Unsupervised machine learning for seismic facies classification applied in presalt carbonate reservoirs of the Búzios Field, Brazil

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Summary

The purpose of this work is to improve the characterization of the presalt carbonate reservoirs of the Búzios Field, Brazilian offshore, through the application of seismic attributes and unsupervised machine learning techniques. The methodology relied on the application of structural and stratigraphic attributes to identify the main reservoir seismic patterns, and a multiattribute seismic facies classification, based on K-means and hierarchical clustering algorithms, to map the distribution of these patterns and structural features within those reservoirs. As a result, we could evaluate the target zone by correlating the classes to its tectonostratigraphic elements.

Introduction

The massive volumes of hydrocarbons at the Brazilian presalt carbonate reservoirs and their elevated production rates make them extremely relevant to the Oil and Gas industry. In 2021, these reservoirs produced around 989.7 million boe, which represent 72.4% of the total oil and gas Brazilian production (ANP, 2021). However, even after years of exploration, the presalt zone remains a challenge to geoscientists due to the limitations of the geophysical methods to illuminate below salt layers and the geological complexity associated with carbonate rocks.

The heterogeneity of carbonate rocks is a product of their depositional conditions, genetic processes, and susceptibility to diagenesis, which generates complex pore systems and considerable spatial variety. At seismic scale, such rocks may produce weak amplitude anomalies, low impedance values, and often ambiguous responses, making them particularly challenging to map and characterize (Jesus et al., 2019).

As an attempt to overcome these limitations and to better understand the geological settings and the permoporous properties of rocks overall, seismic attribute analysis and seismic facies classification methods have become widely applied in reservoir characterization to produce more reliable interpretations (e.g., Jesus et al., 2019; Ferreira et al., 2021; Oliveira et al., 2022).

Seismic attributes are all the information obtained from seismic data (Taner, 2001). They can be acquired from different measurements and properties to provide mathematical, geophysical, and geological information to better characterize the subsurface, both qualitatively and quantitatively. They are used to emphasize information not always visible on seismic amplitude data. Meanwhile, the objective of the facies classification process is to describe enough variability of the seismic data to reveal details of the geologic features (Coléou et al., 2003). It leans on the artificial intelligence capabilities to learn and predict from large amounts of data, yielding to advanced reservoir characterizations.

The present work aims to improve seismic interpretation by classifying and distributing seismic facies and structural features in the presalt carbonate reservoirs of the Búzios Field, located at Santos Basin, offshore of Brazilian southeast margin (Figure 1). For this, we performed a multiattribute unsupervised classification using K-means (MacQueen, 1967) and agglomerative hierarchical clustering (Kaufman and Rousseeuw, 1990) algorithms. We generated volumes of acoustic impedance, instantaneous phase, hybrid spectral decomposition, coherence, and curvature attributes, both to distinguish seismic patterns and to operate as input data to the classification.

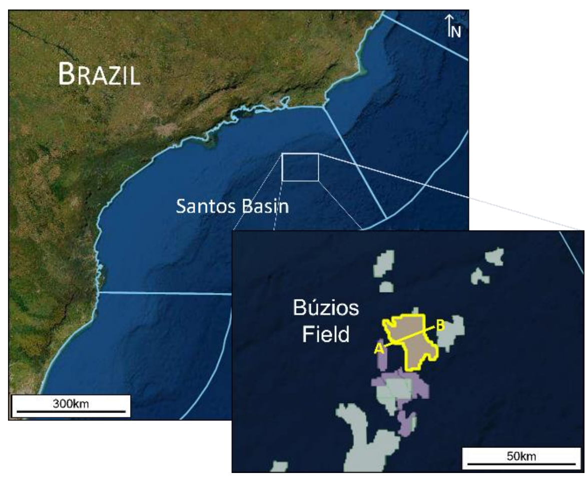

Figure 1: Búzios Field location in the Santos Basin, Brazil.

