

Seismic characterization of the overburden – A methodological contribution applied to an ENI CCS asset

Introduction

Accurate subsurface characterization is a prerequisite for a sustainable CO₂ storage. In this context, Seismic Reservoir Characterization (SRC) plays a central role in constraining reservoir architecture, assessing seal integrity and predicting CO₂ plume migration.

However, CCS projects commonly target depleted hydrocarbon reservoirs or saline aquifers, where data availability is limited and legacy datasets are often incomplete or inconsistent hampering the application of leading-edge techniques commonly used in the O&G business for quantitative interpretation (QI).

Lack of elastic logs (density, compressional and shear logs) and absence of seismic dataset sorted into partial angles stack (PAS) are common situations when applying SRC to CCS studies.

Luoni and Ferla (2024) proposed the concept of “tailored workflow” as mindset approach to overcome this issue and use seismic quantitatively, even in the early assessment phases. In practical terms, a tailored approach means adapting and tailoring workflows upon data availability.

Following these considerations, a tailored seismic-driven methodology has been applied to a depleted Field selected for CO₂ storage. The objective of the seismic characterization was to compute a cube of shale volume (VSH) in the overburden to be used as trend for the fault seal analysis (FSA) addressed to evaluate the sealing capacity across faults and therefore preventing the definition of the elastic behaviour of the overburden lithologies.

The proposed workflow provides a practical way to extract from seismic meaningful quantitative geophysical information emphasising the importance of exploring alternative geophysical workflows capable of mitigating data scarcity.

Methodology

The shale volume was computed from the available seismic dataset following a machine learning (ML) approach (Hampson, Schuelke and Quirein, 2001) (Figure 1) addressed to fully exploit the statistical relationship between the amplitude variations across the PAS and a target log property, that was in our case the shale content (VSH). However, this relationship is not supported by physical or elastic evidence due to the absence of shear-wave data in all reference wells.

The workflow consists of two main steps: a) the training phase and b) the full Field application.

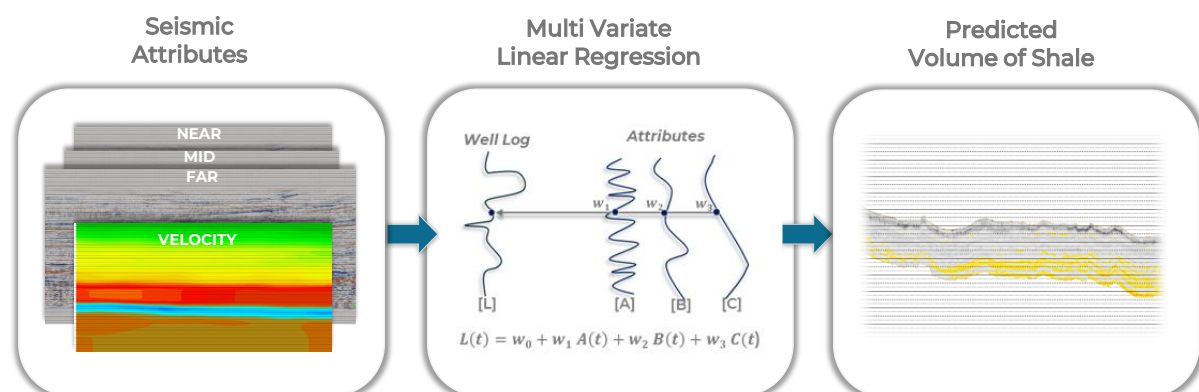


Figure 1: High level machine learning workflow for the shale volume characterization.

After a preliminary data collection and QC, during the training phase, at each well location, the relationship between seismic attributes (i.e., seismic velocities, PAS and derived attributes computed on the fly by the software) and VSH log was optimized to derive the most robust multivariate linear relationship between the two domains. Model validation was carried out using a leave-one-out strategy, whereby each well was excluded in turn from the training dataset, and predicted responses at the withheld well was subsequently compared with the measured values using correlation metrics and error analyse. The optimization process focused on the two key parameters: 1) the operator length (to take into account the different resolution between seismic and logs) which defines how many n-operator points of the attribute are averaged to predict the target log sample and 2) the number of seismic attributes considered through the stepwise regression, ensuring an optimal balance between modelled complexity and predictive performance and therefore avoiding overfitting. Once the training phase is concluded, the optimized relationship was applied to the full Field scale, and a 3D shale volume was finally computed.

Application to a Case History

The seismic shale volume prediction based on a ML approach was applied to a depleted Field selected for CCS storage.

The main objective of the seismic characterization was the generation of a VSH cube to be used as trend for the FSA, addressed to evaluate the sealing capacity across faults therefore impacting on the evaluation of the containment risk. The overburden lithology is very complex, including shale, and evaporites with an area transition from anhydrite to halite.

