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APPLICATION OF WAVEFORM CLASSIFICATION AND MULTI-ATTRIBUTE ANALYSIS TO MAP DIFFERENT LITHOFACIES: CASE STUDY FROM VULCAN SUB-BASIN, AUSTRALIA

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ABSTRACT

Modern seismic techniques such as waveform classification and multi-attribute analysis can define facies and reservoir parameters with detail than traditional time and amplitude mapping. This report tries to establish link between lithology and seismic waveform classification by using 3D seismic and well data of Vulcan Sub-Basin, North West Shelf, Australia. Moreover, multi-attribute analysis was also performed and used in combination with waveform classification to predict different lithofacies in the area. At first step, maps were produced through unconstrained or unsupervised classification using different number of classes varying from five to ten. These maps are seismic data driven and without any guidance from well data. In the second step, constrained or supervised classification uses the known information at well locations. Facies maps of three reservoir intervals of Montara, Plover and Nome formations were computed based on both supervised and unsupervised classification. Waveform classification successfully mapped facies such as limestone, cemented sandstone and sandstone. In order to improve the prediction, multi-attribute analysis was applied to predict GR and density for key reservoir intervals. Horizon slices of GR and density predicted volumes differentiate limestone and sandstone. Combining waveform classification and multi-attribute analysis detail depositional environment for three reservoir formations can be predicted. Pre-rift Triassic -Nome Formation indicates shallow marine and shelf margin environment. Plover Formation is characterized by fluvial sedimentation of sand and shale. This formation is eroded in some parts due to tectonic uplift. Uppermost studied reservoir of Montara is interpreted as regressive to transgressive shoreface-delta.

Keywords: Vulcan Sub-Basin, Bonaparte Basin, Unsupervised waveform classification, Supervised waveform classification, Multi-attribute analysis

1. Introduction

Seismic attributes are powerful tool for seismic interpreters. They allow geoscientists to interpret faults, channels and recognize depositional environment more accurately and rapidly. This study attempts to predict lithofacies distribution at different levels within Vulcan Sub-basin, Australia by using waveform classification and multi-attribute analysis.

The study area is a part of Vulcan Sub-basin, part of Bonaparte Basin (Figure1) which is characterized by fluvio-deltaic to shallow marine depositional systems and controlled by several tectonic events. Based on only conventional seismic interpretation ,it is difficult to identify the reservoir distributions in complex structural and depositional setting. Therefore, it is required to develop a geophysical workflow, which can help to predict

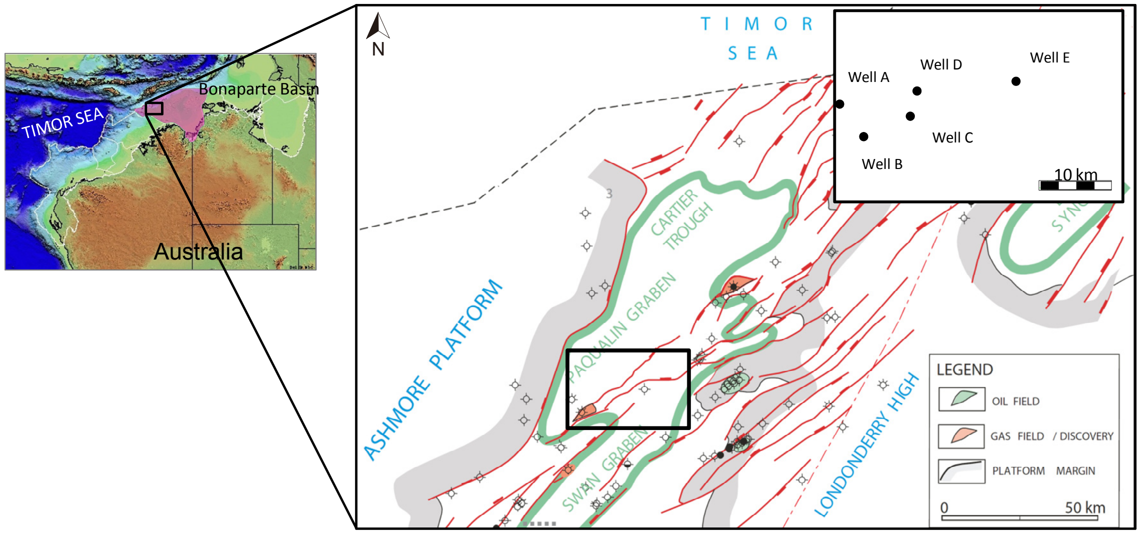

Figure 1. Location map of study area (modified after Peresson et al., 2004)

geometries of different reservoirs in the study area.

