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Rifting-related reservoirs mapping by unsupervised multi-attribute clustering applied to 3D seismic data

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Abstract Summary

We applied Self-Organizing Maps to a PCA-filtered set of post-stack seismic attributes related to lithological variation, fluid presence, and tectonic influence to map rift-lake shale oil in the central Recôncavo Basin, Northeastern Brazil. The same group of four neighboring neurons that identified the only two known shale oil accumulations also mapped 11 of 13 late pre-rift fluvial–eolian sandstone reservoirs, with strong (8) or weak (3) correlation, without prior knowledge of reservoir presence or location. Despite differences in sedimentary texture and basin phase, both reservoir types are genetically linked to rifting and share similar seismic facies, spatial arrangements, structural settings, and stratigraphic boundaries. These results demonstrate the potential of unsupervised multi-attribute clustering, when integrated with seismic interpretation, to identify geologically related reservoirs.

Introduction

Unsupervised machine learning (ML) techniques can identify patterns in data without prior knowledge of the correct answer (Deisenroth et al., 2020), enhancing seismic interpretation by uncovering previously unrecognized structures (Troccoli et al., 2022). As a result, ML has seen growing application in the oil and gas industry. In mature basins like Recôncavo Basin (Northeastern Brazil), under productive decline, ML can aid in identifying new reservoirs, especially unconventional ones (UR). Although URs have significant potential (Jarvie, 2012), their exploration in Recôncavo Basin remains limited, despite documented shale oil occurrences (ANP public data).

The Recôncavo Basin is an Early Cretaceous aborted rift arm associated with the opening of the South Atlantic Ocean, structured as a NE–SW-oriented half-graben bounded by a border fault to the east (Silva et al., 2007). Rift basins evolve through episodic tectonic pulses of varying magnitude, which generate synchronous depositional and erosional events (Holz et al., 2017), defining three second-order sequences in the basin's stratigraphic framework (Silva et al., 2007).

The pre-rift sequence (Late Tithonian–Early Berriasian) comprises three fluvial–eolian cycles and lacustrine transgressions predating faulting. The rift sequence (Berriasian–Valanginian) reflects extensional tectonics and hosts the only source rock and potential shale oil (lacustrine shales of Candeias Fm.). The post-rift (Hauterivian–Barremian) preserves deltaic and fluvial deposits under thermal subsidence.

Tectonic activity controlled hydrocarbon migration and trapping, enabling pre-rift reservoirs (Sergi and Água Grande Fms.) to contact the source rock via normal faults. Shale oil above these units is similarly fault-associated.

This study applied Self-Organizing Maps (SOM) to a PCA-filtered set of seismic attributes from 3D post-stack data to: (i) map the reference shale oil reservoir; and (ii) test if the same cluster identifies the other known shale oil and pre-rift accumulations without prior labeling.

Theory

A seismic attribute is any quantity extracted from seismic data by a filter that attenuates components to highlight a specific information from the original signal. It is widely used to aid interpretation by revealing, for example, faults and fractures, depositional environments, fluid anomalies, and other relevant features (Barnes, 2016). Figure 1 shows the selected attributes: (a) square root of average trace energy; (b) average amplitude over a window; (c) magnitude of the complex trace; (d) amplitude acceleration; (e) sign at envelope maxima; (f) envelope over square root of instantaneous frequency (Barnes, 2016). Principal Component Analysis (PCA) is a dimensionality reduction technique that projects normalized seismic attributes onto a lower-dimensional orthogonal basis, capturing the highest variance while minimizing the influence of noise (Deisenroth et al., 2020). Self-Organizing Maps (SOM) is an unsupervised neural network method that organizes data into a structured grid of neurons using competitive learning. Through training, similar inputs activate nearby neurons, preserving the topological relationships within the network. The weight vectors of the winning neuron and its neighbors are adjusted iteratively until convergence, enabling self-organization (Kohonen, 1982).

