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First EAGE/PESGB Machine Learning Workshop

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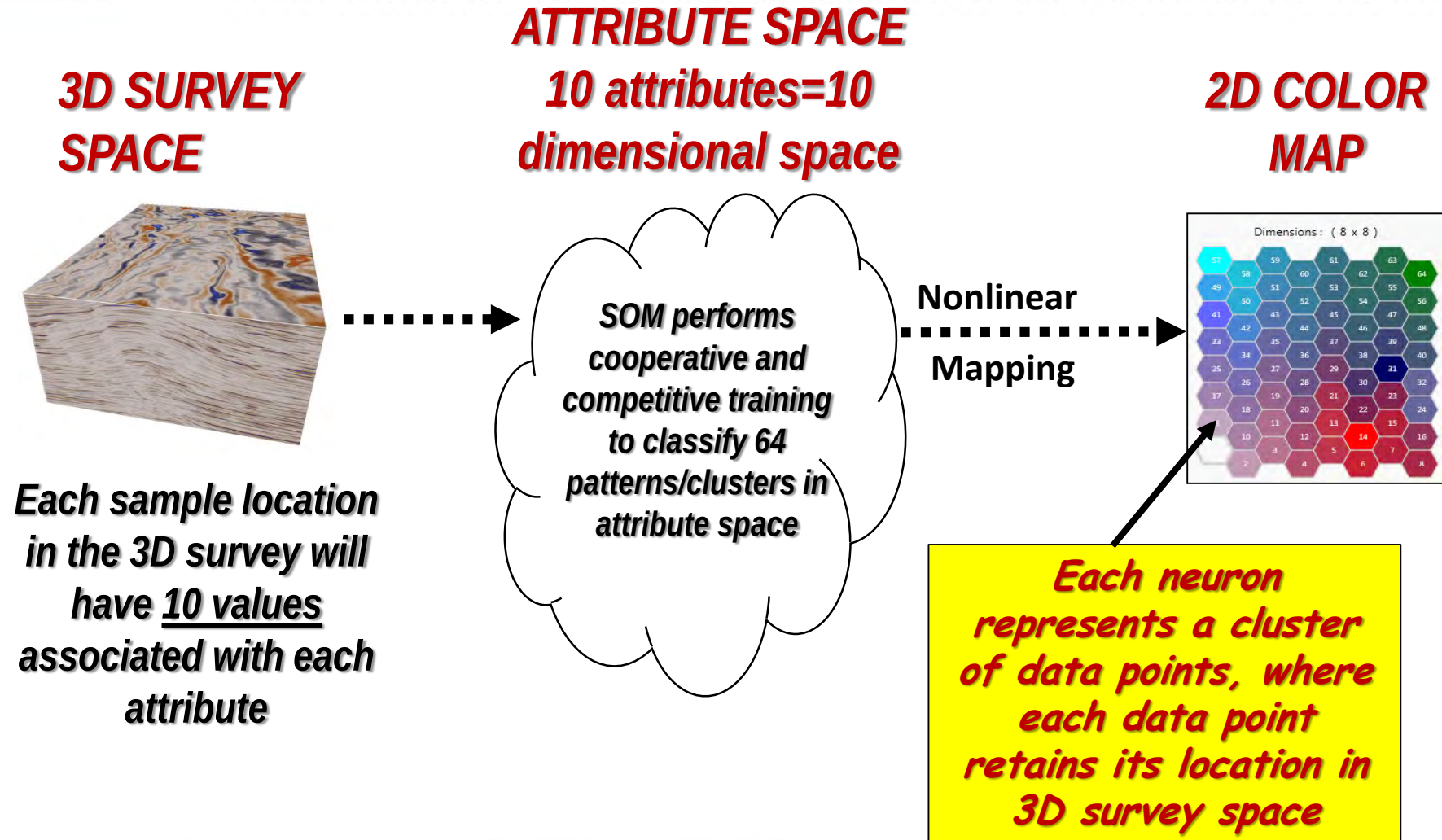
How Machine Learning is Replacing Conventional Interpretation

Deborah Sacrey, Owner – Auburn Energy
Rocky Roden, Sr. Geoscience Consultant– Geophysical Insights

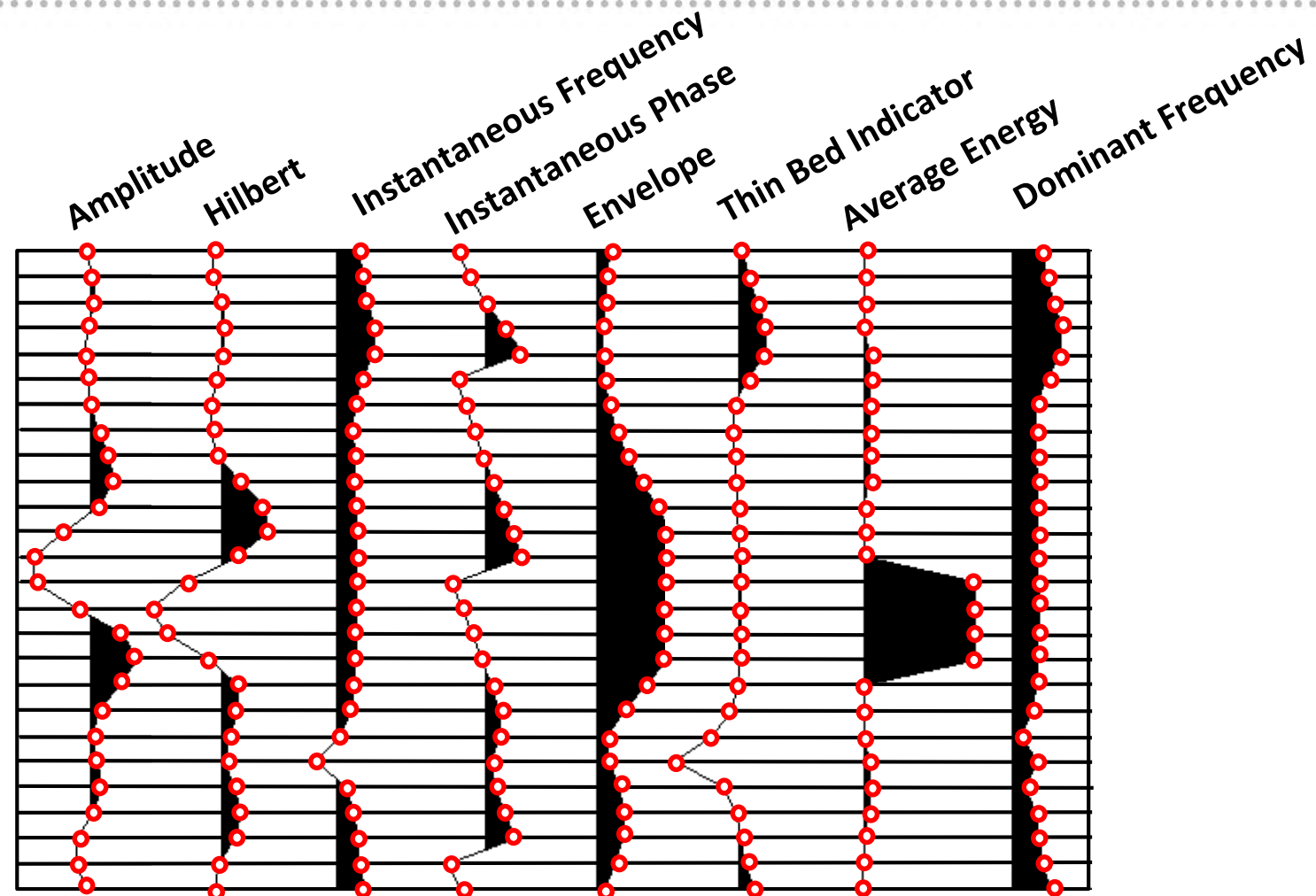
Not your “Daddy’s” Neural Analysis

- Unsupervised neural analysis has been around for some time – but the technology has drastically changed because of increased computer power, the invention/creation of hundreds of new attributes and looking at the statistical classification based on sample rate versus the wavelet.
- This is **NOT** “black box”, but employs advanced understanding of various attributes and their contribution to finding solutions to specific problems in the seismic world. It can be “GIGO” if not used carefully.

