Feasibility of the quantitative time-lapse seismic characterisation of a heterogeneous CO₂ injection

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SUMMARY

CO₂ injection into elastic brine-saturated reservoirs leads to a detectable reduction of the elastic moduli of the reservoir rocks. However, quantitative interpretation of the time-lapse seismic anomalies obtained for CO₂ storage projects is challenging, because the injected gas can form thin plumes with low saturated narrow streaks. That is why, the time-lapse interpretation is often limited to qualitative detection of CO₂ leakages. This paper is concerned with two questions: what CO₂ plume parameters can be estimated from realistic bandlimited seismic data and how noise in the data affects the quality of the estimates. To this end we perform stochastic rock physics simulations of the injection reservoirs. The reservoir realisations differ in thickness, net-to-gross, contrast between the permeable and impermeable sediments and vertical distribution of the CO₂. The rock physics analysis suggests that maximum and integral value of the relative acoustic impedance changes are most sensitive to the parameters of the plume. The remainder of the analysis of the noise focuses on the survey repeatability and errors in the wavelet estimation. We show that both of the noise types strongly affect the accuracy of the time-lapse inversion. The proposed workflow provided rigorous means to estimate limitations of the time-lapse seismic inversion for CO₂ storage projects. It may be easily adapted to real projects and guide the monitoring system design or optimisation of data analysis workflows.

Key words: Time-lapse quantitative interpretation, inversion robustness, CO₂ monitoring

INTRODUCTION

Injection of the CO₂ reduces the stiffness of saline aquifers with good porosity. Thus, time-lapse surface seismic is an effective tool for the CO₂ sequestration monitoring. However, the interpretation of the results is often limited to visual analysis of the time-lapse anomaly, which may indicate whether the CO₂ is contained within the target reservoir. In order to calibrate reservoir models to the time-lapse data, we need to progress to quantitative interpretation: plume morphology, CO₂ saturation etc. Often, the interpretation techniques assume a homogeneous rock uniformly saturated with CO₂. Then, tuning analysis is applied to estimate the plume thickness, and sometimes, saturation. In reality, CO₂ filtration is driven by buoyancy and thus the plume tends to have multiple levels with heterogeneous distribution of the injected gas. Here, we examine the capabilities and limitations of a conventional time-lapse acoustic inversion to characterise multi-layered CO₂ plumes.

The first part of the paper focuses on stochastic rock physics modelling of the seismic effects caused by a CO₂ injection. We aim to establish relationships (in a statistical sense) between the parameters of the injection reservoir, CO₂ distribution (e.g. saturation, total thickness of the CO₂-saturated rocks) and time-lapse seismic attributes (relative change of the acoustic impedance ΔAI, root-mean square intensity of the difference seismic rBMS). The second part examines effect of the imperfections in the seismic data (limited resolution and presence of noise) on the accuracy of the quantitative interpretation.

MODELLING WORKFLOW

Our analysis is based on a typical clastic saline reservoir embedded between impermeable shales. Each reservoir model consists of interbedded brine or CO₂ bearing sands and shales. Instead of using geological and fluid flow simulation, we generate realistic heterogeneous reservoir in a stochastic manner using a 1st-order Markov chain process. This approach allows preserving physical features like gravitational fluid ordering etc. Our implementation is based on the approach of Elfeki & Dekking, 2001.

We generated models for different combinations of reservoir properties:

- Total reservoir thickness \( H_{TOT} \): 10, 15, 20m, sample interval \( dh = 0.2m \);
- Fraction of gas-bearing sands \( GTG = \frac{H_{CO2}}{H_{TOT}} \) (gas to gross) uniformly distributed in intervals: [0; 0.2), [0.2; 0.4), [0.4; 0.6), [0.6; 1]
- Rock properties:
  - \( AI_{SHALE} < AI_{CO2,SAND} < AI_{H2O,SAND} \) (Low-impedance shales)
  - \( AI_{CO2,SAND} < AI_{SHALE} < AI_{H2O,SAND} \) (High-impedance shales)
- Gas saturation \( S_{CO2} \) (fraction of pores filled with gas): from 0.1 to 1 with 0.1 interval
- Porosity: 20%

Where \( H_{CO2} \) total thickness of gas-bearing sands, \( AI_{SHALE}; AI_{CO2,SAND}; AI_{H2O,SAND} \) – acoustic impedance of shale, gas- and water-bearing sands respectively.

We generated 100 of baseline (BS) ‘dry’ models for each \( H_{TOT} \) and GTG combination resulting in 2400 models. To do so we generated facies sequence using Markov chains (Figure 5 (a, d)) which then were assigned with corresponding fine-scale parameters \( V_p, V_s, \rho \) and acoustic impedance \( AI \) (Figure 5 (b, e)). To simulate geologic variability of these properties, we added low-amplitude correlated noise to these models. We used Backus averaging to upscale the models to seismic scale.
Our aim is to find integral parameters of the reservoir that strongly affect the seismic response. It is a twofold problem because we also need to engineer the seismic attributes that are sensitive to the integral parameters of the reservoir.

