Modeling processed seismic data to improve seismic facies prediction

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Abstract

Interpreters need to screen and select the most geologically robust inversion products from increasingly larger data volumes, particularly in the absence of significant well control. Seismic processing and inversion routines are devised to provide reliable elastic parameters ($V_P/V_S$ and $\rho$) from which the interpreter can predict the fluid and lithology properties. Seismic data modeling, for example, the Shuey approximations and the convolution inversion models, greatly assist in the parameterization of the processing flows within acceptable uncertainty limits and in establishing a measure of the reliability of the processing. Joint impedance facies inversion (Ji-Fi®) is a new inversion methodology that jointly inverts for acoustic impedance and seismic facies. Seismic facies are separately defined in elastic space ($V_P/V_S$ and $\rho$), and a dedicated low-frequency model per facies is used. Because Ji-Fi does not need well data from within the area to define the facies or depth trends, wells from outside the area or theoretical constraints may be used. More accurate analyses of the reliability of the inversion products are a key advance because the results of the Ji-Fi lithology prediction may then be quantitatively and independently assessed at well locations. We used a novel visual representation of a confusion matrix to quantitatively assess the sensitivity and uncertainty in the results when compared with facies predicted from the depth trends and well-elastic parameters and the well-log lithologies observed. Thus, using simple models and the Ji-Fi inversion technique, we had an improved, quantified understanding of our data, the processes that had been applied, the parameterization, and the inversion results. Rock physics could further transform the elastic properties to more reservoir-focused parameters: volume of shale and porosity, volumes of facies, reservoir property uncertainties — all information required for interpretation and reservoir modeling.

Introduction

Seismic interpreters require data from efficient, robust processing with associated seismic inversion of products, from increasingly larger data sets in shorter time frames, often in frontier areas with limited or no significant well control. A reliable interpretation requires an understanding of the processes applied to the acquired data, a critical assessment of the parameter selection within the processing and inversion algorithms, and a method of quantitatively assessing the validity of the result. A quality control (QC) image is one that shows how a process may have improved or disimproved in a meaningful sense. We outline how modeling and graphical QCs are used to aid better selection of the appropriate parameters to apply in seismic processing and estimation of the uncertainty in those results. Hence, quantitative graphical QC displays are key in illustrating how observed results differ from “known” results of models, thereby increasing our understanding of the subsurface imaged in the seismic data and quantifying the reliability of the final inversion products.

The Shuey (1985) approximation of the amplitude versus offset (AVO) model and the convolution model are used to compare the observed results of processing of real data with the model. Joint impedance facies inversion (Ji-Fi®) (Kemper and Gunning, 2014) is a new inversion methodology that successfully inverts seismic data for $V_P/V_S$, $\rho$, and facies. We show how to quantitatively assess improvements using a quantitative numerical confidence level of a Ji-Fi inversion result. This quantitative QC is independent of the well data and provides additional assurance on the quality of the product provided to the interpreter.

Background to modeling and inversion

Modeling the complete seismic data is an unrealistic expectation because it would require an anisotropic elastic parameterization of the overburden through...
which we would propagate the seismic wavefield between sources and receivers. A simpler alternative is to model the processed seismic data, assuming that the processing sequence has removed any effects from the overburden and correctly imaged the data. An earth model based on a simple Shuey approximation and convolution models allows calculation of the expected seismic response. Conversely, it allows estimation of possible models from seismic data. In this paper, we show how half-space/AVO and convolutional models can be used to parameterize the processing, validate the process by comparing the results with the known model, and, finally, evaluate the fit of the data to models at well locations, where available.

The Shuey (1985) simplification, can be used to determine a linear function of reflection amplitudes versus \( \sin^2 \theta \), where \( \theta \) is the incident angle at the interface. For incident angles of less than 30\(^\circ\), this approximation is characterized by two simple terms, intercept \( i \) and gradient \( g \). Hence, the amplitude versus angle (AVA) model is \( R(\theta) = i + (g \sin^2 \theta) \). Using an appropriate velocity function, the angle to offset transform enables the AVO model to be used. Rutherford and Williams (1989) and later Castagna and Swan (1997) use this model to classify AVO responses at the top of a sand overlain by a different lithology (generally shale) (Figure 1).

