Machine learning-based workflow for identifying fractures and baffles from Formation Micro Imager (FMI) log: A practical application in Illinois Basin Decatur

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

Summary

- ML workflow automates fracture and baffle identification in completion design for CO_2 storage and geothermal systems.
- Manual interpretation of FMI logs is time-consuming and uncertain.
- Computer vision and deep learning detect fractures and baffles, reducing cost, time, and bias.
- Applied to IBDP, workflow achieves time and cost reductions, identifies fractured zones, baffles, and enhances CO_2 pressure forecasting.
- Validated by microseismic and image log interpretations, workflow provides accurate mapping, improving post-injection analysis.

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.
- Extensive research and well logging identify suitable formations and assess baffles and fractures.
- Post-injection micro seismic analysis detects challenging-to-quantify fractures beneath Eau Claire Shale seal.
- Objective is to develop ML workflow for automated fracture and baffle identification reducing cost, time, and bias.
- *Figure 1* shows Integration of multiple logs and baffle intensity using effective porosity and gamma ray correlation.

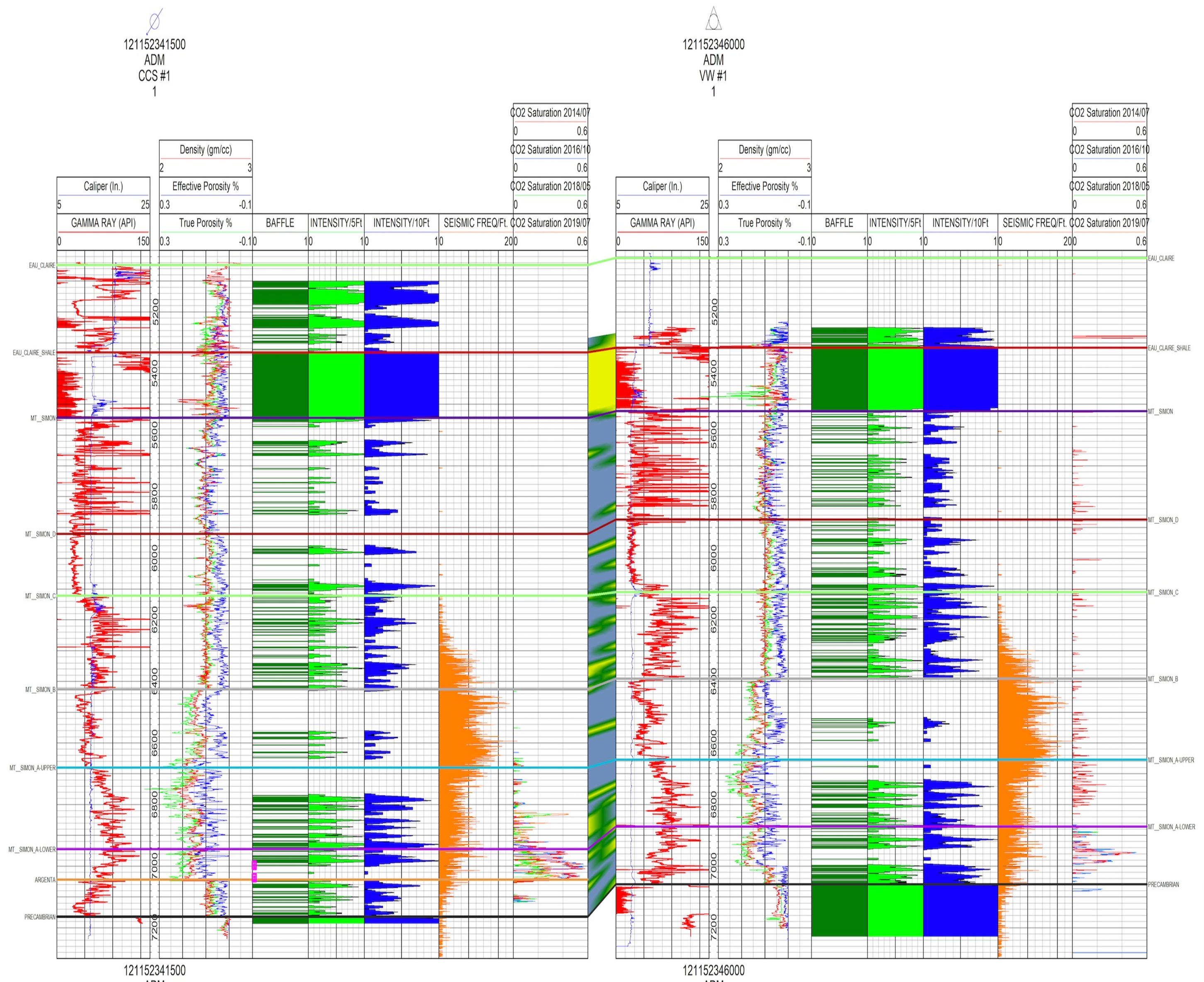

Figure 1 Baffles intensity log using well logs.

