Estimation of reservoir fluid saturation from 4D seismic data: effects of noise on seismic amplitude and impedance attributes

To cite this article: Rafael Souza et al 2017 J. Geophys. Eng. 14 51

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1. Introduction

Time-lapse (4D) seismic analyses can be used to better understand oilfield behaviour, improve reservoir performance, and assist in reservoir management decisions. These techniques have been applied successfully to numerous oilfields throughout the world (Lumley 2001, Calvert 2005, Johnston 2013), and have provided insight into changes in fluid saturation and pressure after the onset of oil production. This information has proved invaluable for aiding in the development and calibration of fluid-flow models that are essential for evaluating and forecasting reservoir performance (Oliveira et al 2007). Calibrating fluid-flow models traditionally relies heavily on very sparse well data (Oliver et al 2008). However,
changes in time-varying dynamic properties such as water saturation and pressure, derived from time-lapse (4D) seismic techniques, can provide more robust and reliable volumetric constraints between wells than those developed by interpolating borehole properties (Simm and Bacon 2014). Therefore, calibrating fluid-flow models by incorporating both seismic and well data can improve both their reliability and consistency with geological models of the producing oil field.

Information from 4D seismic image volumes can be presented in a number of different domains and various stages of analyses; for example, as amplitude information obtained directly from seismic data or as acoustic impedance information derived through seismic inversion. Subsequently, data in either of these domains can be used to derive fluid-flow model updates by iteratively comparing forward modelled and observed data through application of inverse and optimization theory (Parker 1977, Oliver et al 2008). Updating reservoir model properties using 4D seismic is a difficult non-linear problem with significant uncertainties, not least of which is related to 4D seismic data quality. The quality of seismic data depends directly on signal-to-noise ratio (S/N) levels and, in 4D studies, on the repeatability of the seismic surveys over time. While data in the seismic amplitude and impedance domains are available to integrate seismic-derived attributes into the update of reservoir properties, their respective characteristics are subject to different modelling assumptions and data-handling workflows, with each domain exerting a different influence on the quality of the resulting fluid-flow models (Sagitov and Stephen 2012).

The seismic impedance domain is a common choice for integrating seismic and reservoir-engineering data. This is because local impedance estimates can be computed at each reservoir model grid cell, through a large but highly parallelizable cell-by-cell inverse problem that is easily integrated into the reservoir property updating workflow (Stephen and Macbeth 2006, Sagitov and Stephen 2012). However, there are significant issues with using seismic impedances because they require applying a nonlinear seismic inversion step that is inherently unstable and may introduce significant uncertainties into the resulting impedance estimates. These issues are compounded by the use of theoretical petro-elastic models for seismic reservoir modelling, which introduce additional uncertainties due to modelling assumptions, measurement errors and the inherent heterogeneity of available petrophysical and fluid data (e.g. core, logs, PVT) (Mavko et al 2011). Because combining these errors generates a highly nonlinear output, it is crucial to estimate the associated uncertainties when using 4D attributes for updating reservoir models. To account for these issues, an uncertainty analysis should be carried through all procedural steps (Lumley 2006). Although most inversions performed are deterministic (Landa and Kumar 2011), the corresponding estimates of fluid saturation changes may lead to erroneous reservoir property updates in fluid-flow models as well as increasing the uncertainty in predictions of oil reservoir performance and financial risk management.

The seismic amplitude domain is an alternate choice to impedance for integrating seismic and reservoir-engineering data. Amplitude information is a primary attribute derived from image-processed seismic data and, unlike the acoustic impedance domain, amplitude-based analyses do not require inversion and are thereby free from additional uncertainties related to inverse problem instability and non-uniqueness. Thus, amplitude-domain procedures typically are more straightforward and stable than impedance-domain approaches and allow for more efficient tracking of corresponding uncertainties. However, amplitude-domain approaches can be less common than impedances due to the difficulties in updating 3D fluid-flow model grids directly from 2D amplitude maps or from the low vertical resolution seismic trace waveform information derived from 3D seismic volumes.

One important issue is the effects of 4D seismic data noise on procedures to estimate reservoir properties as this noise is usually assumed to be minor or non-existent (Davolio et al 2012, Sagitov and Stephen 2012); however, non-repeatable 4D noise can be an important consideration when choosing the optimal domain in which to integrate seismic, borehole and reservoir engineering data. The effects of noise are a ubiquitous issue in 3D and 4D seismic acquisition, processing and inversion (Yilmaz 2001). In particular, 4D seismic techniques are very sensitive to acquisition non-repeatability and a high S/N ratio and level of repeatability are paramount for ensuring high-quality analyses (Lumley and Behrens 1998). Thus, two important questions are: Can 4D seismic noise be incorrectly interpreted as true dynamic changes within the reservoir? If so, how robust are amplitude and impedance workflows in the presence of noise?

We demonstrate that for 4D seismic data exhibiting a range of commonly observed S/N ratio values, the amplitude domain is a more accurate and robust choice than the impedance domain for quantifying fluid saturation changes. We illustrate this by analysing the changes in seismic image amplitudes and seismic acoustic impedances as a function of water saturation changes (∆Swp) and S/N ratio levels. Using principles from information theory (Rubner et al 2000), we present an innovative method for cross-domain comparison based on the histogram of amplitude (∆A) and impedance (∆Ip) changes. We also introduce a method for estimating errors in water saturation changes as a function of S/N ratio. These techniques allow us to evaluate the consistency of seismically derived attributes across amplitude, impedance and water saturation domains using an unbiased comparison method.

