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Matthew G. Lamont
lead author

Drilling Success As A Result of Probabilistic Lithology and Fluid Prediction A Case Study in the Carnarvon Basin, WA

M.G. Lamont[1], T.A. Thompson[1] and C. Bevilacqua[2]

[1]DownUnder GeoSolutions Pty Ltd
80 Churchill Ave
Subiaco WA 6008

[2]Apache Energy Limited
Level 3, 256 St Georges Tce
Perth WA 6000

mattl@dugeo.com
troyt@dugeo.com
carlo.bevilacqua@ausapachecorp.com

ABSTRACT

The aim of quantitative interpretation (QI) is to predict lithology and fluid content away from the well bore. This process should make use of all available data, not well and seismic data in isolation. Geological insight contributes to the selection of meaningful seismic attributes and the derivation of valid inversion products. Uncertainty must be taken into account at all stages to permit risk assessment and foster confidence in the predictions. The use of the Bayesian framework enables prior knowledge, such as a geological model, to be incorporated into a probabilistic prediction, which captures uncertainty and quantifies risk.

Nostradamus is a fluid and lithology prediction toolkit that forms part of a comprehensive QI workflow. It utilises a Bayesian classification scheme to make quantitative predictions based upon inverted seismic data and depth-dependent, stochastic rock physics models. The process generates lithology and fluid probability volumes. All available information is combined using geological knowledge to create a realistic pre-drill model. Separately, stochastically modelled multidimensional crossplots, which account for the uncertainty in the rock and fluid properties (based on petrophysical analyses of well data), are used to build probability density functions such as acoustic impedance (AI) vs Vp/Vs and LambdaRho vs MuRho. These are then compared to crossplots of equivalent inverted data to make predictions and quantitatively update the geological model. Individual probability volumes as well as a most-likely lithology and fluid volume are generated. This paper presents a case study in the Carnarvon Basin that successfully predicts fluids and lithologies away from well control in a way that effectively quantifies risk and reserves. Two of the three successful gas exploration wells were drilled close to dry holes.

KEYWORDS

Inversion, case study, quantitative interpretation, gas, probability, Carnarvon Basin, Mungaroo Formation.

INTRODUCTION

The Mungaroo Formation is a major exploration target in the Carnarvon Basin, offshore Western Australia. The Mungaroo Formation sandstones (referred to as sands hereafter) were deposited during the Late Triassic (Carnian-Norian) as part of an extensive fluvial system. This system comprises stacked braided channel belts that attain thicknesses of several tens of metres, typically as a complex network of interconnecting sandstones encased by overbank shales, siltstones, carbonaceous shales and thin coals in parts. The porosity and permeability of sandstones from the Mungaroo Formation can be high and are relatively well preserved with depth.

Tectonic activity initiated in the Early Jurassic led to extensional faulting and block rotation resulting in significant erosion and the emergence of a structural NNE–SSW horst and graben trend. Subsequent sea level rises and subsidence following the cessation of rifting along Australia's northwestern margin led to the deposition of the Cretaceous Muderong Shale which drapes the Mungaroo Formation horsts and grabens. The Muderong Shale consists of regionally thick marine shales with excellent sealing capabilities. In this study area the Muderong Shale overlies the subcropping Mungaroo Formation at a major unconformity surface.

Gas migration into the Mungaroo Formation is believed to have occurred through a combination of selective fault and sand channel conduits, however, not all apparently sealed sandstone channels were charged, possibly because of complete isolation from the migration fairway. Gas saturation in these sands is usually associated with high seismic amplitudes, however, ambiguity exists due to high seismic amplitudes associated with high porosity brine sands and also carbonaceous shales. This study outlines the comprehensive quantitative interpretation (QI) workflow that was successful at identifying the gas bearing sands.

Prior to the QI study four dry holes had been drilled in the block. The initial QI study was based on these four dry holes. Three significant gas discoveries have now been drilled. The discovery wells are close to and, in one case, down dip from the previously drilled dry holes. The study has been updated after each new well.

The aim of the study was to predict lithology and fluid content away from the well bore, and in particular to identify gas sands. The process made use of all available data, not just well and seismic data in isolation. Geological insight contributed to the selection of meaningful seismic attributes and the derivation of valid inversion products. Uncertainty modelling was taken into account to permit risk assessment and foster confidence in the predictions. The use of the Bayesian framework enabled prior knowledge such as a geological model to be incorporated into a probabilistic prediction, which captured uncertainty and quantified risk.

Nostradamus is a fluid and lithology prediction toolkit. It utilises a Bayesian classification scheme to make quantitative predictions based on inverted seismic data and depth-dependent, stochastic rock physics modelling.

Stochastically modelled multidimensional crossplots, which account for uncertainty in rock and fluid properties (based on petrophysical analyses of well data), were used to build 2D probability density functions (AI vs Vp/Vs). These were compared to crossplots of equivalent inverted seismic data to make predictions and quantitatively update the geological model. Individual probability volumes as well as a most-likely lithology and fluid volume were generated.

The study incorporated petrophysics, rock physics, geology, geophysics and uncertainty to successfully predict fluids and lithologies away from well control in a way that effectively assists the determination of risk and reserves.

BACKGROUND

QI is concerned with making lithology and fluid predictions based on a limited amount of known data (the wells) and widespread observed data (the seismic data). Prior geological knowledge needs to be used to set the context for the analysis. Figure 1 shows the QI workflow used for this project.

QI relies on the seismic observations being a direct result of the impedance contrasts of the rock strata being studied. That is, the relative seismic amplitudes need to be preserved. Adequate preparation of seismic data for QI is imperative, and in our observation this is often done poorly. On this occasion good quality angle stacks were available, therefore the seismic data preparation was confined to:

- Amplitude preserving frequency enhancement, geared to both enhance frequencies generally, and also to help balance the frequency content of the angle stacks; and,
- Angle stack alignment. The inversion assumes that each event is at the same time on each stack. This final alignment process applies a residual fine tuning.

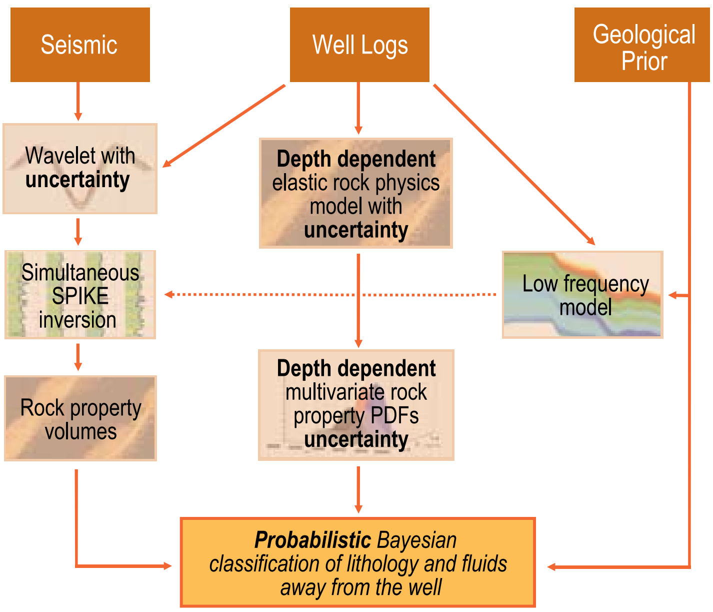

Figure 1. The comprehensive QI workflow used in this study.

PREPARATION OF THE ROCK PHYSICS MODEL

The impedance of rocks (and hence the impedance contrast of different rocks) is due to their elastic properties. Critical geologic factors that control elastic properties can be related to both depositional environment and burial history (Avseth et al, 2003). Quantifying depth dependence imposes a meaningful geologic trend which constrains uncertainty and the expected range of seismic responses.

Therefore, a rock physics model was needed which described the elastic behaviour of all the possible lithology and fluid combinations that were expected (as interpreted in the wells as significant for the delineation of hydrocarbons) as a function of depth.