The main objective of this study is to apply waveform classification and multi-attributes analysis techniques to map the three main reservoirs within study area. These three reservoirs are Nome, Plover and Montara Formation. The result of this application will be useful to develop sand distribution and depositional model of the area and will help to predict potential reservoirs for future exploration and development programs.

2. Methods

The 3D Post Stack seismic volume covering approximately 800 sq. km, conventional logs of five wells along with core description from two wells were available for the study (Figure 1).

Well data were used to construct stratigraphic section across the study area. Top formation markers and core data were used to describe the stratigraphic sequences and depositional environment.

In order to construct reservoirs distribution and map of different lithofacies , the synthetic seismogram were generated to tie seismic to well data and three key horizons comprise of Callovian unconformity,Plover Formation and Intra-Triassic marker were interpreted.

2.1 Waveform Classification

This method was implemented in this study to classify seismic data into regions of individual characteristic. This method considers on seismic trace shape tracking along the target horizons in proper time window. By the basis of seismic wave, seismic properties such as amplitude, frequency and phase are resulted in variation of lithology, porosity, fluid effect etc.

This approach performs based on Manhattan distance measurement (V.B Singh et al., 2004). Hermann Minkowski provides the function that is given by

$$M= \quad \sum_{i=1}^{N} |A_i - B_i|$$

Where M is Manhattan distance

A is Reference waveform

B is Target waveform tracking along horizon

N is the number of time sample in each waveform

There are two types of classification method comprises of unsupervised and supervised. Unsupervised method is an analysis of wave shape over the same interval without using any extra information such as well logs data. A supervised method is an analysis of waveform by identifying its facies based on well logs data.

2.2 Multi-attribute analysis

This approach is used to predict reservoir properties by integrating target logs with several internal seismic attributes derived from mathematical transform such as amplitude, trace envelop instantaneous frequency and instantaneous phase etc (Hampson et al., 2001).

The number and types of attributes are determined by using cross plot between seismic attributes and reservoir properties to be measured. A linear relationship of actual and predicted parameters was assumed good quality. The correlation coefficient indicates fit-error of prediction data.

A linear relationship between target log and seismic attributes is defined by

$$y = a + bx$$

The correlation coefficient a and b in this equation may be derived by minimizing the mean-squared prediction error. The equation is defined by

$$E^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - a - bx_i)^2$$

Where the sum is overall point in cross plot

The correlation coefficient and prediction error were estimated based on training data and validation data. Validation is process in which a well is removed from established relationship during training of the data and log values are predicted by using established empirical relationship. The optimum attribute providing the lowest validation errors will be selected to generate pseudo gamma ray and density cubes.

In this study, gamma ray and density logs from five wells are selected to be target log in order to discriminate different lithofacies and generate distribution maps.

3. Results

3.1 Waveform Classification

In this method, the study intervals were defined by using the interpreted horizons Montara, Plover and Nome. Figure 2 shows example of the analysis windows and typical waveforms over interpreted horizons at the well locations. The window length is variable for each horizon in order to cover reservoirs zones.

The waveform classification of Montara and Plover reservoirs were covered by 30 ms (10 ms above and 20 ms below interpreted horizon) while Nome reservoir was covered by 20 ms windows centered at interpreted horizon.

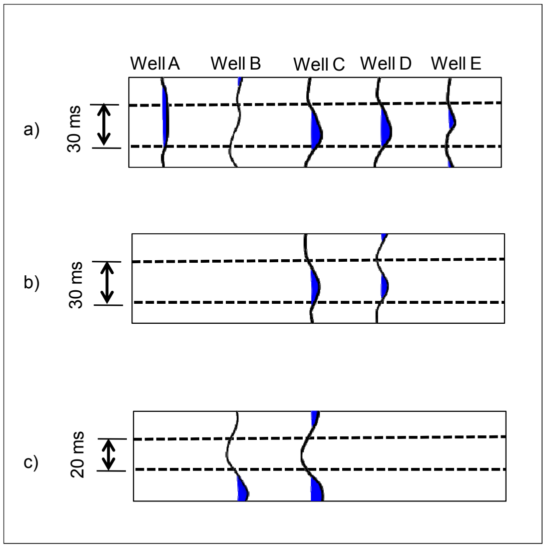

Figure 2. Typical traces of the three analyzed window intervals at well location of a) Montara, b) Plover, and c)Nome reservoir

The unsupervised waveform classification with 10 and 5 classes were based on wells drilled in different fault compartments are comparing to RMS amplitude. The result points out these classes are matching to high and low amplitude. Moreover, some of high amplitude matches to different waveform class that may causes of it contains different in phase or frequency of seismic (Figure 3).