This paper begins by exploring a number of inverse theory concepts associated with the instability of seismic inversion operators and, specifically, when using coloured seismic inversion (Lancaster and Whitcombe 2000). We then discuss the relationship between the presence of noise in seismic data and the corresponding uncertainty in seismic inversion results. We apply these principles with time-lapse seismic studies by presenting a 1D earth model example and a 3D case study based on a benchmark fluid-flow model built on observations from the Namorado Field in Campos Basin, Brazil (Avansi and Schiozer 2015). We then quantify the errors in water saturation estimates using 4D seismic amplitude data versus 4D seismic impedance inversion values. The paper concludes with a discussion on the implications of these results for 4D seismic workflows to update reservoir properties and fluid-flow models.
2. Theory

2.1. Seismic modeling

When a seismic wave encounters a boundary between two materials with different physical properties, the energy in the wave will be partially reflected at the boundary, while the remainder energy will be transmitted through the boundary. The seismic impedance contrast between these two boundaries determines the reflection coefficients (RC) in the normal-incidence approximation (Telford et al. 1990),

\[
RC = \frac{(Ip_2 - Ip_1)}{(Ip_2 + Ip_1)} = \frac{(\rho_2 V_2 - \rho_1 V_1)}{(\rho_2 V_2 + \rho_1 V_1)},
\]

where \(Ip_1\) and \(Ip_2\) are the P-wave impedances given by the product of P-wave velocity and density \((V_i\) and \(\rho_i\), respectively) in the upper (1) and lower medium (2). In general the reflection coefficients \(RC(x)\), seismic data \(d(x, t)\) and impedance values \(Ip(x)\) vary as a function of the 3D spatial coordinate \(x\), but we suppress the \(x\) dependency in the notation for compactness in the following equations.

The comparison between synthetic and observed seismic data is often used to validate static and dynamic reservoir models. Estimates of \(RC\) can be obtained from well-log data or fluid-flow model outputs to validate against observed seismic traces. Equation (1) also indicates that \(RC\) is proportional to the depth derivative of P-wave impedances \((RC \propto \partial Ip(x))\); however, as seismic data are acquired in time and often imaged in pseudo-depth time \(t\), while well-logs are in depth, we first need to convert P-wave impedance estimate from depth to time obtaining,

\[
RC(t) \approx \partial Ip(t) \approx A(t),
\]

which indicates that \(RC\) is proportional to the time derivative of P-wave impedances that are also approximations of stacked or migrated seismic amplitudes \(A(t)\). We can then derive synthetic seismic traces \(d(t)\) as a result of the convolution of a wavelet \(S(t)\) with the temporal derivative of P-wave impedances \((\partial Ip(t))\),

\[
d(t) = S(t) \otimes RC(t),
\]

where \(\otimes\) denotes temporal convolution. In general, both \(RC\) and \(d(t)\) are also functions of the 3D surface map coordinates \(x = (x, y)\) but we often suppress this notation.

To extract a seismic amplitude map \(A(x, t_i)\) from the seismic trace volume \(d(x, t)\) requires an operator \(F\) that involves integrating these seismic traces over time,

\[
A(x, t_i) = F[d(x, t)] = \int \delta(t - t_i) d(x, t) dt,
\]

where \(\delta\) is a Dirac delta function, and \(t_i\) is the surface or horizon time of a given reflection boundary. We can now add the seismic noise \(n(t)\) to the synthetic traces and equation (4) becomes,

\[
A'(x, t_i) = F[d(x, t)] = \int \delta(t - t_i) [d(x, t) + n(x, t)] dt
\]

where \(A'(x, t_i)\) is the resulting modelled seismic amplitude map with noise. Then, if we substitute equation (3) into equation (5) we obtain,

\[
A'(x, t_i) = F\{d(x, t)\} = \int \delta(t - t_i) [S(t) \otimes RC(x, t) + n(x, t)] dt.
\]

Equation (6) illustrates that seismic amplitudes are dependent on reflection coefficients \(RC(t)\) the source wavelet \(S(t)\) and the seismic noise \(n(t)\). Note also, that the noise is added to the modelled traces \(d(t)\) before the amplitude extraction, indicating that the seismic noise directly affects the magnitude of the modelled amplitudes \(A'(t)\).

Equations (1)–(6) demonstrate the dependence of seismic amplitude values on the source wavelet, the reflection coefficients and seismic noise.

2.2. Seismic inversion

Coloured inversion is a seismic inversion method that provides estimates of impedance values within the band-limited frequency range of the seismic data (e.g. 10–80 Hz). Away from the wells, seismic data are typically the most reliable information available and band-limited approaches are likely to offer a more robust result than inversion methods attempting to estimate absolute P-impedances by adding the missing seismic low frequency trends based on well-log interpolation (i.e. defining low frequency models). One of our goals is to quantify the uncertainties of amplitude and impedance estimates as a function of S/N levels and therefore we begin characterizing the inherent errors of the post-stack \(Ip(t)\) inversion method by deriving its operator.

For coloured inversion the seismic forward model operator \(C\) that generates synthetic seismic trace data \(d(t)\) can be defined as the convolution of a seismic source wavelet \(S(t)\) with the derivative of P-wave impedances \(Ip(t)\),

\[
d(t) = S(t) \otimes \partial Ip(t).
\]

The coloured inversion operator is derived in the frequency domain by shaping the mean seismic amplitude spectrum to the mean spectrum of the calibrating P-wave impedance log (Connolly 2010). Thus, we need to convert equation (7) to the frequency domain by applying a Fourier transform (FT) to derive the coloured inversion operator (Arfken and Weber 2005). Since convolution in time domain is equivalent to multiplication in the frequency domain \((\omega)\), equation (7) may be rewritten as,

\[
d(\omega) = i\omega S(\omega)Ip(\omega),
\]

where \((i\omega)\) is the representation of the temporal derivative operator in the frequency domain responsible for the \(-90^\circ\) phase shift of the inversion operator. Solving equation (8) for P-wave impedances we obtain,

\[
Ip(\omega) = \frac{1}{i\omega} \frac{d(\omega)}{S(\omega)}.
\]

