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Identifying High Potential Well Targets with 3D Seismic and Mineralogy

R. J. Mellors

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3.1.1.2 Identifying High Potential Well Targets with 3D Seismic and Mineralogy

FY15 Technical Report

Robert Mellors
Lawrence Livermore National Laboratory
*mellors1@llnl.gov 925-423-0578

Satish Pullammanappallil
Optim, Inc

John Casteel and Trent Yang
Agua Caliente, LLC

LLNL-TR-662240
Lawrence Livermore National Laboratory

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1.1.1 Introduction

Seismic reflection the primary tool used in petroleum exploration and production, but use in geothermal exploration is less standard, in part due to cost but also due to the challenges in identifying the highly-permeable zones essential for economic hydrothermal systems [e.g. *Louie et al*., 2011; *Majer*, 2003]. Newer technology, such as wireless sensors and low-cost high performance computing, has helped reduce the cost and effort needed to conduct 3D surveys. The second difficulty, identifying permeable zones, has been less tractable so far. Here we report on the use of seismic attributes from a 3D seismic survey to identify and map permeable zones in a hydrothermal area.

The simplest form of seismic interpretation uses the seismic amplitudes as a function of time (or depth) to estimate sub-surface structure. A more sophisticated technique uses alternate characteristics (attributes) of the seismic traces to infer additional constraints on the sub-surface. Considerable work in this area has been conducted by the petroleum industry in refining this type of analysis (*Barnes,* 1999; *Barnes* 2006, *Chopra and Marfurt*, 2007, *Marfurt et al*., 1998) and it has led in some cases to significant improvement in exploration success rates. As the cost of a seismic reflection survey is generally less than that of a single test drill hole, an improved ability to detect and assess geothermal resources would lead to lower costs in geothermal exploration and production.

The primary goal in geothermal exploration is to find a location with sufficient temperature and flow rate. Seismic wave propagation is largely insensitive to temperature variations and therefore indirect effects such as related changes in lithology or fractures must be found. Mineralization associated with water flow may increase velocities [*Majer,* 2004] while fractures are expected to decrease velocities and increase attenuation [*Nakagone et al*., 1998]. The resolution of seismic surveys is much larger than the fracture size and therefore fractures cannot be imaged directly in most cases. Hydrothermal alteration may also decrease velocities [*Unruh et al*., 2001]. In some cases where a clear fluid boundary exists, either near the surface or in a vapor dominated reservoir it may be possible to image the boundary. These effects are difficult to detect using standard interpretation based on amplitudes and attributes are one possible approach to extracting the information. Other approaches may be possible such as inverting for acoustic impedance for lithology, azimuthal variations in amplitude to infer fractures, or amplitude versus offset may be useful. The use of 3D component data for attenuation or anisotropy may be applicable. Here, motivated in part by successes reported in the petroleum industry, we test the use of seismic attributes to reduce the risk associated with drilling additional production wells.

As a test-bed, we will use a dataset of 3D seismic reflection data and ancillary well data from the Walker Ranch (adjacent to Raft River) geothermal area, Idaho. The 3D dataset from Walker Ranch was acquired and processed by Optim, Inc under contract to Agua Caliente. An area of approximately 7 square miles was covered (Figures 1 and 2). The intent is to find an attribute, or combination of attributes, that allows specific parameters relevant to geothermal production to be estimated throughout the volume of the survey. This will allow better estimates of the expected geothermal production at a specific site prior to drilling.

The Raft River/Walker Ranch area has been the site of geothermal investigation since 1974. It is located in southern Idaho and is a large, moderate temperature resource (135-146 C) that produces from fractured Precambrian basement and overlying Tertiary sediments (e.g. *Jones et al.*, 2011; en.openei.org, 2015; Figure 1). Current production from Raft River is about 11 Mw from four production wells. The area is currently the site of an enhanced geothermal system demonstration project. As part of this project microseismicity has been recorded from a local network. In this paper we refer to the producing geothermal area as Raft River and the adjacent area, which is the focus of this investigation, as Walker Ranch.

As we are primarily focused on testing the concept in general, proprietary details specific to the Walker Ranch prospect (e.g, exact locations of cross-sections) that are not relevant to the overall process flow will be omitted. This allows the broad dissemination of information. This report covers the work accomplished during the second year of funding (FY15). Due to a 5 month delay in funding sent to LLNL, a no cost extension was requested (from 9/30/15 to 2/30/16) with the goal of presenting at the Stanford Geothermal Workshop.

