A seismic reservoir characterization and porosity estimation workflow to support geological model update: pre-salt reservoir case study, Brazil

Laryssa Oliveira1*, Francis Pimentel2, Manuel Peiro1, Pedro Amaral2 and João Christovan2 present an integrated study that combines geophysical and geological approaches to estimate porosity and populate the reservoir geological model.

Introduction
Quantitative seismic interpretation plays an important and growing role for reservoir characterization, as seismic data become increasingly reliable as a result of the latest advances in acquisition and processing techniques.

With these advances, the multi-disciplinary integration between geology, geophysics and engineering becomes increasingly effective at reducing operational risks relating to reservoir exploration and production. In addition, a multi-disciplinary approach is essential for a better understanding of reservoir features.

In this paper, we present an integrated study that combines geophysical and geological approaches to perform porosity estimation and populate the reservoir geological model (static model). For pre-salt oilfields, owing to the complex porosity distribution in carbonate reservoirs, predicting a reliable porosity is a fundamental step for reservoir modelling.

After presenting some of the specific challenges associated with pre-salt reservoirs, we will describe pre-stack seismic data preconditioning. This first step is important to improve the seismic data set at the target level in terms of signal-to-noise ratio and resolution before it is used as input to seismic inversion, the second step in this workflow. In the seismic inversion process, reservoir elastic properties are estimated. From these inverted elastic properties, it is possible to perform a Bayesian lithofacies classification and, as the final products for this step, litho-probability volumes are generated in co-operation with the field’s geologists to be subsequently used as input to the geological modelling.

For the third and last step, we used facies probability volumes and acoustic impedance to estimate porosity. To use probability volumes in porosity model building, we designed a workflow to transform probability values into 3D porosity trends: first, a categorical facies volume is created by applying cut-offs on lithofacies probability volumes. For each layer of this model, a mean porosity per categorical region (facies), based on porosity logs at wells is calculated. Then, a relationship between acoustic impedance and mean porosity values was determined to create the final trend porosity volume to guide the porosity prediction away from wells.

Finally, we ran flow model simulations to quantify the benefits of the integrated workflow compared to a more commonly used 2D porosity map-based approach, showing the improvement in matching static and dynamic reservoir properties, mainly for pressure and Gas Oil Ratio (GOR) predictions.

Brazilian pre-salt reservoirs
Brazilian pre-salt fields are located in ultra-deep waters (around 1900 to 2400 m depth) in the Santos basin, southeast Brazil. The pre-salt area covers approximately 160,000 km² and around 20 oil fields have already been mapped since its initial discovery in 2006.

Pre-salt reservoirs are predominantly composed of lacustrine carbonates, especially microbialite carbonates in the higher reservoir zones (Estrella et al., 2008; Doborek, 2012) and carbonates with coquinas in the lower reservoir zones. In the lower reservoir zone, fractured volcanic rocks with some minor oil-filled porosity can also be found (Chang et al., 2008).

In general, pre-salt carbonates are very heterogeneous reservoirs, in terms of facies, and consequently, in terms of porosity and permeability. Processes such as diagenesis and recrystallization can modify the primary porosity and make the lithofacies heterogeneous. The higher reservoir zone is separated into two main groups: high-energy carbonates, composed mainly of stromatolites and grainstones, and low-energy carbonates, composed of laminites and spherulites.

Low-energy carbonates could present clay content and are associated with poor-quality reservoirs or non-reservoir. Meanwhile, high-energy carbonates present good porosity and permeability and are free of clay particles and are associated with good-quality reservoirs.

Feasibility and rock physics studies conducted on the basis of available wells (not further detailed in the present work) suggest a potentially good separation for reservoir and non-reservoir carbonate facies when crossplotting acoustic impedance (Ip) and Vp/Vs elastic attributes as shown in Figure 1.

In this context, a reliable seismic reservoir characterization study plays an important role in pre-salt reservoir characterization by making it possible to discriminate the different carbonate lithofacies, and separate reservoir and non-reservoir intervals based on the elastic properties derived through elastic inversion using seismic data.
depth-migrated input gathers. The application of pre-stack and post-stack processes helped to mitigate the effects on seismic amplitudes of the salt layer located above the main reservoir.

This sequence involves processes such as noise attenuation and an increase in vertical resolution performed in the pre-stack and post-stack domains.

In the pre-stack domain, steps such as muting from incident angles and f-k filtering were performed. The f-k filtering application was effective at attenuating coherent noise present in far offsets on common image gathers (CIGs).

Structurally-conformable and inverse-Q filtering were the main steps performed in the post-stack domain. The structurally-conformable filtering (Hoeber et al., 2006) attenuates coherent noise generated by salt flanks. This kind of noise appears as vertical stripes in seismic data, that is easily removed by structural filtering owing to dip discrimination between noise and the primary signal reflection.

