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# ASSESSMENT OF NET-TO-GROSS UNCERTAINTY AT RESERVOIR APPRAISAL STAGE: APPLICATION TO A TURBIDITE RESERVOIR OFFSHORE WEST AFRICA

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## ABSTRACT

*The appraisal stage net-to-gross (NTG) uncertainty of a deepwater turbidite reservoir is assessed using a comprehensive workflow that accounts for uncertainty due to different geological scenarios, incorporates historical information and company expertise through prior probability distributions, and integrates seismic data to correct for the potential bias in NTG estimate due to preferentially drilled wells. Results show that the impact of the geological scenario on NTG uncertainty is larger when the facies geometries are very different. Both the range and shape of the prior distribution impact the posterior NTG probability distributions; the range of the posterior distribution is smaller than that of the prior distribution because of the underlying Bayesian framework. With each additional well, the posterior distributions becomes narrower, indicating that more data reduces uncertainty about the global NTG value.*

## INTRODUCTION

The quest for new hydrocarbon reservoirs and technical advances take the industry deeper offshore, opening new domains for exploration and appraisal. In such a context, due to the high cost of reservoir development, a reliable uncertainty assessment of the original hydrocarbon in place (OHIP) is a must to decide on the economic viability of a field.

Due to high cost of drilling in offshore environments, wells tend to be sparse and preferentially located in high pay zones. Assessing the uncertainty from such sparse data requires identifying and ranking the major parameters that control the OHIP uncertainty, and defining a sound method to make these parameters variable. Geostatistical simulation methods (Goovaerts, 1997; Chilès and Delfiner,

1999; Lantuejoul, 2002) do not produce a good measurement of *global* uncertainty. Indeed, the variations resulting from such techniques are fluctuations about some global target distribution, which typically are insignificant compared to the uncertainty due to poorly constrained reservoir volume and geological scenario.

Global Net-to-Gross (NTG) of a reservoir is a major source of OHIP uncertainty during exploration and appraisal. In case of turbidite reservoirs, NTG ratio is essentially the proportion of sand in the reservoir. Various techniques have been proposed to assess this uncertainty from the classical Bootstrap technique (Efron, 1979), to the Dirichlet distribution approach (Biver et al., 1996, 2002; Haas and Formery, 2002), to Spatial Bootstrap (Journel, 1993; Norris et al., 1993; Bitanov and Journel, 2004).

More recently, a novel methodology for global NTG uncertainty assessment was proposed by Caumon and Journel (2004), and further developed by Maharaja (2007). This methodology overcomes some of the limitations of the previous approaches. It builds on spatial bootstrap by recognizing that the two key input parameters for generating stochastic realizations, namely the geological scenario and the global NTG, are both uncertain, hence randomized. Geological scenario,  $G$ , is randomized by retaining all alternate depositional models that fit the available data (Figure 1, Panel A). Next, the global NTG value  $A$  associated with each geological scenario is randomized by considering a distribution of global NTG values,  $P(A|G)$ , which specifies both the range and prior probability of NTG values that a particular scenario can take. The prior NTG distribution can be obtained by pooling together NTG information from analog fields and outcrops studies. The goal of the workflow is to update this prior NTG distribution given actual observed data,  $\mathbf{D} = \mathbf{d}_0$ .

