Utilizing Machine Learning for Mineral Prospectivity Mapping and Target Generation of Critical Raw Materials

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GTK

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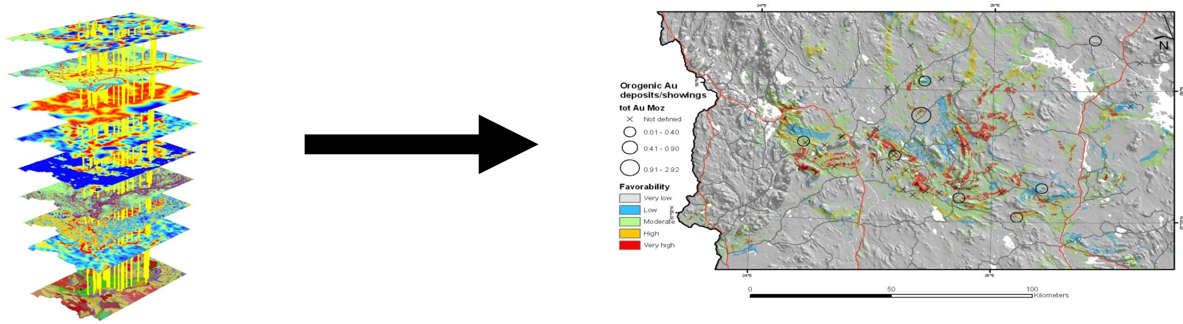
Overview of the talk

- Introduction
- Background and Overview of MPM
- Machine Learning Methods in MPM
- Applications of Machine Learning in MPM
- Future Directions and Challenges
- Conclusion
- Q&A and Discussion

Introduction

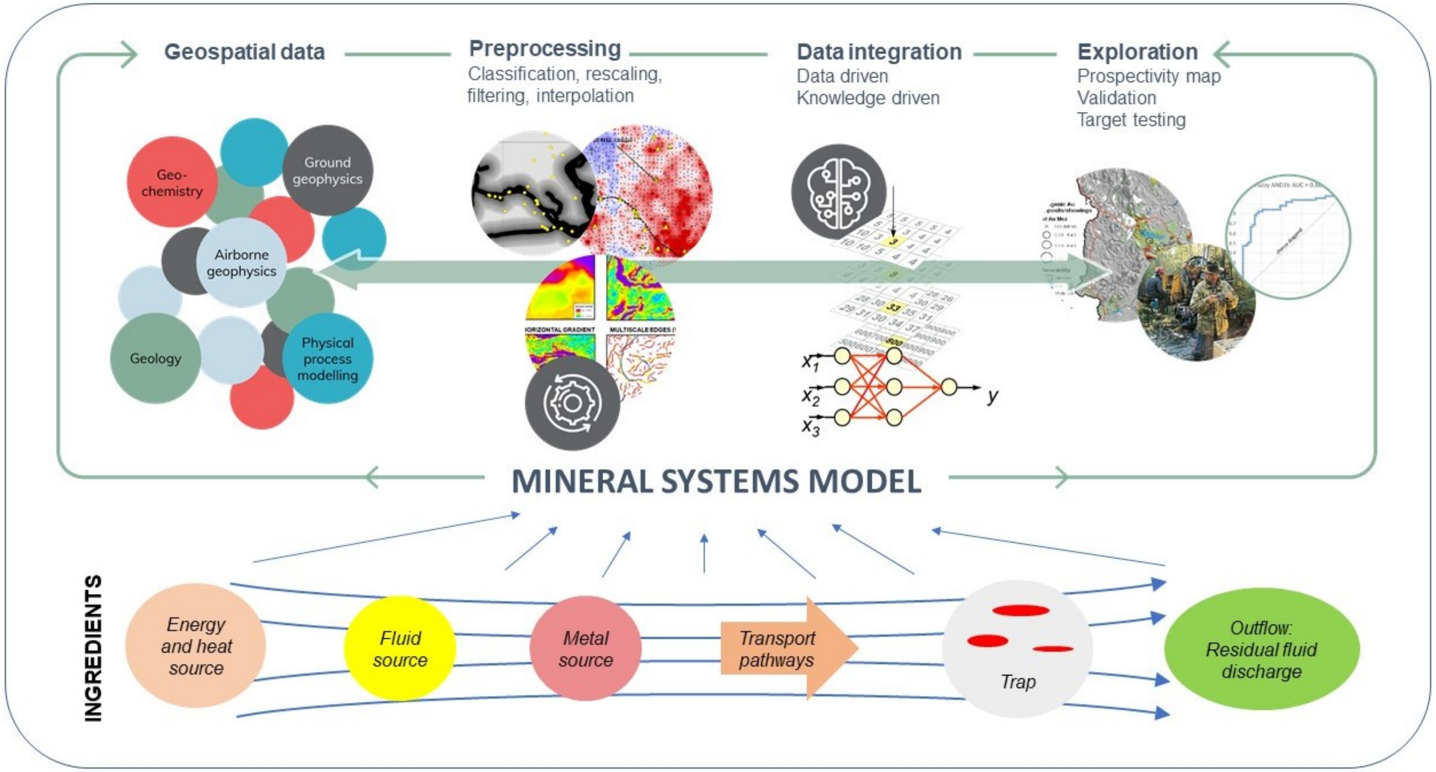
- Mineral prospectivity mapping (MPM) aims to delineate areas favorable for mineral exploration, being time-saving, cost effective and environmentally neutral exploration technique
- MPM can be thus used to find exploration target areas for critical raw materials (CRM)
- Machine learning can enhance MPM by learning from data and automating complex processes



Dynamic mineral prospectivity mapping and mineral systems

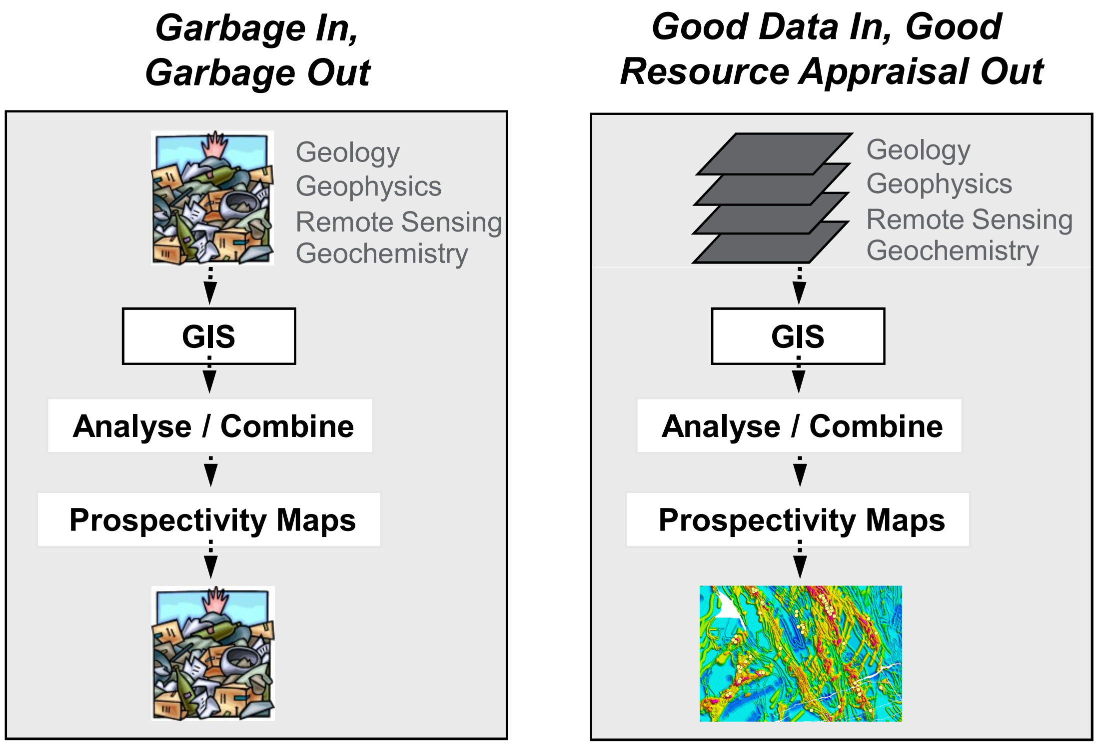
The mineral prospectivity mapping workflow includes the following steps:

1. *Mineral system model*
2. *Selecting primary data*
3. *Creating the proxies to the mappable critical parameters.*
4. *Data integration using appropriate methods.*
5. *Model validation.*



Overview & History

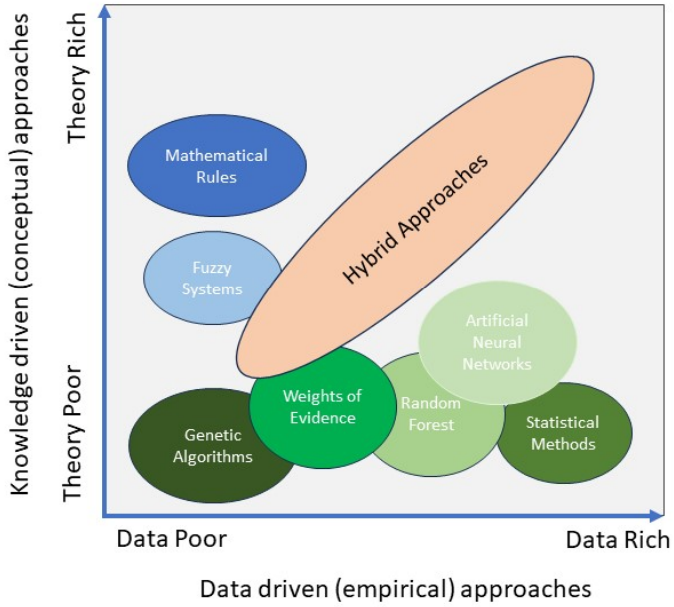
- Data preprocessing philosophy



Courtesy of Dr. Stephen Gardoll

Background and Overview of MPM

- Two main approaches
  - *Empirical approach:*
    - *The algorithm finds the dependencies by itself*
    - *We need training points*
    - *We can find only what we know already (based on training)*
    - *Weights of evidence, artificial neural networks, random forests, regression*
  - *Conceptual approach:*
    - *We know controlling factors and use that knowledge*
    - *We do not need training points*
    - *Can test easily different models*
    - *Fuzzy logic, mathematical rules*

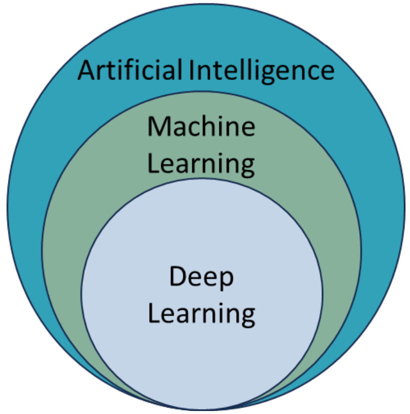


Modified from: Andreas Knobloch, Beak Consultants

- Digital maps allow quantitative analysis of data and numerical modeling for MPM -> Vast exploration data requires GIS based data-analysis and spatial data mining techniques
- Some of the challenges associated with MPM are coming from data scarcity and uncertainty

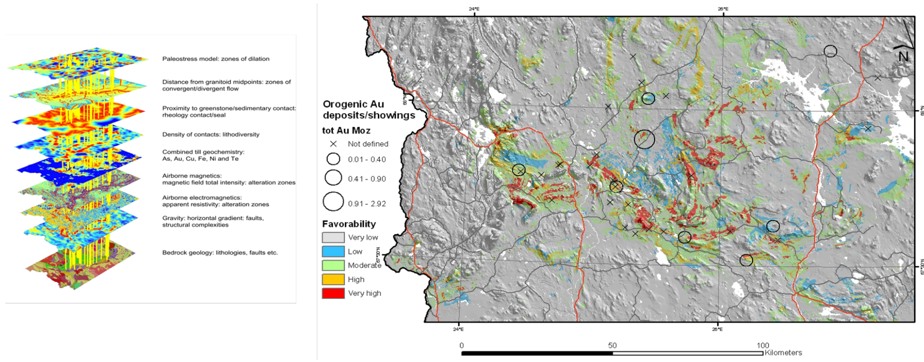
Machine learning

- Machine learning is a field of study in artificial intelligence that focuses on the development of algorithms and statistical models that enable computer systems to learn and improve from experience, without being explicitly programmed.
- In other words, machine learning is the process of training a computer to automatically recognize patterns and make predictions based on data inputs, without human intervention or explicit instructions.
- Machine learning algorithms are designed to identify patterns in the data, learn from those patterns, and use that knowledge to make predictions or decisions about new data inputs.
- Machine learning has a wide range of applications, including natural language processing, computer vision, robotics, data analytics and mineral prospectivity mapping.

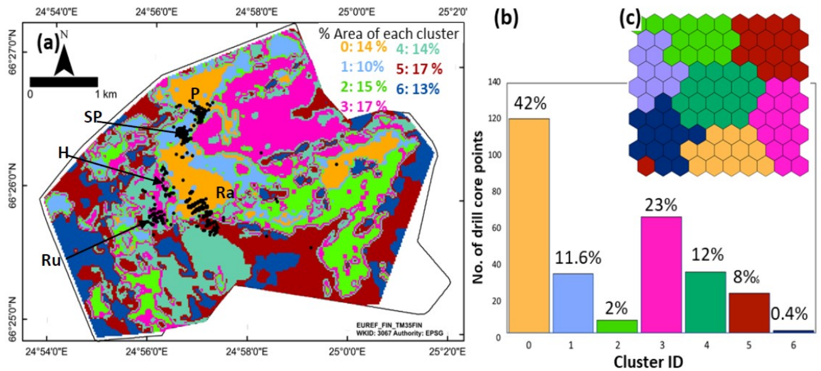


Machine learning: supervised and un-supervised

- Supervised machine learning methods can be used in mineral prospectivity mapping to develop predictive models that identify areas with high mineral potential based on labeled data.



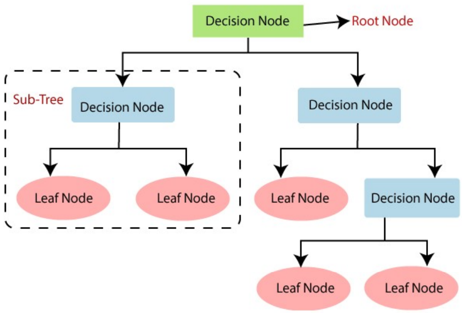
- Un-supervised machine learning methods can be used in mineral prospectivity mapping to identify patterns and relationships within the data sets without relying on labeled data.



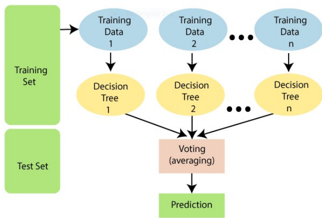
From: Chudasama et al. (2021)

Supervised machine learning methods in MPM

- Decision Trees:
  - This is a type of machine learning algorithm that can be used for both **classification**[1] and **regression**[2] tasks. It works by recursively splitting the data into subsets based on the most important features, and it can be used to identify the key factors that contribute to mineral prospectivity



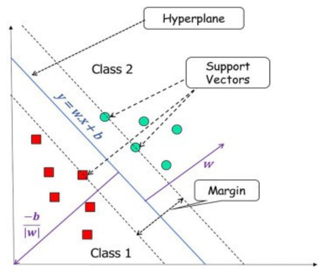
- Random Forest:
  - This is a popular ensemble machine learning algorithm that can be used for **classification** and **regression** tasks. It builds multiple decision trees during training and outputs the class that is the mode of the classes of the individual trees. In mineral prospectivity mapping, it can be used to **classify areas into different categories** based on the geological, geochemical, and geophysical data.
  - Does not necessarily require a lot of labelled data for training



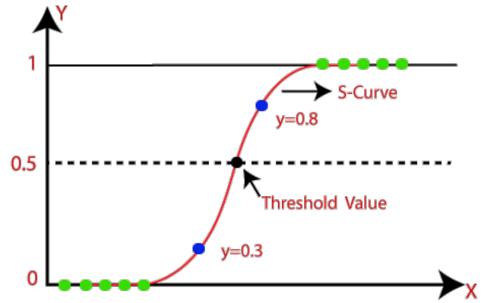
- [1]Classification is a supervised machine learning method where the model tries to predict the correct label of a given input data.
- [2] Regression analysis is a set of statistical methods used for the estimation of relationships between a dependent variable and one or more independent variables.