The amplitude absorption effects were compensated by applying an inverse-Q filter. The Q volume was defined using geometric anisotropy and anisotropic elastic parameters at a priori velocity models. As a result, the low-Q layers were back-azimuthally stacked to prevent lateral shifts in the stacked sections.

For this purpose, a specific workflow was adapted to predict reliable reservoir properties, minimizing the uncertainties associated with the seismic data and considering the high heterogeneity of pre-salt reservoirs.

**Geophysical approach: seismic preconditioning, elastic inversion and lithofacies classification**

Improving the quality of seismic data prior to starting any quantitative analysis is an important task to ensure a successful reservoir characterization study. This seismic data conditioning is performed prior to elastic inversion and focuses on the reservoir interval at reservoir scale and its main features. Also, quality control (QC) is performed after the completion of each step to monitor data improvements and ensure preservation of the Amplitude Versus Offset (AVO) response.

**Seismic data preconditioning**

In order to improve the signal-to-noise ratio, seismic amplitude reliability and vertical resolution in the reservoir interval, we designed a specific data preconditioning workflow for the depth-migrated input gathers. The application of pre-stack and post-stack processes helped to mitigate the effects on seismic amplitudes of the salt layer located above the main reservoir.

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The amplitude absorption effects were compensated by applying an inverse-Q filter. The Q volume was defined using geometric anisotropy and anisotropic elastic parameters at a priori velocity models. As a result, the low-Q layers were back-azimuthally stacked to prevent lateral shifts in the stacked sections.
Finally, we applied a time misalignment correction to remove residual time shifts that could remain between angle stacks. This procedure is important before the inversion process as time misalignment between angle stacks implies a wrong estimation of the AVO gradient and has a direct impact on the Vp/Vs estimation during elastic inversion.

Regional surfaces such as water bottom, salt top and salt base. The Q factor values estimated using data from vertical seismic profiles (VSP) was used to fill the stratigraphic model built from the available horizons. By doing so, we created a 3D factor Q volume to be used during the amplitude deabsorption correction.
Stringent QC steps must be performed during pre-conditioning, in particular, to ensure preservation of the AVO response for primary reflection after each step. Using the available well data as support, each step and its impact on the AVO response was carefully analysed. AVO modelling was performed to compare the real and synthetic AVO response.

Figure 2 shows the results from all the pre-stack preconditioning processes and Figure 3 shows a comparison between the synthetic gather, generated by AVO modelling from well logs, and the raw and pre-stack preconditioned gather. This result shows that the AVO gradient was preserved and the AVO curve is more stable, without losing frequency content.

In addition to the AVO QC for each preconditioning step, QC was performed on sections crossing through key wells. Figure 4 displays the post-stack filtering results showing mid-angle stack sections. After removal of the linear dipping noise, the
lateral continuity is improved. The results from inverse Q filtering are presented in Figure 5. From these results, it is possible to observe the dominant frequency increase, providing an enhancement in seismic resolution.

The final type of QC we performed to monitor the improvement in seismic data quality during pre-conditioning is elastic inversion, applied on a small area around key control wells. We generated five angle stacks from each preconditioning step, with a minimum and maximum angle of incidence of 5° and 45°, respectively.

The QC at the well shows clearly that the inversion results from the preconditioned data are much better, yielding excellent estimates of Ip and a more stable Vp/Vs Ratio (see Figure 6).

**Elastic inversion**

This section shows elastic inversion results and lithofacies classification performed over a pre-salt carbonate field, highlighting how these results aggregate information for reservoir characterization and geological modelling.

The 3D, multi-cube simultaneous inversion scheme starts from an initial layered elastic model defined in the time domain (Coulon et al., 2006). During inversion, the initial model is perturbed by multiple iterations using a simulated lateral continuity is improved. The results from inverse Q filtering are presented in Figure 5. From these results, it is possible to observe the dominant frequency increase, providing an enhancement in seismic resolution.

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annealing procedure to find a global solution that optimizes simultaneously the match between the five input angle stacks and the corresponding synthetics calculated by convolution with full Zoeppritz reflectivity equations. In addition to the data mismatch term, the objective function contains 3D spatial continuity constraints that are used to attenuate the effects of random noise. The inversion works by perturbing Vp, Vs and density in each cell of the 3D stratigraphic grid. During inversion, independent perturbations of the different elastic parameters can be applied or perturbations can be coupled via correlations between Vp-Vs and Vp-density. In addition to updating the elastic parameters, the time-thickness of the micro-layers is also adjusted during the inversion process in order to maximize the coherence between the observed seismic events and the inversion layer framework.

Figure 7 shows the inversion results at a well location. The black line is the original well log; green, the well log upscaled to the stratigraphic grid resolution; and red, the inversion results. With respect to the seismic traces, the black trace is the input (real) seismic trace; red, the synthetic trace created from the inversion results. The comparison between upscaled blocky well log and blocky inversion results demonstrates that the inversion provided good estimates of the Vp/Vs ratio with a good decoupling between Ip and Is. Despite the definition and inclusion of an ultra-far angle stack (~45º), the inverted density cube obtained for this carbonate reservoir was difficult to stabilize and was not considered as a reliable input for the Bayesian lithofacies classification.

