Neural network unsupervised classification as an advanced presalt reservoir characterization technique: a Buzios Field case study

Danilo Jotta Ariza Ferreira[1,2], Wagner Moreira Lupinacci[1], Thais Mallet de Castro[1], Nathalia Ladeira Casado[1,2], Marcelo Alvarenga[2], Yuri Bezerra[2], José Fernando Caparica Junior[2], Marco Antonio Cetale Santos[1]

Universidade Federal Fluminense[1]

Schlumberger[2]

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Abstract

This paper proposes the use of unsupervised neural network classification using multiple seismic attributes as a methodology for advanced reservoir characterization applied the pre-salt Barra Velha Formation carbonate reservoirs in the central portion of the Buzios Field, Santos Basin. The need of this advanced approach is to the fact that these reservoirs are known to be very complex due to its high level of heterogeneity and anisotropy, that affects directly its porosity and permeability. The acoustic impedance, rms amplitude and variance attributes were used for the unsupervised seismic facies classification. Coupled analysis of amplitude seismic features and the classification results allowed the differentiation of two seismic patterns within the study area: aggradational/ progradational carbonate platforms and build-ups. Potential areas for drilling new wells were identified in the eastern part of the field from the seismic facies probability occurrence and zonation maps.

Introduction

The pre-salt reservoirs in the Santos Basin are one of the most challenging targets for the exploration and production of oil and gas, due to their geological heterogeneity and anisotropy requiring the deep understanding of depositional and post-depositional processes coupled with advanced reservoir characterization techniques for precise positioning of wells (Bruhn et al., 2017).

Seismic facies associated to these reservoirs during the sag and upper rift phases, comprised in the Barra Velha formation, are represented mainly by buildups, aggradational or progradational carbonate platforms, and debris (Wright, 2012; Buckley et al., 2015; Kattah and Balabekov, 2015; Saller et al., 2016; Jesus et al., 2019; Ferreira et al., 2019).

Facies associated with these seismic features are comprised, predominantly, of stromatolites/shrubs, grainstones, spherulitic packstones and pelagic carbonates (Terra et al., 2010; Boyd et al., 2015; Muniz and Bosence, 2015; Rezende and Pope, 2015), eventually intercalated with subaerial basaltic lava flow units with high evidence of hydrothermal fluid percolation in a lacustrine environment (Szatmari and Milani, 2016; Fornero et al., 2018).

One of the most promising advanced approaches for seismic facies characterization of the Barra Velha Formation carbonate reservoirs is the unsupervised facies classification using neural network algorithms coupled with the used of stratigraphic and structural attributes, as described in the works of Johann et al. (2012), Jesus et al. (2019) and Ferreira et al. (2019).

We propose the use of multiple seismic attributes in an unsupervised neural network algorithm for seismic facies classification of the Barra Velha Formation within an area of the Buzios Field, Santos Basin, in order to better characterize the reservoir and to determine new areas for drilling (Figure 1).
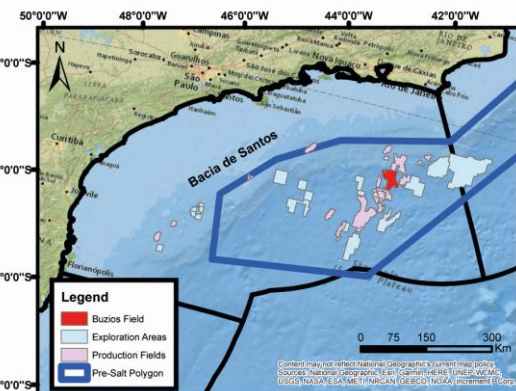

Figure 1: Location of Buzios field in Santos basin.

Methodology

The dataset available consisted in approximately 770 km^2 of 3D post-stack depth migrated seismic (PSDM) and migration-velocity model, and 16 wells located in southern part of the Buzios Field. All the data as well as the seismic lines represented in this study are shown in Figure 2.

The base of the salt (upper Aptian age), Pre-Alagoas (lower Aptian age) and the top of the basement unconformities as well as the faults of the rift and sag phases were interpreted according to the concepts of

seismic stratigraphic reflector terminations, as described in Brown Jr. and Fisher (1977) and Della Fávera (2001). The map of the base of the salt is shown in Figure 2 and an seismic line, with the basement, Pre-Alagoas and base of the salt unconformities and the faults interpreted, is shown in Figure 3.

