Keynote address Reservoir Characterization - 16 years ago, today and tomorrow

Brian Wm. Schulte
Schiefer Reservoir Consulting

Summary

In the past reservoir characterization was about the proper Amplitude versus Offset (AVO) analysis and involved calibration to geological, geophysical and production data to characterize fluid and lithology properties. It took large amounts of time and effort to confirm AVO anomalies, and interpretations were inconsistent. This was due to AVO not being a DHI but is one of the tools utilized in exploratory data analysis (EDA) helping to focus our attention upon possible drill locations for further consideration.

AVO should not be the sole reason for drilling a prospect & need to look at various factors including:

1) CDP gather that produced AVO anomaly
2) How data was acquired and processed
3) How anomaly fits with geology
4) How AVO fits with the well modeling
5) Is AVO present after inversion since inversion removes the effect of the wavelet and reduces sidelobe energy providing higher resolution and detunes the data
6) Pore pressure and seal integrity.

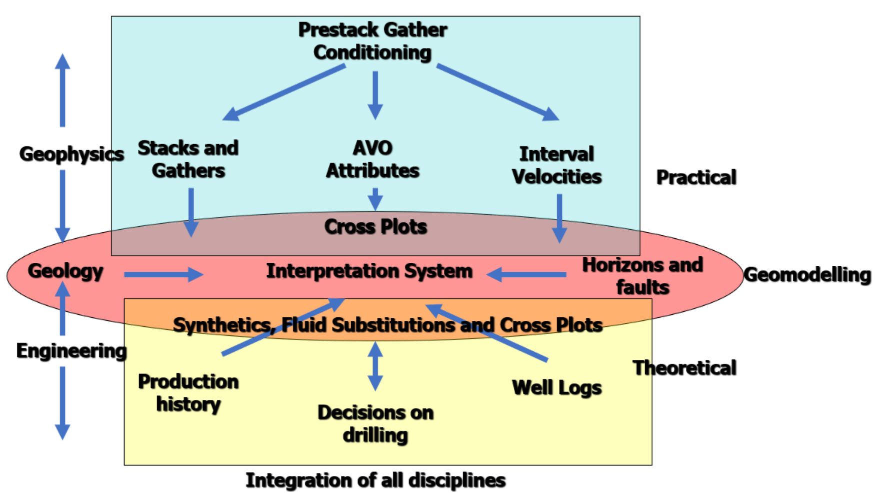


Figure 1: Flow chart which exemplifies integrated multi-discipline reservoir characterization. This slide was presented in CSEG Luncheon presentation in 2006.

When a multi-disciplinary approach is utilized in AVO analysis it integrates geology, geophysics, petrophysics, & engineering to understand porosity, water saturation, lithofacies, permeability and barriers to flow to determine fluid flow (figure 1) and it is a form of reservoir characterization.

To integrate data from multiple disciplines it is best to use standards and then calibrate the data throughout the project. Most common place to do this is in a data repository referred to as a geomodel.

The utilization of standards in data such as well logs mnemonics, tops, seismic horizons picked, seismic volumes, etc. and the calibration of data reduces uncertainty. In the past due to issues with the data geomodels could take months but if standards are followed geomodels can incorporate new data and be run over producing consistent results.

