Facies-Driven Modelling of Reservoir Properties

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Summary

We examine how a knowledge of reservoir facies can be leveraged to gain an understanding of certain reservoir properties. The facies usually come from an analysis of the outcomes of seismic inversions. Then the reservoir models are constructed from the facies probability volumes and per-facies trends from logs or analogues.

There are two basic workflows. The first is aimed at improving the results of inversion. A first-pass inversion might incorporate a low frequency model which, although structurally compliant, is otherwise constant, containing no well log interpolation. The first-pass facies estimation from these inversions can be used to determine elastic models with valid spatial variability. They have been shown, when used as low frequency inputs to a second pass of inversion, to result in improved inversions with better ties to wells (Pendrel and Schouten, 2020).

The second workflow involves the modelling of derivative inversion properties such as clay volume (Vclay), water saturation (Sw) and effective porosity (Peff). Having first determined the efficacy of the facies definition to model the properties in question, probability-weighted per-facies trends are used to estimate the required properties. Perturbations can be applied to the trends to develop a whole set of viable outcomes from which uncertainties in the form of standard deviations are determined. The results in this paper follow this second workflow.

Introduction

Bayesian inference brings together prior information and newly available evidence to make probabilistic assessments of hypotheses. In the context of reservoir characterization, the prior information can come from well curves, geologic models or previous geophysical measurements. The primary goal is one of facies estimation and the new evidence is most often the outcomes of seismic inversions. Bayesian facies estimation is implemented in this case by the construction of per-facies, per-layer probability density functions (PDFs) in multi-dimensional cross-plot space (Pendrel et al., 2006). Integrating over the probability density functions centered at the inversion values with a range governed by the inversion uncertainties results in estimates of the probabilities of occurrence of each of the possible facies at each sample in the 3D project space. This analysis can take place in either time or depth. The estimation of the priors is a key component, the success of which drives the entire estimation process. Knowledge of facies, when combined with trend information can facilitate the building of low frequency models for inversions and lift that procedure from a naive interpolation of well logs to a true data-driven process. We apply this procedure to not only the estimation of reservoir facies but other derivative properties not usually associated with deterministic seismic inversions.

Method

We undertake a three-stage workflow toward the estimation of facies and inversion derivative products. At each stage our primary approach is Bayesian inference.

Stage 1: We design and estimate petrophysical facies at well locations and simultaneously view and interpret them in the elastic domain (Pendrel et al., 2017). This ensures that the goal of facies identification from seismic inversions is a tenable one. The design can be aided by rock physics template overlays from appropriate models. In addition, the Bayesian estimation of petrophysical facies produces facies probability curves as a by-product. These can then be used to build a 3D prior model for the Bayesian estimation of the facies from inversion data.

Stage 2: The facies PDFs designed in the elastic domain in Stage 1 are used to create 3D volumes of facies and their respective probabilities from seismic inversions. The inversion products are commonly P Impedance and Vp/Vs and might sometimes include density or other associated properties. The facies probability priors from Stage 1 provide geologic context. Their effects can be tempered by the assignment of prior uncertainties on a per-layer and per-facies basis. Other features include rock physics overlays and the estimation and inclusion of uncertainties in the inputs from the seismic inversions (Pendrel et al., 2016).

Stage 3: The facies and their associated probabilities are used to estimate various reservoir properties. An immediately obvious candidate is density which is usually difficult to obtain unless there are sufficiently large angles of acquisition. But P Impedance and Vp/Vs are also possible. An initial inversion might be derived using a generic low frequency model that is structurally compliant but otherwise constant. This is the opportunity to create a true spatially-variable model. This is done by creating per-facies trends from logs and marrying them with facies probabilities from Stage 2. Then the modelled property is the weighted average of the per-facies trends, the weights being the probabilities (Pendrel and Schouten, 2020). A simpler approach is to use the facies PDF means instead of trends although no inter-facies value variability is possible in this case, except from the natural variability in the facies probabilities themselves. We also admit the possibility of uncertainties in the trend information that can be adjusted on a per-layer and per-facies basis. This is also useful in a final calibration of the model against logs.