The interest interval for the seismic facies classification is comprised between the Pre-Alagoas and base of the salt unconformities and represent, respectively, the base and top of the Barra Velha Formation (Moreira et al., 2007). Seismic patterns present in this interval were also identified and analyzed and allowed to build an initial geological model and assisted the interpretation of seismic facies obtained from neural network classification.
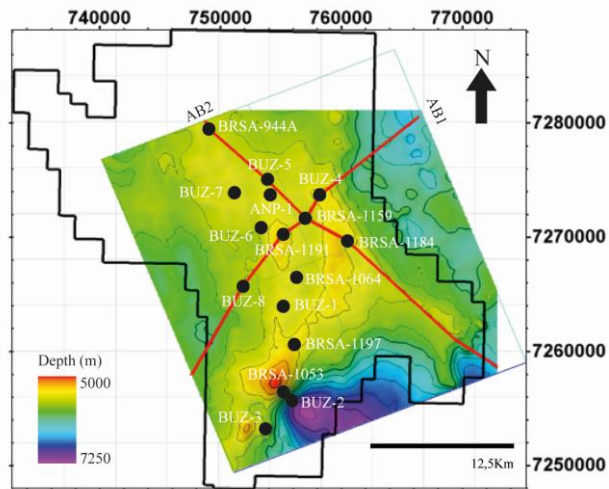

Figure 2: Dataset available in the Buzios Field (black polygon) area including the wells (black circles) and 3D seismic (green square). Also, the arbitrary seismic lines represented in the study are highlighted as red lines.

Prior to the generation of the seismic attributes used for classification, the seismic data was preconditioned using a structural smoothing filter (Hale, 2009) to reduce the influence of structurally oriented noise.

The response of several attributes extracted based on amplitude, phase and frequency of preconditioned seismic data need to be analyzed for identification of stratigraphic and structural characteristics that could individualize the seismic patterns in the area, as proposed by Ferreira et al. (2019) and Jesus et al. (2019).

Three seismic attributes were chosen as input for unsupervised classification: the acoustic impedance obtained using the inversion algorithm described by Barclay et al. (2008), Dai et al. (2011) and Basha et al. 2012), rms amplitude extracted using the method proposed by Taner et al. (1979), and variance calculated using the approach created by Bemmel and Pepper (2000). The stratigraphic and structural characteristics highlighted by the attributes related to the seismic patterns were also discriminated.

Neural network technique was developed by McCulloch and Pitts (1943) based on the brain learning process through interaction amongst neurons when given a stimulus. We used a multi-layered perceptron network with lateral connections for inhibition architecture and competitive learning method (Russell and Norvig, 2010; Du and Swamy, 2014) for unsupervised discrimination of five seismic facies. The ideal number of facies was defined after a series of trial and error attempts ranging from 3 to 10 facies.

Finally, the seismic facies classification volume was further analyzed for a better geological understanding of seismic patterns distribution. In addition, it was used to build probability occurrence and zonation maps for the seismic patterns in the study area, considering average facies quantity for the target interval.
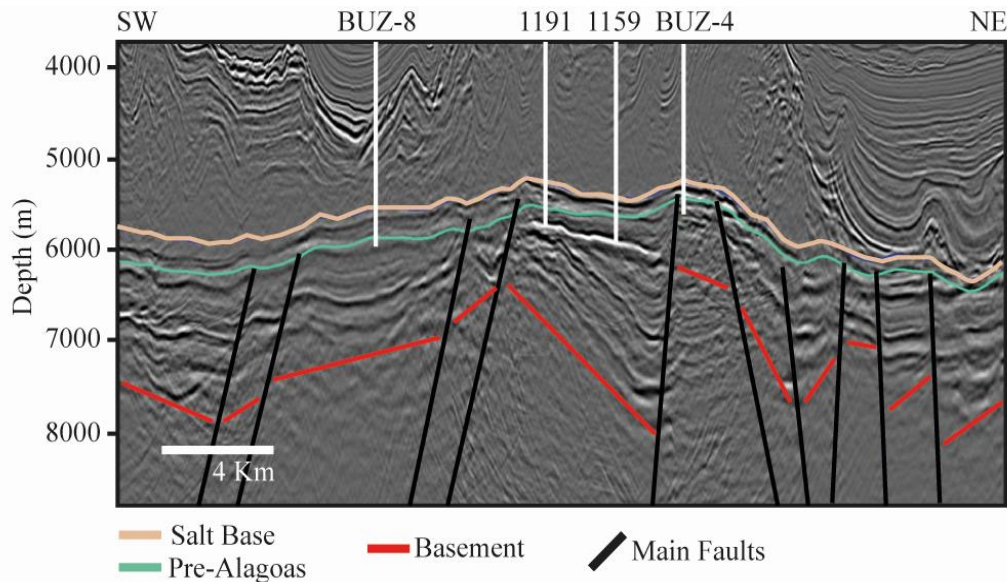

Figure 3: Interpreted seismic horizons on arbitrary line 1 (AB1).

