Optimizing AI and geologist's collaboration for structural mapping: The case of naturally fractured carbonates at subseismic scale

Jimmy Daynac*†[1], Thibault Cavailhes‡[2], Thierry Mulder[2], Vincent Marieu[3], and Hervé Gillet[2]

[1]Laboratoire de Planétologie et Géosciences - Le Mans – Laboratoire de Planétologie et Géosciences [UMR$_C$6112] – –$France$

[2]Environnements et Paléoenvironnements OCéaniques – Ecole Pratique des Hautes Etudes, Université de Bordeaux, Institut National des Sciences de l'Univers, Centre National de la Recherche Scientifique – France

[3]Environnements et Paléoenvironnements OCéaniques – Ecole Pratique des Hautes Etudes, Université de Bordeaux, Institut National des Sciences de l'Univers, Centre National de la Recherche Scientifique, Bordeaux-INP – France

Résumé

In recent years, *Artificial Intelligence* (AI), especially deep learning, has emerged in geosciences for 3D mapping of structural heterogeneities (faults, fractures, fracture corridors) in *Naturally Fractured Rocks* (NFR), using outcrop or seismic data. The goal is to improve *Discrete Fracture Network* (DFN) models, essential for both static and dynamic reservoir modeling. To validate and constrain AI results, we compare a structural map produced using deep learning with one obtained through classical field-based structural analysis. To reduce bias during training, the AI was supervised by geologists who collected the field data themselves.
The study area is located in northwestern Spain, on a perched syncline of about 15 km^2, composed of Upper Cretaceous limestones, at an elevation of ˜1200 m. This plateau of recrystallized Turonian–Santonian limestones, approximately 42 m thick, overlies conglomeratic and sandy valleys of the Albian–Cenomanian, separated by a thin layer of Lower Turonian grey marls. The site is highly karstified, and the presence of caves allows for subsurface structural observations. Aerial photo-based structural analysis enabled the mapping of fractures and the quantification of their orientation, density, length, connectivity, and node types (I for isolated, X for intersecting, Y for abutting fractures; Manzocchi, 2002).

Methodologically, AI operates by analyzing local pixel similarities without extrapolation, providing a factual, no-interpretive analysis. The geologist's role is to train the model on structurally sound examples in unambiguous areas. Once calibrated, AI can map large areas faster than manual methods. Vectorization in GIS enables quantitative analysis of morphometric attributes. As of 2025, AI-based mapping remains limited by vegetation cover, except where vegetation follows fractures. To address this, two optimizations are proposed:

*Intervenant

†Auteur correspondant: jimmy.daynac7@gmail.com

‡Auteur correspondant:

(i) combining multi-source imagery (aerial photos, processed topography, vegetation maps), and *(ii)* ranking structures by their control on permeability (aperture-dependent).
AI supports geologists in validating their interpretations but does not replace the need to contextualize the mapping (structural framework, deformation timing, lithologies, vegetation, anthropogenic features). Each image type requires calibration, complex or vegetated areas must be completed, and field validation remains essential. Each heterogeneity must be linked to a structural porosity that controls its intrinsic permeability (e.g. open vs cemented fractures).

Mots-Clés: Structural heterogeneities, Artificial Intelligence, NFR, DFN, Structural porosity, Karstification