Mapping high frackability and high TOC zones in the Barnett Shale: Supervised Probabilistic Neural Network vs. unsupervised multi-attribute Kohonen SOM

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1. Introduction:

- The Barnett Shale is one of the most important unconventional shale plays in the USA.
- Key of success in such unconventional gas plays is determining the zones of high frackability (brittleness) and high TOC.
- Frackability increase with increase in quartz content, which corresponds to decrease in gamma ray value, where as the organic rich and clay rich shale gives high gamma ray values.
- In the Barnett Shale from north-central Texas, fourteen gamma ray parasequences (GRP) has been identified based on gamma ray behavior (Singh, 2008).
- Here, we attempt to perform regional distribution of such characteristics through gamma ray volume prediction, with supervised neural network analysis.
- Extend, this prediction to unsupervised SOM, for areas lesser well control.

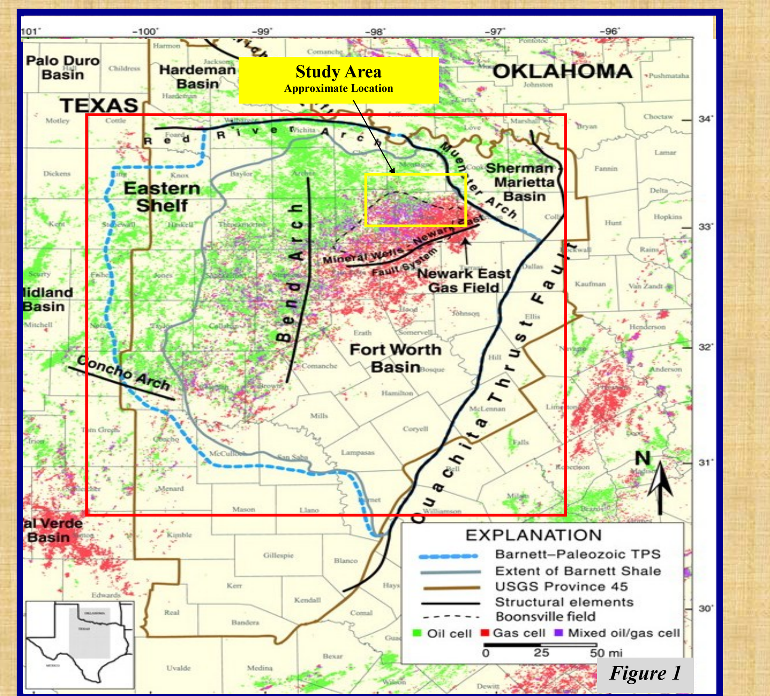

Figure 1

2.Regional Geology:

- The Fort Worth Basin (north Texas) is a shallow N-S elongated foreland basin.
- It was formed during the late Paleozoic Ouachita orogeny.
- The basin is delimited in the east by the Ouachita Thrust Front, to the north by the Red River Arch, to the north – northeast by the Muenster Arch, to the west by the Bend arch, Eastern shelf and Concho arch, and to the south by the Llano Uplift.
- *Figure 1* shows the area of USGS Bend arch–Fort Worth Basin province 45. Yellow rectangle, indicates study area .

