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

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SUMMARY

Time-lapse (4D) seismic data sets have proven to be extremely useful for reservoir monitoring. Seismic-derived impedance estimates are commonly used as a 4D attribute to constrain updates to reservoir fluid flow models. However, 4D seismic estimates of P-wave impedance can contain significant errors associated with the effects of seismic noise and the inherent instability of inverse methods. These errors may compromise the geological accuracy of the reservoir model leading to incorrect reservoir model property updates and reservoir fluid-flow predictions. To evaluate such errors and uncertainties we present a time-lapse study based on a 3D reservoir model example, thereby exploring a number of inverse theory concepts associated with the instability and error of coloured inversion operators and their dependence on seismic noise levels. In this example, we use an oilfield benchmark case based on the Namorado Field in Campos Basin, Brazil. We introduce a histogram similarity measure to quantify the impact of seismic noise on maps of 4D seismic amplitude and impedance changes as a function of S/N levels, which indicate that amplitudes are less sensitive to 4D seismic noise than inverted impedances. The root-mean-square errors in the estimates of water saturation changes derived from 4D seismic amplitudes are also smaller than for 4D seismic impedances, over a wide range of typical seismic noise levels. These results quantitatively demonstrate that seismic amplitudes can be more accurate and robust than inverted seismic impedances for quantifying water saturation changes from 4D seismic data, and emphasize that seismic amplitudes may be more reliable to update fluid-flow model properties in the presence of realistic 4D seismic noise.

Key words: Time-lapse, fluid flow models, amplitude and impedance domains.

INTRODUCTION

Time-lapse (4D) seismic analyses can be used to better understand subsurface fluid flow and therefore 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 (Dong & Oliver 2003; Ementon et al. 2004; 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 pore 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 & 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, especially 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 & Stephen 2012).

The seismic impedance domain is a popular 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 parallelisable 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 (PEM) 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). Propagating these combined errors in a nonlinear forward and inverse problem generates a highly variable output, thus 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 procedure steps (Lumley 2006). Although most inversions performed are deterministic (Landa & 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 waveform information extracted from 3D seismic trace volumes.

One important issue is the effect of 4D seismic data noise on procedures to estimate reservoir properties as this noise is usually assumed to be minor or non-existent (Lumley & Behrens 1997; Davolio et al. 2012; Sagitov & Stephen 2012) ; however, non-repeatable 4D noise can be an important consideration when choosing the best 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 (Lumley & Behrens 1998; 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? And if so, how robust are amplitude and impedance work flows 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 (ΔSw) 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 (ΔA) and impedance (ΔIp) 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 applies these techniques in a time-lapse seismic scenario by presenting a 3D case study based on a benchmark fluid-flow model built on observations from the Namorado Field in Campos Basin, Brazil (Avansi & 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 work flows to update reservoir properties and fluid-flow models.

NUMERICAL 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 realistic tests in 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 & Schiozer 2015) to test 4D seismic changes in amplitude/impedance estimates as a function of ΔSw and S/N levels.

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, including the structural geological framework, facies models and petrophysical constraints derived from seismic and well log data. Porosity was modelled using a sequential Gaussian simulation, while correlations between permeability and porosity estimated from core were used to specify reservoir permeability. The UNISIM-H model has 36,739 active cells at a grid cell interval of [Δx, Δy, Δz] = [100, 100, 8] meters.

We generate 4D seismic data using the convolutional method by assuming that the baseline and monitor surveys were acquired pre-production and 4018 days (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 days (5.4 years) of production. Significant ΔSw saturation change occurs due to the injected water pushing oil down dip towards the aquifer. Figure 1 illustrates the 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..

SEISMIC MODELING

We start applying a petro-elastic modelling flow to extract both static (i.e., porosity, net-to-gross, etc.) and time-varying dynamic (i.e., water saturation, pressure, etc.) UNISIM-H data at the times of baseline and monitor seismic acquisitions. We apply standard Gassmann fluid substitution equations (Lumley 1995; Mavko et al. 2011) to estimate the P- and S-wave impedance volumes. 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-Wang (1992 Did you wish to add this as a reference?) relationships to model the fluid response to pressure and temperature, which we subsequently hold constant between surveys to help isolate the effects of ΔSw on the amplitude and impedance inversion estimates. However, we emphasize that these variables change in general during real scenarios and thereby affect the petro-elastic model outputs.

We convert the UNISIM-H model from depth to two-way travel time (TWT) assuming a constant average P-wave velocity of $V_p = 2.5\ \mathrm{km/s}$. 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 50Hz 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.

