

Feasibility of crosswell electrical resistivity tomography for monitoring hydrogen storage in the saline sandstone aquifer at the Devine test site, Texas

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SUMMARY

We study the feasibility of cross-borehole Electrical Resistivity Tomography (ERT) as a monitoring tool for geological hydrogen storage in a shallow saline sandstone aquifer (~500 m depth) representative of the Devine Test Site, Texas. Through reservoir-driven simulations combined with forward modeling and inversion, we assess how hydrogen injection alters bulk resistivity and how reliably those changes can be recovered over time. The results show that hydrogen-induced resistivity variations are both measurable and reconstructible from early injection to long-term post-injection stages, with resistivity exhibiting substantially greater sensitivity than compressional velocity. The inverted saturation distributions closely track the simulated plume evolution, and stability tests indicate that the method remains reliable under moderate noise levels representative of field conditions.

INTRODUCTION

Hydrogen is emerging as a promising carrier for the transition toward a clean, renewable-based energy system (Akpasi et al., 2025). Large-scale subsurface hydrogen storage in porous reservoirs offers a practical pathway for seasonal energy balancing, however its storage and transportation pose significant challenges due to its high buoyancy, high diffusivity, and potential for leakage. Ensuring the safety and effectiveness of underground hydrogen storage is critical (Miocic et al., 2023).

Geophysical methods are increasingly being used to monitor the long-term fate of subsurface hydrogen plumes (Zhang and Li, 2024). Seismic methods are widely used for time-lapse reservoir monitoring, but their sensitivity to gas saturation changes diminishes at moderate to high gas saturation. Additionally, Electrical Resistivity Tomography (ERT) is a minimally invasive method to monitor localized changes in pore-fluid conductivity. Replacement of conductive brine by resistive hydrogen gas produces strong resistivity contrasts, suggesting that ERT may provide enhanced sensitivity for tracking gas migration and serve as a powerful complement to traditional seismic techniques. ERT has been successfully applied for monitoring CO_2 storage (Schmidt-Hattenberger et al., 2011; Breen et al., 2012; Carrigan et al., 2013), but its feasibility for hydrogen storage monitoring remains less explored.

In this study, we evaluate the feasibility of cross-borehole ERT for time-lapse monitoring of hydrogen injection at the Devine Hydrogen Test Site, Texas Bakulin et al. (2025b). Using synthetic reservoir simulations integrated with multi-physics forward modeling and inversion, we quantify the relative sensitivity of electrical resistivity and seismic velocity to hydrogen saturation changes and assess the resolution limits under real-

istic acquisition geometries and noise conditions.

METHODOLOGY

We employ a synthetic forward modeling and inversion workflow built upon dynamic reservoir simulations of H_2 injection for the Devine Hydrogen Test Site, Texas. The reservoir simulation models with H_2 saturation are converted to resistivity models using Archie's law (Archie, 1947; Archie et al., 2003) given by the equation:

$$\rho_{bulk} = \alpha R_w \phi^{-m} S_w^{-n} \quad (1)$$

where ρ_{bulk} is the bulk resistivity, α is the tortuosity factor, R_w is the water resistivity, ϕ is the porosity, S_w is the water saturation, m is the cementation exponent, and n is the saturation exponent. For this study we use the following values: $\alpha = 1$, $m = 2$, $n = 2$, $\phi = 30\%$, and $R_w = 0.215\Omega m$.

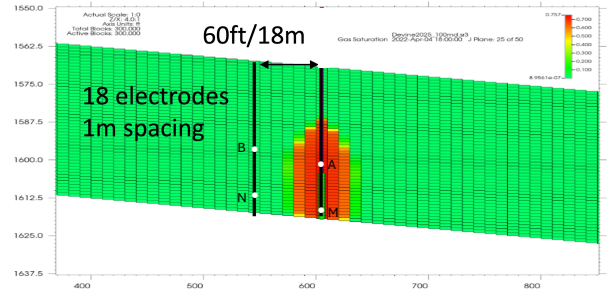


Figure 1: Schematic of the synthetic setup featuring two wells spaced 18m (60ft) apart, each equipped with 18 electrodes at 1m spacing. Reservoir simulation model in the background.

