From seismic pre-stack elastic attributes to rock properties. A case study in the Permian Basin, onshore USA

Marianne Rauch[1*], Aravind Nangarla[1], M. Falk[2] and M.Lovell[2] showcase an innovative approach and its application using the LambdaRho-MuRho cross plot for the estimation of rock properties.

Abstract

The Permian Basin contains significant oil and gas-bearing shale deposits. Extending over 55 counties in West Texas and southeast New Mexico, it covers a vast region. It is the largest contributor to the oil shale boom in the US and in February 2022 accounted for more than 40% of US oil, Figure 1 (Federal Reserve Bank of Dallas 2022). Figure 2 displays the increase in produced oil from this basin from 2018 to 2022, Chevron News Room 2022.

During the first years of production from these tight shales, seismic data weren't considered to be essential for locating and drilling high-producing wells. However, the value of seismic data are now recognized and extensively used to design and execute lateral drilling programmes into the most prolific shale units. The shale deposits are widespread but highly heterogeneous in composition. Specifically notable is the lateral variability of Total Organic Content (TOC) and rock properties, such as porosity within the formations. In addition to varying shale properties, carbonate units were deposited simultaneously and are difficult to distinguish when only using reflectivity. Traditionally, the sonic and density values were inputted into supervised and non-supervised neural network applications to estimate rock properties. However, it is difficult to calculate density from conventional seismic data, and the results are typically questionable and have a high uncertainty element. To calculate density from seismic data, we need long offsets that are usable; most of the time, these data are not available (Aki, K., 1980). This study showcases a unique approach and its application using the LambdaRho-MuRho cross plot to estimate rock properties. The LambdaRho and MuRho values are derived from pre-stack inversions and are correlated to existing well data over the zone of interest. The results indicate that this is a more elegant and valid methodology, especially since it seems to produce a better, more accurate distinction between shale and carbonate domains.

Geological setting

The three main sub-basins of the Permian Basin are the Delaware Basin, Midland Basin and Central Basin Platform, Figure 3. The most prolific shales in the Delaware Basin are the Bone Spring and the different members of the Wolfcamp. Another high-producing shale oil basin is the Midland Basin, where the best reservoirs are within the Sparberry and Wolfcamp Formation. In this publication, we are concentrating on the Bone Spring and Wolfcamp shales.

The Wolfcamp Shale, an organic-rich formation, extends in the subsurface in all three sub-basins of the Delaware Basin, Midland Basin, and Central Basin Platform and is the most prolific

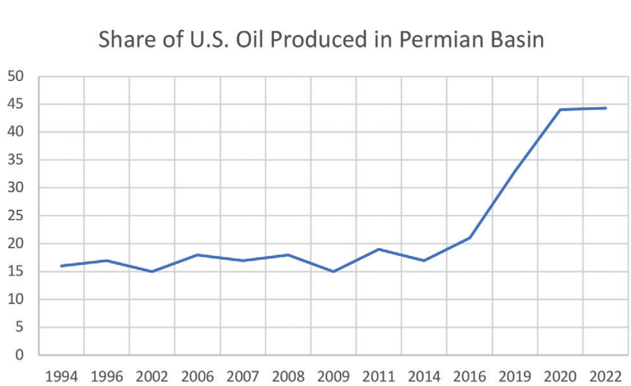

Figure 1 Share of oil production from the Permian Basin between 1994 and 2022. Federal Reserve Bank of Dallas, 2022.

