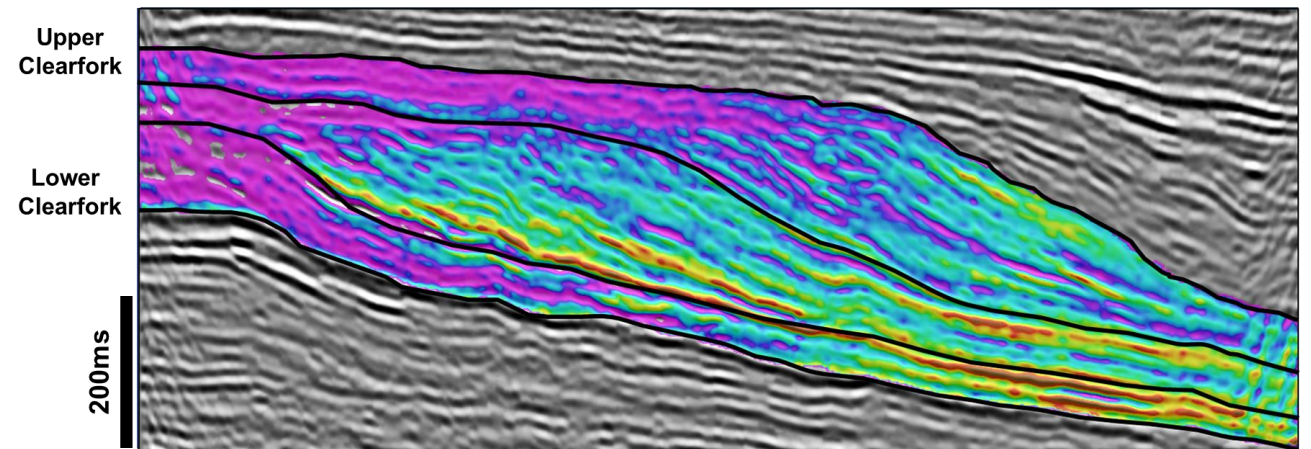
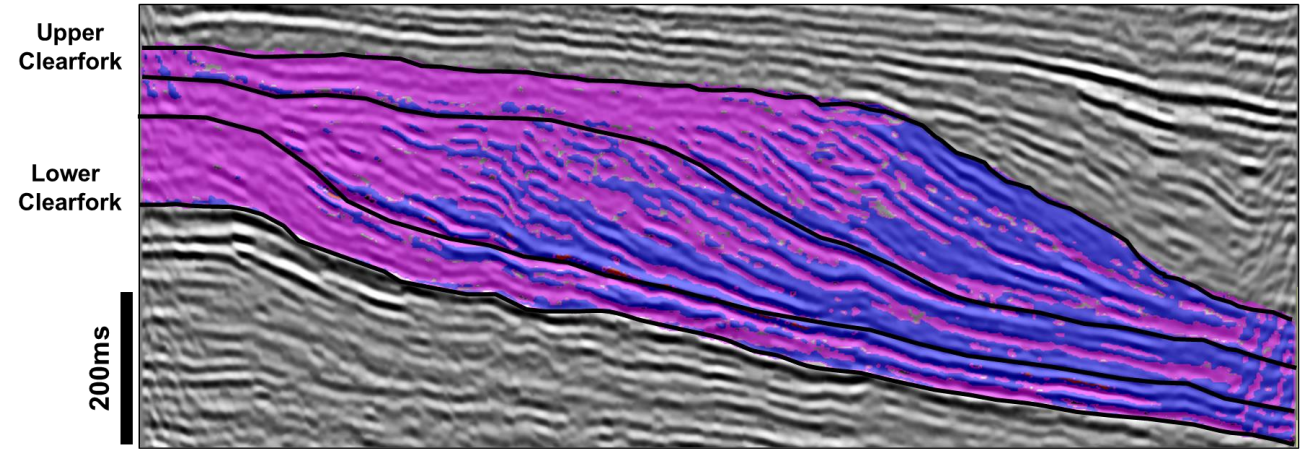
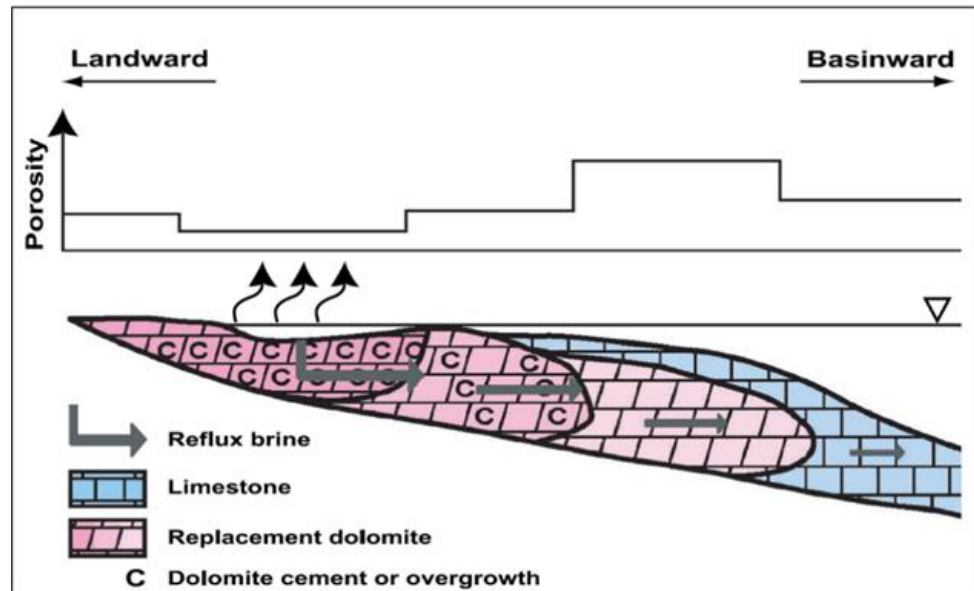
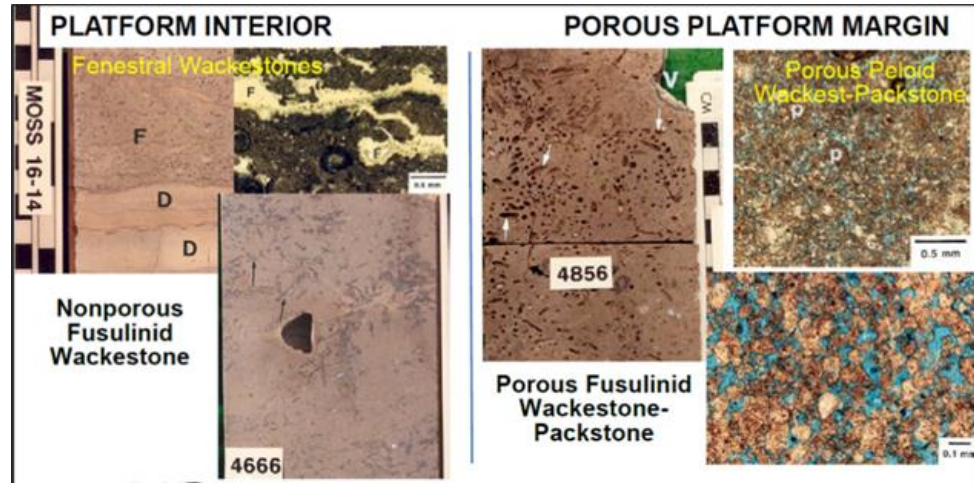