How SOM works (10 attributes)



Every Sample from each Attribute is Input into a PCA or SOM Analysis



Scale of SOM Results

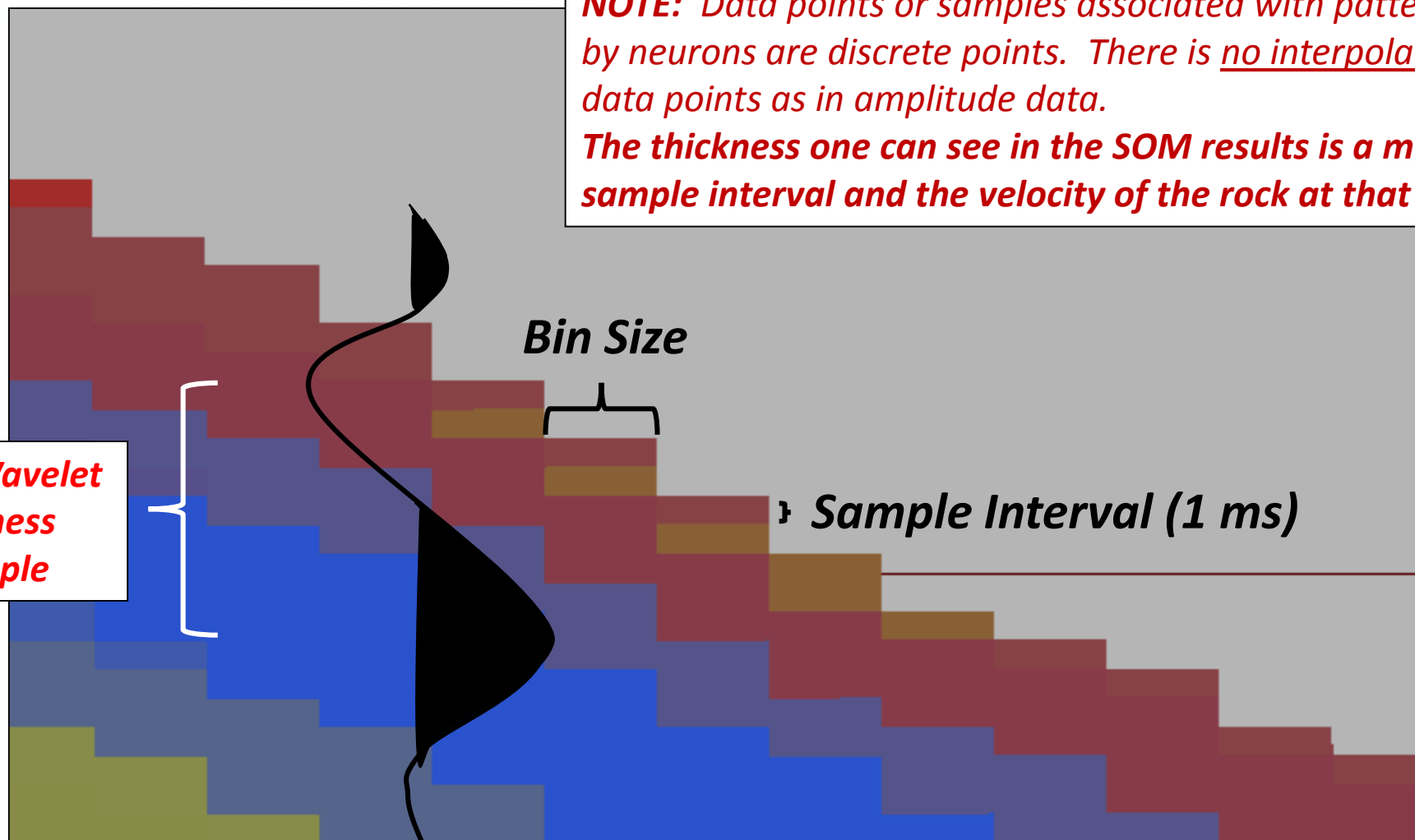
NOTE: Data points or samples associated with patterns identified by neurons are discrete points. There is no interpolation between data points as in amplitude data.

The thickness one can see in the SOM results is a matter of the sample interval and the velocity of the rock at that sample

Bin Size

Sample Interval (1 ms)

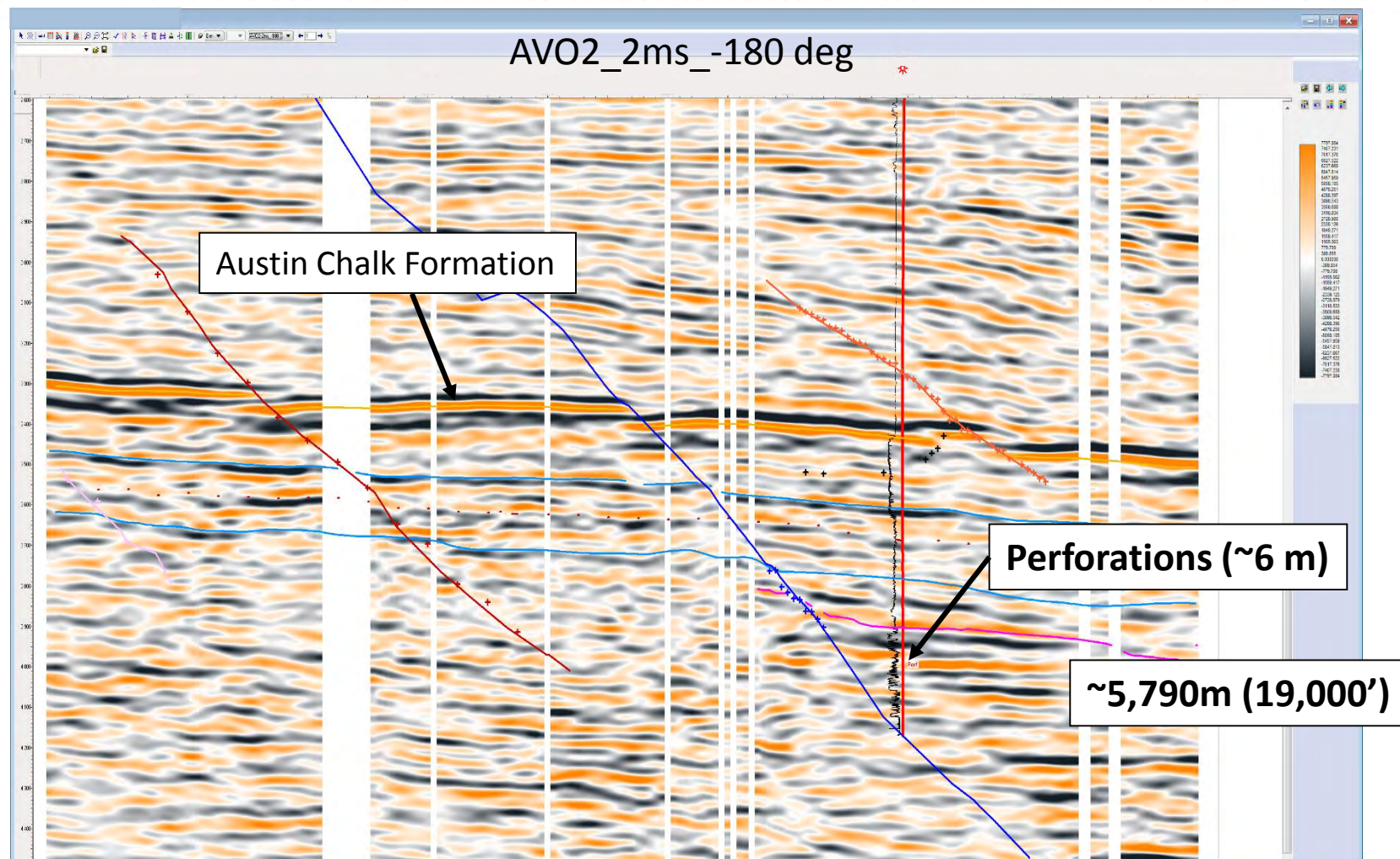
**Conventional Wavelet
Tuning Thickness
for this example**