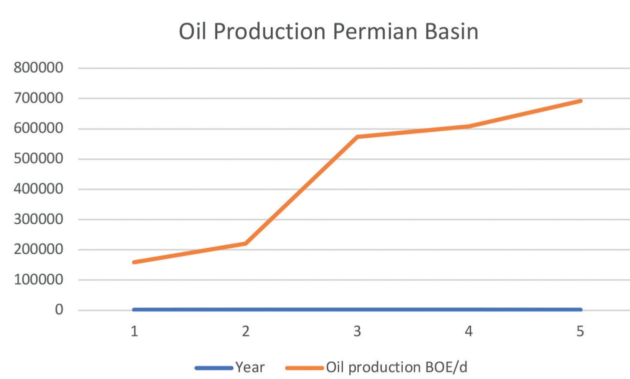

Figure 2 Oil production from the Permian Basin 2018 to 2022. Retrieved from: https://www.chevron.com/newsroom/2022/q2/chevron-to-boost-permian-oil-production-as-demand-for-reliable-energy-grows?gclid=CjOKCQjwxIOXBhCrARIsAL1QFCYmT4QIziorFbKQMUgWmrn2L1ajzfRMkBwP5Y_7bErIpT_4lqSvN24aAtsSEALw_wcB&gclsrc=aw.ds.

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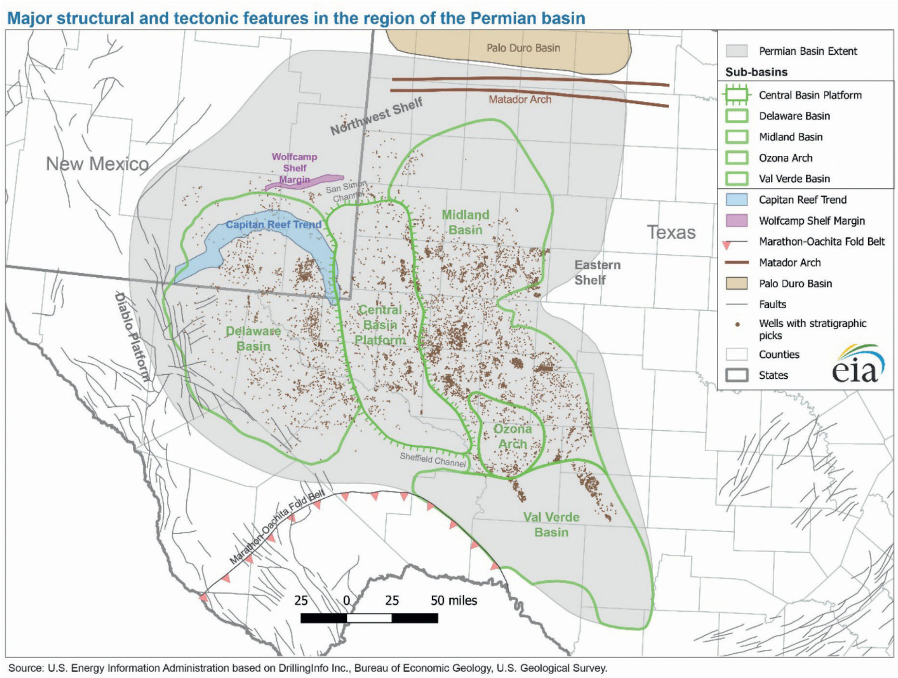


Figure 3 Permian Basin onshore North America with sub-basins outlined. Retrieved from: https://www.eia.gov/maps/maps.htm.

Era	System	Stage	Group/Formation	
Paleozoic	Permian	Ochoan		Salado
				Castile
		Guadalupian	Delaware Mountain Group	Bell Canyon
				Cherry Canyon
				Brushy Canyon
		Leonardian		Avalon
				1st Bone Spring
				2nd Bone Spring
		Wolfcampian		Wolfcamp A
				Wolfcamp B
				Wolfcamp C
	Pennsylvanian			Cisco
				Canyon
				Strawn
				Atoka

Figure 4 Stratigraphic section of the Permian Basin. Modified from Rowe, H., 2018.

hydrocarbon-bearing formation present. The Wolfcamp Shale is divided into four sections, or benches, known as the Wolfcamp A, B, C, and D, with A and B being the most productive of the units. The thickness of the entire Wolfcamp section varies from 200ft to 7050ft across the Permian Basin at a depth between 0ft (outcrop) and 10,000ft (Gaswirth, 2017).