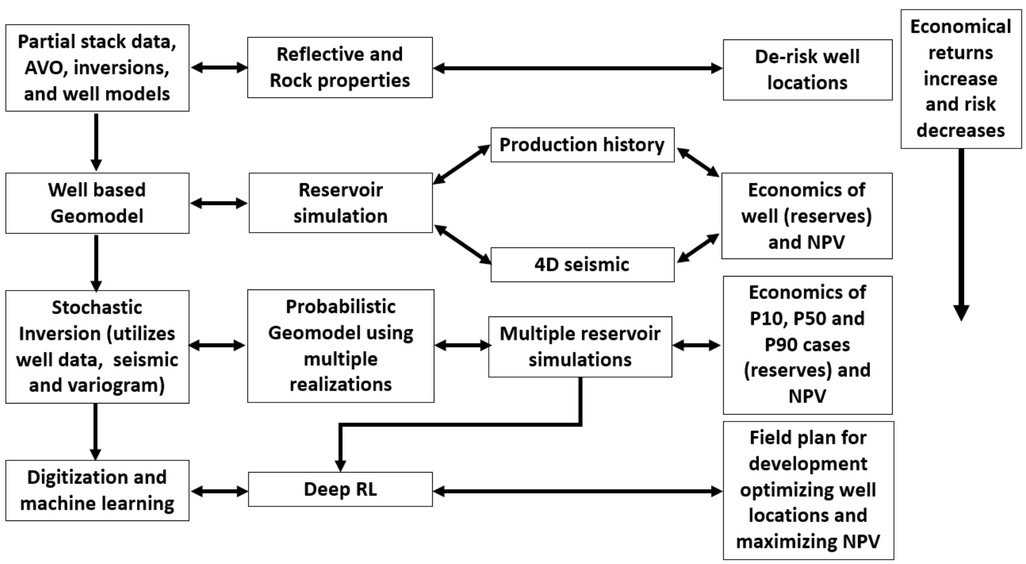


Figure 2: Diagram showing the progression of technologies with reservoir characterization, geomodelling and reservoir simulation. Reservoir simulations enable us to determine fluid flow. Most small to mid-size companies are working with AVO, deterministic inversion and basic rock properties such as V_p, V_S and density. Larger companies are working with geomodels through Petrel but the majority of the geomodels are based upon well data since deterministic inversions lack resolution and hard to transfer rock properties into geomodel unless neural network is used to calculate porosity, water saturation, etc. With deep water fields companies are moving towards the stochastic inversion due to the economics involved and the ability to get the project sanctioned by the board. The future will be Deep Reinforced Learning or RL and the development of a field plan.

There has been a progression of geomodel technologies (figure 2) which this presentation will examine.

Geomodels are geophysical and geological measurements that are utilized to create computerized representations of the subsurface and include detailed 3D petrophysical property models that are contained within a geological framework. Well data tends to be used for the generation of the petrophysical parameters that populate this 3D model, and seismic data is used to provide a structural interpretation for the generation of the framework.

The issues with the use of seismic to populate the 3D petrophysical properties are:

1) Inability to relate seismic data quantitatively to reservoir properties
2) Lack of sufficient vertical resolution to generate detailed property models

Most approaches of integrating seismic data into reservoir model are statistical in nature, that is, a statistical calibration is done between seismic attribute(s) and the petrophysical properties of interest. The statistical calibration tends to be CoKriging which calculates estimates for a poorly sampled data such as well log data with help of a well-sampled data such as seismic.

With geomodels can do reservoir simulations and understand fluid flow. This has caused a shift in how we see reservoir characterization. Currently reservoir characterization is about simulating the behavior of fluids within the reservoir under different conditions to maximize production by determining the optimal production techniques including EOR.

This is an important step in the development of our technologies.

To incorporate seismic into the geomodel can utilize stochastic inversion (figure 3). Stochastic inversion incorporates the vertical resolution of well log data and the horizontal resolution of seismic data. Utilizing Bayes Theorem and stochastic inversion can incorporate more rigorous probabilistic estimates of reservoir properties and pore fluid. Probabilistic inversion utilizes seismic attributes in a quantitative manner for risking exploration and development prospects.