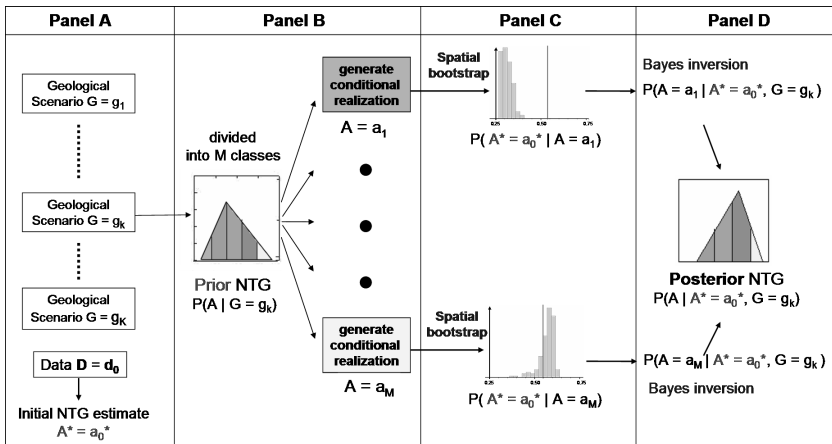


Figure 1: Workflow for global net-to-gross uncertainty assessment.

To perform this update, the prior NTG distribution is first discretized into  $M$  classes. For each class, a representative facies realization is simulated from the

corresponding geological scenario, while honoring all available data (Figure 1, Panel B). Synthetic data sets are re-sampled from this realization by following the initial drilling strategy. The NTG estimates computed from these synthetic data sets provide the likelihood of observing the initial NTG estimate in a simulated reservoir with that global NTG (Figure 1, Panel C). Then using Bayes rule, the prior probability of the global reservoir NTG being in any given class  $m$  is updated into a posterior probability given the observed NTG estimate. Repeating this procedure for all prior global NTG classes and pooling together the posterior probability of each NTG class provides the posterior probability distribution of global NTG (Figure 1, Panel D). This distribution is a model of uncertainty specific to the reservoir under study and for a particular geological scenario. Posterior distributions corresponding to different geological scenarios can be combined into a single posterior, but this calls for a prior probability of occurrence of each scenario.

The reader is referred to Maharaja (2007) for a detailed description of the methodology and a comprehensive presentation of its application to a turbidite reservoir offshore West Coast of Africa, hereby called the WCA reservoir. In this paper, the key results of the WCA reservoir case study are presented to demonstrate the practicality of this method. The information available at appraisal stage is presented in the next section.

## WCA RESERVOIR DATA SET

### Geological scenarios

The seismic data quality for the WCA reservoir is sufficiently good to identify it as a part of multiple slope channel complexes, or slope valley system. The depositional facies filling the slope valley, however, cannot be easily inferred from the seismic data. This facies uncertainty is expressed through the three different training images (Ti) shown in Figure 2. A Ti is a necessary input to multiple-point simulation (mps) algorithms (Remy et al., in press). It is a repository of types of structures deemed present in the reservoir. It must depict not only the shapes and dimensions of all facies, but also how these facies interact with one another (Maharaja, 2008). In this case study, the *snesim* algorithm is retained to generate the conditional geological scenarios (Strebelle, 2002).

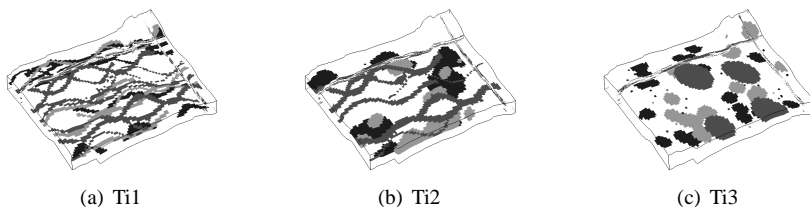


Figure 2: Three facies scenarios retained to study the impact of geological scenario.

Four depositional facies with varying NTG ratios are identified from core analysis. In Ti1 and Ti2, which represent actual scenarios for the WCA reservoir, facies 1

is the poor quality background shaly facies and facies 4, which is interpreted as sand-filled channels, is the good quality reservoir rock. The two scenarios differ in interpretation of facies 2 and 3, which are both intermediate quality facies. In scenario 1, both facies 2 and 3 are classified as channels, while in scenario 2 they are considered to be lobate deposits. In Ti3, which is a hypothetical scenario retained to study the impact of geological scenario, facies 2, 3 and 4 are in form of lobes.

