

Fast-Track and Robust Reservoir Modeling Using Probabilistic Neural Network*

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Search and Discovery Article #42205 (2018)**

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Abstract

In highly heterogeneous basins with complex subsurface geology, as the Nile Delta basin, the accurate prediction of reservoir characteristics is a must. The reservoir characterization is a continuous process that begins with the field discovery and ends with the last phases of production and abandonment. Reservoir static modeling is the final step in the reservoir characterization process and consists of building an upscaled geologic model to be an input to the fluid simulations. The geostatistical reservoir modeling (stochastic modeling) methods are widely used instead of the traditional deterministic modeling methods to consider the spatial statistics and uncertainties. However, the modeling workflows are slow, requiring months from initial model concept to flow simulation or other outputs; Moreover, the early stages errors become cumulative and are difficult to retrospectively change. The neural network inversion gained popularity over the last decades for its ability to establish nonlinear relationships between the petrophysical logs and seismic data. It has been used to predict various reservoir properties with a reasonable amount of accuracy. Its main limitation resides at seismic resolution, and to overcome this problem a resolution-enhancing workflow has been adopted. This case study is from a Pliocene turbidite field in the offshore Nile Delta to illustrate the proposed modeling workflow. As a beginning, the resolution enhancement of seismic data is accomplished using derivative attributes and structural smoothing. Then, after proper well-log data conditioning, the training and cross-validation of Probabilistic Neural Network (PNN) are performed to produce shale volume (V_{sh}), porosity (ϕ), and water saturation (S_w) 3D volumes. The permeability (k) is calculated from poro-perm relationship inside the reservoir. The results are then sampled in 3D grids and tested using dynamic simulation method to assimilate production history. After the initial history match process, PNN parameters are adjusted to improve the match. The final model represents the best match to original field measurements and production data, which is then used in drilling decisions and production planning. The proposed neural network workflow reduces the reservoir modeling construction time by 80-90%, mitigates the cumulative error problems, and decreases the statistical uncertainty as it depends purely on seismic data to distribute the reservoir properties.

References Cited

Cross, N.E., A. Cunningham, R.J. Cook, A. Taha, E. Esmail, and N. El Swidan, 2009, 3-D Seismic Geomorphology of a Deepwater Slope Channel System: The Sequoia Field, Offshore West Nile Delta, Egypt: Search and Discovery Article 20078, Web Accessed April 29, 2018,

http://www.searchanddiscovery.com/documents/2009/20078cross/ndx_cross.pdf

Mohamed, I., O. Shenkar, and H. Mahmoud, 2017, Understanding reservoir heterogeneity through water saturation prediction via neural network - A case study from offshore Nile Delta: *The Leading Edge*, v. 36, p. 298-303, Web Accessed April 29, 2018, <https://library.seg.org/doi/abs/10.1190/tle36040298.1>

Mohamed, I., H. El-Mowafy, D. Kamel, and M. Heikal, 2014, Prestack seismic inversion versus neural-network analysis: A case study in the Scarab field offshore Nile Delta, Egypt: *The Leading Edge*, v. 33/5, p. 498–500, 502, 504, 506.

Samuel, A., B. Kneller, S. Raslan, A. Sharp, and C. Parsons, 2003, Prolithic deep-marine slope channels of the Nile Delta, Egypt: *AAPG Bulletin*, v. 87, p. 541–560.



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Conference and Exhibition

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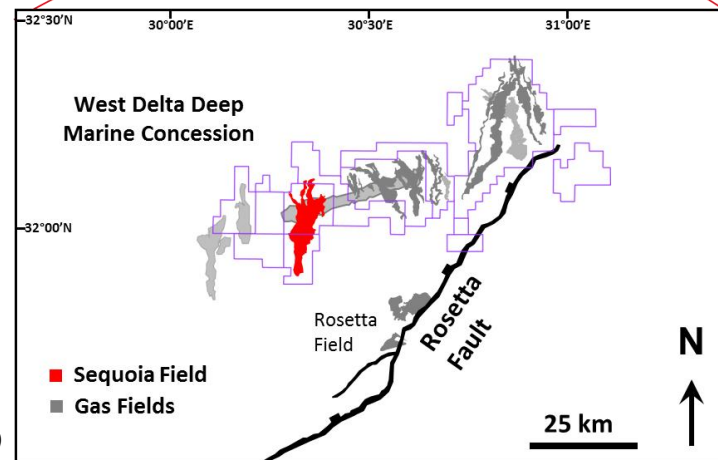
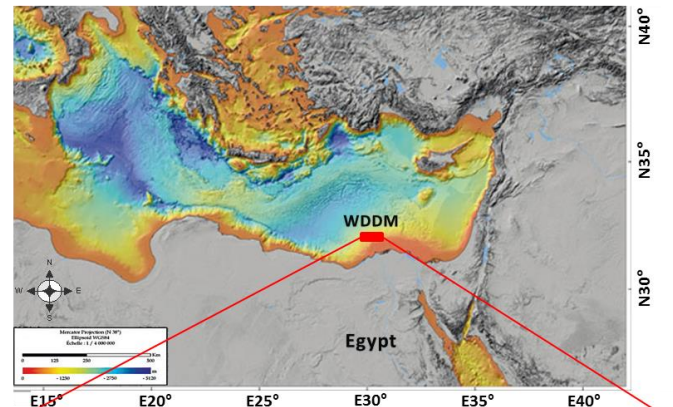


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- Methodology
 - Data Conditioning
 - Probabilistic Neural Network
 - Static Modeling
 - Dynamic Testing
- Conclusion

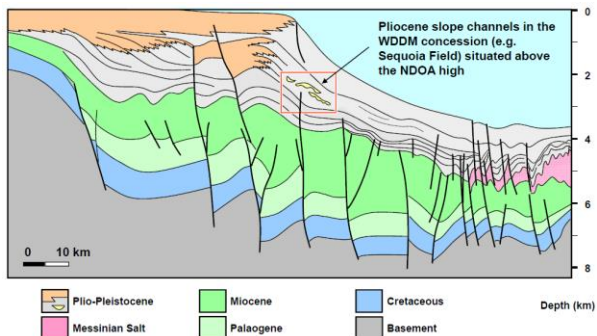
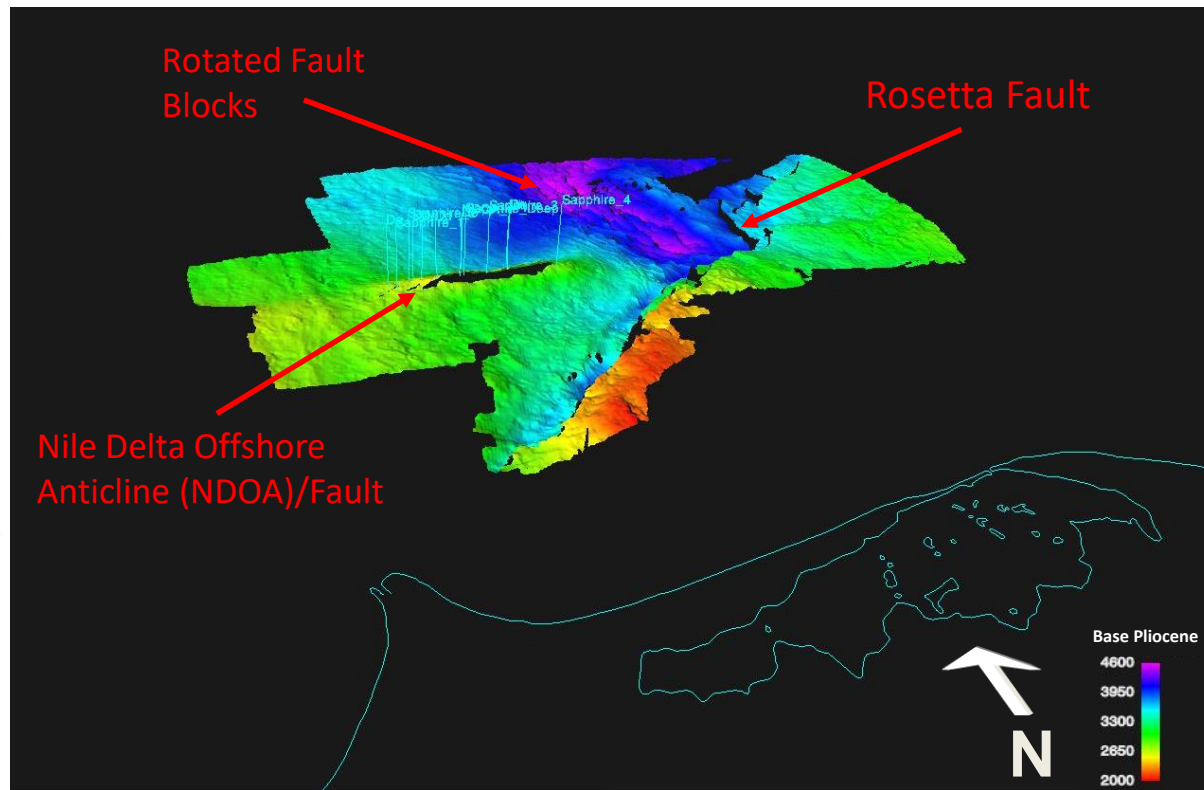
Area of Study

- Location
 - Egypt, Offshore Nile Delta, West Delta Deep Marine (WDDM) concession
- Sequoia field
 - One of the biggest Pliocene gas fields



(modified from Mohamed et al., 2014 and Samuel et al., 2003)

