

PS Black Shale Lithofacies Identification and Distribution Model of Middle Devonian Intervals in the Appalachian Basin*

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Search and Discovery Article #10410 (2012)**

Posted June 25, 2012

*Adapted from poster presentation at AAPG Annual Convention and Exhibition, Long Beach, California, April 22-25, 2012

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Abstract

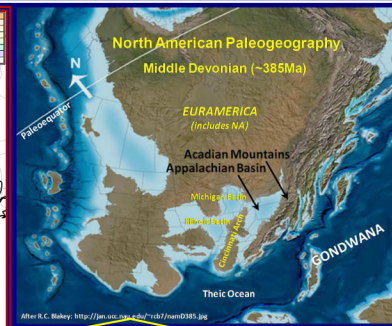
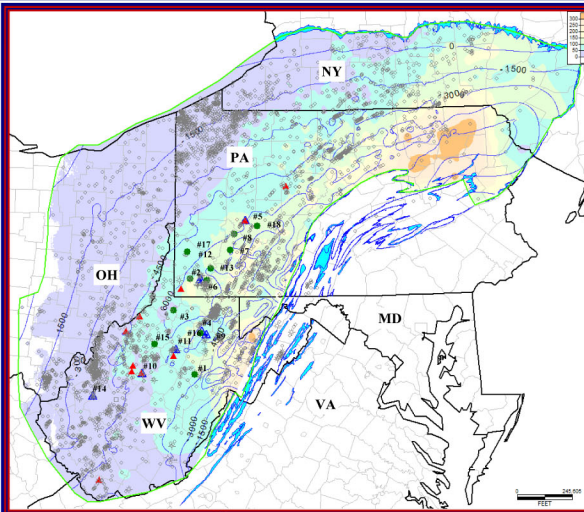
The Marcellus Shale, a marine organic-rich shale deposited during Middle Devonian in the Appalachian Basin, is considered the largest unconventional shale-gas resource in the United States. Two critical factors for shale-gas reservoirs are units amenable to hydrologic fracture stimulation, and high free and adsorbed gas content. The effectiveness of hydrologic fracture stimulation is influenced by rock geomechanical properties, which are related to rock mineralogy. The natural gas content in shale reservoirs has a strong relationship with organic matter, which is measured by total organic carbon (TOC).

For this study in the Appalachian Basin, a 3D shale lithofacies model was constructed using mineral composition, rock geomechanical properties and TOC content. This model could be applied to optimize the design of horizontal well trajectories and stimulation strategies. Core analysis data, log data and seismic data were used to build a 3D shale lithofacies model from core scale to well scale and finally to regional scale. Artificial neural network (ANN) was used for lithofacies prediction. Core XRD and chemical analysis data, and wireline logs were utilized as inputs and target outputs to petrophysical analysis and various pattern recognition methods. A limited set of eight derived parameters from common logs were determined as critical inputs. Advanced logs such as elemental capture spectroscopy (ECS) with mineral composition and TOC data were used to improve and confirm the quantitative relationship between common logs and lithofacies. Seismic data, and interpreted sequence stratigraphy and depositional environments were used as soft data to constrain deterministic and stochastic 3D lithofacies models.

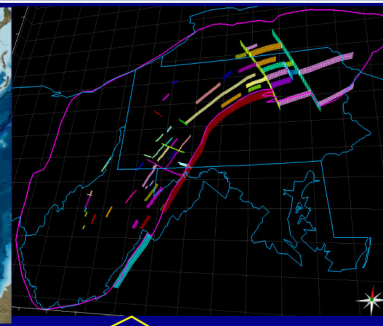
Abstract

The Marcellus Shale, marine organic-rich shale deposited during Middle Devonian in the Appalachian basin, is considered the largest unconventional shale-gas resource in US. Two critical factors for shale-gas reservoirs are units amenable to hydrologic fracture stimulation and high free and adsorbed gas content. The effectiveness of hydrologic fracture stimulation is influenced by rock geomechanical properties, which are related to rock mineralogy. The natural gas content in shale reservoirs has a strong relationship with organic matter, which is measured by total organic carbon (TOC). For a study in the Appalachian basin, a 3D shale lithofacies model is constructed using mineral composition, rock geomechanical properties and TOC content. This model could be applied to optimize the design of horizontal well trajectories and stimulation strategies. Core analysis data, log data and seismic data were used to build a 3D shale lithofacies model from core scale to well scale and finally to regional scale. Artificial neural network (ANN) was used for lithofacies prediction. Core XRD and chemical analysis data and wireline logs were utilized as inputs and target outputs to petrophysical analysis and various pattern recognition methods. A limited set of eight derived parameters from common logs were determined as critical inputs. Advanced logs such as pulsed neutron spectroscopy (PNS) with mineral composition and TOC data were used to improve and confirm the quantitative relationship between common logs and lithofacies. Seismic data, and interpreted sequence stratigraphy and depositional environments were used as soft data to constrain deterministic and stochastic 3D lithofacies models.

