Machine Learning Applications in Analyzing the Role of Shale Barriers and Baffles for CO2 Storage

Timothy R. Carr, Ebrahim Fathi, and Ikponmwosa Iyegbekedo

West Virginia University, Morgantown, ,WV, USA

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

Summary

- The study employs machine learning to quantify CO_2 plume extents by analyzing microseismic data from the Illinois Basin Decatur Project (IBDP).
- The research leverages a unique dataset comprising well logs, microseismic records, and CO_2 injection metrics to predict the temporal evolution of subsurface CO_2 saturation plumes.
- Machine learning can effectively predict plume dynamics, revealing vertical clustering of microseismic events, consistent with an invasion percolation model.
- CO_2 plumes partially trapped within sandstone intervals breach localized barriers periodically, driven by buoyancy overcoming gravity and capillary forces.
- K-Means clustering outperformed other techniques, showing highest Silhouette Score and lowest Davies-Bouldin Index.

Introduction

- Fossil fuel use disrupts carbon balance, necessitating CCS strategies.
- IBDP showcases CCS viability by capturing and injecting CO_2 into Mt. Simon Sandstone, with Eau Claire Shale as cap rock.
- At the IBDP, natural fractures and baffles impact CO_2 sequestration.
- Baffles Impede vertical CO_2 movement, causing lateral spreading in high permeability zones and Fractures enhance storage via increasing the contact area for processes like dissolution and mineral trapping.
- Within the interval from 5,371.5 feet to 7,198 feet measured depth of the Mount Simon Sandstone, 5,875 baffles were identified
- Some previous interpretations of microseismic events at the (IBDP) site showing events predominately in the Mount Simon while other interpretations show events concentrated in the basement.
- Microseismic monitoring tracks CO_2 injection effects on stress fields and brittle failure in fractures aids in understanding CO_2 plume dynamics and ensuring storage site integrity.
- Machine learning, especially unsupervised learning techniques such as clustering uncover patterns and features within seismic data that traditional methods might miss.