WDDM Major tectonic features

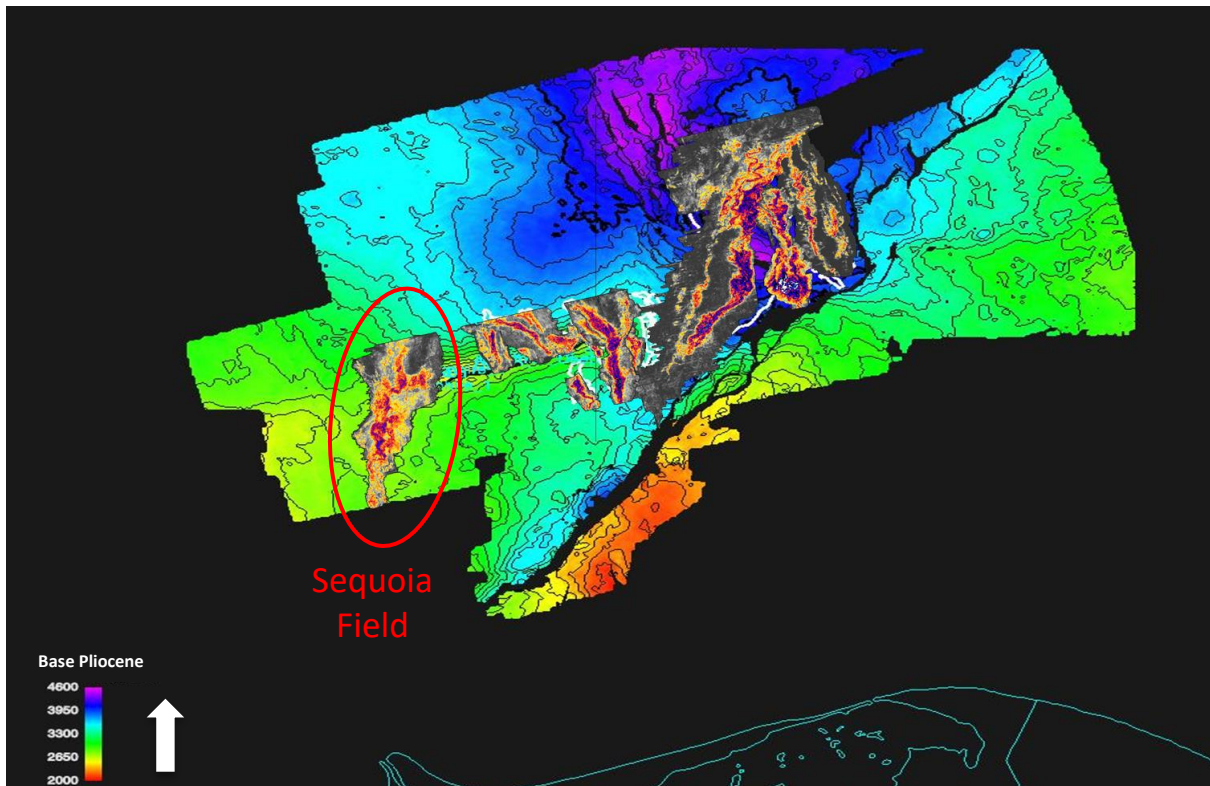


Cross-section modified after Aal et al., 2006

Pliocene reservoirs draped across tectonic elements

AGE	STAGE	BIOZONES		FORMATION	LITHOLOGY	
			NANNO			
HOLOCENE			N23	NN21	BILQAS	
		PLEISTOCENE	LATE	MILAZZIAN	NN20	MIT GHAMR
				SICILIAN EMILIAN		
PLIOCENE	EARLY	CALABRIAN		NN19	BALTIM	
			LATE	PACENZIAN	NN18	EL WASTANI
	NN17					
	NN16					
	EARLY	ZANCLEAN	N 19 - N 20	NN15	KAFR EL SHEIKH	
				NN14		
				NN13		
				NN12		
				NN11		
	UPPER MIOCENE	MESSINIAN		N18	ABU MADI	
N17						
TORTONIAN				N16	QAWASIM	
				N15		

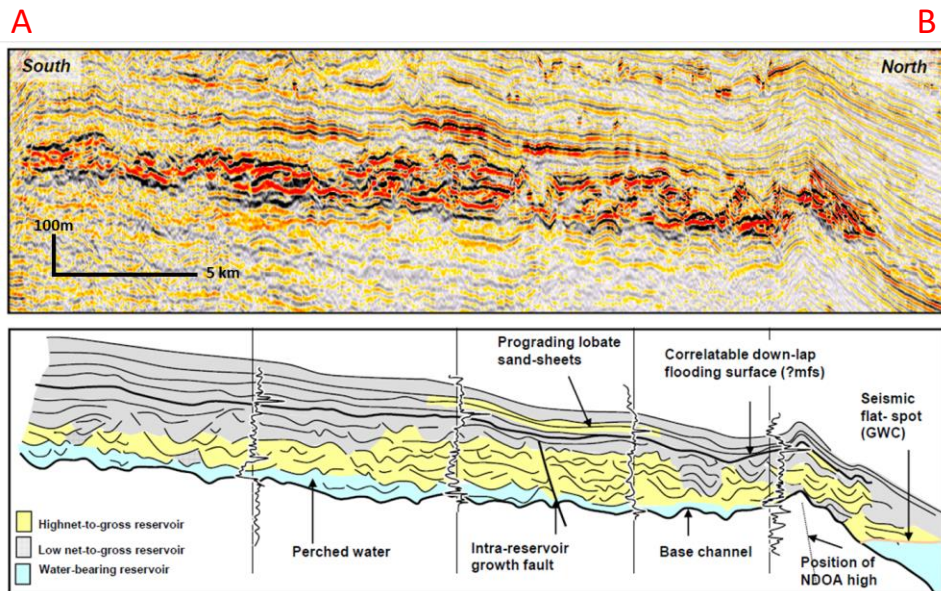
Sheet sand (Ibn Sequoia)
Main sequoia Channel



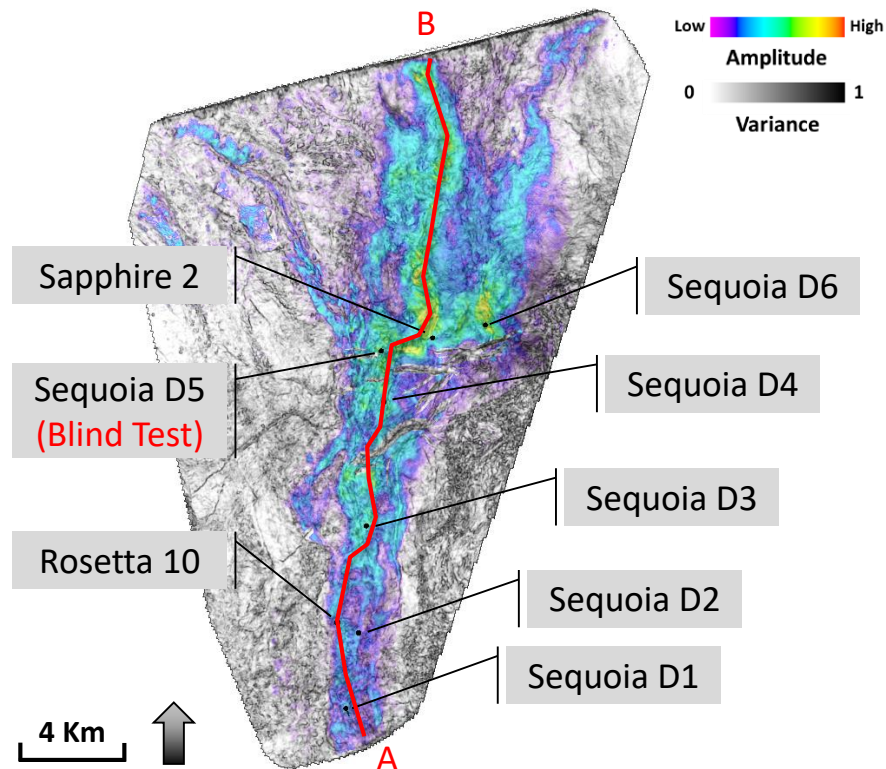
Nile Delta stratigraphic column

Large-Scale Reservoir Architecture

An arbitrary line through Sequoia channel complex



(modified from Cross et al., 2009)



Sequoia Channel Evolution Summary

Ibn Sequoia

Sequoia channel abandonment and minor sheet sands

Stage III

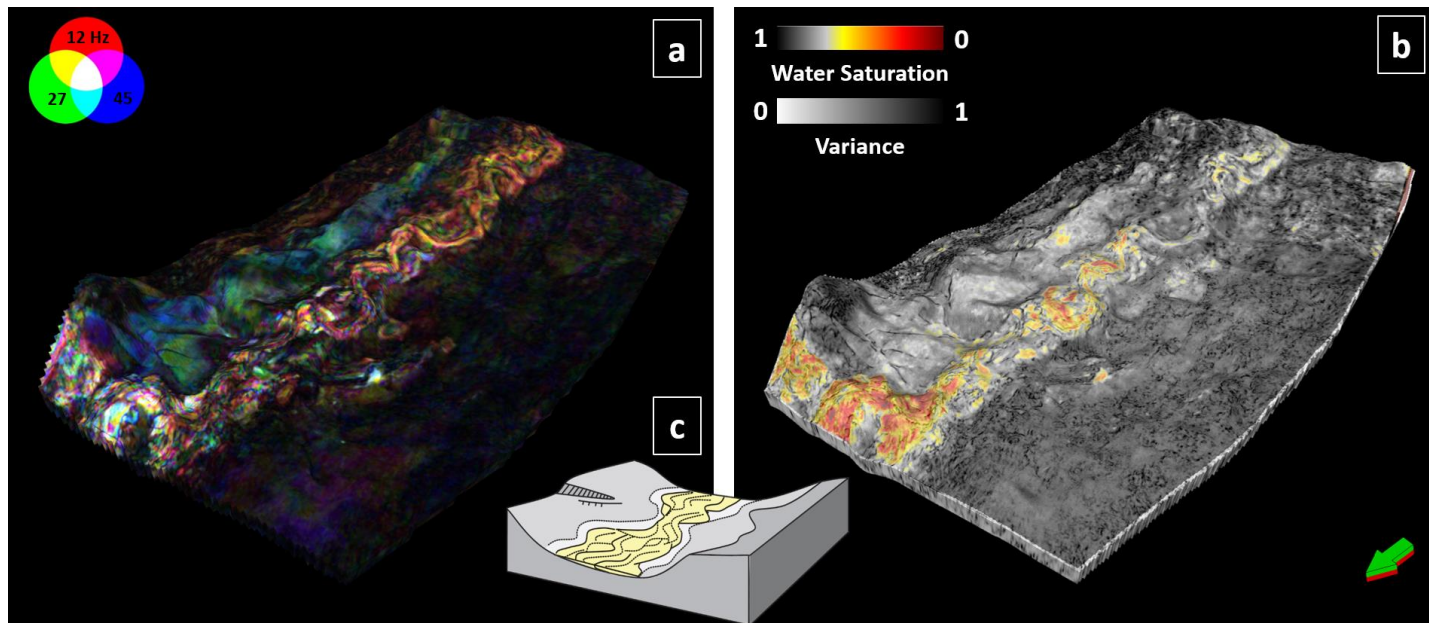
Narrower and straighter channels and splays