Geologic Background



The Appalachian basin was a foreland basin during Middle Devonian, formed by the Acadian orogeny. This figure shows the North America paleogeography during Middle Devonian. (After Blakey, 2010)



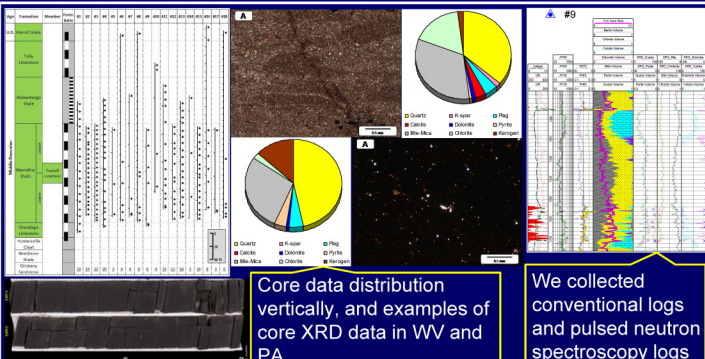
Faults model of the Middle Devonian formations in the Appalachian basin based on wireline logs and 3D seismic volumes

Sys-tem	Ohio	N. Virginia and West Virginia	Western Maryland	Western Pennsylvania	Northwestern New York
Middle Devonian	<ul style="list-style-type: none"> Chazy Shale Plum Brook Shale Delaware Limestone Columbus Limestone Boss Blanc Limestone 	<ul style="list-style-type: none"> Harrell Shale Tully Limestone Mahantango Formation Marcellus Shale Hunterville Shale Needmore Shale 	<ul style="list-style-type: none"> Harrell Shale Mahantango Formation Marcellus Shale Needmore Shale 	<ul style="list-style-type: none"> Genesee Fm. Tully Limestone Mahantango Formation Marcellus Shale Selkroge Limestone Needmore Shale 	<ul style="list-style-type: none"> Genesee Fm. Tully Limestone Mahantango Formation Marcellus Shale Chautauque Limestone Onondaga Limestone Rocky Mountain Fm.
Lower Dev.					

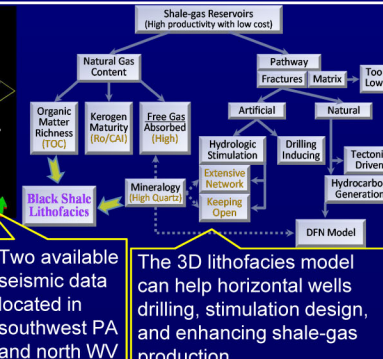
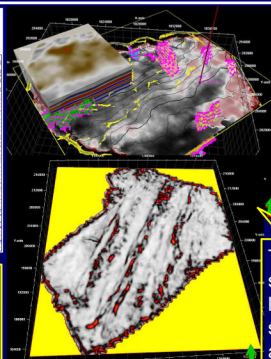
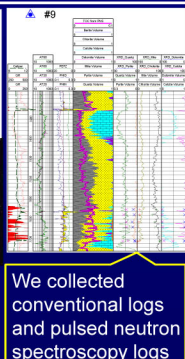
Stratigraphy of Middle Devonian formations, Appalachian basin (Milici and Swezey, 2006).

Map showing study area, the location of more than 3800 wells with wire-line logs, seventeen wells with pulsed neutron spectroscopy (PNS) logs, and eighteen wells with core XRD and TOC data. The gray circle indicates the well having common logs; the green-filled circle implies the well with core XRD and TOC data; the red-filled triangle is the well with PNS logs; the blue-filled circle with triangle indicates the well with both core data and PNS log.