To prevent instabilities arising from zero division caused by potential spectral zeroes in the source wavelet spectrum (i.e. for \(|S(\omega)| = 0\) we rewrite equation (9) including a stabilizing factor \(\varepsilon^2\).
\[
I_p(\omega) \cong \frac{1}{i\omega} \frac{d(\omega) S^*(\omega)}{|S(\omega)S^*(\omega) + \epsilon^2|},
\]  
(10)

where \( S^* \) is the complex conjugate of \( S \) in the frequency domain. The use of the stabilizing factor decreases the accuracy of the impedance estimates especially when \( |S(\omega)| \) is similar to or less than \( \epsilon^2 \) in value, and therefore information is lost; this is the classic trade-off between accuracy and stability in many inverse problems. The impedance estimate \( I_p(t) \) is then recovered by applying an inverse Fourier transform (IFT), such that equation (9) becomes

\[
I_p(t) = \text{IFT} \left[ I_p(\omega) \right] = \int S^{-1}(t) \otimes [d(t) + n(t)] \, dt.
\]  
(11)

Equation (11) indicates that \( I_p(t) \) is estimated by the convolution of the inverse source wavelet (i.e. deconvolution) with the seismic traces \( d(t) \) including the noise \( n(t) \). Equation (11) shows that the instability of coloured inversion is associated with any instabilities in \( S^{-1} \) caused by spectral zeroes of \( |S(\omega)| \). This is expected when the waveform spectrum reaches values that are near zero, or where the wavelet energy is similar to or less than the seismic noise level.

As a band-limited inversion method, coloured inversion uses the seismic bandwidth to provide estimates of relative \( I_p(t) \) which represents impedance changes relative to the background (low-frequency) impedance trend, including a -90° phase shift (compared to the seismic reflection data) due to the integration of the derivative operator in equation (10). This means that the peaks of relative \( I_p(t) \) are located within the impedance layers, rather than at the layer boundaries per reflection data. Alternatively, estimates of absolute \( I_p(t) \) can be obtained by adding the low-frequency impedance trend to the inversion method, not available in the seismic data bandwidth. Low-frequency (LF) models are typically based on sparse well-log data and the absolute impedance inversion reliability correlates with the number of wells available. The lack of well-log data might lead to incorrect predictions of the low-frequency trend in between the wells compromising estimates of absolute acoustic impedance in these areas (Whitcombe and Hodgson 2007, Kumar and Negi 2012, Avseth and Johansen 2014). Prestack depth migration velocities may be also merged with well-logs to mitigate these errors in between the wells (Jones 2010).

We evaluate these instabilities as a function of \( \Delta S_w \) and \( S/N \) levels by presenting two examples. We have shown that migrated stacked seismic data can be approximated as the convolution of a seismic source wavelet with the vertical derivative of impedance, plus additive seismic noise. Amplitudes are extracted directly from the seismic data and can be further used to estimate \( S_w \), however, the noise in the seismic data (and thus extracted amplitudes) results in errors on these estimates.

Seismic data/amplitudes can also be inverted to estimate impedances. Since there is noise in the data, and inversion is inherently unstable, we can expect significant errors in the estimates of impedance. This impedance estimates can be used to further estimate \( S_w \) but due to the noise in the seismic data, plus the instability errors in the impedance inversion, we expect the errors in the \( S_w \) estimates using impedance values to be larger than the errors using amplitudes directly.

Selecting an analysis domain that is most accurate and robust to noise is particularly important in time-lapse 4D seismic studies, since an accurate estimate of (small) time-lapse changes in seismic attributes requires excellent \( S/N \) levels and highly repeatable seismic surveys and image processing.

2.3. Time-lapse analyses

Considering a sequence of seismic surveys acquired at consecutive calendar times \( t_1, t_2, t_3, \ldots, t_N \). Time-lapse seismic analyses are based on differences between a given monitor survey \( d_1(t) \) and the baseline \( d_0(t) \) seismic survey (or an earlier monitor survey). Thus, seismic traces imaged at the time \( t_h \) can be modelled as,

\[
d_1(t) = S(t) \otimes \partial I_p(t) + n(t),
\]  
(12)

where, for mathematical simplicity, we assume \( S(t) \) to be the same for all surveys (this is not generally true and thus source wavelet deconvolution is generally survey-dependent), and the seismic noise \( n(t) \) depends on the errors arising from the 3D noise for each seismic survey. Once a repeat seismic survey is acquired at the time \( t_2 \) the differences between both surveys are given by,

\[
\Delta d_{1,2}(t) = S(t) \otimes [\partial I_p(t) + n_2(t) - n_1(t) + \text{NNR}(t)].
\]  
(13)

where \( \Delta I_p(t) = I_p(t) - I_p(t) \) represents the time-lapse 4D P-impedance changes, \( n_2(t) - n_1(t) \) represent the difference in the respective 3D seismic noise for each survey and \( \text{NNR} \) is the non-repeatable noise associated with the differences in the acquisition parameters and ambient conditions during both surveys. Thus, we define the amplitude level of the 4D noise as,

\[
\epsilon_{4D} = |n_1(t)| + |n_2(t)| + |\text{NNR}(t)|,
\]  
(14)

where we have assumed that the noise sources are random and uncorrelated. In practice, seismic noise sources often include non-random and spatially correlated components, and thus the 4D noise analysis is often more complex than equation (14) indicates, but this is beyond the scope of this paper.

In practice, the non-repeatable noise \( \text{NNR} \) is typically much higher than the 3D seismic noise \(|\text{NNR}| \gg |n_1(t)| + |n_2(t)|\) and therefore dominates the errors associated with 4D seismic noise analysis. Also note that despite the subtraction of baseline and monitor seismic surveys, equations (13) and (14) indicate that their associated noise terms are typically additive consistent with the assumptions of random uncorrelated noise sources (Lumley and Behrens 1998, Lumley 2001, Lumley et al 2003).

