

A Volumetric Approach to Geological Log Normalization at Basin Scale

Patricia E. Rodrigues¹, Reinaldo J. Michelena¹, Keyla Gonzalez², Alejandro A. Valenciano²
¹SeisPetro Geoconsulting, ²TGS

Summary

This work presents a geology-anchored, two-stage workflow for large-scale log normalization designed to remove non-geologic variability while preserving stratigraphic and facies variability. The method integrates systematic reference-well selection with fully automated three-dimensional (3D) percentile-based normalization, enabling basin-wide consistency at unprecedented scale. Applied to approximately 2,700 wells in the Midland Basin (Texas), the workflow achieved 98% successful normalization and was subsequently extended to over 20,000 additional wells using the same 3D statistical volumes and normalization rules. The resulting dataset shows improved stratigraphic continuity, removal of casing-related artifacts, and clearer delineation of regional trends. Beyond Gamma Ray logs, the workflow provides a scalable and reproducible framework for preparing high-quality inputs for seismic-log foundation models and machine-learning-driven subsurface interpretation. Besides, the generation of high-resolution 3D normalized log volumes establishes a practical framework for future extraction of geologically consistent properties along horizontal well trajectories and for subsequent integration with completion and production data.

Workflow

Over the past decades, several authors have addressed the problem of log normalization from different perspectives, establishing the conceptual foundation for consistent data integration. Early practical approaches focused on workflow guidelines and manual corrections, emphasizing calibration and curve alignment within limited stratigraphic intervals (Shier, 2004). Subsequent applications demonstrated the importance of normalization for petrophysical consistency in field-scale studies but were constrained by manual implementation and modest well populations (Aguirre and Antelo, 2001). Commercial software frameworks such as Petra introduced systematic normalization utilities (IHS Markit, 2020), yet these remain primarily interval-based and dependent on local reference wells. Collectively, these methods provided the groundwork for normalization best practices but are limited in scalability and reproducibility when dealing with thousands of wells of variable depth, casing, and tool vintage.

In mature basins like the Midland Basin (Texas), decades of exploration have produced well logs acquired by different service companies, with variable tools, calibrations, and depth corrections. Changes in borehole size and the presence of multiple casing strings frequently alter log responses with depth. These effects, compounded by incomplete coverage and differing acquisition intervals, create a patchwork of data that masks genuine geological trends and make data cleanup and normalization more difficult (Figure 1).

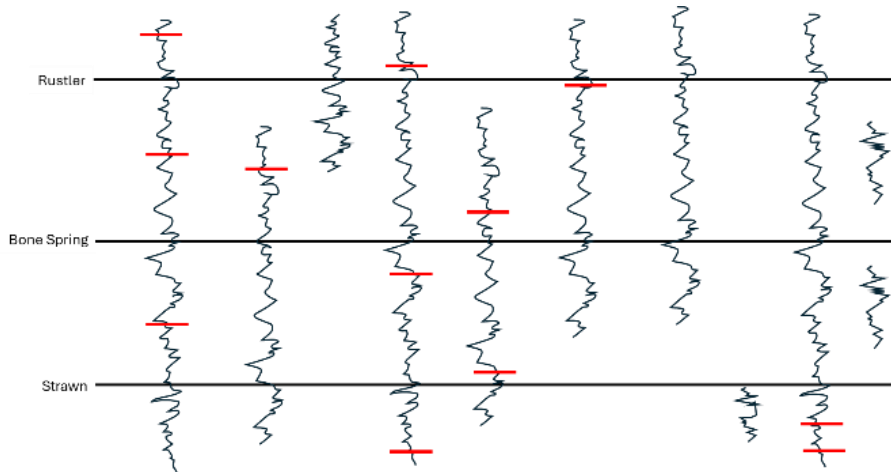


Figure 1. Examples of data coverage heterogeneity and casing locations (red segments) in GR logs across the Midland Basin.

To address these issues, normalization was designed as a progressive, two-stage geology-controlled process transitioning from supervised reference normalization to fully automated volumetric normalization.

In Stage 1, a reference dataset was constructed from an initial population of 6,826 vertical wells. Approximately 3,000 wells were first selected to reduce spatial clustering and achieve uniform coverage. From these, 2,757 wells were retained based on large vertical coverage and minimal casing interference (Figure 2). Additional wells with partial casing-free intervals were included, while complex cases (short, discontinuous, or multi-cased wells) were deferred to Stage 2.