Methodology

- IBDP image logs undergo preprocessing for extracting pad arrays and depth values, visualized using a Python script on the Streamlit platform.
- Pixel normalization, thresholding, and Canny Edge Detection enhance the features through filtering techniques.
- Natural fractures per interval are recorded in a file for export in CSV or LAS format.
- A neural network correlates fractures with other well logs, considering shale beddings and fractures.
- A computer vision tool generates a LAS file with density values, detecting baffles and fractures. It is accessible through an online dashboard, utilizing Python and packages like OpenCV, NumPy, and Pandas (https://ibdp-workflow.streamlit.app/)

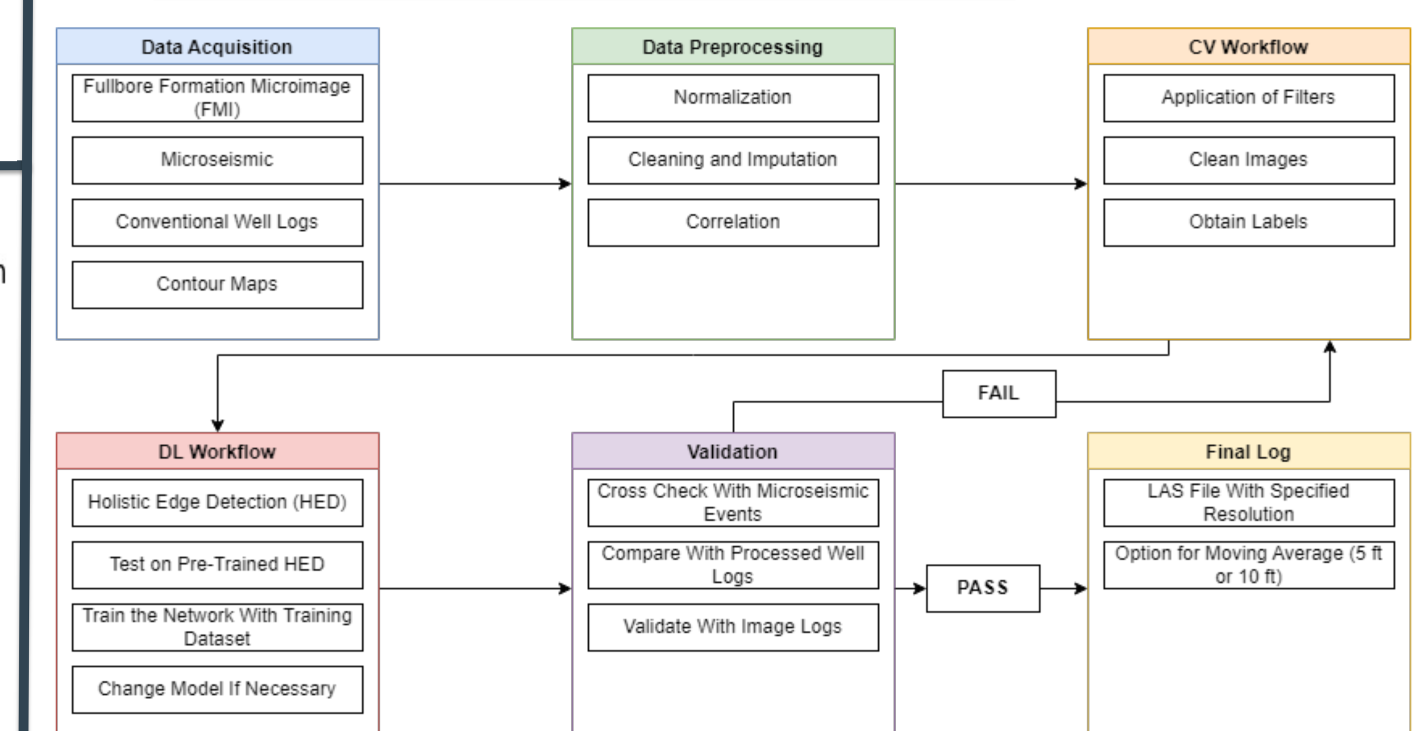

Figure 2 Computer vision (CV) and deep learning (DL) workflow

Results

- The computer vision workflow generates a baffle density log from image logs, accounting for different resolutions and providing user-defined interpolation.
- Figure 2 highlights seven intervals (labeled A to G) on baffle density logs, showing variations in baffle counts.
- The transition from Eau Claire shale to Mt. Simon E (Interval A to B) exhibits moderate spikes in baffle counts.
- Interval E and F show correlations between baffles and micro seismic events, with the computer vision workflow detecting baffles in clean formations and generating logs with less variance and higher average baffles.
- Interval E detects baffles in a clean formation, correlating with micro seismic events.
- Interval F exhibits similar correlations, with the computer vision workflow showing less variance and higher average baffles.
- *Figure 3* shows the baffle count log from the computer vision workflow, interpreted baffles log values from gamma-ray and porosity logs, and manual interpretation of the image log.

