Model-Based Uncertainty Quantification and Seismic Information Value

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Summary

Improvements in seismic data quality can significantly enhance hydrocarbon production, motivating the investigation of methods to acquire more accurate and reliable data. In many cases there will be considerable uncertainty in reservoir properties and in the level of error in the data. We present an approach for determining the potential value of competing seismic survey methods to improve knowledge of reservoir properties to inform decisions related to reservoir management. Monte Carlo simulations using an earth model based on a Gulf of Mexico site, and seismic error models, provide statistical estimates of the ability of seismic amplitudes to infer porosity and reservoir thickness. Bayesian decision analysis methods then facilitate the optimization of an infill drilling program and allow the quantification of the economic value of the different seismic data sets.

Introduction

Seismic data play an important role in reservoir characterization, in application to tasks ranging from the selection of a drilling target to the direct detection of fluids in reservoir formations. Detailed and successful reservoir characterization requires accurate and reliable seismic data for optimal results. Improvements in such factors as signal-to-noise ratio, bandwidth, streamer cable position, or resolution can help improve seismic image quality and the results of interpretation methods such as amplitude variation with offset (AVO) in ways that significantly improve knowledge of reservoir structure or the variation of porosity and thickness, for example.

For these reasons, improving data acquisition to increase seismic accuracy can be very beneficial. The influence of acquisition geometry on seismic imaging, for example, can be quantified to allow a quantitative comparison of the benefits of alternative acquisition geometries. In particular, model-based methods for these comparisons allow survey design to be customized to specific sites (Vermeer, 1999; Gibson and Tzimeas, 2002). However, these approaches tend to rely on comparisons of a small number of models, perhaps only one, to compare the influence of changes in acquisition procedures on image quality, examining factors such as spatial resolution. This neglects uncertainty in the model or acquisition technology.

Bayesian decision theory is a useful tool for addressing this problem. Given statistical models for the relationships between the quantities of interest (e.g., porosity) and some observable form of data (e.g., seismic amplitude), application of Bayes' Theorem provides a means for determining the probability of accurately making decisions based on such data. Recent work has applied an extension of this, Bayesian value of information (VOI) theory, to investigate the role of seismic data in the process of selecting a drilling location (Stibolt and Lehman 1993; Waggoner 2002; Ballin et al. 2005). However, many practical problems include the selection of multiple drilling targets, and much of the previous work has relied on expert assessment rather than quantitative, model-based calculation of the accuracy of seismic data. Houck (2004) presented model-based calculations to quantify the improvement in seismic images resulting from a hypothetical improved streamer positioning system determined the economic value of improved data. Bickel et al (2006) quantify the reliability and value of seismic information in the context of a 3D land example.

In this paper, we extend this previous work in Bayesian decision methods in several ways. First, all results utilize seismic waveforms computed using models based on well logs from the Gulf of Mexico, including measured levels of uncertainty in properties such as porosity or P-wave velocity. Furthermore, we implement a more complex model that includes uncertainty not only in porosity, but also in layer thickness so that we assess the ability of seismic data to infer more than one quantity important for reservoir management. Finally, we perform a sensitivity analysis by comparing results for several levels of uncertainty in reservoir properties and of errors in seismic data. This allows a quantification of the relative importance of these two sources of difficulty in utilizing seismic data. Below we first summarize the seismic modeling methods and describe the Bayesian decision theory and VOI methods, concluding with the sensitivity analysis.

Seismic Model

Synthetic seismograms from stochastic models provide the key results for studying the effects of uncertainty in reservoir properties and of seismic errors associated with possible changes in data acquisition methods. The primary goal is to quantify correlations between seismic amplitudes and properties such as porosity. There are three steps:

1) Computing synthetic seismograms for a specified uncertainty in reservoir properties.
2) Preparing multiple copies of the seismograms with different levels of seismic error.
3) Measuring seismic amplitudes and correlating with porosity and reservoir thickness.

