From Reservoir Characterization, 3D Seismic multi-attribute analysis and machine learning facies classification to Well Performance Simulation: A Woodford Shale Case Study in North of Oklahoma, USA

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1. ABSTRACT

The objective of our study is to use data from every scale for reservoir characterization and eventually reservoir simulation. The current area of study is Woodford Shale in Oklahoma. Due to enormous pay zone and thus oil and gas reserves, the Woodford Shale is the center of attraction for major oil operators in Oklahoma currently.

In this study we have used well logs to obtain high vertical resolution petrophysical and geomechanical properties such as: Porosity, total organic carbon (TOC), Young's Modulus, Shear Modulus, Biot's coefficient, Poisson's ratio, stresses etc. We have used seismic inversion derived impedance volumes to populate these properties in the geo-cellular model area to obtain better stratigraphic control on these properties. To obtain the type curves (TC's), we have used unsupervised machine learning methodologies such as Self Organizing maps (SOM) and Generative Topographic Mapping (GTM) to cluster the reservoir properties together.

From these clusters, we have identified four type curve (TC) areas. To demonstrate the physical significance of these four type curve areas, we have used a fully compositional, fully coupled geomechanical Equation of State (EOS) simulator to simulate the Stimulated Rock Volume (SRV) as a function of stress and eventually production.

Our results show, the integration from seismic to production scale provides excellent control on the reservoir characterization and bolsters confidence on the static model. Out of all clustering techniques, SOM works best in our case and is consistent with the regional geology. More number of samples in case of seismic provides better horizontal control on geomechanical properties and hence modeling of the SRV and ultimately predicting production behavior.

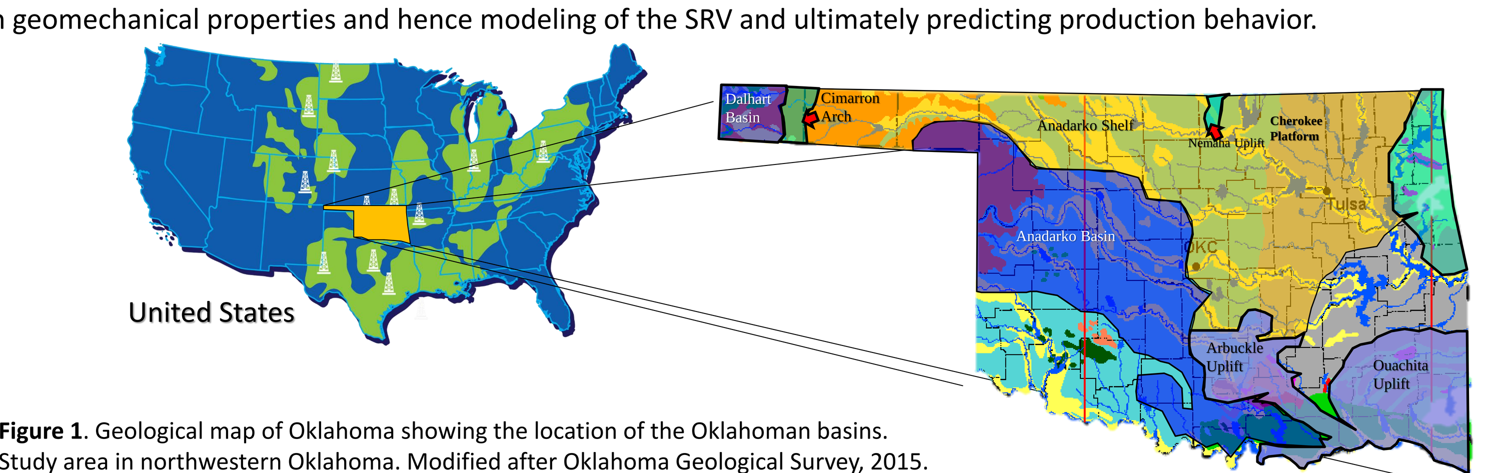


Figure 1. Geological map of Oklahoma showing the location of the Oklahoman basins. Study area in northwestern Oklahoma. Modified after Oklahoma Geological Survey, 2015.

