Integrating Geostatistics and Machine Learning Techniques for 3D Electrofacies Modeling in Early Cretaceous Clastic Reservoirs, Lower Indus Basin, Pakistan

Shakeel Ahmad[1], Shahid Iqbal[1], Shakeel Akram[1], Shahid Ghazi[3], Waqas Arif[1], Taimoor Hassan Bhatti[1], Rizwan Gul[2], Ghayoor Ahmed[1], Imran Khan[1], Rana Faisal Shahzad[1], Shabeer Ahmed Abbasi[1], Uzair Hamid Awan[1]

[1]*Oil and Gas Development Company Limited (OGDCL), Pakistan*

[2]*Next Oil and Gas, Calgary, Canada*

[3]*Institute of Geology, University of the Punjab, Lahore, Pakistan*

Summary

The Lower Goru sand intervals of Early Cretaceous age are established reservoirs in the Lower Indus Basin, a region well-explored for hydrocarbons. The Lower Goru Formation is inherently heterogeneous, with subtle variations in facies. A significant challenge lies in the limited number of core samples available from the many wells drilled in the area, making it difficult to accurately identify facies using conventional petrophysical methods, especially when there are more wells to interpret.

Accurate facies identification, closely reflecting the actual depositional environment, is crucial for developing a refined facies model. A well-defined workflow using machine learning techniques can aid in recognizing lateral and vertical facies variations and contribute to identifying combined structural and stratigraphic traps.

Theory / Method / Workflow

This research focuses on characterizing a reservoir through electrofacies analysis by combining well logs, cuttings, and other data. Intelligent clustering techniques, including K-Means Cluster Analysis and Self-Organizing Maps (SOM), were applied to well-log data to classify facies and determine porosity. Depth matching was initially performed using GR log anomalies, and necessary adjustments were applied where required.

To ensure data validity, facies clustering was carried out by selecting a well (W-16) with high-quality data, which was then used to train the algorithm. Histograms of the selected well logs were analyzed to monitor the distribution and frequency of the well-log data.

The results from the K-Means clustering technique and SOM (supervised and unsupervised techniques) were compared with the real dataset to determine the most effective approach. After comparing and analyzing the results, the supervised SOM method was adopted to calculate facies in all other wells.

The 2D Self-Organizing Map (SOM) approach was employed to categorize the data into different groups. In this method, the number of categories is determined based on both the horizontal and vertical axes. The horizontal and vertical coordinates of each group within the network space were used as inputs for the SOM algorithm. A training algorithm was designed to arrange the SOM ensembles in a way that reflects the entire dataset and its associated weights during each iteration.

At each stage, a horizontal vector from the dataset was randomly selected, and its distance to all weighted vectors within the network was calculated. Upon completing the training phase, SOM clustering was performed, resulting in the identification of seven distinct facies.

The available data on porosity, permeability, and water saturation were distributed across the entire reservoir using geostatistical methods, based on petrophysical log data from wells, including sonic, neutron, and resistivity logs. The results from electrofacies and petrophysical analysis were integrated with seismic data to create a 3D facies model.

Results, Observations, Conclusions

The results demonstrated an appropriate distribution, confirming the suitability of the log selection for proceeding with the evaluation process. Seven distinct facies were identified using K-Means clustering and SOM methods. The results obtained from SOM were more closely aligned with the drilled facies compared to those from K-Means clustering.

Facies 6 and 7 exhibit the most potential reservoir characteristics, with the highest effective porosity (~10%). Facies 1 and 2 represent tight sandstones, with porosities ranging from 2% to 3%, while Facies 3 and 4 correspond to shale units with the lowest effective porosity (~1%).

The SOM-based and K-Means clustering-based 3D facies models indicated that the best reservoir quality facies are located in the eastern and central parts of the study area, whereas in the western and northwestern regions, reservoir quality deteriorates.

Novel/Additive Information

Identification of facies in the Lower Goru Formation is a major challenge in the area owing to their subtle vertical and spatial variations. This research provides significant insights into characterizing the Lower Goru Formation's heterogeneous reservoir properties through advanced electrofacies analysis. Unlike conventional petrophysical methods, which are limited by sparse core samples and subtle facies variations, this study employs a combination of intelligent clustering techniques, including K-Mean Cluster analysis and 2D Self-Organizing Maps (SOM), to classify facies and determine porosity. The integration of sequential indicator simulation (SIS) with well-log and seismic data further enhances the precision of 3D facies modelling. This comprehensive approach of combining clustering, petrophysical, and seismic data ensures a refined 3D facies model, providing a valuable tool for optimizing drilling locations and well planning.