The starting point was a detailed petrophysical interpretation following on from the quality control (QC) and preparation, including environmental corrections, of the available well log data. Synthetic shear logs were generated for two of the wells using petrophysical trend analysis.

An end member rock physics model was built around a petrophysical analysis. An end member is defined as the cleanest example of a lithology present and is indirectly based on mineralogy (Duncan et al, 2004). Once the elastic properties of the end members are known, the elastic behaviour of any rock composed of different proportions of these end members—any Vsand with any fluid saturation—can be determined. Figure 2 shows an example of the end member interpretation. The straw coloured picks are the end member sands and the blue picks are the Mungaroo Shale. Before being used, each pick is upscaled and averaged to become one point on the crossplots shown in Figures 3 and 4.

Depth-dependent end member elastic lithology and fluid property trends, based on available log data, were derived along with their uncertainties. These are shown in Figures 3 and 4. The solid fitted line is the trend, while the dotted line on either side captures two standard deviations of scatter. Quantification of the inherent scatter in end member rock properties was essential to understand the range of seismic responses and associated inversion derivatives that were observed.

It is worth comparing the TVD below mud line (TVDBML) vs Vp trends for the Mungaroo shale and the sand. At about a depth labelled Y metres the trends cross over. What this

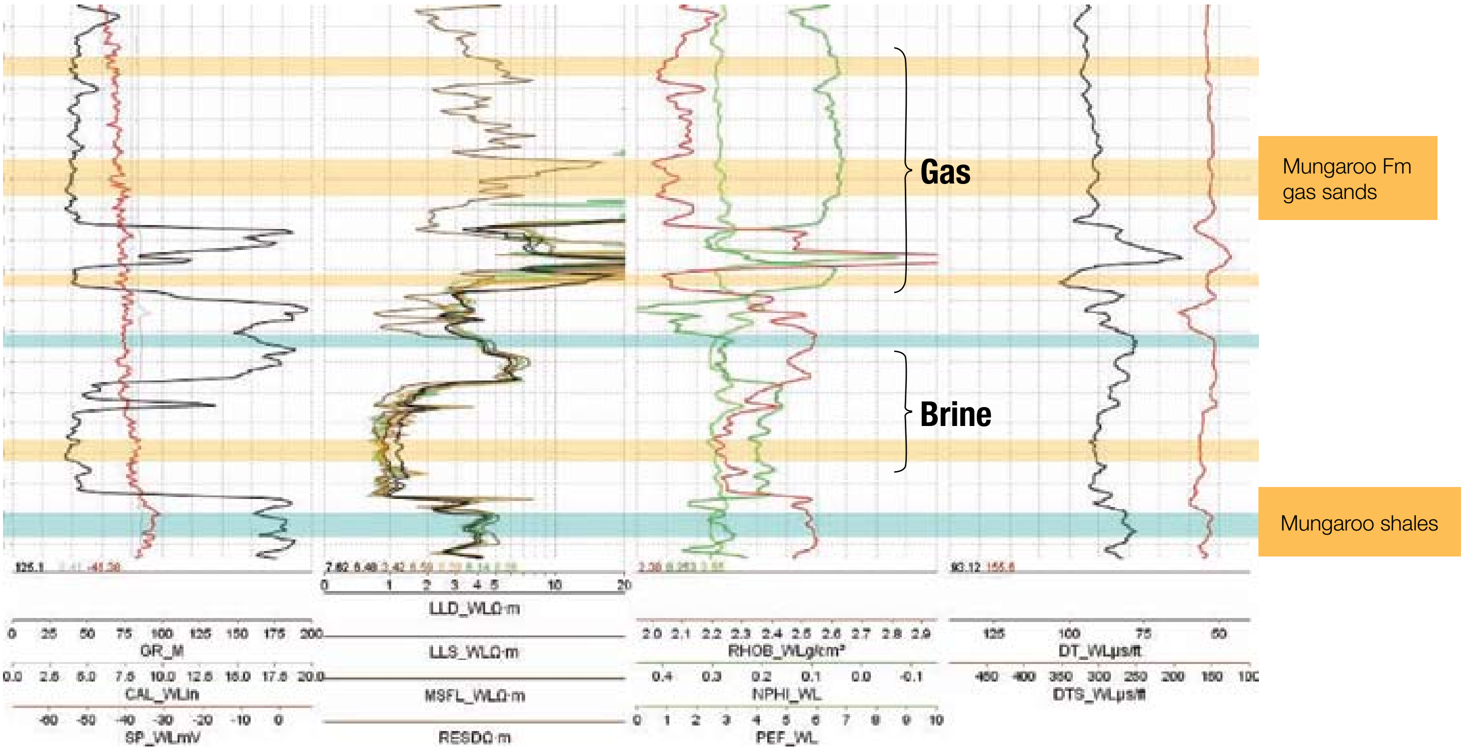

Figure 2. Example well from the study illustrating the end member picks. Sands are straw coloured and the shales are aqua blue.

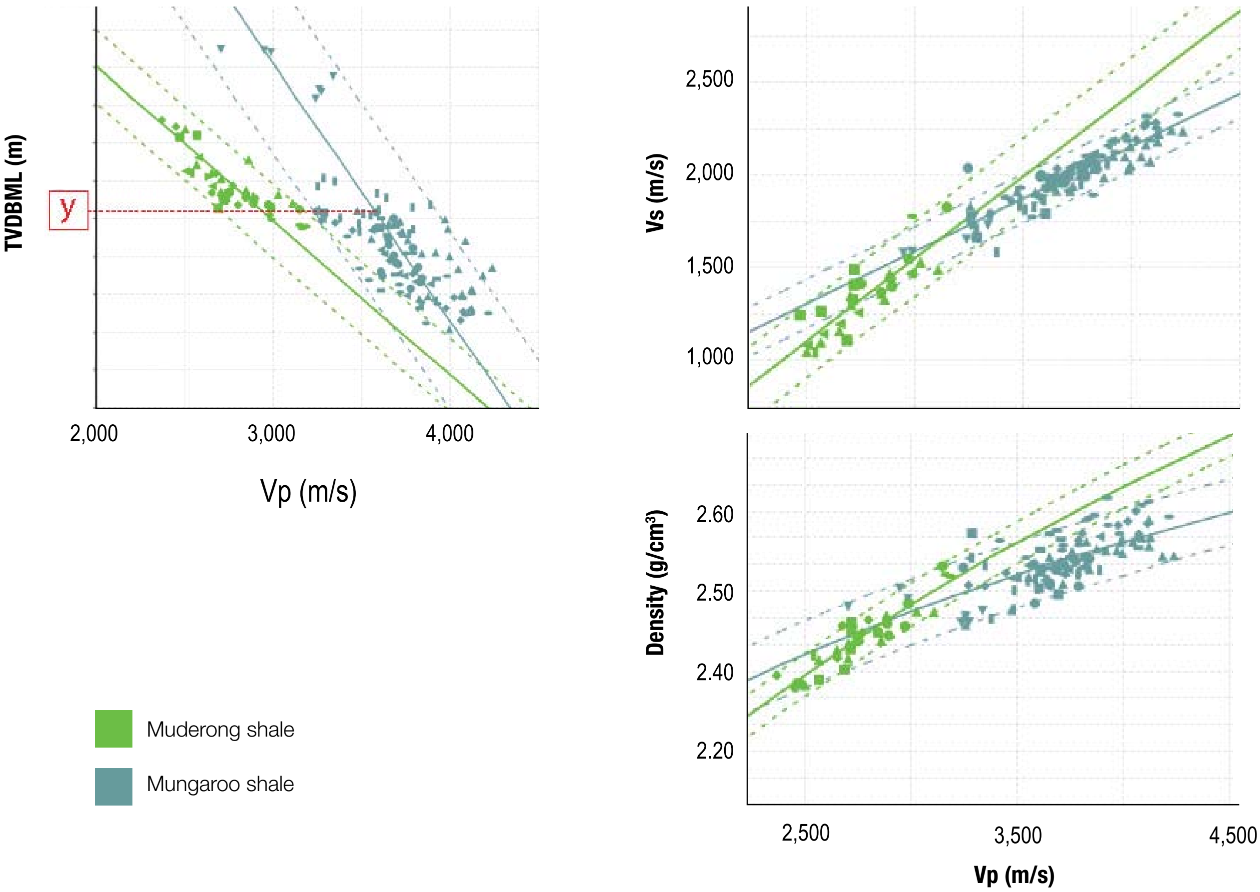

Figure 3. Shale trends for the two dominant shales. Each picked interval from the end member interpretation is upscaled and then plotted as a single point on these cross plots. y indicates the pivot point above which shales are softer than sands and below which shales are harder than sands.