The Bone Spring formation was a hydrocarbon-producing unit from conventional sandstone layers before it became an unconventional target. During the past decade, the Bone Spring formation has been developed as an unconventional play. Unconventional plays are primarily defined as low porosity units that require lateral drilling and fracking of the rock to allow hydrocarbon flow. Often these units are also the sources for the conventional hydrocarbon reservoirs and are referred to as the kitchens. The Bone Spring formation exhibits a thickness exceeding 1000 ft. Figure 4 displays the stratigraphic section of the Permian Basin.

The US Geological Survey (USGS) estimated undiscovered, continuous hydrocarbon resources in the Delaware Basin Bone Spring and Avalon assessment units as follows: 14 billion barrels of oil, 32 trillion cubic feet of natural gas, and 2.3 billion barrels of natural gas liquids; and 2.7 billion barrels of oil, 27.5 trillion cubic feet of natural gas, and 2.8 billion barrels of natural gas liquids, respectively (Gaswirth et al., 2018).

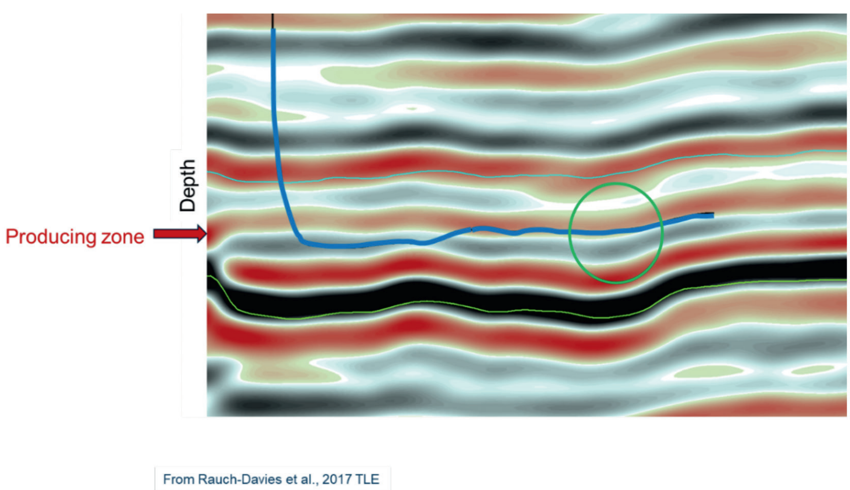
Seismic processing

Various 3D seismic volumes from multi-client libraries are available in the Permian Basin. Due to the difficult near-surface conditions and unusual velocity behaviour in the shallow layers, the seismic processing of these datasets is challenging. Within the shallow interval, the velocities vary from slow (overburden) to fast (Rustler Formation, a fine textured white magnesium limestone unit) to evaporites and to interbedded anhydrides and evaporites. After penetrating these complex rock layers where the velocities increase, decrease, increase, etc., over a relative thin interval, the diving wave will display a classic velocity to depth behaviour, but is extremely anisotropic and challenging. In addition, the mobile salt below the Rustler interface has locally either dissolved or evacuated, resulting in a slow velocity fill zone. The signal beneath these geological features shows very low frequencies, resulting in a poor-resolution seismic image. Conventional approaches such as static corrections are not able to resolve the near-surface sufficiently to recover the amplitudes of deeper events. Full Waveform Inversion (FWI) has been applied with varying success. The main issue still is the unknown and laterally and vertical changing velocity regime in the near-surface where there is little well control to help constrain the initial FWI velocity model.

Pre-stack depth migrations are more successful in recovering the signal than pre-stack time migrations and are more commonly applied (Rauch-Davies, M. et al., 2018). Figures 5a and 5b display seismic data in depth along a lateral drilling path. The seismic data, as shown in Figure 5a, was processed in time and then stretched to depth using a detailed velocity model. The seismic in Figure 5b was pre-stack depth migrated, producing a higher resolution and showing more details. The well encountered a carbonate streak over the area, which is annotated by a circle which is clearly seen on the pre-stack depth migrated data. In comparison, the time migrated data do not show the same feature.

