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Seismic inversion and characterization applied to geothermal energy

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Introduction

Seismic inversion is a method used to obtain models of the subsurface in terms of the elastic properties of rocks, called impedances, using seismic reflection data. Seismic characterization, on the other hand, allows the estimation of the key properties of the reservoir, in 3D, in 2D sections or in map, using, among other possible attributes, seismic inversion outputs. The combination of both disciplines unveils, either in 3D, in 2D sections or as maps, the distribution of key reservoir properties, relative to their matrix, fluid or fracture characteristics, between scarce and irregularly distributed well data. It is therefore crucial either to prospect new areas, in exploration, or to increase the production of an already proven geothermal system.

Unlike the direct model which creates a synthetic signal from impedances, seismic inversion, as an inverse problem, consists in iteratively optimizing an impedance model from observed seismic data (Figure 7.1).

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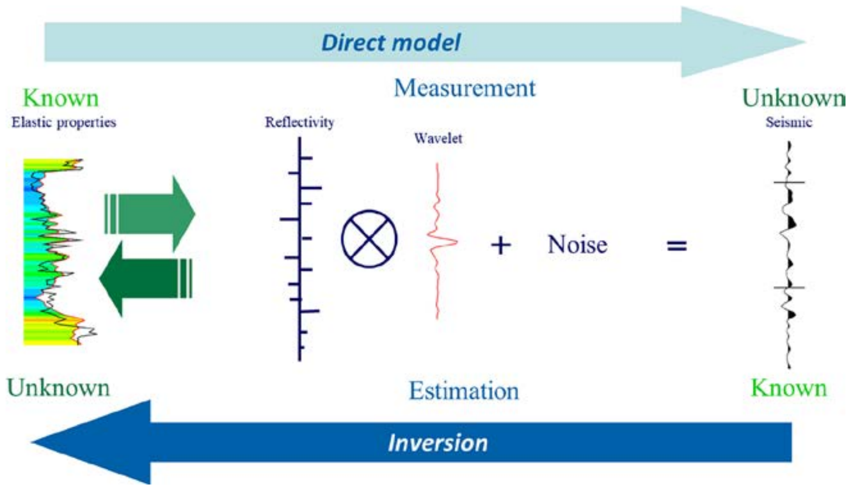


Figure 7.1 *Seismic inversion versus direct modelling.*

The objectives of a seismic inversion are:

- To optimize impedance values. They depend on the intrinsic properties of the rock, while the seismic signal depends on their contrast. Seismic characterization, sometimes called quantitative interpretation, is a discipline that links elastic properties (or other signal derivatives) with key reservoir properties (lithology, porosity, fluid...) or fractures. Learned directly from raw results (unsupervised) or guided by well data (supervised), the discipline allows the estimation of key properties through the application of machine learning techniques.
- To reduce random noise, depending on the inversion technique used, and therefore improve legacy seismic data and its subsequent seismic attributes, revealing better the faults and fractures, or facilitating seismic interpretation.

After describing key concepts related to these disciplines, we will describe the methodology using InterWell, the software solution from Beicip-Franlab, part of IFPen group, for seismic inversion, seismic characterization and time-depth conversion. This will be followed by a practical case study.

7.1 Technical background

7.1.1 *Seismic gathers and partial stacking*

Following acquisition and a sequence of data processing and migration, *preserving amplitudes*, seismic data are *gathered* such that traces correspond to the same CMP (Common Middle Point) or CDP (Common Depth Point) depending on the migration technique used. The delay with the offset, called *NMO effect*, is corrected. For the same time (TWT), they image the same subsurface point. Traces are classified with an *offset* key, defined by the distance between the source and the receiver (Figure 7.2).

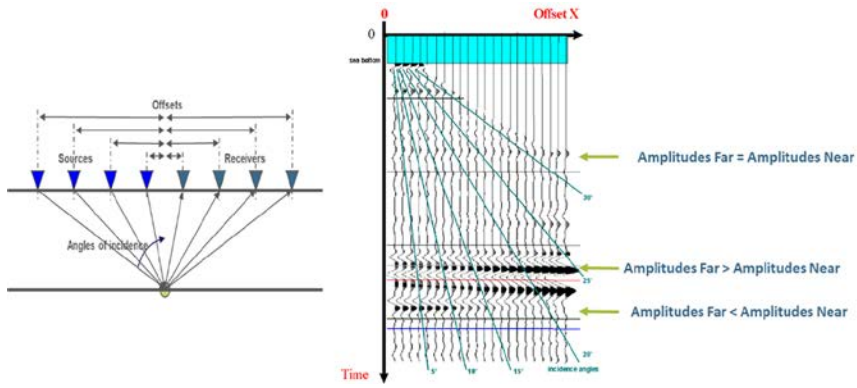


Figure 7.2 *Conceptual view of a seismic gather after the process sequence, including NMO.*

In practice, gathers are stacked to reduce random noise:

- *Full stack*: Information is summed over a wide angle or offset range, allowing a strong reduction of random noise. This result is the basis of seismic interpretation, but in this process, the variation of amplitude with offset and, if available, with azimuth is lost.
- *Angle-stack*: Offsets are converted with a velocity trace into angles, from which theoretical responses can be modeled by wave equations. They are often denominated Near, Mid, Far and UFar to the reference of their angle ranges.