After applying unsupervised classification, supervised approach was studied based on the relationship between seismic wave characteristics and lithology from well data (Figure 4).Overall, based on observation, the seismic waveform can detect lateral variation in lithology.

For example in Nome Formation, the different waveform can distinguish limestone from calcareous cemented sandstone which is difficult to discriminate by using only RMS amplitude (Figure 5).

In Plover reservoir, the relatively similar waveforms corresponded to massive sand and sand-shale interbedded facies. This suggests that thin bed cannot be detected. The unsupervised waveform classification shows these waveforms are relatively matched to the most of waveform for this interval.

As we have more wells available for Montara reservoir, the detail of sandstone and calcareous cemented sandstone distribution can be observed from four different waveform characteristics. The waveform map shows abundant of sandstone and distribution of calcareous cemented sandstone, dolomitic shales and limestone beds (Figure 6).

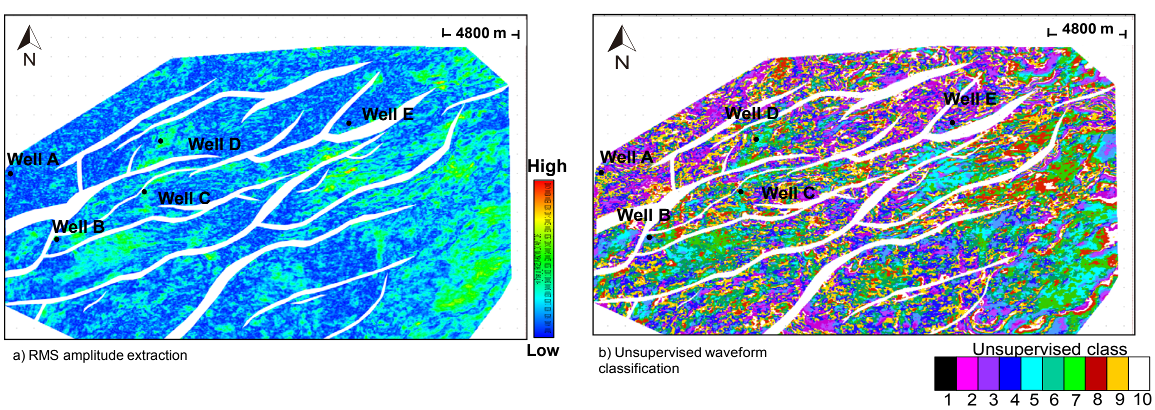

Figure 3. Comparison of a) RMS amplitude ,b) Unsupervised waveform example from 10 classes.

