# Seismic Guided Minerals Exploration


*Tony Marsh*
HiSeis
t.marsh@hiseis.com

*Sian Bright*
HiSeis
s.bright@hiseis.com

*Kevin Jarvis*
kevhui@iinet.net.au

*Jai Kinkela*
HiSeis
j.kinkela@hiseis.com

*Andrew Pethick*
HiSeis
a.pethick@hiseis.com

*Greg Turner*
HiSeis
g.turner@hiseis.com

*Sasha Ziramov*
HiSeis
s.ziramov@hiseis.com



## SUMMARY

Large areas of prospective mineral regions are buried by regolith cover and have been overlooked owing to the difficulty of identifying and verifying deeper targets below. This presents a huge opportunity for mineral exploration as new technologies emerge to address this challenge. New techniques must be able to image buried geological structures in adequate detail for geologists to make informed decisions about the presence of suitable structures to host a mineral deposit. Potential field methods provide a broad scale exploration picture but lack the resolution provided by active source seismic surveys.

A significant impediment to the uptake of seismic techniques in minerals exploration has been the complexity of the outputs. We address this in two ways. Firstly, we use new seismic processing and velocity model building workflows specifically tailored for hard rock environments. These provide considerable uplift over legacy seismic data sets as well as high quality new subsurface imaging results. Secondly, using these high-fidelity results, we use new automated, data-driven workflows to provide more geological outputs which can be used to inform key aspects of minerals systems at multiple scales.

New automated interpretation techniques adapted from the oil and gas industry using machine learning and artificial intelligence are now being applied to mineral 3D data sets for automatic fault detection. Along with this, seismic inversion is now being successfully employed to generate robust 3D rock and rock property volumes incorporating all available drillhole control. The combination of these two approaches results in a comprehensive 3D geologic model of structure and stratigraphy at a resolution rarely seen in the minerals industry.

Our paper will present multiple case histories of how these approaches are transforming the way seismic is being used to advance geological understanding and accelerate mineral exploration under cover.



**Key words:** Machine Learning, Fault Detection, Mineral's 3D, Hard Rock Seismic, inversion


## INTRODUCTION

Imaging of geological structure under thick regolith cover presents a major challenge in exploring for new mineral deposits. Geophysical-based mineral exploration is usually based on a combination of geophysical techniques (e.g.: gravity, magnetics, MT (Magneto Telluric), EM (Elector Magnetic) and IP (Induced Polarization)) where the resolution degrades with depth particularly beyond the top few hundred metres. Reflection seismic imaging, on the other hand, retains resolution from tens of metres from the surface to well below minable depths. Integration of these two data types provides a mechanism to delineate the key geometries which control mineral systems and thereby optimise drill targeting particularly below approximately 300 m depth.

Seismic images can, however, be complex and, until now, a certain level of seismic interpretation experience and specialised software has been required to extract much of the detailed information contained in the data. This has impeded the incorporation of the data into standard minerals exploration and exploitation workflows. In turn, this has limited the potential value-add provided by the ongoing integration of the seismic data with other new datasets (particularly core logs and elemental assays) as they come to hand.

This has been addressed in two areas; 1) application of new seismic processing and velocity model building workflows specifically designed for hard rock environments, and 2) developing and adapting data driven approaches to convert complex seismic data into more geological outputs that are easily brought into the standard geological software packages used by the minerals industry. These datasets are therefore more readily comprehensible by a wider range of geoscientists – not just specialist seismic interpreters.

## Geophysical Imaging for Hard Rock Data Sets – Seeing Under Cover

In the area of seismic processing, application of pre-stack depth imaging to hard rock seismic data provides considerable uplift over legacy pre-stack time imaging. Figure 1a is an example of a legacy PSTM (Pre-Stack Time Migration) dataset from the Barnicarndy Graben of the broader onshore Canning Basin, Western Australia. The legacy PSTM processing does not account for the complex geology and associated velocity structure and does a poor job in on the right-hand side of the image. Pre-stack depth imaging on the other hand shown in Figure 1b, utilizing modern velocity model building methods tailored specifically for hard rock seismic, images the complex "basement" structure and associated velocity field with considerable detail – revealing a large fold associated with a reverse fault in the Precambrian strata (Braunig et al. 2020). This structure occurs along strike to discovered mineral resources in a similar structural style (e.g., Dalstra, et. al. 2022). This unexplored structure is poorly imaged by magnetics/gravity data and is below approximately 200m of cover well within minerals exploration depths. Improved structural imaging is fundamental to the application of machine learning and other fault detection and mapping techniques. If the structures are not imaged, they cannot be detected.

