Assessing the Value of Seismic Amplitude Versus Offset (AVO) Attributes for CO_2 Storage Projects Using a Bayesian Network Model for Decision Support

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Introduction

- Value of information (VOI) analysis quantifies the worth of data or information in enhancing decision-making processes.
- Seismic amplitude versus offset (AVO) attributes are particularly effective for monitoring CO_2 storage sites because leaked CO_2 can alter rock properties and pore fluid compositions, subsequently changing the way seismic waves reflect and their amplitudes. AVO quantifies the reflector with respect to different ray incident angles.
- Analyzing time-lapse changes in AVO attributes from repeat seismic surveys can help identify anomalies or subsurface shifts, potentially serving as indicators of CO_2 leakage.
- A Bayesian network model is a decision support tool that provides probabilistic inference from multiple sources of evidence. Our Bayesian network model answers the question - given observations at a monitoring point, what is the probability of CO_2 saturation exceeding the threshold, hence the presence of a leak?

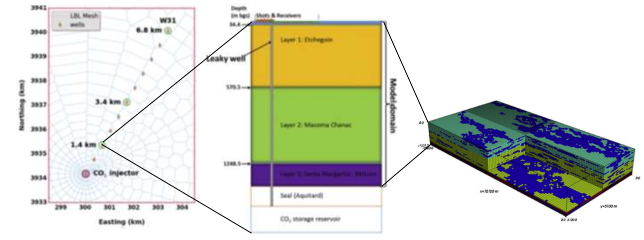

Figure 1. (a) Map showing the locations of a legacy well, (b) wellbore model with geologic layers used in the Kimberlina 1.2 aquifer flow simulation, and (c) aquifer model with spatial distribution of sand and clay bodies.

Data

- The study site is based on a hypothetical industrial scale geologic carbon storage (GCS) site in Kimberlina in the southern San Joaquin Basin in California, USA.
- Multi-phase flow simulations of wellbore CO_2 and brine leakage from a legacy well into shallow aquifers, earlier developed by the Lawrence Livermore National Laboratory's (LLNL) researcher, was utilized to quantify seismic velocity and density structures within the model domain at the study site.
- The 2D acoustic seismic modeling using finite-difference approximation of seismic wave propagation was implemented in Seismic Unix to generate synthetic seismic data.

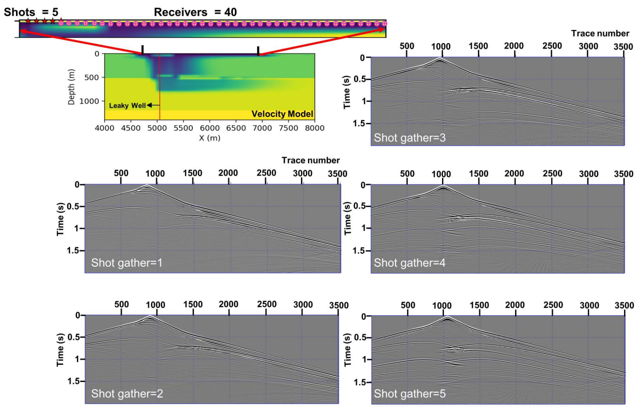

Figure 2. Seismic velocity model for one realization (top left panel) utilized in forward modeling of synthetic seismic data using Seismic Unix.

Methods

- Statistical estimates, including minimum, maximum, variance, and near and far offsets, were calculated for each seismic attribute across all offsets at respective common midpoint (CMP) locations, providing a comprehensive understanding of the data.
- Seismic attributes were assumed to be independent of each other.
- Leak detection threshold was defined by the 99th percentile of CO_2 saturation values at Time = 10 Year.
- Sensitive seismic attributes (i.e., monitoring parameters) at each time period were found using spline regression analysis (MPs ~ CO_2 Sat + CDP No. + Distance), with sensitivity measured by a p-value < 0.05 (statistical significance).
- Leak detection inference for seismic monitoring was conducted using a Bayesian network model. The models represent causal relationships of monitoring parameters and other variables at each time period (shown in Figure 5).

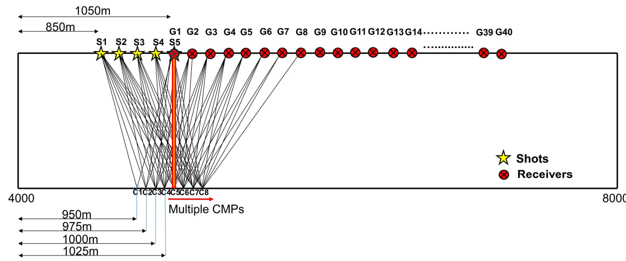

Figure 3. Map showing the distribution of source (yellow stars), receivers (red circles), and CMP locations around the legacy well (yellow vertical trace with red outline).