### Prior probability distribution for global net-to-gross

A prior probability distribution of global NTG for the WCA reservoir is obtained from a database of analog reservoirs (Figure 3). Only one prior NTG distribution is available for the three different scenarios, because the database used to obtain this distribution classifies reservoirs at system scale (here slope valley), not at the reservoir facies scale. Ideally, each of the alternative geological scenarios retained should have a different prior NTG distribution. The goal of the workflow is to update this prior distribution given the actual quantitative data from the WCA reservoir.

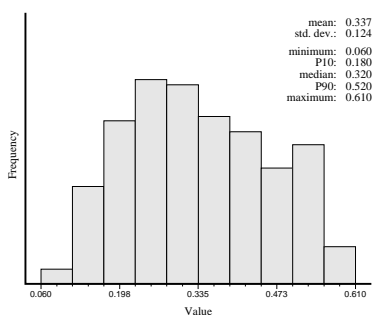


Figure 3: Prior global net-to-gross probability distribution for the WCA reservoir obtained from a database of analog reservoirs.

### Well and seismic data

The four wells available at appraisal stage are shown in Figure 4(a). In reality, the WCA reservoir has been in production for a few years and 28 wells are available, providing a good coverage of the reservoir (Figure 4(b)). The wells are marked with the order in which they were drilled, which makes it possible to study the impact of additional data on NTG uncertainty.

As mentioned earlier, four different facies with varying NTG ratios (sand proportion) are determined from cores, see Table 1. Equation 1 is used to compute the NTG by combining the facies proportions from the wells  $p_i$  and the within-facies sand proportion  $n_i$  given in Table 1 under the constraint that the proportions sum to one. The NTG estimate from the four appraisal wells is 0.484.

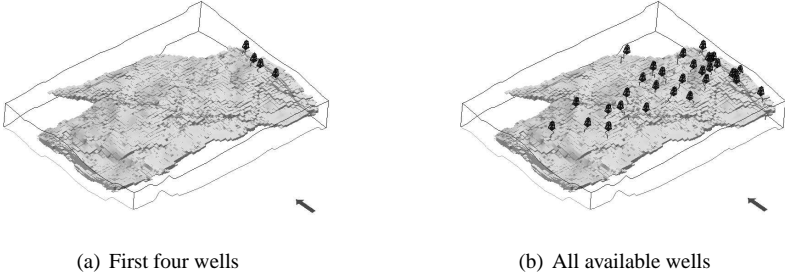


Figure 4: Location of all available wells, and of the four appraisal wells (vertical exag.  $\times 3$ ).

Facies number	1	2	3	4
NTG value, $n_i$ (%)	3.8	47.3	63.0	90.7

Table 1: Within-facies sand proportion for the four facies in the WCA reservoir

$$a^* = \sum_i (p_i \times n_i) \quad ; \quad \text{with} \quad \sum_i p_i = 1 \quad (1)$$

The four appraisal stage wells are clustered in the thicker eastern part of the WCA reservoir, hence the NTG estimate obtained from these wells may not be representative of the whole reservoir. Indeed, integrating acoustic impedance data with the four wells lowers the global NTG estimate to 0.436. Bayes inversion, as described in Bitanov and Journel (2004), is used to calibrate the impedance data. Many different techniques have been proposed to calibrate seismic data with well data (Fournier and Derain, 1995; Goovaerts, 1997; Caers and Ma, 2002; Strebelle et al., 2002); the workflow, however, does not call for any particular technique. Seismic data calibration is a major source of uncertainty at appraisal stage, yet checking robustness of the calibration with cross-validation is difficult due to data sparsity. The uncertainty in NTG estimate due to calibration errors can be assessed by randomizing the parameters of a particular algorithm or by using different algorithms to obtain alternate NTG estimates. Refer to Maharaja (2007) for a discussion on how to incorporate different initial NTG estimates into the workflow.