2. Regional Geological Framework of the Woodford Shale

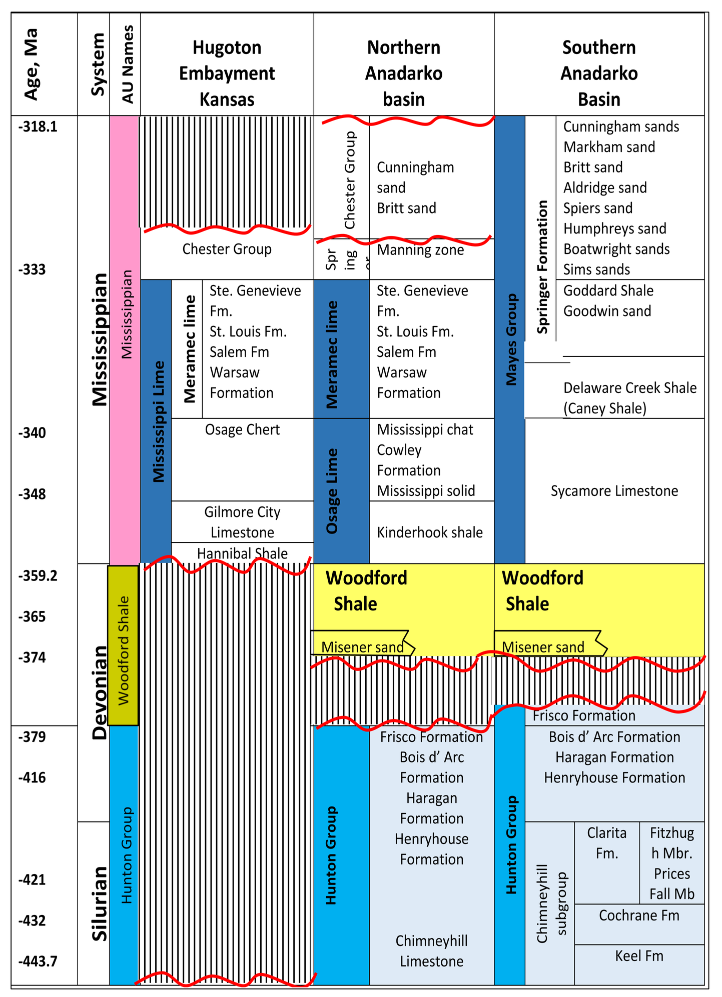


Figure 2. Generalized stratigraphic column of the Silurian through Pennsylvanian section displaying the Upper Devonian Woodford Shale and its major subdivisions. Modified from Higley, D. K. (2013).

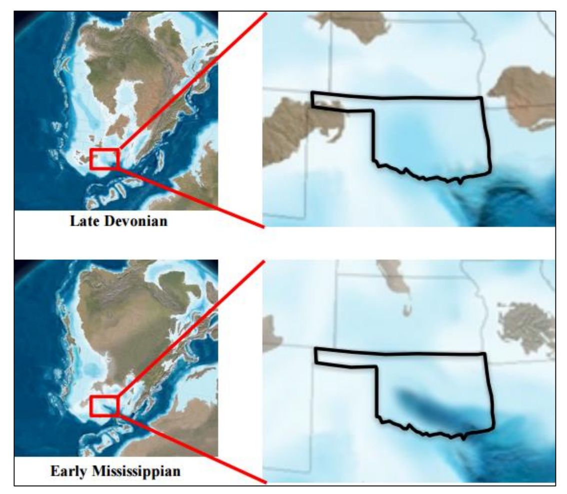


Figure 3: Time lapse of Oklahoma Paleo geography where A is Ordovician, B is Silurian, C is Devonian and D is Mississippian. The Woodford was deposited during a major transgressive event between C and D (Modified from Blakely, 2012)

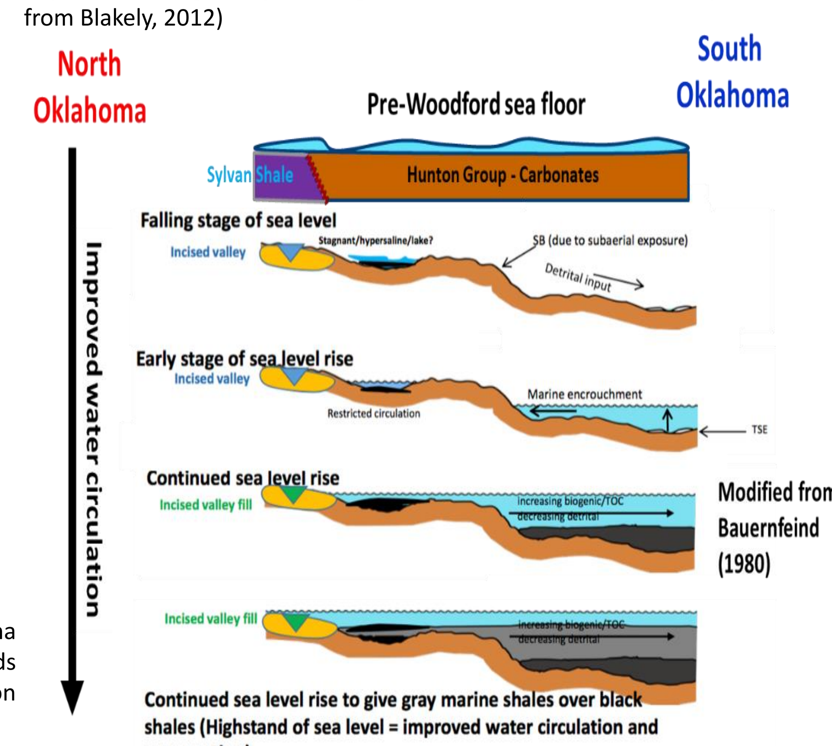


Figure 4. Depositional model from North to South of Oklahoma through a sea level cycle of the Woodford Shale. Note towards the North the occurrence of incised valley fill erosion

3. Proposed Methodologies

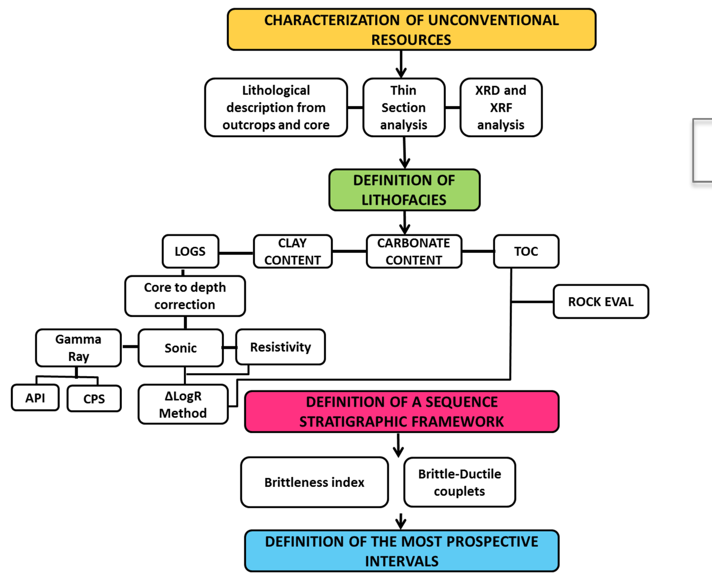


Figure 5.Flow chart for integrated characterization of unconventional gas shales with geological and geochemical data.

