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# Fuzzy logic integration of topological metrics for fault connectivity assessment

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## Abstract Summary

This study applies fuzzy logic to integrate topological metrics from interpreted fault networks, aiming to identify high-connectivity zones across key stratigraphic horizons in a pre-salt reservoir. Using the NetworkGT plugin in QGIS, four parameters were extracted: Fault Intensity, Number of Connections, Connection per Branch, and Connection per Line. After rasterization and fuzzification, the layers were combined using the fuzzy product operator. Results show that the Intra-Alagoas (IAU) horizon exhibits the highest fault connectivity, while the Base of Salt (BSU) horizon shows the lowest. This method offers a flexible framework for fault analysis, pending validation with well or dynamic data.

## Introduction

Fuzzy logic (Zadeh, 1965) is an extension of traditional Boolean logic that enables the identification of elements that partially belong to a set, assigning them membership degrees ranging from 0 (completely outside) to 1 (completely inside). This framework is particularly valuable in geological systems, where class boundaries are often diffuse or gradational, such as in the case of fault connectivity zones. Instead of classifying areas as strictly "connected" or "disconnected," fuzzy logic supports the representation of continuous degrees of potential connectivity, based on multiple geological and structural attributes.

One of the major challenges in reservoir characterization is determining which faults and fractures act as flow conduits and which ones behave as structural barriers. Topological analysis provides a quantitative means to investigate the spatial relationships and connectivity patterns within a fault network, including how faults intersect, branch, and compartmentalize rock volumes. This type of analysis is critical for identifying preferential flow paths or flow barriers, assessing effective reservoir compartmentalization, predicting well-to-well communication, and understanding how the fault network controls reservoir-scale heterogeneity.

To integrate these topological metrics into a unified and spatially continuous model, this study proposes the application of fuzzy logic. This approach allows multiple raster layers, each representing a distinct topological criterion, to be combined into a composite fuzzy connectivity surface. Using the fuzzy product operator, we generate potential maps that highlight zones of high fault connectivity, providing a flexible and interpretable framework to support structural and flow-based reservoir modeling.

## Method and Theory

In this study, topological metrics were extracted using the NetworkGT plugin in QGIS, which computes spatial network attributes from interpreted fault trace data. Faults were classified into nodes: I (isolated), Y (abutting), and X (crossing), and branches: I–I (isolated), I–C (partially connected), and C–C (fully connected), according to their intersection geometry and connectivity behavior (Nyberg et al., 2018).

From these classifications, topological parameters were derived, including: fault intensity (i.e., the number of fault segments per unit area), Number of Connections (calculated from the total count of X and Y nodes), Connection per Branch (CB), and Connection per Line (CL), which collectively describe the structural complexity and connectivity potential of the fault network. These parameters were used as input for this study and were organized into shapefiles derived from gridded topological analyses of the interpreted fault network across three key stratigraphic horizons: the Pre-Alagoas (PAU), Intra-Alagoas (IAU), and Base of Salt (BSU) unconformities.

Based on topological studies, values of CB between 1.5 and 2.0 and CL values greater than 3.5 are considered indicative of high connectivity. For the Number of Connections and Fault Intensity, high-connectivity zones were defined relative to the highest concentrations observed in the spatial distribution maps (Sanderson & Nixon, 2015 and 2018).

As shown in **Figure 1**, the vector layers containing the topological parameters were converted into raster format. Each raster was then subjected to a fuzzification process, transforming the binary or intensity-based data into fuzzy membership maps with values ranging from 0 to 1. In this step, raster cells located closer to high-connectivity features were assigned higher membership values, reflecting a stronger affiliation with the “connectivity potential” class.

