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GEOBODY MAPPING USING TIME-FREQUENCY ATTRIBUTES AND SELF-ORGANIZING MAPS

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Abstract

Seismic facies analysis is a fundamental component of subsurface characterization, offering valuable insights into depositional environments, stratigraphic frameworks, and reservoir heterogeneity. Traditional methods primarily rely on amplitude-based seismic attributes and manual frequency blending, often struggle to detect subtle geological variations in complex depositional settings and are prone to interpreter subjectivity. This study presents an integrated workflow for three-dimensional seismic facies clustering that combines spectral decomposition with unsupervised machine learning to automate the classification of subsurface features. The method utilizes the Continuous Wavelet Transform (CWT) to break down seismic data into a wide spectrum of frequencies, enabling the identification of geological features at multiple scales. These multi-frequency attributes are subsequently clustered using Self-Organizing Maps (SOM), which project high-dimensional data onto a two-dimensional neuron grid while preserving topological relationships. Applying the trained SOM model volumetrically allows the extraction of 3D geobodies, which are then visualized using a 2D color map for interpretation. The methodology is demonstrated on datasets from the South Caspian Basin, successfully delineating meandering channels, levees, and stratigraphic boundaries. This workflow reduces interpreter bias, improves reproducibility, and enables volumetric facies modeling, offering substantial benefits for reservoir characterization, hydrocarbon exploration, and reserves estimation.

Keywords: *seismic facies; geobody; time-frequency transform; self-organizing map; unsupervised learning; machine learning*

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INTRODUCTION

Accurate classification of seismic facies is fundamental to subsurface interpretation as it provides insights into depositional processes, lithological distributions, and reservoir potential [1, 13, 15, 18]. This process involves grouping seismic reflections based on their amplitude, continuity, frequency content, and other attributes to map geological features such as channels, levees, lobes, and carbonate buildups [3]. Beyond hydrocarbon exploration, such classifications contribute to basin analysis [12] and geohazard prediction [22].

Traditionally, seismic facies interpretation relied on visual correlation of reflection geometries and amplitudes, supported by well control [1]. The integration of seismic attributes enabled a more quantitative approach, characterizing amplitude, phase, and curvature [3]. However, amplitude-dominated workflows often fail to capture subtle stratigraphic variations, particularly when these features are frequency dependent. In complex stratigraphic regions, seismic responses are often highly heterogeneous and non-unique. Subtle geological variations within these environments can remain unresolved when traditional amplitude-driven interpretation methods are applied in isolation.

Spectral decomposition techniques, such as the short-time Fourier transform (STFT) [14], the S-transform, and the continuous wavelet transform (CWT) [2, 20], have transformed stratigraphic analysis by representing seismic data in the time–frequency domain. The STFT was among the first approaches to be widely adopted, but its use of a fixed window size imposes a tradeoff between time and frequency resolution. By contrast, CWT has become one of the most widely applied methods in stratigraphic analysis [2, 20]. Its ability to reveal subtle spectral variations has been used for channel detection, carbonate reef delineation, and the identification of fluid anomalies in diverse depositional environments [8, 23]. Yet, while these methods improve resolution, they also generate large, multidimensional datasets that challenge manual interpretation.

In parallel, machine learning approaches have emerged as powerful tools for seismic facies classification. Self-organizing maps (SOMs), an unsupervised clustering algorithm, reduce data dimensionality by projecting multi-attribute inputs onto a two-dimensional grid, thereby revealing patterns that traditional interpretation may overlook [10, 16, 27]. Early SOM applications were restricted to horizon-based 2D analysis, limiting geological understanding to stratigraphic slices. Recent developments extend SOMs to full 3D seismic volumes, creating geobodies that better capture reservoir architecture and connectivity. Nevertheless, questions remain regarding the optimal integration of spectral and machine learning methods to balance interpretability. Similar integration of spectral decomposition and unsupervised learning has been successfully demonstrated by Malikov & Babayev, [2025], who applied CWT-based frequency attributes with SOM clustering to delineate channel systems and facies boundaries in the South Caspian Basin. Their study confirmed that combining multi-frequency decomposition with unsupervised classification enhances the visibility of meandering channels and internal heterogeneity while minimizing interpreter bias. Building upon these findings, the present research extends this concept from horizon-based analysis to fully volumetric clustering for 3D geobody extraction and quantitative facies modeling. Thus, transitioning from surfaces to volumes enables geoscientists to obtain a more comprehensive representation of reservoir architecture and connectivity.

Compared with other techniques, SOMs offer distinctive advantages. For instance, k-means clustering is computationally efficient but assumes spherical clusters and equal variance, which often oversimplifies the heterogeneity of seismic facies [27]. Principal component analysis (PCA) is widely used for dimensionality reduction, yet it only captures linear correlations and may discard subtle nonlinear relationships critical for stratigraphic features [6]. Supervised approaches such as support vector machines (SVMs) or random forests require extensive labelled training data, which is rarely available in seismic interpretation, and their outputs can be biased toward interpreter-defined facies [28]. More recently, deep learning methods, particularly convolutional neural networks (CNNs), have shown promise in learning complex spatial patterns; however, they demand large labelled datasets, intensive computational resources, and their "black box" nature limits geological interpretability [17]. In contrast, SOMs balance dimensionality reduction, unsupervised learning, and visual interpretability, making them especially attractive for seismic facies analysis where ground truth labels are sparse [19, 28].