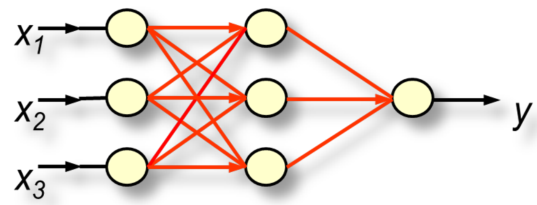
Supervised machine learning methods in MPM

- Support Vector Machine:
  - This is commonly used machine learning algorithm that can be used for **classification** and **regression** tasks. It works by finding a hyperplane that separates the data into different categories, and it can be used to classify areas based on their mineral prospectivity. SVM can be particularly effective when dealing with complex and non-linear geological boundaries.
- Logistic Regression:
  - This is a type of machine learning algorithm that is commonly used for **binary classification** tasks. In mineral prospectivity mapping, it can be used to classify areas as either having high or low mineral potential based on the geological, geochemical, and geophysical data.
- Artificial Neural Networks:
  - This is a type of machine learning algorithm that is inspired by the structure and function of the human brain. It can be used for both **classification** and **regression** tasks, and it can be trained to **recognize patterns** in the geological, geochemical, and geophysical data **to identify areas with high mineral prospectivity**.



Poonia et al. (2022)

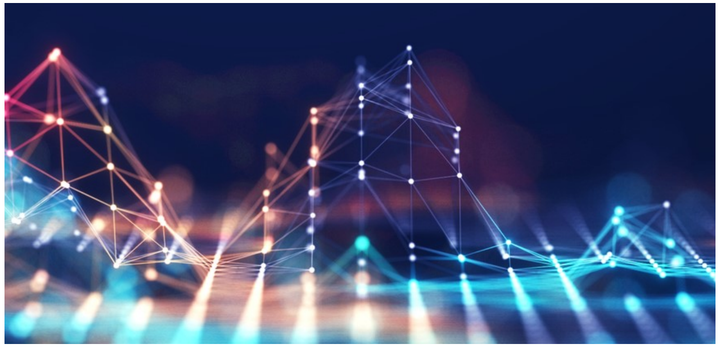




Supervised machine learning methods in MPM

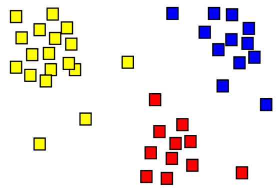
- Boosting Algorithms (e.g., AdaBoost, Gradient Boosting):
  - Collective techniques that **create a strong classifier from a number of weak classifiers**.
  - These methods are used to improve the predictive strength and accuracy of mineral prospectivity models by focusing on areas difficult to classify in previous rounds of modeling.

- Deep Learning (e.g., Convolutional Neural Networks):
  - A class of neural network that is particularly powerful for analyzing visual imagery and is known for its ability to pick up on patterns not visible to the human eye.
  - Although more complex and **requiring significant amounts of data and computing power**, deep learning can be used to process and analyze multi-dimensional geospatial data, potentially identifying subtle features associated with mineral deposits.

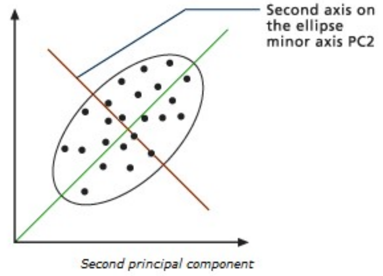


Un-supervised machine learning methods in MPM

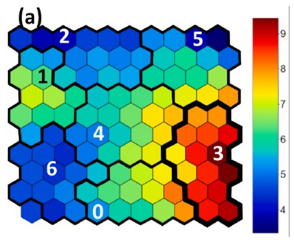
- Cluster Analysis:
  - This method involves **grouping similar data points into clusters** based on their similarities or distances.
  - In mineral prospectivity mapping, it can be used to group areas with similar geological, geochemical, and geophysical features, which can then be analyzed to identify patterns and relationships.



- Principal Component Analysis (PCA):
  - This method involves **transforming the data into a new set of variables, called principal components, that capture the most important variations in the data.**
  - In mineral prospectivity mapping, PCA can be used to reduce the dimensionality of the data and identify the most important variables that contribute to mineral potential.

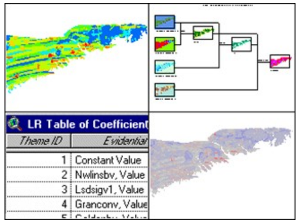


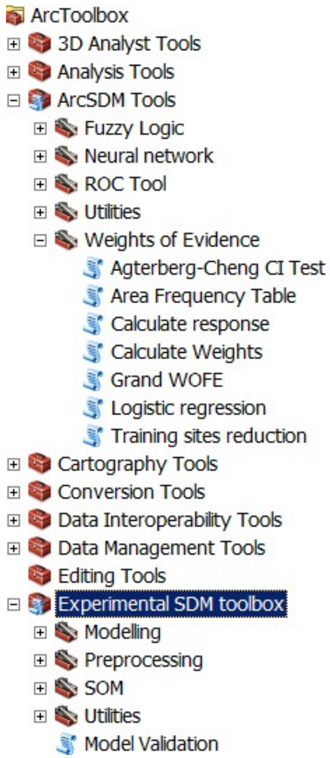
- Self-Organizing Maps (SOM):
  - This method involves **creating a low-dimensional representation of the data** that preserves the topology of the original data space.
  - In mineral prospectivity mapping, SOM can be used to identify areas with similar geological, geochemical, and geophysical features and visualize the relationships between them.



Tools developed for public use by GTK

- ArcSDM: https://github.com/gtkfi/ArcSDM
  - *Spatial Data Modeller*
    - *Weights of Evidence, Logistic regression*
    - *Boosting, Random Forest, Support Vector Machine*
    - *Receiver Operating Characteristics (ROC) validation*
- Originally developed by USGS and GSC and developed by University of Campinas, Sao Paolo, Brazil, http://www.ige.unicamp.br/sdm/
- This toolbox is currently under update and development in a Business Finland funded project called Artificial Intelligence in Mineral Exploration - AIMEX





