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Multiattribute framework analysis for the identification of carbonate mounds in the Brazilian presalt zone

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Abstract

Carbonate mounds, as described herein, often present seismic characteristics such as low amplitude and a high density of faults and fractures, which can easily be oversampled and blur other rock features in simple geobody extraction processes. We have developed a workflow for combining geometric attributes and hybrid spectral decomposition (HSD) to efficiently identify good-quality reservoirs in carbonate mounds within the complex environment of the Brazilian presalt zone. To better identify these reservoirs within the seismic volume of carbonate mounds, we divide our methodology into four stages: seismic data acquisition and processing overview, preconditioning of seismic data using structural-oriented filtering and imaging enhancement, calculation of seismic attributes, and classification of seismic facies. Although coherence and curvature attributes are often used to identify high-density fault and fracture zones, representing one of the most important features of carbonate mounds, HSD is necessary to discriminate low-amplitude carbonate mounds (good reservoir quality) from low-amplitude clay zones (nonreservoir). Finally, we use a multiattribute facies classification to generate a geologically significant outcome and to guide a final geobody extraction that is calibrated by well data and that can be used as a spatial indicator of the distribution of good reservoir quality for static modeling.

Introduction

Brazil has been producing oil from presalt carbonate reservoirs over the past decade. Recently, these reservoirs attained an incredible output of just more than 1.7 million barrels of oil equivalent per day, representing more than half of the country's daily production and demonstrating the importance of these carbonate reservoirs to Brazil. However, it is tremendously challenging to map and characterize these carbonate reservoirs given their considerable spatial heterogeneity, complex pore systems, and often ambiguous seismic responses.

Burgess et al. (2013) define criteria for discriminating different carbonate features in a seismic image that involve: regional constraints, analysis of basic seismic geometries, and analyses of geophysical details and finer scale seismic geometries. For the purpose of this work, we adopted analyses of seismic geometries and geophysical details, as well as amplitude anomalies and the behavior of frequencies in the reservoir interval, together with the high density of faults and fractures, to define carbonate features, many of which were assessed at a subseismic scale (Wright and Rodriguez, 2018).

Here, we propose a workflow for identifying and characterizing carbonate mounds in the Brazilian presalt zone using a combination of hybrid spectral decomposition (HSD) together with geometric attributes and curvature and coherence attributes. For this work, we use the term carbonate mounds to describe almost conical carbonate bodies of pronounced relief that are often difficult to map seismically due to their ambiguous limits and internal low-amplitude reflectors, but that exhibit excellent reservoir quality in terms of matrix and associated fracturing and that have been successfully drilled, evaluated, and tested. It is beyond the scope of this work to interpret these features further or to establish their depositional environment. For a broader perception of the many interpretations of these presalt carbonates we suggest, amongst others, the works of Wright and Barnett (2017) on Barra Velha Formation depositional systems, Buckley et al. (2015) on early Cretaceous lacustrine carbonate platforms, Wright and Barnett (2017) on depositional models for the presalt Barra Velha Formation, and Wright and Rodriguez (2018) on depositional interpretations of presalt environments and their links to seismic facies. Our

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Manuscript received by the Editor 3 January 2018; revised manuscript received 10 November 2018; published ahead of production 08 February 2019; published online 01 April 2019. This paper appears in *Interpretation*, Vol. 7, No. 2 (May 2019); p. T467–T476, 12 FIGS., 2 TABLES.
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workflow is focused on characterizing seismic facies and their relationship to present-day reservoir quality, which we believe can be applied and adjusted to different settings within the Brazilian presalt sequence. Our intent is to detail a workflow that can facilitate mapping of present-day good reservoir quality carbonate mound geometries to enable their characterization from a seismic perspective and to allow assessment of their spatial distribution for the purposes of reservoir modeling during the exploration and appraisal stages.

Seismic attenuation can greatly affect the quality of seismic signals perpetuated at considerable depths (Lupinacci and Oliveira, 2015; Yuan et al., 2017). Consequently, mapping carbonate mounds in the Brazilian presalt fields, which lie at depths ranging between 5000 and 6000 m and below an approximately 2000 m thick layer of salt, is a major challenge for geoscientists because of low seismic illumination and low-amplitude anomalies, low impedance, and the high fault and fracture density that are characteristic of these geologic features. It is difficult to identify and delineate such features in these presalt fields using only seismic data because of the complexity of the seismic image generated and the absence of impedance contrast between the reservoir and adjacent sealing facies (Zheng et al., 2007).

Despite many criteria for presalt seismic data having already been defined, we consider in this study that general information about the acquisition and processing of such data is essential to understanding its ambiguities and limitations. Furthermore, because seismic data can be contaminated by random and coherent noise arising from data acquisition or complex geology that can bias results even after data processing and migration (Chopra and Marfurt, 2007), data preconditioning is crucial to obtain good results (Lupinacci et al., 2017).

With respect to carbonate reservoir characterization, seismic facies analysis is increasingly seen as an effective way of estimating reservoir properties (Matos et al., 2007), combining different seismic attributes through pattern recognition algorithms, such as seismic multiattributes analysis (Rongchang et al., 2017) to identify, for example, lateral changes in a reservoir. Seismic attributes are important tools for reservoir characterization that can help to visually enhance or quantify features of interest (Chopra and Marfurt, 2007). However, selection of seismic attributes for analysis should be made with caution so as not to propagate false interpretations.