Alongside advances in spectral analysis, machine learning has become an integral component of geophysical interpretation workflows. Unsupervised algorithms, particularly SOMs, offer a way to cluster high-dimensional datasets without requiring labeled examples [4, 5, 7, 25]. By projecting multi-attribute input vectors onto a two-dimensional grid while preserving their topological relationships, SOMs allow interpreters to visualize complex patterns among seismic attributes. This approach has been successfully applied to seismic facies analysis, revealing subtle stratigraphic features that are often overlooked by traditional methods [12, 16, 27].

This study addresses these challenges by integrating spectral decomposition using the CWT with SOM-based clustering to generate volumetric seismic facies models. Applied to the South Caspian Basin (SCB), this workflow produces facies clusters that can be visualized in two dimensions and extracted as three-dimensional geobodies. The results demonstrate how combining time–frequency analysis with unsupervised learning improves geological resolution while reducing interpreter bias, providing a more comprehensive basis for reservoir characterization and reserves evaluation.

MATERIALS AND METHODS

The proposed workflow integrates high-resolution spectral decomposition with SOM-based clustering to produce a volumetric classification of seismic facies. This approach expands on previous implementations that applied CWT in combination with SOM for horizon-based facies clustering in the South Caspian Basin [11]. In that work, the authors demonstrated the potential of integrating frequency-domain analysis with unsupervised learning to enhance the discrimination of channel systems and subtle stratigraphic features. The present study advances this framework by applying the methodology volumetrically, enabling the classification of every voxel within a 3D seismic cube and allowing the extraction of continuous, geologically consistent facies geobodies.

The process begins with loading a 3D seismic volume and any available structural or stratigraphic horizons. Unlike conventional workflows that require precise horizon interpretations to constrain attribute extraction, this methodology can operate with approximate bounding surfaces, provided they encompass the stratigraphic interval of interest. Preconditioning steps, such as applying an amplitude gain control (ACG), may be used to reduce amplitude variability caused by acquisition footprints or hydrocarbon-related brightening [26]. This preprocessing step balances amplitude variations, ensuring that the subsequent clustering is driven primarily by geological rather than acquisition-related features or fluid effects.

Once the volume has been preconditioned, spectral decomposition is applied to generate narrow-band frequency representations of the seismic data. The CWT technique is chosen due to its flexibility and time–frequency resolution. For a seismic trace $s(t)$, the CWT is defined as:

$$X(a,b) = \frac{1}{|a|^{\frac{1}{2}}} \int_{-\infty}^{\infty} s(t)\psi\left(\frac{t-b}{a}\right) dt, \tag{1}$$

where $\psi(t)$ is the mother wavelet, a is the scale parameter (inversely proportional to frequency), and b is the translation in time. In this workflow, the Ricker wavelet [24] is selected due to its similarity to zero-phase seismic wavelets.

The scaling property of the CWT allows the seismic signal to be decomposed into a series of frequency bands ranging from 5 Hz to 60 Hz in 2 Hz increments. This wide bandwidth ensures that both large-scale stratigraphic features, such as broad clinoforms, and fine-scale features, such as thin channel deposits, are represented [13]. Each decomposition produces a separate amplitude volume corresponding to a specific frequency band, and together these volumes form a high-dimensional frequency-dependent amplitude dataset.

The spectral decomposition outputs are reorganized so that each voxel is represented by a high-dimensional vector of spectral amplitudes. For example, if 21 frequency components are extracted between 10 Hz and 50 Hz, then each voxel is represented as a 21-dimensional vector. These vectors are clustered using a SOM algorithm, which consists of a two-dimensional grid of neurons with weight vectors of the same dimensionality as the input data.

The SOM is trained iteratively. Initially, each neuron in the SOM grid is assigned to a random weight vector of the same dimensionality as the input data. At each iteration, an input vector is randomly selected and compared with all neurons to identify the Best Matching Unit (BMU) the neuron whose weight vector is most similar to the input. The Euclidean distance metric is used to quantify similarity:

$$d_j = \sqrt{\sum_{i=1}^{n} \left(x_i - w_{ij}\right)^2}, \tag{2}$$

where x_i are the components of the input vector, w_{ij} are the weights of neuron j, and n is the number of frequency dimensions.

Once the BMU is identified, its weight vector is adjusted to more closely resemble the input vector, and neighboring neurons are updated to a lesser degree according to a neighborhood function:

$$w_i(t+1) = w_i(t) + \lambda(t) h_{nei}\big(t, w_i(t)\big)[x - w_i(t)], \tag{3}$$

where $\lambda(t)$ is the learning rate, and $h_{nei}\big(t, w_i(t)\big)$ is the neighborhood function that decreases exponentially with distance from the BMU. Over successive iterations, both the learning rate and neighborhood radius decay, allowing SOM to gradually converge to a stable state that captures the spectral variability of the dataset.

The output of trained SOM represents a two-dimensional map where the range of spectral patterns present in the data, with each neuron corresponding to a generalized frequency signature. Seismic voxels are then classified by assigning them to the neuron that best matches their frequency-dependent amplitude response. The result is a clustered 3D seismic volume in which each voxel belongs to a distinct facies class.

The classified volume can be used to identify connected regions that belong to the same facies class, which generates 3D geobodies. These geobodies can represent geological features, such as channels and floodplain. For interpretation, the 3D results are often examined as horizon slices, time slices, or vertical cross-sections, with the clustered facies visualized using a color-coded scheme. Color-coded maps are generated to depict facies clusters, with each class assigned a distinct color. While the classification is volumetric, 2D maps extracted from the clustered volume provide an efficient means to analyze spatial patterns, identify facies boundaries, and relate seismic clusters to depositional models.

This volumetric approach enables direct measurement of geobody dimensions, which can be combined with petrophysical parameters to estimate volumes, supporting reserve calculations and development planning.