Theory and Method

The proposed workflow (Figure 2) consisted in: (1) data preconditioning, using a structural-oriented smooth filtering (Hale, 2009) to attenuate background noise and enhance signal to noise ratio; (2) tectonic and stratigraphic interpretation; (3) calculation of selected seismic attributes;

(4) main seismic patterns definition; (5) principal component analysis; (6) unsupervised machine learning technique for seismic facies classification; and (7) correlation of structural features and seismic patterns with the classes obtained. The data available comprises a 3D PSDM volume that covers all Búzios Field and fifteen wells along the area.

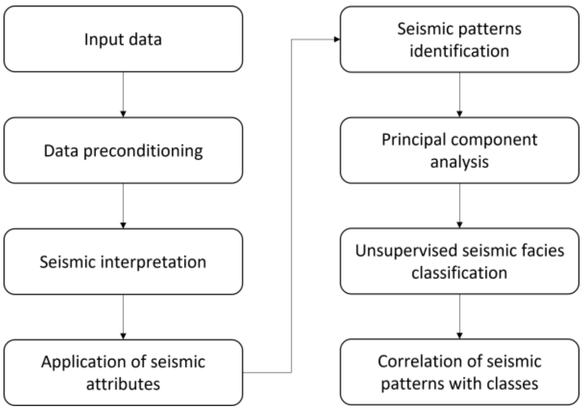

Figure 2: Methodology workflow.

The seismic interpretation consisted in mapping the main faults and horizons present in the presalt zone. It allowed us to analyze the influence of its structural framework in the location of the identified seismic facies, as well as delimitate the interval of the reservoirs for the facies classification.

After qualitative analysis, we selected attributes that highlight the main geologic characteristics found in the reservoirs. They can be divided into two categories, stratigraphic (acoustic impedance, instantaneous phase, and hybrid spectral decomposition) and structural attributes (coherence and curvature).

We used a model-based inversion algorithm (Russell, 1988; Dias et al., 2019) to obtain the acoustic impedance volume. There is an inherent connection between acoustic impedances and lithologies, once the former varies with several rock properties (e.g., porosity, pore fill), making its model well-suited for generation of 3D facies and petrophysical property models (Latimer et al., 2000).

Instantaneous phase is one of the attributes extracted from the complex seismic trace analysis (Taner et al., 1979), where the seismic trace is treated as the product of instantaneous amplitude and cosine of the instantaneous phase. This attribute emphasizes the continuity of events and, since phase is independent of reflection strength, it often makes weak coherent events clearer (Taner et al., 1979).

We performed the frequency spectral decomposition using a wavelet transform method (Sinha et al., 2005). Then, we selected the most representative frequency bandwidth to highlight seismic patterns, and calculated its envelope, generating the hybrid spectral decomposition attribute (Jesus et al., 2019).

We obtained the coherence cube from an eigenstructure-based algorithm (Gersztenkorn and Marfurt, 1999; Marfurt et al., 1999). The similarity between neighboring seismic traces was measured following an estimated dip and the analysis window set to provide resolution in the reservoir scale.

Volumetric curvature attributes measure how much a curve deviates from a straight line at a particular point (Roberts, 2001), being useful to delineate faults and stratigraphic features. The most positive curvature was extracted from dip and azimuth volumes (Klein et al., 2008).

With the combined analysis of the seismic attributes and the configuration of reflections, terminations, lateral changes, and geometry of the seismic units, we determined the main seismic patterns in the Búzios Field presalt reservoirs: carbonate platforms, carbonate build-ups, coquina banks and debris flow deposits. They were identified as means to comprehend the different types of layers behavior and categorize them.

Following, we carried out a principal component analysis (PCA) (Bishop, 1995) to evaluate the correlation between the attributes and obtain the maximum variation between them. The PCA finds the principal directions in the multidimensional data and determines the optimal shift and rotation of the data so that it is expressed in those directions, preserving as much relevant information as possible (Bishop, 1995).

For seismic facies classification, we applied an unsupervised learning method. The technique implemented combines the K-means algorithm (MacQueen, 1967) with an agglomerative hierarchical clustering algorithm (Kaufman and Rousseeuw, 1990). It is divided in three stages (Figure 3): (1) pre-processing, partition of the input data into smaller sets to reduce the number of samples for the clustering phase; (2) aggregation, clustering of the pre-processed data to the defined number of classes using the agglomerative hierarchical algorithm; and (3) tuning, moving the clusters slightly so they fit the original dataset optimally. This approach optimizes the hierarchical clustering and is well suited for large volumes of data. The data was classified into seven classes.