Step one was repeated for 1000 realizations of the reservoir model for each scenario. Receiver spacing and error models were designed to represent 3-D acquisition in a marine environment. The result is a table of correlation values providing the input required for the Bayesian analysis.

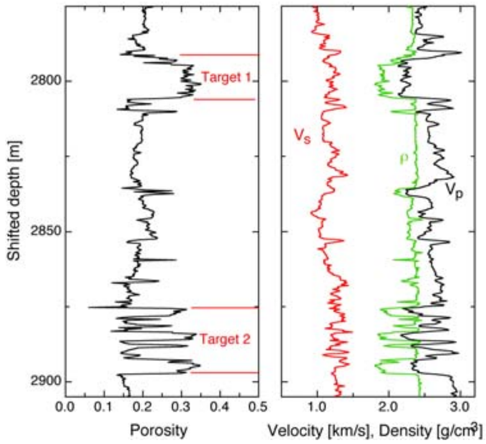

Figure 1: Well logs from an offshore Gulf of Mexico site, with arbitrary depth axis.

Reservoir model

Well logs from a Gulf of Mexico site guide the design of the earth model (Figure 1). The model included a homogeneous reservoir layer bounded above and below by two identical half spaces. Velocities in the half spaces approximate the measured values near the shallower target in Figure 1 (V_p=2750 m/s and V_s=1.250 m/s; density ρ=2.3 g/cm^3), which also suggests a mean thickness of 20 m.

The porosity log has an average and standard deviation of 30.7% and 2.4% in the reservoirs. A porosity for each model was thus selected from the Gaussian probability distribution function (PDF) N(30.7,2.4). Linear regression of data from the reservoirs provided the following relationship for V_p:

$$V_p = 3007 - 2325\phi + N(0, 90\,\xi) \quad (1)$$

$N(0, 90\,\xi)$ is a random value chosen from a Gaussian PDF with 0 mean and standard deviation $90\,\xi$, and it models uncertainty in the V_p–ϕ relationship. The standard deviation of the differences between log velocities at a specific value of ϕ and the value computed using the first two terms on the right hand side was 90 m/s, and the parameter ξ thus controls the level of uncertainty in V_p compared to log data when generating models. Regression also related V_p and ρ,

$$\rho = 1.13 + 0.00035\, V_p + N(0, 0.0735\,\xi), \quad (2)$$

where the last term is a measure of uncertainty defined in the same way as for V_p. Measurements of the V_p/V_s ratio in the reservoir intervals showed a mean value 1.87, with standard deviation 0.05, and values for V_s were computed by selecting values from the Gaussian PDF N(1.87, 0.05). In summary, we first selected a value of ϕ from the Gaussian PDF, then a value for V_p with equation 1 and used that velocity to select density and V_s for each model.

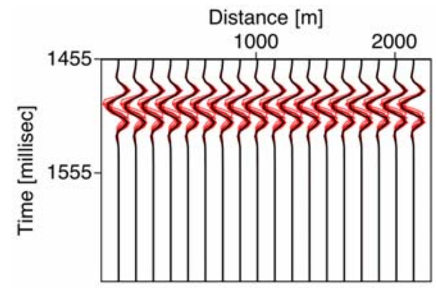

Figure 2: Synthetic seismograms for the model with mean property values (black) and 10 stochastic models (red).

Synthetic Seismograms and Error Models

Seismic waveform modeling used propagator matrices to compute the amplitude of the complete wavefield reflected from the reservoir layer, assuming an incident plane P-wave (e.g., Aki and Richards, 2002). This is the composite reflection coefficient (Gibson, 2005). Evaluating it at discrete frequencies and multiplying by the desired source spectrum $S(\omega)$ for a 30 Hz Ricker wavelet, followed by an inverse FFT, produces the reflected wave. This model does not include geometrical spreading, thus generating an ideal NMO-corrected gather. The receiver spacing was set to 12.5 m, and the longest offset was 2300 m.