7.1.2 *The subsurface as an isotropic elastic medium*

In seismic reflection, in a supposed homogeneous isotropic medium, the reflectivity of the PP (incident P, reflected P) wave at an interface between two layers is governed by the Zoeppritz equation. It depends on three elastic properties, P-wave velocity (VP), S-wave velocity (VS), and density, as well as the incidence angle at which the wave arrives at the interface. In addition, P-impedance, product of velocity (P) and density, is the capacity of a compressive wave to cross a medium. S-impedance, linked to S-velocity, is a similar property, but related to the shear waves.

When seismic data are fully stacked, the amplitude variation with incidence angle is lost. The considered hypothesis is therefore of normal incidence: the amplitude of the reflected wave only depends on the gradient of P-impedance. The optimization of this variable during seismic inversion under this hypothesis is called *acoustic inversion* or *post-stack inversion*.

When working on gathers, or on partial angle-stacked seismic data, the Zoeppritz equation can be applied. In practice, the Aki-Richards equation (Aki and Richards, 1980), a simplification, is preferred during *elastic inversion* or *pre-stack inversion*, whose partial derivatives are linear and offering a valid approximation up to an incidence angle of 45°. These elements allow good behavior during numerical optimization (inverse problem) and good optimization of P-impedances and S-impedances. Density, however, is not well optimized by this process; other techniques allow improving this result. As we will describe later, dealing with not only one but two variables to explain the characteristics of the reservoir allow capturing combined changes (lithology and fluid, or lithology and porosity, for instance).

Figure 7.3 summarizes the two techniques in terms of inputs and outputs, respectively for acoustic inversion (left) and elastic inversion (right).

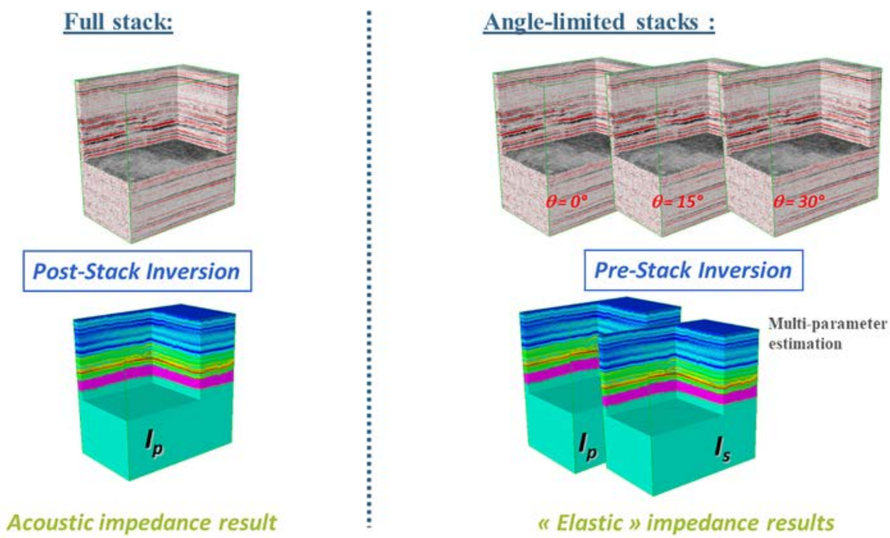


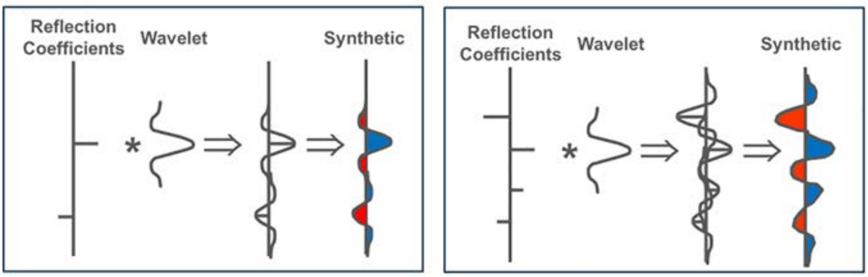
Figure 7.3 *Results obtained according to the full-stack (acoustic) or angle-stack (elastic) assumption.*

7.1.3 *Convolution and resolution*

Considering the medium as a series of reflection coefficients, the seismic response, in the two-way time domain, results from the convolution of this with an impulse response, called a wavelet. This operator has its own characteristics: (1) shape, (2) frequency spectrum, and (3) phase spectrum. It represents the impulse signal of the source, which, after its path, can be deformed (phase, energy) and some frequencies can be absorbed.

Limited by its bandwidth, the result of the convolution acts as a frequency filter. If the reflection coefficients are defined more precisely, the convolution models the interferences; thus, in this case, there are series of reflection coefficients for which the synthetic has the same response (Figure 7.4). This is called a resolution problem.

$$(f * g)(n) = \sum_{t=-\infty}^{+\infty} f(n-t).g(t) = \sum_{t=-\infty}^{+\infty} f(t).g(n-t)$$



No interference

Interferences : the same synthetic can come from a more complex and non-unique reflectivity trace solution

Figure 7.4 *Convolution and model of the interferences.*

In the industry, several considerations are commonly accepted:

- *Resolution*: A contrast is "resolved" when it represents a change of half a period of the signal. The signal has the "time" to reach the expected amplitude value.
- *Detection*: A contrast is "detected" when it represents a change of one-eighth of a period of the signal. The signal retains the dynamics without reaching the expected amplitude value. The response is sufficient to interpret a contrast, however, it is insufficient to deduce a quantitative property.

$$T_{\text{resolution}}(s) = \frac{1}{2f} \qquad T_{\text{detection}}(s) = \frac{1}{8f}$$
$$Z_{\text{resolution}}(m) = \frac{v}{4f} \qquad Z_{\text{detection}}(m) = \frac{v}{16f}$$

where f represents the dominant or maximum frequency of the signal contained in the wavelet (in Hz), and v the instantaneous velocity of the medium traversed (in m/s).