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 ΔSw. 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 (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 2.75s. We then compute and interpret the 4D seismic amplitude difference maps by subtracting the baseline amplitude map from the monitor map.

Figure 2a presents the RMS map of the true ΔSw extracted from the fluid-flow model. Qualitatively, we observe that these changes correlate well with the S/N = 10 amplitude difference map in Figure 2b. Figure 2c shows a map of the S/N = 10 impedance changes resulting from the inversion of the S/N = 10 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 2b). Comparing the S/N=10 amplitude map (Figure 2b) with the true ΔSw (Figure 2a) we observe regions where water saturation is erroneously predicted to increase. Errors are more numerous and of higher magnitude in the impedance map (Figure 2c) than those in the amplitude map. These errors are associated with the inversion operator instability 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.

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 ΔSw maps, and evaluate amplitude and impedance behaviour as a function of ΔSw and S/N levels.

Figure 2d presents a cross-plot of ΔRC and ΔA against the ΔSw map as a function of noise levels. 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. Note that for ΔSw > 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 windows) 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 2d), though, indicates that we have obtained fairly accurate locations of reflection interfaces.

Figure 2d also shows the superposition of ΔA for S/N = 5 and 2 over the previous cross-plot. We observe that data are more scattered than for the noise-free example for both scenarios. Figure 2e shows the cross-plot of the *RMS* maps of ΔIp from the petro-elastic model and ΔSw as a function of noise levels. As in the amplitude case, we observe a similar linear trend as well as scatter associated with reservoir heterogeneity. Also note that the inversion procedure provides an accurate ΔIp estimate as they are consistent with the PEM results. Examining the S/N = 5 inversion results (Figure 2e) 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 the same Figure 2e.

The cross-plots in Figures 2d-e 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 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.

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 dissimilar 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, which are 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

$$\boldsymbol{HS} = \frac{2\sum_i^N h_i . k_i}{[\sum_i^N h_\mathrm{i}^2 + \sum_i^N k_\mathrm{i}^2]}, \tag{1}$$

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

Figure 3a presents a superimposition of the histograms of the ΔA maps. Note the similarity between the ΔRC and noise-free ΔA histograms. Also, the comparison between the histograms of ΔA maps for noise-free and S/N 10 and 5 indicates that the distributions are broadening as noise increases. The additive noise increases the scatter observed in the RMS maps (Figures 2a-b) and therefore explains the broadening in the distributions presented in Figures 3a -b. It is not surprising that we observe the same pattern in the impedance changes (Figures 3b). Overall, these histograms contain information that can potentially be used to quantify the effect of S/N variations in ΔA and ΔIp.

Figure 4 presents calculated 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 ΔA values are more consistent with the ΔRC values than the ΔIp 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 ΔSw. 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 ΔSw, especially for low S/N scenarios. However, we are still missing the link between the effects of seismic data noise and estimates of ΔSw from 4D amplitude and impedance, which we discuss next.

UNCERTAINTIES IN WATER SATURATION ESTIMATES

To estimate water saturation we use a regression (nonlinear in general, linear in this specific example) to represent the changes in reflection coefficients versus ΔSw (Figure 2d). This relationship represents the reflection coefficient response to the porous media hardening due to the increase in water saturation. We perform a linear regression to this data, which provides us with a relationship between water saturation and reflection coefficients.

Figure 5 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 ΔSw estimates are consistently lower in the amplitude domain than in the impedance domain. For the S/N=2 scenario, ΔSw 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 ΔSw 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 ΔSw from seismic amplitudes can be more accurate and robust than estimating ΔSw from seismic inversion impedance values.

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 ΔA maps are more similar to the true ΔRC than inverted ΔIp are to the true P-impedance changes derived from the petro-elastic model. Moreover, RMS saturation errors in ΔSw derived from ΔA are smaller than ΔSw estimates obtained from ΔIp 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.

DOMAINS FOR INTEGRATION

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 ΔA 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. 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.

WATER SATURATION

Estimates of RMS errors in ΔSw provide 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 ΔSw 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, including: (1) seismic noise, (2) source wavelet and impedance inversion errors; and (3) the regression approximation for calculating ΔSw(ΔA,ΔIp). A proper evaluation of these sources of errors needs to be carried out in order to estimate reliable ΔSw from 4D seismic, otherwise there is a risk that the associated uncertainties will be underestimated.

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 this 3D example 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 & Oliver 2008; Davolio et al. 2013; Stephen & Kazemi 2014; Avansi & 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 (Figures 2d-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. 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 in integrating seismic and reservoir engineering data (Oliver et al. 2008; Barkved 2012; Johnston 2013). 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 in 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.

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 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.