RESULTS

The proposed workflow was applied to a full-stack seismic dataset from the SCB, characterized by rapid sediment accumulation, complex depositional architecture, and significant hydrocarbon potential. Geographically situated east of Azerbaijan, west of Turkmenistan, and north of Iran, the SCB represents a Tertiary remnant of the Tethys back-arc basin, with sediment thicknesses reaching up to 20 km and characterized by low compaction, low geothermal gradients, and abnormally high-pressure regimes (Smith-Rouch, 2006; Kaz'min & Verzhbitskii, 2011). The basin's structural and stratigraphic framework has been shaped by extensive deltaic input, subsidence of the sea floor, and pronounced tectonic activity since the Miocene. Sediment supply during this period was dominated by the Paleo-Amu Darya and Paleo-Volga systems, with additional contributions from the Paleo-Kura and Paleo-Sefid Rud rivers. Although the basin is presently deepwater, much of the Pliocene and early Pleistocene record reflects shallow depositional conditions, culminating in the regional clinoform horizon of the Absheron Stage in the Lower Pleistocene, a succession dominated by shale with interbedded marl and sand. Within this geologic context, the proposed workflow was designed to generate clustered seismic volumes and extract three-dimensional facies geobodies, thereby enabling more detailed stratigraphic and reservoir characterization.

Within the study area, the seismic data revealed a stratigraphic interval dominated by deltaic and fluvial systems. Spectral decomposition across the frequency range of 10–50 Hz with a step of 2 Hz, followed by SOM training resulted in a 10 × 10 grid with generalized frequency patterns (Fig. 1). The target interval's average frequency spectrum provided a basis for selecting the frequency range, which was defined by the -10 dB bandwidth (Fig. 2). To effectively display a SOM output with a large number of clusters, a two-dimensional color scheme is employed (Fig. 3). In this scheme, each cluster is assigned a unique color that reflects the generalized pattern it represents within the SOM space. The trained model was then applied to the target seismic volume, converting individual sample points into SOM cluster assignments. The predicted clusters are then visualized by coloring each voxel point according to the cluster to which it belongs, allowing spatial patterns and relationships to be identified.

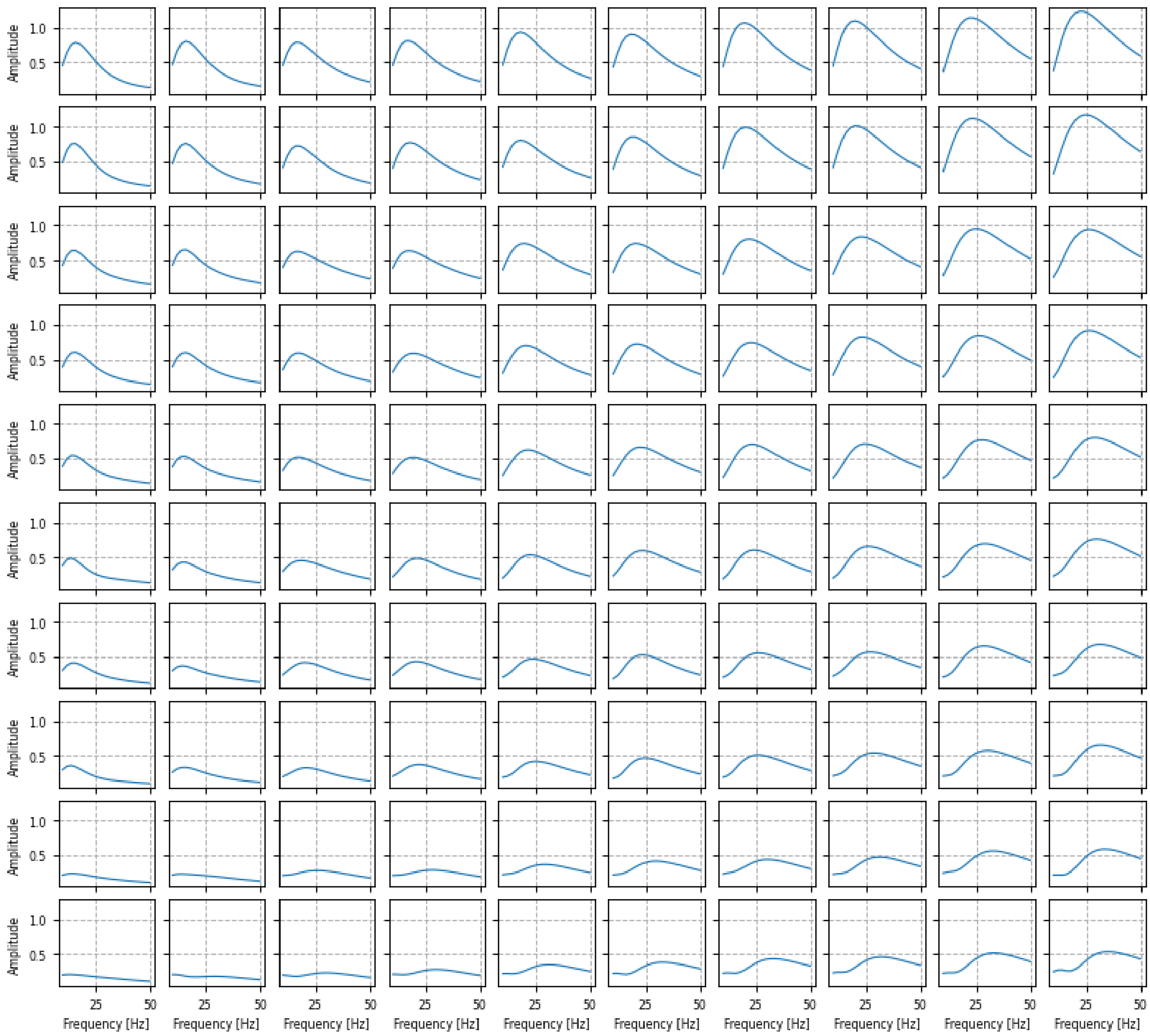


Fig. 1. SOM grid with a 10 × 10 topology of generalized frequency patterns generated after training. All nodes share a common x- and y-axis.