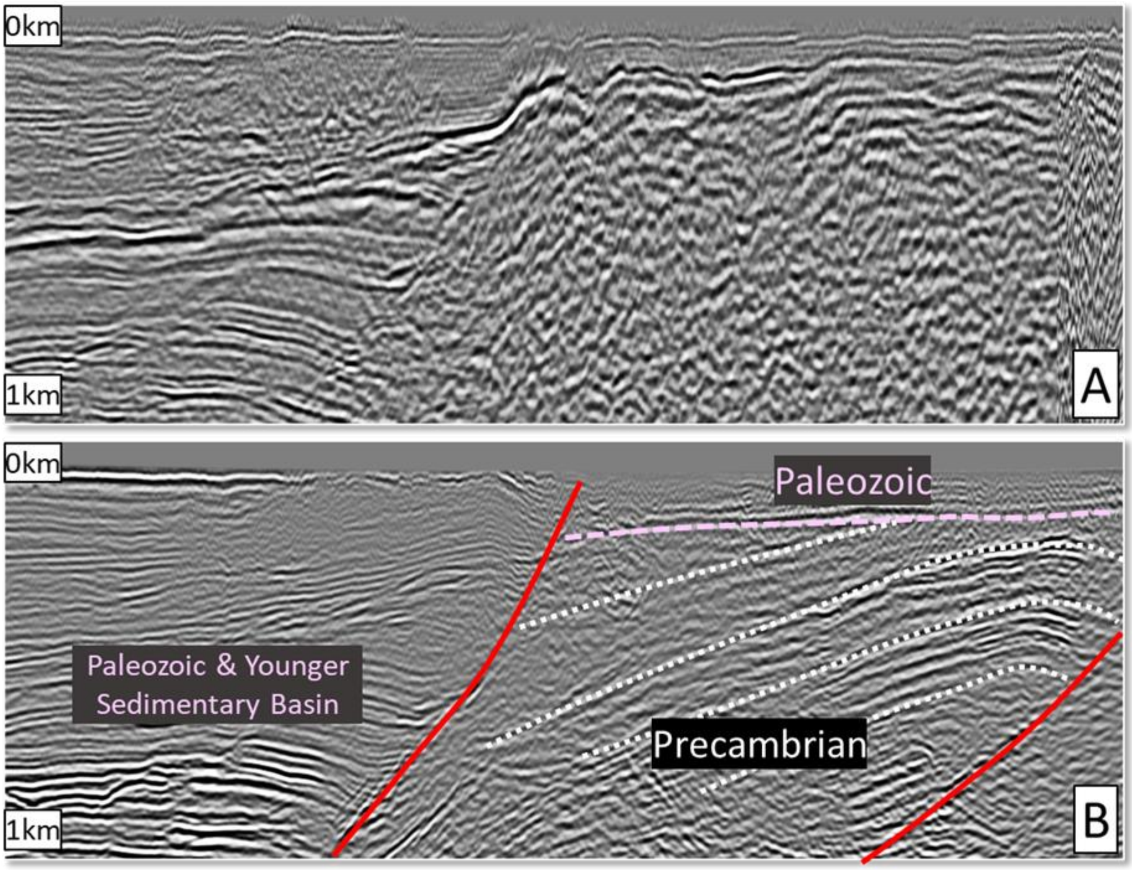


**Figure 1 A) are the result from a legacy pre-stack time migration, the zone of incoherent reflections on the right side of the section is poorly imaged basement structure, B) is the corresponding section from pre-stack depth migration with well imaged Precambrian basement structure. (Images presented with the permission of Searcher Seismic).**

## Automated Fault Detection and Mapping

Fault identification is important in minerals exploration for a variety of reasons. They often provide pathways and conduits for hydrothermal and other mineral bearing fluids during the formation of a mineral deposit and consequently mineralisation is often found in or near to major fault zones. The interconnectivity of faults on a large scale can be important to assess the prospectively of areas proximal to known mineralisation and faults which occur post mineralisation can separate volumes of mineralised rock that were once joined (e.g., Rhys 2017, Campbell, 2017, Groves, 2017)

