Paper SPWLA-2026-0028

Data-Driven Reservoir Characterization And Modelling: From Rock Typing To Unsupervised Machine Learning

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Introduction:

Conventional rock typing is a cornerstone of reservoir modeling, yet it faces significant limitations due to the sparse nature of core data. This study addresses two primary challenges:

- **Resolution Mismatch & Uncertainty:** Routine Core Analysis (RCA) typically provides point measurements at ~0.34 m spacing, while well logs are continuous but vertically averaged. This creates uncertain rock-type transitions between sampling points, often requiring subjective interpretation to translate data into the depth domain.
- **Over-simplification of Heterogeneity:** Traditional workflows artificially divide porosity-permeability (ϕ–k) data into groups (e.g., FZI or Winland r_{35}). This subjective differentiation may impose artificial boundaries on complex geological systems, failing to capture the multi-dimensional nature of reservoir heterogeneity and adding difficulties in propagating the groups in the 3D models.

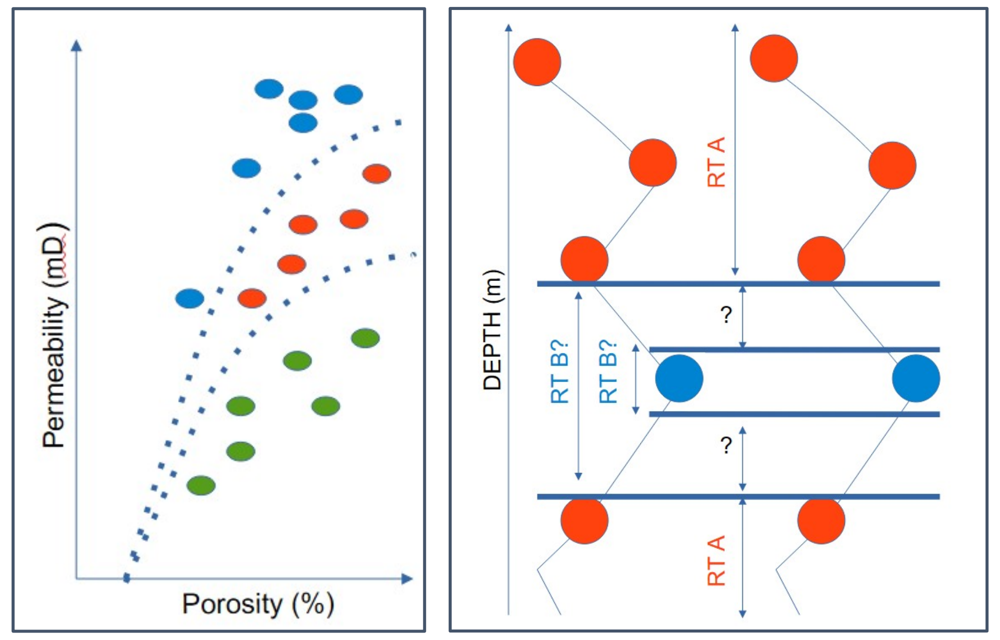
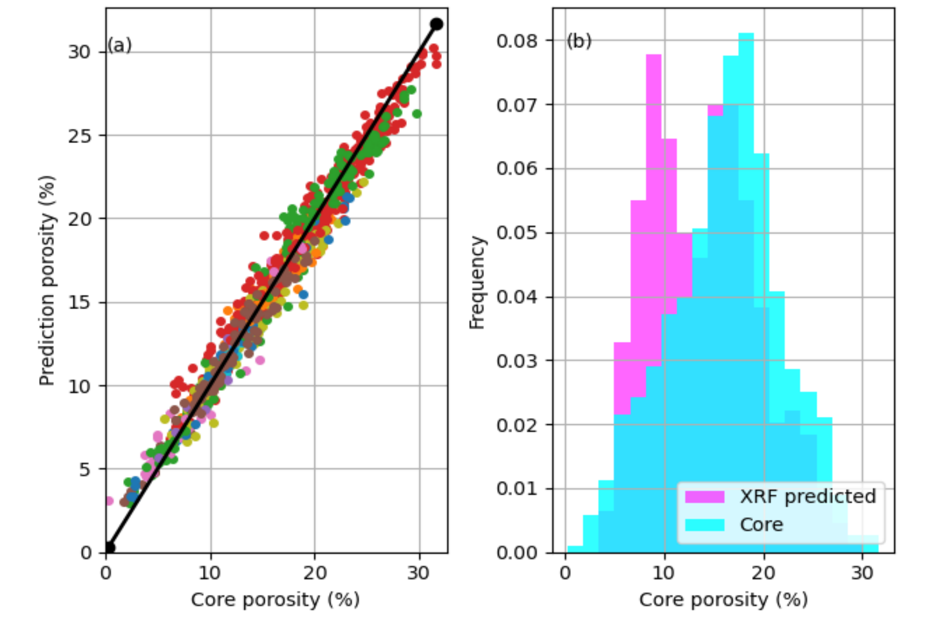


