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Realistic Uncertainty Quantification in Geostatistical Seismic Reservoir Characterization

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SUMMARY

Making informed field development decisions requires taking uncertainty into account. Geostatistical inversion is a key technology for quantifying uncertainties using available seismic and well data. However, the common practice, consisting of choosing the "best possible" parameters, results in unrealistically small uncertainty estimates. In this paper, we propose a multi-scenario approach to geostatistical inversion. By considering various alternative scenarios, a more realistic picture of the overall uncertainty can be built. This is illustrated on a case study, where the traditional single-scenario practice and the proposed multi-scenario approach are compared.

Introduction

Assessing uncertainties is one of the most difficult and controversial aspects of reservoir characterization. It is about quantifying what we know and do not know about the reservoir from indirect and partial measurements. Uncertainty cannot be measured and is inherently subjective (Corre *et al*. 2000, Caumon *et al*. 2004). However, accounting for uncertainty is key to making better field development decisions based on the available data.

Geostatistical inversion is the technique of choice for estimating uncertainty: it can generate multiple high-detail realizations of elastic and petrophysical properties, constrained to the seismic and well data (Doyen 2007). The value of a particular criterion of interest (e.g. average porosity or in-place hydrocarbon volume in the reservoir, reservoir thickness at a target well location) can be calculated for each of the generated realizations and the distribution of these values provides the uncertainty estimate. All too often, users of geostatistical inversion end up choosing a set of input parameters and then generate as many realizations as they can with those parameters. As suggested by Caers (2005), this approach leads to uncertainties that are unrealistically small. In this article, we describe a better approach to capturing the overall uncertainty and illustrate the impact on a case study.

Variance and Bias

In estimation theory, the uncertainty associated with a prediction can be decomposed into two components: variance and bias (Fortmann-Roe 2012). These concepts can be extended to geostatistical inversion.

Variance represents the random fluctuations, or how much the prediction can vary between different realizations of the same prediction model. In geostatistical inversion, the generated realizations are samples of a posterior probability distribution function (pdf), which combines the available data (seismic, wells) and prior information. The prior is defined by various input parameters, which typically include the location of the main horizons and faults, the stratigraphic framework, the pdfs and variograms for the inverted continuous and facies properties. The uncertainty associated to the seismic and well data is also taken into account in the posterior pdf. When all these input parameters are fixed, the different realizations are the result of the same posterior pdf sampling process with a different random seed. They are all consistent with the data and prior information. The variations between them reflect the non-uniqueness of the estimation problem and the range of possible solutions for a given set of parameters. This is the uncertainty from variance.

Bias is the part of the uncertainty due to the error in the prediction model itself. In geostatistical inversion, the choice of input parameters is subjective and based on interpretations and assumptions. An error in some of the input parameters (structural framework, prior facies probabilities, variograms, seismic uncertainty and so on) would translate into a systematic error, or bias, on the estimated criterion. These parameters are not known with certainty, yet they control the range of results that can be obtained. In other words, the uncertainty from bias is the uncertainty related to the choice of input parameters. It can be captured by generating realizations with various alternative scenarios, i.e. different sets of inputs that are all considered to be realistic.

Common practice and recommended workflow

A common practice in many reservoir characterization studies is to choose the "best possible" input parameters and generate a large number of realizations with these fixed parameters. In terms of bias and variance, this means estimating the uncertainty from variance only and neglecting the bias. This practice needs to be challenged because the uncertainty from bias is actually very often and by far the larger part of the overall uncertainty. Moreover, a large number of realizations generated with the same settings may give a false sense of accuracy, where in fact the uncertainty thus estimated will be unrealistically small. This will be illustrated in the case study.