The convolution theory is, and the definition of the wavelet, is the main reason why seismic inversion must be performed in *two-way time* domain.

7.2 Seismic inversion

7.2.1 *About seismic conditioning*

Either to obtain full-stack or angle-stack data, for acoustic or elastic inversion respectively, gather reprocessing can be considered using up-to-date methodologies to enhance the final image, but must be *"amplitude preserved",* meaning that no equalization or gain should have been applied to the data. As the inversion translates the amplitude into impedance changes, such processes can annihilate the vertical and lateral property changes normally observed through seismic inversion.

This aspect is even more critical while considering several angle-stacks, as the *amplitude preserved* sequence ensures consistency between them. As the variation of the amplitude with the offset is meant to be translated into properties, any independent processing of each stack may ruin the desired estimation.

In addition, while considering several stacks, seismic inversion is a computational process, and as such, all involved seismic data must be aligned. The NMO, often not perfect, must be completed by a *mis-alignment correction* (called *trim statics* on gathers, or Residual NMO in case of angle-stacks). The shift estimation in volumes through energy or correlation optimization is often preferred. The shifts are dynamic, and, therefore, are not constant vertically. The shift estimation can be post-processed, using smoothing or editions using an uncertainty analysis to prevent the generation of artifacts.

7.2.2 *Wavelet extraction and optimization*

To link the modeled or optimized reflectivity with a seismic signal, the key operator, the wavelet, must be designed for each seismic dataset. A well-spread methodology in the industry is using a two-step procedure (Richard and Brac, 1988), with a statistical zero-phase wavelet extraction, followed by its optimization in phase and energy.

For each seismic data involved in the process, the initial wavelet is extracted statistically by cross-correlation trace by trace, in a lateral zone and a given time window, if the signal correlates trace by trace while the noise, assumed to be random, does not correlate.

To set up both the phase and energy for the wavelet, the wells are used and calibrated at the same time; the objective is to ensure the best match between synthetic traces, computed at well, and real traces, optimizing the wavelet parameters. To increase the robustness of such prediction, several traces can be considered, as displayed Figure 7.5. In this case, the best parameters can be displayed as histograms.

After the process, the well-tie is often updated. In case of elastic inversion, the optimal location of the wells should then consider all the angle-stacks simultaneously.

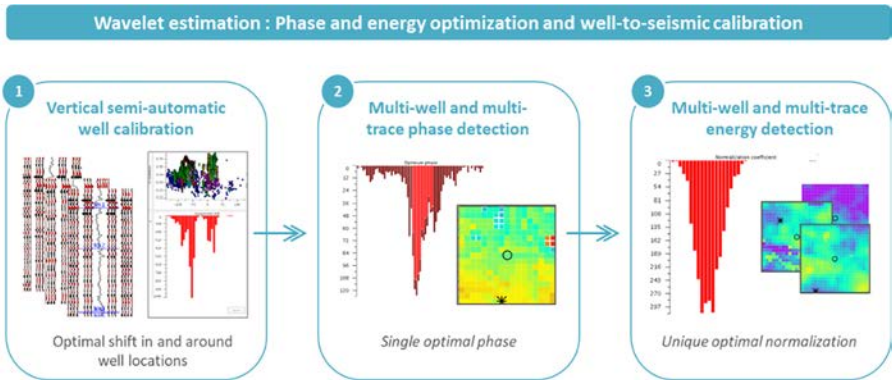


Figure 7.5 *Multi-well and multi-traces approach for a unique wavelet estimation*

7.2.3 Construction of a low-frequency model

Seismic information is limited by its bandwidth, both in low and high frequencies. The high-frequency limit determines the resolution, or the maximum precision of the final inversion results. But there are also low frequencies missing, including compaction trends and other regional changes, that need to be modeled through a *low-frequency model*. In practice, this model is *simple*, so that any complex features retrieved from seismic inversion can only come from seismic data.

Interpreted horizons allow the construction of a structural model, defining different units, and correlation lines. Following the correlation lines the model is obtained by propagating the acoustic impedance values (and S-impedance and density for elastic inversion) from the wells in calibrated positions along the correlation surfaces defined during the creation of the structural grid. The extrapolation method used is inverse distance.

Then, a low-pass filter is applied to eliminate high frequencies coming from the wells, limiting the model at the missing part from seismic data.

The model can be used with several "intensity", playing a strong role for each following proposal:

1. *low-frequency model*: An elastic model, in the low frequencies missing from the seismic, is used, either before (initial model) or after (by adding the missing frequencies).
2. *initial model*: The starting point of the optimization is an elastic model.
3. *prior model*: During optimization, impedance is compared to a prior model, from which it costs the algorithm to deviate (Tonellot et al., 1999).