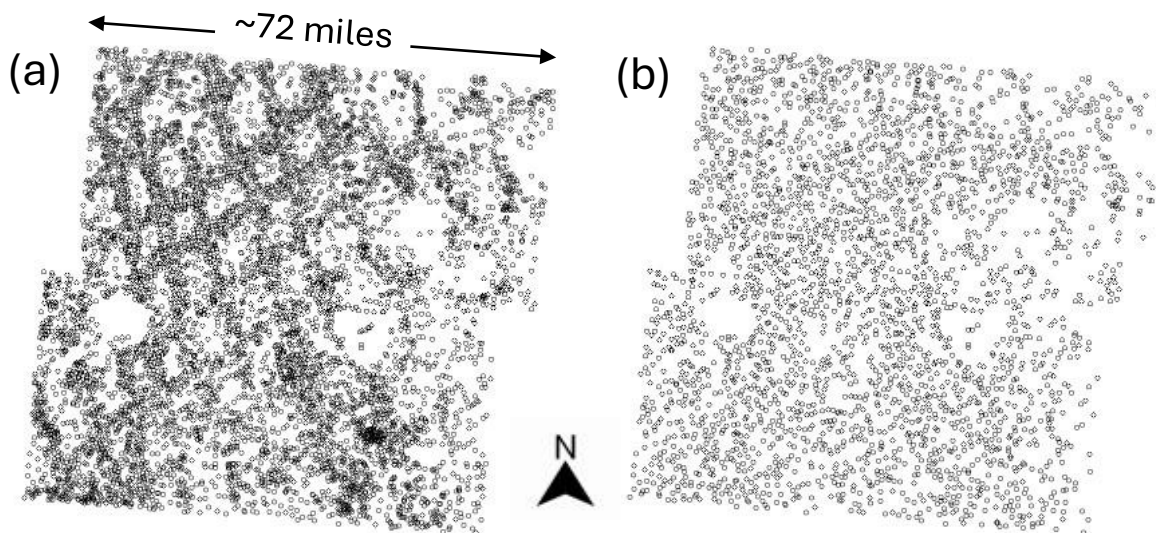


Figure 2. (a) Spatial distribution of vertical wells (6826) and (b) selected subset for reference normalization (2757).

Filtered and smooth 2D percentile-based statistics maps (P10, P90) were computed along key stratigraphic surfaces (Figure 3) generated from formation tops automatically picked using a machine-learning based approach. In regions with structural ramps or abrupt facies changes, local smoothing parameters were adapted to prevent over-flattening of the data. The combination of percentile-based scaling and adaptive smoothing ensured both continuity and preservation of fine-scale variability. These statistics maps were then used to generate normalized reference wells that capture basin-scale geologic trends while removing noise due to different vintages, acquisition contractors, processing parameters and other factors that introduce non-geologic variability.

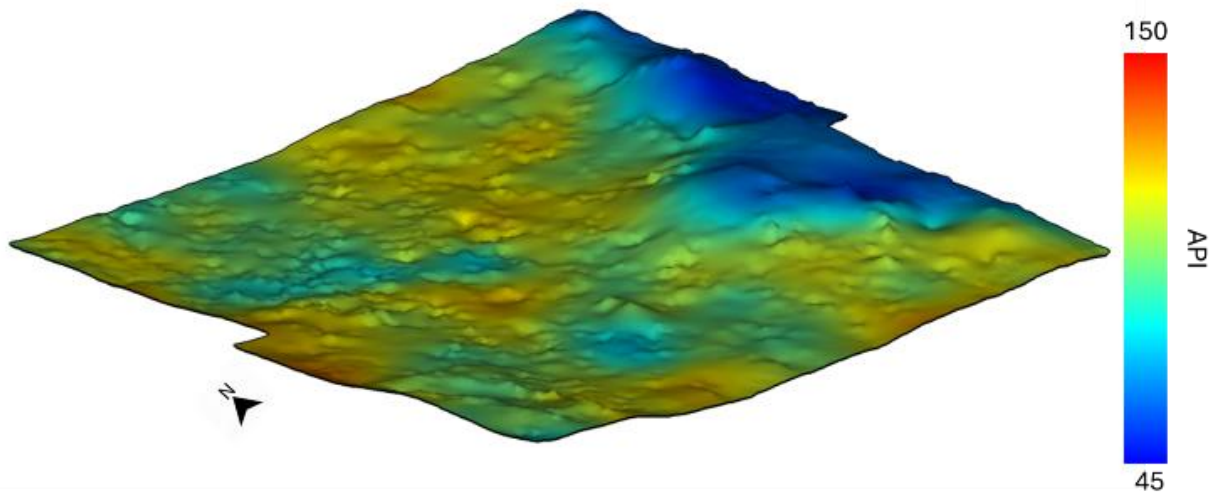


Figure 3. P90 trend along Bone Spring surface.