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Abidin B. Caf

Interpretation and Discussion



(Modified after Jones et al., 2005 and Saller, 2013). Abidin B. Caf

Conclusions and Future Work

- Integration of Supervised Bayesian Classification and Probabilistic Neural Network (PNN) study in the Midland Basin showed that the dolomitization and corresponding reservoir quality can be extracted from seismic data.
- Results tie with the regional Reflux Dolomitization model, in which the porosity is increasing from shelf to slope, while dolomitization is decreasing.
- For the next step in this study, CDP gathers will be utilized to perform pre-stack inversion. Additionally, Results of this study will be compared to unsupervised classification methods.

THANK YOU!!

Questions?

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References

- Mazullo, S., J., 1994, Dolomitization of periplatform carbonates (Lower Permian, Leonardian), Midland basin, Texas, *Carbonates and Evaporites*, 1994, 9, 1, 95.
- Nieto et al., 2013, *Seismic Lithology Prediction: A Montney Shale Gas Case Study*, CSEG Recorder Special Edition, 2013.
- Saller, A. H., and N. Henderson, 1998, Distribution of porosity and permeability in platform dolomites: Insight from the Permian of west Texas: AAPG Bulletin, v. 82, p. 1528– 1550
- Russell, B., Hampson, D., Bankhead, B., 2006, An inversion primer, CSEG Recorder Special Edition, no. 1, 96-103.
- Saller, A. & Dickson, J., 2011, Partial dolomitization of a Pennsylvanian limestone buildup by hydrothermal fluids and its effect on reservoir quality and performance. AAPG Bulletin. 95.
- Saller, A., 2014, Late Pennsylvanian and Early Permian Sedimentation on the Central Basin Platform and Implications to the Wolfberry Deposition in the Western Midland Basin, APG 2014 Southwest Section Annual Convention, Midland, Texas, May 11-14, 2014
- Verma, S., 2015, Seismic data conditioning for quantitative interpretation of unconventional reservoirs, Ph.D. dissertation, University of Oklahoma, Norman, Oklahoma.
- Xiao, Y., Jones, G., D., 2015, Dolomitization, anhydrite cementation, and porosity evolution in a reflux system: Insights from reactive transport models. *AAPG Bulletin* ; 89 (5): 577–601.