Available Data and Motivations

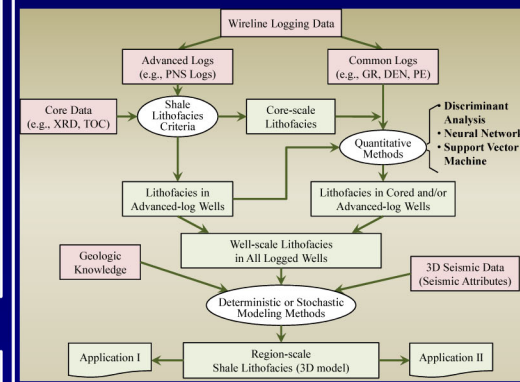


Core data distribution vertically, and examples of core XRD data in WV and PA



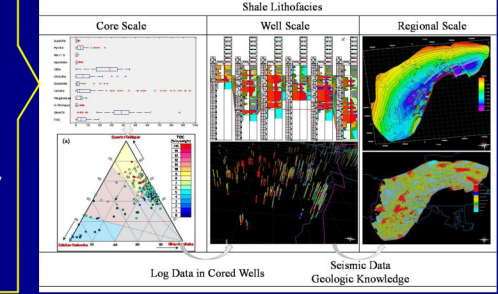
The 3D lithofacies model can help horizontal wells drilling, stimulation design, and enhancing shale-gas production.

Methodology

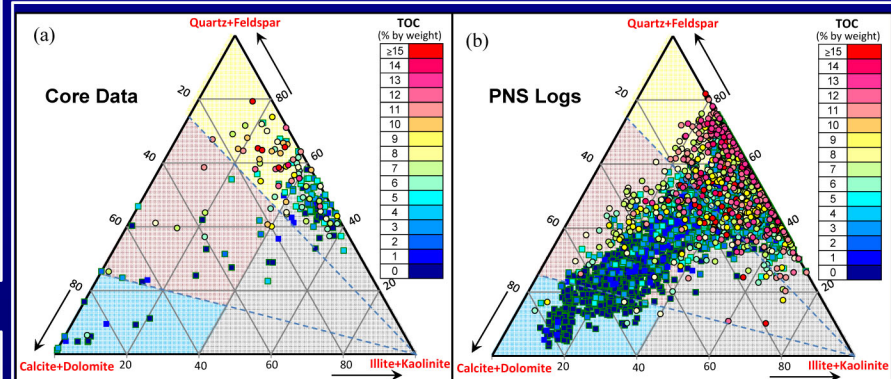


The proposed methodology to build 3D shale lithofacies models by integrating core XRD data, PNS logs and conventional wireline logs and seismic data. The mineral composition and the richness of organic matters are utilized to define Marcellus Shale lithofacies. Core and PNS logs are the basis of lithofacies research in core-scale and consists of the training data sets; the conventional logs and petrophysical analysis are used to predict shale lithofacies through quantitative methods; 3D lithofacies are built by predicted lithofacies and related data.

The experience from Barnett black shale indicates that the key for shale-gas reservoir characterization is to figure out units amenable to hydrologic fracture stimulation and containing rich of organic matters (Bowker, 2007). That is the engineering and geologic sweet spot. A shale lithofacies is a laterally and vertically continuous zone that possesses similar mineral composition and organic matters. The shale lithofacies should be *meaningful, predictable, and mappable*.

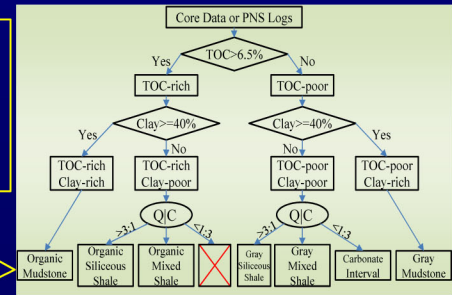


Marcellus Shale Lithofacies



Ternary plot showing the characteristics of mineral composition and organic matter richness and the classification method of Marcellus Shale lithofacies based on core data (a) and pulsed neutron spectroscopy logs (b). The organic-rich facies have TOC values (>6.5%) are indicated by the warmer colors.

The workflow showing the method to define Marcellus Shale lithofacies from core analysis data and PNS logs.