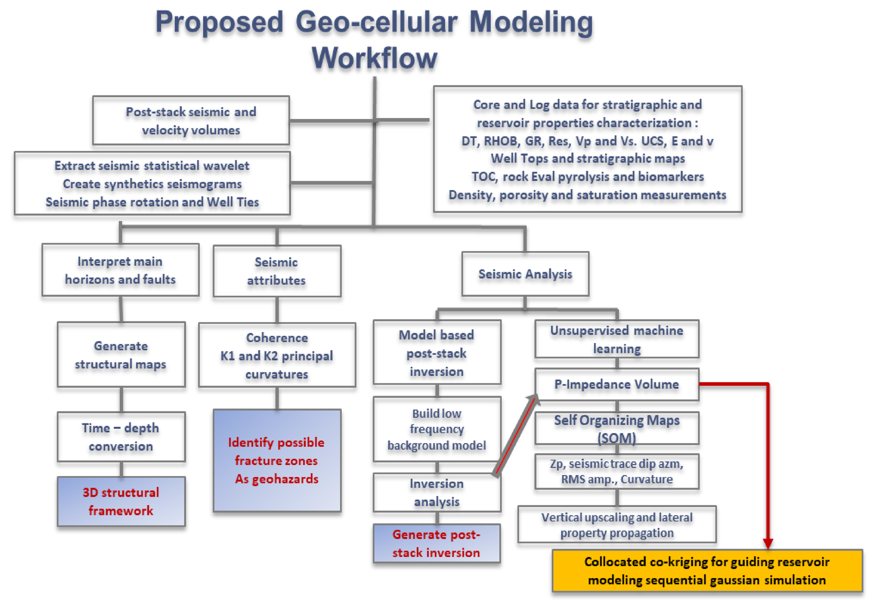


Figure 6. 3D Seismic interpretation and Inversion workflow for "feeding" the geocellular reservoir model. Only post-stack data was available for inversion.

4. Woodford Shale Stratigraphy and Seismic Characteristics

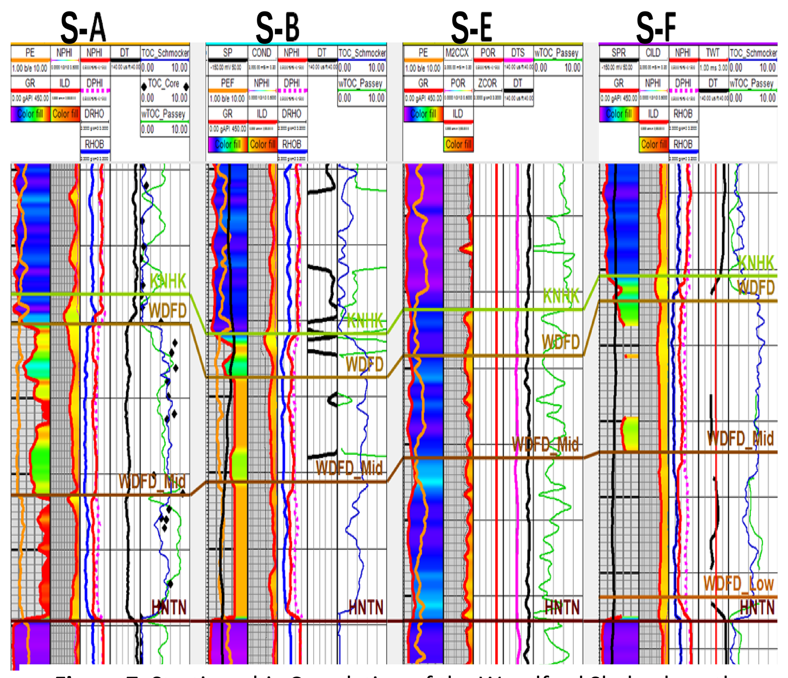


Figure 7. Stratigraphic Correlation of the Woodford Shale along the Study area. Cored Well S-A with measured TOC points and calculated TOC curves for reservoir modeling using Passey (Light green curve) and Schmocker (Dark blue TOC curve) methodologies.

