Mineral predictive mapping - from intuition to quantitative hybrid 3D modelling

De re Metallica ex libre. Georgius Agricola, 1556

Skarn prospectivity model. Beak, LfULG 2016, Project ROHSA3.1

A. Barth, A. Knobloch, A. Brosig, S. Noack, P. Hielscher, S. Etzold
Beak Consultants GmbH, Freiberg, Germany

BRGM Mineral Prospectivity Conference, Orleans, 24th – 26th October, 2017
Agenda

- History
- Maps and Metallogeny
- Exploration models
- Predictive mapping approaches
- Data issues
- Qualitative and quantitative methods
- 2D, 2.5D and 3D predictive mapping
- Result verification
- Value added products
The first book about mineral predictive mapping

- Facts and knowledge grew over centuries
- Trial and error, guessing and intuition help to bring facts together
- Knowledge was fixed on paper for further use and transfer.
- The first exploration models were created.

Georgius Agricola, 1556: De re Metallica ex libre
The first „geological“ maps were about minerals and mining

The Turin Papyrus Map: 1160 BC. Wadi Hammamat with the bekhen-stone quarry, and the location of gold mines and deposits (https://en.wikipedia.org/wiki/Turin_Papyrus_Map)
The first „geological“ maps showed mines, minerals and outcrops

Luigi Ferdinando Marsigli (1726): Mappa Mineralographica

(Mining map of Northern Transylvania (Romania)).

Outcrops were not yet connected under cover to a real map. The real geological map was not yet born.
Real Geological Maps: a collection of facts, knowledge and intuition


Petrographic Map of the Kingdom of Saxony. J. F. W. Charpentier. 1778

In the 19th century geological maps became the standard for fixing geological knowledge.
1913: The birth of Metallogeny

Louis Launay (1913): Traité de métallogénie: gîtes minéraux et métallifères, gisements, recherche, production et commerce des minéraux utiles et minerais, description des principales mines.

"Metallogeny studies mineral deposits ... in order to determine the laws, ruling their predominant appearance in a particular geological zone....

The mineral deposit is understood as a part of its geological environment.
In the 20th century world-wide metallogenic maps were created

Demonstrate the dependencies between minerals and the geological environment.

Synthesis of geology, tectonics, time, and minerals

Exploration models: another abstraction of the reality. Example: Sn in the Erzgebirge

- Tischendorf, 1969
- Baumann & Tischendorf, 1978
- Seltmann, 1992

120 kt Sn in a breccia pipe on top of a subvolcanic stock
Physico-chemistry created the base for modern mineral deposit formation concepts

A milestone in understanding mineral occurrence formation processes, and consequently a key for identification of prospecting criteria.

Evseeva, Perelman, 1962
Formation of sandstone hosted U, controlled by redox processes
Plate tectonics is the base for many mineral occurrence formation models.

Mineral deposit formation cannot be modelled using traditional mathematics. It is far too complex.

But: we have an ever growing understanding of formation rules and details. And we have an ever growing amount of data.

http://www.pnas.org/content/112/44/13484/F4.expansion.html
In the 80ies the preconditions were prepared for new approaches in mineral prediction:

- Metallogenic concepts/maps
- Exploration models
- Ever growing amount of data, incl. remote sensing
- Available and useable personal computers
- Software: GIS, statistics, the roots of AI

→ Computerization and processing of mass data started

The first summarizing publications were released, e.g.: Bonham-Carter, 1994
We are lost in data and knowledge …

Expert’s knowledge / experience was increasingly supported by modern information technology
The term **mineral prospectivity** refers to the chance or likelihood that mineral deposits of the type sought can be found in a piece of land. It is similar to the terms mineral potential and mineral favourability.....(Carranza, 2009)

The physical and chemical principles governing the formation of mineral deposits are for the most part too complex for direct prediction from mathematically expressed theory ... the **model cannot be expressed in purely mathematical terms** (BONHAM-CARTER, 1994).