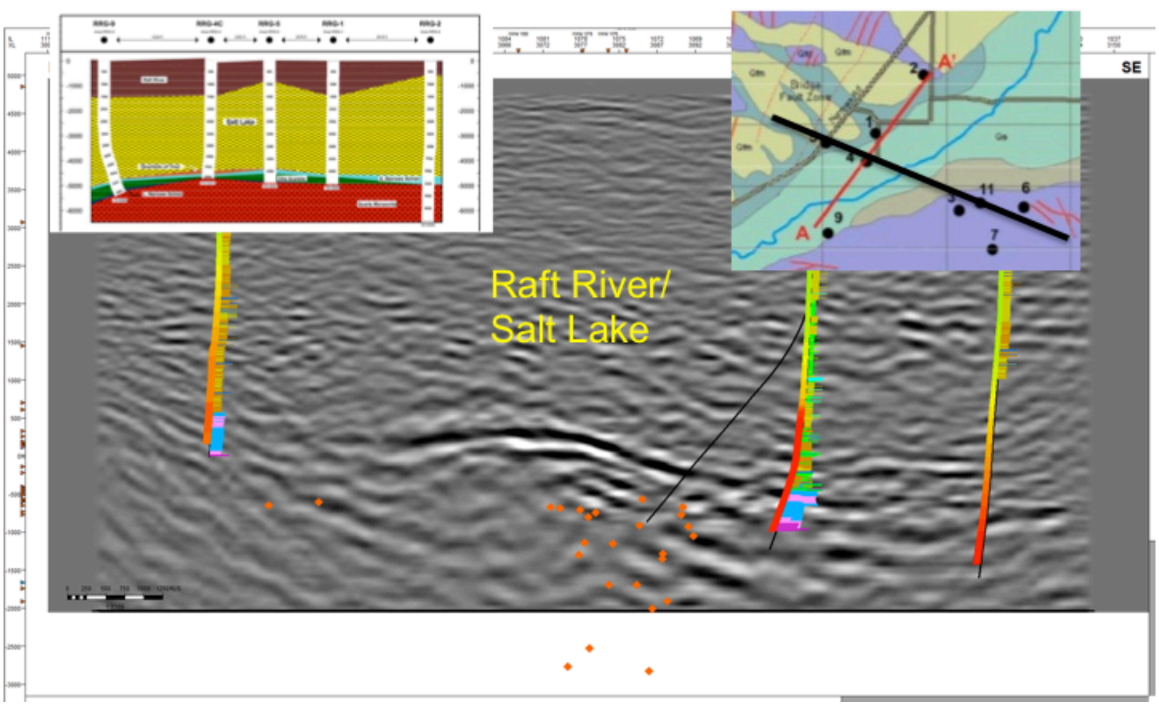

Figure 1. Cross-section of Walker Ranch seismic data with geological cross at upper left and map showing location of seismic section (black line) and geological cross section (red line). Note that the geological cross section and the seismic section are roughly perpendicular to each other. Colored lines represent well tracks and orange dots are micro-earthquakes.