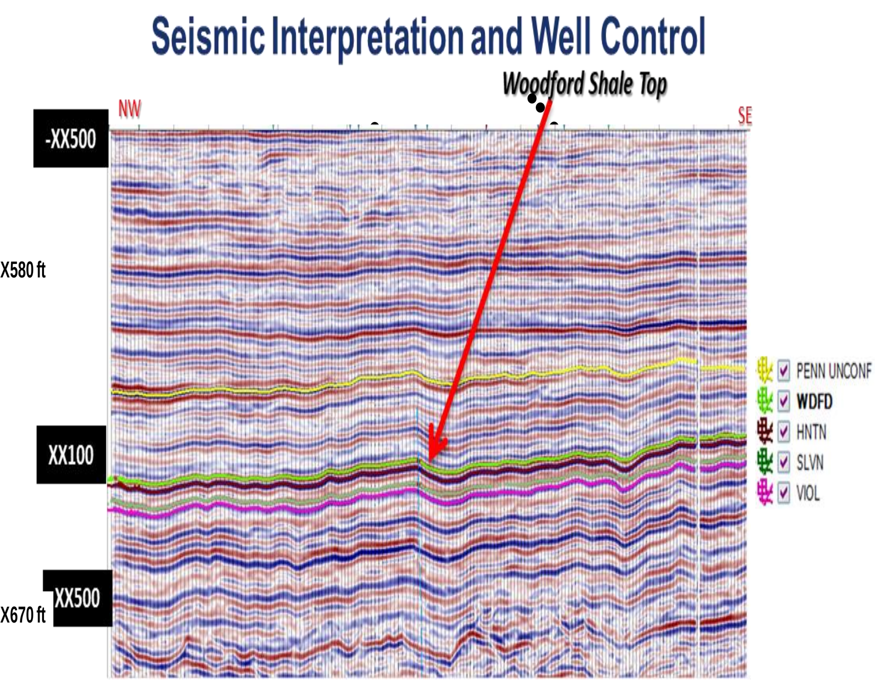


Figure 8. Seismic Expression of the Woodford shale in Study Area. Woodford shale top is a seismic trough (negative amplitude) and Woodford shale base (Hunton Group Top) is a bright positive amplitude horizon.

5. Seismic Multi-attribute analysis and Post-Stack Inversion

WDFD Time structure map (ms)

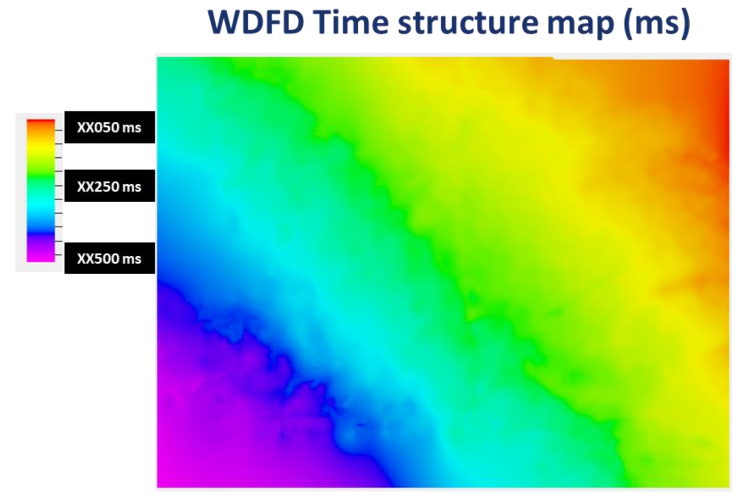


Figure 9. Woodford shale time structure map in study area. Structure converted to depth and applied as reservoir model gridding constrain.

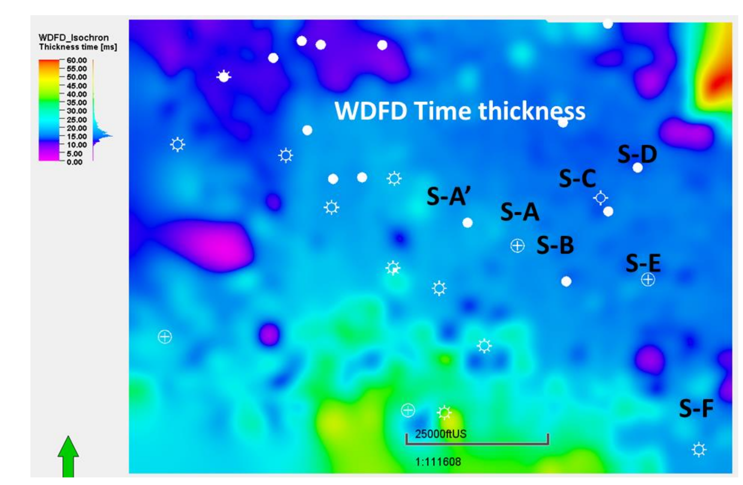


Figure 10. Woodford shale time structure map in study area. Structure converted to depth and applied as reservoir model gridding constrain.

Seismic Attributes and Structural framework

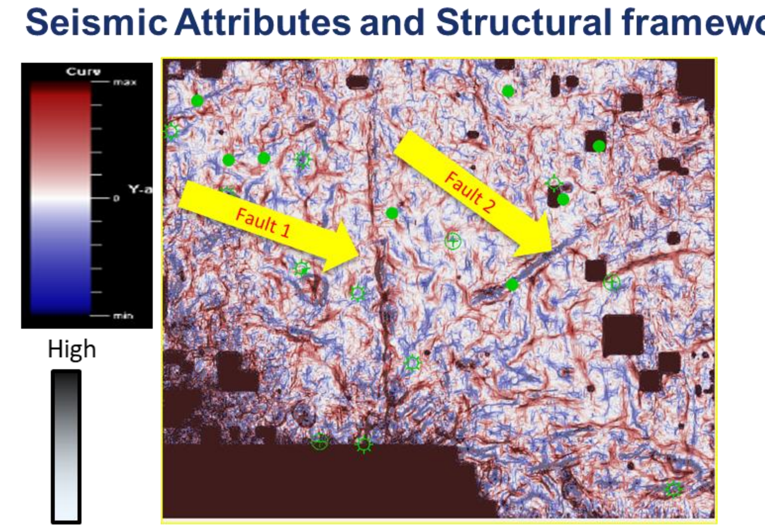


Figure 11. Co-rendering of most positive, most negative curvature and coherency attributes for highlighting faults and fracture areas

