Coordinated by Linda R. Sternbach

Seismic inversion successfully predicts reservoir, porosity, and gas content in Ibhubesi Field, Orange Basin, South Africa

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In 2000 Forest Oil International shot a 312 km^2 3-D seismic survey in South Africa's Block 2A around a well that, despite testing 53 million ft^3/d gas and 342 bbls condensate/d gas, had been abandoned in 1986 (Figure 1). This well (AK-1) was thought to have tested a small noncommercial structural trap. The 3-D showed that the field, now designated Ibhubesi Field, is in fact a giant regional stratigraphic trap. The 3-D survey might only cover a small part of the southern extent of the field, which may eventually produce 15 trillion ft^3 of gas.

Attribute processing and other inversion techniques were used to predict the presence and properties of the reservoir, to assess reserves, and to plan a drilling campaign to delineate the field. Individual gas accumulations in meandering fluvial channels and other component facies of the fluvial-deltaic systems tract were clearly identified in the resulting volumes.

Reservoir and drilling history. A four-well program was undertaken to evaluate the field, and prove up a core area with enough reserves to be economically developed. Figure 2 shows a structure map at the top of the gas-bearing interval. Wells tested individual compartments containing 28-520 billion ft^3; the total was 1.15 trillion ft^3. The first well, A-K2, tested 30 million ft^3 and more than 600 barrels of condensate per day from a 20-m pay sand on a 3/4-inch choke with a flowing tubing pressure of 2200 psi. Reservoir characteristics were better than expected: clean and well sorted with average porosity of 21% (up to 25%) and almost no water saturation. No water was produced and no significant reservoir pressure drawdown seen during the 12-hour test.

The second well, A-V1, had a 15-m gas-bearing sand of similar quality to the A-K2 sand, but the drill string twisted off before drilling a second, deeper sand. This sand was subsequently penetrated in a sidetrack. The lowest gas sand in A-V1 is deeper than the lowest proven gas and highest proven water in A-K1, clearly showing that this is a separate reservoir and stratigraphic trap.

The third well targeted the largest and brightest anomaly in the data set. It found two thick and porous sands as predicted, but they contained low-gas saturation water. Later application of elastic inversion (Figure 3) showed that these sands had less rigidity than others in the area. This factor, combined with high porosity, accounts for its high values in the elastic cross-plot volume.

The fourth and final well was targeted at a feature that looked like a preserved cut-off meander loop. There were also secondary and tertiary targets. The well tested 71 million ft^3/d and 1340 bc/d from combined tests of the upper two zones. This is the highest gas test rate achieved in any well in the history of South Africa.

Bit by bit, as the well results came in, the exploratory vision of a giant regional stratigraphic trap was proved. We were completely successful in predicting the presence of high reservoir quality sands on 10 occasions in five wells. We predicted commercial gas content eight times—a success rate of 80%. Porosity predictions were always within 2 PUs of the target interval average net pay porosity. Thicknesses ranged from about 30% less than predicted to about 30% more than predicted.

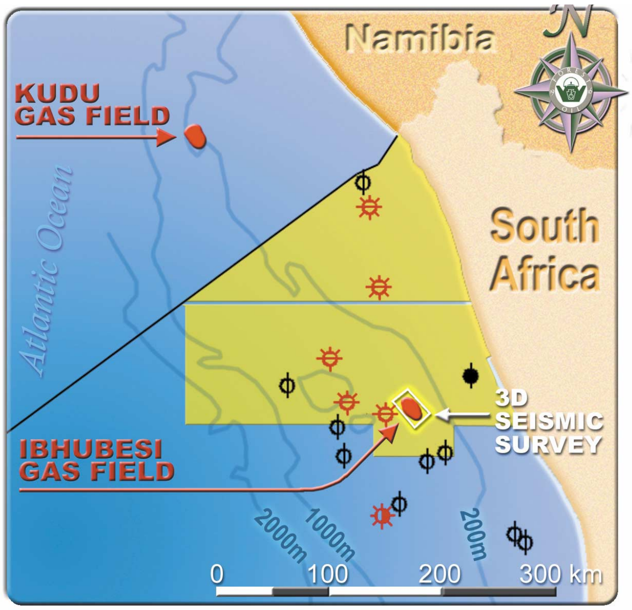


Figure 1. Map of Forest Oil blocks in South Africa.