The convolution model is used to estimate the wavelet from the seismic response, while similarly the goal of inversion is to extract impedances from the seismic response. The model is that seismic \( c_0 = \text{reflection coefficient} \times \text{wavelet} + \text{noise} \) (where the subscript \( \theta \) denotes incidence angle dependence). Prior to inversion, it needs to be verified that the seismic data have been conditioned to follow the relationships defined in the half-space/AVO model. Ideally, the data need to be processed with these assumptions in mind if the data are to be used for inversion. This allows a qualitative assessment of improvements to the quality of the data set.

**Half-space/amplitude versus offset models and parameterization**

Elastic half-space models comprise at least two layers, with each layer characterized by the compressional velocity (\( V_P \)), S-wave velocity (\( V_S \)), and density (\( \rho \)). The Zoeppritz (1919) equations and the Shuey (1985) simplification, are further classified by Rutherford and Williams (1989) and later Castagna and Swan (1997) into four classes of AVO responses at the top of a sand overlain by a different lithology (generally shale) (Figure 1). Sands and shales compact at different rates, and the compaction trends will be more complex than this diagram shows. Hard sands have higher acoustic impedance (\( AI = \frac{V_P}{\rho} \)) than the overlying shale. Sands overlying shale can be classified into classes I/II/III or IV based on their AVO response.

Similarly, the classes may be represented as having a positive or negative intercept and gradient and can be cross-plotted (as shown in Figure 1). With a different fluid fill (gas, oil, or brine, as indicated by the red, green, and blue impedance trends), the curves would shift downward (lower zero-offset amplitude). By accepting this model, we expect that our seismic data should follow the Shuey AVO relationship. Desired outcomes of prestack processing of seismic data are to include a better fit of this model and a quantification of how a process has improved a data set or made it worse. For example, after a data conditioning process, the data should better fit the linear approximation of amplitudes being directly proportional to \( \sin^2 \theta \). AVO analysis of seismic data generally comprises the following steps:

![Figure 1.](https://pubs.geoscienceworld.org/interpretation/article-pdf/3/4/SAC91/3015935/INT-2015-0069.pdf)

(a) A schematic of AVO classes and compaction trends is shown. Impedance increases with depth, with the sand trend starting softer and ending harder than the shale. Sands are shown for gas, oil, and brine fill (red, green, and blue). (b) AVO classes as a function of amplitude versus offset and (c) AVO classes in intercept versus gradient space.
• Data conditioning to correct for approximations in the processing, e.g., a complex overburden that cannot be correctly imaged in the imaging algorithm may cause the gathers not to be flat.
• Transformation of the offset prestack seismic gathers to the incident angle domain.
• Estimation of the intercept and gradient values at each sample on every trace.

A QC display of “AVO error” is a quantitative measure of how far the far-stack amplitude deviates from the straight line defined by the near and midstacks. A predicted far stack is computed using the near and midstacks as the input to the equation (where $\theta_n$ is the angle in the middle of the near stack angle range; similarly $\theta_m$ is the angle representing the middle of the midstack, and $\theta_f$ represents the angle at the middle of the far stack):

$$\text{Far-stack}^{\text{predicted}} = S \cdot \text{midstack} + \text{near-stack} \cdot (1-S).$$

where

$$S = \frac{\sin^2 \theta_f - \sin^2 \theta_n}{\sin^2 \theta_m - \sin^2 \theta_n}.$$  

AVO error is thus the difference of the amplitudes of the far stack from a projection to the far-stack angle from the near and midstacks (Figure 2a). If the input data conform to our AVO equation, this error will be zero. A root-mean-square (rms) map of the error volume (Figure 2b) will quickly highlight areas for investigation and may indicate noise in the input data (misalignment, multiples, and NMO stretch, etc.). Low values in this error volume (blue in Figure 2b) do not mean we have the correct AVO curve, but rather, a good fit to our model. Ideally, it will fit the model better after a beneficial data conditioning step.

A similar QC method is used to determine if there is a systematic error in the overall amplitudes of one of the stacks (e.g., the middle-offset amplitudes are lower relative to the near and far). An rms within a time window of the middle stack is computed and divided by the rms of the predicted middle stack from near and far (Figure 2c).