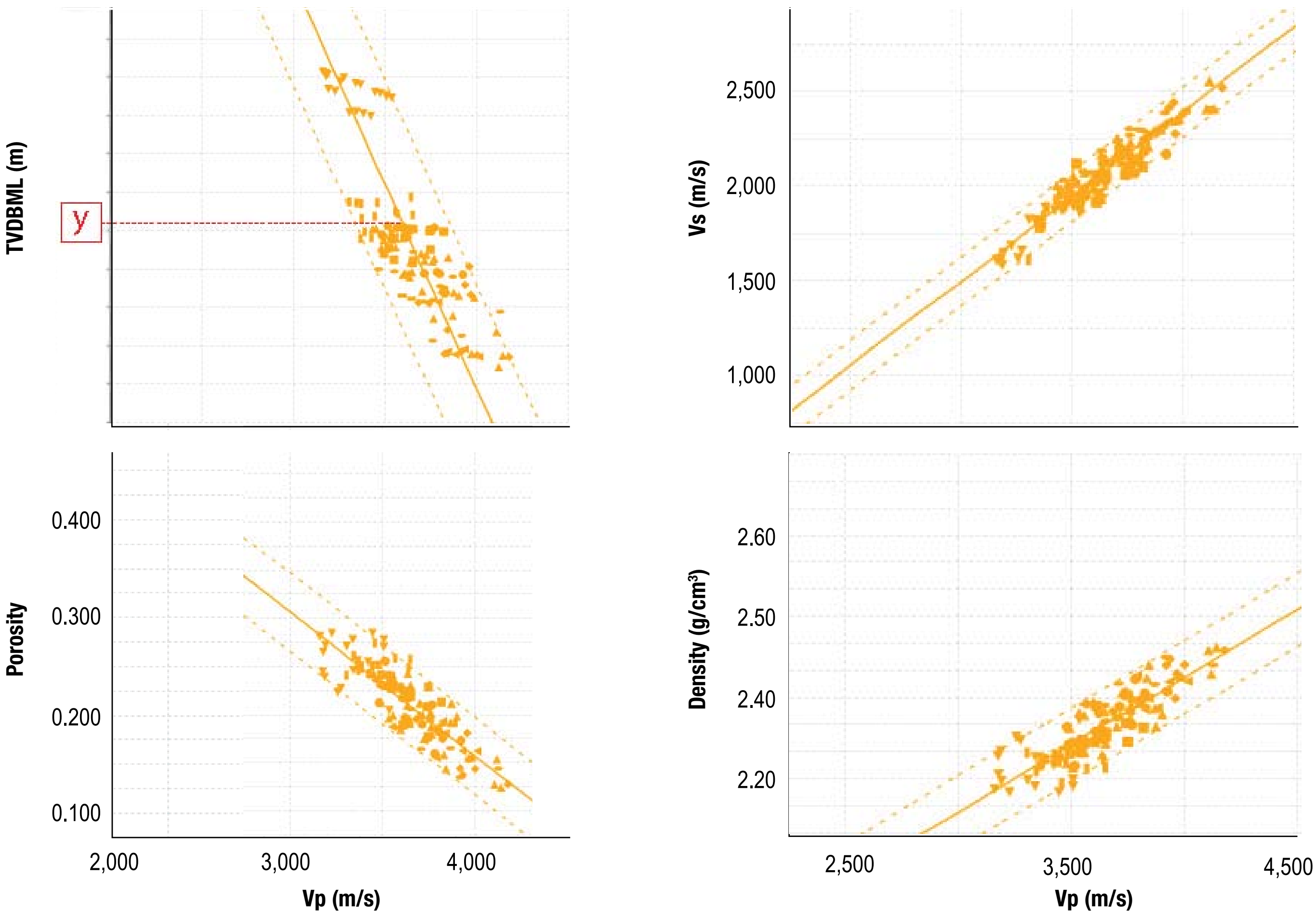

Figure 4. Sand trends for the area. As for the shales, each point represents an interpreted, upscaled end member interval.

means is that above Y metres the shale is softer than the sand. Below Y metres the shale is harder than the sand (Figs 3 and 4). This results in completely different AVO behaviour above Y metres to below it. In fact these trends describe constantly varying AVO behaviour. Therefore, it was imperative to have a depth-based rock physics model.

The analysis determined that the necessary end members in this case were:

- Lithologies
  - Quartz rich sand;
  - The Muderong and Mungeroo shales; and,
  - Coal/Carbonaceous shale.

- Fluids
  - Gas; and,
  - Brine.

To capture the expected range of rock properties and hence the expected range of seismic responses, for all candidate lithology-fluid combinations over the depth range of interest, stochastic forward modelling was performed. Gassmann substitution was an integral part of the modelling. Gas saturations used for modelling were 0% (brine case) and 75+-5% (high saturation gas case). A low saturation gas was not considered in the final analysis due to the poor discrimination from high saturation gas and a low geological risk for the presence of low saturation gas. For this study 10,000 forward models were produced for every depth step of 4 m. The parameters for each model were determined by the Monte Carlo sampling of the multidimensional rock physics model. The rock physics model is comprised of the trends that are displayed in the four separate cross plots, however they should not be sampled from one trend at a time because they are, in fact, coupled; they need to be thought of as one space and a single sample drawn from this multidimensional space to get the correct distribution of properties.

The varying AVO behaviour with depth is further illustrated by the stochastic modelling results shown in Figure 5. Each point on these plots represents one of the 10,000 models. It is clearly evident that over a 600 m depth interval the clusters have shifted both absolutely and relative to one another. The ellipses on these plots represent the two standard deviation contour of the probability density functions (PDFs). That is, these figures are showing both the stochastic modelling results and the resulting PDFs.

A standard workflow used in many QI projects may, if necessary, begin by using Gassmann substitution to alter the well data so that the sands represent the all brine case. In a similar way, the logs may subsequently be altered to represent a particular hydrocarbon case. These logs can then be cross plotted and the different lithologies and fluids identified. The cross plot can be partitioned into different lithology/fluid combinations and these cut offs used to produce lithology/fluid prediction volumes. At times gradations are added stepping away from the centre of the partitions or away from theoretical trends and the resulting volumes are called probability volumes, although they are not technically probability volumes.

Consider this case study where the relative behaviour of the rocks is varying rapidly with depth: this standard workflow will base the partitioning of this space and the subsequent lithology and fluid volumes on the location of the sands and shales in the available wells. If the worker is lucky the lithologies in the available wells are adequately sampled through their depths of interest, and hence an averaging of the modelling results over the depth interval results. This situation is reasonably well illustrated in Figure 6. Here the modelling results represent a 600 m depth interval. Consider the point at the Vp/Vs ratio of 1.65 with a AI of 8,500. In the X+600 m crossplot in Figure 5, this point clearly represents a gas sand. In fact the Bayesian update will give this point a probability of being a gas sand in the 90s. Now consider this same point in Figure 6. This point falls well within the ellipses of gas, brine and shale. Probability volumes produced from this modelling will assign roughly similar probabilities to all three when in fact it is a gas sand. Thus it is imperative to consider depth dependency of the impedance and velocity responses.