Role of seismic inversion. Inversion was used to improve the prediction of reservoir properties from the 3-D seismic. These predictions should become more accurate as wells are added. Thickness and porosity are fairly easy to predict, and some distinction may be made between gas-saturated reservoir and wet reservoir. Although inversions can make quantitative predictions, they remain interpretive, seismic-based data sets with limitations like band width, tuning and interference, noise, nonuniqueness, and so on. Thus, knowledge gained through inversion should be interpreted and combined with other geologic criteria such as trap configuration, facies models, hydrocarbon charge, and migration routes to assess a prospect.

A neural network was applied in an unsupervised mode to determine areas with similar seismic character (facies) or in a supervised (with wells) mode to relate seismic character to a particular geologic regime or reservoir properties. In unsupervised mode, the network did a very good job of identifying and mapping individual fluvial channels. In the supervised mode, the neural network predicted reservoir quality at A-V1 and A-W1, and successfully predicted commercial gas at both wells. Attribute inversion (using Kohonen Self-Classifying Mapping) detected the gas/water contact in the lower sand at A-K1 (Figure 3) and predicted a wet sand

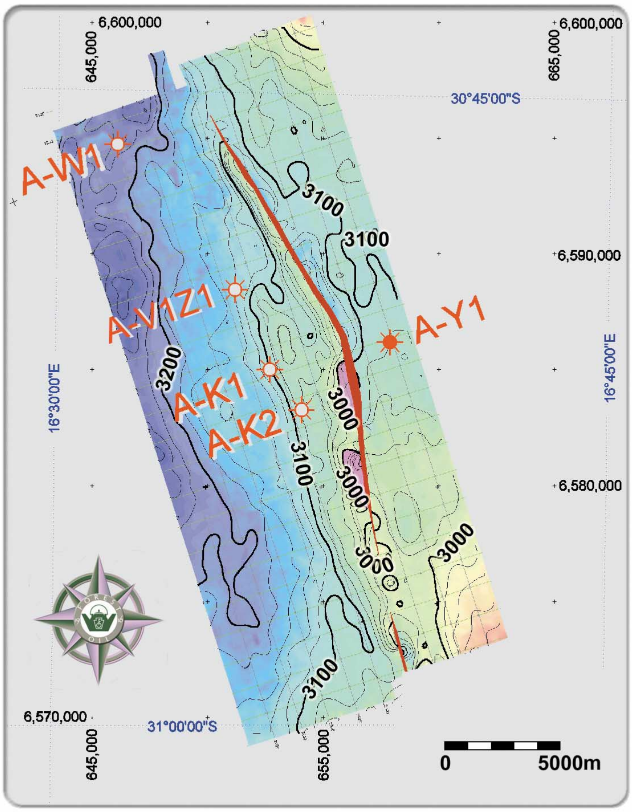


Figure 2. Structure map on the top of the gas-bearing interval showing well A-K1 well and subsequent wells A-K2, A-V1, A-W1, and A-Y1. Note lack of structural closure for A-K1. Mapped from a 3-D depth volume. CI = 20. Datum is sea level.

at A-W1. Unfortunately, this work was not completed until after A-W1 had been drilled.

Most examples in this paper are from cross-lines of the 3-D survey that tie A-K1, the discovery well for Ibhubesi Field. Figure 4 is a log display from the reservoir interval in A-K1. Many forward models have been done of this well and of all wells in the field. The well contains good inversion targets including resolvable gas sands—the "upper" and "middle" sands (although there are actually two pressure compartments in the upper sand with thin perched water). Other targets are a thin and usually unresolvable water sand and a thick, resolvable gas sand with a gas/water contact in it.

An inversion is an attempt to predict rock properties (porosity, thickness, fluid content, hydrocarbon saturation, etc.) from seismic data. There are three fundamental types—acoustic, elastic, and attribute. Each has different requirements for data input and differ in their predictive capability. The right inversion to use depends primarily on the data and an area's stage of exploration or development.

When we talk about inversion as a specific process, usually we mean a numerical process that uses the seismic response to predict rock properties such as velocity, density, compressibility, porosity, and water saturation. An array of methodologies claim to be able to do this.

