

# **AN INTEGRATED CO<sub>2</sub> MONITORING SYSTEM: FIRST INVERSION RESULTS**

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## **ABSTRACT**

History-matching through inverse modeling of pressure monitoring data delivers a first-order approximation of a reservoir model at an industrial-scale CO<sub>2</sub> injection site. The reservoir model forms the backbone of an integrated monitoring system (IMS) for subsurface CO<sub>2</sub> storage, which will ultimately encompass the integrated analysis of pressure-temperature and geophysical seismic monitoring data. First inversion results confirm the existence of a hydraulically isolating thin layer in the lower injection interval, known as mudstone baffle.

## **INTRODUCTION**

Archer Daniels Midland Company's (ADM) world-scale agricultural processing and bio-fuels production complex located in Decatur, Illinois, is the site for two large-scale carbon capture and storage projects. The former Illinois Basin-Decatur Project (IBDP) has already validated the Illinois Basin's capacity to permanently store CO<sub>2</sub> (Finley, 2014). The current Illinois Industrial Carbon Capture and Storage Project (ICCS) is an industrial-scale project demonstrating the carbon capture and store (CCS) technology. The operation goal is to inject and store over 1,000,000 metric tons of CO<sub>2</sub> per year into a deep saline geologic formation, known as the Mount Simon Sandstone.

One primary objective of the ICCS project is the development of an integrated monitoring system (IMS), essentially a control system that delivers critical information for process surveillance that is specific to geologic storage projects. The data input for the IMS is provided by a permanently installed seismic infrastructure with multi-level 3D arrays and distributed acoustic sensing (Daley et al., 2013), in combination with real-time reservoir flow data.

An essential component of the IMS is a reservoir model capable of (1) adequately simulating the injection process, (2) accurately predicting pressure responses in monitoring zones, and (3) coupling to a seismic modeling framework. The latter will ensure that reservoir properties and their fluid-induced alterations are properly mapped to seismic properties and corresponding seismic signal responses. In this work, we address requirements 1 and 2 as a preface to a future coupled hydro-seismic reservoir modeling framework. Here, we summarize preliminary history-matching results of year-1 pressure monitoring data. These results yield a first-order approximation to a reservoir model, which is to be refined continuously once the seismic data stream is fully established.

## **HISTORY-MATCHING OF VERIFICATION-WELL PRESSURE-MONITORING DATA**

A radially symmetric TOUGH2 mesh with 11,288 cells and minimum horizontal/vertical cell size of 10m/5m describes the injection zone between the injection well CCS#2 and one of the monitoring wells (VW#2) at 2600 ft distance (Fig. 1a). The injection occurs between 6630 and 6825 ft and is divided into four perforated intervals. We invert data from 5 pressure-monitoring zones spanning the depth range 4902-7041 ft. The original VW#2 data covers the period 04/01/2017 to 01/01/2018, comprising 6421 hourly samples for each of the 5 zones (Fig. 1b). Pre-processing steps are de-spiking and down-sampling, such that the final data set totals 920 (184 samples per zone). Note that spikes in the data occur because of occasional reservoir fluid sampling, which shuts down the monitoring. The corresponding pressure drops cannot be modeled with the temporal discretization considered here.

Fig. 1b reveals that the pressure response dominates in Zone 2, which lies within the injection interval. The degree of response in the other four zones correlates with their vertical distance from the injection zone, that is, the gradual increases are rather linear, where Zone 5 remains mostly constant.

