FROM EXPERT KNOWLEDGE TO UNSUPERVISED LEARNING: PROSPECTIVITY MODELLING OF FE-TI-V MINERALISATION IN BEJA, PORTUGAL

by

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Exploring buried mineral deposits is challenging due to weak and discontinuous surface geochemical signals obscured by complex surficial processes. We implement two predictive modelling approaches—a knowledge-driven fuzzy inference system and an unsupervised, data-driven self-organising map—within a mineral systems framework. Results show that predictive success depends chiefly on geologically meaningful, process-based predictors that amplify, rather than replace, human reasoning. The on-ground discovery of a new occurrence proves the efficacy of the complementary workflow.

Introduction

Mineral prospectivity modelling has become a central tool in modern exploration workflows, providing a geospatial framework to evaluate the probability of discovering economically viable mineral deposits in underexplored regions. These models integrate diverse geoscientific datasets—geological, geochemical, geophysical, structural and remote sensing—using mathematical, statistical, or artificial intelligence algorithms to predict favourable areas for mineralisation.

However, as emphasised by Hronsky and Kreuzer (2019), within the mineral systems framework, the ultimate success of predictive modelling does not primarily depend on the choice of integration algorithm, but on the quality and geological relevance of the predictor maps. Algorithms merely combine information; geological reasoning gives meaning to the data. Thus, the creative and intellectual focus of exploration geoscience should be on improving conceptual models and developing process-based predictors—a philosophy best described as intelligence amplification (IA) rather than artificial intelligence (AI).

Conceptual Framework and Study Area

This study presents two complementary prospectivity modelling approaches applied to the oxide-rich layered gabbros of the Beja Complex, southern Portugal (Fig. 1)—a region known for Fe-Ti-V mineralisation and considered a potential source of critical raw materials (CRMs) for the European Union. These gabbros represent differentiated mafic intrusions emplaced during late- to post-collisional magmatism along the Ossa-Morena Zone (Jesus et al., 2007). Their economic importance arises from the enrichment of Fe-Ti oxides and associated vanadium within magnetite-ilmenite layers formed by magmatic differentiation processes.

The mineral system model for Fe-Ti-V oxide mineralisation in Beja comprises three key components:

1. Metal source and magma fertility: Primitive mantle-derived mafic magmas emplaced in syn- to post-collisional extensional settings.
2. Transport pathways architecture: Trans-lithospheric faults and suture zones providing conduits for magma ascent.
3. Deposition and concentration (sink) architecture: Dilatational zones and magma chambers where fractional crystallisation and oxide segregation concentrate Ti and V in cumulate horizons.