The seismic method measures only four fundamental rock-physics properties: *P*-wave velocity, *S*-wave velocity, density, and anisotropy. Only the first three properties are measured with the accuracy required for inversion. Inverting seismic data to other rock properties implicitly assumes a relationship between the property and one or more of these fundamental properties. All types of inversion require some

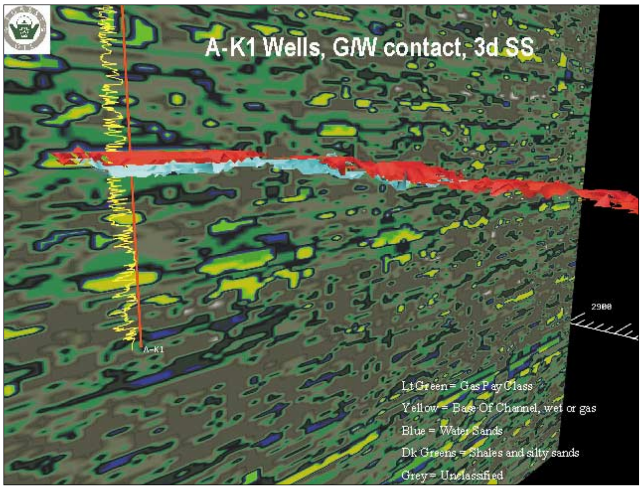


Figure 3. 3-D perspective of a cross-line through A-K1 looking east that shows the resulting Kohonen shape-attribute results. Green = pay; yellow = wet sand. Note transition from pay to wet. This corresponds to the gas/water contact in the third sand in A-K1. The two classes were then seeded through the volume. Red body is the gas pay class and the blue is the wet sand class. Note that the contact between the classes consist of two flat segments and that the gas class always overlies the wet class—compelling evidence that we are actually imaging a gas/water contact.

Table 1. Grouping of popular inversion methods

Method	Results	Input Needed	Predicts
Acoustic	Solves for Density and Velocity	Only stacked P-Wave	Porosity, Thickness
Elastic	Solves for Compressibility, Shear Strength, and Rigidity	Shear or Gather data	Porosity, Thickness Lithology, Sw?
Attribute	Uses wave shapes, seismic characters or derived features	Any form of seismic, Acoustic/Elastic Impedance	Porosity, Thickness Lithology, Sw?

form of constraint and need to be calibrated by tying the result to real or simulated well data. In this paper, we group popular inversion methods into: acoustic, elastic, and attribute inversion (Table 1).

In an exploration setting where little or no well control is available, a simple acoustic inversion may be best. During field development, when there is a lot of well control, an attribute inversion will be more useful.

In our acoustic inversion, the seismic data were transformed into a recursive inversion solution for porosity. A 90° phase shift occurs when the data are inverted. The event is shifted so that the peak corresponds to the bed instead of its boundaries. The volume can then be scaled for porosity and calibrated by well control. Figure 5 shows examples from Ibhubesi Field. We predicted unusually high (average 21%) porosity at A-Y1 using these same data. This was confirmed by drilling.

Some recursive methods allow input from geologic models and well control to constrain the inversion. Another sophisticated approach involves solving the three-term Bortfeld equation (Bortfeld, 1989). This can be considered an acoustic method because it solves for V_P, V_S, and density but

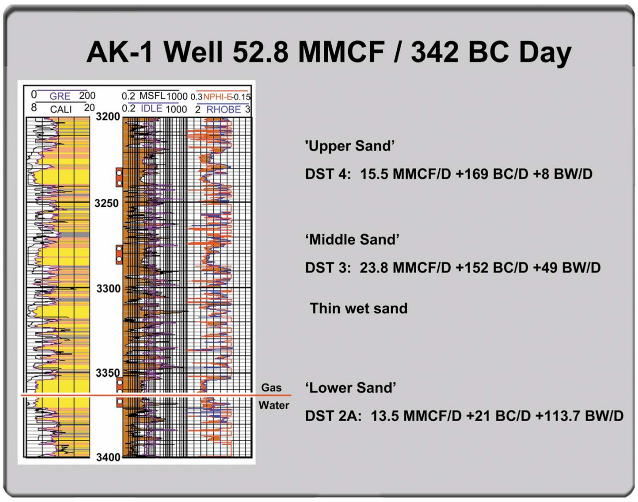
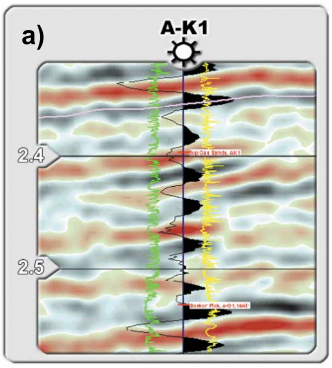
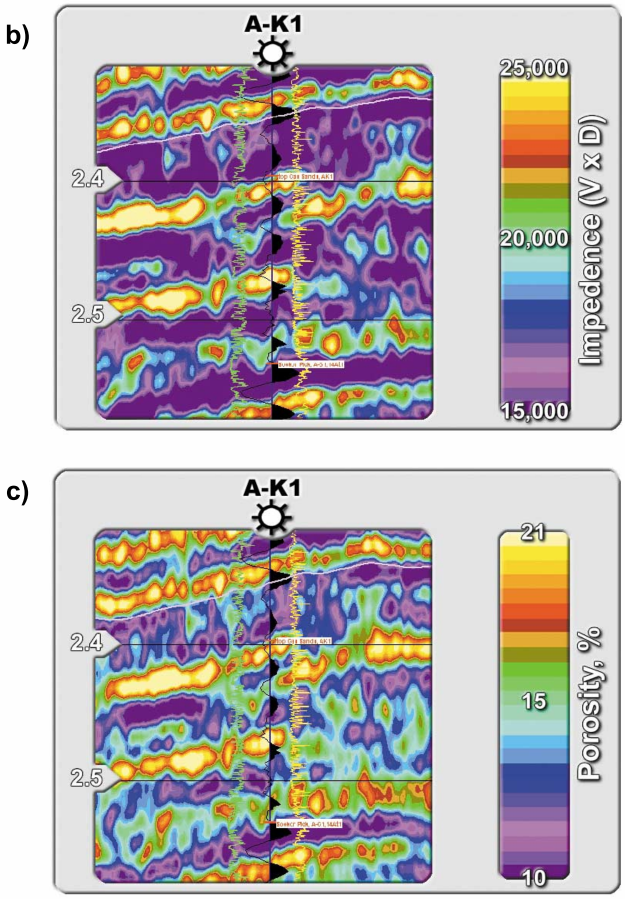