Acknowledgements

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Figures

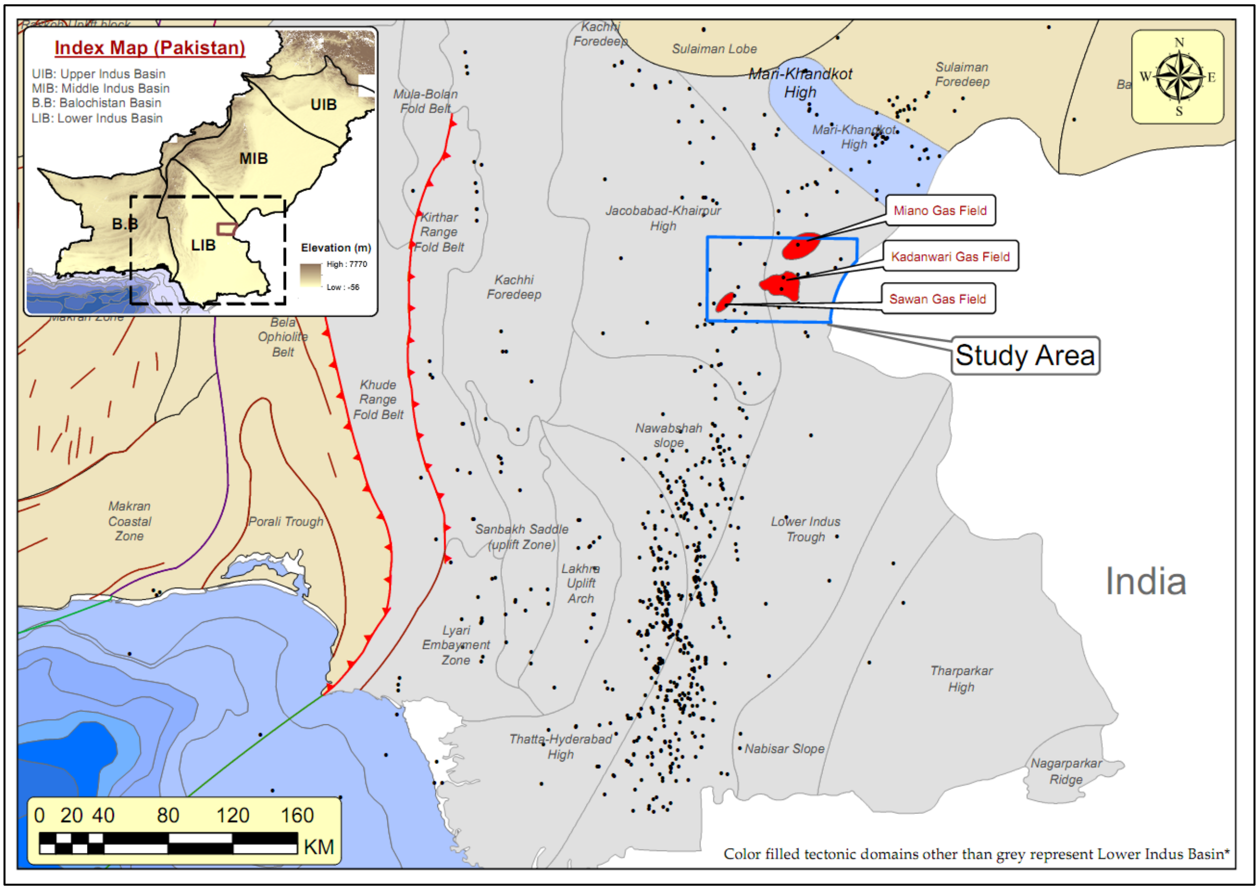

Figure 1: Map showing the location of the study area on the tectonic map. The study area falls in the northern part of the Lower Indus Platform Basin where several fields are producing hydrocarbons.

