Reducing uncertainty in characterization of Vaca Mureta shale with post-stack seismic data

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Summary

The Late Jurassic-Early Cretaceous Vaca Muerta (VM) Formation in the Neuquén Basin has served as an important source rock for many of the conventional oil and gas fields in Argentina. With the interest in developing and exploiting the shale resources in the country, many companies there have undertaken the characterization of the VM Formation in terms of the elements of shale plays.

Shale plays can be identified based on, amongst other characteristics, the total organic carbon (TOC), as better TOC leads to better production. However, there is no way of measuring it directly using seismic data, and it can only be estimated in an indirect way. Considering the influence of TOC on compressional, shear velocities and density, geoscientists have attempted to compute it using the linear or nonlinear relationship it may have with P-impedance. Given the uncertainty in using such a relationship for characterizing the VM formation, a different approach has been followed for characterizing it. In addition to P-impedance, gamma ray (GR) is another parameter of interest for characterizing the VM Formation as a linear relationship seems to exist between GR and TOC.

In this study, using P-impedance and GR volumes, a Bayesian classification approach has been followed to obtain a reservoir model with different facies, based on TOC and its associated uncertainty. As the first step, we defined different facies based on the cutoff values for GR and P-impedance computed from well-log data. Having defined the different facies, Gaussian ellipses were used to capture the distribution of data in a crossplot of GR vs P-impedance. Next, 2D probability density functions (PDF's) were created from the ellipses for each of the facies. Combining these PDF's with GR and P-impedance volumes, different facies were identified on the 3D volume. Poststack model-based inversion was used to compute the P-impedance volume while a probabilistic neural network (PNN) approach was used to compute GR volume. Both derived P-impedance and GR volumes which correlated well at blind wells on the 3D volume, and lent confidence in the characterization of VM Formation.

Introduction

The Neuquén Basin in Argentina was developed as a result of an extensional rifting in the Late Jurassic established between a back-arc to the west, associated to the Sudamerican Plate, and a passive margin to the east. Subsequent deposition, thermal subsidence and structural evolution lead to the recognition of five different geographic areas (Figure 1) in the basin, which are the (1) thrust belt area to the west called the Malargüe-Agrio Foldbelt, (2) Northeast Platform, (3) Embayment in the center, (4) the Huincul Uplift adjoining the Embayment to the south, and (5) Picún Leufú sub-basin to the south west. All these areas form the elongated northwest to southeast shape of the Neuquén Basin as seen in Figure 1.

Based on the subsurface data from the electrical and acoustic log curves, mud logging data, as well as borehole images, extensive facies studies have been carried out in the Neuquén Basin. It has been found that the VM Formation comprises a variety of lithologies that include organic-rich calcareous shales, marls, carbonates, calcareous sandstones and sandstones (Ortiz Sagasti et al., 2014; Fantin et al., 2014; Stinco et al., 2014; Sylwan, 2014).

The present available descriptions of the VM Formation include the following: It is composed of amorphous organic matter associated with marine plankton and equivalent to type II or IIS kerogen (Tissot et al., 1974). With regard to thermal maturity, the maximum vitrinite reflectance, R_o, varies between 0.8 to 2%. The TOC varies between 3 to 8%, and found to be higher in the lower parts of VM Formation (Sylwan, 2014). As studied by Wavrek et al. (1994), the Embayment area is inhabited by Type A-1 oil, which is light (30-45° API) and thermally mature. Similarly, petrophysical analysis on log data shows that porosities vary between 4 and 12% in the VM Formation, with the lower intervals exhibiting porosities with 8 and 12 % and between 4 and 8% in the upper intervals (Di Benedetto et al., 2014).

Theory/Method

For a shale reservoir to become a successful shale resource play, the following characteristics need to be considered: (a) organic richness (TOC), (b) maturation (R_o%), (c) thickness, (d) gas-in-place, (e) permeability, (f) mineralogy, (g) brittleness, and (h) pore pressure. In addition, the depth of the shale gas formation should also be considered as it will have a bearing on the economics of the gas recovery. An optimum combination of these factors leads to favorable productivity (Chopra et al., 2012).