Figure 4. Log display of pay interval in A-K1, DST results, and inversion objectives.

Figure 5. (a) Conventional *P*-wave from the 3-D survey with A-K1 well tie. (b) Recursive inversion of the line in Figure 5a. Note that events have been phase-shifted 90° and that amplitudes are all positive and in impedence units. (c) Section from Figure 5b scaled in porosity units.





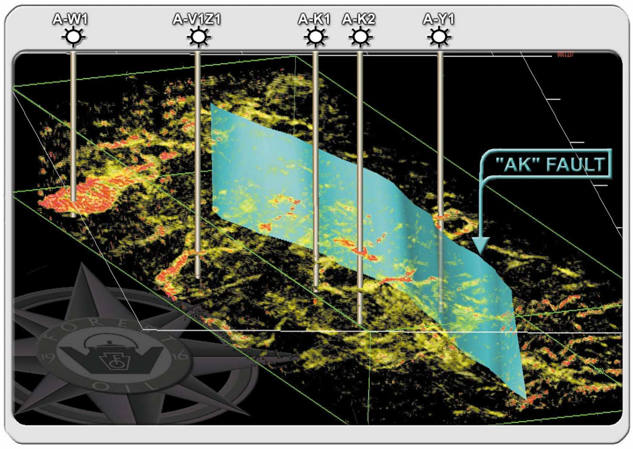


Figure 6. A 300-m volume rendering of an elastic inversion showing the five wells in Ibhubesi Field and the reservoir anomalies they penetrated. A-K1 is the Soekor well drilled in 1986. Forest Oil wells are A-K2, A-V1, A-W1, and A-Y1, drilled in that respective order in 2000-2001. Only A-W1 was wet.

is not recursive. The terms of the equation represent the intercept, gradient, and curvature of the offset amplitudes. By solving for density, wet and gas-bearing sands might be distinguished. The method requires preservation of true amplitudes, offset angles out to the critical angle if possible, and good quality, low-noise data.

More input is required but more predictive output can be obtained by doing an elastic inversion. Elastic inversion requires shear-wave information. If directly recorded shear-wave information is not available, it can be estimated in a number of ways based on AVO and *P*-wave data using some simplified form of the Zoeppritz equations, Shuey's equation, or a Castagna relationship.

Figure 6 is an example of an elastic inversion based on a *P*-wave, *S*-wave crossplot method. This was the primary volume used to site wells for the 2000-2001 drilling campaign in Ibhubesi Field. Ten reservoir predictions were made on the basis of this volume. All found porous reservoir and 8 (80% COS) found gas.

The goal of attribute inversion is to visualize seismic patterns pertaining to a specific geologic interval. An unsupervised neural network performs this task by clustering seismic waveforms around a mapped horizon. Input to the neural network is a set of seismic amplitudes. The number of segments and the time-gate relative to the mapped horizon are user-defined parameters. Each segment is characterized by a waveform-shaped class center (Figure 7). The network first has to learn how to segment the seismic waveforms. This training is done on a representative selection of seismic waveforms. A training set is created by regular sampling at every tenth in-line and cross-line.