Black Shale Lithofacies Identification and Distribution Model of Middle Devonian Intervals in the Appalachian Basin



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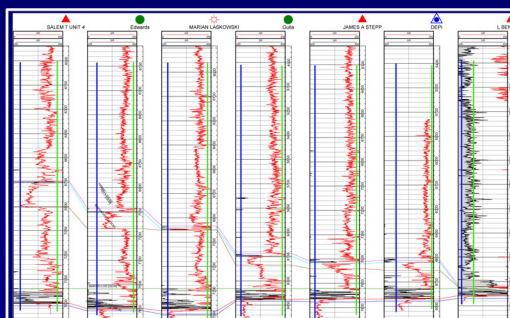


Marcellus Shale Lithofacies Features

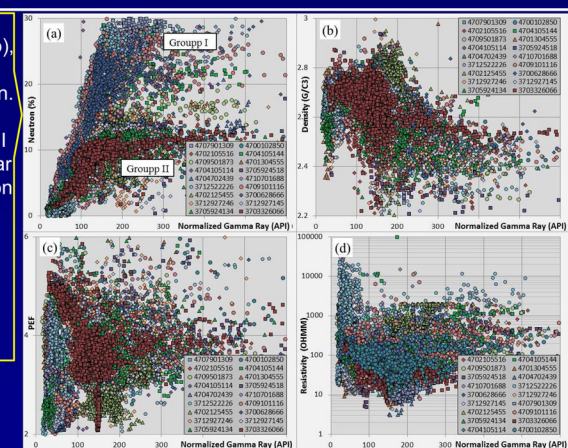
Petrophysical Analysis and Data Pre-processing for ANN

Lithofacies	Features of core data and pulsed neutron spectroscopy logs	Features of common logs					
		GR (API)	DEN (g/m3)	NEU (%)	RESD (ohmm)	PE	URAN (ppm)
Organic Siliceous Shale (OSS)	$TOC > 6.5\%$ (9.7); $V_{clay} < 40\%$ (25.6); $V_{quar}/V_{carb} > 3$	278~785 449	2.1~2.48 2.39	18.0~30.4 24.1	152~2505 854	2.7~7.9 3.5	20~80 40
Organic Mixed Shale (OMS)	$TOC > 6.5\%$ (9.6); $V_{clay} < 40\%$ (19.8); $1/3 < V_{quar}/V_{carb} < 3$	242~628 424	2.3~2.59 2.47	13.3~27.5 20.3	95~1475 450	3.3~6.3 4.3	18~73 34
Organic Mudstone (OM)	$TOC > 6.5\%$ (6.1); $V_{clay} > 40\%$ (47.6); $V_{quar}/V_{carb} > 3$	315~793 491	2.4~2.64 2.53	21.8~29.7 19.8	26~414 164	3.4~7.0 4.4	17~74 36
Gray Siliceous Shale (GSS)	$TOC < 6.5\%$ (4.0); $V_{clay} < 40\%$ (32.0); $V_{quar}/V_{carb} > 3$	115~277 193	2.4~2.62 2.59	15.5~24.1 19.8	20~241 94	2.8~4.8 3.5	2~14 8
Gray Mixed Shale (GMS)	$TOC < 6.5\%$ (2.5); $V_{clay} < 40\%$ (17.1); $1/3 < V_{quar}/V_{carb} < 3$	87~178 131	2.5~2.75 2.66	6.3~23.4 14.4	24~282 103	1.5~12 4.2	1~15 5.4
Gray Mudstone (GM)	$TOC < 6.5\%$ (1.5); $V_{clay} > 40\%$ (46.9); $V_{quar}/V_{carb} < 1/3$	139~229 209	2.4~2.70 2.60	17.2~27.7 22.6	19~121 56	3.3~5.5 3.8	2~15 8.1
Carbonate (CARB)	$TOC < 6.5\%$ (1.3); $V_{clay} < 40\%$ (5.6); $V_{quar}/V_{carb} < 1/3$	24~135 82	2.6~2.75 2.69	1.8~15.2 6.2	61~1432 636	3.9~5.1 4.7	0~7.7 3.1

A summary of characteristics of the seven Marcellus Shale lithofacies defined by core data and pulsed neutron spectroscopy logs.

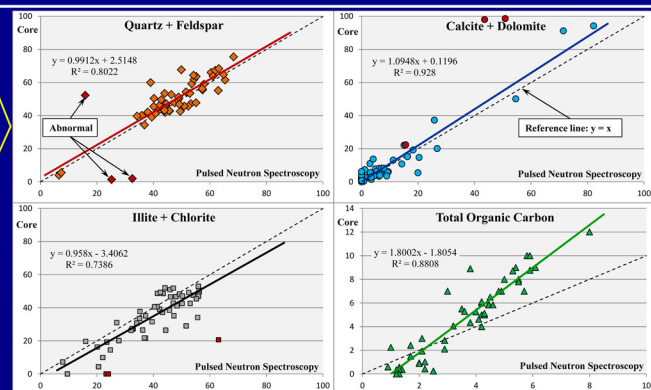


Cross-plots of gamma ray versus neutron (a), density (b), photo-electric (c) and deep resistivity (d) for normalization. There is obvious difference between Group I and Group II for neutron logs, which appear to be related to wells drilled on either air or water, and a scaling factor of 2.27 is utilized to convert Group II to Group I. The other logs are consistent enough and unnecessary to be normalized.