In Stage 2, reference-normalized logs were upscaled into a stratigraphic grid built from modeled formation markers interpreted from reference wells (Figure 4a). After the grid is built, normalized logs are converted to blocked, upscaled logs at the resolution of the grid. Each block contains the extracted percentile (P10 or P90) from the normalized log data within the corresponding layer (Figure 4b). The next step was to interpolate the blocked P10 and P90 logs from the reference set across the entire 3D grid. The result of the P90 interpolation is shown in Figure 5.

During volumetric normalization, each interval between casing points or missing data segments required representative low and high statistics. Analysis showed that average grid P10 and P90 values did not match true interval percentiles, as shown Figure 6. This figure compares the full distribution of normalized logs with that of upscaled P10 and P90 values. It shows that the global P10 and P90 (black curve) align better with the P22 and P72 of the upscaled values (green and red curves respectively), not their P10 and P90. This shift reflects a consistent bias from upscaling and indicates a simple starting point to improve large-scale percentile estimates by additional trial and error.

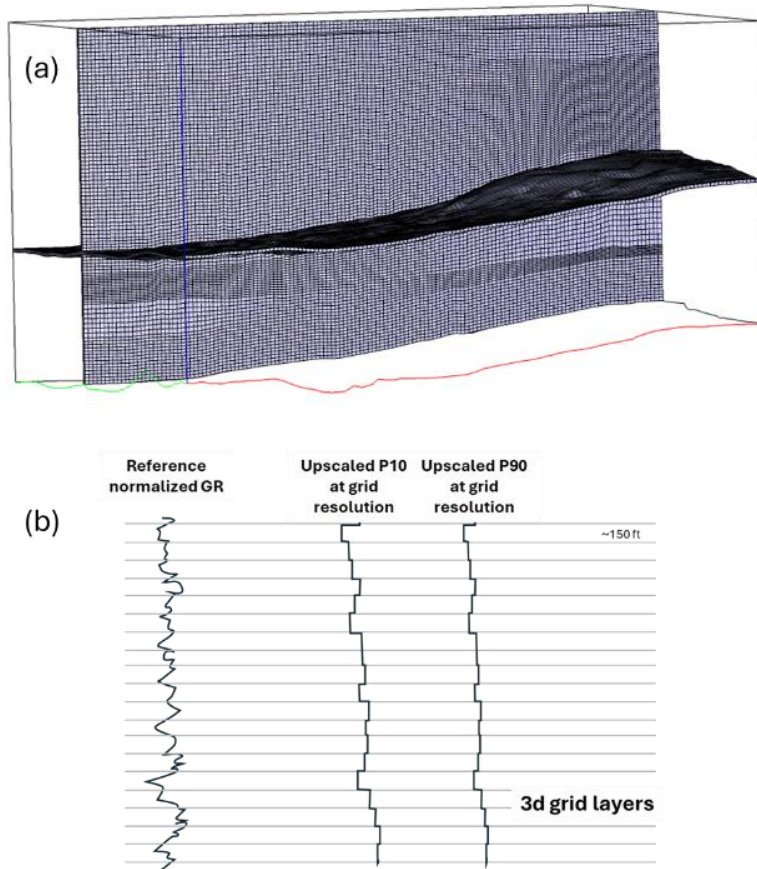


Figure 4. (a) Stratigraphic grid and (b) calculation of upscaled statistics at grid resolution using reference wells. Grid cell dimensions: 2500 ft x 2500 ft x ~150ft.