Curvature and coherence attributes can be used together in seismic multiattribute analyses to increase the reliability of this type of geologic analysis. The curvature attribute describes how bent a curve is at a point along its length (Roberts, 2001), focusing on changes in shape. This attribute is a good predictor of faults, as well as anticline and syncline structures (Klein et al., 2008) because it is not affected by variations in amplitude related to changes in lithology and fluid. The coherence cube attribute — a measure of the similarity between neighboring seismic traces in three dimensions — has been used since 1995 (Bahorich and Farmer, 1995) as a powerful seismic interpretation tool for imaging geologic discontinuities, such as faults and fractures, which are recurrently associated with carbonate mound features in this study area. However, many ways of calculating coherence can be implemented. Here, we applied the eigenvalue-coherence algorithm (Gersztenkorn and Marfurt, 1999; Marfurt et al., 1999), which uses several adjacent traces within a local window to estimate discontinuity for each sample.

Spectral decomposition is another widely used attribute for identifying seismic patterns. It can represent the seismic trace in a frequency domain or in subbands of frequencies. It can be used to identify subtle thickness variations and discontinuities, as well as to predict bedding thicknesses (e.g., Partyka et al., 1999). Spectral decomposition can also be used to identify low-frequency shadow, which may indicate the presence of hydrocarbons (Sun et al., 2002; Wang, 2007) or as in this study, to identify good quality reservoirs upon calibration by the well-log porosity response.

Additionally, a frequency bandwidth related to seismic facies can be selected from a spectral decomposition analysis, so a specific amplitude range can be isolated that represents a reservoir anomaly (called HSD) (Jesus et al., 2017).

Pattern recognition and classification of seismic features is fundamental to seismic data interpretation (Zhao et al., 2015), so uniting different criteria through several seismic attributes and establishing seismic facies classes is an excellent approach for isolating reservoirs of good quality in presalt carbonate mounds from shale or tight zones (nonreservoir).

We propose a workflow for identifying and characterizing carbonate mounds in the Brazilian presalt zone using a combination of HSD with curvature and coherence geometric attributes. We chose those attributes because of their ability to provide useful geologic information and used them to generate a seismic facies classification to specifically identify good-quality reservoirs in carbonate mounds. The extracted geobody was then used as a spatial indicator of the distribution of porosity in the reservoir.

Methodology

As described in Burgess et al. (2013), there is no clear set of diagnostic criteria for identifying many specific carbonate features, especially in frontier regions. From a geophysical perspective, the Brazilian presalt zone is still a frontier area, and given the influence of salt thickness on image quality of seismic data, seismic acquisition and processing details need to be carefully understood prior to performing any proposed methodology for seismic data interpretation.

Our workflow starts with preconditioning of the seismic data (Figure 1) using structural-oriented filtering (SOF) to remove some background noise and preserve fault edges. The SOF volume is then used to generate

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the curvature attribute. In parallel and to improve the overall vertical resolution, an image enhancement is applied to the SOF volume to calculate a coherence cube, which facilitates better identification of the faulted and fractured character of these presalt carbonate mounds.

We also apply HSD to the SOF volume to identify low-amplitude zones, which correspond to areas of good porosity. All of these seismic attributes are then combined to classify the seismic facies, which allow us to distinguish the most important facies representing good reservoir quality carbonate mounds and to extract a geobody that can then be used as a spatial control for porosity distribution in reservoir modeling.

Our methodology for characterizing carbonate mounds is thus divided into four stages: (1) seismic data acquisition and processing overview, (2) preconditioning of seismic data, (3) calculation of seismic attributes, and (4) classification of seismic facies. We describe these processing stages in detail in the following sections.

Seismic data acquisition and processing overview

The seismic acquisition was performed in 2013 from a single vessel equipped with 12 streamers, 8000 m in length and dual sources. The seismic data were recorded with an azimuth direction of 123°, a sampling rate of 2 ms, and a nominal fold of 80. Seismic acquisition parameters are presented in Table 1.

Depth imaging and velocity model building (VMB) in deepwater environments with complex and large evaporated layers is challenging for seismic illumination. These seismic acquisition parameters are not ideal for seismic illumination of presalt reservoirs. Had the seismic data been acquired as broadband, we could have applied a more efficient seismic processing.

The initial VMB was rendered on legacy data to obtain a more realistic and geologically relevant outcome by first applying an isotropic model for the initial step and then deriving a tilted transversal isotropic model from the tomographic data along with the seismic inversion (Bakulin et al., 2010). To decrease the well-to-seismic mistie, we updated the anisotropy models based on the well markers. Another important strategy we adopted for the VMB was to divide the salt layer using intermediate horizons that separated stratified salt from homogeneous salt. The background starting salt velocity for the tomography was 4500 m/s, and then we applied a weighted mask to guide the tomography and produce a stronger update in the stratified salt layer. This strategy made it possible to establish a more precise velocity model for the presalt zone.