Fig. 1, which shows the SOM grid, reveals systematic trends in the spectral behavior of the clusters. It can be seen that the dominant frequency generally increases from the top-left to the bottom-right corner of the grid, while the maximum amplitude decreases from the top-right toward the bottom-left. At the same time, the frequency–amplitude patterns change gradually from node to node, illustrating the continuous spectrum of depositional and lithological variations present in the seismic data. This progression across the SOM space demonstrates how the algorithm preserves geological continuity while discretizing the seismic signal into meaningful clusters that can later be projected back into the seismic volume. By examining the SOM map alongside the clustered seismic volume, interpreters can directly link spectral signatures to geological facies, transforming the abstract frequency domain into a tool for facies classification and depositional analysis.

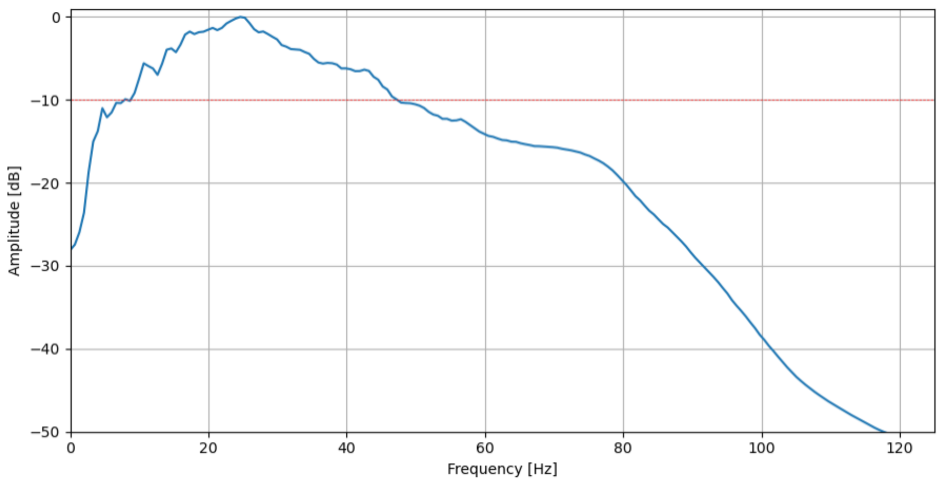


Fig. 2. The average frequency spectrum of the seismic data for the zone of the interest, with the red dashed line indicating the bandwidth at the -10 dB level.

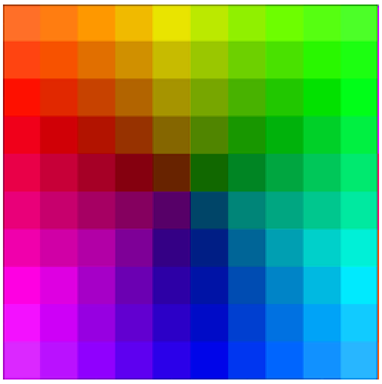
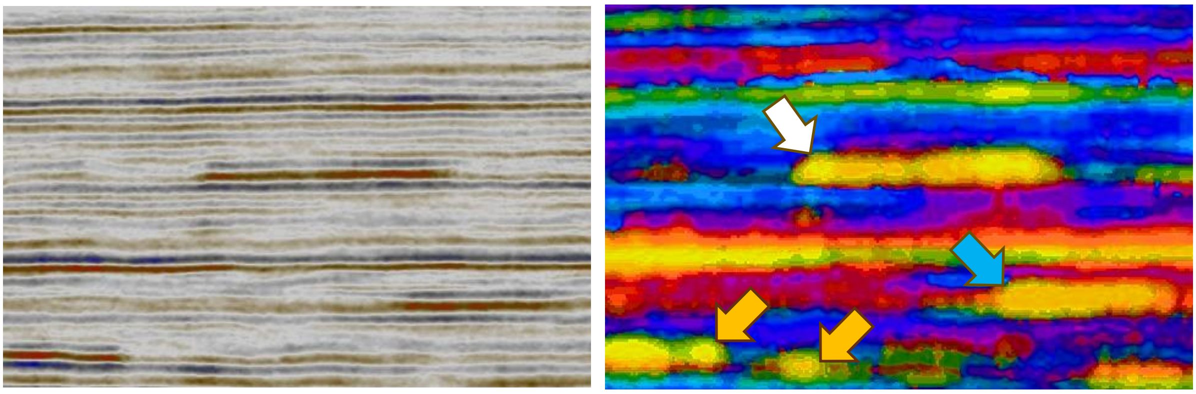


Fig. 3. Two-dimensional color scheme applied to visualize SOM clusters after training.