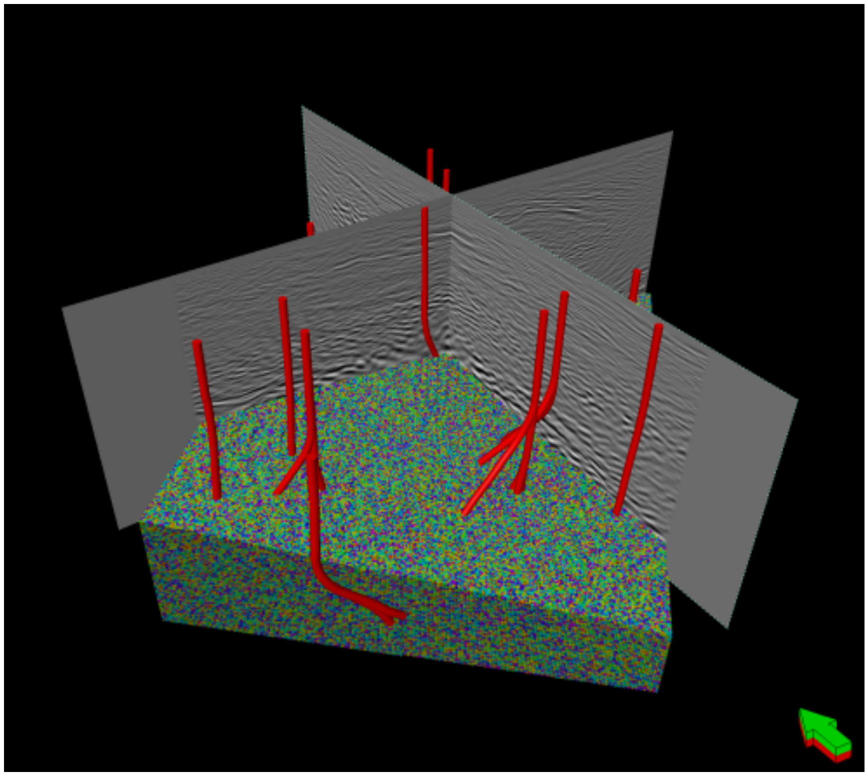

Figure 2. 3D view of 2D seismic amplitude sections overlaid on a 3D cube of attributes. Red lines are well tracks.

1.1.2 Review of work accomplished in the first year of funding

In the first year of work, seismic attributes were calculated on the 3D datasets using both newly developed code and commercial (Petrel) software. In addition, well cuttings were analyzed using X-ray diffraction and petrological analysis. The purpose of the well cuttings analysis was to map the lithology in the well for comparison to the seismic attributes. The results include automated mapping algorithms of the Walker Ranch datasets using attributes derived from the 3D data. Synthetics were generated using finite difference algorithms.

1.1.3 Review of work accomplished this year

A new set of tasks were funded in the FY15 AOP to LLNL, Agua Caliente, and Optim, inc. These tasks included data compilation, neural net analysis, validation, examination of micro-earthquakes and seismic data, and a report. Unfortunately, the majority of funding did not arrive until February, 2015 (approximately 5 months after the planned start date in October, 2014). This led to a delay in sub-contracts and milestones, which is being accommodated by a no cost extension until February 2016.

A presentation at the Stanford geothermal workshop was made in February 2015 and a peer review was presented in May 2015. A major problem was the fact that much of the data is proprietary and could not be presented. In general, the idea seemed reasonable to most reviewers but they were unable to properly comment on results due to the proprietary nature of the data.

1.1.4 Data compilation and neural net analysis

These tasks were undertaken largely by Optimc, Inc, and Agua Caliente. Optim developed a set of neural net analysis software. The goal is to find an algorithm that will automatically search through attributes and find patterns that will predict permeability in wells. Permeability index values were extracted from data from the three wells drilled by Agua Caliente at Walker Ranch and used as the training set. The permeability as a function of depth was estimated on flow records, drilling history, and losses. It is expressed as an index that seeks to rank the different zones within a well with respect to each other. Four different neural net approaches were tested on 11 attributes derived from the 3D data. The shallow subsurface (upper 1900 feet) was excluded from the search. The input attribute file consisted of 2.2 million points and the permeability index (PI) file contained 2,069 points. Validation was accomplished by “leave one out”, i.e. known permeability index values that were not used in the neural net analysis were predicted based on the attributes.

The four approaches were feed forward neural network with resilient back propagation (*Reedmiller and Braun*, 1993; *Brieman*, 1996); generalized regression with Gaussian layer (*Specht*, 1991), radial basis functions with Gaussian functions (*Broomhead and Lowe*, 1988), and support vector machine with Gaussian kernel (1997). The support vector machine algorithm was the fastest and most efficient.

The results were mixed. In the first result the correlation between the expected and observed values was 0.78 with a standard error of 0.25, which is not very good. After smoothing the input attributes, the correlation increased to 0.95 with a standard error 0.11 (Figure 4 and 5). Analysis suggested that the observed permeability index values varied greatly over short spatial distances, which made fitting to more smoothly varying attributes difficult.