The AVO error balance stack shows a leopard pattern at the top (Figure 2d). Seismic waves traveling through a complex overburden are focused in one area and unfocused in another. The amplitude of each angle stack will be affected slightly differently by this, causing the amplitude of the midstack to be a little too high compared with the others in one area (red) and a little too low (blue) elsewhere. This pattern may be removed, usu-

Figure 2. AVO error and AVO balance error QC displays. (a) AVO error (amplitude on far stack — amplitude predicted from near and far). (b) The rms map of AVO error volume. (c) AVO balance error — rms of the midstack/rms of the predicted mid stack and (d) map of AVO balance errors. Ideally, our data should follow the AVO model of reflection amplitudes being directly proportional to $\sin^2 \theta$. The deviation from this linear relationship is referred to as the AVO error. The rms of this error can be easily computed for a volume (b), highlighting spatially areas that need to be closer reexamined, in this case, the highly red areas. In panel (c), the rms of the midstack relative to the rms of the predicted midstack shows that the amplitudes of the midstack are higher in some areas than expected (red) and lower in others (blue). A goal of a complex imaging solution would be to remove this pattern. The leopard-skin appearance of this QC is similar to hit density maps that are produced with ray trace modeling during seismic acquisition planning; except here, the results are derived from the seismic data.

\[ \text{Seismic}_{\theta} = \text{reflection coefficients}_{\theta} \times \text{wavelet}_{\theta} + \text{noise}. \]  

(2)

The seismic wavelet can be estimated using well logs and the seismic trace at the well location. Sonic and density curves are used to calculate the impedance trace and, subsequently, the reflection coefficients. The seismic wavelet can then be estimated from the seismic trace at the well location and reflection coefficients.
Extending from zero-offset to full-offset or angle synthetics, the equations require S-wave velocity logs.

Conventional prestack seismic trace inversion follows a similar process (if appropriately conditioned using the AVO models above); seismic angle stacks and the wavelets are used to estimate the reflection coefficients, and are subsequently used to calculate acoustic impedance. Assuming the wavelets are spatially consistent, they can be used to invert all traces in the seismic volume. Furthermore, assuming the stack represents the zero-offset response, it may be inverted for acoustic impedance or for acoustic impedance and the $V_p/V_S$ ratio if we use multiple angle stacks.

However, seismic data are frequency band limited, lacking in high and low frequencies. The missing high frequencies will limit the vertical resolution of the result and the lack of low frequencies means that we can only determine relative impedances in this manner. Conversion of the relative impedances to more useful absolute values involves the addition of a low-frequency model, typically made by interpolating well data, optionally using the seismic velocities. The uncertainty associated with this low-frequency model away from well control will lead to unquantifiable errors in the final result; if we use the wrong low-frequency model, the output values will be wrong.

**Ji-Fi trace inversion**

Ji-Fi (Kemper and Gunning, 2014) is a new seismic inversion algorithm that uses the convolution assumption. However, unlike industry-standard simultaneous prestack inversion, it does not rely on a single low-frequency model. Instead, it uses a model for each facies, and, using these models, we invert the seismic for facies and elastic parameters. Crucially, the outputs of the inversion are facies with elastic-property volumes: either $V_p$, $V_S$, $\rho$, or $AI$ and $V_p/V_S$, or even as Lamé parameters, which may be converted to more useful properties, such as estimates of volume of shale and porosity using rock-physics models (RPMs). We briefly describe how Ji-Fi operates to define facies in terms of their elastic properties ($V_p$, $V_S$, and $\rho$), apply depth trends per facies, and invert simple models to test their validity. Finally, we detail how to quantitatively assess the error/uncertainty at a well location using the graphical confusion matrix QC concept.

**Ji-Fi facies and low-frequency model definition**

The first step is to define the facies as unique in $V_p/V_S$: AI space (Figure 3). The model for each facies comprises a single depth-dependent trend for $V_p$ and a linear transform between $V_S$ and $V_p$ and between $\rho$ and $V_p$. The trends themselves are actually parameterized in two-way time, but we use the term “depth trend” as it fits with the general understanding of the term and relative to an appropriate datum: sea level or an unconformity. Hence, each facies has unique values of $V_p$, $V_S$, and $\rho$ at every depth.