For (1), the frequency filter, for its higher limit, must be strict with no overlapping with the dataset. The frequency overlap is possible for (2), and even recommended for (3) while building a prior model (Figure 7.6). Indeed, the seismic information will be compared with the model during the inversion process, discarding too discrepant information, considered as noise.

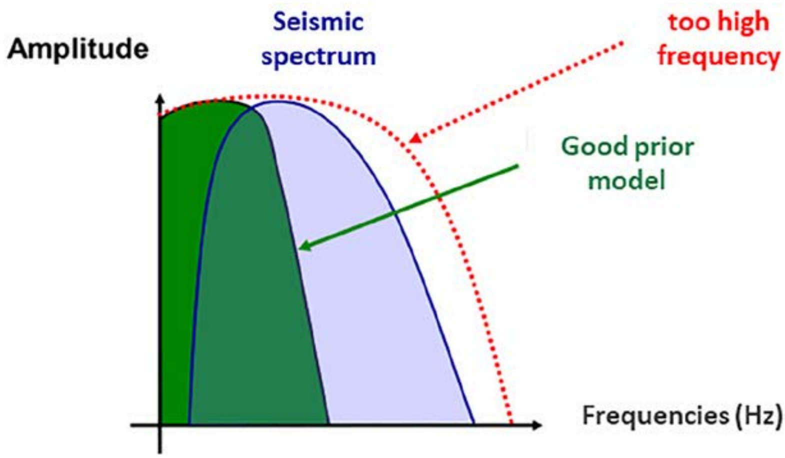


Figure 7.6 *Conceptual amplitude spectrum of the prior model compared to the seismic spectrum.*

7.2.4 *Performing a seismic inversion*

Seismic inversion algorithm

Different algorithms for seismic inversion are available and suit different objectives:

- For the *sparse-spike inversion*, each trace is considered independently, introducing the entire trace. Computationally efficient, this technique is ineffective for reducing random noise. This inversion has no parameter but the number of iterations.
- *Model-based inversion* is based on the objective function, or cost function, this inversion type has two parameters weighing the two terms: the *seismic term*, which controls the distance to the seismic, and the *model term*, which controls the distance to the prior model.

For *stratigraphic inversion algorithms*, often preferred in projects for its noise reduction capability (Tonellot et al., 2001), the correlation length, added to the *model term*, controls the lateral continuity of impedance values along the correlation lines. The inversion is thus “multi-channel” when several traces are considered. It is “grid-based” when this comparison is consistent with a priori dip. In recent advances in seismic inversion projects, this dip is directly deduced from seismic independently from seismic interpretation.

All the inversion methods allow us to optimize the elastic properties. The *stratigraphic inversion algorithm* allows the reduction of random noise present in the initial seismic data, and therefore, does not include it into the inversion results.

Seismic inversion parameters and QCs

In practice, a reduced area is used to optimize the parameters, with the following criteria:

- The *number of iterations* must be adjusted to obtain a maximum decrease in the objective function ending in a plateau (no more improvement by increasing iterations).
- The *residual seismic* must be weak compared to the synthetic, proving that most of the information has been included in the elastic model. If possible, no (laterally) coherent signal must be present in the residuals.

Especially for elastic inversion, additional controls are performed:

- The residual seismic energy must be similar for all angle-stacks or honoring their relative quality.
- The P-impedance and S-impedance, in seismic, must be equally updated and their frequency content comparable, or their difference explainable by a strong frequency difference between the angle-stacks, especially between the Near and the Far stacks.

Extended to the entire seismic, a full-field inversion is performed and generally QC using the following criteria:

- Control in sections (visuals) and control as maps (noise map, frequency map, energy map) to assess the enhancement or *conformity of the synthetic data* compared to the original seismic data. All information in the synthetic is contained in the elastic model.
- *Control of the convergence*, both in terms of plateau and final values (%), expected to be compatible, approximately, with the signal to noise ratio observed in the original seismic.
- *Extraction at well locations* (Figure 7.7), both participating or not (blind wells) in the calibration and modelling process, to assess the predictability of the inversion results. In practice, however, the inversion is often performed with all the wells in a final run, as the well data availability is often rare and valuable.

The correspondence between the inverted properties and the properties computed at wells are often not a surprise for the inversion specialist, as it reflects the quality/difficulties observed during the wavelet estimation. For the professional beginning the seismic characterization, this QC is a good starting point to assess how reliable the inversion results are before propagating valuable reservoir properties.

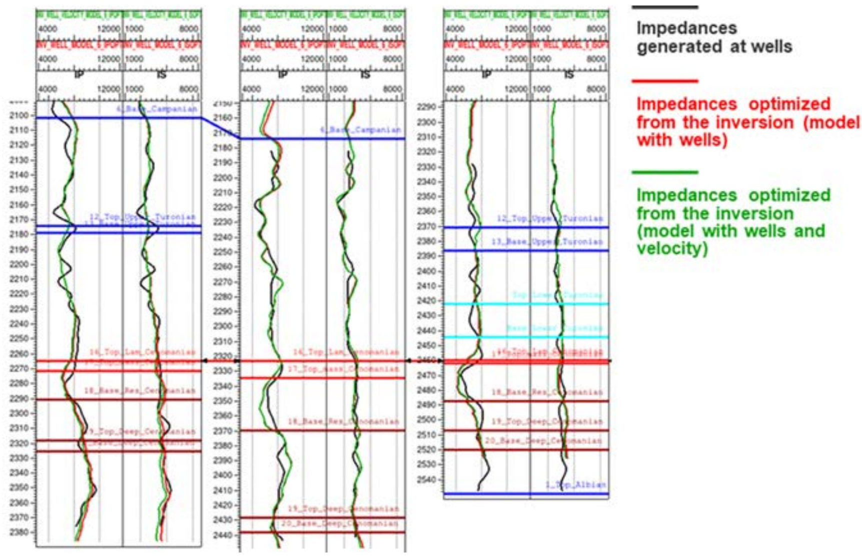


Figure 7.7 *Example of inversion QC at well location: the black curve is the "real" property, while the colored curves are retrieved from seismic inversion.*