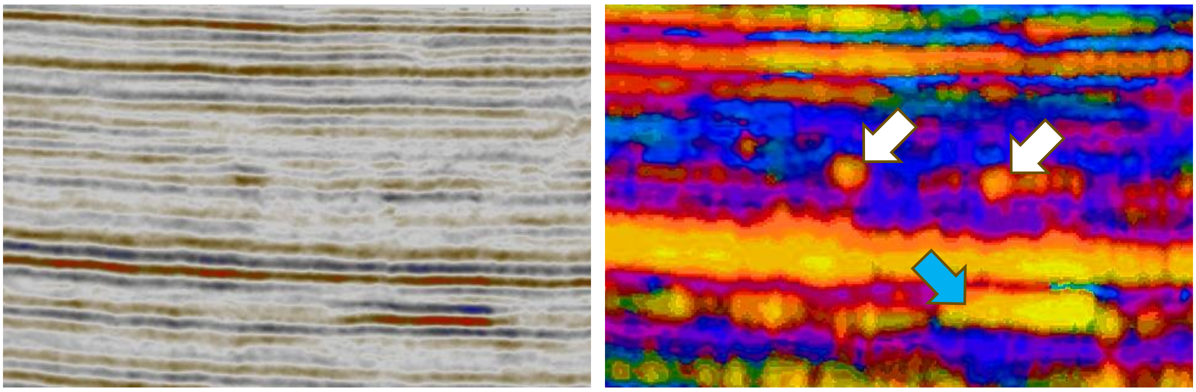
Fig. 4 and Fig. 5 show the comparison of seismic time section with the clustered representation for the zone of interest. In the seismic section, the reflectors exhibit variable amplitudes, which obscure subtle depositional features and complicate stratigraphic interpretation. By contrast, the clustered representation derived from the proposed methodology highlights facies into distinct clusters that align with geologically consistent patterns. Arrows in the image indicate channel systems characterized by high-amplitude seismic responses, which are clearly separated into unique clusters. The comparison of the seismic section with its clustered demonstrates the ability of the methodology to transform complex seismic signals into an interpretable facies model.

In order to analyze how the clusters are distributed laterally, a strata map was extracted from the clustered seismic volume (Fig. 6). This map provides a map-view representation of facies distributions at a given stratigraphic level, allowing the continuity and geometry of depositional features to be examined. The lateral patterns of clusters correspond to distinct geological domains, with channels appearing as sinuous, elongated bodies, while levees and floodplain facies form broader, lower-amplitude clusters. Such maps highlight the spatial arrangement and connectivity of geobodies, offering valuable insight into reservoir heterogeneity and stratigraphic architecture.



(a) (b)

Fig. 4. Comparison of seismic time section and SOM clustering results. (a) Input seismic data. (b) SOM-clustered volume visualized using a two-dimensional color scale. Arrows indicate clusters corresponding to channel features.

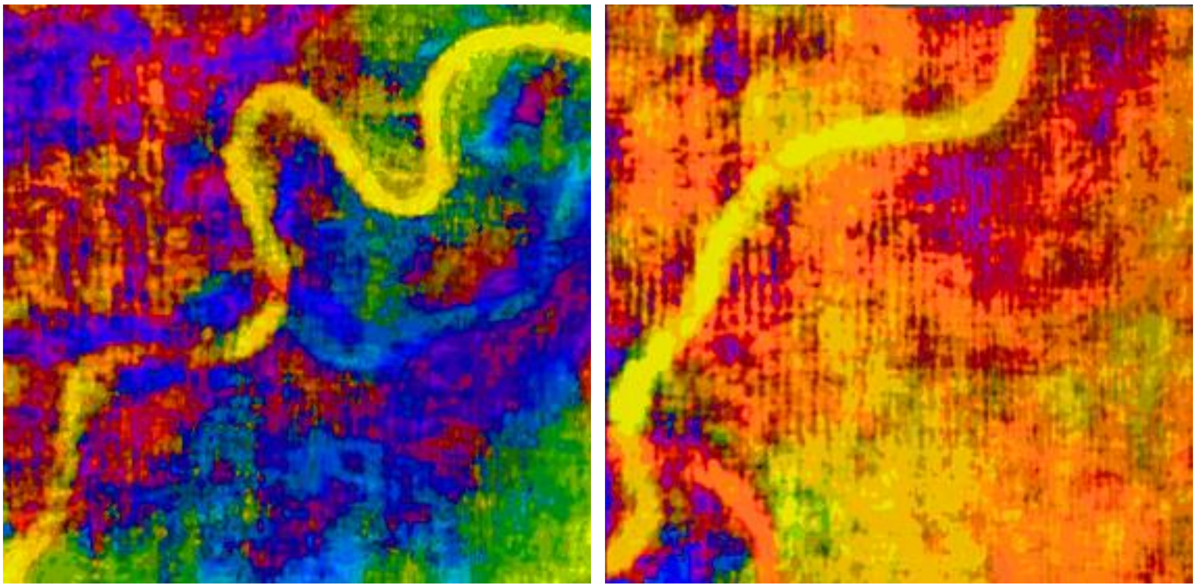


(a) (b)

Fig. 5. Comparison of seismic time section and SOM clustering results. (a) Input seismic data. (b) SOM-clustered volume visualized using a two-dimensional color scale. Arrows indicate clusters corresponding to channel features.

Fig. 6 clearly shows meandering channels with pronounced sinuosity and a predominant southeast-northwest orientation in both primary channel systems on the cluster maps. Including high-frequency components enhances the clarity of these features, enabling better discrimination of smaller tributaries. A notable advantage of the cluster approach is its ability to define distinct facies boundaries, which enables accurate interpretation of channel boundaries. At the same time, the method preserves intra-channel heterogeneity, which is a critical factor for reliable volume estimation. These features provide a more detailed representation of channel architecture and facies distribution, highlighting the usefulness of this approach for geological analysis.

