Lessons Learned from Applying Quantitative Interpretation in Geothermal Projects

Introduction

The increasing global demand for sustainable energy solutions has stimulated the development of geothermal resources across Europe and beyond. Quantitative seismic interpretation (QI) plays a crucial role in reducing subsurface uncertainty and enhancing reservoir characterization throughout the geothermal project lifecycle – from exploration to development.

While QI techniques are well established in the oil and gas sector, their application to geothermal systems presents challenges. These challenges mostly arise from limited data availability, variable data quality, and geological complexity. Addressing such challenges requires adapted workflows and a clear understanding of the limitations and possibilities of QI in geothermal settings.

This paper presents a set of lessons learned from real-world geothermal projects, where QI techniques were applied and adapted to a range of technical and geological constraints. The insights gained are relevant for geothermal professionals aiming to integrate seismic and well data in a meaningful and robust way. Two case studies are used as examples in this paper: one from the Paris Basin (France) and the other from the Central Netherlands Basin (the Netherlands). In the Paris Basin, the goal was to characterize three main geological targets with geothermal potential: the Oxfordian, Dogger and Boissy formations (Guillocheau et al., 2000). The Permian Upper Rotliegend Group was characterized in the Central Netherlands Basin case study, focusing on its depositional environment, thickness, and lateral variations of porosity and permeability (Veldkamp et al., 2022). Locations of seismic lines and wells are shown in Figure 1.

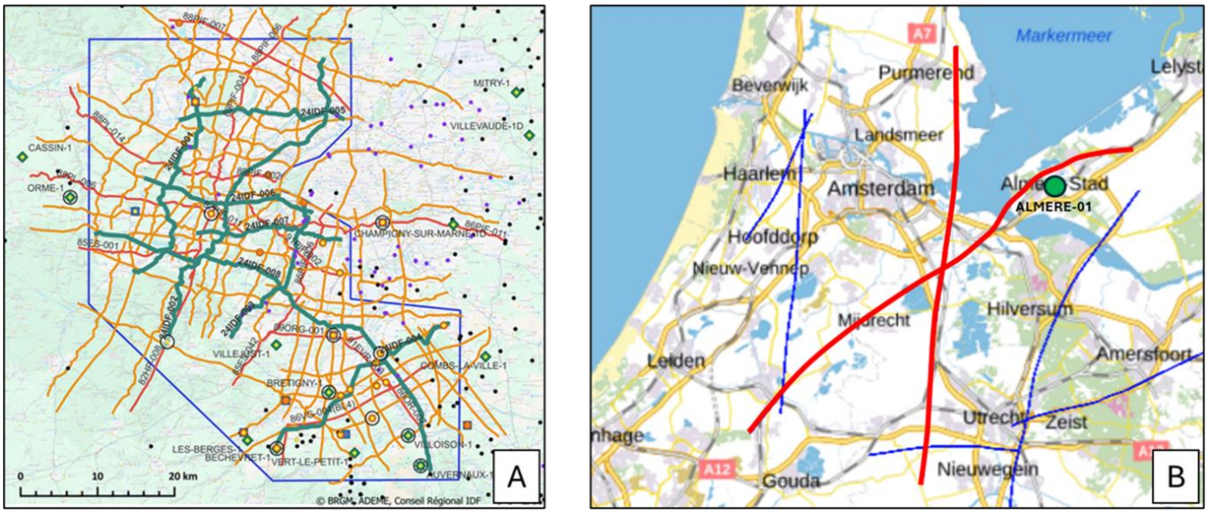

Figure 1 *Seismic lines and wells in the Paris Basin (A) and Central Netherlands Basin (B) case studies.*

On the map of the Paris Basin (A), orange and green lines represent legacy and newly acquired 2D seismic lines, yellow points represent available wells within the area, and the study area is outlined in blue. On the map of the Central Netherlands Basin, red lines represent the 2D seismic lines used in the case study, and the green circle marks the real well used in the analysis.

Challenges and QI-Based Solutions

In this paper, we discuss a series of common challenges encountered when applying QI techniques to geothermal projects and present practical solutions developed through real-world applications. The following key challenges are addressed:

1. Low-quality petrophysical data.

Even in projects with a large number of existing wells, petrophysical data are often incomplete, outdated, or inconsistent. Many wells require re-interpretation or correction of logs to be suitable for QI workflows, and some cannot be used at all. To address this, petrophysical techniques are applied, including rock physics modeling and, more recently, machine learning approaches. These methods allow for the prediction of missing log curves and ensure better consistency across the dataset. The case study from the Paris Basin demonstrates the process of selecting the most suitable wells, followed by the application of petrophysical modeling to overcome such limitations.

