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Quantitative Evaluation of Deepwater Fan Hierarchy: Insights from Full Physics Based Forward Stratigraphic Models

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Abstract

The identification of deepwater fan systems as hierarchical has improved the predictability of rock property distributions from sparse (well log) and low resolution (seismic) datasets. Underlying the definition of geologic hierarchy is the assumption that units within a level of the hierarchy (e.g., elements) display similar characteristics whereas units across hierarchical levels (e.g., elements vs. complexes) display different characteristics. Therefore, within a deepwater fan complex, we expect elements to have similar geometries, property distributions (e.g., net to gross), and spatial transitions (e.g., channel axis to channel off-axis). Due to the limited resolution and spatial coverage of subsurface datasets and the incomplete nature of outcrop datasets, quantitative validation of hierarchy within deepwater fan systems and associated conceptual models has been limited.

Recent advancements in forward stratigraphic modeling (i.e., computational stratigraphy) provide ideal datasets to quantitatively evaluate element-scale hierarchy using high resolution, fully sampled models of deepwater fan systems. In this work, we apply an unsupervised machine learning workflow to elements interpreted within a deepwater fan to test the scale-dependent consistency in reservoir volumes and properties (e.g., net to gross, sand quality, thickness).

Specifically, this approach assigns a label (cluster number) to each element identified within the deepwater fan complex, from which we evaluate map-based geometries, property distributions, and spatial transitions of clusters, allowing us to assess the variability and degree of hierarchical organization in deepwater systems. The novelty of the approach lies in its methodical translation of geologic concepts to a quantitative machine learning workflow and the application of this workflow to state-of-the art models of depositional environments. Collectively, this work closes the gaps in our understanding of deepwater hierarchy that previously had not been possible given the limitations of subsurface and outcrop datasets; the learnings from which reduce the uncertainty associated with predicting key reservoir property distributions from low resolution and sparsely sampled datasets.