The supervised approach requires a representative data set. We train the network by feeding it examples from the representative data set (the training set). The neural network then learns how the input data is related to the desired output. The supervised approach is a form of nonlinear, multivariate regression that is used to quantify or classify data. Examples of quantification are networks that predict, from the seismic response, such properties as porosity or pore volume. Popular supervised learning networks are multilayer perceptrons (MCP) and radial basis functions networks (de Groot, 1995).

In the unsupervised approach, the aim is to find structure in the data themselves, without imposing an a-priori

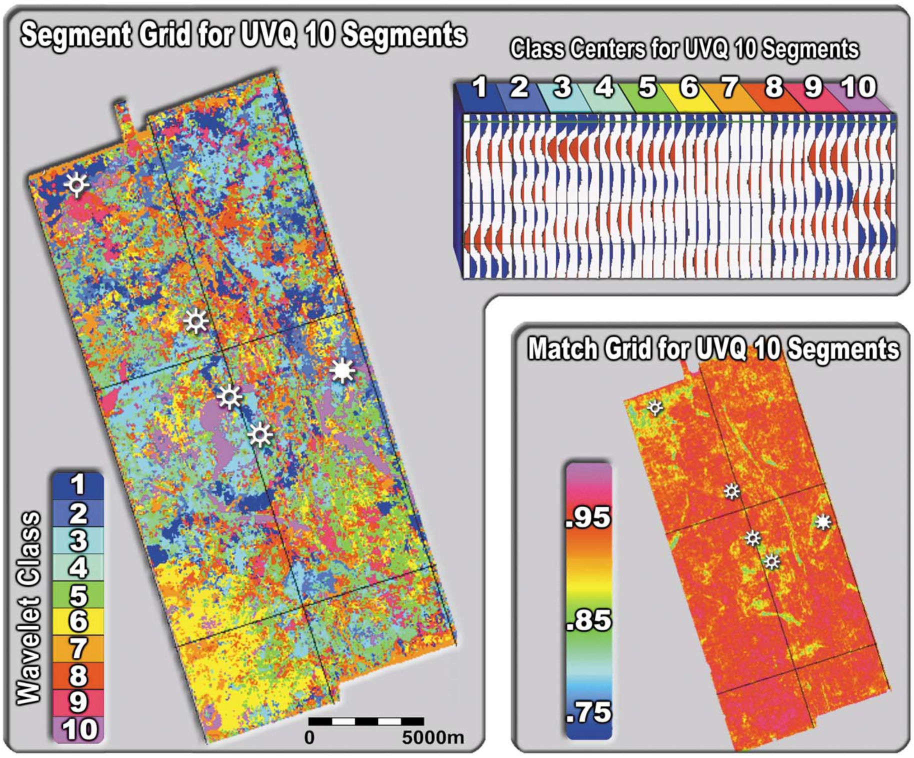


Figure 7. Results for UVQ analysis over time gate [-4,96] relative to Upper Peak horizon.

Table 2. Neural network performance for gas probability

Train data (balanced)			Test data (AK-1, AG-1)		
43.13 %	6.86 %	50 %	5.88 %	0.98 %	6.86
7.26 %	42.74 %	50 %	9.80 %	83.33 %	93.14
50.40 %	49.60 %	Total misclassified 14.12 %	15.69 %	84.13 %	Total misclassified 10.87 %

conclusion. Unsupervised learning is used for data segmentation—i.e., data clustering (Figure 8). The resulting segments (e.g., clusters of similar seismic waveforms at the reservoir level) remain to be interpreted. Popular networks that use unsupervised learning are the unsupervised vector quantifier (de Groot, 1995) and Kohonen feature maps (e.g., Lippmann, 1989).

In interpreting neural network patterns, one must account for the fact that the seismic response is smeared across overlying and underlying sequences. Response from some units may interfere with those from other levels. If the stratigraphic intervals are not parallel, the extraction window cuts through the underlying or overlying geology, and the results become difficult to interpret. However, even with these limitations, we can still extract valuable geologic and petrophysical information from observed patterns. A qualitative interpretation can be based on geologic insight. A more quantitative interpretation involves analyzing the seismic waveforms of each segment in terms of geologic/petrophysical variations using real and simulated wells.