Saro Lee, Hyun-Joo Oh, Chul-Ho Heo, Inhye Park (2014): Au-Ag mineral potential map, Korea
The depending variable: **Likelihood** of presence of a mineral occurrence of a certain type in a defined piece of land.

**Controlling parameters:**
Our datasets.

In the predictive process, we establish relationships between the depending variable and the controlling parameters and apply these rules to areas under question by:

- Intuition
- Intuition with mapping tools
- “IT-intuition”: artificial intelligence

Historically, e.g. in medicine, AI based data analysis were used for a long time:

Relationships between diseases and living circumstances etc. but the spatial component was missing.
How to consider spatial dependencies?

A priori, grid cells do not have information about their neighbors.

We need to “teach” the system:

- Distances from/to something (faults, contacts)
- Properties of lineations (strike, dip, size, nature, shape)
- Properties of surfaces (1st & 2nd derivatives: direction, slope, curvature, nature, ….)
- Angles between lineations, surfaces, bodies, ….

Differences between dipping angles of granite surface and host rock foliation

Tectonics is split into many derived datasets
Exploration models:

- Deep understanding of mineral occurrence formation processes

As much as possible relevant data:

- Geology: Tectonics, Metamorphism, Magmatism, Geomorphology,…
- Geochemistry: stream sediments, soils, rocks
- Geophysics: radiometrics, magnetics, electromagnetics, gravimetry, spectral

Algorithms:

- Artificial Intelligence (AI)
AI algorithms supplement (replace?) the geologist’s intuition

Data sets

Metallogenic Models

Locations

Pre-Processing

Extraction of potentially ore controlling features

The artificial neuronal network “replaces” the experts empirical data analysis

The predictive map = Exploration target map
Different groups of data

- Sharp data with clear relationships to the depending variable:
  - Granite cupola and greisen
  - Granite and limestone = skarn
  - High Au-anomaly = mineralisation outcrop

- Datasets with unclear relationships/multiple sources:
  - Mo anomalies are the result of different sources (black shales, greisens, hydrothermal veins, porphyries, ...)
  - Magnetic properties are the result of multiple lithologies in a complex geology
Geological Data

- Geological maps
- 3D models
- A tremendous amount of independent data can be derived
- Geochemical and geophysical properties can be derived

Lithology & faults

Faults

Contact shist / sandstone

Gneiss

Tect NE/SW
Geochemical Data

- Direct indication
- High information content
- Cumbersome to get
- Depending on the scale and accuracy:
  - Stream sediments
  - Soil
  - Rocks

Sample points & catchment areas

Raster (IDW) 20 Points Influence

Grades

Raster: Focal statistics
- Indirect indication
- High resolution is possible
- Various penetration depth
  - Radiometrics, spectrometry – surface
  - Magnetics, gravimetry – deeper structures
- Simple to get
- Expensive
Mapping of alteration minerals
High resolution data possible
Simple to get
Not expensive
Problematic in vegetated areas
Knowledge based and data driven predictive mapping methods

**Knowledge driven approaches**
- We know something and use that knowledge
- We can find only what we know
- We do not need training points

Fuzzy logic, mathematical rules

**Data driven approaches**
- The algorithm finds the dependencies by itself
- We need training points

Statistics, Weights of evidence, artificial neural networks, random forests, logistic regression

**Hybrid approaches**
Combinations of the above
Knowledge based methods: aggregation of data by functions

Knowledge based methods
- We know dependencies and use that knowledge
- We can find only what we know
- We do not need training points
- Prospectivity map = f (evidential maps)
- Fuzzy logic modelling

The inference network shows the combination of evidential maps using logic functions

E.J.M. Carranza: Geochemical Anomaly and Mineral Prospectivity Mapping in GIS. 2009 Elsevier B.V.
Data driven approaches

- The algorithm finds the dependencies by itself.
- We need training points.