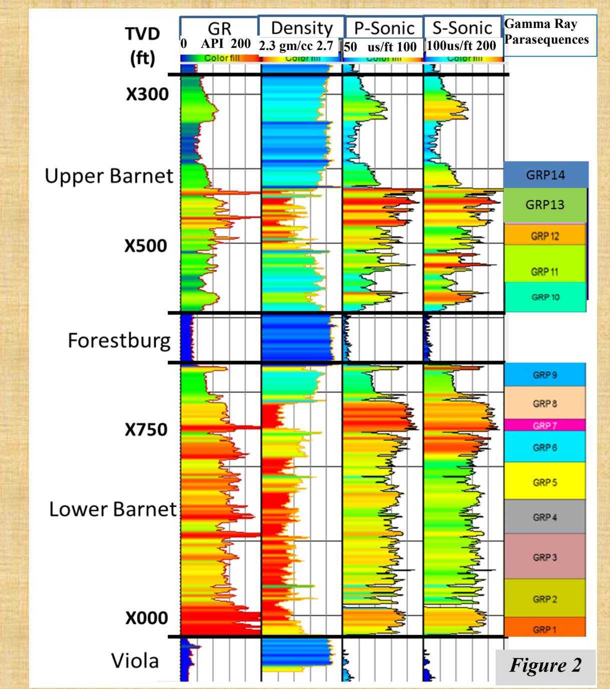

Figure 2

3.Brittleness Index and GR:

$$BI = \frac{Q + Dol}{Q + Dol + Cc + Cl + TOC}$$

Where, Q = quartz, Cl = clay, Dol = dolomite, Cc= calcite, TOC = Total organic carbon .(Wang and Gale, 2009) .

BI is relatively lower in high TOC shale compared to the shale rich with quartz content (BI equation).

The shale with high dolomitic content have higher BI, compared to non-calcite mudstones.

In Barnett shale high Singh,2008, has noticed that high TOC zones are associated with the silica-rich rocks compared to the carbonate rich lithofacies, which corresponds to high Gamma Ray values. Figure 2 shows a typical well log of the area.

4 B. Unsupervised multi attribute Kohonen Self Organizing Maps :

SOM (AASPI S/W) technique was used to classify seismic facies.

SOM training rule is applied to cluster the multi-attribute vectors in in the latent space. The PVs are trained in the 2D latent space and their positions updated after each iteration, resulting in a newly updated position of the PVs. We use 2D HSV color model to assign continuous color to the PVs according to their distance from their center of mass and their azimuth. In this manner, two dissimilar neighboring samples in the seismic volume will be far apart in the latent space and have different colors (Roy et al., 2011). Conversely, two similar samples in the seismic volume will have nearly the same color. Each color represents a seismic facies, most of which are geologic facies, but some which may be seismic 'noise' facies.

Input Volumes
P-Impedance, Coherent Energy | Lambda-Rho, Mu-Rho
↓
SOM Training and Clustering
↓
Facies Classification

4 A. Supervised Neural Network Analyses:

Input Data

Target Log	Initial 3D Volumes		
GR Logs at 19 Wells	P-Impedance, S-Impedance, Vp/VS	Spectral Components, Relative Impedance(RA)	RA Quadrature, Coherent Energy

↓
Multi Attribute Stepwise Linear Regression
Decide convolution operator length & number of attributes
↓
Train Neural Network (PNN)
↓
Apply Trained Neural Network on Volume
↓
Validation
Compare the prediction at wells not used in training

Probabilistic Neural Network work flow used to predict the gamma ray volume from seismic attributes.

Attribute	Train. Error	Valid Error
P-impedance	22.1	22.5
Relative Acoustic Imp.	20.5	21.0
Sweetness	20.0	20.5
Quadrature	19.5	20.2
S-impedance	19.2	20.1
Vp/Vs	18.5	19.5
Coherent Energy	18.2	19.3
Spectral_Mag_20Hz	18.1	19.4

Figure 3: *Table showing training and validation error; with 7 attributes the validation error is minimum.*

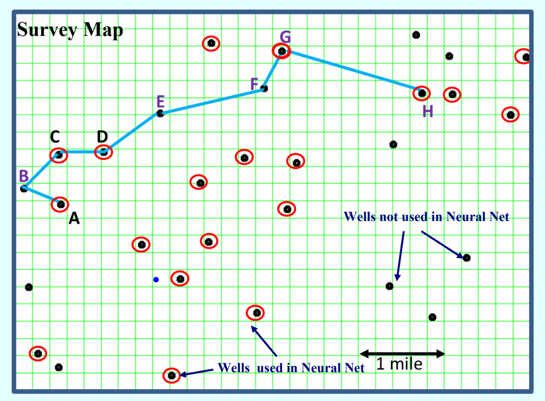

Figure 4: *Distribution of Wells used for neural network analysis, approximate area of study 30 sq. miles.*