Seismic data is well suited to the detection and delineation of fault zones because of the high density of data with a data point every 5-10m in 3D seismic data sets. Traditionally steep faults have been interpreted by looking for breaks in seismic reflections on a section-by-section basis. This is time consuming, and prone to error and interpreter bias. We have been looking at methods of automating the delineation of fault frameworks from 3D seismic data in mineralised terrains building on significant amounts of R&D in the oil and gas sector (Marsh et al 2022). These machine learning-based approaches utilize either pretrained or untrained fault networks. The oil and gas pretrained networks are dominated by high angle normal faults from sedimentary basins in a variety of structural styles and data quality situations. Testing so far indicates these networks work well at detecting high angle structures (either normal or reverse fault displacements) in minerals 3D data sets. However, thrust faults and shear zones which occur at lower angles and may be reflectors themselves are mostly absent from pretrained networks thus requiring the use of untrained/customized fault networks built directly from minerals 3D data sets where these structures exist. Very often minerals data sets contain both high angle structures and thrust/shear structures so pretrained and untrained/customized networks need to be combined.

## AI Detection of High Angle Faults

We have applied a pretrained oil and gas fault network library tuned for small scale faulting to a data set acquired at Jundee Gold Mine. Jundee is an Archean, orogenic, lode-gold deposit located in the Northern Goldfields region of Western Australia (WA). The total resource mineralization plus recovered gold at Jundee exceeds 10Moz. Typical of many orogenic gold deposits in the WA Goldfields, Jundee is made up of multiple zones of mineralization with multiple styles, multiple orientations and within multiple host lithologies. It is however clear that certain generations of structures play a key role. The initial output from the machine learning fault detection is a cube of data where the amplitude represents the assessed probability that a fault occurs at each data point within the seismic data. Fault probability volumes are skeletonized to produce a discrete fault volume rather than a zone of fault probabilities. This is then used to compute azimuth and dip volumes. Figure 2 shows a depth slice from the input amplitude reflectivity volume and corresponding azimuth cube computed from a fault probability cube. The fault azimuth cube identifies 4 fault orientations which correlate well with known mineralization trends at Jundee. The creation of data sets such as fault azimuth, simplifies the original input amplitude volume to a point where geologists can view the results as a geological fault framework map. Fault probability cubes can further be simplified to fault wireframes which are familiar to geoscientists who work within 3D geological software packages.

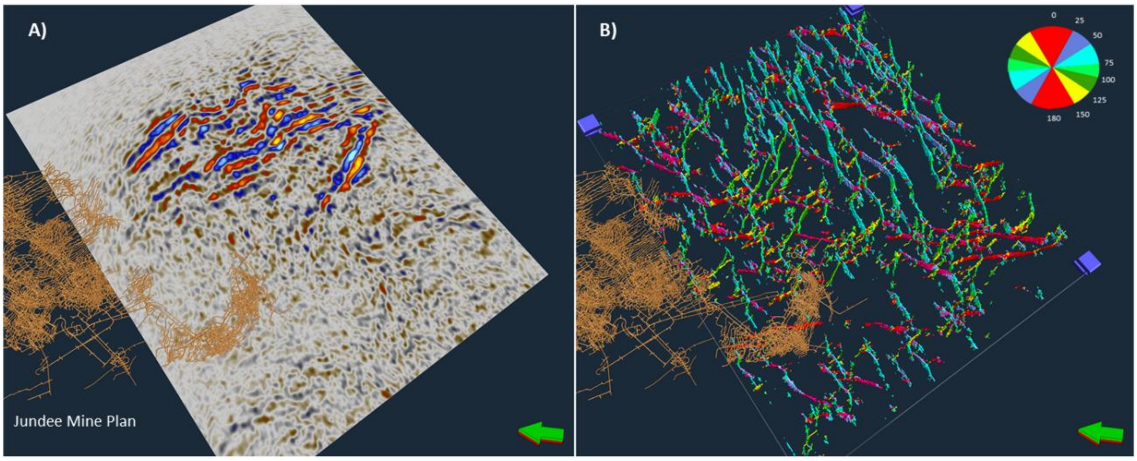


**Figure 2. A) Amplitude depth slice from the Jundee pre-stack depth imaging with active mine plan shown in brown. B) Azimuth volume illustrating the different fault orientation with scale indicating fault orientations.**