Determination of TOC allows us to identify the source rocks. Borehole measurements such as well log curves, and geochemical analysis and measurements on cores and cuttings are the direct ways of estimating TOC. These methods are applicable only at well locations. However, our goal is to characterize the source rocks not vertically, but laterally, for selecting the location of horizontal wells in the area. Thus, seismic data play an important role in identifying the sweet spots as they are acquired over large areas. The determination of TOC directly from the seismic data is a difficult task, but can be attempted indirectly as we describe in this study. It is well known that TOC influences compressional velocity, shear velocity and density of the rock intervals. Thus, it should be possible to detect the changes in TOC from the seismic response. Additionally, there is evidence of a linear relationship between the uranium content in shale and its organic content. Consequently, a large GR response is expected for organic rich shale formations. Thus, we should be able to identify the source rocks with the help of GR response.

As mentioned above, the P-impedance and GR are two important parameters for identifying the source rocks in terms of the TOC. While P-impedance can be determined by the different available methods of impedance inversion, there is no direct way of computing a GR volume from seismic data. Extended elastic impedance (Whitcombe et al., 2002) provides a way of computing it from seismic data, but for the case study at hand the lack of prestack data prevented us from using that approach. As only stacked data was available, a neural network approach was used for achieving our goal. Neural networks make it possible to predict suitable petrophysical properties such as porosity, GR, water saturation, etc. away from the well, using a nonlinear relationship between the seismic data and different derived attributes with petrophysical properties (Chopra and Pruden, 2003; Minken and Castagna, 2003; Pramanik et al., 2004; Singh et al., 2007; Calderon and Castagna, 2007).

Characterization of VM formation

A feasibility study was taken up for characterization of the VM Formation with the use of stacked seismic data along with the

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available well log curves and geochemical data. By using the TOC values from geochemical analysis of source rock cutting samples, and the acoustic impedance from well log data, Løseth et al. (2011) had demonstrated that the acoustic impedance decreases nonlinearly with increasing TOC percent. This relationship was then used to transform a seismic acoustic impedance data volume into a TOC volume. With this in mind and using similar data, we cross-plotted P-impedance and TOC to see if any relationship existed between these two attributes. This crossplot is shown in Figure 2 and it appears that both, a linear or a nonlinear curve could be a reasonable fit to the data points (as indicated). But the important point to note is that whichever relationship is used, the high TOC intervals will remain underestimated both cases. This is a limitation of the Løseth et al. approach. Predicting TOC only based on such an approach would have an inherent uncertainty and so was not considered advisable.

Given the fact that the GR response is related to organic richness, it was used to color-code the crossplot and as seen in Figure 2, a better correlation of high GR with high TOC is noticed. We also crossplotted P-impedance against GR and color coded it with TOC as shown in Figure 3. As high values of both TOC and GR are the characteristics of better quality shale play, we enclosed such points on the crossplot with a red polygon and back projected them to the well log curves shown in the right panel of Figure 3. We notice that most of the points enclosed in the red polygon are coming from the deeper reservoir zone as expected suggesting that the P-impedance and GR can be used in combination to differentiate between the deeper and shallower parts of the reservoir. However, such differentiation was not possible based on the TOC estimated from the P-impedance using a linear/nonlinear relationship. Even if differentiation is possible, the uncertainty would still exist in terms of quality of the shale.

As we are attempting to characterize the VM shale reservoir from seismic data, it is possible that different models that we derive will have the same seismic response. Of course some of these models will be more probable than others, which we could term as being realistic. Consequently, we followed an approach that accounts for the uncertainties associated with the reservoir characterization of VM formation. This work follows the Bayesian classification approach and provides a facies model reflecting the quality of the shale and a related uncertainty analysis.

To execute the Bayesian approach, different facies were defined based on the cutoff values of GR and P-impedance. Armed with the facies information, probability distributions for each facies were generated using Gaussian ellipses. These ellipses are shown in Figure 4 where three facies are defined in green (facies1), dark green (facies2) and red (facies3) colors. Based on the P-impedance and GR values, the quality of shale play must increase from red to green color. Observing the defined facies on the well log panel, it was concluded that quality of the VM formation increases with depth which is reasonable, based on the known geological history.

Having gained confidence in characterizing the VM formation based on the well log curves, we turned to deriving the seismic P-impedance and GR volumes. For computing P-impedance, stacked seismic data was first conditioned in terms of enhancing the S/N ratio. A low-frequency model was created using 5 of the 8 wells, keeping the other three as blind wells. After observing a good correlation at the blind wells, model-based inversion was used to invert the seismic data. The routine QCs were performed in the exercise that included inversion analysis at well locations, overlay of acoustic impedance logs (filtered to the seismic bandwidth) on the acoustic impedance sections, and crossplotting the predicted and actual acoustic impedance values at well locations. When we found all these results encouraging, we proceeded with the inversion of the complete volume. An arbitrary profile passing through the wells was extracted from the inverted impedance volume and is shown in Figure 5. A good match between the inverted and measured impedance is noted, which provided the confidence in the inversion process used.