Figure 1: Schematic of the problems related to defining rock types using RCA/SCAL data. (a)Rock types are defined in the ϕ–k space. (b)When translated to the depth domain, uncertain boundaries appear. Between two sampling points, the persistence of a single rock type is questionable.

Methodology:

The study employs a multi-stage, "hands-off" automated workflow to partition multi-dimensional log data into objective rock types. This process is run in parallel with high-resolution core scanning and compared to the conventional RCA.

- **High-Resolution Rock Typing:** XRF mineralogy and Miniperm measurements at ~1 cm resolution (30x the resolution of standard RCA) is used to predict porosity (via a ML regression)., Permeability was normalized to RCA and paired to high resolution porosity to derive High-Resolution FZI rock types (Figure 2 and 3) .
- **Data Employed:** Slochteren Formation(BLT-01, AMS-01, EDE-01 from NLOG)
- **Features:** 7 log curves (GR, RHOB, NPHI, DTC, DTS, RD, PE) with image-log descriptors. Conv2D Autoencoder compresses CAST acoustic image patches into 8D latent vectors. Dimensionality is then optimized via Principal Component Analysis (PCA)
- **Consensus Clustering:** Five distinct algorithms (K-Means, Spectral, SOM, SOM-TS, and HDBSCAN) are applied independently. Results are combined into a Weighted Co-Association Matrix to minimize single-method bias and ensure robust classification.