7.3 Introduction to seismic characterization

Unlike the seismic inversion workflow, linear, the seismic characterization is composed of diverse techniques to qualitatively or quantitatively link the reservoir properties to the seismic information. In this exploration of methodologies, the seismic inversion results, especially the synthetic seismic data and the impedances, are key inputs, but not the only one, to build a custom-made workflow adapted to each case, considering both its objectives and the data available.

7.3.1 *Exploring well response through a petro-elastic model building*

The analysis of the well response (in terms of impedances) with the key property changes is called a *petro-elastic model*. Performed before the seismic inversion, it can be proposed as *a feasibility study* to assess its added value in projects. Although these considerations may change by projects, the properties are evaluated in this order, impacting less and less the impedances: lithology, porosity, then fluid.

In practice, P-impedance and S-impedance properties are computed from well logs and compared to the petrophysical properties. In a multi-disciplinary project, geologists may identify dozens of lithologies from core or well logs. The number of lithologies must be limited, as the number of independent attributes is limited to P- and S-impedance only. Some guidelines are as follows:

- The problem can be split into several ones by studying the intervals separately.
- Only the most typical lithologies should be kept, such as clean sand. Porous or tight sands are not lithologies, but sub-groups of the sand lithology that can be detected afterward by identifying the corresponding impedance values in the predicted sand.
- The facies can be grouped (one versus all) or to apply a nested approach.
- An upscaling analysis must be performed to identify lithologies/properties detectable from the seismic data.

Figure 7.8 illustrates the lithology and property changes with the upscaling, removing the information with a frequency content greater than various limits, representing the expected quality of seismic data:

- For a discrete lithology column, a *"most of" algorithm* is used, assigning to the cell the most represented lithology. The size of the cell is computed depending on the resolution formula.
- For a continuous property (like a volume of shale for instance), a *frequency filter (low-pass)* is used, adjusting the frequency limit to the resolution.

In this example, it is interesting to assess the critical frequencies from which each sand layer is no longer detected or merged with another one. It allows the interpreter to predict what to expect from a seismic characterization study.

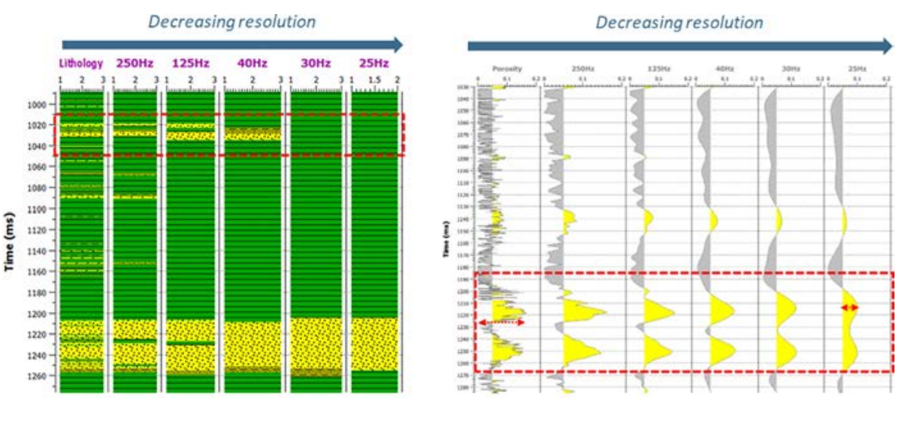


Figure 7.8 *Upscaling of lithology (left) or porosity (right) considering different seismic frequencies.*

The prediction power of impedances, at fine scale and at seismic scale, represents their ability to isolate well-defined clusters corresponding to lithologies or the ability to derive trends. This is validated using cross-plots, before and after upscaling, to ensure that the cluster organization is conserved. In Figure 7.9, the pale color points in background represent the data at a well scale, while the darker points represented the data at seismic scale, sampled at the seismic rate. In practice, the trends should be valid in both scales to be applied on inversion results.

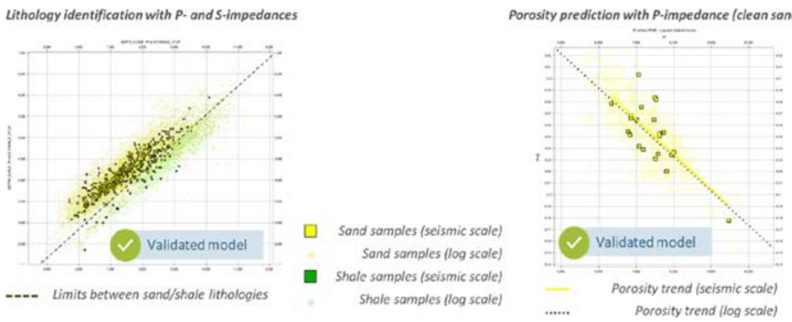


Figure 7.9 *Petro-elastic model with and without upscaling, showing the possibility to separate sands from shales (left) and to derive a porosity trend in sands only (right).*

In the section concerning Machine Learning techniques, the propagation to 2D or 3D inversion results will be discussed using a classifier (discrete lithology) or a regression (continuous properties) based on this well data, called "training samples".