During step 2 of the workflow (Figure 1, Panel B), the global NTG value (i.e. the average sand proportion) is known, but we need to know the proportion of each facies corresponding to that global NTG value in order to simulate a facies realization for that class. In a two facies case, Equation 1 is sufficient to compute the facies proportions because we have two unknowns (the two facies proportions) and two constraints (Equation 1 and  $\sum_i p_i = 1$ ). In the WCA reservoir there are four facies; hence, two additional constraints are necessary to solve for the four unknown facies proportions.

One way to introduce additional constraints is to freeze the ratio of facies

proportions. These facies proportions ratio are uncertain parameters; they can be obtained from analog knowledge. This approach works best when facies proportions are tightly related. In case of the WCA, we froze the ratio of proportions of facies 2 to facies 4 and that of facies 3 to facies 4. These ratios for each scenario were taken from the corresponding Ti. The proportion of the four facies in the three scenarios are similar.

## RESULTS OF GLOBAL UNCERTAINTY STUDY

### Impact of geological scenario

The four appraisal stage wells and a NTG estimate of 0.436 are retained for all three scenarios. All parameters except for the geological scenario are similar for the three cases. Refer to Maharaja (2007) for detailed information about the workflow parameters used in the WCA study and their sensitivity analysis. The posterior distributions conditional to this estimate are given in Figure 5.

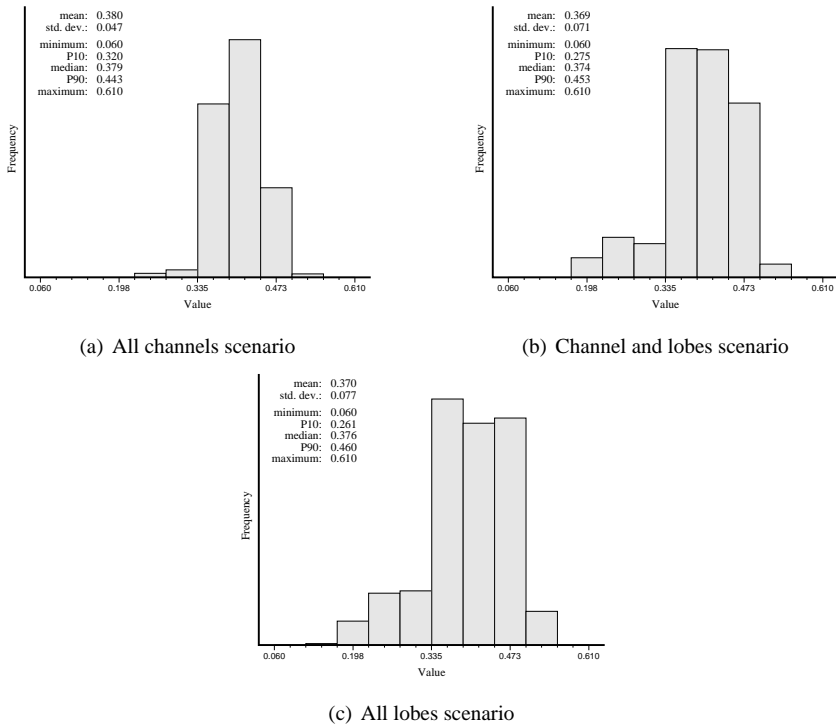


Figure 5: Posterior NTG distributions obtained using scenarios 1, 2 and 3 given a NTG estimate of 0.436.

The mean and median of the three posteriors are comparable. However, the width of the  $[p_{10}, p_{90}]$  interval changes with the scenario. This confirms the fact that geological scenario matters. Hence, if a geological scenario is uncertain, which is likely at appraisal stage, all alternate scenarios that fit the data should be considered.