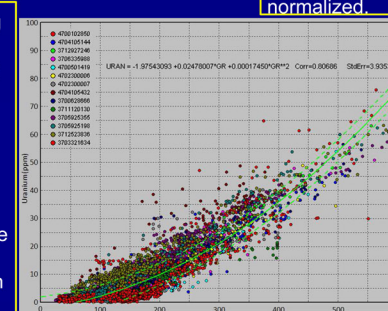
Relationship between Core XRD/TOC Data and PNS Logs

The estimated mineral composition and TOC content in PNS logs have strong relationships with core XRD and TOC data (Figure 9). The PNS logs tend to underestimate the percentage of quartz and carbonate but overvalue the clay content compared to core XRD data. The TOC content by Rock-Eval pyrolysis tool is approximate 1.8 times higher than that by PNS logs.

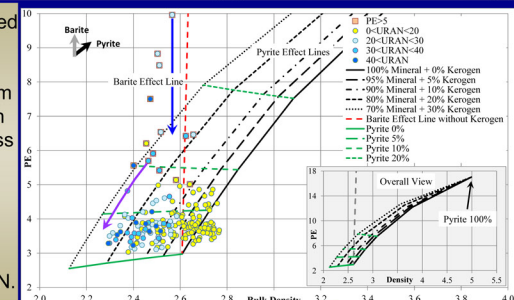


The gamma ray log showing the thick shale unit above Marcellus Shale (green line) and the underlying Onondaga Limestone (blue line). The Onondaga Limestone and the thick shale are the reference layers for GR log normalization. The green line shows the shale base line and the blue line is the clean limestone base line.

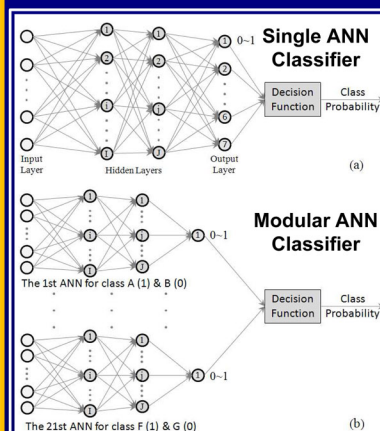
Plot showing the relationship between standard gamma ray and uranium concentration.



Eight recommended parameters for Marcellus Shale lithofacies: uranium concentration; Vsh (or shale brittleness index); RHOMaa; Umaa; average porosity; porosity difference; deep resistivity natural logarithm; GR/DEN.



Artificial Neural Network (ANN)

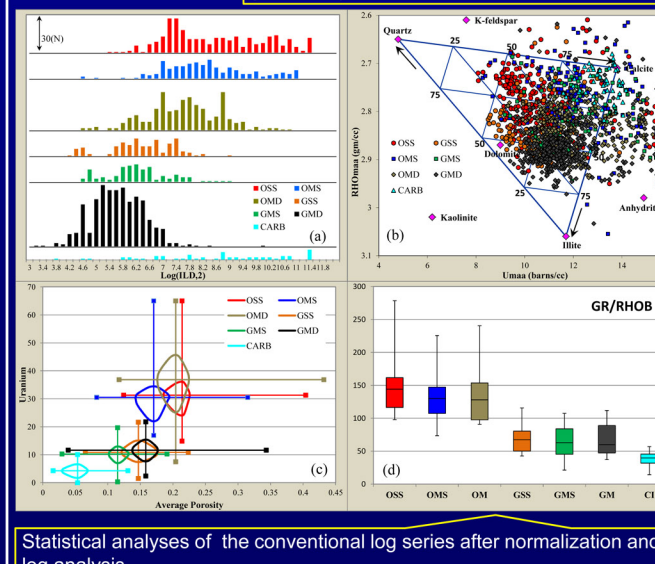


The architecture of an artificial neural network (ANN) for Marcellus Shale lithofacies prediction. (a) One single ANN with seven output nodes for the one-versus-the-rest method; (b) the modular ANN consisting of twenty-one binary ANN classifiers with one output node for the pairwise comparison method.