7.3.2 *Seismic attributes related to faults and fractures*

Avoiding fastidious work for the geophysicists, the computation of seismic attributes for fracture detection is efficient but presents various challenges:

- To separate geological discontinuities from random noise. Model-based seismic inversion helps reduce the noise content. On synthetic seismic data, parameters for attribute computations can therefore be better tuned to better unveil meaningful fracture response.
- To separate the fault and fracture response from other major structural features, such as highly tilted blocks.
- To sort or separate the regional from the local features.

Several types exist (Chopra and Marfurt, 2007):

- *Geometrical* attributes, such as dip and curvature.
- *Correlation-based* (coherency) attributes, including a steering to tilt the computational window.
- Attributes linked to *energy*, such as envelopes, RMS or spectral decomposition.

These seismic attributes dedicated to discontinuity analysis do not only highlight fractures, but they may also be impacted by other effects depending on the algorithm. For example, correlation-based attributes are highly biased by dips or lithology changes, while dip-based attributes are sensitive to both local and broad-scale dip changes. All the attributes quoted here unveil fractures: the fracture image is then redundant, while the perturbations are inherent to each attribute algorithm.

While analyzing the relevance of an attribute, and before any combination, it can be post-processed using smoothing or threshold, achieving the best compromise between its accuracy and its noise level to capture the fracture intensity.

As a control, fracture patterns can be checked in the seismic, although some of them can be too subtle or too discontinuous to be clearly identified and followed from one seismic section to another. Their orientation and continuity can be validated against the conceptual structural model.

Attribute combination can be performed using two main methods (Kumar et al., 2017):

- Meta-attributes: it consists in a linear combination of the attributes, weighted by their quality. This is an interpretative method.
- Clustering or seismic facies analysis: it consists of an unsupervised machine learning technique, as discussed in the next section. The typical responses such as “faults” or “fractures” are highlighted in the map.

Such results will be illustrated in the case study section.

7.3.3 *Characterization empowered by machine learning*

Machine Learning is a powerful tool:

- To infer classifications or trends, either using wells only or even mixing well and attribute data using *supervised approaches.*
- To analyze typical responses in seismic data or inversion results, through *unsupervised approaches*.

Supervised approaches

The supervised approaches (Discriminant Analysis, Neural Networks, KNN, …), consist in building a predictive model to assess a petrophysical property using seismic attributes, commonly, after inversion, P-impedance, S-impedance, and/or their combination (Al-Emadi et al., 2010). This is the *descriptive phase*. A second phase, *predictive phase*, consists in using this model to predict the lithology or facies. These two steps are illustrated by Figure 7.10. In practice, to assess the validity of the model, the prediction is performed on the training sample themselves, before any propagation in 3D. Statistics of good assignments, called *restitution*, are often used. While considering continuous variable prediction, (multi-variable) regression is used, using the same two-step approach. In this case, the *RMS error* (RMSE) is preferred to assess the uncertainty associated with the prediction (De Freslon et al., 2020).

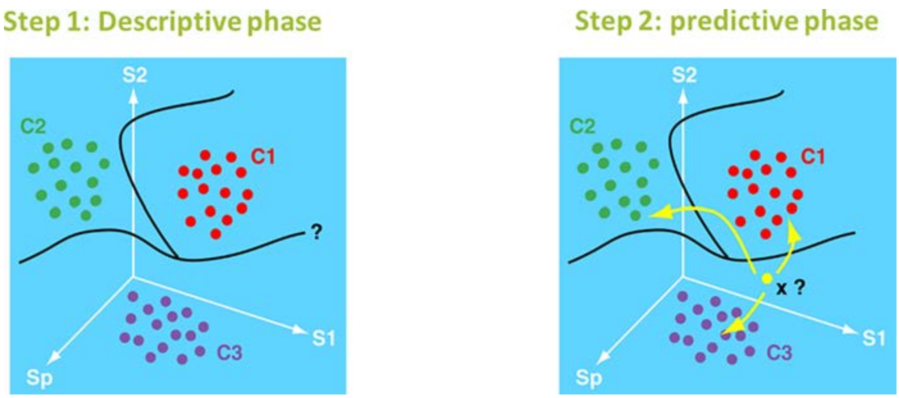


Figure 7.10 *Supervised technique as a two-step problem.*

In Machine Learning, and in data science in general, it is recommended to prepare the data by splitting the dataset into three, respectively for training, validation and predictability assessment. In practice, in geosciences, well data is expensive, and the reservoir samples are rare and often underrepresented, leading to difficulties while applying these rigorous recommendations.

The data is explored, grouping lithology or facies, considering a property or other, separating by interval using markers and horizons, to propose the best model. The limitation is often the number of input variables, which prevents explaining a too complex system.

Another paradigm, often observed in projects, is the homogeneity between the data on which the training is based (wells) and the seismic resolution. Ideally, the upscaling should be performed to ensure compatibility, but the lack of points, especially in the reservoirs, may also lead to high uncertainty during the prediction.