Pseudo wells. Adding pseudo wells can increase the statistical database for training a neural network. Pseudo wells, which simulate the results of drilling, have well logs but no spatial locations. They can be used to quantify waveform segmentation results (also known as seismic facies maps). In this case study, they were used to create the representative learning set for a supervised neural network. The simulation is based on a constrained Monte Carlo procedure and is built around an integration framework, a hierarchical description of the subsurface units. In this study, pseudo wells were needed because only three actual wells had been drilled at the start of the project.

The seismic input for network training came from synthetic seismic (near- and mid-offset) and acoustic impedance traces of 40 pseudo wells. Seismic waveforms of [-20,20] ms length for near- and mid-offset were extracted relative to a reference time, sliding with 4-ms steps. The amplitude of the synthetic impedance trace at the sliding reference time serves as an additional input node to the neural network. Figure 9 shows the neural network topology for the porosity prediction. The output consisted of the amplitude of either the porosity trace or the pay flag trace. The variable called pay flag is simulated as a Boolean variable (1 indicates gas-filled sand and 0 indicates brine-filled sand or shale).

Both were constructed by converting the depth curve to two-way time using the velocity log. The time curve was subsequently resampled with an antialias filter to 4-ms sampling.

In Table 2, the performance is shown for the gas probability prediction to monitor the neural network during training and to stop training before overfitting sets in. Overfitting occurs when the network loses its generalization ability. To avoid overfitting, the two actual wells were used as test data during the training of the network.

The trained networks were applied to the seismic and impedance cube every 4 ms in a time slice of 0-250 ms relative to the mapped upper peak horizon, yielding a porosity and pay flag prediction cube. Figure 9 shows fully connected MLP network to predict the porosity, and Figure 10 shows a slice through the porosity cube 60 ms below the Upper Peak horizon. Figure 11 is an in-line through the gas probability cube. The closer the value is to 1 or higher, the more likely it is that we are dealing with gas-filled sand. As such the output can be considered to represent the gas sand probability.

To validate the inversion method, the network was applied to real wells AK-1 and AG-1. Because the real well data were not used to train the neural network, the real wells are blind test locations. Figure 12 shows the result for pay flag. Each plot shows two curves: the actual pay flag trace in pink and the trace predicted by the neural network in blue. From the predictions on well logs it can be observed that, in general, the neural network is quite capable of transforming acoustic and elastic properties into the target gas probability response. Note the blue curve is not the actual gas probability but the predicted likelihood not scaled to 1. The same applies to the porosity inversion.

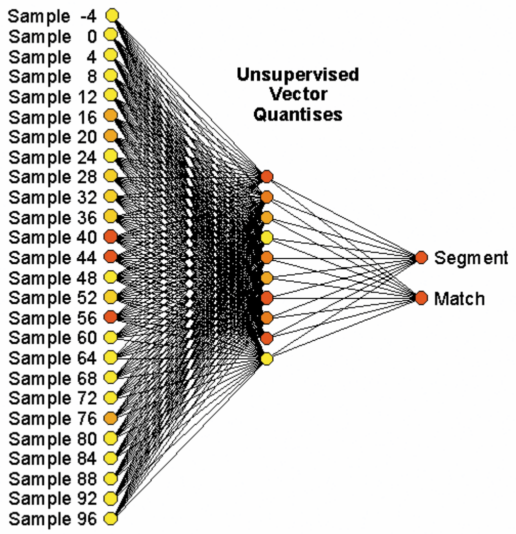


Figure 8. UVQ network topology. Sample X indicates amplitude X ms below mapped reference horizon. Number of nodes in middle layer indicates number of segments. Output is the index number of the winning segment and the "degree-of-match."

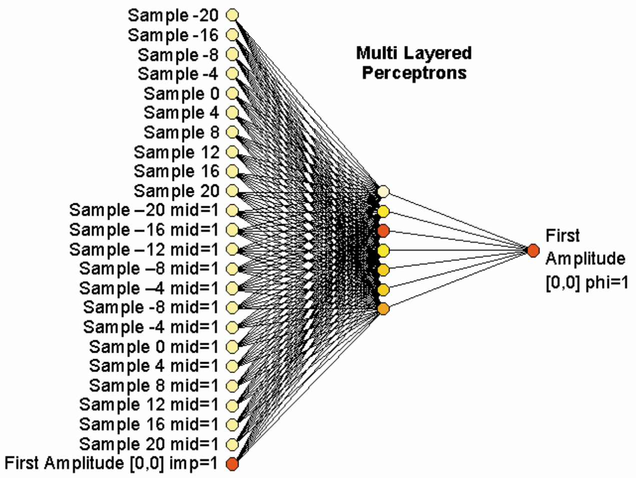


Figure 9. Fully connected MLP network to predict the porosity. Sample X means amplitude X ms below Upper Peak horizon.