Results and Discussion

Two seismic patterns were identified in the study area: build-up and aggradational/progradational carbonate platforms. Their characteristics related to the preconditioned seismic data as well as for the generated attributes used for classification are presented in Figure 4.

Figure 4: Identified seismic patterns in the Buzios Field and their characteristics related to each of the seismic attributes used in the unsupervised seismic facies classification.

The evaluation of the identified seismic patterns and the seismic facies classification results are represented as seismic sections in Figure 5 and Figure 6 and in map view, projected over the salt base horizon in Figure 7.

Aggradational/progradational carbonate platform patterns are the most abundant in the Buzios Field. They are distributed throughout all the flat structural highs and lows and are associated with the plane-parallel intercalation of the seismic facies 1, 4 and 5. We can infer that the predominant facies associated with these patterns are grainstones and packstones in the structural highs and

pelitic and reworked carbonate sediments at the structural lows.

Seismic patterns associated with build-ups are less abundant in the study area and are mainly located near the main structural high, where the wells were drilled, near the fault zones or in local highs in the southern areas. These features are associated with the chaotic intercalation of the seismic facies 2 and 3. It is expected that stromatolite/shrub facies and their reworked facies are more predominant in this pattern and that its origin is related to hydrothermal activity (Wright and Barnett, 2015; Wright and Tosca, 2016). Due to this fact, it is possible that these facies can eventually intercalate with volcanic rocks. Also, it is important to note that since the build-up seismic pattern is associated to chaotic seismic signal it can be mistaken with noise in poorly illuminated areas, thus its occurrence in the Buzios Field area can be overestimated. The average proportion maps of build-up and aggradational/progradational seismic facies are shown, respectively, in Figure 8 and Figure **9**.

In western area of the Buzios Field, 12 wells are located where the occurrence is mainly carbonate platforms and only 4 wells are in areas were build-ups prevail.

A zonation map of the area was built, considering the most probable seismic attribute classification facies according to the probability maps (Figure 10). Again, we observed that most of the wells were drilled in carbonate platform zones.

Several areas that represent potential targets for new drilling can be observed in structural highs in the eastern part. However, the abundance of build-ups could represent different reservoir behavior regarding facies, porosity and permeability heterogeneity, and anisotropy.