Case History #1

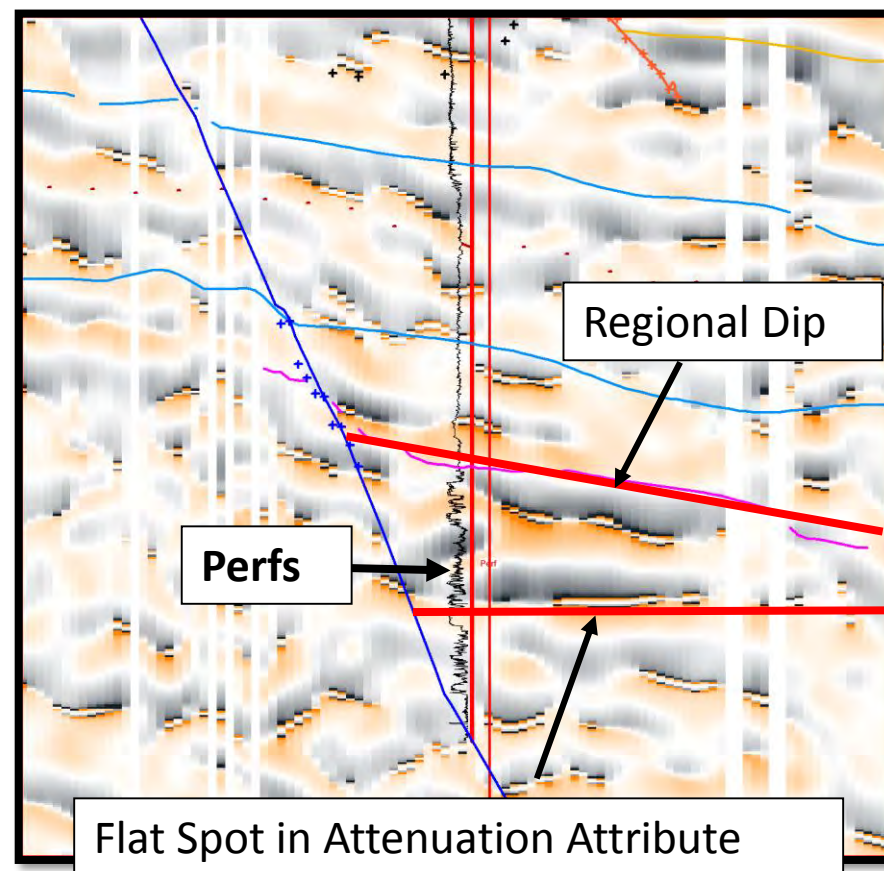
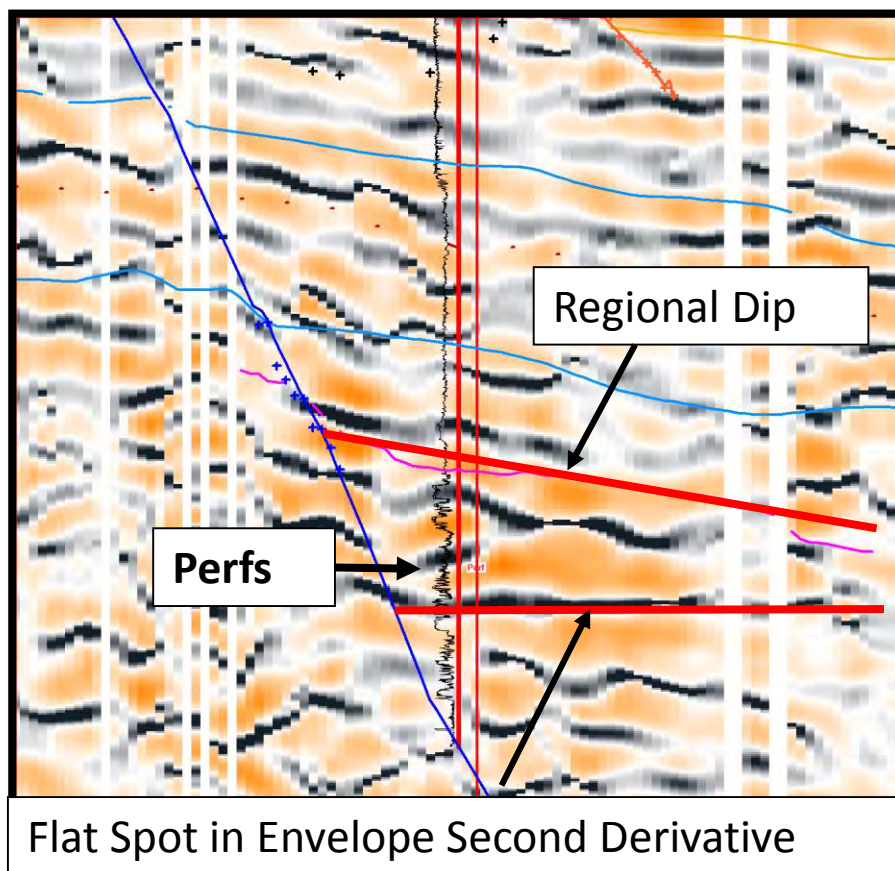
**Defining a reservoir in deep, pressured sands
with poor data quality**

Deep Pressured Tuscaloosa Sands (Cretaceous) in S. Louisiana



Deep Pressured Sands in S. Louisiana

Perforations appear to be close to base of flat spot, which indicates that reservoir is much thicker than just currently producing sand.



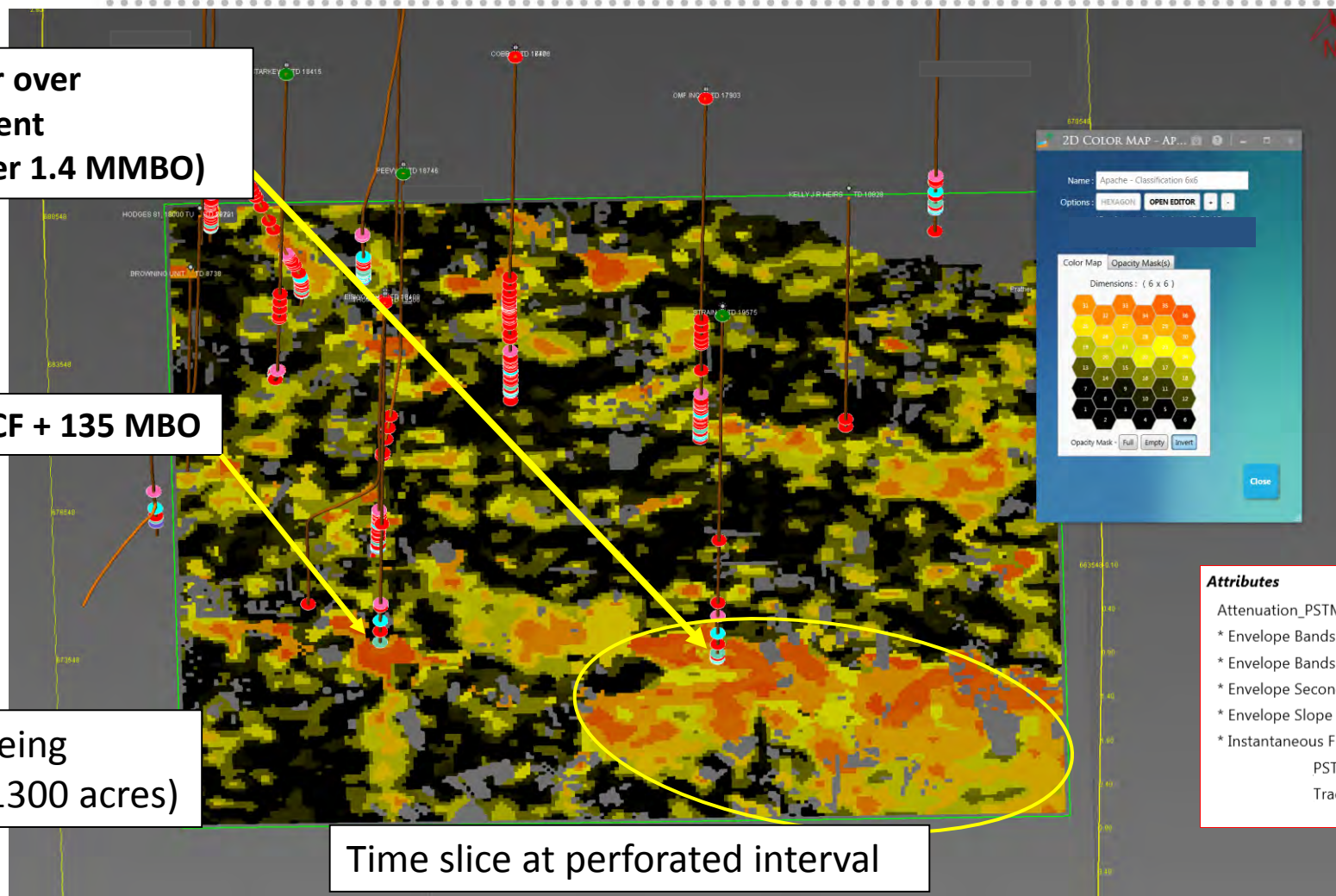
Seeing the reservoir in the Tuscaloosa Sands