For computing the GR volume, multiattribute regression and PNN were used. The detailed theory and workflow on PNN can be found in Hampson et al. (2001), but it involves some training and validation steps. Figure 6 shows the crossplot of the actual and predicted GR response at different well locations, where a correlation of 95% is seen. Validation correlation between the actual and predicted GR logs is shown in Figure 7, and again a good correlation is seen.

Using the probability density function of each facies generated earlier from well log data analysis, and inverted P-impedance and GR volumes, Bayesian classification generated the facies volume and probability volume of each facies. Figure 8 shows an arbitrary line extracted from the facies volume and passing through three wells (that have TOC measurements from cores). We find that the quality of the shale reservoir is better in the lower part of the VM formation and also the thickness of facies 1 (green) increases from the shallower part to the deeper part of the interval, as expected from the geological information. A similar section extracted from the probability volume for facies 1 is shown in Figure 9. The color scheme represents probability of this facies, with brown color representing higher probability of occurrence of facies 1. In a similar way, the probability distribution of other facies can be extracted. For detecting the probable sweet spots horizon slices were extracted from the facies volume at different levels. Figure 10 shows one such horizon slice extracted 8 ms above the base of reservoir, where facies 1 seems to dominate the display. Finally, in Figure 11 we show a map depicting the probability of occurrence of facies 1. The hot colors on this map indicate zones where the probability of occurrence of facies 1 is 85% and above. As facies 1 corresponds to high TOC, these zones were treated as sweet spots. This map correlated well at the well locations, which enhanced our confidence in the results. Similar analyses were carried out for other intervals exhibiting different facies.

Conclusions

Determination of TOC in shale resource reservoirs is a desirable goal in most projects carried out for characterization of unconventional reservoirs. TOC calculations based on linear or non-linear relationships between acoustic impedance from log data and TOC values could lead to uncertainty and was not found suitable for use in the characterization of the VM Formation. The application of poststack model-based P-impedance, and a GR volume derived using PNN, coupled by the Bayesian classification approach, provided a useful workflow for defining different facies in the VM Formation, and hence the quality of the shale. This workflow has the potential to be successfully applied to other shale plays around the world.

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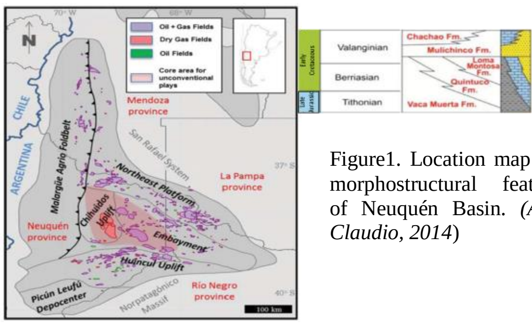

Figure1. Location map and morphostructural features of Neuquén Basin. *(After Claudio, 2014*)

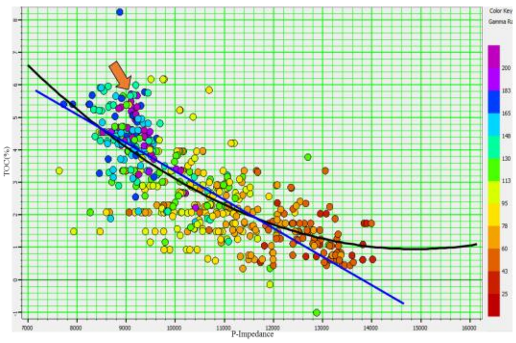

Figure2. Crossplot of measured P-impedance vs TOC color-coded with GR. Linear, non-linear relationship is shown by blue and black line respectively. Both relationship do not capture the high TOC zones indicated by arrow.

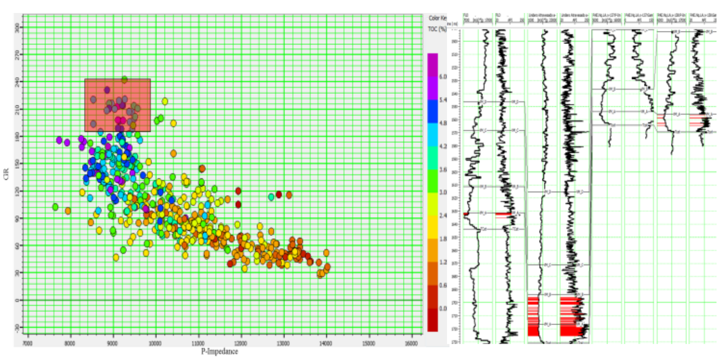

Figure3. Crossplot of measured P-impedance vs GR color-coded with TOC. Somewhat linear relationship is noticed between high TOC and high GR. Points with high values of both are captured (red polygon) and back projected to the well log curves (right).