A fundamental output of the modelling, based on the trends and their uncertainties, was depth dependent multivariate rock property PDFs for each lithology/fluid class. The stochastic modelling also provided the following information:

- AVO aided in the discrimination and prediction of gas sands;
- Quantifying depth dependence was important for optimal fluid and lithology discrimination; and,
- The range of uncertainties allowed discrimination of gas bearing sands.

Figure 7 shows the relationship of porosity with depth as well as the changing resolution with depth. It is apparent that at shallower depths fluids can be easily discriminated (brine sand vs gas sand) and lithologies less so (shale vs brine sand).

SPARSE SPIKE SIMULTANEOUS INVERSION

A multi offset, Bayesian wavelet derivation program was used to estimate the wavelet and its uncertainty (seismic noise level). This was a strong test of the amplitude fidelity of the seismic data. It featured a fully integrated Bayesian approach to the coupled uncertainties in wavelet estimation, a process which is critical in an inversion study (Gunning and Glinsky, 2006).

The wavelet extraction provided maximum likelihood estimates of the wavelet, as well as multiple realisations from the posteriore—the final derived distribution(s) after

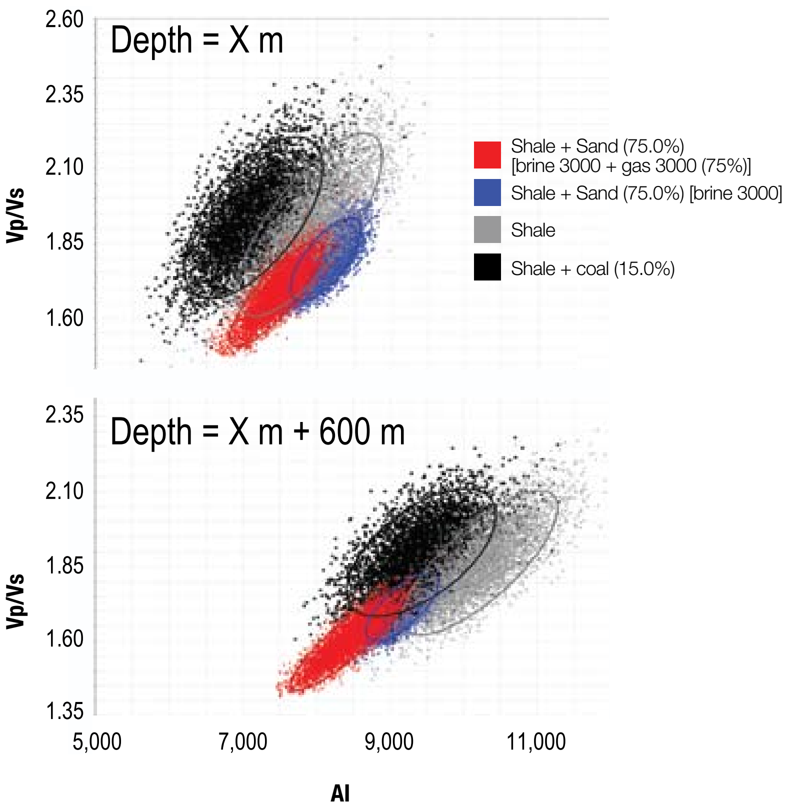

Figure 5. Stochastic forward modelling results. The four major fluid/lithology combinations are represented here. Ellipses represent the two standard deviation contours around the probability density functions. Notice that the 600 m depth step has resulted in the entire four clusters being grossly translocated as well as the shale and brine clusters swapping relative positions.

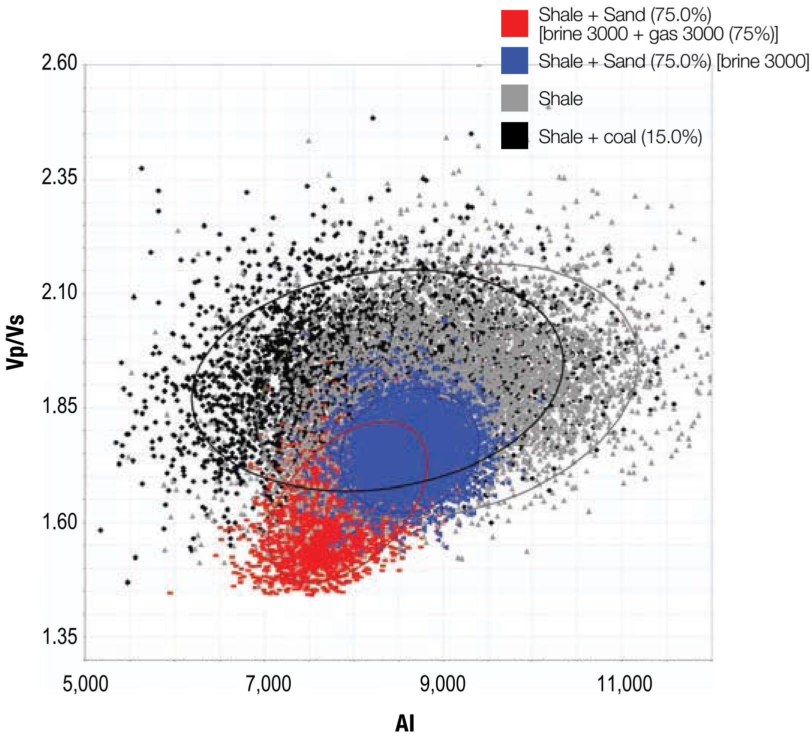

Figure 6. Stochastic forward modelling from the depths of X to X + 600 m combined. Consider the point at the position AI=8,500 and Vp/Vs=1.65. On this plot the probability of it being hydrocarbon, brine or shale is roughly equal. In Figure 5 the same point has an overwhelming probability of being hydrocarbon.

