

Hydrocarbon Saturation Prediction from Full-Stack Seismic Data Using Probabilistic Neural Network*

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Abstract

In complex geological settings with a great degree of heterogeneity in reservoir properties such as submarine channel complexes, as in Nile Delta province, we face the challenge of characterizing the reservoir based on different seismic attributes. Direct Hydrocarbon Indicator (DHI) and Amplitude Variation with Offset (AVO) analysis techniques proved very impressive results delineating the gas bearing reservoirs, especially in the clastic systems. However, low quality facies or low saturation reservoirs give the same seismic amplitude response. The pre-stack seismic inversion products such as P-impedance, V_p/V_s and Lambda-Mu-Rho (LMR) can provide more realistic quantitative reservoir characterization. Absence of control wells and/or pre-stack seismic data makes it impossible to use the pre-stack inversion approach. In addition, quantitative prediction of hydrocarbon saturation from seismic is ambiguous because of their independent nonlinear relationship with conventional seismic attributes and inversion products.

Hydrocarbon saturation prediction away from the well is essential to characterize reservoir effectively. Therefore, a special approach has been adopted which is Probabilistic Neural Network (PNN) analysis to predict hydrocarbon saturation 3D volume using full-stack seismic data and Hydrocarbon saturation logs. In this case study, we applied the proposed neural network workflow over one of the late Pliocene gas sandstone reservoirs in West Delta Deep Marine (WDDM) concession, offshore Nile Delta, Egypt. The resulting volume was then tested using a blind well that hasn't been used in the analysis. The predicted volume contains fine details that will help for better delineation of hydrocarbon-saturated reservoir in 3D space.

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Hydrocarbon Saturation Prediction from Full-Stack Seismic Data Using Probabilistic Neural Network



Islam Ali Mohamed

GEO 2016



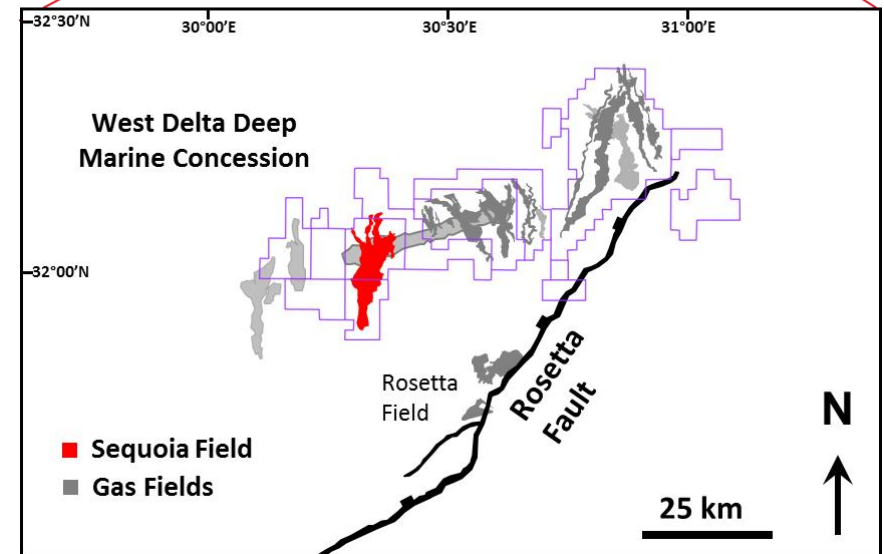
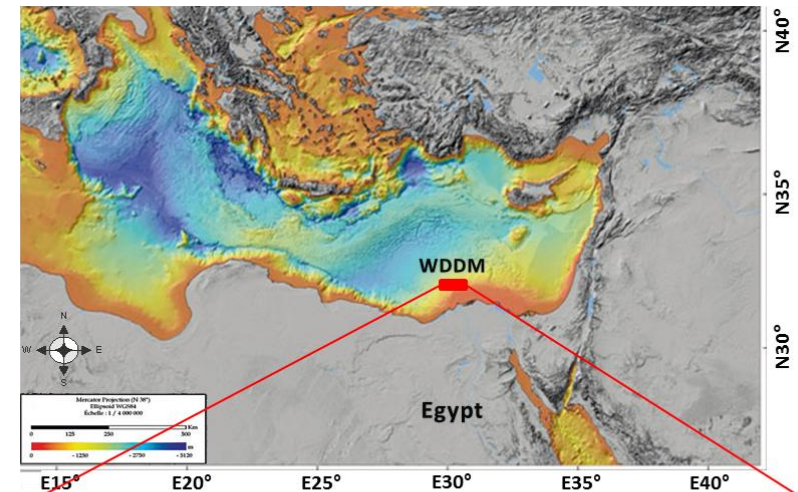
Outline

- Introduction
- Probabilistic Neural Network
- Results
- Interpretation
- Conclusions



Area of Study

- Egypt
- Offshore Nile Delta
- West Delta Deep Marine (WDDM) concession covers 6150 km²
- The Sequoia Field is a Pliocene gas field located 90 km north of Alexandria in water depths of 250-850 m.



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



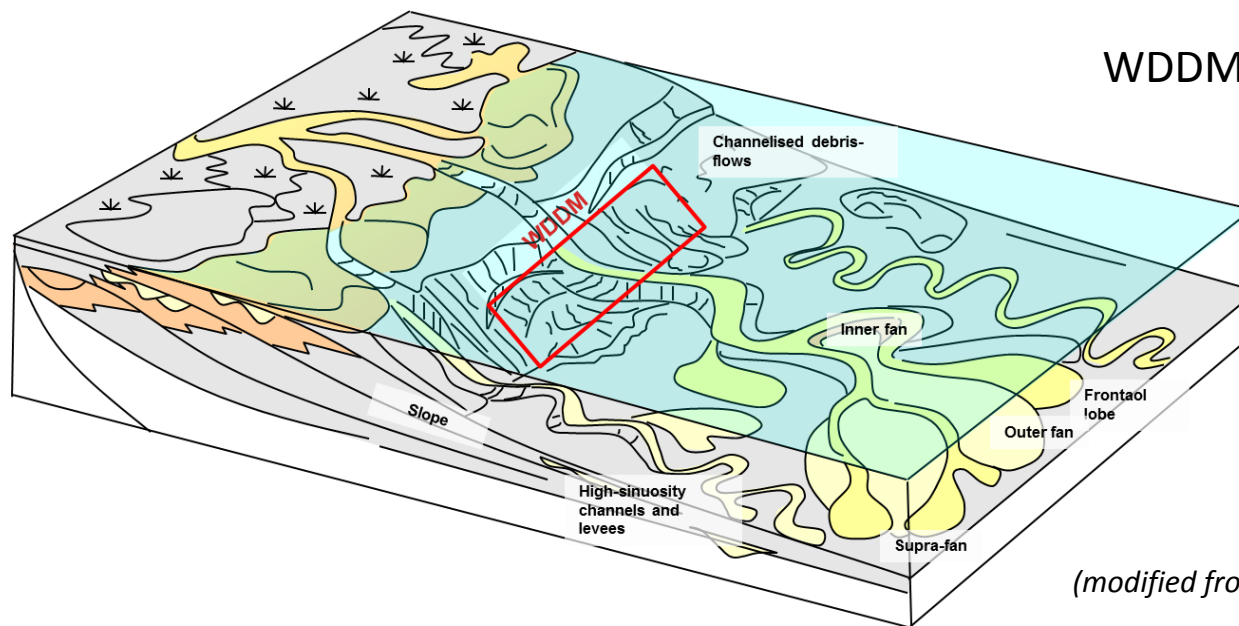
Nile Delta – Tectono-Stratigraphic Setting

AGE	STAGE	BIOZONES		FORMATION	LITHOLOGY		
			NANNO				
HOLOCENE			N23	NN21	BILQAS		
			PLEISTOCENE	LATE	N22	NN20	MIT GHAMR
EARLY	CALABRIAN	NN19				BALTIM	
		PLIOCENE				LATE	N21
NN17							
EARLY	ZANCLEAN		N19 - N20	NN16	KAFR EL SHEIKH		
				NN15			
				NN14			
UPPER MIOCENE	MESSINIAN		N18	NN13	ABU MADI		
				NN12			
	TORTONIAN		N17	NN11	QAWASIM		
				NN10			
				NN9			
			N15	NN8			

Sheet sand (Ibn Sequoia)
Main sequoia Channel

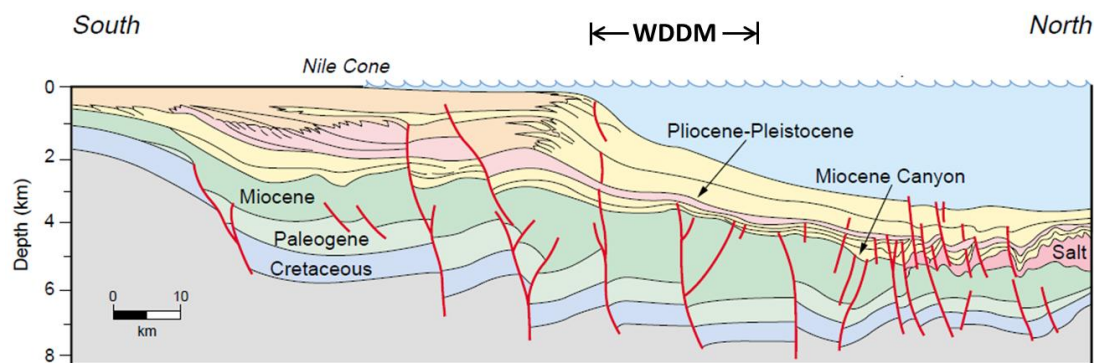
80/90

Nile Delta stratigraphic column



WDDM Simplified Model

(modified from Reading and Richards, 1994)

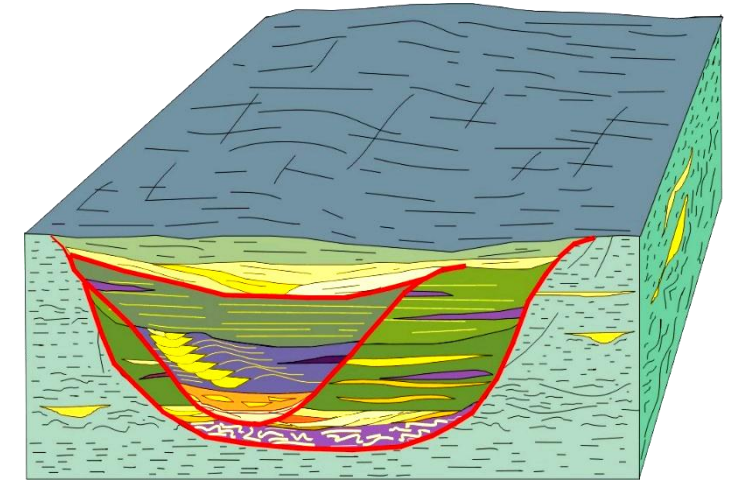
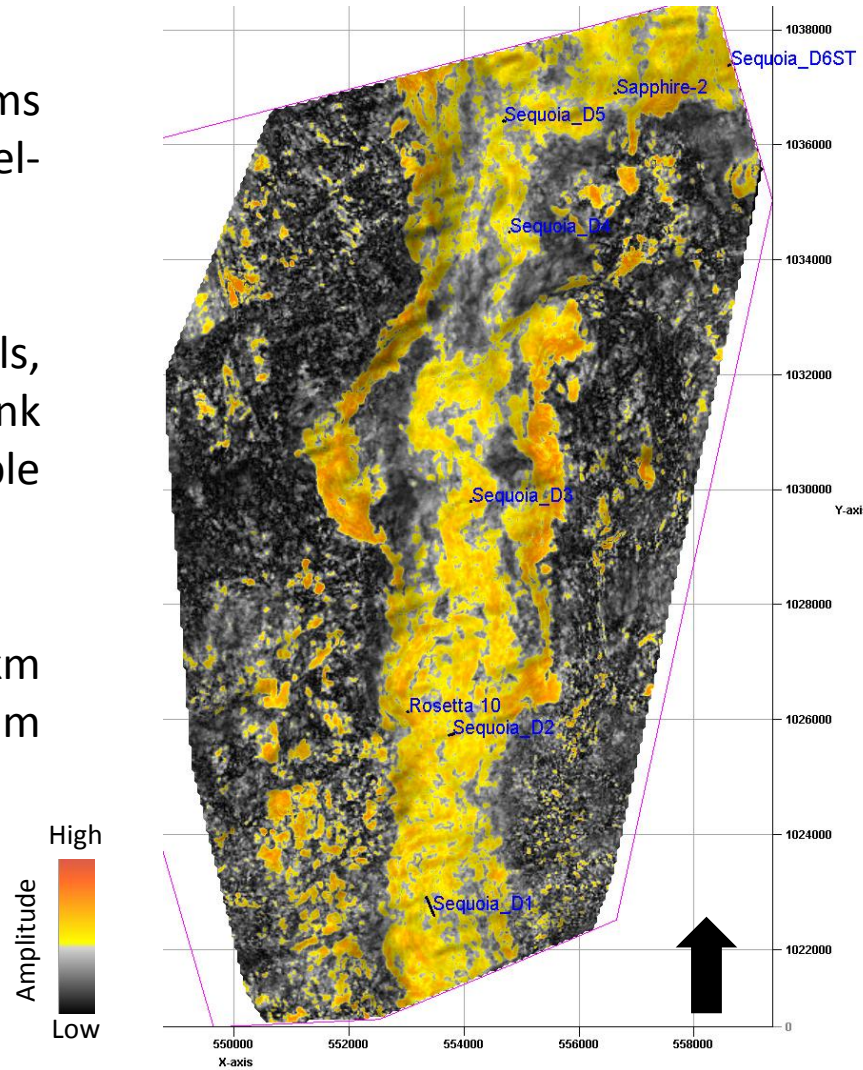


(modified from Abdel Aal et al., 2006)

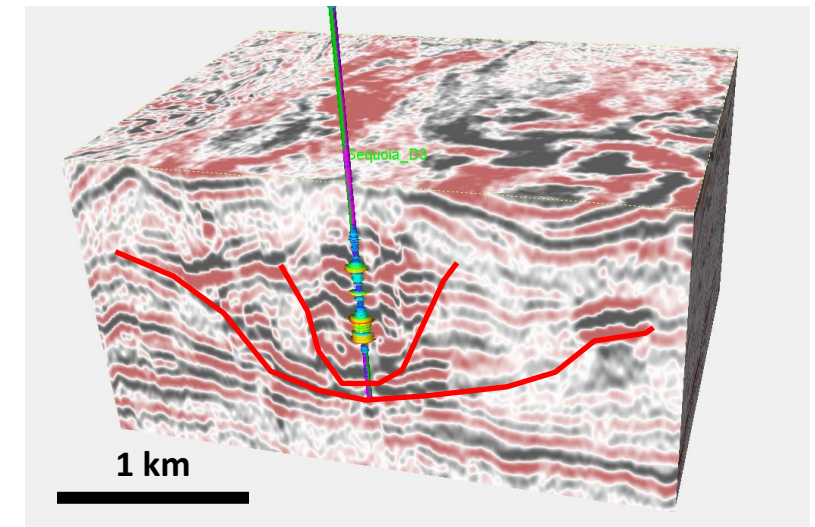


The Sequoia Field – Geological Overview

- Multi-stacked canyon systems with complex turbidite channel-levee reservoirs.
- Canyon-fill of sandy channels, levees, crevasse splays, overbank deposits and slumps with multiple fill and incision.
- Sequoia channel system: 10's km long, c.5km wide and up to 200 m thick.