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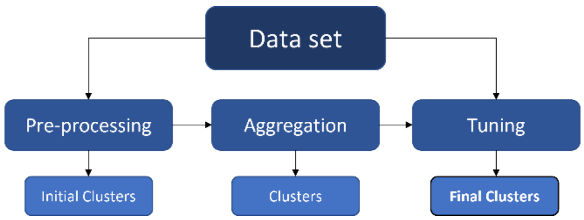

Figure 3: Stages of the unsupervised classification method.

Results

The use of seismic attributes assisted the delineation of the seismic facies patterns observed in the Búzios Field (Figure 4). In this area, the carbonate platforms present parallel to subparallel sedimentation, with medium to high seismic amplitude responses, and are situated at structural highs. The coquina banks, also found at structural highs, show a homogeneous texture at the seismic image. The carbonate build-ups have a mound shape geometry, low seismic amplitude response, and are usually located at the top of large throw faults. The debris flows are recognized by clinoform geometries, typically located at normal fault planes, and their amplitudes often exhibit chaotic internal arrangement. All of them may represent good reservoir rocks in this field (Castro, 2019; Ferreira et al., 2021). However, well data and core samples are essential to more accurate reservoir quality characterization.

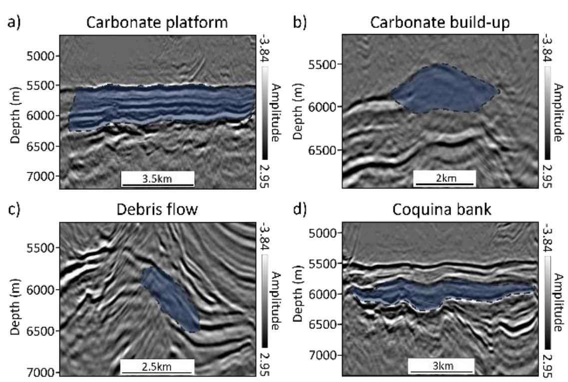

Figure 4: Main seismic patterns of the presalt carbonate reservoirs in the Búzios Field: a) carbonate platform, b) carbonate build-up, c) debris flow deposit and d) coquina bank.

The PCA was applied to re-dimension the data by rotating it into the principal directions. We decided not to reduce dimensionality, as all components made significant contributions to the classification. Although the number of PCA eigenvectors is equal to the number of seismic attributes, the facies classified from the eigenvectors allowed a better association with the seismic patterns than using the original sample space. Table 1 displays the accumulated contributions of PCA eigenvectors, where we observed that the first four components do not reach 90%.

Component	Cumulated contributions
1	28.24
2	53.37
3	71.63
4	86.74
5	100.00

Table 1: Cumulated contributions of each PCA component.

An interpreted seismic section with the main faults, seismic horizons and seismic patterns is displayed in Figure 5a. The presalt reservoirs are delimited at the bottom by the Pré-Jiquiá unconformity (green) and at the top by the base of salt (pink). Figures 5b, 5c and 5d display the acoustic impedance, coherence, and the unsupervised classification respectively.

The reflectors below the base of salt show good continuity, with high coherence and acoustic impedance at the center of the sections. To the left portion, these reflectors present the same behavior but with less continuity. They are correlated with the green facies. In general, these facies are related to high impedance and high similarity. They occur interspersed with purple facies in the upper part of the reservoir, between the Pré-Alagoas unconformity (blue) and the base of salt, where a carbonate platform was identified. The purple facies also associate with high coherence but are mainly linked to low impedance values. Dias et al. (2019) evaluated the relationship between acoustic impedance and porosity at the Búzios Field using well data. According to these authors, low acoustic impedance values are, in general, associated with higher porosities. Considering this, the green facies can be associated with lower porosities, while the purple class may represent facies with good porosity.