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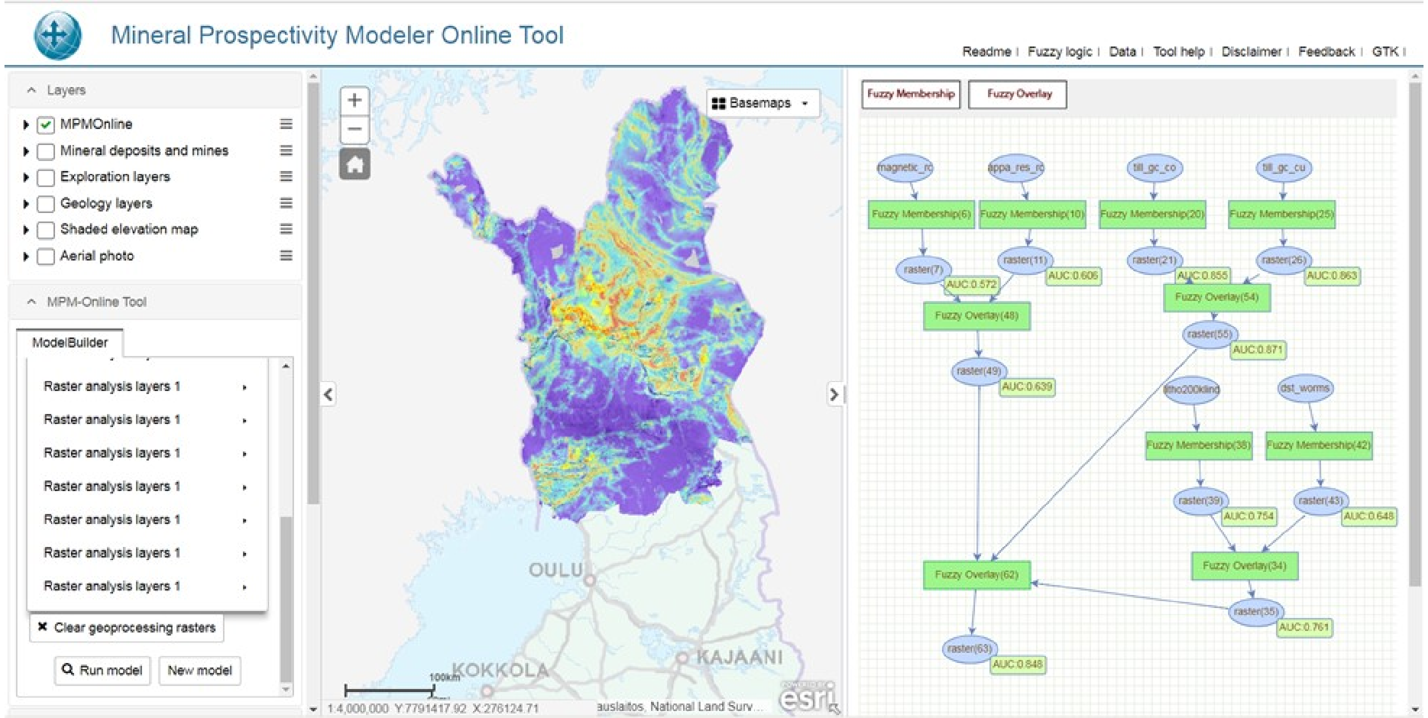
Tools developed for public use by GTK

- MPM on-line can be used to build simple Fuzzy logic overlay models using public geodata from Northern Finland on a web browser-based platform: https://gtkdata.gtk.fi/mpm/
- This tool will be updated in on-going AIMEX project



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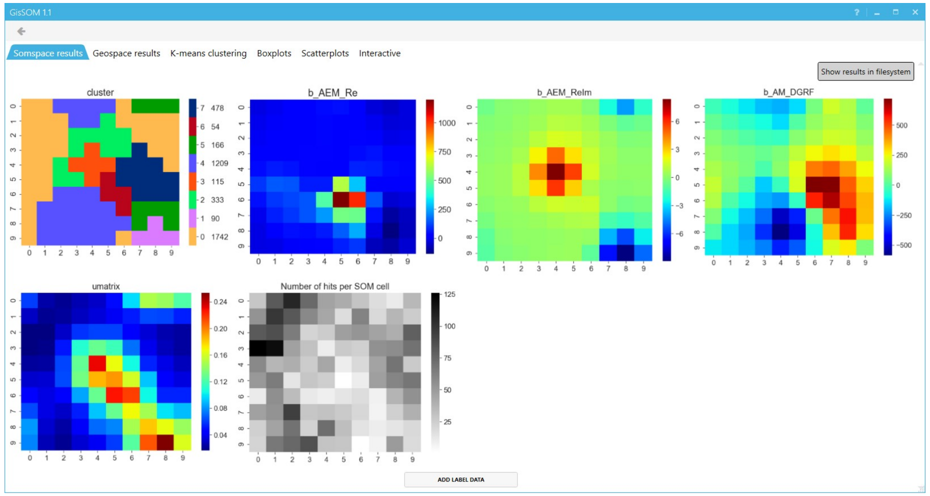
Tools developed for public use by GTK

- GisSOM
    - *Developed originally in an EU funded project entitled NEXT*
    - *Can be used to cluster and visualize data*
    - *Currently being further developed in an on-going EIT RawMaterials-funded project entitled DroneSOM*
    - *https://github.com/gtkfi/GisSOM*

GisSOM



eit RawMaterials
Connecting matters

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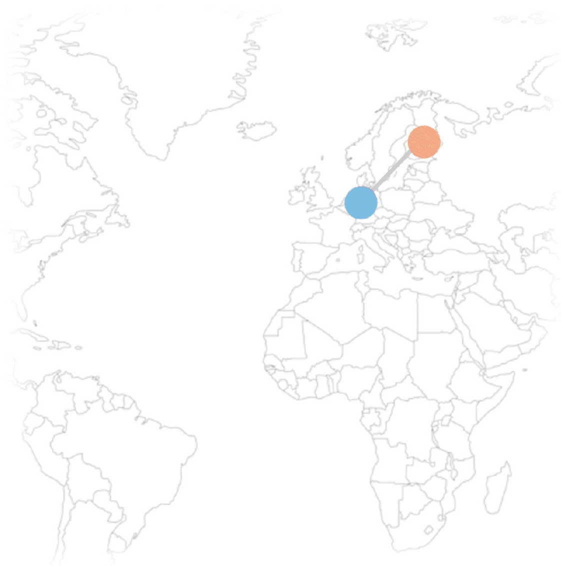
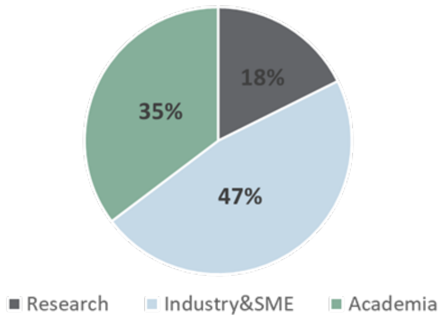
Tools developed for public use

- Exploration Inforamation System – EIS
  - *Funding from European Commission, Horizon Europe, Research and Innovation Action (RIA)*
  - *Pan-European consortium, which consists of 17 partners from research institutes, academia, service providers and industry.*
  - *Partners from 6 EU countries, 2 partners outside EU: Finland (4), Sweden (3), Spain (2), France (2), Germany (2), Czech Republic (2), South Africa (1), Brazil (1) (associate partner)*
  - *EIS will develop new geomodels and novel, fast and cost-effective spatial data analysis tools for mineral exploration.*
  - *EIS website: https://eis-he.eu/*