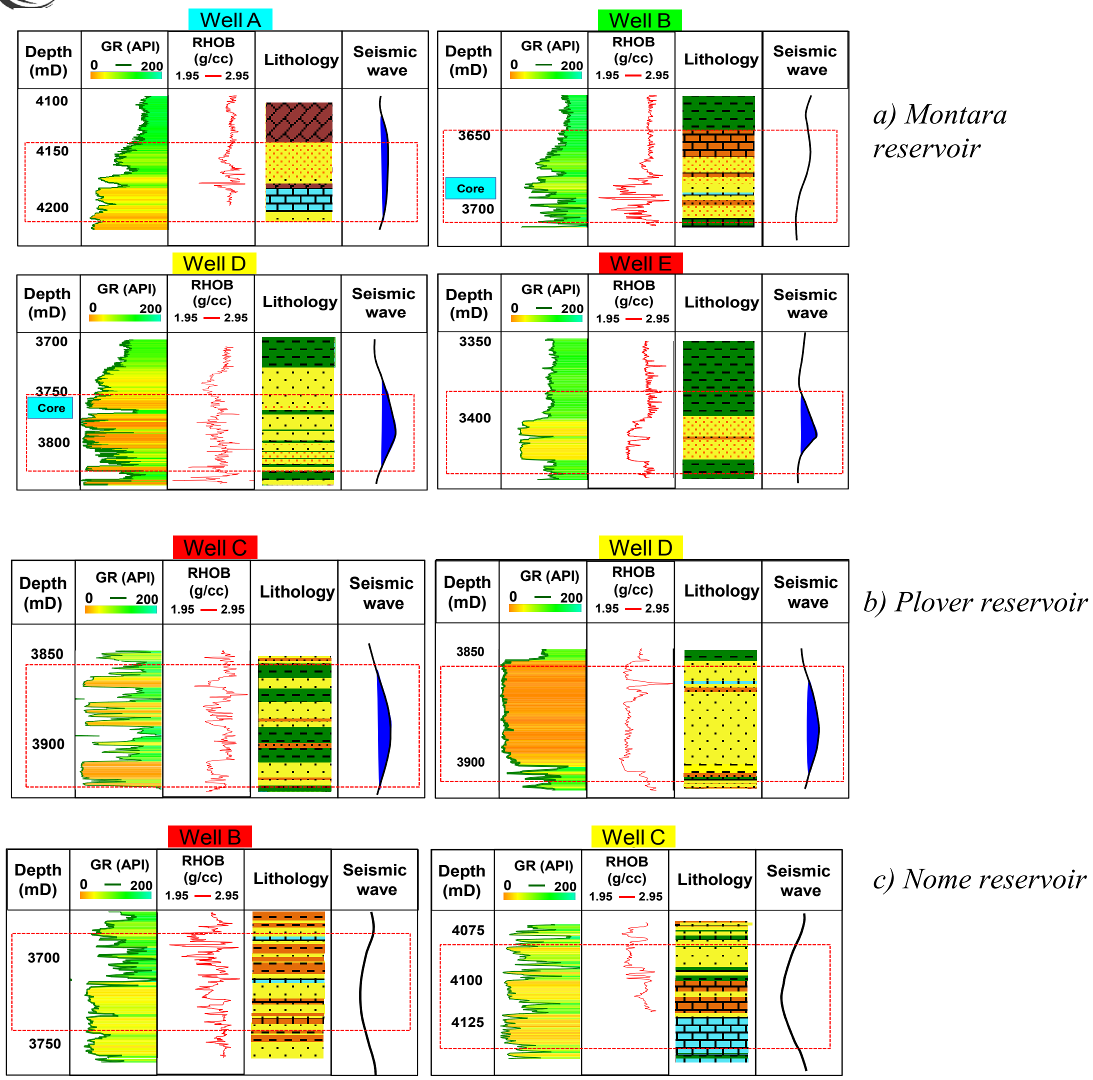

Figure 4. The relationship between waveform characteristic and lithology for Montara , Plover and Nome reservoir

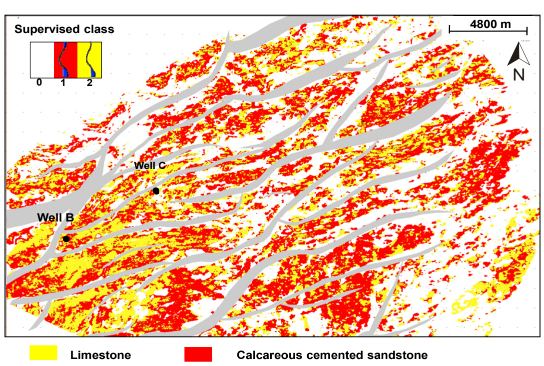

Figure 5. Supervised waveform classification for Nome reservoir

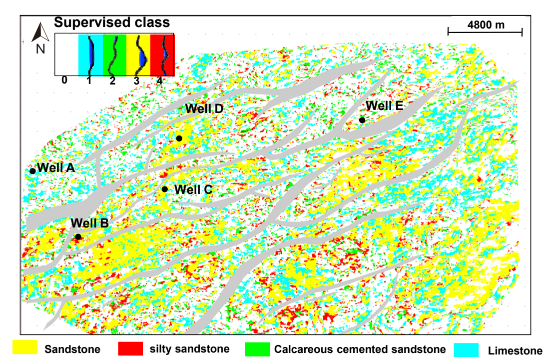

Figure 6. Supervised waveform classification for Montara reservoir

3.2 Multi-attribute analysis

Twenty seismic attributes transform were initially selected to estimate relationship with gamma ray (GR) and density (RhoB) for each reservoir interval separately. Figure 7 shows analysis window for GR and density prediction.