Preconditioning of seismic data

According to Höecker and Fehmers (2002), three premises are required to apply filters successfully on poststack seismic data: orientation analysis, edge detection, and smoothing with edge preservation. Furthermore, considering the criteria we adopted in this case study (which include amplitude, frequency anomalies, geometry, and fault and fracture density), application of SOF should guarantee that the quality of the data improves without having to change the criteria.

To improve the quality of the seismic data contaminated with background noise, we applied SOF and image enhancement (Figure 2b and 2c) to precondition the seismic data (Qi et al., 2014). Preconditioning should be concentrated in the region of interest. The aim of SOF is to improve the lateral continuity of the seismic reflector and increase the signal-to-noise ratio. The SOF algorithm applies volumetric dip and azimuth calculations to avoid smearing of faults, fractures, and other discontinuities using an overlapping window method (Marfurt, 2006). We used the SOF output to calculate an image enhancement through increasing the frequency bandwidth (Bruce and Caldwell, 2003), thereby bolstering weak frequencies to reduce the effect of attenuation (Figure 2c). This step could be considered a type of spectral enhancement, the objective of which was to improve seismic resolution by increasing the frequency bandwidth. This process does not create

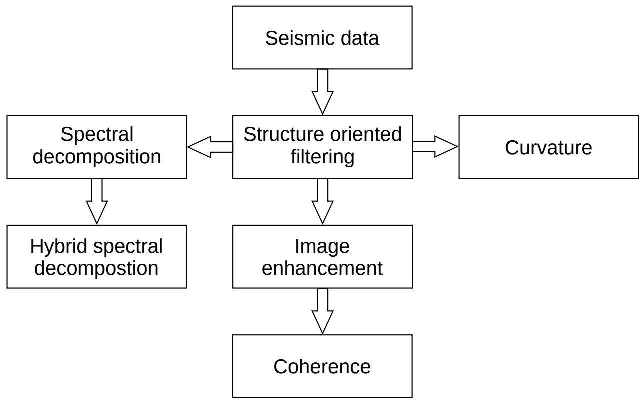

Figure 1. Steps used to calculate the seismic attributes.

Table 1. Acquisition parameters.

Acquisition parameters	
Shot interval	25 m
Cell length	6.25 m
Cell width	12.5 m
Line orientation	123° or 303°
Near offset (inline)	150 m
Source numbers	2
Source separation	25 m
Source depth	7 m
Streamer numbers	12
Streamer length	8000 m
Group interval	12.5 m
Group length	12.5 m
Streamer depth	9 m
Streamer separation	50 m

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new frequencies; it only enhances the contribution of some frequencies existing within the seismic data to better define the reservoir architecture.

Calculation of seismic attributes

The seismic attributes were calculated after SOF and image enhancement. The curvature and spectral decomposition attributes were generated directly from SOF. The coherence attribute was derived from the image-enhancement step. The HSD was obtained from the spectral decomposition step. The steps for calculating the seismic attributes are shown in Figure 1.

The curvature attribute describes how a surface deviates from being planar (Figure 3). Basically, it measures subtle lateral and vertical changes in dip that are often dominated by strong localized deformation; for example, carbonate reefs on 20° dipping surfaces can present the same curvature anomaly as a carbonate reef on a flat surface (Chopra and Marfurt, 2007). In this case study, several curvature attributes were tested, including the most positive, most negative, and dip curvatures. We found that dip curvatures, which are acquired by extracting the curvature in the direction of maximum dip, presented the best result. Volume curvature attributes can enhance seismic resolution, providing more insight into fault delineation and aiding in the prediction of fractures and their orientations (Roberts, 2001; Chopra and Marfurt, 2007). The curvature attribute is very susceptible to noise, so we calculated it after SOF.

The coherence attribute requires a central trace as a reference to make correlations between neighboring seismic traces using a vertical analysis window (Figure 4). Geologically, highly coherent seismic traces or waveforms indicate a laterally continuous lithology. Abrupt changes in waveform can indicate faults and fractures in the sediments (Chopra and Marfurt,