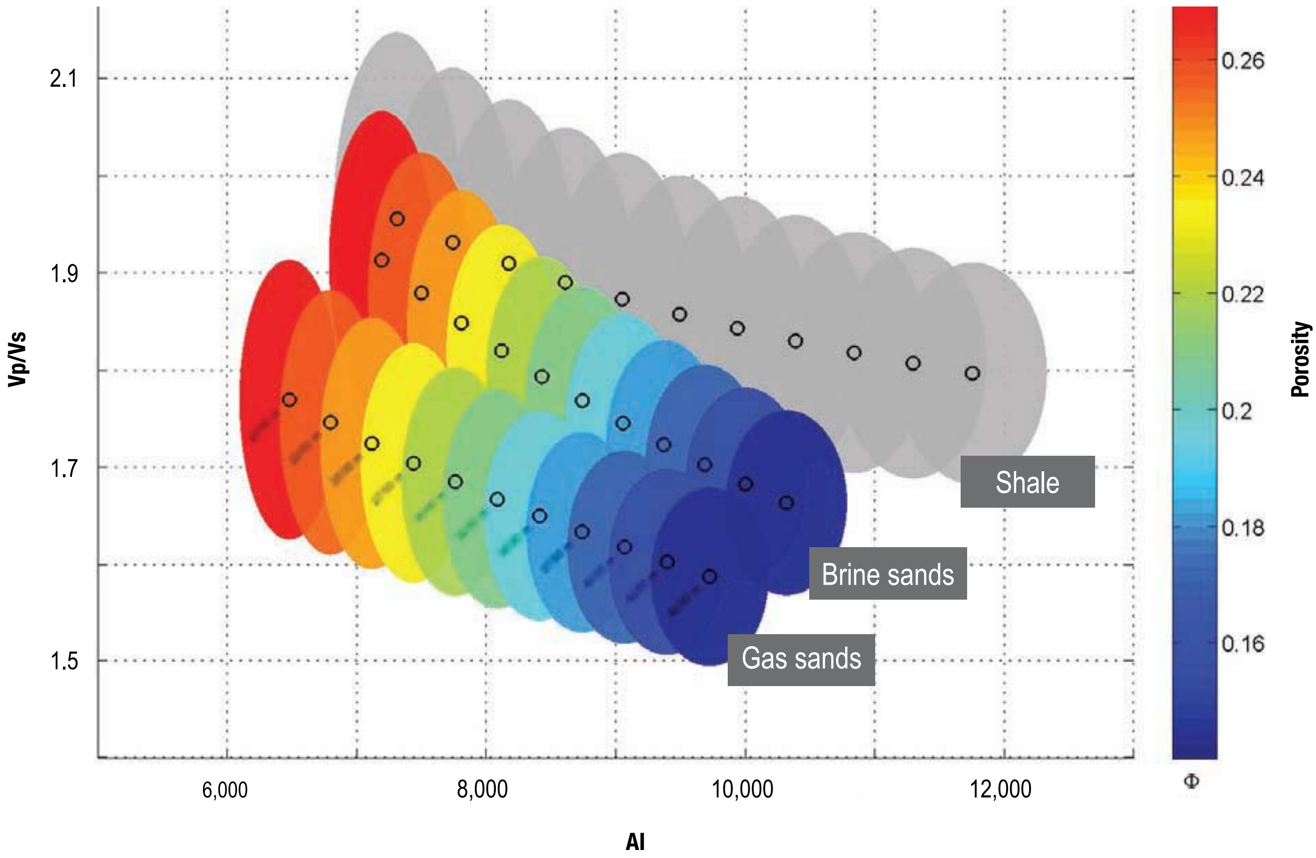

Figure 7. A plot of AI vs Vp/Vs for varying depths and porosities. Ellipses are illustrative of ~1 standard deviation of scatter. Ellipse rotation is not accounted for in this figure. Fluid discrimination is good at all depth levels, however does decrease with increasing depth. Fluid and lithology discrimination is maximised using both P and S attributes. Lithology discrimination increases with depth.

all the observed data and prior information has been considered—highlighting the uncertainly in the wavelet scaling and extent. The final wavelets are shown in Figure 8. The wavelets were extracted from all wells and all angles simultaneously and the final wavelet is approximately zero phase.

A geostatistical methodology was used to build the low frequency model. It utilised all available information (wells, horizons, trends and velocity field) producing a stable model away from well control while providing an exact match at the well locations. Through the initial and subsequent updating of the project, an appreciation was gained as to the importance of the low frequency model in obtaining accurate reservoir predictions away from well control. In this case it was a difficult procedure due to the lack of conformity of the geology. That is, the volume doesn't easily break into layers, and therefore modelling extensive horizons at target level was not possible. Understanding the uncertainty in the model was essential and is an ongoing part of the investigation.

A sparse spike inversion algorithm, SPIKE®, was used for the volume inversion. It is an AVO inversion which in essence inverts for intercept, gradient and curvature (Shuey, 1985) in order to determine P impedance, S impedance and density. Although the inversion can take any number of input stacks, three were used on this occasion. From these fundamental outputs, Vp/Vs, LambdaRho and MuRho were also calculated. LambdaRho and MuRho are rock property attributes that characterise the incompressibility and rigidity of a rock respectively. These quantities can be obtained from the common equations for Vp and Vs, which are a function of Lame's parameters (lambda and mu), the modulus of rigidity and density (rho).

Figure 9 shows the detuning power of the inversion as well as the resolution limits. This wedge modelling is based on the wavelets and parameters from this study and hence is an accurate representation of the resolution limits.

Figure 10 shows the synthetic to seismic ties and the relative P and S impedance match to the well data. A good match was obtained through the zone of interest. Figure 11 shows the absolute inversion tie at one of the wells, with a good match obtained.

DEPTH CONVERSION

The rock physics model was depth based and the resulting probability volumes were needed in depth so as to be easily used for the planning of new wells and as input to

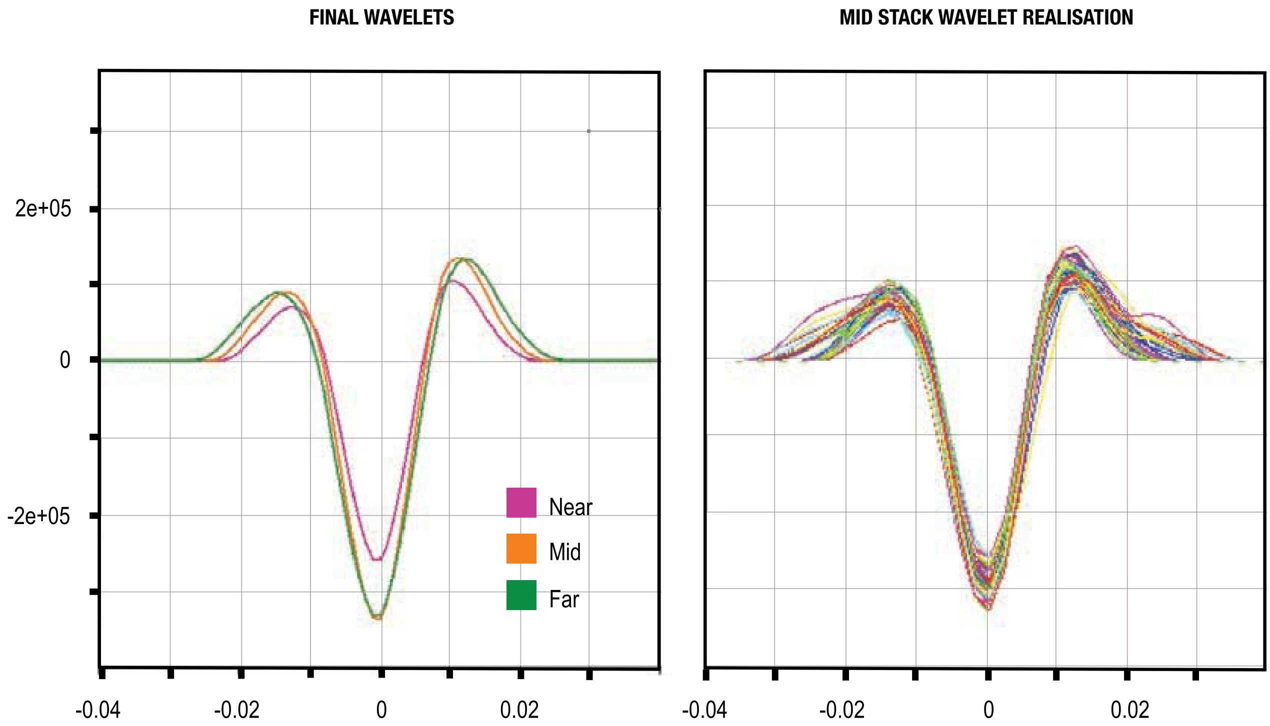

Figure 8. Final wavelets (multi-well extraction). The bunching of the wavelet realisations illicits confidence in the result.