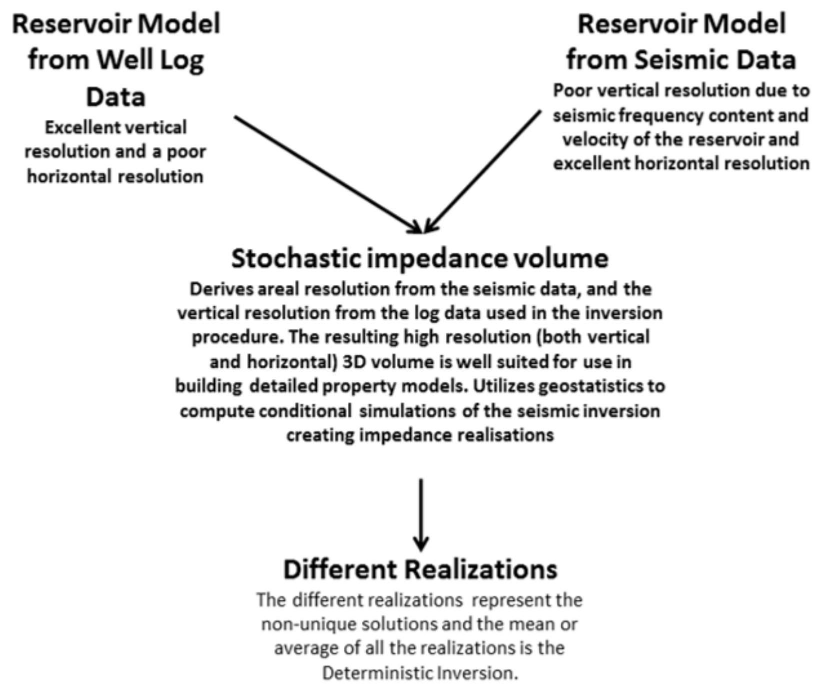


Figure 3: Diagram of stochastic inversion.

Multiple realizations of the stochastic inversion can be incorporated into machine learning using Deep Learning – Recursive Learning to develop a field plan which will increase the NPV, optimize drilling and minimize costs.

Theory / Method / Workflow

In 2006, Reservoir characterization involved AVO analysis and involved the calibration to geological, geophysical and production data to characterize fluid and lithology properties. There are many papers on the AVO attributes to be used to delineate reservoir sands. Developed a methodology to incorporate numerous attributes to distinguish pay sands and probabilistic cases could be created by tightening or loosening the parameters of the attributes.

With today's technologies machine learning can be utilized to cluster seismic attributes into possible classes of rocks that reflect both lithology, fluid content and rock properties.

One of the issues with unconventional plays is thin stringers tend to be drilled which may be below conventional seismic resolution. Use of spectral balance before inversion could help stabilize wavelets and increase the seismic resolution.

It can be applied to the gathers before Deterministic Inversion. Generally spectral balance broadens the wavelet by increasing the low frequencies which help reduce the sidelobes and increases the high frequencies which improve the resolution (figure 4).

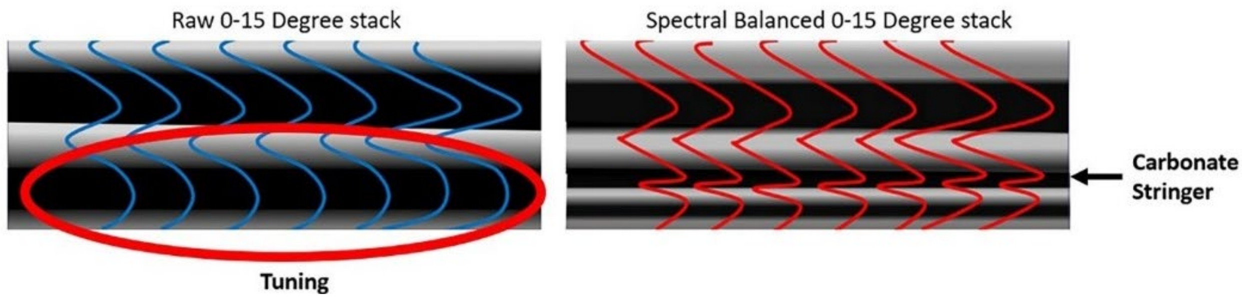


Figure 4: On the left is the seismic, on the right after spectral balanced which brings out a subtle thin bed which is a carbonate stringer (Schulte et al., 2019).

In plays like the heavy oil tend to have stack channel sands and to illuminate these channel sands need frequencies above 100 Hz (Schulte et al., 2019).