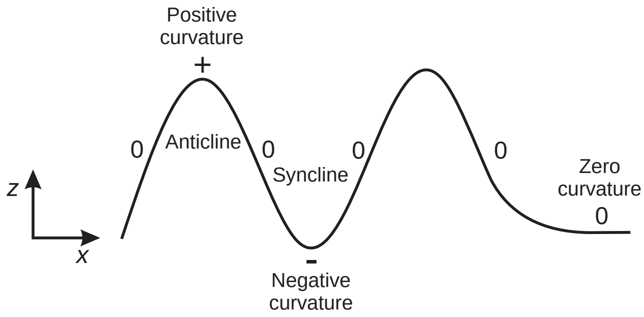
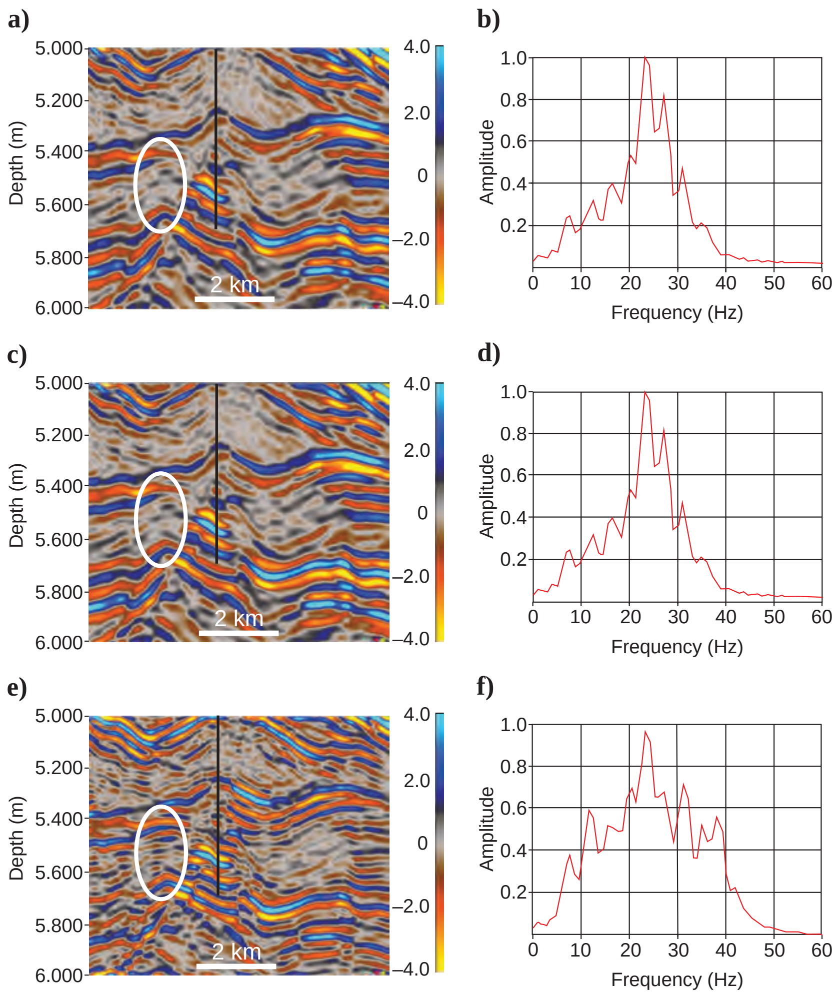


Figure 3. Curvature attribute in two dimensions, indicating that this attribute is positive in an anticline, negative in a syncline, and zero in a flat or dipping plane.

Figure 2. Preconditioning. (a) Input, (b) frequency content of input, (c) SOF, (d) frequency content of SOF, (e) imaging enhancement, and (f) frequency content of imaging enhancement.



2007). According several tests, it was possible to see that the difference between the curvature calculation results before and after image enhancement is that after image enhancement, there is the risk of boost up some noise and this attribute is very sensitive to noise. And, coherence shows to be more effective after improvement of the resolution. We used the coherence attribute to search along structural dips because it helps to reveal the true edges.

After we analyzed the dominant frequency and identified the frequency bandwidth that best represents the target, we used HSD to decompose the seismic data into frequency bands. This frequency bandwidth is selected to calculate the envelope attribute from which a specific amplitude range is isolated (Jesus et al., 2017). We obtained the HSD parameters after SOF application to maintain the proportionality of the amplitude and thereby preserve the reservoir anomalies. To achieve an optimized HSD for the area of interest, two steps are required: a sensitivity study (stage 1); and an isolation study of frequency ranges and representative amplitudes (stage 2).

Stage 1

For the sensitivity study, performed between the top and base of the reservoir of interest, we generated a dominant frequency attribute (Figure 5a) and selected the dominant frequency that best represented the reservoir interval. By analyzing the dominant frequency map at well locations 1, 2, and 3, we identified the dominant frequency as being approximately 8 Hz. Also, as part of our sensitivity study and using the same interval, we generated a root-mean-square (rms) amplitude map to identify low-amplitude zones, which is a recurring characteristic of presalt carbonate mounds. As illustrated in Figure 5b, all wells except for well 4 are in low-amplitude zones.

Stage 2

After our sensitivity study had revealed the frequency best representing the interval of interest and we had identified the respective low-amplitude zones through stage 1, we could isolate the frequency and amplitude ranges by applying a short-time Fourier transform (STFT) with a Hanning window for spectral

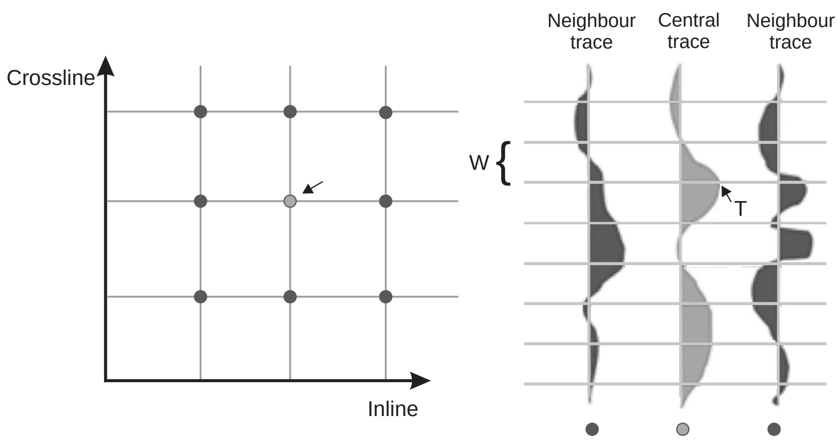


Figure 4. Spatial (or multitrace) analysis windows used to calculate the coherence attribute (W is defined as the vertical analysis window for time T).