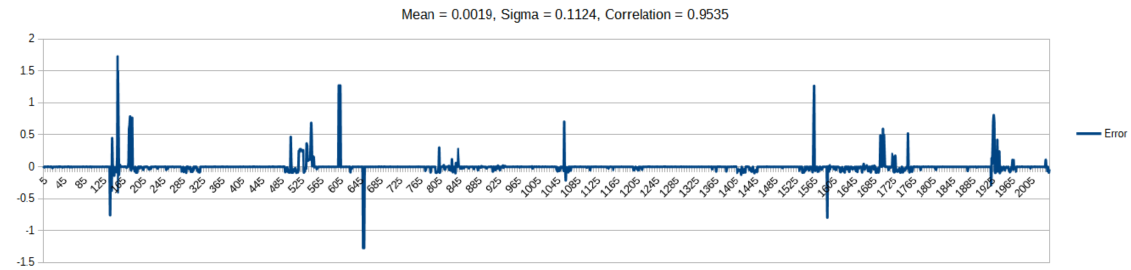

Figure 4. Plot of the difference between observed and predicted permeability index values using the 'leave one out' cross-validation. Large deviations exist even after data smoothing.

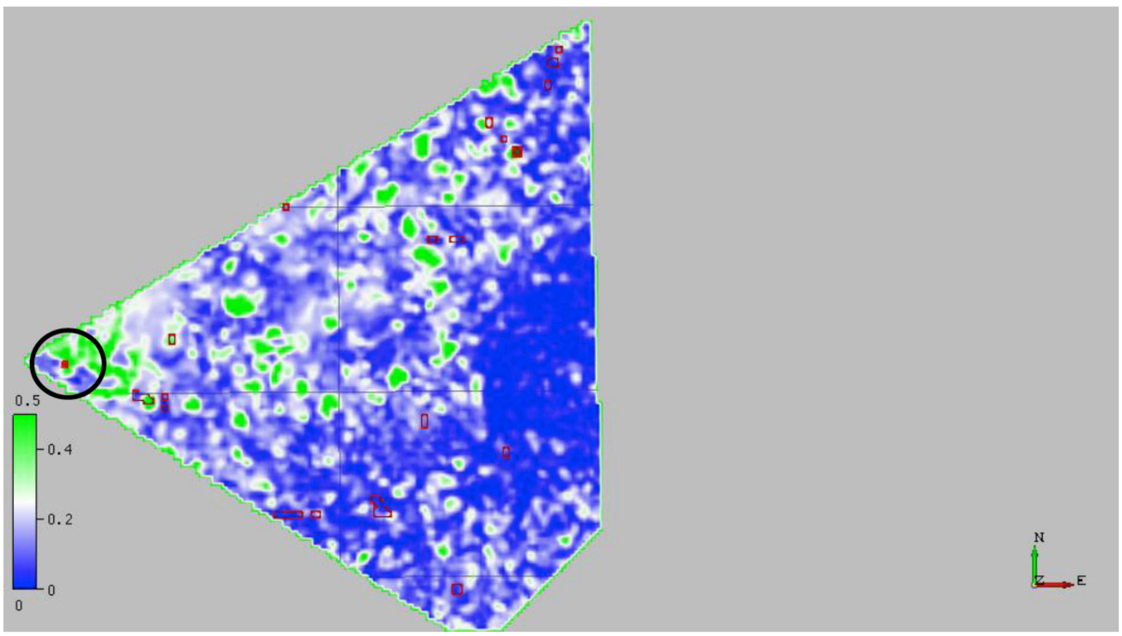

Figure 5. A depth slice showing the predicted permeability and the training points (open red squares). The solid red square with a circle shows a point where the predicted permeability matches the observed permeability.

The second approach used commercial software (Petrel) to identify permeable zones using attributes and other data such as temperature and resistivity. Multiple combinations of parameters were tried. In general, most of the models generated a fairly good fit to the training set (Figure 6). Unfortunately, while the correlation statistic indicated a good fit, examination of the results from a geological perspective did not match expectations. For example, one case where the fit was good showed a series of lateral horizons where the permeability appeared to follow a specific set of reflectors and not the expected vertical faults in a hydrothermal reservoir.