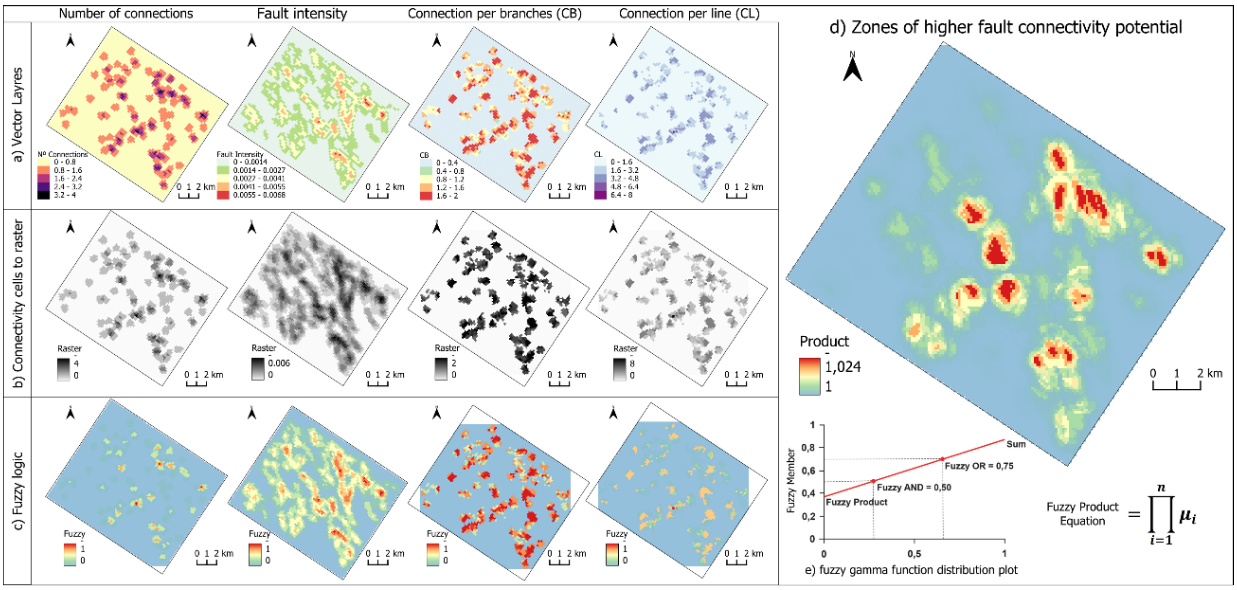


**Figure 1:** Fuzzy operations methodology. (a) Vector layers used as input parameters: number of connections, fault intensity, connection per branch (CB), and connection per line (CL). (b) Raster conversion of input layers to a regular grid. (c) Application of fuzzy logic membership functions for each input parameter, scaled to [0–1]. (d) Final result using the Fuzzy product operator, highlighting zones with higher fault connectivity potential.

The results of the fuzzification were subsequently reclassified into the following intervals:

- **[0–0.25]** no connectivity,
- **[0.25–0.5]** low connectivity,
- **[0.5–0.75]** medium connectivity,
- **[0.75–1.0]** high connectivity.

These intervals were used to construct histograms representing the percentage distribution of each connectivity class within the fuzzy maps. Finally, the fuzzified rasters were integrated using the fuzzy product operator, resulting in a composite surface that emphasizes areas where multiple criteria simultaneously indicate high fault connectivity.

## Results

The fuzzified rasters are shown in **Figure 2**, resulting in color-coded maps where blue indicates zones with no connectivity, yellow represents fuzzy values from 0.25 to 0.5 (low connectivity), orange corresponds to values between 0.5 and 0.75 (medium connectivity), and red highlights values from 0.75 to 1.0 (high connectivity zones). Based on the pixel percentage within each interval, fuzzy interval histograms were generated to quantify the relative spatial distribution of each connectivity class in the resulting maps.