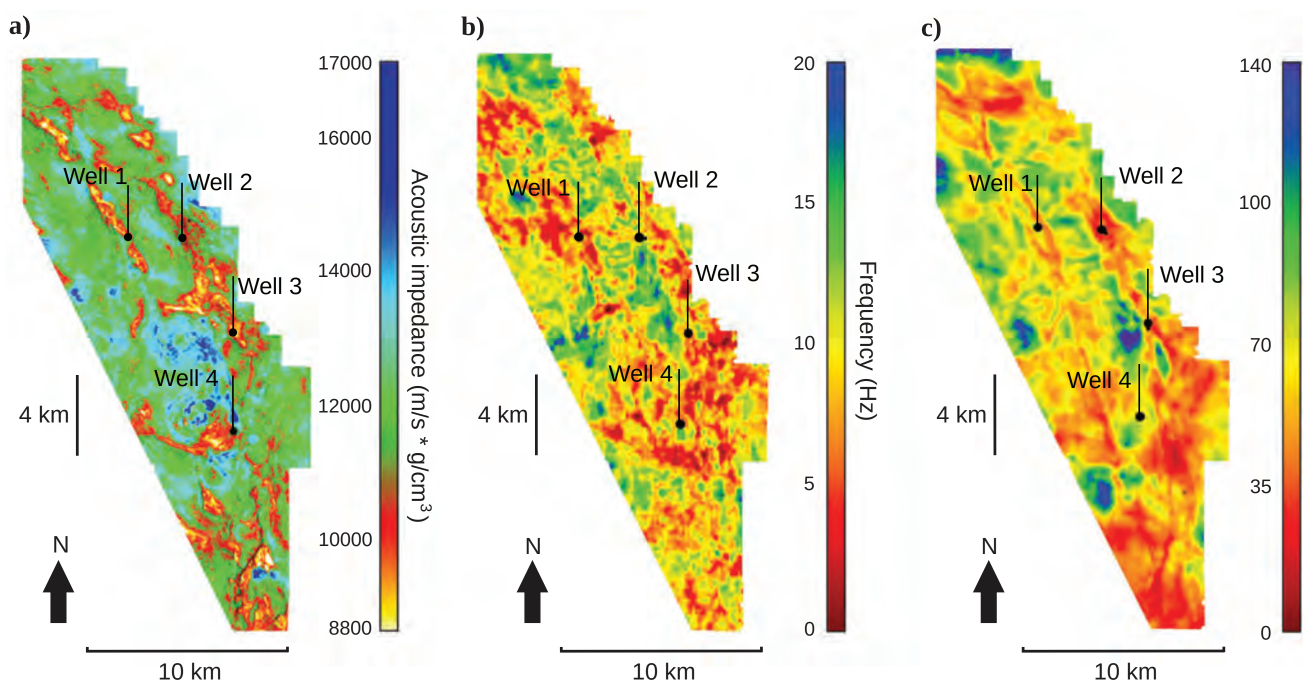


Figure 5. (a) Acoustic impedance, (b) dominant frequency, and (c) rms amplitude maps.

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decomposition of the SOF volume (Figure 6) and decompose the seismic data into frequency subbands. By knowing the representative frequency and well outcomes at the best well locations (wells 1–3) and identifying the low-amplitude zones for the presalt carbonate mounds being investigated, we could isolate the frequency and amplitude associated with the carbonate mounds by selecting a dominant frequency subband of 8 Hz and then calculating an envelope attribute for this subband. To define the interval for the envelope that represents these presalt carbonate mounds, it was necessary to also use the acoustic-impedance volume, which assumes a low-impedance occurrence in the mound zones represented by wells 1–3 (whereas well 4 was defined as nonreservoir).

As well 4 also presented a high value for the 8 Hz envelope, we established a cutoff to effectively isolate the carbonate mounds by combining the 8 Hz dominant frequency with the acoustic-impedance volume representing a low impedance for the carbonate mounds. Where the 8 Hz envelope and acoustic impedance presented low values, the area was considered a carbonate mound, but when only the envelope-attribute value was low, the area was considered a nonreservoir (Table 2). We applied a maximum cutoff value of 0.27 for the envelope attribute to discriminate between reservoirs and nonreservoirs.

Finally, the following script was applied to the envelope attribute for 8 Hz as the dominant frequency (spectral decomposition) to generate the HSD

$$\begin{aligned}\text{HSD} &= \text{IF Envelope Value} <= 540\,\text{THEN Envelope}\\ &= \text{Envelope ELSE Envelope} = 541. \qquad (1)\end{aligned}$$

Accordingly, if the envelope value was less than or equal to 540, then the value was retained (to represent reservoirs); otherwise, the standard value of 541 was assigned (representing nonreservoirs). The spectral decomposition and HSD for the top reservoir horizon are shown in Figure 7. A southeast to northwest trend of low amplitude passing through wells 2 and 3 can be seen in Figure 7a, which can be associated with the carbonate mounds. Figure 7b reveals that HSD was better than spectral decomposition in identifying the main low-amplitude trend corresponding to carbonate mounds (wells 2 and 3).