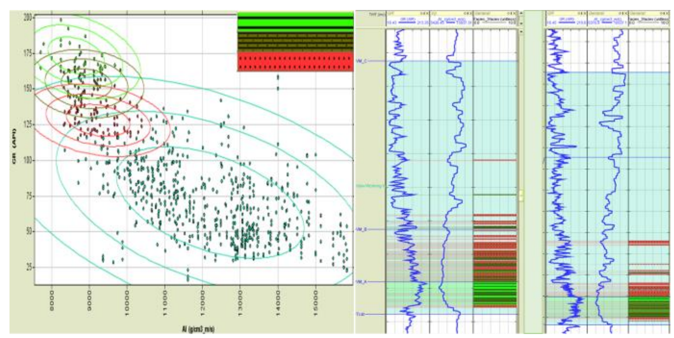

Figure 4: Different facies shown in green, dark green and red colors are defined based on the cutoff values of GR and P-impedance. Observing the defined facies on the well log panel, it can be concluded that quality of VM formation increases with depth which is trustworthy based on the known geological information. To consider the uncertainty analysis in defining facies, Gaussian ellipses shown here are used for creating probability distribution of each facies.

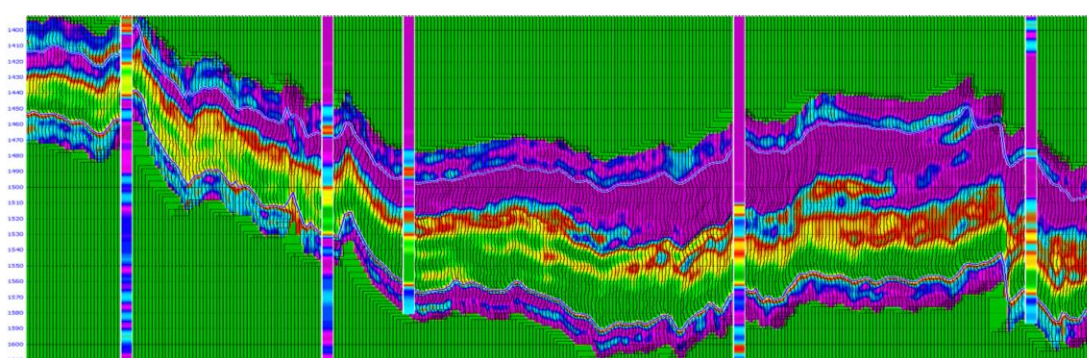

Figure5. Inverted P-impedance section along an arbitrary line that passes through the wells. A reasonable fair match between inverted and measured impedances is noticed.

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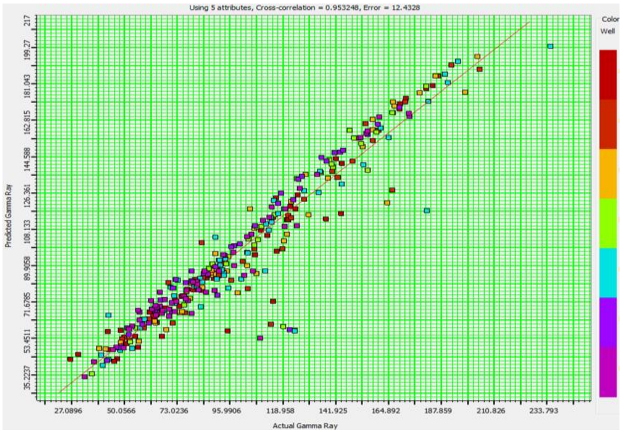

Figure 6: Crossplot of actual (x-axis) and predicted (y-axis) GR response using PNN approach (left). A correlation of 95% is noticed.

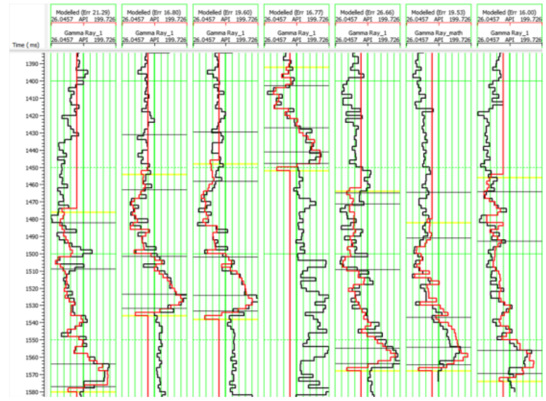

Figure 7: Log panel showing the match between actual (black) and modeled (red) GR log derived using PNN for different wells after validation.

