WHITE PAPER

Log-Derived Multi-Variate Modeling and Subsurface Interpretation

A case study on semi-automated, basin-scale geomodeling

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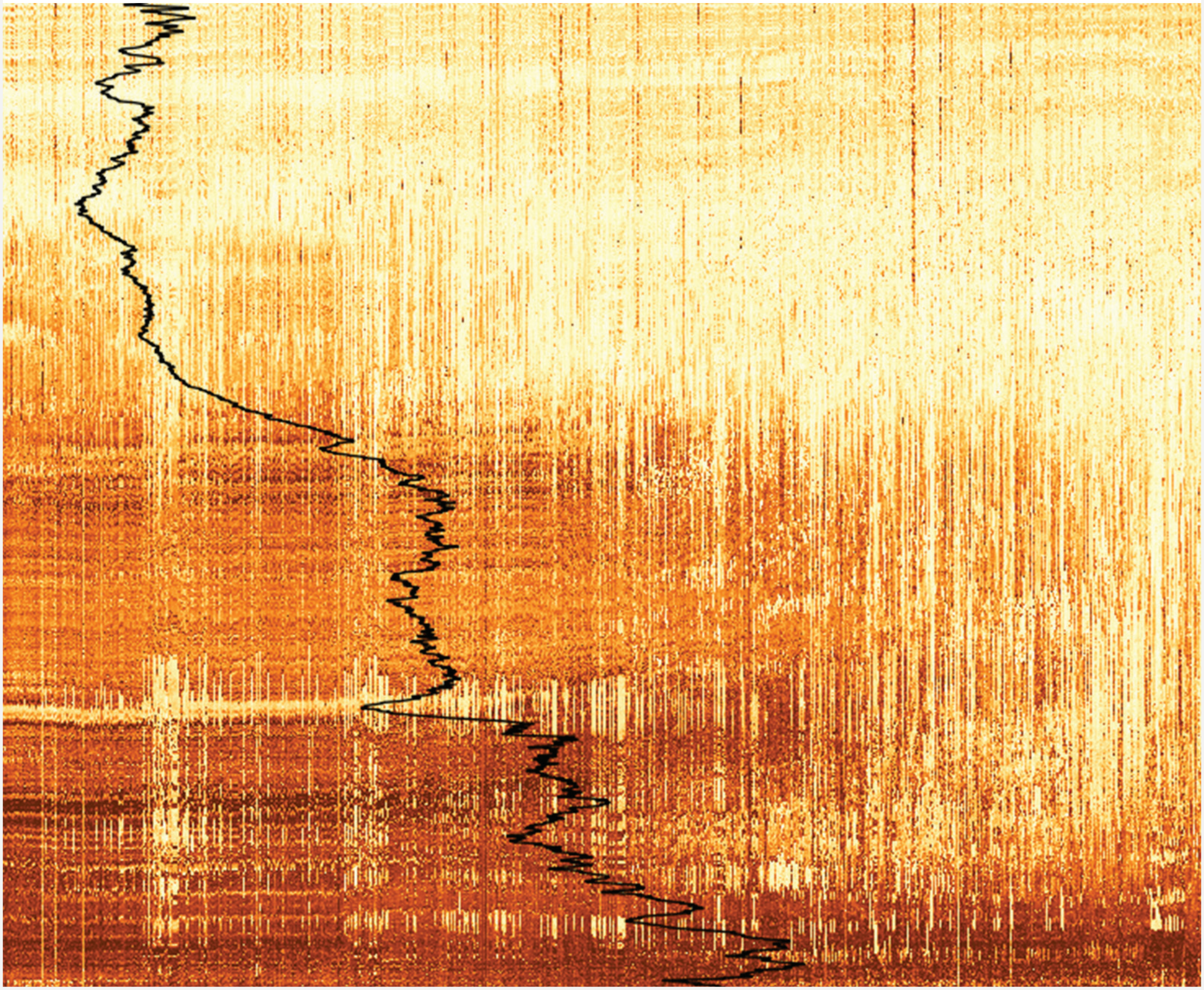

In the current data analytics landscape of artificial intelligence, machine learning, and multi-variate modeling, a key differentiator of a determinative model is the quality and scope of the input data. Predicting well performance with a high level of accuracy requires not only well production and completion data, but also high-fidelity geologic data differentiating well landing zones and reservoir quality. TGS, with an industry leading, high-quality, comprehensive log library, is uniquely positioned to provide the geologic context for the next generation of multi-variate predictive models and subsurface interpretations.