Figure 8 shows the main quality control of HSD, where pseudolog data from HSD was extracted at each well location (wells 1–4) and compared with the total porosity log rescaled to seismic output. The quality control showed a good correlation between HSD pseudolog and total porosity, so for low HSD values, there is an inversely proportional high value for total porosity. This outcome increases the confidence in our HSD.

Seismic facies classification

Seismic facies can be defined as a group of seismic responses with characteristics that distinctly differ

Table 2. Correlation between envelope and acoustic impedance.

Attributes	Reservoir (mounds)	Nonreservoir (shale)
Envelope	Low value	High value
Acoustic impedance	Low value	Low value

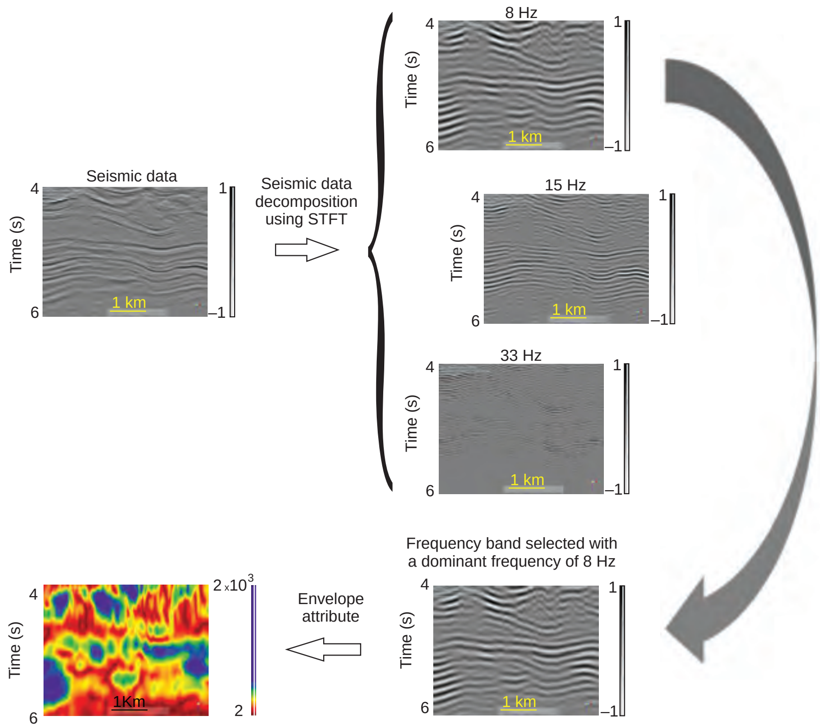

Figure 6. Schematic of stage 2 for optimization and application of HSD. First, the STFT is applied and a frequency band is selected. Then, the envelope attribute is calculated.

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from other facies (John et al., 2008). According to Farzadi (2006), a 3D multiattribute seismic facies classification helps to identify lithofacies and geometric variations within carbonate features.

Our selection of the seismic attributes is based on the geologic information that each attribute could provide to identify the good reservoir quality geometries we sought. The curvature attribute was useful for identifying the fractures and fault zones based on the curvature and discontinuities in the seismic reflector (Figure 9a). The coherence attribute also proved useful for identifying high-density fault zones in the carbonate reservoir (Figure 9b). We apply HSD in our workflow because presalt carbonate mounds typically exhibit low amplitudes due to fractures increasing their porosity. All these attributes (curvature, coherence, and HSD) are then combined for seismic facies classification, which is constrained from the top to the base of the reservoir.

The clustering technique that we use is unsupervised, which aims to partition the data set into clusters without a priori information concerning the membership in a given cluster of a sample input (Xu and Wunsch, 2005). We use a neural network as the algorithm for this unsupervised analysis because a priori tests show that it generates a partition with gradual changes in seismic facies patterns.

The input data are highly dimensional and voluminous, which can be problematic for seismic facies classification. Redundancy and excess dimensionality can be reduced by principal component analysis (PCA) (Zhao et al., 2015), through which the input data set is projected into a lower dimensional space formed by a subset of the highest variance principal components (Bishop, 1995).

PCA and self-organizing maps (SOM) represent multiattributes analyses that have proven excellent approaches for pattern recognition during seismic interpretation and reservoir characterization (Roden et al., 2015; Zhao et al., 2015). PCA can be used to convert statistical relationships among multidimensional data into simple, geometric relationships and to organize a data set of seismic attributes into a geometric SOM (Matos et al., 2007), producing a partition with changing patterns of seismic facies. In this work, we apply PCA with three components. To do this, we organized the model facies into a sequence of reference vectors in one dimension. The main purpose of PCA in this case is to assess the relative weights between curvature, coherence, and HSD, and thereby minimize redundancy. An optimal facies model is established through an iterative adaptation process. The clustering process starts by first specifying arbitrary nodes. Then, a sample input is chosen and mapped to the closest node. The optimal facies model and its adjacent neighbors are adjusted toward the sample input, and this step is repeated for 65 iterations so that the optimal facies model along with its closest neighbors become more like the selected input sample.

