Deepwater Reservoir Connectivity Reproduction from MPS and Process-Mimicking Geostatistical Methods

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Abstract Deepwater unconfined lobe depositional systems are important reservoir targets. High drilling cost and subsalt imaging greatly limit the quantity and quality of data. In the absence of sufficient data, analog architectural studies have identified a variety of potentially important reservoir quality related geometries and trends resulting from the well-understood depositional processes. Internal lobe trends (proximal, dominated by amalgamated sands, to distal, dominated by non-amalgamated sands) impact horizontal connectivity and coupled with compensational lobe stacking impact vertical connectivity (alternating proximal and distal lobe components are superimposed locally).

Current geostatistical algorithms, pixel based or object based, using semivariograms, training images, or geometric parameters, enable the reproduction of spatial statistics inferred from available conditioning data and analogues but rarely integrate information related to depositional processes. Indeed, because conventional geostatistical models are constructed without any concept of time or depositional sequence, their ability to incorporate sedimentological rules, which explain facies geobodies interactions and intra-body porosity/permeability heterogeneity, is quite limited.

Process-mimicking methods provide an improved ability to honor these flow unit stacking patterns and trends, but trade-off precise conditioning to [moderate to dense] well data and detailed seismic informed trend models. To guide geostatistical reservoir modeling practice, a study assesses the incremental impact of process-mimicking relative to a common multiple-point statistics (MPS) approach with respect to reservoir flow response.

A surface-based (a variant of process-mimicking) method coupled with hierarchical trends efficiently reproduces realistic deepwater lobe geometry, stacking

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patterns, and internal lobe heterogeneity. A spectrum of deepwater lobe reservoir models, using archetypal well log data and flow diagnostics and benchmarked with the current MPS approach, quantifies incremental flow significance of these reservoir features. This quantification supports guidance and best practice for geostatistical reservoir modeling workflow design for unconfined deepwater lobes reservoirs.

1   Introduction

Current geostatistical algorithms, pixel based or object based, using semivariograms, training images, or geometric parameters, enable the reproduction of spatial statistics inferred from available conditioning data and analogues but rarely integrate information related to depositional processes. Indeed, because conventional geostatistical models are constructed without any concept of time or depositional sequence, their ability to incorporate sedimentological rules, which explain facies geobodies interactions and intra-body porosity/permeability heterogeneity, is quite limited (Pyrcz et al. 2012).

While we do acknowledge the value and practical success of the more traditional geostatistical models mentioned above, there still remains an opportunity for developing models that incorporate stratigraphic rules that relate to the underlying geologic processes and hence offer an improved representation of depositional heterogeneity. Process-mimicking facies models attempt to increase the level of integration of the geological conceptual model by integrating rules, based on the geological process. The rules constrain the sequential construction of reservoir architecture represented by object or, in our experiment, surfaces (Pyrcz and Deutsch 2014).

Comparisons of modeling approaches are risky and may be misleading. The purpose of this paper is not to determine that one modeling approach is better than another. The authors are motivated by their practical experience in mentoring and directing reservoir modeling on deepwater assets worldwide. The subsurface reservoir modeling teams have consistently asked, "Will more geological process information and realism impact the connectivity of the reservoir model?" This paper demonstrates that in some cases the impact is significant, and with connectivity quantification suggests that there are cases where one technique might be more appropriate than the other, given the reservoir modeling goals aligned with business need.