Stage II

High sinuosity channel and associated splays

Stage I

Braided, poorly confined channel deposition



(modified from Mohamed et al., 2017)

Ibn Sequoia

Sequoia channel abandonment and minor sheet sands

Stage III

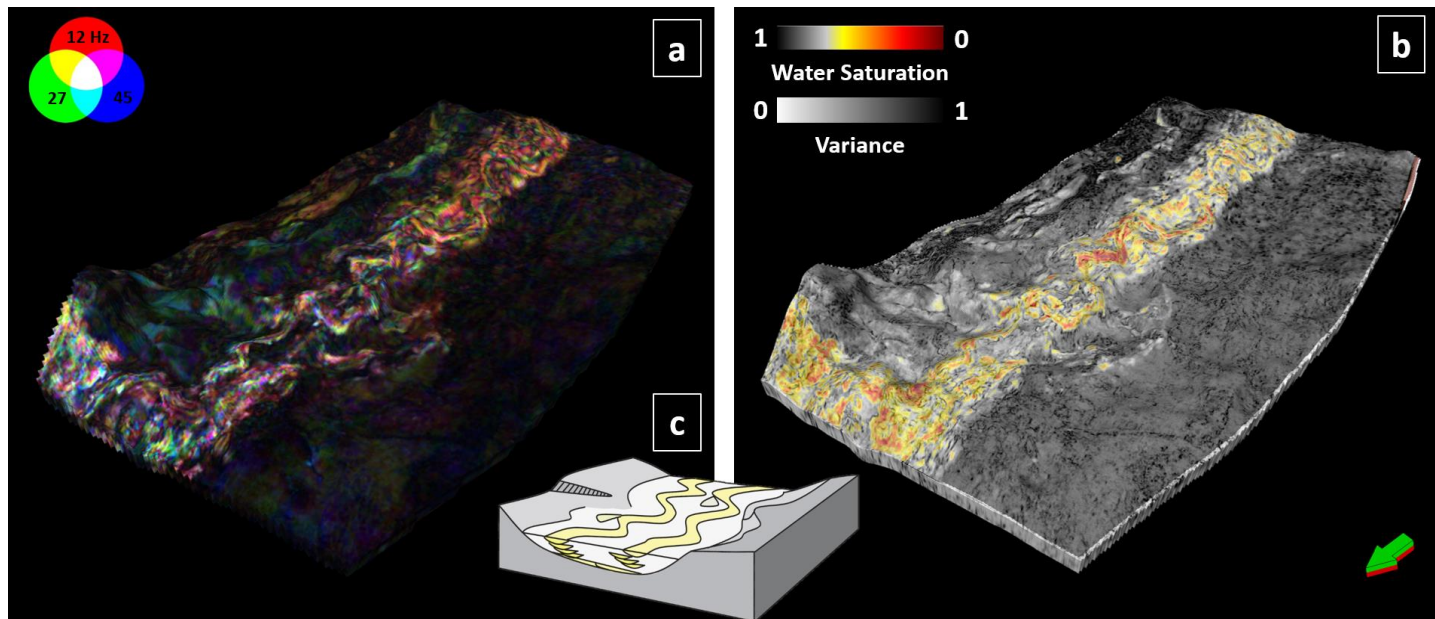
Narrower and straighter channels and splays

Stage II

High sinuosity channel and associated splays

Stage I

Braided, poorly confined channel deposition



(modified from Mohamed et al., 2017)

Ibn Sequoia

Sequoia channel abandonment and minor sheet sands

Stage III

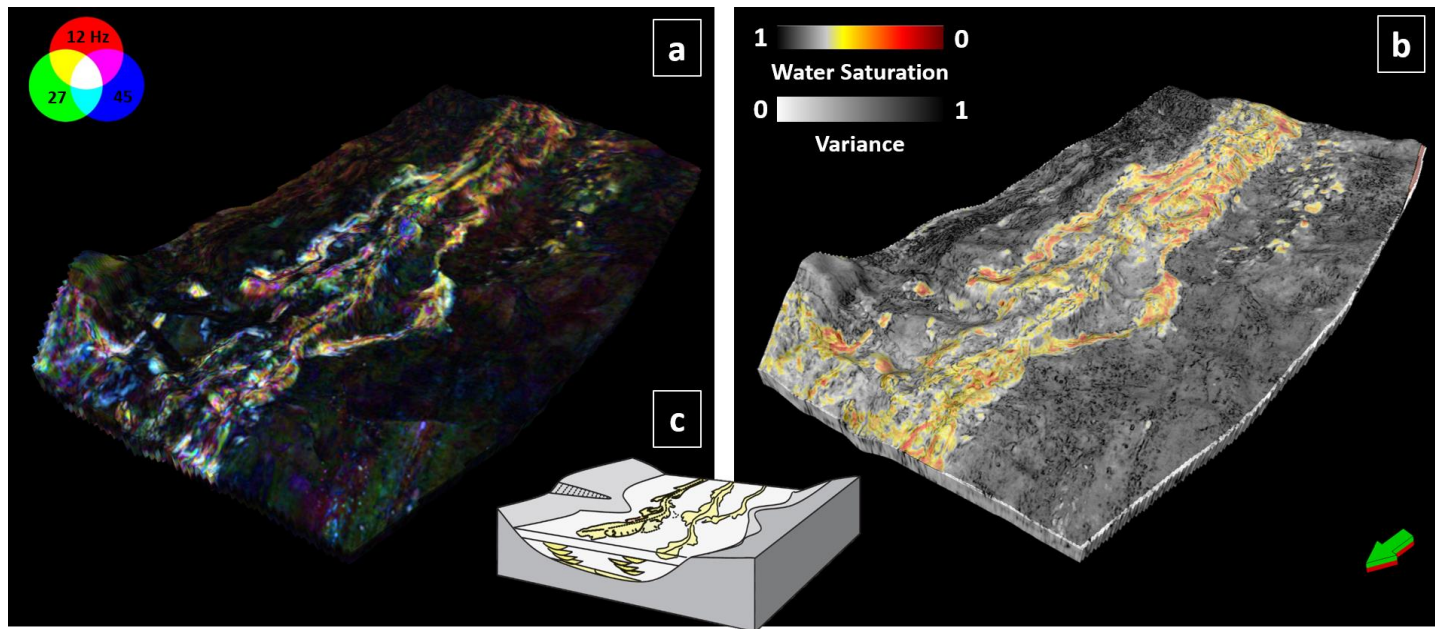
Narrower and straighter channels and splays

Stage II

High sinuosity channel and associated splays

Stage I

Braided, poorly confined channel deposition



(modified from Mohamed et al., 2017)