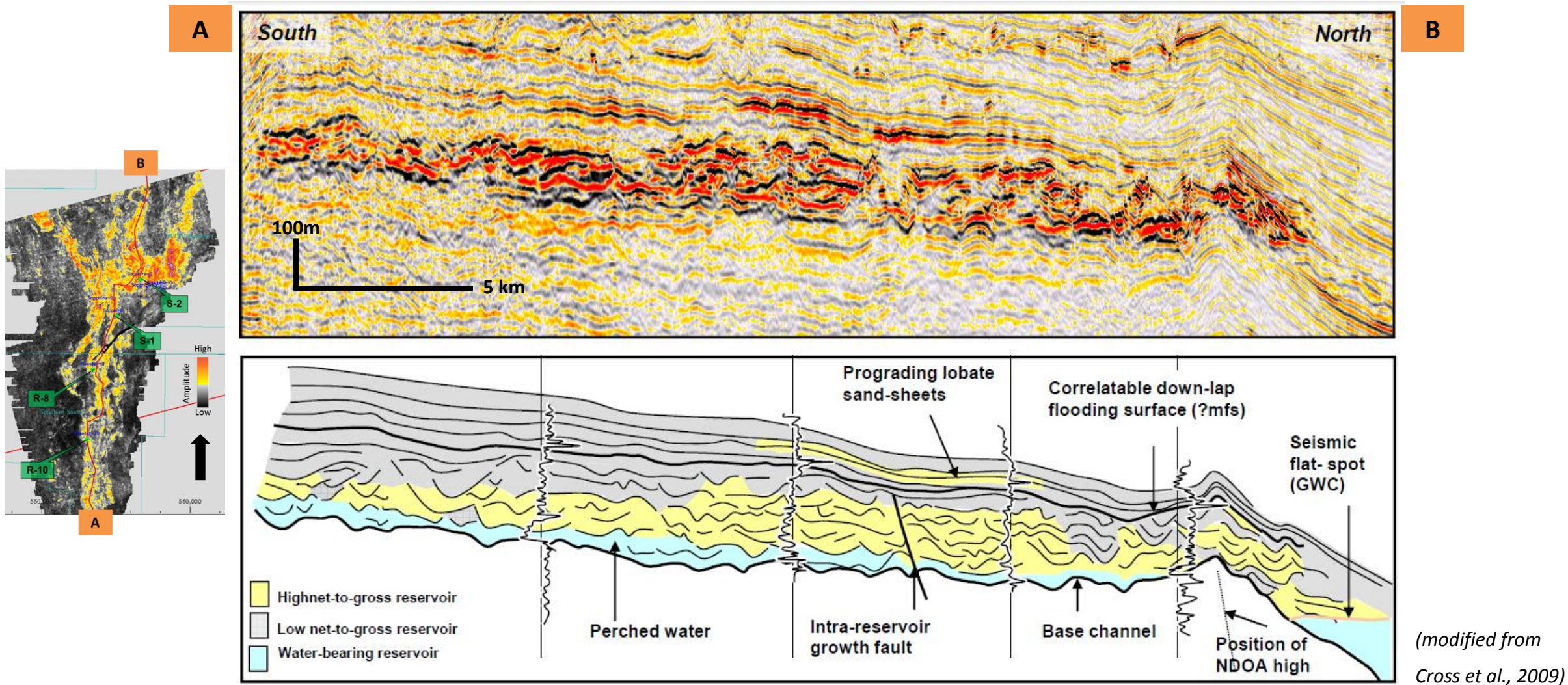


(from Samuel et al., 2003)





Large-Scale Reservoir Architecture



Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



Sequoia Channel Evolution Summary

Ibn Sequoia

*Sequoia channel
abandonment and
minor sheet sands*

Stage III

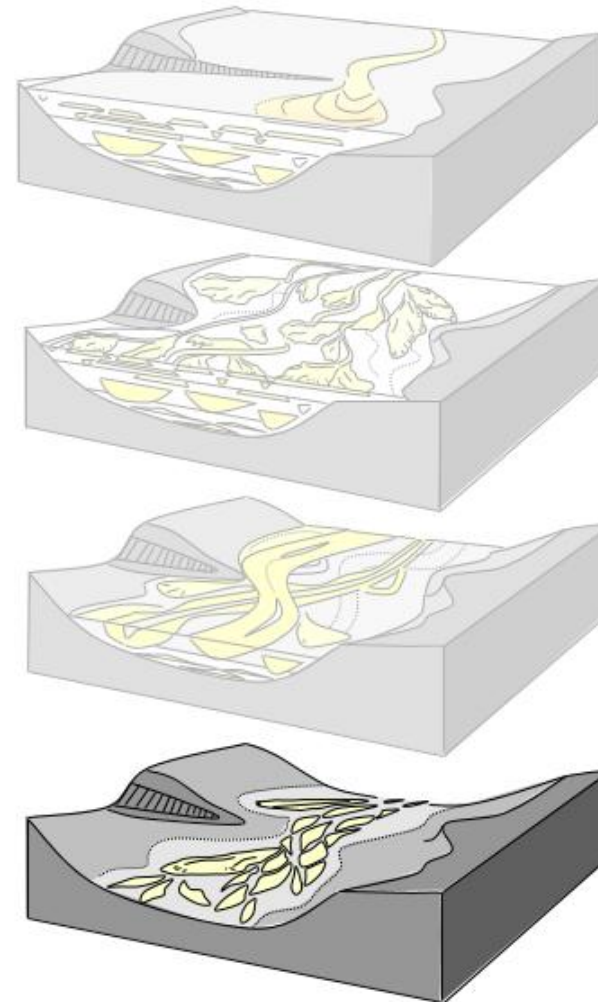
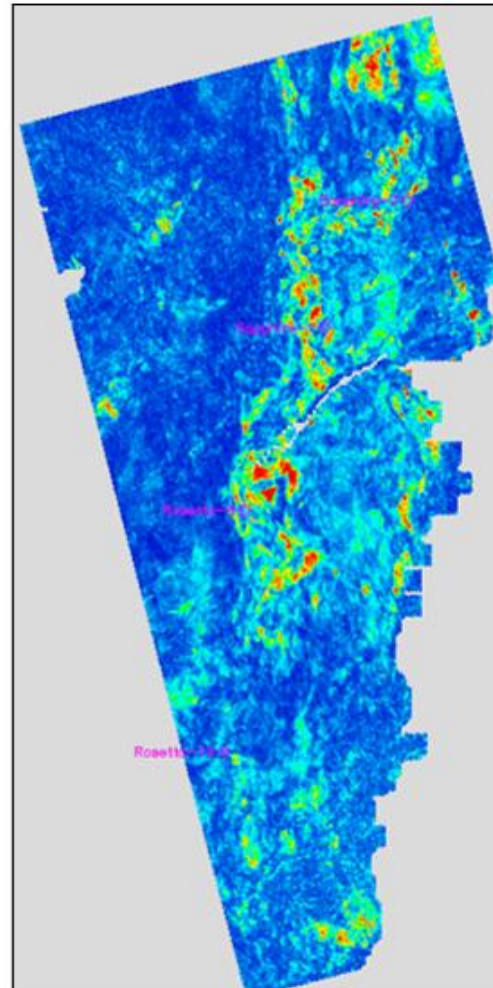
*Narrower and
straighter channels
and splays*

Stage II

*High sinuosity
channel and
associated splays*

Stage I

*Braided, poorly
confined channel
deposition*



(from Cunningham et al., 2010)



Sequoia Channel Evolution Summary

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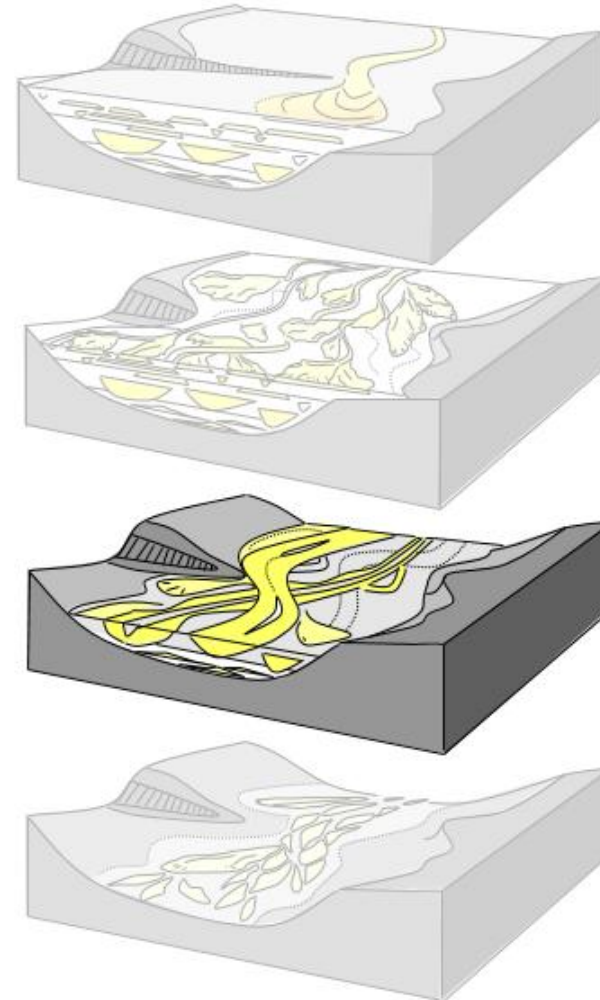
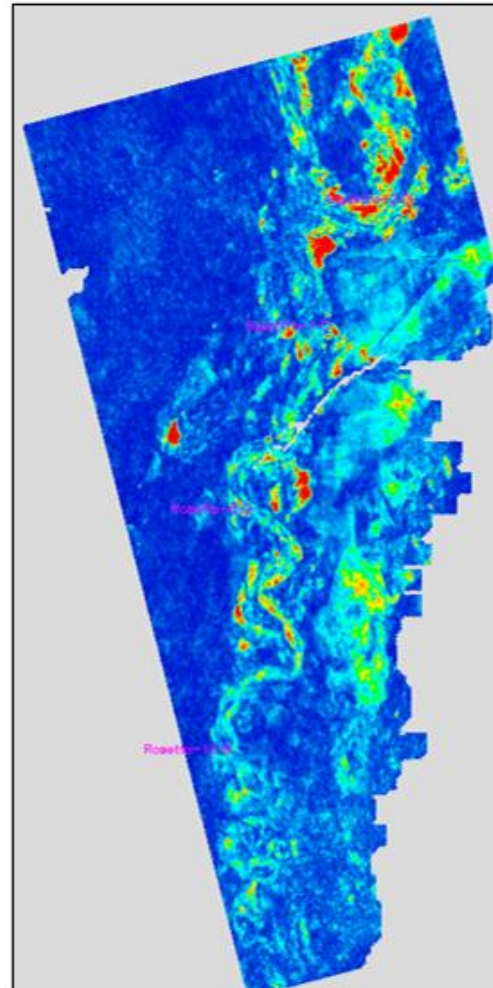
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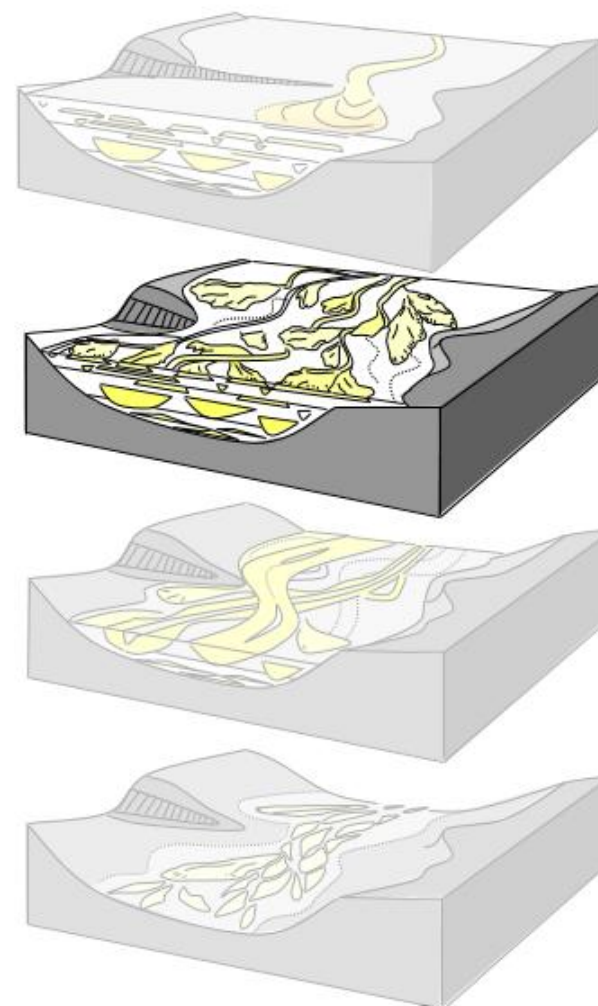
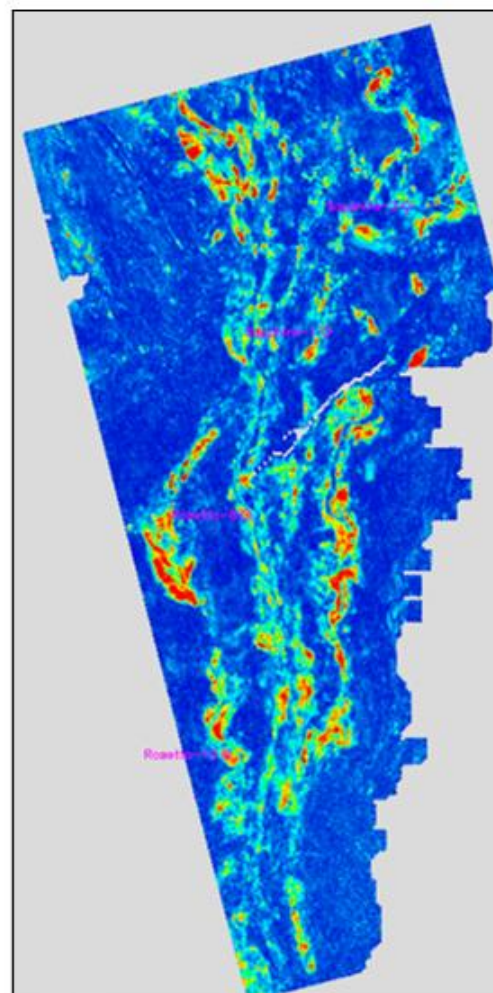
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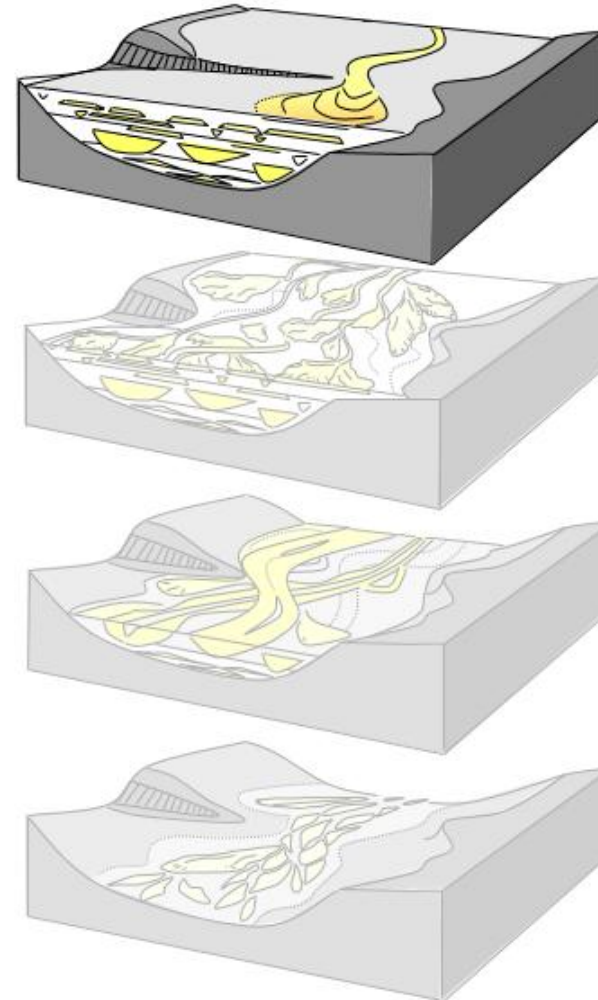
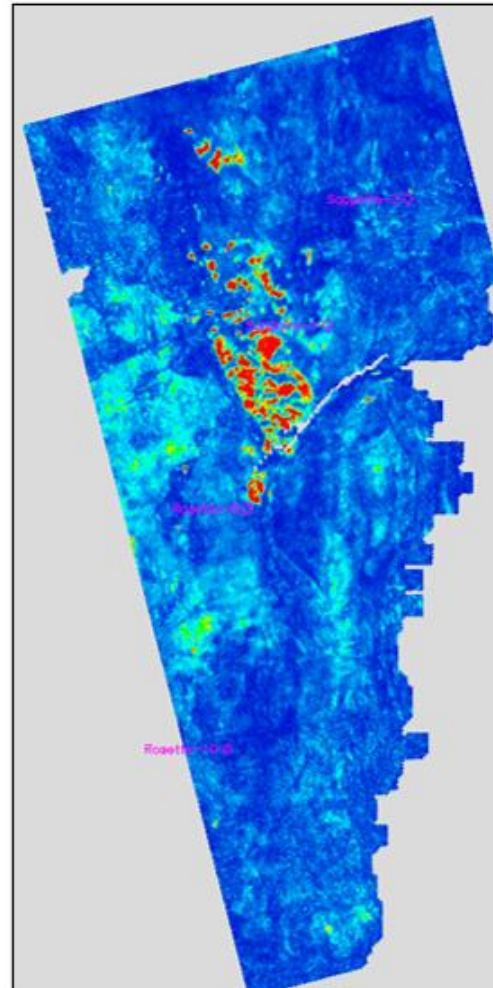
Sequoia Channel Evolution Summary