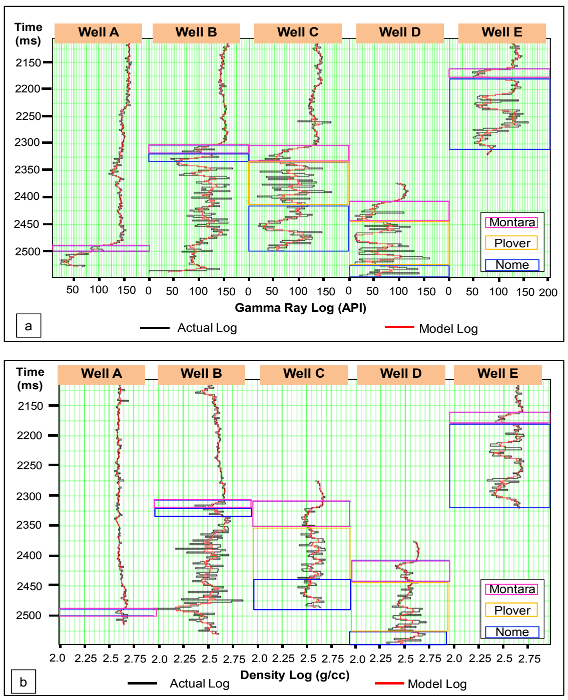

Figure 7. Analysis window with actual and model log plot for a) GR prediction , b) density prediction

The most optimum number of seismic attributes which provide minimum validation error for GR prediction of Montara, Plover and Nome reservoirs are attributes 5, 6 and 3 respectively. The average error of GR prediction for all intervals is ranging between 20-33API (Figure 8).The most optimum number of seismic attributes for density prediction of Montara, Plover and Nome are attributes 4, 5, and 5 respectively. The average error of density prediction for all intervals is ranging between 0.05-0.08 g/cc (Figure 8).

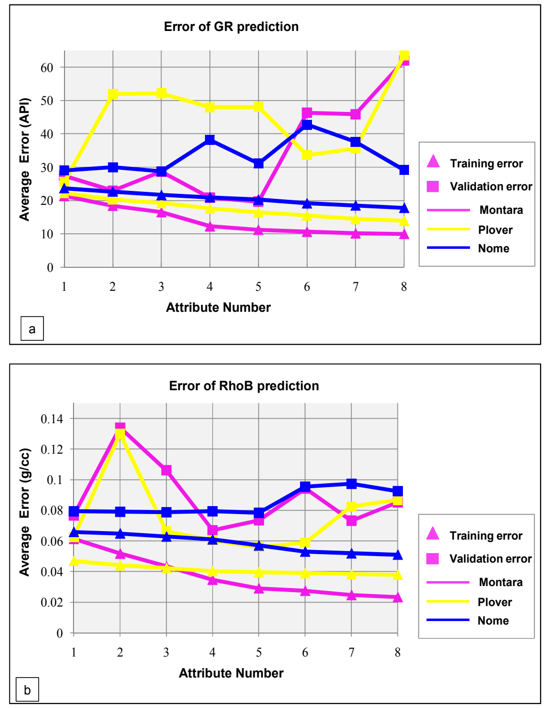

Figure 8.The average error plot versus attribute number for GR and density prediction

Reasonable match between predicted values of GR and RhoB was observed within the zone of interest for Montara Formation (Figure 8). Correlation coefficient for validation in the case of GR and RhoB is 78.46% and 64.72% respectively. While correlation coefficient for validation in the case of Plover is 66.45% to 42.79% for GR and density. Lowest validation correlation coefficient is observed in the case of Nome Formation with 49.55% and 26.78%. This may cause of different in analysis windows.

Based on observation from predicted GR and RhoB at Montara reservoirs, predicted density can differentiate high density of calcareous cemented sandstone at well B from sandstones reservoirs from others well Similarly to horizon slice of Nome reservoirs, the predicted density provided higher density at limestone at Well C while provided lower density at calcareous cement at well B (Figure 9).

However, the horizon slice of Plover reservoirs shows the unrealistic due to availability of few wells for training. Overall, based on the multi-attributes analysis, the predicted GR can differentiate sand reservoirs from shale. Density information can be useful to discriminate sandstone and calcareous cemented sandstone.