Ibn Sequoia

Sequoia channel abandonment and minor sheet sands

Stage III

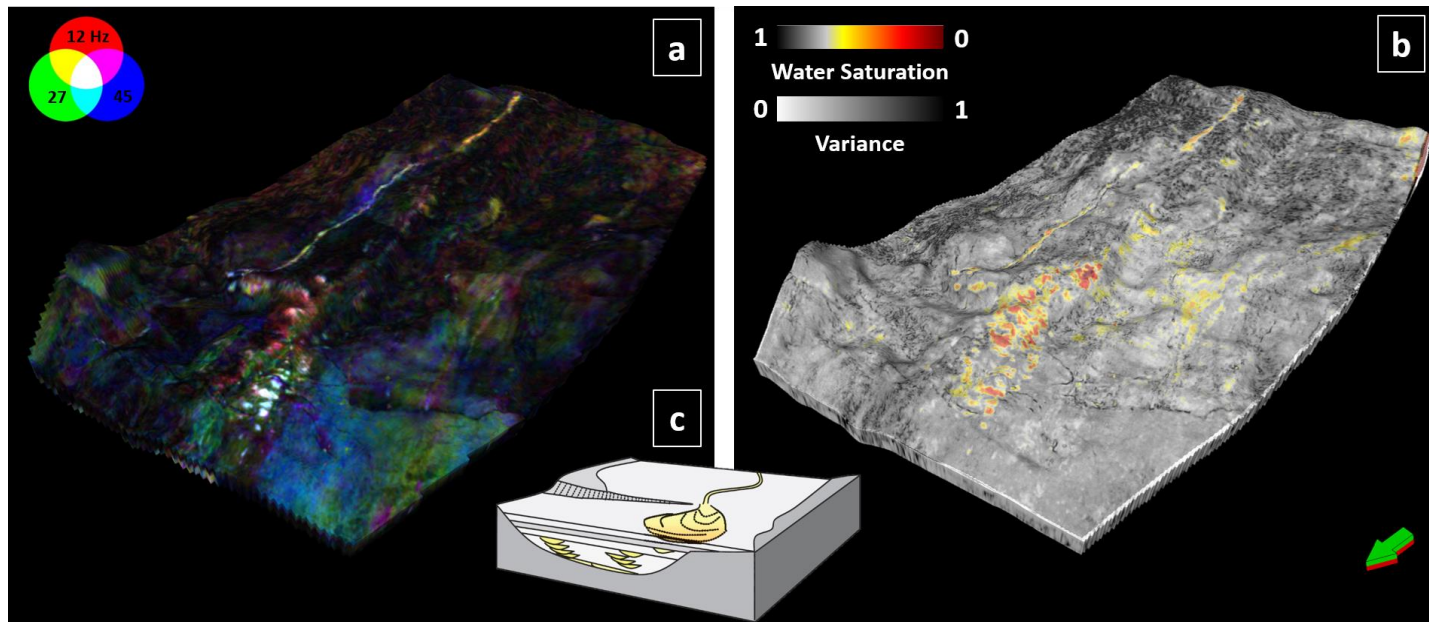
Numerous small channels and splays

Stage II

High sinuosity channel and associated splays

Stage I

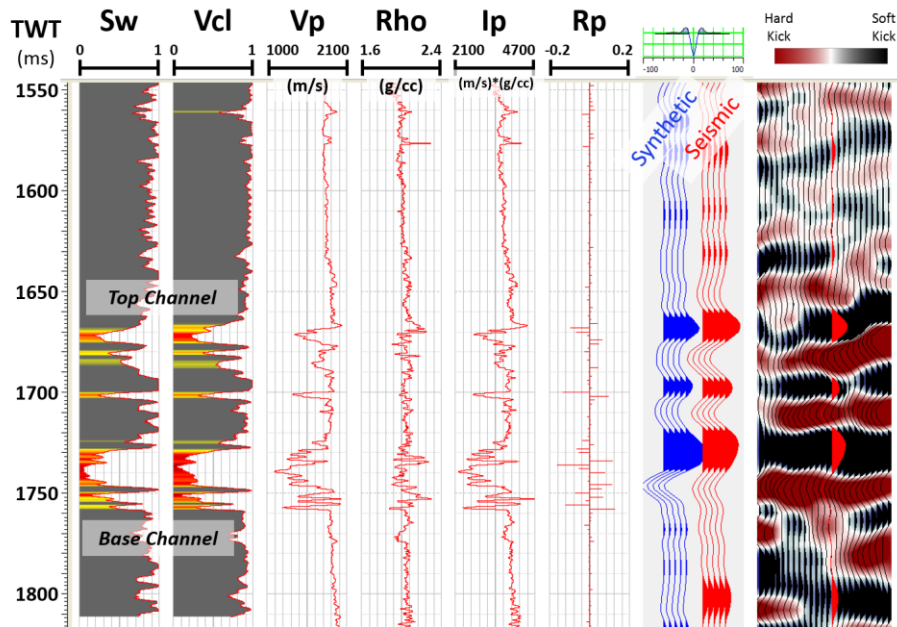
Braided, poorly confined channel deposition



(modified from Mohamed et al., 2017)

Sequoia Field – Reservoir Characteristics

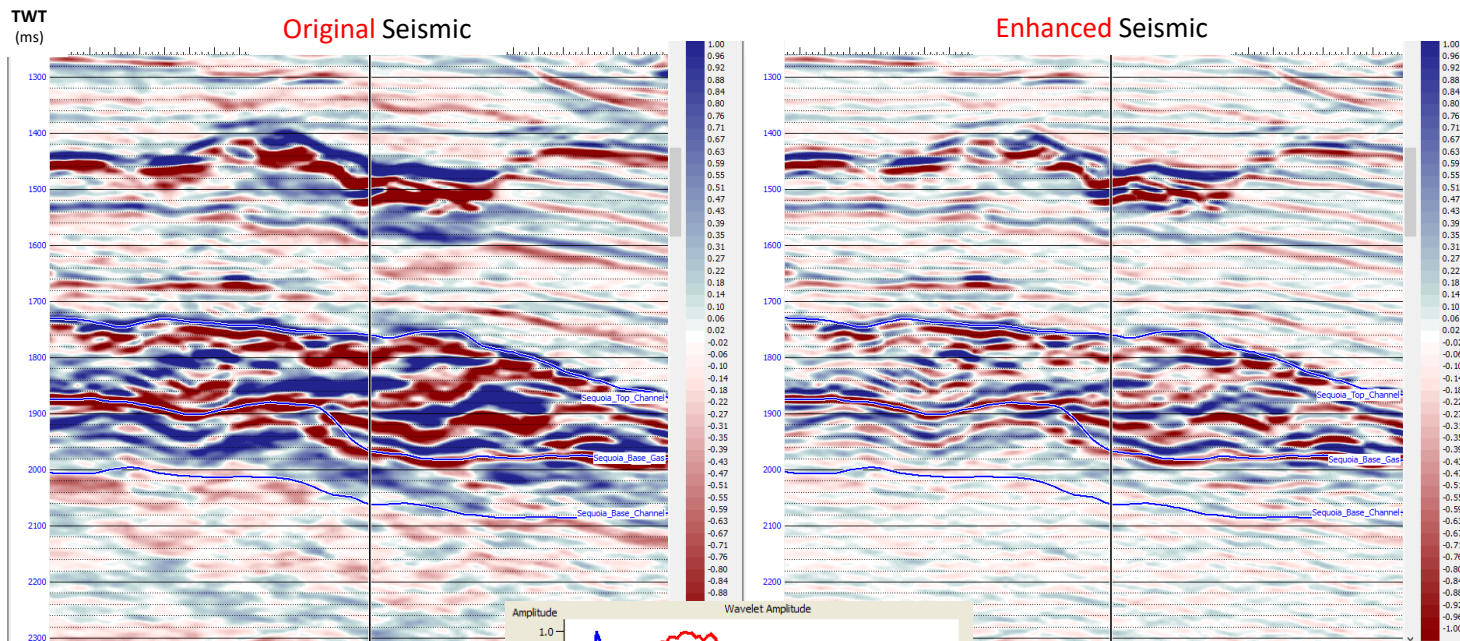
- Multiple stacked channels that are up to 200 m in gross thickness, 77 m of pay
- An average effective porosity of 24%
- An average water saturation of 34%



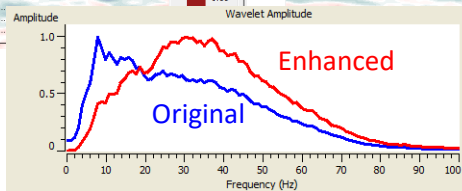
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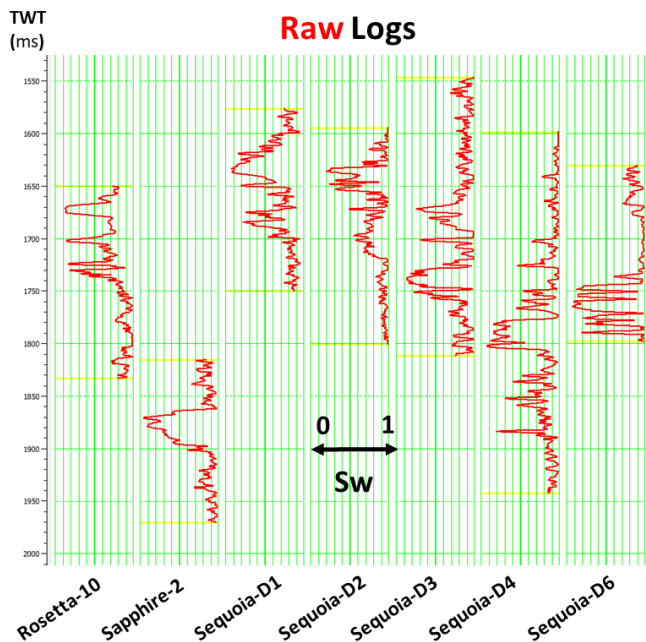
Seismic Resolution Enhancement – Band-Pass Filtering



Band-pass filter frequency range (Hz):
0 / 30 / 120 / 130

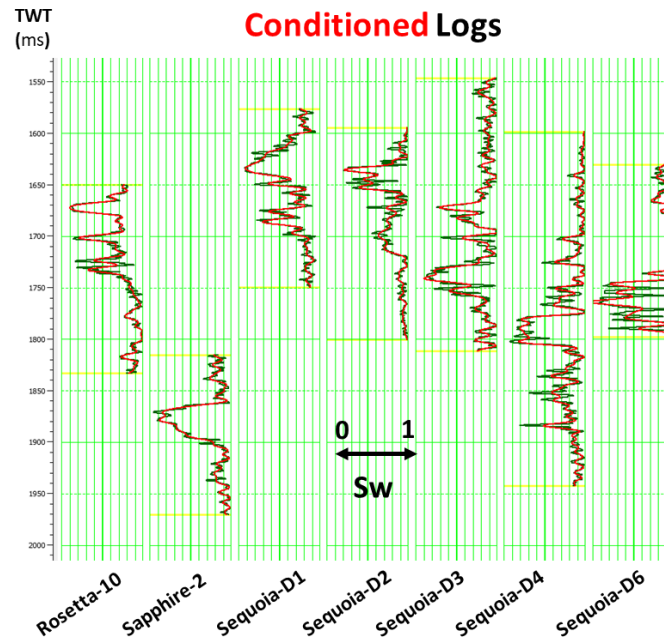


Well Log Conditioning



Conditioning:

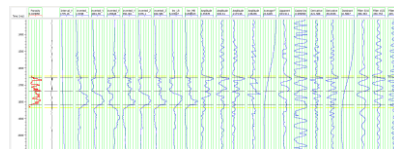
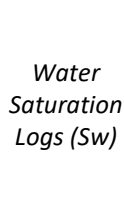
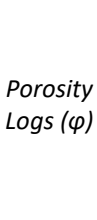
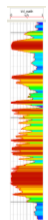
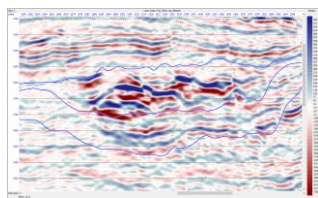
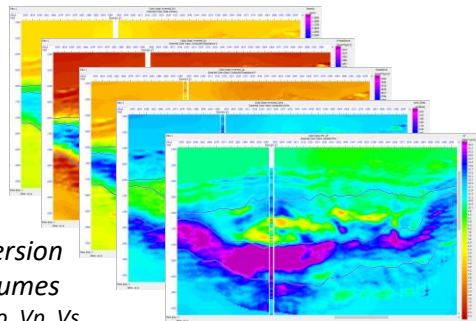
- Resampling @ 4 ms
- Smoothing



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Probabilistic Neural Network

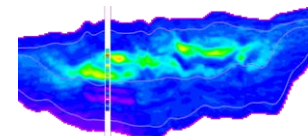
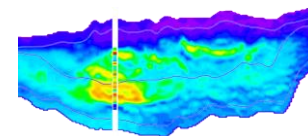
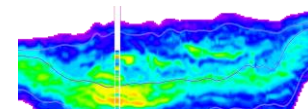
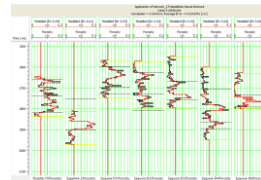
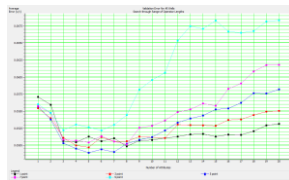


Internal & external attributes

Neural Network

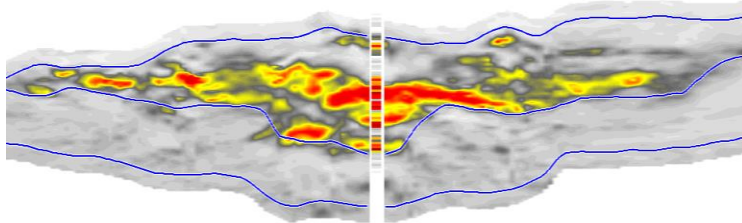
Minimize the error

Training & validation

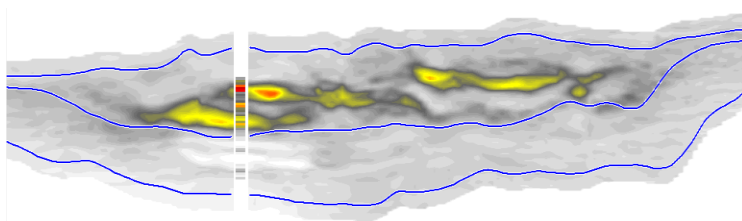


PNN Results – Water Saturation

Water Saturation section (S_w) through Sequoia D5 well (Blind Test)

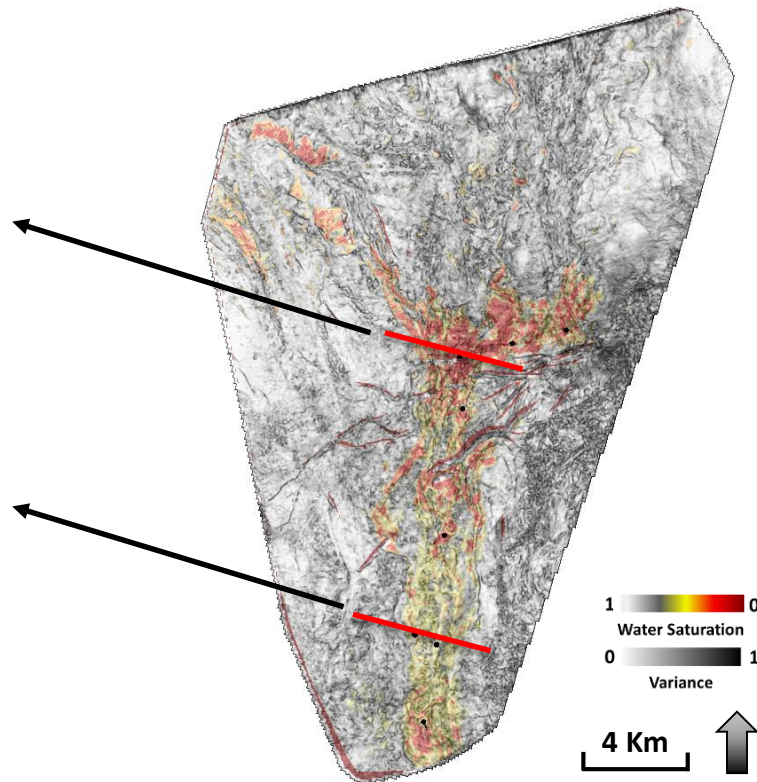


Water Saturation section (S_w) through Rosetta 10 well



100 m
400 m

1 0
Water Saturation

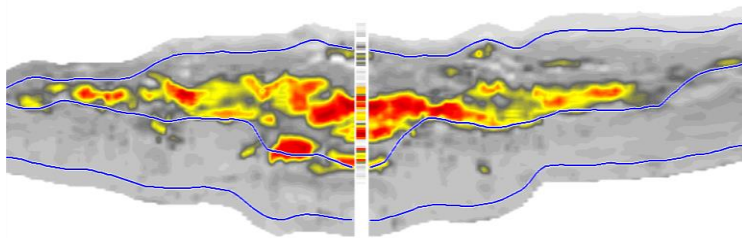


1 0
Water Saturation
0 1
Variance

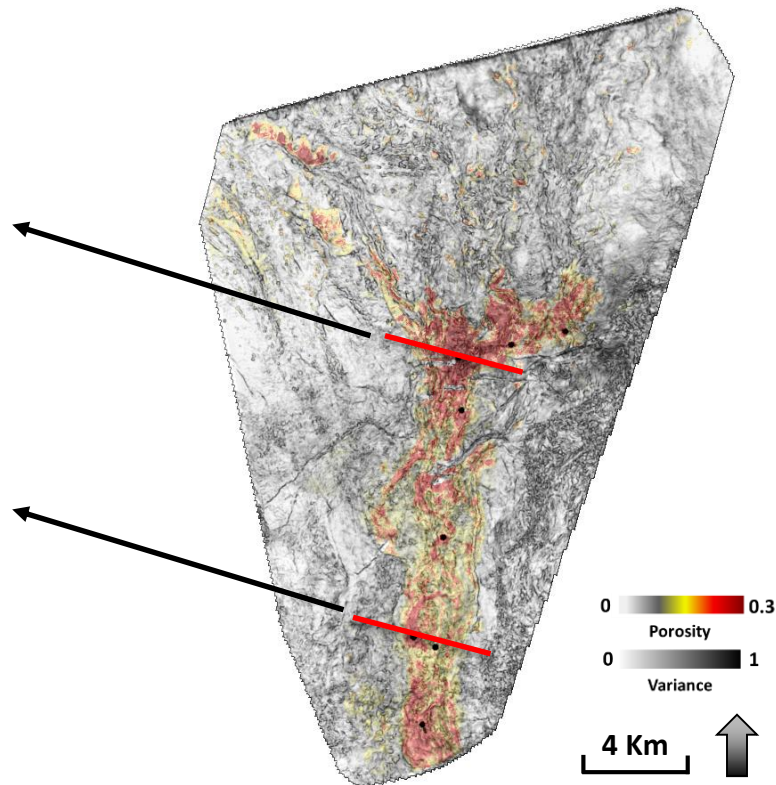
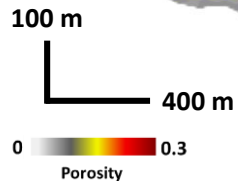
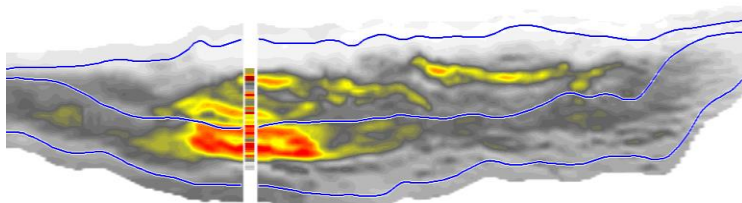
4 Km ↑

PNN Results – Porosity

Porosity section (ϕ) through Sequoia D5 well (Blind Test)

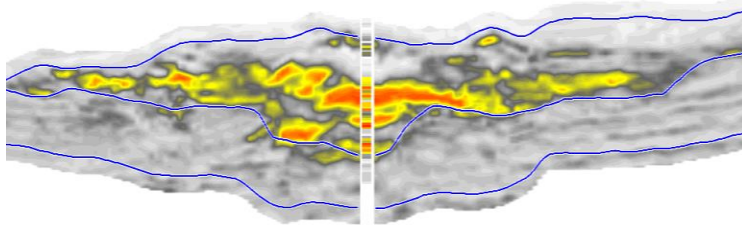


Porosity section (ϕ) through Rosetta 10 well

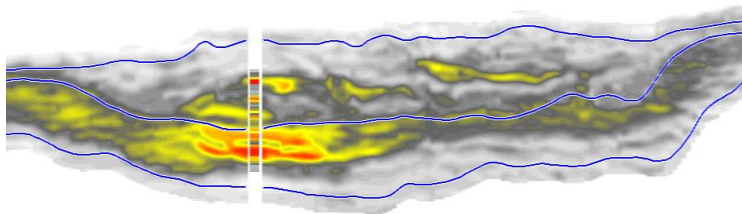


PNN Results – Shale Volume

Shale volume section (*Vsh*) through Sequoia D5 well (Blind Test)