The experimental configuration consists of a cross-borehole environment featuring two wells: one at the injection well and the other at the monitoring well, separated by 18m (60ft). Each well is instrumented with an array of 18 electrodes deployed at a 1m spacing, resulting in a total depth aperture of 18m (60ft) per well, as illustrated in Figure 1. This gives the horizontal to vertical ratio of 1:1, which will allow us to study the maximum allowable noise level for robust inversion using a shorter acquisition aperture. For the data acquisition simulation, we employ a bipole-bipole electrode array in a cross-well configuration. Electrodes A and M are located in the injection well, while electrodes B and N are located in the monitoring well. Current is injected through the A-B electrode pair, and the resulting potential difference is measured between electrodes M and N. This AM-BN configuration was selected to enhance sampling of the resistivity distribution in the interwell region. To accurately map the temporal evolution of the gas plume, forward modeling and subsequent resistivity inversions were

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performed at a series of time steps spanning 1 day to 11 years post-injection.

Before we proceed with ERT inversion, we compared the electrical resistivity response with the seismic velocity response. The seismic response we consider is in a crosswell setting to make the comparison meaningful. Figure 2 shows a comparison of the seismic and electrical resistivity responses. The seismic velocity response is calculated using Gassmann's fluid substitution equation (Gassmann et al., 1951; Bakulin et al., 2025b).

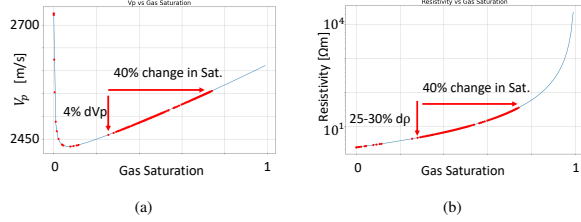


Figure 2: Comparison of seismic velocity and electrical resistivity responses to changes in H_2 saturation. For a 40% increase in H_2 saturation, seismic velocity changes by only $\sim 4\%$, whereas electrical resistivity changes by approximately 25–30%. Red dots show the actual saturation points sampled from the reservoir simulation at different time steps.

We consider a single point in the subsurface and how the seismic velocity and electrical resistivity change with saturation. We consider a constant porosity of 30% and H_2 saturation ranging from 0% to 100%, shown as the solid blue line. We also computed the responses from the reservoir simulation model at a given point for all time steps, plotting them as red dots. The elastic parameters we used are consistent with the site geology as used in Bakulin et al. (2025a,b). The comparative sensitivity analysis highlights a significant operational advantage of electrical resistivity over seismic velocity for long-term monitoring. While seismic methods exhibit a substantial initial change during active H_2 injection, the velocity (V_p) response severely diminishes during the post-injection phase (Figure 2a). In contrast, Figure 2b shows that electrical resistivity exhibits an eventual and exponential change with increasing gas saturation. For a 40% change in H_2 saturation, from 25% to 65%, the seismic velocity changes by only 4%, whereas for the same change in H_2 saturation, the electrical resistivity changes by 25–30%. This shows that the electrical resistivity is more sensitive to changes in H_2 saturation than the seismic velocity.

Forward modeling and inversion were performed for multiple time steps spanning 1 day to 11 years post-injection. Synthetic apparent resistivity data were generated and inverted using a finite-element-based inversion workflow (ZondRes2D). Time-lapse inversion performance was evaluated at both injection and monitoring at 30ft. Noise robustness was assessed by introducing realistic cross-borehole noise levels to evaluate operational feasibility.

Noise Robustness

To represent realistic measurement noise, we perturb the mea-

sured apparent resistivity data d_i with a random noise term ε_i whose standard deviation σ_i follows the model:

$$\tilde{d}_i = d_i + \varepsilon_i \quad (2)$$

where ε_i is a random noise with a standard deviation of σ_i .

$$\sigma_i^2 = (p|d_i|)^2 + \sigma_0^2 \quad (3)$$

The first term represents multiplicative noise proportional to the signal magnitude, controlled by parameter p , and therefore affects all measurements, including the smallest electrode offsets where signal amplitudes are largest. The second term σ_0^2 represents additive background noise independent of signal magnitude and becomes most significant for weak signals, typically associated with larger electrode separations. To evaluate inversion stability, we test different noise scenarios by fixing one parameter while varying the other.