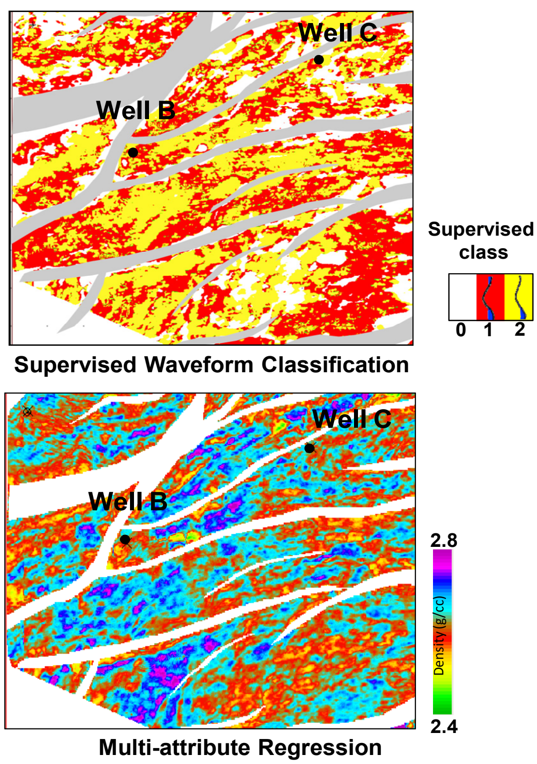

Figure9. Results of supervised waveform classification compared to multi-attribute regression , example from Nome reservoir

4. Integrated Results

The supervised waveform classification illustrates the variation in waveform characteristics corresponded to different lithofacies. The same results were obtained from multi-attributes analysis by predicting GR and density volumes (Figure 10). Consequently, the waveform classification and multi-attributes volumes were used in combination for the prediction of lithofacies.

1) In first step lithofacies were marked based on supervised classification.

2) Interpretation of lithofacies by combining GR and density volumes. Sands are represented by low GR and low density. Whereas calcareous sands/ limestone have low GR and high density.

To map variation of different facies based on combination of two methods, the result were integrated with logs and core data. Two cores were available for Montara interval.

In Nome reservoirs, these two methods give similar results. This level is comprised of cemented sandstones, limestones, and sandstone (Figure 11). The map of lithofacies shows gaps oriented SW-NE, as prediction of lithology could not be done along fault. The lithofacies distribution in this level can be correlated to associate with shallow marine to shelf margins. In Late Triassic, the N-S compression can cause uplift and erosion of carbonate platform.

In Plover reservoir, the lithofacies map do not exhibit reliable results due to

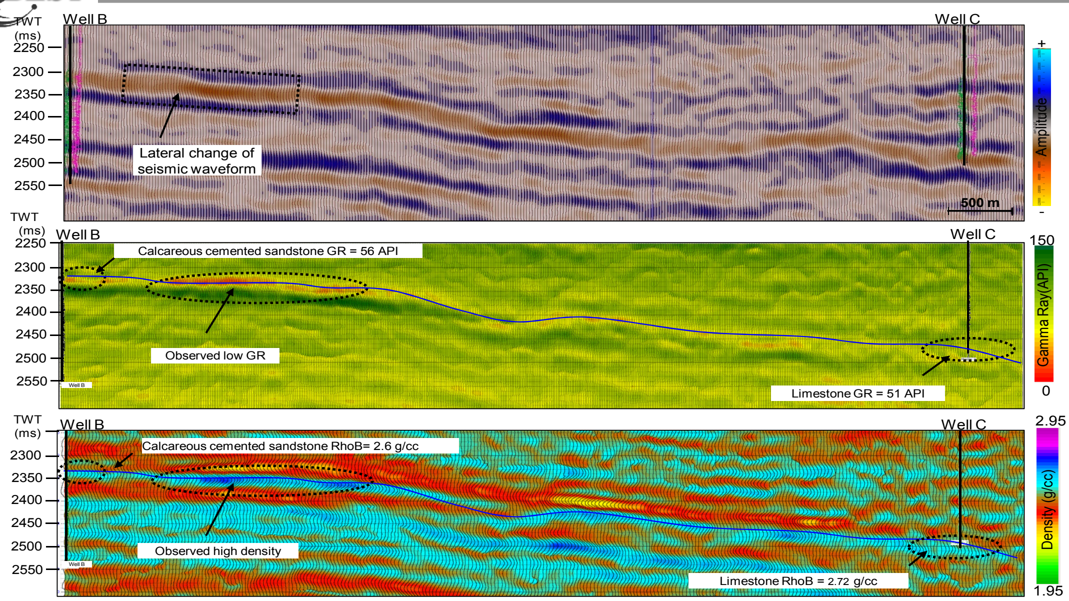

Figure 10. Comparison results of seismic waveform from conventional seismic cube , GR and density prediction volume. It indicates seismic waveform response to different lithofacies and rock properties

only 2 wells; well C and D used as reference waveforms and they contain similar lithofacies. The lithofacies map shows abundant of sandstone or sandstone interbedded shale facies. However, the grey area cannot be interpreted due to lack of well data. The interpreted lithofacies distribution may represent fluvial-deltaic depositional environment. Complex tectonics in Late Triassic caused non deposition or erosion in some part (Figure 12).