The shale and sand depth trends vary in the schematic AVO model in Figure 1, left panel. This model shows the trends in acoustic impedance for sand and shale with three classes representing fluid fill of gas (red), oil (green), and brine (blue). However, Ji-Fi defines the trends in $V_p$, $V_S$, and $\rho$. As seismic responds to all three parameters, this allows a class II AVO sand to be separated from shale because the $V_p/V_S$ ratio will be different even though the AI is the same.

Figure 3 shows four facies trends plotted as lines with their associated error bars in $V_p/V_S$: AI space; soft shale, shale, oil sand, and wet sand (the wet-sand trend is very short). Although the brine sand and shale have similar acoustic impedance, they have different $V_p/V_S$ ratio values, and they are distinguishable in $V_p/V_S$: AI space. Below a certain depth, there will be little variation of the elastic properties with fluid fill, and they are indistinguishable with Ji-Fi or any other seismic inversion method.

**Ji-Fi on model seismic data**

Using model data that conform to the convolution assumption, we can test Ji-Fi. Angle stacks are made directly using the well data for the elastic parameters, the Zoeppritz equations to generate reflection coefficients, and we convolve these with wavelets. We can extend this methodology to test the sensitivity of the inversion to other processes and assumptions we may have made during processing. Table 1 outlines some examples of QC tests that may be performed on model data and the sensitivities they aim to address.
**Ji-Fi on real seismic data**

Because Ji-Fi uses a Bayesian framework for the inversion, all inputs to Ji-Fi come with a measure of uncertainty. Input parameters, including the facies trends and wavelets, must be entered with rms or percentage noise error values. The noise estimates on the wavelets constitute the misfit between the seismic and the convolution assumption and as such, it can be considered the uncertainty on the seismic inputs.

The Ji-Fi outputs are as follows:

- facies volumes
- elastic volumes (\(V_p\), \(V_S\), and \(\rho\))
- derived elastic volumes (AI and \(V_p/V_S\), or \(\lambda/\rho\), \(\mu/\rho\))
- QC volumes and rms QC maps, such as seismic residuals.

At each point in the seismic volume, in the interval of interest, Ji-Fi will output the elastic properties and the predicted facies. The elastic properties for each facies will form a cluster around the depth-varying trends in \(V_p/V_S\): AI crossplot space (Figure 3). Elastic volumes may be transformed into more reservoir-focused volumes (\(V_{\text{shale}}\) and porosity) using RPMs. These continuous properties are required for reservoir modeling, rather than the seismic.

**Ji-Fi inversion quality control**

Assessing the accuracy of the Ji-Fi results and quantifying uncertainty in predictions of facies and elastic parameters is highly important in terms of the reliability of the outputs. The following must be considered: (a) Can we create error volumes to show where the process is unreliable? (b) Do the results resemble geology? (c) Do the results tie the well data? Next, we describe two QC’s output from the Ji-Fi inversion: (a) the residual volumes QC and (b) the null-space QC.

**Ji-Fi residual volumes quality control**

Away from well control, a qualitative assessment of whether the facies inversion resembles geology may be made, similar to the typical test used during seismic processing, which may be highly subjective. Ji-Fi outputs residual volumes, similar to the AVO error map QC described in Figure 2, based on the fit to the convolutional model. The residual volume is the difference between a synthetic seismogram generated from well data of \(V_p\), \(V_S\), and \(\rho\) and synthetic seismic generated from the Ji-Fi output volumes \(V_p\), \(V_S\), and \(\rho\). Low values on the residual volumes indicate where the data fit the model assumptions, not necessarily that we have the correct result. High values in the residual volumes indicate where the data do not fit the convolution model assumptions, indicating perhaps that the seismic is noisy or the wavelets are incorrect.

**Ji-Fi null-space quality control**

All the known facies in the area covered by the inversion window are input to the Ji-Fi inversion. However, there may be unknown facies, which will lie away from the other facies in \(V_p/V_S\): AI space, perhaps in the null space (Figure 3) and will cause a seismic response. Ji-Fi attempts to fit the seismic elastic parameters those defined by the facies, so if an unknown facies is not defined, the output elastic parameters will be dragged away from the known defined facies trends, thereby adding to the error. The distance between the output elastic properties and the trend values provides the null space QC, a quantitative measure of the consistency of the definition of the facies’ elastic parameters.