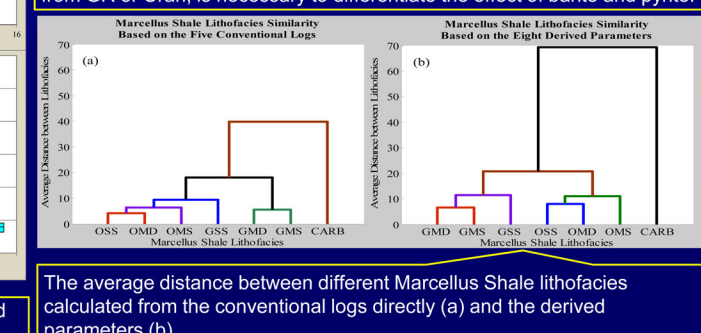
The ERRE matrix for Marcellus Shale lithofacies

$$ERRE = \frac{1}{n} \sum_{i=1}^n (|CM - DM| \times ERRE)$$

The improved NEAT for shale lithofacies prediction



The chart used to weakening or removing the effect of pyrite and barite. The pyrite effect lines are based on the fact that rock density and volumetric measurement are the arithmetic average of all minerals and kerogen weighted by their percentage (Doveton, 1994). Due to the extremely high PE value and low concentration of barite, the occurrence of barite has a negligible effect on rock density but strong effect on rock PE value. The kerogen percentage, which can be approximately estimated from GR or Uran, is necessary to differentiate the effect of barite and pyrite.



Statistical analyses of the conventional log series after normalization and log analysis

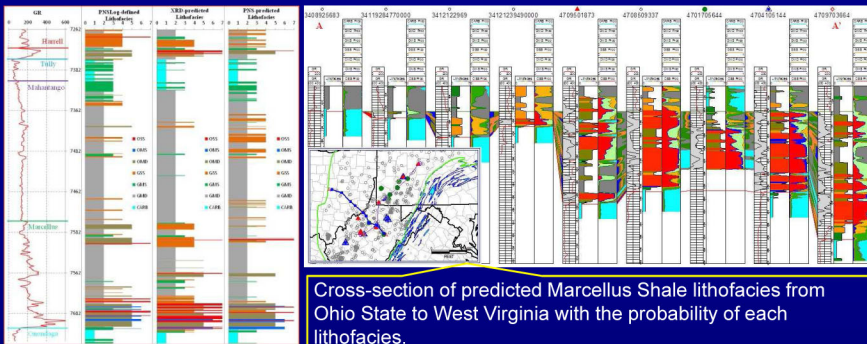
ANN Training and Results

Learning Algorithm		Artificial Neural Network Topology																					
		20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100	105	110	115	120	125
LM	LM	79.7	70.9	81.9	81.3	77.5	75.8	83.0	84.1	76.4	78.6	76.9	84.1	79.1	76.9	79.7	80.8	80.8					
	SCG	82.4	81.3	84.1	80.8	75.3	79.1	85.2	82.4	84.6	59.9	79.7	83.5	81.3	81.3	84.6	85.7	83.5					
	SDG	45.6	56.0	49.5	54.4	54.4	59.3	52.7	51.6	52.2	52.7	47.3	52.7	53.3	31.3	46.2	50.0	49.5					
	SDGM	49.5	55.5	50.0	54.9	53.8	59.9	53.8	52.2	52.2	52.2	47.3	52.2	54.9	33.0	46.2	51.1	50.0					
	GA	78.0	81.3	74.7	74.7	73.6	76.4	74.7	78.0	73.1	74.2	75.8	73.6	74.7	76.4	74.7	72.5	72.5					
	PSO	76.4	76.9	75.3	73.6	76.9	74.7	75.8	73.1	78.0	73.1	76.4	73.6	73.6	76.4	73.6	69.2	67.6					

The figure above shows a real case of the decline curve of MSE optimized by the six supervised learning algorithms. LM: fast; GA and PSO are refined by LM; validation is for avoiding over-training. The table shows the cross-validation right ratio of different topology and learning algorithms. The GA and PSO are more steady to optimize the ANN classifiers for different topologies; the SCG and LM algorithms performs best in optimizing the ANN classifiers but less steady; the SDG and SDGM algorithms are not recommended for shale lithofacies prediction.