Well has been producing for over 37 years and been an excellent producer (over 54 B and over 1.4 MMBO)

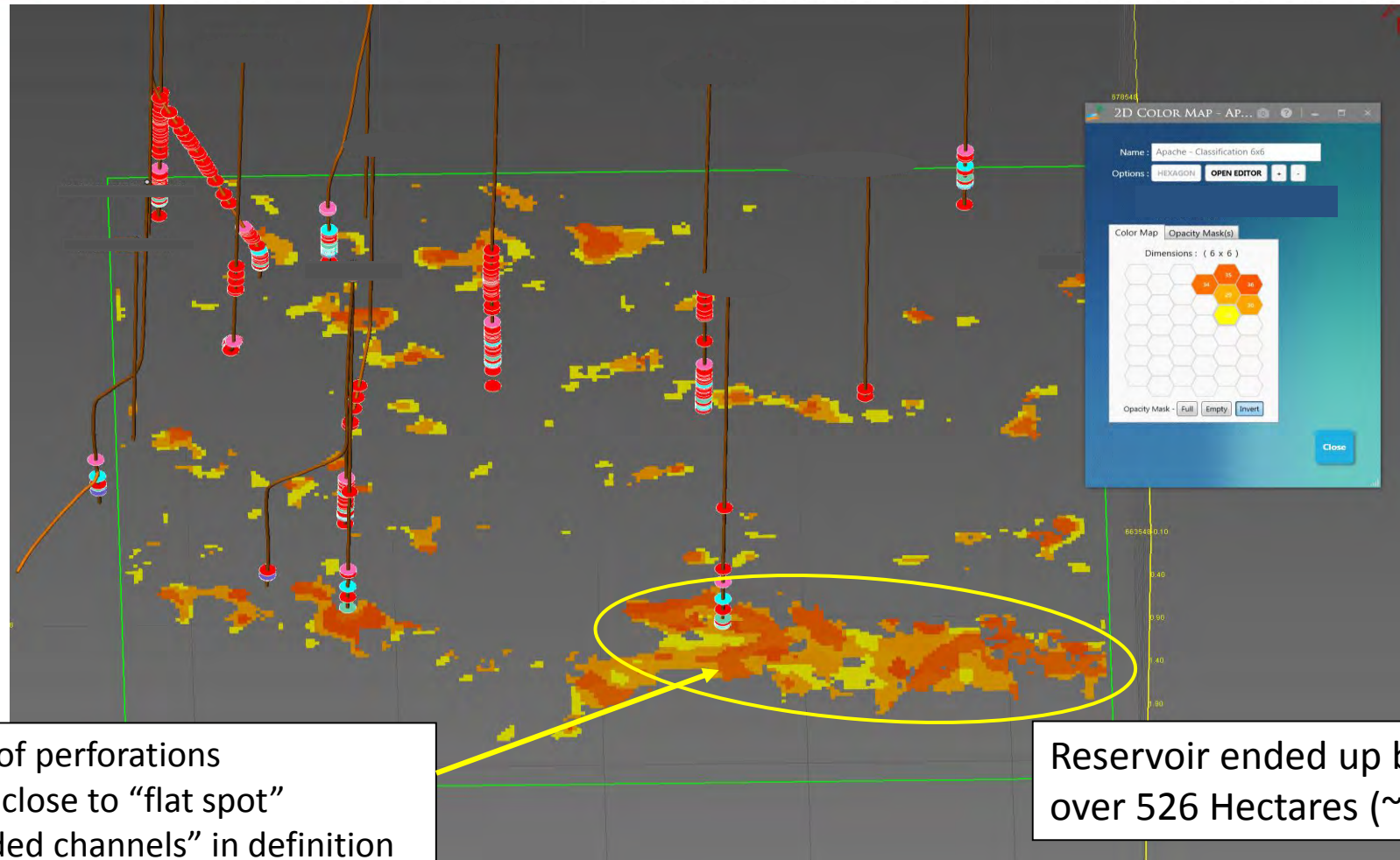
Cum: ~2 BCF + 135 MBO

Reservoir ended up being over 526 Hectares (~1300 acres)

Time slice at perforated interval



Seeing the reservoir in the Tuscaloosa Sands

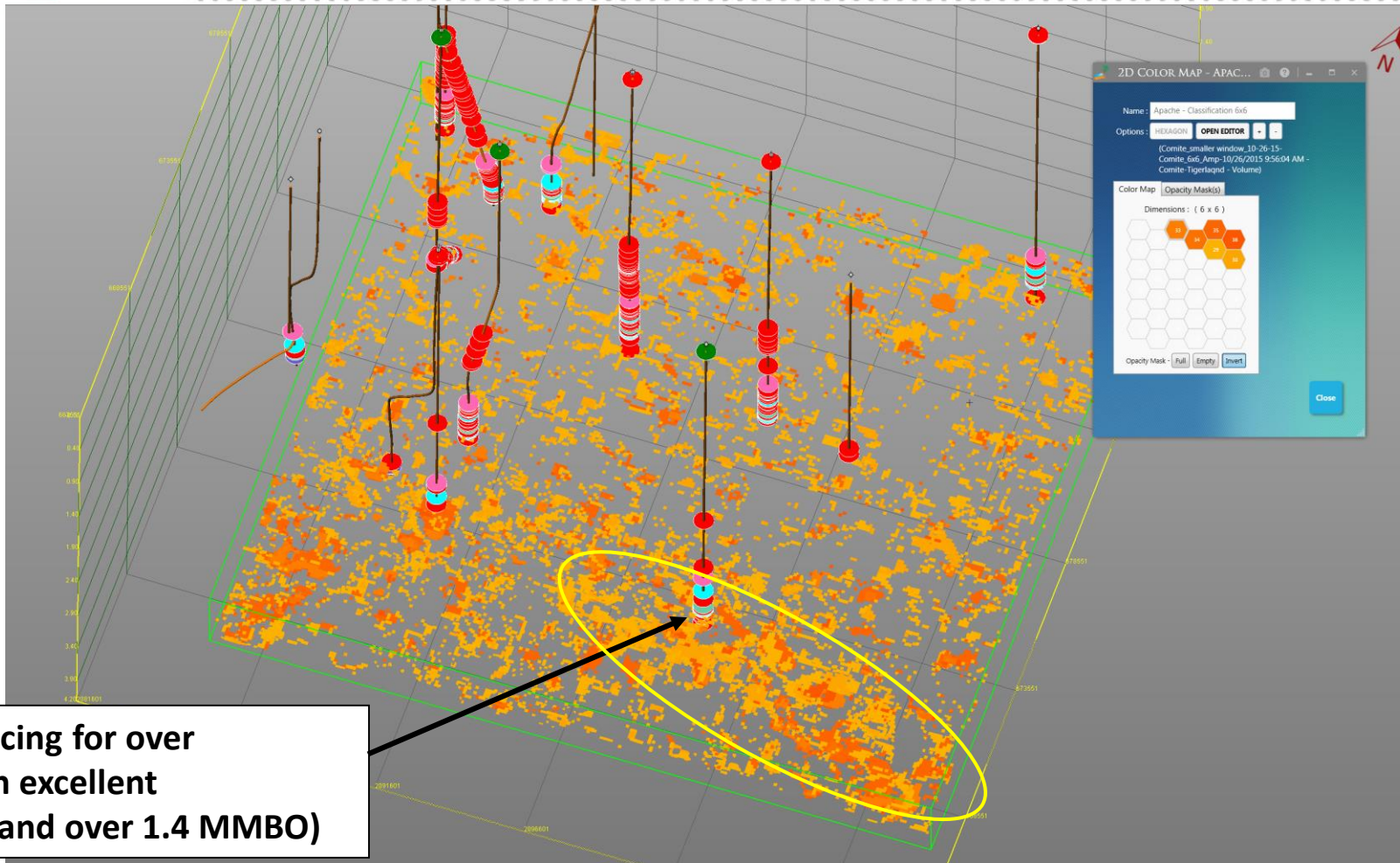


Time slice at level of perforations
Showing reservoir close to “flat spot”
One can see “braided channels” in definition

Reservoir ended up being
over 526 Hectares (~1300 acres)

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Full volume showing sand distribution over the 72.5 square kilometer (28 sq. mi.) area.