Artificial neural networks (ANN)

ANN learn by themselves by considering examples, without task-specific programming, in an iterative process.
Hybrid predictive mapping methods

Hybrid approaches
Combinations of data driven and knowledge based methods

Approach:
- Identification of controlling parameters by knowledge/ separate testing
- Selection and preparation of datasets according to the exploration model
- Analysing the weights of the ANN model
- Analysing histograms of calculation results
- Fitting the model by using the most probable controlling parameters
Qualitative and Quantitative Modelling

**Qualitative Modelling** answers the questions:
- Where?
- What potential (prospectivity/likelihood) at a site (ranked between 0 and 1)?

**Quantitative Modelling** answers the questions:
- Where?
- How much at a site (grades, tonnages or similar)?

Quantitative modelling becomes possible if we use numbers, e.g. grades/ specific resources as input values, e.g. for neural network applications.

The requirements for input data are much higher: we need a reasonable amount of quantities for network training.
Example - Gold in SW Ghana: location and size of potential targets

- 68,000 sqkm
- 350 mineralisation points
- Airborne magnetics
- Geology
- Ranking of mineralisations according to their size


Geological and geophysical data provided by Geological Survey Department, Ghana, 2012
Gold potential in the Birimian, SW Ghana

Qualitative modelling.

The ANN created predictive map is:
- Easy to read
- Sufficient accurate (100 m)
- Represents existing knowledge
- Upgradable
- Usable for national/ regional planning activities
- Base for governance maps:
  - Protect resources
  - Guide big investment
  - Guide small scale mining
  - Analyze conflicts
  - Plan long term land use
Where are the most prospective targets?

The depending variable is the “size” of the occurrence.

- Prospects located in areas with a potential of > 0.8
- All other prospects

Barth, Knobloch, Boamah, 2013
Identification of new opportunities in a traditional mining region

Method: Predictive 2.5D and 3D Modelling with ANN

Sn-occurrences and Sn-anomalies in the Erzgebirge
Data base: Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie

ROHSA 3.1 project
2.5D Model.
Research Project of the Saxon Government. Executed by the Saxon State Office for Environment, Agriculture and Geology. 2016.

Advangeo 3D Model
Erzgebirge
Beak, 2017
Predictive 2,5D and 3D Modelling: approaches and preconditions

2.5 D Modelling: similar to 2D, the data-value is the elevation. GIS is sufficient.

3 D Modelling: using Voxel models. Real 3D software required.

Algorithms:
• Similar to 2D: knowledge based, data driven, hybrid

Preconditions:
• High quality 3D data: geology, geophysics, geochemistry, minerals
• Software
The 2.5D model of the Central Erzgebirge

**Algorithms:**
- ANN

**Software:**
ESRI & advanceo®

**Database:**
- 196 Reports
- 531 Maps
- 423 Sections
- 2014 Bore holes > 20m
- Geochemical data
- Geophysical data

Dipping angle: Difference between Granite surface and Carbonate layers

Skarn formation potential in carbonate rocks
Estimated amount of Sn in skarns in the Central Erzgebirge

Tin content:
- Within the contour > 0.25: 775.888 t
- Within the contour > 0.5: 593.034 t

Known Tin Resources of all classes: 83.490 t
Estimated from model data within these blocks: 86.040 t

11% of the estimated Sn potential are discovered so far

Data base: Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie
2.5D Model of the ROHSA 3.1 Project
Real 3D Predictive Modelling: The Erzgebirge Project

- 9500 sqkm
- Vertical extension: +1214 m → -3000 m
- 250 reports
- 22,000 bore holes
- 800 Maps
- 270 sections
- Geophysical data: magnetics, radiometry, gravimetry

Base Data provided by Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie
Modelling the Northern Rim

Concealed granite modelled by inverse modelling using airborne magnetic and gravimetric data.

Sn skarn and Sn vein potential modelled by using ANN.