Lithofacies classification
Following the inversion process, we apply a Bayesian classification technique to these results to generate lithological probability cubes from seismically derived impedance and from lithological classification at the wells. These models are consistent with the seismic information and at the same time reproduce a priori information in the form of spatial geostatistical distributions between lithological classes. Using Bayes’s theorem, the elastic properties derived from seismic observations, the prior information from well logs and the geological knowledge are all combined to define a posterior probability distribution.

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attributes. The Vp/Vs attribute is stable and this is thanks to the rigorous pre-conditioning step applied to the seismic data. Bayesian lithofacies classification using these inversion results provided final probability volumes for each lithofacies and these final products are illustrated in Figure 11.

According to the results, we observe the predominance of good reservoir facies in the central area, shale content concentration located on the basal portion, particularly associated with structural low and in minor occurrence, and some poor reservoir facies in the southwest area. We also see the superporosity reservoir facies is highlighted in the NW-SE direction, encompassing the best producer wells for this pre-salt field. In this region, the effective porosity could reach values of more than 20%.

Figure 11 Litho-probability maps corresponding to (a) good reservoir, (b) shale, (c) poor reservoir and (d) super-porosity reservoir.

Figure 12 3D geobody extracted from the super-porosity probability volume.
At well locations, well logs are available to predict the porosity, such as neutron-porosity or magnetic resonance, where effective and free-fluid porosity is predicted. These measurements are very reliable at well scale. However, additional information is needed to model the porosity away from the well locations – where the seismic data (and derived acoustic impedance) can be used to guide the porosity estimation. Crossplotting impedance vs effective porosity from well logs makes it possible to establish a relationship between these properties and apply this relationship to the inverted acoustic impedance in order to obtain an effective porosity volume.

However, applying a porosity volume derived from seismic data directly to the geological model is not an easy task: the difference between the seismic and geological grid could create upscaling issues both in vertical and lateral domains. The standard approach used in the oil industry is to compute 2D average porosity maps from the main reservoir zones to be used as an external guide for porosity estimation.

Our purpose is to use not only impedance, but facies probability volumes converted into a lithofacies volume to be used as a guide for porosity estimation.
Porosity estimation for static model building

In this paper we propose a new approach, which involves using not only the acoustic impedance volume from the inversion but also using the previously generated facies probability cubes.

Before describing the methodology, the transfer of properties between the seismic and geological grid is an important discussion point. As we mentioned in the previous section, the seismic inversion and lithofacies classification are steps performed in the time domain and the static model is built in depth. For property transfer, the first step is to convert the probability volumes to the depth domain with the same vertical resolution as the geological grid. Then, another conversion is carried out between the seismic depth domain and the geological depth domain using the main reservoir surfaces as reference to position all reservoir zones in the same depth location. After these steps have been performed, the probability volumes can be transferred to the geological grid.

The first step in the proposed workflow is to build a ‘categorical’ facies volume from the probability facies volumes. This consists in establishing cut-off values on the probability cubes for each defined facies (super-porosity, shale, good and poor reservoir) and for each zone (1 and 2). The facies volume is illustrated in Figure 13.

In the second step of the proposed workflow, the average effective porosity from nuclear magnetic resonance (NMR) well logs are calculated by facies for each layer. As a result of this step, the ‘categorical’ porosity volume is a volume with different porosity values (average values) by facies and by layer, as shown in Figure 14.

The ‘categorical’ porosity volume only represents lithofacies with a constant porosity value per layer, which does not reflect the expected horizontal variability in porosity inside the reservoir. This is updated in the third step of the workflow.

A zone-by-zone relationship between mean porosity values and acoustic impedance by region and by layer is established. The objective of this step is to create a smooth horizontal porosity variability per layer controlled by impedance. Thus, a final porosity trend volume is created for use as a secondary variable in the geostatistical modelling of porosity.
In order to better quantify the value of the information brought by the integrated workflow, both versions of the porosity model (suggested workflow and commonly used trend maps) were brought to the engineering step and used for flow simulation, and the results are described in the next section.

Validation with flow modeling simulations – engineering data

The main function of the flow model is to be able to perform reliable predictions of well production to provide reliable revenue forecasts and support investment and decisions relating to the safety and optimization of oil and gas production.

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use of seismic data is most commonly limited to defining 2D porosity trend maps in order to guide interpolations between wells, an advanced workflow using 3D cubes from the previous steps was designed, resulting in a porosity model consistent with geological, geophysical and well data. The improved match with the field’s production history data, and GOR in particular, during reservoir simulation runs using this approach was the final step to validate the methodology and quantify its benefits from a reservoir management point of view.

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References