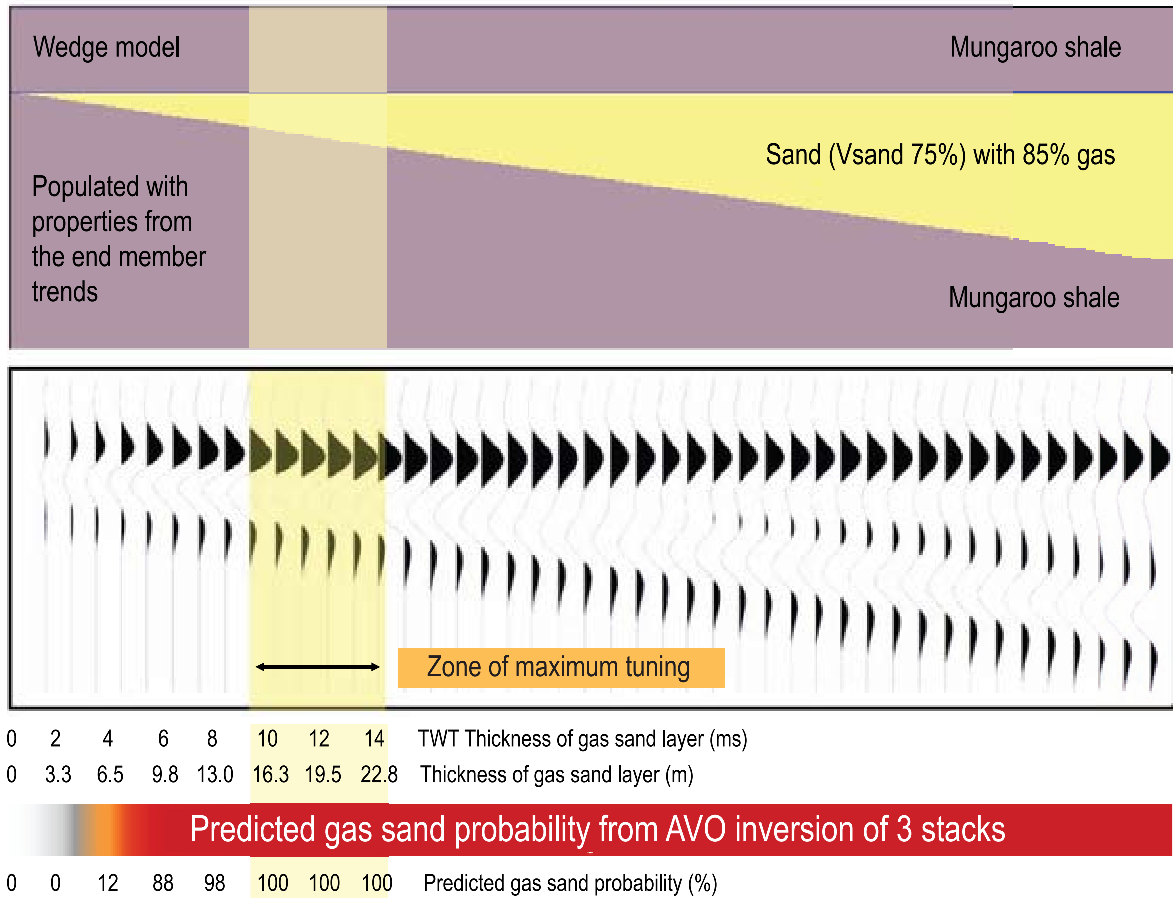

Figure 9. This figure shows the resolution limit of the QI flow. A wedge model, populated with the rock properties from the project, was used as a basis for the generation of near, mid and far seismic stacks. The simultaneous inversion was run on these stacks followed by the lithology and fluid classification procedure. It is clear that the procedure correctly predicts sands down to around 10 m thickness—well below the seismic tuning thickness.

the reservoir model building phase. Therefore it was logical to take the inverted seismic products to depth before the analysis stages. The required depth was depth calibrated to well control as opposed to seismic depth.

The methodology was to take the available time/depth pairs and, using the initial velocity model, convert the times to depth. The differences in the depths at each point can then be used to calculate velocity updates at these times. These velocity updates are built into a 3D volume using geophysically/geologically constrained geostatistics. The time depth points were honoured while a stable and geologically consistent velocity field away from the control was produced. Finally, the update is added to the initial velocity model. This velocity model was then used to depth convert all of the inversion products, which was subsequently tied to the wells.

LITHOLOGY AND FLUID PREDICTION

Figure 12 is a plot made before the drilling of any of the discovery wells. It combines rock property volumes from the inverted seismic data with the ellipses representing the rock property modelling results. Firstly, an anomaly was identified. The points from each of the rock property volumes in the region of the anomaly are the samples in the cross plot. Then three polygons are drawn. The first represents a potential sealing shale, the second represents a potential gas sand and the third a potential down dip brine sand. The points in each polygon are then highlighted on the crossplot and color coded accordingly. Next, the ellipses representing the PDFs at the mid-point depth of the corresponding polygon are superimposed over the top of the plot. They show a remarkable alignment between the model results and cross plotted rock property volumes. This engendered confidence in the inversion and modelling procedures. The next step was a Bayesian update.

Lithology and fluid prediction was based on a Bayesian supervised classification scheme called Nostradamus. It brought together prior information, including stochastic modelling, inverted data, and interpretation to produce lithology and fluid probability volumes through the zone of interest.

At the core of the scheme are multivariate PDFs, one for each depth level of interest. Each lithology/fluid combination was represented in the PDFs and hence resulted in an associated probability volume being produced. In addition, a most likely lithology/fluid volume is produced.

Unlike Avseth (2003) and Anderson (2003) who use a Bayesian approach based on relative interface properties (AVO), this method utilises absolute rock properties to define the possibilities of an inversion resolvable layer. This volume based prediction limits the possibilities to individual layers rather than interfaces between two layers.

Figure 13 shows a slice through the resulting gas probability volume with the subsequent discovery well

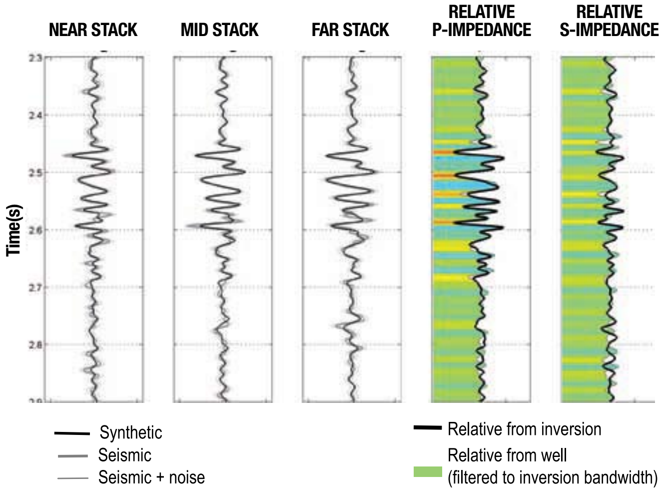

Figure 10. Relative impedance ties at one of the discovery wells.

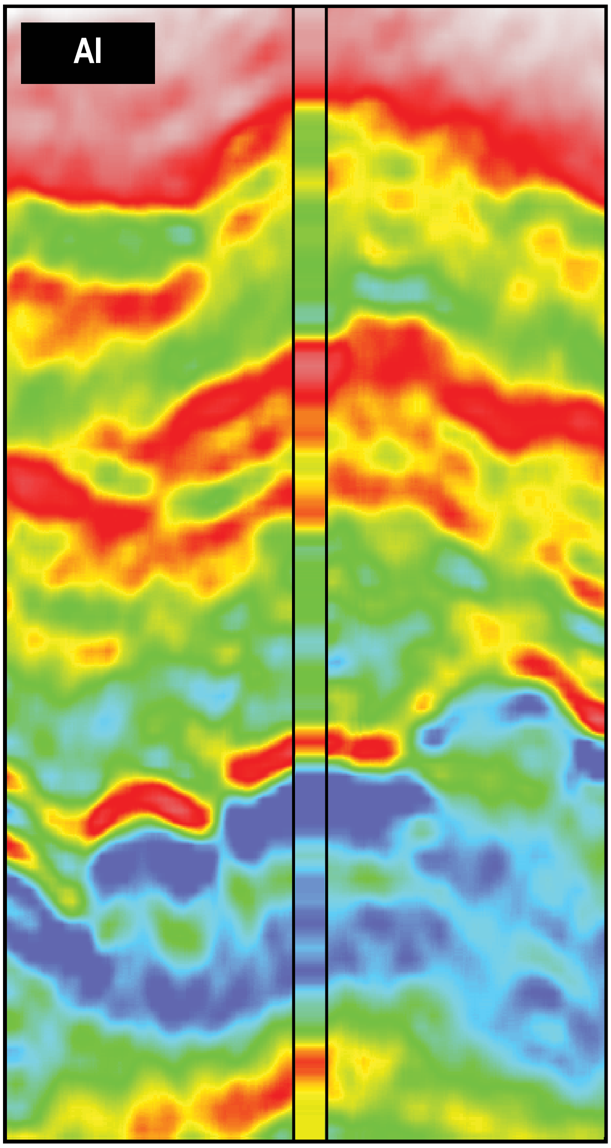

Figure 11. Acoustic impedance tie at one of the wells.