The red facies are associated with fault and fracture zones, as we noticed in the coherence and amplitude attributes. These facies follow the fault planes and are mainly related to debris patterns, corroborating to their chaotic internal arrangements. We can infer that the structural attributes (coherence and curvature) had the most influence in predicting them. These facies also occur above the debris deposit, in a carbonate build-up. This build-up shows chaotic facies distribution and differs from the build-up on the left side, which shows more continuity. The presence of the same seismic pattern with different internal structures emphasizes the intrinsic heterogeneity from the carbonate rocks, especially when affected by structural factors. Ferreira et al. (2021) state that, in the upper reservoirs, build-ups and debris facies hold better permoporous characteristics than carbonate platforms at this study area.

The coquina bank presents medium acoustic impedance values associated with yellow and light blue facies. Based on

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well log evaluation, Castro (2019) describes them as the one with best permoporous properties in the Búzios Field. The presence of fractures, highlighted by the coherence attribute, may contribute to greater porosity and permeability.

Conclusions

The unsupervised seismic facies classification combining K-means and agglomerative hierarchical clustering allowed the association of seismic facies to the main seismic patterns in the presalt reservoirs of the Búzios Field. The attributes were selected to highlight not only stratigraphic elements but also structural ones, therefore, contributing to the pattern recognition of the entire geologic framework. By that, the classification allowed identifying high fault and fracture density zones within the reservoirs. The results obtained suggest the conditions of the reservoir in terms of its architecture, and the distinct characteristics of each seismic pattern allow us to infer the potential of sediment accommodation and the energy of deposition. With assistance of petrophysical properties derived from well data and three-dimensional paleoenvironmental models, further work can be developed to provide quantitative analysis of facies and its correlation to depositional environments and diagenetic processes.

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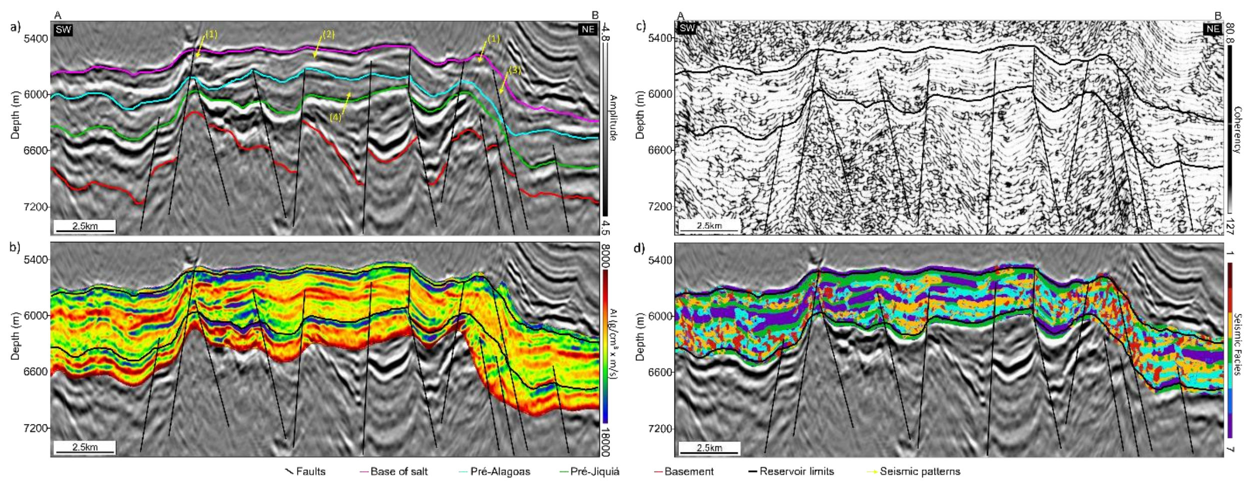

Figure 5: Crossline AB in a) seismic amplitude, b) acoustic impedance, c) coherence and d) seismic facies classification sections. The main horizons at presalt level are interpreted in a while reservoir limits are shown in b, c, and d. Yellow arrows point (1) carbonate build-ups, (2) carbonate platform, (3) debris flow and (4) coquina bank.

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