## AI Detection of Thrust Faults and Shear Zones

Thrust faults and shear zones are not represented in most pretrained fault networks and require survey specific training where labels must be identified and incorporated into a new training network. This approach was used to identify thrust faults occurring at the Yaouré gold mine in central Côte d'Ivoire. Gold at Yaouré is hosted in basalts and granodiorites affected by N-S trending; low angle (30-40°) brittle ductile structures, and NW and NE sub vertical structures. Many of the low angle thrust faults are imaged as reflectors as shown in Figure 3 rather than distinct breaks in reflectors as observed in the high angle faults. A fault untrained/customized network was created using a small subset of the 3D comprising 0.60% of the 3D data set of 5 dip lines and 3 strike lines which is sufficient to interpret the entire data cube (Figure 3). Rendered results of the fault detection are shown in Figure 3. Understanding thrust structures in relationship to gold grade, not only provides a framework for understanding the mineralization at Yaouré but also provides a way of looking at other exploration targets. As with Jundee, the original amplitude data are simplified and condensed down to only contain fault information which geologists can use directly.

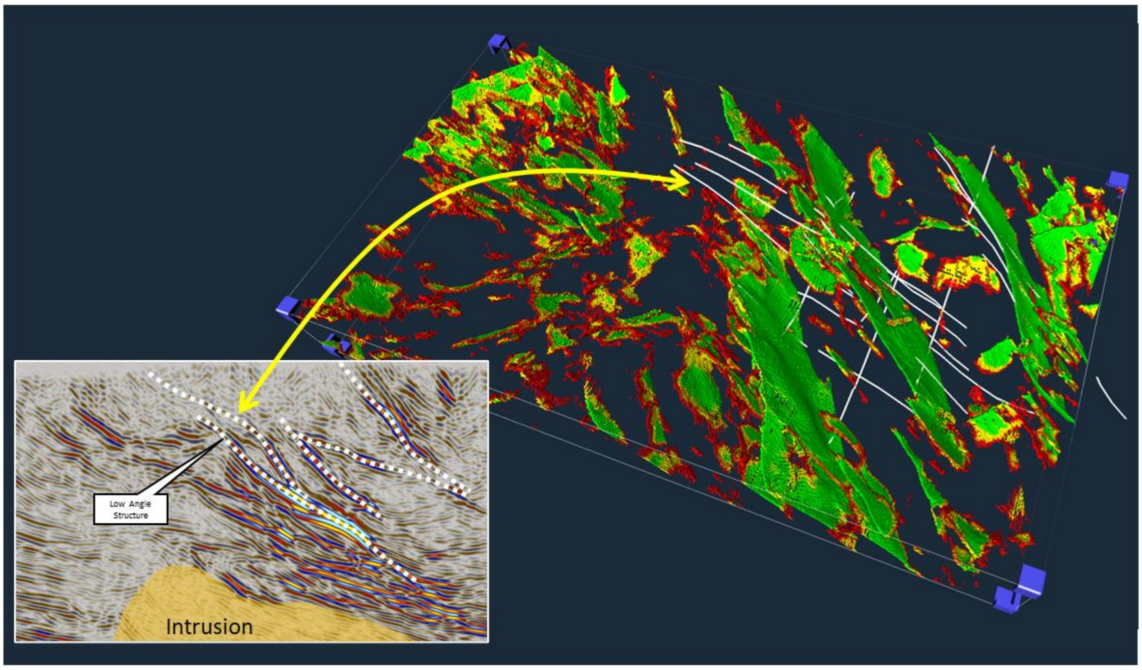


**Figure 3. Dip direction seismic section with fault labels used to train the customized fault network and a 500m thick 3D slab of rendered fault probability results showing all fault sticks used for training in white. Green is high fault probability, red is low. Note that that faults have been picked where trained and into areas with no training data.**

### Seismic Inversion of 3D Seismic

The seismic reflection technique is based on the reflection of seismic waves from subsurface boundaries where there is a change in seismic properties. For normal P-wave reflection data the key property is P-impedance which is equal to the product of density and seismic P-wave velocity. Seismic P-wave velocity depends on the competence of a rock. The softer and more fractured it is, the slower the seismic velocity. Conversely, the harder and less fractured it is, the higher the seismic velocity.