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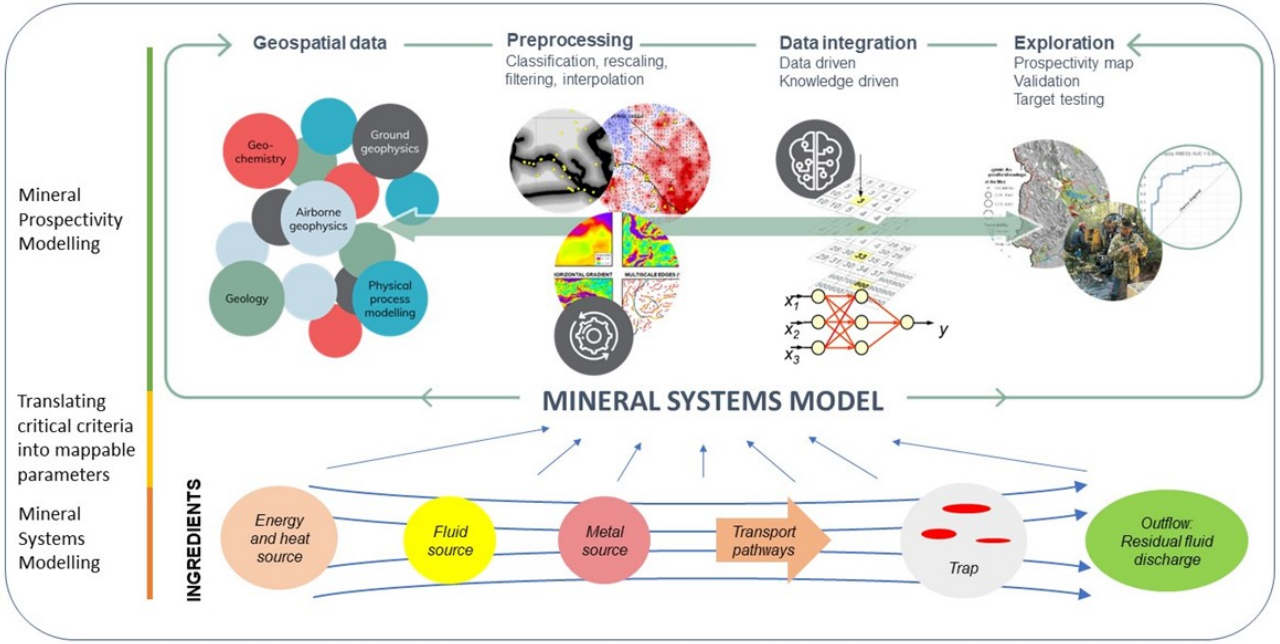
EIS
Exploration
Information
System

Tools developed for public use

- Methodology – EIS combines mineral systems models and MPM
- Mineral system models aim at understanding all controlling factors that lead to the formation of ore deposits (Knox-Robinson et al. 1997). EIS consists of components for different steps of mineral prospectivity analysis (Bonham-Carter 1994).

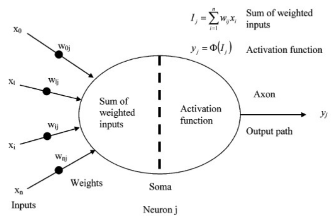


Funded by the European Union

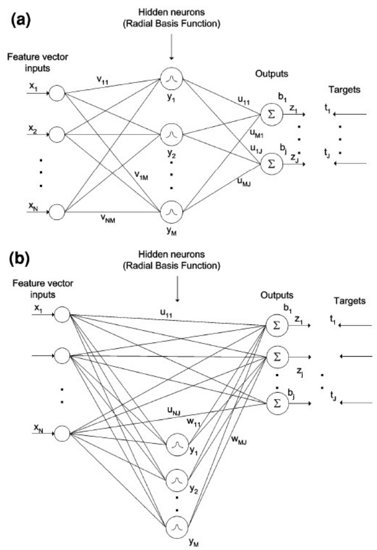
EIS Exploration Information System

Case studies 1: ANN method, orogenic gold, Central Lapland

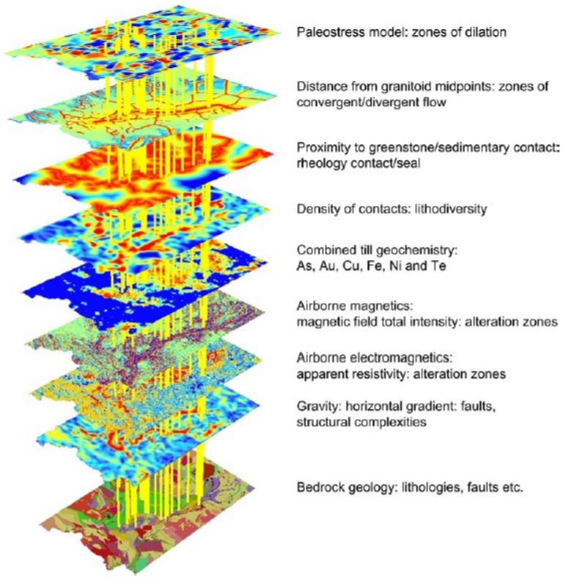
- Nykänen, V. 2008. Radial basis functional link nets used as a prospectivity mapping tool for orogenic gold deposits within the Central Lapland Greenstone Belt, northern Fennoscandian Shield. Natural Resources Research 17 (1), 29-48.

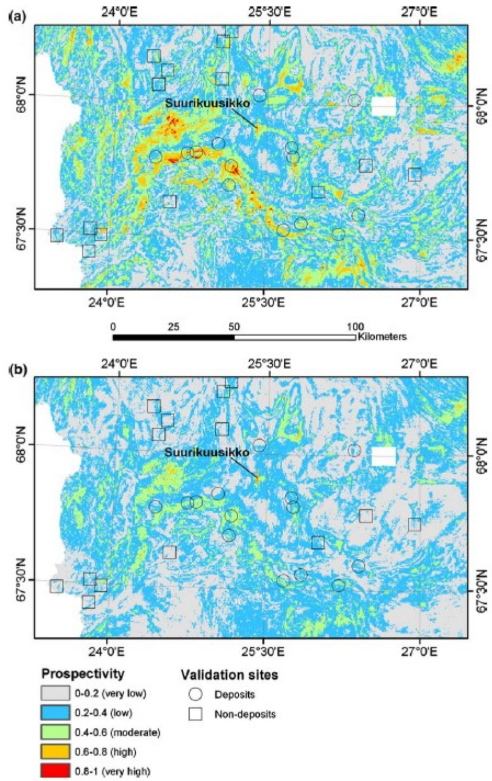


Schematic illustration of an artificial neuron according to Tsoukalas and Uhrig (1997).



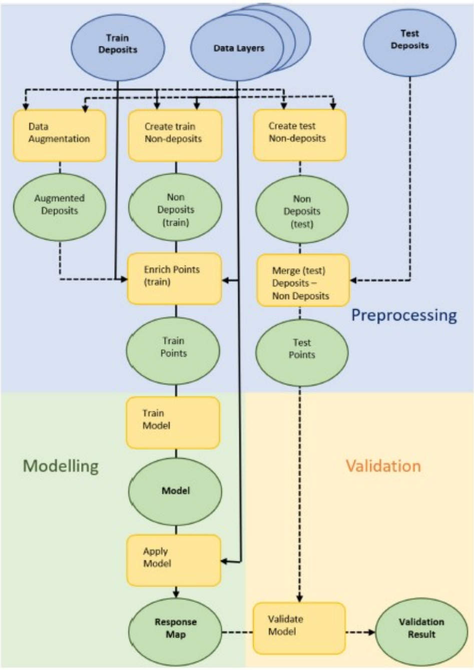
The net architectures of (a) radial basis functional neural network (RBFNN) and (b) radial basis functional link net (RBFLN). Architectures based on Looney (2002). The radial basis function (RBF) resembles a Gaussian density function.