The input data (Figure 2) included: logs (compressional sonic and density), CPI (VSH and porosity) and evaporitic facies indicators (from master logs) for fifteen reference wells (with a good coverage of the area of interest), PSDM seismic (full stack and PAS), depth imaging velocities and horizon interpretation to define the interval of interest.

In summary, the seismic dataset was adequate for quantitative interpretation because it comes from a recent acquisition and processing; on the contrary the well data were not since they were acquired decades ago and shear sonic for none of reference wells was available. This aspect triggered the application of the ML approach.

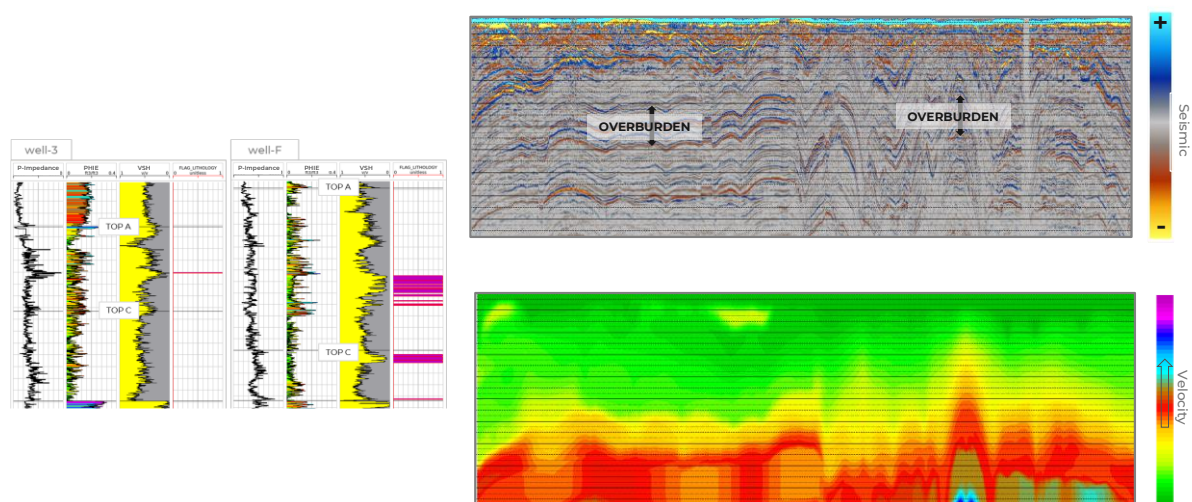


Figure 2: Project input data: well available logs and CPI; seismic and velocity volumes.

After the VSH computation was completed, results have been evaluated (1) at well location by comparing the predicted vs actual VSH log (high cut filtered at 50-80 Hz – Figure 3) and (2) along random lines (Figure 4).

The overall prediction is good, particularly in those areas where the low VSH component is formed by anhydrite and dolomites with an acoustic behaviour faster than the interbedded shales. In other sectors, it was observed that the predicted VSH is not consistent with well data wherever layers with low VSH are present. A possible reason is that these layers are dominated by halite whose acoustic behaviour is very similar to the interbedded shales.

This observation was confirmed from a more quantitative standpoint by analysing the overall correlation between the predicted vs filtered (high cut 50-80 Hz) VSH at well locations.

In the area dominated by anhydrite it is 0.6, while it decreases to 0.4 in those areas where the VSH prediction suffers for the halite occurrence with acoustic characteristics very similar to those of the overlying and underlying shales.

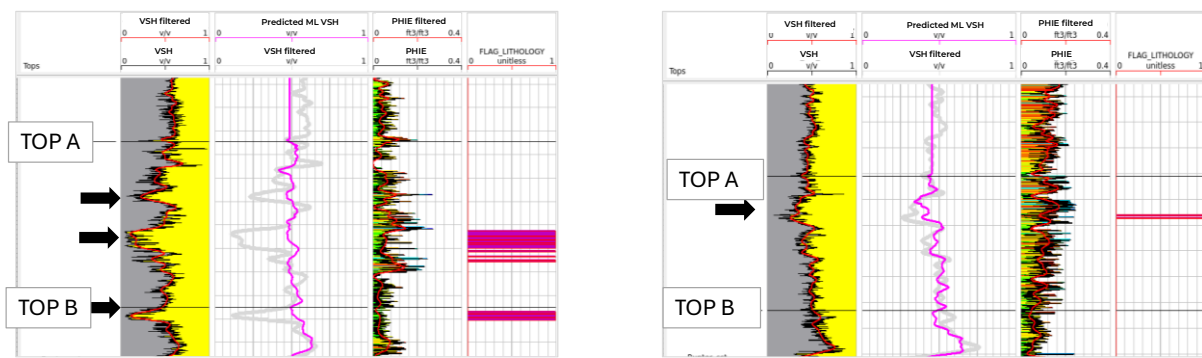


Figure 3: Comparison between actual vs predicted VSH in two wells where evaporites are dominated by halite (left, black arrows) and anhydrite (right, black arrow).