However, correlating and interpreting well logs are necessary, labor-intensive tasks for building large scale stratigraphic models used in multi-variate analytics, geomodeling, and reservoir simulation workflows. Aside from the high resource and time constraints, manual correlation and interpretations can also vary from interpreter to interpreter and often do not make use of all well and log data available. These workflows often require interpreters to focus on fine-scale details in a limited number of logs, making it challenging and time-consuming to assess the large-scale structure of the subsurface. Furthermore, generating accurate 3D property and stratigraphic volumes from well log data, especially in horizontal sections of producing formations, faces obstacles such as data quality variability, lateral reservoir variability, and the complexity of accurately modeling these variations. There is a clear need for automation to improve efficiency and reproducibility. Various approaches have been proposed to automate geological boundary detection from well log data. Dynamic Time Warping (DTW) and artificial intelligence (AI) are promising concepts for correlating signal sequences and extending to the domain of geology for well-to-well correlation (Zoraster et al., 2004; Lineman et al., 1987; Smith and Waterman, 1980; Le Nir et al., 1998; Baldwin et al., 1989; Luthi and Bryant, 1997; Po-Yen Wu et al., 2018; Brazell et al., 2019; Tokpanov et al., 2020).

STUDY AREA

The study area of interest (AOI) is the Midland Basin, spanning Glasscock, Howard, Martin, and Midland counties. We use an extensive dataset of approximately 30,000 vertical and 6,550 producing horizontal wells (Figure 1). The Midland Basin's size, complex geology, stacked pay zones, and variable lithologies make extensive manual interpretation prohibitively expensive and therefore a good test case for this workflow. The ChronoLog (Sylvester, 2023) methodology requires an initial input set of interpreted formation tops to constrain the well log correlation. We select interpreted formations tops that provide the largest span of our 3D property generation spatially and in-depth; these include the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger.

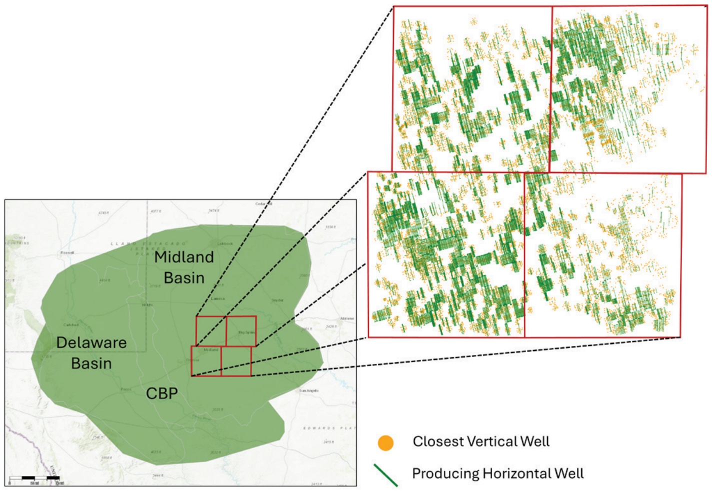

Figure 1: Map of well locations in the Midland Basin, covering Glasscock, Howard, Martin, and Midland counties, indicating vertical and horizontal wells.

METHODOLOGY

Data Selection and Pre-processing

Our well data preprocessing pipeline starts with automated data cleaning. It comprises curve categorization, verification of information, splicing, merging, depth shifting, normalizing, and quality editing. The gamma-ray curves are also standardized to an interval from 0 to 1, an important step when evaluating numerical well-to-well correlation and for the following well-curve imputation step. To maximize the collection of available well data, we fill in missing log curves on the clean well data using a predictive Analytics-Ready LAS (ARLAS) model (Gonzalez et al., 2023) trained specifically for the Permian Basin. Using ARLAS, a consistent collection of five log curves are available in every interpreted well: the bulk density, gamma-ray, neutron porosity, deep resistivity, and compressional sonic curves.