Conclusions

The use of unsupervised neural network as an advanced technique for the facies classification in the Barra Velha formation proved to be very efficient. Build-ups and carbonate platform seismic patterns were identified and zoned in the study area within the Buzios Field. The selected attributes for neural network seismic facies classification were: (a) rms amplitude, which presented an absent signal for build-up pattern and highlighted strong reflectors for carbonate platform pattern, (b) variance, which showed internal fracturing for build-up pattern and almost absent signal for carbonate platform pattern, and (c) acoustic impedance, which presented medium values for build-up pattern and intercalation of high and low values for carbonate platform pattern. All these identified attribute features coupled with the unsupervised seismic facies classification results allowed the zoning of seismic patterns throughout the area and assisted the construction of a better geological understanding of facies distribution. Most of build-up patterns occur on the faulted zones of structural highs suggesting that is origin is intrinsically connected to faulting. Finally, seismic attribute classification facies probability map coupled with seismic pattern zonation map allowed the determination that 4 wells were drilled in areas with build-up seismic pattern predominance and 12 wells were drilled in areas where the carbonate platform seismic patterns prevail.
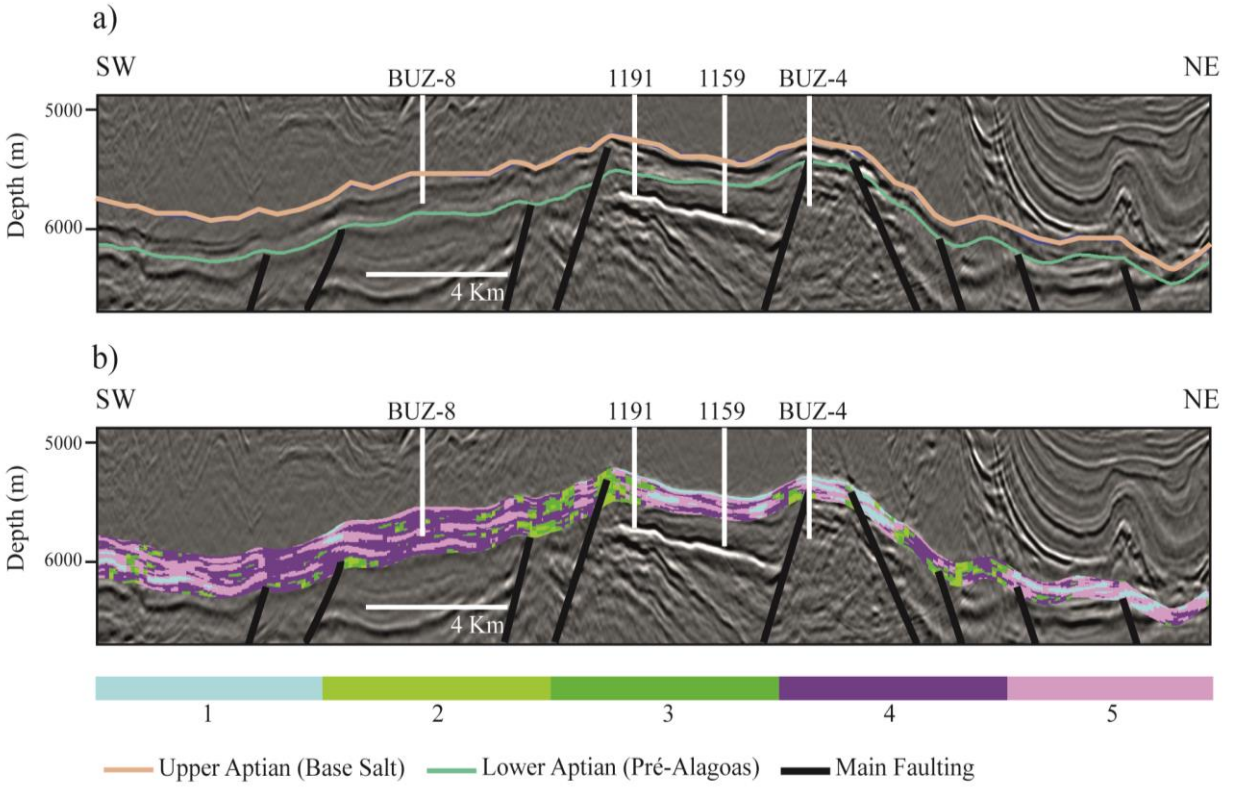
Figure 5: Preconditioned seismic (a) and seismic facies classification results (b) represented in the arbitrary line 1 (AB1).
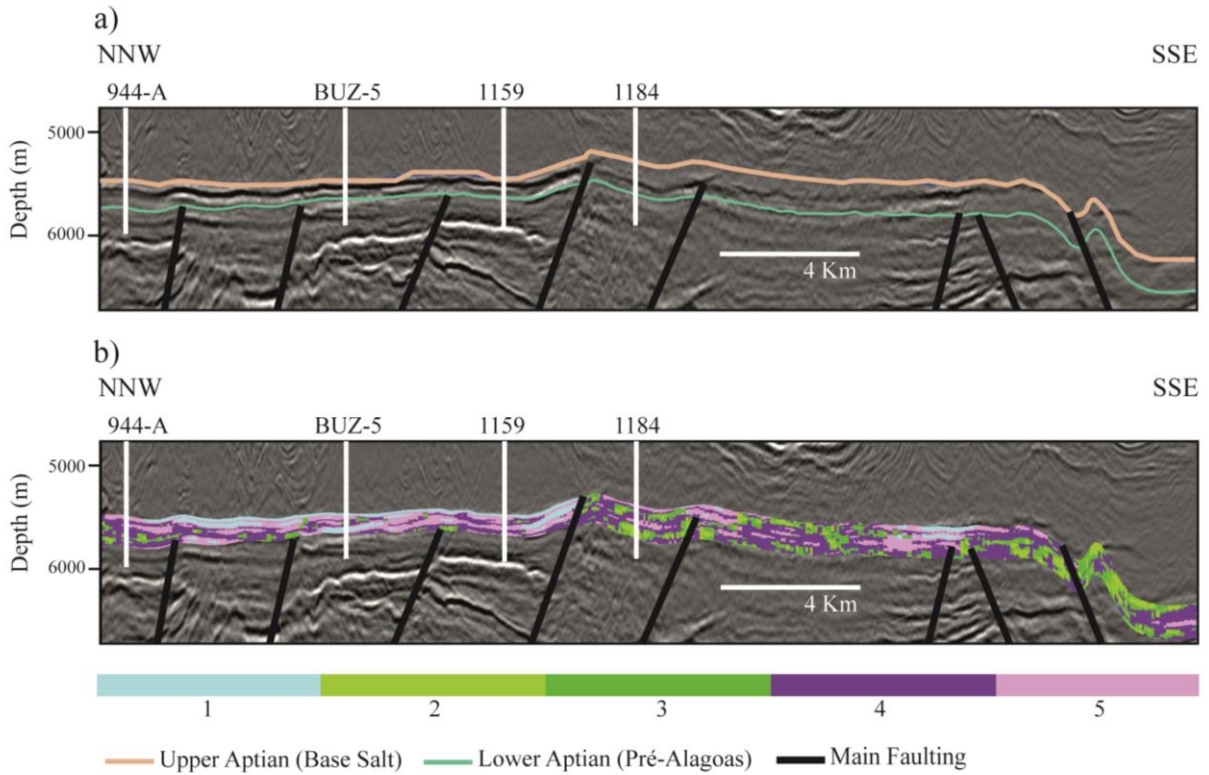