Well has been producing for over 37 years and been an excellent producer (over 54 B and over 1.4 MMBO)

Case History #2

Offshore Gulf of Mexico Reservoir Delineation

Offshore Gulf of Mexico Case Study – Class 3 AVO

3900' Reservoir

- Upthrown Fault Closure
- Approximately 30m Reservoir Sand
- Two Producing Wells
 - #A-1 (gas on oil)
 - #A-2 (oil)

Based upon Principal Component Analysis (PCA)
Eight Instantaneous Attributes were selected for SOM

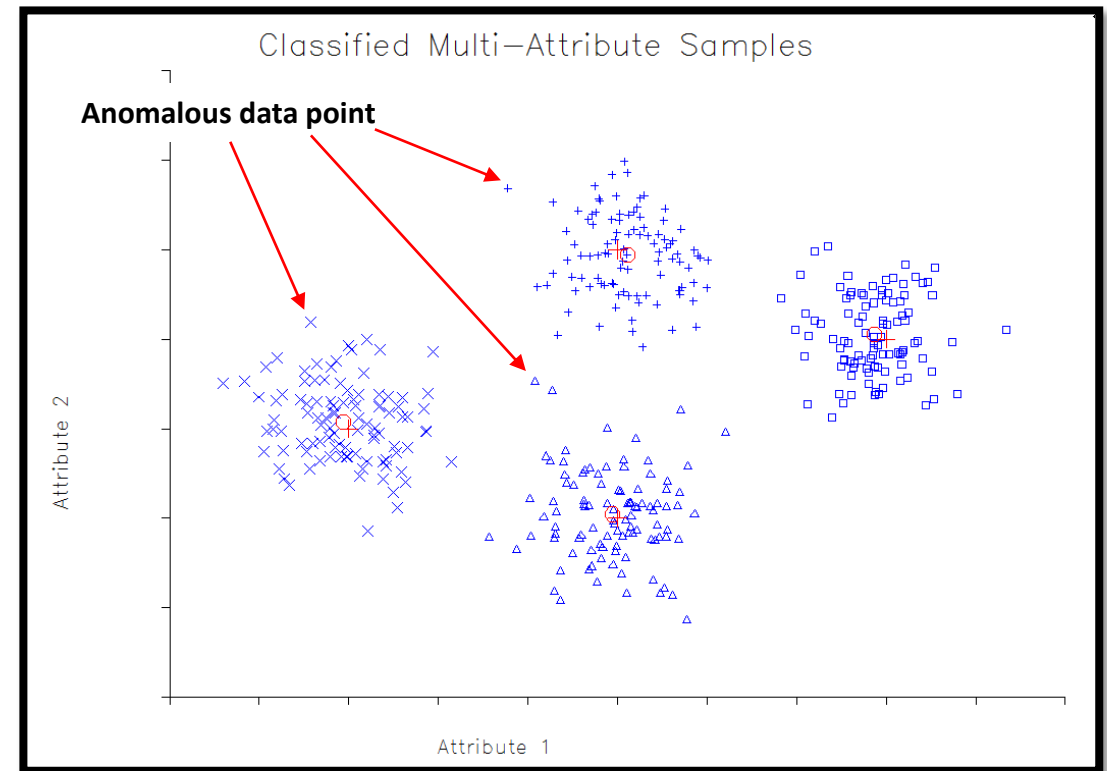
- Sweetness
- Envelope
- Instantaneous Frequency
- Thin Bed
- Relative Acoustic Impedance
- Hilbert
- Cosine of Instantaneous Phase
- Final Raw Migration

Previously 7 wells drilled in area, all wet or low saturation gas

GOAL: What DHI characteristics can be identified to refine reservoir interpretation and employ in the region for further exploration.

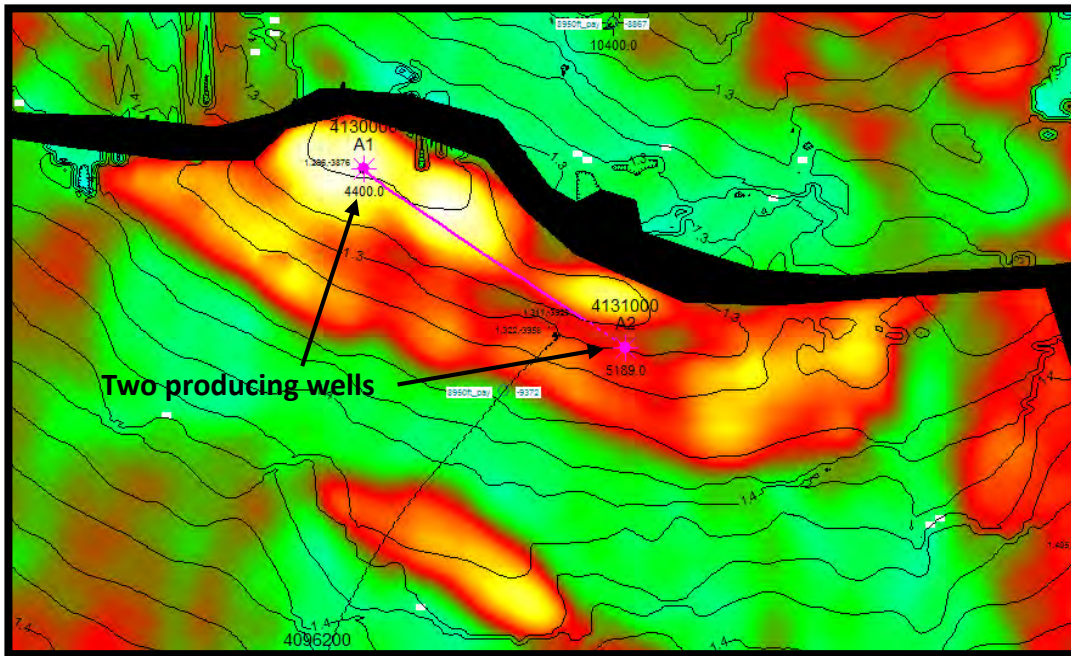
Low Probability

Low Probability Volume – outside “edge” of data points are furthest away from center of cluster – and are considered “most anomalous”. So if attributes are used which are “hydrocarbon indicators”, then the “low probability” anomalies could possibly be hydrocarbon indicators. At the very least, they would tend to show the best of the properties of the attributes used in the analysis.



Top of Reservoir – Amplitude conforms with structure

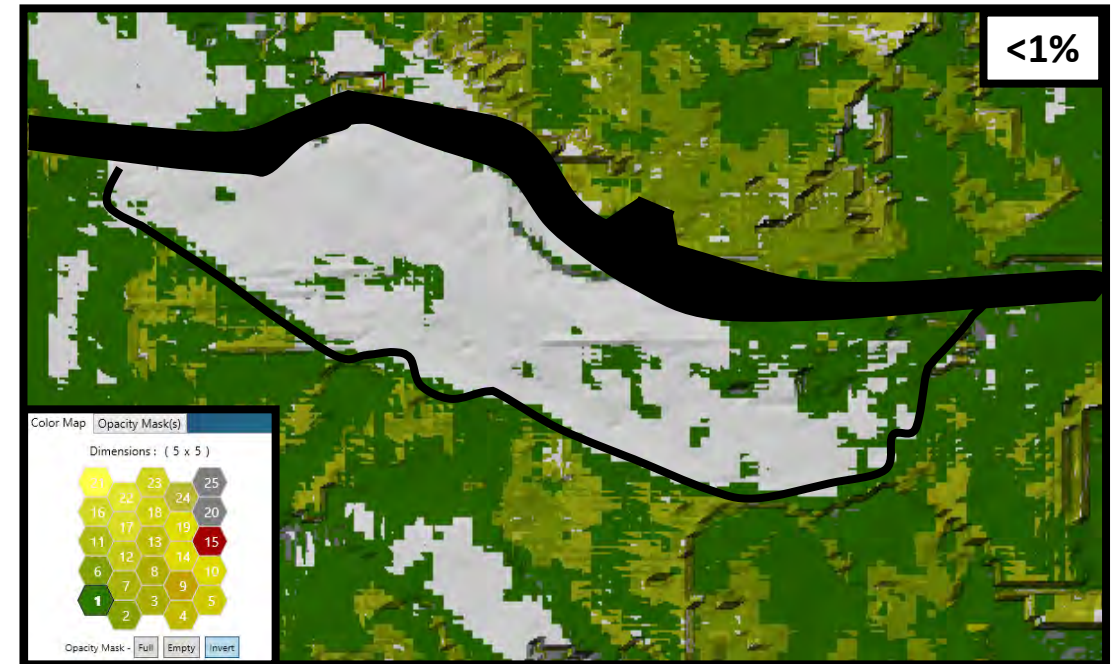
Time-Structure Map (contours) with amplitude overlay