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

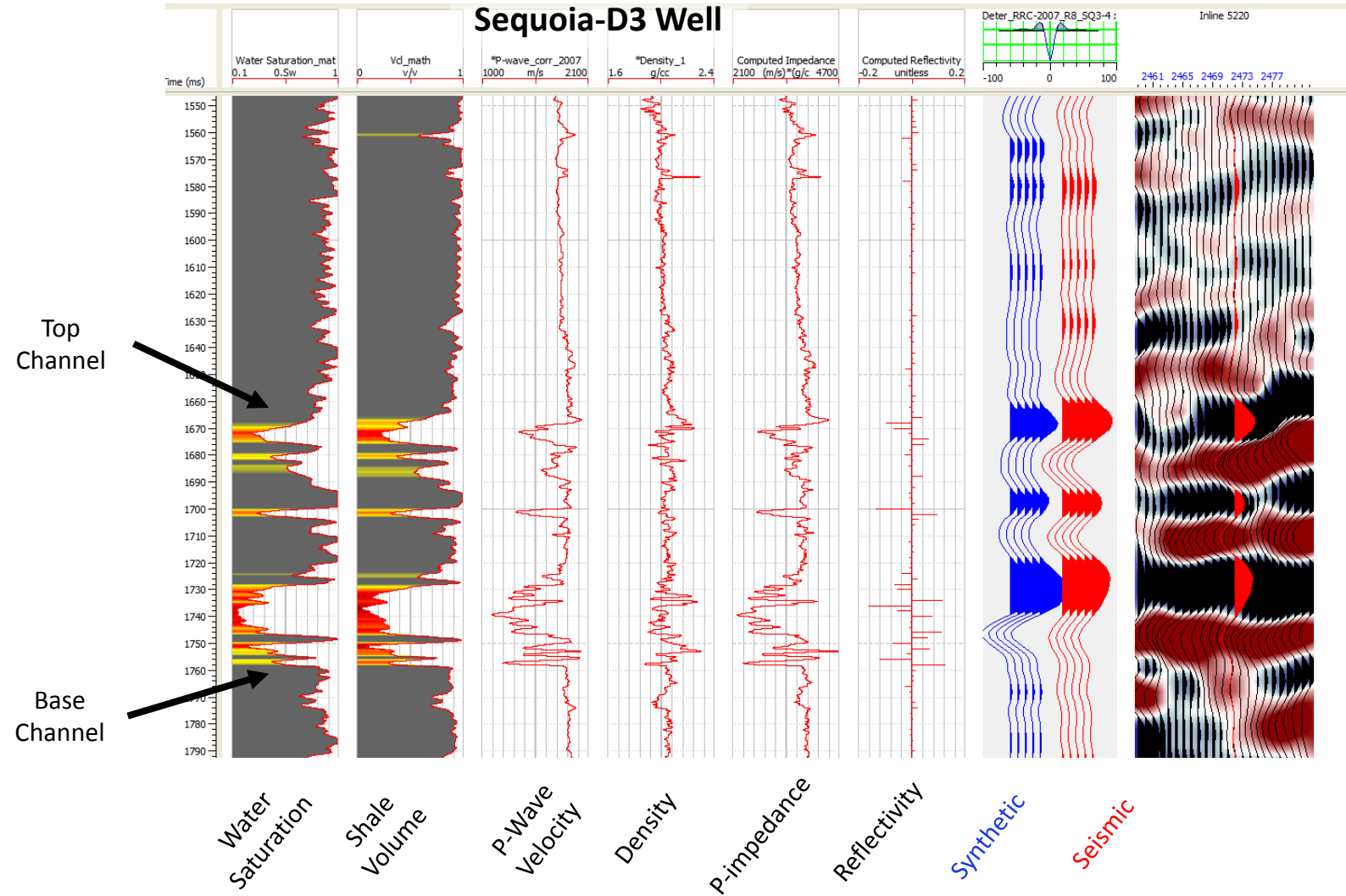


(from Cunningham et al., 2010)



Sequoia Field Well Data

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





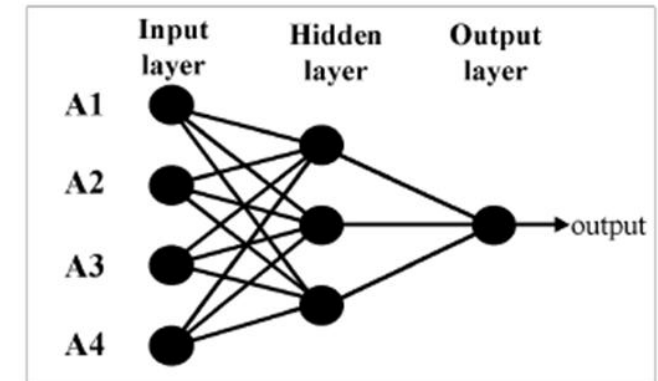
Outline

- Introduction
- Probabilistic Neural Network
- Results
- Interpretation
- Conclusions

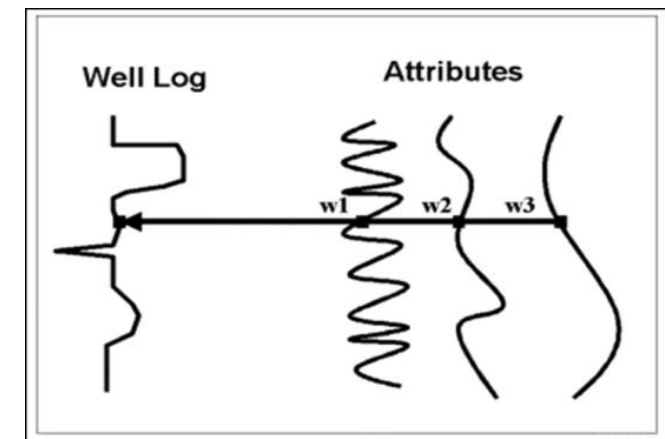


Probabilistic Neural Network

- The PNN can be used either for classification or for mapping.
- How it works
 - The PNN finds the weights that depend on the distance from the desired point to the training points. The distance is measured in multi-dimensional attribute space.
 - The distance is scaled by smoothers (the sigma values), which are determined automatically by cross-validation.
 - The weighting functions are multiplied by the known log values to determine the unknown log values.
- Theoretically, it can predict any log property.

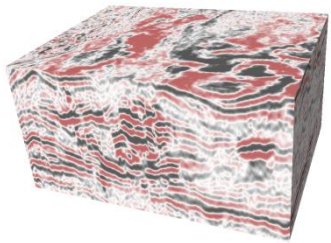


The basic architecture of multi-layer feed-forward neural network (*Hampson et al., 2001*)

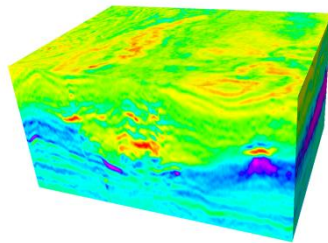




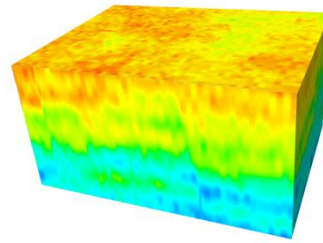
PNN – Workflow



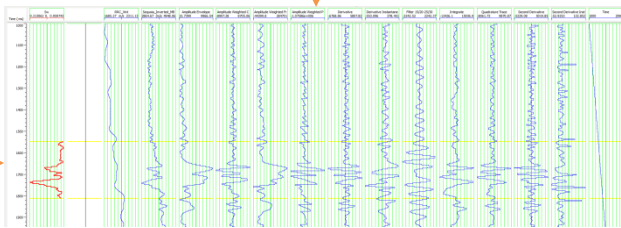
Full-Stack Seismic



P-Impedance
(post stack inversion)



Interval Velocity
(processing)



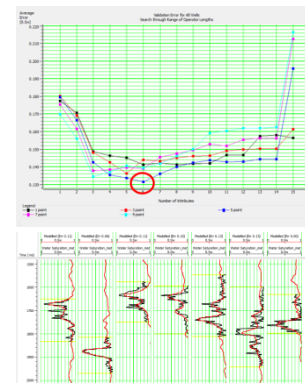
Internal & External Attributes



Sw
(well logs)

Input
Data

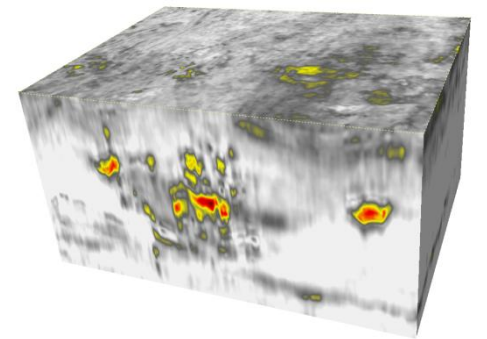
Train and Validate
the Network



PNN



Output Saturation
Volume



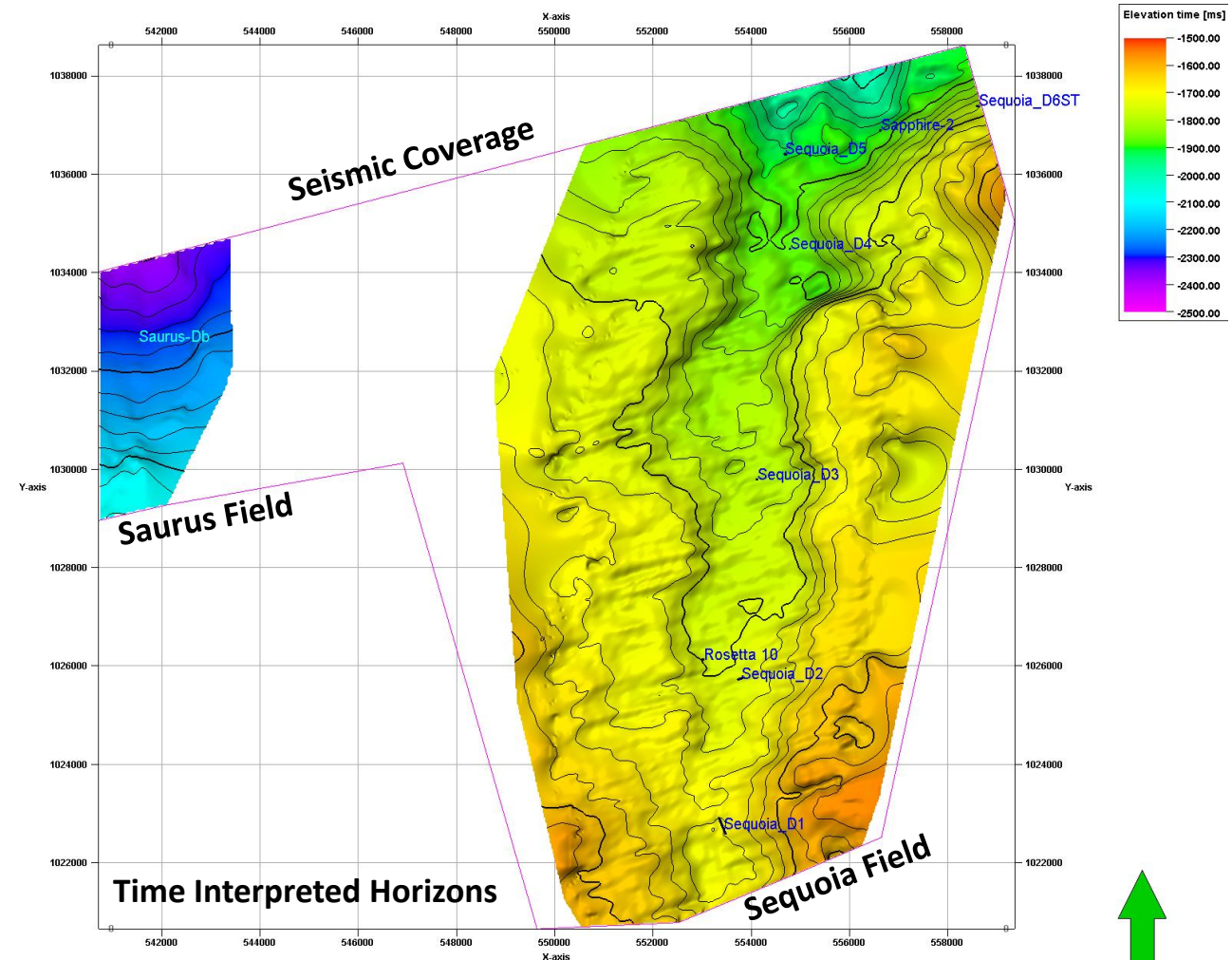
Output
Data

Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



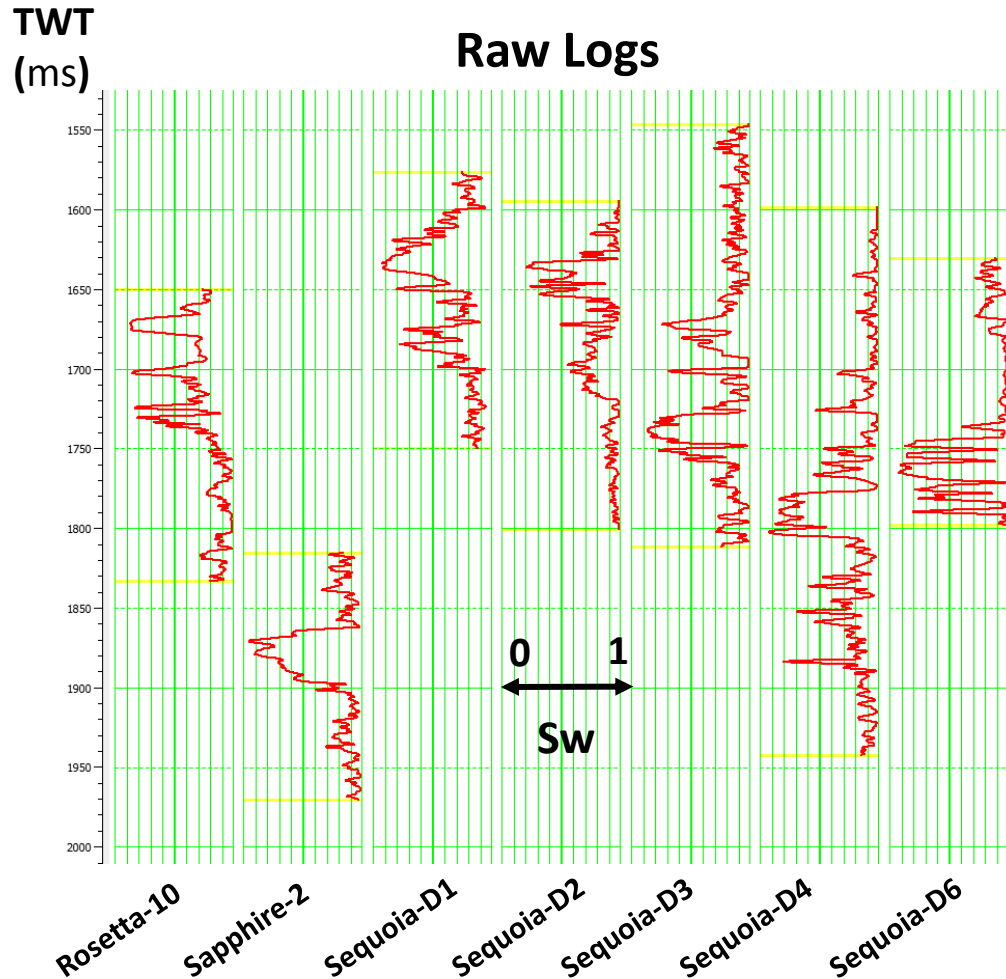
PNN – Input Well Data

- Seven wells used in the study
 - Rosetta-10
 - Sapphire-2
 - Sequoia-D1, -D2, -D3, -D4 & -D6
- Two “blind” QC wells
 - From Sequoia field: Sequoia-D5
 - From Saurus field: Saurus-Db