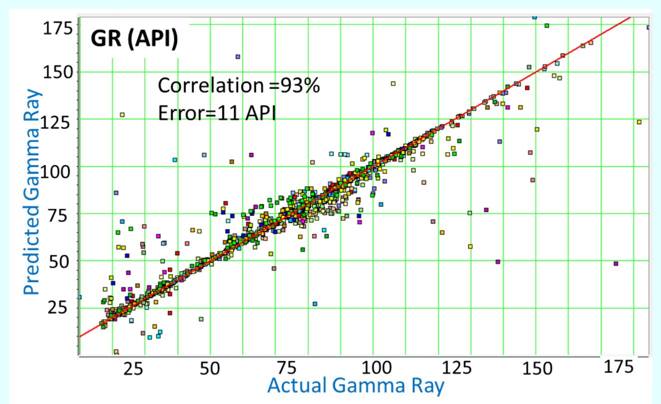

Figure 5: *The plot showing actual (well log) vs predicted gamma ray, the high correlation indicates good prediction.*

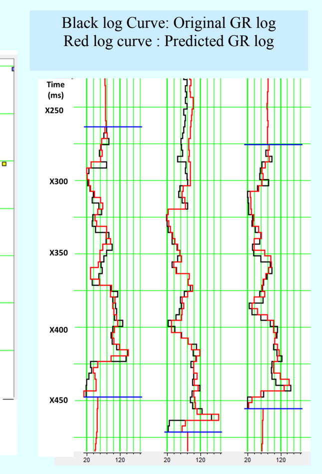

Figure 6: *Wells showing gamma ray logs obtained in neural net validation*

- Few attributes like Instantaneous Phase, were avoided.
- Correlation obtained Multi attribute analysis was 82 % with 7 attributes shown in the Figure 3.