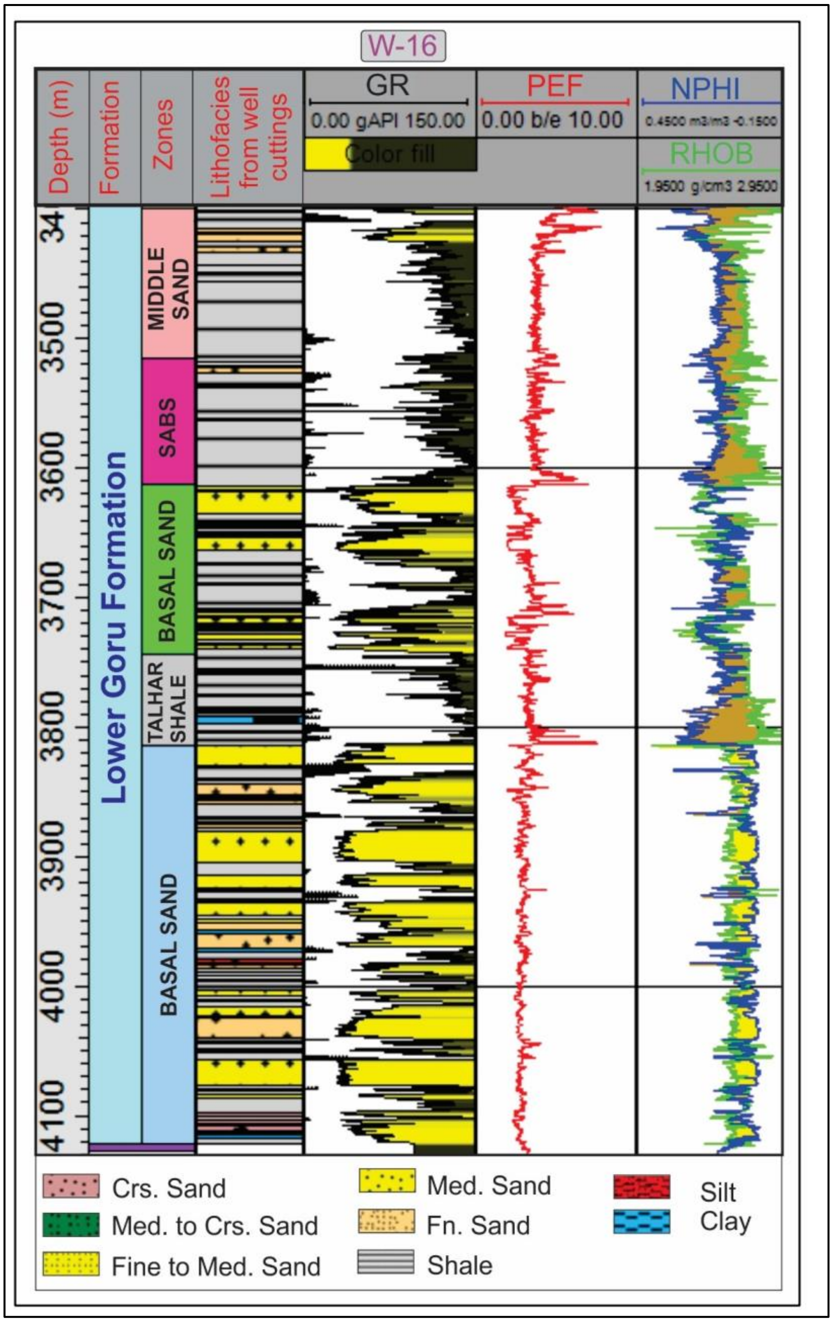

Figure 2: Well log showing facies drilled in well W-16 plotted against the wireline logs. These facies were used to calibrate the result from k-mean clustering and SOM analysis.

