Modeling sub-seismic turbidite lobes using spatial statistics

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Abstract: Deep-water turbidite lobe systems have been one of the most important hydrocarbon reservoirs in the subsurface. However, seismic imaging and sparse well data lead to a high uncertainty level in the resource exploration and development. Identifying hydrocarbon reservoir heterogeneities in a lobe system often requires stochastic models of sub-seismic features. We present a simulation algorithm connecting stratigraphic organization with surface-based reservoir models through statistical metrics. As a new family within a wide array of stochastic geological models, surface-based models and rule-based algorithms effectively represent stratigraphic responses to geological events in both time and space by assigning depositional and erosional surfaces with predefined geometries and rules. In our study, a lobe classification scheme and Ripley’s K-function are utilized to extract information about sub-seismic lobe element organization from physical experimental strata. We utilize these two metrics in conjunction with a surface-based simulation algorithm to 1) integrate clustering patterns of turbidite lobes into reservoir modeling 2) reproduce a numerical stratigraphic framework comparable to physical tank experiments 3) explore a means of imparting stochastic structures to models and improving geological realism.

1. Introduction
Since the 1980s, exploration in the submarine turbidite fans has gained great success in the passive continental margin basins such as Atlantic coast and Gulf of Mexico, and more than one hundred billion barrels of crude oil are found in bottom fans, slope fans, prograding clastic wedges and incised valleys, most of which are stratigraphic and lithologic reservoirs. Statistics of Stow and Mayall (2000) show that 1200~1300 oil and gas fields derive from deep-water depositional systems controlled by shelf slopes. Among these oil and gas fields, there are over 40 giant ones and non-structural reservoirs constitute a large proportion.

Although 'deep-water' denotes the environment of reservoir deposition, the present-day field location of these deposits is still beneath the deep-water bathymetry. Therefore, limited numbers of wells may be the only data source for reservoir characterization. While Seismic imaging is of great use in mapping rock properties and architecture, there are many sub-resolution heterogeneities that cannot be resolved in seismic data. In addition, we may place too much emphasis on one aspect of the evidence and then make further assumptions that bias data acquisition and interpretations (Nickerson, 1998). To this end, reservoir models are invoked to represent poorly known subsurface phenomena and capture objective explanations to obtainable raw data. Specifically, surface-based modeling with rules allows us to generate geostatistical models and understand the risks in the development of a deep-water reservoir given limited availability of field data (Pyrcz et al., 2005; Zhang et al., 2009; Bertoncello, 2011; McHargue et al., 2011). Furthermore, the scarcity of data highlights the importance of analog information sources - physical geomorphic experiments. Surface-based modeling with rule algorithms integrates our understandings from geomorphic experiments, as well as process-based models or
geological inference of depositional processes from experience-rich geologists (Michael et al., 2012; Xu, 2014).

2. Forward Model

In our study, we perform surface-based modeling with rule algorithms and generate reservoir realizations as shown in Figure 1. The basic workflow is to generate the surface of a turbidite lobe geobody, position it on the intermediate topographic surface and then update the realization at each time step as a series of geologic events pile up sequentially (Figure 1).

Dendrogram analysis (Figure 2) has facilitated a correlation framework that has been quantitatively interpreted to demonstrate the similarity between a physical tank experiment and a real depositional system (Xu, 2014). Agglomerative hierarchical clustering is performed to characterize the internal hierarchy of experimental data. Through this method Xu quantitatively evaluate the similarity between lobe stacking patterns in different systems (Figure 2). Because our study is aimed at integration of experimental data in reservoir modeling, we examine the similarity between experimental stratigraphy and interpreted field data. We are able to determine which tank experiment at what interpretation scale is comparable with available field data by performing a search through the hierarchy of
interpretable lobes. Then characteristics of experimental lobes below the comparable scale are informative in terms of inferring invisible small-scale features from visible large scale features. This piece of information is utilized for reservoir modeling in our study (Figure 2).

Figure 2. Demonstration of workflow for reservoir modeling using experimental data

3. Spatial Point Process

We treat the spatial distribution of lobes as a spatial incident point process, providing an opportunity for surface-based simulation algorithm to link stratigraphic hierarchy with reservoir modeling through a spatial statistical metric (Figure 3).

