Quantitatively Evaluating the Preservation of Deep-water Channel Architecture using 3D Synthetic Seismic from Outcrop

Introduction

Growth in exploration of deepwater plays is largely due to advances in 3-dimensional seismic reflectivity data acquisition and processing (Slatt, 2006). Hydrocarbon recovery from deepwater channel systems is strongly impacted by depositional architecture, specifically channel element stacking patterns and internal architecture, because they control compartmentalization and connectivity (Jackson et al., 2018; Meirovitz et al., 2020). However, the scale of architectural elements (10’s of meters thick and 100-400 meters wide; McHargue et al., 2011) make them difficult to resolve in seismic-reflection profiles (e.g., Pemberton et al., 2018). Utilizing seismic attributes improves our ability to interpret deepwater stratigraphy and can lead to better understanding of deepwater architecture (Neal and Krohn, 2012). Nonetheless, facies predication and stratigraphic interpretations from seismic reflectivity data and derivative attributes cannot be validated due to the unknown architecture of subsurface deposits and challenges with resolvability.

Forward seismic reflectivity modelling of digital outcrop models at varying frequencies provides insight into what facies and channel architecture information is preserved and interpretable in a filtered seismic response. Such models are created using architectural information from outcrop data and rock properties from well log data which are together used as the foundation for a convolutional model (Biddle et al., 1992). The resulting models are used to explore how depositional architecture and stratal surfaces are interpretable in a filtered seismic response (Pemberton et al., 2018). However, such studies often stop short at qualitatively assessing the link between underlying depositional architecture and seismic resolvability, and often conclude that decreasing seismic frequency results in a decrease in resolvability without quantification of the error in the prediction.

This study addresses this missing link with a direct quantitative comparison of 3-dimensional facies architecture predicted from seismic with a “ground truth” model to quantify key facies (sandstone as flow pathways and debris flows as flow barriers) preserved in inverted seismic data. The primary goal is to explore how and when facies classification from seismic attributes (i.e., inverted seismic reflectivity data) is correct. Specifically, this study tests the impact of varying seismic frequency and shallow to deep rock properties on the correct or incorrect classification of the facies critical to fluid flow and whether the prediction is impacted by depositional architecture (i.e., channel complex NTG and channel element stacking patterns).

Modelling Method

The dataset used in this study is from the outcropping Late Cretaceous Tres Pasos Formation in the Magallanes Basin, in southern Chile and Argentina (Fildani and Hessler, 2005; Romans et al., 2011). The Tres Pasos Formation is comprised of a prograding deepwater slope system that progressively fills the foredeep of the Magallanes Basin (Romans et al., 2011). The Laguna Figueroa outcrop presents seismic-scale exposures of slope channel systems (Macauley and Hubbard, 2013). Measured sections and mapped surfaces provide the foundation for the seismic-scale, 3-dimensional geocellular model adapted in this study (Figure 1a; Jackson et al., 2019; Meirovitz et al., 2020; Ruetten, 2021). Average acoustic impedance (AI) values from analogous deepwater systems (shallow offshore West Africa and deep Gulf of Mexico) are assigned to each facies of the model (Figure 1b). Forward seismic models are created using 1D convolution with Ormsby wavelets at peak frequencies 15 Hz, 30 Hz, 60 Hz, 90 Hz, and 180 Hz (Figure 1c). No noise is added to the AI models and a constant AI value is used for a low frequency model. The impact of different low frequency models on inversion results is tested but will not be discussed herein. Facies classification of the inverted seismic reflectivity models (Figure 1d) are then quantitatively analysed, and results compared with those of the underlying model.
Classification Method

We test the reliability of facies classification from AI (Figure 1d) by performing Bayesian classification using a calibration with three synthetic wells (Figure 2a; e.g., Avseth et al., 2005). The resulting probability models (Figure 2b) are then tested against the “ground truth” facies model (Figure 1a) to quantify the probability of correct or incorrect classification. We evaluated and quantified the prediction using the Markov-Bayes calibration coefficient, or herein referred to as the “B value”, (Zhu and Journel, 1993; Goovaerts, 1997):

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B = \Delta \mu = E\{P(A|D)\} - E\{P(\bar{A}|D)\}
\]

The B value provides a measure of facies prediction reliability by quantifying the expected value of the probability of correct classification of channel axis sandstone (A=1; Figure 2c) from AI (D; Figure 2a) minus the expected value of the probability of misclassification of channel axis sandstone (A=0; Figure 2d) from AI (D; Figure 2a). When B = 1, the average probability of correct classification is 1 and incorrect classification is 0 (B = 1 – 0, or perfect information). When B = 0, on average, the prediction will be right as many times as it is wrong (no information), and when B = -1, the probability of being incorrect is 1 (misinformation from D). The B value shows how well a seismic attribute (i.e. AI) is able to classify facies.

