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Artificial Intelligence (AI) in Exploration Targeting for Mineral Resources

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Content:

Part 1:

- Different branches or types of AI and developments in their applications in mineral exploration targeting

Part 2:

- A case study on the use of AI to delineate exploration targets

EuroGeoSurveys 56th GM Directors' Workshop
Rovaniemi, Finland, 20th March 2024

Part 1:

Artificial Intelligence (AI) in Mineral Exploration

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What is AI?

- AI is the science of making machines (i.e., computer algorithms) that can "**think**" like humans. It can do things that are considered "smart".
- AI is technology that can **process large amounts of data** in ways unlike humans.
- The goal for AI is to be able to **recognize complex patterns from large amounts of data**.
- AI leverages (i.e., uses to maximum advantage) machines to mimic the **problem-solving** and **decision-making** capabilities of the human mind.

Why use AI in Mineral Exploration Targeting?

- **Mineral Exploration (MinEx)**
  - the process of searching for evidence of any mineralization hosted in the surrounding rocks.*

- Problem to be solved:
  - finding evidence of mineralization
- Decisions to be made:
  - Follow-up evidence with more detailed exploration or not?
  - Which evidence is more important than another?
  - Which area(s) with evidence of mineralization should be prioritized for further exploration?

*from Geological Survey Ireland
(https://www.gsi.ie/en-ie/programmes-and-projects/minerals/activities/mineral-exploration/Pages/default.aspx)

Branches or Types of AI used in MinEx Targeting

- Expert system (ES)
- Fuzzy logic (FL)
- Machine learning (ML)
- Deep learning (DL)
- Natural Language Processing (NLP)

What is an ES?

- It is designed to solve complex, **non-linear** problems by reasoning through bodies of knowledge, represented mainly as if–then rules rather than through conventional procedural code.

- It's a computer program that uses AI technologies to simulate the judgment and behavior of a human or an organization that has expertise and experience in a particular field [https://www.techtarget.com]

- **ESs are usually intended to complement, not replace, human experts**.

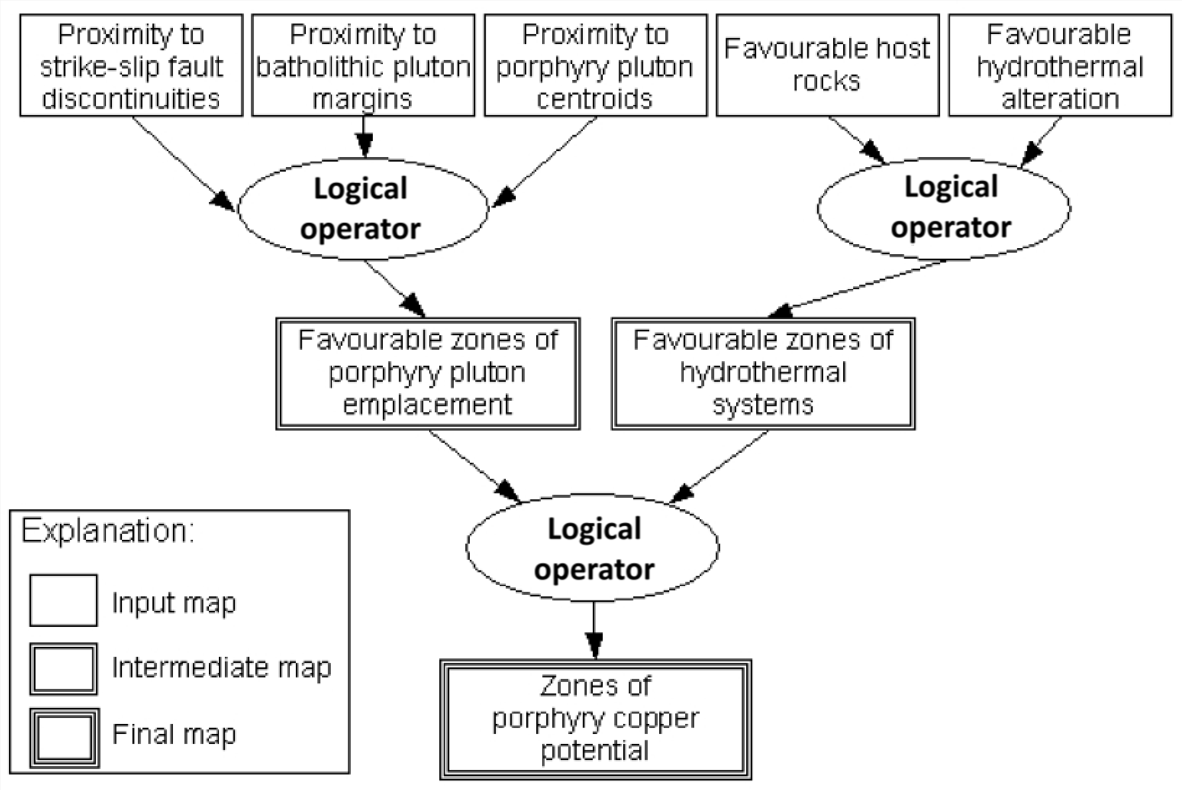
What is an ES?

- The first ESs were created in the 1970s and then proliferated in the 1980s.

- ESs were among the first truly successful forms of AI software.

- An ES is divided into two subsystems: the knowledge base and the inference engine.
  - The **knowledge base** represents facts and rules.
  - The **inference engine** applies the rules to the known facts to deduce new facts.

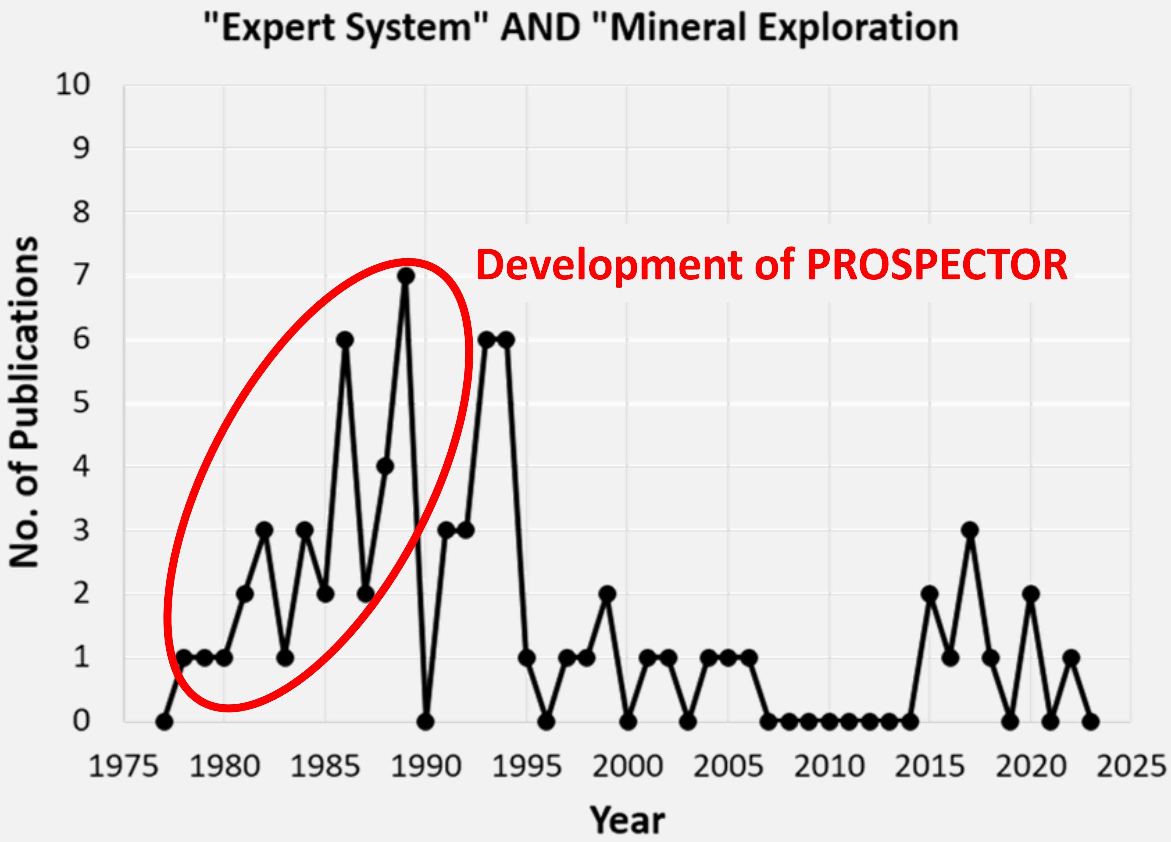
Inference engine



From:

Carranza, E.J.M., 2002. **Geologically-Constrained Mineral Potential Mapping (Examples from the Philippines)**. Ph.D. Thesis, Delft University of Technology, The Netherlands. (ISBN 90-6164-203-5), 480 pp.

Developments of ES in MinEx Targeting



*from Scopus and Google Scholar

ES in MinEx Targeting

Mathematical Geology, Vol. 10, No. 5, 1978

PROSPECTOR—A Computer-Based Consultation System for Mineral Exploration[1]

P. E. Hart,[2] R. O. Duda,[2] and M. T. Einaudi[3]

- Like any ES, it had two subsystems:
  - The **knowledge base** represents facts and rules.
  - The **inference engine** applies the rules to the known facts to deduce new facts.

ES in MinEx Targeting

Science

Recognition of a Hidden Mineral Deposit by an Artificial Intelligence Program

A. N. CAMPBELL, V. F. HOLLISTER, R. O. DUDA, AND P. E. HART Authors Info & Affiliations

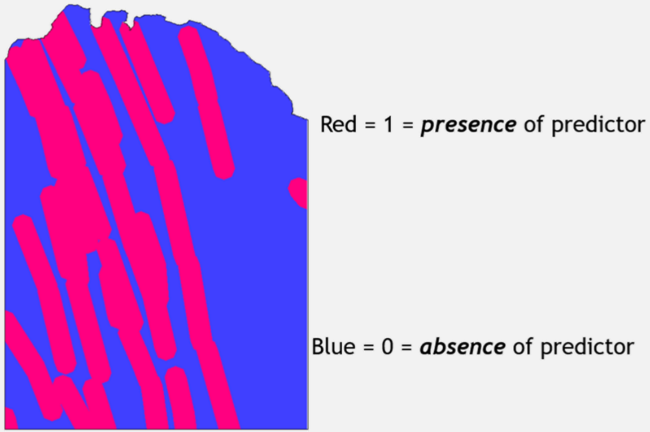
SCIENCE • 3 Sep 1982 • Vol 217, Issue 4563 • pp. 927-929 • DOI: 10.1126/science.217.4563.927

- The PROSPECTOR has successfully identified the location of a porphyry molybdenum deposit.
- This was the only **documented** successful discovery ever made by PROSPECTOR.

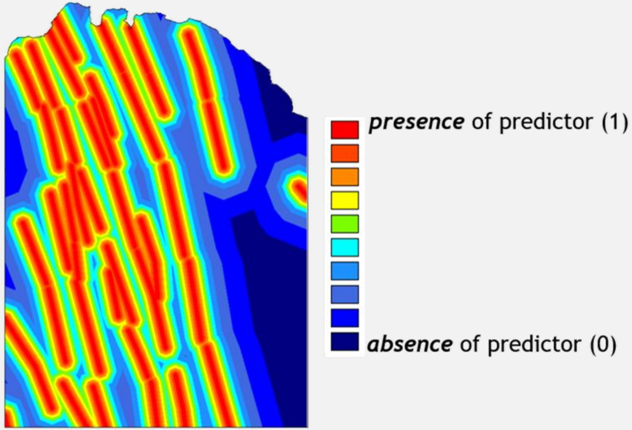
What is FL?

- It is an approach to <u>variable (or data) processing</u> that **allows for multiple possible 'truth' values** to be processed through the same variable.