Figure 3. Demonstration of spatial points indicating locations of preserved lobe complexes
We adopt Ripley’s K function (Hajek et al., 2010) to analyze the spatial pattern of incident point data. Ripley’s K function summarizes spatial dependence (feature clustering or feature dispersion) over a range of distances. This metric provides a way to extract information of sedimentary hierarchy and lobe element organization from a set of experimental strata, and bridge physical tank experiments with numerical models. Ripley’s K function is given by

\[ \hat{K}(d) = \frac{r}{n^2} \sum_{i \neq j} \sum \frac{I_d(d_{ij})}{w_{ij}} \] (1)

where \( r \) indicates the area of study region, \( n \) represents the number of events, \( d_{ij} \) represents the distance between the \( i \)-th and \( j \)-th event, \( I_d \) is an indicator function that takes on the value of one if \( d_{ij} \leq d \), and \( w_{ij} \) is a correction factor for edge effects. Given a physical experiment recording the entire evolution of the lobe system, we are able to transform all the lobes that appear in the geologic time into a spatio-temporal point process. This point process provides both spatial and temporal information for the growth of lobes.

4. Case Study

To perform an application of spatial point process, we utilized two physical tank experiments: TDB-10-1 and DB-03. The TDB-10-1 experiment was conducted at Tulane Sediment Dynamics Laboratory and modeled on the DB-03 experiment detailed in Sheets et al. (2007), but had the added aim of generating a stratigraphic package 2-3 times thicker than the DB-03 experiment. DB-03 was conducted in the Delta Basin at St. Anthony Falls Laboratory at the University of Minnesota (Sheets et al., 2007; Xu, 2014). Both TDB-10-1 and DB-03 were conducted with constant allogenic forcings. The allogenic forcings in the DB-03 experiment, including \( Q_s \), \( Q_w \) and the rate of base-level rise were identical to TDB 10-1. However, because two different basins were used, DB-03 and TDB-10-1 are different in terms of depositional
geometry of stratigraphic package (Figure 4). Figure 4 shows the basin geometry and an overhead photo of TDB-10-1. Details regarding DB-03 are demonstrated in Xu (2014).

By interpreting the overhead photos of DB-03, we create a lobe system that contains 13 lobe complexes. This lobe system is treated as observable pseudo field data, and we have not continued to interpret the lobe elements that may exist in complexes. Conversely, we performed a rather detailed interpretation throughout the experimental stratigraphy of TDB-10-1. To create an archive containing sedimentary information over all the interpretable scales, we initiated our interpretation from relatively small-scale lobes (axial length approximating 0.3 m), and then assembled small-scale lobes to medium-scale (axial length approximating 0.8 m) and large-scale lobes (axial length approximating 1.2 m). The interpretation and geometry extraction procedures are described with more details in Xu (2014). Through a comparability searching (Figure 2), a lobe stacking pattern that we interpreted at a certain scale from TDB-10-1 is of similar characteristics with the lobe system in DB-03. In our study we term features at this comparable scale as large-scale information in TDB-10-1. Below this large scale, it is fairly convenient to extract medium and small scale lobe features, including lobe geometry and spatial distribution, from our archive.

As demonstrated in Figure 4 B, we highlighted the center of large-scale lobes with red dots in a square domain in Figure 5 A. Each red dot refers to a location record of a large-scale lobe or a lobe complex in space. If we consider these lobe complexes as parent events, there are relatively fine-scale offspring events filling up each parent event. These offspring events are often considered sub-seismic lobe elements in seismic imaging. In our case, the medium and
small scale lobes we characterized from TDB-10-1 represent sub-resolution sedimentary features. Our tree-based archive is capable to provide information at any scale below the large scale (Fig. 5).

Figure 4. A) Schematic diagram of Tulane Delta Basin facility. Positions of proximal, medial and distal topographic transects in TDB 10-1 experiment are indicated by red lines on fluvial surface. B) Overhead photograph taken at 76 hours into the aggradational phase of TDB 10-1 experiment. Flow is dyed blue to aid visualization. System is approximately 3.1 m in length from source to shoreline. The location of major large-scale lobes are marked by red dots.

All the points that represent small and medium scale lobes are marked by blue dots in Figure 5. We utilized Ripley’s K function to evaluate the clustering strength of red dots and blue dots depending on the measurement length - d (Fig.5). This measurement length represents distance from random points to their nearest neighbors. The simplest use of Ripley’s K(d) function is to test complete spatial randomness (CSR). If so, then $K(d) = \pi d^2$. In practice, it is easier to use its normalized estimator - Besag’s L function:

$$\hat{L}(d) = \sqrt{\frac{K(d)}{\pi}} - d \quad (2)$$

The advantage of this transformation is that, under the null hypothesis of CSR, the derived L
function has an expectation of 0 for all values of d (Skrarpe 1991). The resulting plots are more informative and also yield a much higher resolution (Figure 5).