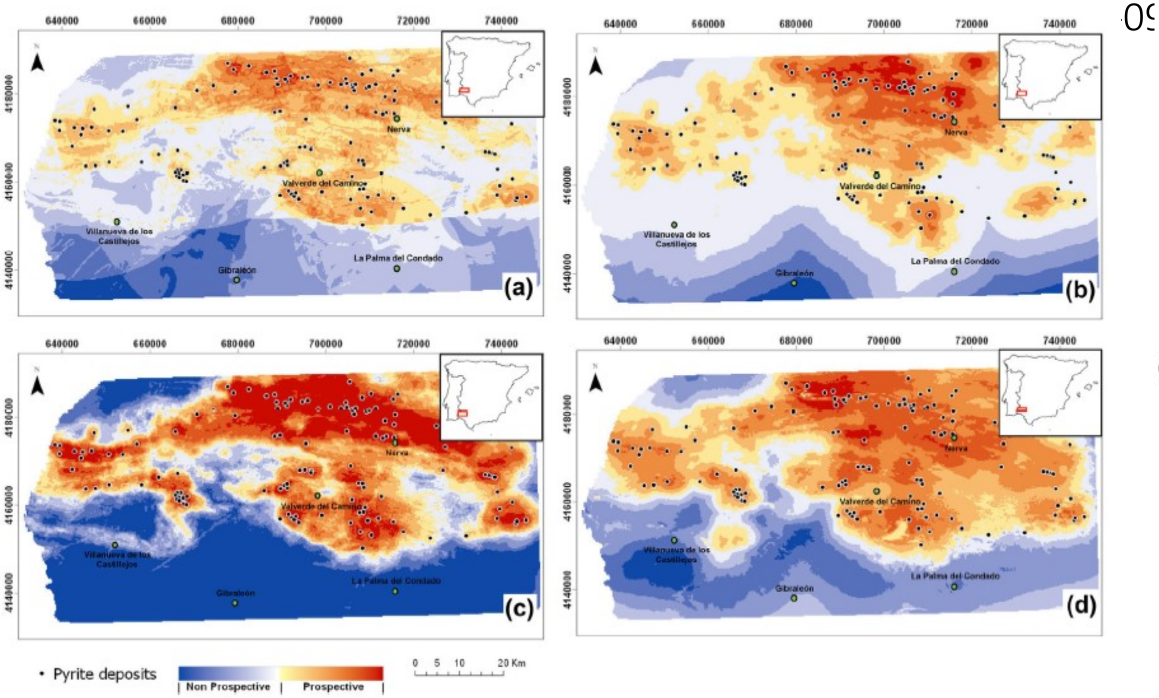


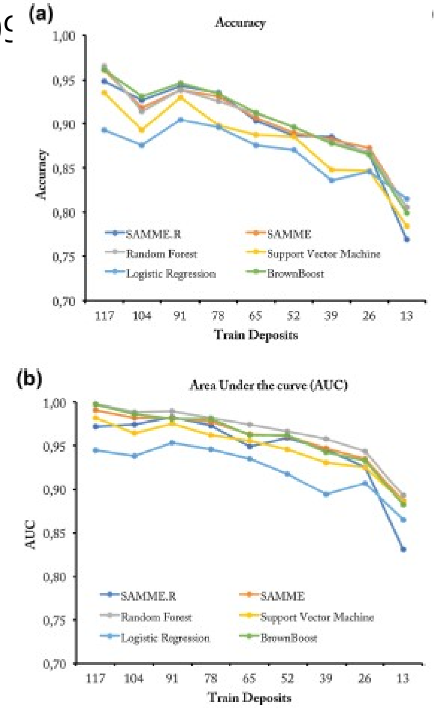


Case studies 2: VMS prospectivity, Iberian Pyrite Belt

- VMS prospectivity map created with 130 training deposits (black dots) using (a) BronwBoost, (b) LR, (c) SVM and (d) RF.
- Performance results relatively similar, especially to Boosting methods, which slightly outperformed LR and SVM
- Brandmeier, M.; Cabrera Zamora, I.G.; Nykänen, V.; Middleton, M. 2020. Boosting for Mineral Prospectivity Modeling: A New GIS Toolbox. Natura... 09

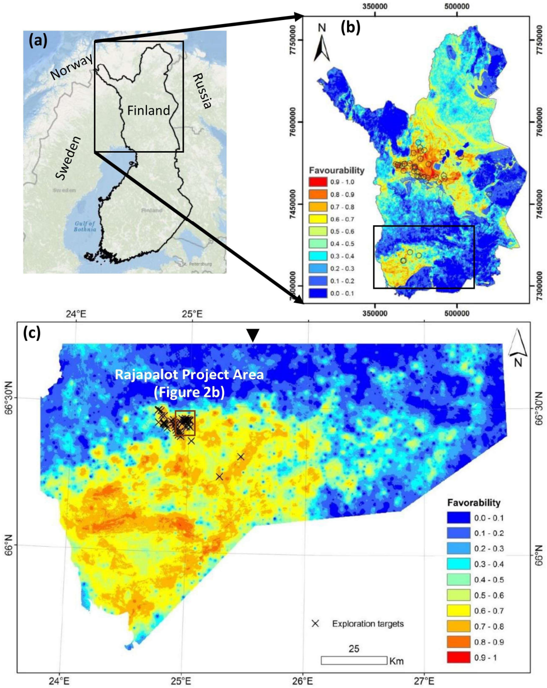






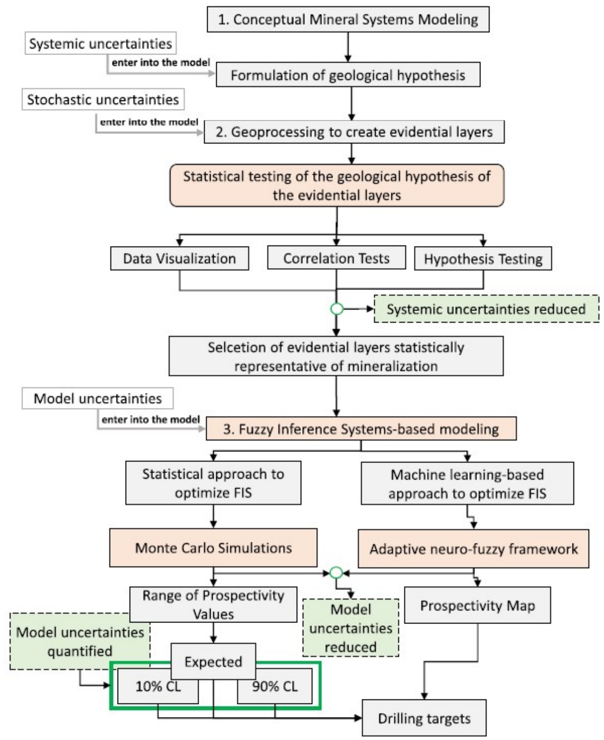
Case studies 3: Rajapalot Au-Co project area

- Chudasama, B., Torppa, J., Nykänen, V., Kinnunen, J., Lerssi, J., Salmirinne, H., 2022. Target-scale prospectivity modeling for gold mineralization within the Rajapalot Au-Co project area in northern Fennoscandian Shield, Finland. Part 1: Application of **knowledge-driven- and machine learning-based-hybrid- expert systems** for exploration targeting and addressing model-based uncertainties. Ore Geology Reviews. Volume 147, 104937, ISSN 0169-1368, https://doi.org/10.1016/j.oregeorev.2022.104937.



Evidential layers:

1. Residual magnetism
2. Distance from magnetic tilt derivative's 0-contour polygon
3. Density of magnetic TD's 0 and +- TD's '0' and '± Π/4' contours
4. AEM: In-phase to Quadrature ratio
5. NW-SE trending anomalies
6. NE-SW trending anomalies
7. Density of gravity worms
8. Residual gravity
9. Density of (interpreted) lithological contacts weighted by their relative competence- OR reactivity- contrasts
10. Densities (interpreted) structures weighted by their sinuosity OR density of structural intersection zones
11. Distance to (interpreted) antiforms-synforms
12. Distance to (interpreted) shear zones
13. Distance to (interpreted) late faults



Case studies 3: Rajapalot Au-Co project area, prospectivity modeling results.