Play analysis and cost benefit of inversion. Fortunately there is enough historical data to do some simple play analysis to quantify the benefit of 3-D inversion in risk reduction (or COS) and added value. Prior to the present drilling campaign, 14 wells had been drilled in the play. It could be argued, being fairly generous, that three wells could have been commercial (A-K1, A-G1, and A-F1), resulting in a COS based on 2-D seismic of 21%. With the benefit of 3-D inversion, we had a COS of 75% (3/4 successes). So application of 3-D inversion improved the play COS by 54%. We estimate that this resulted in cost savings of US$15.2 million in dry hole costs and an added reserve value of $US216 million—savings that exceed the cost of the 3-D seismic and inversion work by about two orders of magnitude—a great investment. The cost of the 3-D survey was $US2.5 million and the inversion about $US300 000.

Conclusions. Forest Oil expects improved results from future drilling in this area. 2-D data beyond the 3-D survey show

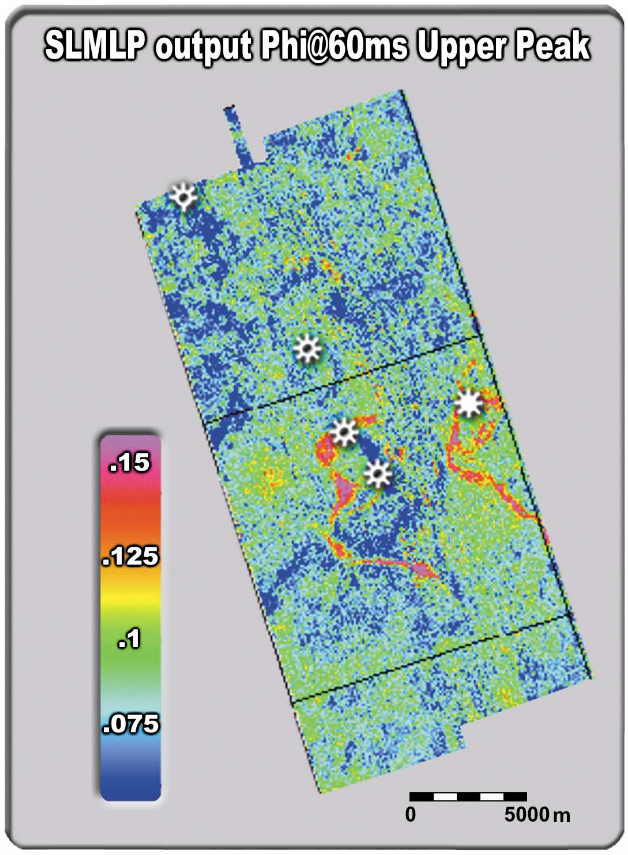


Figure 10. Predicted porosity for a time slice through the porosity cube 60 ms below Upper Peak horizon.

the play has considerable extent. The campaign has proved up about 1 trillion ft^3 in seven inversion anomalies. Exploration finding costs have been about 3.8 cents/mcfg reserves. Had elastic and attribute inversions been finished in time to impact the drilling program, we might have avoided drilling the wet well. It has been a remarkable technical success and a tribute to the power of seismic inversion.

Suggested reading. "Seismic characters and seismic attributes to predict reservoir properties" by Aminzadeh and de Groot (Proceedings of SEG-GSH Spring Symposium, 2001). "Geometrical ray theory: Rays and traveltimes in seismic systems (second-order approximation of the traveltimes)" by Bortfeld (GEOPHYSICS, 1989). "Relationship between compressional and shear-wave velocity in clastic silicate rocks" by Castagna et al. (GEOPHYSICS, 1985). "Geologic log analysis using computer methods" by Doveton (*Computer Applications in Geology*, AAPG, 1994). "Detection of gas in sandstone reservoirs using AVO analysis: a 3-D case history using Geostack technique" by Fatti et al. (GEOPHYSICS, 1994). "Seismic reservoir characterization using artificial neural networks" by de Groot (Mintrop Seminar, Münster, 1999). "Evaluation of remaining oil potential with 3-D seismic using neural networks" by de Groot et al. (1998 EAGE Annual Meeting). "Monte Carlo simulation of wells" by de Groot et al. (GEOPHYSICS, 1996). Seismic Reservoir Characterization Employing Factual and Simulated Wells by de Groot (doctoral dissertation, Delft University Press, 1995). Learning Principles in Dynamic Control by Kavli (doctoral dissertation, University of Oslo, 1992). "Pattern classification using neural networks" by Lippmann (*IEEE Communications Magazine*, 1989). "Mining and fusion of petroleum data with fuzzy logic and neural network agents" by Nikravesh and Aminzadeh (*Journal of Petroleum Science and Engineering*, 2001). "Seismic-guided estimation of log properties" by Schultz et al. (*TLE*,