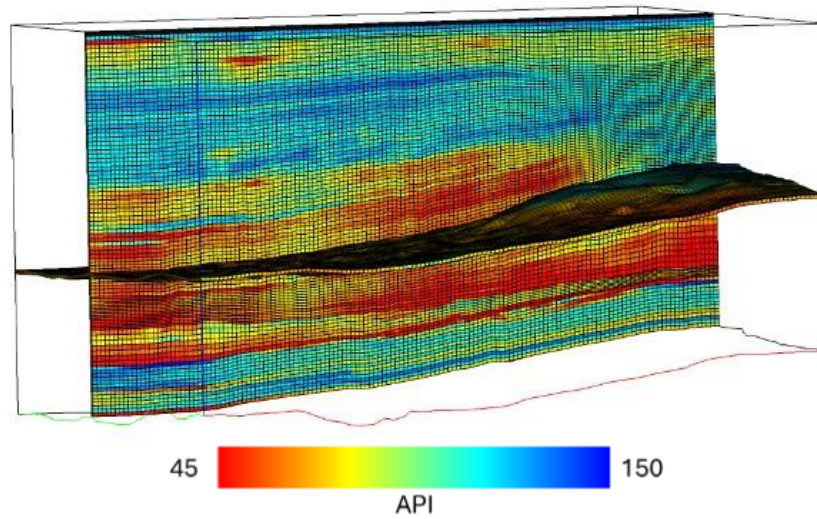


Figure 5. Interpolated upscaled P90 along stratigraphy.

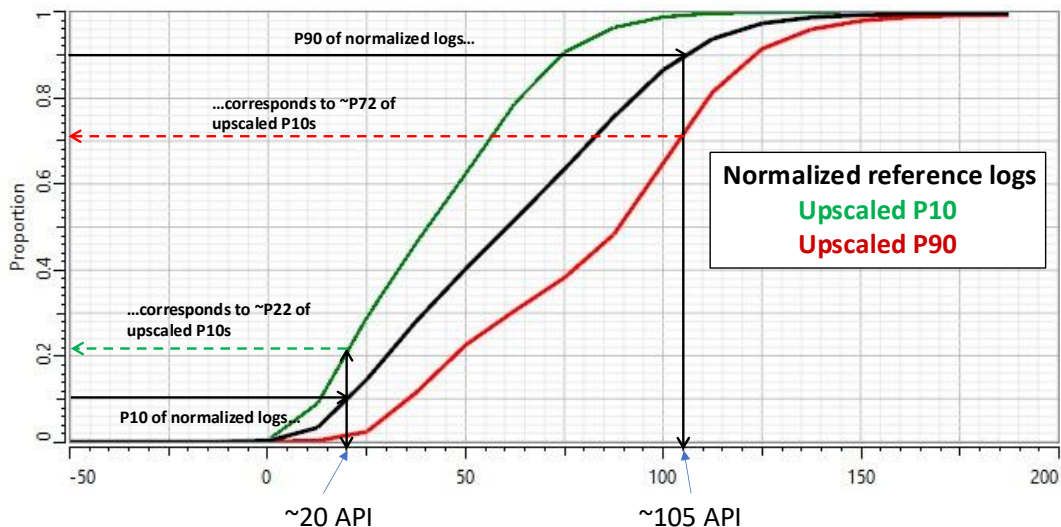


Figure 6. Calibration of upscaled P10 and P90 values to match global percentiles of normalized gamma ray logs. The values obtained from this graphic method serve as starting points to test other values that may yield better normalization results.

Results

The workflow was applied across ~3,900 square miles of the Midland Basin, Texas. Of all wells with GR data, 98% were successfully normalized; remaining wells were excluded due to incomplete or corrupted data. Before normalization, interpolated GR volumes showed strong lateral and vertical inconsistencies caused by casing effects, tool variation, and incomplete depth coverage. After normalization, stratigraphic continuity improved markedly, casing-related artifacts were removed, and regional trends became clearly expressed (Figure 7).

The normalized dataset aligns with known regional markers and shows smooth transitions across the carbonate ramp, while preserving true stratigraphic variability. The same 3D volumes and normalization rules were subsequently applied to more than 20,000 additional vertical wells, producing consistent results without further manual intervention and demonstrating the scalability of the approach.

To illustrate the potential applications enabled by the normalization workflow, the normalized dataset was expanded into high-resolution 3D volumes. Directional survey information was incorporated, allowing property extraction along any defined wellbore trajectory. This provides a framework for linking normalized log properties to horizontal well paths and forms a basis for subsequent integration with production and completion data. Because meaningful correlation with production requires multiple petrophysical properties rather than a single log, the same normalization strategy can be generalized to other log types, enabling future construction of multi-property volumes suitable for production/rock/fluid analysis.

