Talk Abstract

This presentation demonstrates the application of **Paradise® Machine Learning technology** to predict lithofacies distribution within a producing oil field in the Oriente Basin, Ecuador.

The study addressed a particularly challenging geological setting in which target sand bodies occur at depths of approximately 8,900 ft and range in thickness from only 6 to 18 ft (2–6 m)—well below the conventional seismic resolution limit of approximately one-half wavelength (~40 m). As expected, conventional seismic inversion methods were unable to reliably identify or characterize these reservoirs.

The machine learning workflow integrated approximately 100 km² of migrated full-stack and partial-angle-stack seismic data with open-hole log data from 13 wells. Lithofacies were first classified using K-means clustering applied to petrophysical logs. Self-Organizing Maps (SOMs) were then generated to establish multidimensional clustering using seismic attributes. Relationships between SOM clusters (or neurons) and lithofacies were identified, requiring fine time-to-depth calibration. Statistical quality control metrics were used throughout the workflow to evaluate prediction uncertainty and reliability.

The reservoirs were deposited in a coastal-to-fluvial environment characterized by highly heterogeneous lithofacies distribution and predominantly stratigraphic trapping, making seismic characterization particularly difficult.

Results demonstrate that the machine learning workflow successfully delineated the distribution of thin reservoir sands despite their sub-resolution thickness. Moreover, geometries of identified lithologies are consistent with expected trends.

The presentation will discuss the workflow, validation methodology, uncertainty assessment, and the implications of applying machine learning to reservoir characterization in geological settings where conventional seismic characterization techniques reach their practical limits.