RESULTS AND DISCUSSION

The inversion results with noise-free data spanning from 1 day to 11 years are shown in Figure 3b, with the corresponding true resistivity profiles shown in Figure 3a. The results demonstrate that the changes are well captured, and the inverted resistivity profiles closely track the true modeled resistivity variations associated with the migration of the hydrogen plume. When converted back to saturation using Archie's relationship, the inverted resistivity models yield hydrogen saturation profiles that closely match the reservoir simulation results. Figure 4 illustrates this agreement, confirming the accuracy of the inverted saturation profiles at the injection well (Figure 4a) and monitoring well at 30ft (Figure 4b) over time. This comparison assumes perfectly known Archie parameters and, therefore, ideal rock-physics conditions; under these assumptions, resistivity inversion errors do not significantly propagate into saturation estimation.

We assess the noise robustness by introducing different levels of noise that can be tolerated by the inversion. Figure 5 shows how the noise affects the recorded data. The blue dots in both panels represent the noise-free recordings, and the orange dots are the perturbed recordings. The left panels show the data perturbation for $p=0.5$ and $\sigma_0^2=0$. The right panels show the data perturbation for $p=0$ and $\sigma_0^2=0.1$.

Figure 6 shows the inverted saturation profiles for different levels of multiplicative noise controlled by parameter p in Eq. 3, with $\sigma_0^2 = 0$. In this case, the noise is proportional to the signal magnitude and represents measurement-related noise. Figure 7 shows the inverted saturation profiles for different levels of additive background noise by varying σ_0^2 in Eq. 3, with $p = 0$. The results indicate that the inversion remains stable up to approximately $p = 0.1$ and $\sigma_0^2 = 0.01$, beyond which the recovered saturation profiles degrade significantly.

To quantify the degradation of the inversion results with increasing noise, we compute several diagnostic metrics. First, we estimate the RMS error between the true and inverted saturation profiles, expressed as the absolute saturation difference in percentage units (not normalized). Second, we compute the

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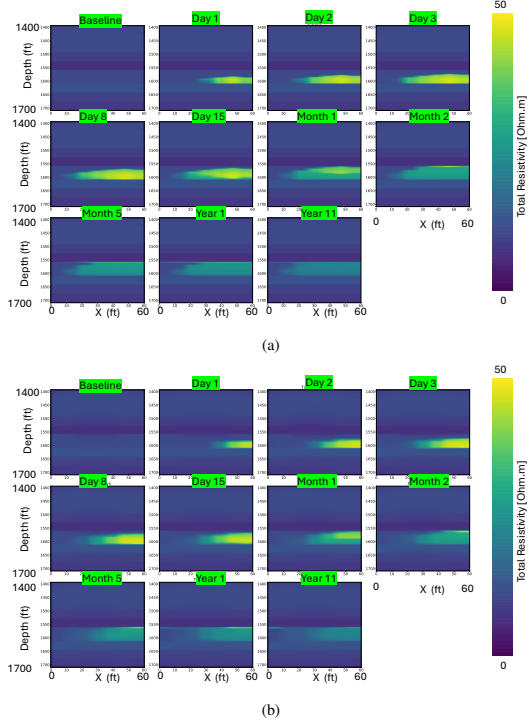


Figure 3: Comparison of the 2D true (a) and inverted (b) resistivity models using noise-free synthetic data corresponding to different time periods. The inverted resistivity closely matches the true resistivity, tracking the migration of the hydrogen plume.