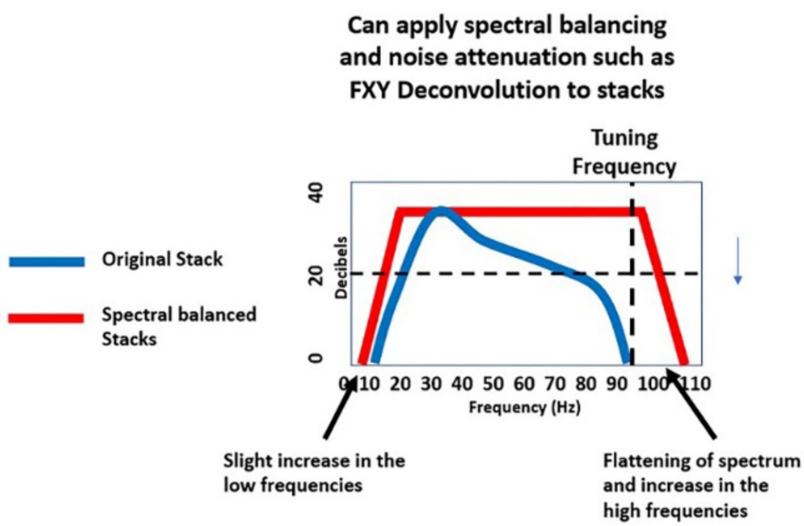
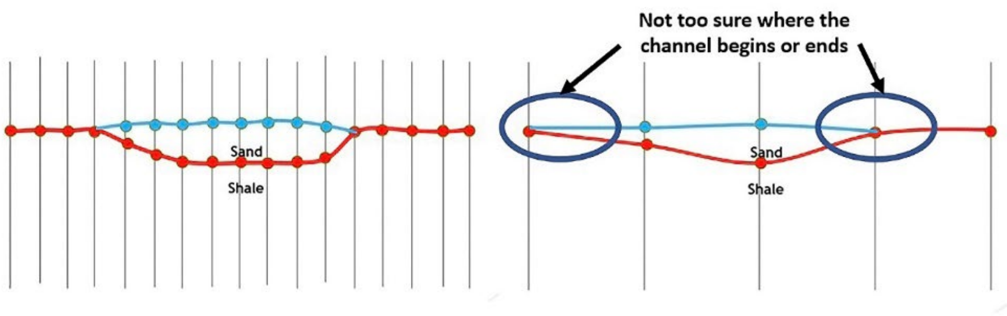


Figure 5: Frequency spectrum is flattened and broadened with spectrum balancing, which increases the high and low frequencies. Spectral balancing can increase the frequencies above tuning. If the tuning frequency of a carbonate stringer is about 95 Hz then the stringer cannot be seen if the frequency is below 95 Hz. Spectral balancing can usefully push the frequencies beyond the tuning frequency (Schulte et al., 2019).

Increase in vertical resolution increases horizontal resolution but it is limited by the seismic acquisition.



A B

Figure 6: (A) is a channel that is sampled with small bin sizes or CDP spacing so that it is clearly defined while (B) is the same channel coarsely defined and we lose the fidelity of the channel (Schulte et al., 2019).

It is also dependent upon whether the data are migrated. With unmigrated data, the horizontal resolution is the migration aperture which is the Fresnel zone.

Relating seismic data quantitatively to reservoir properties

Three methodologies to relate seismic data quantitatively to reservoir properties:

1) Combination of V_p, V_S and density can create reservoir properties:

Seismic Well	Equation
P-Impedance (Acoustic Impedance)	$I_p = AI = \rho * \alpha$
S-Impedance	$I_s = SI = \rho * \beta$
Vp/Vs	α / β
Poisson Ratio	$\upsilon = 0.5 * \lambda\rho / (IP^2 - IS^2)$
Lambda Rho	$\lambda\rho = (AI^2 - 2SI^2) = (I_p^2 - 2I_s^2)$
Mu Rho	$\mu\rho = SI^2 = I_s^2$
Near Impedance	$NI = (AI_2 - AI_1)/(AI_2 + AI_1)$
Elastic Impedance (θ)	$EI = V_p^{(1+\tan^2\theta)} V_s^{(-8k\sin^2\theta)} \rho^{(1-4k\sin^2\theta)}$
Young's Modulus	$E = 2I_s^2(1+\upsilon)/\rho$
Closure stress scalar	$\upsilon / (1-\upsilon)$
Bulk Modulus (κ)	$\kappa = I_p\alpha - 4/3 I_s\beta$

Table 1: Table of attributes that can be calculated from seismic inversion products.