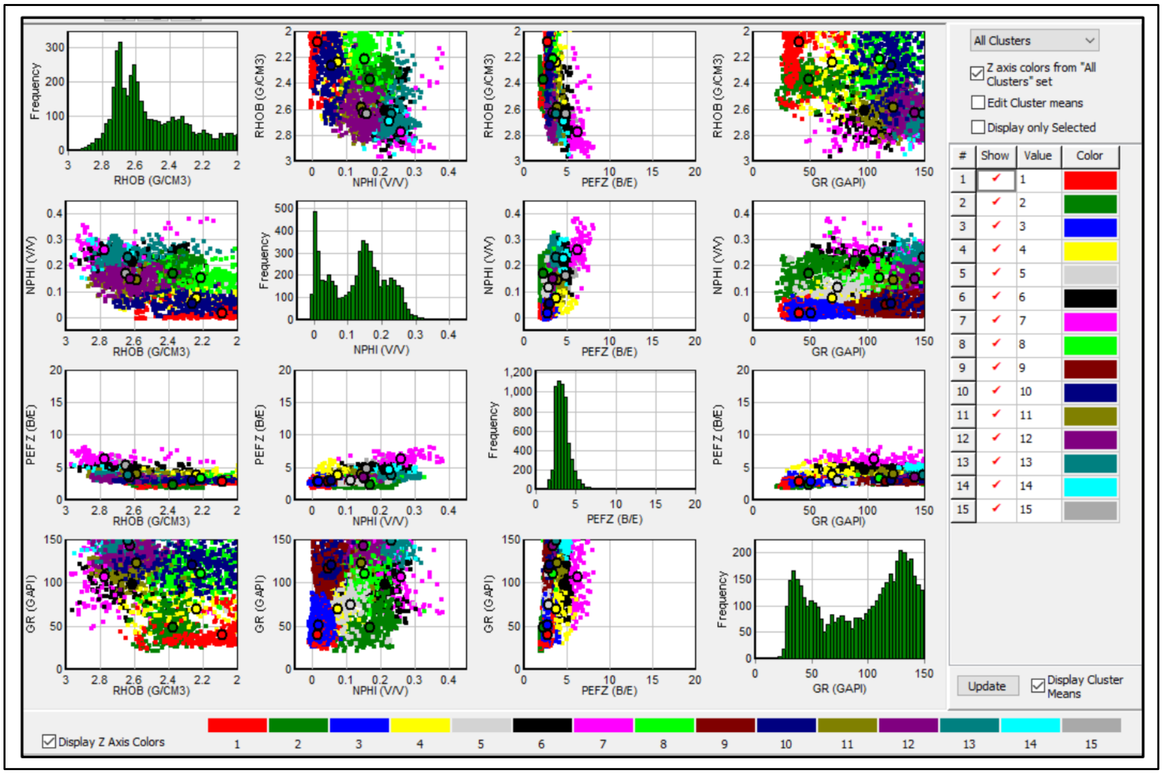

Figure 3: Cross plots of 15 clusters with their mean points. The colors in different clusters represent data concentration. The histograms represent the distribution of frequency of well log data. These 15 clusters were then grouped into 7 facies using dendrograms (hierarchical clustering).