- Main reservoir attributes:
  - \( H_{CO_2} \) – overall thickness of gas-saturated sands
  - \( S_{CO_2} \) – overall gas saturation
  - \( GTG = \frac{H_{CO_2}}{H_{TOT}} \) – fraction of partially gas-saturated sands
  - \( F_{CO_2} = \frac{S_{CO_2}}{H_{TOT}} \) – fraction of open reservoir pores filled with gas

- Main time-lapse seismic attributes (Figure 1):
  - \( dRMS = RMS_{MT} - RMS_{BS} \)
  - \( \Delta AI_{MAX} \) – maximum of time-lapse impedance anomaly \( \Delta AI \)
  - \( \Delta AI_{INT} = \sum_{h \in [H_{TOT}]} \Delta AI \cdot dh \) - the area under \( \Delta AI \) curve
  - \( H_{EQ} = \frac{\Delta AI_{INT}}{\Delta AI_{MAX}} \) – equivalent thickness

\[ \Delta AI \] to Gassmann-Wood boundary and wise versa. For a vertically ‘smeared’ plume, the results plot closer to the Gassmann-Hill limit.

In this study we show only attributes listed above as they are most important; however many other useful attributes may exist.

**INFLUENCE OF THE SEISMIC NOISE**

In the first section, we focused on the sensitivity of seismic data to reservoir parameters. In this section, our goal is to estimate how robust seismic inversion at reconstruction ‘true’ \( \Delta AI \) in the presence of additive noise and wavelet estimation errors. By ‘true’ \( \Delta AI \), we mean Backus averaged acoustic impedance as ‘ideal’ result of inversion analysed in the perevious section.

Inversion of noisy traces was divided into two steps: first, noise-contaminated traces were generated for BS and MT traces with the same noise level but different realisations; secondly, these traces were deconvolved with the original wavelet \( S(t) \) and integrated to \( AI_{MT} \) and \( AI_{BS} \). Their difference is \( \Delta AI \).

To simulate inversion errors, we introduce two types of noise into inverted traces: band-limited additive acquisition noise \( W_{ADD} \) and wavelet estimation errors \( W_{WAVE} \).

To determine noise-free seismic trace \( G(\omega) \) for reflection coefficients \( R_{PP}(\omega) \) and wavelet \( S(\omega) \) we use matrix propagator operator. Then, with some simplification, the resulting trace is:

\[ G(\omega) = R_{PP}(\omega) \cdot S(\omega) \]

Application of the Tikhov regularised deconvolution then converts the seismic trace into reflection coefficients. Even this relatively simple inversion process highly depends on the regularisation parameter. For each model in Figure 5, we have chosen those parameters which produce the least error (~ 5%) in comparison with the ‘true’ AI model.

\[ R_{PP}(\omega) = G(\omega) \cdot S^{-1}(\omega) \]

Acquisition noise is Gaussian noise \( V_{ADD}(\omega) \) with RMS level equal to one whose frequency band is limited to that of the wavelet spectrum \( V_{ADD}(\omega) \). This noise is scaled by \( RMS_{REF} \) to have the same level amplitudes as background reflections form similar rock types and multiplied by \( N_{ADD} \) to produce the required noise level. With this notation, SNR might be calculated as \( SNR_{ADD} = 1/N_{ADD} \)

\( RMS_{REF} \) is RMS amplitude level of traces modelled for background CO2-free rocks consisting of brine-sand and shale sequence. This parameter is different for models with high-impedance shales \( (RMS_{REF} = 0.07) \) and low-impedance shales \( (RMS_{REF} = 0.18) \) which reflects different contrast at the sand-shale boundary,

\[ W_{ADD}(\omega) = N_{ADD} \cdot RMS_{REF} \cdot V_{ADD}(\omega) \]

where \( W_{WAVE}(\omega) \) is scaled Gaussian band-limited noise with unit RMS level, \( V_{WAVE}(\omega) \). \( N_{WAVE} = \sqrt{\frac{E_s}{V_{WAVE}}} \) is the square root of spectral energy of signal \( E_s \) and noise \( E_{WAVE} \).
\[
W_{\text{WAVE}}(\omega) = N_{\text{WAVE}} : V_{\text{WAVE}}(\omega)
\]

Then we used corrupted wavelet \(S'\) and additive noise \(W_{\text{ADD}}\) to produce corrupted trace \(G'\) which is inverted to get erroneous reflection coefficients \(R_{\text{pp}}(\omega)\). Notice that for inversion we used operator \(S^{-1}\) based on noise-free wavelet for both BS and MT.

\[
S'(\omega) = S(\omega) + W_{\text{WAVE}}(\omega) \\
G'(\omega) = R_{\text{pp}}(\omega) : S'(\omega) + W_{\text{ADD}}(\omega) \\
R'_{\text{pp}}(\omega) = G'(\omega) : S^{-1}(\omega)
\]

Figure 6 shows an example of inversion with both noise levels equal to 0.1. The second model is less affected by noise because the amplitude of the anomaly is higher.