Finally, by combining the clusters that correspond to channel facies, it is possible to create a unified channel class that can be distinguished from the surrounding background facies (Fig. 7). This integration enables the extraction of continuous channel systems from the clustered volume, effectively separating them from floodplain, levee, and non-reservoir deposits. The resulting classification forms the basis for constructing three-dimensional geobodies that represent the channel architecture. These geobodies capture both the lateral extent and vertical stacking patterns of channel fills, providing a volumetric depiction of reservoir-scale features.



(a) (b)

Fig. 6. Example of strata map extracted from the SOM-clustered seismic volume. (a) Extraction from the first interval that corresponds to the white arrow. (b) Extraction from the second interval that corresponds to the blue arrow.

The results from the application demonstrate the potential of combining spectral decomposition with SOM-based clustering for seismic facies analysis. Beyond the clear delineation of channels and floodplain facies, the methodology proved capable of capturing transitional zones, internal channel heterogeneity, and subtle depositional boundaries that are typically obscured in conventional seismic sections. The volumetric extraction of channel geobodies illustrates its practical utility for reservoir modeling and reserves estimation, providing interpreters with geologically consistent features that can be directly quantified. The workflow requires careful parameter selection such as frequency ranges, SOM grid size, and post-clustering integration to ensure geological plausibility. While the method reduces interpreter bias by automating facies classification, expert geological input remains essential for validating results and guiding the integration of clustered geobodies into subsurface models. These findings underscore the role of machine learning–based clustering not as a replacement for geological interpretation but as a powerful complement that enhances efficiency, reproducibility, and interpretive accuracy.

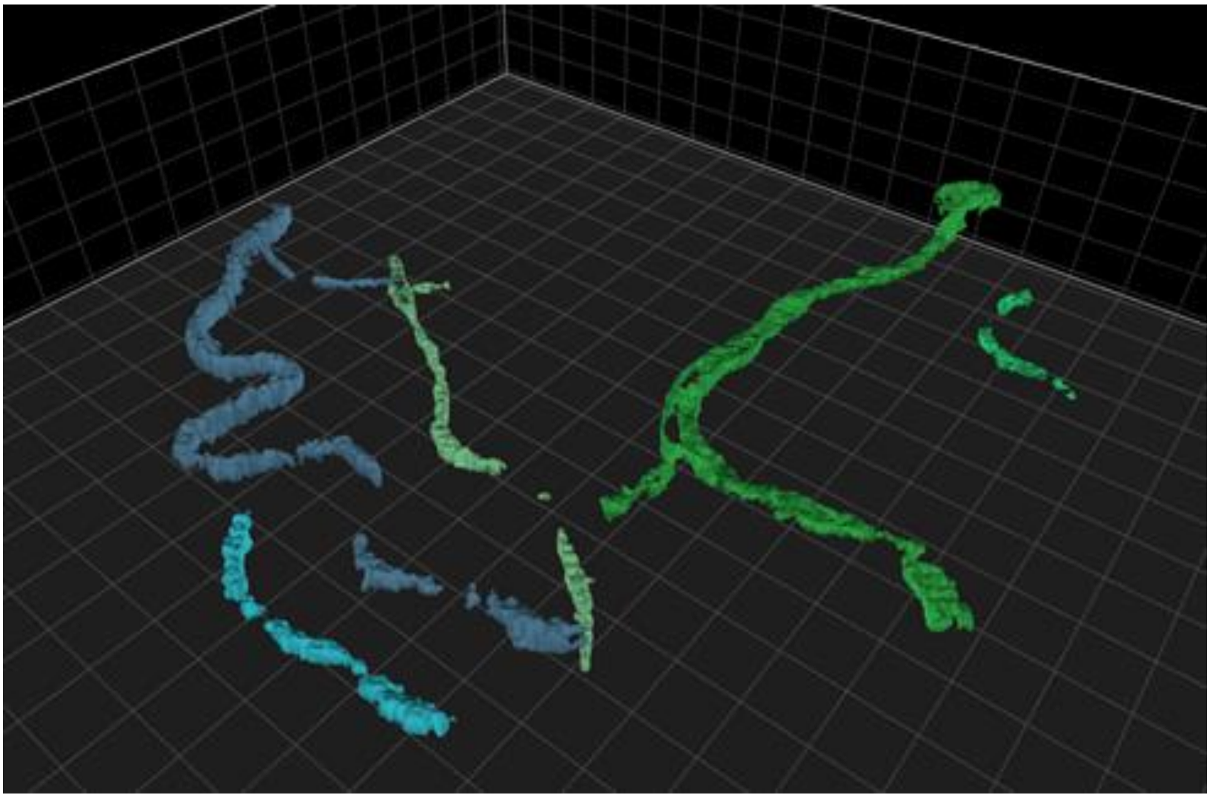


Fig. 7. Extracted three-dimensional channel geobodies from the SOM-clustered seismic volume within the target interval. Distinct colors represent individual channel systems.

DISCUSSION

The integration of CWT and SOMs for volumetric seismic facies classification, as demonstrated in this study, provides a robust and powerful new approach to quantitative reservoir characterization. By moving beyond traditional amplitude-driven workflows and even spectral decomposition applied in isolation, we have successfully addressed the challenge of resolving subtle stratigraphic variations in complex depositional settings like the South Caspian Basin. The results highlight three key advancements over existing methods: enhanced geological resolution, reduced interpreter bias, and the ability to extract quantitative, geologically meaningful geobodies.