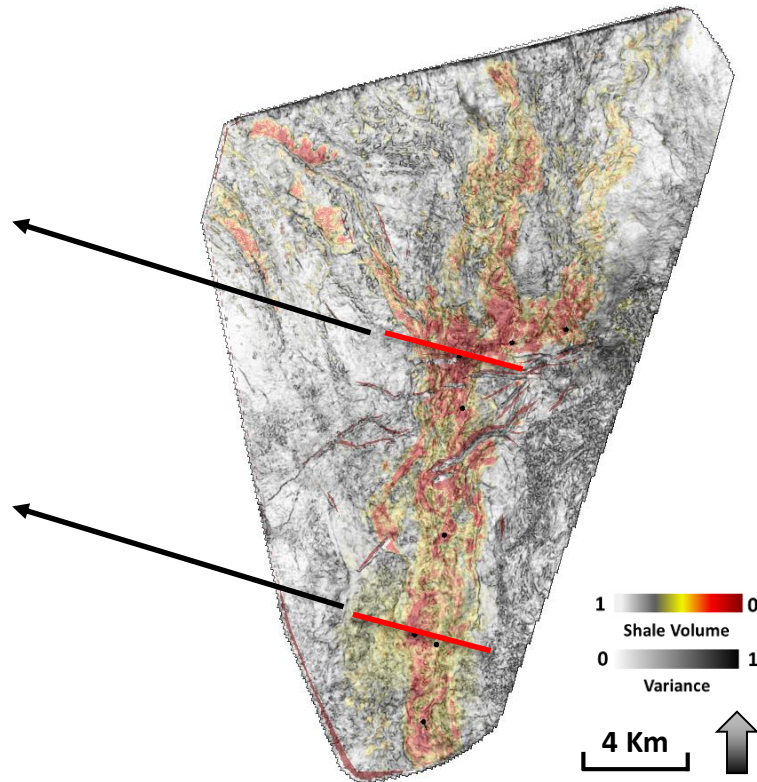


Shale volume section (*Vsh*) through Rosetta 10 well



100 m
400 m

1 0
Shale Volume



1 0
Shale Volume
0 1
Variance

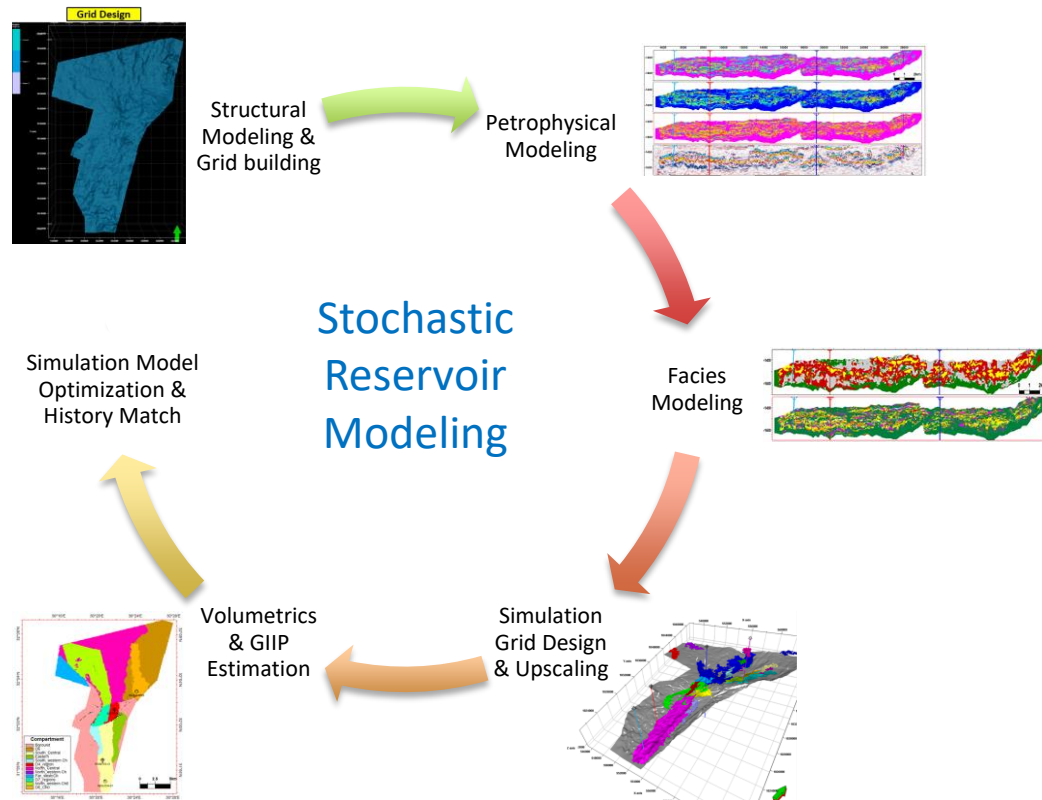
4 Km

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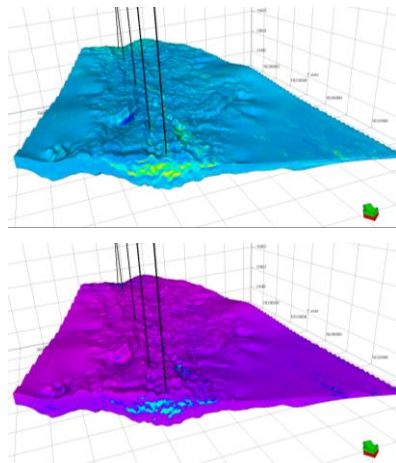
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Stochastic Reservoir Modeling Workflow

- Stochastic reservoir modeling
 - Consider the spatial statistics and uncertainties.
 - Require months from initial model concept to flow simulation.
 - Early stages errors become cumulative and are difficult to retrospectively change.