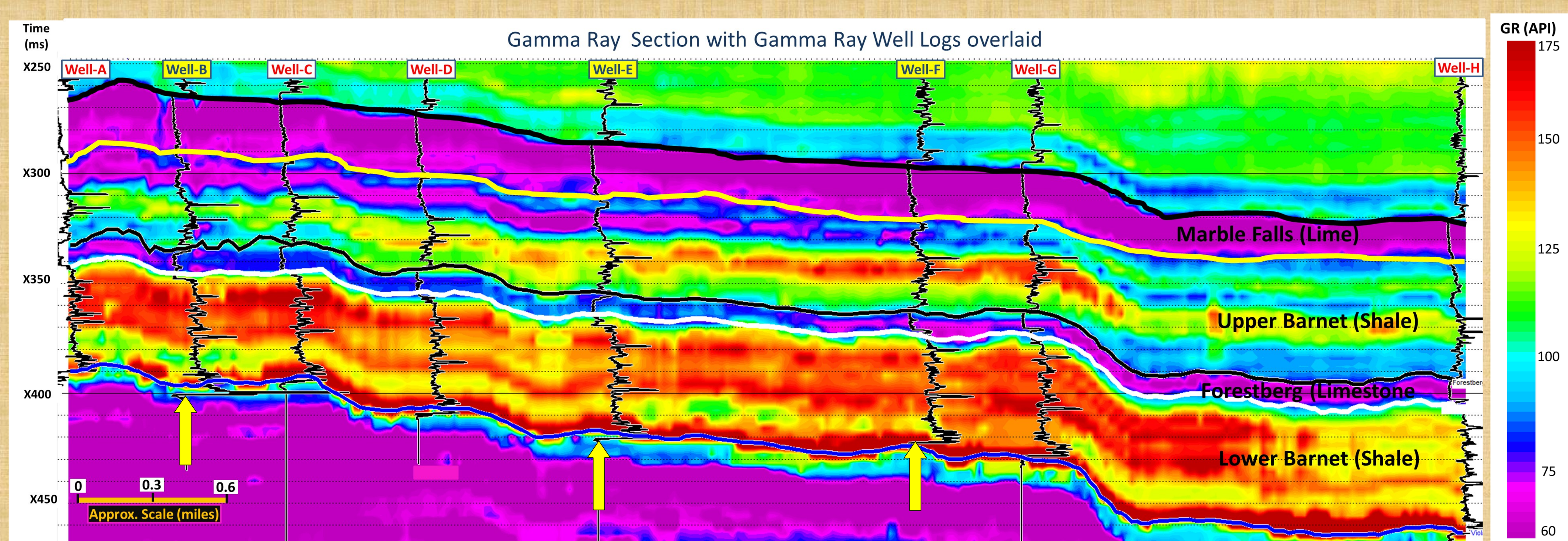

Figure 7: Gamma ray section over arbitrary line (on map view) passing through wells, the wells highlighted with yellow arrow (well B , well E and Well F) were not used in neural network analysis at any stage. A very good match can be seen with actual gamma ray log and the predicted gamma ray volume.

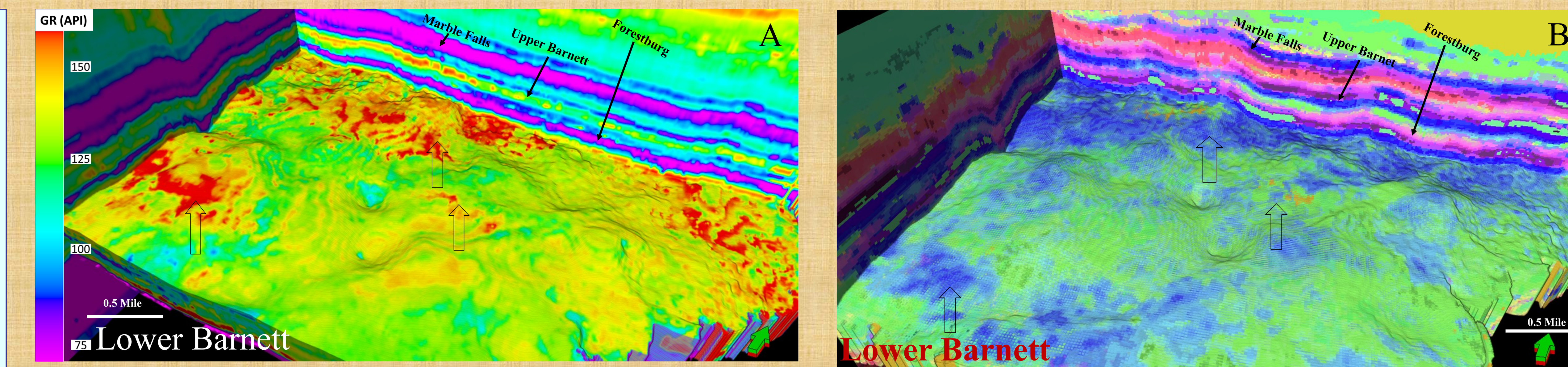

Figure 8: A: *In the lower Barnett high gamma ray values are possible zones of high TOC, indicated by orange to red in the figure; relatively low gamma zones are areas of high frackability. Hence, wells are needed to be placed in the zones with relatively low gamma ray, and are closely associated with high gamma ray, so that the fracture can be initiated in the rock drilled and then fractures can propagate into the high TOC zones so that the well can produce hydrocarbon.*
B: *SOM derived facies distributions is shown in this figure. the color correlation with gamma ray suggests, the pink and the purple are limestone and blue is high gamma ray (high TOC) shale and green is moderate gamma ray (silica rich) shale , the correlation can is indicated by arrow pointing high gamma ray(high TOC) value shale.*