Boolean logic representation of evidence



Fuzzy logic representation of evidence

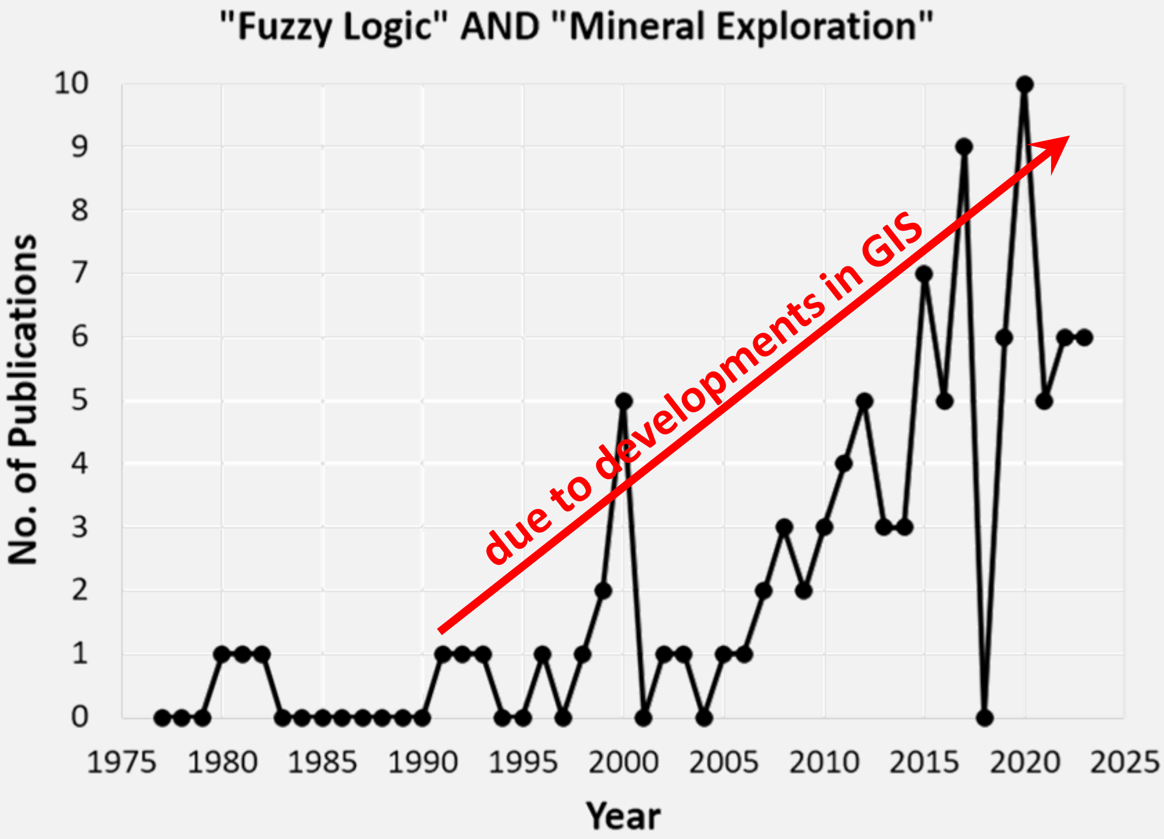


What is FL?

- It attempts to solve **non-linear problems** with an open, imprecise spectrum of data and heuristics (or rules) that make it possible to obtain an array of accurate conclusions.

- Like in an ES, a FL system has two subsystems
  - The **knowledge base** represents facts and rules.
  - The **inference engine** applies the rules to the known facts to deduce new facts.

Developments of FL in MinEx Targeting



*from Scopus and Google Scholar

What is ML?

- It is a branch of AI and computer science that focuses on the use of data and algorithms to imitate the way we humans **learn**, gradually improving its accuracy.

- It involves the use and development of computer systems that are able to learn and adapt **complex, non-linear spatial relationships of mineral deposits and certain predictor variables**, without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data

What is DL?

- DL is a method in AI that teaches computers to process data in a way that is inspired by the human brain.

- **It is a type of ML** based on artificial neural networks in which multiple layers of processing are used to extract progressively higher-level features from data (e.g., **complex, non-linear spatial relationships of mineral deposits and certain predictor variables**).

ML vs. DL

- Both ML and DL are types of AI that can automatically adapt with minimal human interference.

- ML encompasses a broad range of algorithms

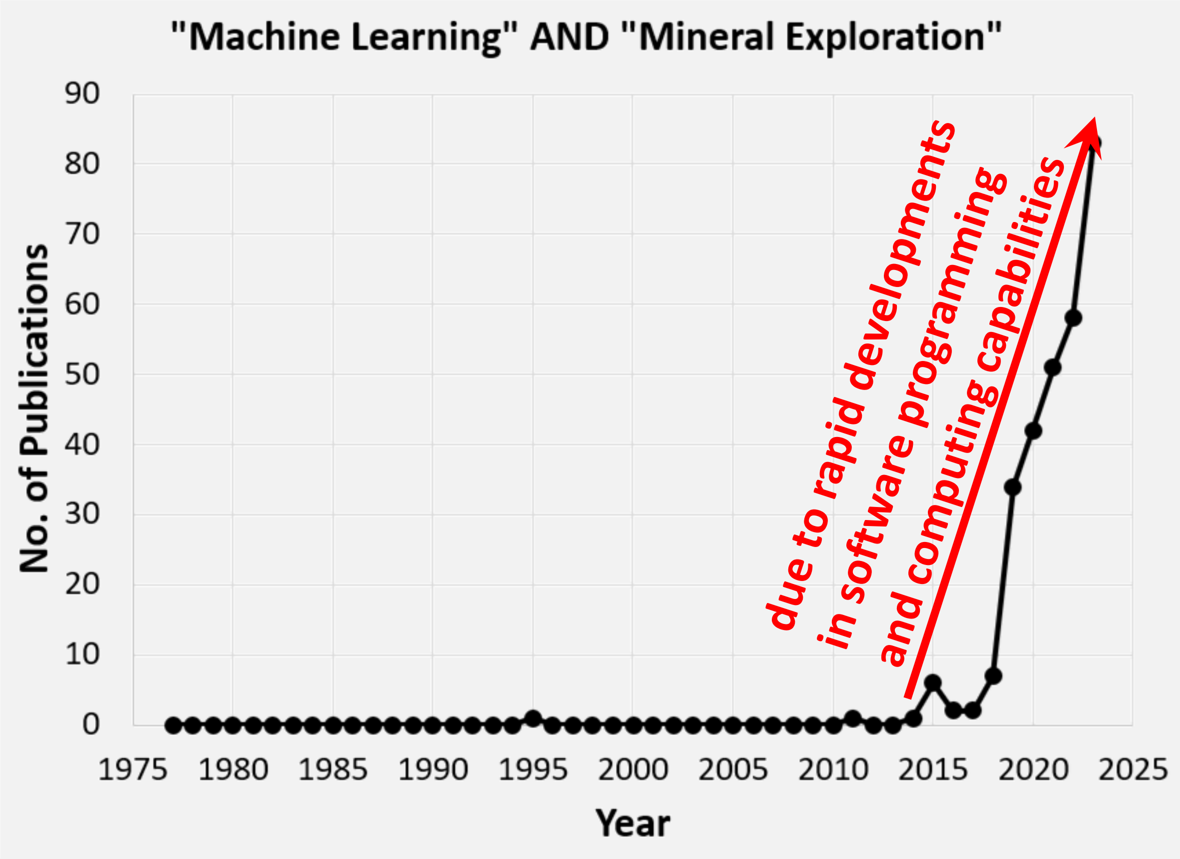
- DL is a specialized subset of ML that uses artificial neural networks **with more multiple layers (deep neural networks)** to analyze data to mimic the learning process of the human brain.

What is NLP?

- It is the ability of a computer program to understand human language as it is spoken and/or written – referred to as natural language.

- It uses ML to process and interpret text and data.

Developments of ML in MinEx Targeting



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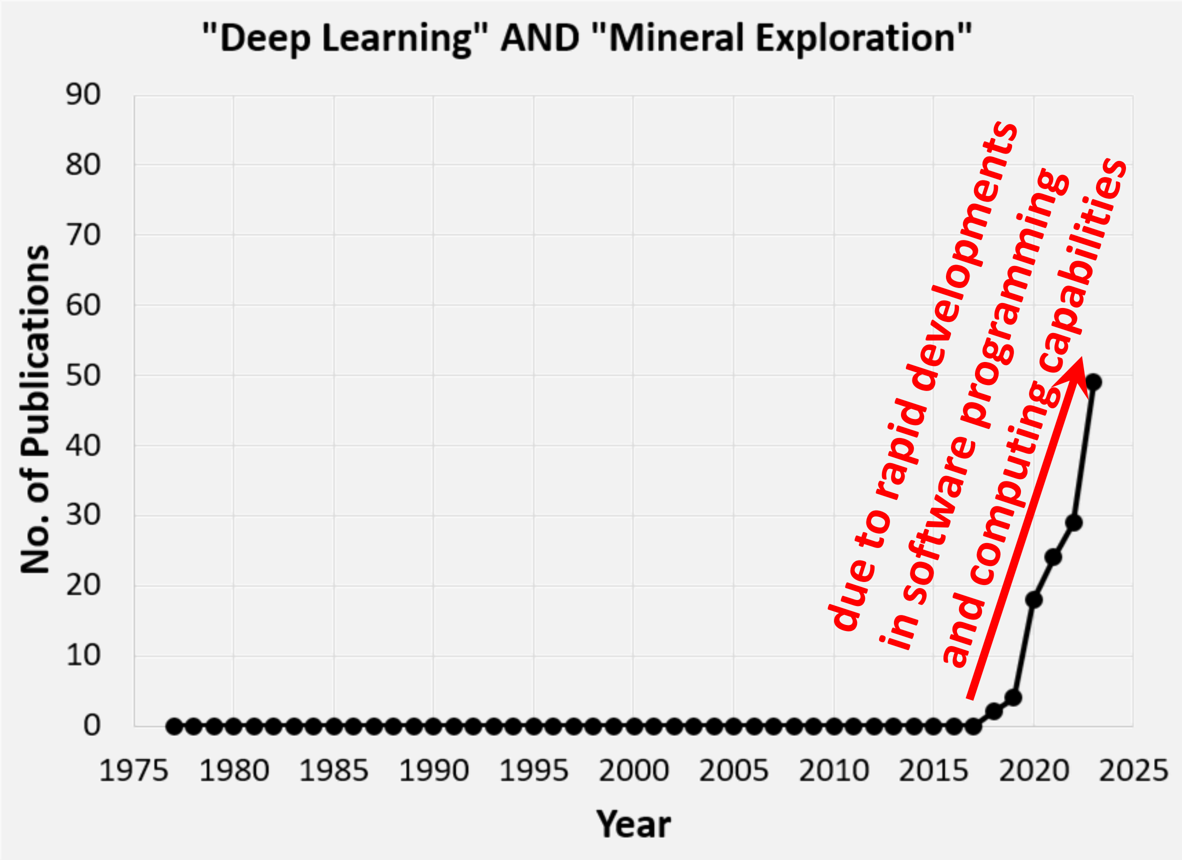
Developments of DL in MinEx Targeting



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Developments of NLP in MinEx Targeting

Natural Resources Research, vol.32, No. 4, August 2023 (© 2023)
https://doi.org/10.1007/s11053-023-10216-1

Check for updates

Original Paper

Applications of Natural Language Processing to Geoscience Text Data and Prospectivity Modeling

Christopher J. M. Lawley,[1,6] Michael G. Gadd,[2] Mohammad Parsa,[1] Graham W. Lederer,[3] Garth E. Graham,[4] and Arianne Ford[5]

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Developments of NLP in MinEx Targeting

Natural Resources Research, Vol. 34, No. 2, April 2025 (© 2025)
https://doi.org/10.1007/s11053-024-10438-x

Check for updates

Original Paper

Pan-Canadian Predictive Modeling of Lithium–Cesium–Tantalum Pegmatites with Deep Learning and Natural Language Processing

Mohammad Parsa,[1,5] Christopher J. M. Lawley,[1] Tarryn Cawood,[1] Tania Martins,[2] Renato Cumani,[1] Steven E. Zhang,[1] Aaron Thompson,[1] Ernst Schetselaar,[1] Steve Beyer,[1] David R. Lentz,[3] Jeff Harris,[4] Hossein Jodeiri Akbari Fam,[1] and Alexandre Voinot[1]