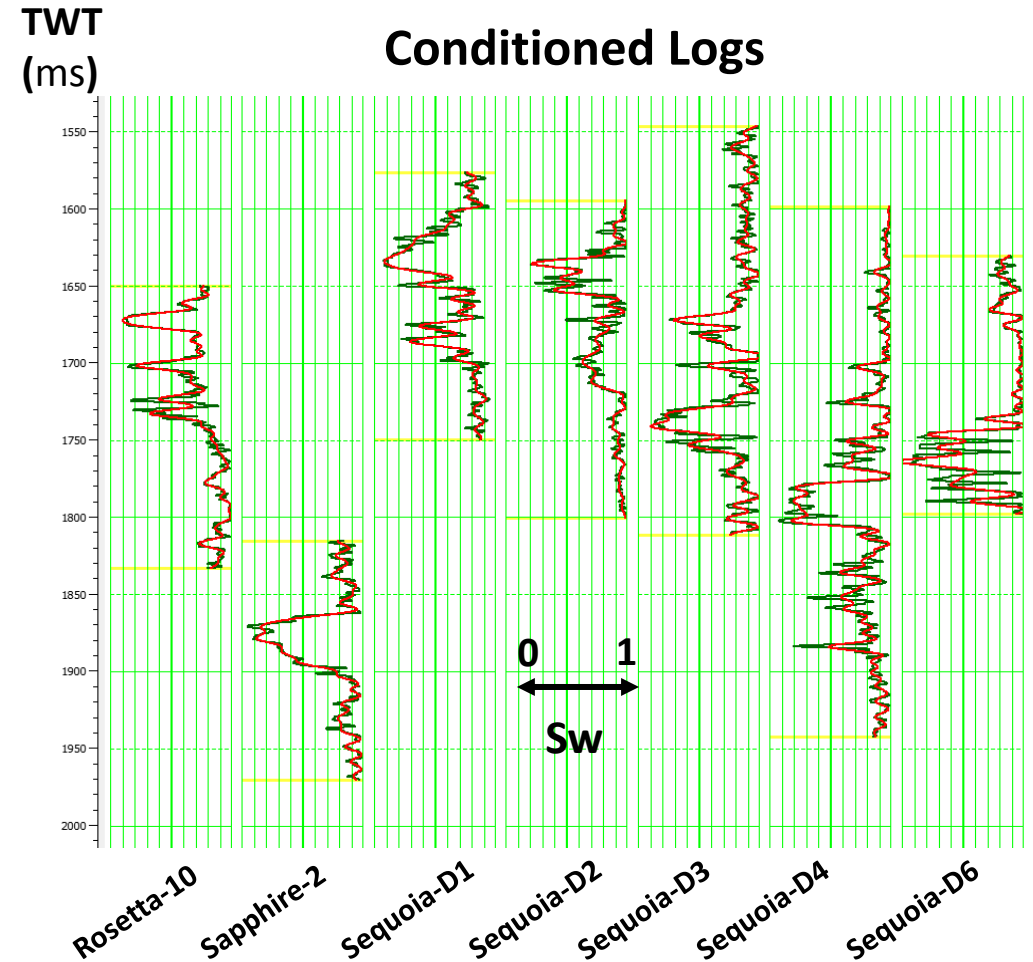


PNN – Well Data Conditioning



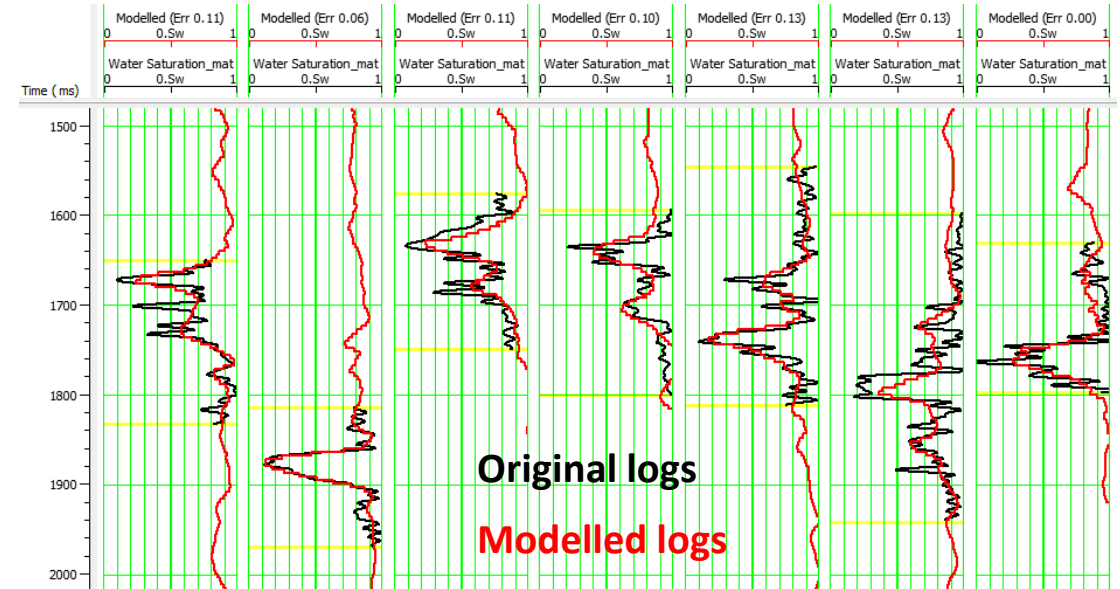
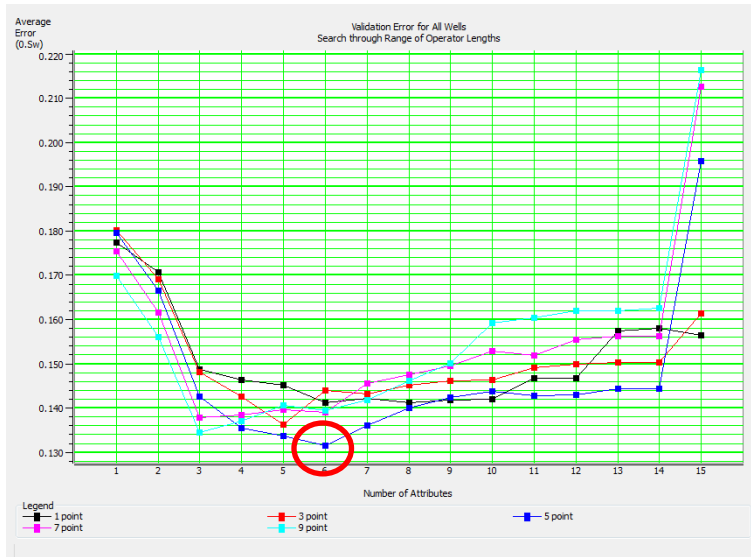
Conditioning:

- Resampling @ 4 ms
- Smoothing



Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions

PNN – Training and Validation of the Network



Average correlation for all wells: 91%

	Target	Final Attribute	Training Error	Validation Error
1	Water Saturation	1 / (Sequoia_Inverted_MB_Zp)	0.166120	0.179746
2	Water Saturation	Amplitude Envelope	0.148741	0.166720
3	Water Saturation	Amplitude Weighted Frequency	0.126962	0.142777
4	Water Saturation	Sqrt(RRC_Vint)	0.117173	0.135564
5	Water Saturation	Amplitude Weighted Cosine Phase	0.112927	0.133839
6	Water Saturation	Second Derivative Instantaneous Amplitude	0.110756	0.131786
7	Water Saturation	Filter 5/10-15/20	0.109959	0.136277
8	Water Saturation	Time	0.109572	0.140145
9	Water Saturation	Integrate	0.109245	0.142615
10	Water Saturation	Quadrature Trace	0.108327	0.143970
11	Water Saturation	Derivative	0.107048	0.142970
12	Water Saturation	Second Derivative	0.106666	0.143122
13	Water Saturation	Amplitude Weighted Phase	0.106361	0.144583
14	Water Saturation	Derivative Instantaneous Amplitude	0.106361	0.144599
15	Water Saturation	Raw Seismic	0.167444	0.195950

The lowest error at:
six attributes with
5-point operator

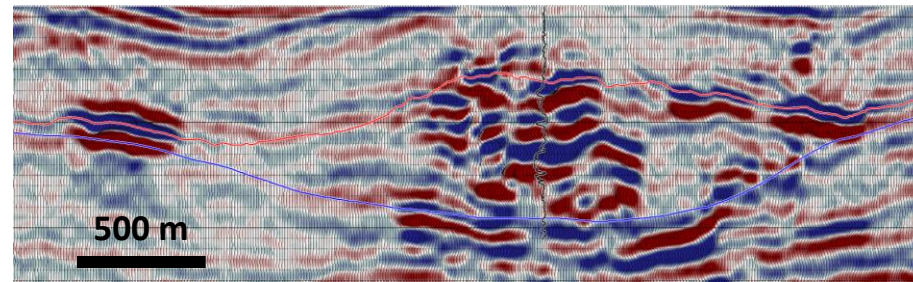
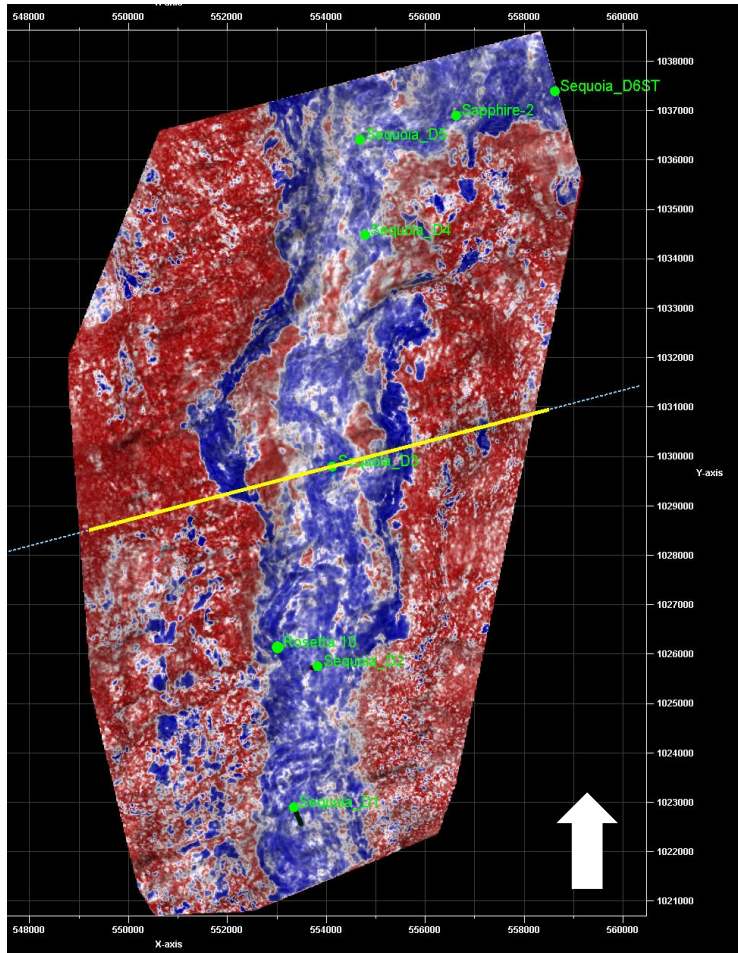


Outline

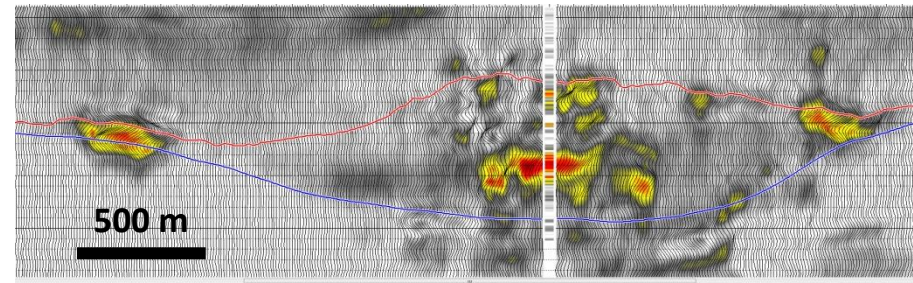
- Introduction
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- **Results**
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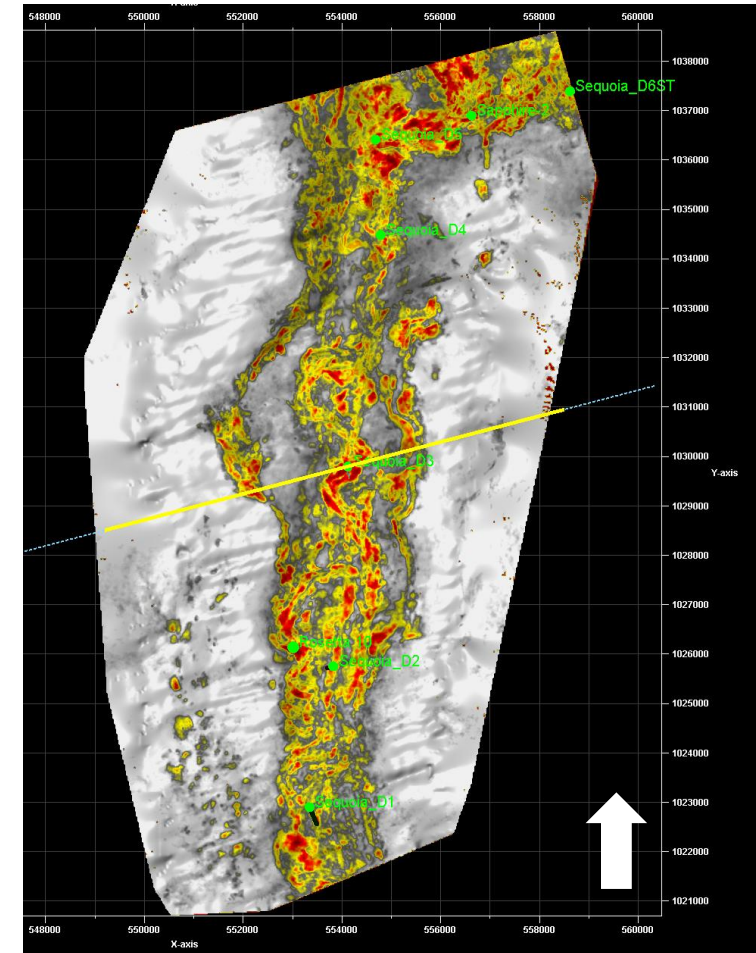
Results – Sequoia Field, Sequoia-D3 Well Location



Seismic
- [color gradient from blue to red] +



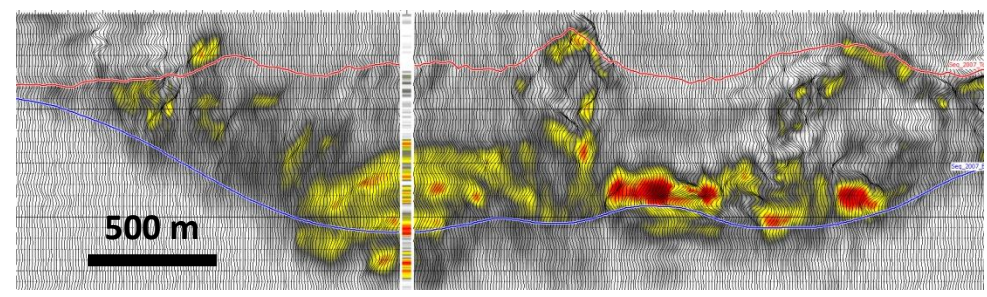
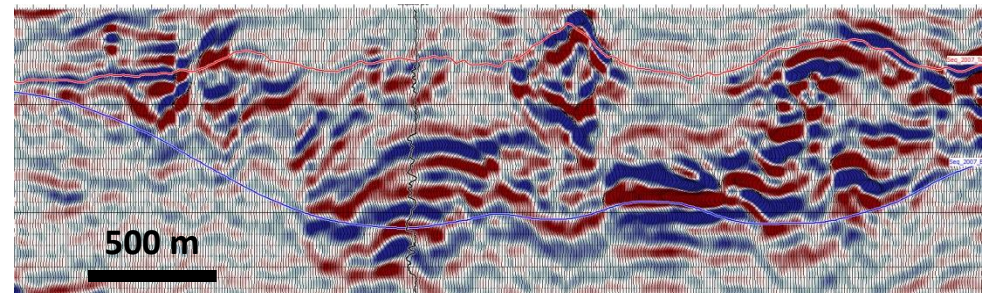
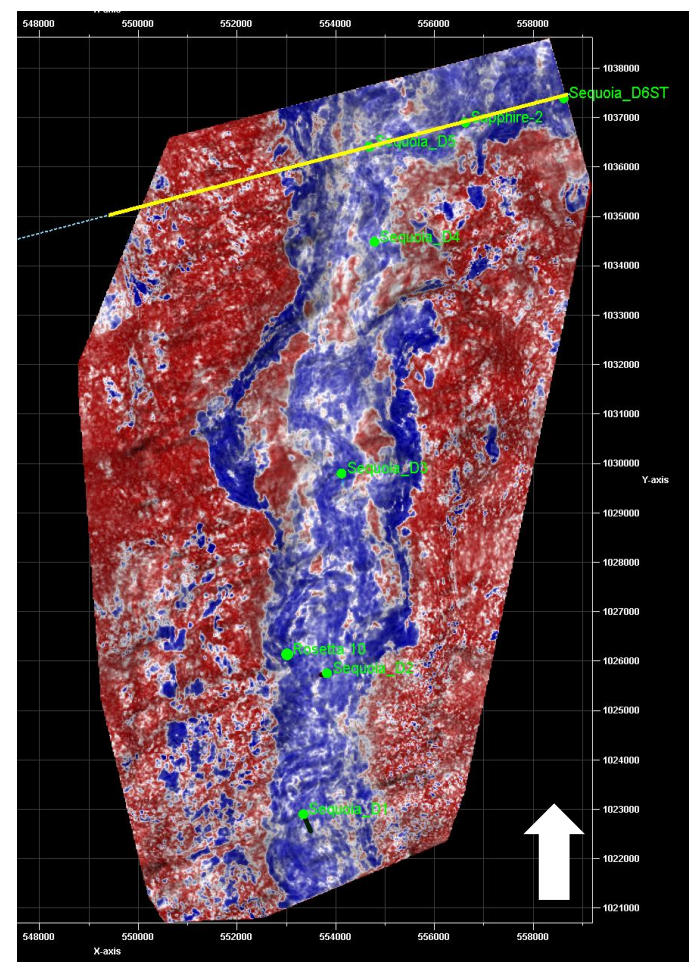
0 [color gradient from grey to red] 1
Hydrocarbon Saturation