The enhanced geological resolution is evident in the comparison between the raw seismic data and the SOM-clustered volume (Fig. 4 and Fig. 5). The traditional seismic sections, while showing broad reflector patterns, obscure the fine-scale architecture of the fluvial-deltaic systems. In contrast, the SOM clustering, trained on a multi-dimensional array of frequency-dependent amplitudes from the CWT, successfully separates distinct seismic facies. The arrows in Fig. 4 and Fig. 5 clearly delineate channel systems that are visually indistinct in the raw seismic data. This is a direct consequence of the CWT's ability to reveal subtle spectral changes related to variations in lithology, thickness, and fluid content, and the SOM's capacity to cluster these high-dimensional patterns into interpretable classes. The resulting facies model is not merely a smoothed version of the input data; it is a representation of the geological architecture that would be exceedingly difficult to achieve through manual interpretation or even simple attribute analysis.

Furthermore, the volumetric and automated nature of this workflow significantly reduces interpreter bias. Manual facies interpretation is inherently subjective, relying on the interpreter's experience and a limited number of visual attributes. The SOM algorithm, by contrast, provides an objective and reproducible classification of every voxel in the seismic volume based on its complete spectral signature. The systematic progression of frequency-amplitude patterns across the SOM grid (Fig. 1) reflects the continuous range of geological variation within the basin, from high-amplitude channel fills to low-amplitude floodplain deposits. This unsupervised classification minimizes the risk of overlooking subtle but significant stratigraphic features and ensures consistency across large datasets and multiple interpreters. While the final assignment of geological labels to the clusters still requires expert knowledge, the initial data-driven clustering provides a strong, unbiased foundation for interpretation.

Finally, the most significant practical outcome of this methodology is the ability to extract quantitative 3D geobodies directly from the clustered volume (Fig. 7). This is a critical step for modern reservoir modeling and development planning. Unlike 2D horizon slices (Fig. 6), which offer a limited view of lateral continuity, the 3D geobodies capture the full complexity of channel stacking, meandering, and connectivity. These volumetric models can be directly incorporated into static and dynamic reservoir simulations. The ability to measure the dimensions, tortuosity, and interconnectedness of these geobodies provides a more accurate basis for estimating reservoir volumes and designing optimal well placement strategies.

While the results are compelling, it is important to acknowledge certain limitations and areas for future work. The success of the workflow depends on the selection of appropriate parameters, such as the frequency range for CWT and the dimensions of the SOM grid. The current study’s average frequency spectrum analysis (Fig. 2) provides a data-driven basis for this selection, but further research could explore more sophisticated methods for parameter optimization.

In conclusion, this study demonstrates that the combination of CWT and SOM provides a powerful, data-driven framework for seismic facies analysis that surpasses the capabilities of traditional methods. It transforms seismic data into a geologically consistent and quantitative facies model, thereby unlocking new insights into depositional processes and enabling more confident decision-making in both exploration and field development. The volumetric geobodies generated by this workflow can be directly incorporated into the reservoir characterization process. This work presents a robust and transferable methodology with broad applications in geosciences.

CONCLUSIONS

This study successfully demonstrates a novel and effective workflow for volumetric seismic facies classification by integrating CWT with SOMs. By leveraging the strengths of both methodologies, our approach advances seismic interpretation from a qualitative, amplitude-based process to a quantitative, spectrally driven one.

The application of this workflow to the South Caspian Basin reveals the intricate, fine-scale architecture of its fluvial-deltaic systems. The CWT provided a frequency-dependent representation of the subsurface, while the SOM algorithm clustered these high-dimensional data into meaningful, geologically coherent facies. This dual approach resulted in a significant improvement in geological resolution, revealing subtle stratigraphic features like channel systems that were previously undetectable.

Furthermore, the automated and data-driven nature of SOM-based clustering reduces interpreter bias, ensuring a reproducible and objective classification across the entire seismic volume. This provides a strong, unbiased foundation for subsequent geological analysis. The main outcome of this methodology is the ability to extract quantitative, three-dimensional geobodies, which capture the full complexity of reservoir architecture, including lateral connectivity and vertical stacking patterns. These geobodies are not just interpretive aids; they are a direct output that can be incorporated into static and dynamic reservoir models for more accurate reserve estimations and optimal development planning.

REFERENCES:

[1] Brown AR. Interpretation of Three-Dimensional seismic data. Society of Exploration Geophysicists and American Association of Petroleum Geologists eBooks. 2011. Available from: https://doi.org/10.1190/1.9781560802884

[2] Castagna JP, Sun S, Siegfried RW. Instantaneous spectral analysis: Detection of low-frequency shadows associated with hydrocarbons. The Leading Edge. 2003 Feb 1;22(2):120–7. Available from: https://doi.org/10.1190/1.1559038

[3] Chopra S, Marfurt KJ. Seismic attributes for prospect identification and reservoir characterization. Society of Exploration Geophysicists and European Association of Geoscientists and Engineers eBooks. 2007. Available from: https://doi.org/10.1190/1.9781560801900

[4] Chopra S, Marfurt KJ. Seismic facies classification using some unsupervised machine-learning methods. SEG Technical Program Expanded Abstracts. 2018 Aug 27; Available from: https://doi.org/10.1190/segam2018-2997356.1

[5] Coléou T, Poupon M, Azbel K. Unsupervised seismic facies classification: A review and comparison of techniques and implementation. The Leading Edge. 2003 Oct 1;22(10):942–53. Available from: https://doi.org/10.1190/1.1623635

[6] Das G, Chattopadhyay M, Gupta S. A comparison of self-organising maps and principal components analysis. International Journal of Market Research. 2016 Nov 1;58(6):815–34. Available from: https://doi.org/10.2501/ijmr-2016-039