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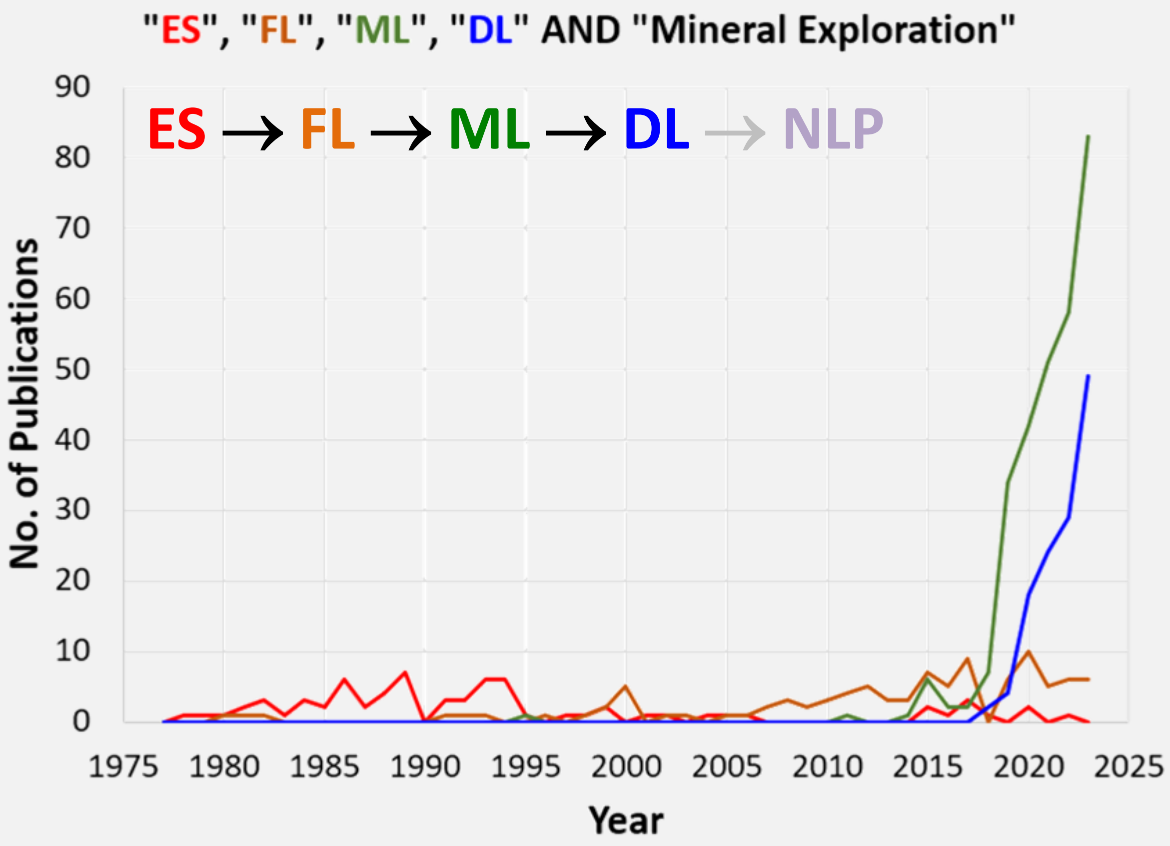
Summary of developments of AI in MinEx Targeting



*from Scopus and Google Scholar

Branches or Types of AI used in MinEx Targeting

- Expert system (ES)
- Fuzzy logic (FL)
- Machine learning (ML)
- Deep learning (DL)
- Natural Language Processing (NLP)

- All of them have been or are used in **mineral prospectivity mapping** (MPM), which supports MinEx targeting.

MPM

Definitions

- Mineral **prospectivity** modeling = quantifying the likelihood of where mineral deposits may be **found** in a study area

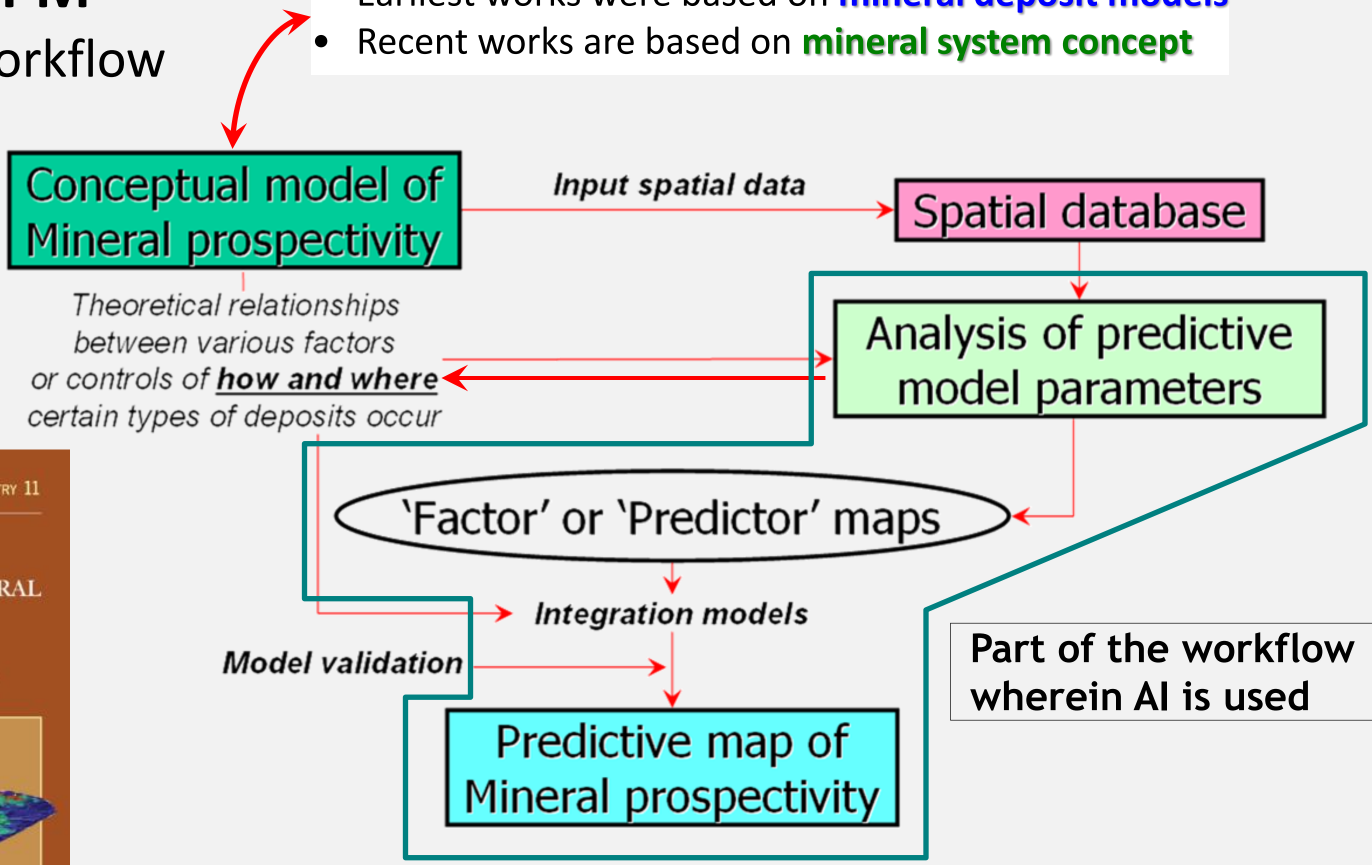
- Mineral **potential** modeling = quantifying the likelihood of where mineral deposits may be **contained** in a study area

- Mineral prospectivity modeling ≅ Mineral potential modeling

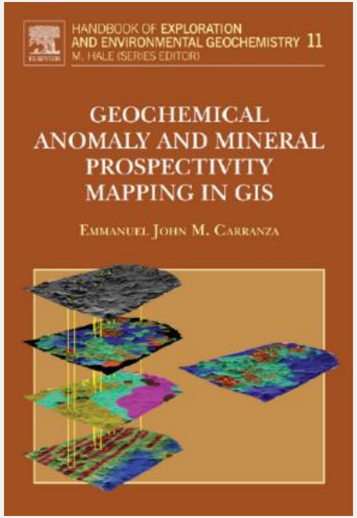
- Note: modeling ≅ mapping

MPM
Workflow

- Earliest works were based on **mineral deposit models**
- Recent works are based on **mineral system concept**



Part of the workflow wherein AI is used

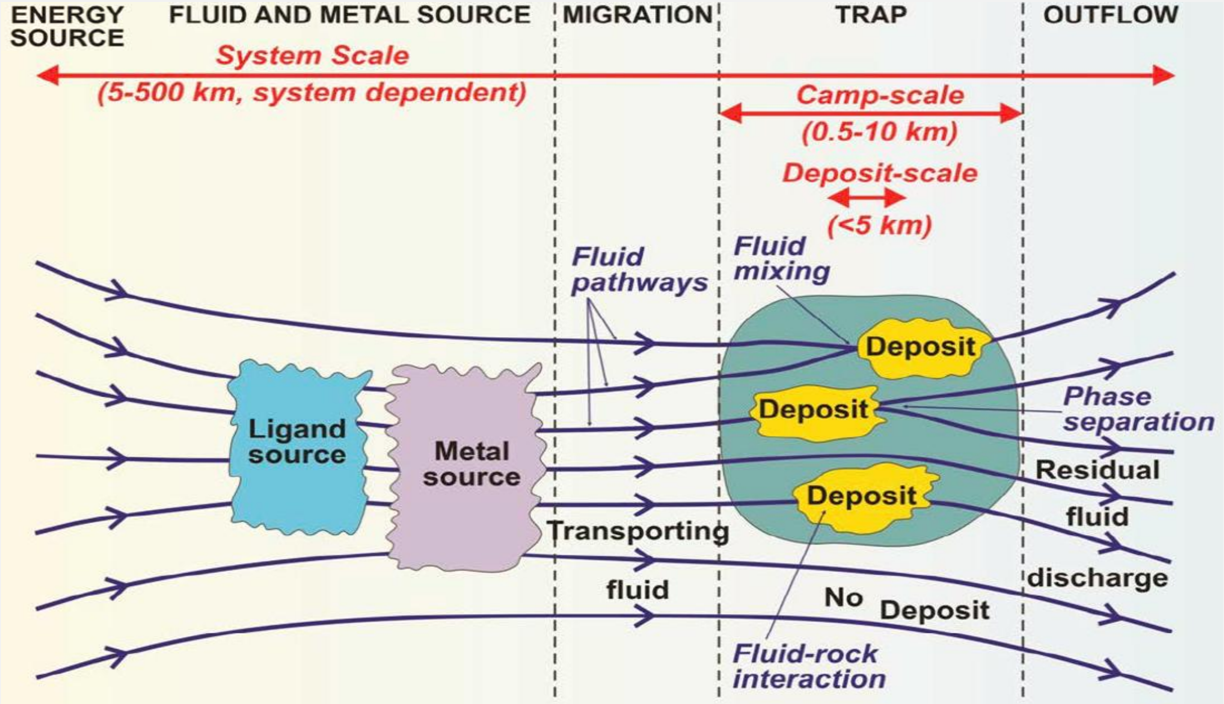


MPM

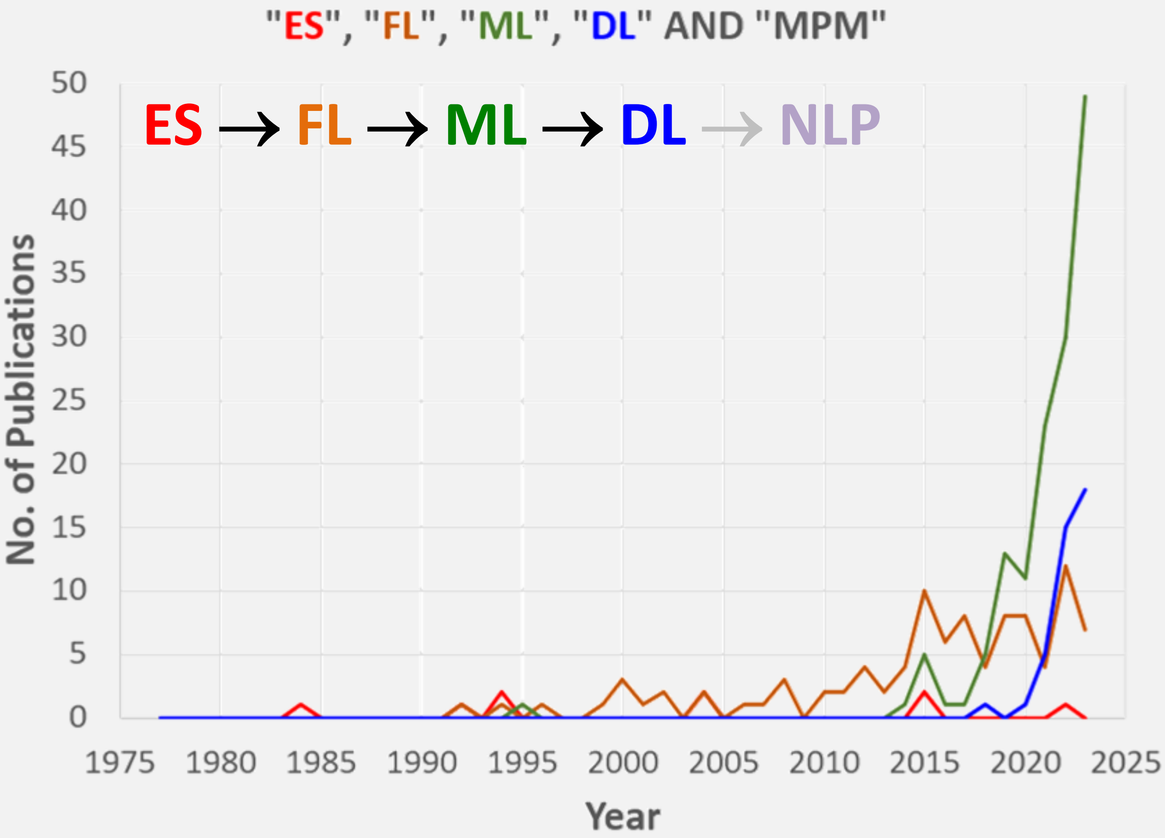
Mineral system concept

Conceptual Mineral System

(Knox-Robinson & Wyborn 1997)