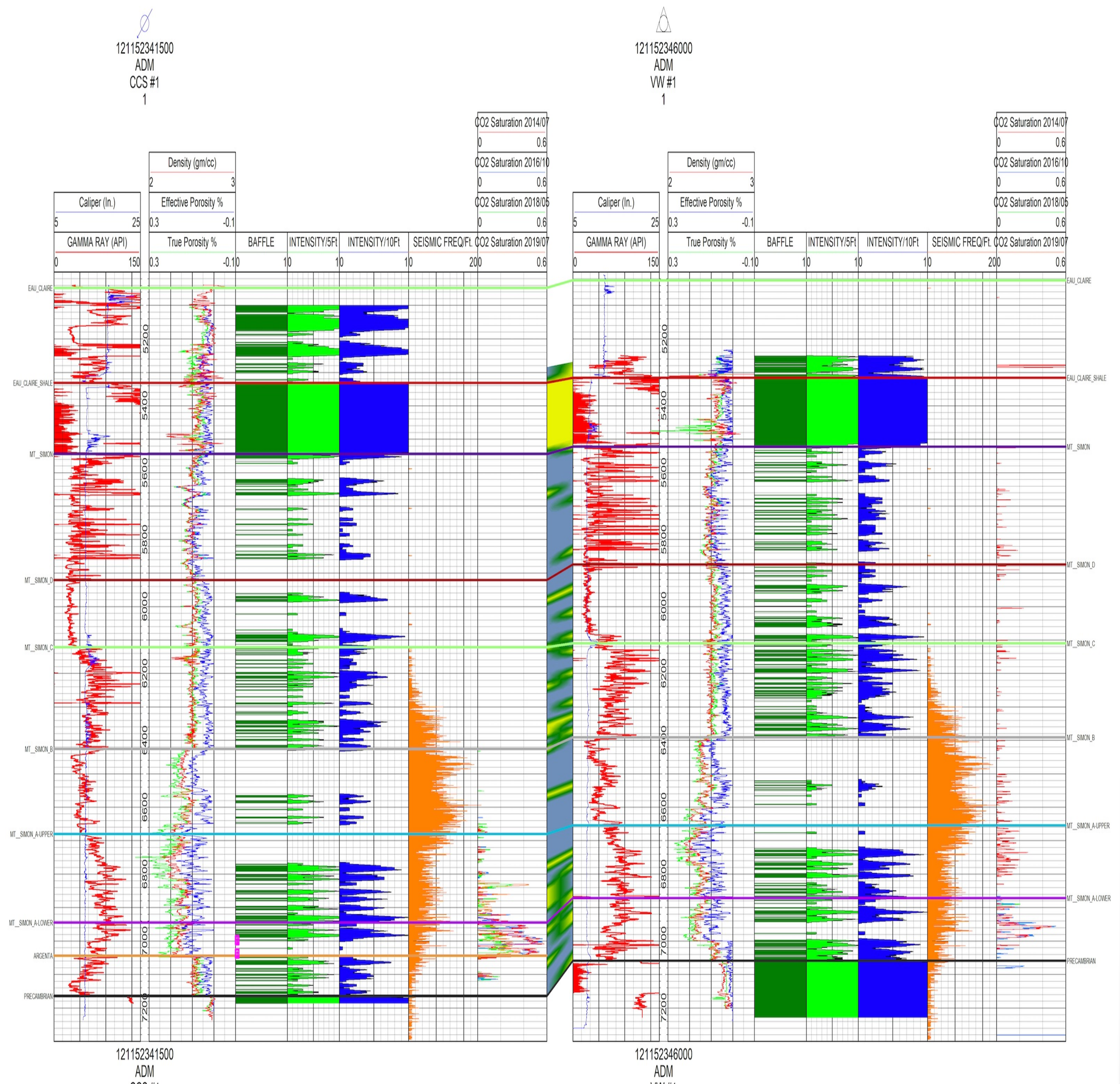

Figure 1 Baffles intensity log using well logs.

Methodology

- An opensource tool was developed to visualize and analyze the microseismic data using both K-Means and DBSCAN clustering techniques.
- This tool, accessible through an online dashboard, utilized the Python programming language and packages such as NumPy, and Pandas, offering data loading and processing functionalities, and is available on https://cz63dzvzquchsikhdpugsq.streamlit.app/.
- The dashboard accounts for varying time spans to detected CO2 plume pressure dynamics both laterally and vertically from the injection point.
- Additionally, the dashboard offers the option to optimize the K-Means and DBSCAN clustering techniques. Once the parameters are set, the workflow is applied to both data sets provided "SLB Data" and "Relocated Data,".
- The optimal number of clusters for each subset was determined using "elbow curves" for both WCSS and Total Variation, and confirmed by the highest Silhouette Score and the lowest Davies-Bouldin Index
- Physical interpretation of clusters aligns with PNL logging observations and FMI log data on baffle intensity, supporting five clusters as the optimal number

Number of Clusters	Silhouette Score	Davies-Bouldin Index
3	0.623	0.464
5	0.651	0.355