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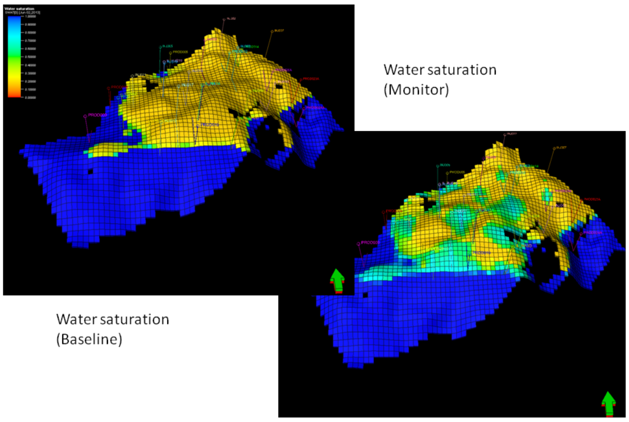


Figure 1. Water saturation distribution on UNISIM-H at the time of the baseline (upper left) and monitor (lower right) synthetic seismic surveys.

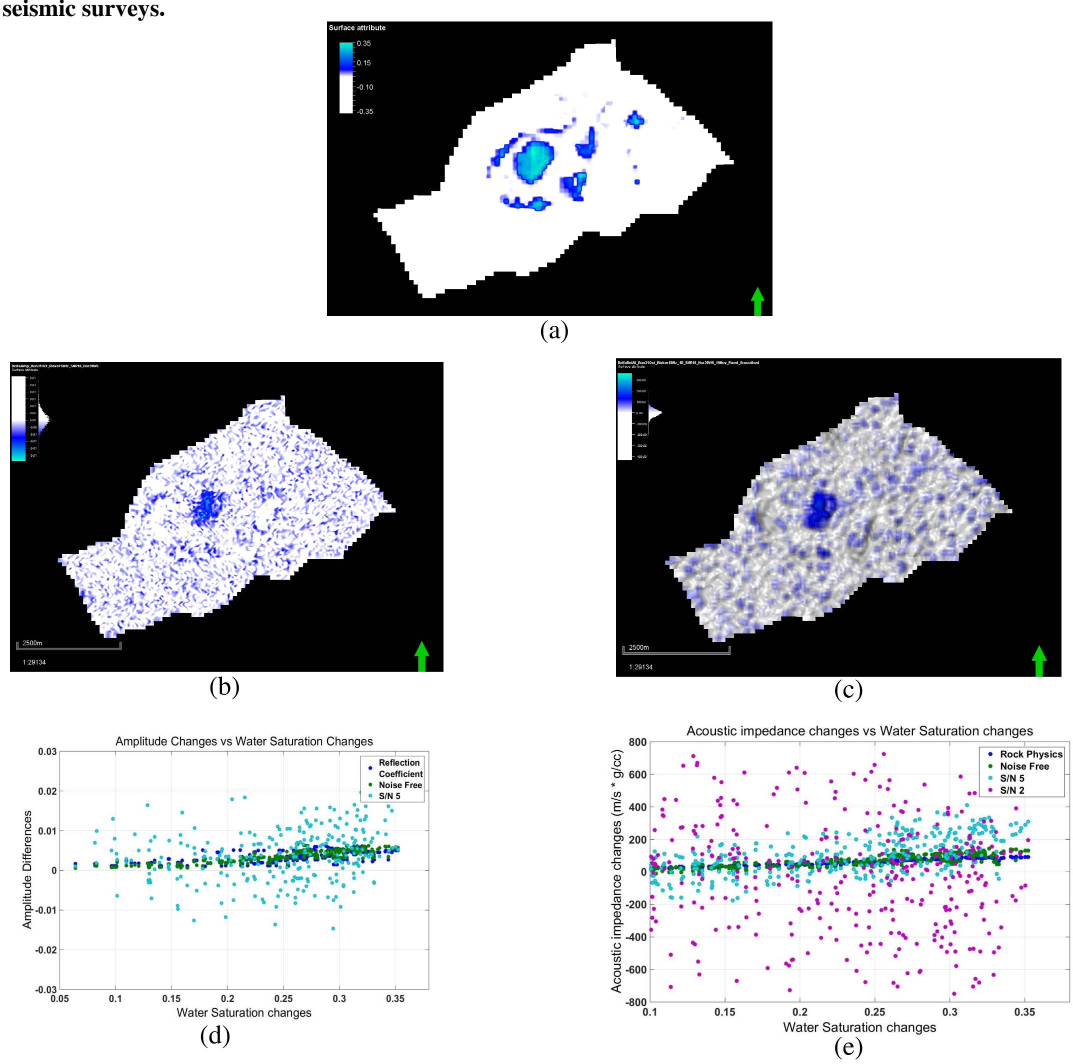
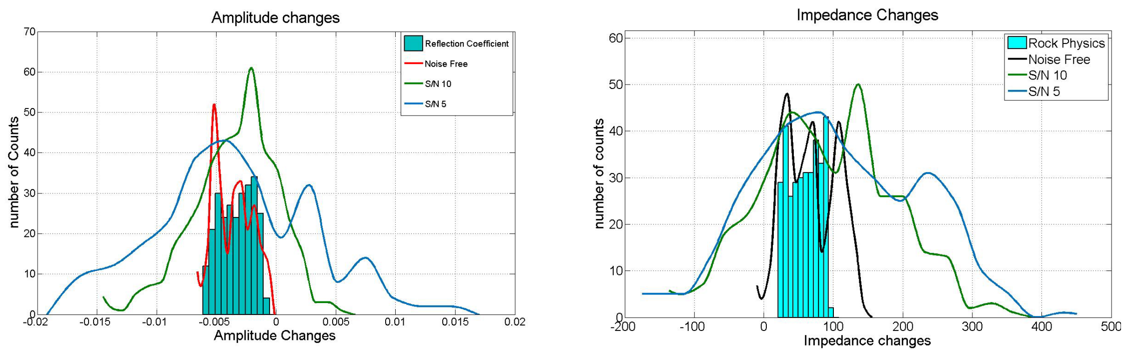