The modelling of other reservoir properties beyond those directly associated with inversions is also possible. PDFs for those properties will not have been previously determined and therefore must be done at modelling time. The means of those PDFs are used by the method described above to build a property model. The PDF standard deviations provide inputs to an estimate of the net uncertainty in the model. A set of simulated results is obtained by sequentially adding and subtracting to each of the N facies trends, its standard deviation. This generates a total of 3^N combinations. Then, the standard deviation in the set of simulations is determined at each point in 3D space. Typically, the results are not a constant but variable spatially and vertically across the project. Thus, a complete model would consist of a mean model and two others - plus and minus the standard deviations.

Results

We demonstrate the above ideas using a Gulf of Mexico data set. Geologically, this is a set of two vertically-stacked deltaic systems of middle Pliocene age. They average about 400 ft. in

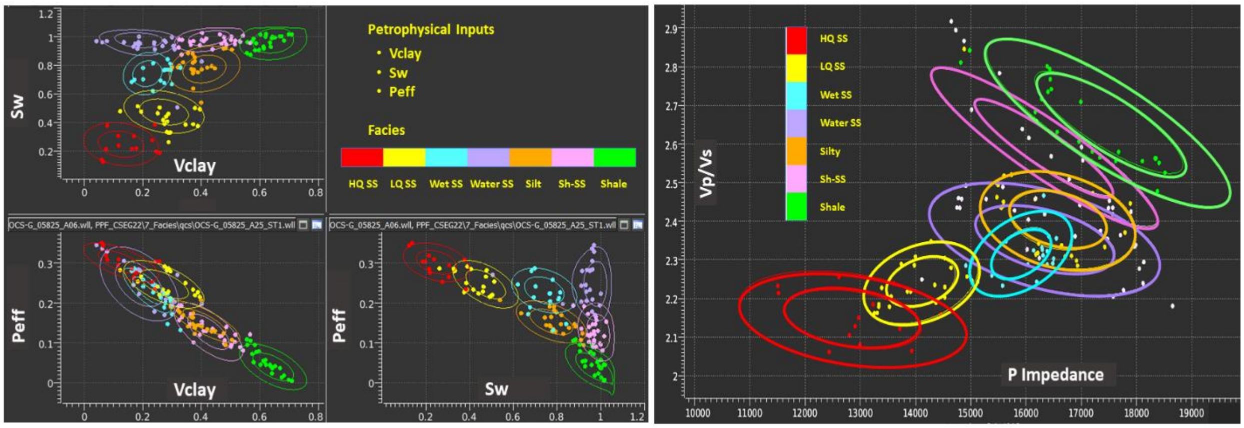

Figure 1: The left figure shows the petrophysical facies design from Sw, Vclay and effective porosity. Pdfs have been constructed corresponding to the seven facies. The first two standard deviations are shown. There is good separation of the facies types. On the right, the same facies have been shown in the elastic domain of P Impedance and Vp/Vs. The separation is not as good here but still enough to identify the facies end members.

thickness and are separated by about 500 ft. Within the play area are delta slope deformation, slump-induced turbidites and thin mouth-bed deposits without the presence of any delta plain facies. Below the key Green horizon, we recognize both upper and lower gas-charged sandstones.

Stage 1: In Figure 1 (left), seven facies members are designed from Vclay, Sw and Peff logs and described by PDFs. They are high and low quality hydrocarbon-bearing sandstones, wet and water-saturated sandstones, silt, shale and shaley sandstones. Facies resolution is good in petrophysical space but less so in elastic space (right). Nevertheless, the key high quality (HQ) facies should be easily resolvable.

Stage 2: In Figure 2 are the most-probable facies from Bayesian inference. Probability volumes (not shown) were also computed for each facies member for use in Stage 3. Various QCs such as entropy-based confidence indices (Pendrel and Schouten, 2019) were also computed.

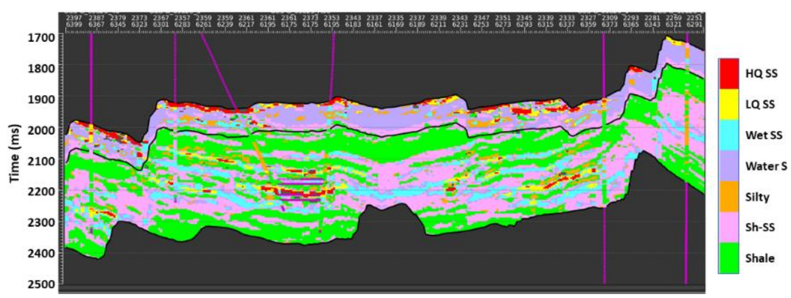

Figure 2: Most-probable facies from the Bayesian inference process described in Stage 2. The inputs were P Impedance and Vp/Vs from inversion.