Rock property estimation from seismic data

3D seismic data imaging has assisted in more accurately planning lateral well paths along the producing zone of established reservoirs using the final pre-stack migrated reflection stack data. The seismic image is used to map and guide the lateral borehole structurally. It is also important to predict rock properties within the producing shales to minimize penetration of non-shale units. Any time the borehole is out of the target zone, either above or below the hydrocarbon-bearing shale, or when the borehole intersects a non-shale rock such as carbonate, it will negatively impact production rates as the well is not producing from the non-shale interval. Seismic data contain most of the geologic information of the subsurface depending on resolution, such as structure, hardness, lithology and more. Figure 6 displays a pre-stack depth migrated seismic section from a 3D dataset located in the Permian Basin. The zone of interest is above the red horizon. Variability within the interval is evident from the reflections and seismic character, but difficult to infer rock type. While 3D seismic data provide significant lateral context compared to well logs, the challenge for interpreters is to identify critical subsurface geologic parameters with the understanding that the vertical scale of measurement may not provide 'resolution' but does provide 'detection'. Resolution and detection are two different things. Resolution is mainly defined as resolving rock boundaries laterally and vertically. Detection can predict these rocks, which



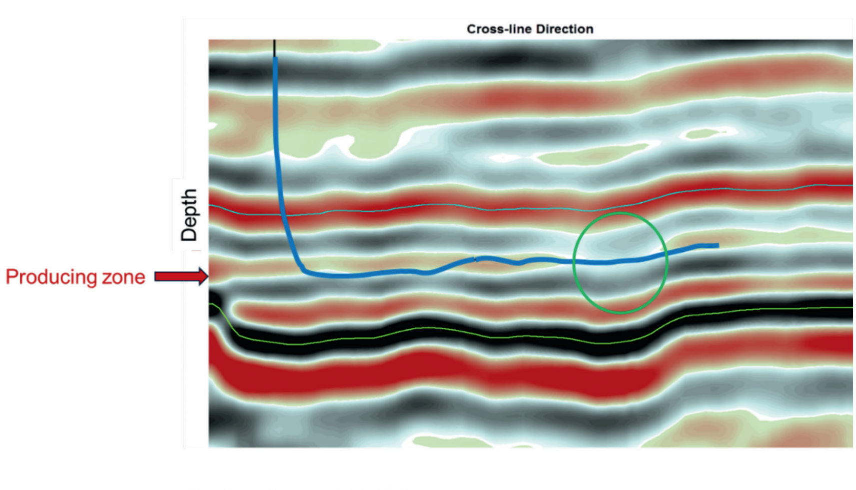


Figure 5a Seismic PSTM converted to depth. b Seismic PSDM. Lateral drilling path annotated. The green circle outlines a change in lithology that is not visible in the time data.

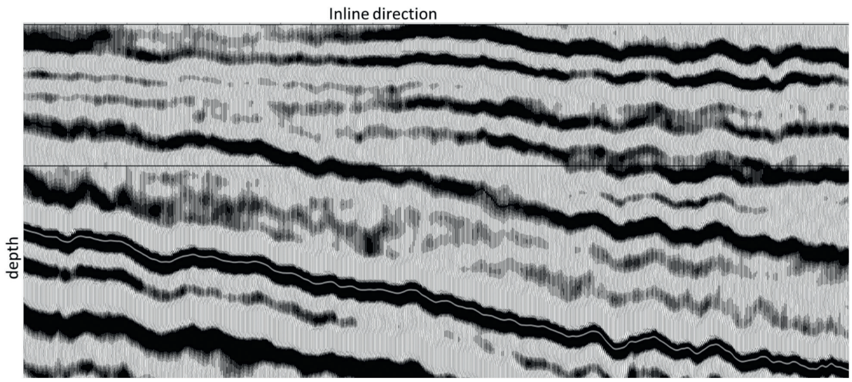


Figure 6 Inline of pre-stack depth migrated seismic data in the Permian Basin. The reservoirs are immediately above the red horizon.

can be beyond the resolution. Integrating all the existing well log data with the seismic is critical in understanding the relationship between the lithologies derived from log data and those predicted from pre-stack seismic attributes.