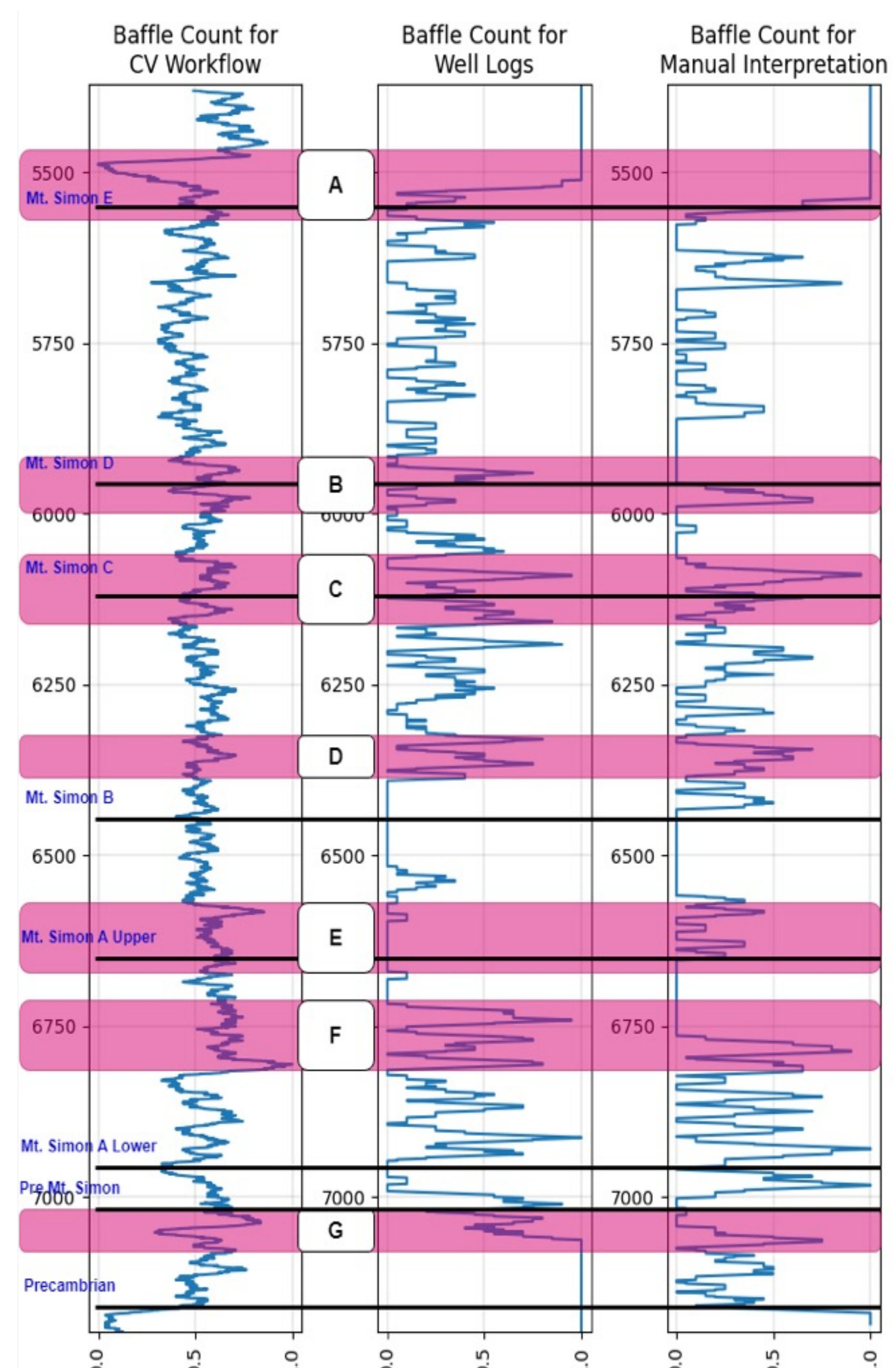

Figure 3 Baffle log correlations between CV, well logs and FMI

