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Integrating 4D Seismic Monitoring Images into a Dynamic Simulation Model for Sleipner CCUS History Matching and Uncertainty Analysis

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Abstract

This study introduces a novel methodology to enhance the reliability of dynamic reservoir simulation and CO₂ plume prediction through integrated use of 4D seismic (time-lapse) monitoring. The developed workflow improves history matching, quantifies uncertainties, provides leakage detection, and ensures conformance with the predicted CO₂ plume.

Introduction

The application of time-lapse (4D) seismic data for history matching of SAGD steam chambers (Hiebert et al, 2014, Tanaka et al, 2010) and CO₂ plumes in CCUS projects is well established in the literature. However, a comprehensive workflow for history matching seismic and dynamic interpretations has yet to be developed. In this study, such a workflow is introduced and conducted in Sleipner CCUS project. Seismic images, seismic conversion velocities, dynamic grids, porosity, and permeability from public data were utilized in the analysis (CO₂ DataShare).

Theory and Methods

After seismic data QC and some remedial processing, Bayesian inversion (Kolbjørnsen et al, 2020) was used to produce probability volumes for the presence of CO₂-bearing sand for each vintage separately (Figure 1 a – b). An interactive deep learning seismic interpretation tool was used with these probability volumes to delineate the geobodies defined by the CO₂ plume. Interactive deep learning methods were employed over automated AI methods to accelerate model convergence and drive latent space drift through

sequential domain adaptation; repeated transfer learning and tuning across seismic monitor vintages progressively specialized the network from a generic mixed methane - CO₂ gas representation into a semantically meaningful division with the ability to discern methane/methane + CO₂ from injected CO₂, without model reinitialization. Time to depth conversion was accomplished using the publicly-available seismic velocities. Coordinates of the plume geobody bounding surfaces were then imported into the dynamic model for comparison of relative spatial positioning of the CO₂-rich intervals.

Details of the dynamic model are explained elsewhere (Solatpour et al. 2025). In a nutshell, this numerical model was built based on a publicly available RESCUE file (CO₂ DataShare) which contained mesh grids, porosity, permeability, and well locations. Perforation locations, injection rates, temperature gradient, and pressure gradient were also provided along with this file. Relative permeabilities and water salinity were based on common values for sandstone and considered as uncertain parameters during calculations.

Importation of the seismic plume to the dynamic reservoir model was managed through use of existing microseismic data import facilities (Figure 1 c - d).

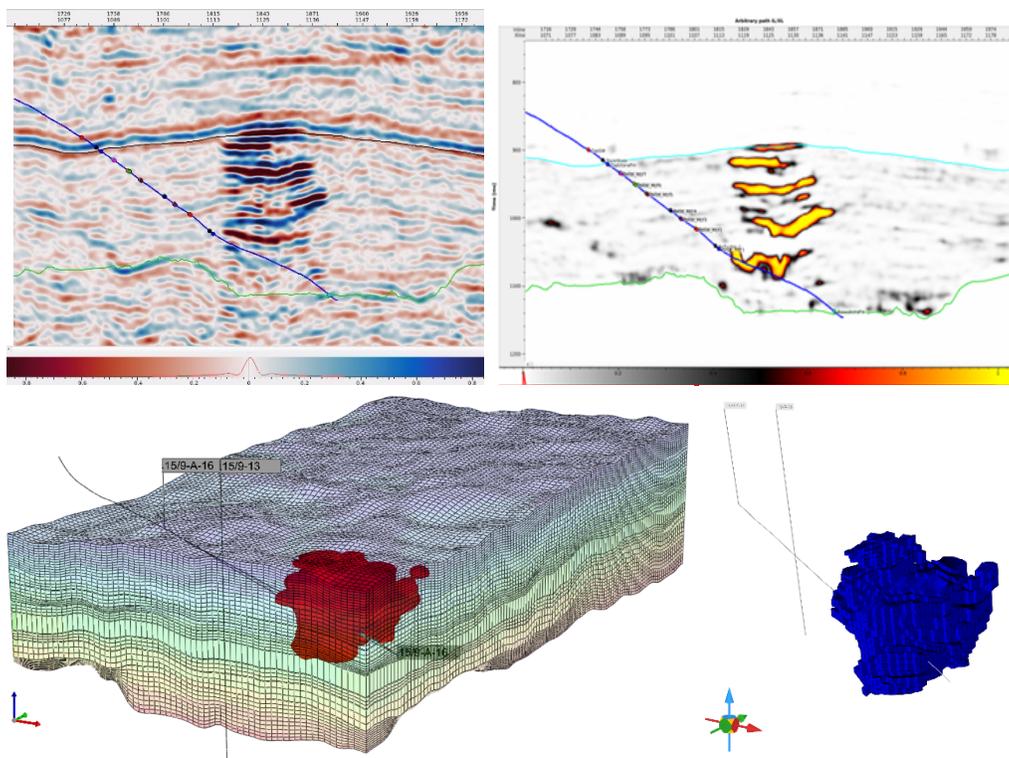


Figure 1. a) Unlabeled seismics in 1999. b) Seismic inversion results for the CO₂ sand probability in a vertical slice intersecting the injection well, shown in blue. Pre-injection zones (low but non-zero probabilities (grey patches) are indicative of noise levels in the seismic data, possibly exacerbated by residual multiples). The hot colours indicate high probability of CO₂ bearing sands. c) Visualizing year 1999 seismic data points in 3D on Grids. d) Seismic plume in 1999 displayed on mesh grids. grids are filtered to show plume only.