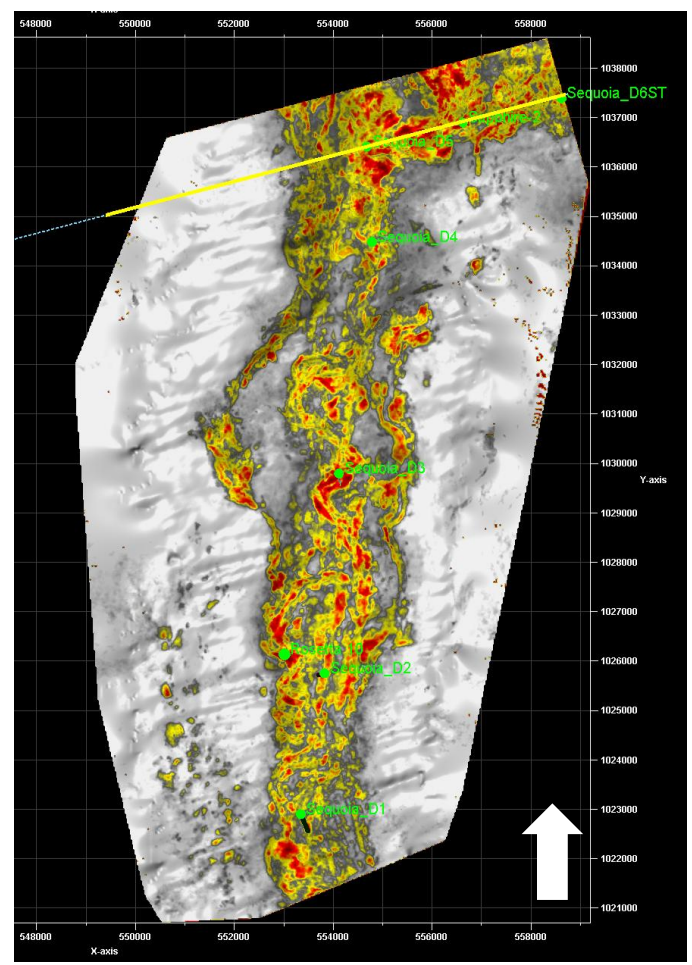
Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



Results – Sequoia Field, Sequoia-D5 “Blind” Well Location



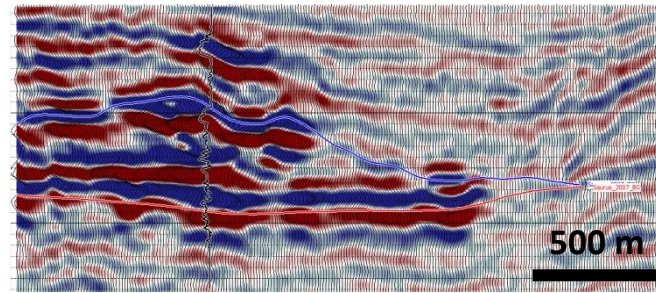
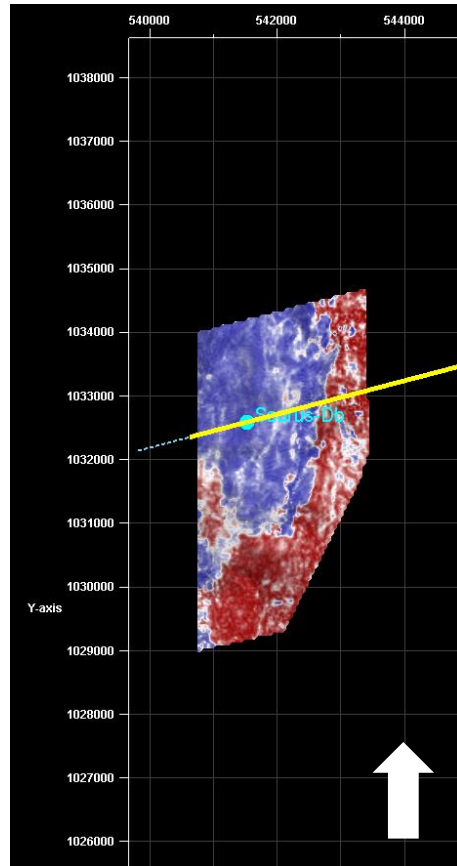
Correlation: 85%



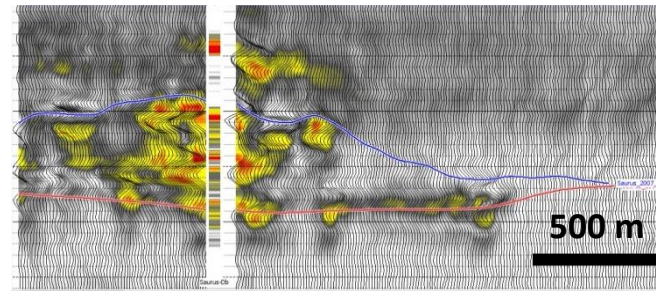
Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



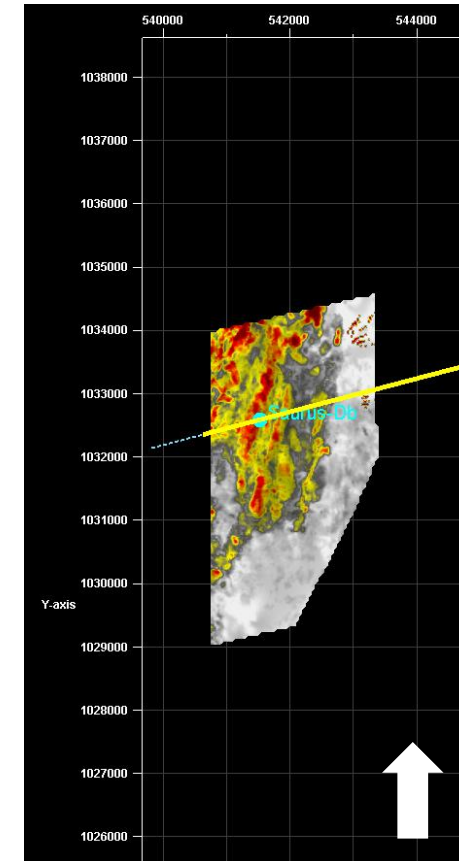
Results – Saurus Field, Saurus-Db “Blind” Well Location



Seismic
- [Color Scale] +



0 [Color Scale] 1
Hydrocarbon Saturation

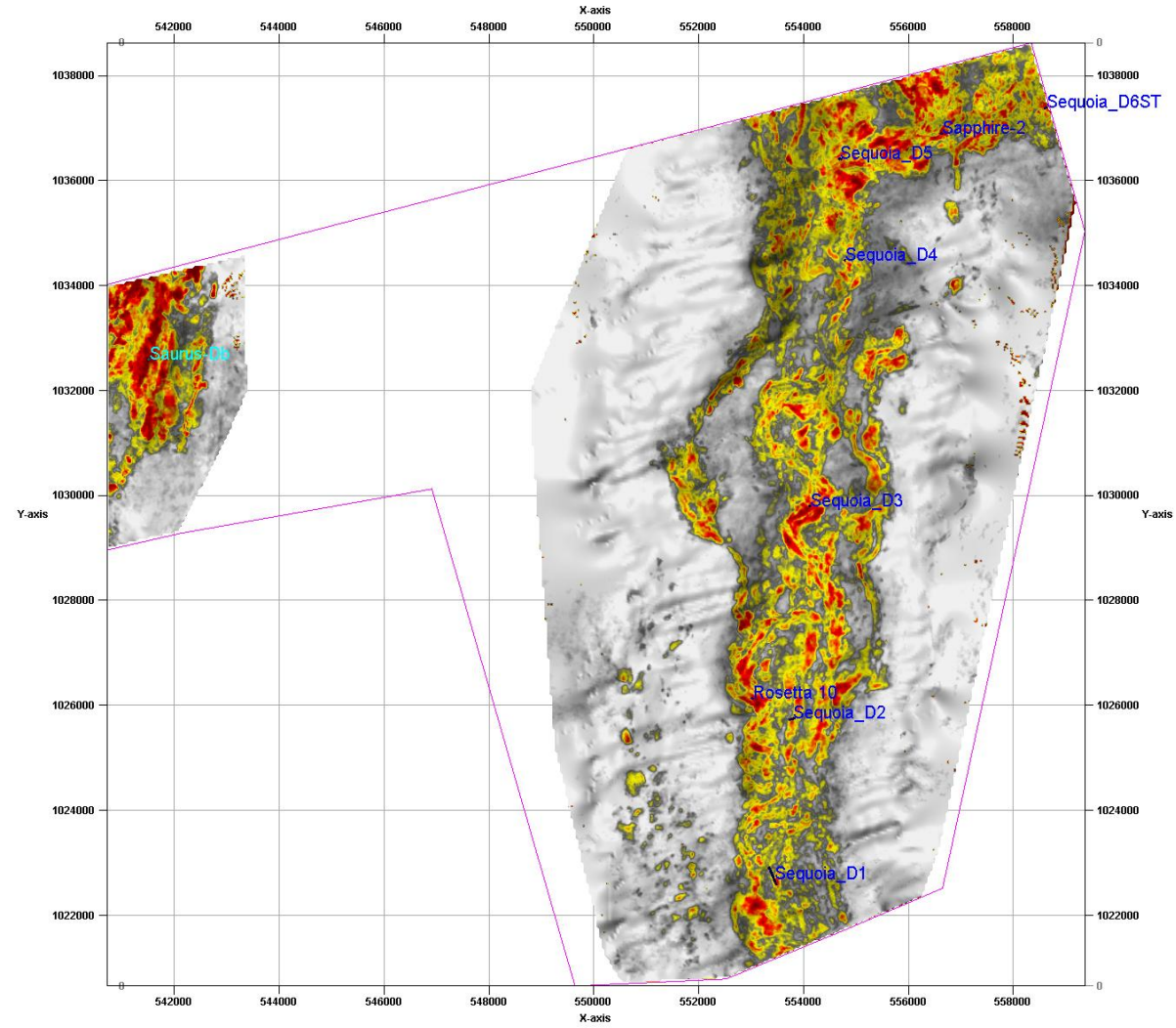


Correlation: 76%

Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



Results – Sequoia and Saurus Fields



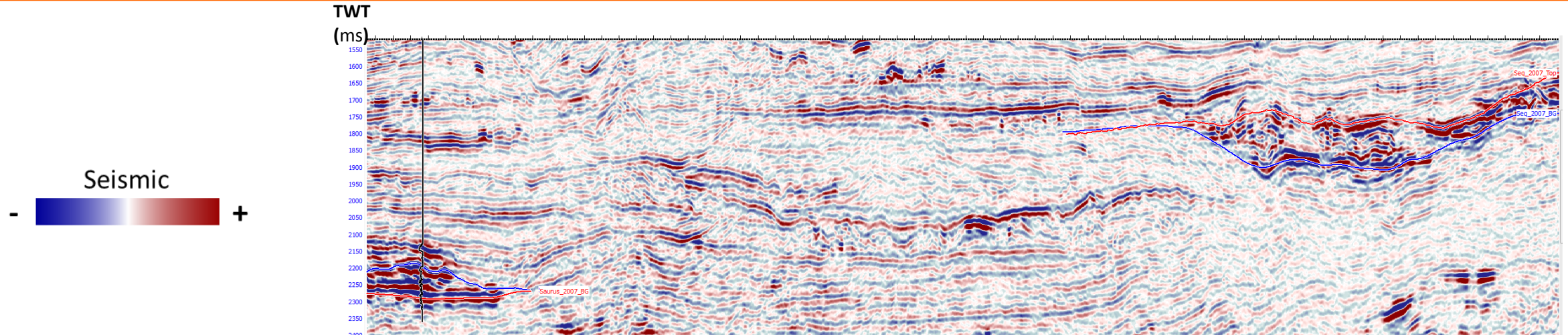
0  1
Hydrocarbon Saturation



Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions

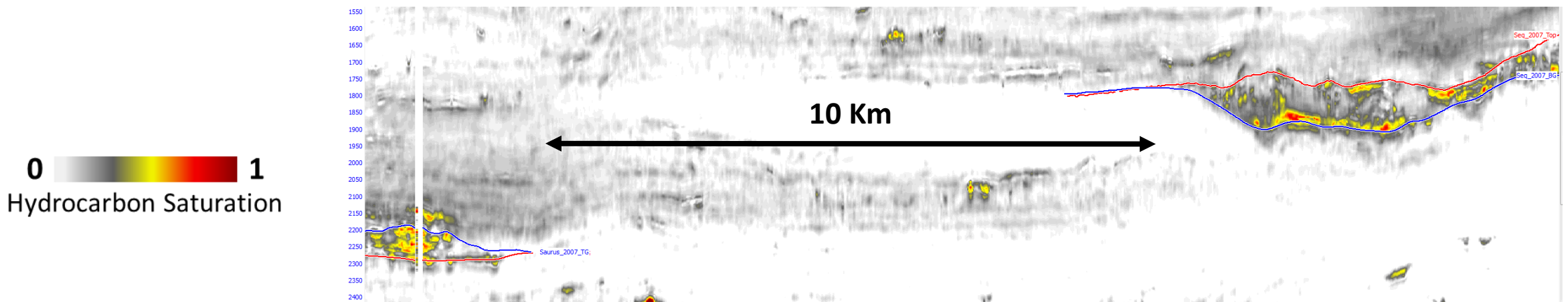


Results – Sequoia and Saurus Fields



Saurus Field

Sequoia Field



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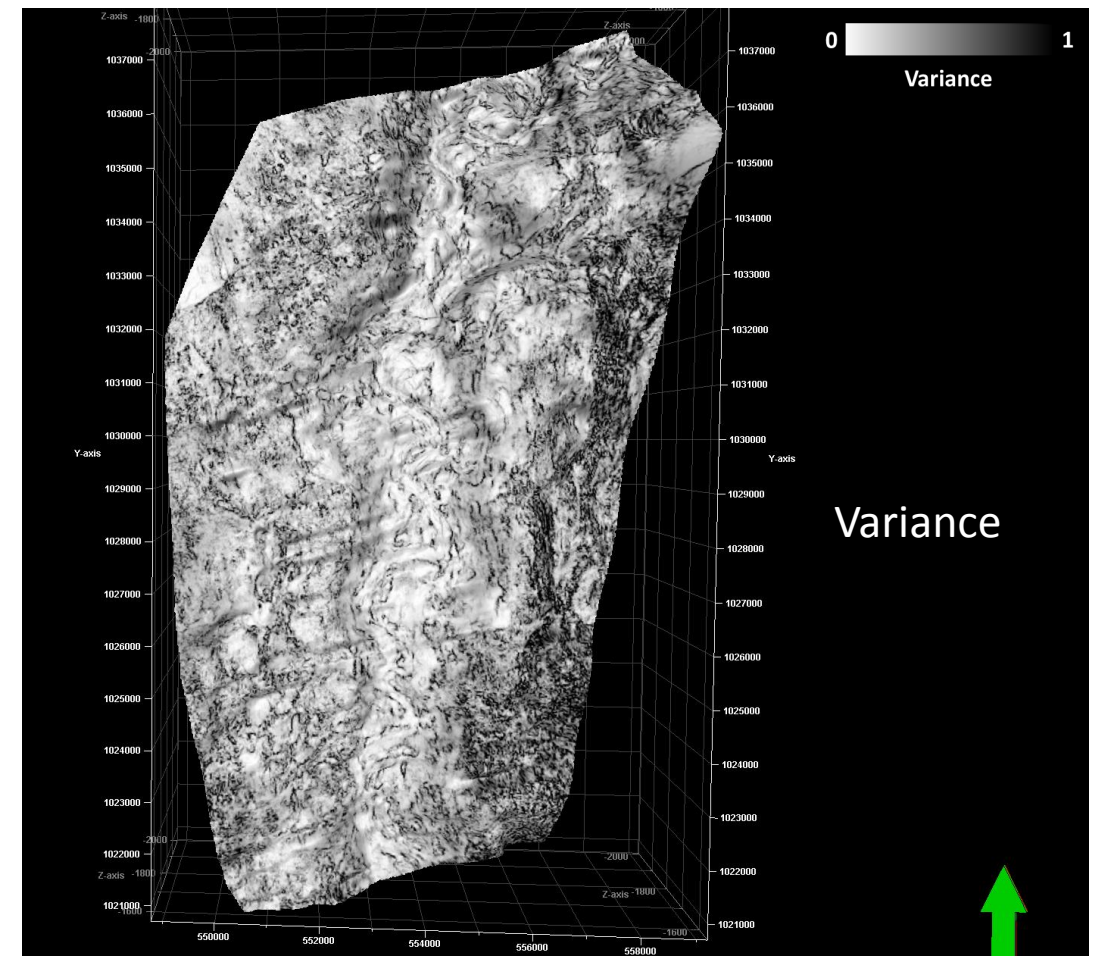
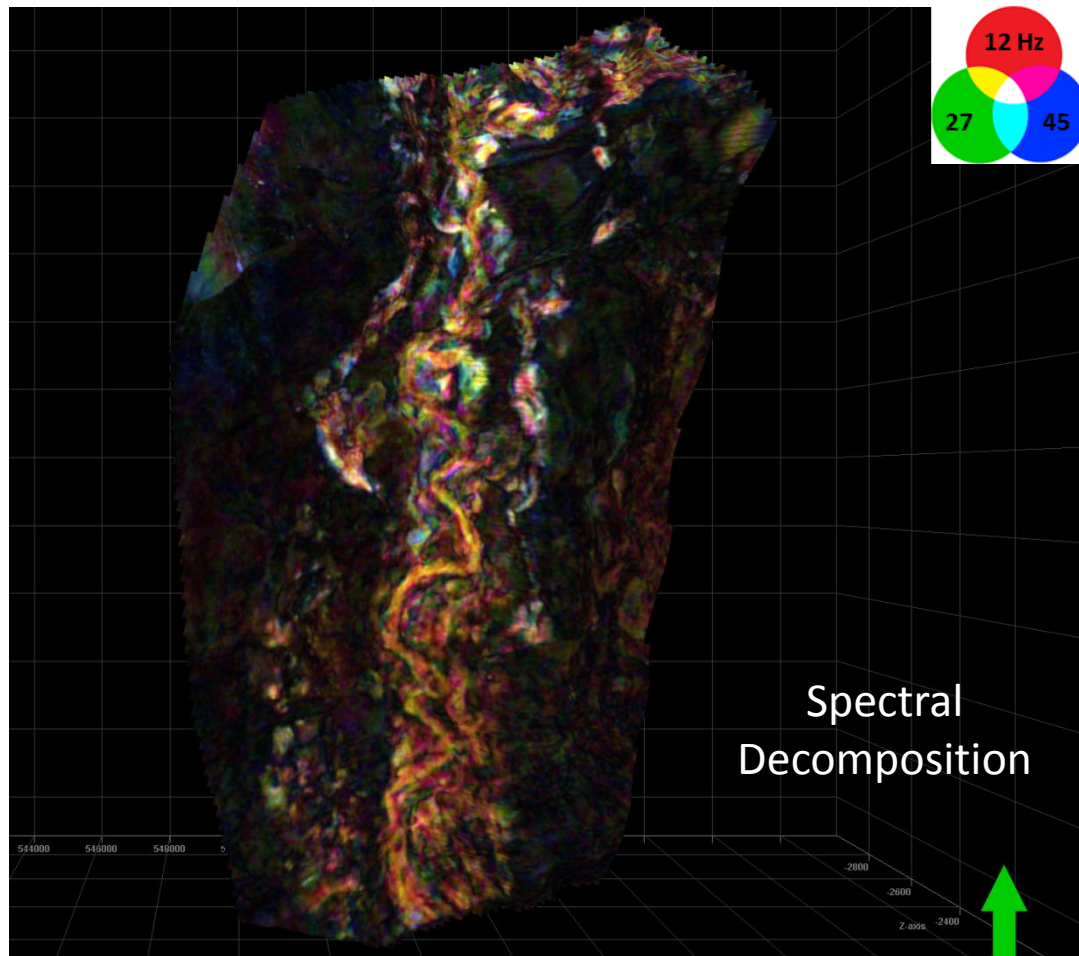