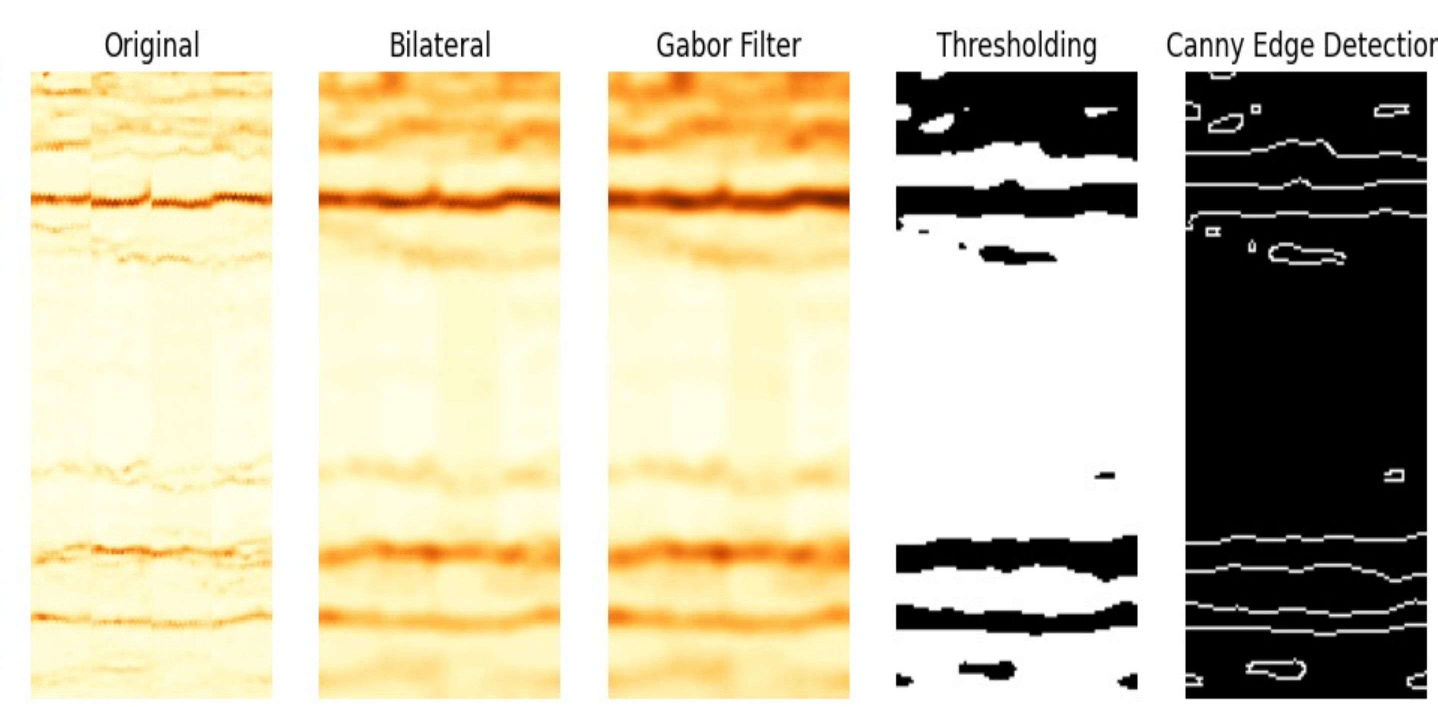

Figure 4 Baffles detection workflow in two-foot interval of CCS1 well.