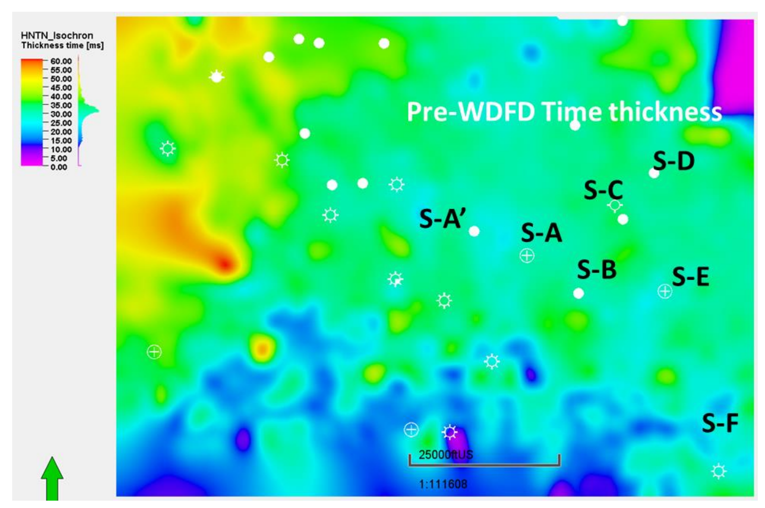


Figure 12. Pre-Woodford shale time structure map in study area. Note that where Woodford shale is thick (Figure 10) the Pre-Woodford Strata is thin.

Post Stack inversion Results

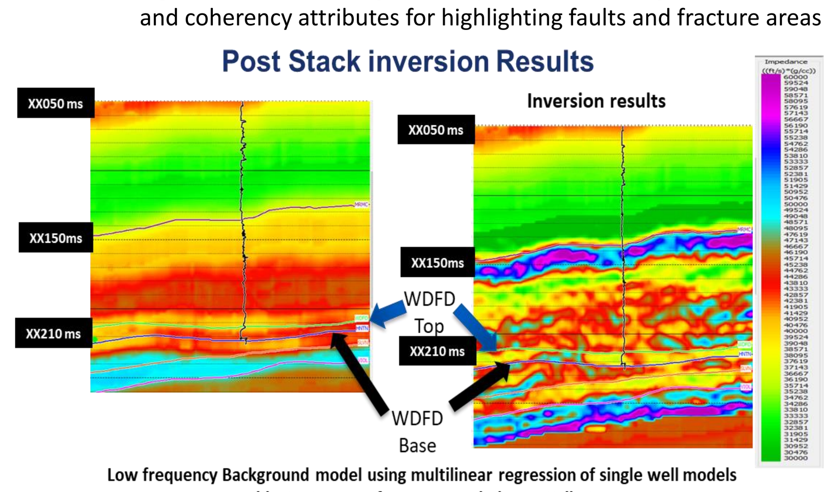


Figure 13. Image on the left correspond to the low frequency P-Impedance Back ground model in a cored well. Image on the right is the P-Impedance volume using model-based calculations. Woodford top is the light green seismic horizon.

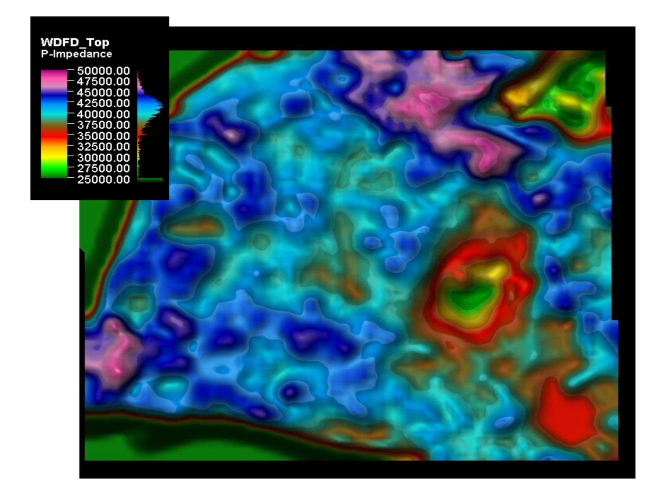


Figure 14. Inverted P-Impedance. Extracted and Interpolated along the Woodford Seismic Window. Higher TOC correlates with the zones of much lower average P-impedance values.