Dynamic Time Warping-Based Well-to-Well Correlation

Chronolog uses a Dynamic Time Warping (DTW) algorithm to align well logs based on manually interpreted formation tops and normalized gamma-ray curves pairwise. This method aligns geological features across pairs of well logs, accounting for discrepancies in deposition times or layer thickness resulting from geological processes. A well connectivity graph is first created to reduce the computational overhead of the dynamic time warping, which is significant at the basin scale. ChronoLog only evaluates pairwise correlations for connected nodes in this graph. The edges of this graph (Figure 2) represent proximity or relational ties to neighboring wells. In parts of the AOI that are well covered spatially by interpretation, the graph is cut between wells more than 3 km apart. We still attempt to include data in parts of the AOI with sparse well coverage; here, a Delaunay triangulation creates edges between wells, which are not subject to the 3 km maximum proximity. The objective is to ensure a comprehensive network that facilitates as much accurate stratigraphic analysis as possible.

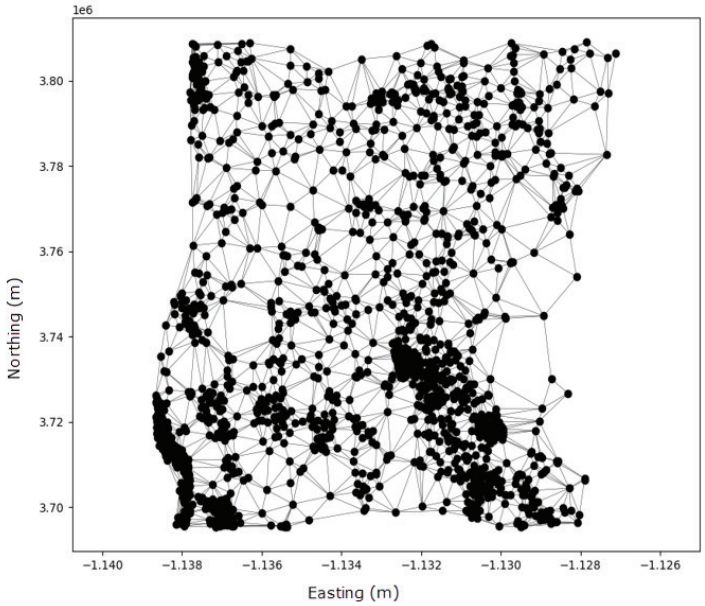

Figure 2: Well connectivity graph showing pairwise well correlations.

DTW will always yield a result, even for unrelated sequences. For this reason, we filter the set of well pairs based on the normalized DTW cost (Rath et al., 2003) for the pair. For two sequences s_1 and s_2 and with length N_1 and N_2, this cost is:

$$C_{norm} = Cost(s_1, s_2)/(N_1 * N_2)$$

After computing this cost across our dataset of wells, we identify pairs where the cost is greater than the 99th percentile. The network connectivity graph is cut for these pairs, and if a well is left unconnected from the graph, it is removed from the analysis. Using least-squares optimization, ChronoLog creates a consistent set of pair-wise depth correlations (Wheeler and Hale, 2014). The result is a chronostratigraphic diagram that aligns the well curves in relative geologic time (RGT) (Figure 3).

ChronoLog then applies a Continuous Wavelet Transform (CWT) and systematically identifies stratigraphic boundaries by detecting zero-crossings in the wavelet transform, indicating geological feature changes (Cooper et al., 2009). This segmentation is later used to create aggregated 3D properties across the basin. The scale parameter in this method can be thought of as the bandwidth of a Ricker wavelet. Less fine detail is retained as the scale increases. This study uses a setting of 4 samples to produce a rich set of stratigraphic layers without additional manual interpretation.