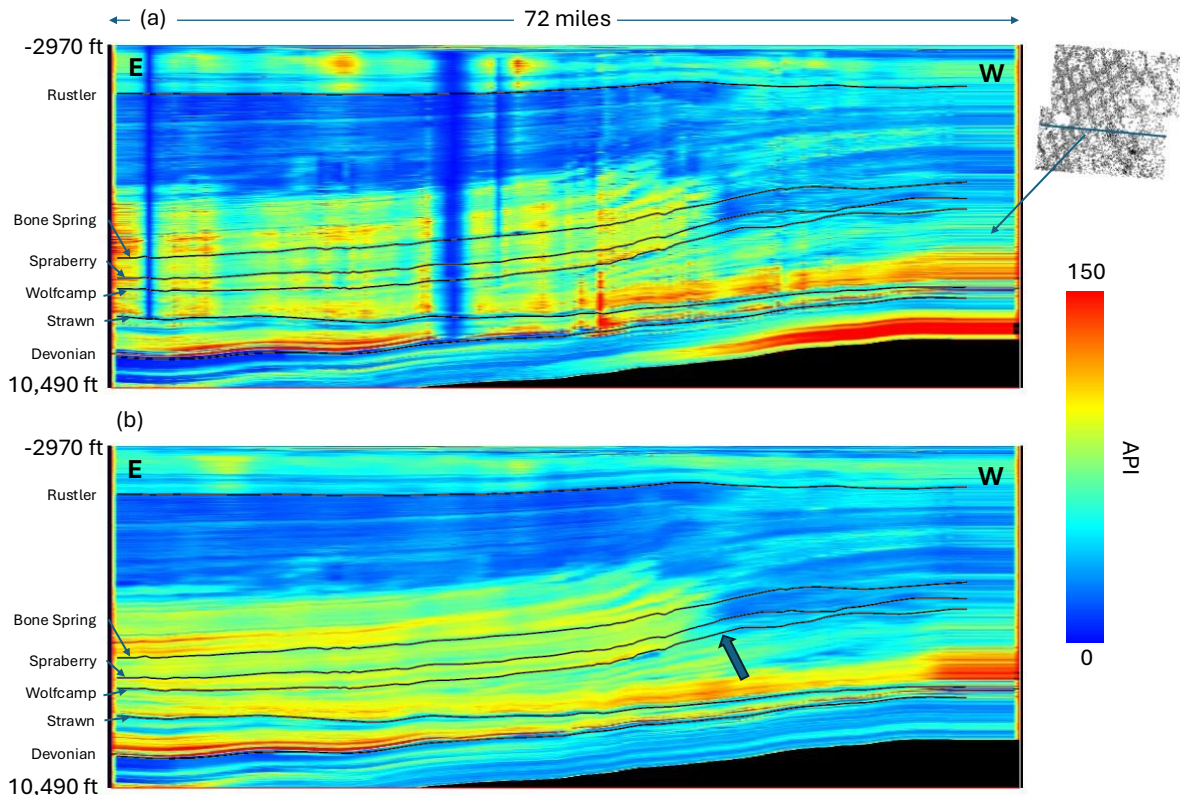


Figure 7. (a) Original GR log interpolated along stratigraphic grid. (b) Interpolated GR log after 3D normalization and 3x3 median filter along stratigraphy. Location of the cross-section relative to well locations is shown in the upper right. Cell dimensions: 2500 ft x 2500 ft x 4 ft.

The study area contains approximately 19,000 horizontal wells targeting unconventional reservoirs across four counties in the Midland Basin, consistent with the area used for normalization. Using the normalized volumes, properties can be extracted along lateral sections, offering a means to investigate stratigraphic and facies heterogeneity relevant to geosteering applications, identify areas of variable reservoir quality, and support planning of future well locations.

As shown Figure 8a, the normalized GR volume define a coherent stratigraphic framework across the study area, and provide a continuous property field from which values may be sampled along arbitrary well trajectories. These capabilities enable future analyses that couple normalized subsurface properties with allocated production (Figure 8b) to assess relationships between stratigraphic architecture, rock-fluid properties, and well performance in unconventional reservoirs.