Since the uncertainty from variance is almost always small compared to the uncertainty from bias, quantifying it precisely is of limited practical use. Our experience is that a few dozen realizations are typically sufficient to adequately estimate the uncertainty from variance. The algorithm being used for geostatistical inversion can have an impact on this number: more realizations may be required with Sequential Gaussian Simulation (SGS)-type algorithms, where realizations share the same random path, than with Markov Chain Monte Carlo (MCMC)-type algorithms, where realizations are independent from each other.

It is comparatively more important to focus attention on the uncertainty from bias. It should be taken into account by considering a range of plausible scenarios, corresponding to realistic variations of the input parameters (including the location of horizons and faults). Considering all scenarios can be very challenging, or even impossible in practice given the large number of parameters. It is therefore advisable to first determine the few most important parameters. These vary from case to case, depending on the reservoir, data and decision criterion of interest. By generating a number of realizations for each scenario, both the variance and bias contributions are taken into account and the overall uncertainty is better apprehended.

Case study

The study field used here is the same as the one described by Marquez *et al.* (2013). Geostatistical simultaneous joint inversion of elastic properties, effective porosity, water saturation and facies (sand and shale) is carried out, with facies proportions, prior pdfs and variograms specified for each facies. In this study, we use a multi-scenario approach to assess the overall uncertainty on the volume of pay in the reservoir.

A set of input parameters is chosen as our reference scenario. Alternative scenarios are considered by varying successively three parameters: the prior probabilities of sand and shale, the model variogram for the facies and the seismic signal-to-noise ratio defining the estimated measurement error on the seismic data. Other parameters such as the structural model or the depth of the oil-water contact are considered deterministic here, even though they could be large sources of uncertainties. However, this does not diminish what this simplified study highlights. In total, we have defined eight alternative scenarios for the prior facies probabilities, five alternative scenarios for the variogram models and two alternative scenarios for the seismic signal-to-noise ratio around our reference scenario.

In order to decide how many realizations to generate for the alternative scenarios, we first generated 180 realizations for our reference scenario, with fixed input parameters. Figure 1 shows the mean and standard deviation of the volume of pay as a function of the number of realizations. They vary greatly when a small number of realizations are being used to calculate them and progressively stabilize around a value when the number of realizations increases. Based on this analysis, we considered that 20 realizations were sufficient to provide an acceptable approximation of the uncertainty from variance. Therefore, we have generated 20 realizations for each scenario in this study.

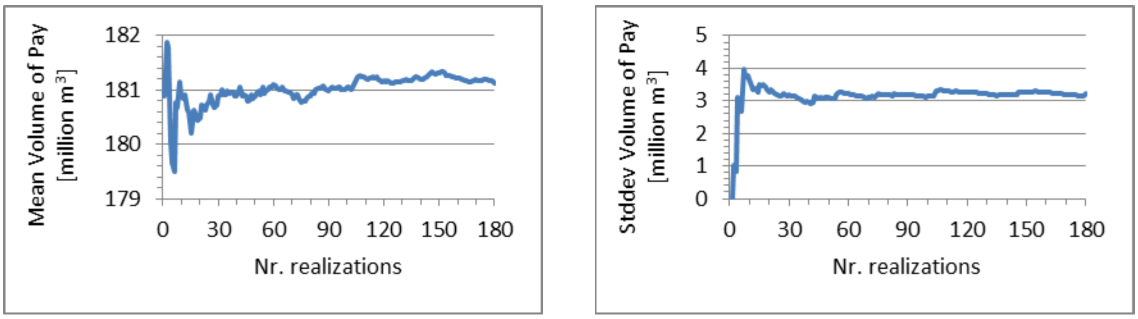
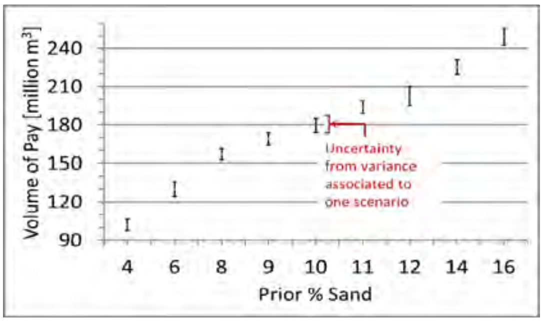