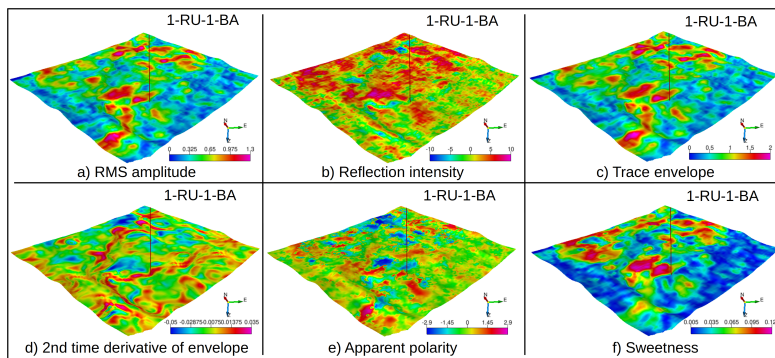


Figure 1: Seismic attributes projected onto SRU around reference reservoir (center).

Method

Figure 2 shows the seismic volume and wells locations, and a cross-section indicating the expected reservoirs. The reference reservoir (RR) is a shale oil from the Candeias Fm., located in the southwesternmost well. The database includes the only other well with (sub-commercial) shale oil (SOA) and 13 wells associated with pre-rift oil reservoirs, although some are sub-commercial. 15 wells were tied for seismic interpretation, which delineated three second-order sequences bounded by the syn-rift unconformity (SRU) and the maximum rifting surface (MRS). The workflow included: (i) median filtering of the seismic volume; (ii) computation of seismic attributes; (iii) PCA-based dimensionality reduction of the seismic attributes matrix; and (iv) SOM clustering of the PCA output.

Results

The NW–SE-trending Mata-Catu fault system cuts across the seismic volume, dividing the basin into two compartments. The Eastern portion is the Quiricó Platform, which lacks imaging quality and well control - thus excluded from the analysis. All wells are located west of the fault, in a faulted block with a depocenter reaching 1700 ms TWT in the South.

Most seismic records are post-rift and outside the scope of this study. Pre-rift top reflectors are laterally continuous, high-amplitude events disrupted only by rifting, and may represent conventional reservoirs. Rift sequence reflectors are less continuous and lower in amplitude, showing facies typical of deep lacustrine turbidites and carbonates. Shales from this interval are potential shale oil targets where fractured or faulted.

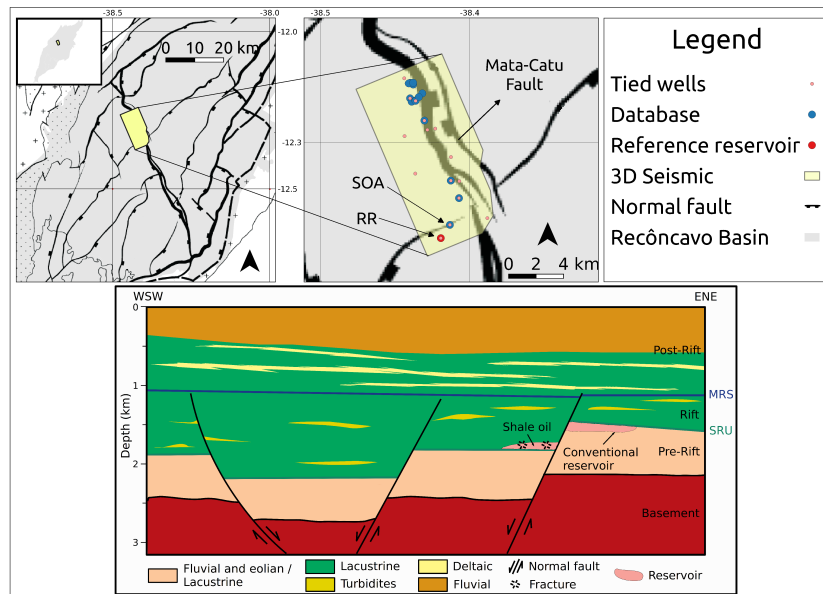


Figura 2: Location of the post-stack seismic volume and wells, and cross-section. Area of interest is around SRU (shale oil and pre-rift conventional reservoirs).

Figure 1 displays time-averaged seismic attributes around RR projected onto SRU, a horizon close to both pre-rift reservoirs and rift-lake shale oil. These rift-related reservoirs share similar set of seismic facies near SRU and geometric arrangement (see inline in Figure 3). The selected attributes capture amplitude information (Figures 1a–c), lithological variation (Figures 1d–e), fluid indicators (Figures 1e–f), and tectonic effects (Figures 1d, f). Rifting provided the structural framework for oil trapping, enabling fracturing of lacustrine shales and migration into pre-rift sandstones. RR is located within a NE–SW-trending fault zone and appears as a low-amplitude, negative-polarity reflector flanked by two zones of higher amplitude and positive polarity.