Finally, considering classification only, the outputs of such approaches are not only labels, but also *scores* or *probabilities*. These latest outputs are key to propose scenarios, considering the uncertainties associated with the predictive model in the seismic characterization (Yareshchenko et al., 2021).

Unsupervised approaches

Clustering methods (K-means, Self-Organizing Maps, …) are algorithms, self-trained, and allow to classify the data regarding "typical responses", labelling the input data as "classes". These algorithms are applied:

- On maps, for example, in risk analysis or seismic fracture characterization (Kumar et al., 2017).
- On horizon-slice, considering typical shapes of trace from channel or karst identification (Voutay et al., 2002).
- On volume, considering each sample, for reservoir, salt or igneous rock identification (Cardoso et al., 2022).

Easy to put in place, these methods always output results which will, of course, highly depend on the selection of attributes used as inputs. The main challenge of such methods is to properly interpret the obtained features. Coupled with supervised techniques, this is a good methodology to prove that the supervised training is a typical response, well identified in the seismic data. Recent advances in this methodology, suitable for exploration, suggest afterward calibration with well data, or with conceptual section from the proposed by geologists.

7.4 Example: identification of lithology, good porosity and fractured areas through a seismic inversion study

In the following example, a seismic inversion and characterization study has been conducted to highlight the most prospective area in carbonates, either in terms of rock properties (lithology, porosity/permeability) and fault/fracture presence over a 3D survey. For this characterization case, the fluid is stored in good matrix properties, while the permeability is ensured by the fractures. In geothermal activities, these parameters are key to ensure the targeted flow rate. The described work can be performed in 2D. This recent case (Baillet et al., 2024) has been scenarized as a geothermal project, and these methodologies have already been applied successfully in this context in Paris basin or in the North of France.

A stratigraphic joint inversion, using angle-stacks, has been performed. Both P- and S- impedance are optimized. The zone is covered by 6 wells, with DT, RHOB and partial DTS completed by empirical laws when needed.

A seismic characterization has been performed to predict lithology (Figure 7.11). A petro-elastic model, built at wells, upscaled at seismic scale, has been used as a training sample for discriminant analysis. Shaly carbonates could have been discriminated against dolomites with a satisfactory rate.

A particularly interesting layer, in terms of porosity/permeability, called unit-C, has been identified, at the limit of the seismic resolution. A connectivity analysis, in 3D, has been undertaken, and proves its connection/extension, invisible in section only. In Figure 7.11, this layer is plotted in orange and has been used to propose an update of the horizon, in red dots.

In each lithology, a law estimating the porosity has been derived from well logs and applied, based on P-impedance. The porosity is very heterogeneous vertically, as observable in another section, Figure 7.12.

If the fluid is present in the most porous matrix lithologies, the provided flow rate might not be enough to sustain a geothermal project. Faults and fractures, identified, can greatly increase the prospectivity of an area. A fracture characterization, processing and mixing key attributes (as dip-steered similarity, spectral decomposition, energy, shift quality, …) led to a final attribute, plotted in black Figures 7.11 and 7.12. Connected fractures, crossing unit C, would be an optimal for the flow rate.

The view in map, Figure 7.12, highlights the areas, between two key horizons, where the dolomites are the most present, and where these dolomites have the greatest porosity. Overlay with faults and fractures obtained by the fracture characterization, these final maps led the future development.

Each of these properties, estimated through this work, has a key role in the interpretation:

- The most porous areas contain most of the fluid.
- The dolomite has a better permeability then the shaly carbonate, even with the same low porosity.
- The fracture presence allows a better connection of the layers, and greater porosity (secondary) and overall, a greater permeability.