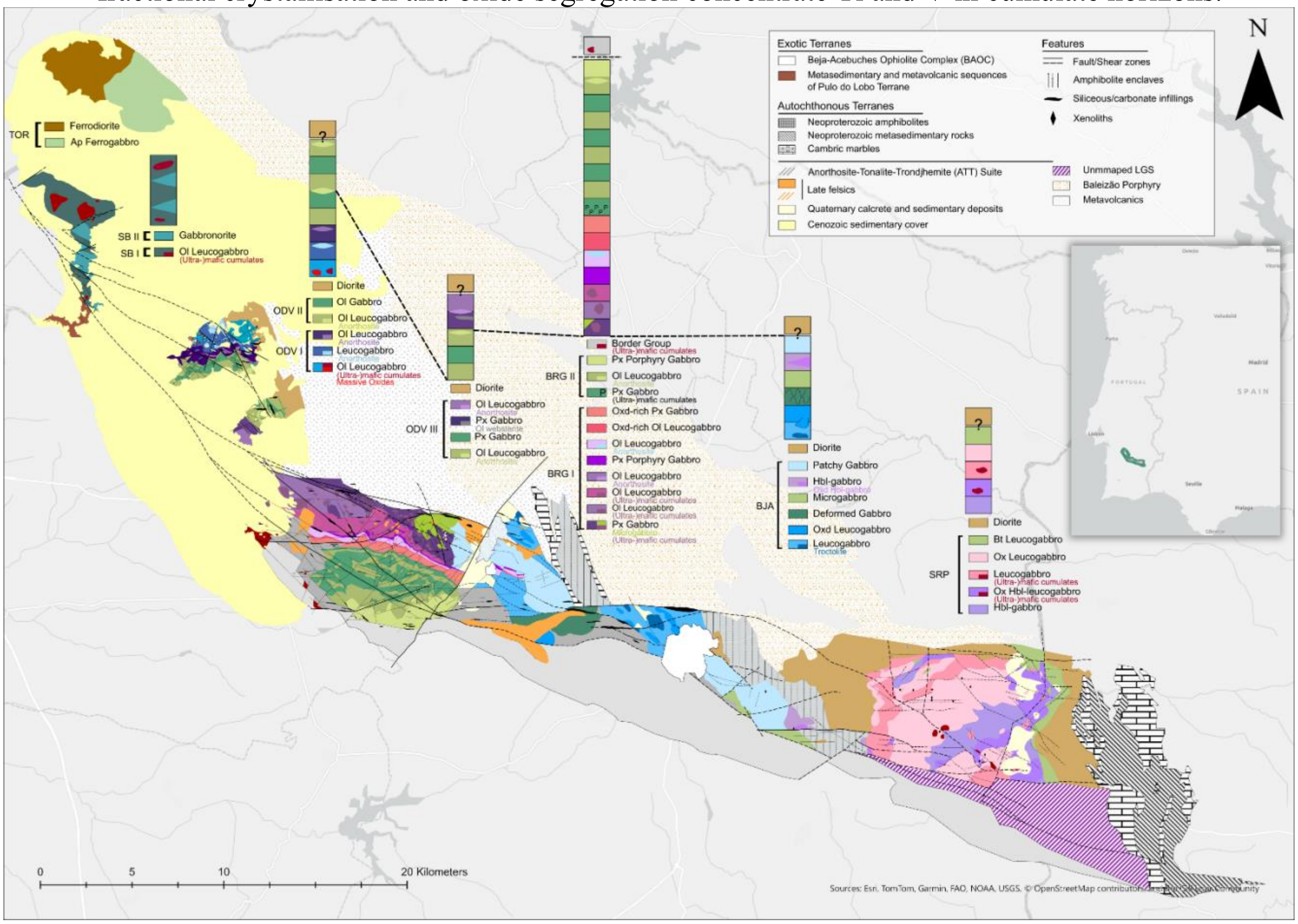

Figure 1: Geology of the Beja Complex. This map has been updated to reflect the outcomes prospectivity model, and the new occurrence identified by this study has been included.

Methods

Two approaches based on Aranha (2023) were implemented to target oxide-enriched gabbros (Fig. 2):

Data-driven, unsupervised approach (Self-Organising Map, SOM)

The SOM approach employed an unsupervised machine learning algorithm to identify natural clusters in the uniformly gridded datasets (magnetics, gravity, topography, electromagnetics). Unlike the knowledge-driven workflow, no prior geological assumptions were embedded—the model self-organised based on the inherent structure of the data. Clusters showing patterns consistent geological principles and with known gabbroic intrusions were then interpreted geologically, guided by expert review.

Knowledge-driven approach (Fuzzy Inference System, FIS)
The FIS approach explicitly encodes expert geological knowledge into a set of fuzzy logic rules representing geological relationships within the mineral system. Predictor maps representing key geological processes were prepared in a GIS environment, including:

- Magnesium coefficient (Indicator of magma evolution)
- Proximity to major faults, lineaments and sutures (magma pathways),
- Real and imaginary components, and apparent resistivity (oxide concentration indicators)
- Magnetic intensity and gradients (oxide concentration indicators), and
- Geochemical singularity maps (anomaly enhancement of Ti, V, Fe, and trace element associations).
- Proximity to differentiated lithological units (likely hosts of oxides)

Each predictor was standardised to fuzzy membership values using mathematical membership functions, and a rule base was constructed based on the knowledge of the mineral system. The predictors were integrated in a multi-stage FIS, simulating the structure of the mineral systems model. The final FIS output was a continuous prospectivity surface highlighting areas of high favourability for Fe-Ti-V mineralisation.

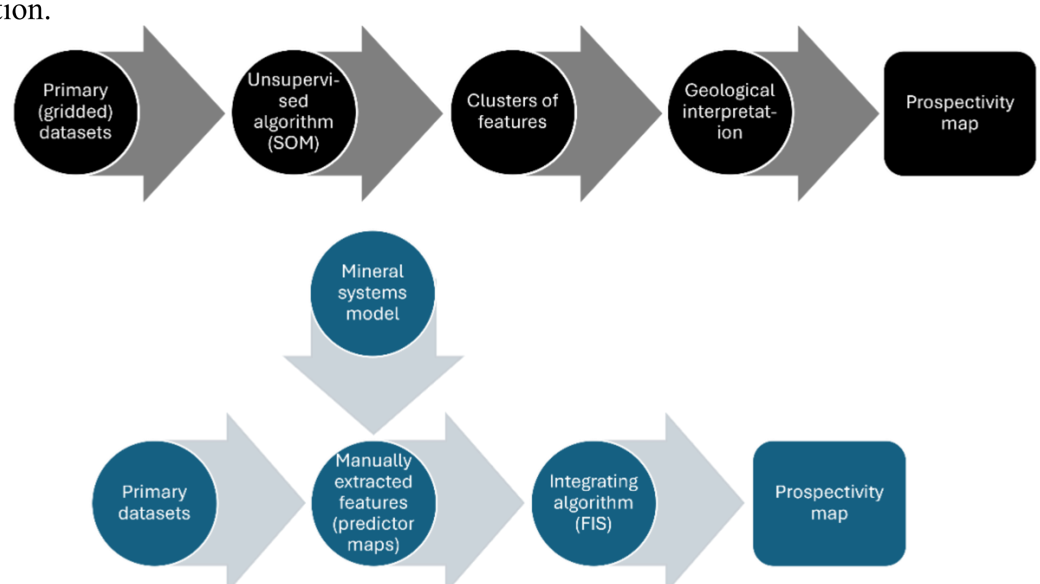

Figure 2: Complementary workflow comprising the data-driven, unsupervised SOM (top) and the knowledge-driven, supervised FIS (bottom) approaches.