NOTE:

- *Amplitude conformance*
- *Consistency in mapped target area*

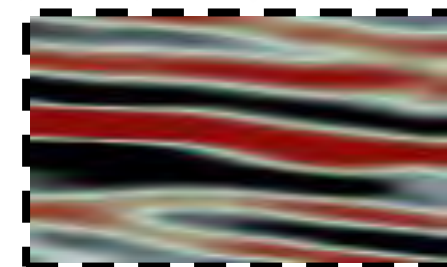
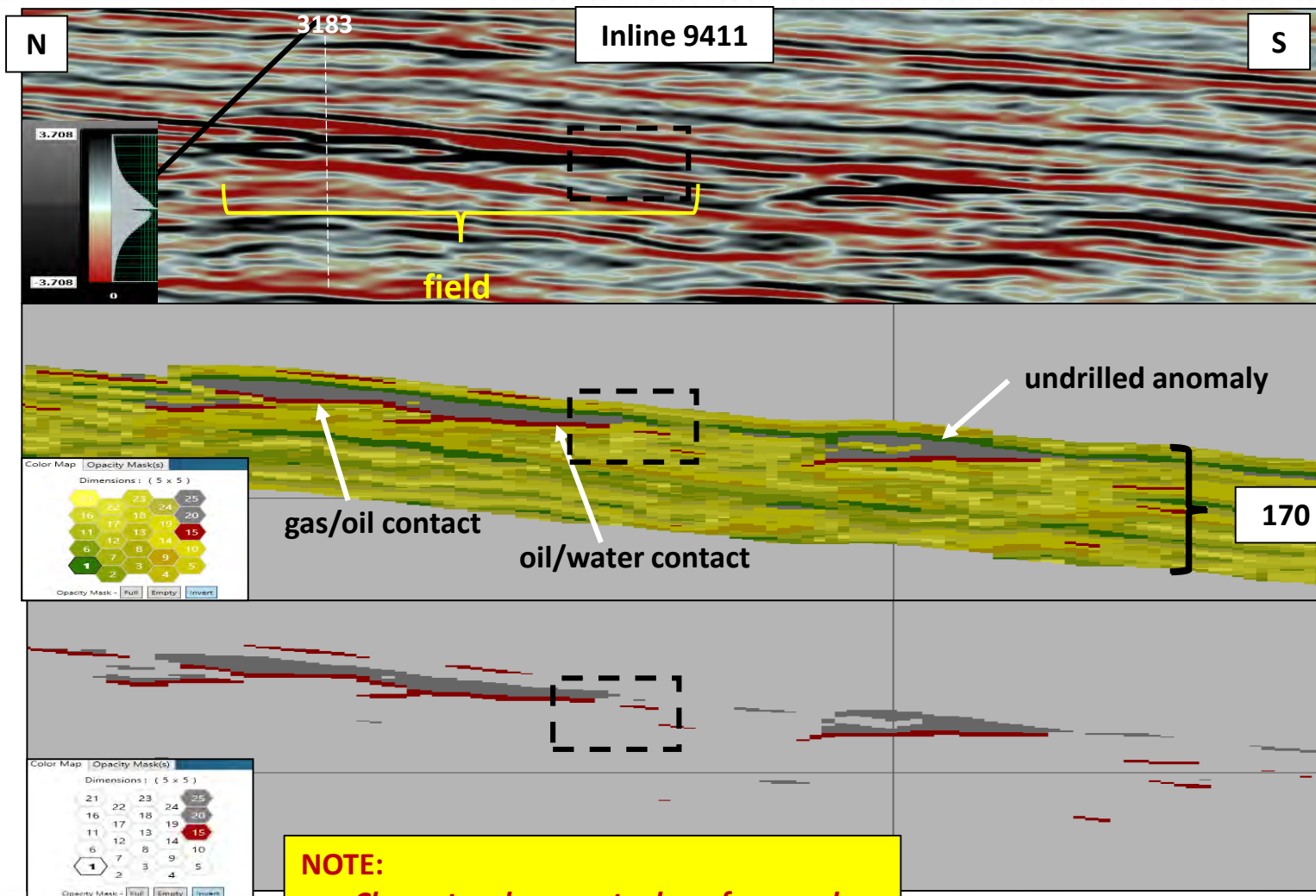
SOM analysis (25 neurons) with low probability in white



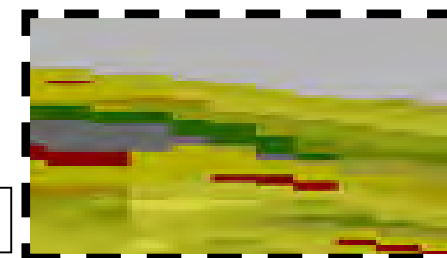
SOM attributes:

Sweetness, Envelope, Instantaneous Frequency, Thin Bed, Relative Acoustic Impedance, Hilbert, Cosine of Instantaneous Phase Final Raw Migration

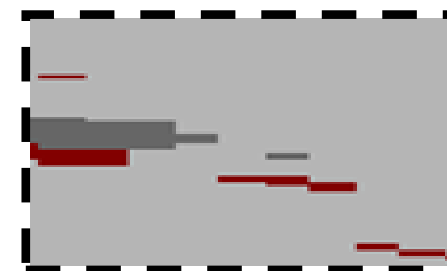
Seeing the reservoir clearly with SOM



Stacked
Amplitude
Line 9411



SOM analysis of
Line 9411
(25 neurons)



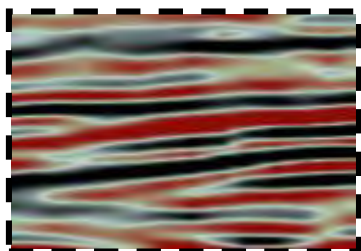
SOM analysis of
Line 9411
(displaying only
3 neurons)

NOTE:

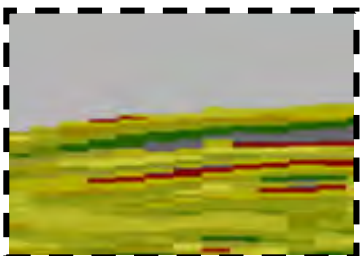
- Character change at edge of anomaly
- Flat spots

Seeing the reservoir clearly with SOM

Stacked Amplitude
Crossline
3183



SOM analysis of
Crossline 3183
(25 neurons)

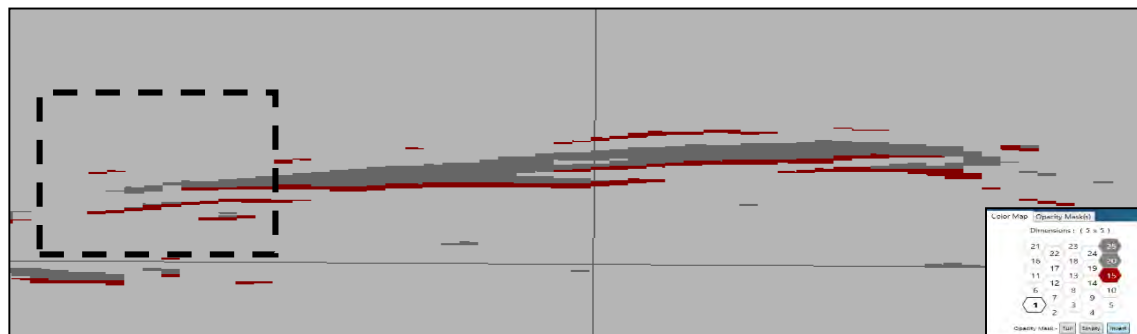
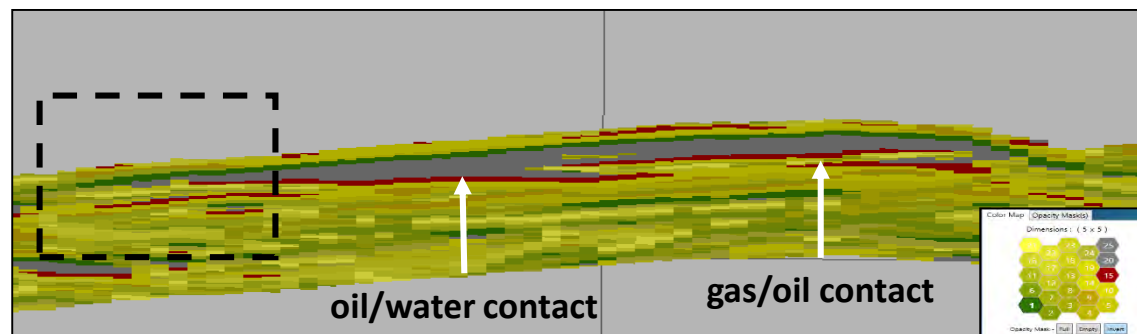
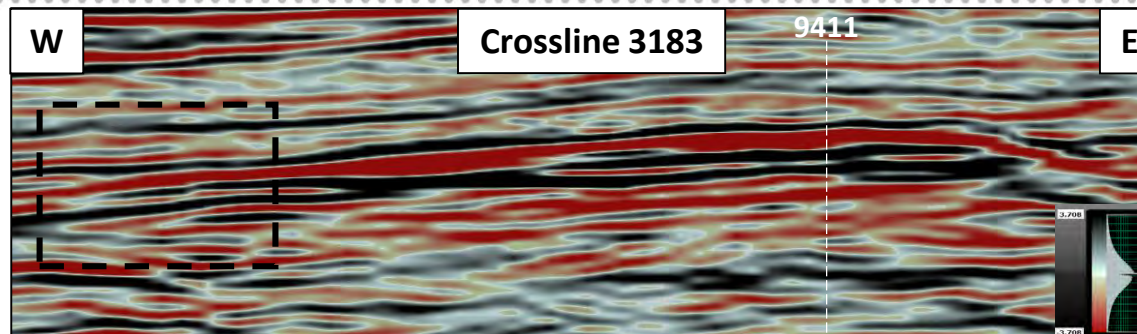