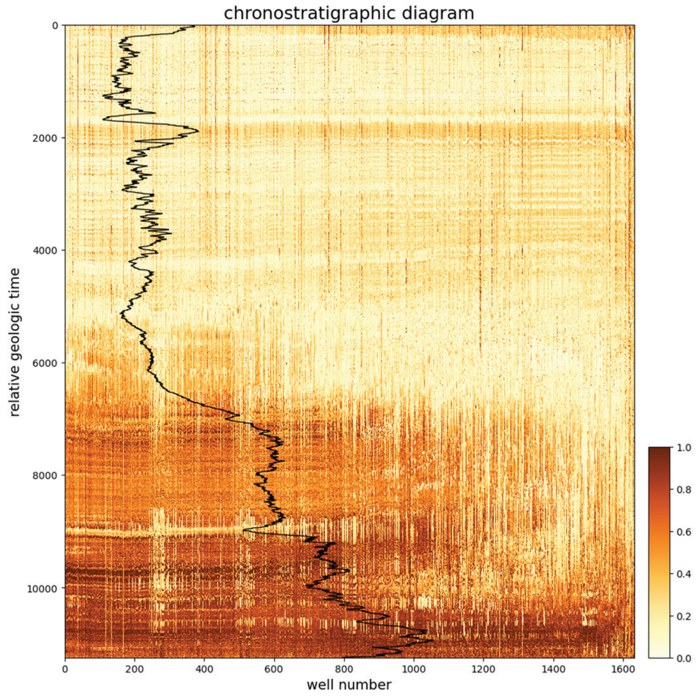

Figure 3: Chronostratigraphic diagram illustrating the alignment of well logs in RGT, utilizing normalized gamma-ray curves for Rustler formation.

Development of 3D Geological Models

Our workflow does not require every well to contain interpreted tops for every formation. Instead, a basin-wide chronostratigraphic diagram is created in a layer cake fashion, stacking diagrams and segmented sequences assembled for the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger formations. For this reason, many of the wells in the dataset may lack certain stratigraphic layers identified by ChronoLog.

A problem with naively filling in the missing sequences by a simple interpolated grid is that the result may not preserve the correct sequence. This is particularly relevant when geology is structurally complex. Instead, we use an iterative method based on interpolating segment thickness relative to a common reference point, as shown schematically in Figure 4. The algorithm starts with an established reference point across the dataset, and then an interpolated map of segment thickness across the basin is computed. This thickness map is then used to forecast the interval of this segment in wells where it is missing. The top of the segment becomes the common reference point, and the algorithm iterates until consistent segmentation exists in all wells.

With every stratigraphic top identified at each well location and characterized by a high spatial density, we can now interpolate depth values and log properties beyond the immediate areas surrounding the wells to generate maps with regular grids. This involves gridding both the identified stratigraphic tops and the average property values found between these tops, which serves as a foundation for building 3D geological models.

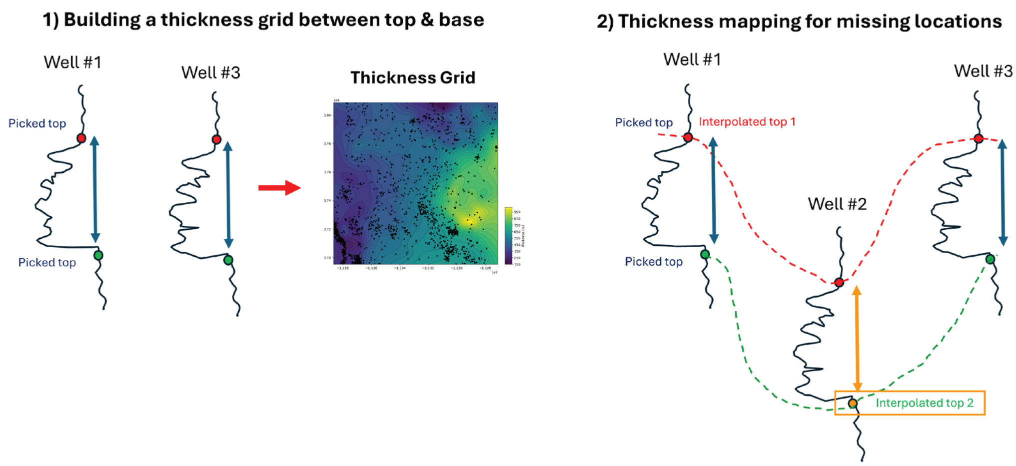

Figure 4: A schematic depicting the iterative process for interpolating missing formation tops, involving two main steps: 1) constructing a thickness grid between identified tops and bases, and 2) applying thickness mapping to estimate missing formation tops.