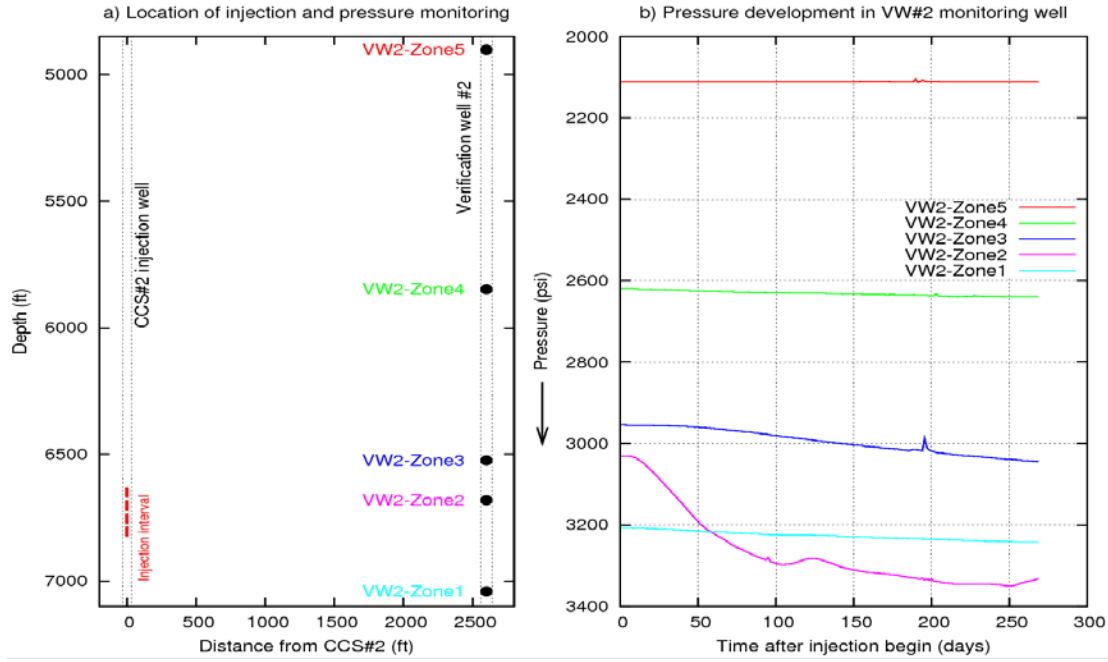


Figure 1: a) Schematic view of reservoir zone between injection well (CCS#2) and monitoring well (VW#2). b) Five vertical monitoring zones in VW#2 produce pressure time-series data over the 268-day injection period. Note that the y-axis points downwards with increasing pressure.

### **Inverse modeling of pressure data using MPiTOUGH2**

We employ the inverse modeling framework MPiTOUGH2, which is a derivative of iTOUGH2 combined with the parallel capabilities of TOUGH-MP, and further includes various geophysical simulators for electrical and seismic data types (Commer et al., 2014; Finsterle et al., 2016).

Preparatory steps for the inverse modeling include the delineation of the interfaces for a horizontally layered model of the intrinsic reservoir permeability. The fast computing enabled by MPiTOUGH2 (parallel forward-modeling combined with parallel Jacobian calculation) let us experiment with a pseudo Monte-Carlo approach, which involved approx. 100 trial inversion realizations. A true Monte-Carlo search would require many more realizations. A random scheme searched for the optimal number of layers with fixed interfaces, varying in number between 3 and 15. We found that a 6-layer model parameterization suffices to describe the main characteristics of the observed pressure responses.

A 20-iteration Marquardt-Levenberg inversion run with the 6-layer setup took approx. 45 minutes using 72 cores of an Intel Xeon (2.4 GHz) cluster.

### **Interpretation of inversion results**

Figs 2 and 3 summarize the final data fitting and model outcome after 20 inversion iterations, where the data fits in Fig. 2a are calculated from the final iteration's parameter estimates. In contrast to all other zones, the characteristic pressure development in Zone 2 involves an initially steep increase and a much more pronounced drop and rebound, correlating well with the large injection decrease at around 100 days (Fig. 2b). This correlation also appears in the data fits for Zone 2, although amplitudes of the pressure differences remain underestimated. On the other hand, the pressure difference during the first 50 days is overestimated for the adjacent Zone 3. However, we found that including additional thin layers between these two zones did not lead to improved data fits for these zones, indicating generally more complex model structures than given by the layered model.

The final model in Fig. 3 shows the estimated permeability, which ranges from 0.01 mD to close to 1000 mD over the 6 layers. No smoothing constraints were imposed on the estimation process, that is, we allowed for discontinuities at layer interfaces, as their existence is also suggested by well log data (see the geological section in Fig. 3).

One notes that despite the proximity of Zone 1 to the injector, its increase is as flat as observed for the more distant Zone 4. This suggests the presence of a pressure-dampening shielding layer between Zone 1 and 2. Our above-mentioned search for an optimal model parameter set also strongly indicated the necessity of a thin layer between Zone 1 and 2.