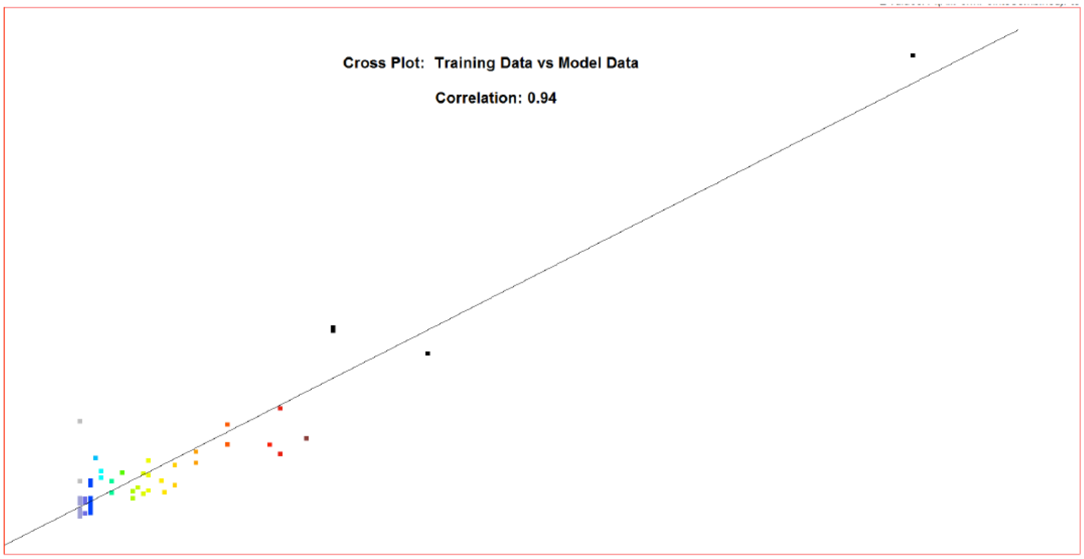

Figure 6. Cross plot of training data versus model.

Validation was also conducted using a 'leave one out' strategy. This showed a poor match in general. A disadvantage of this approach is that omitting some of the training points reduces the overall fit. The two approaches, Optim and Petrel, were compared using the same input data. Results were similar but differed in detail away from the training set. This may be due to subtle differences in implementation of the two codes.

Overall, the key finding is that the neural net is capable of finding relationships between attributes that would be impossible to find manually but we have not yet found a set of inputs that predict permeability in a robust fashion.

One area that needs improvement is the estimate of permeability index (PI). The current estimate used well production and test data. While PI is usually a good estimate of overall well production, for this study we need PI as a function of depth, which requires some approximations. As this data is the key training data, any inaccuracies would lead to poor results. We are now re-evaluating our procedure to estimate PI.

1.1.5 Micro-earthquakes and reflection seismic

Another use of the 3D data is to use the amplitude images to examine structure. In particular, it is of interest to see if the microearthquake locations correspond to clear structural features in the 3D seismic data. Using locations (x,y, and z) from the LBL catalog provided by E. Majer, the microearthquakes (MEQ) were plotted on the depth migrated seismic reflection data.

MEQ were plotted on series of horizontal and vertical slices (Figures 7 and 8). The basement interface is visible as a strong reflector and it is clear that MEQ occur below the reflector. Although the MEQ appear to occur along a roughly linear fashion, no obvious discontinuity is visible in the horizontal section. The vertical sections show some slightly discontinuous features that might be faults cutting the section at high angle, but a single distinct feature is not obvious.

This result is slightly surprising and may indicate that seismogenic faults are challenging to identify in geothermal areas using reflection seismic data. Alternatively, it may be that the relative locations between the MEQ and depth migrated section differ, as both were determined using different velocity models. One way to address this is to use a commaon velocity model but we have not yet done this.

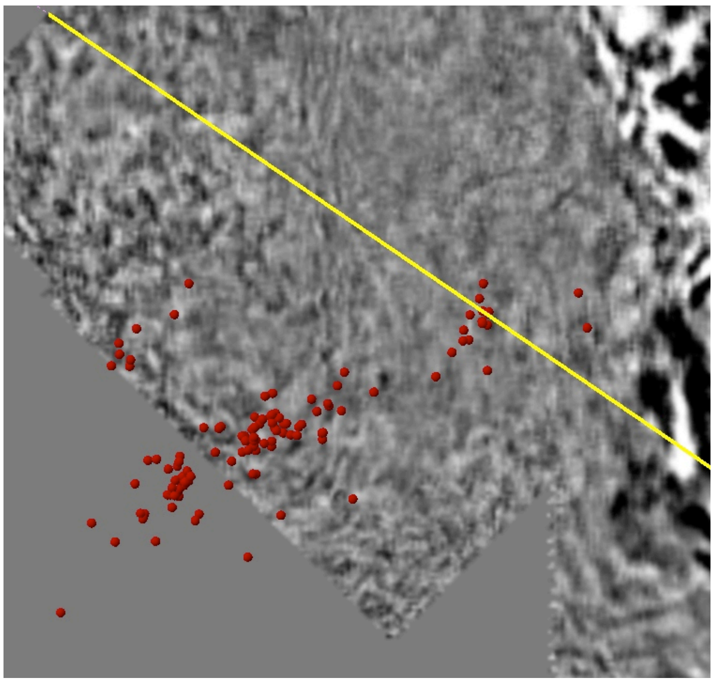

Figure 7a. Depth slice, showing MEQ.