Since seismic reflection techniques respond to boundaries, seismic is particularly good at mapping the geometry of geological contacts. However, through a process called seismic inversion it is possible to convert the seismic data back to P-impedance of the geological units between the contacts (Jarvis, 2022). This P-impedance model can then be used, together with knowledge of the P-impedance of different rock units from drill hole measurements such as wireline logging or core data, to construct a 3D model of the distribution of different rock units throughout a cube typically covering tens of cubic kilometres.

Seismic inversions are routinely performed in sedimentary basins to characterize seismic for reservoir models where rock type and other reservoir properties are required. Seismic inversion of hard rock seismic has been underutilized as it has been assumed there not enough velocity/density contrasts and elastic property variability for the seismic inversion to work as well as the underlying geological complexity. HiSeis has performed numerous feasibility studies from hard rock drill hole wireline data which demonstrate that hard rock data sets are suitable for seismic inversion given appropriate geology. Optimum results for seismic inversion are obtained if identified lithologies show a good separation of elastic properties (Jarvis and Saussus, 2009). The degree to which different lithologies can be accurately identified from seismic data relates directly to how much these separate in the elastic property space. An example of lithology prediction from a geostatistical inversion is shown in Figure 4 where 3D seismic was acquired over the St Ives – Victory gold deposit in 2017. Inversion feasibility studies showed that sufficient elastic property separation existed to model mafic, ultramafic, and ‘other’ units consisting predominantly of felsic and sediments. The inversion process simplifies the complexity of the seismic cube into these 3 distinct rock types that follow known stratigraphy and honour the 5000+ drill holes that exist over the mine. This in turn provides one of the most detailed insights into the distribution of these 3 rock types currently available at this mine site and can be used to guide decisions from exploration through to mine planning.

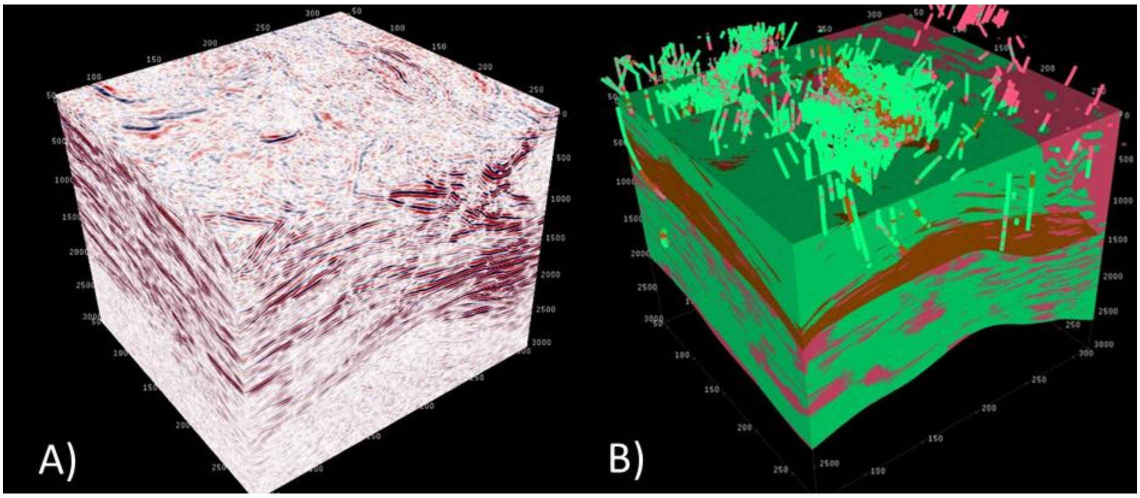


**Figure 4. A) Victory 3D seismic volume showing good reflectivity in the upper 2500m. B) Results from geostatistical seismic inversion showing most probable lithology for mafic (green), ultramafic (brown) and other rock types consisting predominantly of felsic and sedimentary units (red) (modified from Jarvis, 2022).**

## CONCLUSIONS

Mineral deposits commonly occur in complex multiply deformed geological environments. 3D reflection seismic data is the only geophysical method that can image details at scales of tens of metres over tens of cubic kilometres. However, the data has typically been presented in a way that is difficult for non-seismic specialists to understand. We have shown two methods that simplify 3D seismic data sets; 1) creating a fault probability volume which reduces the seismic volume to areas where breaks or discontinuities in reflections occur defining areas where faults most likely to exist, and 2) showing how seismic inversion can be used to simplify a reflectivity cube to several key lithologies. Underlying these approaches are improvements to the subsurface seismic image through the application of pre-stack depth migration and velocity model building workflows specifically tailored for hard rock seismic data sets.