The associated seismic plume and dynamic simulation results were exported as a common RESQML format for automated history matching. History matching compared the gas saturation per block between seismic and dynamic simulation results. The error calculation is made using Dice coefficient which is two times the number of intersect grid cells with plume in both seismic history and simulated results divided by the sum of cells with plume in history and simulated data.

$$\text{Error} = 1 - [2 * \# \text{Intersect blocks} / (\# \text{seismic plume blocks} + \# \text{simulated plume blocks})]$$

After history match, a proxy model was trained to identify the most influential parameters governing system behavior.

Results and Discussions

To quantify the history match, the total global error, which is an average of the error for every year that has the seismic images, is calculated. The global error value for the gas saturation mismatch between the seismic-derived plume and the dynamic simulation, averaged across all available seismic images, was 0.7 (where values closer to 0 indicate a perfect match), indicating a moderate-to-high plume conformance mismatch primarily associated with differences in vertical plume distribution and lateral extent beneath shale layers. This error was then minimized by tuning the uncertain parameters in Sleipner field, which are vertical permeability of shale layers, boundary conditions, water density, relative permeabilities, hysteresis, and maximum residual gas saturation.

Based on seismic data, the plume was formed by 1999 and was identifiable in the seismic survey. With the increase in injection over time, the plume was observed to rise towards the upper layers after which it migrated aerially. The lower layers were observed to not have such lateral migrations and are stabilized in size.

The CO₂ plume at Sleipner is strongly controlled by interbedded shales. This is supported by the outcome of the seismic analysis and dynamic simulation results. The Sleipner plume has a North-South trending migratory directionality, where geological architecture of shale layers has an important role in controlling the associated paths. Vertical expansion of the CO₂ plume is mainly controlled by vertical permeability of these shale layers.

The geothermal gradient of 35 °C/km at Sleipner increases CO₂ buoyancy and reduces viscosity with depth, enhancing upward migration of the injected plume. As CO₂ rises into warmer, lower-density conditions, vertical segregation is accelerated and lateral spreading is promoted beneath low-permeability shale layers.

Conclusions

This study presents an integrated workflow that combines 4D seismic monitoring with compositional reservoir simulation to track and history match CO₂ movement over time. By translating time-lapse seismic data into probabilistic plume geometries and incorporating them into the simulation framework, the approach helps strengthen the link between geophysical interpretation and reservoir modeling for CO₂ storage applications. The workflow was successfully applied to the Sleipner CCUS project, allowing key uncertain parameters to be identified and a reliable history match to be achieved. Incorporating seismic-derived plume constraints significantly reduced uncertainty and improved confidence in predicting CO₂ plume migration. The observed plume behavior, an initial vertical rise followed by lateral spreading in the upper layers, highlights the strong influence of reservoir heterogeneity and shale layering on plume evolution.

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References

Hiebert, A., Pathak, V., Lifshits, G., Kumar, A. 2014. Evaluating the Importance of Geomechanical and Reservoir Properties When History Matching 4D Seismic Data in SAGD Wells. Paper presented at the SPE Heavy Oil Conference-Canada, Calgary, Alberta, Canada, June. SPE-170051-MS. <https://doi.org/10.2118/170051-MS>.

Tanaka, M., Endo, K., and Onozuka, S. 2010. Estimation of Steam Chamber Extent Using 4D Seismic. *J Can Pet Technol* 49: 50–55. doi: <https://doi.org/10.2118/137778-PA>

Sleipner CO2 Reference Dataset License, <https://co2datashare.org/sleipner-2019-benchmark-model/static/license.pdf>

Kolbjørnsen, O., Buland, A., Hauge, R., Røe, P. Ndingwan, A.O. and Aker, E. 2020. Bayesian Seismic Inversion for Stratigraphic Horizon, Lithology and Fluid Prediction. *Geophysics*, 85, R207-R211.

Solatpour, R., Oliveria, G., Yatte, F., Alvarez, A., Fernandes, S. 2025. CCS Plume Dynamics History Matching and Uncertainty Assessment through Integrated Numerical Simulation and 4D Seismic Interpretation. Presented at the First EAGE/ AAPG/ SEG Carbon Capture Utilisation and Storage Workshop (CCUS), Oct. European Association of Geoscientists & Engineers Volume 2025, p.1 – 3, <https://doi.org/10.3997/2214-4609.2025644042>