The following workflow is used to integrate well log and seismic data to generate a calibrated estimation of rock properties at the seismic scale and provide geological mapping based on seismic 3D:

1. **Well log preparation**
   - All available wells and well logs for maximum understanding and detail of reservoir parameters
   - Infill key well logs with neural network prediction (p velocity, s velocity)
   - Extensive geophysical analysis of rock properties in the seismic signal domain by the production of:
     - Cross plot traditional well log properties to evaluate critical relationships of key reservoir criteria. (GR, Neutron, Density, PE, P Velocity)
     - Cross plot 'seismic' properties that are equivalent to well log properties to assess well log to seismic image tie for calibration of seismic geophysical properties for independent use away from well log tie (P Impedance (density), S Impedance (anisotropy), LambdaRho (Incompressibility), MuRho (Rigidity), Vp/Vs Ratio (density/porosity).

2. **Developing the geology at the seismic scale**
   - Model reservoir seismic response with synthetics, especially with an understanding of sparse spikes derived as reflection coefficients from the sampled log
   - Model AVO response for individual reservoirs
   - Run an unsupervised classification of the seismic volume to see how the seismic data alone can discriminate lithology and other geologic aspects with no log input
   - Create a seismic model of the reservoir to better understand the limits of detection of key reservoir properties (porosity, lithology)

3. **Integrating well log scale and seismic scale through inversion and lithology prediction**
   - Analyse the seismic volume to assure zero phase and amplitude compliance
   - Analyse and condition the gathers, especially with an understanding of multiples within the zone of interest
   - Analyse and compare synthetic gather with actual gathers. Do we see the log response in the seismic data?
   - Create a neural network volume of integrated well log and seismic attributes. This approach outputs the target log (e.g.. density porosity) at every seismic trace calibrated to the input well logs. The neural network is iteratively refined to determine those seismic inputs which best predict log response for blind wells.
   - Create a pre-stack inversion for both two-term (P impedance, S impedance) and three-term (P impedance, S impedance, density) calculations.
   - Create additional inversion rock property volumes which further define incompressibility and rigidity as indicators of lithology variability.
   - Create a predictive and probabilistic volume of lithology.

The seismic inversion creates layer characteristics (interval rock property) from boundary properties (depositional event reflectivity) and, as such, is most suitable as input for a rock property estimation workflow using seismic data and, therefore, acoustic wave behaviour in rock material. Traditionally, rock properties derived from seismic data must include the parameters of velocity and density, as demonstrated by Zoeppritz K. (1919). The Zoeppritz equation is very complex and provides the refraction and reflection coefficients along the offset planes of a seismic event considering a plane interface that separates two homogenous, isotropic layers that can be resolved with the available frequency bandwidth.

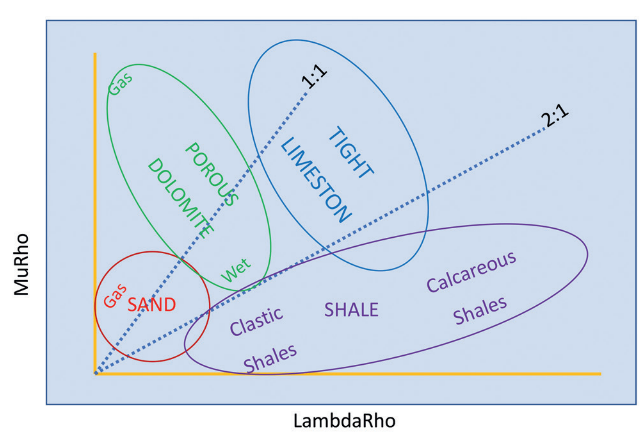


Figure 7 LambdaRho/MuRho cross plot rock definitions as derived by Goodway, B. et al in 1993.

To achieve feasible computing times, various linear approximations have been developed in the past, such as the Aki-Richards equation (Aki, K. 1980). This equation is widely used to estimate elastic properties from the seismic and consists of three terms. The third term is valid for high incidence angles, and long offsets and can, in theory, be used in conjunction with the first two terms to determine rock density. However, it is inherently difficult to extract this value directly from the seismic data; therefore, several methods are available to extrapolate/interpolate/approximate the parameter from seismic, for example, by utilizing neural network schemes (Sharma, R., 2015). However, the results are usually a relatively poor approximation and a different approach to predicting rock properties from seismic is presented in the following. The usage of LambdaRho and MuRho cross-plots, Lambda-Rho representing incompressibility, and MuRho rigidity of the rocks (Goodway, 1998), Figure 7, has been applied in a workflow.