Lithofacies	Predicted Lithofacies							Core Total	Right Rate
	OSS	OMS	OMD	GSS	GMS	GMD	CARB		
OSS	34	1	2	2				39	87.18%
OMS	1	8	1	1				11	72.73%
OMD	6		16			1		23	69.57%
GSS	1		1	15	1			18	83.33%
GMS		1			14	2	1	18	77.78%
GMD			1		2	54		57	94.74%
CARB					1		15	16	93.75%
Predicted Total	42	10	21	18	18	57	16	182	85.71%
Predicted Core	1.077	0.909	0.913	1.000	1.000	1.000	1.000	ERRE Score	54.05

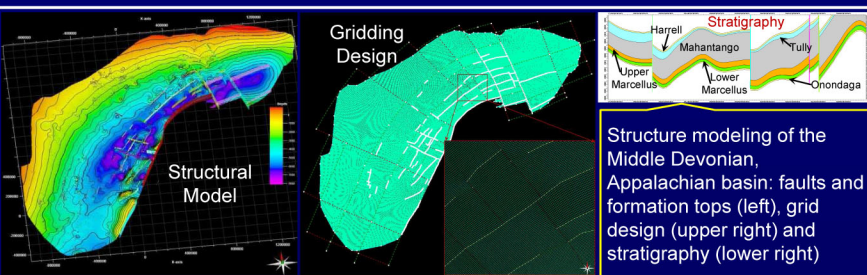
The confuse plot of the predicted seven shale lithofacies with ERRE (left) shows correctly predicted lithofacies on the diagonal and miss-classified lithofacies in the off diagonal locations. Adjacent facies are most similar. The cross plot in the left shows the effect of ERRE on cross-validation right rate of the six learning algorithms. The table in the lower right indicates the ratio of samples located above or below the reference line.



Cross-section of predicted Marcellus Shale lithofacies from Ohio State to West Virginia with the probability of each lithofacies.

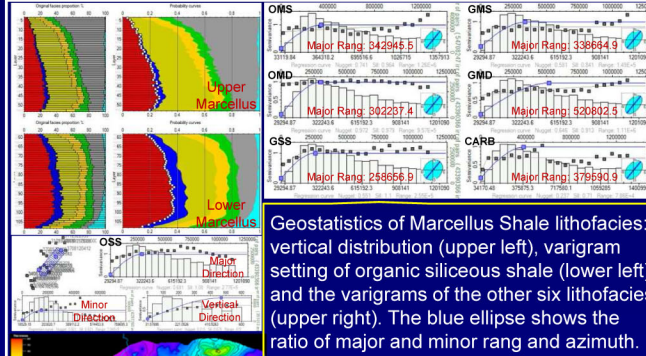
An example of predicted shale lithofacies by single ANN based on core training dataset (3rd track) and modular ANN based on pulsed neutron spectroscopy (PNS) log training dataset (4th track) compared to PNS-defined lithofacies in Well #6 of Middle Devonian intervals, Appalachian basin.

3D Structural Model

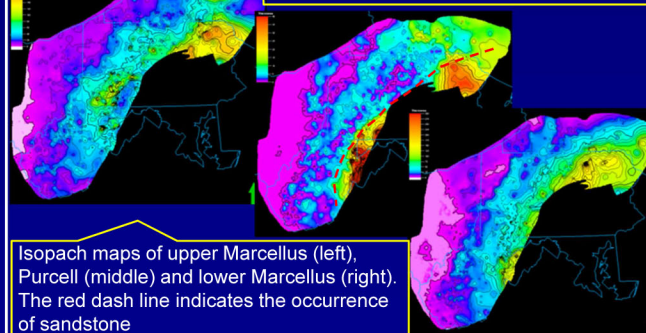


Structure modeling of the Middle Devonian, Appalachian basin: faults and formation tops (left), grid design (upper right) and stratigraphy (lower right)

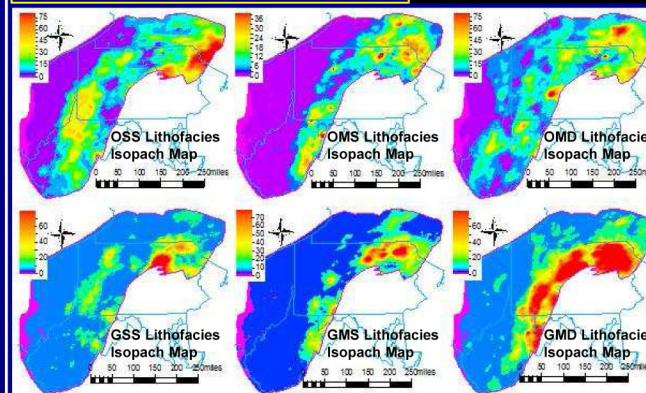
Marcellus Shale lithofacies geostatistic modeling



Geostatistics of Marcellus Shale lithofacies: vertical distribution (upper left), variogram setting of organic siliceous shale (lower left), and the variograms of the other six lithofacies (upper right). The blue ellipse shows the ratio of major and minor rang and azimuth.