Results and Discussion

The SOM analysis effectively delineated several clusters spatially corresponding to known layered gabbros in the central Beja region, confirming the algorithm's ability to differentiate among the different types of gabbros. More importantly, additional high-probability clusters were identified in the northwestern part of the study area—locations not previously mapped as gabbroic. Subsequent field verification confirmed new outcrops of evolved gabbros with oxide-rich layers, validating the approach as a first-pass targeting tool.

The FIS-based model, informed by refined geological inputs, produced a high-resolution prospectivity map integrating geological, structural, geophysical, and geochemical proxies. The highest favourability zones corresponded closely with known mineralised horizons and extended into unexplored areas adjacent to the main Beja intrusion, thus refining exploration focus areas.

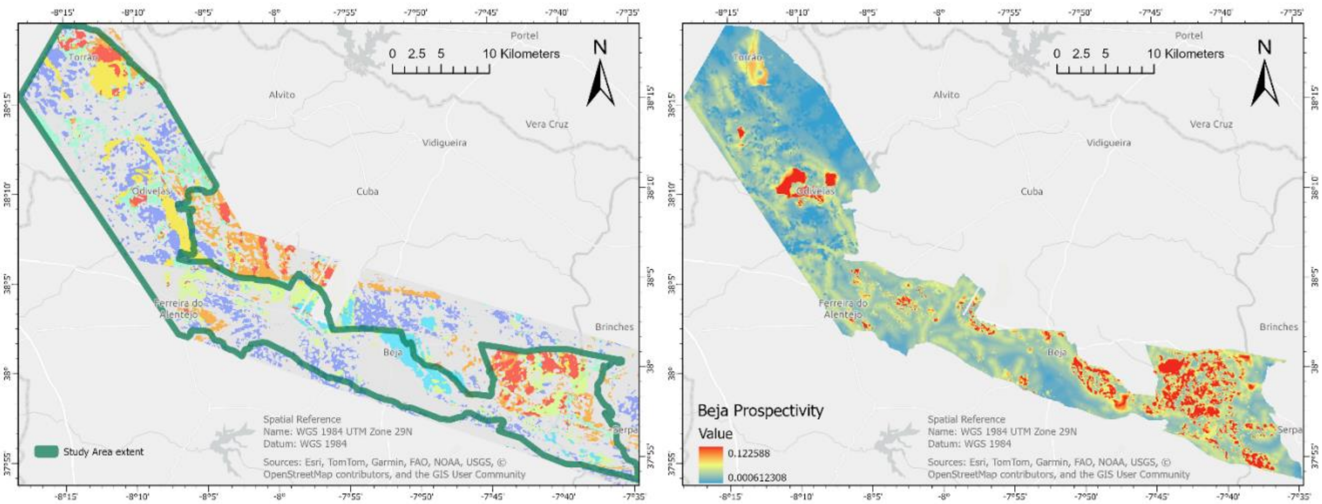

Figure 3: Comparative prospectivity maps generated from the data-driven, unsupervised SOM (left) and the knowledge-driven, supervised FIS (right) workflows.

The comparison between the data-driven SOM and the knowledge-driven FIS underscores a key principle of mineral prospectivity modelling: while machine learning techniques can efficiently detect structure and correlation in complex datasets, they remain dependent on the conceptual framing and geological interpretation that follow. The integration algorithm is not the determinant of success; instead, the geological validity and process-based construction of predictors ultimately control model performance.

In this context, artificial intelligence (AI) should be viewed as an extension of human reasoning—a means to amplify, not replace, geological intelligence. The SOM provided a valuable first-pass tool for recognising patterns and refining datasets, while the FIS served as a transparent, interpretable framework for embedding geological understanding. Together, they form a complementary workflow, where human creativity drives predictor design, and computational tools assist in synthesising and visualising multi-dimensional relationships.

Conclusions

- The choice of integration algorithm (e.g., SOM vs. FIS) is secondary to the quality and geological relevance of predictors derived from a robust mineral systems model.
- Machine learning methods are powerful for initial data exploration and identifying new patterns, but require geological validation to ensure interpretability and credibility.
- Knowledge-driven models remain indispensable for transparent reasoning and for transferring geological expertise into quantitative frameworks.
- Intelligence amplification, where algorithms enhance rather than replace human insight, is the most effective and productive approach to mineral exploration targeting.

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