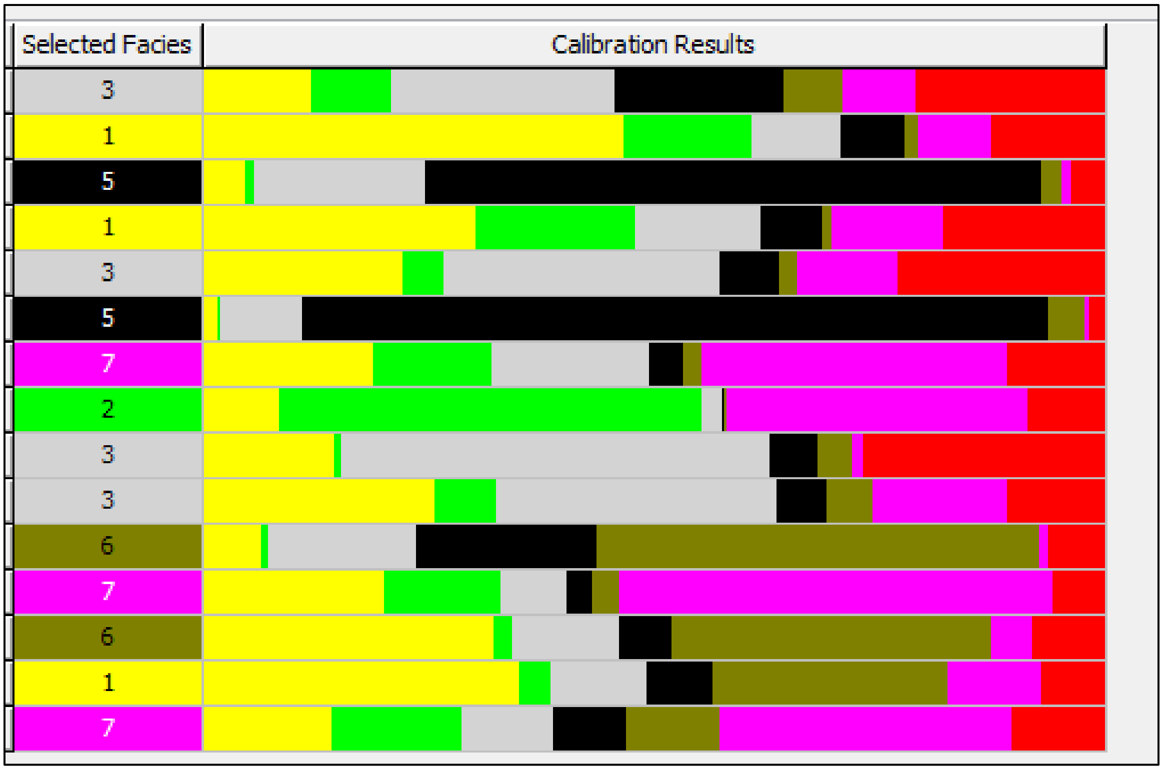

Figure 4: Calibration from K-mean cluster analysis against facies drilled in the wells showing moderate to poor correlation.

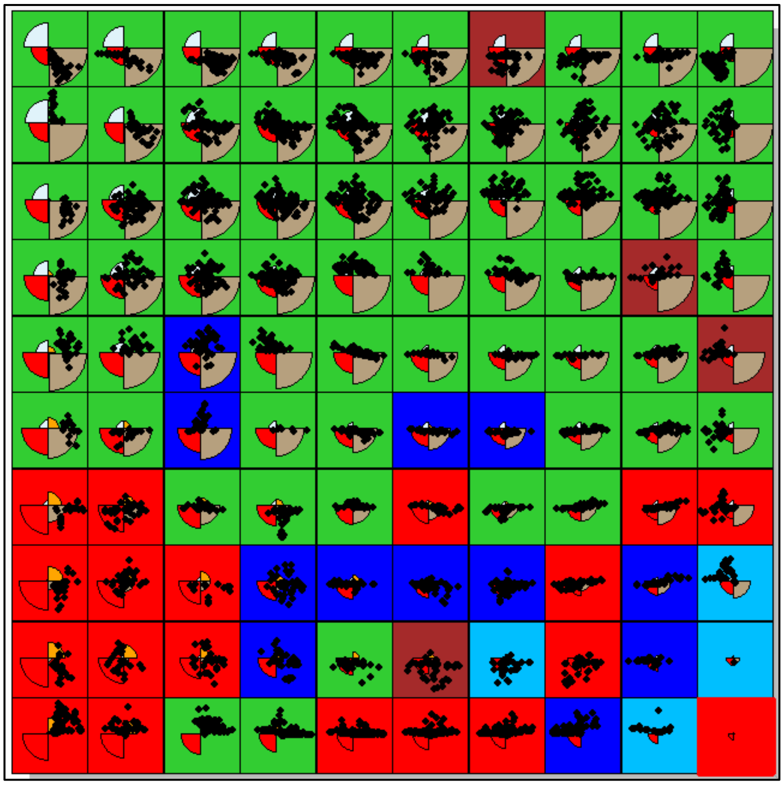

Figure 5: 2D Self-Organising Map (SOM) grid, each small square (node) represents a learned cluster from the dataset (black dots). Different colours represent different facies clusters. The pie charts inside each node indicate the distribution of input parameters (e.g., porosity, gamma ray, shale volume, etc.).