We then apply a simple model of error that is spatially correlated along the streamer. Specifically, a weight value is chosen for each trace from a Gaussian PDF $N(1,\sigma)$. The resulting discrete series is filtered so that it is spatially correlated with a correlation length of 50 m (Sato and Fehler, 1996). Each trace is multiplied by its weight, so that each has its amplitude scaled by values near 1, but with a specified standard deviation.

Examples of synthetic seismograms are shown in Figure 2, which shows traces for the reference model with mean values chosen for all properties, and results for several realizations of the stochastic models. Variations in the reflection duration are caused by changes in thickness, while amplitude is also affected by porosity variations.

Seismic Amplitude Measures

The seismograms include a single reflection, so the RMS amplitude of each trace is a useful measure. Figure 3 shows correlations of RMS amplitude with porosity, comparing uncertainty in reservoir properties (Figure 3B) with seismic error (Figure 3A). The parameter ξ defining uncertainty in velocities and density is defined in Equations 1 and 2. For seismic error, the standard deviation of the error level σ was 0, 4, 8 or 12 in arbitrary amplitude units. The maximum, 12, corresponds to a level of 10 dB down from the reflection amplitude.

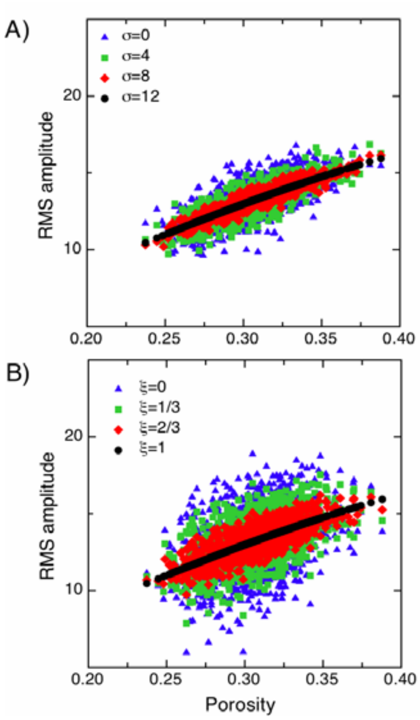

Figure 3: Correlations between amplitude and porosity with different model configurations. (A) Results for four levels of seismic error, and (B) results for four levels of uncertainty in properties (σ, ξ are defined in the text).

Bayesian Uncertainty and Decision Analysis

Consider an oil and gas company that is designing an infill drilling program. They identified N infill targets, but face a budget constraint such that they can only drill b wells. Let $\boldsymbol{d} = (d_1,\ldots,d_i,\ldots d_N)$ be an N-vector of drilling decisions, or a drilling program, where $d_i = 1$ if target i is to be drilled and 0 otherwise. Without the benefit of seismic information the company first chooses its drilling program and then observes the reservoir properties, which relate to drilling results (e.g., dry hole). The drilling decision and the vector of reservoir properties $\boldsymbol{\omega}_i$ (e.g., porosity, thickness, water saturation) combine to generate profit (or loss) for the company, which we take to be the net present value (V) of the cash flow resulting from operation of the well. The value of this drilling program is the value without seismic information ($VwoS$). We represent this decision as

$$VwoS = \left\{ \begin{array}{l} \max\limits_{\mathbf{d}} \sum\limits_{i=1}^{N} d_i E_{\boldsymbol{\omega}_i}[V(\boldsymbol{\omega}_i)] \\ \text{subject to: } \sum\limits_{i=1}^{N} d_i \le b \end{array} \right. , \qquad (3)$$

where E is the expectation operator taken with respect to $f(\boldsymbol{\omega}_i)$, which is the prior probability distribution of reservoir properties at location i.