In our study we use a surface-based method to generate our geologically realistic lobe model (see Fig. 1). Surface-based methods are a modified version of object-based methods that produces and track surfaces that delineate objects. Within a process-mimicking framework, surface-based methods incorporate aggradation and erosion of surfaces based on geometric templates. For greater details on this method
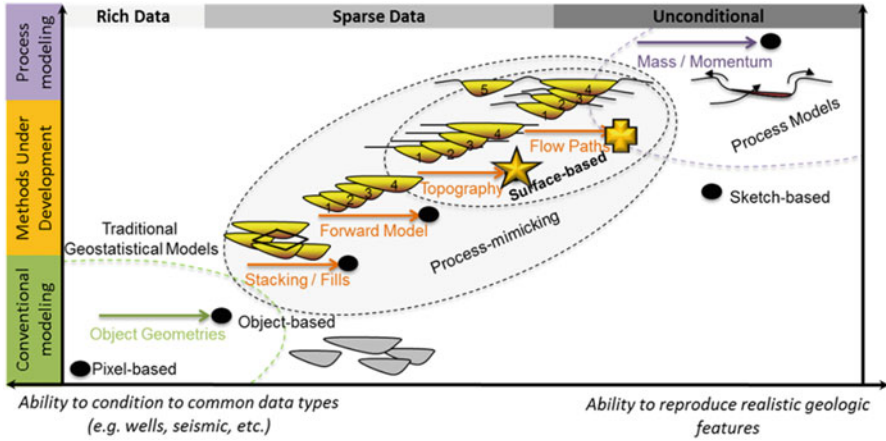
Fig. 1 Continuum of process-mimicking approaches that allow us opportunities to produce more geologically realistic reservoir models

and other process-mimicking approaches, the reader can refer to various publications including Pyrcz and Deutsch (2005), Wen (2005), Miller et al. (2008), Michael et al. (2010), Sylvester et al. (2010), and Pyrcz et al. (2015).

This technique allows for inclusion of realistic lobe stacking patterns and internal lobe heterogeneity, which is not typically captured by conventional modeling approaches. Stacking is a fundamental characteristic of lobes, as well as the internal architecture (proximal, dominated by amalgamated sands, to distal, dominated by non-amalgamated sands).

This study endeavors to quantify the added value of utilizing a process-mimicking approach compared to conventional modeling approaches. A simple multiple-point statistics (MPS) model is utilized as a benchmark, because it represents the common modeling approach in this setting. To achieve our objective we propose to generate typical deepwater lobe reservoir models using archetypal well log data and perform flow diagnostics to estimate the impact recovery. Previous studies have shown the importance of reservoir connectivity and heterogeneity on reservoir performance (e.g., Larue and Hovadik 2006). Our results quantify the incremental impact of connectivity (lobe stacking) and heterogeneity (within-lobe trends) for different net-to-gross scenarios modeling with process-mimicking models benchmarked with standard MPS workflow. This is useful to justify the additional effort to adopt emerging process-mimicking methods rather than utilizing widely available MPS workflows.

2   Methodology

The experiment is based on the application of three parallel modeling workflows from stratigraphic characterization to reservoir modeling to connectivity analysis. The first workflow is based on a standard MPS approach with associated training image construction. The second workflow, based on the surface-based modeling process described previously, generates lobes that capture the large-scale lobe geometry and compensational stacking. The third workflow includes the features of the second workflow with the added within-lobe reservoir property (porosity and permeability) trends that include fining (decrease in reservoir quality) distally and laterally, as well as sedimentary cycles vertically. Each workflow from 1 to 3 represents increasing integration of the stratigraphic characterization. The quantification of impact is based on a flow diagnostic tool that calculates the dynamic Lorenz coefficient, a global measure of the degree of connectivity complexity. The experiment includes 20 stochastic realizations from each workflow for 40, 60, and 80 % NTG (ratio of lobe related to overbank facies).

2.1   Geologic Characterization

Deepwater lobe characterization is based on a hierarchical architecture. Individual lobe elements are lenticular in cross section and lobate in map view, with high aspect ratios on the order of 1,000:1 (Beaubouef et al. 1999; Sullivan et al. 2004; Prélat et al. 2009, 2010). They represent the unconfined deposition of genetically related sediment gravity flows. Lobe elements that are genetically related show similar grain size and facies distribution and similar architectural styles and stack in a compensational manner to form a lobe complex.

Lobe elements are characterized by individual depositional packages known as stories. These include general trends in depositional grain size with fining from proximal to distal and inner to outer lobe and vertical cycles (Fig. 2).