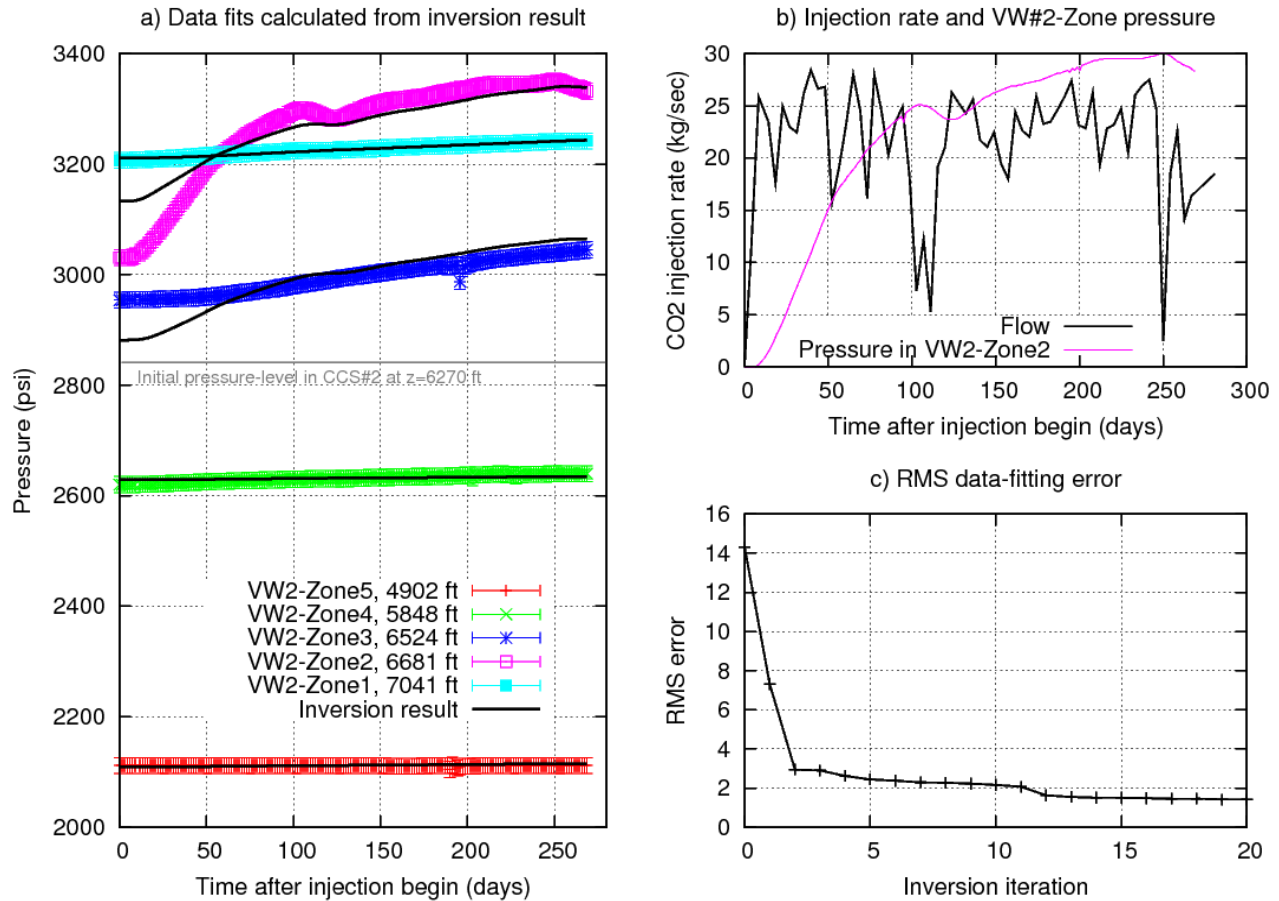


Figure 2: a) Final data fits produced by inverse modeling for a 6-layer model of vertically varying intrinsic permeability. Black curves show the data fits calculated from the final inversion iteration (the final model is shown below in Fig. 3). b) Injection rate (black curve) over the monitoring period, revealing a correlation between rate decreases and corresponding pressure drops in VW#2-Zone 2. c) Total RMS data fitting error over the course of 20 inversion iterations. Error convergence occurs at the RMS of 1.4.