Figure 6: Preconditioned seismic (a) and seismic facies classification results (b) represented in the arbitrary line 2 (AB2).
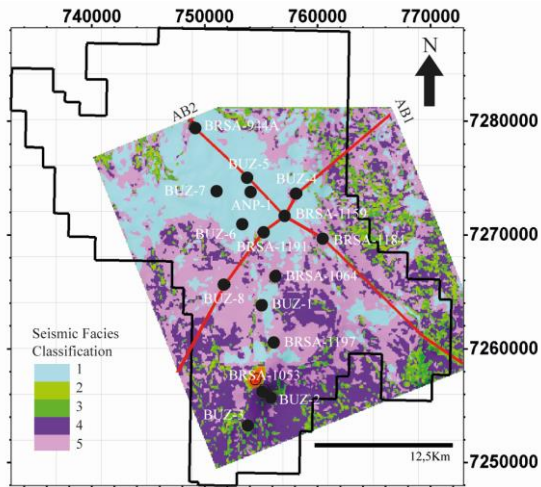
Figure 7: Seismic facies classification results represented in map view over the base of the salt (Barra Velha formation top).
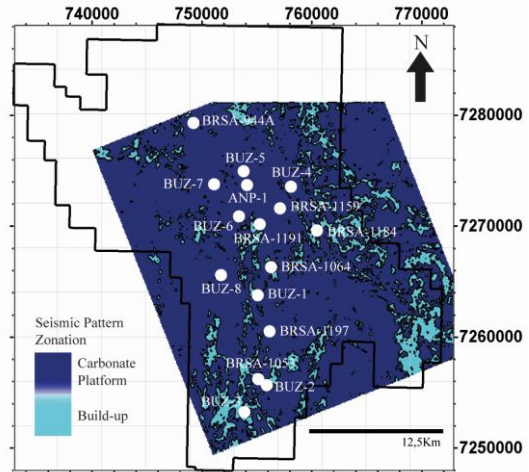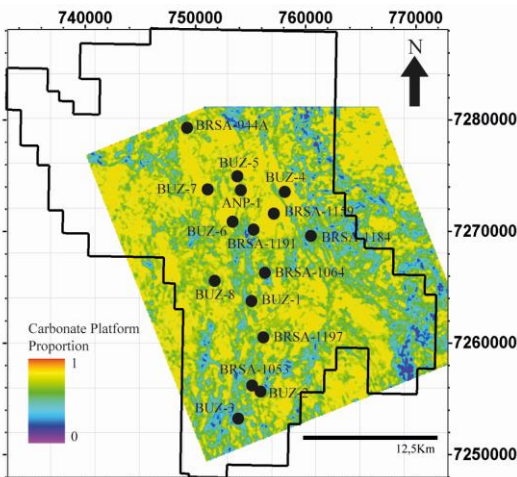

Figure 8: Carbonate platform probability map obtained from seismic facies classification.
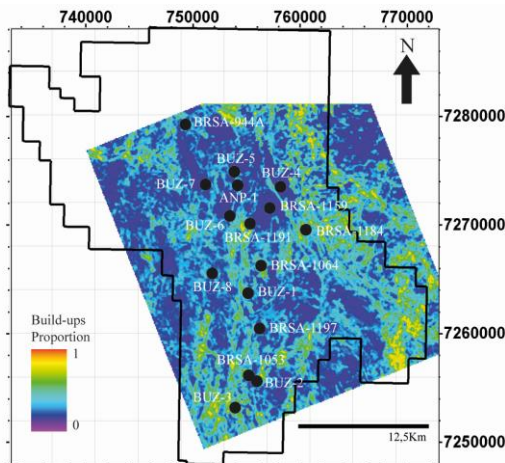
Figure 9: Build-ups probability map obtained from seismic facies classification.

Figure 10: Seismic pattern zonation map built from the most probable seismic facies classification.

Acknowledgments

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