The seismic facies (Figure 10) we obtained in this work were generated using the following parameters: five classes, PCA with three components, and an unsupervised neural network method. The number of classes is defined empirically through what we term a "360° approach" (Figure 11) that consists of the following iterative loops: (1) obtain all seismic attributes and analyze them to see if they honor the defined criteria; (2) perform quality control using well information (in this work, we compare total porosity with HSD); (3) run unsupervised seismic facies classification; (4) select representative facies with features of good reservoir quality carbonate mounds and observe the resultant geobody extraction; (5) crosscheck the geobody distribution versus hydraulic flow unit (HFU), where HFU 2 and 3 means there is no flow and HFU 4 means there is flow; and (6) finish the process if the results are consistent with the well-log response

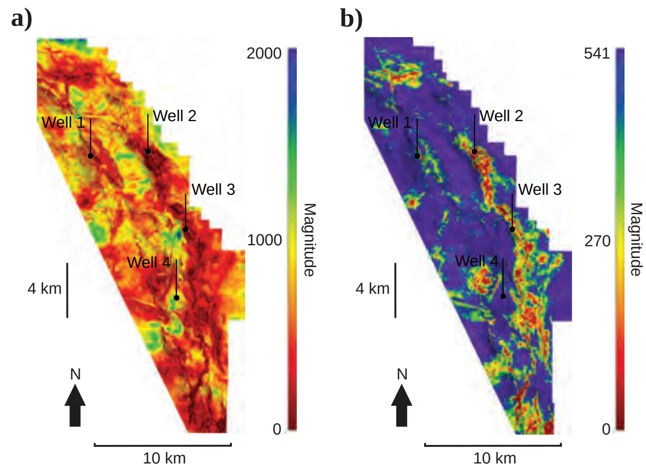

Figure 7. (a) Spectral decomposition and (b) HSD.

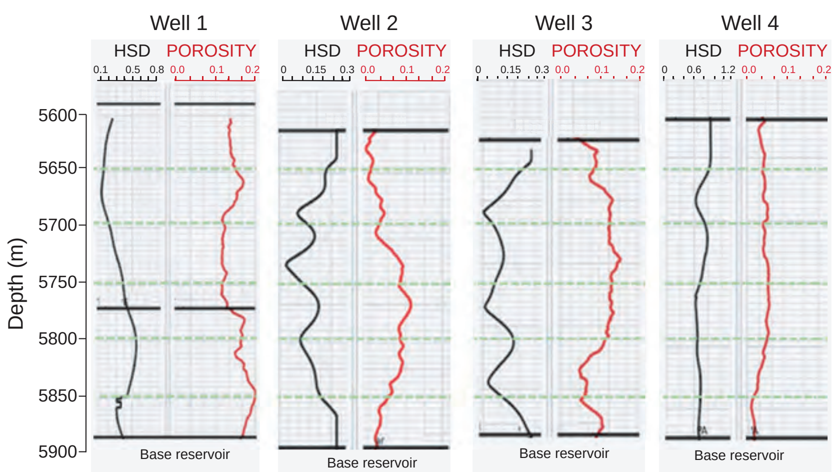

Figure 8. The HSD pseudolog (black) and the porosity log (red) are well-correlated (inversely). These logs were used as a quality control.

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and, if not, rerun it but change the key parameters (in our case, we changed the HSD cutoffs and the number of seismic facies).

Results and discussion

The outcomes of applying the curvature and coherence attributes to the structural map of the top of the reservoir are shown in Figure 9a and 9b. Low coherence values and high variations in curvature were found around the carbonate mounds, indicating a high density of faults and fracture zones.

We use the wells as a quality control to interpret the results of our HSD. We first calculate pseudologs of the HSD with a central frequency of 8 Hz that behaved similarly to the background model for seismic inversion. Inverse correlations between the pseudologs of the HSD and porosity for each well are presented in quality control (Figure 8). Well 4, which is in a clay zone, presents low HSD values.

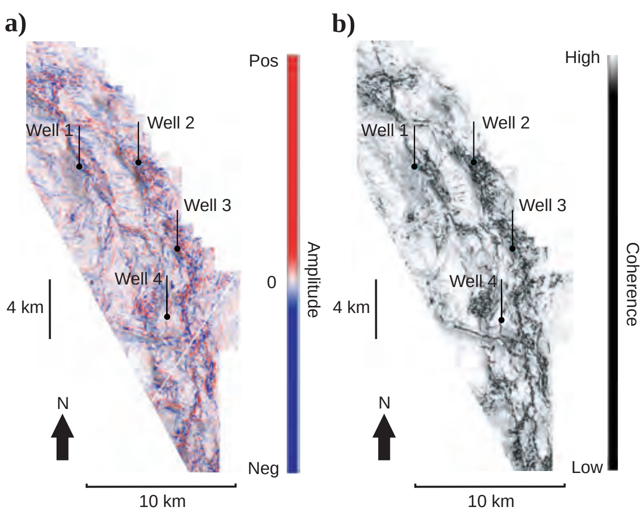

Figure 9. (a) Curvature and (b) coherence attributes applied to the structural map of the top of the reservoir, revealing faults and fracture zones around the wells.