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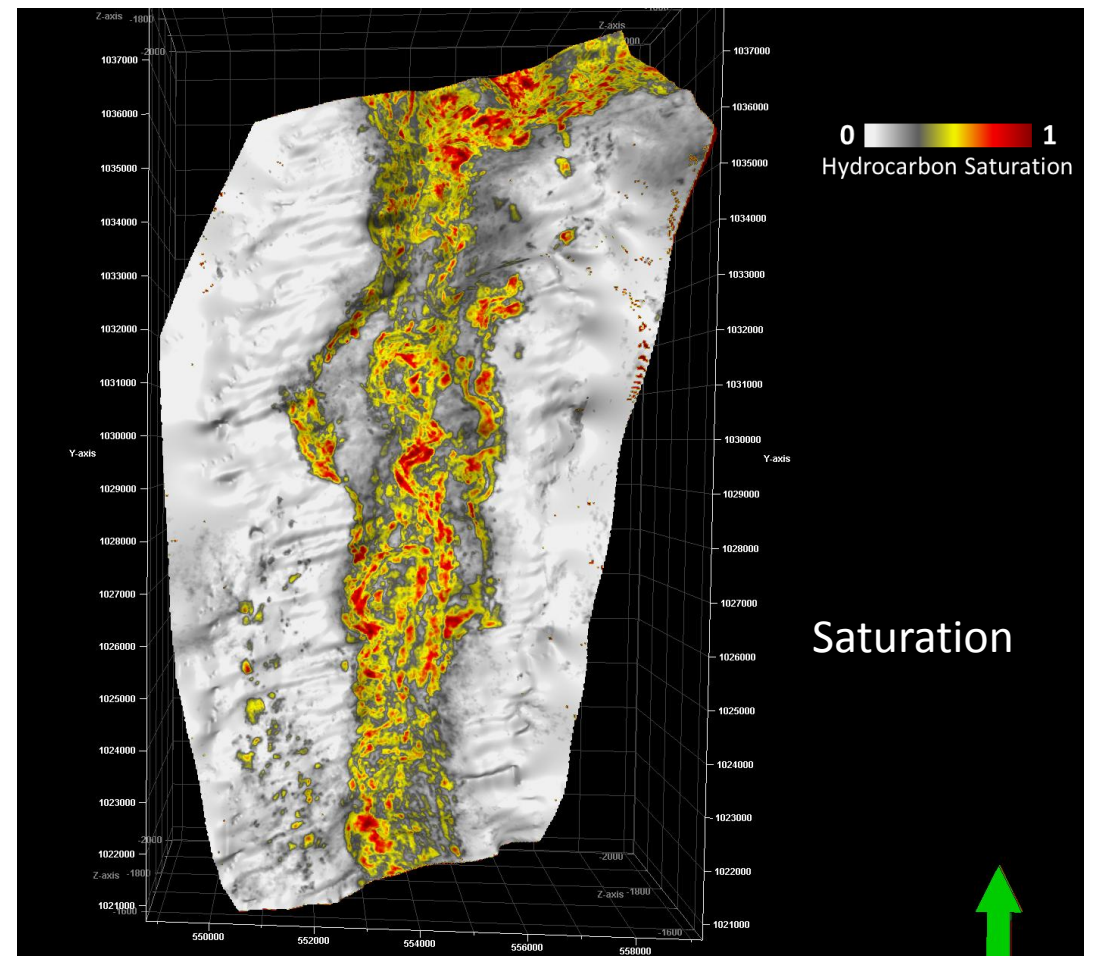
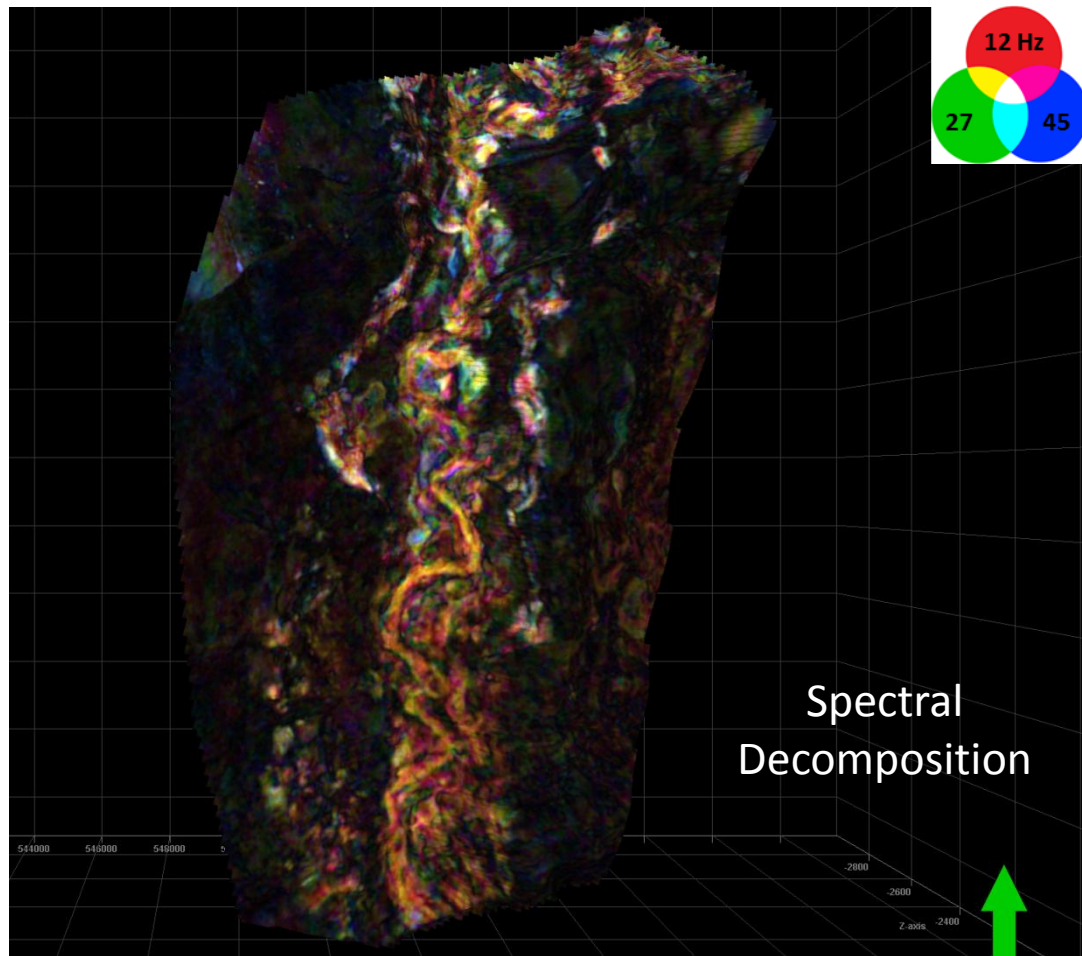
Interpretation – Spectral Decomposition, Variance and Saturation



Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



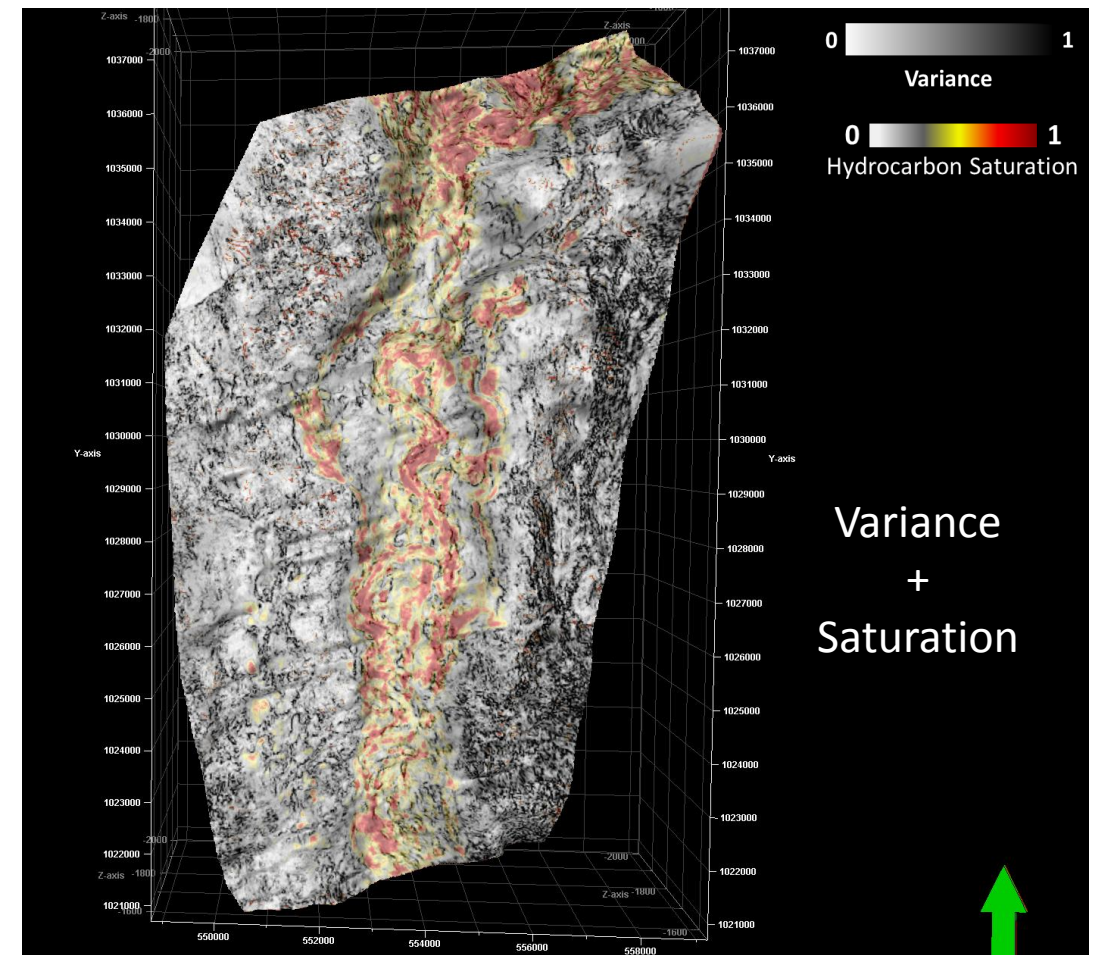
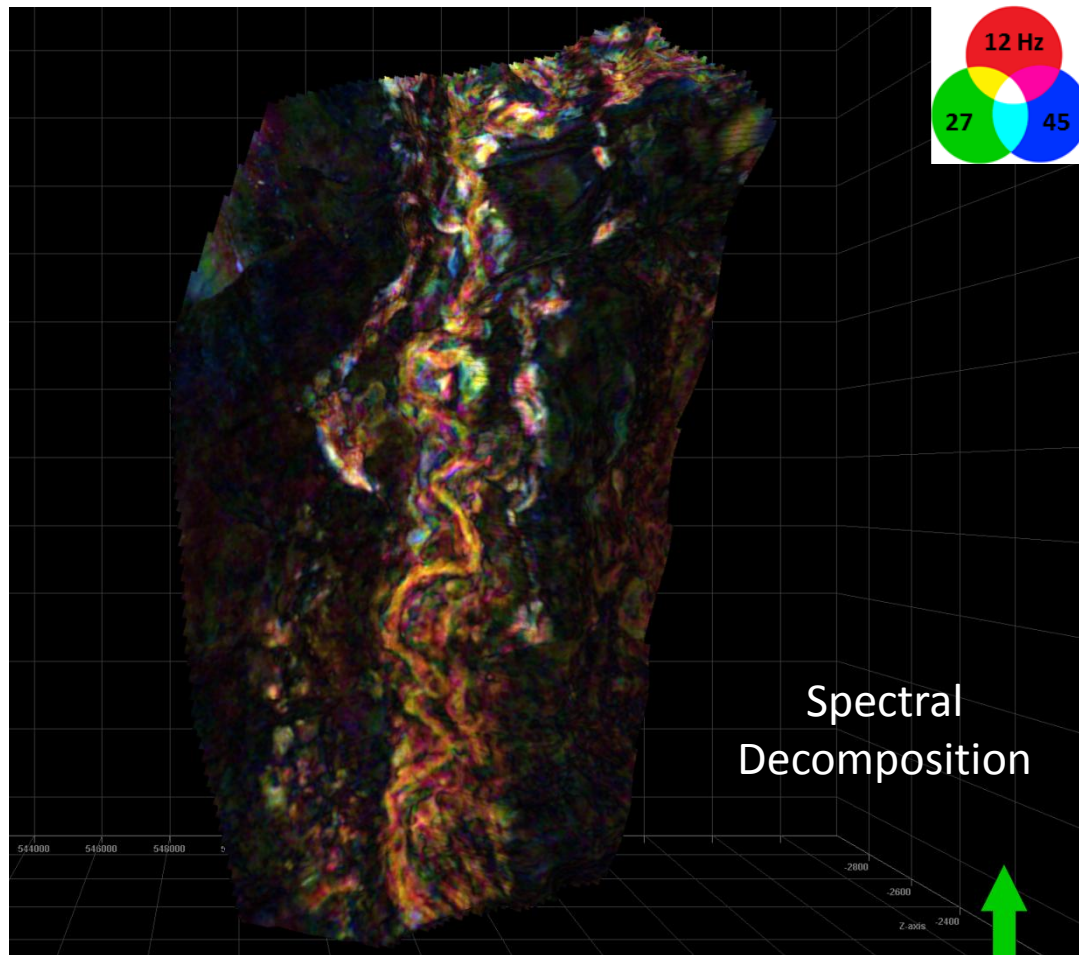
Interpretation – Spectral Decomposition, Variance and Saturation



