Bayesian Joint Seismic-CSEM Inversion: Application to CO_2 Storage Monitoring and Leakage Detection

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Summary

We propose a novel Bayesian framework that integrates joint seismic full waveform inversion (FWI) and controlled-source electromagnetic (CSEM) data inversion with rock-physics information, such as fluid saturation, to reconstruct the geometry and saturation levels of CO_2 plumes, including potential leakage, while providing uncertainty quantification. We apply our method to a simplified realistic synthetic model of the Johansen formation in the North Sea. Given the well-known geometry of the reservoirs, we can perform sparse parameterization and make stochastic methods such as Markov chain Monte Carlo (MCMC) feasible. Our results demonstrate accurate estimations of both the CO_2 plume geometry and saturation levels, highlighting the framework's effectiveness in subsurface CO_2 storage monitoring and leakage detection.

Introduction

Seismic data inversion is the primary tool for CO_2 storage monitoring because of its high sensitivity to subsurface velocity changes. However, its effectiveness can be limited when used alone. With a small amount of injected CO_2, there is a drastic change in the velocity (Figure 1), but as the injection continues and the CO_2 saturation exceeds 15%, the velocity changes become negligible. This behavior makes seismic data highly effective for detecting the boundary of CO_2 plumes but less useful for accurately assessing saturation levels. On the other hand, electromagnetic data are not sensitive to small amounts of CO_2 injection, but are responsive once CO_2 saturation exceeds 60% (Figure 1). By combining seismic and electromagnetic datasets, we can effectively study CO_2 plume geometry, evaluate the potential leakage, and estimate saturation levels throughout the reservoir (Gasperikova et al., 2022; Dupuy et al., 2021; Liu et al., 2023; Dupuy et al., 2019; Eliasson et al., 2014).

In this study, we present a novel Markov chain Monte Carlo (MCMC)-based approach based on joint seismic full waveform inversion (FWI) and controlled source electromagnetic (CSEM) data inversion coupled with rock-physics information such as saturation to efficiently reconstruct the geometry and saturation of a CO_2 plume and a potential leakage scenario while quantifying the uncertainty in these estimates. The method is applied to a realistic synthetic model representative of the Johansen formation in the North Sea, an ideal candidate for CO_2 sequestration (Gassnova, 2012). Using the well-defined structure of the reservoir, we track the horizontal migration of CO_2 assuming that the plume remains trapped within the reservoir due to an impermeable caprock. However, leakage may occur through the injecting well. Due to the dip of the reservoir, the injected supercritical CO_2 is expected to migrate laterally, primarily to the west, driven by buoyancy as the lighter CO_2 rises and spreads horizontally within the reservoir until it reaches a seal, such as a sealing fault (Figure 3). To simplify the problem, we assume that only the east boundaries of both the main and the leakage plumes need to be constrained, which reduces the dimensionality of the model. This assumption helps to minimize the computational costs typically associated with MCMC inversion techniques and formulates the problem as a more tractable problem.

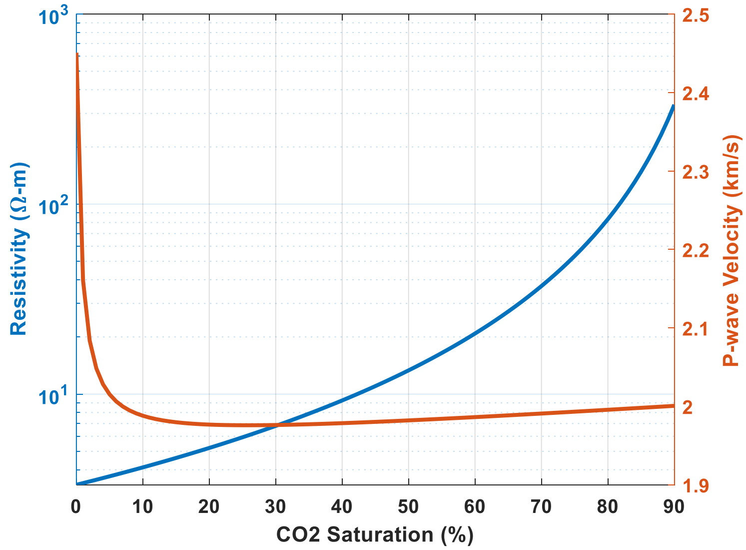

Figure 1. Reservoir velocity and resistivity as a function of CO_2 saturation calculated based on Equations 3-4 for a reservoir with 30% porosity and specifications given in Table 1.