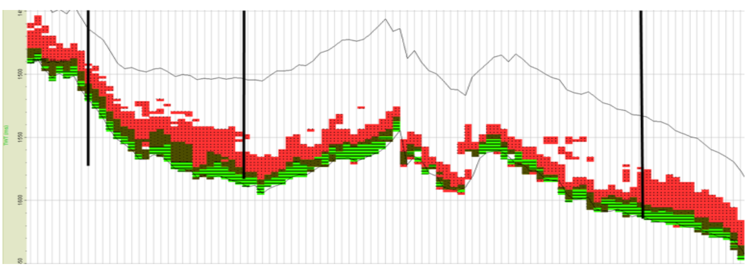

Figure 8: Arbitrary line extracted from the facies volume and passing through three wells. Better quality of the shale reservoir is noticed in the lower part of the VM formation also the thickness of facies 1 (green) increases from shallower part to the deeper part of the interval, as expected from the geological information.

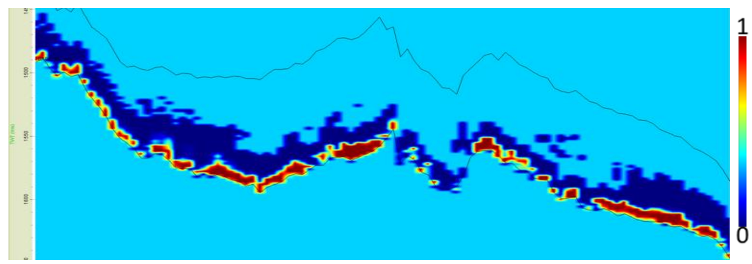

Figure 9: Arbitrary line extracted from the probability volume for facies1. High probability of occurrence of this facies is represented by brown color.

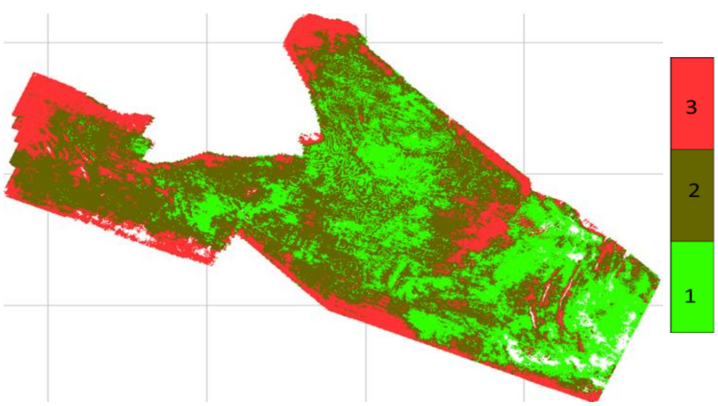

Figure 10: Distribution of different facies along a horizon slice taken 8ms above the base of reservoir. Facies 1 seems to dominate the display.

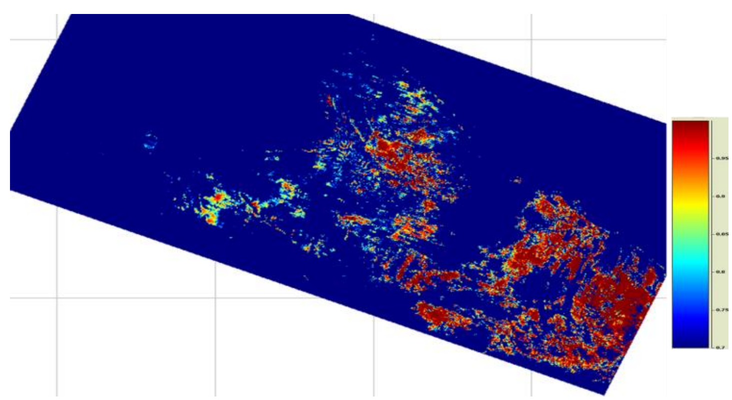

Figure 11: Map depicting the probability of occurrence of facies 1. The hot colors on this map indicates the zones where the probability of occurrence of high TOC zone is greater than 85%

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EDITED REFERENCES

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