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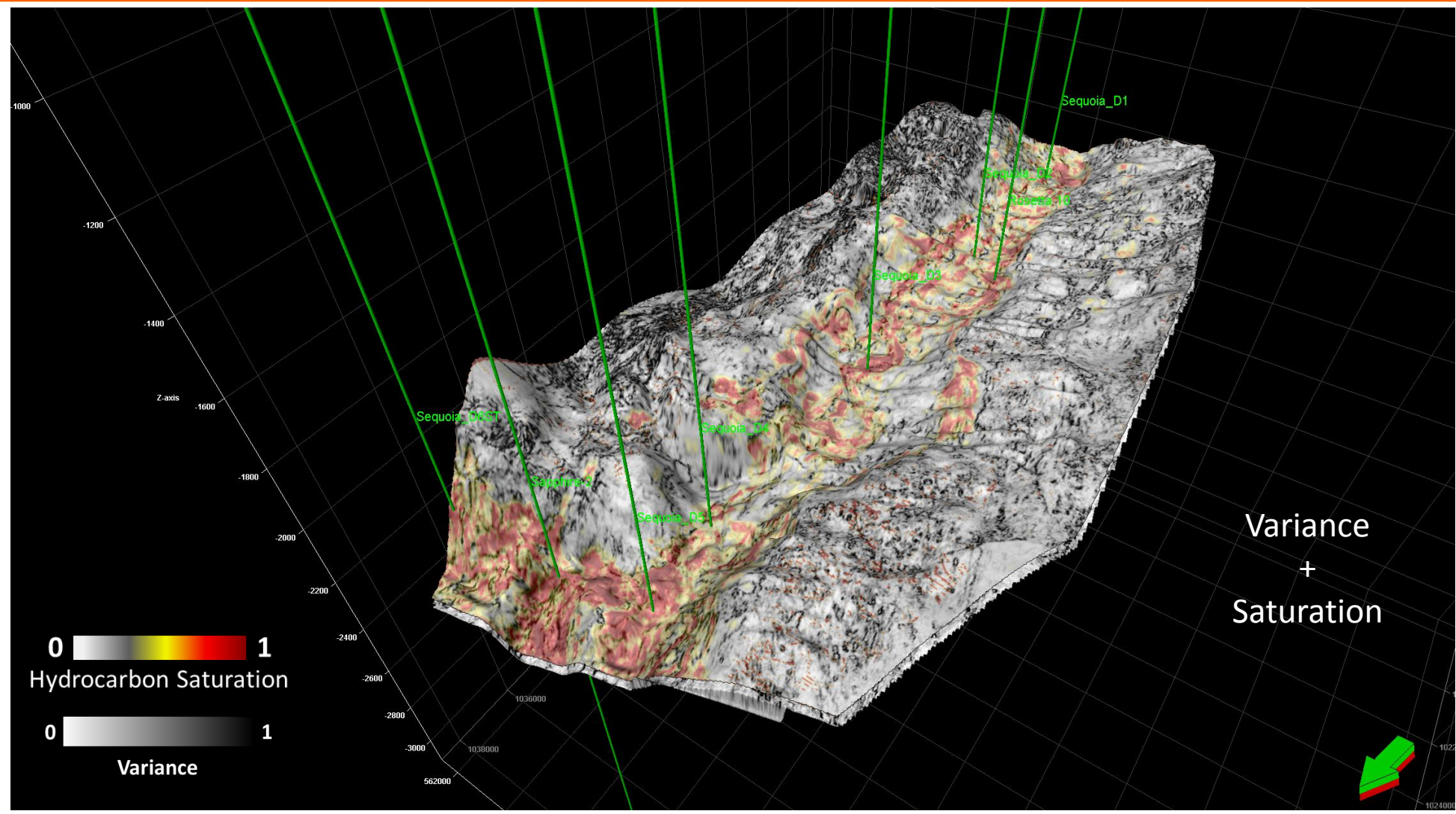
Interpretation – Spectral Decomposition, Variance and Saturation



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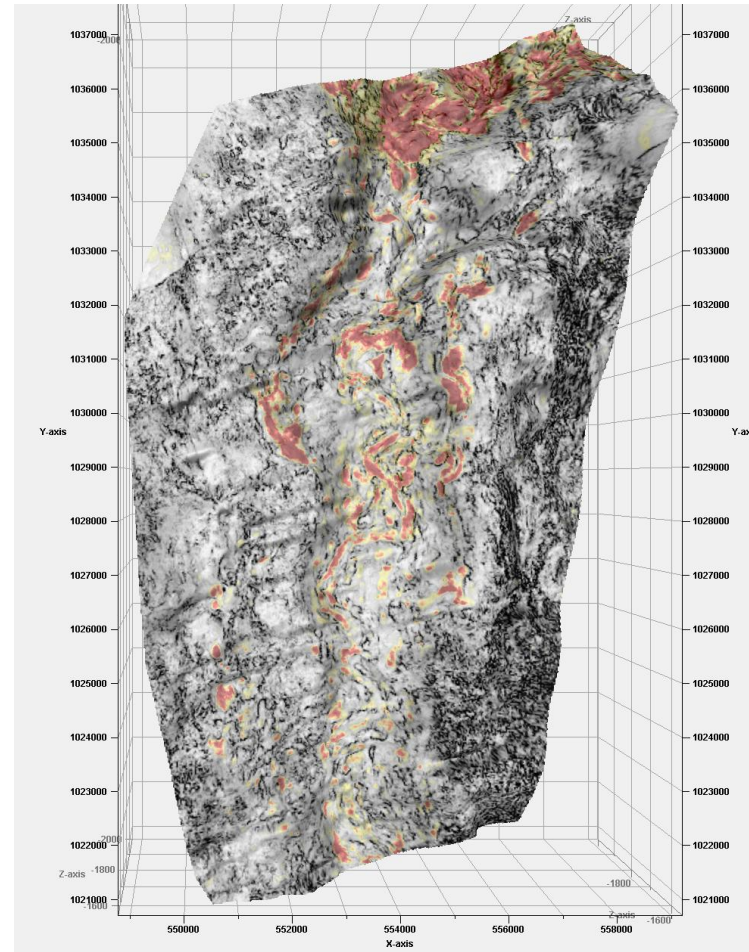
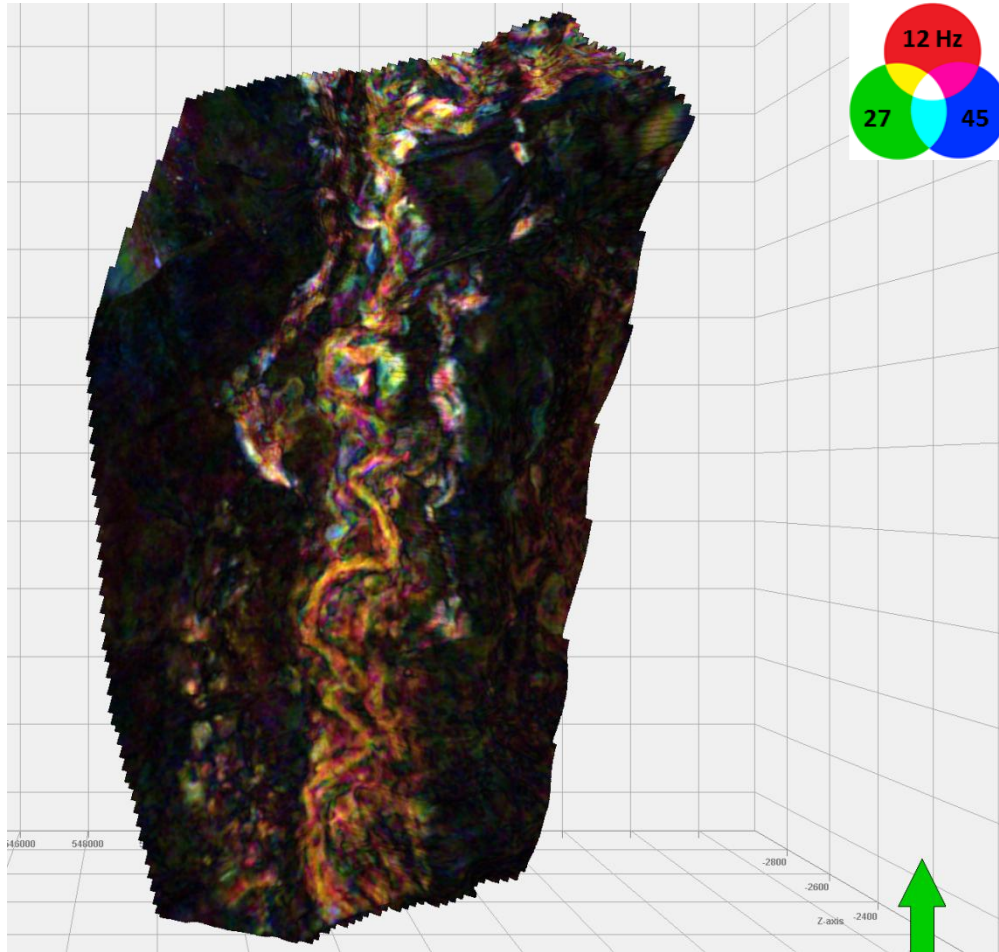
Interpretation – Variance and Saturation 3-D View



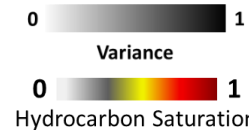
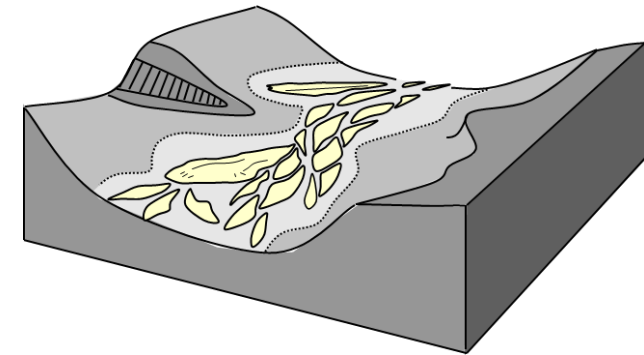
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Interpretation – Sequoia Channel Evolution



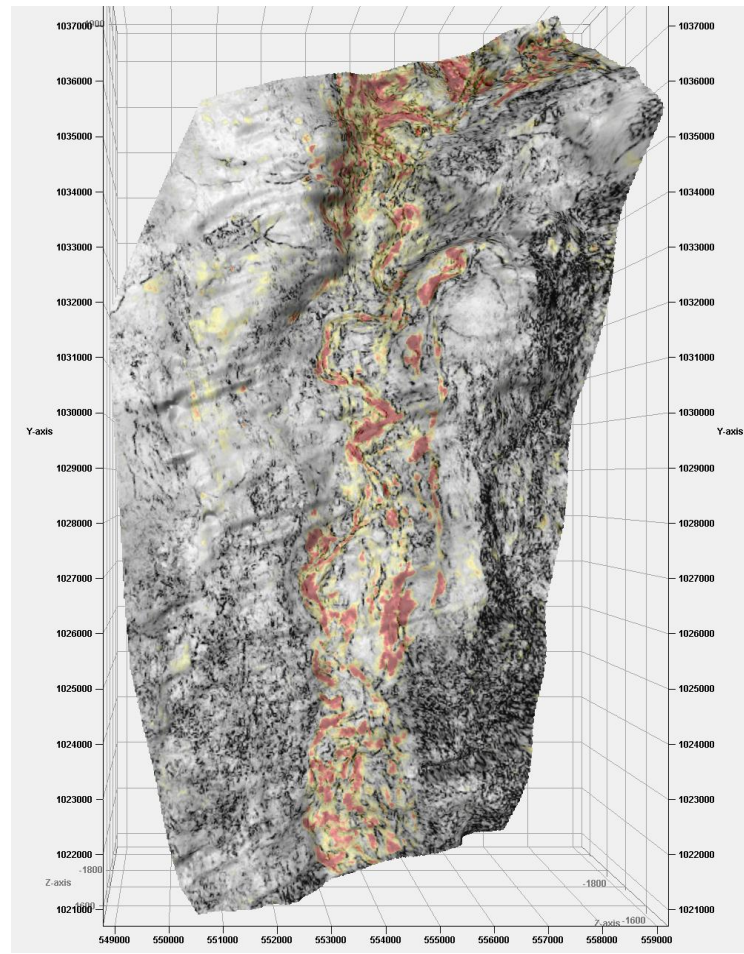
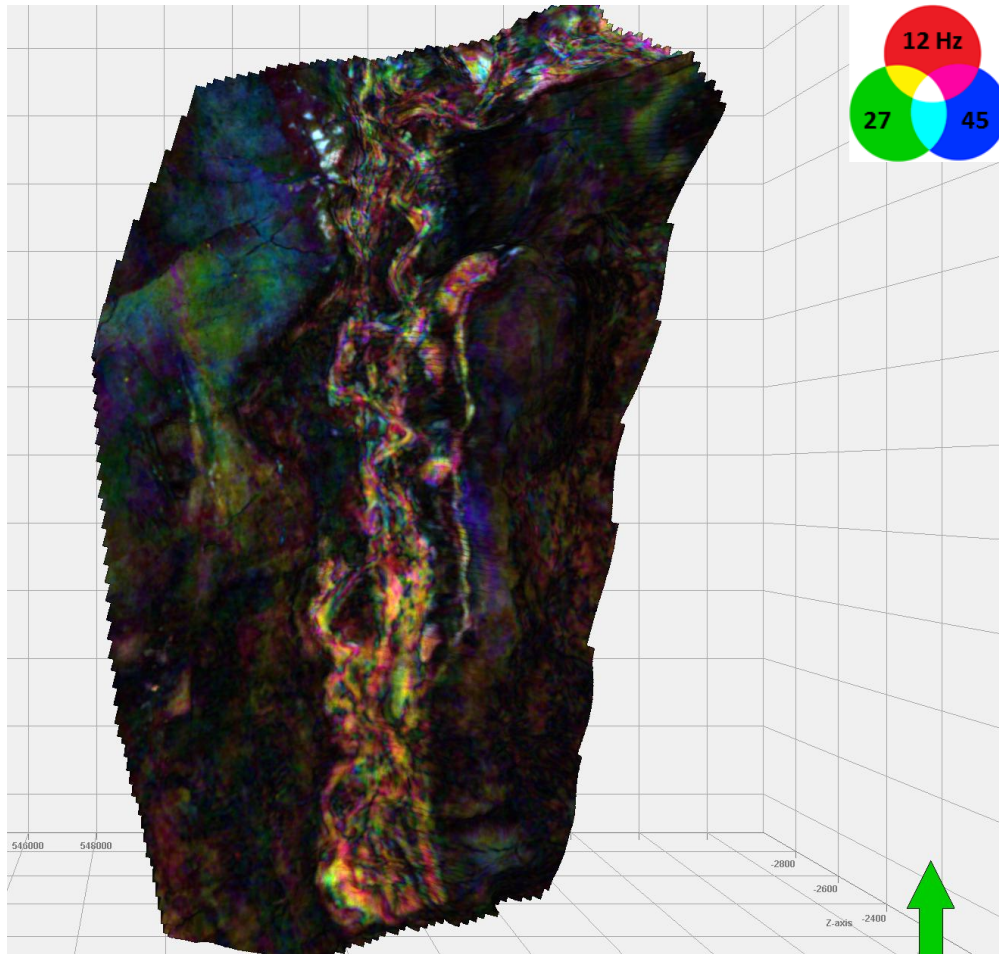
Stage I
Braided, poorly confined channel deposition



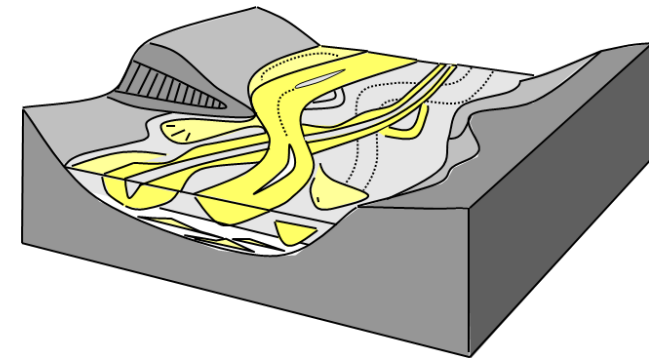
Introduction => Probabilistic Neural Network => Results => **Interpretation** => Conclusions