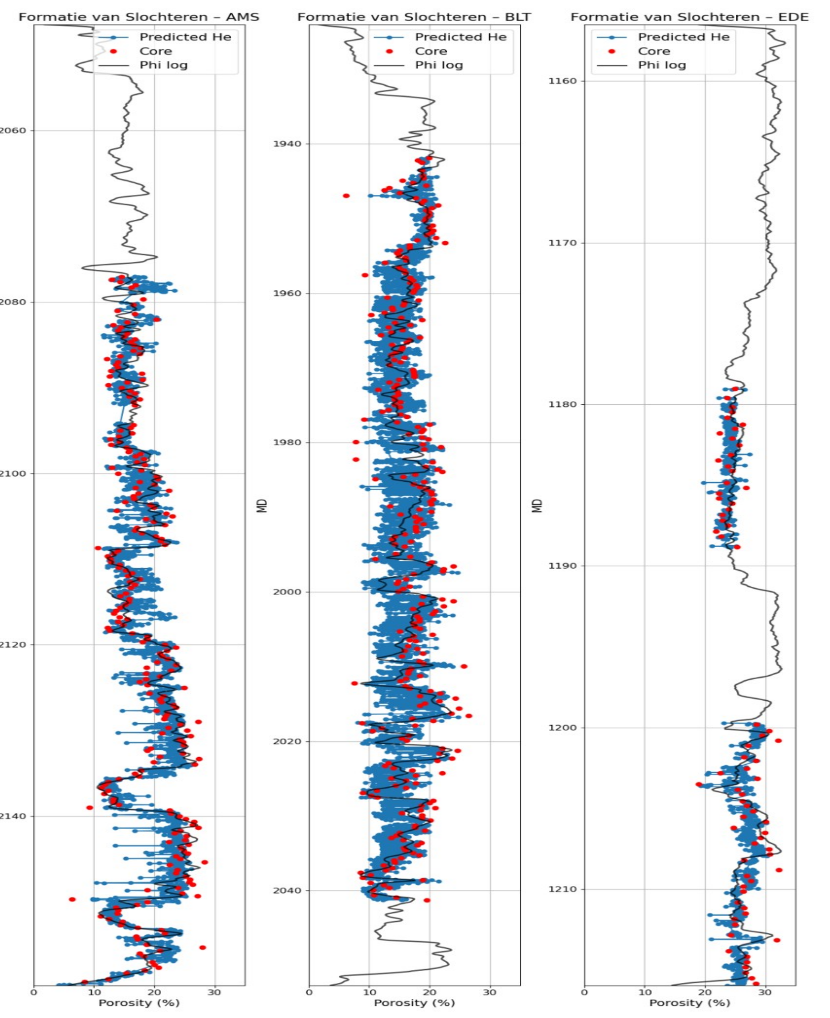


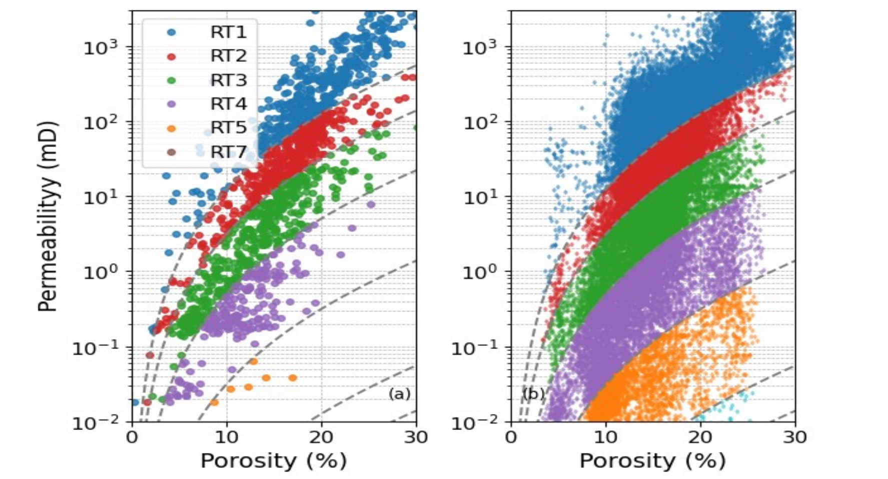
Figure 2: (a)Predicted vs. measured porosity at RCA points. (b)Porosity distribution: measured (RCA, unimodal) vs. predicted (high-resolution, bimodal), revealing a sampling bias toward more porous intervals.

Figure 3: Porosity vs. depth over the Slochteren formation for 3 wells. For each well, core porosity (RCA) is plotted alongside high-resolution (HR) predicted porosity and log porosity.

Results/Discussion:

High-Resolution Core Scanning comparison to RCA

- **Sampling Bias:** RCA based Rock Typing overestimates the most permeable rock type (RT1) by approximately 10% (Figure 4 and 5).
- **Missing Rock Types:** Denser sampling at ~1 cm resolution identified low-permeability rock types (RT5 and RT6) that were entirely absent in the sparse RCA dataset (Figure 4).
- **Permeability Mismatch:** RCA-based methods can result in permeability prediction errors reaching a factor of 4 for individual rock types, particularly in lower-quality units like RT4 (Figure 6 and 8)