Now assume the company is able to acquire the seismic information matrix $\boldsymbol{\Theta} = (\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_n)$, where $\boldsymbol{\theta}_i$ is a vector of seismic signals for location i (e.g., amplitude for location i). The posterior distribution of the reservoir properties at location i, via Bayes' Rule, is $g(\boldsymbol{\omega}_i|\boldsymbol{\theta}_i)=f(\boldsymbol{\omega}_i)\, l(\boldsymbol{\theta}_i|\boldsymbol{\omega}_i) / h(\boldsymbol{\theta}_i)$ where $l(\boldsymbol{\theta}_i|\boldsymbol{\omega}_i)$ is the likelihood function for observing seismic signal $\boldsymbol{\theta}_i$ given $\boldsymbol{\omega}_i$ and $h(\boldsymbol{\theta}_i)$ is a normalizing factor. The company now observes a seismic signal for each target location and designs the optimal drilling program, yielding the value with seismic information (VwS),

$$VwS = E_{\boldsymbol{\Theta}} \left[\begin{array}{l} \max\limits_{\mathbf{d}} \sum\limits_{i=1}^{N} d_i E_{\boldsymbol{\omega}_i|\boldsymbol{\theta}_i}[V(\boldsymbol{\omega}_i \,|\, \boldsymbol{\theta}_i)] \\ \text{subject to: } \sum\limits_{i=1}^{N} d_i \le b \end{array} \right] . \qquad (4)$$

The inner expectation is taken with respect to $g(\boldsymbol{\omega}_i|\boldsymbol{\theta}_i)$. The value of seismic information (VoS) is the most the company should be willing to pay for seismic data, which, in this case, is equal to the value with seismic information less the value without seismic information: $VoS = VwS - VwoS$. In the current study, we assume both reservoir properties and seismic data are spatially uncorrelated and that the joint distribution $f(\boldsymbol{\theta}_i,\boldsymbol{\omega}_i)$ is multivariate normal, which greatly simplifies the Bayesian calculations. See Bickel et al (2006) for more detail. We assume $NPV(\phi,h,S_w) = 35.7\ \phi h\ (1\text{-}S_w) - 150$, in millions of \$US, which is a simplified version of the model used by Houck (2004), and wells cost \$5 MM to drill.

Example results

Monte Carlo simulations were completed for layer thickness standard deviations of 0, 1, 2, 3 and 4 m, with 1000 realizations for each case. Mean thickness was 20 m. The level of uncertainty in reservoir properties, ξ, took values of 0, 1/3, 2/3 and 1 (Equations 1, 2). Thus a total of 20,000 sets of synthetic seismograms was computed. We also added three levels of seismic error, with σ=4, 8 and 12. Figure 4 shows how correlation between amplitude and porosity, and between amplitude and layer thickness changes with thickness standard deviation, σ and ξ.

Figure 5 displays the value of seismic information for the small (σ = 4) and large (σ = 12) levels of seismic error assuming 12 targets, no uncertainty in reservoir thickness, and the medium level of seismic property uncertainty (ξ = 2/3). If the well budget is 0, seismic information has no value. In addition, if the well budget constraint is not binding, seismic also has no value, because the wells are profitable in isolation and seismic information is unlikely to change this. The value of seismic information peaks at a well budget of 6 and can be quite valuable since it helps better prioritize drilling. For example, when the budget is 6, seismic information is worth almost \$36 million in the small error case and \$32 million in the large error case.

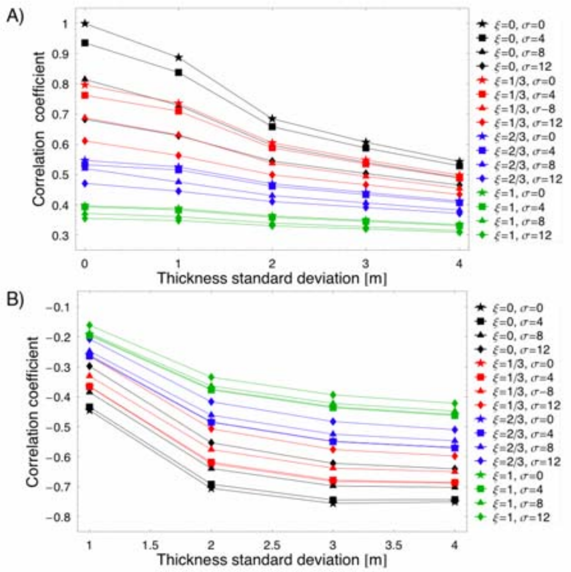

Figure 4: Correlations between (A) porosity and amplitude and (B) thickness and amplitude as a function of the standard deviation of reservoir layer thickness (σ and ξ measure error and uncertainty and are defined in the text).