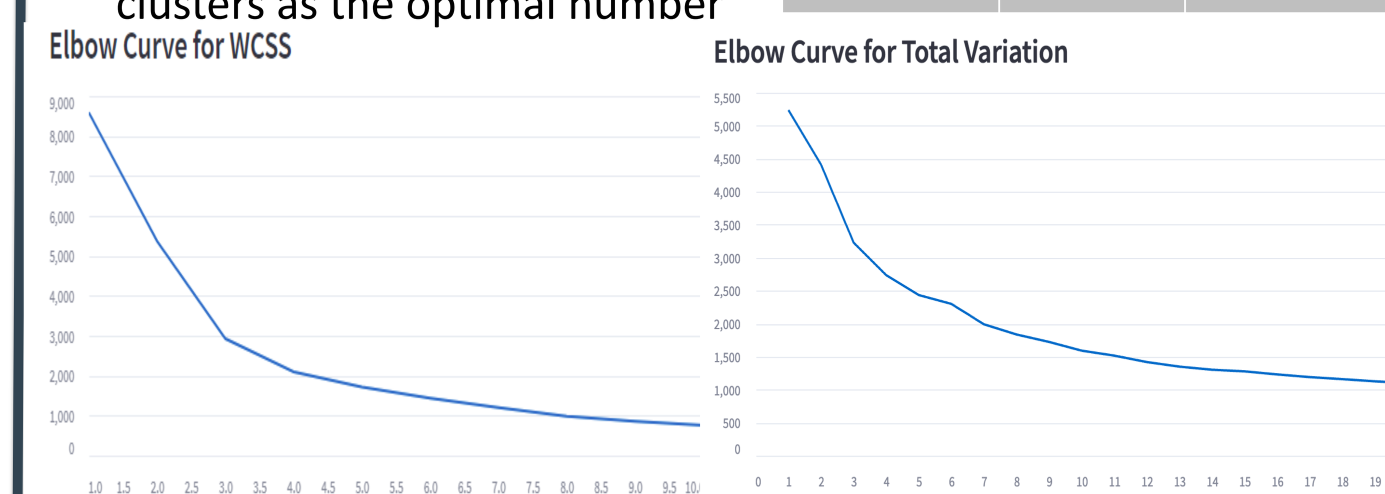

Figure 2. (a) Optimal K-Means clusters by WCSS; (b) by Total Variation for 2D subset

Results

- Figure 3 Left illustrates the Map of microsesimic events extension from Dec 2011-Feb 2018. At early time of injection extending away from the injection point to Southeast and later concentrating around the East of injection point.
- Figure 3 right shows these events spreading both vertically (ranging from -500 ft to 1100 ft) and horizontally (extending up to 9000 ft) away from the injection point, suggesting the CO_2 plume's extension and interaction with various geological layers, including the Mt. Simon sandstone and the Precambrian basement.
- Initially, the CO_2 plume spread laterally away from the injection point, accumulating around 9000 ft away (December 2011-February 2012).
- It then moved back toward the injection point during March 2012 and concentrated around the injection point for the rest of the injection time and post-injection period until February 2018.
- Post-injection events mainly occurred between 2600 to 3900 ft away from the injection point, extending up to lower Mount Simon C.

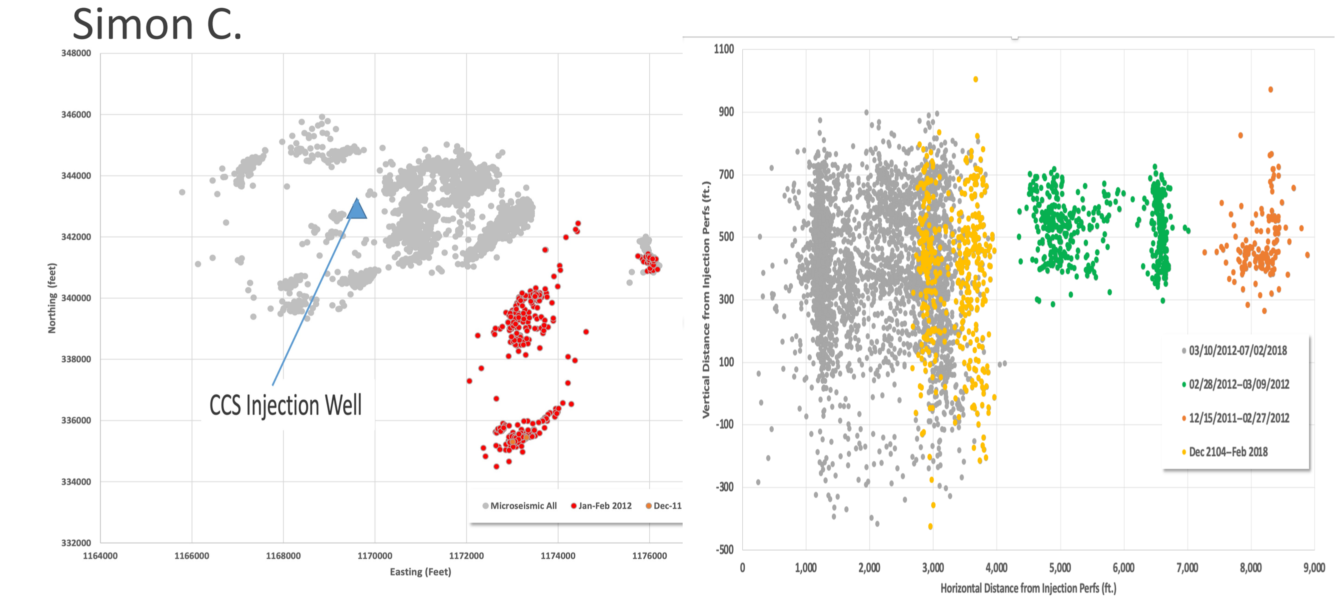

Figure 3 Left . Map of microsesimic events extension from Dec 2011-Feb 2018. Right Vertical and lateral expansion of microseismic events during CO2 injection and post injection time (Dec 2011-Feb 2018)