[7] De Matos MC, Osorio PL, Johann PR. Unsupervised seismic facies analysis using wavelet transform and self-organizing maps. Geophysics. 2006 Dec 13;72(1):P9–21. Available from: https://doi.org/10.1190/1.2392789

[8] Kazemeini SH, Juhlin C, Zinck-Jørgensen K, Norden B. Application of the continuous wavelet transform on seismic data for mapping of channel deposits and gas detection at the CO2SINK site, Ketzin, Germany. Geophysical Prospecting. 2008 Jul 8;57(1):111–23. Available from: https://doi.org/10.1111/j.1365-2478.2008.00723.x

[9] Kaz'min VG, Verzhbitskii EV. Age and origin of the South Caspian Basin. Oceanology. 2011 Feb 1;51(1):131–40. Available from: https://doi.org/10.1134/s0001437011010073

[10] Kourki M, Riahi MA. Seismic facies analysis from pre-stack data using self-organizing maps. Journal of Geophysics and Engineering. 2014 Nov 6;11(6):065005. Available from: https://doi.org/10.1088/1742-2132/11/6/065005

[11] Malikov R, Babayev G. Applying spectral decomposition to seismic facies clustering with unsupervised machine learning. Geofizicheskiy Zhurnal. 2025 Jun 9;47(3). Available from: https://doi.org/10.24028/gj.v47i3.320290

[12] Nanda NC. Seismic data interpretation and evaluation for hydrocarbon exploration and production. Advances in oil and gas exploration & production. 2021. Available from: https://doi.org/10.1007/978-3-030-75301-6

[13] Owusu P, Raef A, Sharaf E. Carbonate Seismic Facies Analysis in Reservoir Characterization: A Machine Learning Approach with Integration of Reservoir Mineralogy and Porosity. Geosciences. 2025 Jul 4;15(7):257. Available from: https://doi.org/10.3390/geosciences15070257

[14] Partyka G, Gridley J, Lopez J. Interpretational applications of spectral decomposition in reservoir characterization. The Leading Edge. 1999 Mar 1;18(3):353–60. Available from: https://doi.org/10.1190/1.1438295

[15] Posamentier HW, Kolla V. Seismic geomorphology and stratigraphy of depositional elements in Deep-Water settings. Journal of Sedimentary Research. 2003 May 1;73(3):367–88. Available from: https://doi.org/10.1306/111302730367

[16] Roden R, Smith T, Sacrey D. Geologic pattern recognition from seismic attributes: Principal component analysis and self-organizing maps. Interpretation. 2015 Aug 14;3(4):SAE59–83. Available from: https://doi.org/10.1190/int-2015-0037.1

[17] Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence. 2019 May 13;1(5):206–15. Available from: https://doi.org/10.1038/s42256-019-0048-x

[18] Samakinde CA, Van Bever Donker JM, Durrheim R, Manzi M. Application of seismic stratigraphy in reservoir characterisation: a case study of the passive margin deposits of the northern Orange Basin, South Africa. Journal of Petroleum Exploration and Production Technology. 2020 Dec 1;11(1):45–61. Available from: https://doi.org/10.1007/s13202-020-01050-9

[19] Samuel SA, Knapp CC, Knapp JH. Seismic Facies Classification of salt structures and sediments in the Northern Gulf of Mexico using Self-Organizing Maps. Geosciences. 2025 May 19;15(5):183. Available from: https://doi.org/10.3390/geosciences15050183

[20] Sinha S, Routh PS, Anno PD, Castagna JP. Spectral decomposition of seismic data with continuous-wavelet transform. Geophysics. 2005 Jan 1;70(6):P19–25. Available from: https://doi.org/10.1190/1.2127113

[21] Smith-Rouch LS. Oligocene–Miocene Maykop/Diatom Total petroleum system of the South Caspian Basin Province, Azerbaijan, Iran, and Turkmenistan. 2006 Jan. Available from: https://doi.org/10.3133/b2201i

[22] Sukmono S, Machado V, Adelina R, Ambarsari D. Integration of 3D seismic attributes for preliminary shallow geohazard identification in deep water exploration area with no well data. First Break. 2017 Aug 1;35(8). Available from: https://doi.org/10.3997/1365-2397.35.8.89810

[23] Von Hartmann H, Buness H, Krawczyk CM, Schulz R. 3-D seismic analysis of a carbonate platform in the Molasse Basin - reef distribution and internal separation with seismic attributes. Tectonophysics. 2012 Jul 2;572–573:16–25. Available from: https://doi.org/10.1016/j.tecto.2012.06.033

[24] Wang Y. Frequencies of the Ricker wavelet. Geophysics. 2015 Feb 2;80(2):A31–7. Available from: https://doi.org/10.1190/geo2014-0441.1

[25] Wrona T, Pan I, Gawthorpe RL, Fossen H. Seismic facies analysis using machine learning. Geophysics. 2018 Jun 12;83(5):O83–95. Available from: https://doi.org/10.1190/geo2017-0595.1

[26] Yilmaz Ö. Seismic data analysis. Society of Exploration Geophysicists eBooks. 2001. Available from: https://doi.org/10.1190/1.9781560801580

[27] Zhao T, Jayaram V, Roy A, Marfurt KJ. A comparison of classification techniques for seismic facies recognition. Interpretation. 2015 Aug 14;3(4):SAE29–58. Available from: https://doi.org/10.1190/int-2015-0044.1

[28] Zhu Z, Chen X, Ren H, Tao L, Jiang J, Wang T, et al. Seismic facies analysis using the multi-attribute SOM-K-Means clustering. Computational Intelligence and Neuroscience. 2022 Oct 10;2022:1–11. Available from: https://doi.org/10.1155/2022/1688233