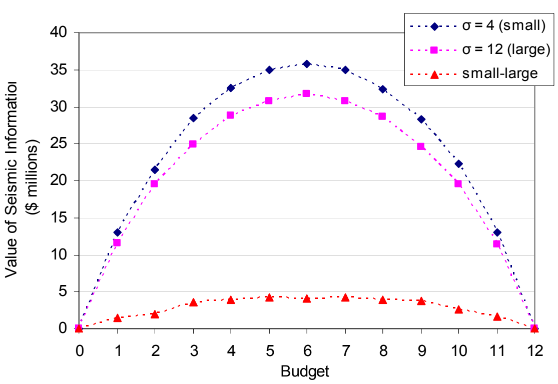

Figure 5: Value of seismic information for the medium level of reservoir property uncertainty (ξ = 2/3) with 12 drilling targets and no uncertainty in reservoir thickness.

Discussion and conclusions

As one might expect, the value of seismic information is quite sensitive to uncertainty in the reservoir seismic properties and the level of seismic error. Table 1 details a sensitivity analysis of the value of seismic information when the well budget is equal to 6. For example, if the thickness has a standard deviation of 4 m and the uncertainty in the reservoir-seismic properties is low (ξ = 1/3) then small error seismic is worth almost \$87 million and large error seismic is worth almost \$76 million.

Within the context of our example, we can draw a few conclusions regarding the value of seismic information:

- Seismic information can be quite valuable and increases in accuracy add value.
- Increasing uncertainty in the reservoir-seismic property relationship (increasing ξ) or error (increasing σ) decreases seismic value.
- The difference in value for small error and large error seismic decreases with increasing reservoir-seismic property uncertainty (increasing ξ). That is, improvements in seismic error are less valuable in more heterogeneous reservoirs.
- Small increases in thickness uncertainty (e.g., between 1 m and 2 m) decrease the value of seismic information as uncertainty in thickness confounds our ability to learn about porosity (see Figure 4). However, further increases in thickness uncertainty result in large values of seismic information because the correlation between seismic amplitude and thickness enables us to better select drilling locations.

		Seismic Error Case			
		small	medium	large	
h std dev	Res Case	σ = 4	σ = 8	σ = 12	small - large
0 m	ξ = 1/3	51.2	46.5	41.2	10.0
	ξ = 2/3	36.5	35.1	31.7	4.8
	ξ = 1	26.4	25.0	24.0	2.4
1 m	ξ = 1/3	32.0	28.1	26.3	5.8
	ξ = 2/3	23.1	21.2	20.7	2.3
	ξ = 1	17.2	16.5	16.4	0.8
2 m	ξ = 1/3	14.5	14.2	10.7	3.8
	ξ = 2/3	11.4	11.4	8.8	2.6
	ξ = 1	8.8	9.0	7.1	1.8
3 m	ξ = 1/3	52.8	50.4	44.1	8.7
	ξ = 2/3	42.9	41.5	37.1	5.8
	ξ = 1	34.1	33.4	29.9	4.2
4 m	ξ = 1/3	86.9	83.7	75.8	11.1
	ξ = 2/3	72.4	70.0	65.0	7.5
	ξ = 1	58.3	57.6	52.6	5.7

Table 1: Sensitivity of seismic information value (\$ millions) to model uncertainties for a 6 well budget.

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EDITED REFERENCES

Note: This reference list is a copy-edited version of the reference list submitted by the author. Reference lists for the 2007 SEG Technical Program Expanded Abstracts have been copy edited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

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