Figure 1 *Mean and standard deviation of the volume of pay as a function of the number of realizations, for the reference scenario (fixed parameters).*

1. Impact of prior facies probabilities on uncertainty. Based on the available well data, we estimated the reservoir zone to contain 10% of sand and 90% of shale. The estimate takes into account the fact that wells tend to be biased and preferentially drilled in the best reservoir quality rocks. The value of 10% was chosen for the prior sand probability in our reference scenario, but values ranging from 4% to 16% were also considered plausible. We therefore defined nine different scenarios in total (reference scenario and eight alternative scenarios) covering that range.

Figure 2 left shows the volumes of pay calculated on the 20 realizations generated for each scenario. The estimated volume of pay is sensitive to the prior sand probability and tends to increase significantly with it. This does not come as a surprise: the more sand, the bigger the volume of pay. There is no direct linear relationship between the prior sand probability and the volume of pay because the realizations are also constrained to honour the seismic data. But the two are nevertheless strongly correlated. Figure 2 right compares the estimates of volume of pay from the multi-scenario case with the estimates from the reference scenario only. The two histograms are made from the same number of realizations, 180 in total in both cases. In the multi-scenario case, the uncertainties from bias and variance are captured, whereas in the common practice of generating realizations from a single scenario, the uncertainty from bias is ignored. It is clear from this figure that relying only on realizations generated from a fixed set of parameters results in an overall uncertainty that is drastically underestimated. The standard deviation of the estimated volume of pay is about 43 million m^3 in the multi-scenario case, whereas it is about 3 million m^3 in the single-scenario case.



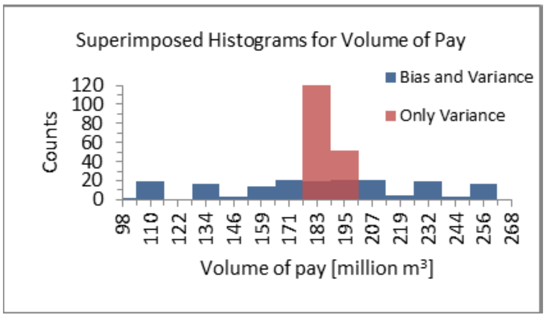


Figure 2 *Volume of pay calculated for nine different prior sand probability scenarios, each with 20 realizations. Left: the range of volumes is shown for each scenario as uncertainty bars. Right: the histogram of the volume of pay is shown for the 180 realizations from all nine scenarios (blue) and compared to the histogram for 180 realizations from only the reference scenario of 10% prior sand probability (red).*

2. Impact of facies variograms on uncertainty. For the facies variograms, we have chosen the following scenarios, based on the well data and amplitude attributes:

1. Reference: 100% exponential with medium-long range (10m vertically, 1000m laterally)
2. 100% Gaussian with medium-long range (10m vertically, 1000m laterally)
3. 100% exponential with long range (15m vertically, 1025m laterally)
4. 100% exponential with medium range (10m vertically, 875m laterally)
5. 100% exponential with short range (5m vertically, 750m laterally)
6. 50% Gaussian - 50% exponential with medium-long range (10m vertically, 1000m laterally)

For each of these scenarios, 20 realizations are generated. As can be seen on Figure 3, the facies variogram has a big impact on the overall uncertainty. The variogram models in scenarios 2 and 6, corresponding to smoother facies variations, tend to be associated to larger volumes of pay and uncertainties compared to the exponential models. The volume of pay varies between 175 and 192 million m^3 for the reference scenario only versus 164 and 220 million m^3 in the multi-scenario experiment. The wider histogram distribution in the multi-scenario case highlights the importance of taking into account both uncertainties from bias and variance.