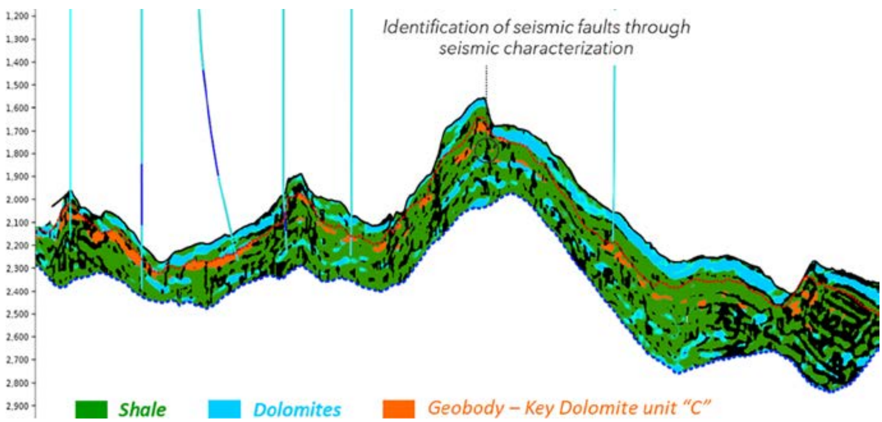


Figure 7.11 *Predicted lithology in section.*

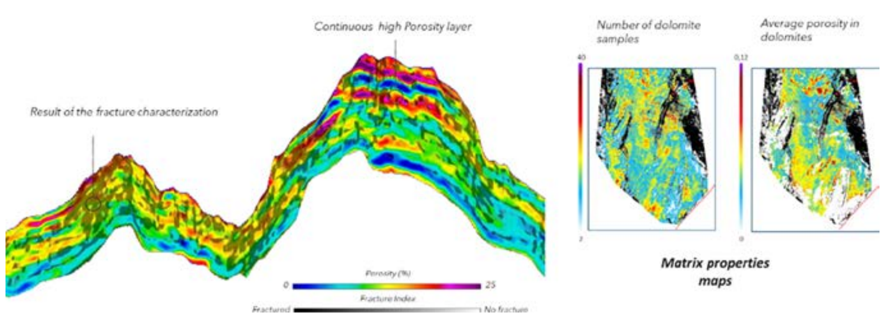


Figure 7.12 *Predicted porosity in section and final maps.*

Conclusions and perspectives

The seismic inversion and characterization are disciplines that aim at converting seismic amplitude into key reservoir properties, leading to valuable information between wells to lower the risk while planning exploration or development of geothermal production, either with low or high depth objectives. The state-of-the-art, originally designed for the oil and gas industry, is also perfectly adapted for the geothermal industry, either based on 2D or 3D seismic data.

Either in prospection or development phase for a geothermal project, all available data, including legacy ones, has a lot of value. The proposed case study illustrates how the reservoir presence and quality could have been identified between wells. The fracture characterization plays a crucial role in identifying zones with secondary porosity and enhanced permeability, increasing the prospectivity. This fracture connectivity must be evaluated, not to connect with aquifer of different temperatures. Both matrix and fracture characterization together help build scenarios and derisk the development of the geothermal project.

If any seismic data is available in a studied area, this kind of analysis is always a good option, either to identify and confirm the presence, the depth or the thickness of the reservoir, or evaluate the potential flow rate by estimating the porosity (then permeability, by lithology) or the presence of sub-seismic faults and fractures. The petro-elastic model can be analyzed even before acquiring or reprocessing seismic data, to assess what results could be obtained, although some recent advances in unsupervised machine learning techniques may overcome these expectations.

The seismic characterization results are key information to assess the economic viability of geothermal development, completing information from other disciplines such as the thermal gradient assessment, the estimation of the drilling cost to be put against a reasonable time of depreciation of the geothermal project.

References

Aki K., Richards P.G. (1980) *Quantitative seismology: Theory and methods*, 1: W. H. Freeman and Co.

Al-Emadi A., Robinson S., Jedaan N., Desgoutte N., Blum M., Lecante G., Caline B., Fraisse C. (2010) Use of Pre-Stack Seismic Data to Guide the 3D Rock-Type Distribution of Arab-D inMaydan Mahzam High-Resolution Geological Model, https://doi.org/10.3997/2214-4609-pdb.248.458.

Baillet R., de Freslon N., Thomas V., Castellanos R., Denogean E. (2024) Fracture and matrix characterization using wide-azimuth and multi-component seismic data: a case study from offshore Mexico, *Fourth International Meeting for Applied Geoscience & Energy,* 144-148, https://doi.org/10.1190/image2024-4101418.1.

Cardoso G.L., Kolisnyk A., Bronizeski E., de Abreu E., Laudon C. (2022) Applying unsupervised multiattribute machine learning for 3D stratigraphic facies classification in a carbonate field, offshore Brazil, *SEG Technical Program Expanded Abstracts* 2022, 441-445, https://doi.org/10.1190/image2022-3750985.1.

Chopra S., Marfurt K.J. (2007) Seismic attributes for fault/fracture characterization, *SEG Technical Program Expanded Abstracts* 2007, 1520-1524, https://doi.org/10.1190/1.2792785.

De Freslon N., Lucet N., Pain A., Desgoutte N. (2020) Comparison of Two Reservoir Characterization Workflows for Estimating 3D Shale Distribution from Seismic Data, EAGE 2020 Annual Conference & Exhibition Online, Dec 2020, Volume 2020, p. 1-5.

Kumar R., Al-Kanderi J., Kumar Mishra P., Al-Mutairi T., Baillet R., Stozicky E., Lecante G. (2017) Innovative seismic fracture attributes for fracture characterization workflow: Application in formations affected by interbed multiples, *SEG Technical Program Expanded Abstracts* 2017, 3255-3259, https://doi.org/10.1190/segam2017-17467633.1.

Richard V., Brac J. (1988) Wavelet analysis using well log information, *SEG Technical Program Expanded Abstracts* 1988, 946-949, https://doi.org/10.1190/1.1892398.

Tonellot T., Macé D., Richard V. (2001) Joint stratigraphic inversion of angle-limited stacks, *SEG Technical Program Expanded Abstracts* 2001, 227-230, https://doi.org/10.1190/1.1816577.

Tonellot T., Macé D., Richard V., Cuer M. (1999) Prestack elastic waveform in version using a priori information, *SEG Technical Program Expanded Abstracts* 1999, 800-803, https://doi.org/10.1190/1.1821149.

Voutay O., Fournier F., Royer J. (2002) Seismic interpretation with new attributes extracted from a prestack multicube analysis, *SEG Technical Program Expanded Abstracts* 2002, 1762-1765, https://doi.org/10.1190/1.1817022.

Yareshchenko S., De Freslon N., Cuilhé L., Rudling C., Lucet N., Desgoutte N., Machault V., Solodkyi Y., Gafych I. (2021) 82nd EAGE Annual Conference & Exhibition, Oct. 2021, Volume 2021, p. 1-5.