Summary of developments of AI in MPM



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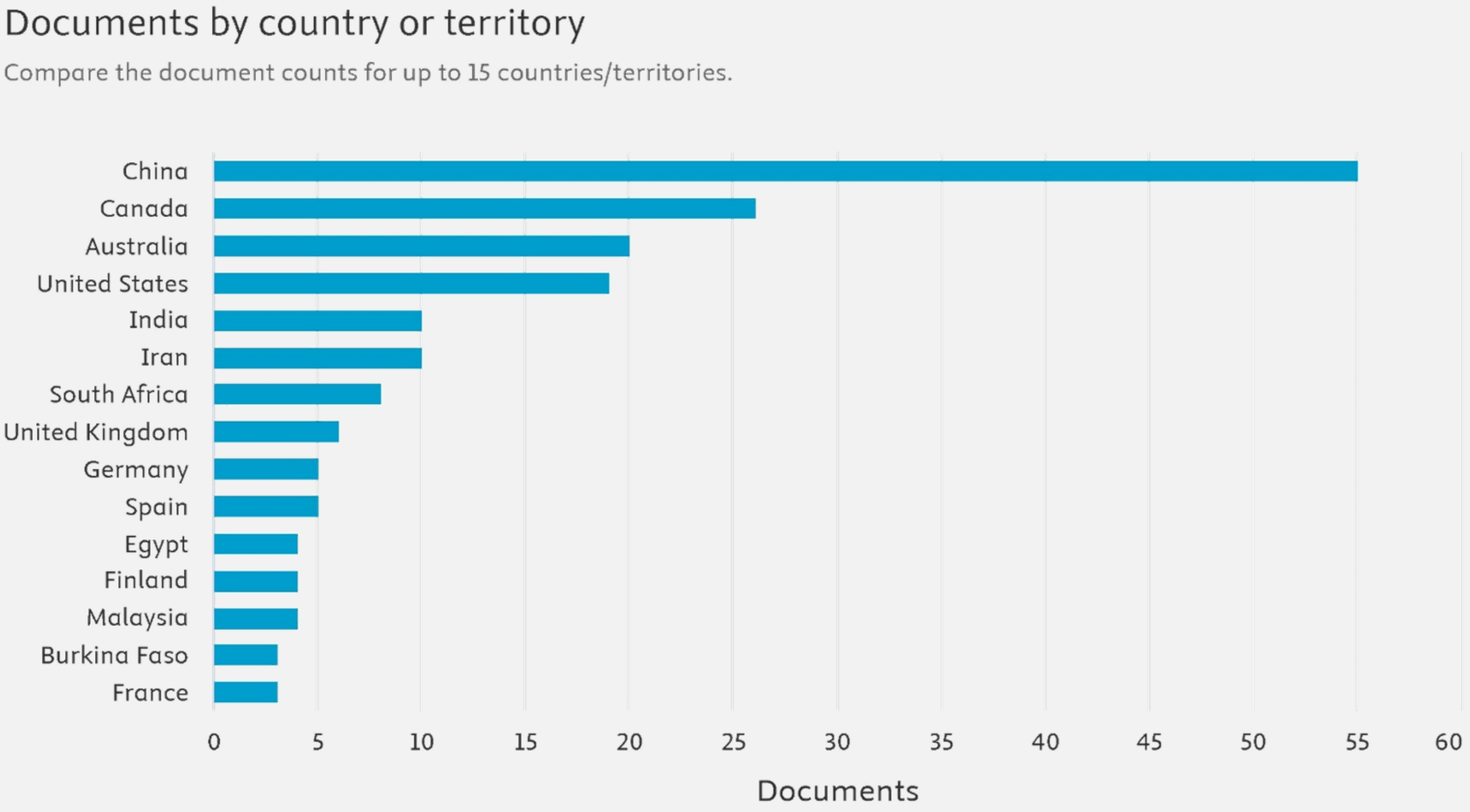
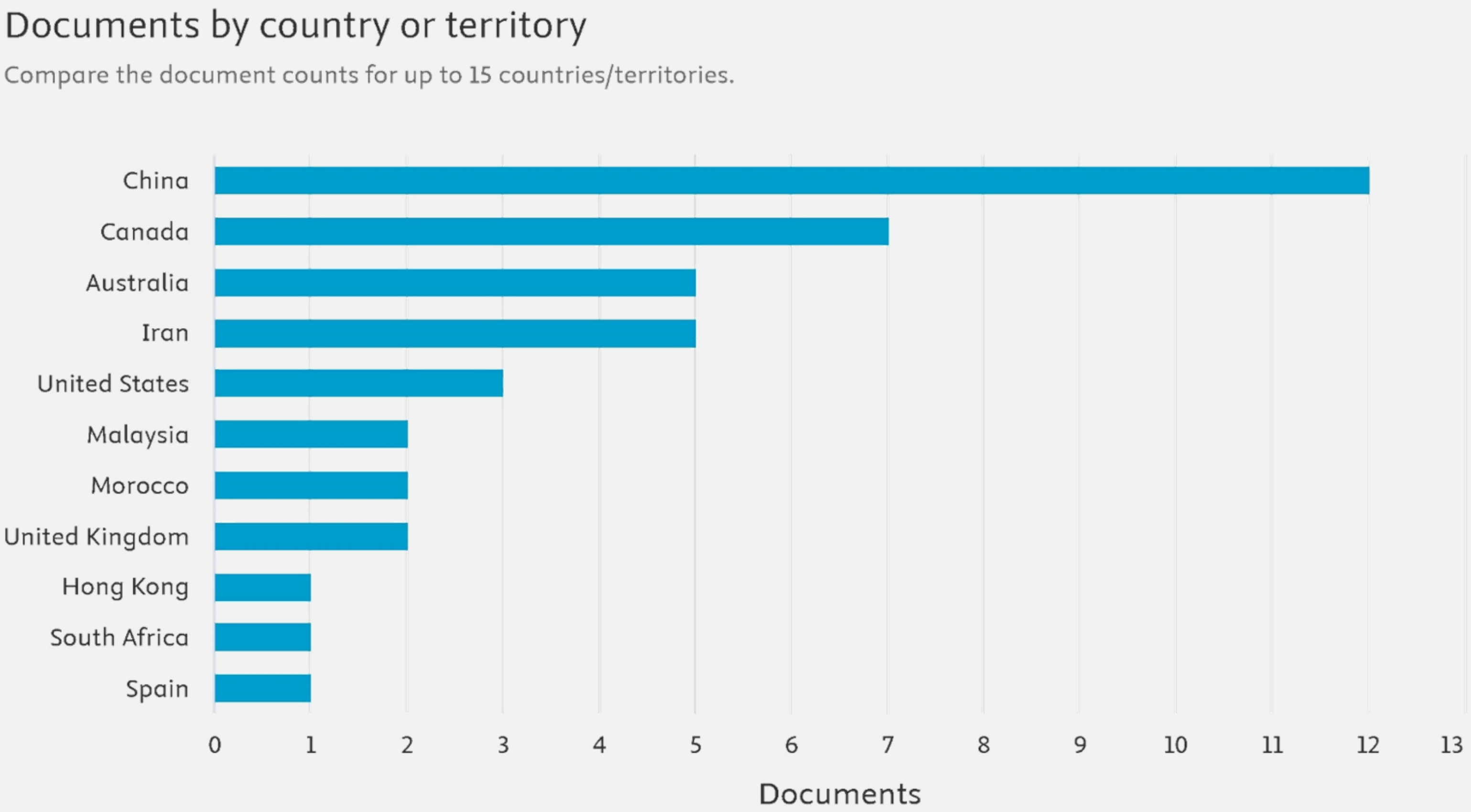
Use of AI in MinEx Targeting by country



*search terms in Scopus: **“artificial intelligence” AND “mineral exploration”**

Use of AI in MPM by country



*search terms in Scopus: “**artificial intelligence**” **AND** “**mineral prospectivity mapping**”

MPM in South Africa – Scopus search

Search within
Article title, Abstract, Keywords

Search documents *
"mineral prospectivity mapping" AND "south africa"

+ Add search field

Reset Search

Documents | Preprints (Beta) | Patents | Secondary documents | Research data

Are you searching for: TITLE-ABS-KEY ("mineral **prospectively** mapping" AND "south africa")

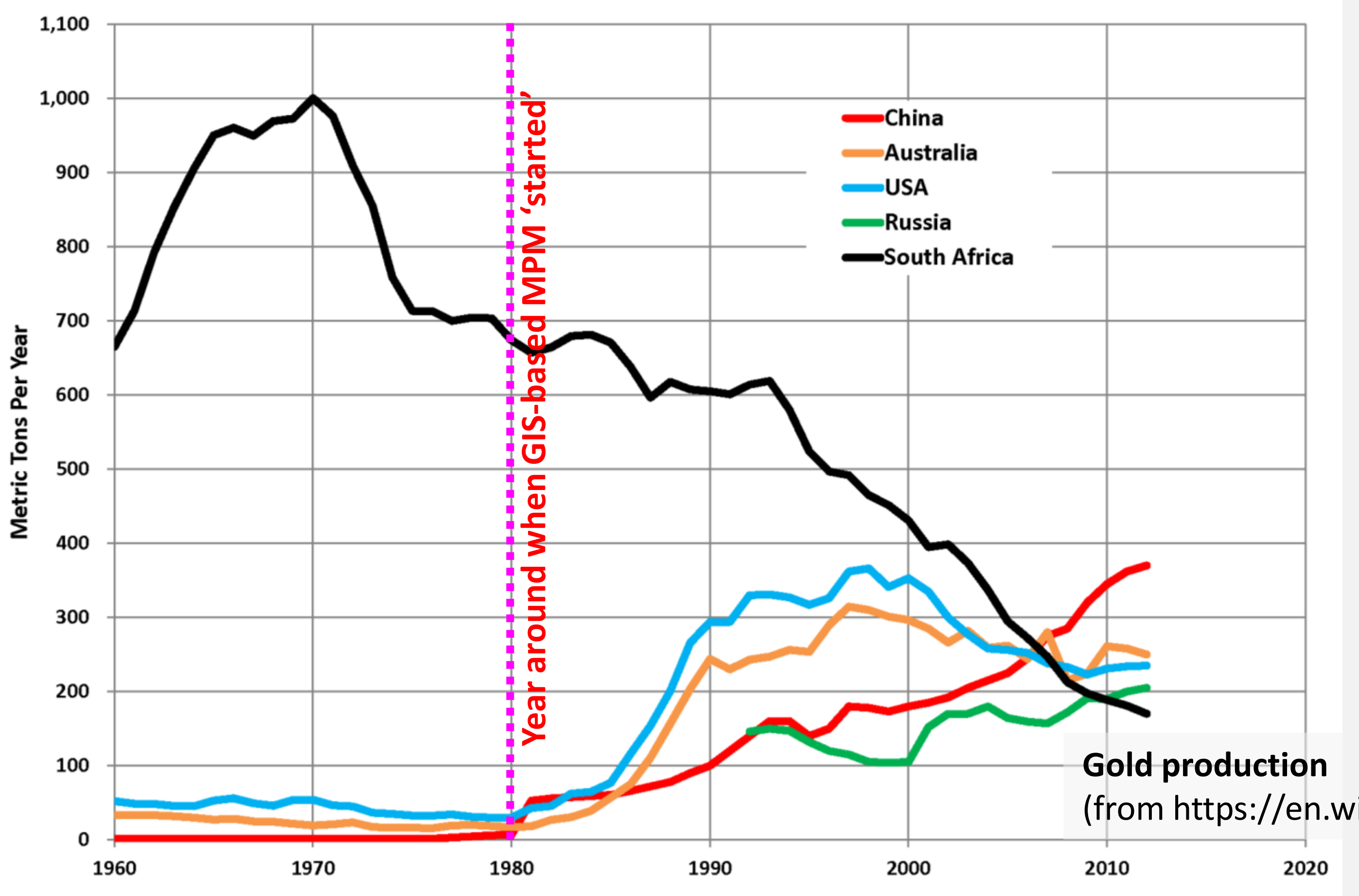
3 documents found

Analyze results

All | Export | Download | Citation overview | ••• More | Show all abstracts | Sort by Date (newest)