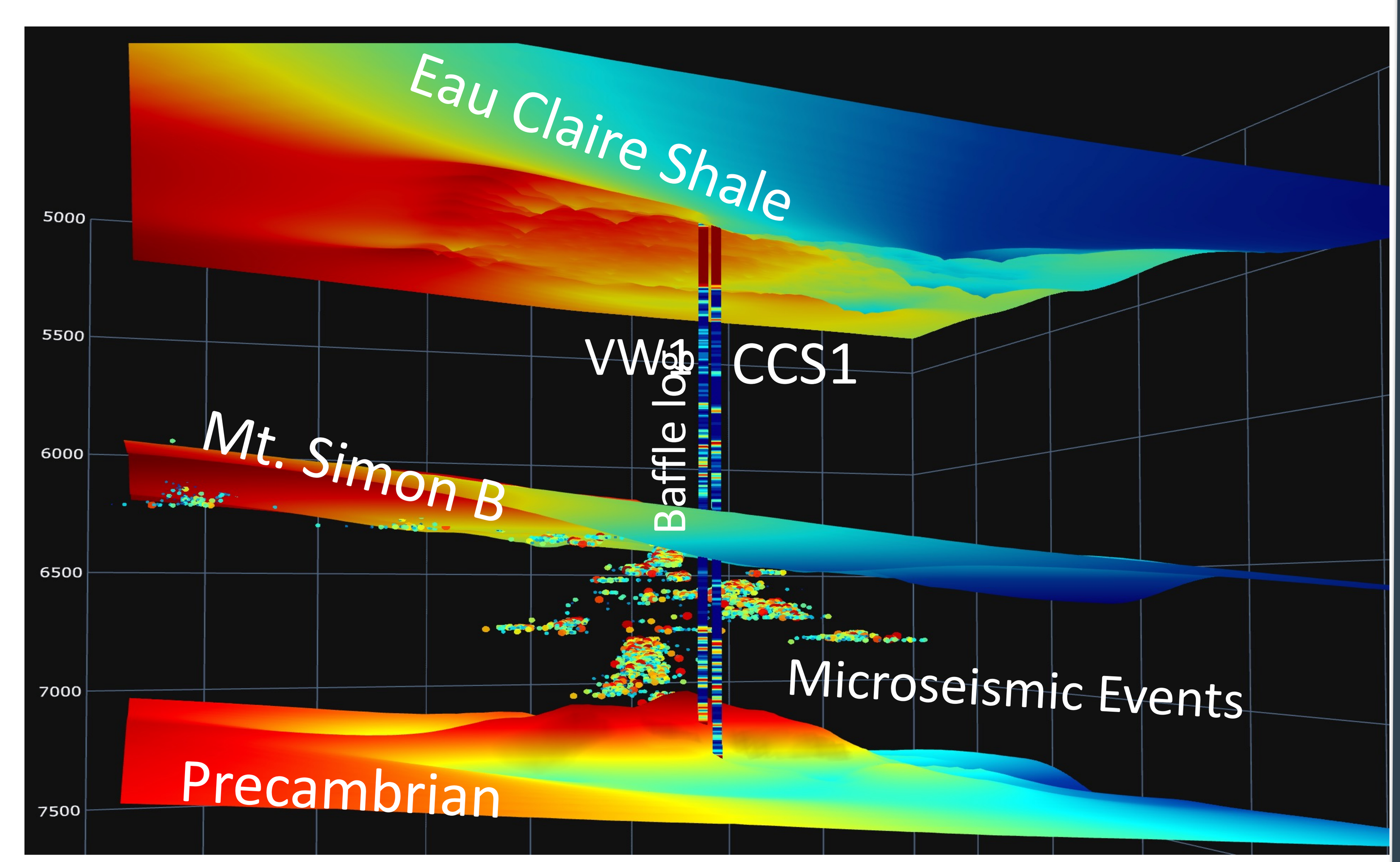

Figure 5 Microseismic contained within Mt. Simon B and Precambrian.

Conclusions

- The computer vision workflow detects baffles and fractures in image logs, providing valuable information for reservoir analysis and integration into simulators.
- The study highlights variations in baffle density across logs and correlations between baffles and micro seismic events.
- The online dashboard offers an open-source tool for baffle and fracture detection, enabling data processing, normalization, and export for reservoir simulators.

Figure 6 Fracture identification from FMI log using automated CV and DL workflow .

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