In order to illustrate the scales of statistical significance, we generated a confidence envelop dyed by gray in Figure 5. This envelop is approximated by average 100 point patterns that include the existing sampled points and 99 Monte Carlo simulations with the same point number. The gray-dyed confidence envelope describes a point process where point events at every measurement scale occur in a completely random fashion. If the deviation of the sample statistic from zero expectation is positive, and above the upper limit of the confidence envelope, a clustered distribution of the sampled points can be assumed, while negative deviation indicates a dispersed or regular pattern. If the sample statistic remains within the bounds of the confidence envelope for any given t, the null hypothesis of complete spatial randomness cannot be rejected (Haase, 1995).

Ripley's K function allows us to quantitatively describe a distributary turbidite lobe system from an angle of spatial point process. When we have some observations on parent events from available data, we are able to transfer the spatial distribution and time sequence of these parent events into modeling rules, making models conditional to observable information (Fig.6). The point process characterized by K function provides features of offspring point clusters at different scales, such as the average radius of blue dot clusters and the average number of offspring events that occur in the domain of each parent event (Fig.6). In addition, we adjust the geometry of turbidite lobes during simulation based on width and length CDFs of lobes at different scales.
When we incorporate a point process into the model, the resulting stratigraphy is characteristic of lobe clusters whereby each cluster would be recognized as a parent event that is visible in our seismic data. Meanwhile the lobe complexes in the model stratigraphy match the location and temporal order of each parent event because observable events are utilized as model inputs. A comparison of model inputs and results is illustrated in Figure 7. It demonstrates less bias on clustering areas, but as we increase measurement length and step into blank areas without so many points, simulation results differ from the original inputs. If we consider those blank areas as places of no interest in terms of reservoir forecasting, our modeling workflow provides promise in capturing the hierarchy of turbidite lobes as a whole.

![Image of Ripley's K plots at three major interpretation scales.](image)

**Figure 5.** Demonstration of Ripley’s K plots at three major interpretation scales.
Figure 6. Model inputs and associated realization demonstration. L indicates the size of lobe clusters and N provides the number of offspring events. The time sequence of large-scale lobe complexes is transformed into modeling rules to control the time order of lobe cluster generation. The cluster patterns of small-scale and medium-scale lobes depend on our interpretation of lobe locations in TDB-10-1. The Black dotes in realizations denotes locations of generated lobe elements in the simulation.

Figure 7. Comparison between K functions of inputs and modeling results

5. Discussion

Our modeling method is relatively straightforward and allows us to control the stratigraphic
patterns globally. However, this approach requires a data source providing a high-resolution interpretation on spatial locations of lobe elements, if we expect the modeling is capable to assist with forecasting sub-seismic features. Both seismic data and well data have limitations. Thus, tank experiments and process-based models are very helpful sources to provide inputs for modeling small-scale stratigraphic features. However as far as tank experiments are concerned, no one has proved that they contain informative contents that are exactly the same with natural systems though they have some degree of geometric similarity. A rationale is still needed to directly use experimental data and process-based models to infer stratigraphic information in the real reservoirs.

6. Conclusion

Surface-based modeling with rule algorithms, or we call rule-based reservoir modeling, facilitate incorporation of other information, such as understanding of sedimentary processes, into reservoir modeling. It provides a flexible space for modelers to manipulate geological concepts in an applicable manner and perform numerical experiments. In our study, we assume if an experiment is comparable to field data at a certain interpretation scale, the sedimentary processes and associated structures are informative and provide at least some references resulting in sedimentary features at the comparable scale.

Ripley’s K-function is utilized to analyze and extract spatial clustering information of lobe elements at a given scale from experimental strata. We converted K function to modeling rules allowing us to integrate clustering patterns of turbidite lobes into surface-based models. Observable data provide a population of scattered parent events which are comparable to lobe organization pattern at a certain scale in the experiment. We input this
point pattern and generate a series of 'parent' points that then become cluster centers for a random number of "offspring" events. Surface-based models successfully produce a clustered point behavior and a stratigraphic framework comparable to the chosen physical tank experiment. These models can be used to better assess subsurface spatial uncertainty under such a stochastic framework constrained by experimental information. Further questions will be how to condition a surface-based model to our well data in the context of a hierarchy imposed by spatial point process.

Bibliography