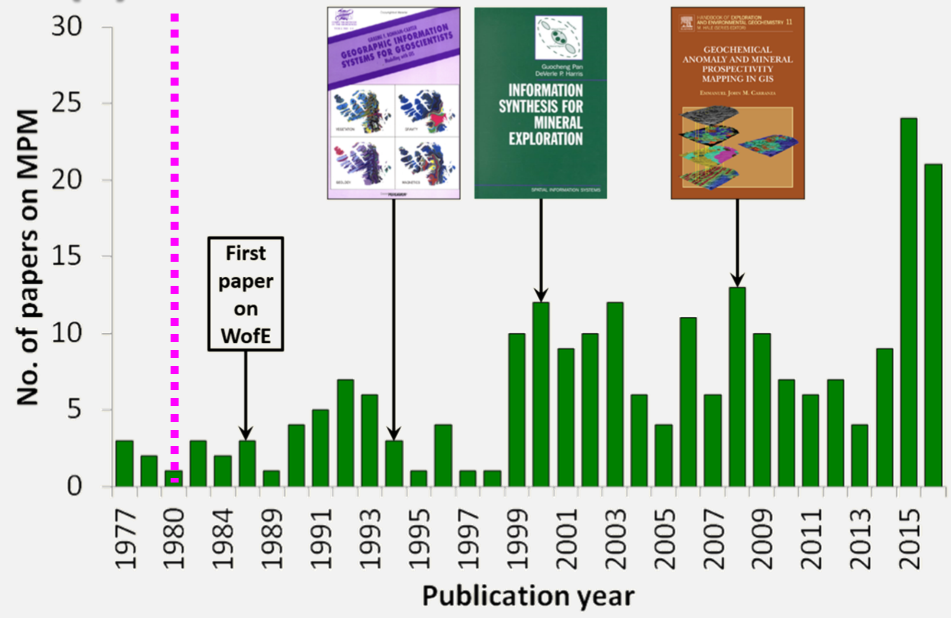
	Document title	Authors	Source	Year	Citations
1	Article • Article in Press • *Open access* **Mineral Reconnaissance Through Scientific Consensus: First National Prospectivity Maps for PGE–Ni–Cu–Cr and Witwatersrand-type Au Deposits in South Africa** Show abstract · View at Publisher · Related documents	Nwaila, G.T., Zhang, S.E., Bourdeau, J.E., ... Andriampenomanana, F., Ghorbani, Y.	Natural Resources Research	2024	0
2	Article **Knowledge-Driven Prospectivity Mapping for Granite-Related Polymetallic Sn–F–(REE) mineralization, Bushveld Igneous Complex, South Africa** Show abstract · View at Publisher · Related documents	Mutele, L., Billay, A., Hunt, J.P.	Natural Resources Research, 26(4), pp. 535–552	2017	12
3	Article **Predictive mapping of prospectivity for orogenic gold, Giyani greenstone belt (South Africa)** Show abstract · View at Publisher · Related documents	Carranza, E.J.M., Sadeghi, M., Billay, A.	Ore Geology Reviews, 71, pp. 703–718	2015	30

Impact (?) of GIS- or AI-driven MPM on metal production

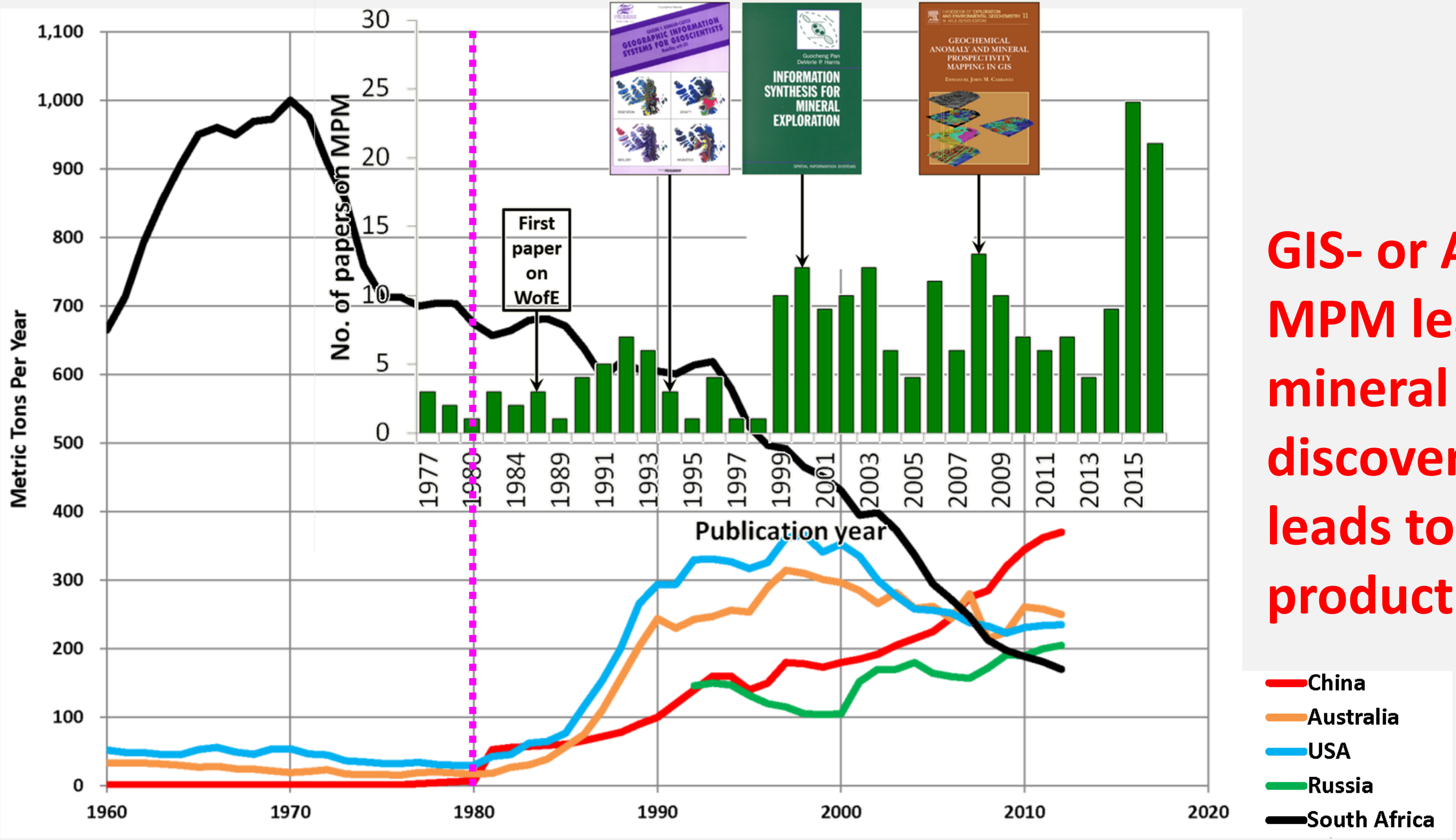


Gold production
(from https://en.wikipedia.org/wiki/Peak_gold)

Impact (?) of GIS- or AI-driven MPM on metal production



Impact (?) of GIS- or AI-driven MPM on metal production



GIS- or AI-based MPM leads to mineral deposit discovery, which leads to metal production

Part 1: Some final remarks

- As MinEx targeting proceeds deeper and deeper and as more and more MinEx data become available, recognizing deposit-related anomalies or modeling of mineral prospectivity from big data will become more and more challenging, justifying the need to use AI methods especially ML and DL.
  - Research on the use of AI in MinEx targeting worldwide is [still] growing.

- **Uncertainty** in AI-based predictions of deposit-related anomalies or mineral prospectivity, to assist MinEx targeting, will be an increasingly hot topic for research in the years to come.

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Part 2:

Detection of Significant Multielement Geochemical Anomalies by an Infomax – Deep Autoencoder Network

Saeid Esmaeiloghli[a], Seyed Hassan Tabatabaei[a], Emmanuel John M. Carranza[b]

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journal homepage: www.elsevier.com/locate/cageo

Infomax-based deep autoencoder network for recognition of multi-element geochemical anomalies linked to mineralization

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[a] *Department of Mining Engineering, Isfahan University of Technology, Isfahan, 8415683111, Iran*
[b] *Department of Geology, University of the Free State, Bloemfontein, 9301, South Africa*

Motivation

- Most techniques of geochemical anomaly mapping (GAM) depend on idealized assumptions about known probability distributions (e.g., Gaussian and multivariate Gaussian), linear characteristics, and lower-order statistics of uni-element and multi-element concentration data.

- However, geochemical data distributions are often characterized by non-linearity and non-stationarity properties.

- Since the 2010s, **ML** algorithms have been used for GAM to avoid parametric statistical assumptions about the unknown probability distribution of geochemical data and, thereby, model complex geochemical anomaly patterns.

Motivation

- More recently, **DL** methods have been used for recognition of complex anomaly patterns in non-linear Earth systems.

- In particular, the deep ***autoencoder*** network (DAN) has become a dominant method for recognizing anomalous geochemical patterns linked to mineralization (Xiong and Zuo, 2016; Zuo et al., 2019).
  - An ***autoencoder*** is a neural network consisting of an encoder and a decoder trained to learn reconstructions (cf. predictions) close to the original input.

MOTIVATION

- By training a DAN, multielement geochemical background is learnt by higher-level depictions of input signals, furnishing important indications for quantifying ***reconstruction errors*** associated with convoluted patterns of mineralization-vectoring geochemical anomalies.
  - A ***reconstruction error*** is the difference between the original input and the reconstruction output in an autoencoder.

- However, the ability of DAN to learn geochemical background could be stifled by (a) superfluous joint information from inter-element relationships and (b) assorted information from elemental values due to various geological/geochemical processes.

MOTIVATION

- To address the mentioned concerns, we propose a novel DL architecture called **Infomax–DAN**, which connects the Infomax (information maximization) processor to a DAN for geochemical data training.

- The **Infomax–DAN** is demonstrated in the analysis of drainage geochemical data from the Moalleman district (Iran) to assess its usefulness in detecting significant geochemical anomalies.