2.2   Geostatistical Modeling

Lithofacies modeling, for Workflow 1 geostatistical modeling, utilizes MPS. The MPS variant is the standard SNESIM approach (Strebelle 2002). The training image is composed of sand facies lobes in an overbank background (see Fig. 3). It was built using a simple object-modeling tool that generates lobular shapes with dimensions 60,000 ft in length, 40,000 ft in width, and 40 ft in thickness. The global proportions are constrained by firstly designing training images with the target facies proportions and updating conditional distributions from the training images based on mismatch with target global proportions during simulation.
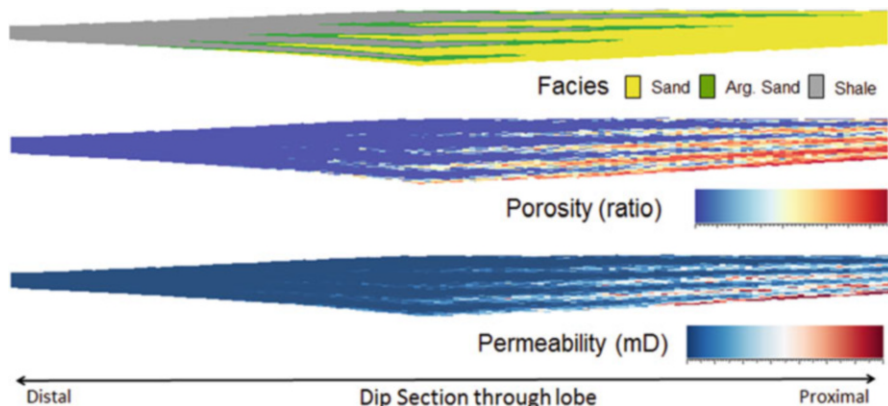
Fig. 2 Dip section of a simple conceptual model of within-lobe heterogeneity for a simple lobe geometry
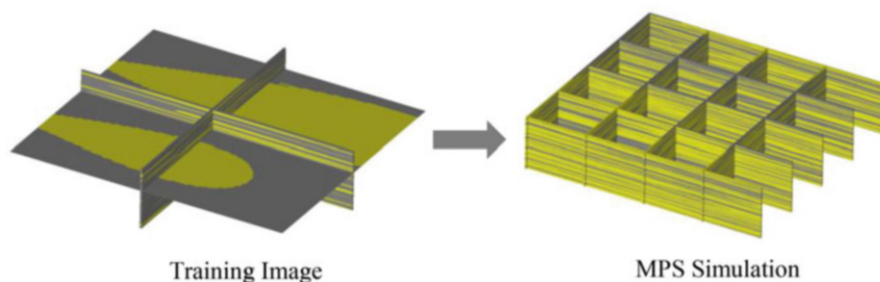

Fig. 3 Training image used in MPS simulation at a sand proportion of 60 %

For workflows 2 and 3 our surface-based method was applied to simulate compensationally stacked lobes (Pyrcz et al. 2015). The same dimensions mentioned above were used in the construction of these lobes. Our tool also generates an azimuth field within the lobe objects, as well as longitudinal, transverse, and vertical trends which are combined to produce our hierarchical trend. More information on the hierarchical trend approach is found in Pyrcz et al. (2005). The hierarchical trend is crucial because it is used to guide the petrophysical modeling in Workflow 3 (Fig. 4).

Sequential Gaussian simulation is applied to simulate porosity within the reservoir facies using a histogram of values ranging from 0.04 to 0.26, and a variogram range of 2,000 ft in the longitudinal direction and 1,300 ft in the transverse direction is assumed. For workflows 1 and 2, no trends are applied for the porosity simulation. However, for workflow 3 within-lobe trends, which mimic the hierarchical architecture recognized in deepwater lobes, are added. These trends are integrated as a secondary variable with a correlation coefficient of 0.8.