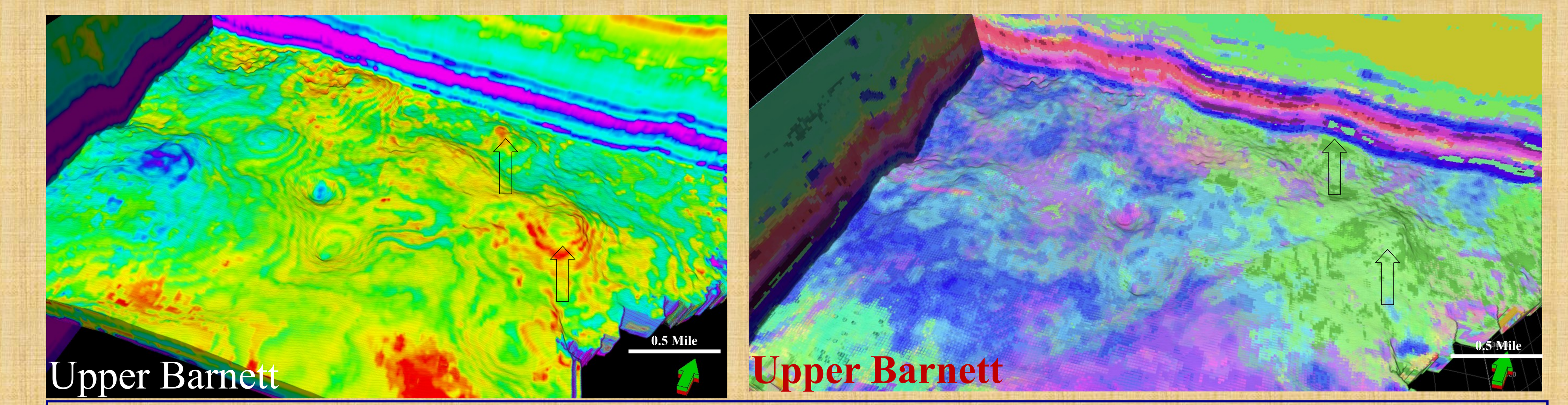

Figure 9 A: *Gamma Ray in upper Barnett the, high gamma ray values are possible zones of high TOC, orange to red; similar to the lower Barnett the fracturable zones can be identified as relatively low gamma ray value. Color scale is same as for figure 7A.*
B: *SOM derived facies is shown in the figure, the color correlation changes with respect to the lower Barnett, in upper Barnett as the high GR is associated with green color and relatively low gamma ray is associated with the purple and pink color, the correlation can be seen on by indicated arrow pointing high GR(high TOC) value shale.*