- Figure 4 illustrates the K-Means clustering of microseismic events on the 2D plane of depth difference and horizontal distance from the injection point, highlighting the horizontal and vertical extension of the CO_2 plume.
- Clusters 0, 1, and 2 with lower event densities occurred early (Dec 2011 - Mar 2012), indicating initial horizontal CO_2 spread due to baffle confinement.
- From mid-2012 to post-injection (Nov 2014 - Feb 2018), CO_2 accumulated around the injection point after initial breakthroughs.
- Figure 5 shows, Initially (C0), microseismic events spread up to 9000 feet from the injection point but later concentrated closer (C1, C2, C3).
- Post-injection activities primarily occurred between 2600 and 3900 feet away, with fewer events near the injection point (C4).
- This pattern suggests that high-density baffles and barriers near the injection point closed after injection stopped and pressure decreased below the closure pressure.
- Figure 6 reveals vertical CO_2 movement throughout the injection and post-injection periods.
- Being lighter than formation water, CO_2 accumulated in highly saturated sandstone layers, overcame gravity and capillary forces, and breached barriers to migrate vertically.
- Most microseismic events were concentrated in Mt. Simon A upper and Mt. Simon B, with fewer events in Mt. Simon A lower and some extending to Mt. Simon C and the Precambrian.

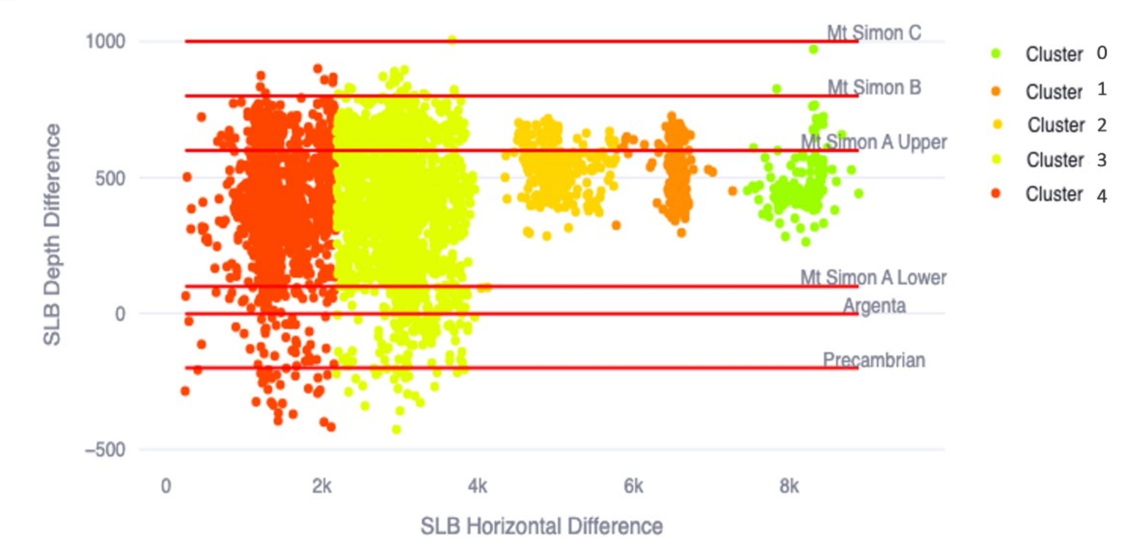

Figure 4 K-Means clustering showing horizontal and vertical extension of five clusters