Stage 3: In Stage 3, we compute our final models from the facies probabilities in Stage 2 and per-facies trends from logs (not shown). In this way, we have computed models for density, Sw, Peff and Vclay. The PDF design for Vclay is illustrated in Figure 3. Note the facies-dependent variability in the PDF means, indicating that Vclay can be considered to be a candidate for modelling in this stage. The mean result for Vclay with Vclay logs overlain is shown in Figure 4 (upper) along with the final Vclay standard deviations determined by the method described above (lower). In our prototype algorithm here, we considered the facies in groups of three for the standard deviation computations in order to make them tractable. The Vclay values are intuitive, following from the facies model in Figure 2. Agreement with the logs is fair enough. We have not followed up on disagreements to determine if the quality of the Vclay logs might be suspect in some areas.

Conclusions

We have shown how Bayesian inference can be used to establish facies definitions in both petrophysical and elastic space and be used in the estimation of derivative reservoir properties. The method includes an estimation of uncertainties from property standard deviations which are observed to be facies-dependent and variable both laterally and vertically.

Acknowledgments

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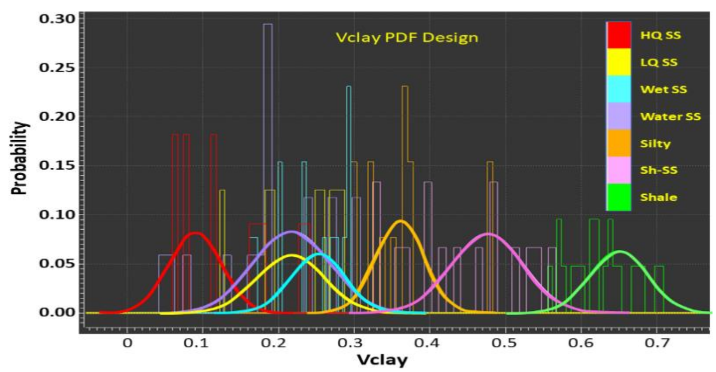

Figure 3: PDF design for Vclay estimation is shown in the figure. The background histograms are from log data.

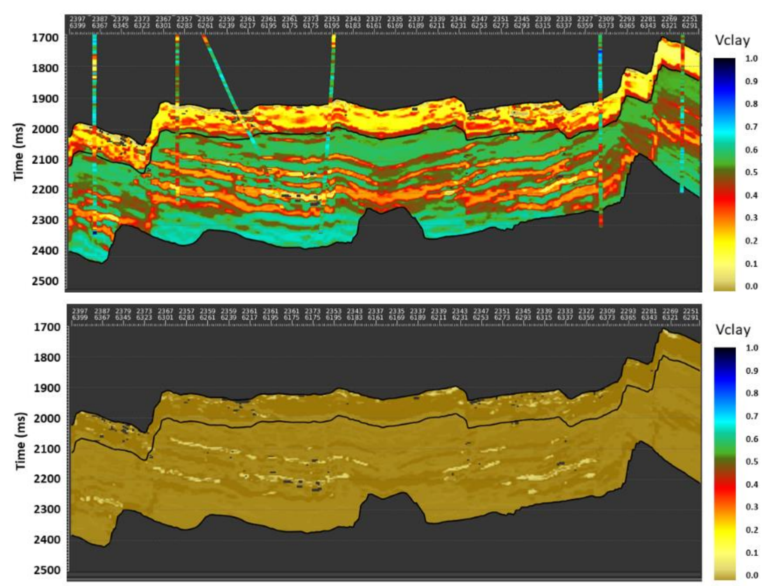

Figure 4:The upper panel shows the estimated Vclay from facies-driven modelling. Vclay logs have been overlain. The lower panel is the estimated standard deviation in Vclay from a set of facies probability assumptions. The possible range of the facies probabilities was estimated for each facies separately from the standard deviations of their Vclay PDFs. Note the variability in Vclay standard deviation across the figure.

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