6. Total Organic Carbon (TOC) wt% calculations

Calculation of TOC with well logs

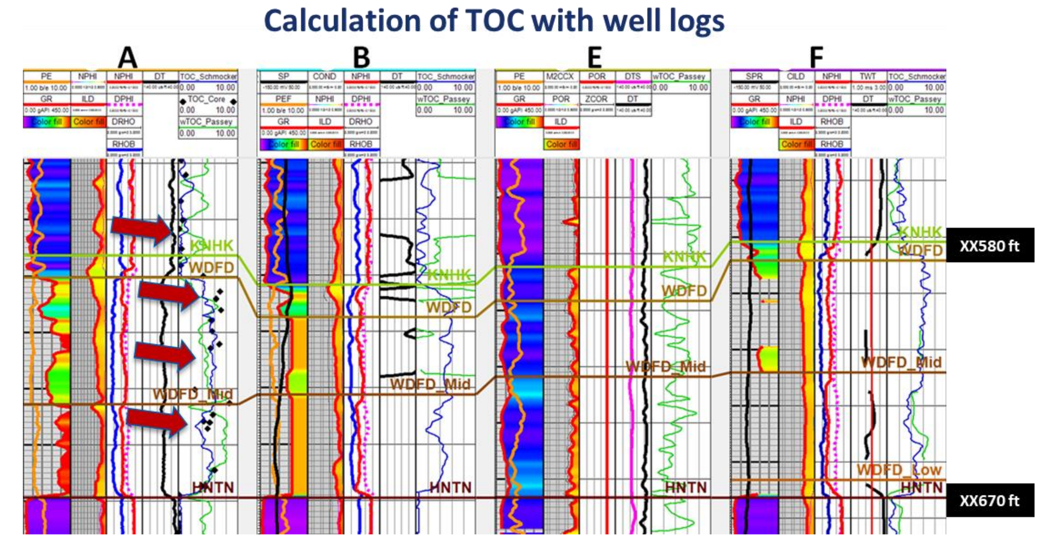


Figure 15. Distribution of the TOC in Lower, Middle and Upper Woodford shale in from a core in Northern Oklahoma. We calibrated and applied this equation:

$$TOC\ [wt\%] = [(-56.547*RHOB) + 154.867] / 2$$

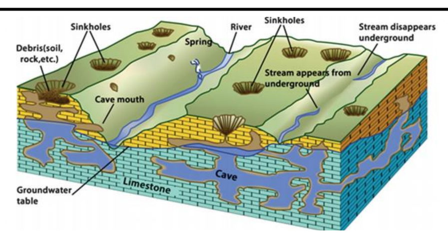


Figure 16. Generalized model of surface features on a Carbonate unconformity (after Grotzinger and Jordan, 2010) that fits the model represented by the cross section. TOC catchment areas are over eroded pre-Woodford Strata

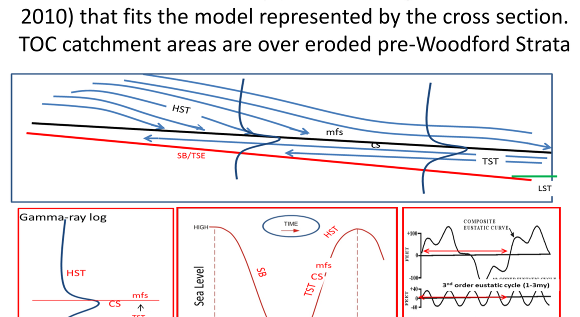


Figure 17. General sequence stratigraphic model for deposition of resource shales. Slatt et al. (2012). Higher TOC content during TSTs.

7. Machine Learning applications for supporting the geocellular reservoir model

The Woodford shale seismic characteristics in the study area make this formation amenable to semi-automated interpretation using seismic attributes as an input to machine learning algorithms and promises to be a very effective way to accelerate the interpretation from a more homogeneous background (Woodford shale top is a seismic through [negative amplitudes], and Woodford shale base is a bright Seismic reflector [Figure 8, Figure 11]). Because seismic attributes are quantitative measurements of both amplitude and geometry, a key component to machine learning is determining which seismic attributes best differentiate a feature of interest from the background. The self-organizing maps (or SOM) simply organize the input attributes in a manner that voxels with similar characteristics (input attributes) are grouped and colored similarly. The algorithm does what it is supposed to do, it organizes the data and finds patterns without any constrain or bias (Figure 19). The main challenge for interpreters in applying SOM and similar algorithms to seismic data is the attribute selection. The 3D seismic attributes that were input for the SOM are RMS amplitude, dip azimuth of the seismic traces, P-Impedance, Most Positive Curvature, Most Negative curvature and Peak Frequency. Similar colors correspond to similar rock facies as seen on Figures 13, Figure 14 and Figure 19. The SOM output was used for the Woodford Shale seismic window to laterally propagate the reservoir properties by collocated co-kriging.

The focus of our seismic interpretation has been on applying and comparing different machine learning methods including multilayer perceptron network, self-organizing maps, support vector machine, K-means, generative topographic maps (Meldahl et al., 2011; Roy and Marfurt, 2013; Snyder, 2016; Zhao et al., 2016; Qi et al., 2016) respectively. According to Infante-Paez (2018), in seismic interpretation, self-organizing maps (SOM) is a clustering technique that extracts similar patterns across multiple seismic attribute volumes and displays those similarities as a color-coded map (Figure 19), with similar colors representing clusters that a human interpreter can visualize as similar facies (Zhao et al., 2016).

Infante-Paez (2018) highlights that the most appropriate input attributes to feed the SOM are of three types: attributes that highlight the continuity- how layer cake the reflectors are- (homogeneity and entropy), the amplitude (peak magnitude) and the frequency (peak frequency) of the target patterns. These attributes are extracted from the raw amplitude data using software developed at the University of Oklahoma AASPI consortium 2018 version.

8. Machine Learning Results and Applications - Lateral variations of reservoir properties

Reservoir model

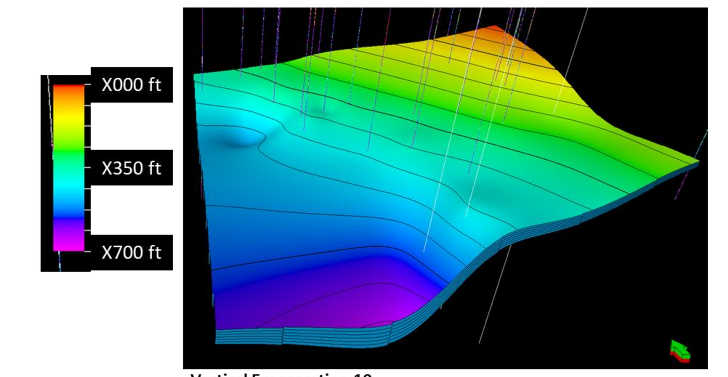


Figure 18. Woodford Reservoir Model. Wells displayed in study area with Shear and Compressional Sonic logs. Reservoir grid from seismic-well tie and depth domain conversion of Woodford Seismic Top and Bottom surfaces.