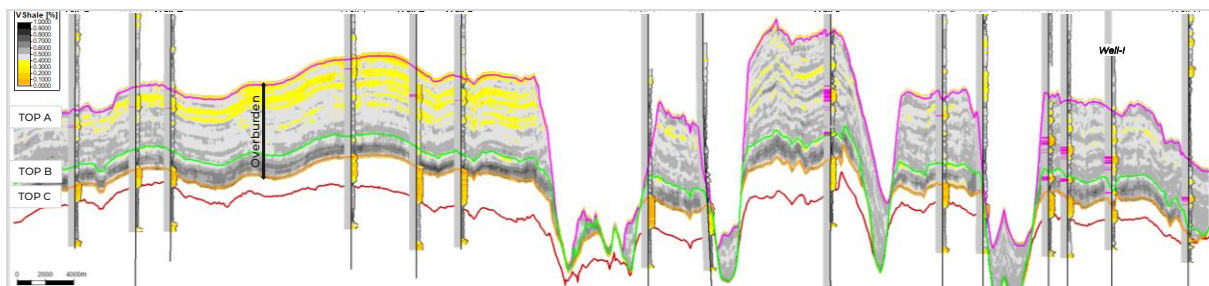


Figure 4: Random line extracted from the seismic VSH and comparison with the filtered VSH logs. It is evident the transition between the areas dominated by anhydrite (left) and halite (right) and how the match with the actual VSH changes

As blind well test, a recently drilled well, not available at the time of the study, was compared with the seismic VSH prediction in the area dominated by the anhydrite. Although this well is pretty close to an existing well (about 2 km), it is striking to observe the overall consistency between actual and predicted shale content. In particular, the shallowest low VSH seismic geobody thinning (indicated by the arrow) is related to a decrease of the low VSH content from CPI (Figure 5).

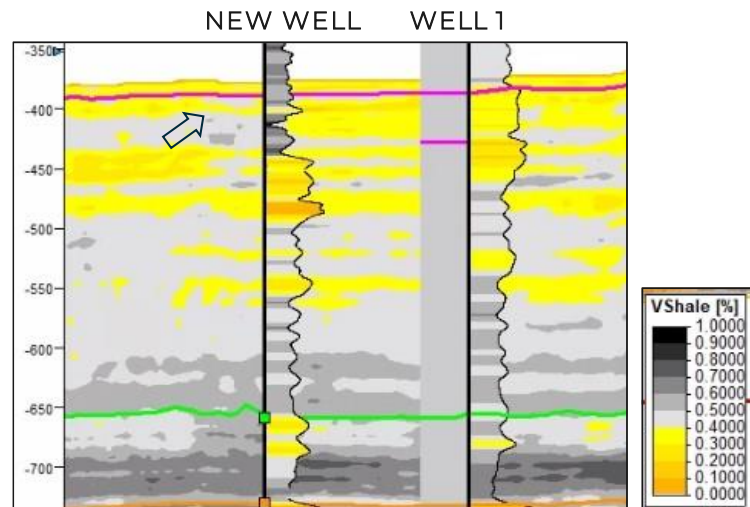


Figure 5: Comparison between actual vs predicted VSH at the new well

Conclusions

A ML approach has been applied to compute a VSH cube in the overburden to be used as trend for the FSA addressed to evaluate the containment risk associated with the CO₂ injection in a depleted Field.

The tailored workflow approach allowed to overcome the lack of shear sonic and the definition of the elastic behaviour of the overburden lithologies therefore preventing the application of the elastic inversion for SRC.

At full Field scale the VSH seismic prediction is very consistent with well data wherever evaporites are dominated by anhydrite; on the contrary, it is overestimated in those areas where evaporites are dominated by halite because of their acoustic similarity with the overlying and underlying shales. This apparent inconsistency of results, related to physical reasons, however, confirms how the ML approach was not applied as a black box therefore enhancing its predictive capability away from wells (as demonstrated by the new well).

The proposed workflow turned out to be a practical approach to derive quantitative geophysical information from seismic even if data are scarce or incomplete. This point is very important since it allows to apply quantitative interpretation to support the risk assessment even in the early phases of a CCS project.

Finally, it must be pointed out how the overburden characterization might be improved if shear sonic logs are available and a more classical elastic inversion SRC workflow is applied.

Acknowledgements

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References

- Luoni F. and Ferla M., Revisiting the seismic characterization workflows to respond to the energy transition challenges: Third EAGE Conference on Seismic Inversion - 14-16 October 2024, Naples, Italy.
- Hampson, D.P., Schuelke, J.S., and Quirein, Use of multiattribute transforms to predict log properties from seismic data: Geophysics, 66, 220-236