2.4. Estimating water saturation changes from time-lapse attributes

Estimating water saturation changes from time-lapse seismic data is an inverse problem. In our case the forward model operator is defined by the fluid-flow model that provides time-varying dynamic data such as pressure and water saturation.
As a consequence, we can now derive an approximate inverse operator to estimate water saturation changes from seismic impedance,

\[ \tilde{G}^{-1} \{ \Delta I_p \} = \Delta S_w + \epsilon_{\Delta I_p} \]  

(18)

where \( \epsilon_{\Delta I_p} \) is the error in the estimate of water saturation change as a function of impedance change. This error includes seismic noise, impedance inversion errors and instabilities. Note that a seismic inversion is required to generate the input \( \Delta I_p(t) \) in equation (18). This means that the errors associated with equation (18) include two inversion procedures (for both impedance and saturation) and are thus likely to be higher than those using \( \Delta A \) as input \((\epsilon_{\Delta A} \gg \epsilon_{\tilde{G} A})\). As a consequence, estimates of water saturation changes from seismic impedances are likely to contain more errors and uncertainties in comparison to the saturation estimates resulting directly from seismic amplitudes.

3. 1D example

3.1. Experiment and results

To illustrate the impact of seismic noise on impedance estimates derived from coloured inversion we present a synthetic study based on a 1D earth model. We begin by calculating reflection coefficients using impedance log data \((I_p\text{-log})\) shown in figure 2(a) and convolving the resulting time series with a band-limited wavelet with frequency corners at 5, 10, 80 and 90 Hz. Figure 2(b) shows the resulting modelled synthetic seismic traces. We generate and add a number of Gaussian random noise traces that are band-pass filtered (with the same corners as above) to the noise-free traces. Four realistic \( S/N \) scenarios of 10, 5, 3 and 1 are generated (figures 2(c)–(f), respectively). We define the \( S/N \) ratio as the RMS amplitude of the noise-free seismic data, compared to the RMS amplitude of the noise traces, in a window centred on the (reservoir) zone of interest. Figure 2(c) shows the equivalent of very high-quality \( S/N = 10 \) seismic data, while figure 2(f) shows a contrasting scenario where the signal and noise are of equal magnitude \((S/N = 1)\). The \( S/N \) ratios at 5 and 3 in figures 2(d) and (e), respectively, are representative of what is typically observed in average quality seismic data. We note that increasing the noise level deteriorates the data quality to a point where the trough at 1300 ms corresponding to a low-impedance reservoir sand is barely visible for \( S/N = 1 \).

For this example we derive the coloured inversion operator for the noise-free and \( S/N = 3 \) scenarios presented in figure 2. Figure 3(a) shows the calibrating \( I_p\text{-log} \) and the seismic data amplitude spectra. Note that the noise-free seismic spectrum has lower energy than the \( S/N = 3 \) spectrum, as expected. This is due to the additive noise and therefore affects the impedance estimates since the inversion operator changes due to its dependence on \( S^{-1}(\omega) \) in equation (11). Comparing the frequency domain response of the inversion operator for the noise-free and \( S/N = 3 \) scenarios in figure 3(b), we observe that the additive noise results in spurious variations (errors) in the inverse operator.

To further illustrate the effects of seismic noise, we apply these inversion operators to estimate 4D band-limited impedances. We simulate production effects by fluid substituting the \( I_p\text{-log} \) in figure 1(a) for saturation conditions of \( I_p(S_w = 10) \).
(e.g. oil full scenario) and \( I_p(Sw100) \) (e.g. water swept scenario). Water-swept scenarios are usually limited to the residual oil saturation (\( S_{or} \)) typically about 80%; however, we choose to explore the full sensitivity range of our saturation estimation procedure up to and including \( S_w = 100\% \). Figure 4(a) presents low-passed fluid substituted logs with upper corner frequencies 80 and 90 Hz. In figure 4(b) we superimpose the \( I_p(Sw10) \) and the band-limited noise-free inversion result. Figure 4(b) compares the curves for \( I_p(Sw100) \) with its respective noise-free inversion result. Assuming that the oil-full and water-swept scenarios have associated baseline and monitor 4D seismic data, the monitor minus baseline difference provides our 4D information \( \Delta I_p \) in figure 4(d). Similarly, we present in figures 4(e)–(f) the \( S/N = 3 \) scenario.

We have also inverted the noise-free and \( S/N = 3 \) amplitudes in figure 2 for full bandwidth absolute impedances. In doing so we are able to evaluate the impact that seismic noise has on estimates of absolute impedances and also understand the impact of the additive low frequencies. Usually in 4D seismic studies there are no repeated time-lapse \( I_p \)-log data acquired at the time of the monitor survey and therefore the same low frequency model is often used as input to derive the absolute impedance estimates for both the baseline and monitor seismic surveys. Here, we build independent low-frequency models for the baseline and monitor scenarios to quantify the errors associated with seismic-noise levels and the inversion method.

In figures 5(a) and (b) we superimpose the low passed \( I_p(Sw10) \) and \( I_p(Sw100) \) logs with their respective noise-free absolute impedance inversion results and in figure 5(c) we compare the inverted and \( I_p \)-log absolute \( \Delta I_p \). Figures 5(d)–(f) present results with noisy seismic data (\( S/N = 5 \)) as input into the inversion. We then calculate the RMS errors at each panel in figures 4 and 5. Figure 6 shows these RMS errors as a function of the different water saturation, seismic-noise levels and inversion methods presented. Note that the band-limited inversion RMS errors are smaller for the noise-free and \( S/N = 5 \) scenarios while for the noisier \( S/N = 3 \) estimates from both absolute and relative impedances present similar behavior. Further, the RMS error for noise-free band-limited \( \Delta I_p \) is 238% smaller than its absolute counterpart and is 138% smaller in the \( S/N = 5 \) scenario.