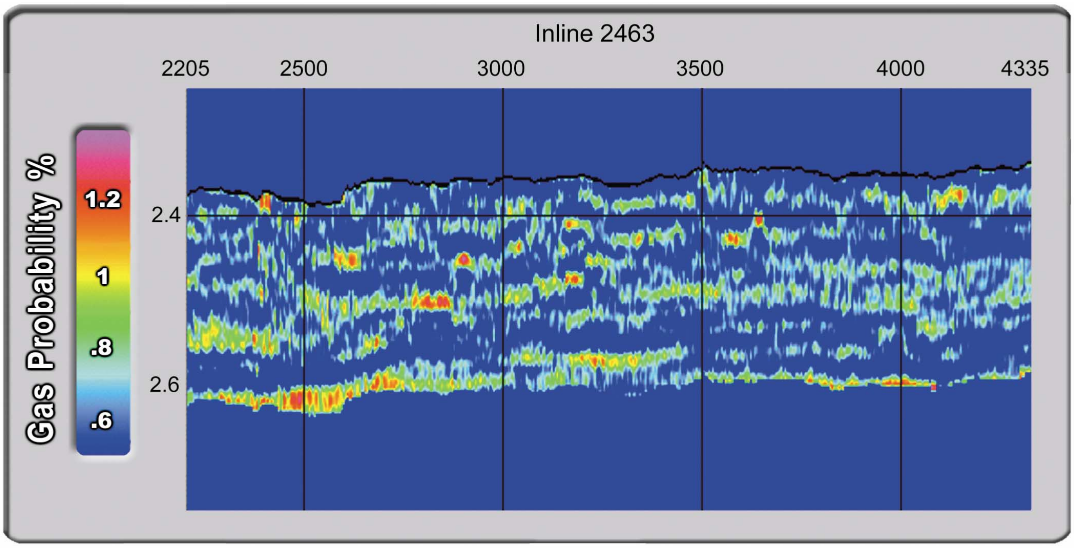


Figure 11. Predicted gas probability for in-line 2463. Black line is Upper Peak horizon. AK-1 was drilled at cross-line 3181.

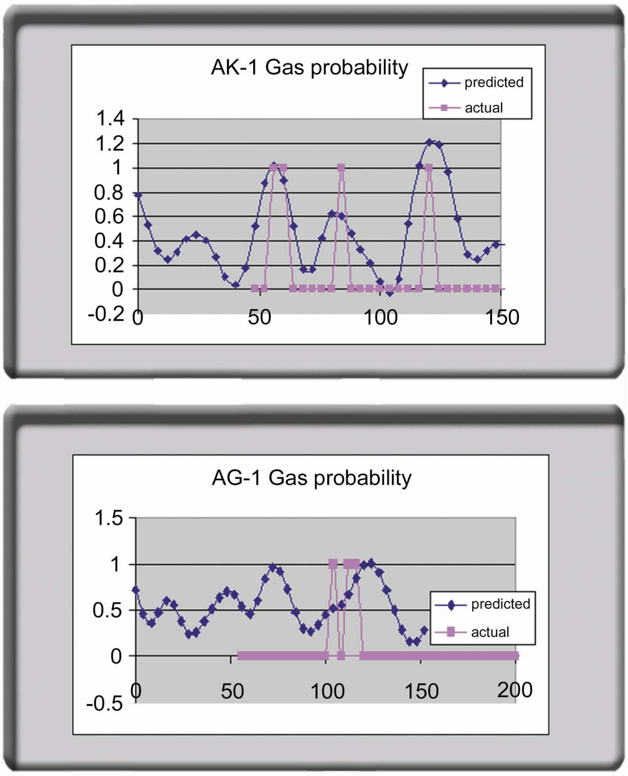


Figure 12. Gas probability as predicted by MLP neural network (blue) plotted against actual pay flag (pink) in AK-1 (top) and AG-1 (bottom). The curves for AG-1 do not align perfectly due to a small time shift.

1994). "A simplification of the Zoeppritz equations" by Shuey (GEOPHYSICS, 1985). E

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