The  $[p_{10}, p_{90}]$  interval corresponding to scenario 1 (all channels) is the narrowest. The  $p_{10}$  of both scenario 2 (channels and lobes) and scenario 3 (all lobes) is lower than that of scenario 1, because lobes, as opposed to channels, increase the likelihood that the four wells are either all contained inside or outside the lobes. Moreover, in scenario 2 the high NTG channel facies is thicker than in scenario 1 and the channels tend to be more clustered. Scenario 2 is a hybrid between scenarios 1 and 3, so it is consistent that its posterior statistics fall between those of the two more extreme scenarios. It is important to freeze the well configuration when resampling from stochastic realizations, especially in the case of sparse, clustered wells.

### Impact of prior distribution

As mentioned earlier, only one prior probability distribution for global NTG is available for the three facies scenarios. To study the impact of prior probability distribution, we retain two additional distributions - a triangular distribution between  $[0.25, 0.65]$  with a mode 0.50 and a uniform distribution over  $[0.25, 0.65]$ . These distributions are narrower than the distribution obtained from the analog database (Figure 3). Only scenario 3 (all lobes) is retained for this study.

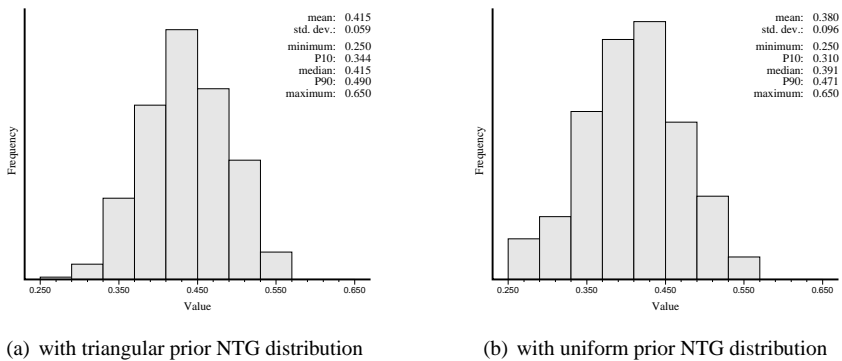


Figure 6: Posteriors for scenario 3 resulting from triangular and uniform prior distributions.

Figure 6 compares the posteriors resulting from using the triangular and uniform prior distributions. Note that the initial NTG estimate, 0.44, is the same in both cases because the same set of four initial wells and acoustic impedance data are retained. Hence, the differences in the posterior distributions is solely due to the different prior probabilities. Both posteriors are narrower than the one resulting from using the analog prior distribution (Figure 5(c)), since the triangular and uniform prior distributions are narrower than the analog prior. Note that the posterior distribution cannot be wider than prior distribution because the prior probability of any NTG value that is outside the bounds of the prior distribution is zero, hence the posterior probability of that NTG value will also be zero according to Bayes rule.

## Impact of additional data

The impact of additional data on the posterior NTG distribution is studied using the channel scenario 1, which is considered the mostly likely scenario by the geologist. The goal is to see how the posterior NTG distribution likely changes as additional well data become available. We repeat the entire workflow four times, first using only well 1, then adding well 2, then well 3 and finally with all four appraisal stage wells. The only parameters that change from one run to another are the number of wells and the corresponding initial NTG estimates. The same acoustic impedance cube is used in all four runs, but the calibration is repeated as new data becomes available. Table 2 summarizes the well NTG and the updated NTG estimates after integration of acoustic impedance data. The mean and  $[p_{10}, p_{90}]$  of the corresponding posterior distributions are also given.

Nb wells	Well NTG	Updated NTG	Posterior mean	Posterior $[p_{10}, p_{90}]$
1	0.36	0.35	0.33	[0.23, 0.44]
1,2	0.47	0.45	0.43	[0.36, 0.50]
1,2,3	0.47	0.43	0.38	[0.32, 0.45]
1,2,3,4	0.48	0.44	0.38	[0.32, 0.44]

Table 2: Well NTG and the corresponding updated NTG estimates for wells 1 to 4. The updated estimates are retained for the study.