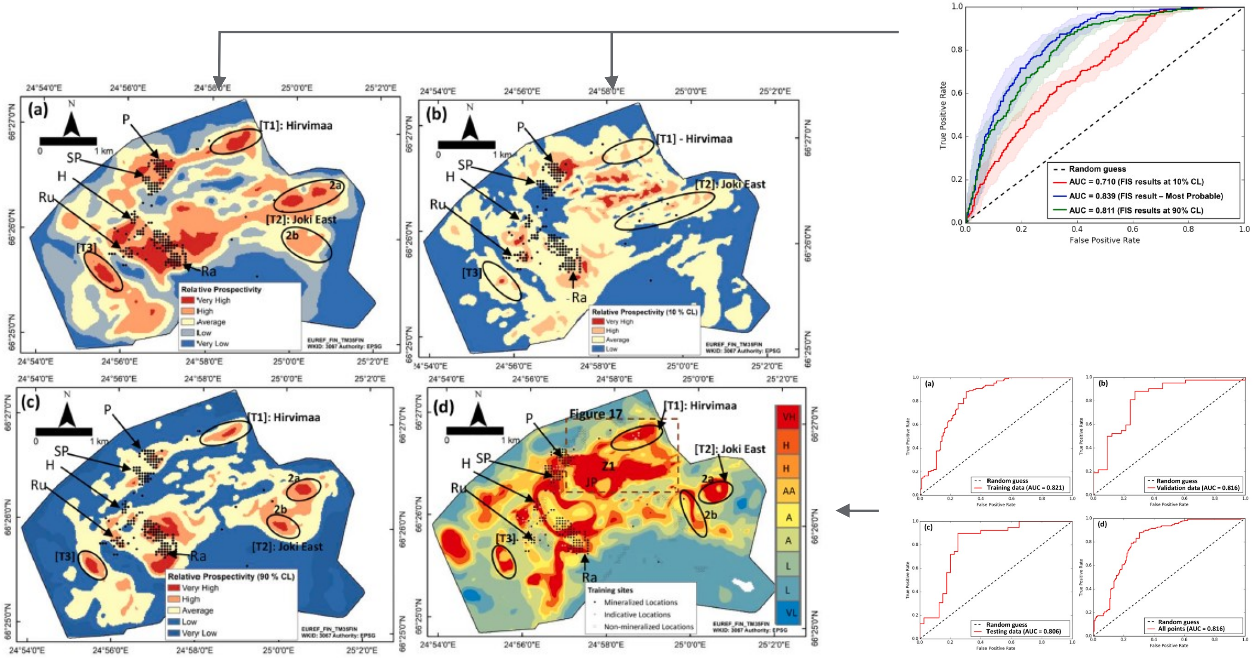
(a) Prospectivity map from the Fuzzy Inference System (FIS) optimized using Monte Carlo Simulation (MCS).

(b) FIS-based prospectivity map at 10% confidence level.

(c) FIS-based prospectivity map at 90% confidence level.

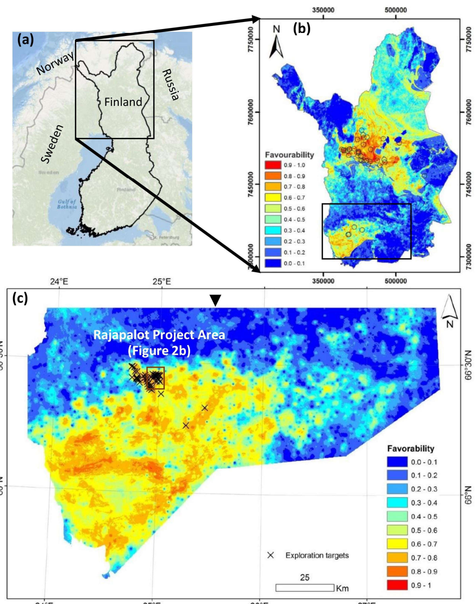
(d) Prospectivity map from ANFIS.

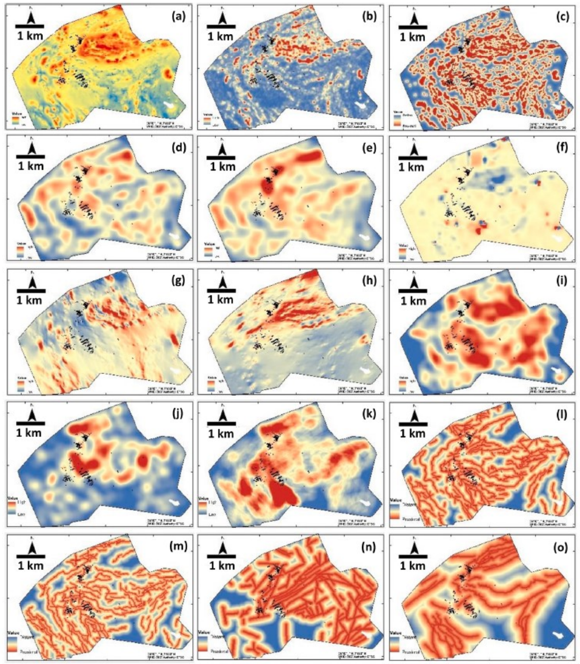
- The known prospects are labelled as
- P: Palokas, SP: South Palokas, Ru: Rumajärvi and Ra: Raja in (a), (b), (c) and (d).
- Exploration targets T1, T2 and T3 are identified in all the prospectivity maps.
- Their prospectivity values increases from the 10% confidence level result in (b) to 90%- confidence level results in (c).
- Hence these exploration targets have high prospectivity values at high confidence



Case studies 4: Rajapalot Au-Co project area

- Chudasama, B., Torppa, J., Nykänen, V., Kinnunen, J. 2022. Target-scale prospectivity modeling for gold mineralization within the Rajapalot Au-Co project area in northern Fennoscandian Shield, Finland. Part 2: Application of **self-organizing maps and artificial neural networks** for exploration targeting, Ore Geology Reviews, Volume 147, 104936, ISSN 0169-1368, https://doi.org/10.1016/j.oregeorev.2022.104936.