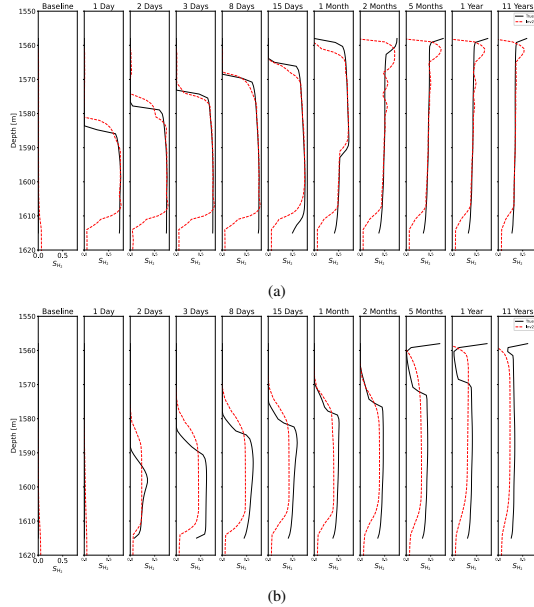


Figure 4: Comparison of the inverted and true saturation profiles at injection (a) well and monitoring (b) well at 30ft for different time periods. The inverted saturation profiles closely match the true saturation profiles at the injection and monitoring wells.

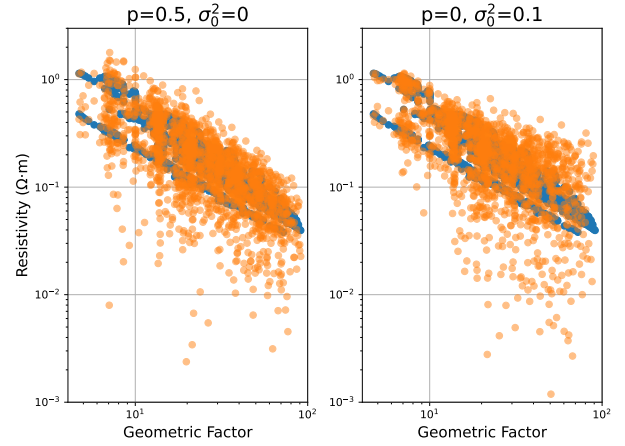


Figure 5: Effect of the two noise components on the recorded data. Blue dots denote noise-free data and orange dots the perturbed recordings. Left: multiplicative noise ($p = 0.5$, $\sigma_0^2 = 0$) spreads the data proportionally across all offsets. Right: additive background noise ($p = 0$, $\sigma_0^2 = 0.1$) mainly affects weak signals at large geometric factors.

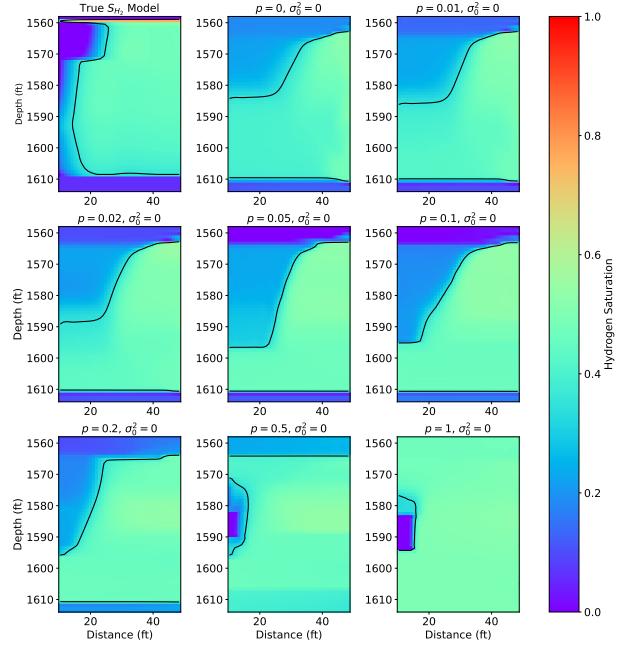


Figure 6: Comparison of the true and inverted saturation models with different levels of noise by only changing p in Eq. 3. The solid black line represents the plume boundary estimated from the models by thresholding the saturation values above 35%. The parameter p is varied from 0 representing no noise to 1 representing maximum noise level due to the measurement equipment. The results show that the inversion is robust up to $p=0.1$ and beyond that the results are significantly degraded.