Interpretation – Sequoia Channel Evolution



Stage II
*High sinuosity
channel and
associated splays*



Variance

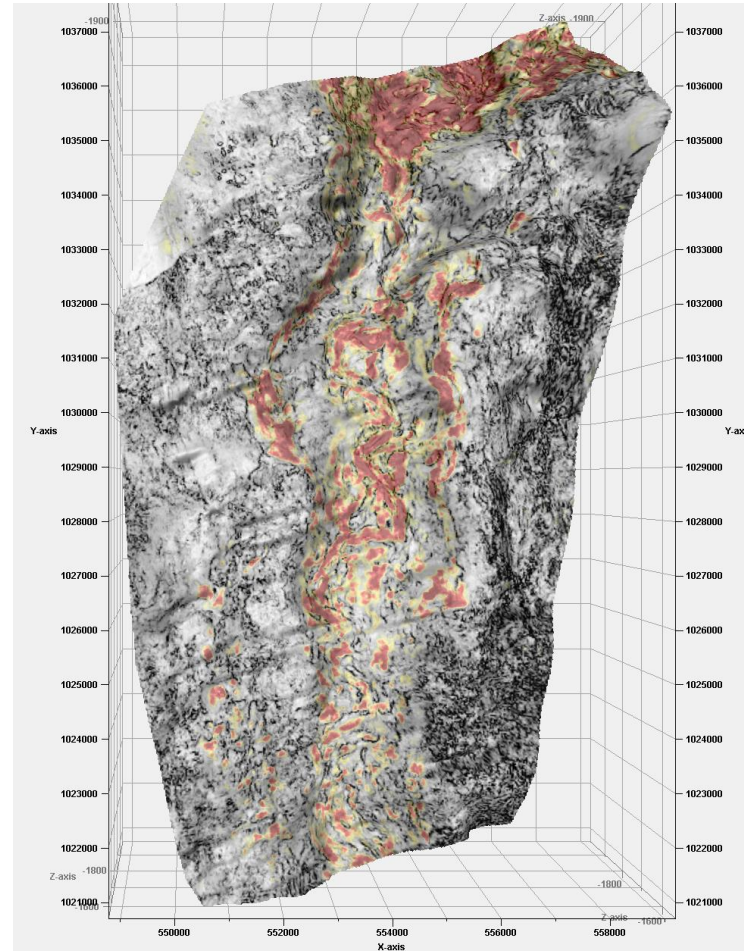
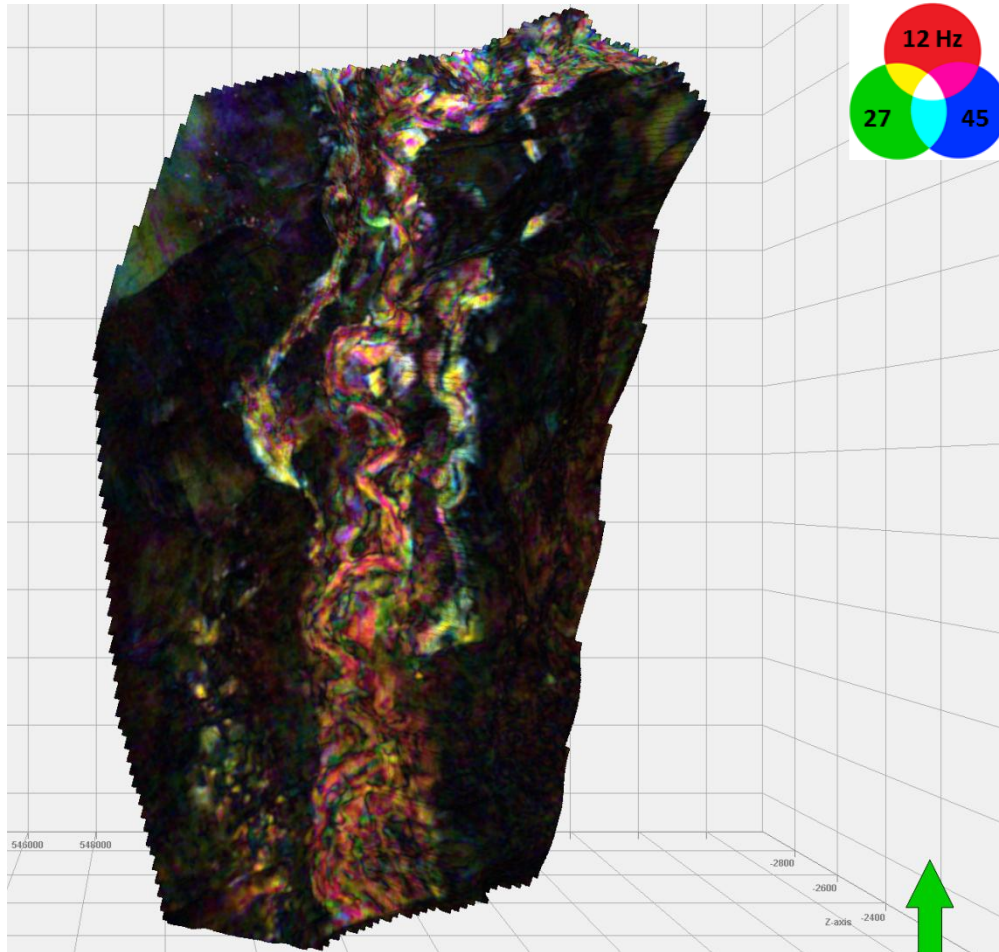


Hydrocarbon Saturation

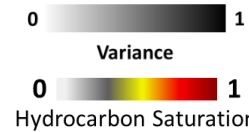
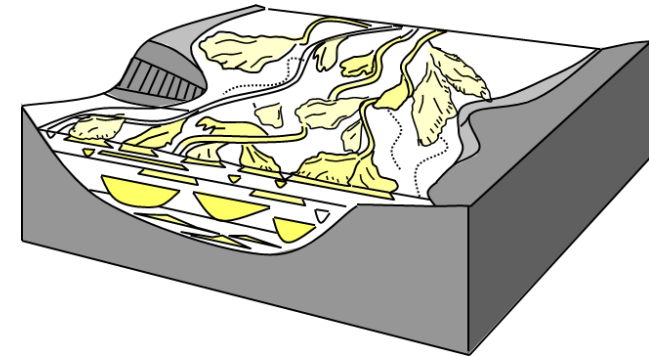
Introduction => Probabilistic Neural Network => Results => **Interpretation** => Conclusions



Interpretation – Sequoia Channel Evolution



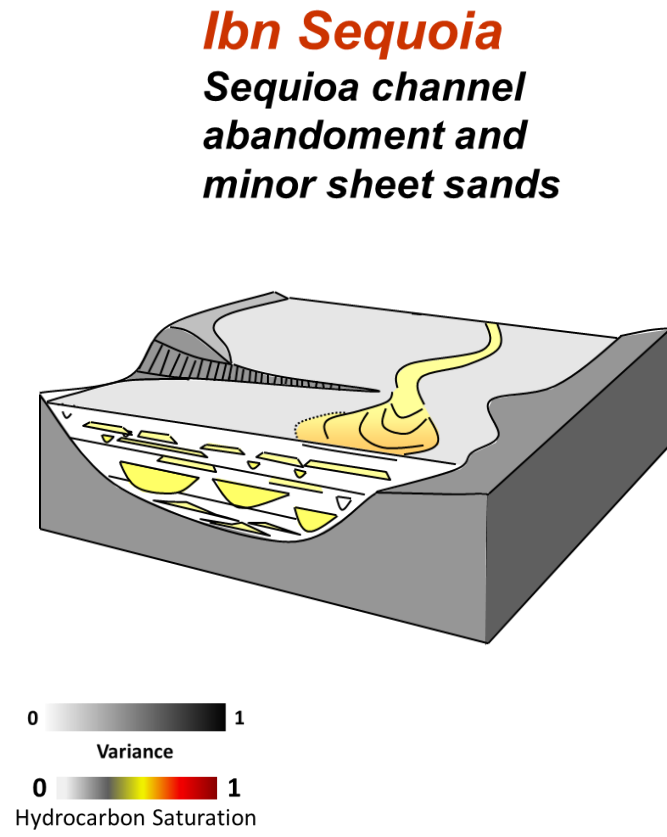
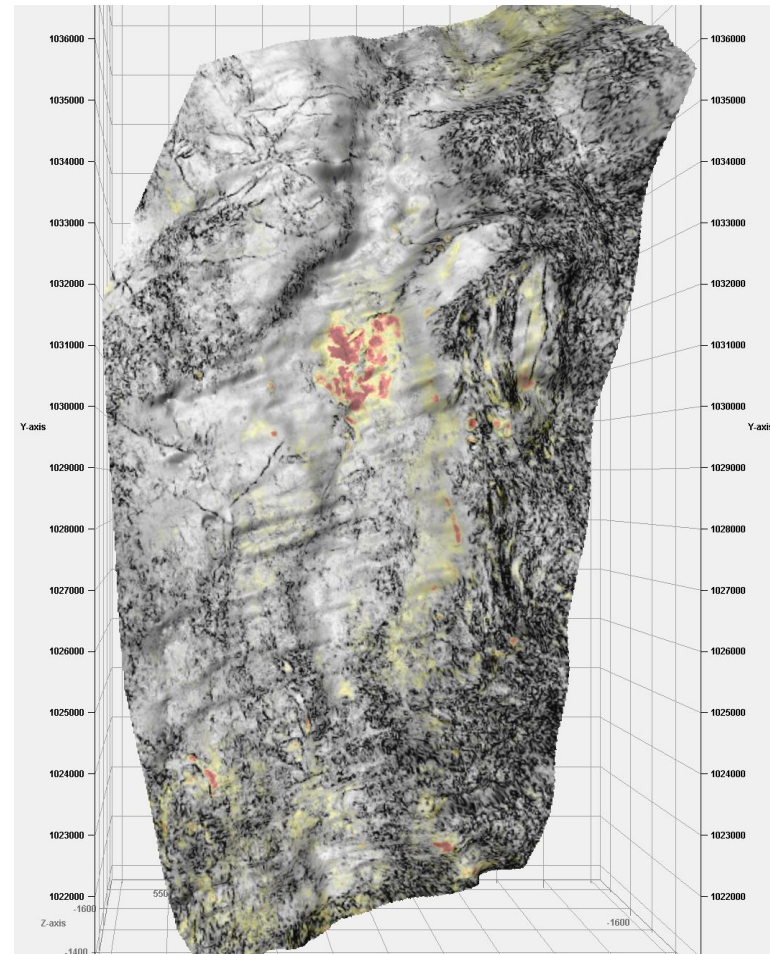
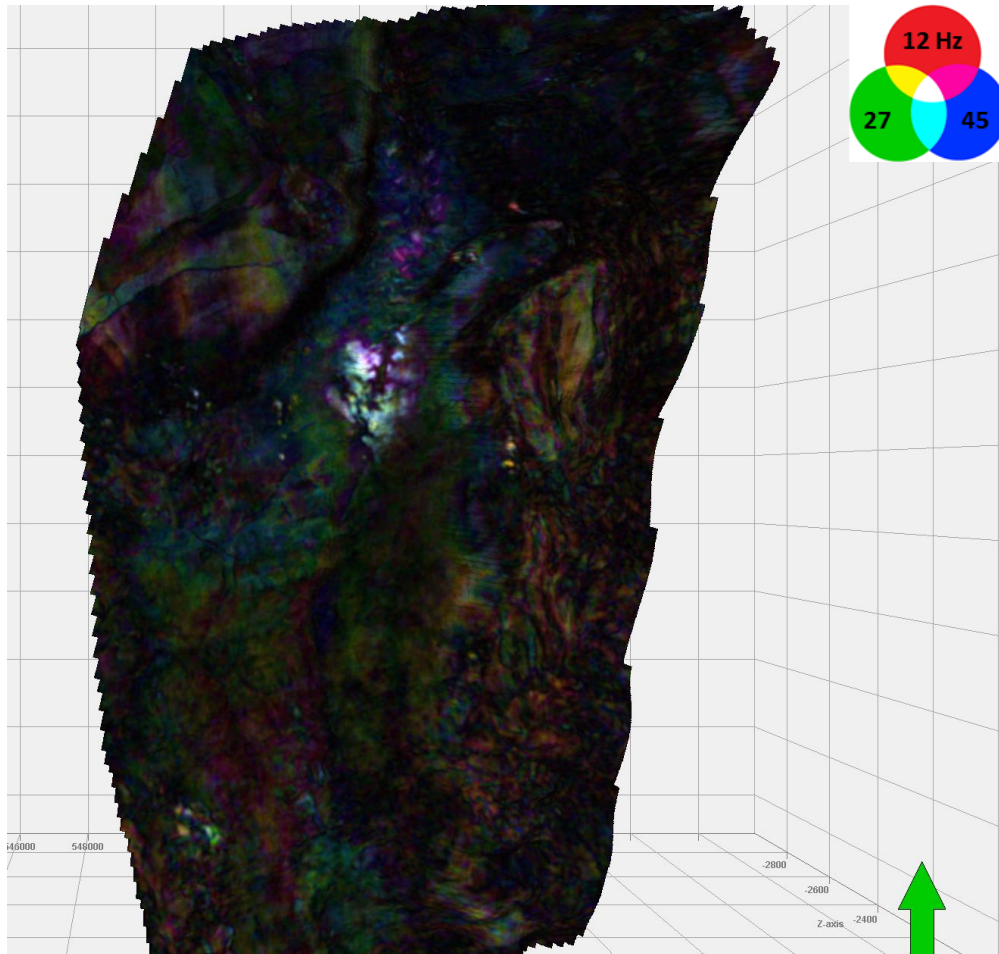
Stage III
*Narrower and
straighter channels
and splays*



Introduction => Probabilistic Neural Network => Results => **Interpretation** => Conclusions



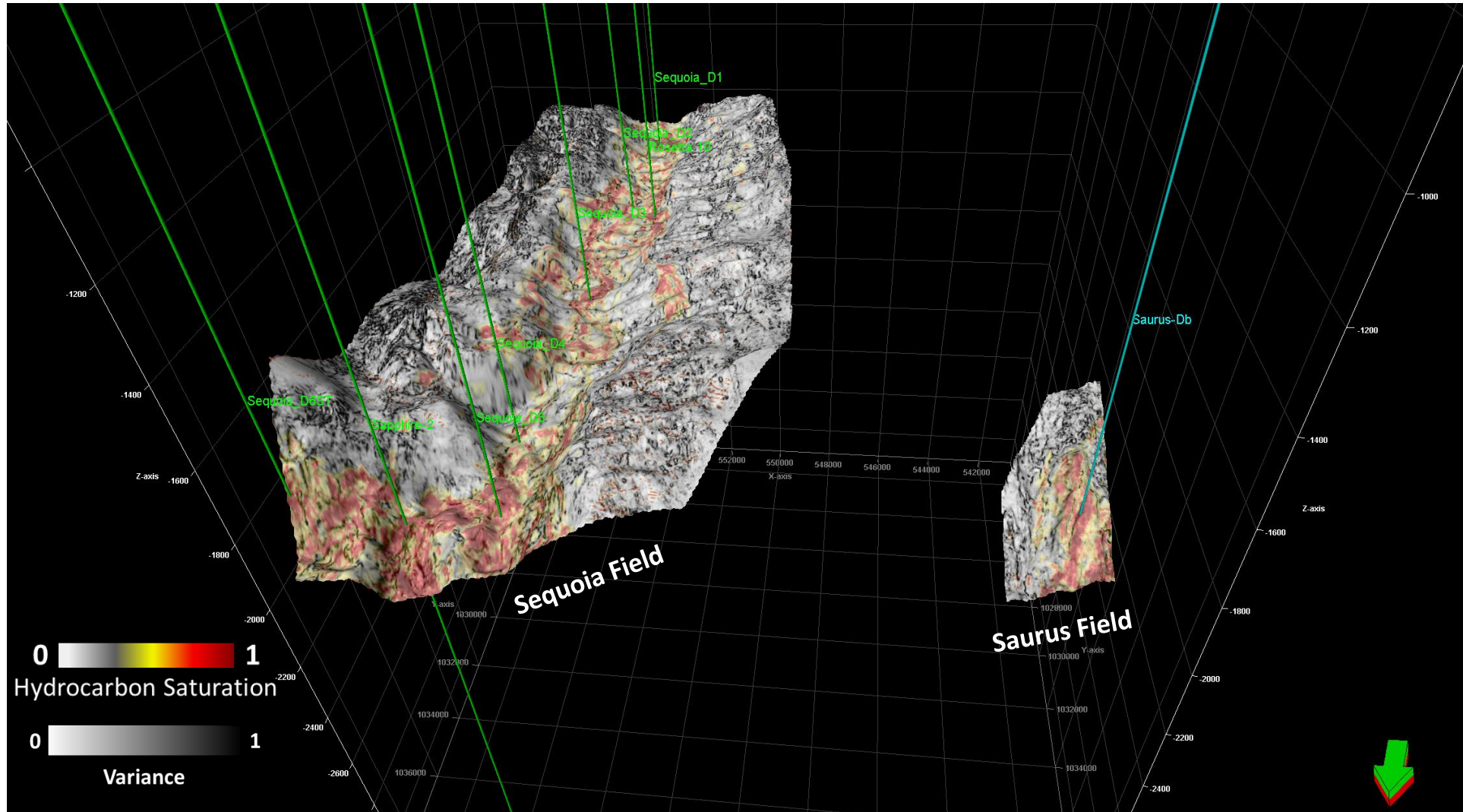
Interpretation – Sequoia Channel Evolution



Introduction => Probabilistic Neural Network => Results => **Interpretation** => Conclusions



Interpretation – Saturation Prediction for New Exploration Targets



Introduction => Probabilistic Neural Network => Results => Interpretation => Conclusions



Outline

- Introduction
- Probabilistic Neural Network
- Results
- Interpretation
- **Conclusions**



Discussion

- Advantages
 - Fast training process
 - Can invert the full-stack seismic to any log property
 - Results show acceptable correlation even with far fields
- Disadvantages
 - Large memory requirements
 - Application time to the 3D volume is large
 - Application time is proportional to the number of training samples
 - Needs at least three wells



Conclusions

- Probabilistic neural network successfully predicts hydrocarbon saturation 3-D volume with good accuracy
 - Better delineating hydrocarbon-saturated reservoir in 3-D space.
 - Contributes to optimal well placement, Gas Initial In-Place (GIIP) calculation and improves the field development plan.
- Using of high-resolution spectral decomposition along with variance and hydrocarbon saturation provide an excellent 3-D insight into the sand-body makeup and depositional evolution.

Future work

- Apply the PNN to produce other petrophysical important volumes such as V_{cl} , porosity ...etc.
- Apply the proposed workflow to other Pliocene gas fields.



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