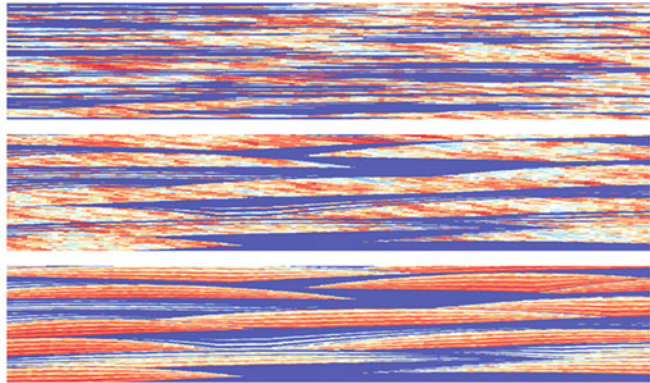**Fig. 4** Surface-based lobe model with sand and argillaceous sand proportion of 60 %
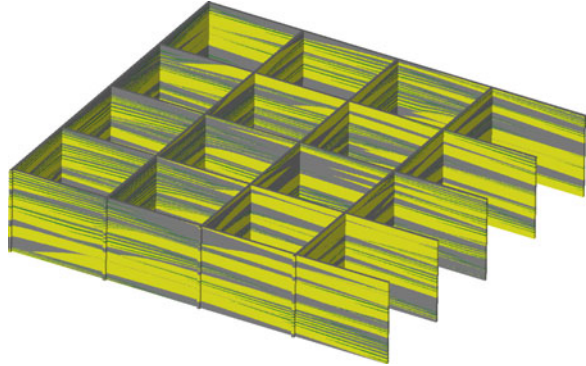
Fig. 5 Strike sections of a porosity realization from each of the workflows

Cloud transform is applied to simulate permeability conditional to the simulated porosity realizations using the same variogram mentioned previously. Permeability values range from 5 to 30 mD within the reservoir facies. Examples of strike sections for realizations from each workflow are shown in Figs. 5 and 6.

2.3 Flow Diagnostic Assessment

Flow diagnostic assessment was used to derive quantitative information on reservoir connectivity. These methods utilize standard reservoir property models (porosity and directional permeability) along with efficient, simplified flow simulation to provide immediate information on the impact of modeling decisions on flow heterogeneity (Shook and Mitchell 2009; Shahvali et al. 2012; Møyner et al. 2015).

In this case study a steady-state pressure field is calculated that induces a displacement or flux from injectors to producers across the reservoir. Importantly,
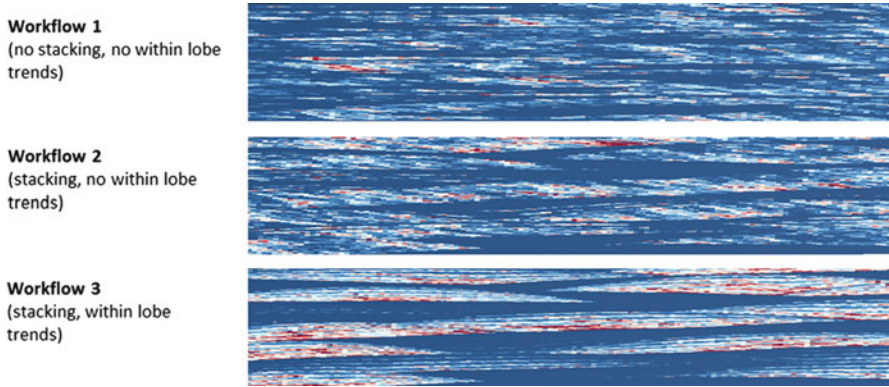
Fig. 6 Strike sections of a permeability realization from each of the workflows
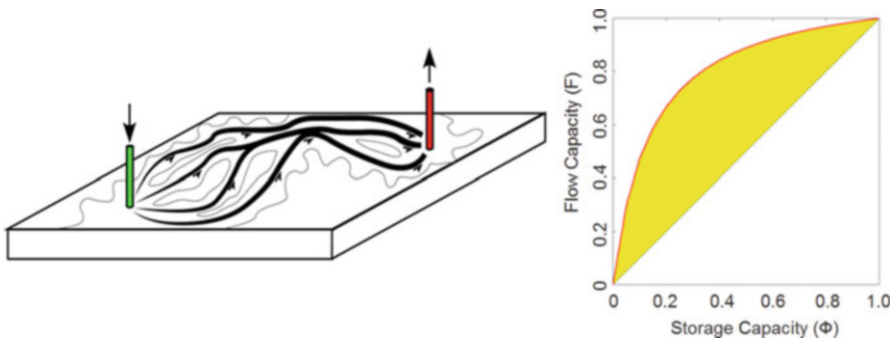

Fig. 7 Dynamic Lorenz coefficient to quantify reservoir connectivity heterogeneity as a summarization of the storage capacity subtracted from the flow capacity based on a set of injectors and producers

the computed flux does not account for the full physics of the flow between two wells as the calculation of flux within the model makes several assumptions. Firstly, the flow is assumed to be steady state and single phase; therefore, the phase of the flow will not change due to buoyancy, well controls, or fluid mobility changes. Secondly, a main assumption is that the flow is incompressible and well-driven flow; any independent reservoir compartment or fault block in the model must have at least one producer and one injector well to initiate some flow.