**Ji-Fi — Quantitative well analysis**

Ji-Fi does not require the facies or depth trends to be defined from wells within the area of interest. Hence, at well locations, we can compare the Ji-Fi predictions against the well. It is imperative to note that Ji-Fi will not force the result to match the wells. All wells can be used as independent locations at which to evaluate the result. In conventional simultaneous inversion, the low-frequency model will fit the wells used to build the model. Thus, the low-frequency component of the output, which determines the scale of the absolute values, will also fit the wells. In Ji-Fi, for each facies, we use a depth trend that best fits all the wells; it does not vary to match each well.

With well control, we can make a direct comparison between the Ji-Fi predictions and the known lithology, with the following caveats: (1) we assume the well data represent the truth; (2) the well data are optimally tied to the seismic in time at the well location; (3) we apply some upscaling to the well data by matching the data in two-way time — where the curves have been upscaled using the seismic sample interval.

<table>
<thead>
<tr>
<th>Table 1. Suggested tests to examine the sensitivity of the Ji-Fi inversion.</th>
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<tr>
<td><strong>Tests to perform on model data to test Ji-Fi</strong></td>
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<tr>
<td>Create a model gather in offset domain and subsequently angle stacks.</td>
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<tr>
<td>Create a wedge model of a thinning reservoir sand.</td>
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<tr>
<td>Create a model gather with anisotropy in some facies.</td>
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<tr>
<td>Use different wavelets in modeling and inversion.</td>
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</table>
Ji-Fi model validation — A Bayesian visual quality control

To validate the Ji-Fi models, a Bayesian approach is used; i.e., after Ji-Fi inversion of the seismic data, what facies do we predict given the facies trend models and the elastic properties in the logs? The results are presented graphically in Figure 4; column 1 shows the true facies log, defined using several well logs, whereas columns 2, 4, and 6 show the facies predicted from the depth trends, model seismic, and real seismic data, respectively. Columns 3, 5, and 7 are the Bayesian classification of the results of the predictions when compared with the “true” case (column 1).

For simplicity, results are classified using a single prediction, such as “sand” or “not sand.” With this QC, the following questions are being answered: If there is sand, do the depth trends predict “sand”? If there is no sand, do the depth trends predict “not sand”? The outcomes of this test can be classed as follows:

- True positive (TP): Well data are sand (truth), and predicted facies is sand.
- True negative (TN): Well data are not sand, and prediction is not sand.
- False positive (FP): Well data are not sand and prediction is sand.
- False negative (FN): Well data are sand, and prediction is not sand.

This QC display is a convenient method to qualitatively compare the results of the Ji-Fi inversion on different data sets at the well location. In column 2, for example, there is a reasonable fit between each of the predicted and actual facies; hence, the facies prediction using nonelastic logs was successful. All the results are picked and identified the first thick sand; however, the real seismic data case misidentified the basal sand. This QC would indicate that further parameterization of the inversion on the real seismic data may be required.

Ji-Fi quantitative visual confusion matrices

The facies predicted from the seismic data by Ji-Fi at the location of the well and the successes or failures of that prediction are illustrated in columns 6 and 7 of Figure 4. However, this is a qualitative display rather than a quantitative error estimate of how good the prediction is. We use a visual representation of a confusion matrix (Kohavi and Provost, 1998) to further understand the uncertainty in the result (Figure 5). The three plots in Figure 5 show the result of this test applied to all the facies predictions from Ji-Fi, classified by sand/shale (it can also be applied to other predictions such as hydrocarbon sands): (a) facies predicted from the depth trends and well elastic parameters, (b) facies predicted from Ji-Fi on the modeled seismic, and (c) actual facies predicted.

The boxes and rows are all scaled relative to the number of times that result was recorded. The top row represents the depths, where the well has sand and the bottom row, where there is no sand; the depths have been scaled according to the number of points, of 49 total measurement points 13 are sand and 36 not sand. Hence, the probability of sand occurring at any point in the well is 27% (13/(13 + 36) = 0.27).

