Identification of Vuggy Zones in Carbonate Reservoirs from Wireline Logs Using Machine Learning Techniques*

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Abstract

Vugs are irregular cavities inside rocks, formed by dissolution processes that may result in higher permeability zones. Vugs are identified through the analysis of image logs and cores. These datasets are generally sparse because they are expensive to acquire. Vugs are not readily identified with the common triple combo logging suite. We seek to develop decision rules to correlate triple combo logs with the presence or absence of vuggy zones as determined from image logs and cores.

Image Logs from six wells in the Appalachian Basin were analyzed for the presence of vugs and translated into a binary vuggy zone indicator log. Multiple machine learning models were trained to predict the indicator based on logged values for gamma ray, neutron porosity, photo electric, and bulk density.

Performance was assessed using well-level cross-validation. Each well's data was held out of the dataset, a model was trained using data from the other five wells, and the model was used to predict the vuggy zone indicator for the held-out well. The support vector machine (SVM) model was the top performer with a 78% correct identification rate. The proportion of entries in the held-out wells that were correctly predicted as either Vug or No-Vug ranged from 71% to 91%.

Note that many techniques, including SVM, result in predictive models that do not have a simple closed-form representation. A recursive partitioning tree analysis is also presented, which correlates the logs and vuggy zone indicator in a way that is easier to interpret and visualize.

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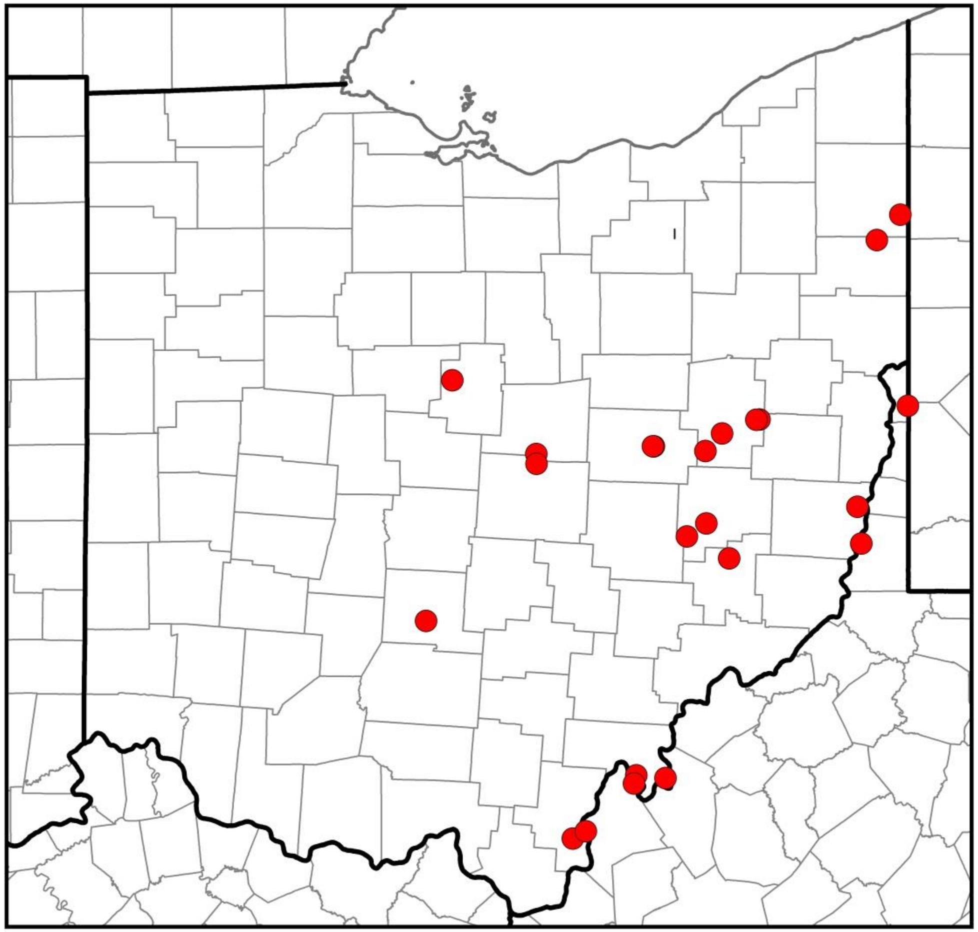
American Association of Petroleum Geologists
Eastern Regional Meeting, Fall 2015

Project Goal: Create "Road Map" for CO2 sequestration in saline reservoirs in the Upper Ohio River Valley area.

- Determine extent of potential reservoirs and caprocks
- Characterize and map petrophysical and geomechanical properties
- Continue gathering new data through piggyback opportunities



MRCSP Piggyback Wells

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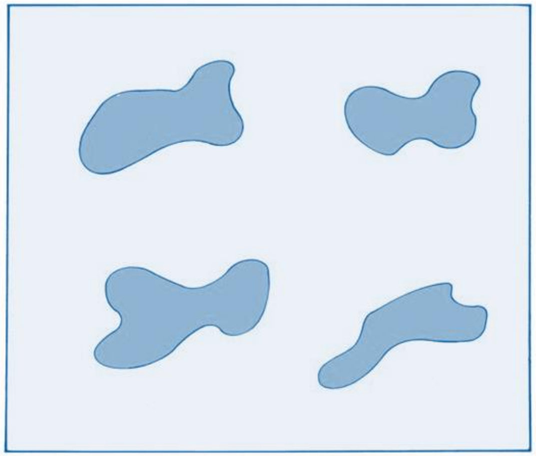
Vug Porosity