Petrophysical properties upscaling and variogram distribution for lateral interpolations based on collocated co-kriging

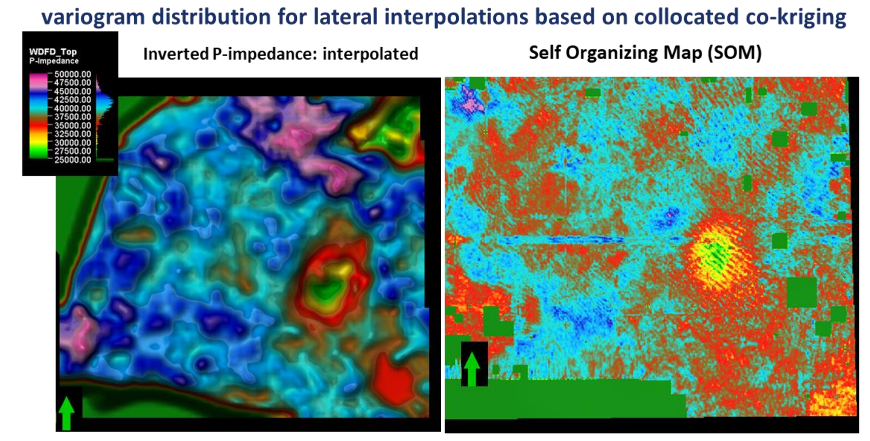


Figure 19. Self-Organizing Maps [SOM] volume using Mahalanobis distance (image on the right). Average values extracted in the Woodford shale seismic window. Attributes that were input for the SOM are RMS amplitude, dip azimuth of the seismic traces, P-Impedance, Most Positive Curvature, Most Negative curvature and Peak Frequency. Similar colors correspond to similar rock facies according to Zhao et al. (2016) and Infante-Paez (2018).

Geomechanical Properties from Well Logs
Reservoir modeling guided with seismic rock properties

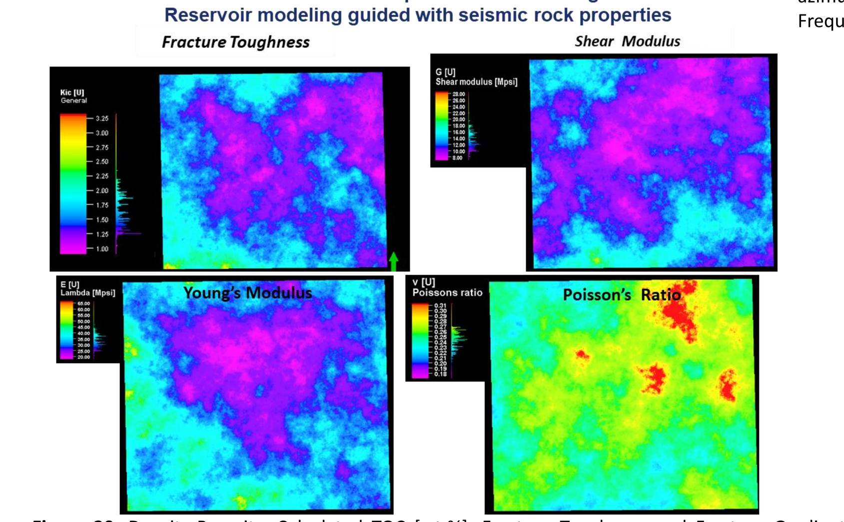


Figure 20. Density-Porosity, Calculated TOC [wt.%], Fracture Toughness and Fracture Gradient variation Maps of the zone 3. This zone corresponds to brittle-ductile Woodford shale couplets between the upper portion of middle member and the lower portion of the upper Woodford shale member. The lateral variations were guided by the SOM and inversion cubes