2. Legacy seismic datasets and data integration.

In many geothermal projects, QI workflows rely heavily on legacy 2D seismic lines (Maurel et al., 2025). These datasets often suffer from a low signal-to-noise ratio and limited bandwidth. In some cases, they coexist with newly acquired 2D lines of higher quality, making it necessary to merge data of different vintages. The case study from the Paris Basin illustrates a methodology for integrating seismic lines from different acquisition periods into a coherent framework for QI, where seismic frequency and amplitude characteristics must be taken into account during low-frequency model (LFM) building, wavelet estimation, and well-to-seismic ties.

3. LFM construction.

Seismic data alone lack the low-frequency content necessary for absolute property prediction, requiring the construction of a LFM through well log interpolation. However, when wells are sparse or offset from the seismic lines, the resulting model may lack geological consistency. In such cases, velocity models are recommended to guide LFM construction and improve the geological realism of the model. This approach was successfully applied in the Paris Basin and Central Netherlands Basin case studies, where velocities were used to constrain the lateral trends of interpolated elastic and petrophysical properties.

4. Well-to-seismic misalignment.

In projects relying on 2D seismic, wells are often not located directly on seismic lines, leading to challenges in calibrating well data to seismic amplitudes. Direct use of such wells in inversion may introduce bias or misinterpretation. One solution is to use these wells indirectly, through rock physics–based generation of a synthetic catalogue of pseudo-wells (Downton and Hampson, 2018). This synthetic dataset can then be used to train machine learning models, enhancing the robustness of property prediction. This rock physics–based machine learning workflow is shown in Figure 2 and was successfully applied in both the Paris Basin and Central Netherlands Basin case studies.

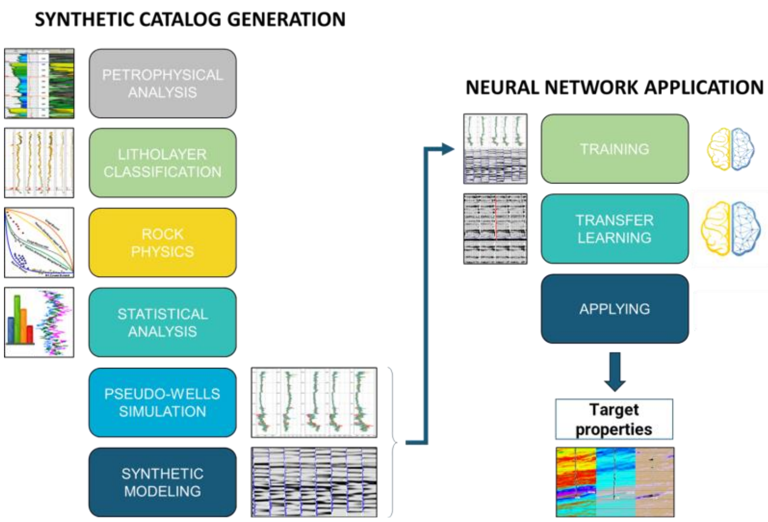

***Figure 2** Workflow for generating a synthetic well catalog and training a neural network for direct target property prediction.*

The workflow consists of two main steps: first, generating a synthetic well catalogue based on a rock physics model (RPM), and second, using this catalogue to train neural networks. The synthetic catalogue incorporates property scenarios expected in the study area, including those not encountered in existing wells. In the Paris Basin case study, the Keys-Xu RPM was used, while in the Central Netherlands Basin a modified Unconsolidated Sandstone RPM was applied.

5. Indirect property prediction from inversion results.

In most conventional QI workflows (inversion-based), reservoir properties such as porosity and permeability are predicted indirectly by first performing seismic inversion and then applying transforms to the inverted volumes. However, this two-step approach can introduce compounding errors and uncertainty, particularly when the inversion result is not sufficiently reliable.

As an alternative, the previously described rock physics–based machine learning workflow can be used for direct property prediction. In the case study from the Central Netherlands Basin, this hybrid workflow was used to predict P-impedance and porosity models, followed by permeability prediction using a porosity–permeability relationship derived from core laboratory measurements. Results for one of the seismic lines are shown in Figure 3. The results indicate strong lateral continuity of the porous reservoir layer, confirming its high geothermal potential (Siraev, 2024). Additionally, a very good match is observed at the well location.