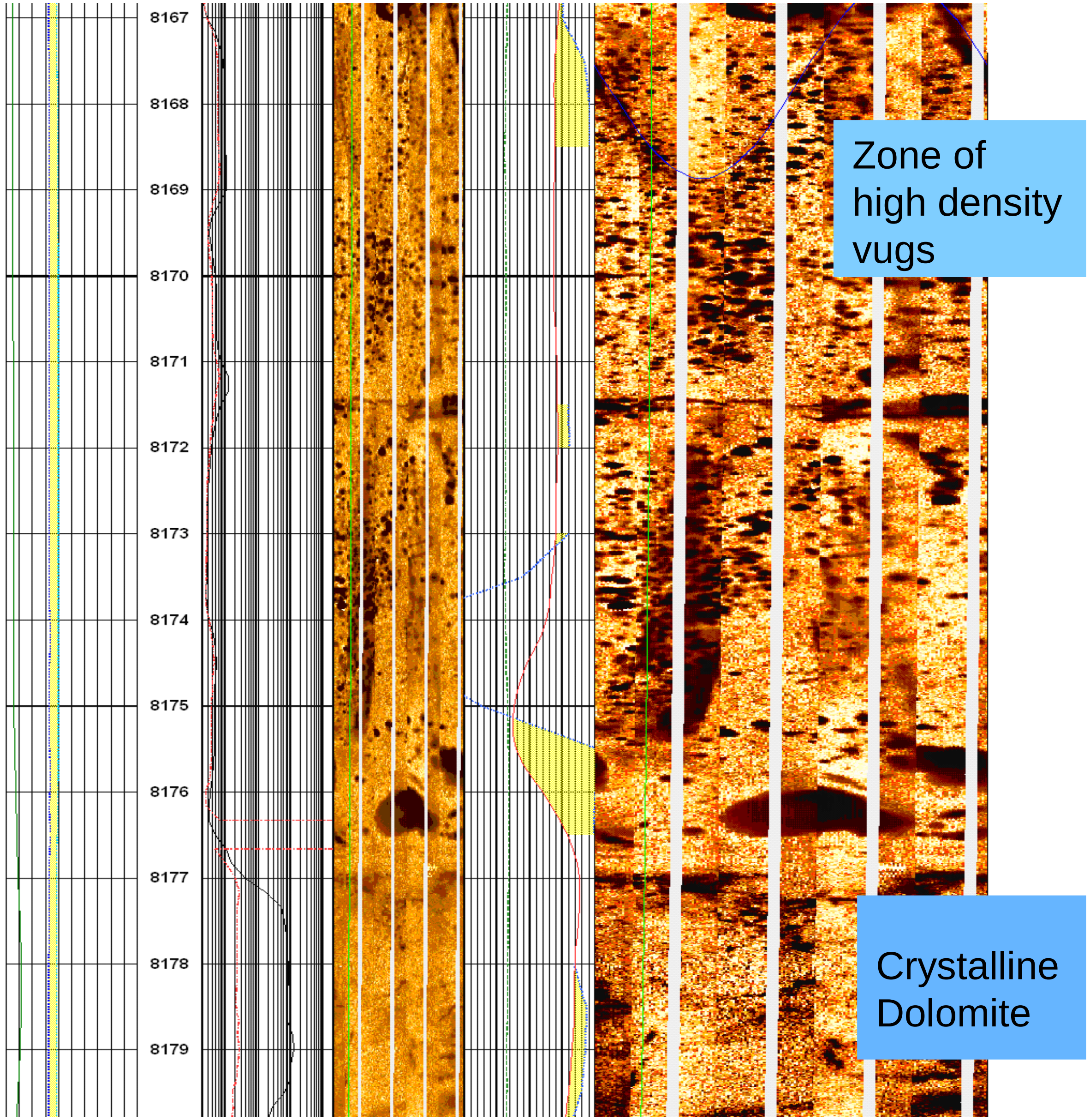


- **Vugs** are small to medium-sized cavities inside rock typically formed by dissolution processes, leaving behind irregular voids
- In vuggy carbonates, well-connected vugs may result in higher permeability zones within the reservoir

http://epicroadtrips.us/2009/texas/week1/week1_day3_monday26jan2009/hres/day3-monday26jan2009_18.jpg

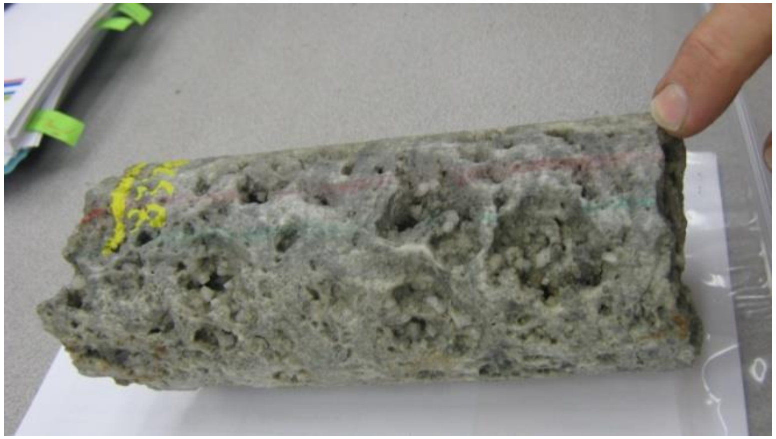
Image Log with Vugs

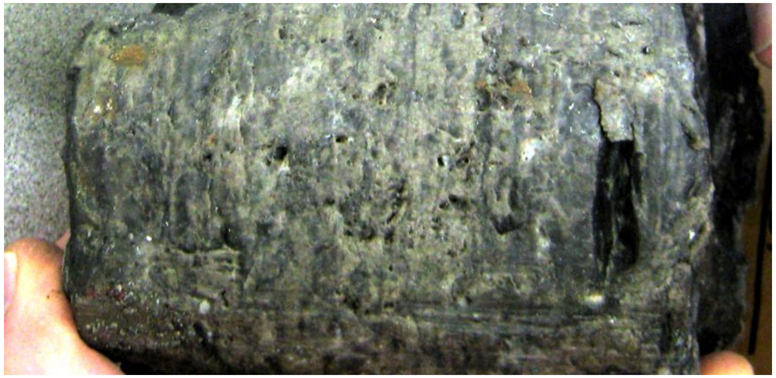
- Image Logs allow the positive identification of vugs, which are not readily identified with a standard triple combo logging suite