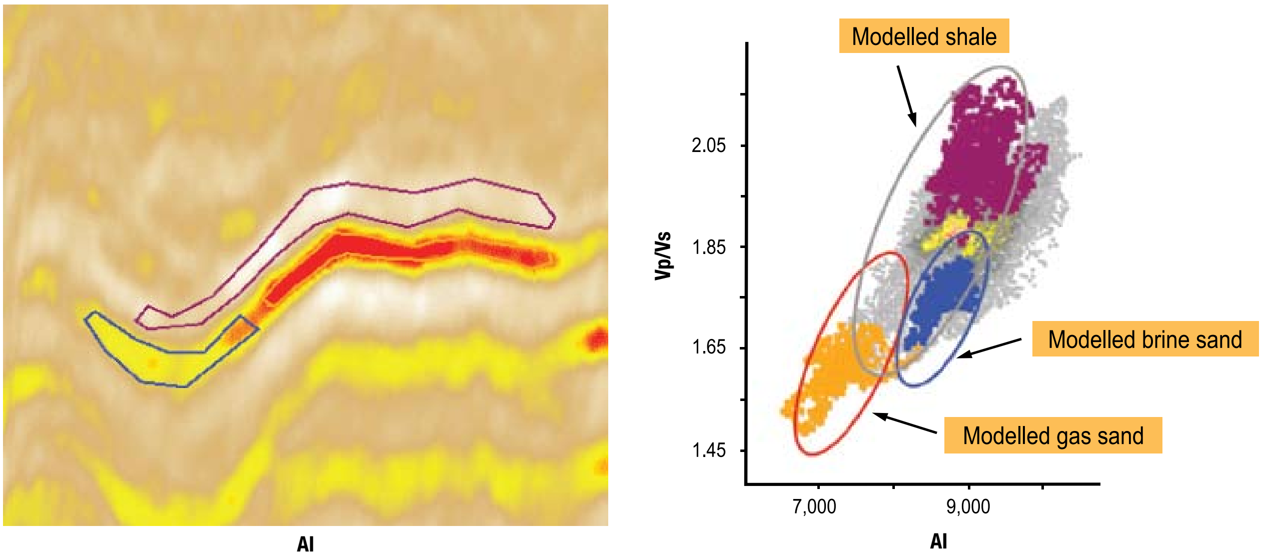

Figure 12. Comparison of rock properties from the seismic inversion with the PDFs (from the appropriate depth) produced from the rock physics model.

locations and the original dry holes. It starts to reveal the nature of the high gas probability sands as well as showing how close two of the discovery wells are to the original dry holes.

Figure 14 shows the first discovery well. It was drilled close to and down dip from an earlier dry hole. The new well encountered gas sands as predicted. The location of the dry hole comes out as a ~10% chance of gas in the probability volume. Figure 15 shows the gas probability volume in 3D in the same area as Figure 14. It reveals the channelised geometry of the gas sands as highlighted by the gas probability volume.

Figure 16 shows the second discovery well. It was drilled at 67 degrees to intercept multiple high gas probability bodies. Again the gas came in as predicted.

Figure 17 is the third and, at the time of writing, most recent discovery. This well is also close to a previously drilled dry well.

The gas probability volume has now been used as the basis for a reservoir model.

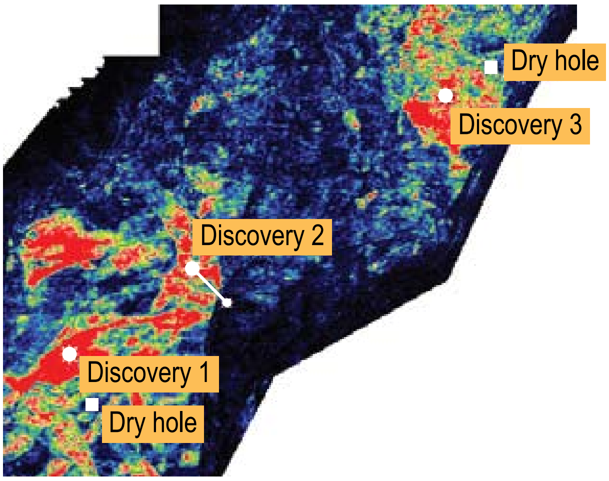

Figure 13. Locations with high gas probability in a 200 ms window below Top Mungaroo. The map shows previous dry holes and the three new discoveries.

CONCLUSIONS

Three significant gas discoveries have been made in an exploration permit following a comprehensive QI study. Two of these wells were close to dry holes. In addition, one of the discovery wells was down dip from an earlier dry hole.

The workflow described here assimilates geology, geophysics, petrophysics, rock physics and uncertainty. Simultaneous inversion products were compared with multivariate rock property PDFs to make probabilistic, volume-based fluid and lithology predictions using a Bayesian framework.

A depth dependent rock physics model is essential. The sparse spike inversion was able to detune the seismic data to a large extent.

Probability volumes were built using a Bayesian classification scheme utilising rigorously derived, depth dependent, PDFs. They were not derived from empirical or arbitrary lines drawn on crossplots.

Although this workflow involves considerably more work than the standard approach, it is scientifically justifiable and has delivered remarkable success.

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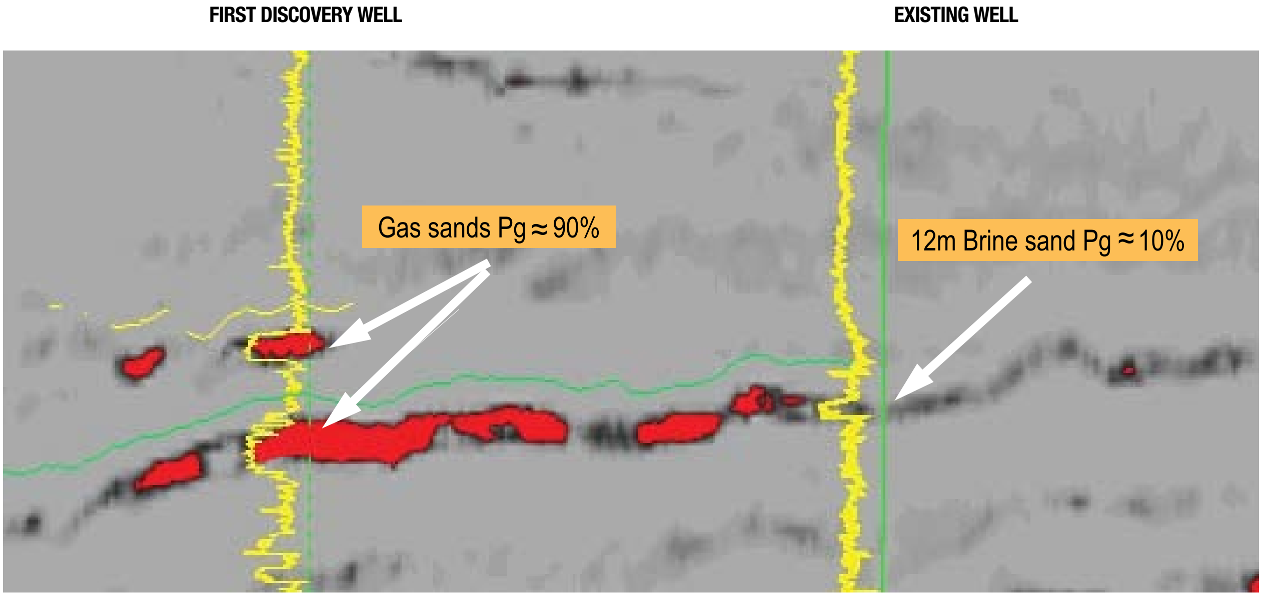

Figure 14. Gas probability data provided confidence to drill downdip of a 12 m brine sand resulting in the first discovery.