The interpreter uses cross-plots from well data to define the different rock types that are present in the data set, see Figure 8a. The LambdaRho and MuRho values extracted from seismic pre-stack inversion volumes over the reservoir interval are also cross-plotted, and the same quadrant polygons are applied, which provides a direct comparison to the lithology definitions and vertical distributions identified at the borehole Figure 8b.

Figures 9a and 9b compare the traditional, full 'electofacies' volume that uses the velocity and density term and, in this instance, an unsupervised neural network approach and the LambdaRho-MuRho method. Although both estimations have merit, the new method using the LambdaRho-MuRho cross-plot is less prone to noise and more geologically valid as cross-validated with lithologies from available well data and structure from seismic 3D data. But even without geophysical and geological QC, the second approach gives better conformity with depositional

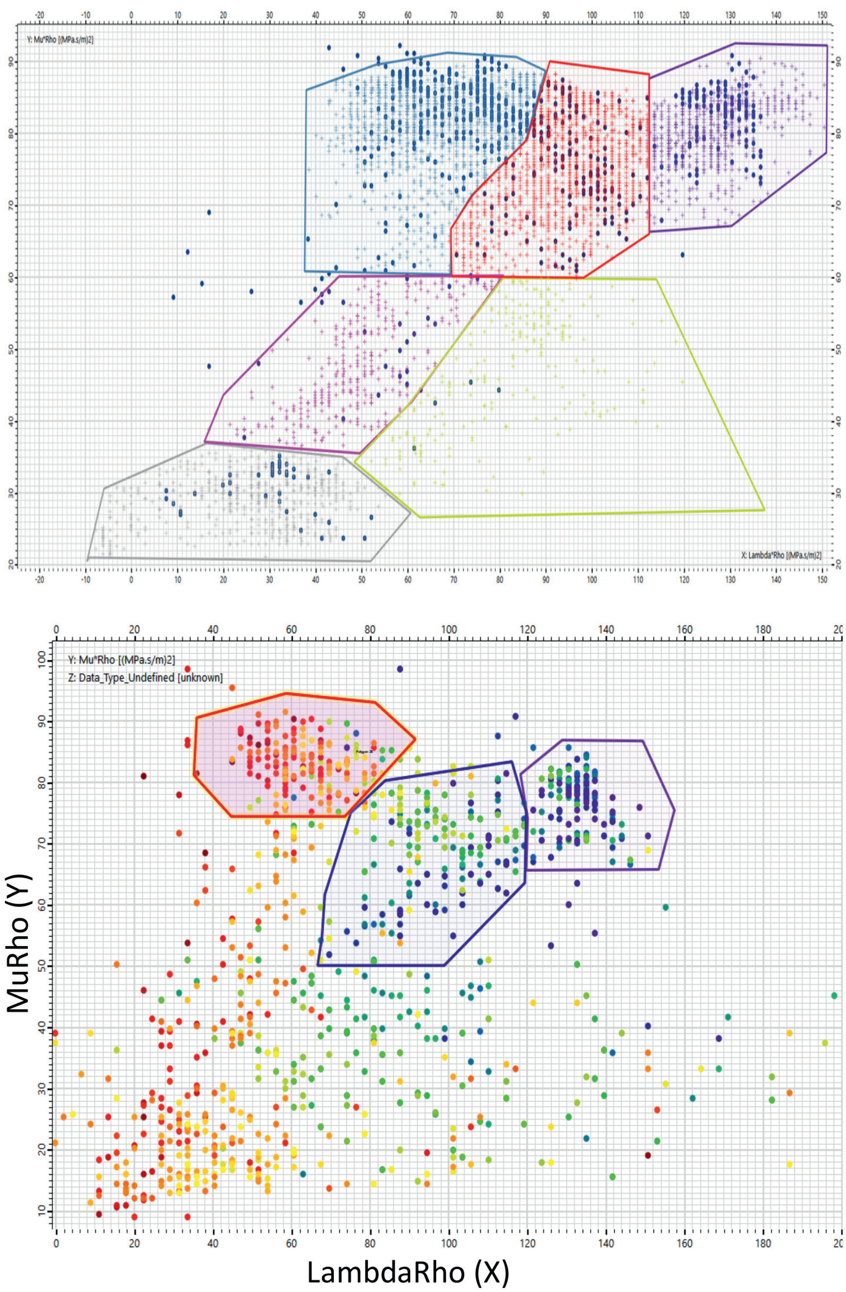


Figure 8a (top) Lambda/Rho-Mu/Rho cross plot of well data from a number of wells within the reservoir interval. Polygons represent various lithologies. Figure 8b (bottom) LambdaRho/MuRho cross-plot derived from seismic pre-stack inversion attributes. The polygons indicate different lithologies.

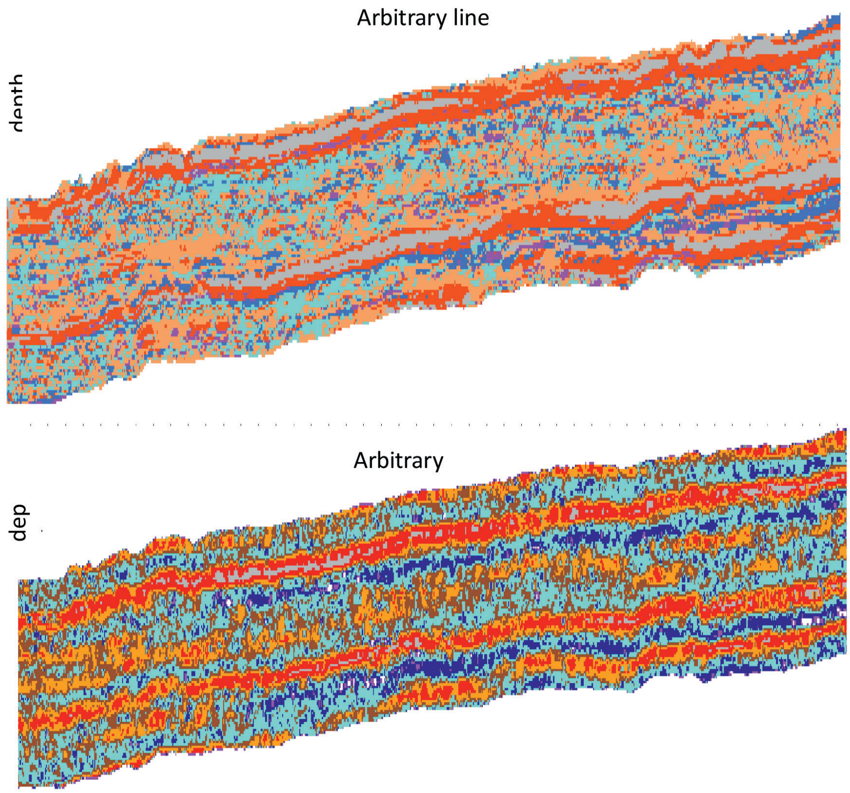


Figure 9a (top) and Figure 9b (bottom). Traditional lithology prediction using velocity, density, and unsupervised neural network. b: Lithology prediction using the LambdaRho-MuRho cross-plot method. Line location is annotated in Figure 8. The various colours represent different lithologies.