Case Study Area

Moalleman District, Iran

Cenozoic

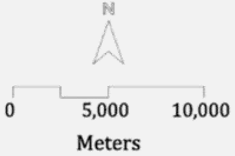
Quaternary		Alluvium
Quaternary		Terraces, Clay, Salt, Silt, Gravel
Quaternary		Conglomerate
Neogene		Cataclastic Metamorphic Rock
Palaeogene		Quartz Monzonite, Quartz Trachyandesite, Quartz Diorite
Palaeogene		Andesite, Andesite-Dacite
Palaeogene		Trachyandesite
Palaeogene		Basalt, Basaltic Andesite, Basaltic Trachyandesite
Palaeogene		Pyroclastic Rocks, Conglomerate with Volcanic Particles
Palaeogene		Rhyolite-Rhyodacite, Rhyolitic-Rhyodacitic Tuff
Palaeogene		Volcanic Breccia, Andesitic Lava

Mesozoic

Sandstone, Conglomerate, Shale, Limestone

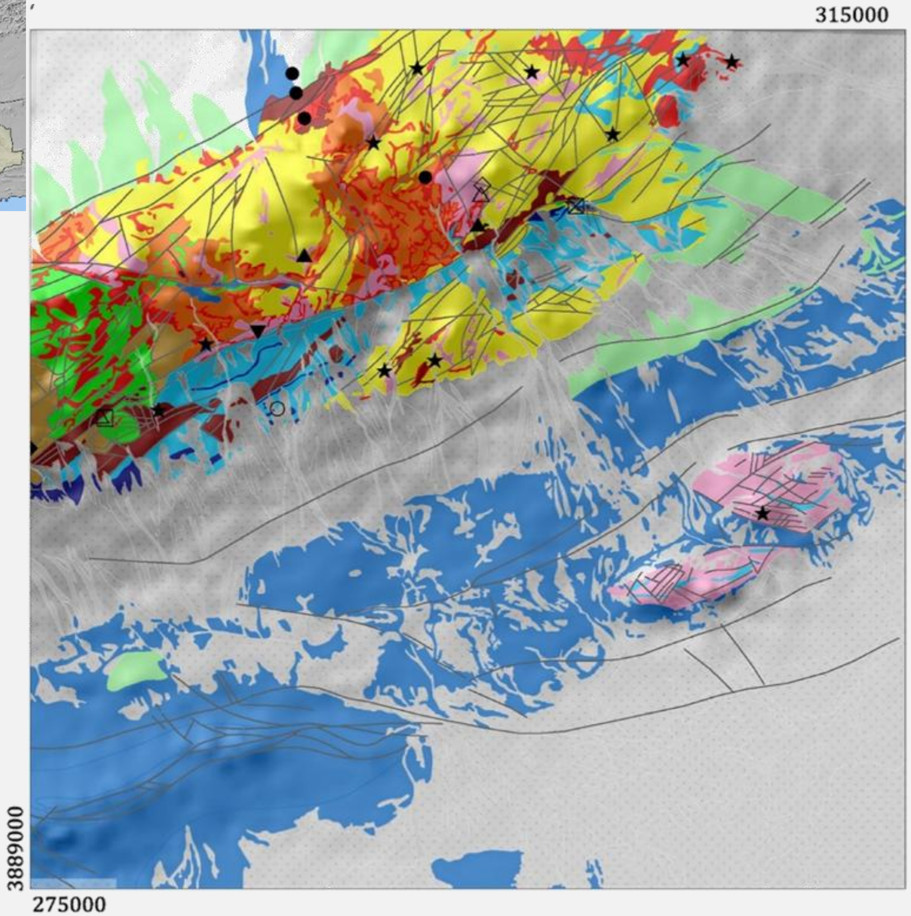
Paleozoic

Limestone, Dolomite, Schist

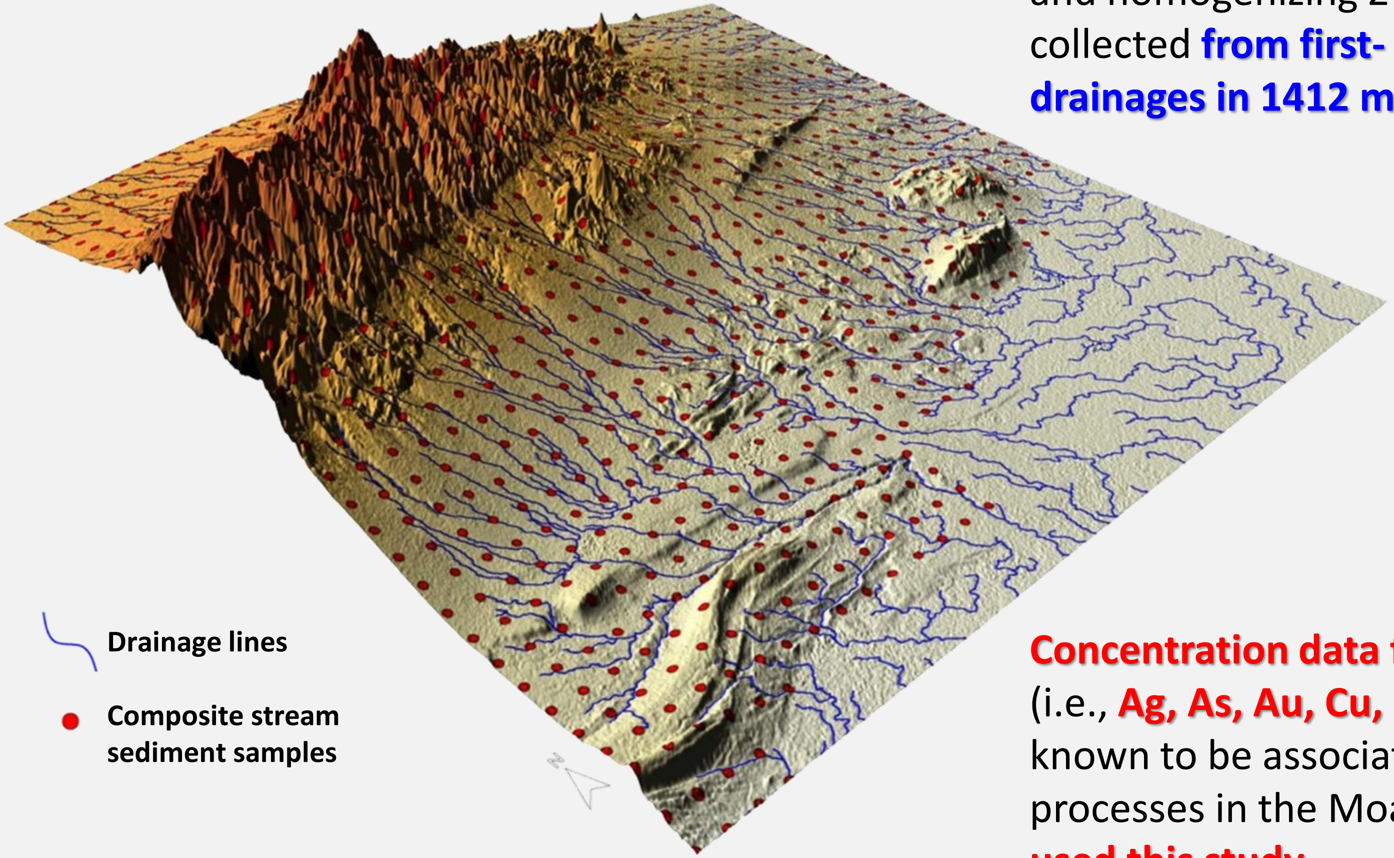


Metal Occurrences

★ Cu	▼ Cu, Pb
● Au	○ Au, Pb
△ Pb	▲ Pb, Cu
□ Zn	◇ Pb, Cu, Zn
⊠ Cu, Ba	◆ Zn, Pb



Geochemical Data

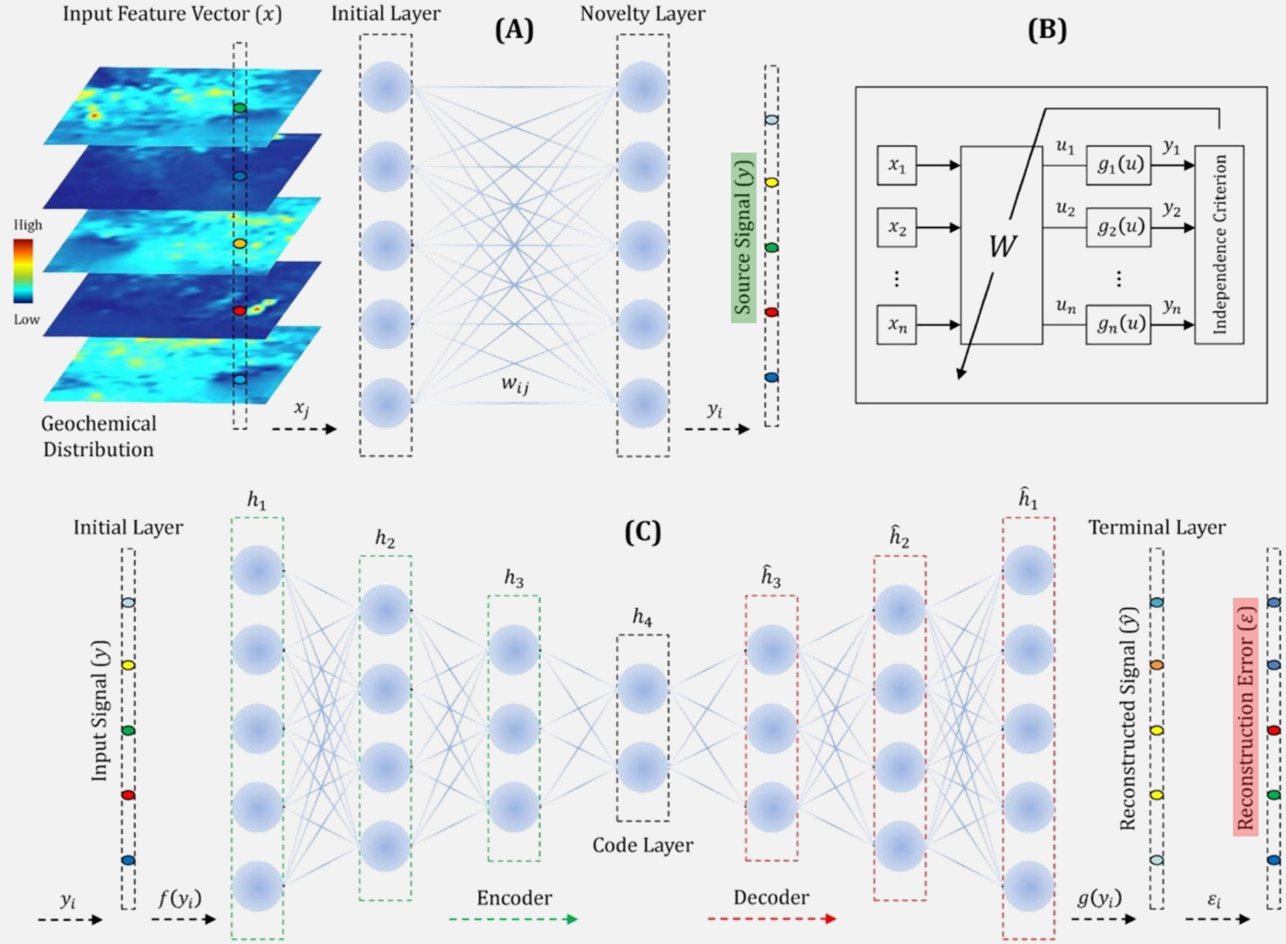


819 representative **composite stream sediment samples** were collected by mixing and homogenizing 2–4 sub-samples collected **from first- or second-order drainages in 1412 m × 1412 m grid cells**.

The samples were analyzed for Au by AAS and for 27 other elements by ICP–MS.

Concentration data for 9 trace elements (i.e., **Ag, As, Au, Cu, Mo, Pb, Sb, W, Zn**) known to be associated with ore-forming processes in the Moalleman district **were used this study**.

Processing Module of Infomax–DAN Algorithm



A. General structure of the Infomax algorithm.

B. Diagram indicating the learning procedure of the Infomax algorithm

C. General structure of the DAN

Circles and lines are neurons and connections, respectively.