We further divide each row proportionally, according to the success of the prediction. In the leftmost figure (depth trend facies prediction), the sand is predicted correctly 11 times (TP), but twice it is predicted incorrectly as “not sand” (FN). Where there is “not sand,” the prediction is correct 30 times (TN) and incorrectly six times (FP). The accuracy of the prediction given as “sand” is 11/13 = 0.85, and the accuracy of prediction given as “not sand” is 30/36 = 0.83. Sands are predicted 17 times (TP = 11 + FP = 6), with 11 correct predictions and six false. The probability of sand, given a prediction of sand, is thus 11/17 = 0.65.

The success of the Ji-Fi inversion of real seismic data is illustrated on the right in Figure 5. From Figure 5 and Table 2, we see that sands are predicted by Ji-Fi correctly nine times and incorrectly seven times. The probability of a sand given Ji-Fi predicts a sand is 9/(9 + 7) = 0.56. If tests at other wells confirm this accuracy, we assume that the reliability remains constant. Then, anywhere that Ji-Fi predicts sand, we can assign a probability of there being sand of 0.56. It is a significant advancement to deliver an inversion product with qualitative and quantitative uncertainty estimates, particularly in graphical form.
Conclusions

In this paper, we have shown how two of the simplest models, the AVO model and the convolution model, can be used to improve the processing of seismic data, parameter selection, and ultimately inversion products from seismic data. We have presented methods of assessing the parameter selection and whether they improve the data, thereby fitting these models better. Two examples of quantifying the improvement or disimprovement of processing steps/parameter selections were introduced: AVO error maps and AVO error balance maps. If a process increases the fit to the AVO linear trend, it has improved the data. Thus, this model can be used to test data-conditioning algorithms and parameters prior to AVO or inversion. Similarly, the concept of convolution model is used throughout the seismic industry — it is how we naturally think of seismic data and how they are used in the generation of synthetic seismograms/gathers.

We have briefly described a new inversion methodology, Ji-Fi, its QC outputs, and a new method of quantitatively assessing the error/uncertainty in the inversion result. Ji-Fi combines a few simple models for an inversion algorithm that does not suffer the low-frequency uncertainty of conventional simultaneous inversion methods. We use a novel method, based on the confusion matrix concept of quantifying the uncertainty in the result of the Ji-Fi inversion. Thus, using these simple models and the Ji-Fi inversion technique, we have a much better and more quantified understanding of our data, the processes that have been applied, the parameterization, and the inversion results. Rock physics can further transform the elastic properties to more reservoir focused parameters of interest to the interpreter: the vol-

Table 2. The quantification of the Ji-Fi prediction results compared with the well-log facies. This data are displayed visually on the right of Figure 5.

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Confusion</th>
<th>Description</th>
<th>Accuracy</th>
<th>Accuracy (%)</th>
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<tbody>
<tr>
<td>Sand</td>
<td>TP</td>
<td>Sand correctly predicted nine times</td>
<td>9/13</td>
<td>69%</td>
</tr>
<tr>
<td>Sand</td>
<td>FN</td>
<td>Sand incorrectly predicted as not sand</td>
<td>4/13</td>
<td>30%</td>
</tr>
<tr>
<td>Shale</td>
<td>TN</td>
<td>Shale correctly predicted as not sand</td>
<td>29/36</td>
<td>77%</td>
</tr>
<tr>
<td>Shale</td>
<td>FP</td>
<td>Shale incorrectly predicted as sand</td>
<td>7/36</td>
<td>22%</td>
</tr>
</tbody>
</table>

Sand is predicted $9 + 7 = 16$ times.

Probability of sand given a sand prediction is $9/16 = 56%$.

Figure 5. Ji-Fi prediction success and failure. (a) From depth trends, (b) Ji-Fi inversion of model, and (c) Ji-Fi inversion of seismic (right). When compared with the well, which has sand in 27% of locations. Ji-Fi successfully predicts sand (TP) when sand is present nine times.
ume of shale and porosity. This gives us the information required for interpretation and reservoir modeling: volumes of facies, reservoir properties, and uncertainties.

Acknowledgments

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Adrian Pelham received a B.S. in mathematics from Bristol University, UK. He is a principal geophysicist at Tullow Oil plc, which he joined in 2007. Previously he worked for many years for a number of seismic contracting companies in various areas of seismic processing, amplitude versus offset (AVO) and inversion in many geological settings. His current role in the Geophysical Technology and Operations group focuses on quantitative interpretation, AVO, and seismic inversion on the company’s worldwide assets.