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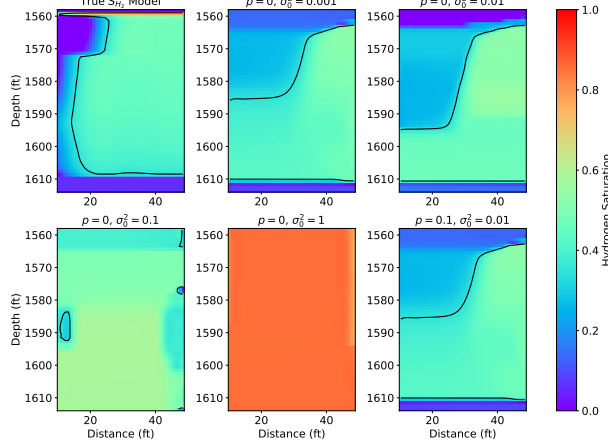


Figure 7: Comparison of the true and inverted saturation models with different levels of noise by only changing σ_0^2 in Eq. 3. The value of parameter σ_0^2 is varied from 0.001, representing low ambient noise, to 1, representing the maximum noise level. This shows that σ_0^2 greater than 0.01 significantly degrades the inversion results. The last panel shows the inversion results for $p=0.1$ and $\sigma_0^2=0.01$, the combination of both noises at the acceptable level.

Pearson correlation coefficient between the true and inverted saturation profiles, which measures structural similarity and ranges from -1 to 1 . Finally, we compute the mean hydrogen saturation over the entire model domain, representing the average H_2 volume fraction across all cells and providing a simple mass-balance check. The resulting values are summarized in Table 1.

Table 1: Diagnostic metrics for the inverted saturation models with different levels of noise.

P	σ_0^2 (Ωm) ²	RMS Error (%)	Pearson Correlation Coefficient	Mean Saturation (%)
0	0	13.7	0.58	33.3
0.01	0	14.8	0.51	33.4
0.05	0	17.5	0.36	33.1
0.1	0	17.6	0.34	33.1
0.5	0	16.6	0.31	41.3
1	0	21.17	-0.34	47.6
0	0.001	15.1	0.5	35.2
0	0.01	17.9	0.32	36.0
0	0.1	24.4	-0.12	51.2
0	1	53.0	-0.56	85.3
0.1	0.01	15.1	0.5	35.2

The results summarized in Table 1 indicate that the inversion remains robust for noise levels up to approximately $p < 0.1$ and $\sigma_0^2 < 0.01$. Under these conditions, the Pearson correlation between the true and inverted saturation profiles remains high, the RMS saturation error stays relatively small, and the mean saturation remains close to the true domain-average value

of 34.9%.

In Figures 6 and 7, plume boundaries are indicated by black solid lines obtained by thresholding the true saturation above 35%. At low noise levels, the inversion preserves the plume geometry reasonably well, whereas higher noise levels lead to significant degradation in the recovered plume boundaries.

CONCLUSIONS

We have demonstrated the technical feasibility and quantitative sensitivity advantages of cross-borehole Electrical Resistivity Tomography (ERT) for time-lapse monitoring of geological hydrogen storage. Using dynamic reservoir simulations integrated with forward modeling and inversion, we show that hydrogen injection produces measurable and recoverable resistivity changes from early injection (Day 1) through long-term post-injection conditions (up to 11 years). A representative 40% increase in hydrogen saturation results in a 25–30% change in bulk resistivity, compared to only $\sim 4\%$ change in compressional velocity, highlighting the stronger long-term sensitivity of electrical methods relative to seismic velocity, particularly during the post-injection phase when seismic response diminishes.

Time-lapse inversion successfully reconstructs plume evolution under realistic acquisition geometry, and saturation estimates derived from inverted resistivity models closely match the reservoir simulations at both injection and monitoring wells. Noise analysis indicates that the inversion remains stable for multiplicative noise levels up to approximately 10% ($p < 0.1$) and additive background noise up to $\sigma_0^2 < 0.01$, corresponding to roughly one-fifth of the smallest ~ 10 th-percentile signal amplitudes in the dataset. Beyond these levels, plume recovery degrades significantly. These results suggest highlight that ERT is not merely feasible but practically informative for monitoring hydrogen migration and containment in the shallow saline aquifers. The joint seismic and electrical monitoring could significantly improve plume tracking, combining seismic structural imaging with ERT sensitivity to saturation. Overall, cross-borehole ERT emerges as a robust, time-resolved, and operationally viable monitoring approach that complements seismic methods and is well suited for tracking the long-term evolution and containment of subsurface hydrogen plumes.

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