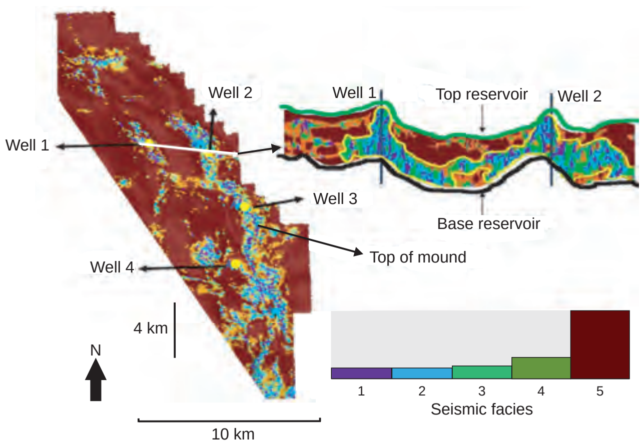

Figure 10. Seismic facies. Structural map of the top of the reservoir, highlighting the carbonate mounds.

Geometric attributes (curvature and coherence) were used to identify zones with a high density of faults and fractures, typical of carbonate mounds, for the seismic facies classification. Those attributes are also combined with the HSD data. We chose five classes of seismic facies, and a facies map indicating reservoir heterogeneities is provided in Figure 10. This map reveals facies connectivity. Facies 1–3 were identified in our 360° approach as carbonate mounds with high porosity and a high density of fractures, representing the best reservoirs. In this work, we consider classes 4 and 5 as nonreservoirs in terms of their quality. Figure 12 shows the extracted geobody of facies 1–3

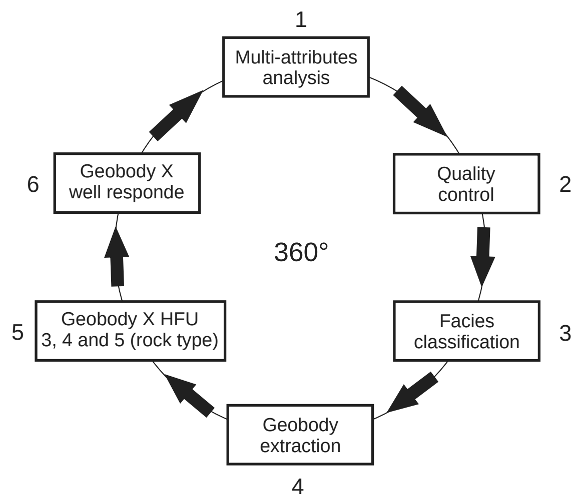

Figure 11. Illustration of our 360° approach applied in this work.

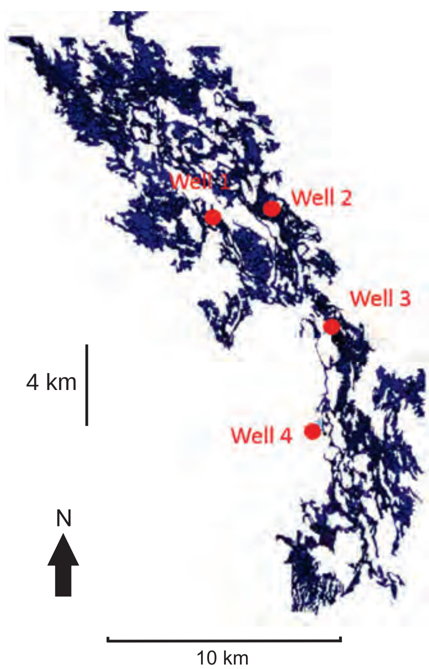

Figure 12. Geobody of carbonate mounds extracted from seismic facies classification.

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classified as good reservoir quality carbonate mounds. It is noteworthy that wells 2 and 3 are in this geobody, whereas wells 1 and 4 are in an area not identified as a carbonate mound, corroborating the well-log response.

Conclusion

The proposed workflow proved efficient in identifying good reservoir quality carbonate mounds within the complex environment of the Brazilian presalt zone. The coherence and curvature attributes were useful tools for identifying faults and fracture zones, high densities of which represent one of the most important characteristics of carbonate mounds. Because low seismic amplitude is also a typical feature of presalt carbonate mounds, we used HSD that allowed us to discriminate good reservoir quality carbonate mounds from poor reservoir zones (as identified for well 4). Our multiattributes facies classification generated a geologically significant outcome for static modeling, and the extracted geobody was used as an additional spatial indicator of porosity distribution. This workflow has been successfully applied in three other presalt carbonate fields.

Acknowledgments

The authors thank Petrogal Brasil for providing seismic data and support, especially the Exploration and Development Group. The authors also thank our partners, Petrobras and Shell, for their helpful feedback.

Data and materials availability

Data associated with this research are confidential and cannot be released.

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