3.2. 1D example discussion

Examining this 1D model study is helpful for better understanding how \( S/N \) levels affect seismic amplitudes and 4D relative and absolute seismic inversion results. The observed increase in the RMS error as a function of \( S/N \) levels in estimates of relative and absolute impedances is important as often these errors are neglected or underestimated while applying impedance behaviour to guide reservoir property updates. Moreover, the fact that the absolute impedance RMS error is higher than those of the relative impedances for noise-free and \( S/N = 5 \) scenarios suggest that low-frequency information should be added with great care since it can significantly impact the accuracy of the inversion results. We have observed that band-limited and broadband inversion RMS errors are equally high in the \( S/N = 3 \) scenario. In figure 2(e) we observe that \( S/N = 3 \) is a high level of seismic-noise that strongly affects both relative and absolute impedance estimates.

This increase in seismic noise levels affects our capability to identify reflection boundaries on seismic traces (figures 2(b)–(f)) therefore compromising seismic interpretation and further quantitative analysis. This increase in the noise level also contaminates the seismic amplitude spectrum in figure 3(a) affecting the inversion operator accuracy and stability (figures 3(b) and (c)).
Our results indicate that combining the low frequencies extracted from logs with the band-limited information from seismic data does not guarantee improved accuracy. This combination of information in the frequency domain results in absolute impedances that are not as accurate as the relative impedances obtained from the band-limited seismic data. The increased errors in estimates of absolute $\Delta I_p$ in comparison with those from relative impedances indicate that subtracting

Figure 3. (a) Spectrum of mean seismic amplitudes: noise free (blue) and S/N = 3 (red) and the spectrum of the acoustic impedance log (data points in light grey) and its exponential fit (in black); (b) inversion operator amplitude spectrum for noise-free and S/N = 3 amplitudes; and (c) inversion operator in time domain for noise free (blue) and S/N = 3 (red) amplitudes.
absolute impedances does not mean that the additive low frequencies are entirely subtracted compared to the coloured inversion method.

These results suggest that band-limited approaches are more reliable and robust than full-band seismic inversions up to $S/N = 5$. Low-frequency models are a potential source of uncertainties and should be applied with careful quality control, particularly in exploration scenarios when the amount of well-log data is often sparse. In this context, band-limited approaches may be a more reliable alternative.
4. 3D example

Benchmark models commonly play an important role in the testing of methodologies for the calibration of fluid-flow models. These models also provide the opportunity to conduct tests similar to the 1D example above but for more realistic 3D reservoir scenarios. The heterogeneity of these models can generate changes in amplitude and impedance maps that would present complex trends and increased uncertainty of the inversion results derived from them. We build on the analysis of the above 1D example by using the benchmark model UNISIM-H (Avansi and Schiozer 2015) to test 4D seismic changes in amplitude/impedance estimates as a function of $\Delta S_w$ and $S/N$ levels. We begin this section by describing the UNISIM-H model followed by a description of our procedure for modelling the petro-elastic and seismic reservoir responses. We then present a qualitative interpretation of the 4D seismic results followed by the more quantitative approach for cross-domain comparison based on data histograms and RMS errors in $\Delta S_w$ versus $S/N$ levels.

4.1. UNISIM-H model

UNISIM-H is a synthetic black-oil fluid flow model constructed as part of a benchmark case for history matching and uncertainty quantification. This model was developed for studies in an advanced stage of reservoir production based on observations from the Namorado field in Campos Basin, Brazil (figure 7), including the structural geological framework, facies models and petrophysical constraints derived from seismic and well log data. Porosity is modelled using a sequential Gaussian simulation, correlations between permeability and porosity estimated from core are used to specify reservoir permeability. The UNISIM-H model has 36,739 active cells at a grid cell interval of $(\Delta x, \Delta y, \Delta z) = (100, 100, 8)$ m.
We generate 4D seismic data using the convolutional method by assuming that the baseline and monitor surveys were acquired pre-production and 4018 d (11 years) after the start of production, respectively. The UNISIM-H model includes a scenario where water injection to maintain reservoir pressure was started after 1979 d (5.4 years) of production. Significant $\Delta S_w$ saturation change occurs due to the injected water pushing oil down dip towards the aquifer. Figure 8 illustrates these changes in the baseline and monitor water saturation distributions from the UNISIM-H model. Having specified these scenarios we can now define our procedure for addressing our main time-lapse study goal of quantifying changes in amplitude, impedances and water saturation, as well as the respective uncertainties associated with seismic data noise. Using these changes to subsequently update flow model properties remain a topic of active research (Stephen and Kazemi 2014, Avansi and Schiozer 2015).

4.2. Petro-elastic modeling flow

To start the petro-elastic modelling flow we first extract both static (e.g. porosity, net-to-gross) and time-varying dynamic (e.g. water saturation, pressure) UNISIM-H data at the times of baseline and monitor seismic acquisitions. We apply standard Gassmann fluid substitution to estimate the P- and S-wave impedance volumes (Lumley 1995, Mavko et al 2011). As input to this model we use net-to-gross estimates to infer shale percentage at each grid cell and invoke the Hertz–Mindlin model to derive the pressure sensitivity of dry bulk and shear rock moduli (Avseth et al 2011). We use the Batzle and Wang (1992) relationships to model the fluid response to pressure and temperature, which we subsequently hold constant between surveys to help isolate the effects of $\Delta S_w$ on the amplitude and impedance inversion estimates. However, we emphasize that these variables generally change during real scenarios and thereby affect the petro-elastic model outputs.

4.3. Seismic modeling

We convert the UNISIM-H model from depth to two-way travel time (TWT) assuming a constant P-wave velocity of $V_p = 2.5$ km s$^{-1}$ within all the simulation cells for the baseline and the monitor survey. We calculate reflection coefficients (RC) from the P-wave ‘acoustic’ impedance estimates using the normal incidence approximation per equation (1). We convolve the computed reflection coefficients with a 50 Hz Ricker wavelet to generate the synthetic 3D seismic data image volumes. We then use additive Gaussian random noise traces filtered using this wavelet to generate noisy seismic data volumes with commonly observed $S/N$ ratios (i.e. 10, 5 and 2) (Lumley and Behrens 1997). We repeat this modelling procedure to generate the monitor survey data.