The next step is to evaluate how close \(\Delta A'\) is to \(\Delta A\). We used two metrics to measure similarity: correlation coefficient \(\rho\) and average standard deviation between \(\Delta A'\) and \(\Delta A\) scaled by \(\Delta A_{\text{MAX}} : \sigma_{\Delta A}/\Delta A_{\text{MAX}}\). These metrics were calculated in \([-5, 15]\) ms window. We varied \(N_{\text{ADD}}\) from 0 to 1 and \(N_{\text{MULT}}\) from 0 to 3 with 0.05 interval. For each \(N_{\text{ADD}}\) and \(N_{\text{MULT}}\) we calculated 150 realizations of noisy inversions.

Figure 2 and Figure 3 suggest that noise contaminated \(\Delta A\) estimation of low-saturated heterogeneous reservoir is affected by both \(N_{\text{ADD}}\) and \(N_{\text{WAVE}}\) while a homogeneous reservoir with high-amplitude response is mostly affected by wavelet estimation errors.

**CONCLUSIONS**

This synthetic feasibility study focused on the effect of vertical heterogeneity of a \(\text{CO}_2\) injection interval on the time-lapse seismic inversion of the plume parameters. Our modelling confirms that \(\text{CO}_2\) saturation cannot be reliably obtained from the seismic data, due to the abrupt drop in the rock stiffness at small \(\text{CO}_2\) saturations and the effects of layering in the plume. The morphology of the \(\text{CO}_2\) plume can be reliably mapped by the anomaly of the relative acoustic impedance change \(\Delta A\). Analysis of thousands of stochastic simulations shows that \(\Delta A_{\text{MAX}}\) and \(\Delta A_{\text{INT}}\) are most sensitive to the total thickness of gas-saturated sediments, while the total thickness of the plume (including the unaffected sediments) has large uncertainty. Both the acquisition noise and errors in the wavelet estimation have a strong effect on the time-lapse inversion for low-saturated plume, while only the wavelet repeatability matters for inversion of a thick homogeneous \(\text{CO}_2\) plume.

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Figure 2. Correlation coefficient between inverted and initial AI model in the presence of additive noise $N_{\text{ADD}}$ and wavelet estimation errors $N_{\text{MULT}}$. Letters A and B corresponds to models in Figure 5. Purple line is intersection of surface with correlation coefficient = 0.85. Gaussian averaging was applied to image.

Figure 3. Scaled average deviation of inverted AI in presence of additive noise $N_{\text{ADD}}$ and wavelet estimation errors $N_{\text{MULT}}$. Letters A and B corresponds to models in Figure 5. Purple line is intersection of surface with correlation coefficient = 0.85. Gaussian averaging was applied to image.
Feasibility of the quantitative TL seismic characterisation for CO₂ injection

Isaenkov, Glubokovskikh and Gurevich

Figure 4. Dependence of maximum ∆AI on the amount of gas saturation. Abbreviations ‘GW’ and ‘GH’ points on ∆AI predicted from Gassmann-Wood and Gassmann-Hill saturation models. Colour – GTG (fraction of gas-saturated sands in reservoir). Magenta arrows show direction of $S_{CO2}$ increasing, red arrows show direction of GTG increasing. Yellow and red circles point the position of models A and B from the previous figure. Notice that some data points falls out of GW-GH boundary which is caused by presence of correlated geological noise.

Figure 5. Examples of reservoir models for GTG = 0.3 (a - c) and 0.8 (d - f). (a) and (d) columns show lithology, (b) and (e) - acoustic impedance and (c) and (f) - 1D seismic response. Next abbreviations in legend stand for BS – Baseline, MT - monitor and TL – time-lapse traces. Notice that time-lapse acoustic impedance trace is shifted so its zero-value aligns with background shale impedance. Also, that for BS brine and gas saturated sand have the same properties. Letters A and B refer to these models at other figures.
Figure 6. Inversion ability to recover initial $AI$ model in the presence of additive noise and wavelet estimation errors. Left column demonstrates inversion for noise-free, additive only and both type of noise. Right column show inversion results spread for 1000 realisation of additive noise and wavelet errors. Notice that y-axis is scaled to $\Delta AI_{MAX}$. Letters A and B corresponds to models in Figure 5.