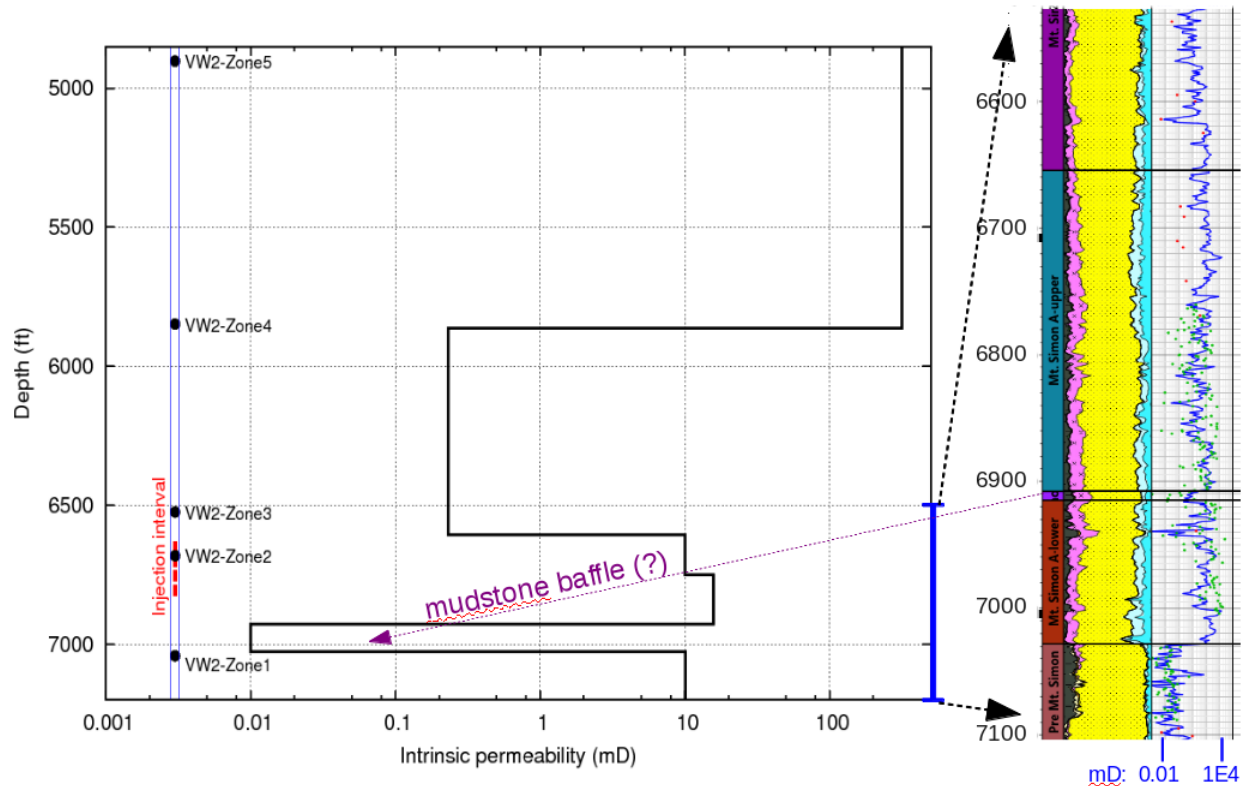


Figure 3: Final model produced by 20 inversion iterations (Fig. 2c). The model consists of 6 parameters describing a vertically varying permeability layering. The geological section to the right includes a vertical permeability profile (blue curve) obtained from approx. 600 ft of core data.

## CONCLUSIONS

Inverse modeling of year-1 pressure monitoring data led to a first-order approximation of a reservoir model to be continuously refined and incorporated into an integrated monitoring system for CO<sub>2</sub> storage.

Thin interspersed layers of mudstones and siltstones of low porosity and permeability have been identified through well logs and reservoir modeling of the earlier IBDP data (Finley, 2014). The present inverse-modeling results maintain the necessity of such hydraulically shielding structures in the reservoir modeling.

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