SOM analysis of
Crossline 3183
(displaying only 3
neurons)



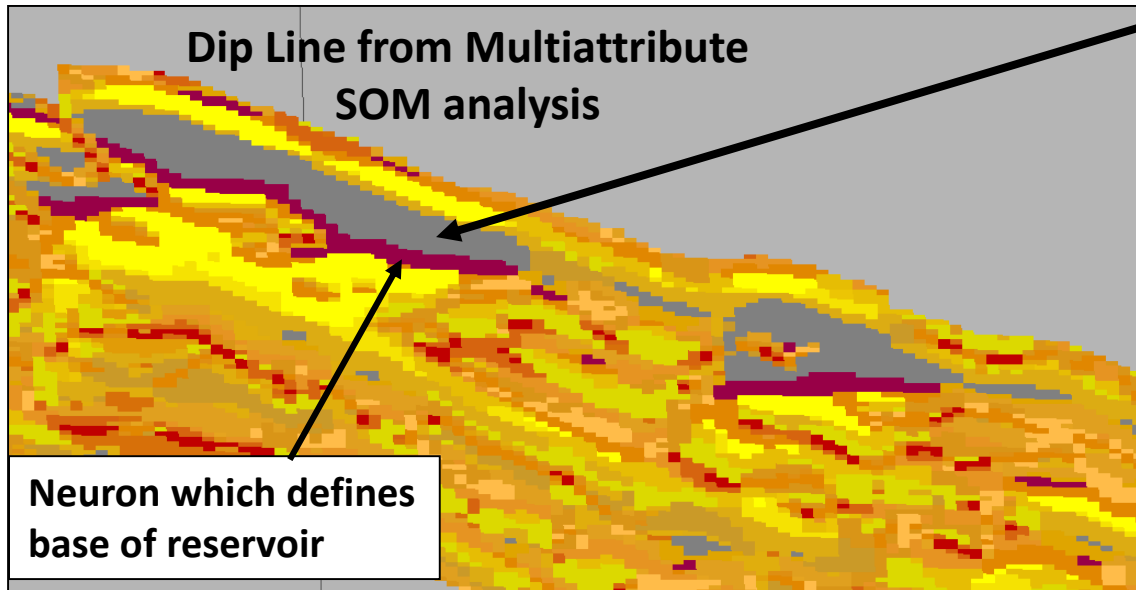
NOTE:

- *Character change at edge of anomaly*
- *Flat spots*

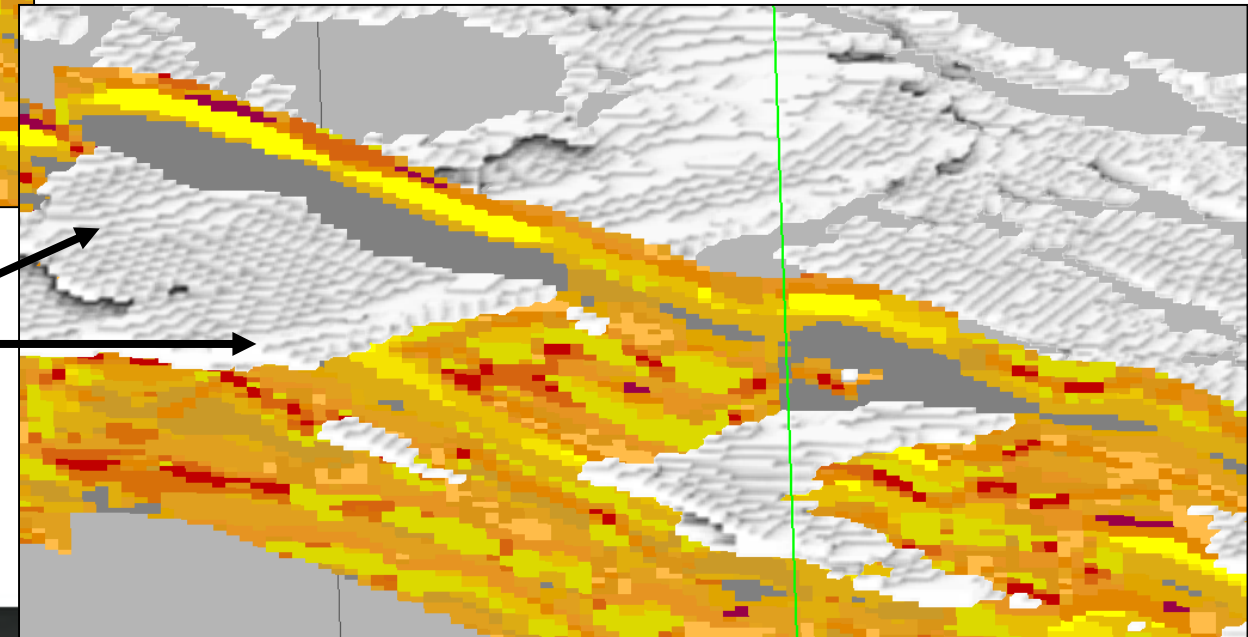


Geobody presentation

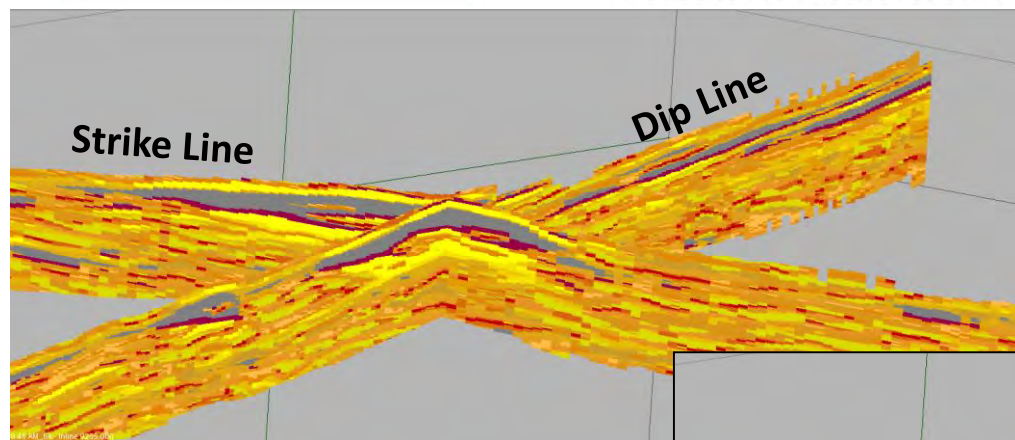
Oil and Gas Field displayed previously



Geobody identifying the gas/oil and oil/water contacts

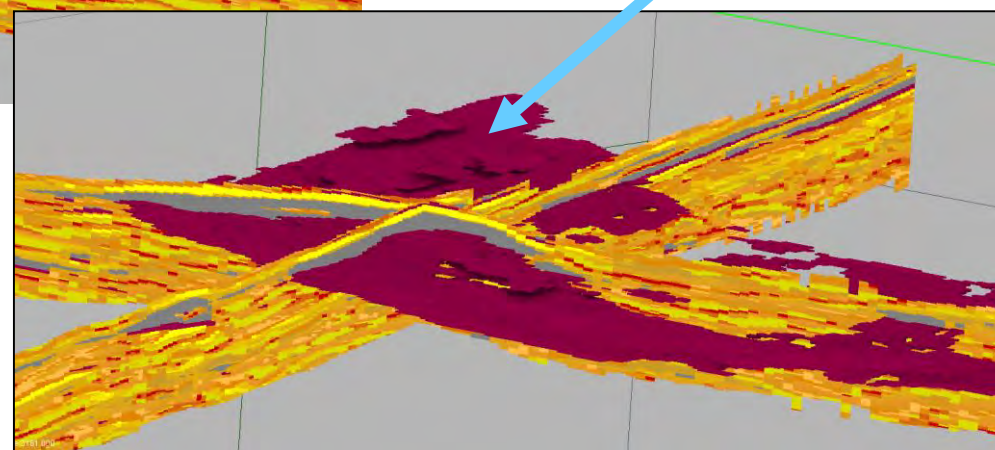


Geobody presentation



Geobody Groups			
	Neuron	Geobody Count	Color Range
☐	18	115	
☐	19	96	
☒	20	24	
☐	21	212	
☐	22	100	
☐	23	197	
☐	24	37	
☐	25	23	