This approach yields a number of outputs including dynamic Lorenz coefficient (DLC) and time of flight information. Once the flux across the volume and time of flight are calculated, the F-Φ relationships can be calculated. When plotted this generates a curve representing the relationship between normalized, cumulative flow capacity (F) against storage capacity (Φ). Specifically, the curve explains the ratio between the volume of injected and swept reservoir pore volume. Twice the area under this curve and above the 1:1 line is the DLC and can be used to rank the heterogeneity of multiple models (see Fig. 7). This is a good quantification of flow

complexity (reservoir heterogeneity) as it describes whether flow in the reservoir represents a simple piston displacement or highly impacted by high permeability streaks and barriers (indicated by high DLC).

3 Results

The flow diagnostic assessment quantified by DLC (a good indicator of recovery factor) suggests that the level of reservoir connectivity and heterogeneity is impacted by the additional features such as lobe stacking pattern and within-lobe trends that are available with process-mimicking model. Visually, we see this behavior in Fig. 8 where the volume that is being swept shrinks and is less uniform as we go from the simplistic model from workflow 1 to a more complex model from workflow 3.

The expectation over several model realizations, for each workflow, was calculated and plotted. It demonstrates increasing flow complexity with increasing model complexity (see Fig. 9).

We assessed at each net-to-gross scenario which features, stacking patterns (connectivity) or within-lobe architecture, contributed more significantly to the change in the DLC. The proportion increase of DLC, as we move from a purely geostatistical method to a geological method that incorporated stacking patterns and within-lobe architecture, was calculated. At lower net-to-gross regimes, we see
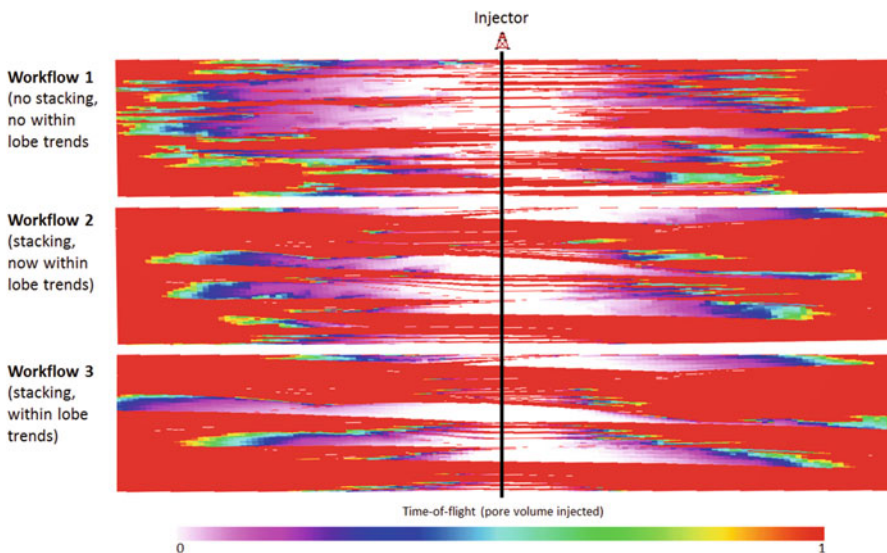