The lithofacies map of Montara reservoir shows abundant of sand facies in the west and east flank of the area (Figure 13). While the scatter facies of calcareous sandstones and dolomite can also be observed. Based on log response, it represents symmetrical GR log shape represent regressive to transgressive environment during syn-rift. The interpreted depositional environment from core of well B is marine shelf .While core data from well D indicates deltaic and shoreface environment.

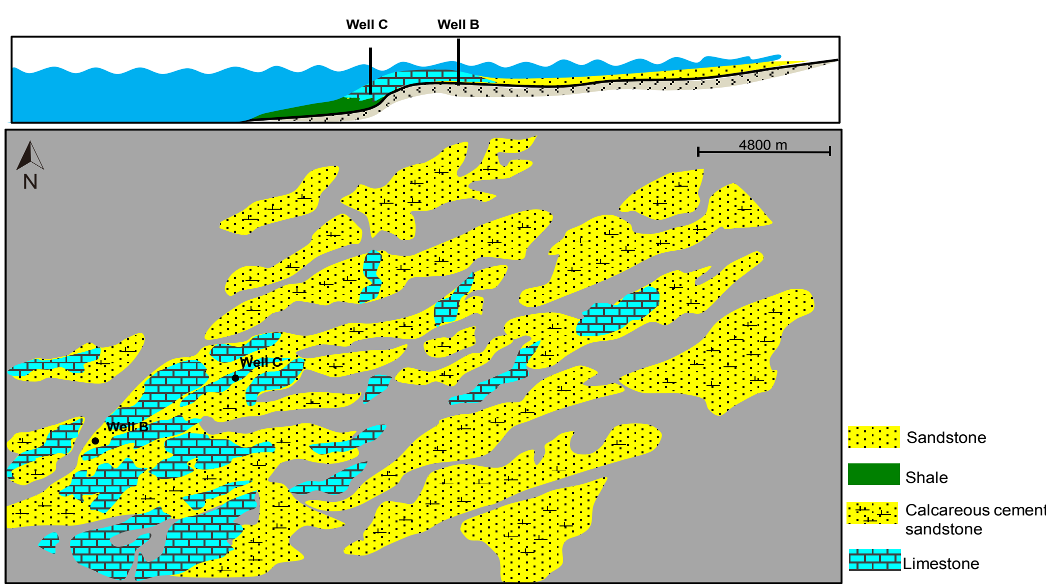

Figure 11. Lithofacies map of Nome reservoir

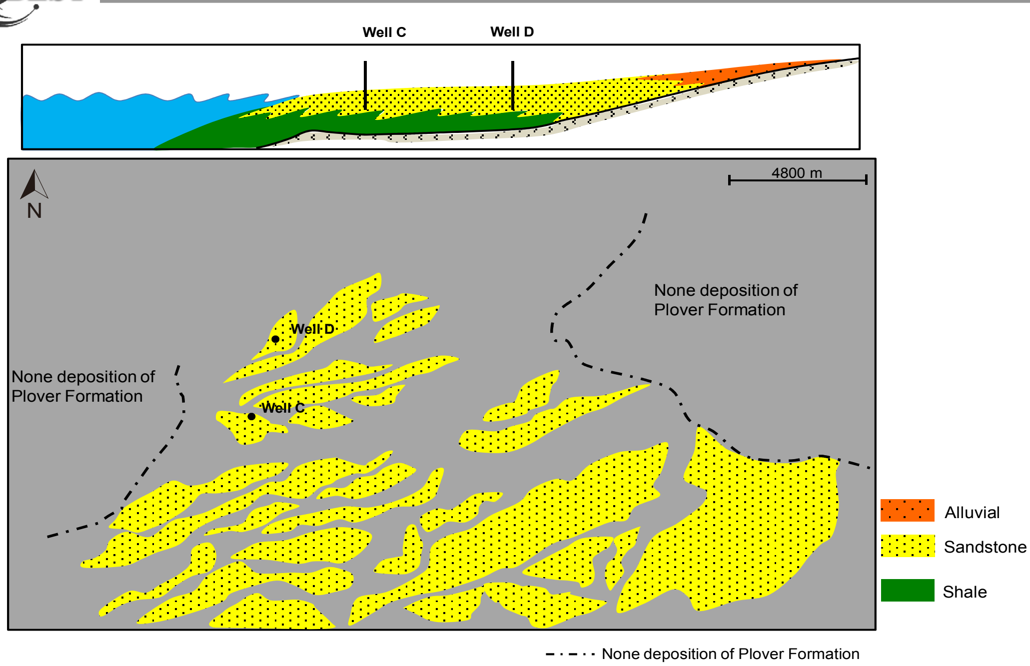

Figure 12. Lithofacies map of Plover reservoir

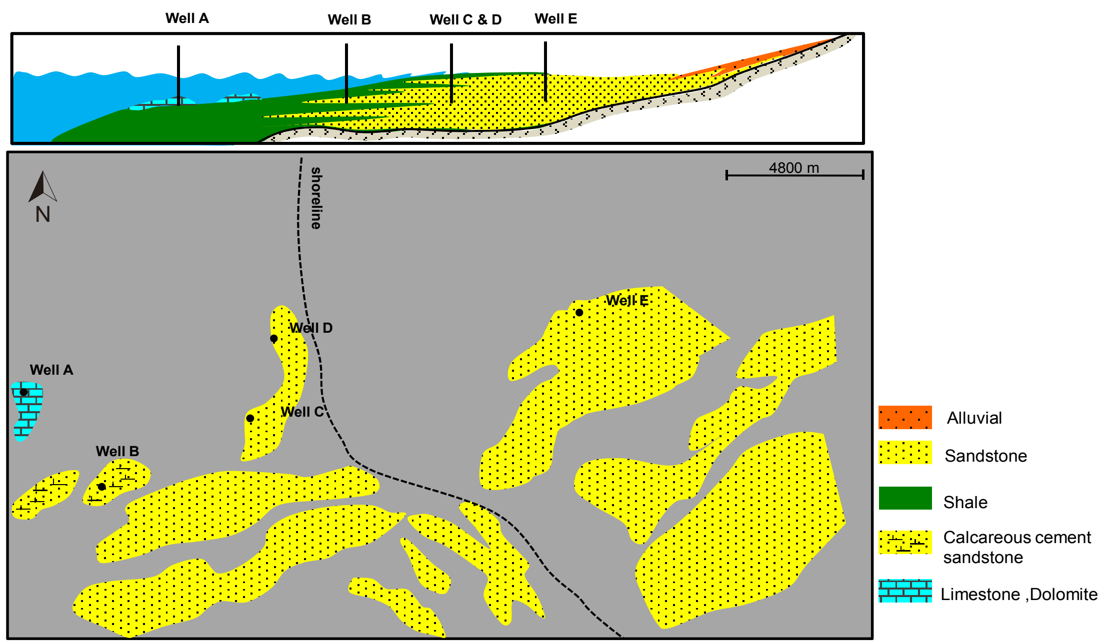

Figure 13. Lithofacies map of Montara reservoir

The derived lithofacies from integrated seismic approaches can be mapped across fault as elongated sand body oriented N-S at well C and D. It may represent shore deposits. In this case, shoreline can be estimated parallel to sand body. The limestone and calcareous cemented sand facies at well A and B can be mapped based on integration of waveform classification and density prediction. It indicates shallow marine environment. While at well E, GR log signatures show cylindrical shape. This indicates massive sands associated with channel fills. According to core data, paleodepositional environment for

Montara Formation is varying from deltaic to shallow marine.

5. Conclusions

The main findings are summarized as;

- Unsupervised waveform classification reveals that these classes are matching with high and low RMS amplitude. This means that waveforms are function of rock properties such as acoustic impedance.
- It is inferred that each lithology is represented by different waveform characteristics. Waveform characteristic at well locations were determined for limestone, calcareous cemented sandstone, and sandstone.
- Supervised Waveform Classification highlights similar waveforms for different lithofacies associated at well log data.
- Multi-attribute analysis for GR and density prediction show reasonable correlation coefficient for the prediction of these two rock properties. GR is used to differentiate sand and shale, whereas, density volumes can differentiate calcareous cemented sands and clean sands. However, this prediction is poor at locations away from wells.
- Lithofacies maps were prepared by combining results of waveform classification, multi-attributes and RMS attribute. These maps show distribution of limestone, calcareous sandstones and sandstone within different reservoir intervals.
- Mapping of lithofacies can represent reservoir distribution of landward or seaward during geological age. These can be related to sedimentary deposition, tectonics condition and sea level changes.

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