3. Impact of seismic signal-to-noise ratio on uncertainty. The uncertainty associated to the input seismic volumes can be specified as signal-to-noise ratios in geostatistical inversion. In our reference scenario, we have chosen 10 dB for each partial stack. The two alternative scenarios that we consider are signal-to-noise ratios of 9 and 11 dB. Figure 4 shows how this impacts the estimates of volume of pay. The results show a lower sensitivity to small variations in seismic signal-to-noise ratios.

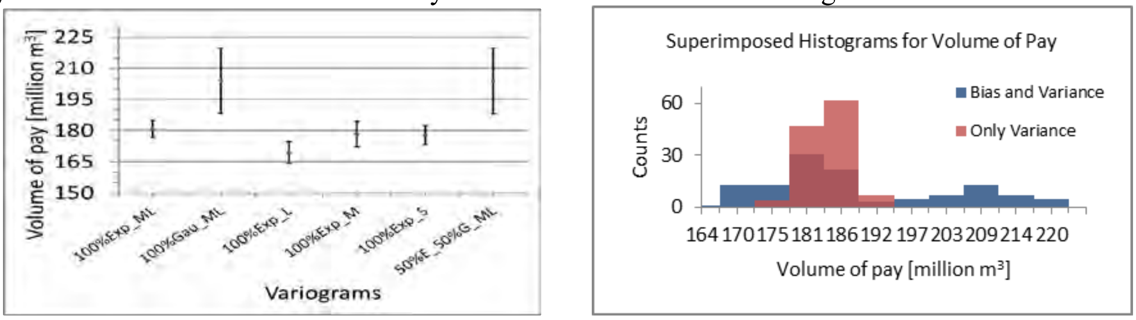


Figure 3 *Volume of pay calculated for six variogram scenarios, each with 20 realizations. Left: the range of volumes is shown for each scenario as uncertainty bars. Right: the histogram of the volume of pay is shown for the 120 realizations from all six scenarios (blue) and compared to the histogram for 120 realizations from only the reference scenario (red).*

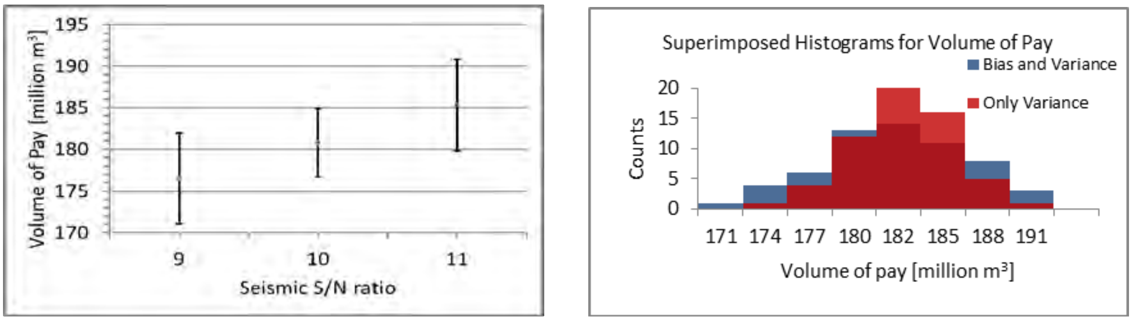


Figure 4 *Volume of pay calculated for three seismic signal-to-noise scenarios, each with 20 realizations. Left: the range of volumes is shown for each scenario as uncertainty bars. Right: the histogram of the volume of pay is shown for the 60 realizations from all three scenarios (blue) and compared to the histogram for 60 realizations from only the reference scenario (red).*

Conclusions

As illustrated by this case study, combining realizations generated with different parameters is necessary for realistic estimates of the overall uncertainty. This multi-scenario approach to geostatistical inversion allows for more robust uncertainty assessment and therefore provides a sturdier foundation for making informed decisions.

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