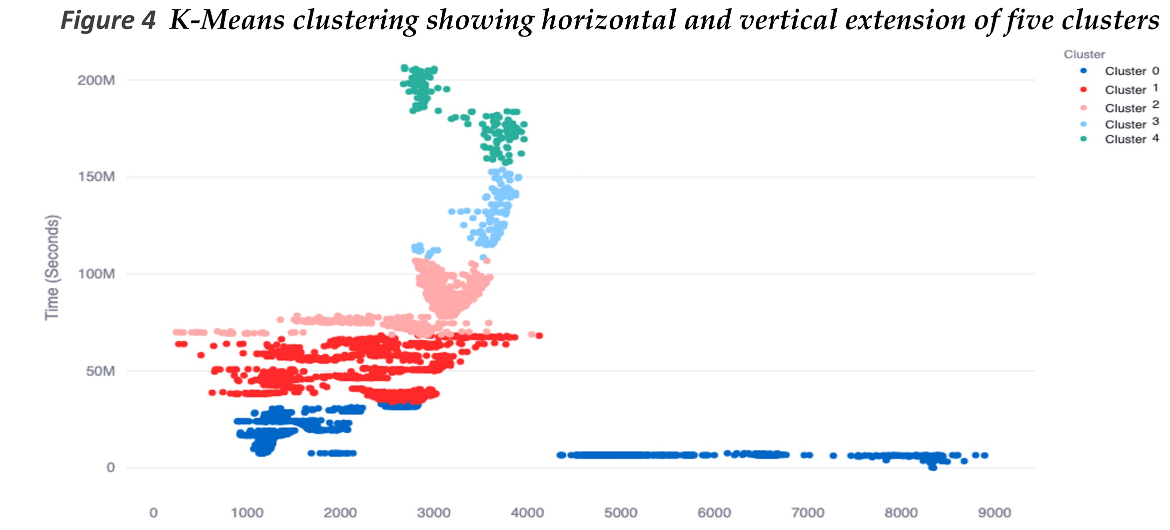

Figure 5 clustering in 2D space of Time and Horizontal distance to injection point.

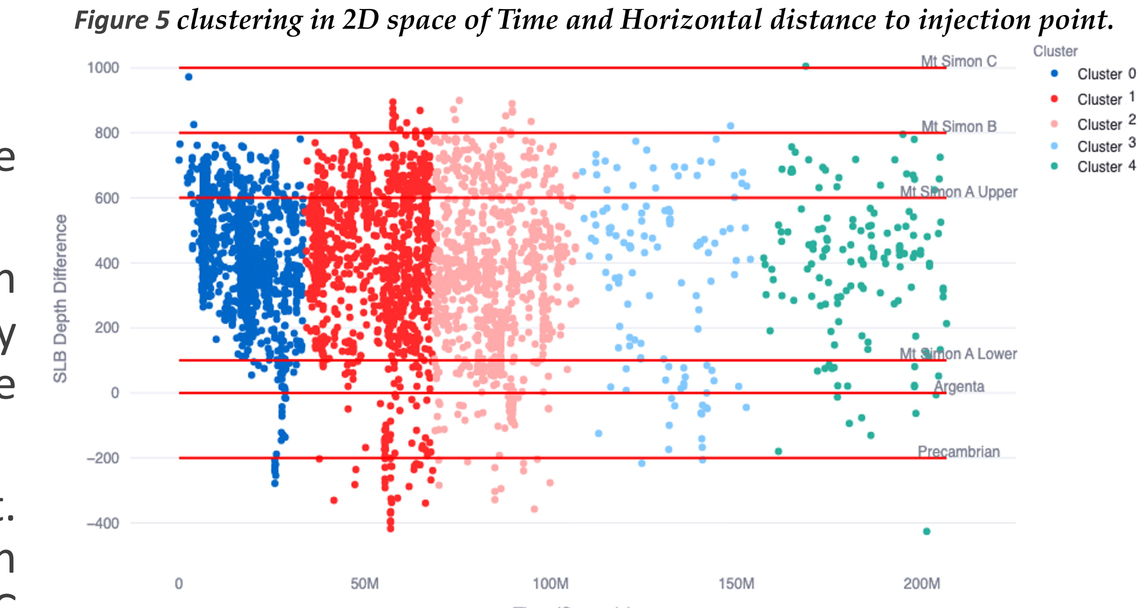

Figure 6 K-Means clustering showing horizontal and vertical extension of five clusters

Conclusions

- The IBDP dataset included 10,123 microseismic events from Nov 2011 to Dec 2014, monitored by geophones in the injection well CCS#1 and monitoring well VW#1.
- K-Means and DBSCAN clustering of microseismic events revealed CO_2 plume dynamics, identifying vertical and horizontal distributions influenced by geological features like baffles and barriers.
- Initial clusters (Dec 2011 - Mar 2012) showed lateral CO_2 spread up to 9000 ft due to baffle confinement, followed by upward migration from mid-2012 as pressure increased.
- From mid-2012 to Feb 2018, microseismic events concentrated near the injection point, showing cyclical CO_2 migration and accumulation patterns.
- K-Means clustering aligned well with physical data from FMI and PNL logs, outperforming DBSCAN in providing actionable insights, enhancing subsurface modeling and CO_2 sequestration strategies.