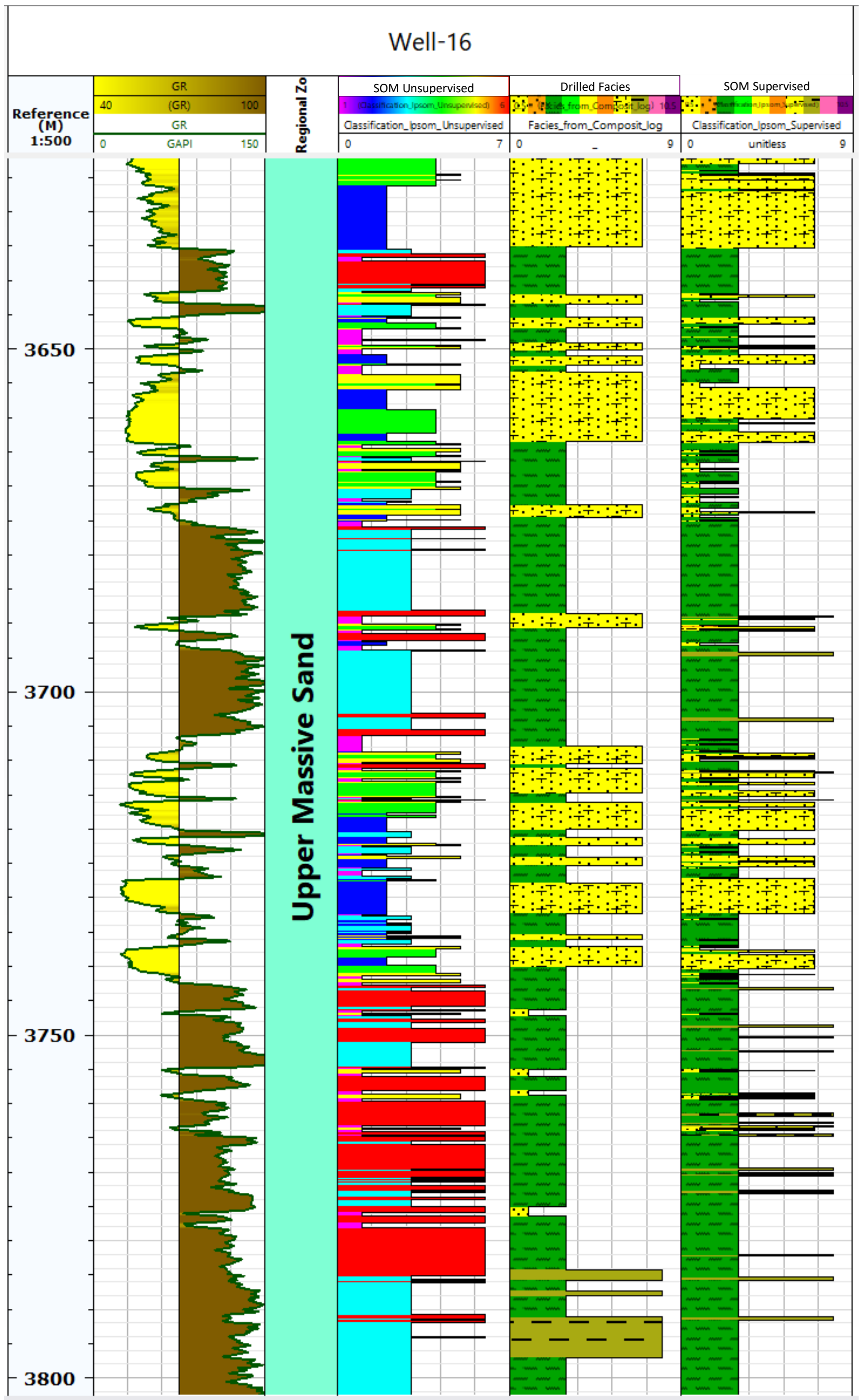

Figure 6: Comparison of drilled facies (facies from SOM supervised and unsupervised against facies drilled in the well W-16. SOM supervised has a good correlation with real facies.