4.4. 4D seismic interpretation

Undertaking a 4D seismic interpretation requires computing 4D seismic data attributes such as amplitudes and impedances from the baseline and monitor data. We first examine changes in their respective modelled amplitudes and in the inverted relative impedance estimates used to derive $\Delta S_w$. We assume that the seismic data image polarity is equivalent to a zero-phase wavelet, and use the convention that positive values correspond to positive reflectivity and 4D differences are defined as monitor minus baseline data (i.e. as in equation (13)) (Lumley 1995, 2001). We extract the RMS value of each attribute separately for both the baseline and monitor surveys within a time window centred on a seismic surface conforming to the base reservoir horizon at a TWT of 2.75 s.
We then compute and interpret the 4D seismic amplitude difference maps by subtracting the baseline amplitude map from the monitor map. Figure 9(a) presents the RMS map of the true $\Delta S_w$ extracted from the fluid-flow model. Qualitatively, we observe that these changes correlate well with the noise-free amplitude difference map in figure 9(b). Note that the low horizontal spatial resolution of UNISIM-H model generates artefacts in the vicinity of the main water saturation trend due to the abrupt differences in the depths of laterally adjacent grid cells. Figure 9(c) shows a map of the noise-free impedance changes resulting from the inversion of the noise-free amplitude volumes. These results mirror the main features of the water displacement map; however, by visual inspection they are more poorly correlated than those calculated from the amplitude results (figure 9(b)). Note also that the errors present in the impedance map are absent in the amplitude map. Comparing the $S/N = 10$ amplitude map (figure 9(d)) with the true $\Delta S_w$ (figure 9(a)) we observe regions where water saturation is erroneously predicted to increase. Errors are more numerous and of higher magnitude in the impedance map (figure 9(c)) than those in the amplitude map. These errors are associated with the inversion operator instability (equation (10)) providing incorrect water location and volumetric estimates. Therefore, based on qualitative observations we see that the presence of noise in 4D seismic data may lead to erroneous interpretations. However, qualitative analysis is insufficient for fully understanding the full magnitude of the problem.

Figure 9. Maps extracted at the bottom of the reservoir. (a) True $\Delta S_w$ from the flow simulator; (b) noise-free 4D amplitude changes; (c) noise-free inverted impedance changes; (d) $S/N = 10$ amplitude changes; and (e) $S/N = 10$ inverted impedance changes.
4.5. Quantitative analyses

The results above highlight that a quantitative analysis of the impact of noise level in 4D seismic data is important to derive reliable error estimates for reservoir property changes. Also, determining the most accurate and robust domain to integrate seismic and reservoir engineering data is fundamental to update reservoir properties using 4D seismic data. To address this, we quantify the differences between RMS maps by cross-plotting the 4D seismic attribute and $\Delta S_w$ maps, and evaluate amplitude and impedance behaviour as a function of $\Delta S_w$ and $S/N$ levels.

Figure 10(a) presents a cross-plot of $\Delta RC$ against the $\Delta S_w$ map. We observe a linear trend proportional to saturation as well as a scattering of $RC$ due to the heterogeneity of reservoir properties (e.g. porosity, net-to-gross) as incorporated in the PEM. In figure 10(b) we superimpose the previous plot with the noise-free $\Delta A$ versus $\Delta S_w$. Note that for $\Delta S_w > 0.25$ the amplitudes diverge from the reference trend provided by the reflection coefficients. Reflection coefficients theoretically should indicate the true locations of the interfaces between two lithologies. However, in practice there are a number of user-defined choices (e.g. seismic image processing, amplitude picks and time window) that affect the location of $RC$ estimates from seismic waveform data and therefore the accuracy of the RMS maps. The very good correlation of amplitude and reflection coefficient changes reported (figure 10(b)), though, indicates that we have obtained fairly accurate locations of reflection interfaces.

In figures 10(c) and (d) we superimpose $\Delta A$ for $S/N = 5$ and $2$ over the previous cross-plot, respectively. We observe that data are more scattered than for the noise-free example for both scenarios. Figure 11(a) shows the cross-plot of the RMS maps of $\Delta I_p$ from the petro-elastic model and $\Delta S_w$. As in the amplitude case, we observe a similar linear trend as well as scatter associated with reservoir heterogeneity. In figure 11(b) we superimpose the noise-free inversion results over the previous cross-plot observing that the inversion procedure provides an accurate $\Delta I_p$ estimate. Examining the $S/N = 5$ inversion results (figure 11(c)) we observe that the data are significantly more scattered than both the reference values and the noise-free estimates. Similar trends are observed for other levels of noise, as illustrated by the $S/N = 2$ example in figure 11(d).

The cross-plots in figures 10 and 11 indicate that changes in amplitudes and impedances are affected by seismic data noise. While the scatter is proportional to the seismic noise levels in both domains because these cross-plots are scale dependent, it remains unclear which domain is more sensitive to the noise and therefore contains greater uncertainty. However, the correlation between data scatter and $S/N$ levels

Figure 10. Cross-plots of 4D amplitude changes versus water saturation changes: (a) reflection coefficient (RC) changes; (b) noise-free amplitude (A) changes; (c) $S/N = 5$; and (d) $S/N = 2$.  

\[ \text{Amplitude Changes Vs Water Saturation Changes} \]
is useful for quantifying the impact of seismic noise in both domains. Thus, further analyses of these data distributions are necessary before obtaining a reliable quantitative cross-domain comparison procedure.