Extended Stratigraphic and Property Model

Expanding on the initial model, we now include all vertical wells in the dataset, regardless of whether their formation tops have been manually identified. By plotting the locations of these wells on the stratigraphic grids, we can identify previously missing formation tops while using all existing log curve data from those wells. We address gaps in the log curve data using the k-nearest neighbors algorithm, creating a comprehensive dataset and a complete property model with both formation tops and comprehensive well log data.

This expanded effort allows us to develop 3D stratigraphic and log property models, capturing each vertical well's known formation top and the log curve data. Following the methodology of the initial model, we use spline interpolation to fine-tune the log curve attribute grids. This technique ensures that geological features are depicted accurately, avoiding overlaps, and ensuring continuity in our models.

CASE STUDY

In this section, we describe chronostratigraphic diagrams and log correlations generated with the automated stratigraphic correlation workflow and highlight their value in interpreting geological features. The workflow starts by selecting formations with well-supported tops, such as the Rustler, Bone Spring/Upper Spraberry, Wolfcamp, Strawn, Devonian Carbonate, and Ellenburger. We limited the distance between well pairs to 3,000 meters for correlating wells. With a segmentation scale set at 4, we identified 1,570 stratigraphic units for 1,939 wells, which helped us create a detailed gridded model. This setup enabled precise spatial analysis.

Development of Stratigraphic and Property Models

We developed a 3D geological model using well log data, featuring one stratigraphic volume and six property volumes, including normalized gamma-ray, sonic, neutron porosity, density, and resistivity. Each property volume offers insights into different aspects of the geology. The model is structured as a volumetric array, resembling a stack of layers, each representing a geological layer or formation (Figure 5b). This setup, visualized in Figure 5a, assigns a specific X-Y-Z coordinate to every point in the grid. We chose a 50-meter spatial resolution for the X and Y axes to balance detail with computational efficiency. To validate the accuracy of our 3D models, we generated synthetic logs for vertical wells within the AOI. We calculated the normalized Root Mean Square Error (RMSE) against the existing ARLAS logs. An example log track of a selected well in Figure 6 displays a comparison for the neutron log, with ARLAS logs in blue and synthetic logs in red. Validation focused on depth intervals with overlapping signals, showcasing the synthetic logs' capability to reconstruct a continuous signal throughout the wellbore. The findings show a normalized RMSE between 10–15% across all compared well logs, indicating a relatively close match.

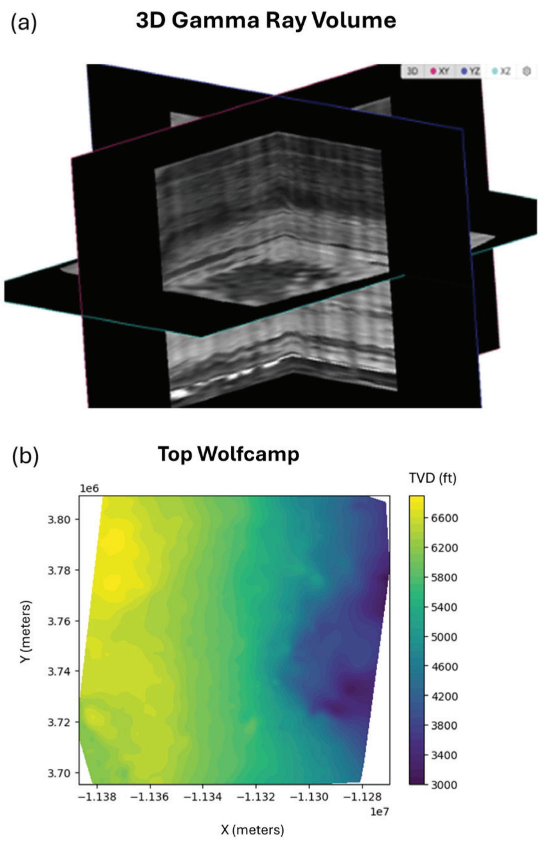

Figure 5: (a) 3D gamma ray model; (b) Map view showing the Wolfcamp formation top, represented as a stacked 2D layer within the stratigraphic volume.