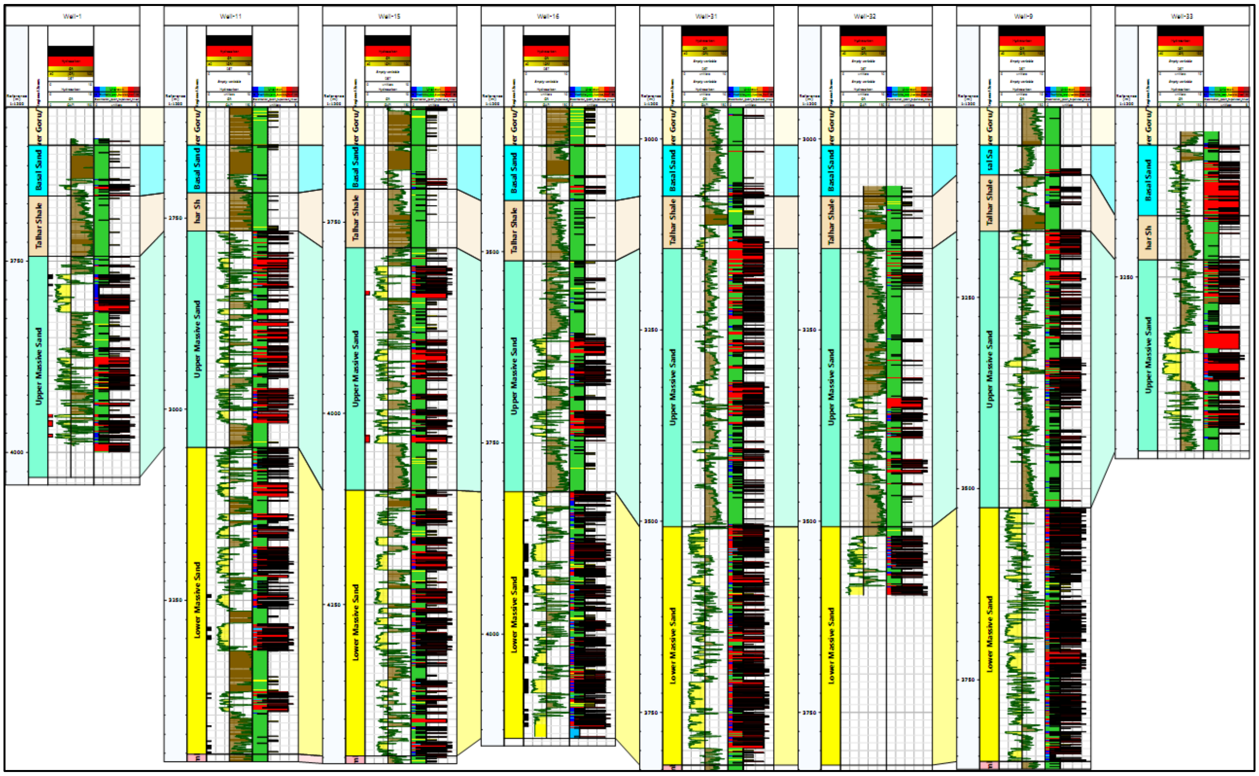

Figure 7: Well correlation panel showing facies produced using the supervised learning method of self-organized maps (SOM).

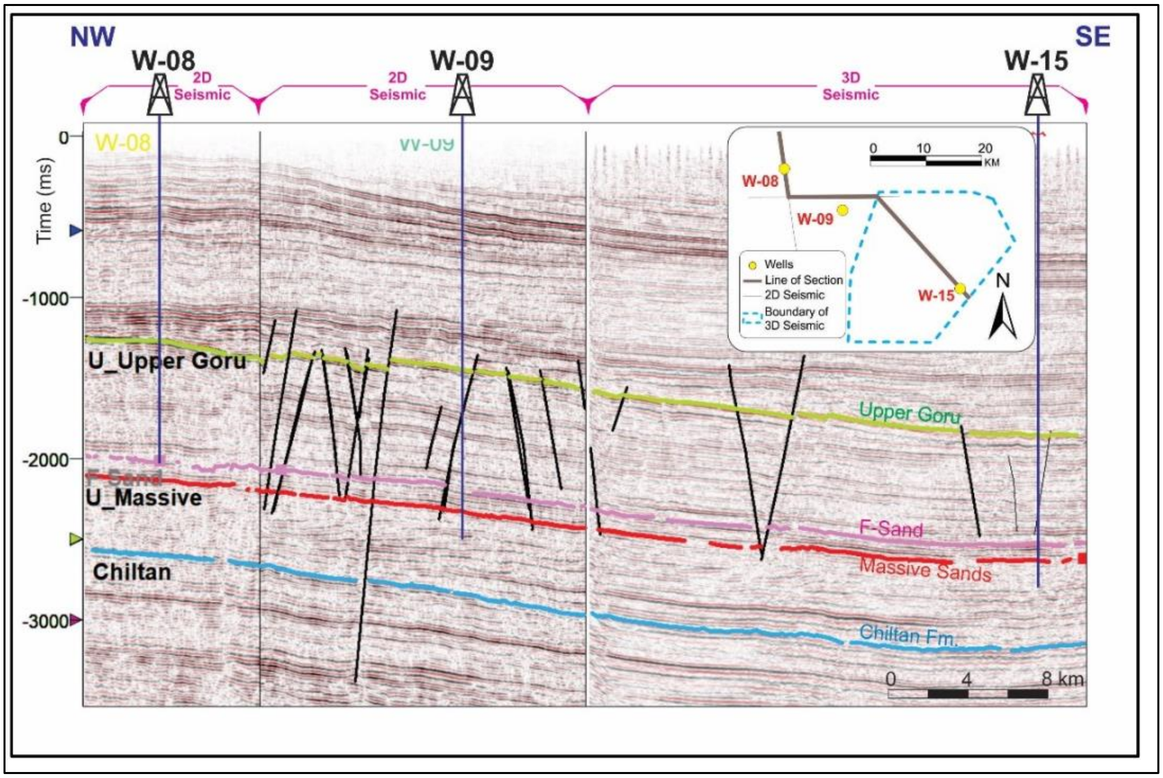

Figure 8: Composite seismic section showing structural style across the study area. Normal faults (thick black lines) have their limit just above the Base Tertiary Unconformity (a few reflectors above the Upper Goru) the in Lower Indus Basin.