Software: GoCAD, Geomodeller, 3D advangeo®
Sn in the Northern Rim

Consideration of real 3D properties derived from the geological model.

Sn skarn and Sn vein potential modelled by using ANN.

Please see the poster session:
Brosig et. al: Mineral predictive mapping in 2D, 2.5D and 3D using Artificial Neural Networks – Case study of Sn and W deposits in the Erzgebirge, Germany

Base Data provided by Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie
How reliable is the model?

What kind of ore bodies are behind this drilled pattern?
This interpretation looks reasonable…….
But this is possible as well.
Model verification procedures

How close is the model to the truth? How reliable is the model?

Important approaches:
• Cross validation: discovery of “yes” values not used for modelling, but: we miss their information as training points
• Statistics: histograms of all data vs. “yes” points
• The error curve (ANN)
• X-Y plots in case of quantitative modelling (ANN)
• Verification by other methods
• Repeated calculation (ANN)
• The plausibility/ value of the weights (ANN)

E.J.M. Carranza, 2009
The Contest Data: ANN based Sensitivity Analysis

RTP abs value

100 iterations
Error: 0.22
Max. prosp: 0.44

RTP slope

100 iterations
Error: 0.20
Max. prosp: 0.52

All points
“yes” points
100 iterations
Error: 0.17
Max. prosp: 0.99
1000 iterations
Error: 0.17
Max. prosp: 0.99

The approximation is much better, but the model is overfitted
Our final model – mainly controlled by geological parameters

19 data layers

100 iterations
Error: 0.045
Max. prosp: 1.0

All points

“yes” points

The Weights

BRGM Mineral Prospectivity Conference, Orleans, 24th – 26th October, 2017
Example: Quantitative Modelling of Mn Nodule Resources

- 17 input layers
- 1000 iterations
- Excellent verification of ANN resources by classic statistics (Kriging Model)


Measured vs. Predicted Nodule Coverage Density

ANN Resource vs. Kriging Resource
Predictive maps as value added products

• Guide exploration activities
  • Support exploration targeting
  • Attract investment
  • Support small scale mining

• Protect resources !!!
  • No further blocking by roads, settlements, water dams,….
  • Keep resources available for the future

• Integrate mining into social and economic development

• Minimize conflicts with:
  • Agriculture
  • Nature conservation
  • Ground water protection…. 
Gold in SW Ghana: Conflict with forest reserves

Prospects located in areas with a potential of > 0.7

All other prospects

Forest reserves
Detailed conflict map

Forest areas

High potential areas

Major prospects/ mines

Artisanal Placer Gold Mining in Ghana
The spatial planning process

Spatial planning decision process

Mineral deposits & mining preferences
- forestry preferences
- Infrastructure preferences
- housing preferences
- agriculture preferences
- Nature conservancy preferences
- other preferences

National Development Plan
(covers 10 – 15 years)
Set of thematic maps and explanations
A few words about the future

- Further development of technologies and approaches: AI, 3D, remote sensing data, verification procedures, interactive technologies

- We need user friendly application software.

- Process more data: The problem is not missing data but missing data processing.

- Make practical use of the results: Exploration targeting, land use planning, Resource protection, etc.

→ Internet

http://www.europe-geology.eu/mineral-resources/mineral-resources-map/
Conclusions

• MPM are ready to use reliable approaches. Even in traditional mining regions new opportunities can be identified.

• Most accurate results provide hybrid methods.

• MPM create important value added products for decision making & investment attraction.

• Required are easy to use software products, integrating data pre-processing, data analysis, reliability evaluation and visualization features.
Thank You!

We wish all of us a successful conference, new ideas, contacts, interesting discussions, and of course new projects and discoveries.

https://www.rohsa.sachsen.de/download/A_Barth_Hoeffigkeitsbewertung_des_Mittleren_Erzgebirges.pdf

www.beak.de
andreas.barth@beak.de