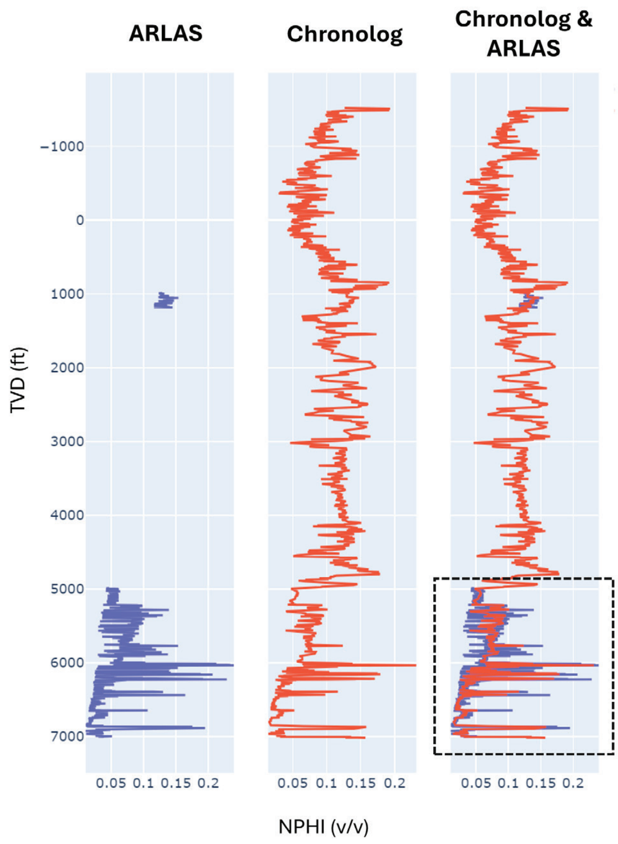

Figure 6: Log track comparison between synthetic logs (red) and ARLAS (blue) for a selected well.

Deriving Log Data for Horizontal Wells in Reservoir Analysis

Extracting log data from horizontal sections of wells is a critical step in understanding and evaluating reservoirs. This process provides key insights that help make informed decisions to optimize production, manage reservoirs effectively, and improve profitability. To do this, we rely on two main data sources: directional surveys (DS), which give us the X-Y coordinates for the paths of horizontal wells, and a set of 3D models of the stratigraphy and property data from well logs (Figure 7. a - 7. c). Using the X-Y coordinates obtained from DS, we map and collect the log curve data and the stratigraphic tops for horizontal wells from the 3D models. We compute a comprehensive statistical analysis on these sections to determine critical metrics such as the 2nd and 98th percentiles, median, minimum, maximum, and average log responses (Figure 7b). This approach allows the statistical analysis of any curve attributes, including petrophysical properties, at any X-Y-Z coordinate.