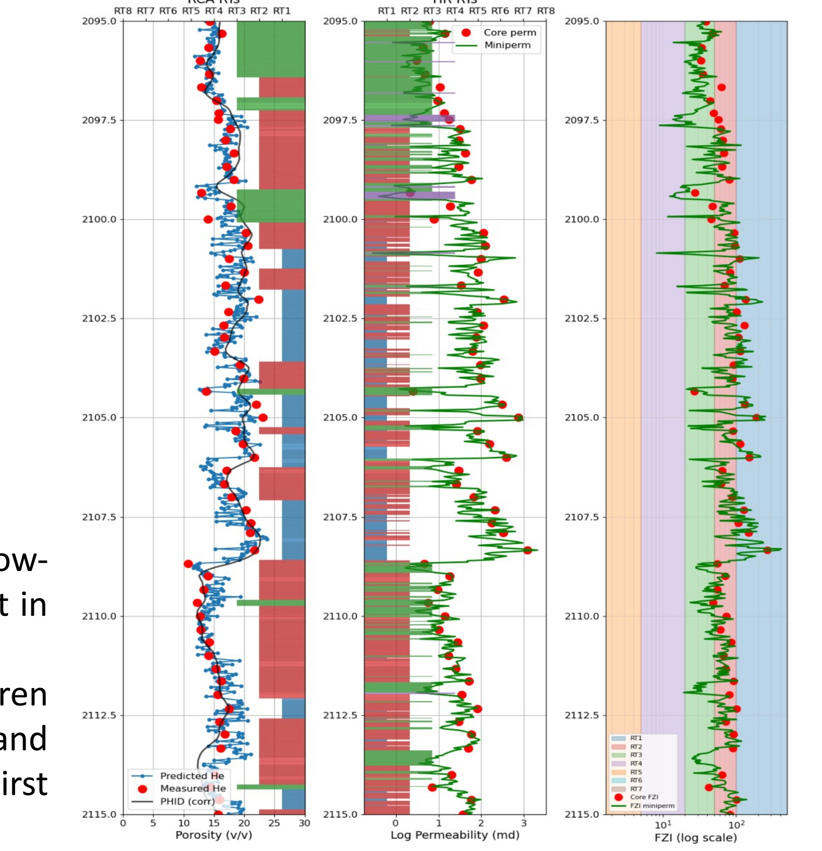


Figure 4: Denser sampling at ~1 cm resolution identified two low-permeability rock types (RT5 and RT6) that were entirely absent in the sparse RCA dataset.

Figure 5: Rock type vs depth example over the Slochteren formation: comparison between RCA-driven (low-resolution) and HR-driven allocated RTs. RT1 (blue) is overestimated by RCA. First track adds log derived porosity as "upscaled" guide to the eye.

Data-Driven Clustering

- **Overlap & Scalability:** Log-derived clusters overlap in ϕ–k space, proving that properties like grain size and cementation do not map uniquely to porosity-permeability pairs. Despite this, joint clustering across three wells successfully identifies distinct lithological units and geological variations (Figure 7)
- **Image Log Value:** Integrating image features sharpens cluster boundaries and resolves textural gradations that remain invisible to conventional logs.