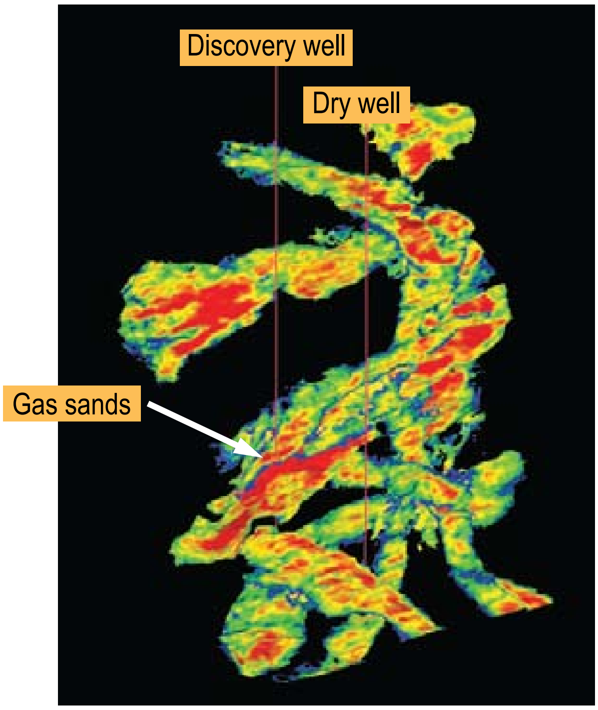

Figure 15. The gas probability volume shows the complex gas sand geometries around the first discovery well. Original well failed to intersect a gas reservoir.

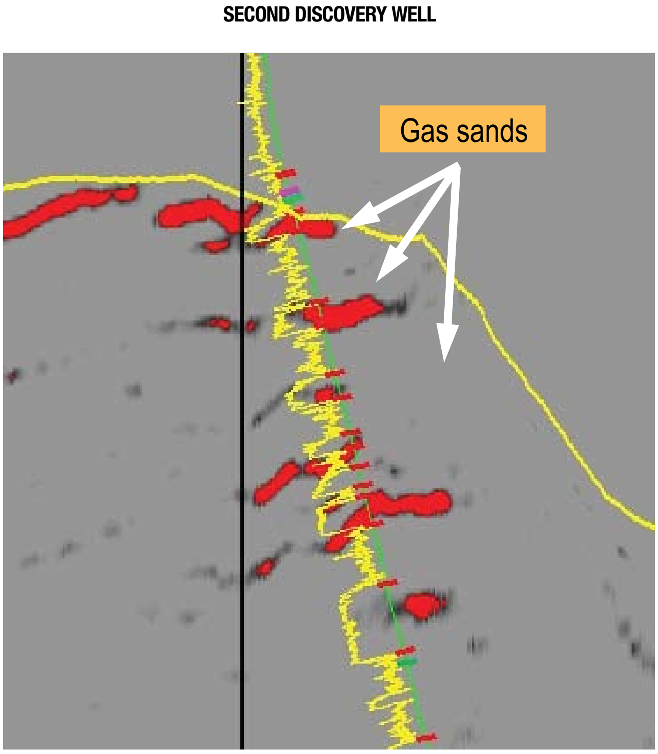

Figure 16. A cross section through the gas probability volume at the second discovery well.

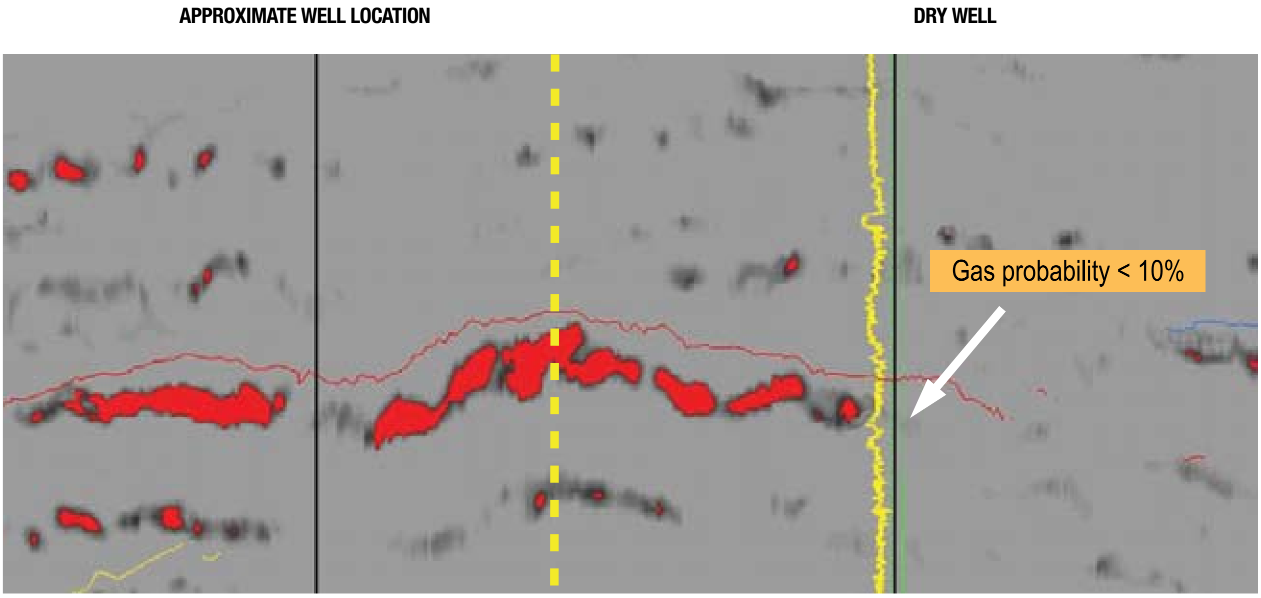

Figure 17. Third well, third discovery. Arbline showing discovery well position along with previous dry hole.

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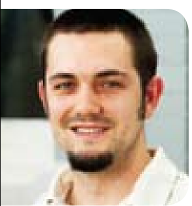
Matthew Lamont's academic qualifications culminated in a Ph.D. in Geophysics from Curtin University of Technology. His first class honours discertation was on seismic stratigraphy and his Ph.D. topic was seismic multiples. He is an adjunct associate professor at Curtin University. His working career spans over 15 years including working in Woodsides geophysics group performing depth migrations and depth conversions. He worked for BHPB as the seismic processing and imaging technical lead in Houston. Back in Australia with BHPB he worked in the quantitative interpretation area in addition to processing and imaging. Matthew started DownUnder GeoSolutions in 2003. He continued with depth imaging, reflection tomography, depth conversion and quantitative interpretation research and application. Matthew was the ASEG distinguished lecturer in 2005. The subject of the talk and paper was spectral decomposition. Member: ASEG, SEG, EAGE, APPEA and PESA.



Troy Thompson received a PhD from Curtin University of Techonology. His topic was automated prestack event picking. He received a first class honours degree at Curtin working on anisotropy. Troy was a founding partner in DownUnder GeoSolutions. Today he is a principal geophysicist, managing the QI services division, and a director of DownUnder. He has written papers on a variety of subjects including anisotropy, prestack autopicking and quantitative interpretation. Member: ASEG, SEG, EAGE and PESA.

Carlo Bevilacqua graduated in 1979 from the West Australian Institute Of Technology with a Bachelor of Applied Science (Physics). After two years of seismic acquisition and processing with Geophysical Services Inc in Perth he joined Oil Company of Australia in Sydney. Carlo then joined LASMO Energy as a staff geophysicist in Brisbane, and relocated to London and Rome. In 1990 Carlo joined Enterprise Oil where he worked in serveral positions including Chief Geophysicist (Rome), Team Leader Southern North Sea (London) and International Exploration Coordinator (London). Carlo joined Apache in 1999 in Perth where he works as a senior geophysical advisor. Member: ASEG, SEG, EAGE, APPEA and PESA.

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