Closure stress is not common to most geophysicists, and it is the stress needed to hold open a fracture in rock once it has been created. Rocks with high closure stress are harder to frac than the same rocks with lower closure stress (Goodway et al. 2010; Perez et al., 2012; Crain, 2016).

2) Extended Elastic Impedance developed to generate seismic volumes of petrophysical logs such as V-shale, porosity, and saturation, as well as lithology logs, such as gamma ray using the following equation:

$$EEI(\chi)=\alpha_0\rho_0[(\alpha/\alpha_0)^p(\beta/\beta_0)^q(\rho/\rho_0)^r] \quad \text{Equation 1}$$

Where:

$$q = (\cos\chi + \sin\chi)$$
$$r = -8\,\kappa\sin\chi$$
$$r = \cos\chi - 4\,\kappa\sin\chi$$

Can create a scaled reflectivity using the following equation (Whitcombe, et al., 2004):

$$Rs=A\cos\chi + B\sin\chi$$ where A is the intercept and B is the gradient

and χ is the angle to optimize the parameters to match the EEI log.

3) Neural networks (machine learning) can generate seismic volumes of petrophysical logs such as V-shale, porosity and saturation, as well as lithology logs, such as gamma ray using attribute prediction.

   The neural net utilizes a combination of datasets that will give the best conditional correlation to the reservoir property and will then use that correlation set to create a rock property volume. To QC the rock property volume blind well data is used; this is done by excluding blind wells entirely from the modeling and are the ultimate benchmark for the success of the modeling.

Deterministic inversion is non-unique where there are many scenarios which will cause the same results. There are also undesirable side effects (Francis, 2005):

i. Output impedance histograms have smaller variation than impedances observed at wells. It is therefore inappropriate to apply well log derived cutoffs to indicate the presence or absence of lithology, fluids, etc. and the results of the inversion estimates will be biased.

ii. Deterministic inversion produces average impedances over intervals. Any attempt to recover impedances at a higher resolution will result in estimates which are unconstrained and therefore arbitrary.

iii. Deterministic inversion tends to exaggerate reservoir connectivity and underestimate net reservoir volumes.

The purpose of stochastic seismic inversion is to produce the property models at the same vertical scale of resolution as the well control but use the seismic information between wells (Shrestha and Boeckmann, 2009). It integrates the fine vertical sampling of the log data with the dense areal sampling of the seismic data to create detailed, high resolution rock property such as acoustic impedance, density or velocity models utilizing geostatistical algorithms (Shrestha and Boeckmann, 2009) (Haas and Dubrule, 1994).

Rock physics links elastic parameters such as impedances and velocities to reservoir properties of interest such as lithologies, porosity, and pore fluids. Geostatistical methods add constraints of spatial correlation, conditioning to different kinds of data and incorporating subseismic scales of heterogeneities (Bosch et al., 2010).

Stochastic Inversion can be combined with Bayes' Theorem to give rigorous probabilistic estimates of reservoir properties and pore fluid (brine vs water vs gas). This allows us to use seismic attributes in a quantitative manner for risking exploration and development prospects (Cooke and Cant, 2010).

Permeability pathways are hard to get from poorly sampled data well log data but utilizing probabilistic models of lithofluid distribution and facies geobody connectivity can derive permeability pathways to determine where to place injection wells (Bellatreche, et al., 2016).

Understanding the placement of production and injections wells is important is for oil wells since oil wells have a recovery factor of only 20%-40% while the recovery factor for natural gas is 80%-90%.