RAW DATA

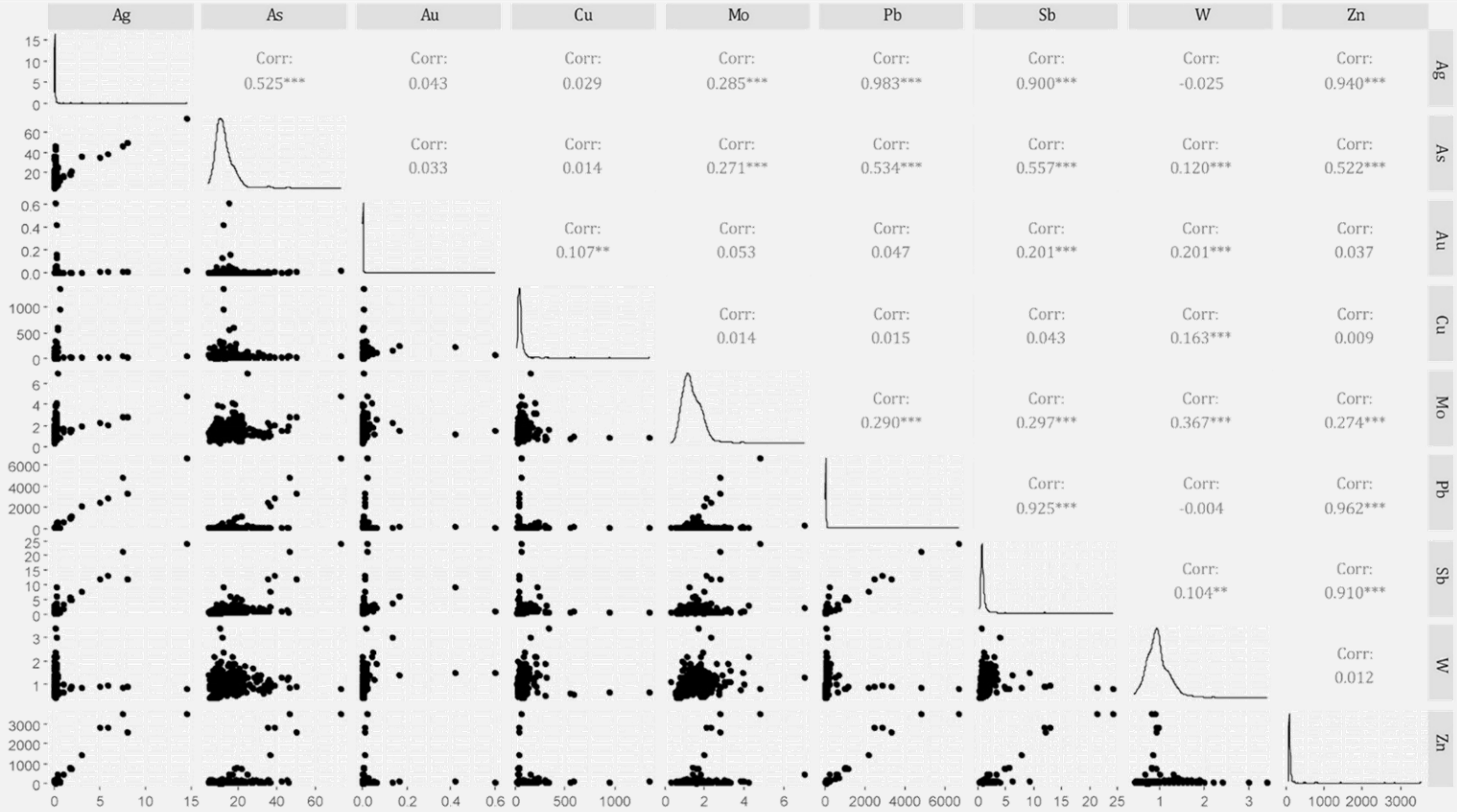


Fig. 4. Pairwise scatter plots, kernel density curves, and Pearson product-moment correlation coefficients for original raw data of multi-element concentrations. Significance asterisks stand for $p-$ value $< 0.01^{**}$ and $p-$ value $< 0.001^{***}$.

ILR-TRANSFORMED DATA

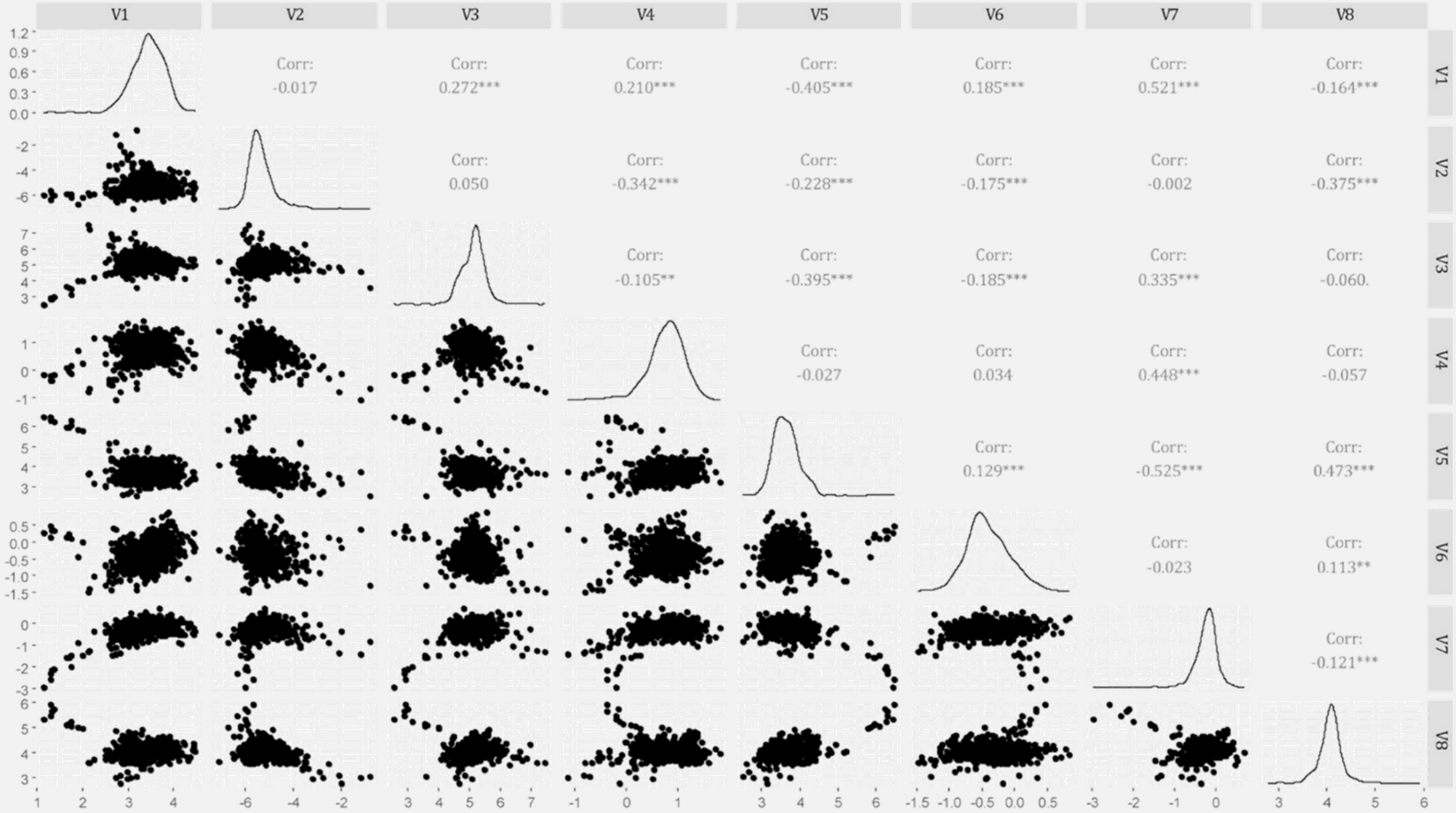


Fig. 5. Pairwise scatter plots, kernel density curves, and Pearson product-moment correlation coefficients for ilr-transformed data of multi-element concentrations. Significance asterisks stand for $p -$ value $< 0.01^{**}$ and $p -$ value $< 0.001^{***}$.

Source Signals Recovered by Infomax

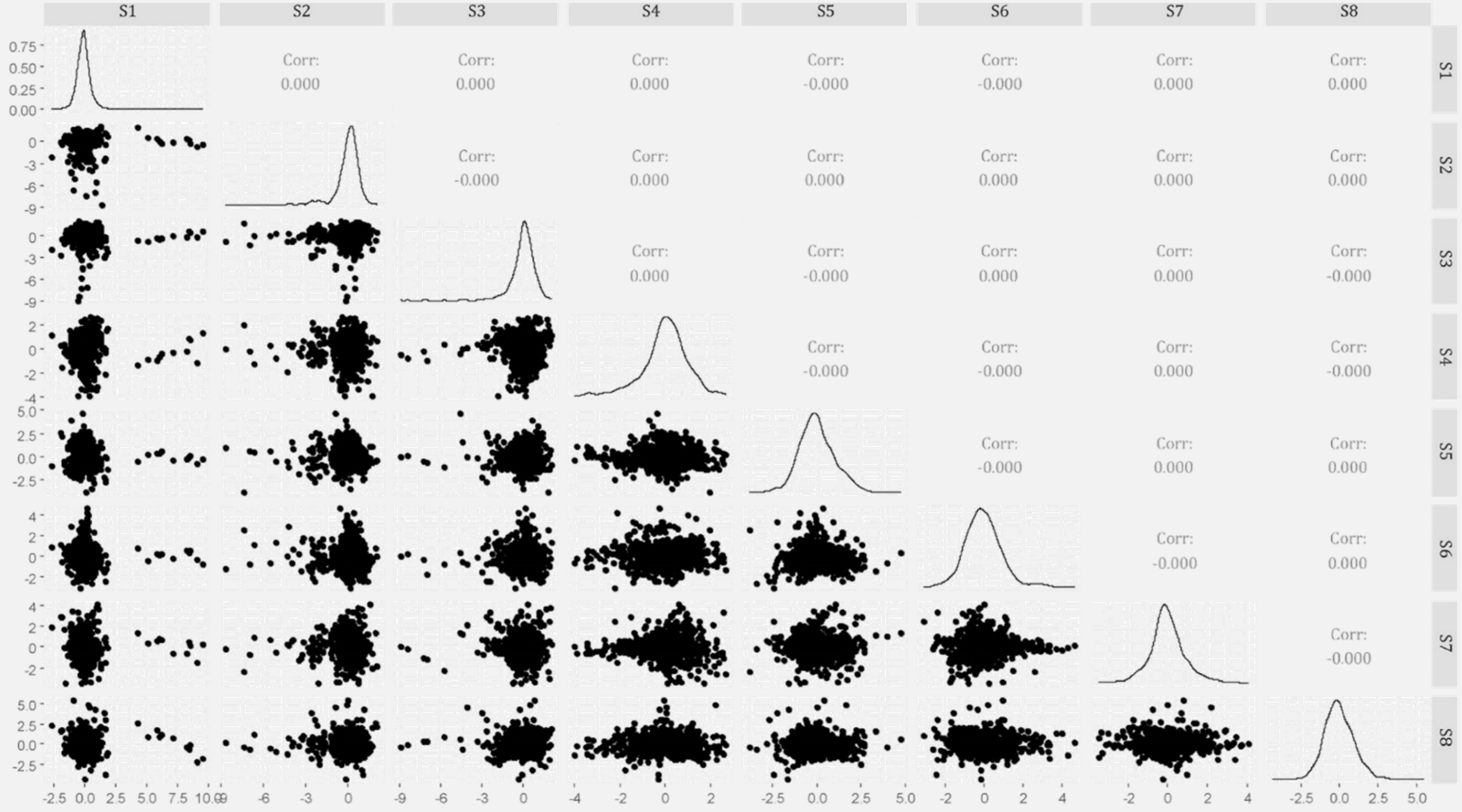
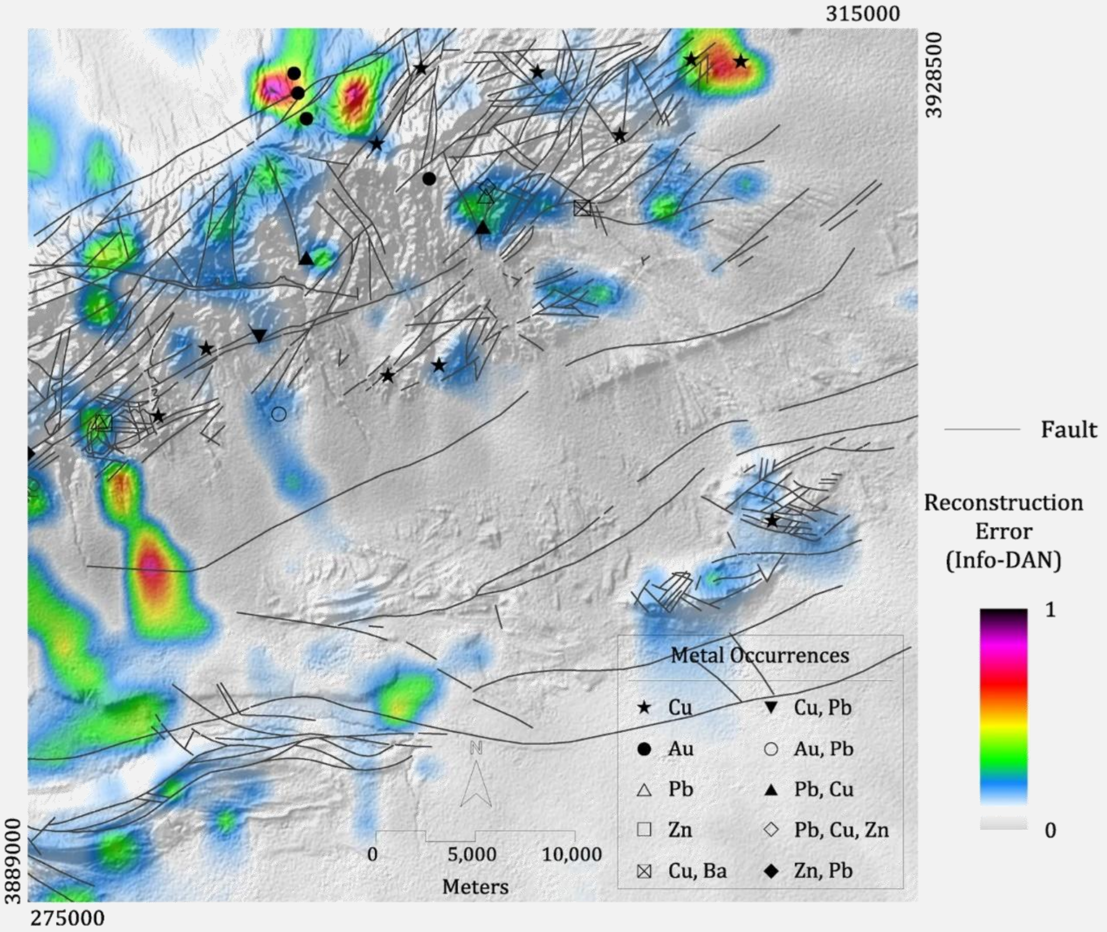
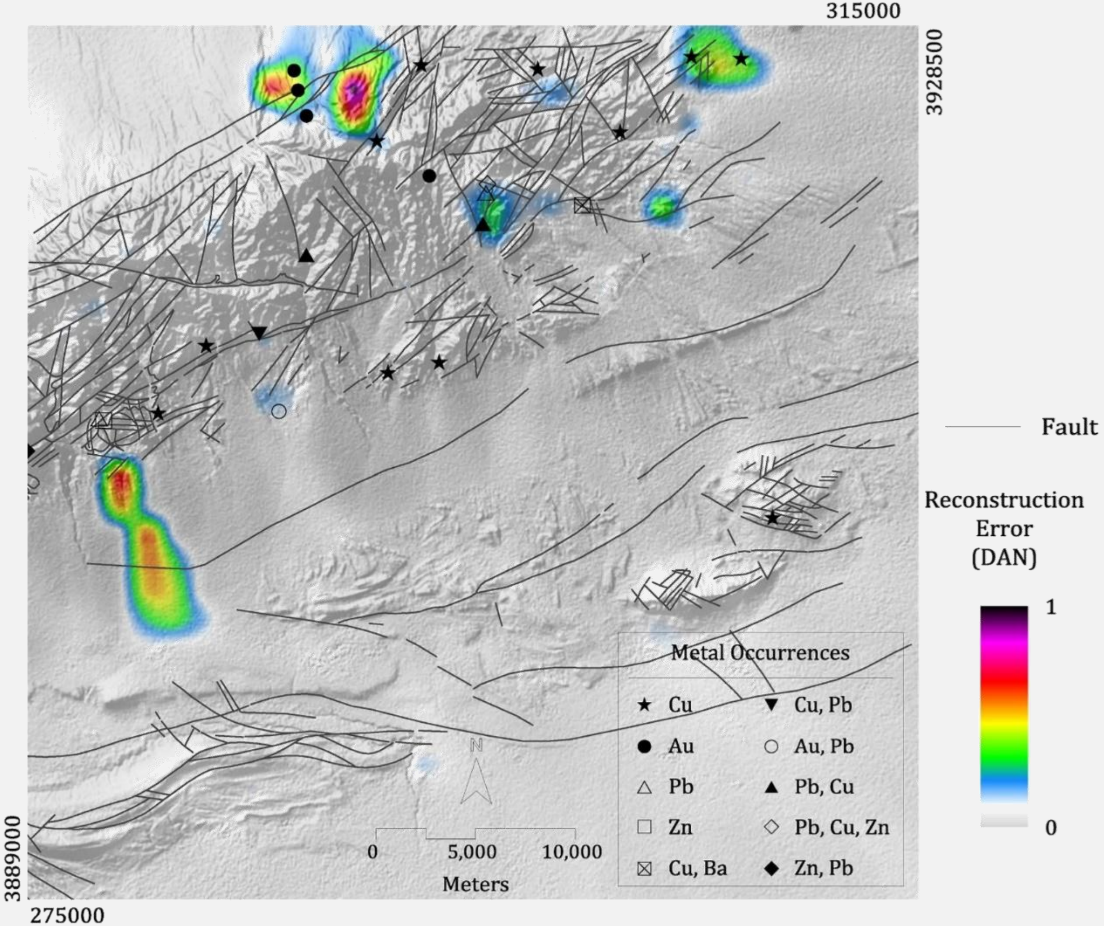