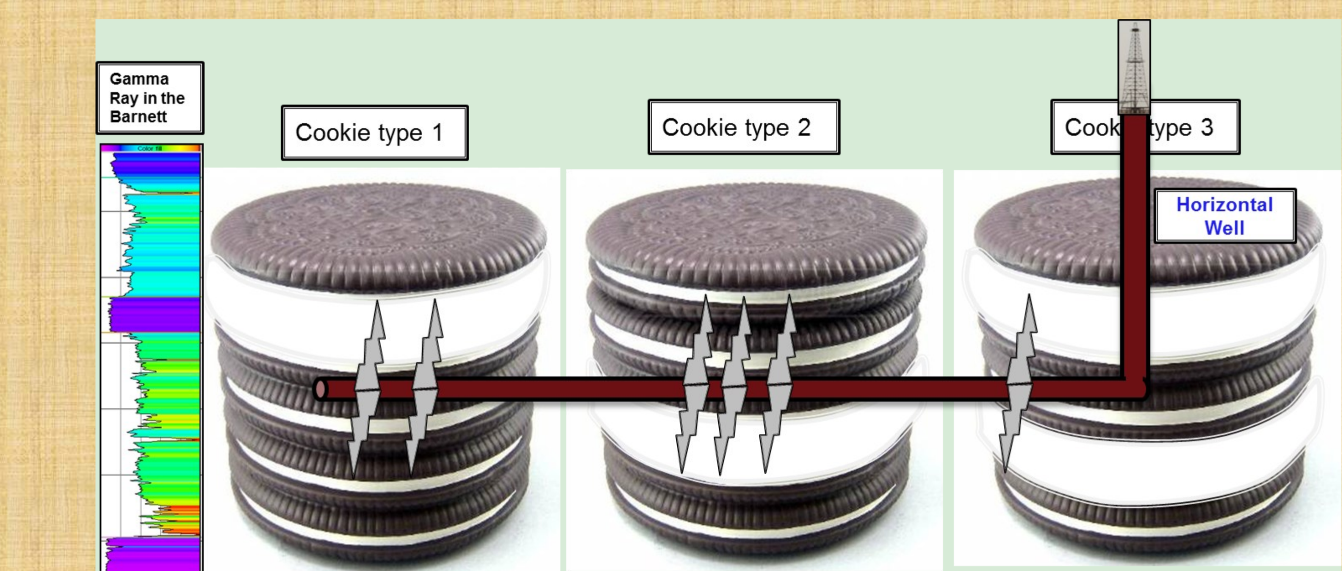

Figure 11 : *Oreo cookie model for Barnett shale. The well goes through tight crunchy cookie and it is fractured, and the soft cream is sipped.*

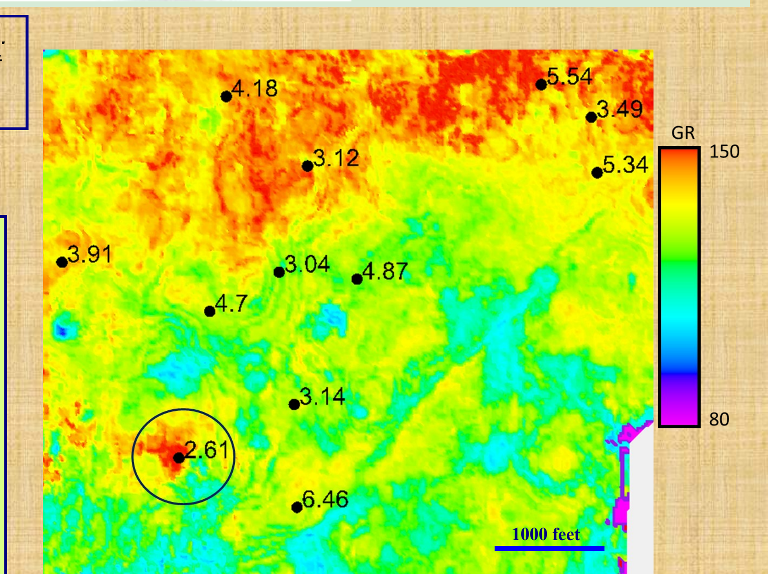

Figure 10 : *First 90 days of production (scaled from 0-10) of wells posted on average gamma ray map for the lower Barnett shale interval. Here, the low production value (2.61) corresponds to high gamma ray area.*

Conclusions and Limitations:

- Gamma ray can be related to frackability (or brittleness index); high silica rich facies has high BI, and high TOC shale is more ductile.
- Gamma ray volume generated using the Neural Network matches closely with the gamma ray well log from the wells which were used and also with the wells (blind wells) which were not included in neural network training.
- SOM results are matching with the gamma ray volume, analyzing the colors of facies at the known location, helps it to extend the classification to areas with lesser well control.
- Although, gamma ray is a good TOC proxy for the Barnett shale, but in the initial analysis for Woodford shale the resistivity and porosity are found to be good proxy for TOC. Which indicated that, a separate analysis is required in order to find the proxy for TOC.

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