Injection of water (water flooding) is first used to displace the oil from the injector to the producer, while maintaining reservoir pressure. When the reservoir pressure falls natural gas will come out of solution and create a gas cap. Water flooding tends to be done before a gas cap forms. In the initial stages of waterflooding the injected water fills up the pores previously occupied by gas, which is redissolved in solution, and the reservoir pressure is restored (Satter and Iqbal, 2016).

As the water cut increases the life of production is limited and several problems are created such as: corrosion, sand production and facilities cost to separate excessive water. Surfactant may be used which reduces the interfacial tension between oil and water and is able to wipe out the trapped oil from the reservoir rock and increase oil production. Hydrogel polymer can also be used to increase the viscosity of fluid containing water so that the fluid is more difficult to flow than oil, and as a result, oil production increases (Abidin, et al., 2012).

If the reservoir is greater than 800 m then CO_2 injection can be used. The CO_2 increases reservoir pressure and oil fluidity, which enables the oil to escape from rock pores and flow more readily toward production wells (Chen and Reynolds, 2018; Petroleum Technology Research Centre, 2022; Schulte, 2022).

Advantages of using CO_2 for EOR is the reservoir geometry and properties are well known, there is a physical or well-understood stratigraphic trapping mechanism, the cap rock integrity is established, and fluid flow within the reservoir has often been history-matched at production wells (Lawton, 2010; Schulte, 2022).

When the CO_2 is injected into the reservoir a water-alternating-gas (WAG) injection is used to improve sweep efficiency during the injection, with the injected water controlling the mobility of CO_2 and stabilizes the gas front (Chen and Reynolds, 2018; Petroleum Technology Research Centre, 2022; Schulte, 2022).

In Weyburn where CO_2 injection is taking place, stochastic inversion is used to detect the CO_2 distribution that is controlled by the reservoir permeability. It also defines spatial distribution of physical trapping mechanisms that will keep the CO_2 in the reservoir over long time periods.

The Stochastic Inversion realizations can be utilized in Deep Learning to select optimal values for parameters like water injection rates to reduce costs and maximize profits or to create optimized field plans based on reservoir parameters, rock properties, and fluid properties (Shiraly, 2021).

Conclusions

In the early days reservoir characterization was about the proper Amplitude versus Offset (AVO) analysis and involved calibration to geological, geophysical and production data to characterize fluid and lithology properties.

With advent of geomodels reservoir characterization has become about simulating the behavior of fluids within the reservoir under different conditions to maximize production to determine the optimal production techniques including EOR.

With geomodels well data is used for generation of petrophysical parameters that populate the 3D model, and seismic data is used to provide a structural interpretation for the generation of the framework.

Difficult to use seismic to populate the 3D petrophysical properties because of:

1) Inability to relate seismic data quantitatively to reservoir properties
2) Lack of sufficient vertical resolution to generate detailed property models

To integrating seismic data into the geomodel statistical calibration is done between seismic attribute(s) and the petrophysical properties of interest. The statistical calibration tends to be Cokriging which calculates estimates for a poorly sampled data such as well log data with help of a well-sampled data such as seismic.

To properly incorporate seismic into the geomodel can use stochastic inversion which incorporates the vertical resolution of well log data and horizontal resolution of seismic data.

By utilizing Bayes Theorem and stochastic inversion a more rigorous probabilistic estimates of reservoir properties and pore fluid can be made which utilizes seismic attributes in a quantitative manner for risking exploration and development prospects.

The stochastic inversion can be used in machine learning Deep Learning to select optimal values for parameters EOR like water injection rates to reduce costs and maximize profits or to create optimized field plans based on reservoir parameters, rock properties, and fluid properties (Shiraly, 2021). By using Deep Learning want to maximize oil production, minimize costs of EOR and increase NPV.

Novel/Additive Information

Stochastic inversion and machine learning can be incorporated in workflow to:

1) Find and develop saline aquifers for CCUS and/or geothermal;
2) Monitor fracking using CO_2 frac fluids for natural gas wells;
3) Monitor EOR using WAG (water and gas) CO_2.

This will be invaluable as we transition to using CCUS to remove CO_2 from carbon intensive industries and in the development of geothermal.