AEP #1

Carbonate Core with Vugs





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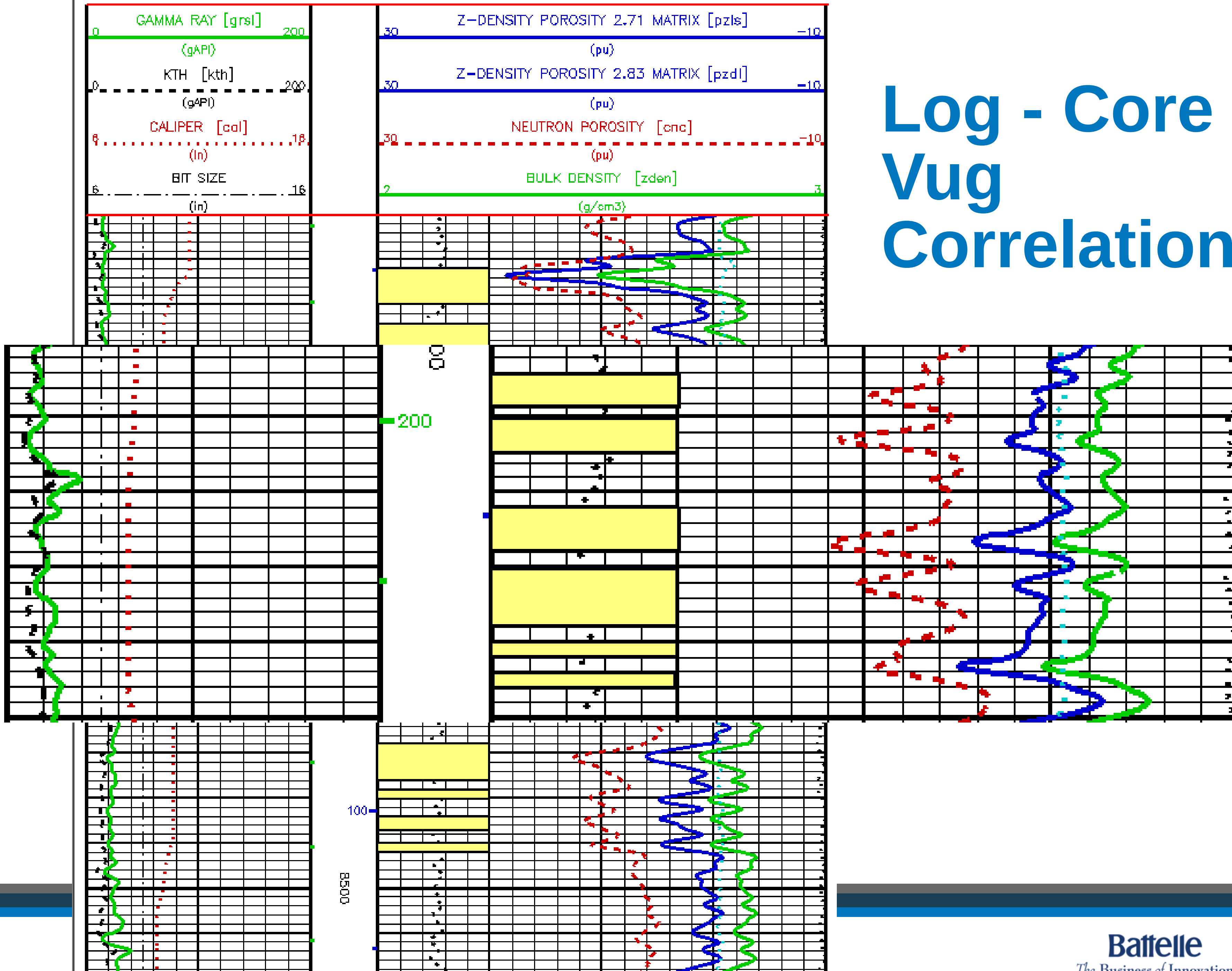
Log - Core Vug Correlation

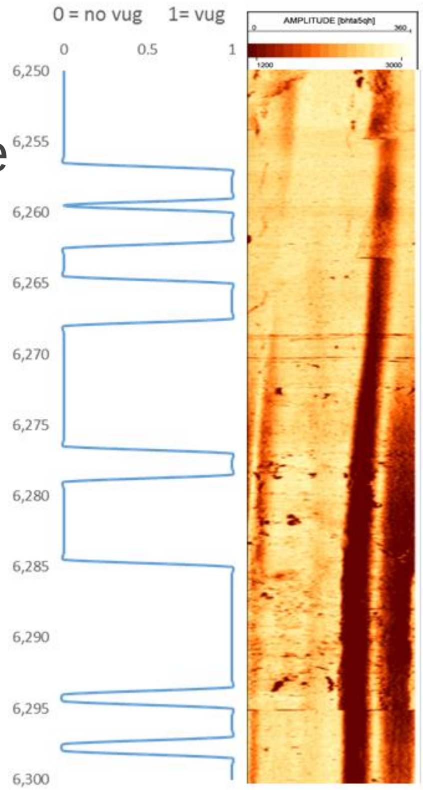


If image logs or whole core are not available, how can we find the vugs?

Use machine learning techniques to determine the key log indicators

Machine Learning Phase 1

- Identify vugs in a single well using image logs and core samples
- Using that “truth” data, train several models to detect vugs using sensor log data only



- Compare the different models
  - Random Forest
  - Naive Bayes
  - Logit Boost
  - Gradient Boosting Machine
  - Logistic Regression
  - K-Nearest Neighbor
  - Support Vector Machine
  - Conditional Inference Tree
  - Recursive Partitioning

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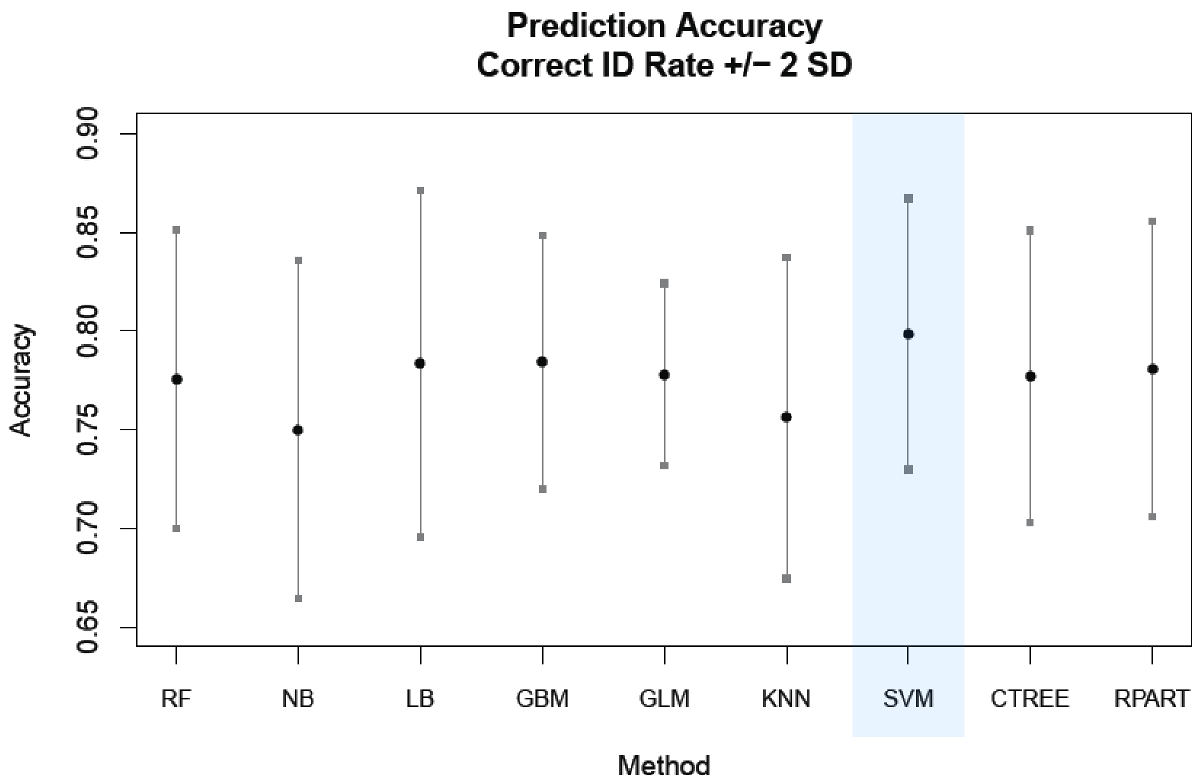
Comparing Model Performance for a Single Well