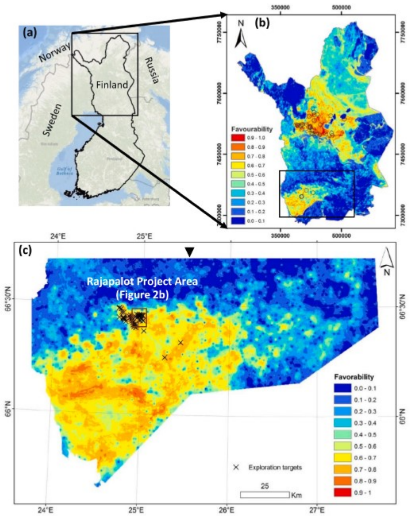


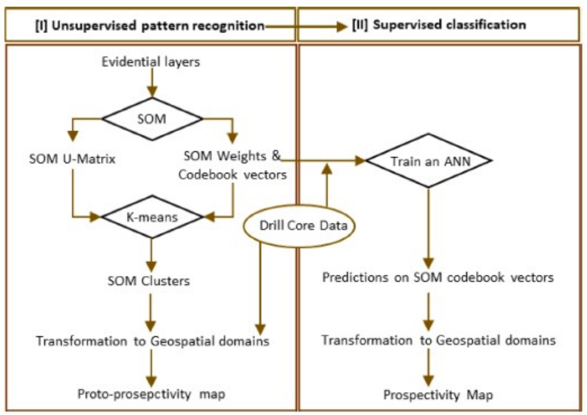


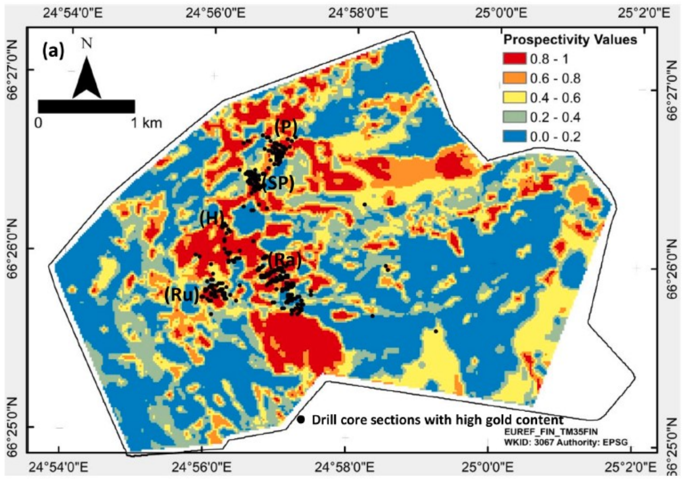
Evidential layers:
(a) Total magnetic intensity corrected for remanent magnetization (nT),
(b) Residual magnetism grid (nT),
(c) Distance from magnetic tilt derivative's 0-contour polygon (m),
(d) Density of (interpreted) lithological contacts weighted by the relative competence contrasts,
(e) Density of (interpreted) lithological contacts weighted by the relative reactivity contrasts,
(f) Ratio of in-phase and quadrature components of airborne electromagetic data,
(g) NW-SE trending magnetic anomalies,
(h) NE-SW trending magnetic anomalies,
(i) Density of magnetic tilt derivative contours,
(j) Density of intersection zones of (interpreted) structures,
(k) Densities of (interpreted) structures weighted by their sinuosity. Distances (in metres) to the following (interpreted) structures-
(l) Antiforms,
(m) Synforms,
(n) Late faults and
(o) Shear zones.
The color scheme represents rescaled values from Low (0) to High (1), grading from blue to red for layers (a) – (k); and Proximal to Distant grading from red to blue for rescaled-distances values in layers (l) – (o).

Case studies 4: Rajapalot Au-Co project area

- Here we demonstrate the application of ML methods such as unsupervised self-organizing maps (SOM) and K-means clustering and supervised artificial neural networks (ANNs).
- The results from SOM allowed the mapping of deposit-related geological patterns in the evidential layers.
- K-means clustering of the SOM results identified data clusters favorable for gold enrichment.
- Quantitative prospectivity values were computed using an ANN model trained on the SOM codebook vectors.
- This improved the resolution of the prospective-exploration areas mapped within the geospatial domains of the clusters, and, reduced the exploration search areas.







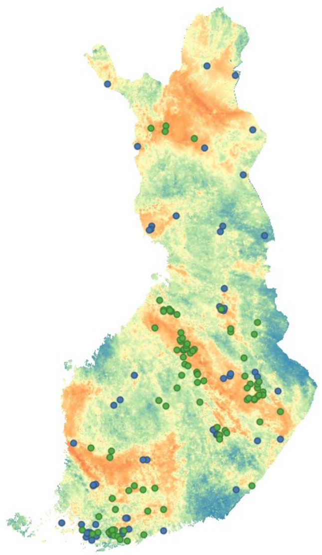
Case studies 5: VMS mineral system (on-going project)

Mineral system component	Mappable Ingredient	Type of data	Regional scale		Camp scale		Deposit scale		VMS model dataset/original data	VMS model dataset/grid
			Vector	Value	Vector	Value	Vector	Value		
	Oceanic crust remnants	Lithology	Metabasalts	high	Metabasalts	high	Metabasalts	high	Volcanic_Rock_and_Serpentinite_proterozoic_yonger_than_2100.shp	Dst2_volcrock_marine.tif
	Oceanic crust remnants	Geophysics	Magnetic or gravimetric anomalies	high	Magnetic or gravimetric anomalies	high	Magnetic or gravimetric anomalies	high	mag_100_dgrf_anomaly.tif	mag_100_dgrf_anomaly.tif
									Gravity worms	dst2_gravwrms_over10k_100.tif
	Clastic-sedimentary input to the basin	Lithology	Quartzite	medium	Quartzite	medium	Quartzite	high	lito_quartz_para_gneis.shp	dst2_qtz_paragn.tif
	Black shales	Lithology	Black shale	high					Black_shale_200k.shp	dst2_blackshale_100.tif
	Intermediate and felsic dikes	Lithology	Not related to VMS processes	high	Not related to VMS processes	high	Not related to VMS processes	high		
Active pathway	Synvolcanic faulting	Regional scale faulting	Shear zones, faults and fractures	high	Shear zones, faults and fractures	medium	Permeable zone	medium	Major_Structures.shp	dst2_major_stru_100.tif
Depositional processes	Geochemical anomalies	Soil geochemistry			Ore elements (Cu, Co, Sb, Pb, Zn, Ag, As, Sn)	high	Ore elements (Cu, Co, Sb, Pb, Zn, Ag, As, Sn)	high	Co_till_idw.tif, Cu_till_idw.tif, Zn_till_idw.tif	Co_till_idw.tif, Cu_till_idw.tif, Zn_till_idw.tif
	Geochemical anomalies	Stream geochemistry			Positive anomaly of ore elements	low	Positive anomaly of ore elements	medium		
	Hydrothermal alteration	Carbonate halo (siderite)			elevated	high	elevated	high		
	Hydrothermal	Positive Eu								

Case studies 5: VMS mineral system

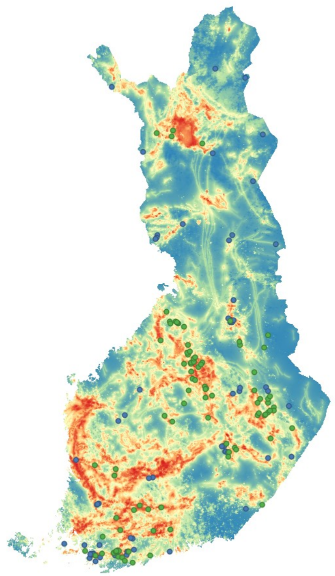
- Case study: Paleoproterozoic VMS prospectivity in Finland
- Methods used: Fuzzy logic, Logistic Regression, Random Forest
- Data used based on critical mineral system parameters
  - *Fuzzy Logic*

ROC AUC = 0.62



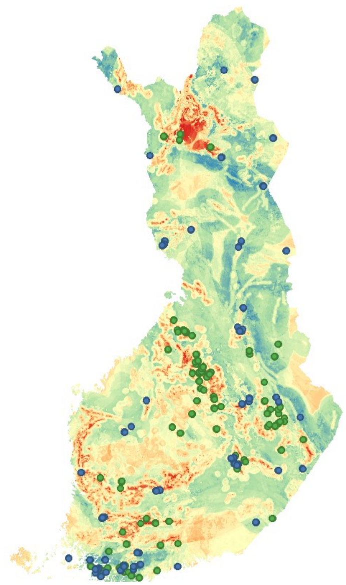
Logistic Regression

ROC AUC = 0.73



Random Forest

ROC AUC = 0.93



Future directions and challenges

- Summary and the key takeaways
  - *Many methods available but no silver bullet*
  - *Data pre-processing i.e. feature engineering is crucial -> garbage in, garbage out*
  - *Machine learning has potential to discover new mineral deposits and areas that were previously overlooked (survival bias) when we use un-supervised methods that can learn from the data and can become aware of also the weak signals*
  - *Machine learning methods have improved the accuracy and efficiency of the MPM in some cases and can therefore reduce the exploration costs and environmental impacts*
  - *Data quality, interpretability and various biases can cause challenges for usage of machine learning in MPM*

Conclusions

- Recommendations for future research and development
  - *Feature engineering needs to be developed*
    - *From mineral systems models into mineral prospectivity models*
    - *How to translate the critical parameters of the mineral systems into mappable proxies of the mineral systems*
  - *Model validation techniques are also important*
    - *What is a meaningful model?*
    - *How to measure performance?*

References

Reference 1
Spatial Data Modeler 5 for ArcGIS pro - ArcSDM
https://github.com/gtkfi/ArcSDM

Reference 2
Mineral Prospectivity Modeler Online Tool - MPM Online
https://gtkdata.gtk.fi/mpm/

Reference 3
Mineral Prospectivity Modeller, MPM project
http://projects.gtk.fi/mpm/index.html

Reference 4
Exploration Information System –EIS
https://eis-he.eu/

Reference 5
Drone Geophysics and Self-Organizing Maps - DroneSOM
https://dronesom.com/

Reference 6
GisSOM
https://github.com/gtkfi/GisSOM

Reference 7
AIMEX
https://projektit.gtk.fi/aimex/

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