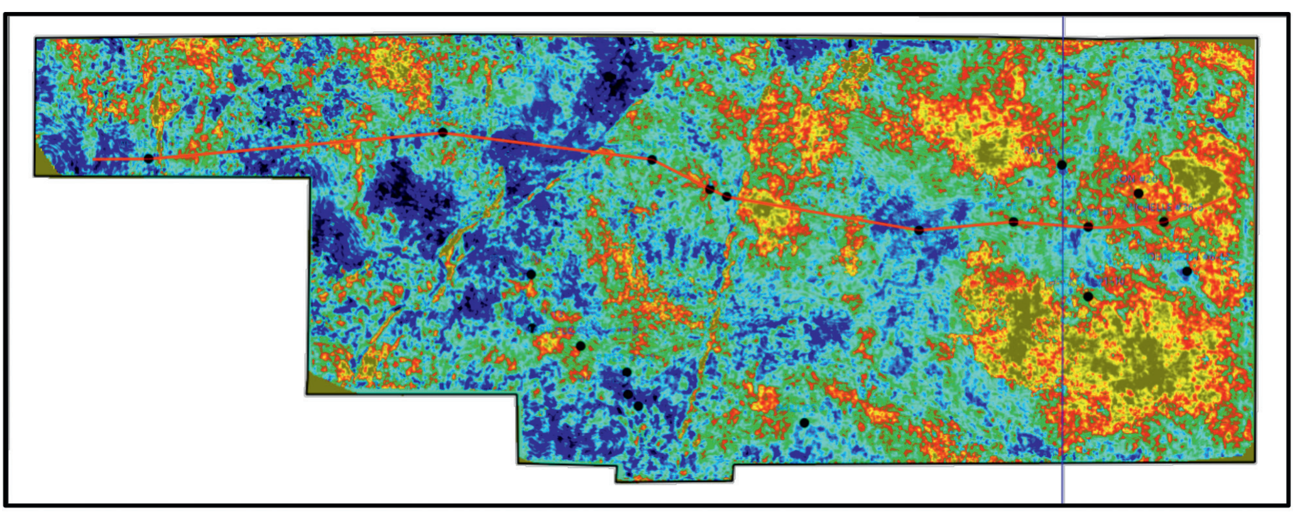


Figure 10 Rock properties along one of the key target horizons based on the newly presented application. Yellow/red areas are high TOC regions (good producing shales), and blue colours represent carbonate deposits (dark blue) and lower TOC intervals (lighter blue/green) at this interval.

structure is evident. The LambdaRho-MuRho is a more valid approximation of rock properties and can be easily linked to various lithologies.

Furthermore, when analysing the map view of the results, Figure 10 represents the rock distribution along one of the target horizons. The location of the image displayed in Figures 9a and 9b is annotated in Figure 10. Yellow/red colours indicate areas with high TOC; blue colours indicate different lithologies or very low TOC intervals. These resulting images provide a superior and very detailed tool to design the landing zone and plan the direction and location of the lateral well and the borehole path more confidently than with conventional seismic depth-migrated stacks only.

Conclusions

At the beginning of the shale boom, seismic data were ignored as a useful tool to assist in drilling the lateral wells. This play type was considered to be a 'mining' operation since the hydrocarbon shale extends over the largest parts of the basins, which guarantees the presence of the reservoir at every well location. Since then, more production wells have provided ample information and data for analyses to present evidence of the large variation of shale quality, TOC, porosity, and rock type. This eventually led to the re-evaluation of seismic data to refine geophysical methods to better and more confidently locate 'sweet spots' within the established production layers.

Pre-stack depth migration is the preferred input data for a detailed assessment based on the presented application and resulting interpretation. Reflection data only indicates rock boundaries based mainly on velocity variations but does not necessarily indicate the rock type or rock properties. Elastic pre-stack migrations produce relative high-resolution P and S velocities that can then be used to calculate parameters like LambdaRho (incompressibility) and MuRho (rigidity), the equivalent to geological rock properties, such as lithology for example. Traditionally, the velocity and density were inputted into neural network applications to estimate rock properties from seismic directly based on wave propagation relations. However, it is very difficult to calculate density from seismic, and estimations are highly uncertain as extracting rock density requires long good-quality offsets that are normally not available. We have presented a more reliable method that uses the Lambda/Rho-MuRho relationship concept resulting from elastic inversion, which provides a high-resolution volume of rock property values. Those results can directly be tied to lithologies once calibrated with well log data and produce an excellent dataset as input for the engineering (drilling, producing) part of the operations.

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