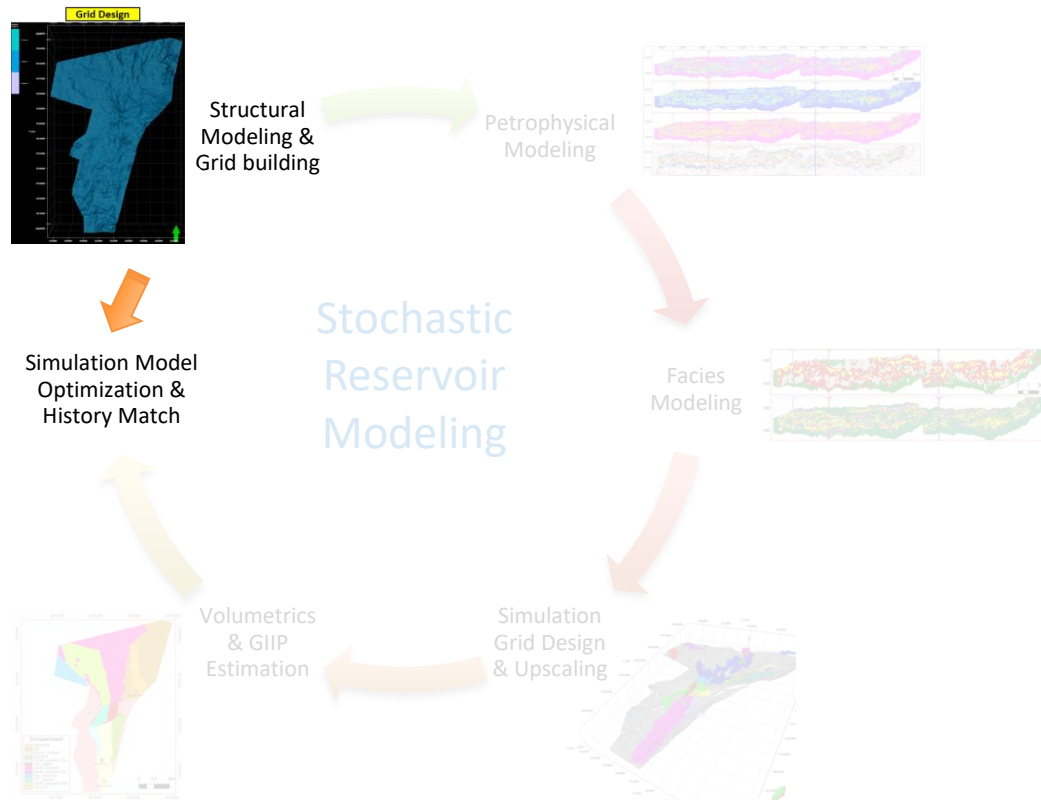


The Proposed Workflow



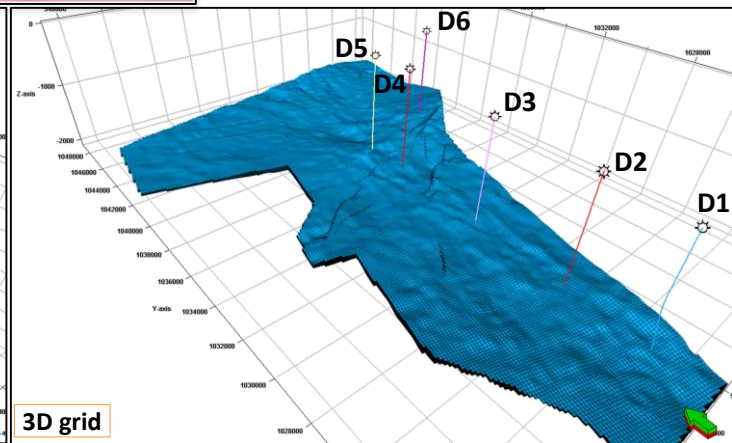
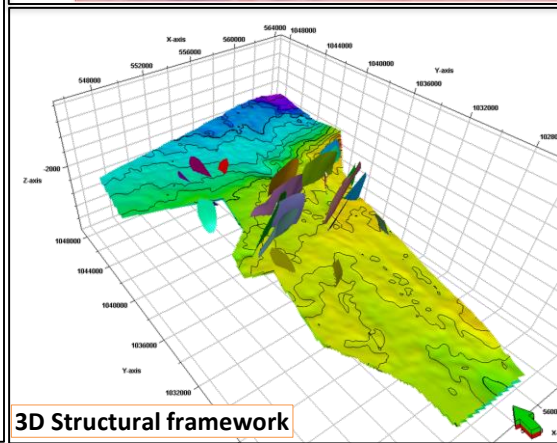
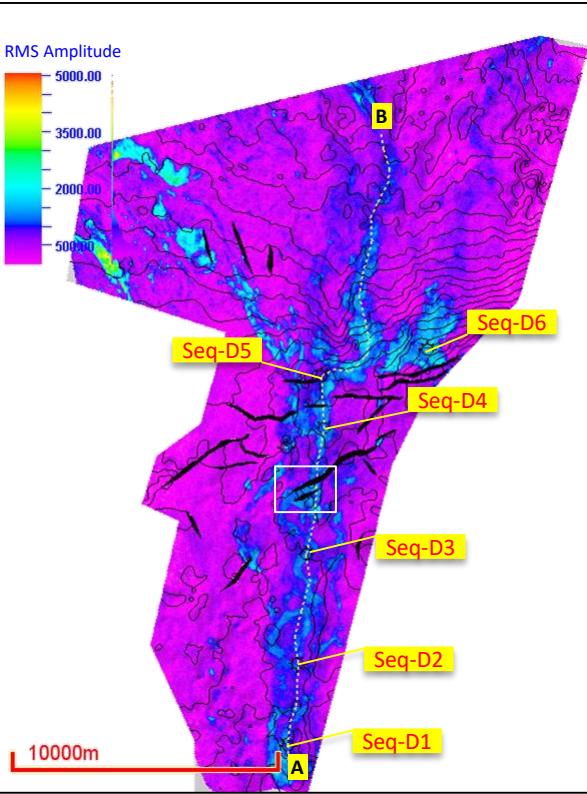
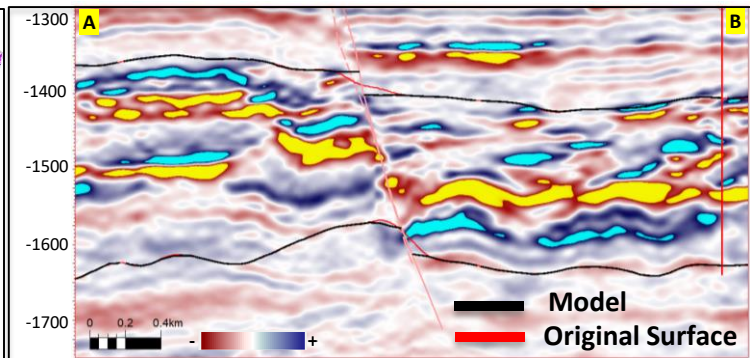
Water Saturation and Porosity from PNN

- Decreases the statistical uncertainty.
- Reduces the reservoir modeling construction time by 80%.
- Mitigates the cumulative error problems.

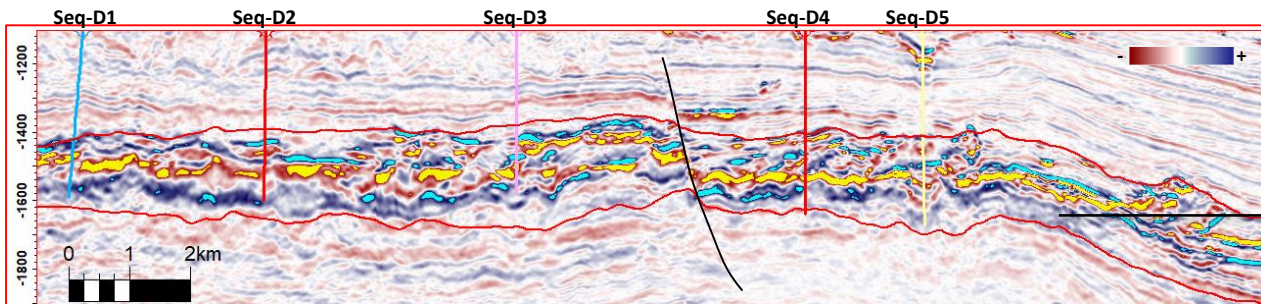


Static Modeling

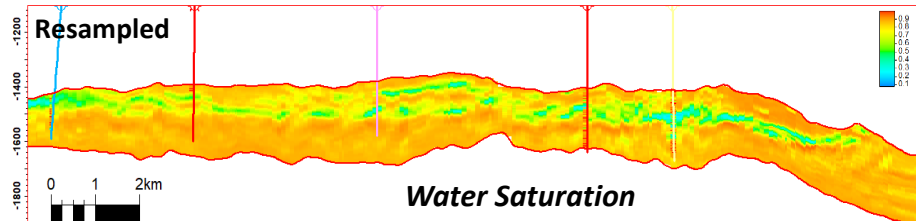
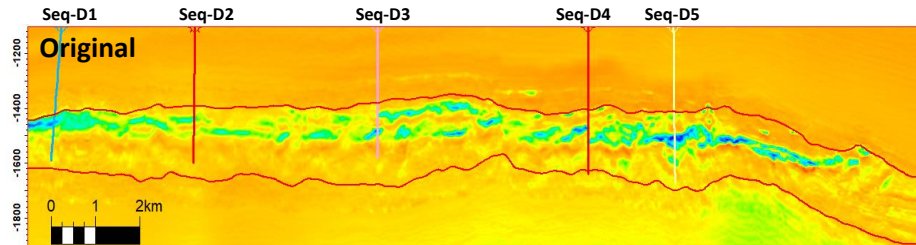
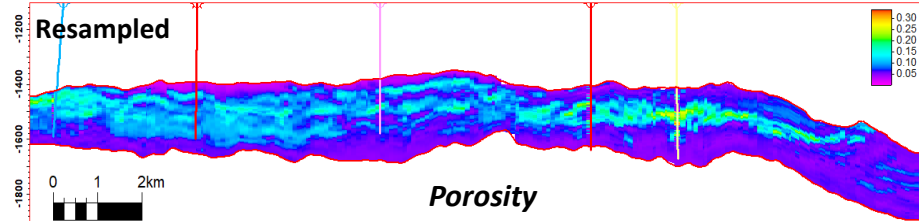
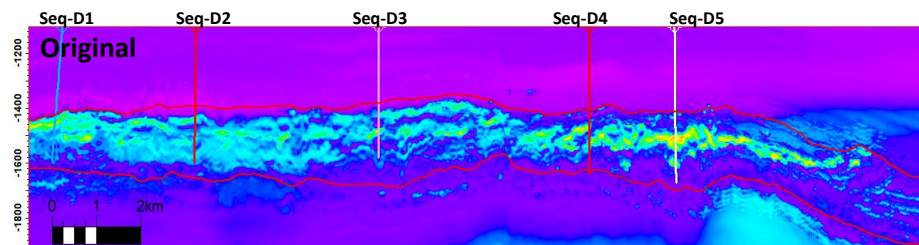
- Structure model:
 - Structural framework method
- Cell size:
 - 100m*100m using proportional layering (1.5m Average cell thickness)



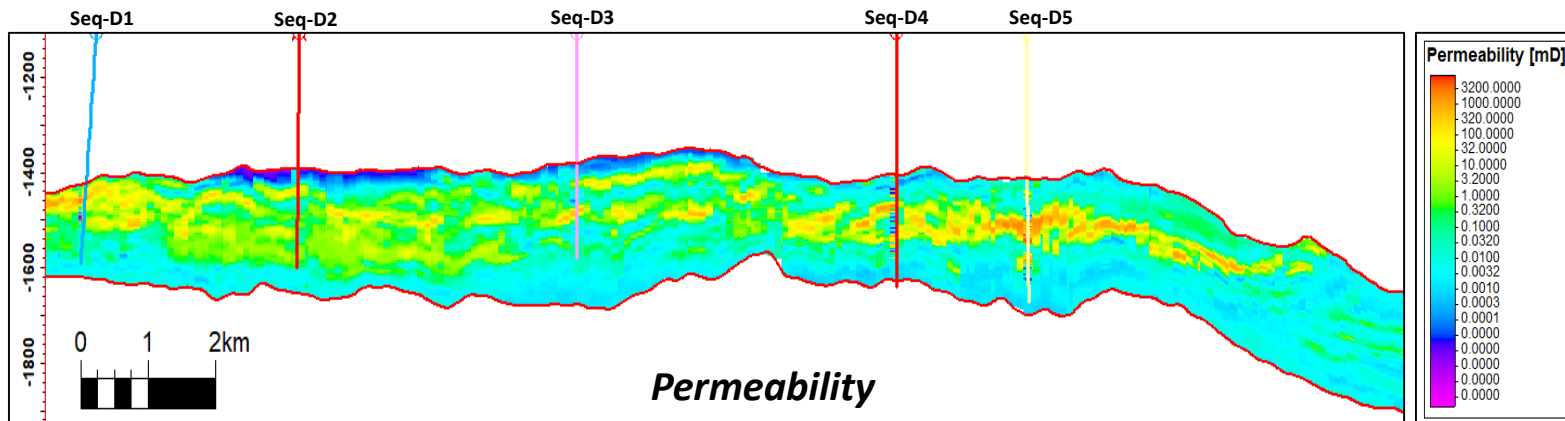
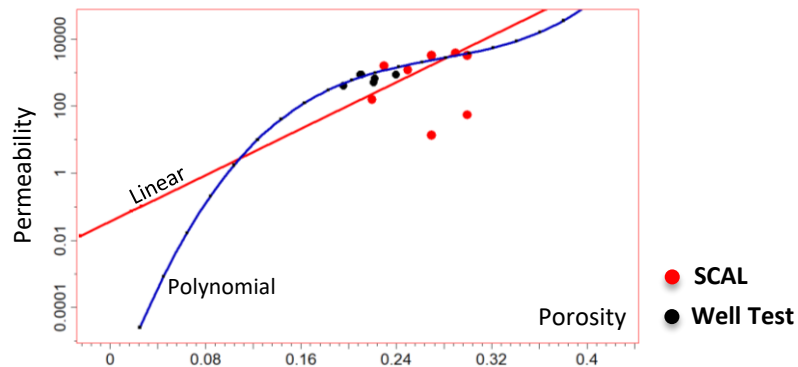
Porosity and Water Saturation Resampling