Fig. 8 Time-of-flight represents the time it takes (in pore volumes injected) for injected fluid to travel from an injector to a given point in the reservoir
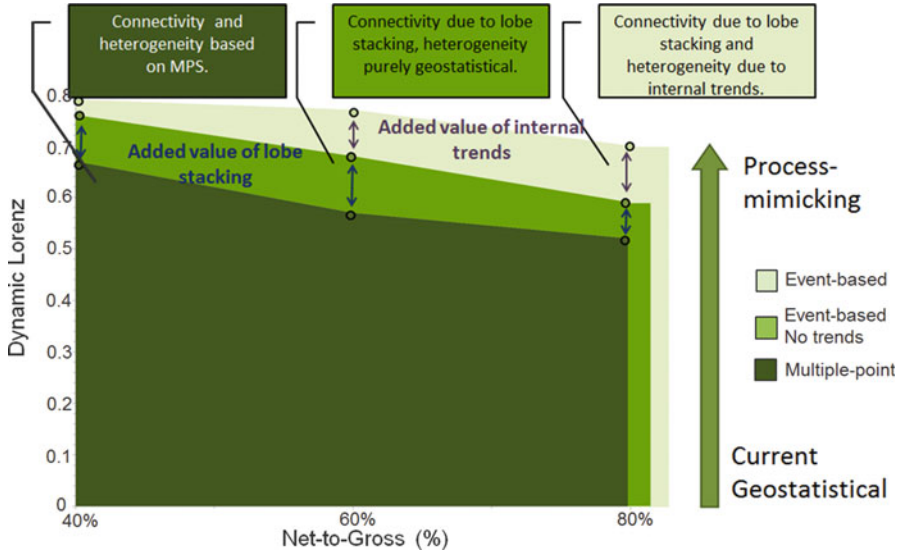
Fig. 9 Graph showing the DLC at 40 %, 60 %, and 80 % net-to-gross. It is apparent that as we add compensational stacking and within-lobe trends, we see an increase in the DLC
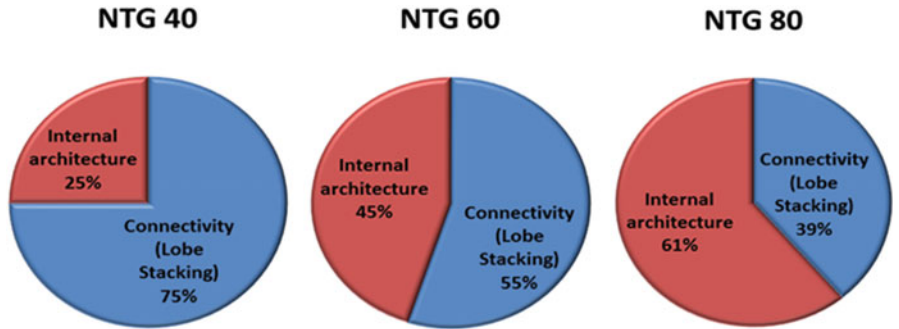

Fig. 10 Graphs showing the proportion of DLC increase due to lobe stacking pattern and within-lobe internal architecture

that connectivity has more of an effect on the DLC; hence more emphasis should be placed on modeling shale placement (e.g., drapes, baffles, etc.) within the reservoir. As the net-to-gross increases, the modeling of internal trends (lobe architecture) becomes more critical (see Fig. 10).

4   Discussion

This work has demonstrated that the additional reservoir model complexity, namely, lobe stacking patterns and detailed within-lobe trends, impacts reservoir connectivity heterogeneity. This motivates adoption of new process-mimicking technology that integrates these geologic features, depending on modeling objective. For example, this approach will be more appropriate for evaluating the detailed flow behavior of a deepwater lobe reservoir in the presence of mud drapes and within-lobe trends.

Conversely, this work suggests that current widely available reservoir modeling approaches (such as MPS) may underestimate reservoir fluid flow complexity, without the inclusion of addition constraints to directly capture these heterogeneities. In our experience, this may translate into overestimation of recovery factor and time to water breakthrough. Generating more realistic models may assist in managing and mitigating risk that may arise with conventional modeling methods.

Future work includes performing a full flow simulation which provides us with measures of heterogeneity other than the DLC.

5   Conclusions

Deepwater lobes are important reservoir targets. New insights from geological characterization suggest a hierarchy of heterogeneities including compensationally stacked lobes and within-lobe reservoir property trends. The incremental impact of these heterogeneities is determined through three workflows: (1) a traditional MPS workflow, (2) a process-mimicking workflow that captures lobe stacking patterns, and (3) a process-mimicking workflow that captures lobe stacking patterns and within-lobe trends.

Each of these additional complexities has a significant impact on flow heterogeneity as represented by DLC.

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