Faults are often play a key role in mineral deposit formation and are a very important component of many mineral systems. Faults and shear zones often provide pathways for hydrothermal and other mineral bearing fluids to accumulate within the fault zone itself or associated deformation zones around faults. The detail in the seismic generated fault models highlights flexures where the maximum dilation occurs and thus where greater mineral prospectively can be. In addition, faults which occur post mineralisation can separate volumes of mineralised rock that were once joined. Fault frameworks created from fault probability volumes directly show the 3D distribution of faults in a form geologists can immediately incorporate into their geological models. They can be integrated with other mine data such as assay data or other geophysical techniques such as magnetics helping to understand the significance of faulting. This might include understanding intersections of faults of different azimuths, cross cutting relationships between faults, and establishing fault timing and relationship to mineralization.

Seismic inversions provide information about the spatial distribution of rock units in three dimensions and provide confidence estimates indicating where the model is best constrained and levels of uncertainty elsewhere. Inversion can be used to identify domains more likely to contain mineralisation and to sterilize other zones not likely to be prospective.

The greatest insights are achieved when fault detection and inversion are combined. When both data sets are combined it can be possible to not only see where faults are but also predict where better fracture porosity may occur due to changes in rock rheology and where mineralisation is more likely to have been precipitated due to favourable rock chemistry

## ACKNOWLEDGEMENTS

The authors would like to acknowledge the collaboration with Geoteric for results provided for Yaouré in Figure 3. We would like to thank Perseus Mining for permission to show the Yaouré data, Northern Star Resources Limited for permission to show the Jundee data, and Searcher Seismic for permission to show Figure 1.

## REFERENCES

Bräunig, L., Buske, S., Malehmir, A, Bäckström, E., Schön, M., Marsden, P., 2020. Seismic depth imaging of iron-oxide deposits and their host rocks in the Ludvika mining area of central Sweden, Geophysical Prospecting, Volume 68, Issue 1 - Cost-Effective and Innovative Mineral Exploration Solutions, Jan 2020, p. 24 - 43

Campbell, M., Dilles, J., Geology of the deformed and dismembered Kerr-Sulphurets-Mitchell porphyry Cu-Au-Mo district, British Columbia, Canada

Dalstra, H., Black, A., Chembeya, E., Maguire, J., Ewington, D., Rayner, M., Mudrovska, I., 2022. The Winu-Ngapakarra Cu-Au-Ag deposit ("Winu"), Australian Institute of Geoscientist, MEGWA May Monthly Meeting, Video. MEGWA18 May 2022: The Winu-Ngapakarra Copper Gold Deposit - YouTube

Groves, D., Exploration for orogenic gold deposits: Structural sequence vs structural geometry, SEG 2017 Annual Conference.

Jarvis, K., Foley, A., Falconer, M., Turner, G., Kinkela, J., Smith, R., Bright, S. and Ziramov, S., 2022. Finding Blind Ore Bodies Using 3D Seismic: St Ives-Victory, Western Australia, First Break, 40(8), 75-77.

Jarvis, K. and Saussus, D., 2009, Extracting detailed lithology from seismic data, ASEG Extended Abstracts.

Marsh, T., Young, C., Turner, G., Kinkela, J., Smith, R., Bright, S. and Ziramov, S. 2022, Fast, objective, structural frameworks from 3D seismic data: automated fault tracking tools and their ability to map minerals system controls and post mineralization structural offsets, AIG Symposium: Structural Geology and Resources 2022 Kalgoorlie Abstracts.

Rhys, D., 2017, Advances in the understanding of the structural controls on Carlin deposits in Nevada: Implications for Chinese Carlin-like systems, SEG 2017 Annual Conference.