PCA reduced the attribute matrix to two principal components, retaining 73% of the variance, preserving attribute coherence while minimizing noise. SOM was then applied using a 400-neuron rectangular grid. As shown in Figure 3, the same cluster of four adjacent neurons that mapped RR (a), hereinafter referred to as RR cluster, also identified SOA (b) - as expected - but additionally mapped the pre-rift reservoir (c). Although only (a) and (b) are shale oil accumulations from the rift phase, their associated seismic facies and spatial arrangements are similar to those observed in pre-rift reservoirs like (c): all are trapped by normal faults, sealed by lacustrine shales, and underlain by strong, continuous reflectors from the late pre-rift. These similarities explain RR cluster's consistent mapping, despite differences in sedimentary texture and basin's phase.

Among the 13 pre-rift oil wells, 8 showed strong correspondence with RR cluster, and 3 showed weak correlation (i.e., ≤ 80 m horizontal offset), an encouraging result. However, some false positives were also observed, underscoring that unsupervised clustering should be combined with prior

seismic interpretation to reliably identify prospective zones.

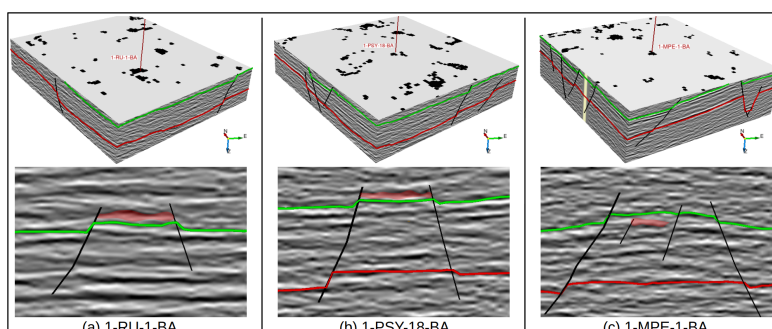


Figura 3: Time slices of RR cluster within three reservoirs (top) and interpretation in inline (bottom). Top basement (red line), SRU (green line) and reservoir (light red). Details in the text.

Conclusions

The same neighboring neuron cluster that mapped the reference reservoir also identified the only other known shale oil accumulation, as well as 8 of 13 known pre-rift reservoirs with strong correlation and 3 with weak correlation, all without prior labeling. These reservoirs share similar seismic facies and geometric patterns, reflecting their genetic link to rifting. The results underscore the potential of unsupervised multi-attribute clustering to delineate geologically related reservoirs.

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Referências

- Barnes, A. E., 2016, Handbook of poststack seismic attributes: Society of Exploration Geophysicists.
- Deisenroth, M. P., A. A. Faisal, and C. S. Ong, 2020, Mathematics for machine learning: Cambridge University Press.
- Holz, M., D. B. Vilas-Boas, E. B. Troccoli, V. C. Santana, and P. A. Vidigal-Souza, 2017, Chapter four - conceptual models for sequence stratigraphy of continental rift successions, *in* Advances in Sequence Stratigraphy: Academic Press, volume 2 of Stratigraphy and Timescales, 119–186.
- Jarvie, D. M., 2012, Shale resource systems for oil and gas: Part 2 - shale-oil resource systems, *in* Shale Reservoirs—Giant Resources for the 21st Century: American Association of Petroleum Geologists.
- Kohonen, T., 1982, Self-organized formation of topologically correct feature maps: Biological Cybernetics, **43**, 59–69.
- Silva, O. B. d., J. M. Caixeta, P. d. S. Milhomem, and M. D. Kosin, 2007, Bacia do recôncavo: Boletim de Geociências da Petrobras, **15**, 423–431.
- Troccoli, E. B., A. G. Cerqueira, J. B. Lemos, and M. Holz, 2022, K-means clustering using principal component analysis to automate label organization in multi-attribute seismic facies analysis: Journal of Applied Geophysics, **198**, 104555.