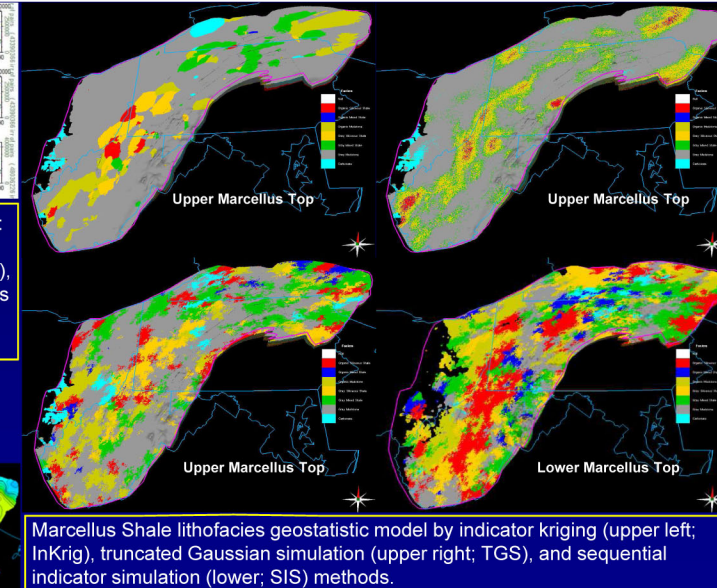


Isopach maps of upper Marcellus (left), Purcell (middle) and lower Marcellus (right). The red dash line indicates the occurrence of sandstone

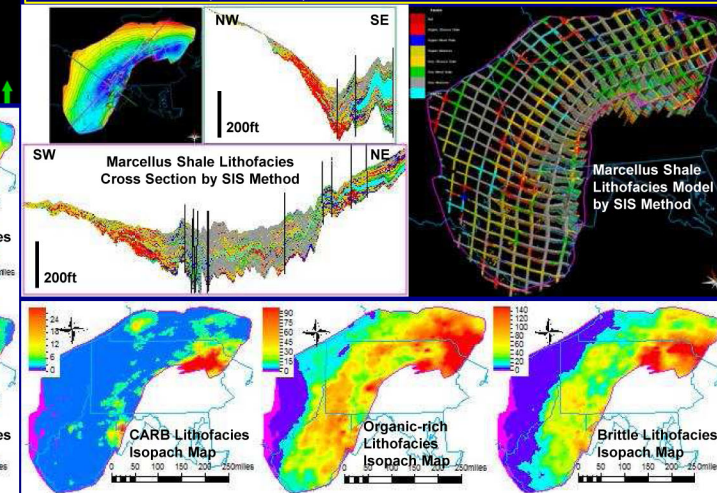


Conclusions

- ❖ Marcellus Shale lithofacies is defined from core and PNS logs in terms of mineral composition and organic matter richness; clay percentage, the ratio of quartz and carbonate and TOC content are the primary parameters.
- ❖ Petrophysical analysis, instead of conventional feature selection method, is used to improve the input variable space for classifiers; eight derived parameters from conventional logs are the input variables for ANN; the effect of pyrite and barite was studied and partly removed.
- ❖ Artificial neural network is the major quantitative method to predict Marcellus Shale lithofacies with conventional logs; scaled conjugate gradient is the best learning algorithm for lithofacies prediction.
- ❖ 3D modeling was to better understand the distribution of Marcellus Shale lithofacies in the Appalachian basin



Marcellus Shale lithofacies geostatistic model by indicator kriging (upper left; InKrig), truncated Gaussian simulation (upper right; TGS), and sequential indicator simulation (lower; SIS) methods.



Acknowledgements

Special thanks to Energy Corporation of America, Consol Energy and Petroleum Develop Corporation for providing data. We also thank MathWorks, Schlumberger and Geopius Corporation for providing access to Matlab, Petrel and Petra.

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