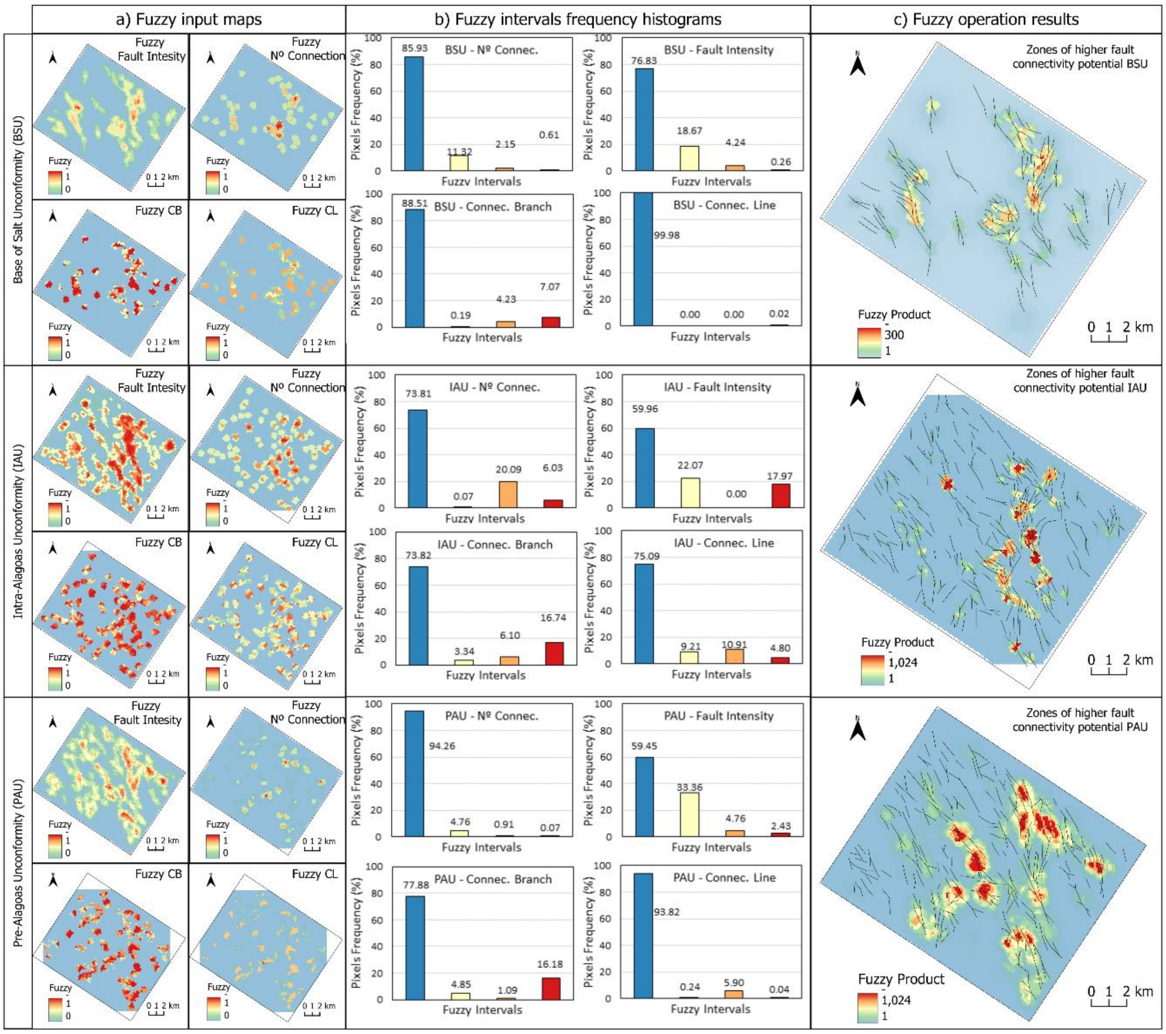


**Figure 2:** Fuzzy-based fault connectivity analysis across three horizons: PAU, IAU, BSU. (a) Fuzzified input maps for each topological parameter: Fault Intensity, Number of Connections, Connection per Branch (CB), and Connection per Line (CL). (b) Histograms showing the frequency distribution of pixel values across four fuzzy intervals: [0–0.25] (no connectivity), [0.25–0.5] (low connectivity), [0.5–0.75] (medium connectivity), and [0.75–1.0] (high connectivity). (c) Final fuzzy product maps combining all input rasters, highlighting zones of higher fault connectivity potential based on the spatial intersection of multiple topological criteria.

The results from the fault intensity maps reveal that both the PAU and IAU horizons exhibit a broad spatial distribution of structural intensity, with the IAU displaying overall higher values compared to the adjacent horizons. According to the fuzzy interval histograms, 17.97% of the IAU area falls within the 0.75–1.0 fuzzy interval, whereas the BSU accounts for only 0.26% within the same range.

In the Number of Connections maps, the high-value zones exhibit a predominantly circular geometry, which reflects the influence of Y and X nodes in the underlying topological analysis. These circular features are more spatially dispersed within the IAU horizon, indicating a more widespread occurrence of highly connected fault intersections relative to the other stratigraphic levels. Specifically, 6.03% of the IAU area corresponds to high fuzzy values, while only 0.07% of the PAU is classified within the same interval.

In the case of Connection per Branch, both PAU and IAU show similar proportions of high fuzzy values—16.18% and 16.74%, respectively—each exhibiting broader spatial distributions compared to the BSU. The Connection per Line parameter, on the other hand, shows consistently low representation of high fuzzy values across all horizons, with 4.80% of the IAU and only 0.02% of the BSU falling within the upper fuzzy interval.

The resulting maps from the fuzzy product operation highlight the zones of high fault connectivity in combination with the interpreted fault traces. From base to top, the high-connectivity zones progressively retreat toward the central portion of the area, while still showing prominent concentrations along the eastern and western flanks. In the BSU horizon, connectivity is significantly lower, with only medium-connectivity zones being observed.

## Conclusions

The application of fuzzy logic proved to be an effective method for integrating the various topological outputs generated by the NetworkGT plugin. This approach enabled the construction of a single, continuous surface representing the fault connectivity potential of the study area. Although fuzzy gamma operators are commonly used for multi-criteria integration, in this study, the fuzzy product operator was chosen due to its conservative nature, multiplying the fuzzy membership values of all input criteria. As a result, the output value is always lower than the individual inputs, and if any input has a membership value of zero, the final product will also be zero. This behavior was particularly useful for eliminating zones of low or no connectivity, ensuring that only areas meeting all high-connectivity conditions were highlighted.

However, it is important to note that the resulting connectivity zones were defined based solely on one source of information: the interpreted fault network. While well data are often spatially limited and potentially biased, incorporating additional data sources, such as dynamic flow data, core analysis, or 3D seismic attributes, could help validate and refine the fuzzy connectivity model, enhancing its geological robustness and predictive accuracy.

## References


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