Fig. 8. Pairwise scatter plots, kernel density curves, and Pearson product-moment correlation coefficients for source signals of multi-element concentrations.

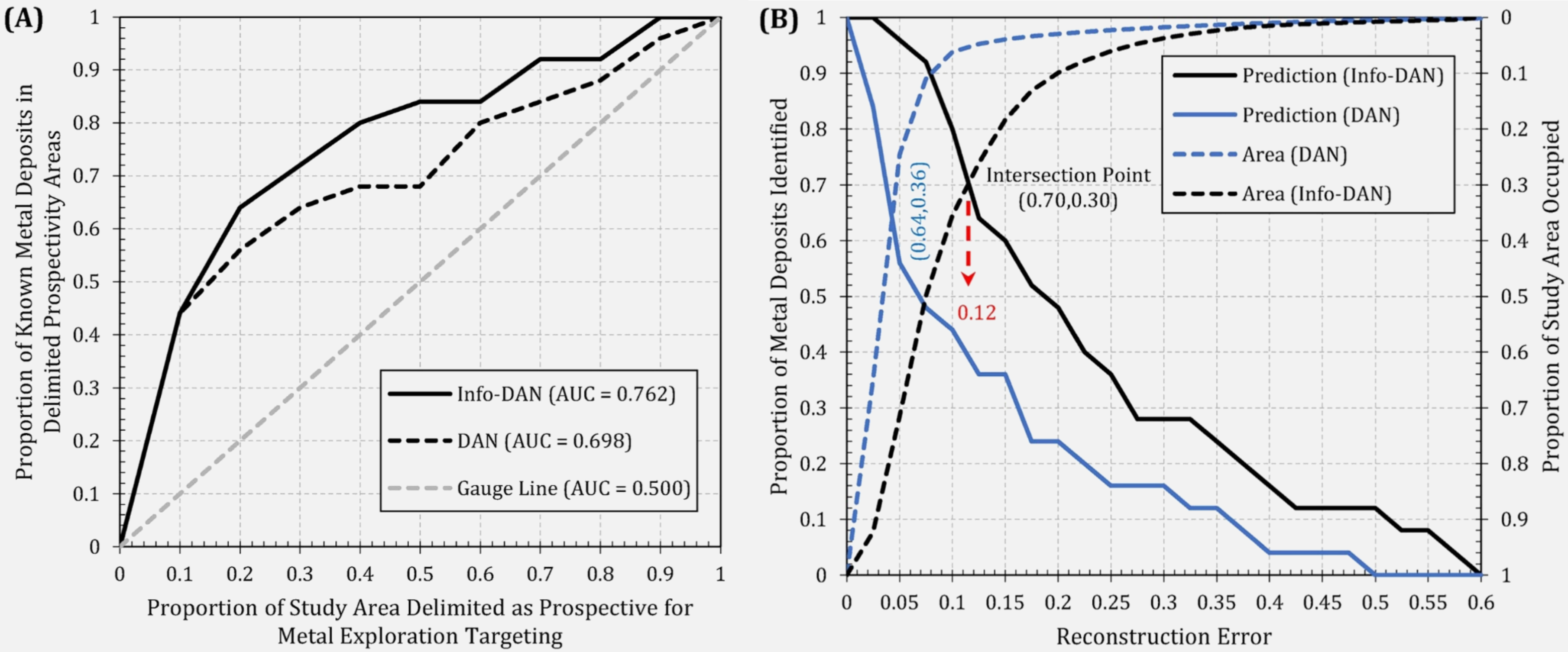
Reconstruction Errors of Reconstructed Multivariate Source Signals



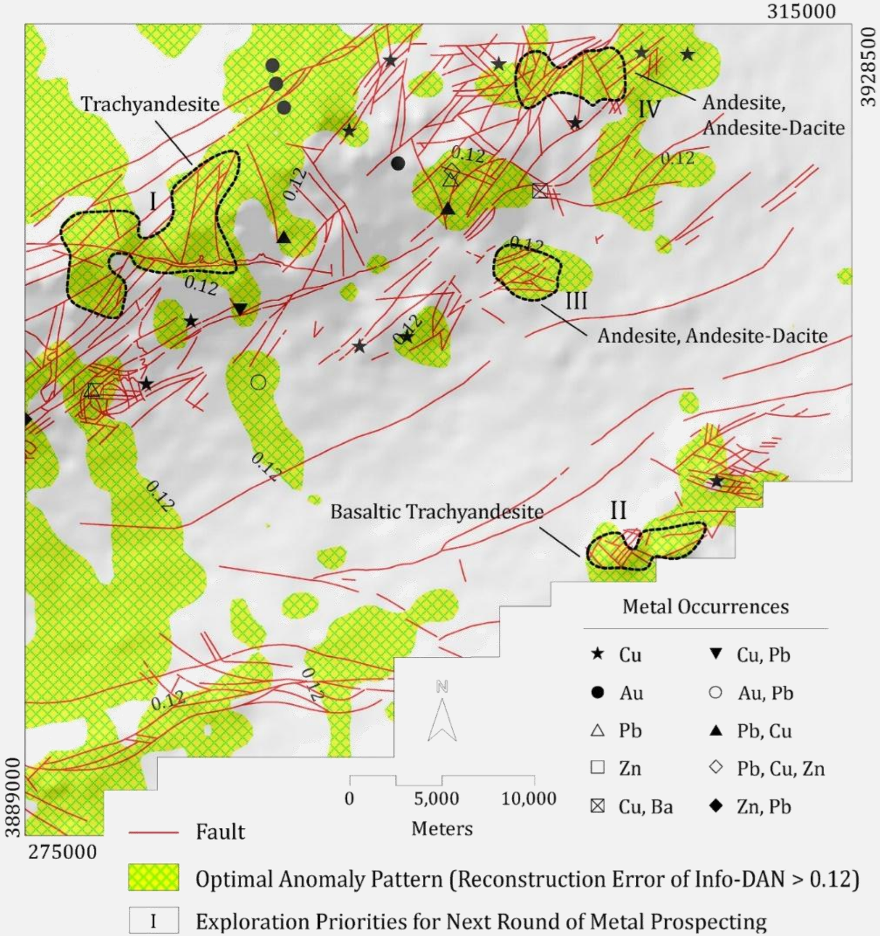
Reconstruction Errors of Reconstructed Multivariate Data



Validation Results



EXPLORATION TARGETS



Why use AI in Mineral Exploration?

- **Mineral Exploration (MinEx)**
  - the process of searching for evidence of any mineralization hosted in the surrounding rocks.*
- Problem to be solved:
  - finding evidence of mineralization
- Decisions to be made:
  - Follow-up evidence with more detailed exploration or not?
  - Which evidence is more important than another?
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*from Geological Survey Ireland
(https://www.gsi.ie/en-ie/programmes-and-projects/minerals/activities/mineral-exploration/Pages/default.aspx)

Part 2: Conclusions

- By using the Infomax–DAN algorithm, the information of original multi-element data can be enhanced so that higher-level representations of background populations could be reconstructed effectively, allowing for improved recovery of complex anomaly patterns
- Compared to a stand-alone DAN, the Infomax–DAN algorithm can detect more effectively complex geochemical anomaly patterns, and so it promotes the interpretation and generalization of geochemical models to support MinEx targeting


THANK YOU!