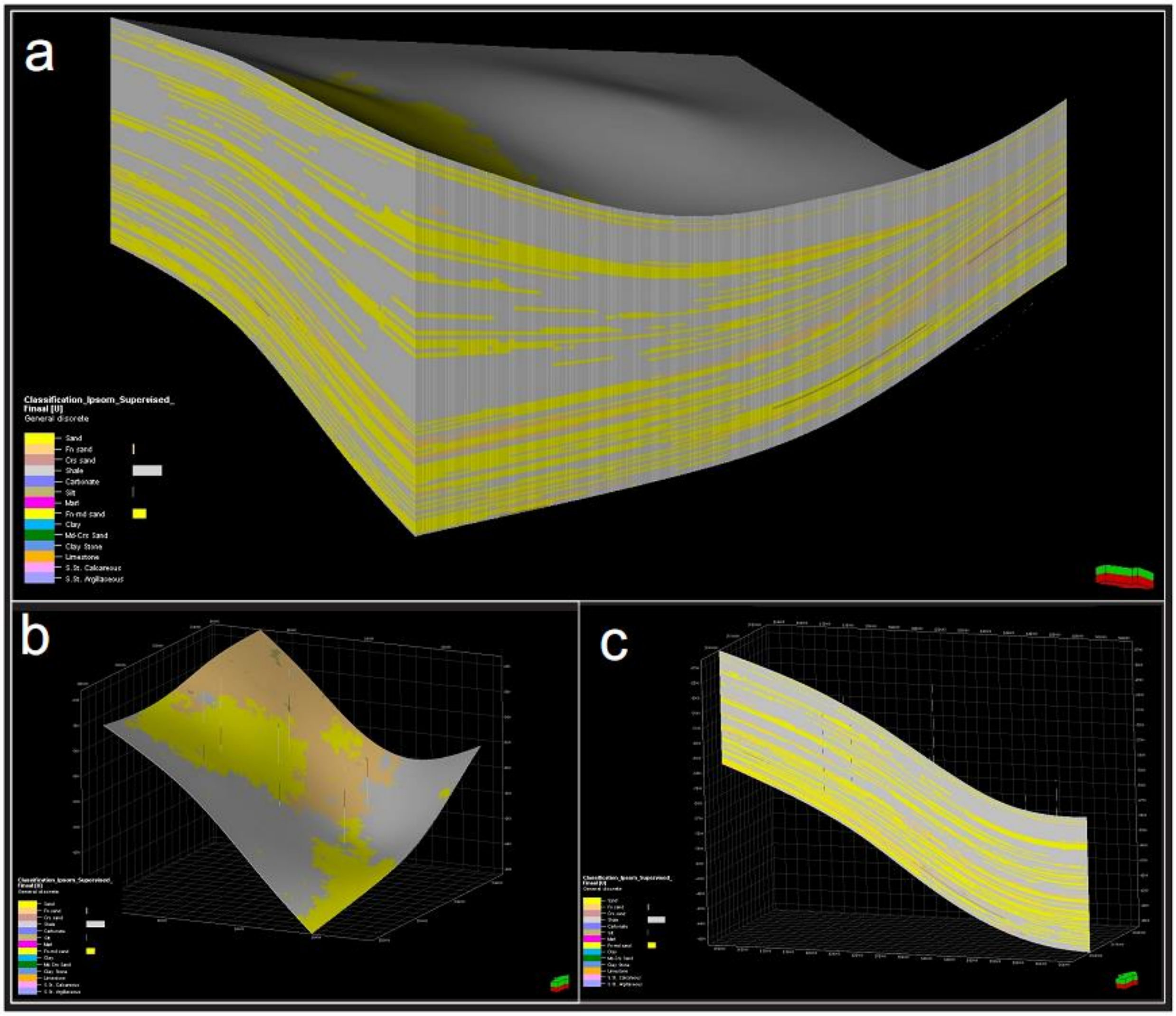

Figure 9: Supervised machine learning-based SOM facies model. (a) A 3D model, (b) a selected surface showing facies variations, and (c) a vertical facies cross-section.

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