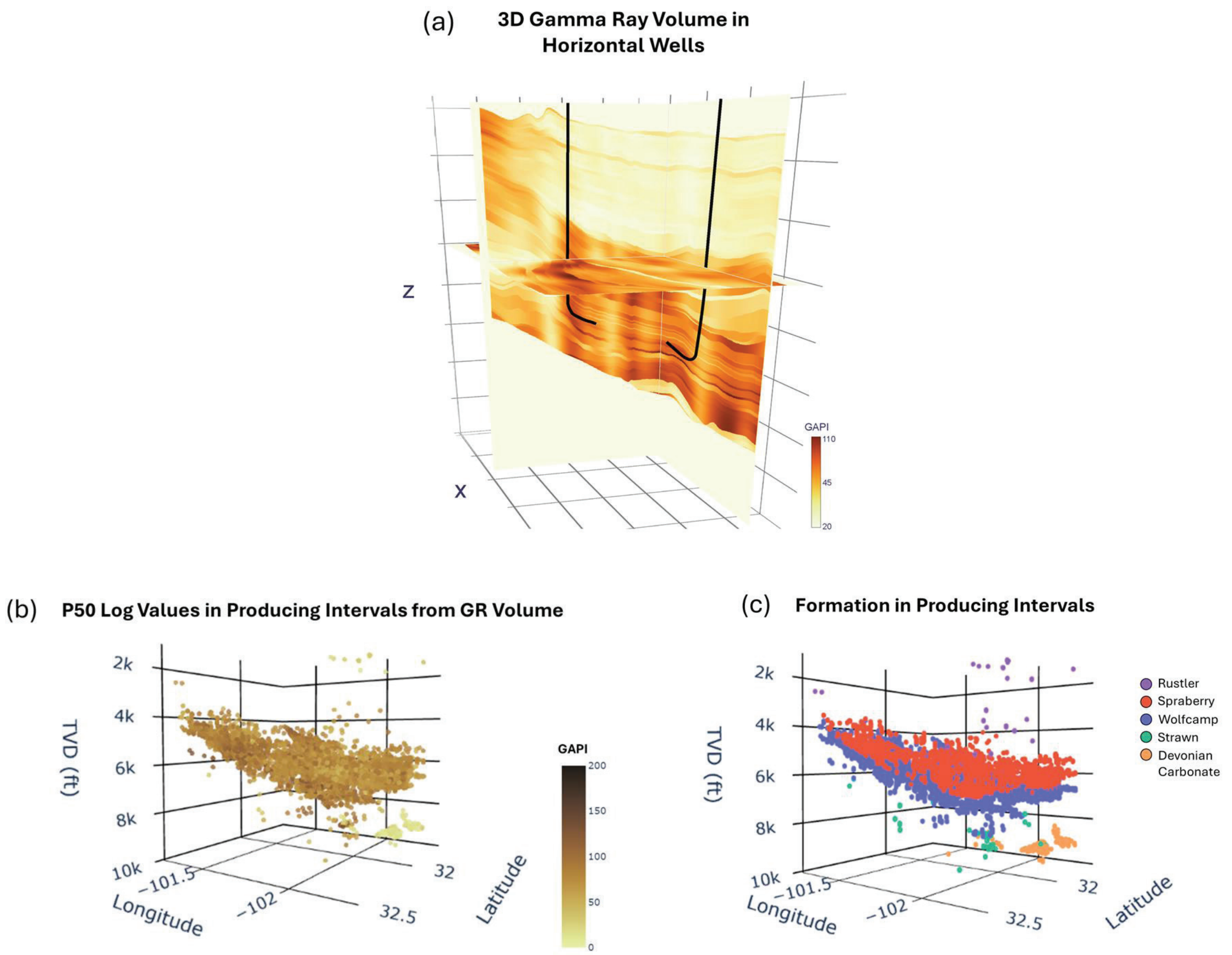

Figure 7: Diagrams showcasing well log data extraction from horizontal wells for reservoir analysis. (a) 3D gamma-ray volume analysis, (b) median gamma-ray values in producing wells, and respective (c) formation names.

CONCLUSIONS

This case study presents a comprehensive overview of the advanced 3D geological modeling and ChronoLog automated stratigraphic correlation pipeline employed to develop a geologic model of the Midland Basin's subsurface geology. These technologies and workflows have enhanced the accuracy and efficiency of constructing 3D stratigraphic and property models. The resulting interpretation is being evaluated or is currently being used across various workflows. Geological properties from this model are extracted and aggregated across the producing interval of actual and proposed horizontal wellbores for use in multi-variate statistical models to benchmark and predict well performance. Additionally, delineated formation horizons are cross-referenced with directional surveys to assign production to detailed benches and landing zones. Furthermore, the full 3D geologic volumes from this model are used to populate geomodels for well planning, geosteering, detailed reservoir studies, and reservoir simulations.

ACKNOWLEDGMENTS

Special thanks to Dr. Vi Ly for assistance in executing the ChronoLog code at a basin scale. ChronoLog is a product of the Quantitative Clastics Laboratory research consortium at the Bureau of Economic Geology (http://www.beg.utexas.edu/qcl).

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