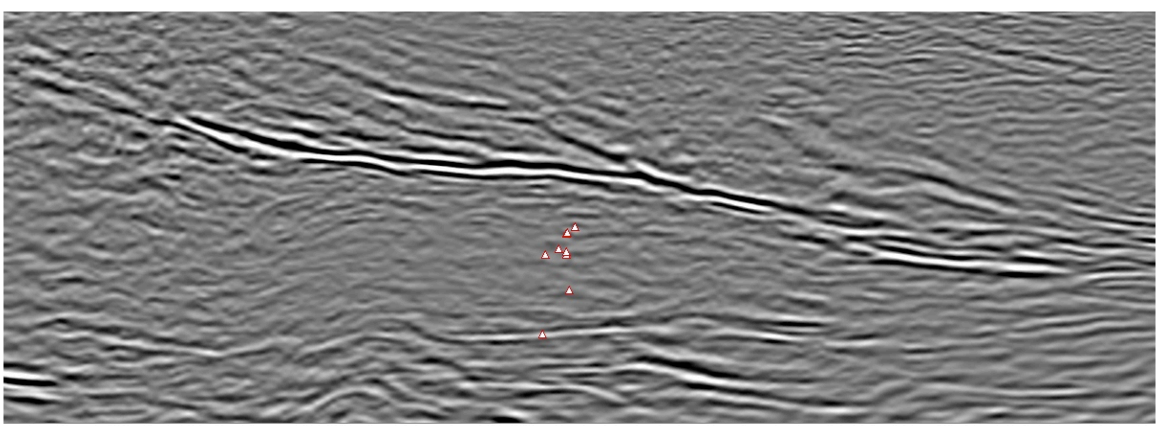

Figure 7b. Vertical slice, with MEQ within 250 feet shown.