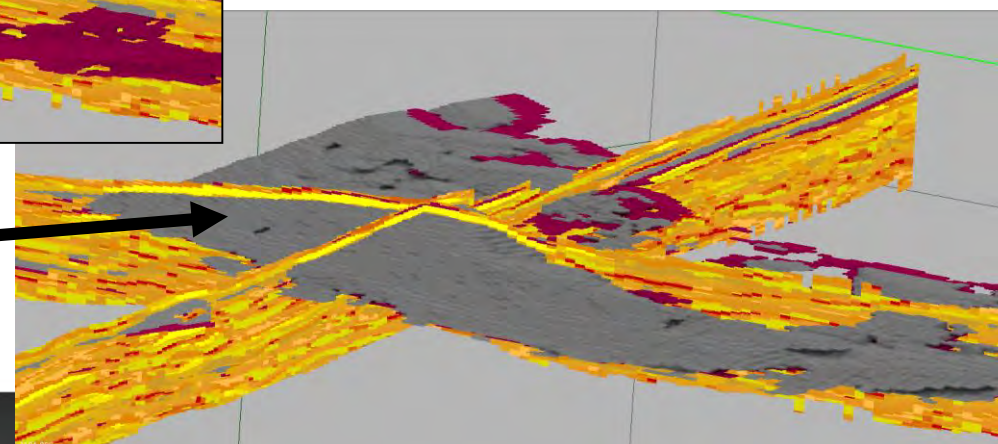
Geobodies (Neuron 20)				
Normal Colors				
☒	Lock user specified colors	Name		
	Id	Name	Sample Count	Opacity
☒	1214	Geobody_1214	148,682	100%
☐	1228	Geobody_1228	1,454	100%
☐	1222	Geobody_1222	708	100%
☐	1224	Geobody_1224	577	100%
☐	1220	Geobody_1220	414	100%
☐	1230	Geobody_1230	336	100%
☐	1229	Geobody_1229	310	100%
☐	1216	Geobody_1216	258	100%



Neuron 20 (Geobody 1214) has identified the gas/oil and oil/water contacts in this field

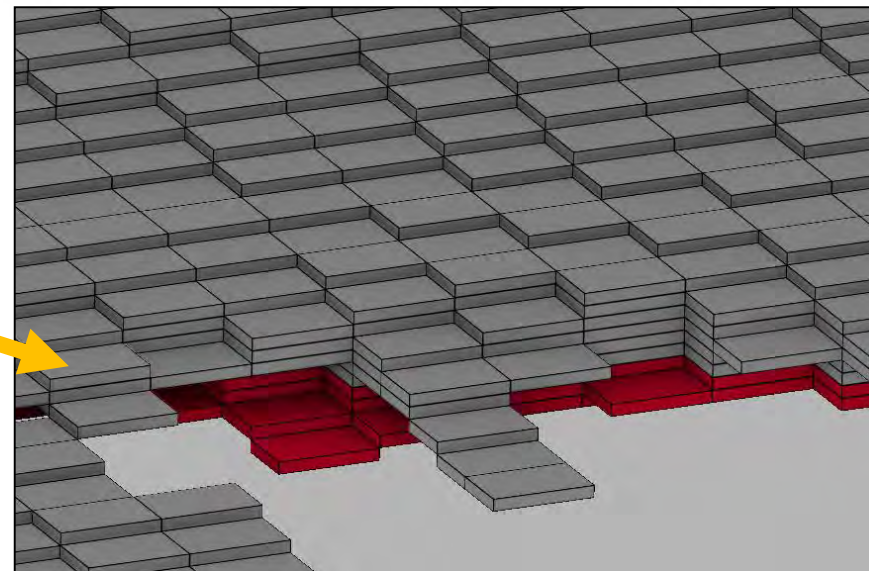
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☒	24	37	
☒	25	23	

Geobodies identified by Neurons 20, 24, and 25 reveal the reservoir above the hydrocarbon contacts



Geobodies are on a scale of bin X sample increment, therefore, geobodies can be quantified.

Each bin X sample increment can be quantified to compute Gross Rock Volume, Hydrocarbon Pore Volume, etc.



Sample Volume (Depth)
Sample Volume (Time)
Depth Conversion Velocity

Gross Rock Volume

Net Rock Volume

Pore Volume

Hydrocarbon Pore Volume (HCPV)

Net Rock Factor

Porosity

Water Saturation (SW)

Calculated (Bin X * Bin Y * Bin Z) (survey units)

Calculated (Bin X * Bin Y * Bin Z (Sample in time/msec. * Velocity))

5 Digit Value from User: 12000 Feet or Meters/sec (survey units)

$GRV = \text{Sample Volume} * \text{Sample Count}$

$NRV = GRV * \text{Net Rock Factor (0 -1)}$

$PV = NRV * \text{Porosity}$

$HCPV = PV * (1-Sw)$

0 to 1 (from User)

0 to 1 (from User)

Percentage (By User from Log Data)



Picture has been deleted due to sensitive client information

The two key neurons have been scanned for Geobodies. The Geobody which may be contributing to the production in the best well has been highlighted in green. Highlighting that geobody allows one to know the sample count it contains – which in this case is 32,439 samples (1ms x 110’x110’)

Volumetrics, if all values are known, could be calculated to show possible reserve amounts and calibrate to known production for reservoir extents. Values used are “estimates” for the Meramec in this area

Velocity (ft/s) :	14,000 ft/sec
Net/Gross (0-1) :	0.60
Porosity (0-1) :	0.06
Water Saturation (0-1) :	0.4

Geobody Details

Id

67

Name

ID	NAME	NEURON	SAMPLE COUNT	EXTERIOR SAMPLE COU	INTERIOR SAMPLE COU	VELOCITY (FT/S) (>=	NET/GROSS (0-	POROSITY (0-1	WATERSATURATION (0	SAMPLE VOLUME (CUBIC FE	GROSS ROCK VOLUME (CUBIC FE	NET ROCK VOLUME (CUBIC F	PORE VOLUME (CUBIC FE	HYDROCARBON PORE VOLUME (CUBIC FEET)
67	Geobody_67	72	32,439	24,925	7,514	14000.00	0.60	0.06	0.40	169400.10	5495169000.00	3297102000.00	197826100.00	118695700.00

32,439 samples

118695700 cubic feet

$118,695,700 \text{ CuFt} / 43,5460 = 2725 \text{ ac-ft} \times 225 \text{ BOE/ac-ft} = 613,125 \text{ BOE}$ Actual is: 611,685 BOE for the well (less than 1% error)

Conclusions:

The machine learning process, using PCA and SOM, continues to improve our seismic interpretation by providing much more detailed results.

In the first case, this process helped to define the areal extent of a thinly laminated reservoir in deep, pressured sands not seen in the original amplitude data

In the second case, machine learning helped to clearly define hydrocarbon contacts and sand distribution to provide a higher resolution picture of the reservoir extent

The SOM classification takes advantage of natural patterns in multiple seismic attribute space that is not restricted to the resolution limits of conventional wavelet data. This process enables interpreters to produce higher resolution interpretations of reservoirs, facies, depositional environments, DHIs, etc.

Acknowledgements:

The Authors would like to thank the staff of Geophysical Insights for producing the software to generate the results in this presentation.

Thanks also to various clients and sources that have allowed the showing of these classification results

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