Method

Due to the existing measurement uncertainties in subsurface properties and the inherent non-uniqueness of geophysical data, stochastic inversion is important for uncertainty quantification in CO_2 storage monitoring. Mosegaard and Tarantola (1995) describe how Bayesian inversion updates the prior knowledge ($p(\boldsymbol{x})$) with the observed data ($\boldsymbol{y}$) to obtain the posterior probability density ($p(\boldsymbol{x}|\boldsymbol{y})$) of the model parameters ($\boldsymbol{x}$). Tarantola (2005) introduces the use of the product of likelihood functions $p(\boldsymbol{y}|\boldsymbol{x})$ for joint inversion, where multiple datasets are integrated to improve model accuracy as

$$p(\boldsymbol{x}|(\boldsymbol{y_1},\boldsymbol{y_2})) \propto p(\boldsymbol{y_1}\,|\,\boldsymbol{x})p(\boldsymbol{y_2}\,|\,\boldsymbol{x})p(\boldsymbol{x}) \propto \frac{\gamma}{(2\pi\sigma_1)^{\frac{N_1}{2}}(2\pi\sigma_2)^{\frac{N_2}{2}}} exp^{\left(-\frac{1}{2N_1w_1}\frac{r_1{}^Tr_1}{\sigma_1{}^2}-\frac{1}{2N_2w_2}\frac{r_2{}^Tr_2}{\sigma_2{}^2}\right)} p(\boldsymbol{x}), \qquad (1)$$

where $r = \boldsymbol{y} - A(\boldsymbol{x})$, $A(\boldsymbol{x})$ is the forward modeling operator, σ^2 is the variance of the noise, and superscript T represents the transpose. To balance the influence of different datasets in the joint inversion, we normalize the likelihood by the number of observed data (N_1, N_2) and weighting factors (w_1, w_2).

Each proposed model goes through a Metropolis-Hastings sampler, and we use the following acceptance criteria to decide whether to accept or reject a proposal candidate ($\boldsymbol{x}'$)

$$\alpha = \min\left(1, \frac{p(\boldsymbol{y_1}|\boldsymbol{x}')p(\boldsymbol{y_2}|\boldsymbol{x}')}{p(\boldsymbol{y_1}|\boldsymbol{x})p(\boldsymbol{y_2}|\boldsymbol{x})}\right). \qquad (2)$$

This algorithm allows the exploration of high-probability regions but sometimes accepts lower-probability candidates. To control the acceptance rate, we introduce another temperature parameter (γ), which changes the probability that we accept lower-probability states.
We integrate seismic and EM data through the water saturation coupling term. We use Archie's equation (Archie, 1942)

$$\rho = a\rho_b \emptyset^{-m} S_w^{-n}, \tag{3}$$

and Gassmann's equation (Gassmann, 1951)

$$V_P = \sqrt{K_{dry} + \left(1 - \frac{K_{dry}}{K_{ma}}\right)^2 \left(\emptyset\left(\frac{S_w}{K_w} + \frac{S_g}{K_g}\right) + \frac{1-\emptyset}{K_{ma}} - \frac{K_{dry}}{{K_{ma}}^2}\right)^{-1} \left((1-\emptyset)\rho_{ma} + \emptyset\left(S_w\rho_w + S_g\rho_g\right)\right)^{-1}}, \tag{4}$$

to relate the formation's saturation to resistivity (ρ) and velocity (V_P), respectively. Here a is the tortuosity factor, ρ_b is the brine resistivity, n is the saturation exponent, m is the porosity/cementation exponent, and $\emptyset$ is the porosity. The term $K_{dry} = 1 - \frac{\emptyset}{\emptyset_c} K_{ma}$ represents the dry rock bulk modulus, where $\emptyset_c$ is the critical porosity (40%) and K_{ma} is the matrix bulk modulus. Additionally, S_w and S_g are the water and gas saturation, respectively, while ρ_w and ρ_g are the water and gas density, respectively. The brine and gas bulk moduli are K_w and K_g, respectively.