4.5.1. Histogram similarity ‘HS’ analyses. To address this issue we present a method based on the histograms of amplitude and impedance changes, which define a common domain for quantifying attribute differences. Histograms are commonly used to examine different features of images by partitioning the underlying values into a fixed number of bins, usually of predefined size (Rubner et al. 2000). Thus, they are a powerful way to represent an entire data set and provide valuable information for quality control. We exploit these characteristics by introducing the histogram similarity (HS) measure, which compares two histograms of a given property to provide a single number (i.e. a HS value) indicating the (dis)similarity of two histograms within a normalized (0, 1) range. HS values for dis-similar distributions and low S/N (≪ 1) levels will tend to zero. Conversely, for cases of similar distributions where S/N ≫ 1, HS values tend toward 1. For intermediate cases, the scenarios of interest here, the histogram similarity measure conceptually establishes a normalized domain in which to compare amplitude and impedance distribution behaviour. We compute HS values according to

\[
HS = \frac{2 \sum_{i=1}^{N} h_i k_i}{\sum_{i=1}^{N} h_i^2 + \sum_{i=1}^{N} k_i^2}.
\]

where \(h_i\) and \(k_i\) represent the histograms bins to be compared, \(i\) is the bin index and \(N\) indicates the number of bins.

Figure 12(a) presents a superimposition of the histograms of the \(\Delta A\) maps. Note the similarity between the \(\Delta RC\) and noise-free \(\Delta A\) histograms. Also the comparison between the histograms of \(\Delta A\) maps for noise-free and \(S/N = 10\) and \(S/N = 5\) indicates the distributions broadening as the noise increases. In figure 12(b) we expand the scale and show histograms of \(\Delta A\) for the \(S/N = 2\) and \(S/N = 1\) scenarios. The additive noise increases the scatter observed in the RMS maps (figure 9) and therefore explains the broadening in the distributions presented in figures 10 and 11. It is not surprising that we observe the same pattern in the impedance changes (figures 12(c) and (d)). Overall, these histograms contain information that can potentially be used to quantify the effect of S/N variations in \(\Delta A\) and \(\Delta I_p\).

Figure 13 presents HS values for both the amplitude and impedance domains and as a function of S/N levels. We note that the HS values for the amplitudes are higher than those for the impedances along the entire S/N range. This indicates that the \(\Delta A\) values are more consistent with the \(\Delta RC\) values than the \(\Delta I_p\) values are to true impedance values. This observation suggests that amplitudes are less sensitive than impedances to noise and, therefore, may be more reliable for quantifying \(\Delta S_w\). This example also shows that HS values are able to quantify the effects of S/N levels in both amplitude and impedance domains. This supports our hypotheses that seismic amplitudes are more reliable than impedances for quantifying \(\Delta S_w\), especially for low S/N scenarios. However, we are still
missing the link between the effects of seismic data noise and estimates of $\Delta S_w$ from 4D amplitude and impedance, which we discuss next.

4.5.2. Uncertainties in water saturation estimates. Figure 14(a) presents the regression used to estimate water saturation changes as a function of the changes in reflection coefficients. This relationship represents the reflection coefficient response to the porous media hardening due to the increase in water saturation (equations (16)). Figure 14(b) presents the regression used to estimate water saturation changes as a function of impedance changes (equation (17)).
Figure 15 presents the RMS error versus $S/N$ levels for the changes in amplitude and impedance volumes. Note that apart from the extremely noisy $S/N = 1$ scenario the errors in $\Delta S_w$ estimates are consistently lower in the amplitude domain than in the impedance domain. For the $S/N = 2$ scenario, $\Delta S_w$ estimates from amplitude have errors of approximately 18% while for impedances these errors increase to approximately 30%. This trend persists for the entire range of noise levels considered and for high $S/N$ values the relative difference decreases suggesting asymptotic behaviour.

We have shown that the RMS errors in $\Delta S_w$ estimated using seismic amplitude information are smaller than those errors derived from seismic impedance. This suggests that in the presence of realistic 4D seismic noise levels, estimating $\Delta S_w$ from seismic amplitudes can be more accurate and robust than estimating $\Delta S_w$ from seismic inversion impedance values. Although impedance changes are commonly used in 4D seismic studies to enhance data interpretation and integration (Johnston 2013), our results indicate that they may possibly lead to more erroneous $\Delta S_w$ estimates than derived from seismic amplitude information, which in turn may prove detrimental for reservoir management decisions.

5. Discussion

We confirm our hypothesis that for a realistic range of $S/N$ levels in 4D seismic data, the amplitude domain is generally a more accurate and robust choice than the impedance domain for quantifying fluid saturation changes. The histogram similarity method (HS values) indicate that the histograms of $\Delta A$ maps are more similar to the true $\Delta RC$ than inverted $\Delta I_p$ are to the true P-impedance changes derived from the petro-elastic model. Moreover, RMS saturation errors in $\Delta S_w$ derived from $\Delta A$ are smaller than $\Delta S_w$ estimates obtained from $\Delta I_p$ for the entire $S/N$ ratio investigated. We discuss below the implications of these experimental findings to the choice of domains for integration of seismic and reservoir engineering data and practical implications for quantifying fluid saturation changes using 4D seismic data.
5.1. Domains for integration

5.1.1. Amplitudes and impedances. To quantify fluid saturation changes using 4D seismic data it is crucial to understand how seismic amplitudes and impedances respond to fluid-flow changes. Our results suggest that amplitudes are more accurate and robust than impedances and therefore time-lapse data in the amplitude domain should be used to update reservoir fluid-flow model properties.

In the UNISIM-H model ∆A are caused by water replacing hydrocarbons due to injection. An increase in water saturation leads to an increase in the acoustic impedance within the reservoir and therefore alters the energy of the seismic data spectrum which thereby affects impedance estimates. The comparison between the noise-free and S/N = 3 amplitude spectra in figure 3(a) illustrates that an increase in noise leads to an increase in spectral energy and therefore could mask the effect that an increase in water saturation has on amplitudes. This increase in spectral energy dictates whether relative impedance estimates are reliable or not as the coloured inversion operator is based on the seismic data spectrum.

This band-limited approach enables us to analyse the uncertainties associated with S/N levels in the seismic bandwidth, avoiding any potential issues associated with low-frequency models required by seismic inversion methods to estimate absolute impedances. Seismic inversion methods often apply rock physics and/or low frequency model constraints in order to improve vertical resolution by adding the missing low frequencies in the seismic data (Russell and Hampson 1991, Kemper 2010, Kemper and Gunning 2014). However, such low-frequency constraints should be used with care as they might suppress or distort valuable seismic signal.