- Best performer was a support vector machine (SVM)

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Machine Learning Phase II

- Identify vugs in multiple wells
- Evaluate using the best performing model from Phase I on the new data

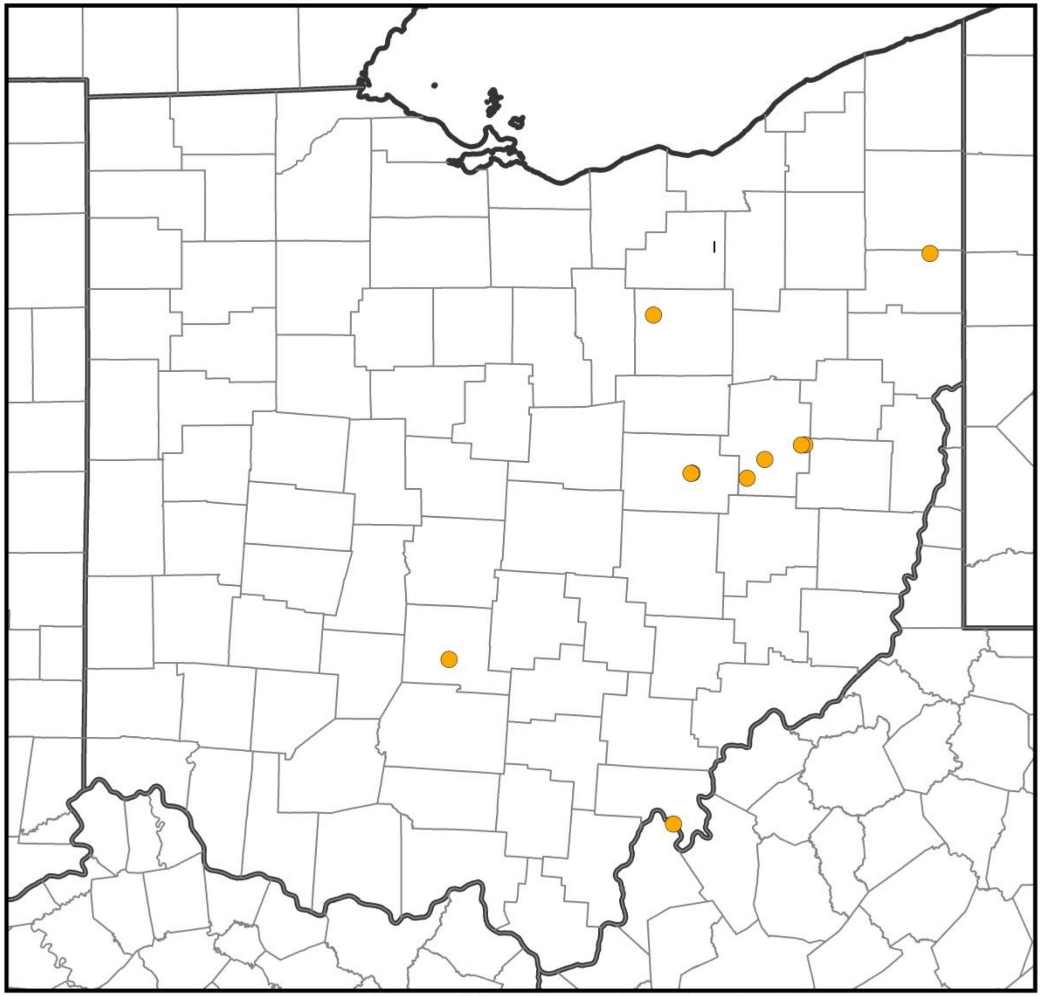


Image Logs Used for Vug Analysis

Log Availability

- Vug models were trained using the largest subset present in most of the wells

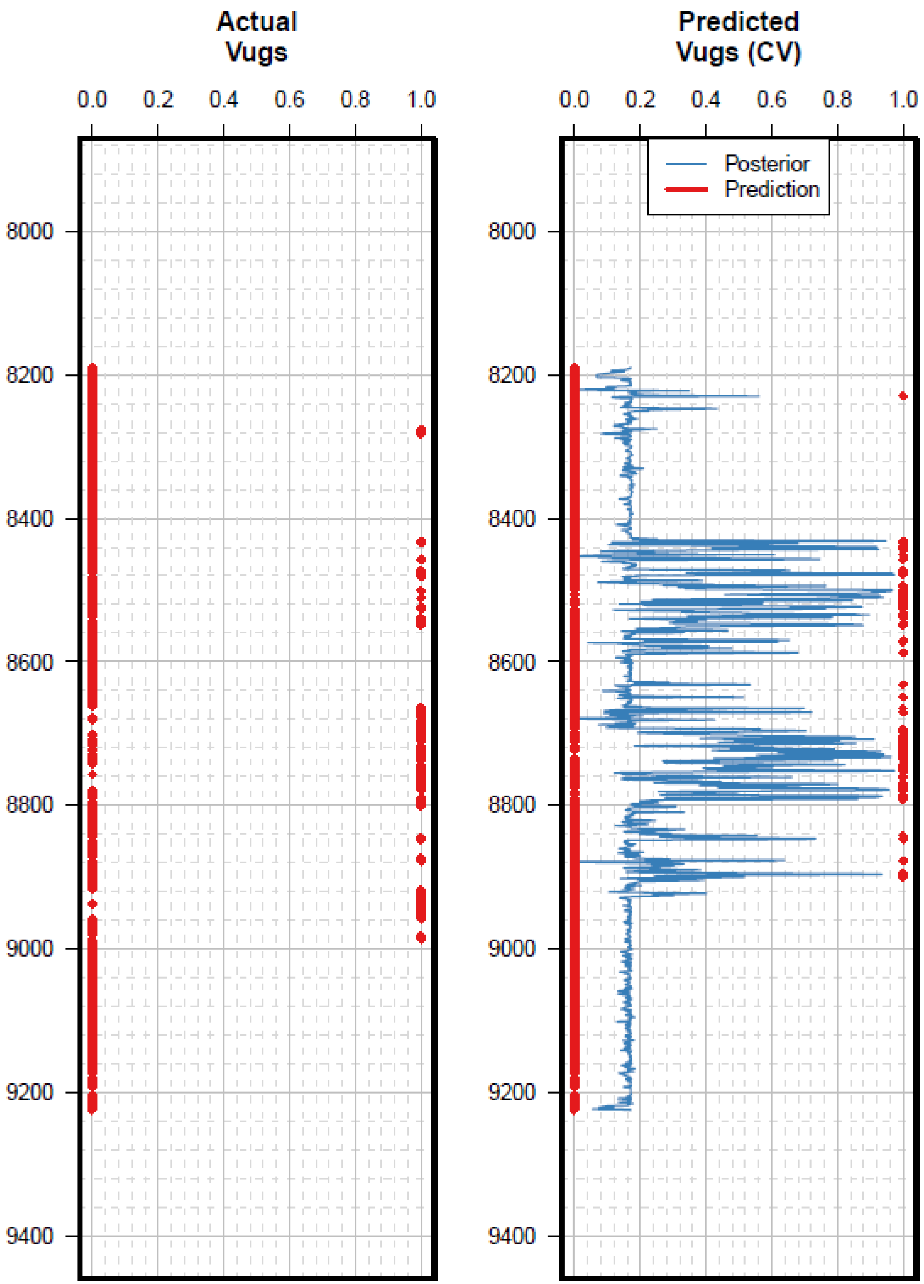
Well	Available Logs														
	XDPHI	XGR	XNPHI	XPE	XRHOB	XRT	XSW	XAPHI	XCAL	XTEN	XPHIA	XBIT	XPHI	XKCALC	XKCALK
#1	X	X	X	X	X	X	X								
#2		X	X	X	X			X	X	X					
#3		X	X	X	X				X	X	X				
#4	X	X	X	X	X	X			X			X			
#5	X	X	X	X	X	X		X	X		X		X		
#6	X	X	X	X	X				X	X	X	X			
#7	X	X	X	X	X	X			X		X		X	X	X
#8		X	X	X	X										
#9		X	X	X	X										
#10		X	X	X	X										

Model Performance Cross Validation

- Wells held out one at a time