Results and Discussion

Johansen Formation: Comprehensive seismic studies and geological modeling show suitable reservoir characteristics for the Johansen formation, with a depth range of 2000 m to 3000 m below mean sea level and effective caprock seals (Aker et al., 2021; Jackson et al., 2022; Sundal and Hellevang, 2019). These specifications make the Johanson formation a good candidate for permanent CO_2 storage.

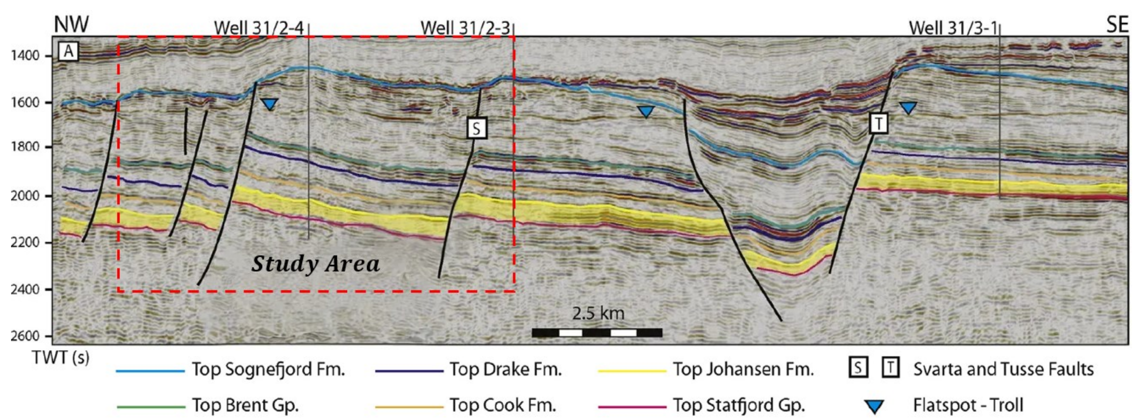

Figure 2. A seismic composite line from 3D volume GN10M1 adapted from Sundal et al. (2016). The study area is shown by a red dashed line.

The Johansen formation, located in the northern North Sea, under a 300-350 m water layer, is the target reservoir for injection in the Northern Lights CO_2 capture and storage project (Jackson et al., 2022). The reservoir has an average thickness of 75 m to 100 m with a high porosity, ranging from 20% to 30%, and an average permeability of 300 mD. In this study, the Johansen and Cook formations are the primary targets for CO_2 injections, with the Brent Group being considered a potential unit for capturing any leaked CO_2 through the injecting well (Figure 2).

Full Waveform Seismic Forward Modeling: We model seismic data using an isotropic acoustic finite difference approach in the time domain, with a 10m-by-10m grid resolution. The source wavelet is a Ricker wavelet with a peak frequency of 15 Hz. The seismic velocity in the reservoir is derived from Gassmann's equation, which translates saturation into velocity for a homogeneous reservoir with a constant 30% porosity.

Table 1. The parameters used in joint seismic and CSEM simulation.

K_{ma}	32 GPa	a	1
K_w	2.81 GPa	n	2
K_g	0.016 GPa	m	2
ρ_{ma}	2560 kg/m^3	ρ_b	0.3 Ωm
ρ_w	1050 kg/m^3	main CO_2 plume resistivity	148 Ωm
ρ_g	680 kg/m^3	leaked CO_2 plume resistivity	100 Ωm
Johansen-Cook formation resistivity	0.6 Ωm	Troll field resistivity	50 Ωm
Drake formation resistivity	3 Ωm	Statfjord group resistivity	3 Ωm
background resistivity	1 Ωm	Brent group resistivity	1 Ωm

Using seismic inversion results and well logs from Gassnova (2012), we assign a constant velocity for the remaining layers of the subsurface model. The velocity for the water layer is 1.45 km/s, and the derived velocity model is shown in Figure 3. For values used in the simulation please refer to Table 1.