5.1.2. Water saturation. The estimate of RMS errors in ∆S_w provides a cross-discipline domain allowing a more efficient communication between geophysicists, geologists and reservoir engineers to evaluate the effects of seismic noise in the amplitude, impedance and fluid saturation domains. The saturation domain is the natural choice of domain for reservoir engineers to work in as there is no requirement for data domain transformations and therefore it is possible to directly compare seismic derived ∆S_w estimates with those provided by fluid-flow simulation models. However, while seismic amplitudes are available and impedances depend on seismic inversion methods, it is challenging to obtain reliable estimates of water saturation from seismic data (Lumley et al 2003). As showed above, this relationship between seismic attribute and water saturation requires and additional inversion procedure that may also suffer from instability, inaccuracies and non-uniqueness.

It is also important to realize that there is an accumulation of different sources of uncertainties in the impedance domain: (1) the seismic noise; (2) errors in the source wavelet and impedance inversion estimates; and (3) the regression approximation applied to obtain water saturation as a function of amplitudes and impedances. A proper evaluation of these sources of errors needs to be carried out in order to estimate reliable ∆S_w from 4D seismic, otherwise there is a risk that the associated uncertainties will be underestimated.

5.2. Practical implications

The main message of this study is that uncertainties associated with seismic noise need to be considered when deciding whether amplitude, impedances or water saturation domains should be used to update reservoir fluid-flow model properties. Through the 1D and 3D examples presented we have demonstrated that overlooking noise in seismic data can mislead 4D attribute interpretation and potentially lead to an incorrect update of reservoir properties in fluid flow models.

In practice, most applications of 4D seismic data to update fluid-flow models are manual and 4D seismic interpretation is used as a guide for adjustments of simulation parameters such as fault transmissibility and permeability multipliers (Dong and Oliver 2008, Davolio et al 2013, Stephen and Kazemi 2014, Avansi and Schiozer 2015). By honouring 4D seismic data during the update of these models, the range of simulation-model uncertainty can be reduced substantially. However, this manual process may be compromised by the artefacts in the maps associated with seismic noise uncertainties presented in figures 9(d) and (e).

Our results have a direct impact on procedures to update fluid-flow models using 4D seismic attributes. Inverted acoustic impedances resulting from seismic inversions are usually applied to guide reservoir property updates and the errors that might exist within the seismic data are often neglected. We have demonstrated that these sources of errors should be accounted for as they may impact model predictions and geological consistency. We have shown that absolute impedance estimates can be biased by low-frequency trends and therefore applying this approach in areas where there is a limited knowledge of the lateral heterogeneity can lead to significant errors.

The methods introduced in this study are potential alternatives to properly evaluate whether amplitudes, impedances or water saturation domains should be used to apply 4D seismic data to update reservoir properties. The histogram similarity method is a simple approach that quantifies the differences in values between two images and therefore may be used in quantitative workflows to update fluid flow models. The estimate of RMS saturation errors in ∆S_w as a function of S/N levels provides a cross-discipline domain allowing geophysicists, geologists and reservoir engineers to evaluate the quality of the seismic derived property and properly consider the uncertainties associated with seismic noise. These uncertainties are often underestimated and it would be of great value to consider them not only in qualitative interpretation but also within workflows to generate reservoir properties updates.

In general, there are many uncertain parameters to be considered when integrating seismic and reservoir engineering data (Oliver et al 2008, Barkved 2012, Johnston 2013). Herein, we have explored seismic noise and concluded that seismic amplitudes are generally more reliable than seismic inversion impedances for quantifying changes in water saturation, in cases of moderate to high levels of seismic noise (S/N < 10). For cases of excellent quality seismic data (S/N > 10), seismic impedance inversion methods can and have been important for assisting 3D/4D seismic interpretation. While the domain of integration should be defined on a case-by-case basis, it is important to develop an interdisciplinary understanding of the
uncertainties associated with each discipline involved and de-risk reservoir management decisions.

6. Conclusions

We conducted a number of numerical experiments aimed at examining the response of seismic amplitudes, impedances and water saturation changes as a function of S/N seismic noise levels. This work demonstrates that in the presence of realistic 4D seismic noise, the amplitude domain is generally more accurate and robust than the impedance domain for quantifying changes in water saturation.

The 1D example demonstrates the impact of the different sources of uncertainties associated with the amplitudes and impedances. Our results show that band-limited inversion is in general more accurate than full-band inversion, suggesting that the additive low-frequency components can introduce significant errors into the inversion results. We have also observed that subtracting time-lapse absolute impedance estimates does not necessarily mean that we eliminate the low frequency error effect since they are coupled within the seismic bandwidth.

The UNISIM-H 3D seismic example allowed us to compare the seismic noise impact on amplitude, impedance and water saturation changes in a realistic 3D reservoir model. Using our histogram similarity method we infer that seismic amplitudes are less sensitive to 4D seismic noise than seismic inversion impedances, and that seismic amplitudes result in more accurate and robust estimates of water saturation than impedances.

This study highlights that the errors associated with 3D and 4D seismic noise need to be quantified and properly accounted for when selecting the optimal domain to use 4D seismic information to help constrain reservoir fluid-flow model property updates. Careful consideration regarding 4D seismic signal quality and noise levels can result in more accurate reservoir property estimates, and thereby improve the management of reservoir complexity and financial risk.

Acknowledgments

We thank our colleagues at the UWA Centre for Energy Geoscience for discussions and insights that contributed toward the findings in this article. We thank Dr Alessandra Davolio, Dr Guilherme Avansi and Professor Denis Schiozer for their comments and assistance with the UNISIM-H reservoir model and fluid-flow data. We thank Capes Foundation, the ASEG Research Foundation and the UWA: RM Consortium Sponsors for partial financial support of this research. We also thank Schlumberger and CCG for providing some of the software used in this research.

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