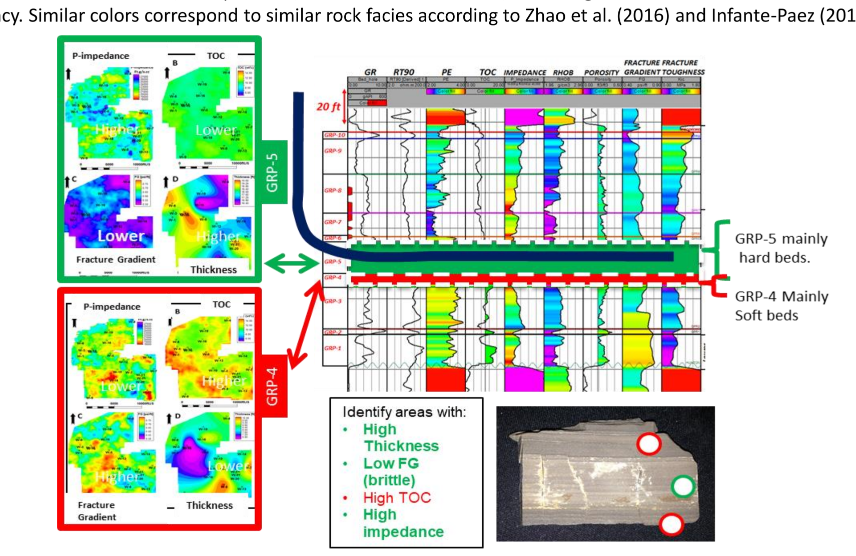
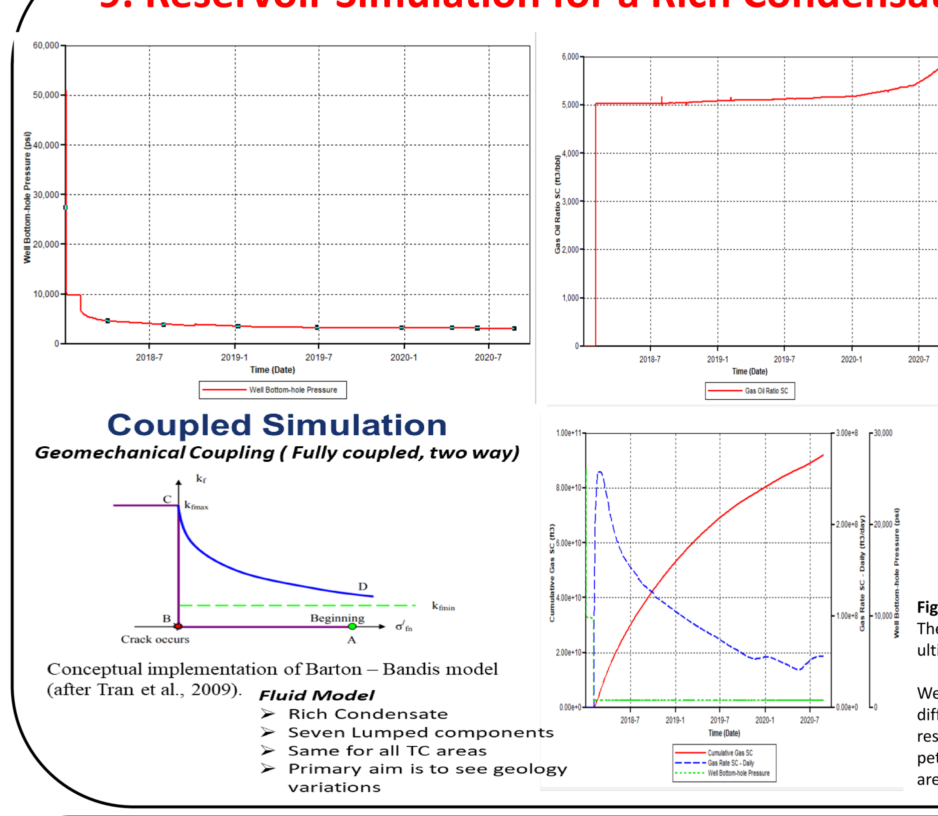


Figure 21 Reservoir Model of a sub-area that highlights the Woodford shale Para-sequences and horizontal well placement for production simulation.

9. Reservoir Simulation for a Rich Condensate Type Curve (TC) – EUR forecasting



Simulation Results

Area	TC Well EUR (MBOE)
1	1802
2	1624
3	803
4	729

Operator xxx Results

Area	TC Well EUR (MBOE)
1	2000
2	1702
3	1385
4	509

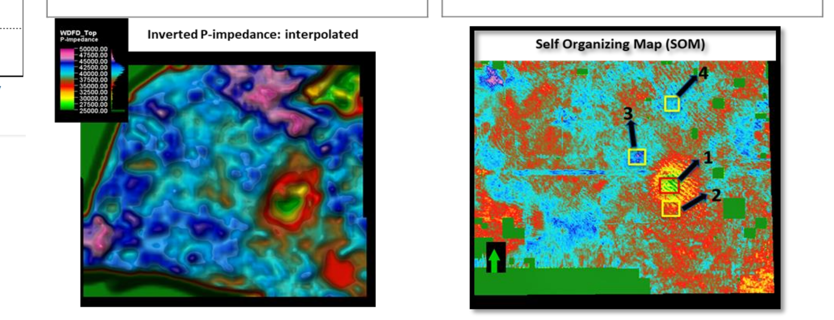


Figure 22. Well bottom-hole pressure for the injection. Notice when crack occurs, the pressure falls down quickly. The initial high bottom-hole pressure (BHP) show the injection as the well is hydraulically fractured. The expected ultimate recovery is considered as the five years' cumulative gas and condensate production respectively.

We repeat the same procedure for all the areas. Table 1 show the oil EUR's for four areas. Notice the dramatic difference in EUR's in all areas. As completion and fluid is kept constant in the study, the change is attributed to the reservoir characterization only. In this case, a high resolution comprehensive characterization including petrophysical and geomechanical properties in the reservoir can add enormous value in identification of high value areas, lateral landing zones and well interference studies and ultimately well spacing optimization.

Conclusions

- Our study identifies geological sweet spots and type curves in the Woodford shale (TOC, geomechanical parameters)
- Study shows using best of all available dataset can enormously increase the resolution and confidence on static model
- Results show multi-attribute analysis provide a promising alternative way of deriving the type curves
- Geomechanical simulation provides a robust way to model gradual closing of fractures and hence a time variant "shrinking" simulated rock volume instead of conventional history matching with multiple permeability zones

A HUGE THANK YOU!!!

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- Rafael Pires da Lima