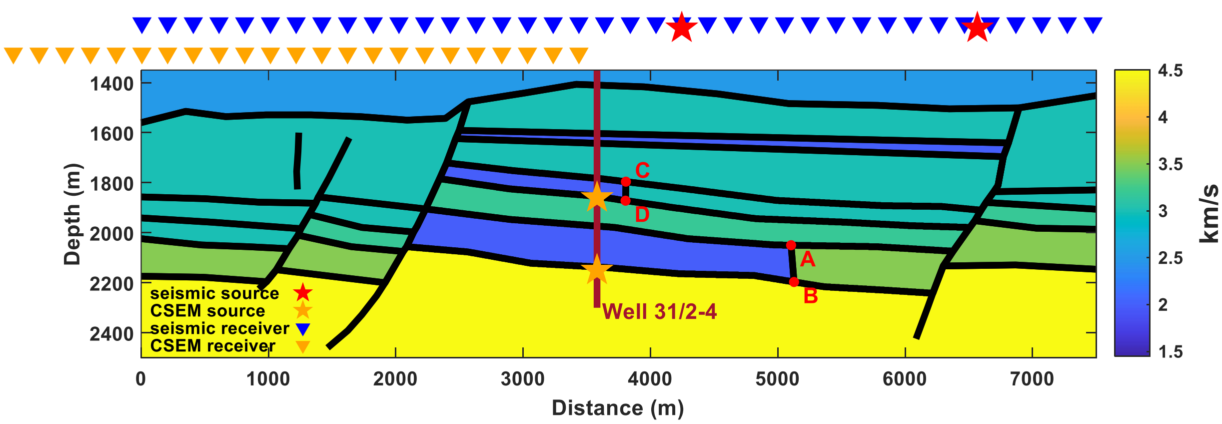

Figure 3. The velocity distribution of the study area (Figure 2). Points A to D indicate the boundary location of the main and leaked CO_2 plume, injected from well 31/2-4.

We locate two seismic sources at depths of 10 m, and horizontal distances of 4.2 km and 6.5 km (Figure 3). Receivers are placed at 100 m intervals along the sea surface. To simulate realistic conditions, we add 5% Gaussian noise to the observed data.

CSEM Forward Modeling: To address the challenge of insufficient response in conventional CSEM data acquisition from target reservoirs due to the presence of multiple resistive layers, we propose an alternative acquisition geometry. Instead of placing the electric dipole sources in the water, we position two vertical electric dipole sources with a frequency of 1 Hz a few metres below the bottom of each of the reservoirs (Figure 3). Receivers are placed every 100 m along the seabed. Putting sources at the bottom of the reservoir rather than the top, results in a greater contrast in the response after injection compared to the background, as the receivers are located at the seabed. For CSEM forward modeling, we use the MARE2DEM package (Key, 2016), and for the values used in modeling, please refer to Table 1. We added 5% Gaussian noise to the data (Figure 4).

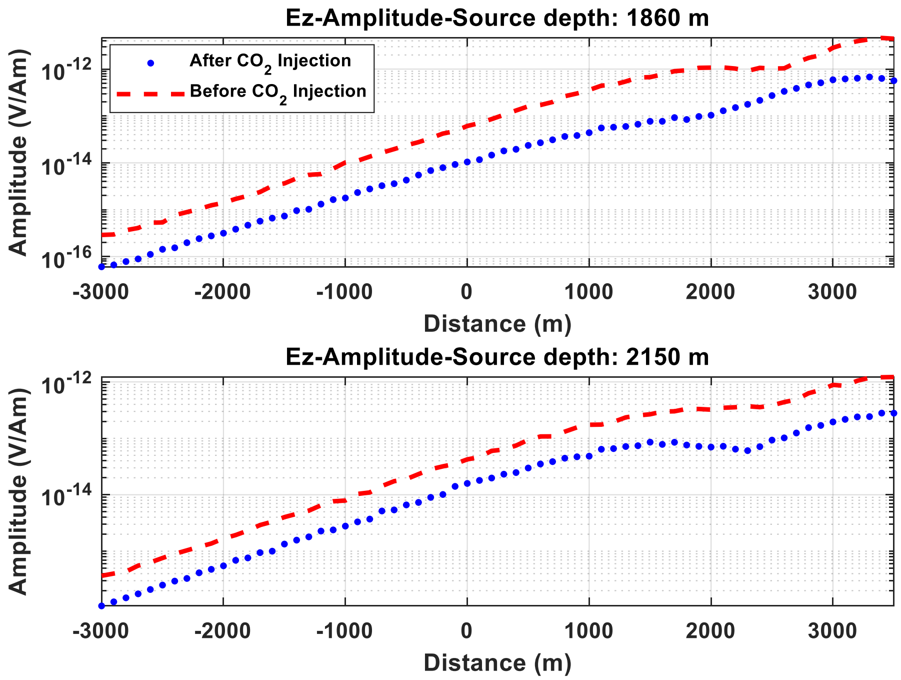

Figure 4. The calculated CSEM responses for the reservoir before injection, when fully saturated with brine (represented by a red dashed line), and after injection, when saturated with CO_2 (shown by blue dots).