Property	resampling
Porosity	Arithmetic
Saturation	Arithmetic



Porosity-Permeability Relationship



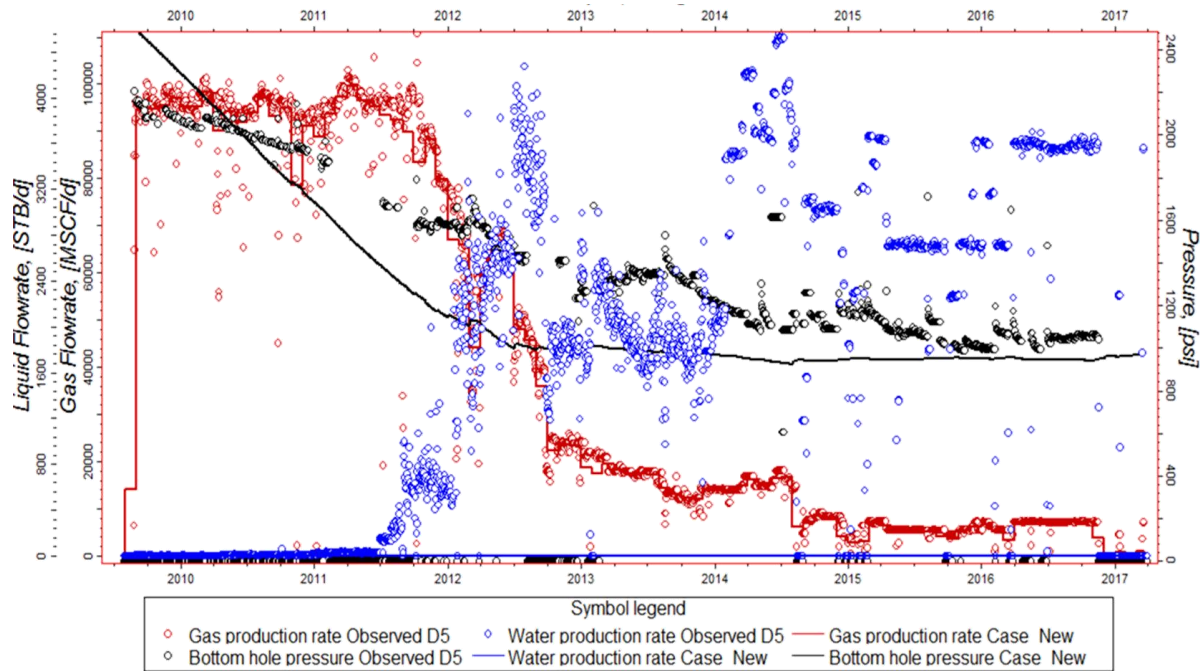
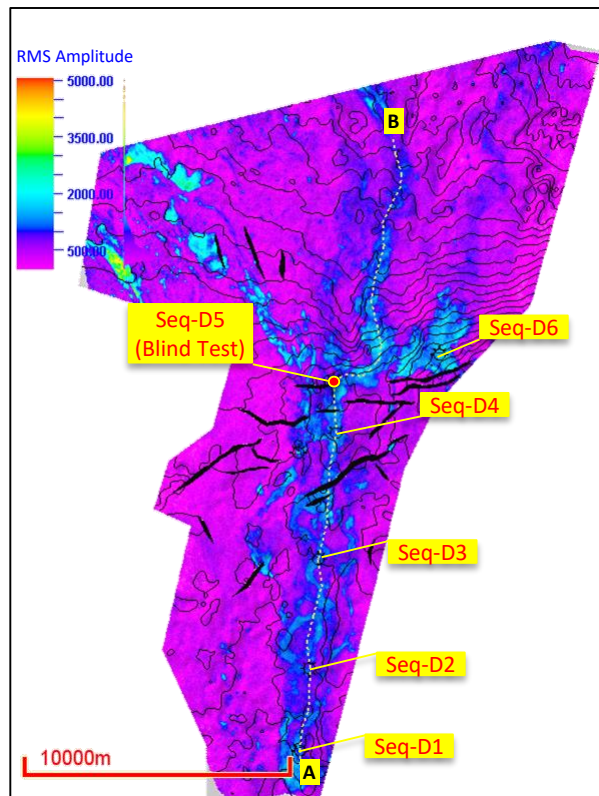
Permeability is calculated from the porosity using a polynomial equation

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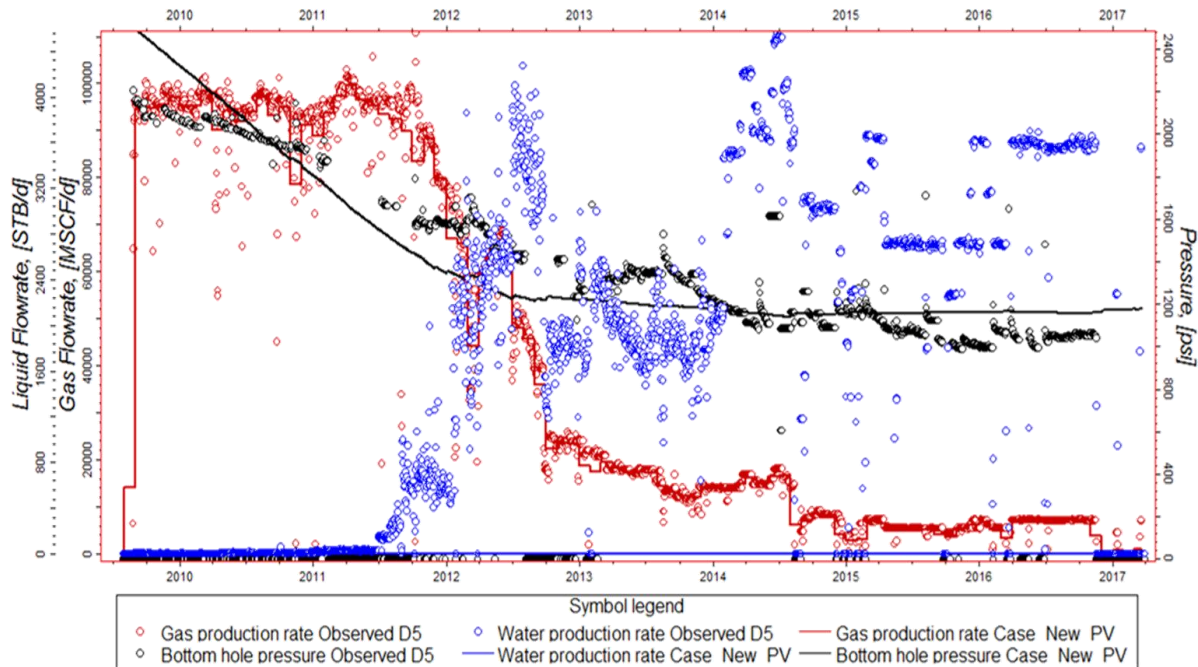
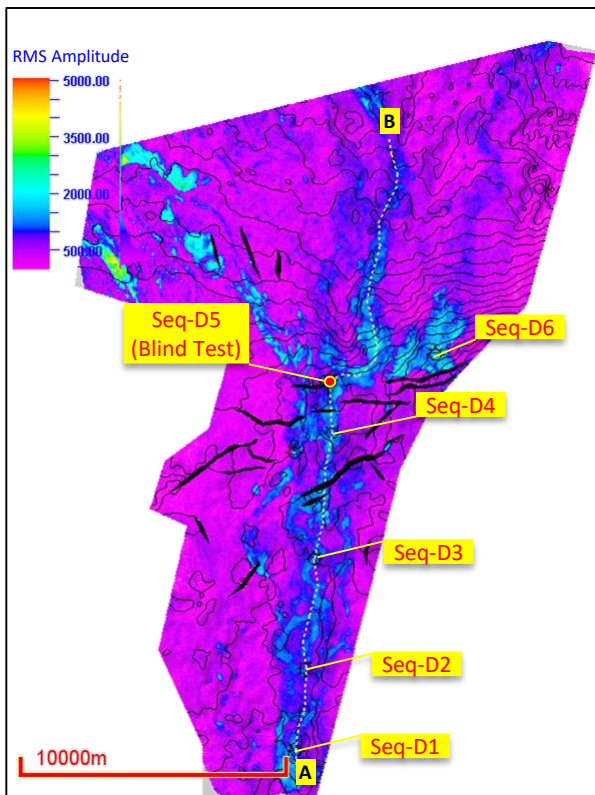
Dynamic Testing

Dynamic simulation results at the blind well (Sequoia D5)



Dynamic Testing

Dynamic simulation results at the blind well (Sequoia D5), additional multiplier is applied for the pore volume (adding 20%)



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Conclusion

- Probabilistic neural network predicts shale volume, porosity, and water saturation 3-D volumes
 - Fast training process
 - Results show high accuracy
- Integrating the PNN in the static modelling
 - Decreases the statistical uncertainty and mitigates the cumulative error problems
 - Reduces the reservoir modeling time by about 80%
- Some details may be lost during the resampling process
 - Finer grid is required or multi-segment model
 - Apply multipliers

Acknowledgement

Rashid Petroleum Company (RASPETCO) and Egyptian General Petroleum Corporation (EGPC) are acknowledged for granting permission to publish this work



THANKS

References

Cross, I., Cunningham, A., Cook, R., Taha, A., Esmail, E., and Swidan, N., 2009, 3-D Seismic Geomorphology of a Deepwater Slope Channel System: The Sequoia Field, Offshore West Nile Delta, Egypt: AAPG Convention, Denver, Colorado.

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Samuel, A., B. Kneller, S. Raslan, A. Sharp, and C. Parsons, 2003, Prolithic deep-marine slope channels of the Nile Delta, Egypt: AAPG Bulletin, v. 87, p. 541–560.