- Model trained using the other wells, then predicted on the held out well
- Vug correct identification rate ranges from 60% – 90%

Held Out Well	Correct ID Rate
Well #1	0.721
Well #2	0.675
Well #3	0.748
Well #4	0.820
Well #5	0.767
Well #6	0.885
Well #7	0.733
Well #8	0.604
Well #9	0.810
Well #10	0.820

Example Predictions on a Well



- Train a final model using all the wells, then use it to identify vugs in wells for which no image logs are available
- Output file is a Synthetic Vug Log: SVL (0-1)

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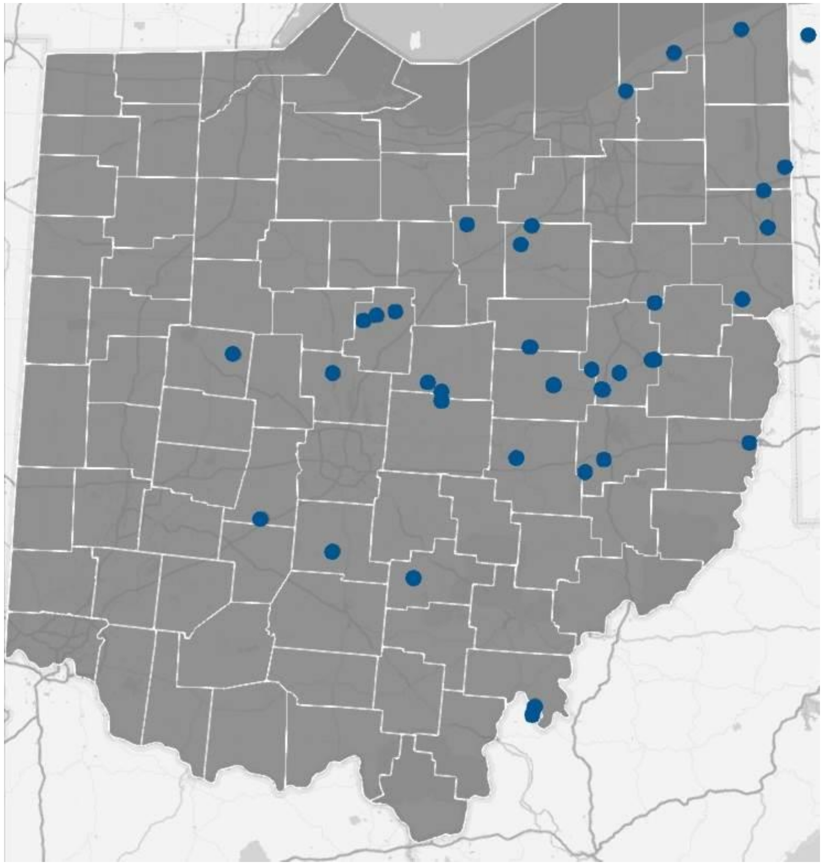
Applied Vug Analysis

- All wells which penetrated the Lower Copper Ridge Formation and have triple combo data available were run through the SVL model
- Total of 40 wells had XGR, XNPHI, XPE, XRHOB
- XGR < 75 and XPE >1.81 cutoffs used to eliminate shale and sandstone