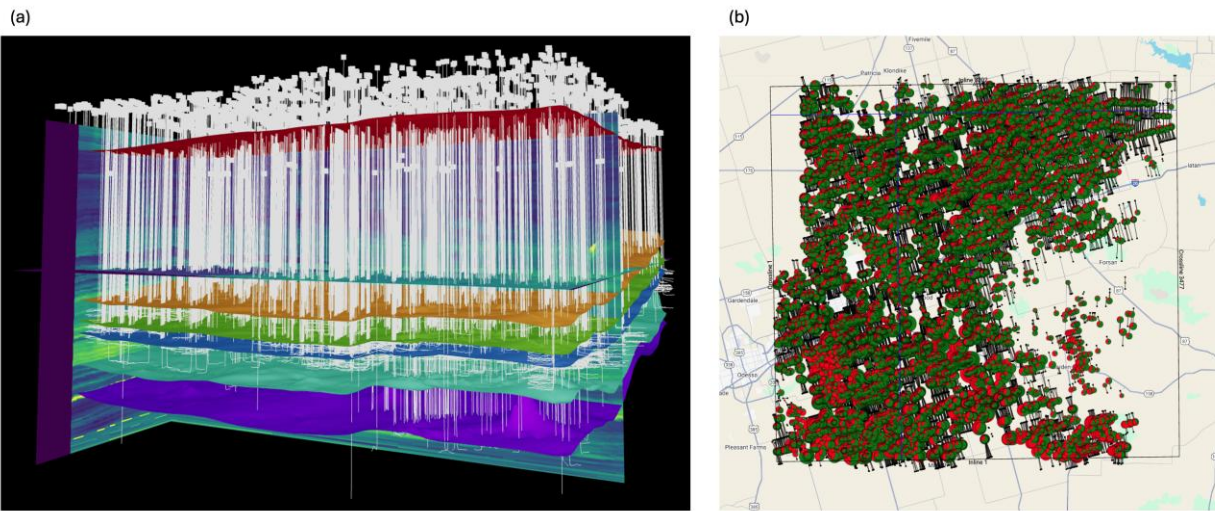


Figure 8. (a) Three-dimensional view of normalized GR values along stratigraphic surfaces, illustrating horizontal well trajectories derived from directional surveys. (b) Map view of allocated production for all horizontal wells in the study area, showing the spatial distribution of well performance across the field.

Novel / Additive Information

This study advances log normalization from a per-well (or limited area) correction task to a volumetric, basin scale, stratigraphy-guided process. The key innovation is the generation of calibrated 3D percentile volumes from a selected reference dataset, enabling rapid, automated normalization of tens of thousands of wells while preserving geological fidelity. The resulting normalized logs form a consistent basin-scale dataset directly compatible with seismic attributes and well-log foundation models, establishing a practical pathway toward AI-enabled subsurface characterization.

The construction of high-resolution 3D, normalized log-property volumes also provides a natural framework for sampling geologically consistent properties along any defined wellbore trajectory. While this study demonstrates the process using Gamma Ray logs, the same normalization workflow is directly extendable to other petrophysical logs, enabling the creation of multi-property 3D volumes. These volumes form the necessary foundation for future studies that integrate subsurface rock properties, horizontal well geometry, and production data to investigate drivers of well performance.

Acknowledgements

Thanks to TGS for permission to publish this work. Thanks also to Ben Lasscock for providing the well tops for different intervals from his machine-learning approach to automatic tops interpretation.

References

Aguirre, A., and J. Antelo, 2001, Log normalization: A very important task in the petrophysical evaluation for La Peña and Tundy fields: SPE 69607, Latin American and Caribbean Petroleum Engineering Conference (LACPEC), Society of Petroleum Engineers. <http://www.biblioteca.iapg.org.ar/iapg/ArchivosAdjuntos/LACPEC2001/SPE69607.PDF>

HIS Markit, 2020, Log normalization overview: Petra Online Help Library. https://onlinehelp.ihs.com/Energy/Petra/2020/Content/main_lognormalizationoverview.htm

Lasscock, B., A. Sansal, K. Gonzalez, and A. Valenciano, 2025, Well log foundation model – Making promptable AI models for interpretation: IMAGE 2025, Technical Library, TGS. <https://www.tgs.com/technical-library/well-log-foundation-model-making-promptable-ai-models-for-interpretation>.

Shier, D. E., 2004, Well log normalization methods and guidelines: Petrophysics, 45 (3), 171056. <https://onepetro.org/petrophysics/article-abstract/171056/Well-Log-Normalization-Methods-and-Guidelines>