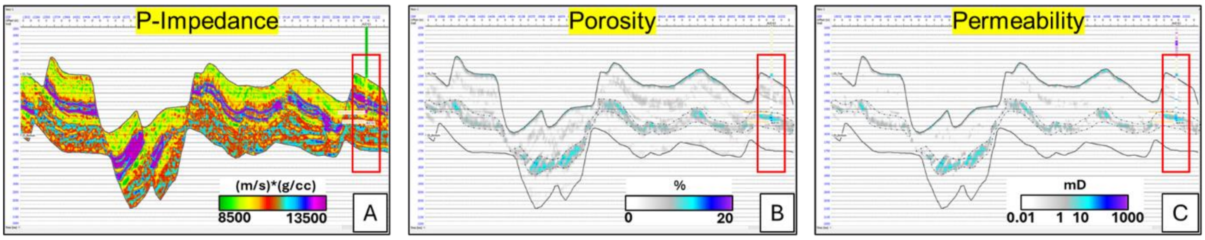

Figure 3 *Seismic line L2EBN2020ASCAN025: Prediction results. P-Impedance (A), Porosity (B), Permeability (C).*

In the Paris Basin case study, the same workflow was used to predict total porosity and clay volume models, followed by effective porosity calculation based on the relationship between total porosity and clay volume. Permeability was then estimated using a porosity–permeability relationship derived from core laboratory measurements. Results for one of the seismic lines are shown in Figure 4.

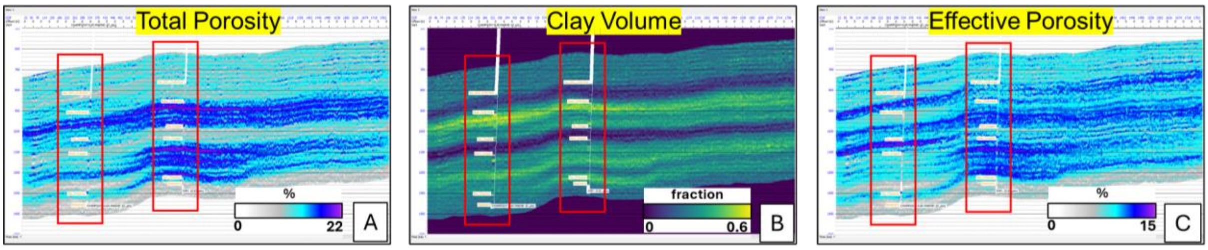

Figure 4 *Seismic line 86PIF-011: Prediction results. Total Porosity (A), Clay Volume (B), Effective Porosity (C).*

The results show good matches at the well locations and clear lateral continuity. In this case study, the objective was to evaluate three reservoir layers for their geothermal potential, and QI significantly contributed to this assessment.

6. Variable porosity-permeability trends.

Permeability is typically predicted from porosity using core measurements. In geothermal systems, however, multiple porosity–permeability relationships may exist across different reservoir intervals. Applying a single trend across the entire section may lead to inaccurate predictions. Instead, permeability estimation should respect interval-specific trends, which can be derived from detailed core–log integration. This approach allows for more accurate permeability modeling.

7. Lack of uncertainty quantification.

Deterministic inversion, while widely used in QI workflows, produces only a single realization of the subsurface and does not allow for uncertainty estimation – a critical factor in geothermal development due to high drilling costs and project risk. To address this, neural networks combined with statistical techniques such as the Jackknife method can be used to generate multiple realizations and estimate the uncertainty of predictions. This enables interpreters to better understand the range of possible outcomes and make more informed decisions.

Conclusions

The application of QI techniques in geothermal projects requires careful adaptation to the specific limitations and constraints of the available data. This paper has outlined a set of typical challenges encountered in real-world geothermal settings, including poor petrophysical data quality, legacy seismic datasets, limited well coverage, and the need for uncertainty quantification.

Through case studies from the Paris Basin and the Central Netherlands Basin, we have demonstrated practical solutions to each of these issues. These lessons learned may serve as useful guidance for practitioners working on geothermal reservoir characterization, particularly in areas with similar data conditions and project maturity. Adapted QI workflows can improve subsurface predictions and support better-informed decision-making in geothermal development.

Acknowledgements

The authors would like to thank colleagues from BRGM for their valuable contributions to the joint project on geothermal potential assessment in the Paris Basin.

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