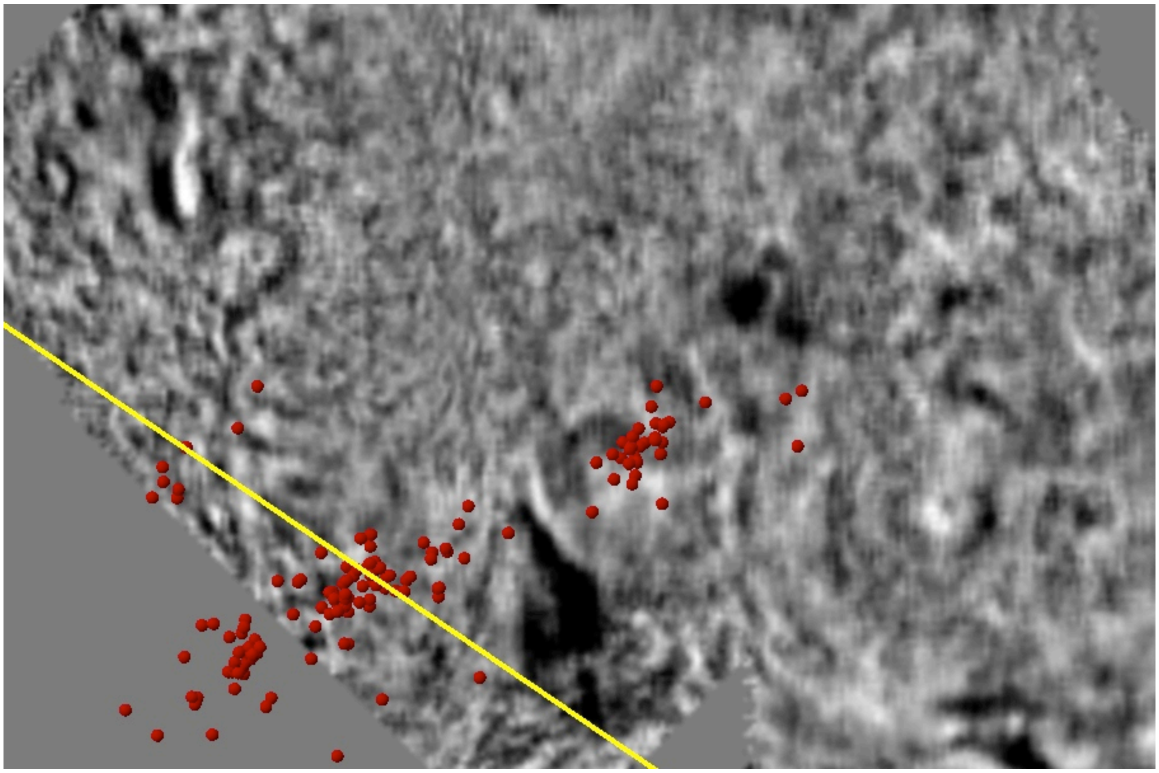

Figure 8a. Depth slice (1000’ below Figure 7a). MEQ in red.

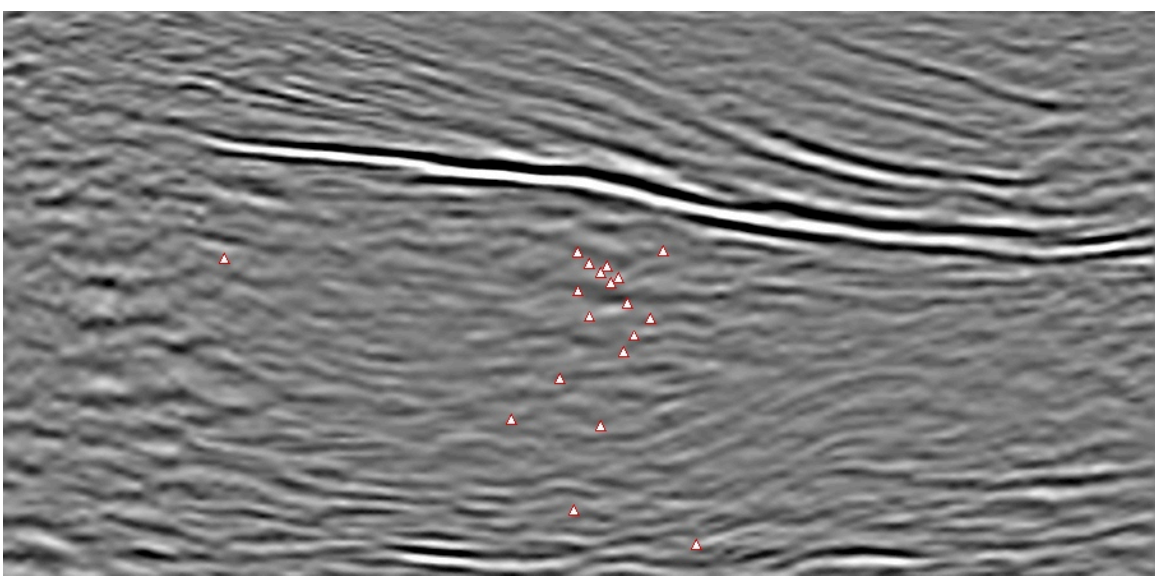

Figure 8b. MEQ within 250 feet of the section.

1.1.6 Conclusions

The neural net analysis indicates that the method is effective at finding relationships between attributes and permeability that are not obvious otherwise, but a clear relationship that matches the geology and is effective at predicting permeability has not yet been discovered. One possible reason for the difficulty is the permeability estimates used to train the neural network, as errors in the input dataset would cause significant problems with correlation. Preliminary examination of microearthquake locations and 3D seismic data show that the earthquakes do not appear to correlate well with significant features in the seismic data.

1.1.7 Milestones

Five milestones were planned.

1) Milestone 1. Incorporation of all geophysical data and permeability data into model. **Complete**.
2) Milestone 2. Calculation of attributes using neural net and application to 3d data. **Complete.**
3) Milestone 3. MEQ locations with respect to seismic and geology. Do they match 1) structural boundaries or 2) other interfaces?. **Complete**.
4) Milestone 4. (SMART) Final report and evaluation of usefulness of technique - can we estimate permeability? **In progress**, **50% complete; continuing into FY15 (no additional cost).**

Presentations

Mellors, R. J., N. Marks, S. Pullammamappil, J. Casteel, T. Yang, J. Moore, and C. G. Jones, Imaging geothermal resources with 3D seismic attributes, Stanford geothermal workshop, Feb 26-28, 2015, Palo Alto, CA.

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