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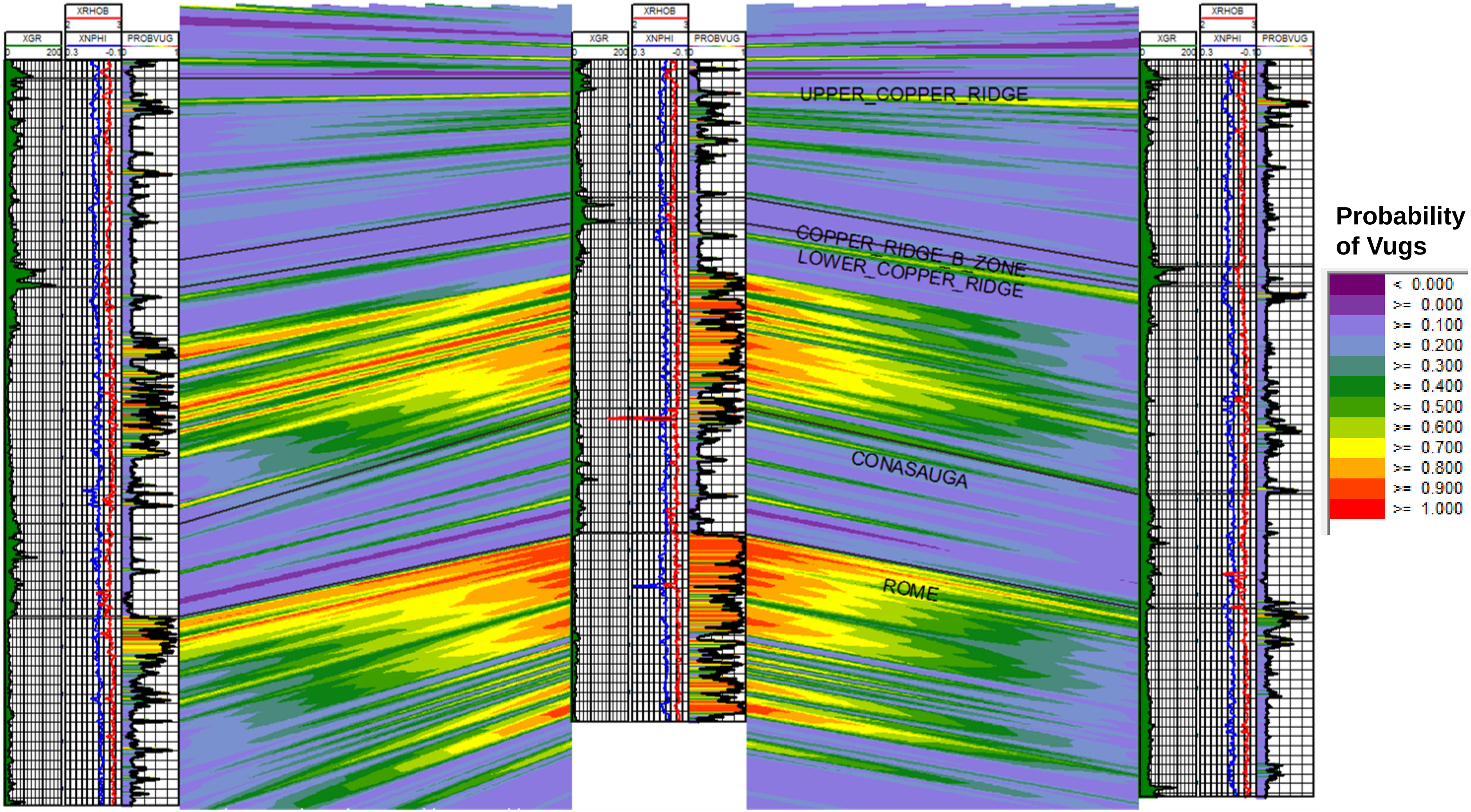
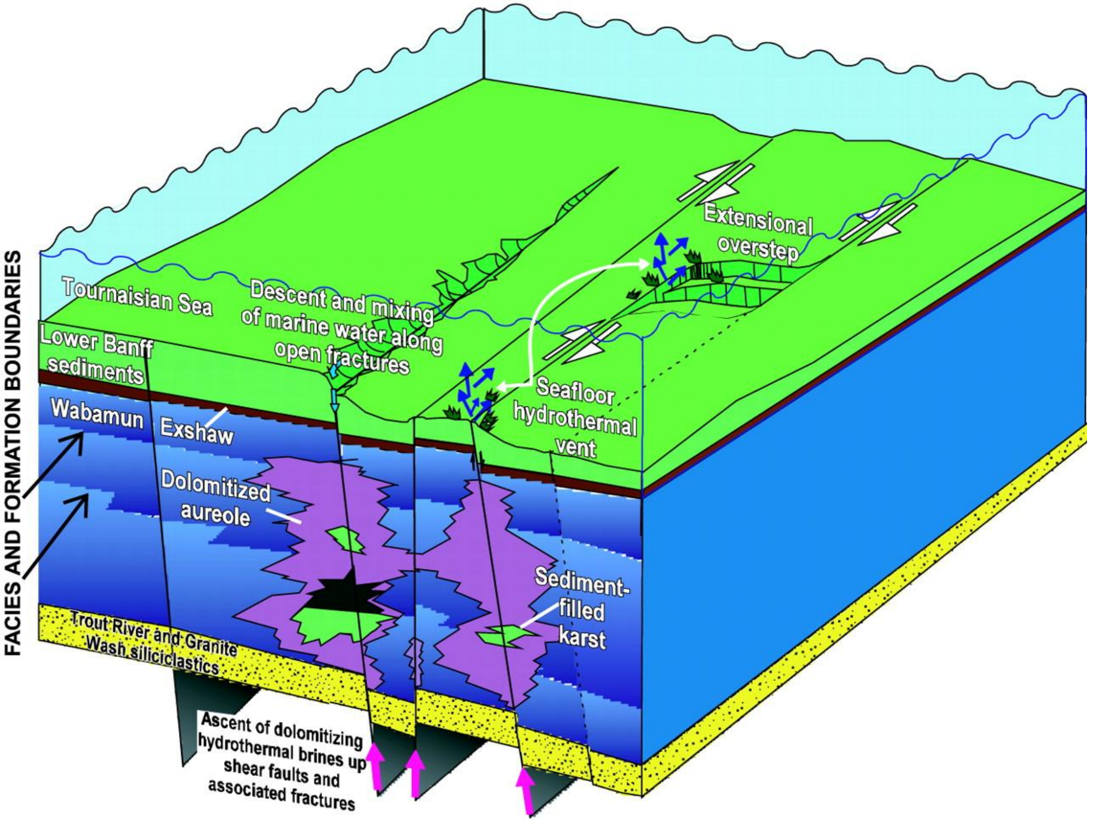
Vug Prediction in Brine Disposal Wells