Figure 2  Facies classification and analysis that starts with an a) inversion model and synthetic well used in calibration for Bayesian classification that produces b) channel axis sandstone probability, P(A|D), where A is channel axis sandstone and D is AI, from Bayesian classification. This model (b) has a B value of 0.469 resulting from the difference of the mean value of the probability of correct prediction (shown in c) and the mean value of the probability of incorrect prediction (shown in d).
Results and Discussion

We evaluate the B value for channel axis sandstone and mass transport deposits (MTDs) and see how the coefficient changes as a function of seismic frequency, deep and shallow rock properties, and if there are depositional architectural configurations (NTG and channel stacking patterns) that improve or hinder predictability. We found that the B values decreased for channel axis sandstone with increasing frequency, contrary to what was hypothesized. With increasing frequency, the probability of misclassifying background mud as channel axis sand increases, leading to lower B values at higher frequencies. This is apparent in the prediction values above 0 in the inner levee and outer levee area (Figure 2d). The tuning thickness at 30Hz is equal to the channel element thickness of 25m. Anything above that frequency will resolve the channel axis sandstone, anything below it will not. In contrast, B values increased for MTDs with increasing frequency. This is because at frequencies less than 150 Hz, the 5m thick MTDs are below tuning thickness. When comparing shallow Offshore West Africa rock properties and deep Gulf of Mexico rock properties, the B value is significantly lower for deep rock properties than shallow rock properties (Figure 3).

The result of decreasing B with increasing frequency for channel axis sandstone is counterintuitive, so we tested the hypothesis that interference from successively stacked channel elements reduces channel sand axis imaging due to the loss of AI contrast. We test the hypothesis by evaluating stacking patterns using 1) NTG as a proxy for stacking (i.e., high NTG represents vertically aligned/stacked channels and low NTG represents channels that are spread out) (Figure 3b, 4), and 2) the cumulative distance between stacked channel elements (Figure 4). To do so, the model is broken up into 18 sectors, and NTG is evaluated by sector. As NTG increases, B values decrease for channel axis sandstone, supporting the hypothesis.

Figure 3 a) Sandstone B value decreases with increasing frequency, while it increases for MTD. b) B value decreases as NTG increases for each of the 18 sectors (30Hz models) showing how predictability is stronger when channel elements are isolated in background facies.

Figure 4 a) Plot of channel to channel base stacking distance vs. net-to-gross (NTG). Organized stacking patterns (b) show lower B values than disorganized stacking patterns (c), similar to NTG results in Figure 3b.

Another way to capture stacking patterns is through the cumulative distance between successively stacked channel elements, or stacking distance (Figure 4). Channel complex sets with a short stacking distance were organized or vertically aligned (higher NTG), whereas a longer stacking distance meant
the channels were more disorganized or laterally spread out (lower NTG). Disorganized stacking patterns isolate channel elements within background levee facies, allowing for better imaging of top and base of sandstone, and thus more accurate prediction.

Conclusions

The primary goal of this study is to explore the reliability of facies classification from seismic attributes (i.e., inverted seismic reflectivity data). We found that prediction reliability decreased for channel axis sandstone with increasing frequency, and increased for MTD with increasing frequency. Shallow reservoirs or slower seismic velocities more accurately predict facies than deep reservoirs or faster seismic velocities. Channel axis sandstone is less easily interpreted in systems characterized by higher NTG elements, while MTDs are more easily interpreted. This study highlights what architectural information is preserved in 3-dimensional inverted seismic data, built from deep-water outcrop data, which can aid directly in interpretation, reservoir prediction, and modelling.

Acknowledgements

Thank you to colleagues from Chile Slope Systems and our generous phase 3 sponsors, BHP, CNOC, ConocoPhillips, Equinor, Petrobras, and Repsol. Colorado State University Geosciences Dept. and AAPG Grants-in-Aid.

References