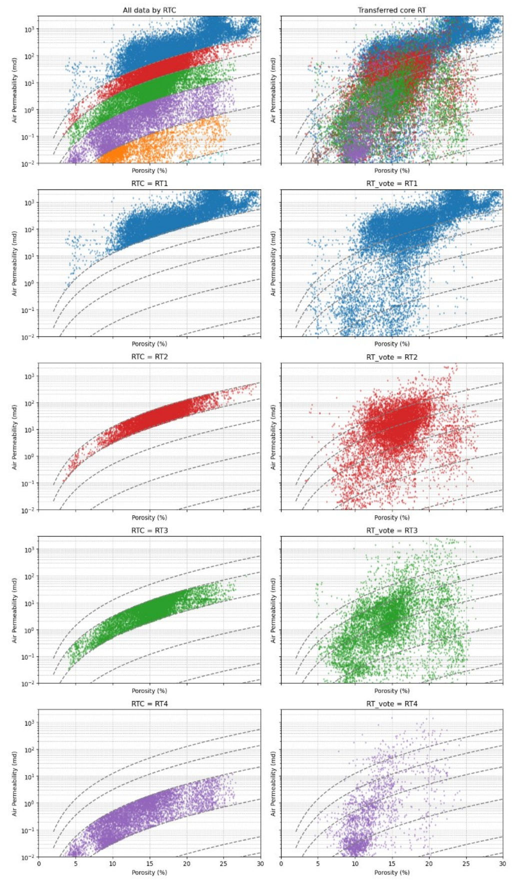


Figure 6

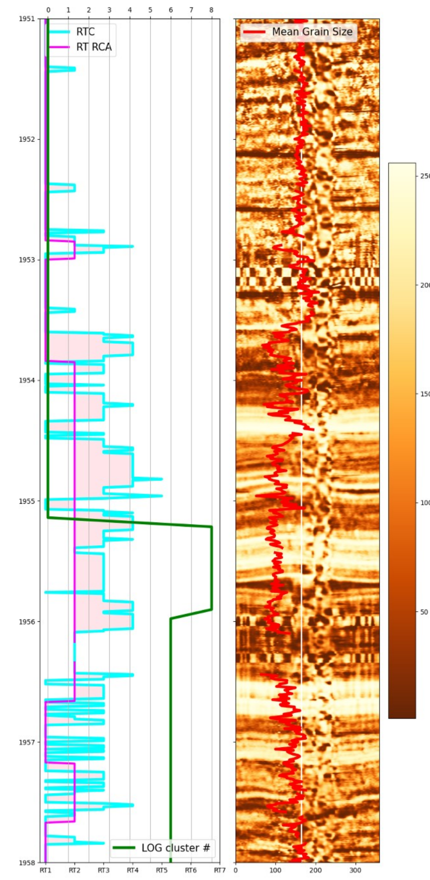


Figure 7

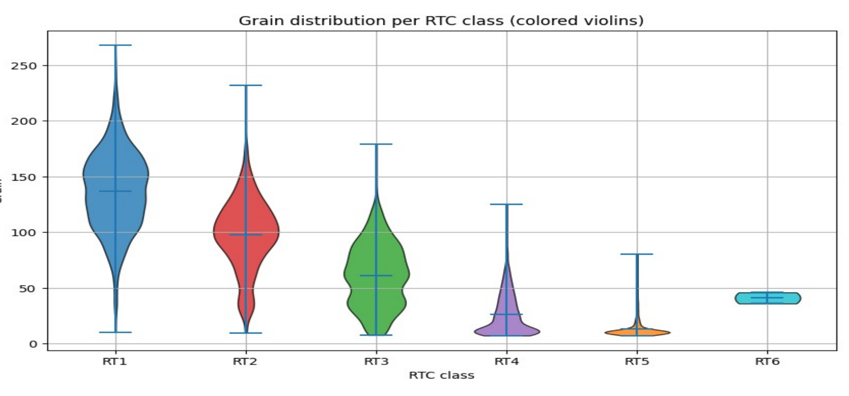


Figure 8

Figure 6: Porosity–permeability data grouped by RT: (left) allocation via high-resolution FZI; (right) same data allocated via RCA-interpolated RT. The coarser RCA method smears data across RT boundaries leading to poor defined transforms.

Figure 7: RT vs. depth from RCA and from this work, plotted alongside a dynamic BHI image and the log-derived consensus cluster assignment (left strip).

Figure 8: Rock types vs grain size. They appear to be confirmed by grain size as measured from core images. analysis.

Conclusions:

- High-resolution core scanning allows high-resolution RTs to be accurately sampled, conventional RCA only might misrepresent critical reservoir features. Dominant rock type (RT1) is overestimated by RCA by ~10%, missing low-permeability rock types), distorting modelled reservoir architecture.
- The mismatch in rock-type fractions propagates to permeability predictions, with errors reaching a factor of 4 for individual rock types. Furthermore, high-resolution data identify wider distibution K_v/K_h ratios, more representative inputs for dynamic simulation.
- The multi-algorithm consensus clustering demonstrates cross-well scalability and robustness. Log-derived rock types capture textural details through image-log integration; however they display extensive ϕ–k overlap, wich challenges the propagation of core-based RTs into the log/3D domains.

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