5 BBL/min　　5 BBL/min　　1 BBL/min

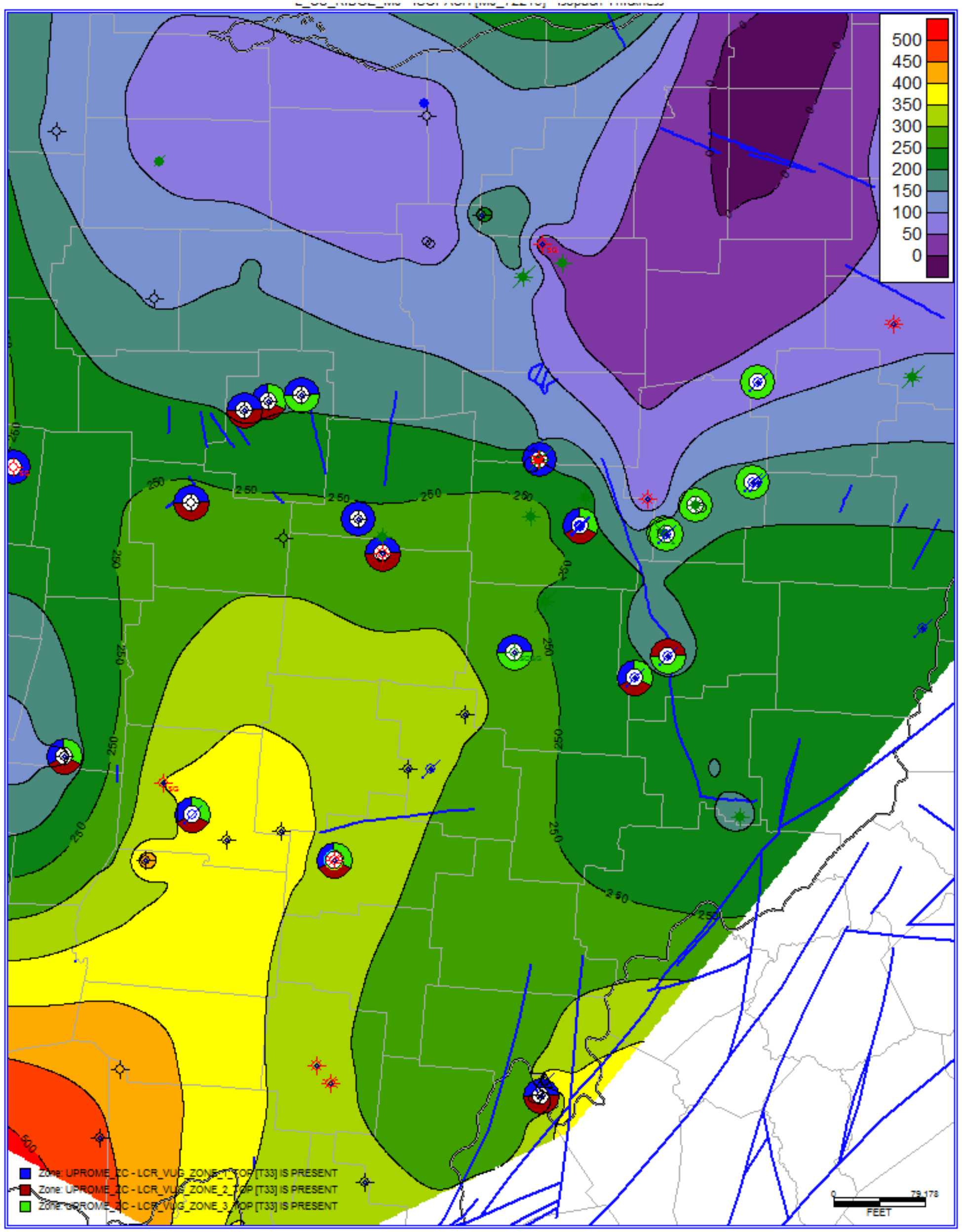
Vug Zones within Lower Copper Ridge

- Vugs occur in three different zones
  - Zone 1- top of the Lower Copper Ridge near contact with B zone
  - Zone 2- Middle of the Lower Copper Ridge (~130-180ft)
  - Zone 3- Base of the Lower Copper Ridge
- Could this be showing hydrothermal vs karst?



http://bc.outcrop.org/images/groundwater/press4e/figure-13-19.jpg
http://aapgbull.geoscienceworld.org/content/90/11/1641.abstract