Figure 2. Maps extracted at the bottom of the reservoir. (a) true ΔSw from the flow simulator; (b) S/N = 10 4D amplitude changes; (c) S/N = 10 inverted impedance changes; Cross-plots of 4D (c) amplitude changes versus water saturation changes and (d) ΔIp as a function of seismic noise levels.



(a) (b)

Figure 3.—Comparison of the histograms of *RMS* maps of 4D Amplitude and Impedance changes as a function of noise. (a) 4D Amplitude changes and (b) 4D Impedance changes.

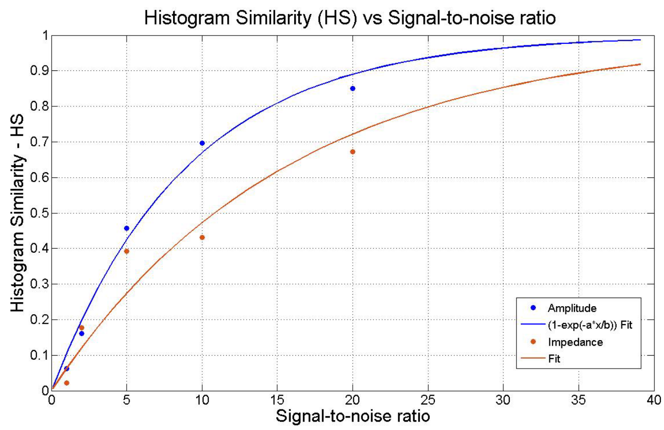


Figure 4. Histogram Similarity (HS) versus signal-to-noise (S/N) ratio for 4D seismic amplitudes (blue trend) and 4D impedances (red trend) caused by reservoir water saturation changes. Note that the Histogram Similarity values are consistently better for 4D seismic Amplitudes over a wide range of realistic seismic noise levels.

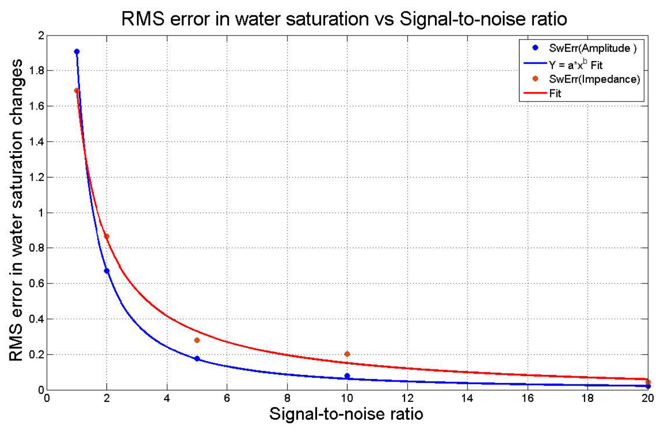


Figure 5. RMS Saturation Errors for changes of water saturation estimated from 4D seismic Amplitude changes (blue trend) and 4D seismic Impedance changes (red trend). Note that the water saturation estimates are consistently more accurate using 4D seismic Amplitudes over a wide range of realistic seismic noise levels.