The  $[p_{10}, p_{90}]$  interval of the posterior distribution with the first well is much narrower than that of the prior NTG distribution [0.18, 0.52] (Figure 3). The posterior distribution mean and the  $[p_{10}, p_{90}]$  interval shifts to the right when well 2 is introduced because the combined NTG estimate of wells 1 and 2 is much higher than that of well 1. Also, the  $[p_{10}, p_{90}]$  interval of the posterior with two wells is narrower than that with well 1 only. This trend is also observed when wells 3 and 4 are introduced. In all four cases the  $[p_{10}, p_{90}]$  interval is roughly centered over the corresponding posterior mean as expected. The initial NTG estimates (Table 2) are included in all posterior  $[p_{10}, p_{90}]$  intervals. The mean and the  $[p_{10}, p_{90}]$  intervals of the posterior distributions are strongly impacted by the initial NTG estimate as demonstrated by this study. Hence, when estimating NTG, it is critical to use all available data and choose the estimation algorithm carefully.

For verification purposes, the workflow is run with all available 28 wells using the channels scenario and the analog prior distribution. NTG estimate from the 28 wells is 0.43; using seismic data lowers this estimate to 0.41, a small reduction since the 28 wells sample the reservoir adequately (Figure 4(b)). The means of the two posteriors are similar, however, the  $[p_{10}, p_{90}]$  interval of the posterior with 28 wells [0.36, 0.42] is significantly narrower than the  $[p_{10}, p_{90}]$  resulting from using the four appraisal wells [0.32, 0.44]. This is expected, because with 28 wells the global NTG is closely estimated.

## DISCUSSION

Any NTG uncertainty model obtained using this workflow is tied to the sampling domain. The reservoir volume, however, was frozen for this study. A joint randomization of volume and NTG is a top consideration for future work. Reservoir volume uncertainty is linked to uncertainty about seismic data processing and interpretation. Time-to-depth conversion is one of the largest sources of uncertainty about the seismic data because of the poorly understood velocity models required for this conversion. The uncertainty about reservoir volume and NTG can be jointly assessed by carrying out the NTG workflow in alternate reservoir volumes resulting from widely different velocity models or different horizon interpretations.

This workflow was applied to a deepwater turbidite reservoir with sparse appraisal stage wells. However, it is general enough to be applied on any depositional environment with any number of facies. Training image-based mps simulation was used to generate the geological scenario, however, any simulation technique that honors all available data, including seismic, and adequately reproduces geological scenario and the target NTG can be used. In case of sparse, preferentially located wells it is especially important to correct any bias in NTG estimate by incorporating seismic data. Calibrating seismic data to wells is a major source of uncertainty and should be accounted for by randomizing the parameters of a particular calibration algorithm or by using different algorithms to obtain alternate NTG estimates.

Results with the four appraisal wells showed that the posterior distribution became narrower as more wells were introduced. This is because the geological scenario and the prior NTG distribution were the same. If the additional well drastically changes the geological scenario, then the prior distribution should be revised. If the revised prior distribution is wider than the previous one, then the posterior distribution may be wider as well, implying more uncertainty.

From a value of information perspective, before drilling a new well we can study its impact on reduction of NTG uncertainty by carrying out the workflow with different well locations. The posterior distributions depend on the size and distribution of the heterogeneities and the configuration of the wells that sample them.

The workflow can also be applied to assess uncertainty about continuous variables, such as average porosity of a reservoir. In this case, the prior distribution provides the range that *average porosity* can take based on historical information. For a given class of global mean porosity, additional assumptions must be made regarding the shape of the distribution to perform porosity simulations. This approach provides more informed models of global porosity uncertainty than simulating multiple realizations using the same global porosity distribution.

As with any uncertainty assessment, each posterior distribution is one model of global NTG uncertainty for the WCA reservoir, that depends completely on the various assumptions and decisions that went into building the model. It would be incomplete without a clear statement enlisting all these assumptions and decisions.

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