Lower Copper Ridge Isopach



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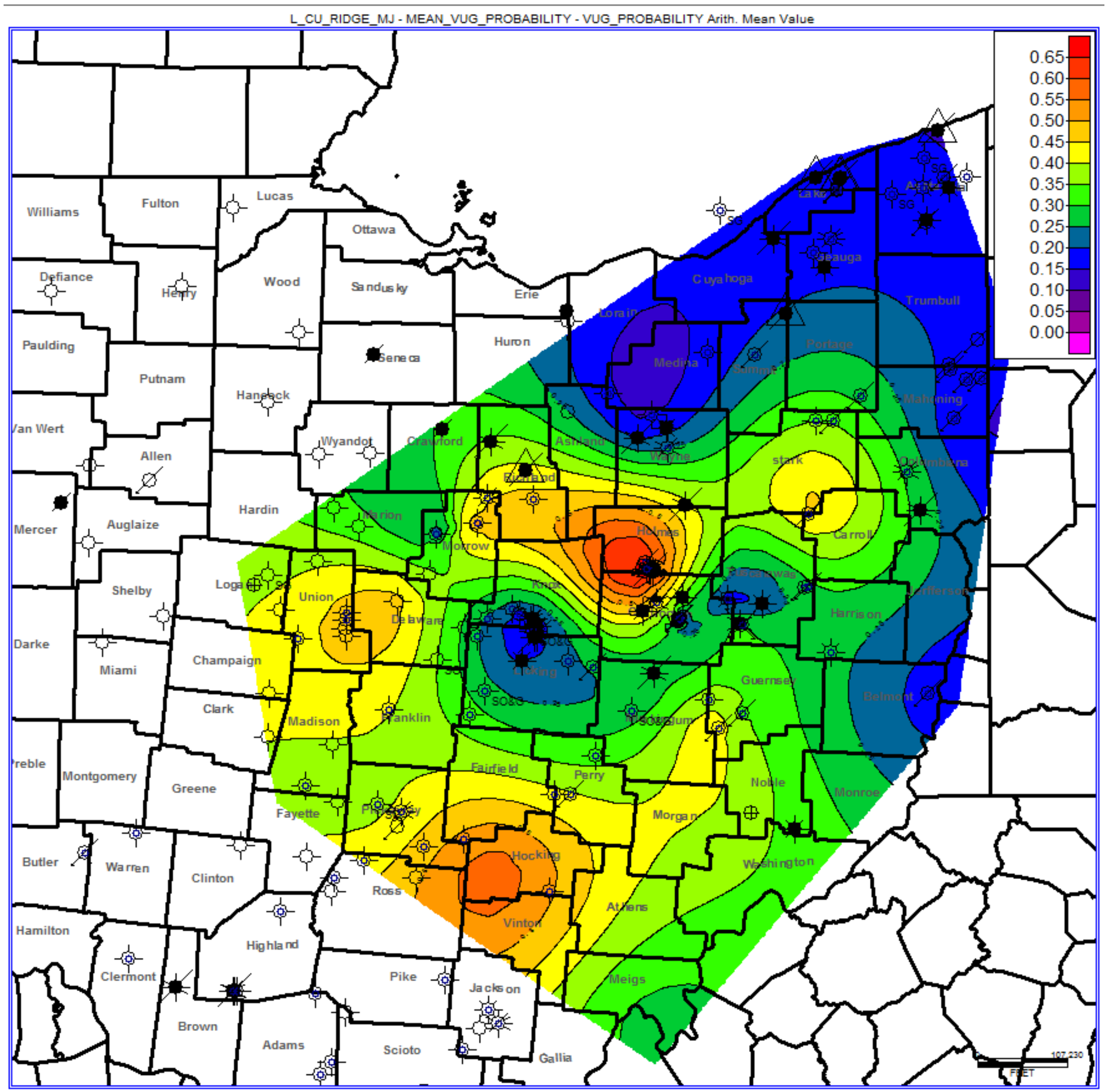
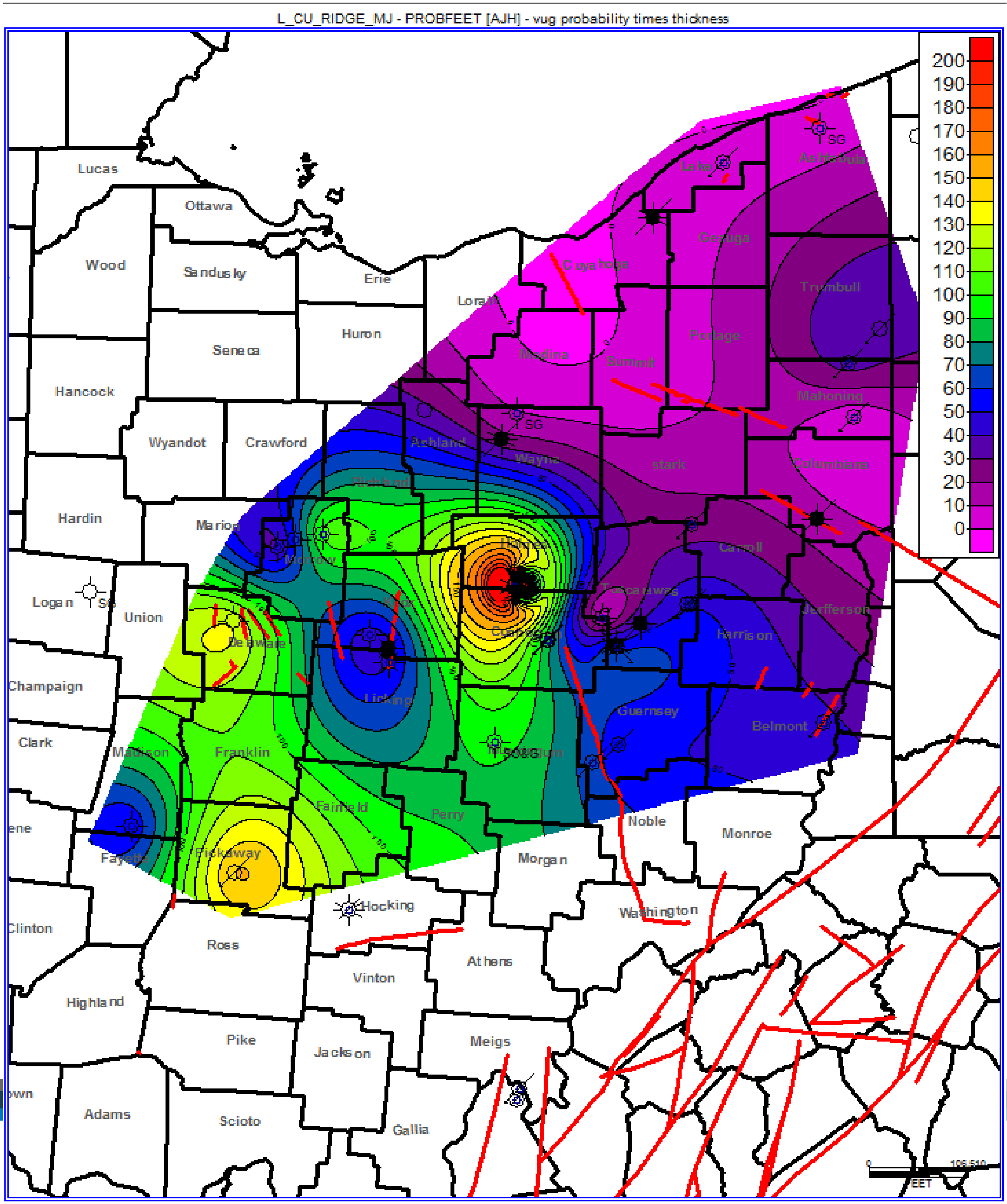
Synthetic Vug Log Probability



Isopach * SVL Probability



Conclusions

- Machine learning techniques can be used to detect vugs in wells without image logs and core samples from triple combo log signatures
- Results vary from well to well, but correct identification rates range from 70-90%
- The vug model is being tested on wells in eastern Ohio
  - These wells have no image logs, so no “truth” known
  - Results are being examined for consistency with other known geologic features

Acknowledgements

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