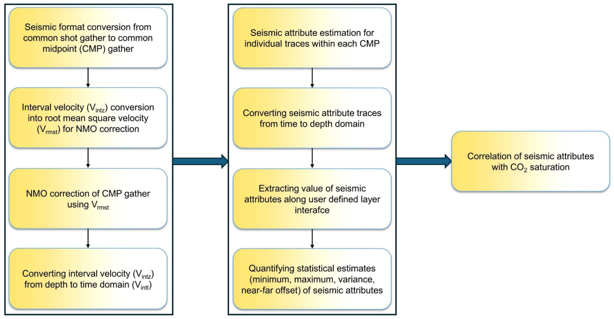

Figure 4. Diagram showing the workflow of the current study for seismic data processing and attribute versus offset quantification.

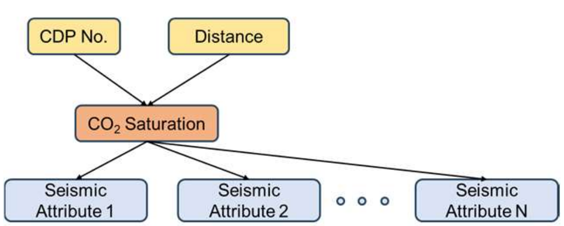

Figure 5. Influence diagram of variables for the Bayesian network model. CMP number and distance to the leaky well cause changes in CO_2 saturation, and in turn cause changes in the seismic attributes.

Results

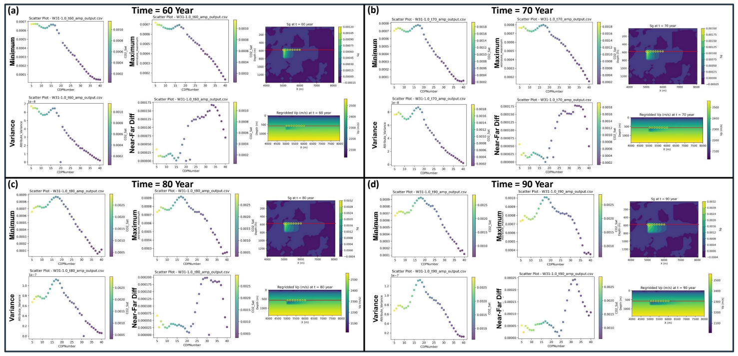

Figure 6. Time-lapse of statistical estimates of seismic attribute (amplitude) at time periods of: (a) 60 year, (b) 70 year, (c) 80 year, and (d) 90 year. Corresponding variations in CO_2 saturation and P-wave velocity are shown in the right side of each sub-figure. The red horizontal line in the CO_2 saturation and P-wave velocity plots represents top surface of the Macoma Chanac aquifer layer. The yellow circles represent CMP location.

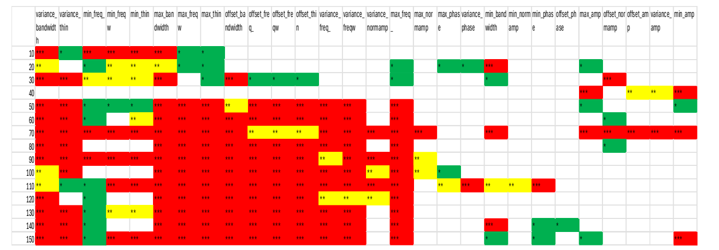

Figure 7. Table of sensitive monitoring parameters at each time period. Rows are the monitoring parameters. The columns are the time periods. Significance levels are indicated by the color of the cells and the number of * in the cells. Red with ***: p-value < 0.001, yellow with **: p-value < 0.01, and green with *: p-value < 0.05.

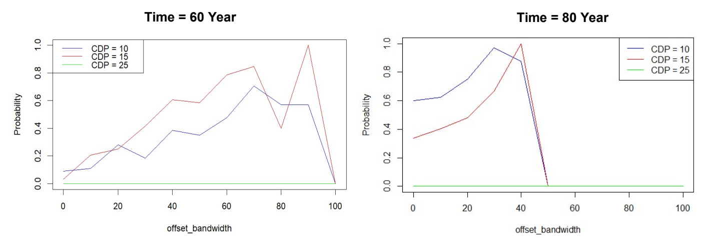

Figure 8. Probability of leak detection at CDP numbers = 10, 15, and 25 based on the measurements of the near and far offset of bandwidth at Time = 60 Year and Time = 80 Year. .

Acknowledgements

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