Joint Inversion: In this study, we have six unknowns, four of which relate to the geometry of the CO_2 plumes (A to D, in Figure 3), and two of which relate to the saturation values. At each iteration, we update each of these unknowns by randomly selecting their values from a uniform distribution with a standard deviation of 50 m for positions and a 0.01 Ωm for resistivity. We then generate velocity and resistivity models and calculate the corresponding seismic and electromagnetic responses. The temperature changes during the simulation to maintain an acceptance rate between 15% and 20% (Gelman et al., 1996). The result of the inversion is shown in Figure 5.

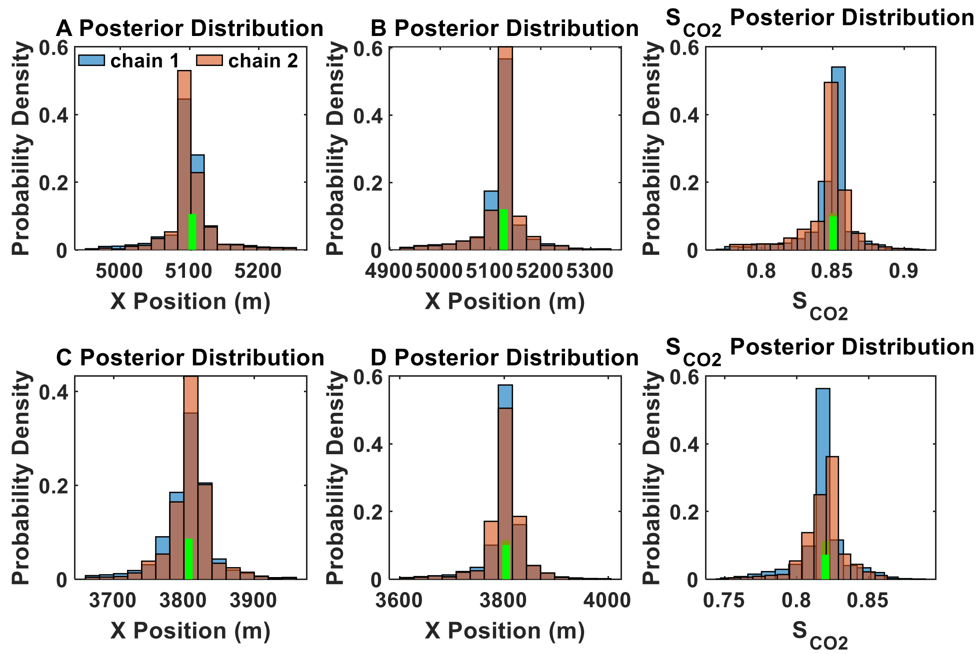

Figure 5. The result of the joint seismic-CSEM inversion for two different chains, each with 10,000 iterations and illustrated with a different color. The figures on top are the constrained parameters for the main CO_2 plume, and the figures on the bottom are for the CO_2 leakage plume. For the location of A to D, see Figure 3. The green line indicates the true value.

We use the Gelman-Rubin diagnostic R-value (Gelman and Rubin, 1992) to investigate the quality of convergence for two different chains, each with 10,000 iterations. The R-values of A to D are 1.0052, 1.0059, 1, 1, respectively, and the R-values of saturations are both 1.0002.

Conclusions

In this study, we present a novel Bayesian framework that integrates seismic FWI with CSEM data inversion, incorporating rock-physics information such as fluid saturation for the CO2 plume and leakage monitoring. Our approach is applied to a realistic synthetic model based on the Johansen formation in the North Sea, using a simplified reservoir model. Considering the well-defined geometry of the reservoir, we reduced significantly the number of parameters of the model, making a sampling approach like MCMC feasible. We successfully reconstructed both the primary CO2 plume and potential leakage, including their geometry and saturation levels, as well as the associated uncertainties.

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