Acknowledgements

Summation of the people around me, learnt and developed because of the people I have worked with in the past. The interactions allowed me to become a much better geoscientist who is well rounded. Also I learn a lot through my work as Chief Editor of the Canadian Society of Exploration Geophysicists Recorder.

References

Abidin, A.Z, Puspasari, T., Nugroho, W.A., 2012, Polymers for Enhanced Oil Recovery Technology, Procedia Chemistry, Volume 4, Pages 11-16, ISSN 1876-6196, https://doi.org/10.1016/j.proche.2012.06.002. (https://www.sciencedirect.com/science/article/pii/S1876619612000034).

Bellatreche, K.E., Couch, A. and Evans, D., 2016, Detailed seismic lithofluid distribution using Bayesian stochastic inversion for a thinly bedded reservoir: A case study over Huntington UK Central North Sea. SEG, https://library.seg.org/doi/abs/10.1190/int-2016-0161.1?journalCode=inteio.

Bosch, M., Mukerji, T., and Gonzalez, E.F., 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics: A review. SEG, Geophysics Sept. 2010, https://library.seg.org/doi/full/10.1190/1.3478209.

Chen, B., and Reynolds, A.C., 2018, CO2 water-alternating-gas injection for enhanced oil recovery: Optimal well controls and half-cycle lengths. United States: N. p., 2018. Web. doi:10.1016/j.compchemeng.2018.03.006.

Cooke, D., and Cant, J., 2010, Model-based Seismic Inversion: Comparing deterministic and probabilistic approaches. CSEG Recorder, Vol. 35 No. 04, https://csegrecorder.com/articles/view/model-based-seismic-inversion-comparing-deterministic-and-probabilistic.

Crain, E. R. (Ross), 2016, Crain's Mechanical Properties. Retrieved from: https://spec2000.net/10-closurestress.htm.

Francis, A., 2005, Limitations of Deterministic and Advantages of Stochastic Seismic Inversion, CSEG luncheon abstract

Goodway, B. & Perez, M. & Varsek, J. & Abaco, C., 2010, Seismic petrophysics and isotropic-anisotropic AVO methods for unconventional gas exploration. The Leading Edge. 29. 1500-1508. 10.1190/1.3525367.

Haas, A., and Dubrule, O. 1994, Geostatistical Inversion – a Sequential Method of Stochastic Reservoir Modeling Constrained by Seismic Data, First Break, V. 12, No. 11, pp. 561-569

Lawton, D., 2010, Carbon Capture and Storage: Opportunities and Challenges for Geophysics. CSEG Luncheon June 21st 2010, Carbon Capture and Storage: Opportunities and Challenges for Geophysics | CSEG.

Petroleum Technology Research Centre, 2022, Weyburn-Midale. Petroleum Technology Research Centre, https://ptrc.ca/projects/past-projects/weyburn-midale.

Perez, M. & Goodway, B. & Purdue, G., 2012, Stress Estimation through Seismic Analysis. 1-5. 10.1190/segam2012-1480.1.

Satter, A., and Iqbal, G.M., 2016, Waterflooding and waterflood surveillance. Reservoir Engineering.

Schulte, B.Wm., Bridge, D., Lyatsky, H., 2019, Methods of fault detection with geophysical data and surface geology. CSEG Recorder, https://csegrecorder.com/articles/view/methods-of-fault-detection-with-geophysical-data-and-surface-geology

Schulte, B.Wm., 2022, Review of Global warming, climate change, renewables, CCUS, Geothermal and the geoscience involved Part 3. CSEG, Recorder.

Shiraly, K., 2021, How Machine Learning in Oil and Gas Is Slashing Costs. WIDTH.AI, https://www.width.ai/post/machine-learning-in-oil-and-gas.

Shrestha, R.K. and Boeckmann, M., 2009, Stochastic Seismic Inversion for Reservoir Modeling, CGG Technical papers.

Whitcombe, D.N., Dyce, M., McKenzie C.J.S., Hoeber, H., 2004, Stabilizing the AVO gradient, Soc. Expl. Geophys., Expanded Abstracts.